VISUAL ANALYSIS OF FACES WITH APPLICATION IN BIOMETRICS, FORENSICS AND HEALTH INFORMATICS

PH.D. DISSERTATION

by

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CV

Mohammad A. Haque

Mohammad A. Haque received the BS degree in Computer Science and Engineering from the University of Chittagong, Bangladesh, in 2008 and the MS degree in Computer Engineering and Information Technology from the University of Ulsan, South Korea, in 2012. He started his PhD study in Computer Vision at the Department of Architecture, Design and Media Technology, Aalborg University, Denmark, at Nov 2012.

Mohammad was a tenured lecturer at the Department of Computer and Communication Engineering, International Islamic University Chittagong, Bangladesh. He started his research career by working on Biometrics and Image Processing during his undergraduate study. Later he expressed his interest to machine learning and audio-visual signal processing, and defended his Master's thesis on machine learning. His PhD study was aiming to developing computer vision methods for automatic in-home patient monitoring by focusing on the analysis of human facial videos.

Mohammad has a number of publications in indexed journals and peer-reviewed international conferences in all of the aforementioned research areas. He received scholarships and funding from Bangladesh, South Korea, Denmark, and European Union for his study and research. He is a member of Visual Analysis of people Lab, Aalborg University, Denmark. He was also a member of Center for Machine Vision, Oulu University, Finland as a visiting researcher and Embedded Systems Lab, Ulsan University, South Korea as a research assistant.

Mohammad has supervised a number of individual students and groups for research and project works. His current research interests are visual analysis of people, biometrics, and decision support systems in health informatics.

ENGLISH SUMMARY

Computer vision-based analysis of human facial video provides information regarding to expression, diseases symptoms, and physiological parameters such as heartbeat rate, blood pressure and respiratory rate. It also provides a convenient source of heartbeat signal to be used in biometrics and forensics. This thesis is a collection of works done in five themes in the realm of computer vision-based facial image analysis: Monitoring elderly patients at private homes, Face quality assessment, Measurement of physiological parameters, Contact-free heartbeat biometrics, and Decision support system for healthcare.

The work related to monitoring elderly patients at private homes includes a detailed survey and review of the monitoring technologies relevant to older patients living at home by discussing previous reviews and relevant taxonomies, different scenarios for home monitoring solutions for older patients, sensing and data acquisition techniques, data processing and analysis techniques, available datasets for research and development, and current challenges and future research directions.

Face quality assessment theme include works related to the application of a face quality assessment technique in acquiring high quality face sequence in real-time and alignment of face for further analysis.

In measuring physiological parameters, two parameters are considered among many different physiological parameters: heartbeat rate and physical fatigue. Though heartbeat rate estimation from video is available in the literature, this thesis proposes an improved method by using a new heartbeat footprint tracking approach in the face. The thesis also introduces a novel way of analyzing heartbeat traces in facial video to provide visible heartbeat peaks in the signal. A method for physical fatigue time offset detection from facial video is also introduced.

One of the major contributions of the thesis is introducing heartbeat signal from facial video as a novel biometric trait. The way to extract and utilize this biometric trait in person recognition and face spoofing detection is described.

In the last part, the thesis introduces an approach for generating facial expression log as a decision support tool by employing a face quality assessment technique to reduce erroneous expression rating.

Despite of the solutions introduced in this thesis, ample of new research questions have brought forward to be solved in advancing the areas of health informatics, biometrics and forensics.

DANSK RESUME

Videoanalyse af ansigter med computer vision kan give information om udtryk, sygdomme, symptomer og fysiologiske parametre som hjertefrekvens, blodtryk og respirationsfrekvens. Det er også en oplagt kilde til pulssignaler til brug i biometri og kriminaltekniske formål. Denne afhandling er en samling af arbejde indenfor fem områder af billedanalyse på ansigtet: Overvågning af ældre patienter i private hjem, kvalitet af ansigtsbilleder, måling af fysiologiske parametre, kontaktfri måling af puls, samt et beslutningsstøttesystem til medicinsk brug.

Arbejdet med overvågning af ældre i deres hjem inkluderer en detaljeret oversigt og gennemgang af teknikker relevante for ældre patienter, der bor i egne hjem. Tidligere publikationer og relevante taksonomier gennemgås, sammen med forskellige scenarier for overvågningssystemer i ældres hjem, sensor- og dataoptagelsestekninner, databehandlings- og analyseteknikker, tilgængelige datasæt, samt nuværende udfordringer og fremtidige forskningsspørgsmål.

Vurdering af ansigtskvalitet har været brugt for at finde højkvalitets ansigtsbilledsekvender i realtid sammen med justering af ansigtets position på tværs af billederne til videre analyse.

De fysiologiske parametre der er målt er to blandt mange: Hjertefrekvens og fysisk træthed. Selvom bestemmelse af hjertefrekvens i video er kendt fra litteraturen, fremlægger denne afhandling en forbedret metode, der anvender en ny mønstergenkendelse af hjertefrevens i ansigtet. Afhandlingen introducerer også en ny måde til at analysere spor af hjerteslag i ansigtsvideo, der giver synlige spidser i hjertesignalet. Yderligere introduceres også en metode til måling af fysisk træthed fra ansigtsvideo.

Et af de mest markante resultater af arbejder er anvendelsen af hjertesignaler fra ansigtsvideo som et biometrisk signal. Det beskrives hvordan dette kan måles og anvendes til persongenkendelse og forhindring af svindel med ansigtsgenkendelse.

I det sidste kapitel introduceres en metode, der kan generere en log over ansigtsudtryk som et beslutningsstøttesystem. Den bruger en ansigtskvalitetsvurdering for at mindske mængden af fejl i klassifikationen.

Trods de nye løsninger som denne afhandling introducerer er der også fremkommet en række nye forskningsspørgsmål, der kan give fremskidt indenfor sundheds-IT, biometri og kriminaltekniske applikationer.

ACKNOWLEDGEMENTS

PhD study is not simply reading, defining scientific problem and finding out solution. Contributing in generating new knowledge (also learning how to) is sometimes joyful and interestingly challenging. But it is not a bed of roses and sometimes full of anxiety and depression. Realizing these in every moment in the last three years of continuous endeavor I would like acknowledge some significant points here.

This PhD thesis is an expedition that I could not be completed without the blessings of the almighty Allah and motivation from the sunnah of prophet Muhammad (peace be upon him).

I would like to express my sincere gratitude to my mentors Prof. Thomas B. Moeslund and Kamal Nasrollahi, for their support, encouragement and guidance throughout this research. They directed this research with competence, instilling their enthusiasm, providing support in uncountable occasions. When Thomas showed me the roadmap, Kamal gave me the vehicles along with his academic accompany to accomplish this journey. This work would not have been completed without their help and practically infinite supply of comments and ideas. It has been a great honor to work with them during my stay at Aalborg University. I would also express my gratitude to Prof. Abdenour Hadid, Zinel and Elhocine for their warm welcoming and collaboration during my stay at Oulu University, Finland.

I would like to thank all of my colleagues in the Visual Analysis of People Laboratory (especially Rikke, Andreas, Humain, Chris, Jeppe, Wazahat and Theodore) and, at a larger extent, my colleagues in the Media Technology section of the Department of Architecture, Design and Media Technology. Their cordial attitude to help me set up in new to me Danish academic environment, occasional comments on my research, help in experimental data collections, and collaborations made my study easier and enjoyable.

I would like to especially express my gratitude to Ramin Irani - my colleague and my friend - who spent hours of time, talked positively, collaborated in research, and provided courage in the time of anxiety throughout my PhD study. Special thanks also go to Mahmudul Hasan who was here in Aalborg for around one year and, during that time, gifted me some of the memorable moments by providing spiritual time and deeply thought words both academically and socially.

At this point, I would delightedly like to acknowledge the contributions of my friends of a tiny but joyful Bangladeshi community in Aalborg. Tanvir Ahmed Masum, Md. Saifuddin Khalid and Mohammad Bakhtiar Rana along with their family deserve my gratitude for their hospitality and warm support both academically and spiritually during my life in Aalborg. Mahfuza Begum and her family also provided me mental peace in the sense of guardianship and spiritual binding. Other members of this community are also just remarkable to be accompanied with during this stressful period of PhD endeavor.

While pursuing my PhD, I was socially engage in social and spiritual volunteering with substantial dedication under the umbrella of Islamic Welfare Society of Denmark. I would like to share a great deal of my achievement with my brothers and sisters involved in this organization for their support and encouragement in my spiritual life in Denmark that helped me balancing my study and social life during last three years.

Last but not least, I would like to mention the sacrifice of my family members. My father Muhammad K. Alam, mother Murshida Akter, elder sister Khurshida Yeamin (and her family), brother Muhammad N. H. Ashif (and his family), and younger sister Sharmina Alam don't like my stay out of their company, but they accepted it for the sake of the achievement of this thesis. My wife Umme S. Maryam and children (two little angels Raiyaan Zaheen and Rashdan Zawad) simply suppress their rights of having my presence with them and sacrificed years of warm family moments to help me finishing this expedition. Maryam may not get a PhD from a university as recognition for her effort and sacrifice during this period, but she definitely deserves a degree of honor for her support to me while managing her own full-time undergraduate study and two young kids. I can do nothing but supplicating (d'ua) for all of them to get rewards hereafter and express my heartfelt gratitude for their sacrifice.

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THESIS DETAILS

Thesis Title: Visual Analysis of Faces with Application in Biometrics, Forensics and Health Informatics

PhD Student: Mohammad A. Haque

Supervisor: Prof. Thomas B. Moeslund, Aalborg University

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This thesis has been submitted for assessment in partial fulfillment of the PhD degree. The thesis is based on the submitted or published (at the time of handing in the thesis) scientific paper which are listed below. Parts of the papers are used directly or indirectly in the extended summary of the thesis in the introductory section. As part of assessment, co-author statements to explicitly mentioning my contributions have been made available to the assessment committee and are also available at the Faculty.

The main body of this thesis consists of the following book and papers divided into five research themes presented in the thesis (the index number of the articles refers to the part and chapter of the thesis it is presented):

PART II: Literature review: Monitoring elderly patients at private homes

[2] J. Klonovs, M. A. Haque, V. Krueger, K. Nasrollahi, K. Andersen-Ranberg, T. B. Moeslund, and E. G. Spaich, *Distributed Computing and Monitoring Technologies for Older Patients*, 1st ed. Springer International Publishing, 2015.

PART III: Face quality assessment

[3] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, "Real-time acquisition of high quality face sequences from an active pan-tilt-zoom camera," in *10th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, 2013, pp. 443–448.

[4] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, "Quality-Aware Estimation of Facial Landmarks in Video Sequences," in *IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2015, pp. 1–8.

PART IV: Measurement of physiological parameters

[5] M. A. Haque, R. Irani, K. Nasrollahi, and T. B. Moeslund, “Heartbeat Rate Measurement from Facial Video (accepted),” *IEEE Intell. Syst.*, Dec. 2015.

[6] M. A. Haque, R. Irani, K. Nasrollahi, and T. B. Moeslund, “Facial Video based Detection of Physical Fatigue for Maximal Muscle Activity (accpeted),” *IET Comput. Vis.*, 2016.

[7] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, “Multimodal Estimation of Heartbeat Peak Locations and Heartbeat Rate from Facial Video using Empirical Mode Decomposition (Submitted),” *IEEE Trans. Multimed.*, 2016.

PART V: Contact-free heartbeat biometrics

[8] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, “Heartbeat Signal from Facial Video for Biometric Recognition,” in *Image Analysis*, R. R. Paulsen and K. S. Pedersen, Eds. Springer International Publishing, 2015, pp. 165–174.

[9] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, “Can contact-free measurement of heartbeat signal be used in forensics?,” in *23rd European Signal Processing Conference (EUSIPCO)*, Nice, France, 2015, pp. 1–5.

[10] K. Nasrollahi, M. A. Haque, R. Irani, and T. B. Moeslund, “Contact-Free Heartbeat Signal for Human Identification and Forensics (submitted),” in *Biometrics in Forensic Sciences*, 2016, pp. 1–14.

PART VI: Decision support system for healthcare

[11] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, “Constructing Facial Expression Log from Video Sequences using Face Quality Assessment,” in *9th International Conference on Computer Vision Theory and Applications (VISAPP)*, 2014, pp. 1–8.

In addition to the focal papers listed above, following scientific articles have also been published during the time of PhD:

[1] M. S. Hossain, M. A. Haque, R. Mustafa, R. Karim, H. C. Dey, and M. Yusuf, “An Expert System to Assist the Diagnosis of Ischemic

Heart Disease (accepted)," *Internatinal J. Integr. Care*, pp. 1–2, May 2016.

[2] M. A. Haque, K. Nasrollahi, and T. B. Moeslund, "Efficient contact-less heartbeat rate measurement for health monitoring," *Internatinal J. Integr. Care*, vol. 15, no. 7, pp. 1–2, Oct. 2015.

[3] R. A. Andersen, K. Nasrollahi, T. B. Moeslund, and M. A. Haque, "Interfacing assessment using facial expression recognition," in *2014 International Conference on Computer Vision Theory and Applications (VISAPP)*, 2014, vol. 3, pp. 186–193.

[4] M. S. Hossain, E. Hossain, M. S. Khalid, and M. A. Haque, "A Belief Rule-Based (BRB) Decision Support System for Assessing Clinical Asthma Suspicion," presented at the Scandinavian Conference on Health Informatics (SHI), 2014, pp. 83–89.

PREFACE

This thesis is submitted as a collection of paper in partial fulfillment of a PhD study in the area of Computer Vision at the Section of Media Technology, Aalborg University, Denmark. It is organized in six parts. The first part contains the framework of the thesis with a summary of the contributions. The rest of the parts contain layout-revised articles published in different venues in connection to the research carried out during the PhD study.

The focus of this thesis is analyzing human facial video and extracting meaningful information in health monitoring scenarios. The core contributions of the thesis are divided into five themes: Monitoring elderly patients at private homes, Face quality assessment, Measurement of physiological parameters, Contact-free heartbeat biometrics, and Decision support system for healthcare. One book (with seven chapters) and 9 articles have been included in the thesis.

The work has been carried out from Nov 2012 to Mar 2016 as a part of the project 'Patient@Home' that is the Denmark's largest welfare-technological research and innovation initiative with focus on new technologies and services aimed at especially rehabilitation and monitoring activities within the Danish public health sector. The project aimed to have collaborations between health professionals, patients, private enterprises and research institutions. While writing this thesis I have collaboration with academicians from the other departments of Aalborg University, Denmark, Oulu University, Finland and doctors from university hospitals. Some of the works have also been accomplished by collaborating people from Chittagong University and International Islamic University Chittagong, Bangladesh; however these works haven't been included in the core contributions of the thesis. I was employed as a PhD fellow with both research and teaching responsibilities during the time of PhD study.

Computer vision-based health monitoring is a relatively new but rapidly growing field. Numerous research groups in all over the planet is working to pace up the development. This thesis's contribution is a new leaf in this area and, along with some solutions proposed here to some problems it also provides an overview of the advances in this field with ample of future research questions.

Have a nice reading!

PART I

OVERVIEW OF THE WORK

CHAPTER 1. FRAMEWORK OF THE THESIS

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1.1. ABSTRACT

Human facial video can convey information regarding to expression, mental condition, diseases symptoms, and physiological parameters such as heartbeat rate, blood pressure and respiratory rate. It also provides a convenient source of heart-beat signal to be used in biometrics and forensics. This dissertation includes stories of facial video analysis with application in biometrics, forensics and health informatics. This chapter presents the main themes and summary of the contributions of the research endeavors during last three years in pursuance of a doctoral degree.

1.2. INTRODUCTION

Traditionally elderly people living with family members or a house-keeper are monitored and helped manually by their house mates with the help of professional care givers. Their health conditions were checked by visiting hospital, and in case of adverse condition patient got admitted to the hospital. Demographic changes due to the aging of population exhibit rapid increase of elderly population. Two major problems that come along with such change are increase living alone and lack of supervision when needed in a vulnerable health condition [1]. Such problems in turns demand the development of technologies for independent elderly living at private homes. Healthcare providers also have long sought the ability to continuously and automatically monitor patients beyond the confines of physicians' concerns. Improvement of human activity and health monitoring technologies provides the notion to address such need.

Advances of computing and sensing technologies in last few decades have created, with many other, an amazing field called computer vision, where the question is answered- how computer sense and reason by looking into a scene. Computer vision techniques are now-a-day not only used in safety, comfort, fun and access control but also in health monitoring and security. Computer-vision based non-contact diagnostic and monitoring systems get considerable attention in research and development of health technologies in order to setup a proactive and preventive healthcare model. In addition to healthcare technologies, improved well-being of life long ago initiated an era of vision-based biometrical recognition and forensic investigation.

Computer vision uses camera to capture a scene in visual color, depth and/or thermal domain. When human facial video is captured by a camera, by employing computer vision techniques it conveys information regarding to expression [2], [3], mental condition [4], [5], diseases symptoms [6], and physiological parameters such as heartbeat rate, blood pressure and respiratory rate [7], [8]. It also provide a convenient source of information to be used in applications like biometrics and forensics [8]–[10].

Facial video analysis for an application follows a multi-step procedure. The first step is acquisition of facial video by camera. This step requires selection of appropriate camera and need to be certain that suitable facial video has been captured. The second step is selecting appropriate facial features to analyze, which are depending upon the applications. The third and final step is employing the selected features to obtain the outcome. There are a number of challenges exist in utilizing facial image in different applications by following the aforementioned procedure. Among these, three of the challenges are introduced as follows.

The first challenge is associated with acquisition of qualified and applicable facial images from a camera setup or a video clip [11]. When a video based practical image acquisition system produces too many facial images to be processed for further analysis, most of these image are subjected to the problems of low resolution, high pose variation, extreme brightness or image blur [12]. The application performance greatly depends upon the quality of the face in the image. For example, a human face at 5 meters distance from the camera subtends only about 4x6 pixels on a 640x480 sensor with 130 degrees field of view, which is mostly insufficient resolution for further processing [13]. Thus, a quality aware method for facial image acquisition is necessary. Moreover, the influence of face quality assessment in the outcome of an application is still unknown due to lack of methodical study on this topic.

The second challenge arises in selection of appropriate facial features to be tracked in an application. Different applications require different set of features to be used. For example, Viola et al. extracted some haar-like features for automatic face detection [14], Palestra et al. used variation of geometrical features for facial expression recognition [2], Li et al. used appearance based features from lip for disease diagnosis [6], and Balakrisnan et al. tracked some facial feature points to estimate heartbeat [15]. Thus, which features to be selected is necessary to be investigated.

The third challenge is associated with how to employ the selection features to obtain the outcome of an application. While some application requires simple template matching based on facial features [2], [6], [9], other applications may need tracking the facial region in the video frames [16], finding out facial color changes in the video frames [7], [17], aligning face [18], and tracking facial feature or landmark points [15]. How to utilize the feature to generate the outcome, thus, implies a challenge to be addressed.

The motivation of this thesis is associated with addressing the aforementioned three problems occurred in facial color video analysis in the light of an application. The solutions are proposed by focusing the application: *physiological parameter measurement*. Among various physiological parameters, two vital signs heartbeat and physical fatigue are estimated and detected, respectively, from facial video. While proposing the solutions, this thesis answers the questions like:

a) How low quality faces in the video affect the performance of measuring these parameters
b) How to acquire high quality face sequences
c) Which features to extract and how to extract for analysis
d) How to analyze these features to obtain the outcome

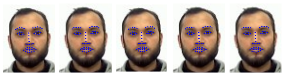
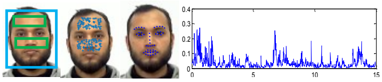
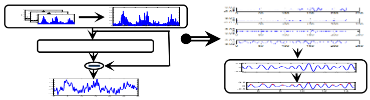
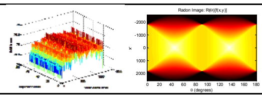
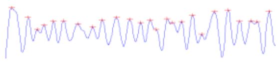
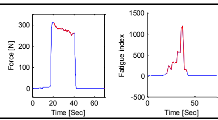
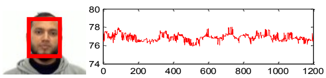
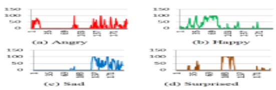
In addition to the aforementioned three major challenges, facial image based research may exhibit question like 'what can be new applications based on facial video'. Besides the traditional application like surveillance, recent advances in automatic facial video analysis showed other incredible applications like diseases diagnosis, heartbeat rate estimation, surveillance, biometric and forensic analysis, etc. However, the trend shows that these applications are just the tip of the iceberg that represents the potential of automatic face analysis. Thus, this thesis also presents a quest to propose a new application of automatic facial video analysis by extracting heartbeat signal from facial video as a new biometric trait.

In summary, this dissertation includes stories of facial video analysis with application in biometrics, forensics and health informatics. The thesis provides a descriptive introduction to the monitoring technologies available for assisted elderly living, addresses the methodical problems of existing facial video-based heartbeat (and rate) estimation and physical fatigue detection approaches, proposed a novel biometric trait from facial video with application in forensics, and proposed a face-quality aware decision support system using facial expression from a video. The contributions are arranged into the following five themes:

I. Literature review: Monitoring elderly patients at private homes
II. Face quality assessment
III. Measurement of physiological parameters
IV. Contact-free heartbeat biometrics
V. Decision support system for healthcare

These five themes are chosen in such a way that the thesis are divided into parts representing the themes and individual chapter (consisting of single published articles) in these parts present homogeneity of application area for visual analysis of face under each part. The following sections provide a brief introduction of each theme and associated contributions of the thesis in that theme along with the mentioning of '*where to find that contribution*' in the thesis. Table 1-1 shows the key contents of the thesis in relation to the challenges of facial video analysis discussed before along with some descriptive figures.

Table 1-1 Contents of the thesis in relation to the challenges associated with of facial video analysis

	Content description	Figurative illustration	Where to find
	Raw facial video frames from camera		
Preprocessing	Face quality assessment to select good quality faces		Ch. 3
	Quality-aware face alignment by detecting the landmarks		Ch. 4
Feature selection and tracking	Facial feature points and landmarks to track periodic color change and motion due to heartbeat		Ch. 5, 6, 7 & 8
Feature processing	Filtering and decomposition		Ch. 5 & 7
	Energy estimation		Ch. 6
	Transformation		Ch. 8
Applications	Heartbeat rate estimation		Ch. 5 & 7
	Physical fatigue detection		Ch. 6
	Heartbeat signal from facial video as biometric		Ch. 8, 9 & 10
	Facial expression log		Ch. 11

1.3. LITERATURE REVIEW: MONITORING ELDERLY PATIENTS AT PRIVATE HOMES

Demographic and cultural changes in industrialized countries induce an increased risk of living alone and with having a potentially smaller social network [19]. These imply the necessity of automatic health monitoring and assisted living systems to be used more frequently for timely detection of health threats at home. In-home monitoring technology can nowadays be used on both healthy older adults, for detecting health threatening situations, and geriatric patients, for detecting adverse events or health deterioration. Therefore, there is a vastly growing interest in developing robust unobtrusive ubiquitous home-based health monitoring systems and services that can help older home dwellers to live safely and independently. However, due to the high variety of possible scenarios and circumstances, keeping track on health conditions of an older individual at home may be exceedingly difficult. Figure 1-1 shows a scenario in laboratory environment that was implemented to capture data for automatic contactless heartbeat monitoring using a camera.

This theme of the thesis includes the issues regarding to automated in-home monitoring technologies for elderly by describing- a) which health threats should be detected, b) what data is relevant for detecting these health threats, and c) how to acquire the right data about an older home dweller. We summarize recently deployed monitoring approaches with a focus on automatically detecting health threats for older patients living alone at home. First, in order to give an overview of the problems at hand, we briefly describe older adults, who would mostly benefit from healthcare supervision, and explain their eventual health-threats and dangerous situations, which need to be timely detected. Second, we summarize possible scenarios for monitoring an older patient at home and derive common functional requirements for monitoring technology. Third, we identify the realistic state-of-the-art technological monitoring approaches, which are practically applicable to older adults, in general, and to geriatric patients, in particular. In order to uncover the majority of applicable solutions, we survey the interdisciplinary fields of smart-homes, telemonitoring, ambient intelligence, ambient assisted living, gerotechnology, and aging-in-place technology, among others. Consequently, we discuss the related experimental studies and how they collect and analyze the measured data, reporting the application of sensor fusion, signal processing and machine learning techniques whenever possible, which are shown to be useful for improving the detection and identification of the situations that can threaten older adults' health. Finally, we discuss future challenges and offer a number of suggestions for further research directions, and conclude by highlighting the open issues within automatic healthcare technologies and link them to the potential solutions.

This part of the thesis consists of a book, title 'Distributed Computing and Monitoring Technologies for Older Patients' as published in [1] with seven subchapters.

Figure 1-1 A scenario in laboratory environment for physiological signal acquisition aimed at automatic health monitoring (obtained from [20]).

1.4. FACE QUALITY ASSESSMENT

Acquisition of facial image (or video) is the first step of many important facial image-based applications related to surveillance, medical diagnosis, biometrics, expression recognition and social cue analysis [8]. Traditional camera-based of facial image acquisition systems often capture low quality face images. This is mainly due to the distance between the camera and subjects of interest, movement of subjects, and changing head poses and facial expression. Furthermore, the imaging conditions like illumination, occlusion, and noise may change. However, the application performance greatly depends upon the quality of the facial image. In order to get rid of the problem of having low quality facial image, a Face Quality Assessment (FQA) technique can be employed to select the qualified faces from the image frames captured by a camera. On the other hand, if a facial video has low quality faces, further processing for application like face alignment exhibits low accuracy in detecting facial landmarks. When a high quality face image is provided to a face alignment system, it detects the landmarks very accurately. However, when the face quality is low, the detected landmark positions are not trustworthy. Figure 1-2 illustrate a case of low quality face (in terms of high pose variation) and associated challenge in face alignment. To deal with the alignment problem of low quality facial images, a FQA system can be employed before running the alignment algorithm. Such a system uses some quality measures to determine whether a face is qualified enough and provides assistance to further analysis by providing the quality rating.

This part of the thesis consists of two chapters by following [21] and [12]. The first chapter proposes an active camera-based real-time high-quality facial image acquisition system, which utilizes pan-tilt-zoom parameters of a camera to focus on a human face in a scene and employs a face quality assessment method to log the best quality faces from the captured frames. The chapter also shows how a FQA module automatically discards the low quality faces during video acquisition. On the other hand, the second chapter proposes a system for quality aware face alignment by using a motion based forward extrapolation method. The basic method of face alignment used in this chapter is obtained from [18], however novel application of the FQA module greatly improve the alignment accuracy in challenging videos available in a relevant public database.

(a) *(b)*

Figure 1-2 Detection of landmarks in a low quality face can be erroneous as shown in (a).An assessment of face quality can help improving the alignment procedure as shown in (b). Images have taken from "Youtube Celebrities" dataset [21].

1.5. MEASUREMENT OF PHYSIOLOGICAL PARAMETERS

Physiological parameters are measurements describing the physical condition of a human body. They are also known as vital signs given their relevance to the patient's condition in medical scenarios. Examples of physiological parameters include heartbeat rate, respiration, blood oxygen saturation, and fatigue. Among these heartbeat rate is the most important physiological parameter providing information about the condition of cardiovascular system in applications like medical diagnosis, rehabilitation training program, and fitness assessment. For example, increasing or decreasing a patient's heartbeat rate beyond the norm in fitness assessment or rehabilitation training can show how tired the trainee is, and indicate whether continuing the exercise is safe. Heartbeat rate is typically measured by an Electrocardiogram (ECG) through placing sensors on the body. However, recent studies proposed methods such as [7], [15], [17], [22] to estimate heartbeat rate from facial video by utilizing the facts that blood circulation causes periodic subtle changes to facial skin color (which can be observed by Photoplethysmography) and invisible motion in the head (which can be observed by Ballistocardiography). Figure 1-3 shows a scenario of heartbeat peak detection in the heartbeat signal obtained from facial video. The method proposed by Balakrisnan et al. [15] is based on head motion and this method extract facial feature points from forehead and cheek by a method called Good Feature to Track (GFT) [23]. The authors then employ the Kanade-Lucas-Tomasi (KLT) feature tracker from [24] to generate the motion trajectories of feature points and some signal processing methods to estimate cyclic head motion frequency as the subject's heartbeat rate. However, these calculations are based on the assumption that the head is static (or close to) during facial video capture. This means that there is neither internal facial motion nor external movement of the head during the data acquisition phase. We denote internal motion as facial expression and external motion as head pose. In real life scenarios there are, of course, both internal and external head motion. Current method, therefore, fails due to an inability to detect and track the feature points in the presence of internal and external motion as well as low texture in the facial region. Moreover, real-life scenarios challenge current methods due to low facial quality in video because of motion blur, bad posing, and poor lighting conditions. These low quality facial frames induce noise in the motion trajectories obtained for measuring the heartbeat.

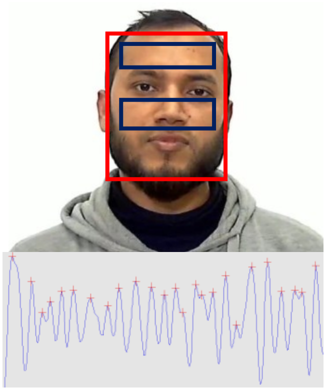


Figure 1-3 An example of heartbeat peak detection in the heartbeat signal obtained from facial video. Red rectangle presents the automatically detect face in a video frame and blue rectangles present region of interest to track for heartbeat footprint in the face. The '+' marks indicate the detected peaks (implies heart pulse) in the signal.

Another important physiological parameter is 'fatigue', which usually describes the overall feeling of tiredness or weakness. Fatigue may be either mental or physical or both. Stress, for example, makes people mentally exhausted, while hard work or extended physical exercise can exhaust people physically. Physical fatigue is also known as muscle fatigue, which is a significant physiological issue, especially for athletes or therapists. By monitoring a patient's fatigue during physical exercise, a therapist can change the exercise, make it easier or even stop it when he/she realizes that the level of fatigue is harmful for the patient. To the best of our knowledge, the only video-based non-invasive system for non-localized (i.e., not restricted to a particular muscle) physical fatigue detection in a maximal muscle activity scenario is the one introduced in [25] which uses head-motion (shaking) behavior due to fatigue in video captured by a simple webcam. It takes into account the fact that muscles start shaking when fatiguing contraction occurs in order to send extra sensation signal to the brain to get enough force in a muscle activity and this shaking is reflected in the face. Figure 1-4 shows an experimental scenario of the occurrence of physical fatigue during maximal muscle activity. Inspired by [15] for heartbeat detection from Ballistocardiogram, in [25] some feature points on the region of interest (forehead and cheek) of the subject's face in a video are selected and tracked to generate trajectories of the facial feature points, and to calculate the energy of the vibration signal, which is used for measuring the onset and offset of fatigue occurrence in a non-localized notion. However, the feature point selection and tracking methods used in [25] from [23], [24] are not robust in the presence of voluntary head motions induced by facial expression or pose changes. Thus, this video-based method for physical fatigue detection also exhibits similar problem as we discussed in the previous paragraph for heartbeat estimation method in [15].

This part of the thesis consists of three chapters by following [26]–[28]. The first chapter defines the problems of using facial features used in [15] from [23], [24] for heartbeat estimation and proposes an improved solution by using a combination of facial feature points used in [15] and landmarks used in [18]. The proposed method provides robustness in heartbeat rate estimation against the presence of voluntary head motions. This chapter also shows the influence of employing a face quality assessment technique in heartbeat rate estimation from facial video. The second chapter proposes a facial video based physical fatigue detection approach in a maximal muscle activity scenario. The proposed approach in this chapter improved the method of [25] by a novel application of a combination of facial feature points and landmarks tracking for physical fatigue detection. This chapter also analyzes the effect of employ a face quality assessment technique in physical fatigue detection from facial video. The last chapter of this theme proposes a novel approach to estimate heartbeat peak locations and heartbeat rate from the heartbeat signal obtained from facial video. This method employs an Empirical Mode Decomposition (EMD) [29] based approach to obtained heartbeat signal from facial video in a noise free form. Unlike the other video-based heartbeat signal processing methods, the proposed method accomplishes the calculation in time domain and thus is able to provide visible heartbeat peaks in time domain. This chapter also shows a comparison between color- and head motion-based heartbeat rate estimation. A fusion of both modalities (color and motion) is also presented.

Figure 1-4 Physical fatigue can occur during maximal muscle activity by pressing a hand-grip dynamometer.

1.6. CONTACT-FREE HEARTBEAT BIOMETRICS

Heartbeat signal can be obtained by Electrocardiogram (ECG) using electrical changes and Phonocardiogram (PCG) using acoustical changes. Both ECG and PCG heartbeat signals have already been utilized for biometrics recognition in the literature. ECG based authentication was first introduced by Biel et al. [30]. On the other hand, The PCG based heartbeat biometric (i.e. heart sound biometric) was first introduced by Beritelli et al [31]. A review of the important ECG-based authentication approaches can be obtained from [32] and a review of the important PCG-based method can be found in [33]. However, both of these heartbeat signal acquisition approaches require obtrusive sensor to be put in the body, which is not always possible, especially when subject is not cooperative. As heartbeat is reflected in the human face by subtle periodic color change, heartbeat signal can be obtained from facial video instead of obtrusive electrocardiogram or phonocardiogram. As ECG and PCG-based heartbeat signal have already showed its potential in biometric applications, heartbeat signal from facial video may also be used as a biometric trait. Figure 1-5 shows an example of a raw noisy heartbeat signal and a denoised signal obtained from a facial video, respectively in *(a)* and *(b)*.

a)

b)

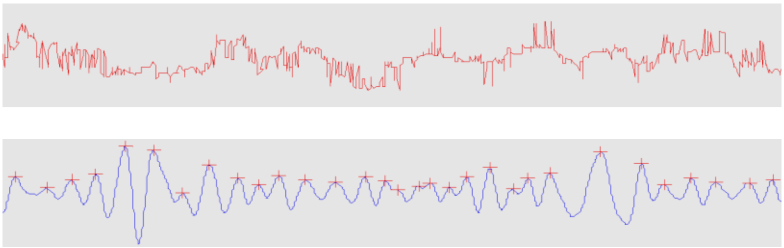


Figure 1-5 An example of a raw heartbeat signal in (a) and a denoised signal in (b) obtained from a facial video. The signal is contaminated with noise due to noises induced from lighting, voluntary facial motion, and the act of blood as a damper to the heart pumping pressure to be transferred from the middle of the chest (where the heart is located) to the face.

This part of the thesis consists of three chapters by following [34]–[36]. The first chapter proposes the heartbeat signal from facial video as a novel biometric trait and an application of that new biometric trait for person identification. Unlike ECG and PCG based heartbeat biometric, the proposed biometric does not require any obtrusive sensor such as ECG electrode or PCG microphone. Thus, the proposed HSFV biometric has some advantages over the previously proposed biometrics. It is universal and permanent, obviously because every living human being has an active heart. It can be more secure than its traditional counterparts as it is difficult to be artificially generated, and can be easily combined with state-of-the-art face biometric without requiring any additional sensor. The second chapter reports the outcome of an investigation regarding to using heartbeat signal from facial video in a forensic application, more specifically face spoofing detection. As face recognition systems need to be robust against spoofing attacks and printed face spoofing attack is very common in this regard, this chapter investigates the potential of heartbeat signal from facial video as a soft-biometric for printed face spoofing attack detection. The results on a publicly available PRINT-ATTACK database [9] imply that this biometric carries some distinctive features to be useful for forensic applications. The last chapter reports a review of the characteristics of heartbeat signal from facial video in regards to the applications of human identification and forensic investigations.

1.7. DECISION SUPPORT SYSTEM FOR HEALTHCARE

Recent advances in healthcare informatics open up the application of numerous decision support systems. Among various decision support systems, the systems for facial image analysis are pretty common in applications like medical diagnosis, biometrics, expression recognition, and social cue analysis. As human facial expression can express emotion, intension, cognitive process, pain level, and other inter- or intrapersonal meanings, facial expression recognition and analysis systems find their applications in medical diagnosis for diseases like delirium and dementia, and social behavior analysis. However these applications often require analysis of facial expressions acquired from videos in a long time-span. A facial expression log from long video sequences can effectively provide this opportunity to analyze facial expression changes in a long time-span. Generating such facial expression log from a video sequence involves expression recognition from each frame of the video. However, when a video based practical image acquisition system captures facial image in each frame, many of these images are subjected to low face quality [11], [16]. This state of affairs can often be observed in scenarios where facial expression log is used from a patient's video for medical diagnosis. Extracting features for expression recognition from a low quality face image often ends up with erroneous outcome and wastage of valuable computation resource. In order to get rid of this problem, a face quality assessment technique can be employed to select the qualified faces from a video before recognizing the expression to log. Figure 1-6 illustrates five emotion-specified facial expressions (neutral, anger, happy, surprise, and sad) of a person's image.

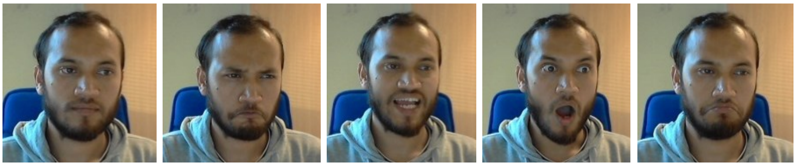


Figure 1-6 Five emotion-specified facial expressions: (left to right) neutral, anger, disgust, surprise, and sad.

This part of the thesis consists of one chapter by following [37]. This chapter proposes an automatic facial expression log creation system by discarding low quality faces that may incur erroneous expression rating. The chapter also presents and analysis of the effect of discarding face frames while making expression log. The proposed system is expected to be employed as a decision support system in healthcare domain.

1.8. SUMMARY OF THE CONTRIBUTIONS

During this study, a collection of work done in five themes framed in the field of computer vision, however applicable in health informatics and security applications. The contributions are summarized as follows:

- **Review of the monitoring technologies:** This contribution includes a detailed survey and review of the monitoring technologies relevant to older patients living at home and included in Chapter 2 in multiple sections in the thesis. These sections discuss previous reviews in this field, relevant taxonomies and different scenarios for home monitoring solutions for older patients, sensing and data acquisition techniques, data processing and analysis techniques, available datasets for research and development, and current challenges and future research directions.

- **Facial image acquisition and alignment:** The first contribution presents a method of acquiring high quality face sequence in real-time by employing a face quality assessment technique. The second contribution is employing a face quality assessment technique in face alignment to obtain more accuracy. These contributions are included in Chapters 3-4.

- **Heartbeat signal estimation and physical fatigue detection from facial video:** While heartbeat rate estimation from facial video have already introduced in the area of computer vision, Chapter 5 proposes an improved method for this purpose by using an improved heartbeat footprint tracking approach in the face. Chapter 6 introduces a novel method for physical fatigue detection from facial video. The last chapter of this part introduces a novel way of analyzing heartbeat traces in facial video by a method called empirical mode decomposition. Unlike the other methods in the literature, the most significant notion of this method is providing visible heartbeat peaks in the signal.

- **Heartbeat signal from facial video as a novel biometric trait:** The major contribution of this part is introducing the heartbeat signal from facial video as a new biometric trait. Chapter 8 – 10 introduces the way to extract and utilize this biometric trait in person recognition and face spoofing detection. The pros and cons of this biometric trait have also analyzed.

- **Generating facial expression log as a decision support tool in patient monitoring:** Chapter 11 introduces an approach for generating facial expression log by employing a face quality assessment technique to reduce erroneous expression rating.

1.9. CONCLUSIONS

In the pursuance of a doctoral degree from Nov 2012 – Mar 2016, I worked in the broad area of computer vision and thrived to contribute in two applications health monitoring and biometrics. While doing this, the focus was using facial video. This thesis comprises the stories of facial video by addressing the questions like how to acquire, how to assess the face quality, how to extract heartbeat signal, how to detect physical fatigue, and how the face quality influence expression rating. One of the major contributions of this study is introducing the heartbeat signal from facial video as novel biometric trait. All the contributions have altogether opens up an affluence of future research works.

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PART II

MONITORING ELDERLY PATIENTS AT PRIVATE HOMES

CHAPTER 2. DISTRIBUTED COMPUTING AND MONITORING TECHNOLOGIES FOR OLDER PATIENTS

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2.1. ABSTRACT

In this chapter we summarize recently deployed monitoring approaches with a focus on automatically detecting health threats for older patients living alone at home. First, in order to give an overview of the problems at hand, we briefly describe older adults, who would mostly benefit from healthcare supervision, and explain their eventual health-threats and dangerous situations, which need to be timely detected. Second, we summarize possible scenarios for monitoring an older patient at home and derive common functional requirements for monitoring technology. Third, we identify the realistic state-of-the-art technological monitoring approaches, which are practically applicable to older adults, in general, and to geriatric patients, in particular. In order to uncover the majority of applicable solutions, we survey the interdisciplinary fields of smart-homes, telemonitoring, ambient intelligence, ambient assisted living, gerotechnology, and aging-in-place technology, among others. Consequently, we discuss the related experimental studies and how they collect and analyze the measured data, reporting the application of sensor fusion, signal processing and machine learning techniques whenever possible, which are shown to be useful for improving the detection and identification of the situations that can threaten older adults' health. Finally, we discuss future challenges and offer a number of suggestions for further research directions, and conclude the chapter by highlighting the open issues within automatic healthcare technologies and link them to the potential solutions.

2.2. INTRODUCTION

In recent years, distributed computing and monitoring technologies have gained a lot of interest in the cross-disciplinary field of healthcare informatics. This introductory section reveals the growing need for timely detection of numerous health threats of older people, who are challenged by various chronic and acute illnesses, and are susceptible to injuries. First, we give a concise overview of the relevant terms, which are often used for representing state of the art technologies and research fields dealing with monitoring of older patients. Second, we guide the readers through the contents of this chapter, which are intended for both geriatric care practitioners and engineers, who are developing or integrating monitoring solutions for older adults. Then, we provide a summary of notable worldwide smart-home projects aimed at monitoring and assisting older people, including geriatric patients. The underlying aim of these projects was to explore the use of ambient and/or wearable sensing technology to monitor the wellbeing of older adults in their home environments.

Due to the changing demographics in most industrialized countries, the number and the proportion of older adults is rapidly increasing [1], [2], [3]. The risk of having to face health problems increases with advancing age. Advancing age is also associated with an increased risk of living alone and with having a potentially smaller social network [4]. Living alone also means having no supervision or proper care when needed, e.g. in case of a disease or an adverse event [5]. Timely detection of *health threats*[1] at home can be beneficial in numerous ways; for example, it can enable independence and can potentially reduce the need of institutionalization [6], facilitating so called *aging in place* paradigm [7]–[9], which is defined as "the ability to live in one's own home and community safely, independently, and comfortably, regardless of age, income, or ability level" [10].

Eventually, when facing health problems, many older adults may prefer to stay in their own home, often due to the fear of losing the ability of managing their private life or possibility of being involved in their social relationships [11], [12]. Researchers argue that older adults who are staying at home with an appropriate assistance have a higher likelihood of staying healthy and independent longer [3], [13]. For example, there is evidence that older adults may experience significantly higher risk of becoming delirious at a hospital than at home [14]. For this and other reasons, geriatric patients should, in principle, be sent from a hospital to their home as quickly as possible. Consequently, this raises several challenges associated with the necessity of intensive monitoring by home care staff, which may be inadequate and privacy intrusive, to avoid further aggravation but secure recovery [15]. On the other hand, for those older adults, who are mobile and independent, but at risk of the consequences of ageing, early detection of deteriorating health is also essential for avoiding the necessity of hospitalization and eventually of moving to a nursing home. As a solution, in-home monitoring technology, if applied properly, can nowadays be used on both healthy older adults, for detecting health threatening situations, and geriatric patients, for detecting adverse events or health deterioration. Therefore, there is a vastly growing interest in developing robust unobtrusive ubiquitous home-based health monitoring systems and services that can help older home dwellers to live safely and independently [16]. However, due to the high variety of possible scenarios and circumstances, keeping track on health conditions of an older individual at home may be exceedingly difficult.

In this chapter, we are looking for a) *which* health threats should be detected, b) *what* data is relevant for detecting these health threats[1], and c) *how* to acquire the right data about an older home dweller. In particular, a) and b) include a proper understanding of the problems at hand, the possible constraints and the needs seen by patients and medical staff, while c) includes a choice of sensors and their placement. Furthermore, a), b) and c) are closely interrelated. Then, we aim to uncover

[1] In this chapter, we define a *health threat* as any possible health-threatening situation, condition or risk factor, including external, such as environmental hazards, or internal, such as evolving diseases, as well as dangerous and life-threatening occurrences, such as falls or medication misuse.

which approaches can automate detection of the health threats and extraction of relevant information and knowledge for supporting further decision-making.

In the past fifteen years a great number of monitoring technologies, which can gather patient-specific data automatically, have been developed to monitor and support frail older adults at home. The application of these technologies have become increasingly popular mainly due to the rapid advances in both sensor and information and communication technologies (ICT). They allow reduction of chronic disease complications and better follow-up, allow accessing health care services without using hospital beds, and reduce patient travel, time off from work, and overall costs [17]. Automated monitoring systems, which are becoming cheaper and less intrusive with each year, have been made possible for clinical use by reducing the size and cost of monitoring sensors, as well as of recording and transmitting hardware [18]. These hardware developments, coupled with the available wired (e.g. PSTN, ISDN, IP)[2] and wireless (e.g. IrDA, WLAN, GSM)[3] telecommunication options, have led to the development of various home-monitoring applications. For the deployment of these kinds of technologies, several terms have been coined, such as *smart-home* [19]–[25], *home automation* [19], [23], [25]–[28], *ubiquitous home* [24], [29]–[31], *ambient intelligence* (*AmI*) [32]–[37], *assistive technology* [38]–[40], *assisted living technology* (*ALT*) [41]–[43], *ambient assisted living* (*AAL*) [33], [34], [37], [44]–[49], *home telehealth* [50]–[52], *telemonitoring* [18], [50], [53]–[55], *wireless body area sensor networks* (*WBASNs*) [56]–[60], *aging-in-place* technologies [8], [9], [61], *gero(n)technology* [39], [62]–[64], *eHealth* [65], [66] and others. All these technologies are related (for example, all incorporate *sensor technology*), however each of them usually has diverse aims and they can be supplementary to each other in terms of contributing to the monitoring purposes of older patients at home.

The schematic overlap of these most notable technological research areas is illustrated in Figure 2-1. As it becomes evident, investigating automated monitoring of older patients with comorbidities at home requires us to understand and recognize the different related fields. Thus, definitions of these research fields along with discussion of relevance to this chapter are presented in the next section.

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[2] *PSTN* – Public Switched Telephone Network; *ISDN* – Integrated Services for Digital Network; *IP* – Internet Protocol.

[3] *IRDA* – Infrared Data Association; *WLAN* – Wireless Local Area Network; *GSM* – Global System for Mobile Communications.

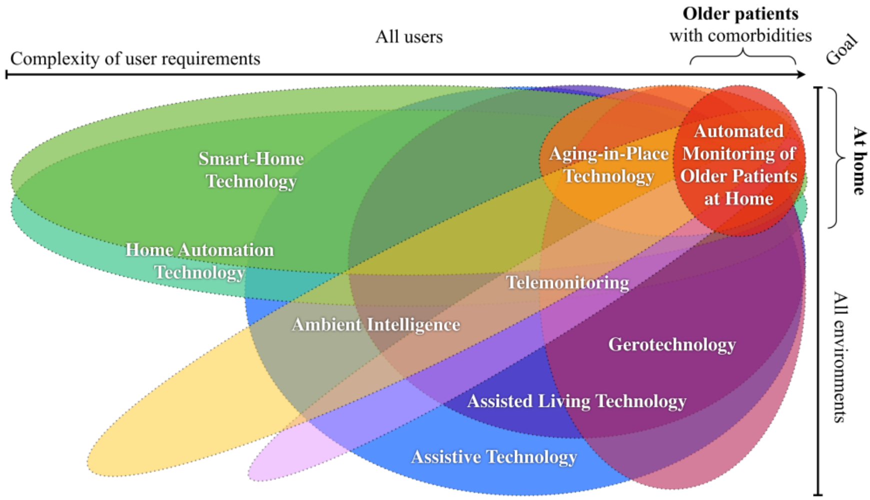

Figure 2-1 An overlap of the most notable and emerging state-of-the-art technological research fields that contribute to automated monitoring of older patients at home. In this graph, we focus only on those technological domains, which explicitly or implicitly facilitate patient-centred care. Other related areas, such as ICT, wireless sensor networks, telematics, sensor fusion, machine learning, software engineering, etc. (purely from a technological point of view) and homecare, telehealth, telecare, telemedicine, mobile health (i.e. mHealth), etc. (which already indicate a healthcare point of view), are not visualized for redundancy reasons. The horizontal axis abstracts the domain of user requirements (with complexity increasing from left to right), while the vertical axis encapsulates the variety of different environments. Generally, the requirements of monitoring older patients at home are very complex, and thus a very limited selection of all possible technological advances can be practically useful for monitoring this target group. Hence, we schematically illustrate the applicability of the existing state-of-the-art monitoring technologies for older patients at home as a red oval in the upper-right corner of the figure.

2.2.1. DEFINITION OF TERMS AND RELEVANCE TO THIS CHAPTER

The term *smart-home* has many diverse definitions [19]–[25]. A *smart-home* is often defined as a residence equipped with technology that observes its inhabitants and provides proactive services [21]. Most commonly, it refers to *home automation* [19], [23], [25]–[28], which by definition tackles four main goals: comfort, security, life safety, and low-cost [28]. In the context of this chapter, we focus our analysis primarily on improving life safety, which is achieved by incorporating *telemonitoring* technology that can be a part of a *smart-home* as well.

Telemonitoring is originally defined as the use of audio, video, and other telecommunications and electronic information processing technologies to monitor patient status at a distance [67]. Thus, all the other systems intended for increasing the comfort of home inhabitants by automating their tasks or controlling home appliances (e.g. automatic light switches, dish washers, etc.) as well as energy management systems intended for reducing costs (e.g. by preventing unnecessary heating and lighting) do not fall into the scope of this chapter. It is also worth noting that the term *telemonitoring* is often used in different contexts, and, thus, one should be very careful in identifying the methods of data collection and communication chosen for remote patient monitoring. Often in literature, manual self-reporting of health status via telephone (e.g. in [68]) is already considered as *telemonitoring*. Meanwhile, numerous automated ICT options exist in *telemonitoring,* enabling automatic and preferably more reliable data collection and transmission from home, which therefore are of interest for this chapter. For example, Paré et al. in their systematic review [55] defined the term *home telemonitoring* as an automated process for the transmission of data on a patient's health status from home to the respective health care setting. However, one should notice that this definition does not imply that the data collection is also automated. They further explained that only patients, when necessary, are responsible for keying in and transmitting their data without the help of a health care provider, such as a nurse or a physician. However, since we are also interested in monitoring technologies, which might require health care provider being present and being responsible for acquiring the right data at a patient's home (e.g. during their homecare visits), our scope is not limited to *home telemonitoring* alone.

Health smart home (HSH) [22], [24], [69], [70] is another relevant term derived from the marriage of *smart-home* technology and *medicine*. *HSH* is defined as a residence equipped with automatic devices and various sensors to ensure the safety of a patient at home and the supervision of their health status [71], which fits well with the focus of this chapter. *HSH* is a specialization of the general *smart-home* concept, which integrates sensors and actuators to ensure a medical *telemonitoring* to residents and to assist them in performing their activities of daily living (*ADL*) [22]. It also facilitates an *aging-in-place* process [22], because it aims at giving an autonomous life to older people in their own home, thus avoiding or postponing the need for institutional care.

Following the rapidly increasing deployment of wireless sensing devices, such devices have a growing impact on the way we live, and they open up possibilities to many healthcare applications that were not feasible previously. For maximizing the value of collected data, *wireless sensor networks* (*WSN*), *distributed computing*, and *artificial intelligence* (AI) as individual research domains have come together to build an interdisciplinary concept of *Ambient Intelligence* or *AmI* [35], [72]. The definition of *AmI*, however, is highly variable [34], [35], [73]. Most commonly, *AmI* is described as an emerging discipline that brings intelligence to everyday environments and makes those environments sensitive, adaptive, and responsive to human needs [32], [34], [35]. In addition, several studies require that *AmI* systems should be transparent (i.e. unobtrusive) [35], [74] and ubiquitous (i.e. present everywhere anytime) [32], [34], [35], [73], [74]. All this correlates well with the general requirements for *aging-in-place* technologies [8], [9] and *gerotechnology* [62], because these systems should be able to adapt to the needs of older adults, to sense hazardous or unsafe situations with minimal human intervention, and to inform the involved medical personnel and/or family members if something is truly 'wrong' [9]. While *smart-home*, *home automation*, *ubiquitous home*, and *ambient intelligence* technologies can be intended for any user group and irrespective of age, *gerotechnology* is explicitly focusing on older adults, including older patients with comorbidities, while *aging-in-place* technology limits the deployment of the *gerotechnology* to private homes. *Aging-in-place* technology is a popular and a relatively general term, which refers to increasing the ability of older adults to stay in their own home as they age [75], [76], and is recognized as a part of *gerotechnology* (which is consequently derived from combination of two words: gerontology and technology). *Gerotechnology* plays a crucial role in the *aging-in-place* process and is defined as *"an interdisciplinary field of research and application involving gerontology, the scientific study of aging, and technology, the development and distribution of technologically based products, environments, and services"* [77]. However, *gerotechnology* does not necessarily involve intelligence in the sense of being sensitive and adjustable to patient's needs. Different ageing associated aids (e.g. vision and hearing aids [78], or even walking aids [79] and toileting aids [80]) are often considered as appliances of *gerotechnology*, however these do not directly fall into the scope of this chapter, unless they are capable of collecting meaningful medically relevant data, which we will reveal in the further sections.

Most commonly, when dealing with geriatric or disabled patients, a majority of the aforementioned technologies employ *Assistive Technology* (*AT*), which by definition serves three major purposes relevant to life safety of patients at home [81]: 1) detecting hazards or emergencies, 2) facilitating independence and improving functional performance, and 3) supporting medical staff (i.e. caregivers) by facilitating provision of personal care. For this chapter, the main focus is put on the first purpose. One of the most important aspects that can differentiate *ATs* from other technologies is the *User-Centered Design*, which can be achieved by complying with numerous requirements defined by both medical and technical factors. Generally, it is considered to be a good practice to comply with *Universal Design* principles (often called as *Design for All*) [82]. These fundamental principles include [82]: (a) usage equitability, i.e. the design should be useful and marketable to people with diverse abilities; (b) flexibility in use, i.e. the design accommodates a wide range of individual preferences and abilities; (c) simple and intuitive use, i.e. easy to understand regardless of experience, knowledge, language skills, or current concentration level of the user; (d) perceptible information, i.e. the design communicates necessary information effectively to the user despite ambient conditions or sensory abilities of the user; (e) tolerance for error, i.e. the design minimizes hazards and the adverse consequences of accidental or unintended actions; (f) low physical effort, i.e. effective and comfortable usage with minimum of fatigue; and finally (g) size and space for approach and use, i.e. appropriate size and space should be provided for approach, reach, manipulation, and use regardless of human body size, posture, or mobility of a user, such as older patient.

Assisted living technologies (*ALTs*) is another relevant and broad term, which often remains undefined and may have different meanings throughout *aging-in-place* related literature [43]. Commonly, it refers to sensors, devices and communication systems (including software), which, in combination, help to assist older adults and those who are physically or cognitively impaired in accomplishing their daily tasks towards independent lives and an improved quality of life, by delivering *assisted living services* [83], [84]. These services may include *telehealth services* (i.e. delivering medical care, treatment, and monitoring services at home from a remote location), *telecare services* (i.e. delivering social care and related monitoring services at home from a remote location), *wellness services* (i.e. delivering services for healthy lifestyles at home from a remote location), *digital participation services* (i.e. which remotely engage older and disabled people in terms of social, educational or entertainment activities at home), and *teleworking services* (i.e. in which older and disabled people work remotely from home for an employer, a voluntary organisation or themselves and need remote computing to work successfully) [84]. Noteworthy, *telemedicine services* (i.e. which involve delivering medical services and advices from one practitioner to another at a remote location) are not considered to be a part of *ALTs* [84].

Assisted living technologies based on *Ambient Intelligence* are called *Ambient assisted living* (*AAL*) *tools* [33] and they are respectively broader than our scope of monitoring and detecting health-threatening problems. *AAL* in general can be used for preventing health problems, treatment, and improving health conditions and well-being of older individuals. These tools can be installed in (*health*) *smart-homes* and therefore can greatly support monitoring purposes by collecting contextual information and by recording *activities of daily living* (*ADL*) [85]–[88], for example. *ADL* may include any activity, which can be observed in daily living of an individual (e.g. walking, laying, sitting, which are considered as basic activities, or preparing a coffee, laundering, cooking meals, shopping groceries, considered as instrumental activities). A huge number of *AAL* tools exists, such as medication management tools [55], [89], [90], fall detection [91]–[95] and prevention systems [96]–[98], video surveillance systems [6], [99]–[101], indoor location tracking [102], [103], communication systems [8], [104], [105], mobile emergency response systems [8], [63], [106]–[108], and diet suggestion systems [109], which in general can be built and implemented with the purpose of health monitoring and improving safety, connectivity and mobility of older adults at home.

The term *eHealth*, which nowadays seems to serve public as a general "buzzword", is currently defined by World Health Organisation (WHO) as "*the use of information and communication technologies (ICT) for health. Examples include treating patients, conducting research, educating the health workforce, tracking* *diseases and monitoring public health*" [65]. In the light of this definition, this chapter is focused on tracking diseases and monitoring public health for older adult users. Apparently, definitions of *eHealth* seem to vary with respect to the functions, stakeholders, contexts and various theoretical issues targeted [110]. The Medical Subject Headings (MeSH) [111] library directly relates *eHealth* to the term *Telemedicine*, defining it as a "*delivery of health services via remote telecommunications. This includes interactive consultative and diagnostic services.*" One may by intuition anticipate that *eHealth* refers to "electronic" healthcare, because of the prefix "*e*". However, the meaning of the letter "*e*" is rather ambiguous, and therefore *eHealth* term can be found in a very broad context. Furthermore, *eHealth* and *E-Health* are often used interchangeably and are considered as synonyms [110]. However, one might find it rather confusing that WHO itself has another and slightly different definition for the term *E-Health*, which is following: "*the transfer of health resources and health care by electronic means. It encompasses three main areas:*

- *The delivery of health information, for health professionals and health consumers, through the Internet and telecommunications.*
- *Using the power of IT and e-commerce to improve public health services, e.g. through the education and training of health workers.*
- *The use of e-commerce and e-business practices in health systems management.*" [112]

Eysenbach [113], on the other hand, provided the following definition to *e-health* as a term and as a concept, and his definition remains to be broadly accepted till this date: "*e-health is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide by using information and communication technology.*" He also explained that the letter "*e*" in the term *eHealth* might refer to ten qualities: (1) efficiency, (2) enhancing quality of care, (3) evidence based, (4) empowerment of consumers and patients, (5) encouragement of a new relationship between the patient and health professional, (6) education of consumers and physicians through online sources, (7) enabling information exchange and communication in a standardized way between health care establishments, (8) extending the scope of health care beyond its conventional boundaries, (9) ethics, and (10) equity, so that everyone who needs *eHealth* would be able to receive it. For the context of this chapter, *eHealth* provides various monitoring services for older adults in need. For example, Cabrera-Umpiérrez et al. [66] described the developed functionalities of the *eHealth* services for European co-funded projects, which provided (a) personalized health monitoring, (b) health coaching, and (c) alerting and assisting services to assure the well-being of the older adult users during their daily activities. This chapter is thus focused primarily on the *eHealth* services referring to the use cases (a) and (c) in that context.

Although much research has been carried out in the aforementioned fields that deal with older people monitoring at home in the recent years, several unsolved problems with existing tools persist, such as privacy issues [11], [64], [100], a lack of accuracy in detecting health-threatening problems [114], invasiveness [115] and intrusiveness [116], [117] of monitoring devices, and the fact that the monitoring systems are mostly meant for direct patient-physician communication, while physicians have a very limited time available per patient [16], [46], [118], [119]. Furthermore, the size and complexity of the available data from different electronic healthcare records is growing, which makes it harder for medical staff to analyse it and to make clinical decisions [120]. Thus, an automated detection of health threatening situations and clinical decision support systems have become a new prerequisite for an effective home healthcare with limited manning [121].

2.2.2. CONTENT AND AUDIENCE OF THIS CHAPTER

This chapter is intended for both geriatric care practitioners and engineers, who are developing or integrating monitoring solutions for older adults. On the one side, this chapter helps health care practitioners to familiarize with the available home monitoring technologies, and on the other side, it helps engineers to better understand the purposes and problems of monitoring older people at home through the insight into different scenarios and potential health-threatening situations and conditions of older adults with physical, cognitive and/or mental impairments.

We start with reviewing a variety of well-known smart-home projects, which present an overview of the needed infrastructure and give an insight of what should be taken into consideration, when monitoring older people at home. The third section includes the summary of the existing notable reviews and the taxonomies of most common home-monitoring scenarios. Subsequently, the fourth section reveals the spectrum of geriatric diseases and conditions mentioning the known approaches of solving them in home settings. Section five further reveals the available monitoring technology and possible automation of monitoring approaches, followed by examples of how to realize these solutions, what the pros and cons are, and what must be taken into consideration when implementing them in real home environments. The sixth section summarizes the available datasets, which are practically useful for developing health-threat detection algorithms based on already monitored empirical data. Finally, in section seven we discuss some anticipated future challenges of applying monitoring technology for older adults and consequently propose possible measures and directions towards dealing with some common issues.

This chapter is based on numerous scientific articles, which were exclusively published in English, in a peer-reviewed text, and were available as full works.

Because of the rapid progression in technology and the relative lack of information in earlier years [24], our search was limited to articles in journals, book chapters, and conference proceedings written within the last fifteen years, i.e. between 2001 and 2015; only few key relevant articles or book chapters with original sources from earlier years were included as exceptions. Additionally, several reports were cited to give more illustrative examples of approaches identified to be useful for monitoring geriatric patients at home, but which were not yet tested on older adults explicitly. As few exceptions, some web sites describing systems, devices, prototypes, and projects were included as references when the published literature did not offer adequate presentations of the projects. Searches using relevant keywords were conducted either in *Scopus, Elsevier, IEEE Xplore, Springer, PubMed,* and *PubMed Central* or using the *Google Scholar* Search Engine.

2.2.3. AN OVERVIEW OF THE RELEVANT SMART-HOME PROJECTS

Table 2-1 summarizes several notable smart-home projects that are generally aimed at monitoring and assisting older people, including geriatric patients. The underlying aim of such projects was to explore the use of ambient and/or wearable sensing technology to monitor the wellbeing of older adults in their home environment.

The majority of the relevant smart-home projects are originating from Europe and America. For example, the well-known CASAS project, named for the Center for Advanced Studies in Adaptive Systems, at Washington State University (WSU) is active since 2007 and has established numerous smart home test-beds equipped with sensors, which mainly aim to provide a non-invasive and unobtrusive assistive environment by monitoring ADL of the residents, including older patients [122]–[125]. The latest initiative of the CASAS project is to develop a “Smart home in a Box” (SHiB), i.e. a small and portable home kit, lightweight in infrastructure, which can be implemented in a real home environment and extendable with minimal effort [123]. Noteworthy, the WSU CASAS database is the largest publicly available source of ADL datasets to date [126]. Meanwhile, researchers at the University of Missouri are using passive sensor networks installed in apartments of residents called as TigerPlace to detect changes in health status and offer clinical interventions helping the residents to age in place. The TigerPlace project aims to provide a long-term care model for seniors in terms of supportive health [9]. As another example, Elite Care is an assisted living facility equipped with sensors to monitor indicators such as time in bed, bodyweight, and sleep restlessness using various sensors [119], [127]. The Aware Home project at Georgia Tech [128] employs a variety of sensors such as smart floor sensors, as well as assistive robots for monitoring and helping older adults. The MavHome [129], [130] at University of Texas at Arlington is another smart-home environment equipped with sensors, which records inhabitant interactions, medicine-taking schedules, movement patterns, and vital signs. It aimed at providing health care assistance in living environments of older adults and people with disabilities. MavHome is one of the first projects, which proposed to apply machine learning approaches to create a smart-home that can act as an intelligent agent, i.e. which can adapt to its inhabitants, identify trends that could indicate health concerns or a need for transition to assisted care, or detect anomalies in regular living patterns that may require intervention. Other notable smart home test-beds include DOMUS [131] at the University de Sherbrooke, and House_n project at the Massachusetts Institute of Technology [132]. Several smart home projects in Europe include iDorm [133], Grenoble Health Smart Home [134], GiraffPlus [135], PROSAFE [136], Gloucester Smart House [137] and ENABLE [138] for dementia patients, and Future Care Lab [47], [139]. The majority of these research projects monitor a subset of ADL tasks. There are also related joint initiatives such as the "Ambient Assisted Living Joint Programme" or "The Active and Assisted Living Joint Programme", supported by the European commission with the goal of enhancing the quality of life of older people across Europe through the use of AAL technologies and to support applied research on innovative ICT-enhanced services for ageing well [44], [140]. As an example, in one of the most recent European projects, called as Giraff-Plus [135], researchers develop and evaluate a complete system that collects daily behavioural and physiological data of older adults from distributed sensors, performs context recognition, a long-term trend analysis and presents the information via a personalized interface. Giraff-Plus supports social interaction between primary users (older citizens) and secondary users (formal and informal caregivers), thereby allowing caregivers to virtually visit an older person in the home.

Also in Asia, some notable smart home projects were developed, such as the early "Welfare Techno Houses" across Japan [141], promoting independence for older and disabled persons, and for improving their quality of life. For example, the large Takaoka Techno House [141] measured medical indicators such as electrocardiogram (ECG), body and excreta weights, and urinary volume, using sensor systems placed in the bed, toilet and bathtub. The Ubiquitous Home project [142], [29] is another Japanese smart home project, which applied passive infrared (PIR) sensors, cameras, microphones, pressure sensors, and radiofrequency identification (RFID) technology intended for monitoring living activities of residents, including older adults. The SELF smart home project, also in Japan, monitored posture, body movement, breathing, and oxygen in the blood, using pressure sensor arrays, cameras, and microphones [143]. In South Korea, a POSTECH's U-Health smart home project [144] is focused on establishing autonomic monitoring of home and its aging inhabitants in order to detect health problems, by applying different environmental wireless sensors and a wearable ECG monitor, and to provide assistance when needed.

In Oceania region, there are several noteworthy projects as well. For instance, the Hospital Without Walls project [145] is an early example of home-telecare project in Australia that used a wireless wearable fall monitoring system based on small on-body sensors, which measured heart rate and body movements. The initial clinical scenario was monitoring older patients who were at risk of repeated falls. More recent projects include the Smarter Safer Home project [146] and the Queensland Smart Home Initiative (QSHI) [147]. The Smarter Safer Home platform [146] is aimed at enabling ageing Australians to live independently longer in their own homes. The primary goal of the proposed approach is to enhance the Quality of Life (QoL) for older patients and for the adult children supporting their aged parents. The aforementioned platform uses environmentally placed sensors for non-intrusive monitoring of human behaviours, extracting specific ADLs and predicting health decline or critical health situations from the changes in those ADLs. The Queensland Smart Home Initiative (QSHI) [147] program included so called Demonstrator Smart Home, which involved feedback gathering from stakeholder visits, such as consumers, family members, care providers and policy-makers, as well as 101 homes that are equipped with home telecare technologies and occupied by frail older adults or other people with special needs.

Table 2-1 Smart-home projects with a perspective of monitoring geriatric patients

Reference(s)	**Coordinating Research Institution, Country**	**Smart-home project**	**Datasets***	**Type***
Cook et al. [123]	Washington State University, USA	CASAS, SHiB	✓, 65+, p	2, 4
Ranz et al. [9]	University of Missouri, Colombia	TigerPlace	✓, 65+, p	4
Stanford [119]	Oregon Health & Science University, USA	Elite Care	-, 65+, p	3
Abowd et al. [148]	Georgia Institute of Technology, USA	Aware Home	-	2~3
Kadouche et al. [131]	University of Sherbrooke, Canada	DOMUS	✓, s	2
Intille et al. [132]	Massachusetts Institute of Technology, USA	PlaceLab House_n	✓	3
Fleury et al. [134], Noury et al. [149]	TIMC-IMAG Laboratory of Grenoble, France	Health Smart Home, HIS[2]	✓, s	2
Orpwood et al. [137]	Bath Institute of Medical Engineering, UK	Gloucester Smart House	-	2
S. Bjørneby et al. [138]	The Norwegian Centre for Dementia Research, Norway	ENABLE	-, 65+, p	4

Continued from previous page….

Reference(s)	**Coordinating Research Institution, Country**	**Smart-home project**	**Datasets***	**Type***
Beul et al. [47]	Aachen University, Germany	Future Care Lab	-	1
Helal et al. [150]	University of Florida, USA	Gator Tech Smart House	✓, 65+, p	2
Yamazaki et al. [142], [29]	National Institute of Information and Communications Technology, Japan	Ubiquitous Home	✓, 65+, p	2
Tamura et al. [141]	Chiba University, Japan	Welfare Techno House	-, 65+, p	2
Kim et al. [144]	Pohang University of Science and Technology (POSTECH), South Korea	POSTECH's U-Health Smart Home	-	1
Chan et al. [136], Bonhomme et al. [102]	Laboratory for Analysis and Architecture of Systems (LAAS), France	PROSAFE, PROSAFE-extended	-, 65+, p	3
Callaghan et al. [151], [152]	University of Essex, UK	iDorm, iDorm2 (iSpace)	-	3
Nishida et al. [143]	Electrotechnical Lab, Japan	SELF	-	1
Iversen [153]	Danish Technological Institute (DTI), Denmark	DTI CareLab	-	1
Sundar et al. [154]	University at Buffalo, USA	ActiveHome (X10)	-	4
Youngblood et al. [130]	The University of Texas at Arlington, USA	MavHome	-	1
Orcatech Technologies [155]	Oregon Center for Aging and Technology, USA	ORCATECH: Life Lab, Point of Care Lab	✓, 65+, p	2, 4
Coradeschi et al. [135], Palumbo et al. [156]	Örebro University, Sweden Real houses and apartments in Italy, Spain, Sweden	GiraffPlus	-, 65+, p	4

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Reference(s)	Coordinating Research Institution, Country	Smart-home project	Datasets*	Type**
Soar et al. [147]	University of Southern Queensland, Australia	Queensland Smart Home Initiative (QSHI)	-, 65+, p	1, 4
Wilson et al. [145]	Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia	Hospital Without Walls	-, 65+, p	2
Dodd et al. [146]	Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia	Smarter Safer Home	-, 65+, p	4

* "Datasets" column indicates, which smart-home projects have collected empirical datasets ('✓'), and whether these projects include data form real older adults ('65+'), and whether real medical patients were involved ('p'), or only simulated patients were used ('s'), i.e. healthy persons (often younger students) imitated symptoms of certain illnesses or alarming events, such as falls, or other behaviours of older patients.

** "Type" column classifies the test-beds of the reviewed smart-home projects into four main types, according to Tomita et al. [157]: 1 = "Laboratory Setting" (i.e. a facility at a research institution, which utilizes an infrastructure and sensory equipment that researches find sufficient, but is not meant for actual habitation), 2 = "Prototype smart-home" (allows actual habitation, usually for a short-term, and is specifically designed for research purposes), 3 = "Smart-home in use" (necessary infrastructure and monitoring technology is implemented in actual community settings, apartment complexes, and retirement housing units), 4 = "Retrofitted smart-home" (i.e. a private home or an individual apartment is converted to a smart-home, by integrating (retro-fitting) monitoring technology on top of existing home infrastructure).

2.3. REVIEWS AND TAXONOMIES

This section summarizes the existing review articles in the field of monitoring and diagnosing older adults at risk of health deterioration, in the context of smart-homes. We classified these review articles based on their aims and reviewing approaches of proposed monitoring systems capable of detecting health threats in smart-home settings. We included reviews, which focused on describing technology, applications, costs, and quality of monitoring services. These reviews greatly help to obtain an overview of the assortment of available monitoring solutions for various scenarios.

Over the past decade, the number of publications concerning the field of monitoring older adults at home has grown significantly. To structure an overview of the individual review articles, including their purpose and approaches, taxonomy was defined to arrange them into various groups having similar characteristics.

Various categories may be used for a taxonomy to distinguish between different approaches, e.g. (in random order): patient-centric vs. physician-centric approaches, vision-based vs. non-vision-based systems, active vs. passive sensing, mobile vs. stationary sensors, various scenario assumptions (health condition and disabilities, single patient vs. multiple patients, number of rooms at home, etc.), cost, number of monitored parameters, sensor modality, long-term monitoring vs. short-term monitoring, non-intrusive vs. holistic intrusive methods, etc. The various review works that are discussed in the next section have used different taxonomies.

2.3.1. PREVIOUS REVIEWS

A number of comprehensive reviews were written which summarized the important proposals of monitoring and diagnosing at home older adults at risk of health deterioration, in the context of smart-homes, the last one published in March 2015. All reviews discuss both vision and non-vision based monitoring technology. Some of these reviews explicitly mentioned medical application contexts [5], [18], [20], [33], [49], [51], [158]–[164], and some did not [99]. These reviews can be classified into different overlapping groups according to the view-points used during the review process. The viewpoints are: a) Technology centric, b) Application centric, c) Cost centric, and d) Quality of Service (QoS) centric. Figure 2-2 illustrates these four groups and corresponding reviews from the literature. Technology centric reviews included discussions and summarized methods regarding core technologies, such as object segmentation, feature extraction, activity detection and recognition, clinically important symptom detection, etc. Application centric reviews discussed and summarized methods related to applications such as fall detection, detection of ADL, detection of instrumental activities, detection of sick samples for diagnosis, etc. Cost centric reviews discussed the expenditures required for implementation of activity monitoring systems. The QoS centric reviews discussed and summarized the service quality of the methods in the area of activity monitoring and elderly assisted smart-homes. Service quality can be defined in terms of validation study, performance, user adaptability, sensitivity, etc., which is usually assessed based on the outcomes. Service quality naturally is focused on benefitting an end user (an older adult), and when this end user is a patient, QoS centric reviews often discuss patient-centeredness of the reviewed approaches. They often tend to summarize outcomes of different telemonitoring solutions and to give best practice recommendations for improving quality of service for older adults.

Among the previous reviews, technology and application centric reviews achieved good consideration in the study of automated monitoring and diagnosis in smart homes. Though technology centric reviews in the literature thoroughly addressed the core technologies used in this area (e.g. describing system architecture, integrated sensors, proposed algorithms, communication protocols, etc.), application centric reviews focus on particular application area and may, for example, merely consider some subgroups of ADLs, or instrumental activities, or generalized human activities in both medical and non-medical contexts [5], [33], [49], [158]. Most of these application-centric reviews did not include comprehensively the issues of older patients in an assisted living environment, however, they have mentioned general scenarios of monitoring older adults at home. There is a very limited discussion of patient-centeredness among these reviews, which only includes some discussions and summaries of the methods in terms of patient's necessity, services and measuring parameters, such as handling adverse condition, assessing state of health, in-home diagnosis methods. Moreover, the previous reviews did not discuss the methods for in-home diagnosis of patients and include less discussion regarding collection of datasets in the patient-centred contexts. Thus, in this chapter we systematically summarize the methods that came up as solutions by utilizing monitored data to the issues related to patient's necessity, services and measuring diagnostic parameters of older adults in smart-home scenarios.

Table 2-2 further summarizes the main features and contents of these key review works in the domain of monitoring technologies and health-threat detection in older adults, where the column *Topic* presents the reviews' context such as the algorithms for activity recognition, hardware tools available for monitoring, hospitality services available at home, and/or evaluation methods for monitoring systems. The column *Contents* presents the summaries of reviews, *Types of Analysis* notes the types of data (either quantitative or qualitative) used in the review in order to assess the existing literature and the application types (medical or general) considered in the reviews. The medical application in column 4 was drawn from the setup related to the medically ill patients, whereas the non-medical or general application context was drawn from the setup not necessarily related to real patients or geriatrics. The column *Sensors discussed* presents the types of sensors discussed in the reviews. In Table 2-2 we have also included reviews covering non-medical applications, because the contents of the reviews included the literatures and the underlying objectives of monitoring activities and measuring physiological parameters of geriatric patients at home. In column 5, vision based sensors include, for example, thermal cameras, RGB cameras, and/or infrared (IR) cameras such as depth-sensing cameras. On the other hand the most common non-vision based sensors are microphones, accelerometers, heat sensors, flow sensors, pressure sensors, electromagnetic sensors, ultrasonic sensors, and particle sensors.

A notable study by Morris et al. [20] systematically reviewed smart-home technologies that assisted older adults to live well at home. This review is mainly Quality of Service (QoS) centric, because the authors only reviewed works, which assessed smart-home technologies in terms of effectiveness, feasibility, acceptability, and perceptions of older people. They indicated that only one study assessed effectiveness of a smart home technology in the context of monitoring and assisting older adults at home [154], while majority of studies reported on the feasibility of smart-home technology and other studies were purely observational.

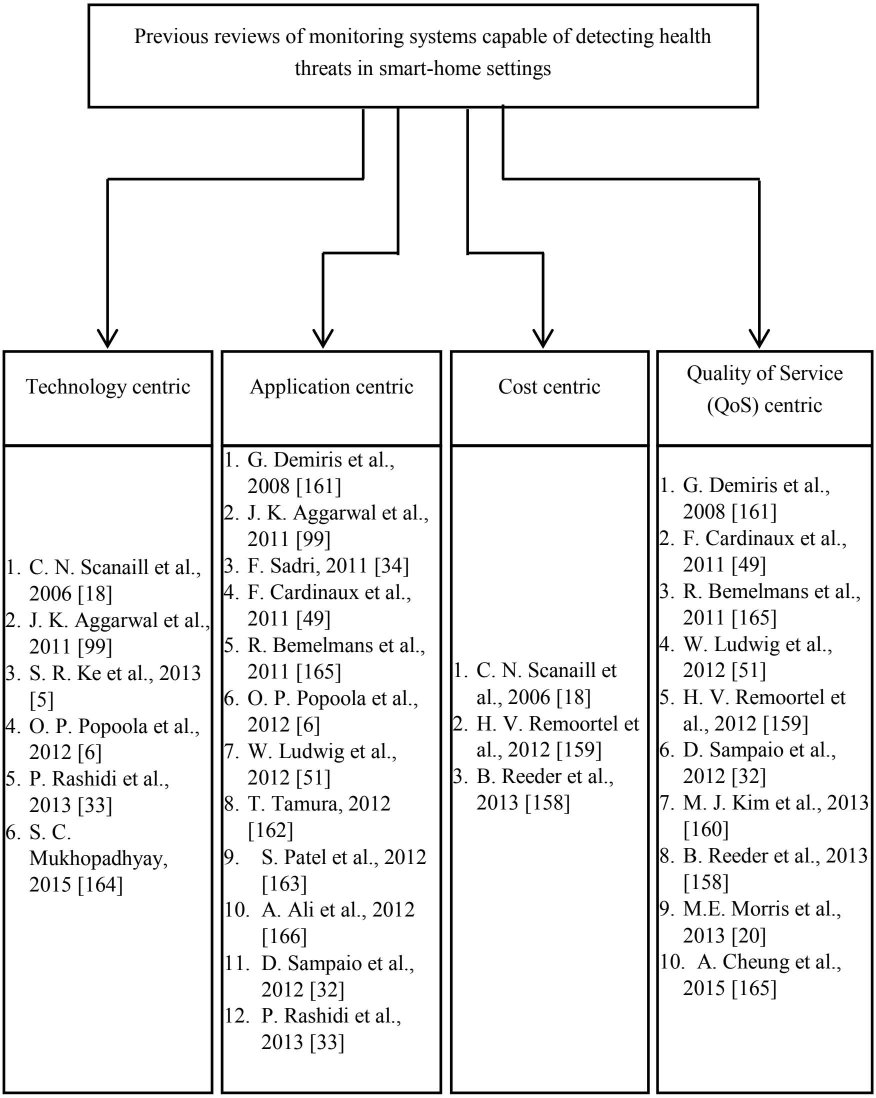

Figure 2-2 Categories of existing reviews in the literature in terms of their viewpoints (mentioning the first author and year of publication for each reference).

Demiris and Hensel [161] conducted a systematic review of smart-home projects worldwide, discussing applied technologies and models used, categorizing these projects according to different goals, as for example, the monitoring of physiological vital signs, functional outcomes (e.g. abilities to perform ADLs), safety (e.g. detecting environmental hazards, such as fire or gas leaks) and security (e.g. alerts to human threats), social interactions (i.e. measuring and facilitating human contact including information and communication applications), emergency detection (e.g. falls), and cognitive and sensory assistance (i.e. cognitive aids such as reminders and assistance with deficits in sight, hearing, and touch). They stressed that the design and implementation of informatic applications for older adults should not be determined simply by technological advances but by the actual needs of end users. Furthermore, the current smart-home research needs to address such important questions as health outcomes, clinical algorithms to indicate potential health problems, user perception and acceptance, and ethical implications [161].

Table 2-2 Summary of the review works in the fields of vision-based and non-vision-based patient monitoring and health-threat detection technologies

Reference	**Topic**	**Contents / Main contributions**	**Type of the analysis**	**Sensors**	**View-points covered**	**Number of reviewed works**
J.K. Aggarwal, 2011 [99]	Human activity analysis	Taxonomy of human activity in terms of automated recognition complexity, tools for recognition, summarizing the services of different proposed methods, discussion about dataset creation and availability	Both qualitative and quantitative in non-medical applications	Vision based	Technology and application centric	102
S.R. Ke, 2013 [5]	Tools for activity recognition	Discussing object detection methods, feature extraction and representation methods, machine learning methods, some example activity recognition systems	Qualitative in both medical and non-medical applications	Vision based	Technology centric	145
O.P. Popoola, 2012 [6]	Video analysis for abnormal human behavior detection	Summarizing the focus of previous review articles for behavior recognition, organizing the references for common tools and paradigms used, theme based classification of previous research, listing of datasets	Qualitative in medical and surveillance applications	Vision based	Technology and application centric	141

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Reference	**Topic**	**Contents / Main contributions**	**Type of the analysis**	**Sensors**	**View-points covered**	**Number of re-viewed works**
C.N. Scanaill, 2006 [18]	Sensors used for mobility telemonitoring of elderly	Estimating expenditure for assisted independent aging, summarizing the characteristics of sensors, and corresponding pros and cons	Qualitative in medical applications	Vision and non-vision based	Technology and cost centric	59
F. Cardinaux, 2011 [49]	Video analysis for ambient assisted living	Application centric listing of existing methods, services of existing methods for action detection, visual processing and privacy of visual data	Qualitative in medical applications	Vision based	Application and QoS centric	72
G. Demiris, 2008 [161]	Systematic review of smart-home applications for aging society	Discussing technologies and models used in existing smart-home projects, categorizing them in accordance to monitoring of physiological, functional outcomes, safety and security, social interactions, emergency detection, and cognitive and sensory assistance.	Qualitative in medical applications	Vision and non-vision based	Application and QoS centric	31 (114)
B. Reeder, 2013 [158]	Health smart homes and home-based consumer health technologies for independent aging	Classifying technologies into emerging, promising and effective groups, summarizing the contribution of each article instead of sub-division of methods used, analysing the study environment for each article	Qualitative in medical applications	Vision and non-vision based	QoS centric	83 (31 key articles out of 1685 articles)
W. Ludwig, 2012 [51]	Services from health-enabling technologies	Handling adverse conditions such as fall detection and cardiac emergencies, assessing state of health such as recognition of diseases and medical conditions, consultation and education for the use of services, motivation and feedback from the user, service ordering, social inclusion of telehealth services	Qualitative in medical applications	Vision and non-vision based	Application and QoS centric	47 (27 key articles out of 1447 articles)

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Reference	**Topic**	**Contents / Main contributions**	**Type of the analysis**	**Sensors**	**Viewpoints covered**	**Number of reviewed works**
H.V. Remoortel, 2012 [159]	Validity study of activity monitors	Summarizing the features of commercially available activity monitors, performance evaluation and comparison of different activity monitors in terms of different statistical measures	Quantitative in medical applications	Non-vision based	QoS centric	154 (134 key articles out of 2875 articles)
M.J. Kim, 2013 [160]	Identifying significant evaluation methods adapted in user studies of health smart homes	Listing of system effectiveness evaluation of user studies, analysis of user experience evaluation	Qualitative in medical applications	Vision and non-vision based	QoS centric	41 (20 readable articles in this context out of 82 articles)
T. Tamura, 2012 [162]	Home geriatric physiological and behavioural monitoring approaches	Discussing several sensory devices and appliances, which intend to monitor and assist older adults and disabled people in their living environments	Qualitative in medical applications	Vision and non-vision based	Application centric	91
S. Patel et al., 2012 [163]	Wearable sensors and systems with application in rehabilitation	Summarizing wearable and ambient sensor technology (incl. off-the-shelf solutions) applicable to older adults and subjects with chronic conditions in home and community settings for monitoring health and wellness, safety, home rehabilitation, treatment efficacy, and early detection of disorders.	Qualitative in medical applications	Non-vision based	Application centric	124
M.E. Morris et al., 2013 [20]	Systematic review of smart-home technologies assisting older adults to live well at home	Summarizing studies, which assessed smart-home technologies in terms of effectiveness, feasibility, acceptability and perceptions of older people.	Qualitative in medical applications	Vision and non-vision based	QoS-centric	50 (21 out of 1877 key articles)

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Reference	**Topic**	**Contents / Main contributions**	**Type of the analysis**	**Sensors**	**View-points covered**	**Number of reviewed works**
P. Rashidi et al., 2013[33]	Sensors and research projects of ambient assisted living (AAL) tools for older adults	Summarizing emerging tools and technologies for smart-home implementation; classifying the AAL tools and technologies into a) smart-homes, b) mobile and wearable sensors, and c) robotics for supporting ADL, summarizing general sensor types and measurement parameters used in the existing smart-home projects.	Qualitative in medical applications	Vision and non-vision based	Technology and application centric	192
A. Cheung et al., 2015 [165]	Systematic literature review of studies, which integrated bedside monitoring equipment to an information system.	Gathering evidence on the impact of the patient data management systems (PDMS) on both organisational and clinical outcomes, derived from English articles published between January 2000 and December 2012.	Qualitative in medical applications	Non-vision based	QoS-centric	39 (18 out of 535 key articles)
S. C. Mukhopadhyay, 2015 [164]	Reported literature on wearable sensors and devices for monitoring human activities	Summarizing architecture and sensors for human activity monitoring systems, mentioning design challenges for wearable sensors, energy harvesting issues, as well as market trends for wearable devices.	Qualitative in both medical and non-medical applications	Non-vision based	Technology centric	103

In a recent and comprehensive technology- and application-centric surveys, Rashidi et al. [33] summarized the emergence of *ambient assisted living* (*AAL*) tools for older adults based on *ambient intelligence* (*AmI*) paradigm. They summarized the state-of-the-art AAL technologies, tools, and techniques, and revealed current and future challenges. They divided the AAL tools and technologies into a) smart-homes, b) mobile and wearable sensors, and c) robotics. They also summarized the general sensor types and measurement parameters used in the smart-home projects.

Another related application-centric article written by Sadri [34] surveyed *AmI* and its applications at home, including care of older adults. The main focus was on ambient data management and artificial intelligence, for example, planning, learning, event-condition-action (ECA) rules, temporal reasoning, and agent-oriented technologies. Sadri found that older adults, typically, need initial training, and often follow-up daily assistance, to use *AmI* devices. Finally, security threats as well as social, ethical and economic issues behind *AmI* were discussed.

One application-centric systematic review by Ali et al. [166] studied specifically gait disorder monitoring using vision and non-vision based sensors. They showed strong evidence for the development of rehabilitation systems using a marker-less vision-based sensor technology. They therefore believed that the information contained in their review would be able to assist the development of rehabilitation systems for human gait disorders.

Sampaio et al. [32] in his survey on *AmI* made a comparative analysis of some of the research projects, with a specific focus on the human profile, which in the authors' point of view is a crucial aspect to take into account when searching for a correct response to human stimuli. This survey explains both application-centric and QoS centric matters. The main objective of their work was to understand the current necessities, devices, and the main results in the development of these projects. The authors concluded that most projects do not present the different characteristics and needs of people, and miss exploring the potential of human profiles in the context of ambient adaptation.

Another application and QoS centric review was conducted by Bemelmans et al. [167], where the authors searched the domain of socially assistive robotics and studied their effects in elderly care. They found only very few academic publications, where a small set of robot systems were found to be used in elderly care. Although individual positive effects were reported, the scientific value of the evidence was limited due to the fact that most research was done in Japan with a small set of robots (mostly off-the-shelf AIBO, Paro [168] and NeCoRo [169]), with small sample sets, not yet clearly embedded in a care need driven intervention. The studies were mainly of an exploratory nature, underlining the initial stage of robotics as monitoring and assistive technology applied within health care.

The recent QoS centric systematic review by Cheung et al. [165] studied organisational and clinical impacts of integrating various bedside monitoring equipment to an information system, i.e. a computer-based system capable of collecting, storing and/or manipulating clinical information important to the healthcare delivery process. The authors drew a special attention that implementation of so called patient data management systems (PDMS) potentially offers more than just a replacement of a paper-based charting and documentation system, but also ensures considerable time savings, which can lead to more time left for direct patient care. Additionally, authors concluded that improved legibility, consistency and structure of information, achieved by using a PDMS, could result in fewer errors.

In one of the most recent technology centric reviews by Mukhopadhyay [164] the latest reported systems on human activity monitoring based on wearable sensors were discussed and several issues to tackle related technical challenges were addressed. The author pointed out that development of lightweight physiological sensors could lead to comfortable wearable devices for monitoring different types of activities of home dwellers, while the cost of the devices is expected to decrease in the future.

2.4. RELEVANT SCENARIOS FOR HOME MONITORING SOLUTIONS FOR OLDER ADULTS

In this section, we describe three common scenarios of older people's living situation in order to increase the understanding of when and how home monitoring can be used among older people at risk of worsening health. We aim at describing the different circumstances under which monitoring approaches and personal care solutions can be applied. Then, we describe relevant geriatric conditions and threats of deteriorating health and functional losses, which are considered to be of paramount need for suitable monitoring solutions. Finally, we summarize these needs in a concise list of conditions and activities that shall be automatically monitored.

We acknowledge that older people are individuals with very different health, social, and socio-economic characteristics, which make them as a whole a very heterogeneous group of the population. Yet, we will describe three common scenarios, which we believe cover a majority of the situations encountered by older adults in need of special attention to prevent health deterioration. This includes, but it is not limited to, the description of the involved persons[4] that are receiving or potentially will receive in-home health and personal care. The descriptions may include, for example, the older persons' general health condition (i.e. their physical, mental and cognitive functional abilities), the current living environment and daily activities, the health care services and technologies that they already have or are potentially available, and the possible ethical and legal issues. These basic conditions have to be considered before proposing any home monitoring solution. It is important to understand the various scenario descriptions in order to identify the key requirements and needs for an optimal monitoring solution in each single case. For example, the use of video cameras is legally restricted in many countries for privacy reasons, which means that it does not make sense to propose video-based solutions

[4] In this book we have a primary focus on older adults, mainly aged 70 and over (70+), who are being monitored. Other involved persons may include formal caregivers (nurses, social- and health care assistants and helpers), informal caregivers (family, neighbours, and friends).

if the legal situation does not allow their installation. But even when it is legal, cognitively or mentally impaired persons may not be able or willing to cooperate with caregivers and thus would require other solutions.

Finally, emphasis should be put on establishing seamless and consistent information and communication flow between the different actors in health care, i.e. formal home care, general practitioner (family doctor), and secondary healthcare, which requires accessibility to Electronic Health Records (EHR), also for mobile units, to retrieve updated information on health, diseases and actual treatment, as well as for documentation [104]. Appropriate analysis of which in-home monitoring tools may be used when and where requires principally a broad cooperation between involved engineering teams and health care professionals.

The most relevant factors that ultimately influence in-home monitoring scenarios are the older person's conditions and abilities, types of living environment, types of activities, existing infrastructure, current care and medication plans, parameters that need to be monitored, intensity of monitoring, and data transmission, among others.

2.4.1. HEALTHY, VULNERABLE, AND ACUTELY ILL OLDER ADULTS

The older we get the more diverse we become in terms of health and functions. It is therefore a challenge to categorize older adults into a few descriptive groups and scenarios. Most commonly, and depending on the general abilities of older adults, three main groups of in-home monitoring scenarios can be observed: 1) scenarios involving relatively 'healthy' older adults, 2) scenarios involving 'vulnerable' older adults, and 3) scenarios involving 'acutely ill' older adults.

Although the meaning of being healthy can be discussed at length, we describe the main actors of our first scenario as older adults who seem relatively 'healthy', as they most likely are independently living in their own home, and do not show any particular symptoms of health deterioration [45], [170]. These older adults may still have a few comorbid diseases, e.g. cataract and osteoarthritis, but are not yet hampered in their activities of daily living, although they may have had a few incidents in the past such as falls. Thus, they would benefit from early detection of health-threatening situations and potential risks, e.g. poor lightning at night when they have to go to the bathroom, or fast movements before the body has gained stability, for instance, when rising from a chair. Another monitoring example could be the detection of declining mobility, which may happen, for instance, due to inadequate relief of a bodily pain caused by osteoarthritis in the knee. Less physical activity would lead to a negative spiral with not only worsening of the pain but also disuse of muscles, which in turn leads to muscle wasting and loss of muscle mass and strength, i.e. *sarcopenia*, a disabling disease.

The second scenario type is the most commonly described in the home monitoring literature. It involves 'vulnerable' older adults diagnosed with one or more chronic medical conditions [54], [55], [106], [171]–[174], e.g. chronic obstructive pulmonary disease (COPD), diabetes, cardiovascular diseases, stroke, hypertension, depression etc., and/or with impaired physical, mental or cognitive functions. Older adults with chronic diseases are at higher risk of worsening health, e.g. chronic atrial fibrillation increases the risk of getting a stroke and cognitive impairment. Within this scenario, the older persons would in many cases benefit from regular (daily/weekly) attention and possibly assistance from a caregiver. In addition, the monitoring equipment should be adaptable to other requirements for this more vulnerable group of persons, compared to the first scenario, e.g. being applied to older adults who would have difficulties in interacting with the technology, perhaps even accept its presence.

The third scenario type involves older adults, either belonging to the first or the second scenarios, but who are developing an acute illness, on top of chronic diseases or conditions, and thus at threat of an acute hospitalization, as exemplified in [172], [175], [176]. This scenario has the most complex requirements for monitoring technology, and is often called *Hospital at Home* (HH) scenario [177]. In addition to monitoring technology there is usually a need of appropriate assistive technology that makes it feasible for older adults with multiple geriatric conditions to avoid acute admission, or, if admitted to the emergency department, to be discharged earlier to their own dwelling with the appropriate technology.

It is important to note, that the aforementioned three main types of scenarios are only rough approximations of patient groups. The boundaries between the three groups are often blurred, while the real-life scenarios would require much deeper insight into the individual patient's characteristics, institutional factors, the current social network situation, the comorbidities, and the main health care tasks and goals. Therefore, the next subsection describes possible geriatric conditions, which are relevant and worthy to have an insight to, in order to understand the challenges of applying in-home monitoring of older adults in their dwellings. Such geriatric conditions would also be involved in the ultimate decision on which type of monitoring devices should be used in one of the three scenarios. Apart from getting insight to the various, but common, geriatric conditions it is also important to understand that with advancing age the risk of suffering from multiple diseases at the same time increases. Two different words are commonly used when describing disease profiles in older patients: comorbidity and multi-morbidity. The first is mainly defined by the co-existence of at least one chronic disease or condition with the disease of interest, while multi-morbidity is usually defined as the co-occurrence of at least two chronic conditions within one person at a given time [178]. Multi-morbidity is very common within the geriatric population and increases with age [179].

2.4.2. RELEVANT GERIATRIC CONDITIONS AND THREATS OF DETERIORATING HEALTH AND FUNCTIONAL LOSSES

This subsection gives a general brief description of common health conditions and diseases of older adults, focusing on the scenarios of type 2 and 3. Also, we will discuss the most relevant adversities for which monitoring solutions are needed.

We will start with discussing some key terms. With advancing age, older persons undergo some ageing-related physical, mental and cognitive changes, which increase their vulnerability [180]. The type 2 scenario of vulnerable older adults may also include, but not only, persons at risk of *Frailty.* Frailty has been coined as a state of increased vulnerability to poor resolution of homeostasis after a stressor event, which increases the risk of adverse outcomes, including falls, delirium and disability [181]. Frailty is a complex condition, which is not only defined by diseases, but also by socio-economic status and social network [182], as well as with an increased level of inflammatory markers [183]. Moreover, frailty is associated with disability and mortality [180], [181], and identifying or detecting some of the factors leading to frailty would be an important scope of *gerotechnology*. As frailty is not only complex but also very common in old age, older people with frailty would benefit from being treated by specialist doctors in *geriatric medicine* or *geriatrics*, which however are underrepresented in many countries despite the demographic challenges of the future [184]. Geriatric medicine is *"a branch of general medicine concerned with the clinical, preventative, remedial and social aspects of illness in old age. The challenges of frailty, complex comorbidity, different patterns of disease presentation, slower response to treatment and requirements for social support call for special medical skills."* [185]. Consequently, a geriatric patient may be defined as an older person with comorbid conditions and co-occurring functional limitations, in other words, a host of conditions. Further, the geriatric patient is challenging for health care professionals by showing atypical symptoms of disease, delaying diagnosis [186]–[188] and treatment, and consequently, at higher risk of developing disability, loss of autonomy, and lower quality of life [189].

In order to keep the autonomy of an older person, the health hazards associated to old age must be addressed from various angles, including the framework of *gerotechnology*, by applying appropriate monitoring technology, which is described in more detail in section five.

In the reminder of this section we outline and describe the potentially dangerous situations and health threats that occur most frequently in older and very often co-morbid and frail patients in our scenarios. We start with discussing falls and injuries in older geriatric patients, since these are among the most frequently reported health problems and serious threats to independent living. Then we review a list of potential health threats, which are the most alarming in the older co-morbid population, such as delirium, stroke, hypertension, and heart failure, among others. For each situation, we first define the problem. Then, we discuss its importance and refer to the epidemiology of these occurrences. Finally, we discuss if these problems can be detected, mentioning what data might be necessary to acquire.

For clarity, we are not focusing on diagnostic approaches for major chronic conditions, such as dementia, but rather describing potential adverse events and dangerous situations, which are of potential interest for automated detection.

2.4.2.1 Falls and Injuries

Across the main three scenario types, falls are very common and may lead not only to injuries and adverse outcomes, such as hip fractures or brain concussions, but also to a secondary effect of fear of falling, which in itself increases the risk of falling and reduced physical activity [190]. As a consequence, social interaction is reduced, loneliness becomes frequent, and quality of life is diminished [191]. A negative spiral may begin and may eventually lead to death, if left unrecognized. Therefore, detection of falls is of paramount importance, not only for identifying those who have fractures or intracranial hematomas, but also because many fallers are simply unable to get up by themselves and are therefore at risk of lying on a floor for several hours, even days, with the subsequent risk of dehydration, muscle damage and consequent damage of the kidneys, or even death [192], [193]. Falls could also be the outcome of a stroke or a cardiac arrest. To lower the risk of subsequent further health threatening complications fast identification and diagnosis is required.

The adoption of a definition of a fall is an important requirement when studying falls as many studies fail to specify an operational definition, leaving space for interpretation to researchers. This usually results in many different interpretations of falls in the literature [193]. For example, older adults including their family members tend to describe a fall as a loss of balance, while health care professionals generally refer to an event which results in a person coming to rest inadvertently on the ground or floor or other lower level leading to injuries and health problems [194], [195].

The geometry of the human body in motion requires an individual to remain balanced and upright under a variety of conditions. Balance is adversely affected by intrinsic and extrinsic factors [97]. Intrinsic factors are, for example, side effects of medication (e.g. orthostatic hypotension), medical conditions (e.g. stroke), ageing-related physiological changes (e.g. declining muscle strength), and nutritional factors (e.g. vitamin D deficiency), while extrinsic factors are, for example, poor lighting conditions, loose carpets, slippery surfaces, stairs, etc. [196],[197]. A systematic review and meta-analysis of risk factors for falls in older adults, who live at home, can be found here [198]. Since in real-life scenarios a great majority of fall incidents in older adults who live alone are not reported to healthcare providers [192], automated detection of falls is of high practical research interest [199].

2.4.2.2 Delirium

Patients of all three scenarios are potentially at risk of developing delirium, but the more frail and impaired an older person is, the higher is the risk [200]. Delirium is described as an acute confusional state [200]. Delirium may develop as a reaction to infection, dehydration, pain and painkillers, and has a within-hours fluctuating course from cognitively intact to a state of confusion and even agitation (hyperactive delirium), although silent (hypoactive) delirium also occurs [200]. Furthermore, neurological disorders, such as dementia, significantly contribute to the risk of having delirium. Being in an unfamiliar and busy place with many disturbances and strange faces, e.g. a hospital emergency ward, does not enhance recovery in frail older adults, nor does surgery [201]. Some diagnostic tools, such as the Confusion Assessment Method (CAM) [202], are often used to recognize delirium, and help distinguishing delirium from other forms of cognitive impairment. Treatment should be targeted towards the underlying disease, not the symptoms of delirium, and the delirium will gradually disappear as the initial condition is treated, normally within hours to a few days. Apart from severe causes of delirium, e.g. severe infection, in which intravenous medication is imperative, delirium may not always need to be treated in a hospital setting, but may be cared for in the patient's own dwelling if the necessary surveillance can be established. Discharging older persons at risk of delirium to their own home with in-home monitoring soon after establishing a diagnosis and starting targeted treatment will reduce the risk of delirium or shorten the time period of delirium [203].

2.4.2.3 Wandering and Leaving Home

In cases of cognitive impairment, both unrecognized and recognized, the risk of accidents and getting lost while being outdoors (mostly referring to scenario type 2 and 3) can be rather high. A frequent symptom of cognitive impairment and dementia is geographical disorientation, and in more advanced stages demented persons may leave their dwelling to find their childhood home, a typical delusion of parents being still alive. Such condition may lead to fatal situations, e.g. with wandering in cold weather without proper clothing followed by hypothermia and subsequent death. Therefore, it is important for the caregiver to know whether and when the demented person is leaving the dwelling, and more importantly, when and where wandering behaviour may have occurred [204], [205]. However, despite of several attempts to define wandering behaviour, no commonly accepted definition of wandering exists so far [206], assumingly because the underlying behaviour is very complex and it may present differently depending on the person's physical location (e.g. person's own home, hospital, care facility or a nursing home). One of the latest and most cited definitions of wandering, proposed by Algase et al. [207], is: *"a* *syndrome of dementia-related locomotion behaviour having a frequent, repetitive, temporally disordered, and/or spatially disoriented nature that is manifested in lapping, random, and/or pacing patterns, some of which are associated with eloping, eloping attempts, or getting lost unless accompanied."* Detecting and analysing leaving and returning home habits, as well as travel patterns of older people are therefore of high importance.

2.4.2.4 Malnutrition

Malnutrition and weight loss are mostly relevant for scenarios 2 and 3, but also valid for scenario type 1. Cognitive impairment, loneliness, and depression, as well as poor appetite due to undiagnosed or diagnosed disease, or gastrointestinal side effects of commonly used medicines may lower the appetite of older people and lead to malnutrition and its typical symptom: weight loss. Apart from a geriatric assessment of the etiology of weight loss, securing adequate intake of energy and protein is of paramount importance to revert the otherwise resulting development of sarcopenia (defined previously on page **Error! Bookmark not defined.**), and subsequent functional loss. Surveillance of adequate food intake, liquids and medicine, as well as automated monitoring of body weight would help to identify older persons at risk of adverse outcomes, and thus lead to the initiation of preventive actions. Sarcopenic older persons are at high risk of severe disability, falls, fractures and institutionalisation [208]. It has in recent years been acknowledged that sarcopenia may also be present in obese older adults, so-called 'sarcopenic obesity', caused by excess intake of energy of poor quality, physical inactivity, and hormonal alterations [209]. Such persons have the same adverse outcomes as low weight sarcopenic persons, and may too benefit from surveillance of adequate food intake.

2.4.2.5 Sleeping Disorders

Another potential problem, again mostly relevant for scenarios 2 and 3 but also valid for type 1, is disturbances in sleep. In fact, the majority of the geriatric patients experience significant alteration of their sleep patterns and thus overall bad quality of sleep. Changes in sleep pattern are considered to be normal changes with advancing age, with a greater percentage of the night spent in the lighter sleep stages [210],[211], but other causes exist too, and can be divided into intrinsic conditions of an individual patient and extrinsic factors related to the environment, where the patient is sleeping. Intrinsic conditions may include pain (e.g. from arthritis), nocturia, medication effects, depression, restless legs syndrome, obstructive sleep apnoea (long pauses in breathing associated with snoring), and paroxysmal nocturnal dyspnea (sudden pauses in breathing, experienced during exacerbations of congestive heart failure) [212]. Extrinsic factors may include acoustic noise, lightning, vibration or physical movement, fluctuations of environmental temperature, draught at home, dust, and poor air condition, among others. Thus, monitoring sleep and detecting possible causes of sleep disturbances are of high importance for revealing causes of disturbed sleep.

2.4.2.6 Shortness of Breath

With advancing age certain physical activities, such as walking upstairs, may cause dyspnoea in older adults, who in turn would adapt their physical activities to less challenging activity levels, or even inactivity. Ageing is associated to ageing-related changes in the respiratory organs leading to lower oxygen uptake from the air to the blood, lower lung volume, and less lung compliance, all leading to shortness of breath when extra respiratory capacity is needed. Diseases such as osteoporotic compression or vertebral deformities of the thoracic vertebras may also affect normal lung function by diminishing the thorax volume [213]. Environmental factors such as smoking and previous employment in jobs associated with dust may reinforce these eventually pathologic changes.

A common medical breathing condition is chronic obstructive pulmonary diseases (abbreviated as COPD), which shares many symptoms with pulmonary emphysema, chronic bronchitis, and asthma. Co-occurring diseases such as chronic heart failure, anemia, and cancers may worsen breathing, as well as acute pneumonia. Also snoring with apnoea is considered as a breathing problem, which may lead to lower oxygen intake during sleep and subsequent cognitive impairment [214]. Other reasons of breathing problems may include smoking habits, poor air quality in the living environment and non-pulmonary infections. Due to the vital importance of pulmonary function, many studies aim at detecting, monitoring, and preventing respiratory problems in older adults at their living environments [215]–[218].

2.4.2.7 Hygiene and Infections

Poor hygiene, and not the least in combination with a weaker immune system associated to ageing, may increase the risk of contracting infections, often leading to fever (elevated body temperature). Oral hygiene and oral infections, such as dental caries and oral fungal infections are important to care about, especially for those individuals who use artificial dentures [219], as it may lead to malnutrition and weight loss, and may furthermore cause systemic infections.

Urinary tract infections (UTIs), as another example, can be a serious health threat to older people [23]. UTIs are common in older adults, especially in women [23]. Many cases are self-limiting in healthy individuals, but in vulnerable and diseased older persons a UTI, if untreated, may spread to the blood stream causing systemic infection, kidney damage, delirium, and even death. Common symptoms of UTIs include urgency, frequent and painful urination, and incontinence, but may be absent in older adults.

An infection of the lungs (pneumonia) [220], may lead to multiple symptoms, such as cough, fever, shortness of breath, and weakness. The pneumonia may stress the heart and lead to acute heart failure and atrial fibrillation, which further worsens the situation and demands immediate medical attention.

2.4.2.8 Problems Related to Physical Environment

Finding potential threats in older adult’s living environment is relevant for all three scenarios. However, not many studies investigating health conditions of older adults at home were able to thoroughly assess the environmental threats of the older persons’ dwellings. For example, levels of environmental noise, lighting, vibrations, ambient temperature, humidity, climate and air condition, and other matters, such as availability of household facilities, all can significantly influence the quality of life of an older individual, especially when the individual suffers from comorbid chronic heart and/or lung conditions. Other environmental hazards may include obstacles in pathways, slippery surfaces, tripping hazards, loose rugs, unsafe or unstable furniture, etc., which may contribute to injuries or falls [221], [222]. Indeed, the most frequently cited causes and risk-factors of falls are ‘accidental’ and ‘environment-related’, accounting for approximately 30–50% of all older adult falls [223]. However, many falls attributed to accidents stem from the interaction between identifiable environmental hazards and increased individual susceptibility to such hazards from accumulated effects of age and diseases [223].

2.4.2.9 Underlying Medical Conditions and Multimorbidity

The concept of multimorbidity has been explained earlier and refers to co-occurrence of two or more chronic diseases or conditions within the same individual [178], [179], [224]. Multimorbidity, associated polypharmacy (i.e. using 5 or more different medications per day), and adverse side effects of medication increase with advancing age, resulting in that more than half of older adults suffer from three or more chronic diseases simultaneously [225]. The most frequent comorbid conditions in older people are [226]: hypertension, coronary artery disease, diabetes mellitus, history of stroke, chronic obstructive pulmonary disease, and cancer. Early recognition of acute illness and diagnosis, followed by timely and adequate treatment is not only the key to prevent severe deterioration in health, but also the key to reducing the risk of functional impairments and mortality in geriatric patients. The Comprehensive Geriatric Assessment (CGA) is a tool that has proven effective in terms of reducing mortality and institutionalisation [227]. The same principle of comprehensive assessment by monitoring medical parameters and features in older persons at risk, e.g. multimorbid geriatric patients, would be valuable for the individual as well as to the society. However, it requires an understanding of the multidisciplinary nature of health and health deterioration in older adults, and therefore, a broad range of medically sensitive parameters, both objective and subjective, that can detect and measure such deterioration, needs to be considered. Novel automated monitoring technology yet needs to be identified or developed, which will create new perspectives on using in-home monitoring.

2.4.3. SUMMARY OF THE NEEDS

A list of conditions and activities that may be monitored is listed below. The list is far from being exhaustive, but addresses the most common needs given by the individual's living style, culture, and acceptance of remote surveillance and monitoring in private homes. The future may bring new conditions, e.g. economic challenges, changed family structures and intergenerational support and care, improved health literacy as well as IT-literacy of caregivers and the target population itself, which may identify new ways of monitoring older adults in their dwellings.

The focus is on the following topics:

- Gait and balance monitoring
- Detecting falls
- Detecting problems related to physical environment
- Detecting wandering
- Detecting delirium
- Recognizing abnormal activity, such as, absence of meal preparation or disturbed day-night cycle
- Monitoring physiological vital status parameters, including body weight
- Monitoring food intake
- Detecting adherence to medication

In the next section, we will summarize the available monitoring technologies, which directly or indirectly address and attempt to contribute to the aforementioned topics. Most of these monitoring technologies share common ground as organized in the next section.

2.5. MONITORING TECHNOLOGY

This section aims at giving an insight into a variety of available monitoring technologies and techniques, which aim to provide solutions to the issues listed in the previous section. First, we start with discussing possible data collection approaches, by revealing choices of available sensors and underlying constrains. Second, we provide a summary of sensors used for data acquisition in regard to needed medical applications, revealing what relevant parameters can be derived from those sensor measurements. We then summarize what common data processing and analysis techniques are used for interpreting this data, with a special focus on machine learning approaches. Third, we derive important requirements and underlying challenges for the involved machine learning strategies, and discuss possible implications for applying the different monitoring approaches. Finally, we refer to a number of established standards, which are needed to be complied with, when developing and implementing home monitoring systems for older adults.

Most of the smart-home projects, which were briefly introduced in section 2.2.3, significantly contribute to the research and development of automated monitoring technologies related to the topics listed in section 2.4.3. Many of these projects proposed holistic approaches, which aim at solving multiple problems simultaneously within one smart-home environment. However, these topics are highly abstracted and thus many of them are treated differently, depending on different scenario constraints, on what sensors are applied for data acquisition, and on what information is available a-priory. For example, recognition of abnormal activity highly depends on the monitored subset of ADLs, and furthermore the abnormality may be defined differently. For instance, abnormality may mean a certain deviation from the learned baseline of “normal” everyday activities, or it can be strictly predefined based on prior expert knowledge, e.g. a known sequence of activities that is considered to be abnormal and health threatening.

The most common monitoring approach for recognizing health problems at home is motion capture (e.g. for classifying and assessing ADL). Recordings are usually examined manually by health care professionals, such as nursing staff, physiotherapists, and occupational therapists, which is very time consuming [228]. In previous studies about automated monitoring, movement is usually captured using inertial sensors [229], computer vision [230]–[232], electromyography (EMG) [233], radio-frequency (RF) sensors, or infra-red (IR) sensors [234]. For detecting different health-threats, video monitoring and computer vision has been widely presented and discussed in the literature, but the main two purposes of these systems were surveillance and communication applications. Video (incl. audio) transmission is usually made in real-time over an ordinary telephone line [38] or Internet [235]. The video can be either viewed directly on a tablet or a monitor by a nurse or doctor, or a video processing system is used to automatically interpret the video data and present the relevant (alarming) information to the medical staff [236] only when some abnormality is detected. The main problem with these video-audio solutions is the ethical issues, i.e., the majority of older adult users are concerned about being monitored by video, as discovered by usability studies, e.g. in the EU-funded Seventh Framework Programme (FP7) Project Confidence [237]. Another common problem is insufficient bandwidth or the quality of Internet connectivity and poor mobile network coverage in some geographic areas such as rural areas. Therefore, it may be impossible to establish real-time video link with sufficiently high resolution of e.g. complicated wounds, which may need to be treated by a visiting nurse, perhaps guided by a surgeon watching the video in his or her hospital office. Nevertheless, as a communication tool to allow older adults communicating with medical staff on their own request, video-audio technology is already commonly applied [236], [238], [239], when connectivity allows it.

2.5.1. SENSING AND DATA ACQUISITION

There are numerous ways of collecting data about the older persons' health condition, which can be accomplished by asking specific questions and registering answers (considered to be a subjective approach) or by using various sensors (an objective approach). In this chapter we are mainly interested in collecting objective data, which can be acquired automatically, by using sensors and data capturing devices. However, very often both subjective and objective approaches are combined, to provide as full information as possible.

2.5.1.1 Types of Sensors and Data Capturing Devices

The different types of sensors used in the field of patient monitoring and the purpose of their employment in regard to the topics listed in section four are shown in Table 2-3. The most common purpose of employing these sensors has been for fall detection applications. Fall detectors [95], [240], in most cases, measure motions and accelerations of the person using tags worn around the waist or the upper part of the chest (by using inertial sensors: accelerometers, gyroscopes, and/or tilt sensors). In general, if the accelerations exceed a threshold during a time period, an alarm is raised and sent to a community alarm service. By defining an appropriate threshold it is possible to distinguish between the accelerations during falls and the accelerations produced during the normal ADL. However, threshold-based algorithms tend to produce false alarms, for instance, standing up or sitting down too quickly often results in crossing a threshold and an erroneous classification of a fall [228]. Several machine learning approaches were also proposed for detection and identification of falls [241], [242], [91], [243], [92], which help to minimize those false alarms by automatically adapting to specifics of the monitored person. The use of indoor localization sensors (both IR- and RF-based) have also been reported [241], [244], which are intended for localizing persons in 3D space and analysing their movements, useful for detecting accidental falls or abnormal activity.

Another common technology for fall and/or accident detection is emergency alarm systems, which usually include a device with an alarm button [60], [245], e.g. embedded in a mobile phone, pendant, chainlet, or a wrist-band. These devices can be used to alert and communicate with a responsible care center. However, such devices are efficient only if the person consciously recognizes an emergency and is physically and mentally capable to press the alarm button. Also static alarm buttons exist, which are often placed in the toilet or bathroom, as required by the BS 8300 and ISO 21542 standards [246], [247].

The sensors reported in the literature included (but were not limited to) infrared (IR) and near-infrared (NIRS) sensors [254], [322], [326]–[330], video [49], [248], [275], [331] and thermal cameras [332], [333], bioelectrical sensors (used in ECG, EMG, EEG) [174], [306], [334], [335], [294], ultrasonic sensors and microphones

[336]–[340], radio-frequency (RF) transceivers, piezoresistive and piezoelectric sensors [341]–[343], inertial sensors (such as accelerometers, gyroscopes, and tilt sensors) [90], [91], [170], [240], [287]–[291], [294], [344], electrochemical sensors (such as smoke detectors, CO_2 meters, blood glucose and hemoglobin testers) [345]–[349], as well as mechanical measurement devices (such as weighing scales).

Table 2-3 Summary of sensors used for data acquisition in regard to needed medical applications

Sensor type / Sensing modality	**Data of interest**	**Purpose of application***	**References**
Video cameras	Pose estimation, location, movement speed, size and shape changes, custom defined visual features, temporal semantic data, facial skin colour, head motion, face alignment positions	Gait and balance monitoring, Fall detection, Monitoring the activity of daily living, Abnormal activity recognition, Activity detection in first person camera view, and Detection of activity of taking medicine, Measurement of physiological parameters, and Tracking medical conditions, Elopement detection	[173], [248]–[276]
Microphones	Heart sound, speech, coughing sounds, snoring sounds, Stethoscope signal, environmental noise, etc.	Physiological vital status parameters monitoring, Environmental threat detection	[277]–[283]
Infrared (IR) sensors (incl. motion detectors and depth cameras)	Indoors location, movement	Fall detection, Abnormal activity recognition, Wandering detection	[254], [267], [284], [285]
Accelerometers	Body movement	Fall detection, Abnormal activity recognition, Wandering detection, Gait and Balance monitoring, Food intake monitoring	[240], [286]–[293], [170], [294]
Gyroscopes	Body movement, orientation	Fall detection, abnormal activity recognition, gait and balance monitoring	[90], [91], [286], [295], [296]

Continued from previous page….

Sensor type / Sensing modality	**Data of interest**	**Purpose of application***	**References**
GPS trackers	Outdoor (and limited outdoor) location,	Wandering detection	[159], [297]
Pulse Oximeter / Near-infrared (cuffless)	SpO_2, blood pressure, heart rate	Physiological vital status parameters monitoring	[272], [277], [298]
Blood pressure monitor (cuffed)	Systolic and diastolic blood pressures and heart rate	Physiological vital status parameters monitoring	[117], [277], [298]–[304]
Impedance pneumography (IP) sensor	Respiration rate	Physiological vital status parameters monitoring	[305]
ECG device	ECG signal; Heart rate; including: RR-interval; beginning, peak and end of the QRS-complex; the P- and T-waves; the ST-segment, etc.	Physiological vital status parameters monitoring, arrhythmia detection, delirium detection	[68], [174], [277], [294], [304], [306]
EMG device	EMG signal and related parameters	Abnormal activity (incl. inactivity) detection	[294], [304], [307]
EEG device	EEG signal, blood glucose levels	Physiological vital status parameters monitoring, Detection of various health-threats, such as Hypoglycemia, Epilepsy, Sleep apnea, Dementia and other uses	[59], [107], [307]–[314]
Weighting scale	Body weight	Physiological vital status parameters monitoring, Food intake monitoring	[277]

Continued from previous page….

Sensor type / Sensing modality	**Data of interest**	**Purpose of application***	**References**
Spirometer	Spirometric parameters, such as Forced Vital Capacity (FVC), Peak Expiratory Flow (PEF), and Peak Inspiratory Flow (PIF)	Physiological vital status parameters monitoring	[54], [175], [277]
Blood glucose monitor	Blood glucose levels	Physiological vital status parameters monitoring	[156], [277], [298], [315]
Pressure mat / carpet	"step on", "sit on" or "lay on" events	Abnormal activity recognition, Wandering detection	[316]
Stove sensor	Stove on/off events	Environmental threat detection	[317]
RFID sensor	Different events (such as taking pills), localization	Abnormal activity recognition, Tracking medical conditions, Environmental threat detection, Food intake monitoring	[245], [318]–[321]
Temperature sensors	Body temperature, environmental temperature	Physiological vital sign monitoring, Detecting problems of physical environment	[297], [304], [322]–[325], [294]

*'Purpose of Application' column refers to detecting health threats for older adults living alone at home, which is relevant to the list specified in the subsection 2.4.3.

Video cameras and thermal cameras have two different types: static cameras and active PTZ (pan-tilt-zoom) cameras. IR sensors also have two types: active and passive, but the meaning of activeness in this context is different. Instead of being able to rotate or zoom in and out, active IR sensors emit IR radiation pattern and then capture the reflection of the infrared rays. On the other hand, passive IR (i.e. PIR) sensors merely capture the IR radiation from the environment. Ultrasonic sensors, for instance, are typically active, meaning that an ultrasound transmitter is involved, and an ultrasound receiver is tuned to capture the reflected ultrasonic waves initially emitted by the transmitter.

Bioelectrical sensors measure electrical current generated by a living tissue. Electrochemical sensors typically measure the concentration of the substance of interest (such as gas or liquid), by chemically reacting with that substance and consequently producing an electrical signal proportional to the substance concentration. Piezoresistive sensors measure changes in the electrical resistivity of a piezoresistive material (e.g. consisting of semiconductor crystals) when a mechanical stress is applied to it. On the other hand, piezoelectric sensors measure the electrical potential generated by a piezoelectric material itself, which is also caused by applying mechanical force to it.

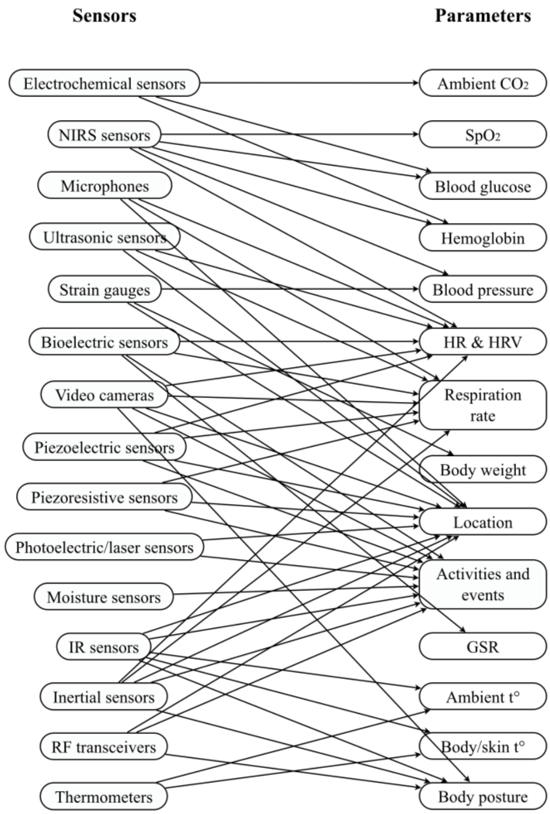

Figure 2-3 The linkage between the identified sensors and the most common corresponding parameters (summarized in 2.4.1.3), which can infer patients' health conditions and therefore can be valuable assets for each of the three scenarios (introduced in section four). NIRS stands for near-infrared spectroscopy; IR - infrared; RF – radiofrequency; CO_2 - carbon dioxide (concentration); SpO_2 - peripheral capillary oxygen saturation, i.e. estimation of the oxygen saturation level; HR and HRV stand for heart rate and heart rate variability respectively; GSR – galvanic skin response; t° - temperature.

Most of these aforementioned sensors have been utilized for data acquisition in different areas of older patient monitoring, such as activity of daily living (ADL), instrumental activity of daily living (IADL), abnormal activity detection such as fall detection or wandering, and extraction of physiological parameters.

Hence, the general goal of using the aforementioned sensors is to measure relevant physical properties for estimating specific medically important parameters (often called as *biosignals* or *biomarkers*), which are summarized in section 2.5.1.3, and which allow to further infer the patients' health conditions [350] followed by manual or automatic analysis.

2.5.1.2 Sensor Location and Placement

Technically, there are infinite location options for placing the variety of sensors intended for in-home monitoring. The choice of these sensors and their placement, however, highly depends on the needs seen by patients and medical staff, on physical and mental conditions of a person, who needs to be monitored, and on the various scenario constrains, including existing infrastructure options, physical layout of the dwelling, etc. In general, these sensors can be divided in the following groups in terms of their placement:

i. *On-body sensors*, such as skin-patches and sensors worn by an individual as an accessory or embedded in the outfit (part of clothing), like:

    a. Electronic skin patches or artificial skin, as exemplified in [285], [351], [352], that can be glued to the skin on a body area of interest, and which may include various sensors for measuring various physiological parameters, such as (but not limited to) body temperature, heart rate, EMG parameters, pulse oximetry for monitoring the oxygen saturation (SpO_2), as well as accelerometers, moisture sensors, and possibly others.

    b. Wrist-watches, wrist-bands and arm-bands [41], [322], [353]–[356] or rings [322], [357], measuring heart rate, body temperature, near-body ambient temperature, galvanic skin response (GSR), and EMG data. Similarly, these sensors can also be incorporated into jewellery, such as necklaces, brooches, pins, earrings, belt buckles, etc.

    c. Clothes, belts and shoes for monitoring gait, motion, vital signs and detection of health emergencies [343], [358]. The most common are chest-worn belts and "smart textile" shirts for measuring vital signs and motion [305], [341], [343], [359], [360]. Other examples may include gloves for recording finger and wrist flexion during ADLs and/or vital signs [40], [361], a waistband with textile sensors for measuring acidity (pH levels) of sweat and sweat-rate [349], or moisture sensitive diapers [362].

d. Headbands and headsets for monitoring brain activity, based on EEG and NIRS signal analysis [56], [307], [363].

ii. *Remote sensors*, which can be placed on ceilings or desks, embedded in pieces of objects, furniture, in the floor of a house, which are usually static (i.e. not mobile). These can include the following:

a. Sensors, which are mounted on ceilings or walls (incl. corners), include video cameras (with or without microphones) [49], [254], [275], [331], [335], IR active and passive sensors (including thermal imaging) [149], [328], [329], [332], [353], [364], [365], and ultrasound sensor arrays [366]. Those sensors are used mainly for localization and motion capture of home residents, and also for measuring various physiological signs, such as breathing rate and cardiac pulse, as well as for assessing functional status of older adults at home, detecting emergencies, such as falls, and recognizing various ADLs. Noteworthy, the majority of the aforementioned monitoring approaches do not require wearing tags or carrying a mobile device for older persons during monitoring, however several IR-based motion capture systems [295], [367] and RF-based localization systems [237], [241], [368], [369] do require wearing dedicated tags or *on-body* devices attached to a subject, and thus are mainly meant for experimental purposes.

b. Pressure-sensitive mats, carpets, beds, sofas, and chairs, or load-sensing floor, which are used for monitoring movement, assessing gait, detecting falls, recognizing sitting and sleeping postures, as well as ADLs [139], [370]–[374]. Various contextual data can be extracted from load-sensing techniques, for example the body weight or position of a person. Other sensors, such as moisture sensors, can be also embedded into bed mattresses or sofas, to detect, for example, possible urinary incontinence [342], [375], or vibration sensors, embedded in the floor, for movement tracking and fall detection [376].

c. Ambient temperature, humidity, CO_2 concentration, vibration, particle, lightning sensors, microphones, and smoke detectors, which are placed in all or certain rooms of older residents, to monitor environmental living conditions, recognize different ADLs, as well as to screen for certain emergencies [156], [281], [324], [377]–[379]. Usually these sensors are also mounted on walls or ceilings.

d. Medication tracking and reminder systems, as well as usage tracking of different items at home, usually based on RFID technology

[264], [320], [321]. These systems could detect how many times an older adult uses his or her preferred items, and thus providing a good measure of the person's ADLs.

iii. *Implantable (In-vivo) devices*, like:

a. Implantable cardiac monitors, i.e. ECG loop recorders [380];

b. Smart pills, e.g. for gastric pressure and pH level measurement [381],

c. Continuous glucose-monitoring biosensors, e.g. implanted into the inner ear of subjects and detecting hypoglycemia from EEG signals [107], [313],

d. Wireless capsule for endoscopy [382].

iv. *Portable (mobile) devices*, like:

a. Smartphones and tablets [40], [90], [271], [288], [291], [344], [383]–[385],

b. Multimedia devices or systems [135], [156], [386],

c. Robots equipped with multimodal sensors [39], [135], [157], [167], [168], [335],

d. Portable video cameras and microphones [236], [387].

For a number of practical and financial reasons, the devices mentioned in the fourth group of the above list are often used as devices for the first and second group. Furthermore, smartphones and tablets typically provide wider range of functionality, including transmission, storage, processing, accessing of the data and relevant information, as well as providing functionality for human-computer interaction.

Systematic evaluation is needed in order to quantify which location and placement is the most suitable for the sensors. For instance, Kaushit et al. [294] evaluated the characteristics of a pyro-electric infrared (PIR) detector to identify any section of a room, where the detector will fail to respond, and assessed the number of detectors required to identify reliably the movements of the occupant. They showed the spatial characteristics of PIR detector and assessed the minimum number of detectors required to sense even small movements (e.g. reading a book) in its defined field of view in order to monitor activities of older people living alone at home. They suggested combining several detectors (four per room - one at each corner of the room) in order to gather reliable data for all types of movements to assess the occupancy patterns of the room, because a single detector was not capable of providing information about the level of activity performed by the occupant.

One of the most promising patient monitoring technologies is based on health monitors that are body-worn (e.g. on the wrist). Most commonly, they are intended to continuously monitor the pulse, skin temperature, movement [115], [388]–[391] and other data of interest. Usually, at the beginning of the systems usage, the pattern for the user is learned. For this purpose, machine-learning approaches are used. Afterwards, if any deviations are detected, alarms are typically sent to the emergency center. Such a system can detect various health-threats, for example, collapses, faints, blackouts, etc. The drawbacks of these systems are poor tracking accuracy [237] and that people are not likely to carry the body-worn devices at all times, even if the transceiver is built into a convenient form, such as a wrist watch, a smart phone or a bracelet.

Finally, the common problem with most of the currently proposed health monitoring systems is that patients are often compelled to wear or even carry-on uncomfortable and/or cumbersome equipment, to be within certain smart home rooms or beds fitted with monitoring devices, which clearly restrict older persons' activity [392]. The challenge of building monitoring system, which can automatically monitor older patients at home and detect dangerous conditions and situations, remains unsolved. In order to solve the above-mentioned problems, it is strategically important to prioritize the most unobtrusive technological solutions with a trade-off of capturing enough *clinically useful* data.

2.5.1.3 Summary of Parameters

All sensible parameters can be categorized into the five main classes, which represent the nature of the target measures:

i. Physiological parameters, as for example in [15], [30], [116], [393]–[395],[396], which represent intrinsic functioning of human body (often called as vital signs) such as pulse, blood pressure, respiration rate, temperature, lung vital capacity, blood oxygenation, blood glucose levels, hemoglobin, cholesterol, blood lactate and others;

ii. Behavioral parameters, as for example in [16], [90], [95], [230], [393], [394], [397]–[400], which can be observed extrinsically (e.g. represented as ADL, cognitive tasks, social interaction, etc.);

iii. Parameters describing sensory, cognitive and functional abilities of a person [401]–[403], e.g. strength and balance, that can be measured, for instance, through a 'hand-grip' test and a balance tests respectively, or other physical and cognitive parameters, which can be assessed by preforming specific ADLs;

iv. Anthropometric parameters [170], [404] (such as weight and height, body circumferences, body-mass index, and knee-heel length), which usually stay constant and are necessary for statistical comparison between diversity of older adults, and in some cases, detecting a body weight loss or gain may be of interest;

v. Environmental parameters [150], [156], [215], [375], [405]–[407] (such as ambient temperature, humidity, pressure, lighting, environmental noise, air quality, etc., which are important factors for health condition);

In general, human health state can be defined by a variety of physiological and behavioral parameters, which usually are self-interdependent. However, not all of them are equally important and not all of those parameters can be easily and precisely measured, requiring different medical equipment and measuring approaches (e.g. invasive, non-invasive, and distance monitoring).

From the reviewed works, it is evident that only few studies covered two or more aspects simultaneously, and no work was found where all the five sensor categories were considered. In practice, there are obvious overlaps between what sensory technology is used, what biosignals are measured, and how and where they are measured. By applying sensor fusion techniques, it is possible to:

i. Make the sensors work in equilibrium (i.e. synchronized in time and cross-dependent, when one or more measured parameters can rectify another parameter of interest being monitored, as described by the heterogeneous approach [103])
ii. Optimally select the hardware, with the aim of achieving maximally accurate, complete and consistent patient records.

In the related works, optimality of sensor selection is generally assessed by the following measures that might play a role in different scenarios:

i. Validity and reliability of the sensor measurements. Validity refers to the degree to which a measurement method or instrument actually measures the concept in question and not some other concept. It often refers to precision and accuracy of a monitored parameter measured by a sensor or estimated by a sensor system. Reliability refers to the degree to which a sensor or a sensor system produces stable and consistent data over time. For example, it should be stable to noise and robust to patient's activity and location [389].

ii. Comfortability, which is often measured based on the non-intrusiveness and non-invasiveness of sensors [408], [409]. For example, on-body non-invasive sensors are more feasible for home appliances than invasive ones, while a remote unobtrusive (distance-monitoring) approach is more comfortable than, e.g. wearable/on-body sensors. Size, form and weight are also considered as important factors for the comfortability measure of wearable sensors [60]. Hensel *et al.* [408] describe in total 8 different types of user perceived obtrusiveness that are caused by home tele-health technology, and which should be considered when evaluating comfortability.

iii. Durability and longevity, which describes how long a particular device can operate, in terms of wear and tear, and in case of necessity to change some parts, such as stickers or patches [410].

iv. Energy efficiency, which is assessed in terms of energy consumption and battery life [410], [411].

v. Observation ranges and location and placement of sensors, which ultimately defines whether or not it is feasible to use the sensors under certain constraints and how many sensory devices should be used [412]. In addition, the effects of potential sensor displacement should be considered as well [413].

vi. Low-cost, which justifies the financial feasibility for applying the proposed sensors [372].

2.5.2. DATA PROCESSING AND ANALYSIS

In this subsection we review the available methods for analysing, using, and understanding the data collected by the sensors described in the previous section.

2.5.2.1 Machine Learning Approaches

Machine learning techniques are able to examine and to extract knowledge from the monitored data in an automatic way, which facilitates robust and more objective decision making. Although the number of potential applications for machine learning techniques in geriatric medicine is large, few geriatric doctors are familiar with their methodology, advantages and pitfalls. Thus, a general overview of common machine learning techniques, with a more detailed discussion of some of these algorithms, which were used in related works, is presented in this section.

Numerous recent studies [90], [94], [114], [123], [314], [395], [414]–[421] have attempted to leverage different machine learning techniques on a wide variety of data-readings to solve problems of detecting potential health threats automatically and to better understand health conditions of older adults at their living environment. Most of the discussed problems are concerned with classification tasks, as for example, where the desired result is a categorical variable, i.e. a class label ([91], [94], [134], [248], [250], [252], [295], [419]–[428]). The most notable examples of classification tasks are fall detection [91], [248], [250], [252], [419], [422], [424], [427], [428] and abnormal behaviour or event detection [94], [420], [423] (which can be caused, for instance, by falls or health deterioration) in older adults. Few other works are solving regression problems, like in [429]–[431], where the goal is to estimate a continuous variable. Regression examples include predicting functional ability [429], estimating mortality risk in geriatric patients [430], or continuously estimating a vital-sign, such as blood-pressure or blood-glucose concentration [298], based on other non-invasively measurable parameters. It is important to note, that regression is often used as an intermediate step before final classification, as for example in [424], [432]–[435], where a continuous regression curve is truncated into two distinct classes or more (most commonly ordinal) categories. It is worthy to mention that sometimes a regression curve is also used to estimate a boundary that explicitly separates two classes, but there are no relevant studies yet, where it is mentioned in our context. For instance, logistic regression can be often used as a classifier.

There are numerous works, which report treating the posed problems in a *supervised* fashion, when a dataset with empirical data including correct classification or regression results is provided as a “learning material” for training and testing machine learning techniques, as for example in studies dealing with recognizing ADLs [85], [255], [258], [259], [263], [436], [437], where datasets with clear labels for each activity annotated by a human expert were used. Most of these studies focus purely on the detection of “alarming situations” (e.g. a fall) commonly treated in *discriminative* fashion, i.e. learning to distinguish an alarming event from non-harmful situations based purely on the previously monitored data and finding dependency of annotations (ground truth). These problems can be solved by *discriminative* (often called as *conditional*) models, such as by Logistic Regression [424], [433], [435], Support Vector Machines (SVMs) [93], [290], [438]–[440], Conditional Random Fields [263], [421], [436], [441], [442], Boosting [443], artificial Neural Networks (ANNs) [444], [445]. Often researchers simplify the problem as a *binary* classification, by considering only two classes, for instance classifying “an alarming situation” versus “a non-alarming situation” (usually applied in short-term monitoring scenarios, e.g. fall detection) or diagnosing a certain impairment (usually applied in long-term monitoring scenarios, e.g. Dementia diagnosis). However, many recent studies attempted solving *multi-class* classification problems, i.e. distinguishing between more than two classes, for instance, in the scenarios, where multiple ADL are recognized [254], [255], [263], [436], [446], [447]. Binary classification approaches are relatively easy to evaluate, compared to multi-class classification methods.

Furthermore, hierarchical classification models exist, which are useful for distinguishing activities or events on different abstraction levels. For example, at first, a fall or a non-fall is classified, then in case of a non-fall, a more specific activity is then returned, and in case of a fall, the type of fall is further estimated [91], [255], [448]. These hierarchies, can be learned and represented as decision trees (DTs) [255] or Random Forests [280]. By default, some of the discriminative approaches, such as logistic regression, SVMs or ANNs can output only a discrete class label for a given sample, while some can provide a probabilistic estimate of a sample being a part of either class, such as CRFs. Thus, in patient-at-home scenarios, when geriatric care requires a probabilistic measure representing a likelihood of a detected health-threat, probabilistic approaches are more preferable [449]. This can be accomplished also by applying several *generative models* (often referred to *probabilistic classification*), such as Naïve Bayesian Classifier (NBC) [94], Dynamic Bayesian Networks (DBN) [249], [450], [451], Hidden Markov Models (HMMs) [289], [398], [421], [452], Gaussian Processes (GPs) [453]–[455], Gaussian Mixture Models (GMMs) [249], [454], [456], or Deep Belief Networks [457]. GPs proved to be very effective in the patient monitoring scenarios both for solving regression [451], [458] as well as for classification [249], [450] tasks. Like SVMs, GPs are kernel methods. GPs proved to handle well multi-dimensional inputs and unequally sampled data points, have a relatively small number of tuneable parameters that does not require lots of training data. However, choosing the right kernel function is a question of experience. Difference between other discriminative and generative models in the light of activity recognition have been discussed in [263].

Popular graphical models, such as Markov chains, Dynamic Bayesian networks [249], [450], [451], [263], [431], [459], [460], Hidden Markov Models (HMMs) [289], [398], [421], [452], and Conditional Random Fields (CRFs) [263], [421], [436], [442], [460], [461] are reported to deal successfully with the sequential nature of data. HMMs are the most common graphical models for activity recognition, and many extensions have been proposed, for example the Coupled HMM for recognizing multi-resident activities, Hierarchal HMM for providing hierarchal definitions of activities, Hidden Semi-Markov model for modelling activity duration, and Partially Observable Markov Decision Process for modelling sequential decision processes.

There are also several works, which treat problems in an *unsupervised* fashion (without knowing “correct” answers a priori), when the task is to automatically discover structure or new patterns in given data, and therefore clustering and/or outlier analysis is used ([266], [268], [286], [414], [420], [443]). Unsupervised and supervised learning is often used in conjunction, when clustering results serve as an extra input for classification, as for example in [286], [443]. For instance, in [286] clustering was used for revealing an uncommon acceleration that potentially indicated a fall, which was used as an input for a classifier; while [443] demonstrated the use of unsupervised classification for amplifying predictability of models describing expert classification of coronary heart disease (CHD) patients, as well as boosting cause-and-effect relationships hidden in the data. As an example of a relatively simple technique, k-means algorithm itself is often used to initialize the parameters in a Gaussian mixture model before applying the *expectation-maximization* algorithm [462, p. 427]. There are also other ways, where a number of studies reported the application of *unsupervised* machine learning approaches for improving the performance of health-threatening event detection systems. For example, Yuwono et al. [286] used the data-stream from a waist-worn wireless tri-axial accelerometer and combined the application of Discrete Wavelet Transform, Regrouping Particle Swarm Optimization, Gaussian Distribution of Clustered Knowledge and an ensemble of classifiers, including a multilayer perceptron and Augmented Radial Basis Function (ARBF) neural networks. Clustering was used for revealing an uncommon acceleration that potentially indicated a fall, which was used as an input for a classifier.

2.5.2.2 Requirements and Challenges of Machine Learning Strategies

The types and distributions of monitored data dictate the specific requirements for machine learning techniques that intend to handle and reason from these data. For example, the following requirements for machine learning techniques that intend solving medical-related tasks can be noted [463]:

- Good performance (e.g. high accuracy and precision)
- Dealing with missing data (e.g. loss of some amount of data should not result in a rapid drop of performance)
- Dealing with noisy data (e.g. when some errors in data are present)
- Dealing with imbalanced data (e.g. when class distribution is not uniform among the classes of interest)
- Dealing with uncertainty (e.g. when imprecision, vagueness or gradedness of training data is present)
- Transparency of diagnostic knowledge (i.e. the automatically generated knowledge and the explanation of decisions should be transparent to the responsible medical personnel, possibly providing a novel point of view on the given problem, by revealing interrelation and regularities of the available data in an explicit form)
- Ability to explain decisions (e.g. the process of decision making of a machine learning approach should be transparent to the user. For instance, when a certain health-threat is automatically detected, an algorithm should

present an explanation of the circumstances, which forced to make such a statement. For example, graphical models and decision trees are more acceptable than so-called “black box” algorithms, where mathematical reasoning is hardly explainable to the responsible medical personnel.)

- Ability to reduce a number of tests without compromising the performance (since the collection of patient data is often expensive and time consuming for the patients, it is desirable to have a classifier that is able to reliably detect a certain health-threat with a relatively small amount of training data about the target patients. A machine-learning approach should be able to select an appropriate subset of attributes during the learning process.)

- Dealing with growing dimensionality (e.g. adding new sensors may provide additional information about a given problem, thus a machine-learning approach should be able to accept extra measurements or new parameters as an input, and the decision making should be susceptible to this input after classifier retraining)

- Continuously learn (and improve) from new data (i.e. when new empirical data is available, a machine-learning approach should be able to relearn from the new input. For example, so-called *Active Learning* approaches may be applied [464]).

In most cases, the performance of a classifier (e.g. a fall detector) is expressed in terms of sensitivity and specificity. For example, in the case of a binary classifier, the sensitivity is the ability of a detector to correctly classify a fall event as a fall, while the specificity is the ability of a detector to correctly classify normal activity as being normal. In other words, sensitivity represents the percentage of how well the algorithm detects a certain event or activity when that event or activity actually occurred (i.e. positive cases), while specificity represents the percentage of how well the algorithm can rule out all other events or activities than the one that is being identified (i.e. negative cases). Another commonly used performance measure is classification accuracy, which represents the percentage of the correctly classified events or activities among all events or activities that are being observed (both positive and negative cases). It is important to note, that accuracy measure alone is not enough for assessing the overall performance of the classifier, because it does not reveal how well the classifier can detect an important health-threat of interest. For example, if a dataset contains very few instances of positive cases, comparing to the number of negative cases, and the algorithm is tuned to classify all instances as negative cases (i.e. the sensitivity is 0), then the accuracy can still be very high (close to 100%), which would be obviously misleading, because such algorithm would not be capable of detecting the important health-threat at all.

Throughout a variety of technical articles on solving medical issues one can easily stumble upon ill-posed problems. For example, the potential problem of class overlap (when a sample is a part of either class simultaneously) is often neglected in the technical articles, which can lead to false evidence with unsubstantiated results. For instance, in [295] the authors attempted to classify a user's gait into one of the following five classes: 1) normal, 2) with hemiplegia, 3) with Parkinson's disease, 4) with pain in the back, and 5) with pain in the leg. However, in a real world scenario these classes can potentially overlap (for instance, people may experience pain in the back and in the leg at the same time), therefore the classification results should not be generalized, and the trained (discriminative) classifier models might not be appropriate, especially when healthy young individuals were used to simulate the gait for each class. This, however, is a general design problem of testing protocols.

More complex examples of classification problems include both the situations with naturally overlapping classes and, furthermore, the situations when the uncertainty of the ground truth is high. These problems are sometimes called as continuous classification problems and the data behind such problems is often referred to fuzzy sets. When it is combined with problems, such as class imbalance (when the total number of available data instances of one class is far less than the total number of data instances of another class), which is implicit in most of the real world applications, the situation becomes even more complicated. Recent works [465], [466] prove that the successful trick to deal with class imbalance problems is to include additional pre-processing steps, such as under-sampling and over-sampling methods, e.g. "Synthetic Minority Over-Sampling Technique" (SMOTE) [467], which oversamples the minority class by creating "synthetic" samples based on spatial location of the samples in the Euclidean space. A recent approach by Das et al. [466], was able to more accurately distinguish individuals with mild cognitive impairment (minority class) from healthy older adults (majority class), by applying so called ClusBUS (a clustering-based under-sampling technique). This technique successfully identified data regions, where minority class samples were embedded deep inside majority class. By removing majority class samples from these regions, ClusBUS preprocessed the data in order to give more importance to the minority class during classification, which outperformed existing methods, such as SVM, C4.5 DT, kNN and NBC, for handling class overlapping and imbalance.

Among the proposed approaches, there was a high ambiguity in the definitions of the classes as well as different training and test datasets were used, and the reported machine learning algorithms have highly varying complexities [241], [286], [295], [424], [442], [460], [468]. Therefore, comparing the performances of these diverse algorithms is fundamentally not feasible in an objective manner, unless benchmarking datasets and well-defined evaluation strategies are used. For example, Khawandi et al. [427] proposed an algorithm of learning using a Decision Tree for fall detection based on the simultaneous input from a video camera and a heart rate monitor, which showed a low error rate of 1.55% in average on test data after training. However, no definition of a falling event was revealed, and a description of the used dataset and the learning speed of the algorithm were missing.

It is important to note that every machine learning strategy has some limitations. For example, Zhang et al. [290] proposed a fall detector based on Support Vector Machine (SVM) algorithm, which used input from one waist-worn accelerometer. The features for machine learning were the accelerations in each direction and changes in acceleration, and their method detected falls with a promising 96.7% accuracy. Despite that SVMs are relatively fast and efficient to compute, they do not output with what probability a sample belongs to either class. Other well-known limitations of SVMs are a choice of the kernel function and high algorithmic complexity.

In order to avoid some limitations of individual machine learning approaches and consequently to improve the overall classification or regression performances, multiple learning methods can be used at the same time, called as Ensemble methods. They use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms. Therefore, ensemble methods are increasingly attractive for research on problems of monitoring older patients [276], [417], [430], [469]. Furthermore, it is often favourable to use a set of relatively simple learners, which can result in a better performance, comparing to a single complex and computationally expensive method.

For combining the above machine learning techniques in an effective manner one should be extremely careful, because there are a number of different learning stages and different learning problems are addressed, so that incorrect treatment of data can accumulate and result in false reasoning. As previous research suggests, for optimal results, a physician or clinical expert will only be able to guide and understand the research if possesses sufficient basic knowledge of the machine learning algorithms [470].

Meanwhile, some recent studies have further attempted to compare the performances of machine learning systems with human experts. For example, Marschollek et al. [433] compared the performances of a multidisciplinary geriatric care team with automatically induced logistic regression models based on conventional clinical and assessment data as well as matched sensor data. Their results indicated that a fall risk model based on accelerometer sensor data performs almost as well as a model that is derived from conventional geriatric assessment data.

2.5.3. STANDARDS

Generally, a wide variety of monitoring technologies for older patients, i.e. the sensory devices, including software, are considered to fall under the definition of a "medical device". A full definition of a "medical device" by World Health Organisation is given here [471]. Medical devices are considered to be a subset of electronic products that may have general regulatory provisions [472]. Numerous national and international standards exist that must be complied with before and after such electronic products enter into commercial use. These standards offer a possibility to cope with the high demands on technical and scientific expertise in the regulation processes of medical devices. These standards are being constantly updated, following the high rate of innovations.

It is important to note, that medical devices may be regulated even for non-medical reasons. For example, if the device (an electronic product) emits or can potentially emit some type of electronic product radiations, such as x-rays and other ionizing radiation, ultraviolet, visible, infrared, microwave, radio and low frequency radiation, coherent radiation produced by stimulated emission, and infrasonic, sonic, and ultrasonic vibrations [472].

There are two main organizations, which are typically issuing international standards, namely the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC). Every region (e.g. EU) or a country (e.g. Japan) has a standards organization that may adopt the established international standards, and in some certain cases may modify it or place limitations on it. Furthermore, the local medical device authorities may recognize the standard, but normally there is no legal obligation to do so. In other words, a certain international standard does not define in itself, where it operates. Consequently, any country or region may adopt them, possibly with certain modifications or limitations. For example in EU, all medical devices, which are intended for use within the EU region, must conform to the Medical Device Directive 93/42/EEC (MDD) [473], which was updated by the Directive 2007-47-EC [474], and must have a CE conformance mark [475].

The following relevant standards are mostly and generally requested (this is not an exhaustive list, and some might not be applicable for the existing solutions, and furthermore at the same time some more standards could be relevant):

- ISO 13485:2012 – Medical devices – Quality management systems – Requirements for regulatory purposes. ISO 13485:2012 is applicable only to manufacturers placing devices on the market in Europe. For the rest of the world, the older version ISO 13485:2003 remains the applicable standard [476].

- ISO 14971:2012 – Medical devices – Application of risk management to medical devices [477].

- IEC 60601-1:2015 SER – Medical electrical equipment – All parts [478].

- IECEE TRF 60601-1-2:2015 – Medical electrical equipment – Part 1-2: General requirements for basic safety and essential performance – Collateral standard: Electromagnetic disturbances – Requirements and tests [479].
- IECEE TRF 60601-1-6:2014 – Medical electrical equipment – Part 1-2: General requirements for basic safety and essential performance – Collateral standard: Usability [480].
- IEC 60601-1-8:2006 – Medical electrical equipment – Part 1-8: General requirements for basic safety and essential performance – Collateral standard: General requirements, tests and guidance for alarm systems in medical electrical equipment and medical electrical systems [481] (Included in [478]).
- EN 60601-1-9:2007 – Medical electrical equipment – Part 1-9: General requirements for basic safety and essential performance – Collateral Standard: Requirements for environmentally conscious design [482] (Included in [478]).
- IEC 60601-1-11:2015 – Medical electrical equipment – Part 1-11: General requirements for basic safety and essential performance – Collateral standard: Requirements for medical electrical equipment and medical electrical systems used in the home healthcare environment [483] (Included in [478]).
- EN 62304:2006 – Medical device software – Software life-cycle processes [484].
- ISO 10993:2009 – Biological evaluation of medical devices – Part 1: Evaluation and testing within a risk management process [485].
- ISO 15223-1:2012 – Symbols to be used with medical device labels, labelling and information to be supplied – Part 1: General requirements [486].
- EN 1041:2008+A1:2013 – Information supplied by the manufacturer of medical devices [487].
- ISO 14155:2011 – Clinical investigation of medical devices for human subjects – Good clinical practice [488].
- MEDDEV 2.7.1 Rev.3:2009 – Clinical evaluation: A guide for manufacturers and notified bodies [489].
- IEC 62366-1:2015 – Medical devices – Part 1: Application of usability engineering to medical devices [490].

- ISO/IEC 27001 – Information security management [491].
- ISO/IEC 25010:2011 – Systems and software engineering – Systems and software Quality Requirements and Evaluation (SQuaRE) – System and software quality models [492].

The aforementioned standards facilitate so-called harmonised medical device regulatory requirements, and more comprehensive and updated list of titles and references of the harmonised standards under Union harmonisation legislation is available on the European Commission web site [493].

As an important note, any software, which is related to the monitoring technology in our context, must also fulfil the aforementioned requirements of the medical device wherein it is incorporated. One can typically divide software in two groups. First, there is so called "embedded" software, which is incorporated in the apparatus, i.e. in a physical device being used for monitoring. Second, there is software that is used in combination with the apparatus, but is separate from the device, i.e. software that is involved, for instance, in transferring, receiving, storing, processing, and accessing the data. Both types of software fall under the definition of a "medical device", as we previously mentioned, since it affects the use of the devices. According to the essential requirements of European Medical Device Directive, such software "*must be validated according to state of the art taking into account the principles of development lifecycle, risk management, validation and verification"* (Annex I, 93/42/EEC as amended by Directive 2007/47/EC [473]). There are numerous specific standards for each area of interest; for example, for the ECG measurement devices, the health informatics standards, such as ISO 11073-91064:2009, ISO/TS 22077-2:2015 and ISO/TS 22077-3:2015, are relevant. Furthermore, in accordance with the current security standards (such as ISO/IEC 27001 [491]), the availability, integrity, and confidentiality of the monitored data and information must be ensured. Last but not least, several generic standards must be followed. For example, ISO/IEC 25010:2011 [492] is necessary for every computer system and software products in general.

In general, most of the national and international standards, for example, those that are published by ISO and IEC, are unfortunately not available free of charge, since there is a certain fee for obtaining them. Furthermore, each individual standard may include many cross-references to other standards. In the field of health telemonitoring, the number of relevant standards is substantially high. Therefore, for many stakeholders this would result in extra investments, which can be increasingly high due to the fact that these standards are frequently updated and manufacturers have to constantly adapt to the state of the art.

As a solution, the responsible authorities for safeguarding the quality and reliability of various health telemonitoring solutions should in principle promote an open access to the relevant standards, or at least help to improve their availability to those who develop and deliver health telemonitoring products and services. This solution is in agreement with previously proposed suggestions [494]. Alternatively, some reimbursement strategies for successful implementation of those standards might be initiated, which could further motivate the compliance with those important standards for further quality improvement of the health care.

2.6. DATASETS

Publicly available datasets constitute the ground to evaluate and compare the performance of proposed approaches for monitoring older patients at home. In this section, we shed light on the importance of using datasets as a benchmarking tool for comparing various monitoring techniques for detecting the health threats, which we discussed in the previous sections. The methods, which are tested by using a standard publicly available dataset as a benchmark, are considered to be more reliable and are more likely to be accepted by the scientific community for their claimed results. Therefore, we summarize the references of available datasets, which are relevant to the field of automatic monitoring of older patients.

In the context of audio-visual content-based monitoring, a dataset contain audio and video clips of human body-parts and/or activities in experimental or real-life environments. In the context of measuring movements and locations of patients, for example, by means of radio frequency sensors, infrared detectors, or inertial sensors, a dataset usually contains annotated recordings of a finite set of specific ADLs. Sampling rate of these recordings may vary, depending on the monitoring equipment, and numeric timestamps are usually assigned to every instance of the recorded data. The attributes of those datasets can be very different, and may simultaneously contain both numeric and categorical variables. Every dataset should in principle contain detailed description about how the data was collected and annotated. Often the data is already pre-processed. Therefore, the detailed description of those pre-processing steps should be included in the dataset description as well, often accompanied with available program source code. Most important dataset descriptions usually are included in a so-called “readme” file.

Though a vast body of literature has been produced for older patient monitoring, in fact, a few methods are tested on real older patients’ data. Most of the methods used their own configuration of sensors for data acquisition and young people as actors in a laboratory environment to create scenes, and tested the system by their custom dataset. The datasets are not only varying in number and placement of sensors, but also varying by objective of data collection (e.g. fall detection or specific set of ADLs detection), environmental description, and subjects’ behaviour. Thus, the results from one method tested on a custom dataset are not comparable with the results of another method tested on some other custom datasets. Also, the results from a method that is tested on the data collected from young volunteers may significantly differ for older adults, because of dissimilarity between the data obtained from real seniors and the data obtained from young volunteers in the laboratory. For example, a real fall of an older adult and an acted fall of a young man in the laboratory may not “look” similar [495]. Thus, it is very difficult to predict the performance of a proposed method in a real-life scenario. Additionally, making a dataset publicly available might be very difficult due to the privacy policy of personal data [100]. Thus, only few publicly available datasets can be obtained from the literature. In previous reviews, Aggarwal et al. [99] divided the available datasets for human activity monitoring in three broad themes: action recognition datasets, surveillance datasets, and movie datasets. However, only the action recognition datasets are well-suited for in-home activity monitoring. On the other hand, Popoola et al. [6] listed a number of publicly available datasets from in-home scenarios for fall detection, kitchen activities, audio-visual activities, and daily activities. A summary of well-known, publicly available and generic action recognition dataset (not specifically for geriatric patients) is presented in [336]. None of these reviews focused on datasets that are strictly relevant to geriatric patient monitoring. Thus, this section provides a description of important datasets used in the literature. Though some datasets are collected by using multimodal sensors and included the scenarios of human activity recognition, e.g. acoustic event detection datasets in [336]–[339] and visual activity detection dataset in [496], we do not include summaries of these datasets in this chapter, because of the too broad activity classes considered in these datasets and they are not relevant to geriatric patient monitoring.

It is also worth noting, that the first study, which proposed to use datasets as a benchmarking tool was [497], however in their rich dataset, which focused mainly on activity recognition, they did not include data on vital signs that are prerequisites for assessing the health state of patients, and thus is very important for finding correlation between ADL data and vital sign data (which can be used to validate ADL data, for example).

Table 2-4 lists the datasets and their key characteristics. We mention the datasets either by the names given by the creators of the datasets or by the first author of the articles that introduced the dataset. The description of the datasets includes the overall data acquisition environment, dataset size, and types of dataset (annotated/non-annotated or real-life/laboratory implementation). Column 4 states the intended application of the dataset collection, e.g. activity recognition, fall detection, wandering detection, and elopement detection. Column 5 mentions the subjects used in the scene to create these datasets. Column 6 indicates the types of sensors used in each dataset collection. The last column in Table 2-4 states whether the dataset is available online or not. We write ‘Yes’ for the datasets which are already available online or can be acquired by filling up an online requisition form. From Table 2-4, it is observed that some datasets, such as ‘Multi-view fall dataset’ were used in a number of works. We found only one dataset in [101], [275] that considered the issue of elopement and wandering detection. Unfortunately, most of the datasets are developed by employing young actors instead of older adults or geriatric patients. Only few datasets are developed by employing older patients. In addition to Table 2-4, other relevant collections of public datasets are available online [498], [499].

Table 2-4 The available datasets relevant to the field of automatic monitoring of older patients

Dataset name / First Author	**Description**	**Objective(s)**	**Subjects**	**Sensors**	**Online**
PLIA1 & PLIA2 [132]	Two annotated datasets of ADLs of several hours	Activity recognition/Unusual activity detection	Young actors	Multi-sensors including microphone and video cameras	Yes
Tap30F and Tap80F [500]	An annotated dataset of 14 days with activities of two subjects in private homes	Activity recognition/ Health threatening conditions detection	A 30 years and a 80 years old women	Environmental stage change sensors	No
WSU CASAS [131]	Activities performed by two residents over three months in a test bed smart apartment	Activity recognition/Unusual activity detection	2 young actors	Environmental stage change sensors	Yes
A. Reiss [437]	A dataset containing both indoor and outdoor activities, where indoor activities are relevant to our topic	Activity recognition	9 young actors	Wearable sensors	Yes
TK26M and TK57M [263]	An annotated dataset of activities of two subjects in a private apartment and a house	Activity recognition/ Health threatening conditions detection	A 26 years and a 57 years old men	Environmental stage change sensors	Yes

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Dataset name / First Author	Description	Objective(s)	Subjects	Sensors	Online
Multi-view fall dataset [249], [501]–[506]	24 fall incidences in 24 scenarios and includes different kinds of fall, e.g. forward and backward fall.	Fall detection	Young actors	Video cameras	Yes
T. Liu [507]	12 hours of video data containing 7 previously instructed activities and fall events	Activity recognition/Unusual activity detection/Fall detection	Young actors	Video camera	Yes
Nursing Home Dataset [101], [275]	13800 camera-hours of video (25 days x 24 hours per day x 23 cameras) obtained from a test bed developed in a dementia unit of a real nursing home	Elopement (leaving home) detection/ Unusual activity detection/ Wandering detection	15 elderly dementia patients	Video camera	No
C. Zhang [508]	A dataset of 200 video sequences with RGB-D information in three conditions: subject is within 4 meters with/without enough illumination and subject is out of 4 meters distance from the camera	Fall detection	Young actors	RGB-D camera	No
D. Anderson [509]	18 video sequences that are captured in 3fps capture rate and a total of 5512 frames (30 minutes)	Fall detection	2 young actors	Video camera	No
I. Charfi [510]	An annotated dataset of 191 videos that are collected by varying different environmental attributes	Fall detection	Young actors	Video camera	Yes

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Dataset name / First Author	**Description**	**Objective(s)**	**Subjects**	**Sensors**	**Online**
CompanionAble [511], [512]	An annotated dataset containing audio files of different environmental and life sound classes	Sound event detection for remote monitoring	Young actors	Microphone	Yes
B. Bonroy [513]	An annotated dataset of 15 minutes video recording containing 80 different events captured by two cameras	Detection of discomfort in demented elderly	6 demented older patients	Video cameras	No
SAR [514]	A non-annotated video dataset that is collected from real elderly living at home	Activity recognition/ Unusual activity detection	6 older adults (age >65 years and 10 days video data for each person)	Video cameras	Yes
E. Syngelakis [515]	An annotated dataset of 200 video clips containing both fall and non-fall events in different variations of laboratory environment	Fall detection	3 young actors	Video camera	No
R. Romdhane [516]	A video dataset of real elderly which are captured by two cameras while performing ADLs in a nursing home	Activity recognition/ Unusual activity detection	3 elderly having Alzheimer's disease (2 male and 1 female)	Video cameras	No

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Dataset name / First Author	**Description**	**Objective(s)**	**Subjects**	**Sensors**	**Online**
C. F. C. Junior [254]	A dataset of ADLs acquired by multiple sensors in a nursing home	Activity recognition/ Unusual activity detection	4 healthy and 5 elderly people with MCI (Mild Cognitive Impairment)	Multiple sensor including video cameras	No
GER'HOME dataset [265], [517]	A dataset of ADLs acquired by multiple sensors in an experimental apartment	Activity recognition/ Unusual activity detection	14 elderly people (aged from 60 to 85 years), each one during 4 hours	Multiple sensor including 4 video cameras and a number of environmental stage change sensors	Yes
REALDISP dataset [413], [518]	A dataset of 33 different physical activities acquired in 3 different scenarios by 9 inertial sensors for investigating the effects of sensor displacement in the activity recognition process in real-world settings	Determining optimal sensor positioning for activity recognition and benchmarking activity recognition algorithms	17 young healthy actors (age ranging from 22 to 37 years old)	3D accelerometers, 3D gyroscopes, 3D magnetic field orientation sensors, 4D quarterions	Yes

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Dataset name / First Author	Description	Objective(s)	Subjects	Sensors	Online
B. Kaluža et al. [519]	A localization dataset for posture reconstruction and person activity recognition, including falling	Activity recognition and fall detection	5 young healthy actors	Attached 4 radio-frequency body tags (chest, belt and two angles) recording 3D coordinates	Yes
D. Cook et al. [123]	A dataset with IADLs and memory in older adulthood and dementia patients in a real-home setting	Mild cognitive impairment (MCI) and dementia detection using IADL data, such as cooking and using the telephone.	400 subjects, including healthy younger adults and older adults with MCI and dementia	Multimodal sensors: motion detectors, door sensors, stove sensors, temperature sensors, water sensors, etc.	Yes

2.7. DISCUSSION

This section briefly discusses the anticipated future challenges within the field of monitoring older adults and provides a number of future research directions. Some of the most notable challenges are lack of publically available datasets, poor measurement accuracy of sensors, user-centred design barriers, and user acceptability for monitoring. We try to draw attention to the importance of acquiring objective information of older patients' health conditions by applying appropriate sensor technology for automated monitoring, which we covered in the previous sections of this chapter. As possible future research directions, we draw attention to the necessary research in the fields of sensor fusion and machine learning for detecting various health-threatening events and conditions in older population.

The need for objective measurements of older patients' conditions in the home environment is a critical ingredient of assessment before institutionalization. In the absence of such measurements, the relationship between certain activities or inactivity, for example, cannot be related to the appearance of a specific health-threatening event or condition. To date, there is no routine procedure available to measure activity in a home setting. Attempts to overcome this have predominantly employed archaic methods using observations and surveys, which are susceptible to observation and interpretation bias, as well as cannot be directly applied to those patients, who are living alone.

2.7.1. FUTURE CHALLENGES

2.7.1.1 Defining Taxonomy

In-home activity monitoring initially requires definitions of activities, level of correspondence between activities, and an established relationship model between the activities. These can be achieved by defining taxonomy of activities systematically. Unfortunately except the work of [258], which manually defined taxonomy of some daily living activities, no systematic study was accomplished in order to define the taxonomy of daily living activities in a private home.

2.7.1.2 Lack of Publicly Available Datasets

The availability of public datasets is necessary to compare the methods proposed to solve similar problems. However, a few datasets are available in public to assess the methods proposed in the literature. Moreover, the available datasets have the limitation of the experimental setup and standard quality assurance. It is also observed from this chapter that most of the previously proposed methods used custom datasets instead of publicly available datasets and furthermore, many of the authors did not make their dataset publicly available due to privacy policies. Thus, there is a need of regulatory initiatives, which would lessen the hurdles for the researchers' community to access and publish datasets necessary for solving the emerging healthcare problems.

2.7.1.3 Inefficiency of Health-Threat Detection Technologies

As discussed in this chapter, a number of health-threat detection methods have been proposed, however the false alarm rates from the methods are still questionable. Moreover, majority of authors used their own custom datasets to generate experimental results for their proposed methods, and thus provided less room for comparison between different methods.

2.7.1.4 Sampling Limitations and Time Delays in Monitoring

Every sensor has temporal sampling limitations, which need to be considered. Every measurement process involves some time delays in data capture, which depend on various factors, such as location of sensors and sensing modality. In general, sensor signals are noisy and thus require digital filtering, which causes certain time delays as well. Furthermore, delays in sensor signals may or may not be constant [315]. If the sampling frequency is too low or irregular, interpolating the measurements reliably over time might not be feasible depending on a given problem. Estimating eventual time delays between irregularly sampled time series is crucial for avoiding possible data processing and interpretation errors. For scenarios, where multiple sensors are used, time synchronization among all sensors is necessary to enable fusion of sensory data, which can be increasingly difficult, because different time delays in data acquisition, transmission and processing may be present. In addition, the time lag between sampling and obtaining the analysis results may be ranging from a matter of milliseconds to several hours, which can be a significant problem if the situation requires immediate decision concerning patient's health.

Choosing an optimal sampling frequency in order to provide sufficient resolution for detecting a certain health-threat is generally not a trivial task. Some sensor types may have an advantage over other sensors in terms of resolution and detection times for certain health-threats. It can be discussed at length whether monitoring a certain parameter is necessary for a given problem, while taking into account various trade-offs between sample sizes, measurement costs, detection accuracy, privacy, and comfortability of monitoring. Understanding these trade-offs would require further research. Furthermore, adaptive sampling techniques might be useful for scenarios, where it does not make sense to continuously measure a certain parameter rather than to take a sample once in a while or only when the risk of a health-threat is detected by analysing other parameters. Such approach may potentially improve energy-efficiency, when certain sensors can be in sleep mode, and are set active only when there is an identified need for using them in time.

Another area of great importance, which we did not have the space to cover, is ICT solutions for the transmission of large data over long distances, which can potentially improve the accessibility of monitoring technologies for those living in rural areas. Network delays in data transmission can have a critical impact on detecting health-threats at home. Even for relatively short distances, the network delay problem may present a significant obstacle for monitoring scenarios. One example is the delay in active camera based systems, which use the pan-tilt-zoom capability of video cameras. Industry standard available cameras exhibit long network delays in executing move instructions. Thus, real time monitoring and tracking suffer from the camera delays and frequently miss the object of interest during monitoring or tracking. Thus, active research is necessary to address network delay problem as well [5].

2.7.1.5 Accuracy in Measuring Physiological Parameters

Although a number of innovative methods have been proposed for physiological parameters measurements, for example, automatic heart rate measurement by using facial image or fingertip image from video cameras, the accuracy of such approach is not up to the standard yet, while successful examples were only possible in highly limited lab conditions. Besides, when the facial expression changes or the face moves in the video frames, the accuracy of heart rate estimation decreases significantly. To overcome this problem, the use of quality assessment techniques as an intermediate step between facial detection and relevant feature extraction was recently proposed [274].

2.7.1.6 User-Centred Design Barriers for Older Adults

Resolving barriers to engagement, participation, and spreading of telemontoring service programs among older populations, is challenging [520]. In [520], authors described the specific issues concerning technological acceptance, human resources development, and collaboration with service systems. They discussed possible strategies and policy implications with regard to human-computer interaction design considerations for telemonitoring of medical and aging conditions of older adults, and possible improvements for the access to technology services and additional training for effective use of the technology. However, it can be increasingly challenging to find a balance between user requirements for designing a dedicated technological solution for a specific need of some target patients and for complying such solution with the *Universal Design* principles [82] at the same time. In our view, the concept of *Universal Design* should not be seen as a synonym to *user-centeredness* for designing and applying monitoring technology to older patients, in other words, ‘one size fits all’ cannot be used in this context. It is important to have end-users involved in the process of designing, testing, and evaluating the monitoring technologies [62].

2.7.1.7 User Acceptability in Monitoring

As stated in [33], accepting monitoring systems in a person’s home, especially when it is the home of an older person, is very difficult. This is due to the fact that people do not want to be monitored for privacy concerns, even if this is necessary for assisted living. However, if it is possible to provide high data and privacy protection by other means, then the acceptability can be increased, as discussed in [49]. Therefore, privacy is a crucial consideration for the design and implementation of monitoring technologies.

2.7.2. FUTURE RESEARCH DIRECTIONS

First, as a prerequisite to further research in this field, a direct involvement of various end-users is needed, including healthy, vulnerable and acutely ill older adults, as well as their family members and health care staff, to ensure the quality and applicability of monitoring technologies in real life settings. Further research is necessary that can contribute to creation of a systematic guideline for developing benchmarking datasets for the topics covered in section four. For collecting new datasets, it would be important to use multiple sensor categories for collecting a wide diversity of measurable parameters and to apply sensor fusion techniques with a purpose of dealing with uncertainties in detecting individual health-threats. For example, those datasets should at least contain both physiological parameters and data about environmental conditions of older adults collected at the same time. More effort should be put on creating and applying generative machine learning methods on these datasets, instead of discriminative methods, with the purpose of detecting new health-threatening events and conditions in older population. Furthermore, the research on machine learning techniques should in principle be done in collaboration with the involved health care personnel to ensure that the algorithms are properly understood. For this reason, further research on graphical models and incorporating them into end user interfaces is expected to be beneficial. For future studies, it is important to clearly communicate the limitations of the developed systems and constrains of their evaluation results. Last but not least, further research is needed to find the balance between privacy constrains of data collection and what data is a strict requirement for successful monitoring of specific geriatric conditions.

2.8. CONCLUSIONS

This section concludes the article by summarizing the current status and visions for research and developments in the cross-disciplinary field of monitoring older populations.

Common data quality standards for patient databases and datasets need to be developed, because currently little is known about how to organize and store data from monitored older patients in an efficient way, which is a prerequisite for learning. Also benchmarking techniques for testing the performance of machine learning techniques on these datasets are currently lacking. As the number of databases and datasets with diverse data about older patients at home is very limited but is on the rise, we are only at the beginning of understanding and analysing these data. Though, the number of possible applications is high. As long as no single machine learning technique proved to be substantially superior to others for some given task, it would be wise to run multiple algorithms whenever possible for objective comparison of these learning approaches.

The described technological applications are mainly aimed at older adults, and as mentioned earlier, it is of utmost importance to understand the enormous heterogeneity of the older populations. This heterogeneity has the effect that there is no such thing as ‘one size fits all’. Also, *eHealth* technology has to be adaptable to the needs of the individual older adults, i.e. to his or hers cognitive, physical, emotional and societal skills as well as the environment. The heterogeneity is further enlarged by the differences in IT skills and competencies of older adults both today and in the near future, as some countries already today have a high proportion of IT literate older adults, while other countries have a majority of older adults with low educational attainment and IT-illiteracy. A further constraint is that, while the most remote and rural areas would benefit a lot in using *eHealth*, these areas are usually also those with the most poorly developed IT-infrastructure, a fact that emphasizes the challenges of using *eHealth* in the health monitoring of older adults. Hopefully, innovative solutions for the transmission of large data over long distances will soon come, and thereby would add to some of the solutions to challenges of ageing societies.

Indeed, the room for innovative solutions in the area of monitoring older adults at home environment is very large, and a lot of improvements of existing solutions can be made. Non-intrusiveness and non-invasiveness of sensor technology will likely be the key factor for successful application. Smaller and cheaper types of sensors, such as piezoresistive and piezoelectric textile sensors, will have the advantage for becoming a part of daily life of older adults, because they have a better potential to be embedded in garments and furniture with prospect of being comfortable and reusable. In terms of advances in software solutions, various machine learning techniques have shown a great potential towards more reliable detection of health-threatening situations and conditions of older adults. There is a large research potential for the interplay of unsupervised and supervised learning, where there is only a small amount of labelled data and a large amount of unlabelled data available, because for many of the patient-at-home scenarios data labelling can be expensive and time consuming. Furthermore, combining the available knowledge from the research results of the various cross-disciplinary fields of smart-homes, telemonitoring, ambient intelligence, ambient assisted living, gerotechnology, aging-in-place technology, and others, which we have mentioned in this chapter, can boost the further development of technological monitoring solutions for health care, long-term care, and welfare systems to better meet the needs of ageing populations.

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PART III

FACE QUALITY ASSESSMENT

CHAPTER 3. REAL-TIME ACQUISITION OF HIGH QUALITY FACE SEQUENCES FROM AN ACTIVE PAN-TILT-ZOOM CAMERA

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3.1. ABSTRACT

Traditional still camera-based facial image acquisition systems in surveillance applications produce low quality face images. This is mainly due to the distance between the camera and subjects of interest. Furthermore, people in such videos usually move around, change their head poses, and facial expressions. Moreover, the imaging conditions like illumination, occlusion, and noise may change. These all aggregate the quality of most of the detected face images in terms of measures like resolution, pose, brightness, and sharpness. To deal with these problems this chapter presents an active camera-based real-time high-quality face image acquisition system, which utilizes pan-tilt-zoom parameters of a camera to focus on a human face in a scene and employs a face quality assessment method to log the best quality faces from the captured frames. The system consists of four modules: face detection, camera control, face tracking, and face quality assessment before logging. Experimental results show that the proposed system can effectively log the high quality faces from the active camera in real-time (an average of 61.74ms was spent per frame) with an accuracy of 85.27% compared to human annotated data.

3.2. INTRODUCTION

Computer-based automatic analysis of facial image has important applications in many different areas, such as, surveillance, medical diagnosis, biometrics, expression recognition and social cue analysis [1]. However, acquisition of qualified and applicable images from a camera setup or a video clip is essentially the first step of facial image analysis. The application performance greatly depends upon the quality of the face in the image. A number of parameters such as face resolution, pose, brightness, and sharpness determine the quality of a face image. When a video based practical image acquisition system produces too many facial images to be processed in surveillance applications, most of these images are subjected to the aforementioned problems [2]. For example, a human face at 5 meters distance from the camera subtends only about 4x6 pixels on a 640x480 sensor with 130 degrees field of view, which is mostly insufficient resolution for further processing [3]. In order to get rid of the computational cost and inaccuracy problem of low quality facial image processing, a Face Quality Assessment (FQA) technique can be employed to select the qualified faces from the image frames captured by a camera [4]. This reduces significant amount of disqualified faces from the captured imagery and keeps a small number of best face images which are named as face sequence or so called Face Log. However, FQA merely checks whether a face is qualified or not, and cannot increase the quality of captured face. Besides, processing time to determine the face quality is also an obstacle to achieve real-time performance while extracting faces from video sequences. A possible solution to low resolution faces from a video sequence is to employ techniques like Super-Resolution (SR) image reconstruction algorithms, to generate high resolution faces [5]. However, it is still an active research area and subjected to problems like huge computational costs, uncertainty in reconstructed high frequency components, and small doable magnification factor [6]. On the other hand, due to improvements in digital Pan-Tilt-Zoom (PTZ) camera technology and availability of PTZ cameras in low cost, acquisition of high resolution facial images in surveillance, forensic and medical applications by directly using camera instead of SR techniques is an emerging field of study [7].

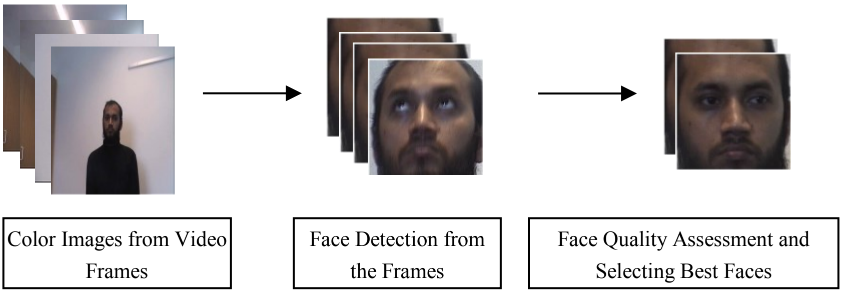

Figure 3-1 Block diagram of a typical facial image acquisition system with face quality measure.

A typical facial image acquisition system including FQA is shown in Figure 3-1, which was proposed in [4]. Given a video sequence in the face detection step the regions including a face are detected and are considered as Region of Interest (ROI) in the frames. Then, a FQA algorithm assesses the ROIs in terms of face quality measures and stores the best quality faces in face log.

A vast body of literature addressed different issues of facial image acquisition. An appearance-based approach to real-time face detection from video frames was proposed in [8] which merely work in real-time in VGA resolution images. For real-time face detection in high resolution image frames, Mustafah et al. proposed two high resolution (5 MP) smart camera-based systems by extending the works of [9-10]. Cheng et al. also proposed a face detection method in high resolution imagery by employing a grid sampling and a skin color based approach [11]. For dealing with too low-resolution faces in surveillance videos in [3] and [12], networks of two active cameras were proposed to detect faces in a wide-view camera and later extract high resolution face images in a narrow-view camera by using PTZ control.

When a face is detected in a video frame, instead of detecting face in further frames of that video clip it can be tracked. Tracking of a face in video frames has been proposed by using still camera and active PTZ camera in [13] and [14-15], respectively. In [14], an adaptive algorithm was employed along with some features extracted from face motion in order to calculate pan and tilt parameters (not including zoom parameter) of the camera to track a face. In [15], the authors however proposed a general object tracking framework by using a multi-step feature evaluation process and applied it to a face tracking application. They further extended their method to extract high resolution face sequences [7].

In addition to the above mentioned face detection and face tracking methods in video, a number of methods proposed for face quality assessment and/or face logging. Kamal et al. proposed a face quality assessment system in video sequences by using four quality metrics- resolution, brightness, sharpness, and pose [4]. This method was further extended for near infrared scenario and was included two more quality metrics- eye status (open/close) and mouth status (open/closed) [16]. In [17-18], two FQA methods have been proposed in order to improve face recognition performance. Instead of using threshold based quality metrics, [17] used a multi-layer perceptron neural network with a face recognition method and a training database. The neural network learns effective face features from the training database and checks these features from the experimental faces to detect qualified candidates for face recognition. On the other hand, Wong et al. used a multi-step procedure with some probabilistic features to detect qualified faces [18]. Kamal et al. explicitly addressed posterity facial logging problem by building sequences of increasing quality face images from a video sequence [2]. They employed a method which uses a fuzzy combination of primitive quality measures instead of a linear combination. This method was further improved in [19] by incorporating multi-target tracking capability along with a multi-pose face detection method.

Through our intensive study so far, we observed that networks of wide-view and narrow-view PTZ camera have been employed for high resolution facial image capture [3, 7, 12]. However, the quality of images was not assessed while the PTZ features of the cameras are active. On the other hand, some FQA methods have been utilized for posterity logging of face sequences from offline video clips [2, 4, 17-18]. Thus, in this article, we propose a way to real-time capturing of high quality facial image sequences by addressing both quality and time complexity issues in an active PTZ camera capture.

The rest of the chapter is organized as follows. Section three presents the proposed approach. Section four describes the experimental environment and results. Section five concludes the chapter.

3.3. THE PROPOSED APPROACH

A typical single PTZ camera based facial image acquisition system consists of a face detection module, a camera control module, a face tracking module, and a face logging module [7]. Face detection module detects face in an image while camera sensor set in wide angle view. Camera control module utilizes the PTZ features of the camera in order to zoom in narrowly the face area of the image. Face tracking module tracks the face in subsequent frames captured by the camera. Finally, face logging module stores the faces for further processing. While logging the faces, low quality faces in terms of resolution, sharpness, brightness, and pose can be stored.

Moreover, non-face images can also be logged due to false positives produced by tracking module. Thus, FQA module can be employed before face logging module. However, all these steps are computationally expensive and need to be solved real-time in order to develop an active camera based acquisition system. This chapter proposes a real-time acquisition of high quality facial image from an active PTZ camera by assessing some quality metrics using a FQA method.

The architecture of the proposed system are depicted in Figure 3-2 and described in the following subsections.

3.3.1. FACE DETECTION MODULE

This module is responsible to detect face in the image frames. A well-known face detection approach has been employed from [8], which is known as Viola and Jones method. This method utilizes so called Haar-like features extracted by using Haar wavelet. The Haar-like features are applied to sub-windows of the gray-scale version of an image frame with varying scale and translation. An integral image is used to reduce the redundant computation involved in computing many Haar-like features across an image. A linear combination of some weak classifiers is used to form a strong classifier in order to classify face and non-face by using an adaptive boosting method. In order to speed up the detection process an evolutionary pruning method from [20] is employed to form strong classifiers using fewer classifiers. In the implementation of this article, the face detector was empirically configured using the following constants:

- Minimum search window size:
  - 10x10 pixels in the initial camera frames
  - 70x70 pixels in the zoomed and tracked frames
- The scale change step: 10% increase per iteration
- Merging factor: 3 overlapping detections

After initializing the camera, face detection module continuously run and try to detect face. Once the face is detected, it transfers the control to the camera control module by sending face ROI of the frame.

3.3.2. CAMERA CONTROL MODULE

When a face is detected in the face detection module, the size of the face is determined by the face bounding rectangle obtained from the output of the face detection module. Suppose, an input image frame is expressed by a 2-tuples $I(h, w)$, where h is the height of the image in pixels and w is the width of the image in pixels. Then, a face ROI in that image frame can be expressed by a 4-tuples $F(x, y, h, w)$, where (x, y) is the upper-left point of the rectangle in the image frame, and h and w are the height and width of the face, respectively. Camera control module utilizes this information from the face detection module and automatically controls the camera to zoom the face.

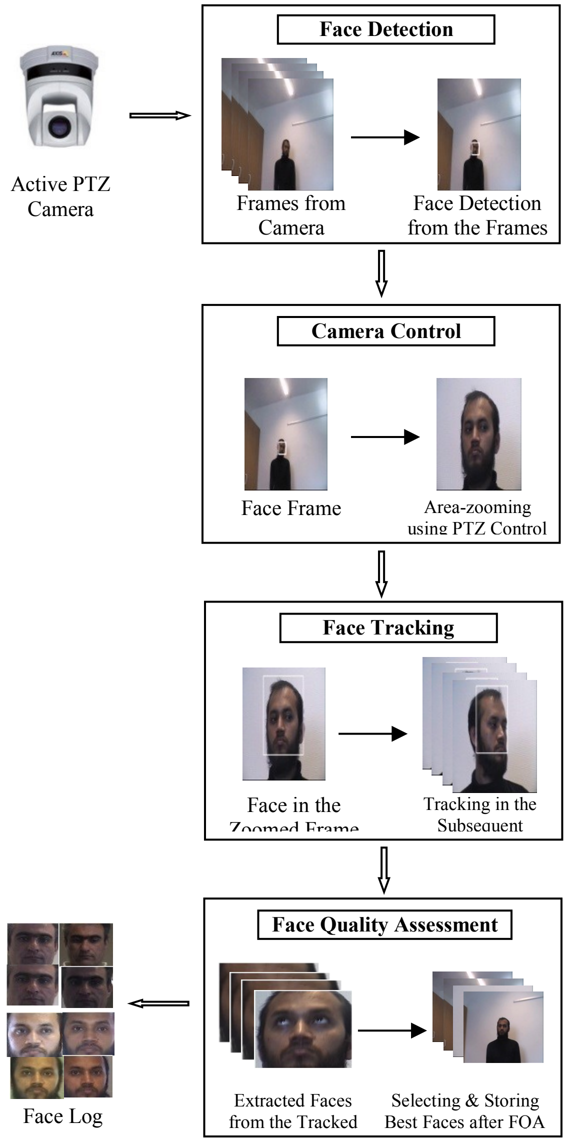

Figure 3-2 Block diagram of the proposed facial image acquisition system with face quality assessment.

An efficient camera control strategy has been defined in [15] and inspired by this we utilized a concept of area zooming in order to control the camera by using PTZ parameters. Area zooming works by combining one pan-tilt command and one zoom command into one package and send it to the camera via a HTTP (Hyper-Text Transfer Protocol) command sending sub-module in the implementation. This command package is expressed by a 3-tuples *AreaZoom(ptX, ptY, Z)* with the following semantics:

AreaZoom ->
{
ptX, x-coordinate of the center of zoomed frame
ptY, y-coordinate of the center of zoomed frame
Z, scale of zooming
}

When we have a face ROI *F(x, y, h, w)* in a frame, the parameters of the AreaZoom can be calculated as follows:

$$ptX = x + \text{int}(h/2) \tag{1}$$

$$ptY = y + \text{int}(w/2) \tag{2}$$

$$Z = \text{int}((f_{\min} /(h * w)) * 100) \tag{3}$$

Where, *int(..)* casts a floating point value to an integer and f_{min} is the minimum expected area size of the face after zooming. When camera receives *AreaZoom* command, it zooms in the face ROI by taking the face center point as the center point of the zoomed frame. However, in practice, zooming process takes some time to be executed. Thus, a rapidly moving face can be out of the expected zoomed frame, while camera is actually zooming in. In order to overcome this problem, we go through a face redetection phase. If there is no face, the camera is set back to the initial position and the system resumes from the initial face detection position.

3.3.3. FACE TRACKING MODULE

Instead of detecting face in each video frame by employing a computationally expensive face detection algorithm in full-size frames, a face tracker can be employed. When the camera control module zooms the face ROI and re-detects face in the zoomed frame, the control is transferred to the tracking module. Tracking module tracks the face and gives the most exactly matching candidate region as the face region in the subsequent zoomed frames by employing a tracking algorithm. Later, face detection algorithm is applied on the candidate region instead of full image frame to detect the face. However, the tracking algorithm should be computationally inexpensive in order to ensure real-time acquisition of face image. Among different tracking algorithms, we select a computationally inexpensive and highly competent tracking method known as *Camshift*. The performance of *Camshift* is evident from [19] and [21].

Camshift tracker takes the input image in HSV color model, finds the object center by iteratively examining a search window in the image frame by employing color histogram technique, and finally detects the window size and rotation for the object in the current frame. The readers are suggested to see [19] and [21] to get a detailed description of *Camshift*. When *Camshift* tracker selects a candidate region as the tracked face and a face detector validates it as face, the face is extracted from the image frame. Later, it is transferred to the FQA module in order to measure the quality metrics.

3.3.4. FACE QUALITY ASSESSMENT MODULE

FQA module is responsible to assess the quality of the extracted faces from the video sequences captured by the camera. Which parameters can effectively determine face quality have been thoroughly studied in [2]. They selected some parameters among a number of parameters defined by International Civil Aviation Organization (ICAO) for identification documents. A short list of important parameters is shown in Table 3-1. Among these parameters four parameters were selected for real-time camera capturing and face log generation. These parameters are: out-of-plan face rotation (pose), sharpness, brightness, and resolution. In this chapter, we utilize these four features in order to determine the face quality. A normalized score with the range *[0:1]* is calculated for each parameter by employing empirical thresholds for the parameters and a linear combination of scores has been utilized to generate single score for each face. Thresholds are determined by using a scaling factor with the analysis of [2]. Best faces are selected by thresholding the final single score for each face. The basic calculation process of the parameters is described in [2], we, however, include a short introduction below for readers' interest. We also include the changes necessary in the equations below in order to make it compatible with our proposed system to run in online real-time mode.

- Pose estimation - Least out-of-plan rotated face: The face ROI is first converted into a binary image and the center of mass is calculated using:

$$x_m = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} ib(i,j)}{A}, \quad y_m = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} jb(i,j)}{A} \tag{4}$$

  Then the geometric center of face region is detected and the distance between the center of region and center of mass is calculated by:

$$Dist = \sqrt{(x_c - x_m)^2 + (y_c - y_m)^2} \tag{5}$$

Finally the normalized score is calculated by:

$$P_{Pose} = \frac{Dist_{Th\_\max} - Dist}{Dist_{Th\_\max} - Dist_{Th\_\min}} \tag{6}$$

Where (x_m, y_m) is the center of mass, b is the binary face image, m is the width, n is the height, A is the area of image, x_1, x_2 and y_1, y_2 are the boundary coordinate of the face, and $Dist_{Th\_max}$ and $Dist_{Th\_min}$ are the delimiters of the allowable pose values.

Table 3-1 Some Significant Face Quality Assessment Parameters Defined by ICAO [2]

No.	Parameter Name	ICAO Requirement
1	Image Resolution	At least 420x525
2	Sharpness & Brightness	Not specified
3	Horizontal Eye Position	Center
4	Vertical Eye Position	50-70% of the image height
5	Head Width	Between 4:7 and 1:2
6	Head Height	70-80% of image height
7	Head Rotation	About 5 degrees

- Sharpness: Sharpness of a face image can be affected by motion blur or unfocused capture:

  $$Sharp = abs(A(x,y) - lowA(x,y)) \tag{7}$$

  Sharpness's associated score is calculated:

  $$P_{Sharp} = \frac{Sharp - Sharp_{Th\_\min}}{Sharp_{Th\_\max} - Sharp_{Th\_\min}} \tag{8}$$

  Where, *lowA(x,y)* is the low-pass filtered counterpart of the image *A(x,y)*, and $Sharp_{Th\_max}$ and $Sharp_{Th\_min}$ are the delimiters of the allowable sharpness to be accepted.

- Brightness: This parameter measures whether a face image is too dark to use. It is calculated by the average value of the illumination component of all pixels in an image. Thus, the brightness score is calculated by (9), where *I(i,j)* is the intensity of pixels in the face image, and $Bright_{Th\_max}$ and $Bright_{Th\_min}$ are the delimiters of the allowable brightness to be qualified.

$$P_{Bright} = \frac{\left(\sum_{i=1}^{n} \sum_{j=1}^{m} I(i,j) \Big/ (m*n) \right) - Bright_{Th\_\min}}{Bright_{Th\_\max} - Bright_{Th\_\min}} \tag{9}$$

- Image size or resolution: Depending upon the application, face images with higher resolution generally yield better results than lower resolution faces. The score for image resolution is calculated by (10), where w is image width, h is image height, $Width_{th}$ and $Height_{th}$ are two thresholds for expected face height and width, respectively.

$$P_{Size} = \min\left\{1, \frac{w}{Width_{th}} \times \frac{h}{Height_{th}}\right\} \tag{10}$$

The final single score for each face is calculated by linearly combining the abovementioned 4 quality parameters with empirically assigned weight factor, as shown in (11):

$$Quality_{Score} = \frac{\sum_{i=1}^{4} w_i P_i}{\sum_{i=1}^{4} w_i} \tag{11}$$

Where, w_i are the weight associated with P_i, and P_i are the score values for the parameters pose, sharpness, brightness and resolution, consecutively. Finally, the faces exceeding a quality threshold $Quality_{Th}$ are selected for logging from the imagery.

3.4. EXPERIMENTAL RESULTS

3.4.1. EXPERIMENTAL ENVIRONMENT

The experimental system was implemented by using an off-the-shelf Axis PTZ 214 IP camera. The camera specification is given in Table 3-2. The camera was connected with the computer via an Ethernet switch and camera control was accomplished by HTTP commands. The underlying algorithms of the system was implemented in Visual C++ environment by utilizing two libraries OpenCV (computer vision) and POCO (network package).

The empirical threshold values used in the implementation are listed in Table 3-3. These threshold values were determined by considering the quality metrics requirements listed in Table 3-1 and the analysis showed in [2, 4]. We recorded several video sequences by using the proposed camera capture system, which involved both male and female objects from indoor and outdoor environment in different lighting conditions. Faces were extracted from the frames of 8 video clips (named as, *Sq1, Sq2, Sq3, Sq4, Sq5, Sq6, Sq7,* and *Sq8*) and manually annotated to high-quality and low-quality faces. This annotated dataset further used to evaluate the performance.

Table 3-2 Camera Specification for Experimental Setup

Parameter Name	Specification
Angle of View, FPS	2.7^0 - 48^0 , 21-30/s
Shutter Time and Resolution	1/10000s to 1s, 0.4MP
Pan Range and Speed	$\pm$ 170^0 range, 100^0/s speed
Titl Range and Speed	-30^0 – 90^0 range, 90^0/s speed
Zoom	18x optical, 12x digital

Table 3-3 Parameters Used in the Implementation

Parameter Name(s)	Value(s)
$Dist_{Th\_max}$, $Dist_{Th\_min}$	95, 30
$Sharp_{Th\_max}$, $Sharp_{Th\_min}$	105, 30
$Bright_{Th\_max}$, $Bright_{Th\_min}$	150, 80
$Width_{Th}$, $Height_{Th}$	310, 275
$Quality_{Th}$	0.65
Weights: w1, w2, w3, w4	0.9, 1, 0.7, 0.5

3.4.2. PERFORMANCE EVALUATION

We employed the proposed approach to extract high quality faces from camera frames. Figure 3-3 depicts some example faces extracted from *Sq1, Sq2, Sq3,* and *Sq4* by the system using FQA. Figure 3-4 shows some example faces which were discarded due to failure to meet the quality requirements. As *Camshift* sometimes track face-colored non-face region and generate false-positive results as shown in Figure 3-4(a), face re-detection after *Camshift* tracking plays important role to reduce this error.

Table 3-4 summarizes the performance analysis data of the proposed approach on the aforementioned 8 annotated video clips. The clips contain 9857 image frames, including 550 faces. From the results it is observed that, in comparison with human perception, the proposed approach effectively determine the quality of the extracted faces with 85.27% accuracy. The recall rate (measure of positive cases can be caught by the system) and precision rate (measure of correct positive prediction) for positive faces are 85.30% and 98.24%, respectively. Beside these measures, the results of the proposed system for computational expenses are also impressive. The proposed system records the experimental dataset and logs good quality faces in an average of 16.20 fps (frames per second). This includes the time required for camera moving operations too. The average time required to process each frame by employing face detection, tracking and quality assessment is about 61.74 ms.

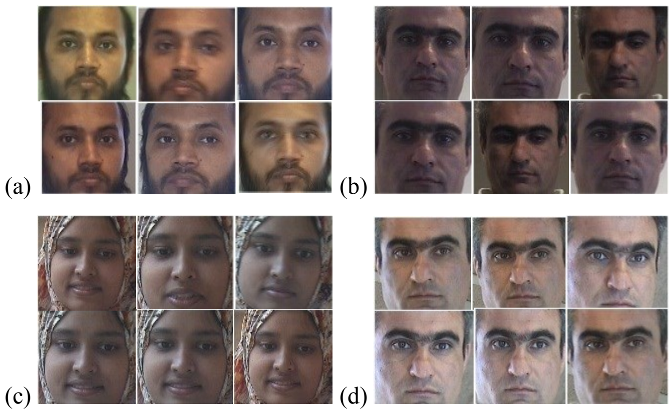

Figure 3-3 Some examples of extracted high-quality face from four recorded video clips: (a) Sq1, (b) Sq2, (c) Sq3, and (d) Sq4.

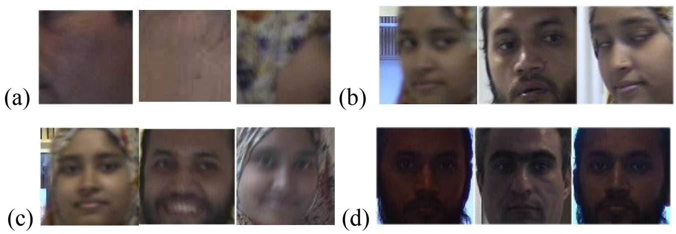

Figure 3-4 Some examples of discarded faces due to failure of meeting quality requirements: (a) Not face, (b) Pose, (c) Sharpness, and (d) Brightness.

3.5. CONCLUSIONS

In this chapter, an active camera based high-quality real-time facial image acquisition system was proposed. The quality of the faces was measured in terms of face resolution, pose, brightness, and sharpness. Only good quality faces were logged on by discarding the non-qualified imagery. Experimental result showed that the system is doable for real-time applications with an overall accuracy of 85.27% while compared with human annotated data. However, the face detection framework (Viola & Jones approach) utilized by the system is not robust to high degree of pose variation and color histogram based *Camshift* tracking often produce false positive results. Therefore, an effort is necessary to improve the system by addressing these issues. Not to mention, incorporating multi-agent tracking within real-time framework of an active camera is also an important issue to be addressed.

Table 3-4 Performance Analysis of High Quality Face Acquisition on the Experimental Dataset

Seq.	**No. of Frames**	**No. of Tracked Frames**	**No. of Faces in Tracked Frames**	**Correct Detection TP/TN**	**False Detection FP/FN**	**Processing Time (s)**	**Accuracy & Speed**
Sq1	1479	890	120	49/49	19/5	91	Accuracy 85.27%
Sq2	1669	683	49	37/4	0/8	103	
Sq3	656	201	48	43/1	1/3	40	Recall
Sq4	1491	813	18	13/4	1/0	94	85.30%
Sq5	2037	1103	82	51/17	4/10	124	Precision
Sq6	447	188	71	52/7	2/10	28	98.24%
Sq7	1034	770	124	48/65	2/9	64	Speed
Sq8	1044	660	38	3/26	3/6	65	16.20 fps

3.6. ACKNOWLEDGEMENT

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CHAPTER 4. QUALITY-AWARE ESTIMATION OF FACIAL LANDMARKS IN VIDEO SEQUENCES

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4.1. ABSTRACT

Face alignment in video is a primitive step for facial image analysis. The accuracy of the alignment greatly depends on the quality of the face image in the video frames and low quality faces are proven to cause erroneous alignment. Thus, this chapter proposes a system for quality aware face alignment by using a Supervised Decent Method (SDM) along with a motion based forward extrapolation method. The proposed system first extracts faces from video frames. Then, it employs a face quality assessment technique to measure the face quality. If the face quality is high, the proposed system uses SDM for facial landmark detection. If the face quality is low the proposed system corrects the facial landmarks that are detected by SDM. Depending upon the face velocity in consecutive video frames and face quality measure, two algorithms are proposed for correction of landmarks in low quality faces by using an extrapolation polynomial. Experimental results illustrate the competency of the proposed method while comparing with the state-of-the-art methods including an SDM-based method (from CVPR-2013) and a very recent method (from CVPR-2014) that uses parallel cascade of linear regression (Par-CLR).

4.2. INTRODUCTION

Automatic analysis of facial image plays an important role in many different areas such as surveillance, medical diagnosis, biometrics, and expression recognition [1]. Detecting facial landmarks, also called face alignment, is an essential step in automatic facial image analysis. The accuracy of alignment, i.e., pertinent detection of facial landmarks, affects the performance of the analysis. Face alignment is considered as a mathematical optimization problem and a number of methods were proposed to solve this problem. The Active Appearance Model (AAM) fitting along with its derivatives are some of the early but effective solutions in this area [2]. The AAM fitting works by estimating some parameters of a model which is close enough to the given image. A number of regression based approaches was proposed for the AAM fitting, e.g., a linear regression based fitting [3], a non-linear regressor using boosted learning [4], a boosted ranking model [5], and discriminative approaches [6-7]. Figure 4-1(a) shows 66 facial landmark points detected in two examples by an AAM fitting algorithm (Fast-Simultaneous Inverse Compositional algorithm (Fast-SIC)) [2].

Though the results of regression based AAM fitting methods are good, they are computationally expensive due to the iterative nature of learning the shape and the appearance parameters. To deal with this problem a number of works were done by optimizing least-square functions. For example, Matthews et al. formulated the AAM fitting as a Lukas-Kanade (LK) problem which can be solved using Gauss-Newton optimization [8, 9]. Similar Gauss-Newton or gradient decent based optimization methods for this problem can be found in [10-11]. Standard gradient decent algorithms when applied to AAMs are, however, inefficient in term of computational complexity [2, 12]. Two fast AAM fitting approaches were proposed recently in CVPR [13, 14]. Asthana et al. proposed a Parallel Cascade of Linear Regression (Par-CLR) to detect the landmarks [13]. On the other hand, Xiong et al. developed a Supervised Descent Method (SDM) to minimize a non-linear least square function and employed it for face alignment [14]. Both of these methods in [13, 14] are able to work real-time and showed competent results. Figure 4-1(b) shows two examples of detecting 49 facial landmark points by the SDM [14].

(a) (b)

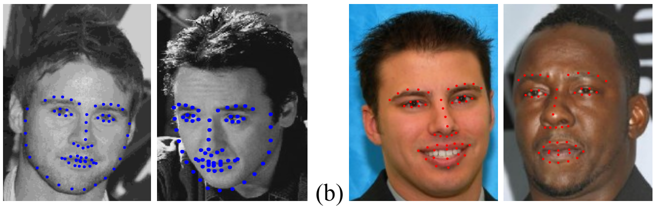

Figure 4-1 Examples of facial landmarks detection: (a) Fast-SIC detected 66 points [2] and (b) SDM detected 49 points in four images of the LFPW database [14].

Although the SDM provides good estimates of the facial landmarks, its detection accuracy is suffered by facial image quality measures like resolution (Figure 4-2, col. 1, row 1), pose (Figure 4-2, col. 1-3, row 2), brightness (Figure 4-2, col. 2, row 1), and sharpness (Figure 4-2, col. 1, row 2). Moreover, the SDM-based face alignment of [14] uses the landmarks of the current frame as the initial points of searching in the next frame in a video, which produces erroneous results when no face is detected in the current frame or when the face is of low quality (Figure 4-2, col. 3, row 1).

When a video acquisition system acquires facial video frames, low quality facial images are very common in many real-world problems [15]. For example, a human face at 5 meters distance from a surveillance camera subtends only about 4x6 pixels on a 640x480 sensor with 130 degrees field of view, which is an insufficient resolution for almost any further analysis [16]. A face region with size 48x64 pixels, 24x32 pixels, or less is not likely to be used for expression recognition due to inadequate information available in the low resolution face [17]. Similar problems are exhibited in facial analysis for high pose variation, very high or very low brightness, and low sharpness value of a facial image [18-20]. When a high quality face image is provided to a face alignment system (e.g., SDM) it detects the landmarks very accurately. However, when the face quality is low, the detected landmark positions are not trustworthy.

To deal with the alignment problem of low quality facial images, a Face Quality Assessment (FQA) system [21] can be employed before running the alignment algorithm. Such a system uses some quality measures to determine whether a face is qualified enough and provides assistance to further analysis by providing the quality rating. Figure 4-3 shows a typical FQA method which consists of three steps: video frame acquisition, face detection in the video frames, and FQA by measuring face quality metrics. In this chapter, we propose a 'quality-aware' estimation method for improved face alignment in video sequence, where facial landmarks in high quality faces are estimated by the SDM and in low quality faces are estimated by a motion based forward extrapolation method.

Figure 4-2 Depiction of bad performance of quality unaware SDM-based method in the alignment of low quality faces in video sequences from Youtube Celebrities dataset [14].

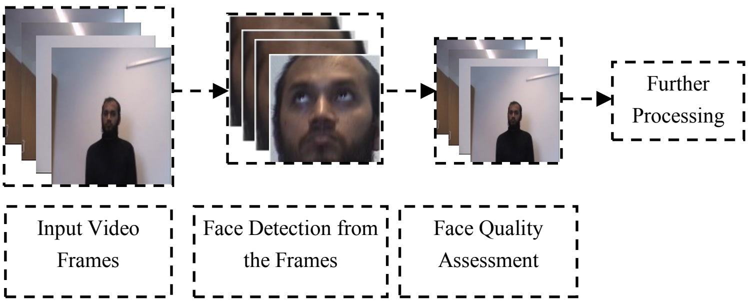

Figure 4-3 Steps of a typical face quality assessment system.

The rest of the chapter is organized as follows: Section three presents the proposed approach. Section four states the experimental results and finally section five concludes the chapter.

4.3. THE PROPOSED METHOD

The SDM based face alignment system results in erroneous landmarks detection when: (1) a face is detected in a wrong position, and (2) the face quality is low. To deal with these problems, we propose a quality aware system as shown in Figure 4-4. The steps of the system are described in the following subsections.

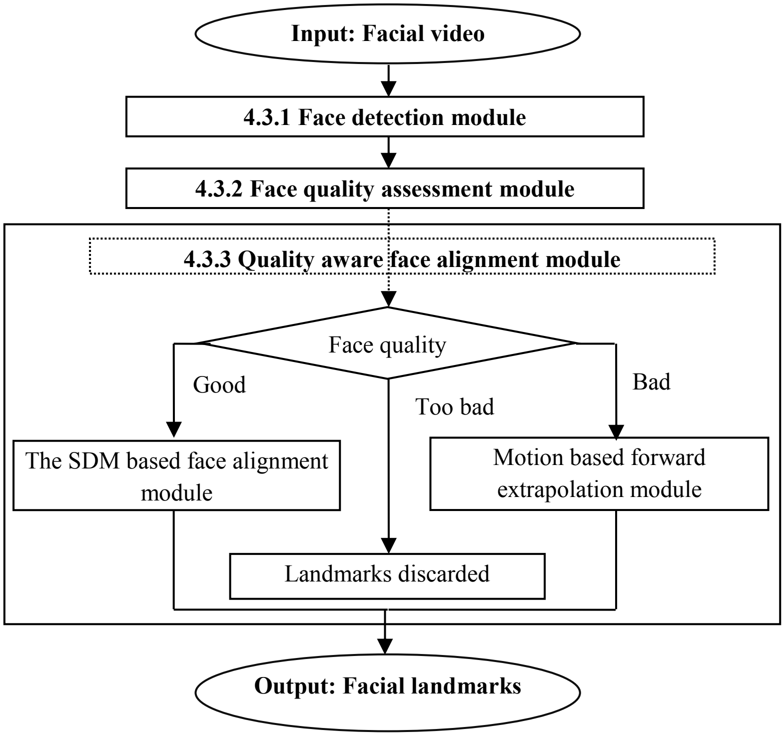

Figure 4-4 Block diagram of the proposed system of face alignment in video with face quality assessment. The steps of the method are explained in this section.

4.3.1. FACE DETECTION MODULE

The first step of face alignment in a video sequence is face detection. We employ the well-known Viola and Jones face detection approach [22] for this purpose. This method utilizes the so called Haar-like features in a linear combination of some weak classifiers to classify face and non-face. In order to speed up the detection process an evolutionary pruning method is adopted in classification in order to form strong face/non-face classifier from fewer weak classifiers [23]. Following Figure 4-4, when a face is detected, the face is passed to the Face Quality Assessment (FQA) module.

4.3.2. FACE QUALITY ASSESSMENT MODULE

The FQA module is responsible to assess the quality of the extracted faces. Nasrollahi et al. proposed a face quality assessment system in video sequences [21]. Haque et al. utilized face quality assessment while capturing video sequences from an active pan-tilt-zoom camera [18]. FQA was also employed in [24] before constructing facial expression log. All of these previous methods used four quality parameters: out-of-plan face rotation (pose), sharpness, brightness, and resolution. For facial geometry analysis and detection of landmarks all of these quality metrics are critical as discussed in the previous section (and Figure 4-2). Thus, we calculate these four quality metrics to assess the face quality. A normalized score is then obtained in the range of *[0:1]* for each quality parameter and a weighted combination of the scores is utilized to generate a single quality score, Q^i, as in [18]. The Q^i which represents the quality of the face in ith frame will be used in the subsequent blocks of the system to make a decision about the method that the proposed system needs to use for the face alignment.

4.3.3. QUALITY-AWARE FACE ALIGNMENT MODULE

The SDM method for face alignment uses a set of training samples to learn a mean face shape. This mean shape is used as an initial point for an iterative optimization of a non-linear least square function towards the best estimates of the positions of the landmarks in facial test images. The minimization function can be defined as a function over Δx as:

$$f_{SDM}(x_0 + \Delta x) = \left\| g\big(d(x_0 + \Delta x)\big) - \theta_* \right\|_2^2 \qquad (1)$$

where, x_0 is the initial configuration of the landmarks in a facial image, $d(x)$ indexes the landmarks configuration (x) in the image, g is a nonlinear feature extractor, $\theta_* = g(d(x_*))$, and x_* is the configuration of the true landmarks. The Scale Invariant Feature Transform (SIFT) [25] is used as the feature extractor g. In the training images Δx and θ_* are known. By utilizing these known parameters the SDM iteratively learns a sequence of generic descent directions, $\{\delta_n\}$, and a sequence of bias terms, $\{\beta_n\}$, to set the direction towards the true landmark configuration x_* in the minimization process, which are further applied in the testing phase [14]. This is done by:

$$x_n = x_{n-1} + \delta_{n-1}\sigma(x_{n-1}) + \beta_{n-1} \qquad (2)$$

where, $\sigma(x_{n-1}) = g(d(x_{n-1}))$ is the feature vector extracted at previous landmark location x_{n-1} and x_n is the new location. The succession of x_n converges to x_* for all images in the training set.

In the proposed approach, following Figure 4-4, the face region is passed to the SDM based alignment module, if the quality score is greater than an empirical threshold, Q_{Th_high}. Otherwise, the face region is passed to the motion based forward extrapolation module in order to estimate the landmarks or reject the landmark if the quality based on an empirical threshold, Q_{Th_low}, is too bad. To be more precise, we first rewrite the SDM's objective function in (1) for a video sequence as:

$$f_{SDM}(x_0^i + \Delta x^i) = \left\| g\left(d\left(x_0^i + \Delta x^i\right)\right) - \theta_*^i \right\|_2^2 \quad (3)$$

where, the i superscript implies the frame number and the other symbols have similar meaning as (1). Then, we include the information Q^i provided by the FQA system as a prior for the processing of the next frame. This will change the objective function of (3) to:

$$f_{Proposed\ system} = \begin{cases} f_{SDM}(x_0^i + \Delta x^i), \ Q^i > Q_{Th\_high} \\ f_{Est}(x^i), \ Q_{Th\_low} < Q^i < Q_{Th\_high} \\ No\ Landmarks, \ Q^i < Q_{Th\_low} \end{cases} \quad (4)$$

where, $f_{Est}(x^i) = \left\| d(x^i) - d(x_*^i) \right\|_2^2$ minimizes the non-likelihood error between corrected landmarks $d(x^i)$ using the landmark configuration of previous good quality frames and the true landmark configuration $d(x_*^i)$. The working procedure of the SDM based method with the minimization function f_{SDM} and the forward extrapolation method with the minimization function f_{Est} are described in the following subsections, respectively.

4.3.3.1 SDM-based face alignment module

In the proposed system, we employed a simple deviation of SDM for good quality faces. We initialize the iterative minimization of SDM for landmark configuration in each frame by giving a shape estimate (initial landmark positions) that is obtained from the mean shape of the training images. This is in contrary with [14] which initializes the landmarks in subsequent video frames by using the detected landmarks of the previous frame. This technique of [14] incurs the problem of getting trapped into local maxima, especially in the videos where the faces have high velocity due to video motion [26] among the frames. Thus, instead of using landmarks of the previous frames to initialize the minimization process, we initialize each frame by following the same procedure of using an estimated mean shape from the training data. This provides a more genuine estimate for initial position of landmarks for high-velocity frames. Moreover, as the mean shape initialization is a low-cost computational process involving merely a translation and scaling operation on the pre-trained landmark configuration, this does not incur any undoable computational complexity for real-time operation in video. Besides, the translation-al and scaling differences are also considered during initialization by scaling the mean shape from training with the size of the present face region.

4.3.3.2 Motion-based forward extrapolation module

As shown in Figure 4-2 when face quality is low, the SDM's minimization function f_{SDM} fails to converge in the right place. Furthermore, when a face is detected in a wrong position, the SDM tries to converge in that wrong place. These can be dealt with by considering the temporal stability that is usually present among subsequent facial images of a video. In another words, the alignment problem in low quality and/or wrongly detected facial frames can be addressed by exploiting landmarks positions in the previous good quality faces. This is exactly the point that we have utilized in this chapter: the landmarks in low quality faces and/or wrongly detected faces are extrapolated from the landmarks of the previous frames that are of good quality.

When f_{Est} is called for action, the FQA module provides some information such as the quality of the detected face, the displacement of the detected face from the face in the previous frame (the velocity of the face in the frames), the degree of pose in the current face and the amount of pose variation in the two previous faces in the video sequence. In order to calculate $d(x^i)$ for a low quality face in the ith frame of a video, let $d(x^{i-m})$ and $d(x^{i-n})$ denote two landmark configurations of the previous good quality face frames. We define the correction polynomial to minimize $f_{Est}(x^i)$ as:

$$d(x^i) = d(x^{i-n}) + \frac{d(x^{i-m}).-d(x^{i-n})}{x^{i-m}-x^{i-n}} \times (x - x^{i-n}) \qquad (5)$$

where, $x^{i-m} - x^{i-n}$ and $(x - x^{i-n})$ are the velocities of face in the corresponding frames with respect to the previous frames, and $(.-)$ indicates the subtraction operation for each landmarks (49 landmarks) separately.

In the proposed method, we utilize the extrapolation polynomial of (5) in two different ways for two different conditions:

Condition 1: When the face is detected in a wrong position. In this case the face motion shows a larger displacement for the current face than the faces in the previous frames and the face quality shows a sharp change than the face quality in the previous frames. We employed *Algorithm I* in order to extrapolate the landmarks. Two parameters, *Displacement* and *Quality_Change*, are compared with two empirically set thresholds and the landmarks in current frame (*Current_Landmarks*) are calculated from the landmarks in the previous qualified frame (*Prev_Landmarks*).

Condition 2: When the face quality is low. In this case the landmarks detected from the previous high-quality facial images are used to incorporate the motion information of the pose variation in the landmarks to extrapolate the landmarks of the current face. We employed *Algorithm II* in order to extrapolate the landmarks in this case. Two face quality parameters for pose and size, *Qual_Pose* and *Qual_Size* are compared with empirically set *Pose_Threshold* and *Size_Threshold*, and used for conditionally estimating *Current_Landmarks* by using *Prev_Landmarks* and *Displacement*. If the correction is not possible due to the missing of face in previous video frames, the landmarks detected in the current low quality face are also discarded in order to reduce false estimation.

Algorithm I

```
WRONG_DETECTION_ESTIMATE (Displacement, Quality_Change) {
IF Displacement > Dis_Threshold AND
            Quality_Change > Qual_Threshold THEN
   Prev_Landmarks = The landmarks of previous qualified face;
   Current_Landmarks = ESTIMATE(Prev_Landmarks,
                  Displacement);
   RETURN Current_Landmarks;
END
}
```

Algorithm II

```
LOW_QUALITY_ESTIMATE (Qual_Pose, Qual_Size, Displacement) {
IF  Qual_Pose  < Pose_Threshold AND
                  Qual_Size > Size_Threshold THEN
  Prev_Landmarks = The landmarks of previous qualified face;
  Current_Landmarks = ESTIMATE (Prev_Landmarks,
                  Displacement);
  RETURN Current_Landmarks;
END
}
```

```
ESTIMATE (Prev_Landmarks, Displacement) {
  temp_Landmarks =
            Landmarks calculated from (Eq. 5)
  Current_Landmarks = Rotation of
             temp_Landmarks with pose variation
  RETURN Current_Landmarks;
}
```

4.4. EXPERIMENTAL RESULTS

The proposed system was implemented in a combination of VISUAL C++ and MATLAB environments. An implementation of SDM along with its trained direction and bias terms is given in [14]. In order to evaluate the proposed system we used the well-known *Youtube Celebrities* database [27]. However, as a general database created for face recognition research, most of the videos in this database are either single-subject video (as we assume single face from the same subject in a video), or too short to provide enough motion information for erroneous frames, or do not subjected to the problem of low-quality face. However, we managed to select 18 videos containing *2537* frames from this database wherein the problem of low face-quality in alignment are exhibited. To generate ground truth data, we manually aligned the low quality faces in all of these selected videos and compared the performance of the proposed system and state-of-the-art facial alignment systems against this ground truth data.

4.4.1. PERFORMANCE EVALUATION

Figure 4-5 shows some results of landmarks detection in some good quality face frames of *Youtube Celebrities* database. The results for SDM [14] and the proposed method are similar for these good quality faces. When the face quality is too bad to detect the landmarks, the proposed algorithm discards the erroneous landmarks detected by SDM. Figure 4-6 shows some example faces from *Youtube Celebrities* database where erroneous landmarks detected by SDM are discarded. Figure 4-7 illustrates some results of landmarks correction by the proposed method in order to provide the mean of qualitative assessment. The first and third rows of Figure 4-7 present the results generated by the SDM, and the second and fourth rows present the results generated by our method. From the results (col. 1, 2, 4, row 1-2 of Figure 4-7) it is observed that when the face detector produces a wrong detection, the proposed approach can detect the error from the face quality and the displacement (face velocity in consecutive frames) parameters, and then extrapolate the landmarks by using the motion information. In the other cases the faces have low resolution problem (col. 3-5, row 1-2), low brightness (col. 6, row 1-2), high pose variation (col. 1-4, row 3-4) and low sharpness (col. 5, row 3-4) in Figure 4-7. Some faces do not exhibit problem from low-quality, instead they get trapped into local minima in the SDM's minimization process due to poor initialization for high velocity face frames (e.g., col. 6, row 3-4).

Figure 4-8 shows the relationship between face quality with the SDM and the proposed methods. We used 84 frames of *0450_03_001_bill_clinton* sequence of *Youtube Celebrities* database in order to generate this result. It can be seen that when the face quality is low (in frames 70-80) the detection error is high in the

SDM-based method. When the proposed method utilizes the face quality metric along with SDM-based method, the detection error reduces.

Figure 4-5 Some examples of good quality facial images from Youtube Celebrities *database for which the proposed method produces similar results to SDM [14].*

Figure 4-6 Some of the alignment results of SDM-based method [14] on the frames of the Youtube Celebrities *database which are discarded by the proposed method due to excessively low face quality. The first row shows the low-quality face images and the second row shows the landmarks points detected by SDM.*

4.4.2. PERFORMANCE COMPARISON

Table 4-1 shows the point to point error in landmark detection by the SDM and the proposed methods compared to the manually generated ground truth of some low quality faces in *0450_03_001_bill_clinton* sequence. From the results it can be seen that when the face quality is low the SDM produces erroneous results, however the proposed method provides better results. The face quality-scores in frames 76 and 77 are very low due to detection of the face in wrong places. However, our landmark correction method, using the motion information, provides better estimates. The result of SDM is a little better than the proposed method in the frame 70. According to our observation this is not because of the slip of the proposed method, instead this is because of trivial difference of few pixels between manual annotation from our perception of true landmarks, and the automatic detection by SDM and the proposed method.

Figure 4-7 Comparing the landmark correction results of the proposed system (second and fourth row) against the results of the SDM-based method of [12] (first and third row) in some low quality frames of the Youtube Celebrities *database.*

Table 4-2 shows the comparison between the Par-CLR based method [13], the SDM-based method [14], and the proposed method in normalized point to point error for all 18 selected video sequences from the *Youtube Celebrities* database. These results are depicted in Figure 4-9. The data for each video in Figure 4-9 is independent of the data for other videos. Because, we have normalized the point-to-point errors of the frames of a video by the highest value of error in that video. Thus, showing higher error in a video does not necessarily mean that the error of detection in this video is higher than that of the other videos. From the results it is observed that the proposed method outperforms both SDM and Par-CLR when the videos have low quality face-frames. Another significant observation of the experimental results is that the proposed method either improves the detection results or at least maintains the accuracy of SDM and does not worsen the detection error in comparison with both SDM and Par-CLR. Thus, the contribution of the proposed method is significant when high accuracy is expected in landmark-based facial image analysis.

Table 4-1 Normalized point to point error for both SDM [14] and the proposed method of some low quality faces of 0450_03_001_bill_clinton *sequence of* Youtube Celebrities *database*

Frame number	Face quality	Method	Normalized Error
1 (32)	0.42	SDM	0.586
		Proposed	0.008
2 (69)	0.31	SDM	0.015
		Proposed	0.010
3 (70)	0.26	SDM	0.025
		Proposed	0.035
4 (76)	0.00	SDM	0.995
		Proposed	0.284
5 (77)	0.00	SDM	1.000
		Proposed	0.306

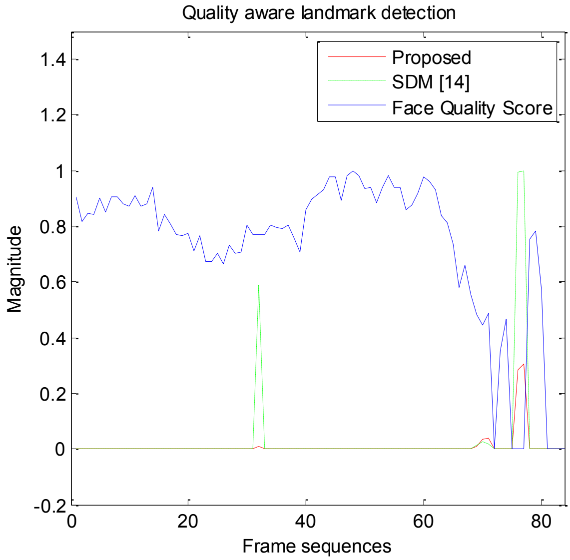

Figure 4-8 Face quality and normalized point to point error for both the SDM [14] and the proposed method on 84 frames of 0450_03_001_bill_clinton *sequence of* Youtube Celebrities *database.*

Table 4-2 Average point to point error of the Par-CLR [13], the SDM [14] and the proposed methods compared to the manually generated ground truth for erroneous frames of 18 experimental videos from the Youtube Celebrities *database. Higher values indicate higher detection errors*

No.	Sequence name	Pt-pt error		
		Par-CLR	SDM	Proposed
1.	0450_03_001	0.3821	0.0315	**0.0081**
2.	0051_03_008	0.7926	0.0786	**0.0021**
3.	0049_03_006	0.8926	0.7506	**0.3246**
4.	1304_01_001	0.9702	0.4145	**0.2841**
5.	0009_01_009	0.8776	0.8369	**0.3506**
6.	0033_02_001	0.8515	0.9000	**0.4402**
7.	0054_03_011	0.8907	1.0000	**0.6834**
8.	0079_01_024	0.5156	0.5060	**0.0067**
9.	0162_02_026	0.6732	0.5000	**0.3321**
10.	0182_03_015	0.9663	0.9515	**0.5956**
11.	0193_01_004	0.5087	0.5064	**0.0018**
12.	0458_03_009	0.7045	0.8898	**0.4913**
13.	0492_03_009	0.7903	0.8973	**0.3456**
14.	0518_03_002	0.8669	0.8096	**0.1920**
15.	0532_01_007	0.9863	0.3348	**0.0012**
16.	0606_03_001	0.6480	0.7661	**0.1547**
17.	0795_01_004	0.8063	0.5039	**0.0027**
18.	1744_01_017	0.7928	0.8552	**0.1675**
Average error in erroneous frames of 18 videos with 2537 frames in total		0.7731	0.6314	**0.2318**

4.5. CONCLUSIONS

This chapter investigated the problem of detecting facial landmarks in low-quality faces of videos. As the SDM-based face alignment system exhibits the problems of misalignment due to low face-quality and initialization by the landmarks of the previous frame for the current frame, we proposed a quality aware method for improved face alignment, where high quality faces were estimated by SDM and low quality faces were estimated by motion based forward extrapolation. The method utilized the quality of the detected face, the displacement of the detected face from the face in the previous frame (the velocity of the face in the consecutive face-frames), the degree of pose in the current face and the amount of pose variation in previous faces in the video sequence in order to extrapolate the landmarks in the face of the current video frame. As the proposed method improves the landmarks detection results in erroneous (low quality) frames and does not worsen the detection error (in high quality frames) while comparing against state-of-the-art approaches, the contribution of the proposed method is noteworthy for facial image analysis. In the future, we will investigate the performance of the proposed face alignment system in facial expression recognition systems and facial image based health monitoring.

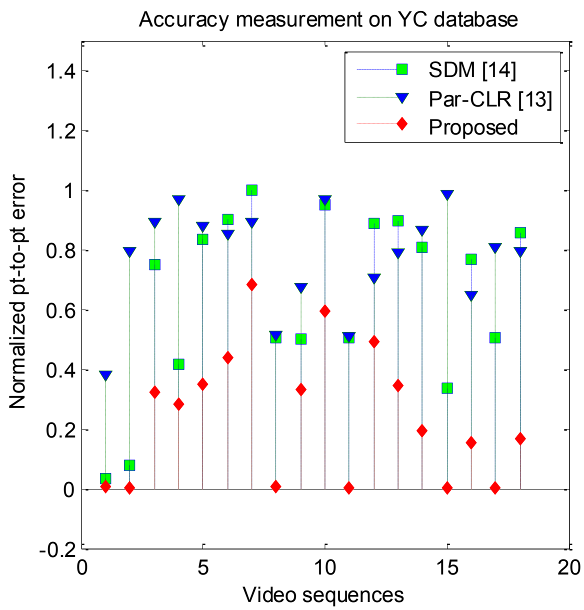

Figure 4-9 Average point to point error of the SDM [14], Par-CLR [13] and the proposed methods compared to the manually generated ground truth for erroneous frames of 18 experimental videos from the Youtube Celebrities *database. Detection error is normalized for each video separately.*

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PART IV

MEASUREMENT OF PHYSIOLOGICAL PARAMETERS

CHAPTER 5. HEARTBEAT RATE MEASUREMENT FROM FACIAL VIDEO

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5.1. ABSTRACT

Heartbeat Rate (HR) reveals a person's health condition. This chapter presents an effective system for measuring HR from facial videos acquired in a more realistic environment than the testing environment of current systems. The proposed method utilizes a facial feature point tracking method by combining a 'Good feature to track' and a 'Supervised descent method' in order to overcome the limitations of currently available facial video based HR measuring systems. Such limitations include, e.g., unrealistic restriction of the subject's movement and artificial lighting during data capture. A face quality assessment system is also incorporated to automatically discard low quality faces that occur in a realistic video sequence to reduce erroneous results. The proposed method is comprehensively tested on the publicly available MAHNOB-HCI database and our local dataset, which are collected in realistic scenarios. Experimental results show that the proposed system outperforms existing video based systems for HR measurement.

5.2. INTRODUCTION

Heartbeat Rate (HR) is an important physiological parameter that provides information about the condition of the human body's cardiovascular system in applications like medical diagnosis, rehabilitation training programs, and fitness assessments [1]. Increasing or decreasing a patient's HR beyond the norm in a fitness assessment or rehabilitation training, for example, can show how the exercise affects the trainee, and indicates whether continuing the exercise is safe.

HR is typically measured by an Electrocardiogram (ECG) through placing sensors on the body. A recent study was driven by the fact that blood circulation causes periodic subtle changes to facial skin color [2]. This fact was utilized in [3]–[7] for HR estimation and [8]–[10] for applications of heartbeat signal from facial video. These facial color-based methods, however, are not effective when taking into account the sensitivity to color noise and changes in illumination during tracking. Thus, Balakrishnan et al. proposed a system for measuring HR based on the fact that the flow of blood through the aorta causes invisible motion in the head (which can be observed by Ballistocardiography) due to pulsation of the heart muscles [11]. An improvement of this method was proposed in [12]. These motion-based methods of [11], [12] extract facial feature points from forehead and cheek (as shown in Figure 5-1(a)) by a method called Good Feature to Track (GFT). They then employ the Kanade-Lucas-Tomasi (KLT) feature tracker from [13] to generate the motion trajectories of feature points and some signal processing methods to estimate cyclic head motion frequency as the subject's HR. These calculations are based on the assumption that the head is static (or close to) during facial video capture. This means that there is neither internal facial motion nor external movement of the head during the data acquisition phase. We denote internal motion as facial expression and external motion as head pose. In real life scenarios there are, of course, both internal and external head motion. Current methods, therefore, fail due to an inability to detect and track the feature points in the presence of internal and external motion as well as low texture in the facial region. Moreover, real-life scenarios challenge current methods due to low facial quality in video because of motion blur, bad posing, and poor lighting conditions [14]. These low quality facial frames induce noise in the motion trajectories obtained for measuring the HR.

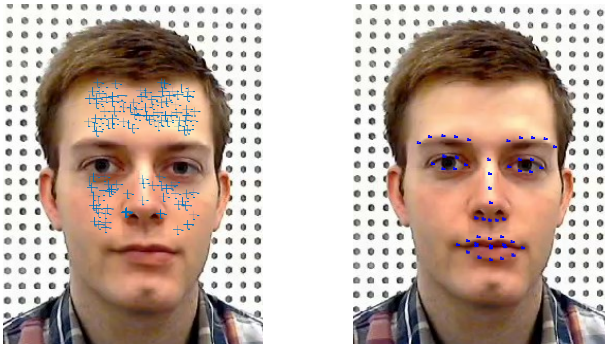


Figure 5-1 Different facial feature tracking methods: (a) facial feature points extracted by the good feature to track method and (b) facial landmarks obtained by the supervised descent method. While GFT extracts a large number of points, SDM merely uses 49 predefined points to track.

The proposed system addresses the aforementioned shortcomings and advances the current automatic systems for reliable measuring of HR. We introduce a Face Quality Assessment (FQA) method that prunes the captured video data so that low quality face frames cannot contribute to erroneous results [15], [16]. We then extract GFT feature points (Figure 5-1(a)) of [11] but combine them with facial landmarks (Figure 5-1(b)), extracted by the Supervised Descent Method (SDM) of [17]. A combination of these two methods for vibration signal generation allows us to obtain stable trajectories that, in turn, allow a better estimation of HR. The experiments are conducted on a publicly available database and on a local database collected at the lab and a commercial fitness center. The experimental results show that our system outperforms state-of-the-art systems for HR measurement. The chapter's contributions are as follows:

i. We identify the limitations of the GFT-based tracking used in previous methods for HR measurement in realistic videos that have facial expression changes and voluntary head motions, and propose a solution using SDM-based tracking.
ii. We provide evidence for the necessity of combining the trajectories from the GFT and the SDM, instead of using the trajectories from either the GFT or the SDM.

iii. We introduce the notion of FQA in the HR measurement context and demonstrate empirical evidence for its effectiveness.

The rest of the chapter is organized as follows. Section three provides the theoretical basis for the proposed method, which is then described in section four. Section five presents the experimental results, and the paper's conclusions are provided in section six.

5.3. THEORY

This section describes the basics of GFT- and SDM-based facial point tracking, explains the limitations of the GFT-based tracking, and proposes a solution via a combination of GFT- and SDM-based tracking.

Tracking facial feature points to detect head motion in consecutive facial video frames was accomplished in [11], [12] using GFT-based method. The GFT-based method uses an affine motion model to express changes in the level of intensity in the face. Tracking a window of size $w_x \times w_y$ in frame I to frame J is defined on a point velocity parameter $\boldsymbol{\delta} = [\delta_x \; \delta_y]^T$ for minimizing a residual function f_{GFT} that is defined by:

$$f_{GFT}(\boldsymbol{\delta}) = \sum_{x=p_x}^{p_x+w_x} \sum_{y=p_y}^{p_y+w_y} \big(I(\mathbf{x}) - J(\mathbf{x}+\boldsymbol{\delta})\big)^2 \qquad (1)$$

where $(I(\mathbf{x}) - J(\mathbf{x}+\boldsymbol{\delta}))$ stands for $(I(x,y) - J(x+\delta_x, y+\delta_y))$, and $\mathbf{p} = [p_x, p_y]^T$ is a point to track from the first frame to the second frame. According to observations made in [18], the quality of the estimate by this tracker depends on three factors: the size of the window, the texture of the image frame, and the amount of motion between frames. Thus, in the presence of voluntary head motion (both external and internal) and low-texture in facial videos, the GFT-based tracking exhibits the following problems:

i. Low texture in the tracking window: In general, not all parts of a video frame contain complete motion information because of an aperture problem. This difficulty can be overcome by tracking feature points in corners or regions with high spatial frequency content. However, GFT-based systems for HR utilized the feature points from the forehead and cheek that have low spatial frequency content.
ii. Losing track in a long video sequence: The GFT-based method applies a threshold to the cost function $f_{GFT}(\boldsymbol{\delta})$ in order to declare a point 'lost' if the cost function is higher than the threshold. While tracking a point over many frames of a video, as done in [11], [12], the point may drift throughout the extended sequences and may be prematurely declared 'lost.'

iii. Window size: When the window size (i.e. $w_x \times w_y$ in (1)) is small a deformation matrix to find the track is harder to estimate because the variations of motion within it are smaller and therefore less reliable. On the other hand, a bigger window is more likely to straddle a depth discontinuity in subsequent frames.

iv. Large optical flow vectors in consecutive video frames: When there is voluntary motion or expression change in a face the optical flow or face velocity in consecutive video frames is very high and GFT-based method misses the track due to occlusion [13].

Instead of tracking feature points by GFT-based method, facial landmarks can be tracked by employing a face alignment system. The Active Appearance Model (AAM) fitting [19] and its derivatives [20] are some of the early solutions for face alignment. A fast and highly accurate AAM fitting approach that was proposed recently in [17] is SDM. The SDM uses a set of manually aligned faces as training samples to learn a mean face shape. This mean shape is then used as an initial point for an iterative minimization of a non-linear least square function towards the best estimates of the positions of the landmarks in facial test images. The minimization function can be defined as a function over Δx:

$$f_{SDM}(x_0 + \Delta x) = \left\| g\big(d(x_0 + \Delta x)\big) - \theta_* \right\|_2^2 \qquad (2)$$

where x_0 is the initial configuration of the landmarks in a facial image, $d(x)$ indexes the landmarks configuration (x) in the image, g is a nonlinear feature extractor, $\theta_* = g(d(x_*))$, and x_* is the configuration of the true landmarks. In the training images Δx and θ_* are known. By utilizing these known parameters the SDM iteratively learns a sequence of generic descent directions, $\{\partial_n\}$, and a sequence of bias terms, $\{\beta_n\}$, to set the direction towards the true landmarks configuration x_* in the minimization process, which are further applied in the alignment of unlabelled faces [17]. The evaluation of the descent directions and bias terms is accomplished by:

$$x_n = x_{n-1} + \partial_{n-1}\sigma(x_{n-1}) + \beta_{n-1} \qquad (3)$$

where $\sigma(x_{n-1}) = g(d(x_{n-1}))$ is the feature vector extracted at the previous landmark location x_{n-1}, x_n is the new location, and ∂_{n-1} and β_{n-1} are defined as:

$$\partial_{n-1} = -2 \times \mathbf{H}^{-1}(x_{n-1}) \times \mathbf{J}^{\mathrm{T}}(x_{n-1}) \times g(d(x_{n-1})) \qquad (4)$$

$$\beta_{n-1} = -2 \times \mathbf{H}^{-1}(x_{n-1}) \times \mathbf{J}^{\mathrm{T}}(x_{n-1}) \times g(d(x_*)) \qquad (5)$$

where $\mathbf{H}(x_{n-1})$ and $\mathbf{J}(x_{n-1})$ are, respectively, the Hessian and Jacobian matrices of the function g evaluated at (x_{n-1}). The succession of x_n converges to x_* for all images in the training set.

The SDM is free from the problems of the GFT-based tracking approach for the following reasons:

i. Low texture in the tracking window: The 49 facial landmarks of SDM are taken from face patches around eye, lip, and nose edges and corners (as shown in Figure 5-1(b)), which have high spatial frequency due to the existence of edges and corners as discussed in [18].
ii. Losing track in a long video sequence: The SDM does not use any reference points in tracking. Instead, it detects each point around the edges and corners in the facial region of each video frame by using supervised descent directions and bias terms as shown in (3), (4) and (5). Thus, the problems of point drifting or dropping a point too early do not occur.
iii. Window size: The SDM does not define the facial landmarks by using the window based 'neighborhood sense' and, thus, does not use any window-based point tracking system. Instead, the SDM utilizes the 'neighborhood sense' on a pixel-by-pixel basis along with the descent detections and bias terms.
iv. Large optical flow vectors in consecutive video frames: As mentioned in [13], occlusion can occur by large optical flow vectors in consecutive video frames. As a video with human motion satisfies temporal stability constraint [21], increasing the search space can be a solution. SDM uses supervised descent direction and bias terms that allow searching selectively in a wider space with high computational efficiency.

Though GFT-based method fails to preserve enough information to measure the HR when the video has facial expression change or head motion, it uses a larger number of facial feature points (e.g., more than 150) to track than SDM (only 49 points). This matter causes the GFT-based method to generate a better trajectory than SDM when there is no voluntary motion. On the other hand, SDM does not miss or erroneously track the landmarks in the presence of voluntary facial motions. In order to exploit the advantages of the both methods, a combination of GFT- and SDM-based tracking outcome can be used, which is explained in the methodology section. Thus, merely using GFT or SDM to extract facial points in cases where subjects may have both voluntary motion and non-motion periods does not produce competent results.

5.4. THE PROPOSED METHOD

A block diagram of the proposed method is shown in Figure 5-2. The steps are explained below.

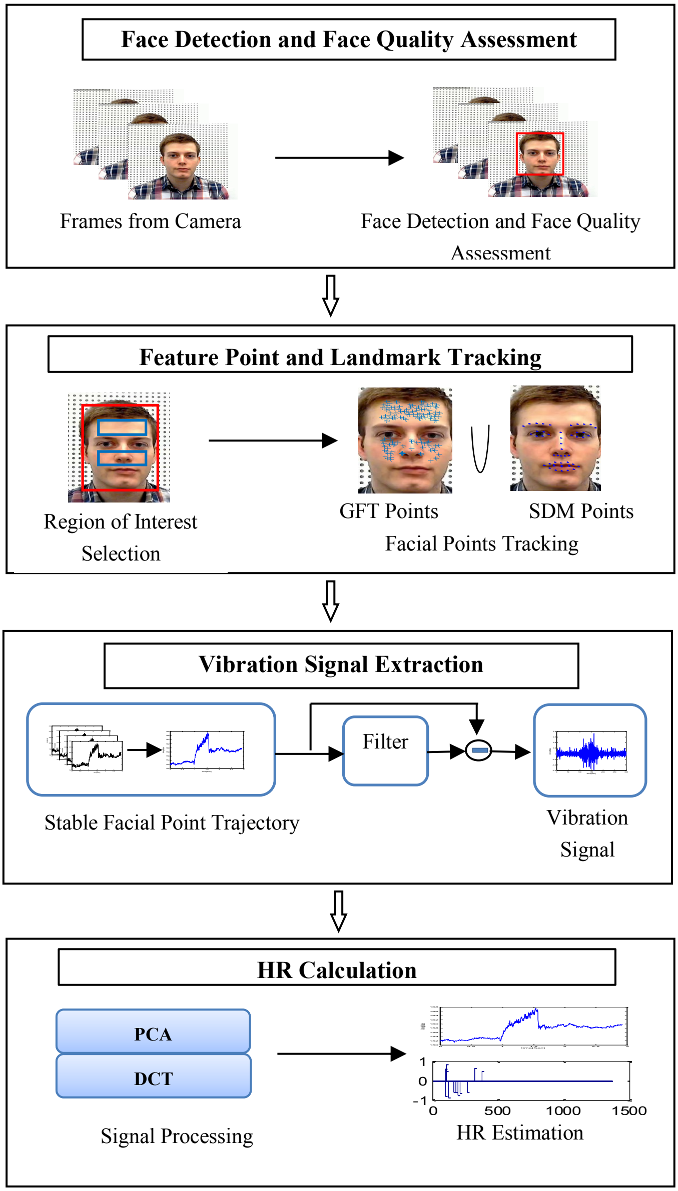


Figure 5-2 The block diagram of the proposed system. We acquire the facial video, track the intended facial points, extract the vibration signal associated with heartbeat, and estimate the HR.

5.4.1. FACE DETECTION AND FACE QUALITY ASSESSMENT

The first step of the proposed motion-based system is face detection from facial video acquired by a webcam. We employed the Haar-like features of Viola and Jones to extract the facial region from the video frames [22]. However, facial videos captured in real-life scenarios can exhibit low face quality due to the problems of pose variation, varying levels of brightness, and motion blur. A low quality face produces erroneous results in facial feature points or landmarks tracking. To solve this problem, a FQA module is employed by following [16], [23]. The module calculates four scores for four quality metrics: resolution, brightness, sharpness, and out-of-plan face rotation (pose). The quality scores are compared with thresholds (following [23], with values 150x150, 0.80, 0.8, and 0.20, for resolution, brightness, sharpness, and pose, respectively) to check whether the face needs to be discarded. If a face is discarded, we concatenate the trajectory segments to remove discontinuity by following [5]. As we measure the average HR over a long video sequence (e.g. 30 secs to 60 secs) discarding few frames (e.g., less than 5% of the total frames) does not greatly affect the regular characteristic of the trajectories but removes the most erroneous segments coming from low quality faces.

5.4.2. FEATURE POINTS AND LANDMARKS TRACKING

Tracking facial feature points and generating trajectory keep record of head motion in facial video due to heartbeat. Our objective with trajectory extraction and signal processing is to find the cyclic trajectories of tracked points by removing the non-cyclic components from the trajectories. Since GFT-based tracking has some limitations, as we discussed in the previous section, having voluntary head motion and facial expression change in a video produces one of two problems: i) completely missing the track of feature points and ii) erroneous tracking. We observed more than 80% loss of feature points by the system in such cases. In contrast, the SDM does not miss or erroneously track the landmarks in the presence of voluntary facial motions or expression change as long as the face is qualified by the FQA. Thus, the system can find enough trajectories to measure the HR. However, the GFT uses a large number of facial points to track when compared to SDM, which uses only 49 points. This causes the GFT to preserve more motion information than SDM when there is no voluntary motion. Hence, merely using GFT or SDM to extract facial points in cases where subjects may have both voluntary motion and non-motion periods does not produce competent results. We therefore propose to combine the trajectories of GFT and SDM. In order to generate combined trajectories, the face is passed to the GFT-based tracker to generate trajectories from facial feature points and then appended with the SDM trajectories. Let the trajectories be expressed by location time-series $S_{t,n}(x, y)$, where (x, y) is the location of a tracked point n in the video frame t.

5.4.3. VIBRATION SIGNAL EXTRACTION

The trajectories from the previous step are usually noisy due to, e.g., voluntary head motion, facial expression, and/or vestibular activity. We reduce the effect of such noises by employing filters to the vertical component of the trajectories of each feature point. An 8th order Butterworth band pass filter with cutoff frequency of *[0.75-5.0]* Hz (human HR lies within this range [11]) is used along with a moving average filter defined below:

$$S_n(t) = \frac{1}{w}\sum_{i=-\frac{w}{2}}^{\frac{w}{2}-1} S_n(t+i)\,, where\ \frac{w}{2} < t < T - \frac{w}{2} \qquad (6)$$

where w is the length of the moving average window (length is 300 in our experiment) and T is the total number of frames in the video. These filtered trajectories are then passed to the HR measurement module.

5.4.4. HEARTBEAT RATE (HR) MEASUREMENT

As head motions can originate from different sources and only those caused by blood circulation through the aorta reflect the heartbeat rate, we apply a Principal Component Analysis (PCA) algorithm to the filtered trajectories (S) to separate the sources of head motion. PCA transforms S to a new coordinate system through calculating the orthogonal components P by using a load matrix L as follows:

$$P = S\,.\,L \qquad (7)$$

where L is a $T \times T$ matrix with columns obtained from the eigenvectors of $S^T S$. Among these components, the most periodic one belongs to heartbeat as obtained in [11]. We apply Discrete Cosine Transform (DCT) to all the components (P) to find the most periodic one by following [12]. We then employ Fast Fourier Transform (FFT) on the inverse-DCT of the component and select the first harmonic to obtain the HR.

5.5. EXPERIMENTAL ENVIRONMENTS AND DATASETS

This section describes the experimental environment, evaluates the performance of the proposed system, and compares the performance with the state-of-the-art methods.

5.5.1. EXPERIMENTAL ENVIRONMENT

The proposed method was implemented using a combination of Matlab (SDM) and C++ (GFT with KLT) environments. We used three databases to generate results: a local database for demonstrating the effect of FQA, a local database for HR measurement, and the publicly available MAHNOB-HCI database [24]. For the first database, we collected 6 datasets of 174 videos from 7 subjects to conduct an experiment to report the effectiveness of employing FQA in the proposed system. We put four webcams (Logitech C310) at 1, 2, 3, and 4 meter(s) distances to acquire facial video with four different face resolution of the same subject. The room's lighting condition was changed from bright to dark and vice versa for the brightness experiment. Subjects were requested to have around 60 degrees out-of-plan pose variation for the pose experiment. The second database contained 64 video clips by defining three scenarios to constitute our own experimental database for HR measurement experiment, which consists of about 110,000 video frames of about 3,500 seconds. These datasets were captured in two different setups: a) an experimental setup in a laboratory, and b) a real-life setup in a commercial fitness center. The scenarios were:

i. **Scenario 1 (normal):** Subjects exposed their face in front of the cameras without any facial expression or voluntary head motion (about 60 seconds).

ii. **Scenario 2 (internal head motion):** Subjects made facial expressions (smiling/laughing, talking, and angry) in front of the cameras (about 40 seconds).

iii. **Scenario 3 (external head motion):** Subjects made voluntary head motion in different directions in front of the cameras (about 40 seconds).

The third database was the publicly available MAHNOB-HCI database, which has 491 sessions of videos longer than 30 seconds and to which subjects consent attribute 'YES'. Among these sessions, data for subjects '12' and '26' were missing. We collected the rest of the sessions as a dataset for our experiment, which are hereafter called MAHNOB-HCI_Data. Following [5], we use 30 seconds (frame 306 to 2135) from each video for HR measurement and the corresponding ECG signal for the ground truth. Table 5-1 summarizes all the datasets we used in our experiment.

5.5.2. PERFORMANCE EVALUATION

The proposed method used a combination of the SDM- and GFT-based approaches for trajectory generation from the facial points. Figure 5-3 shows the calculated average trajectories of tracked points in two experimental videos. We included the trajectories obtained from GFT [13], [18] and SDM[16], [17] for facial videos with voluntary head motion. We also included some example video frames depicting face motion. As observed from the figure, the GFT and SDM provide similar trajectories when there is little head motion (video1, Figure 5-3(b, c)). When the voluntary head motion is sizable (beginning of video2, Figure 5-3(e, f)), GFT-based method fails to track the point accurately and thus produces an erroneous trajectory because of large optical flow. However, SDM provides stable trajectory in this case, as it does not suffer from large optical flow. We also observe that the SDM trajectories provide more sensible amplitude than the GFT trajectories, which in turn contributes to clear separation of heartbeat from the noise.

Table 5-1 Dataset names, definitions and sizes

No	Name	Definition	Number of data
1.	Lab_HR_Norm_Data	Video data for HR measurement collected for lab scenario 1.	10
2.	Lab_HR_Expr_Data	Video data for HR measurement collected for lab scenario 2.	9
3.	Lab_HR_Motion_Data	Video data for HR measurement collected for lab scenario 3.	10
4.	FC_HR_Norm_Data	Video data for HR measurement collected for fitness center scenario 1.	9
5.	FC_HR_Expr _Data	Video data for HR measurement collected for fitness center scenario 2.	13
6.	FC_HR_Motion_Data	Video data for HR measurement collected for fitness center scenario 3.	13
7.	MAHNOB-HCI_Data	Video data for HR measurement from [24]	451
8.	Res1, Res2, Res3, Res4	Video data acquired from 1, 2, 3 and 4 meter(s) distances, respectively, for FQA experiment	29x4
9.	Bright_FQA	Video data acquired while lighting changes for FQA experiment	29
10.	Pose_FQA	Video data acquired while pose variation occurs for FQA experiment	29

Unlike [11], the proposed method utilizes a moving average filter before employing PCA on the trajectory obtained from the tracked facial points and landmarks. The effect of this moving average filter is shown in Figure 5-4(a). The moving average filter reduces noise and softens extreme peaks in voluntary head motion and provides a smoother signal to PCA in the HR detection process.

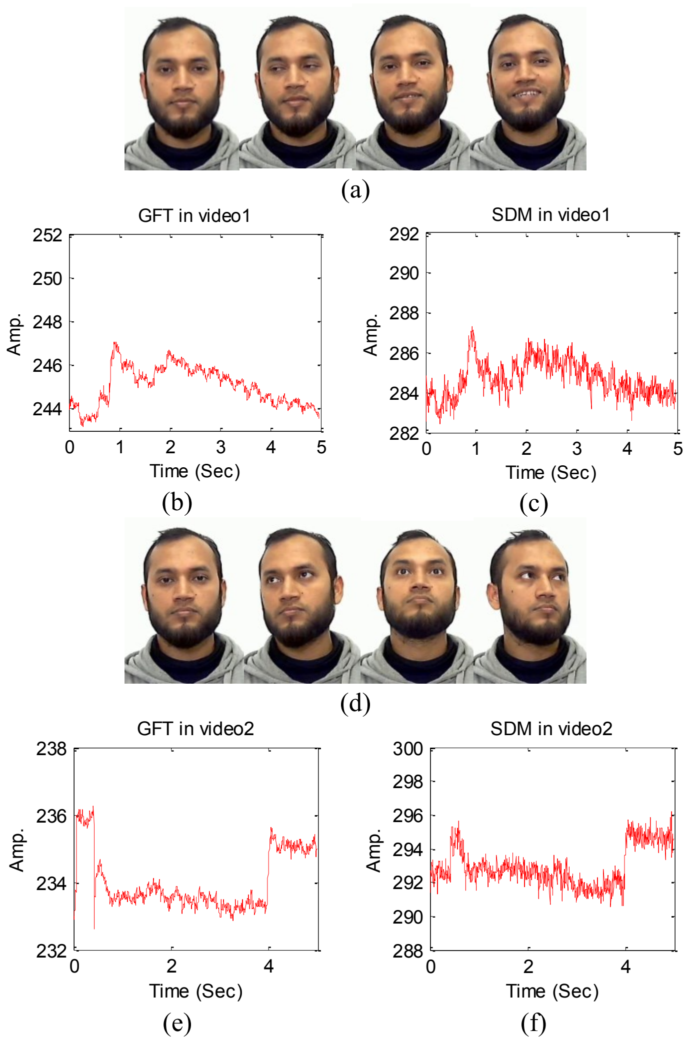
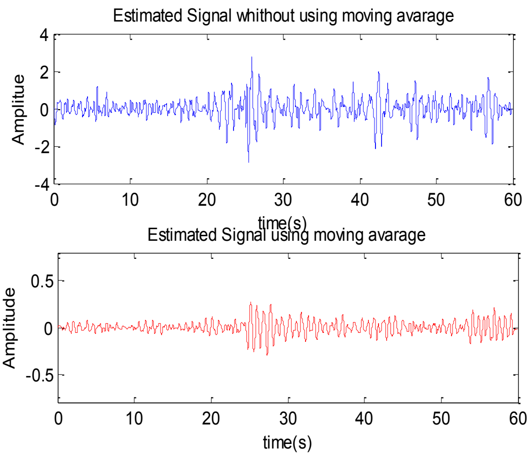
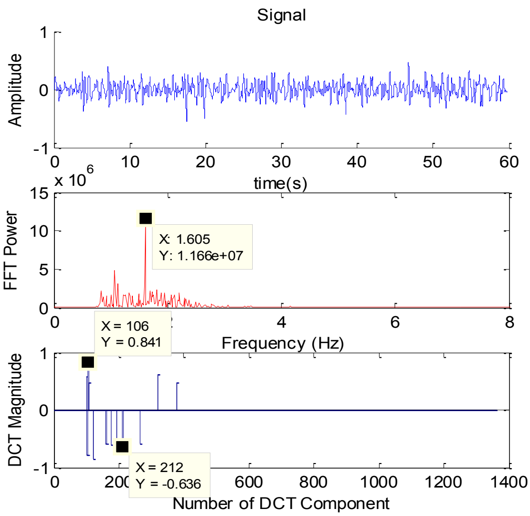


Figure 5-3 Example frames depict small motion (in (a)) and large motion (in (d)) from a video, and trajectories of tracking points extracted by GFT [18] (in (b) and (e)) and SDM [17] (in (c) and (f)) from 5 seconds of two experimental video sequences with small motion (video1) and large motion at the beginning and end (video2).

The proposed method utilizes DCT instead of FFT of [11] in order to calculate the periodicity of the cyclic head motion signal. Figure 5-4(b) shows a trajectory of head motion from an experimental video and its FFT and DCT representations after preprocessing. In the figure we see that the maximum power of FFT is at frequency bin 1.605. This, in turn, gives HR 1.605x60=96.30, whereas the actual HR obtained from ECG was 52.04bpm. Thus, the method in [11] that used FFT in the HR estimation does not always produce good results. On the other hand, using DCT by following [12] yields a result of 52.35bpm from the selected DCT component X=106. This is very close to the actual HR.



(a)



(b)

Figure 5-4 The effect of (a) the moving average filter on the trajectory of facial points to get a smoother signal by noise and extreme peaks reduction and (b) the difference between extracting the periodicity (heartbeat rate) of a cyclic head motion signal by using fast Fourier transform (FFT) power and discrete cosine transform (DCT) magnitude.

Furthermore, we conducted an experiment to demonstrate the effect of employing FQA in the proposed system. The experiment had three sections for three quality metrics: resolution, brightness, and out-of-plan pose. The results of HR measurement on six datasets collected for FQA experiment are shown in Table 5-2. From the results, it is clear that when resolution decreases the accuracy of the system decreases accordingly. Thus, FQA for face resolution is necessary to ensure a good size face in the system. The results also show that the brightness variation and the pose variation have influence on the HR measurement. We observe that when frames of low quality, in terms of brightness and pose, are discarded the accuracy of HR measurement increases.

Table 5-2 Analysing the effect of the FQA in HR measurement

Exp. Name	Dataset	Average percentage (%) of error in HR measurement
Resolution	Res1	10.65
	Res2	11.74
	Res3	18.86
	Res4	37.35
Brightness	Bright_FQA before FQA	18.77
	Bright_FQA after FQA	17.62
Pose variation	Pose_FQA before FQA	17.53
	Pose_FQA after FQA	14.01

5.5.3. PERFORMANCE COMPARISON

We have compared the performance of the proposed method against state-of-the-art methods from [3], [5], [6], [11], [12] on the experimental datasets listed in Table 5-1. Table 5-3 lists the accuracy of HR measurement results of the proposed method in comparison with the motion-based state of the art methods [11], [12] on our local database. We have measured the accuracy in terms of percentage of measurement error. The lower the error generated by a method, the higher the accuracy of that method. From the results we observe that the proposed method showed consistent performance, although the data acquisition scenarios were different for different datasets. By using both GFT and SDM trajectories, the proposed method gets more trajectories to estimate the HR pattern in the case of HR_Norm_Data and accurate trajectories due to non-missing facial points in the cases of HR_Expr_Data and HR_Motion_Data. On the other hand, the previous methods suffer from fewer trajectories and/or erroneous trajectories from the data acquired in challenging scenarios, e.g. Balakrishnan's method showed an up to 25.07% error in HR estimation from videos having facial expression change. The proposed method outperforms the previous methods in both environments (lab and in a fitness center) of data acquisition, including all three scenarios.

Table 5-3 Performance comparison between the proposed method and the state-of-the-art methods of HR measurement on our local databases

Dataset name	**Average percentage (%) of error in HR measurement**		
	Balakrishnan et al. [11]	**Irani et al. [12]**	**The proposed method**
Lab_HR_Norm_Data	7.76	7.68	2.80
Lab_HR_Expr_Data	13.86	9.00	4.98
Lab_HR_Motion_Data	16.84	5.59	3.61
FC_HR_Norm_Data	8.07	10.75	5.11
FC_HR_Expr_Data	25.07	10.16	6.23
FC_HR_Motion_Data	23.90	15.16	7.01

Table 5-4 Performance comparison between the proposed method and the state-of-the-art methods of HR measurement on MAHNOB-HCI database

Method	**RMSE (bpm)**	**Mean error rate (%)**
Poh et al. [3]	*25.90*	*25.00*
Kwon et al. [7]	*25.10*	*23.60*
Balakrishnan et al. [11]	*21.00*	*20.07*
Poh et al. [6]	*13.60*	*13.20*
Li et al. [5]	*7.62*	*6.87*
Irani et al. [12]	*5.03*	*6.61*
The proposed method	*3.85*	*4.65*

Table 5-4 shows the performance comparison of HR measurement by our proposed method and state-of-the-art methods (both color-based and motion-based) on MAHNOB-HCI_Data. We calculate the Root Mean Square Error (RMSE) in beat-per-minute (bpm) and mean error rate in percentage to compare the results. From the results we can observe that Li's [5], Irani's [12], and the proposed method showed considerably higher results than the other methods because they take into consideration the presence of voluntary head motion in the video. However, unlike Li's color-based method, Irani's method and the proposed method are motion-based. Thus, changing the illumination condition in MAHNOB-HCI_Data does not greatly affect the motion-based methods, as indicated by the results. Finally, we observe that the proposed method outperforms all these state-of-the-art methods in the accuracy of HR measurement.

5.6. CONCLUSIONS

This chapter proposes a system for measuring HR from facial videos acquired in more realistic scenarios than the scenarios of previous systems. The previous methods work well only when there is neither voluntary motion of the face nor change of expression and when the lighting conditions help keeping sufficient texture in the forehead and cheek. The proposed method overcomes these problems by using an alternative facial landmarks tracking system (the SDM-based system) along with the previous feature points tracking system (the GFT-based system) and provides competent results. The performance of the proposed system for HR measurement is highly accurate and reliable not only in a laboratory setting with no-motion, no-expression cases in artificial light in the face, as considered in [11], [12], but also in challenging real-life environments. However, the proposed system is not adapted yet to the real-time application for HR measurement due to dependency on temporal stability of the facial point trajectory.

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CHAPTER 6. FACIAL VIDEO BASED DETECTION OF PHYSICAL FATIGUE FOR MAXIMAL MUSCLE ACTIVITY

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6.1. ABSTRACT

Physical fatigue reveals the health condition of a person at for example health check-up, fitness assessment or rehabilitation training. This chapter presents an efficient noncontact system for detecting non-localized physical fatigue from maximal muscle activity using facial videos acquired in a realistic environment with natural lighting where subjects were allowed to voluntarily move their head, change their facial expression, and vary their pose. The proposed method utilizes a facial feature point tracking method by combining a 'Good feature to track' and a 'Supervised descent method' to address the challenges originates from realistic scenario. A face quality assessment system was also incorporated in the proposed system to reduce erroneous results by discarding low quality faces that occurred in a video sequence due to problems in realistic lighting, head motion and pose variation. Experimental results show that the proposed system outperforms video based existing system for physical fatigue detection.

6.2. INTRODUCTION

Fatigue is an important physiological parameter that usually describes the overall feeling of tiredness or weakness in human body. Fatigue may be either mental or physical or both [1]. Mental fatigue is a state of cortical deactivation due to prolonged periods of cognitive activity that reduces mental performance. On the other hand, physical fatigue refers to the declination of the ability of muscles to generate force. Stress, for example, makes people mentally exhausted, while hard work or extended physical exercise can exhaust people physically. Though mental fatigue is related to cognitive activity, it can occur during a physical activity that comprises neurological phenomenon, for example directed attention as found in the area of intelligent transportation systems [2]. Unlike mental fatigue that is related to cognitive performance, physical fatigue specifically refers to muscles' inability to force optimally due to inadequate rest during a muscle activity [1]. Physical fatigue occurs from two types of activities: submaximal muscle activity (e.g. using a cycle ergometer or motor driven treadmill) and maximal muscle activity (e.g. pressing a dynamometer or lifting a load with great force) [3]. This kind of fatigue is a significant physiological parameter, especially for athletes or therapists. For example, by monitoring the occurrence of a patient's fatigue during physical exercise in rehabilitation scenarios, a therapist can change the exercise, make it easier or even stop it if necessary. Estimating the fatigue time offsets can also provide information in posterity health analysis [1].

A number of video-based non-invasive methods for fatigue detection and quantification have been proposed in the literature. The methods utilized some features and clues, as shown in Figure 6-1(a), automatically extracted from a subject's facial video and discriminate between fatigue and non-fatigue classes automatically. For example, the works in [4] use eye blink rate and duration of eye closure for detection of fatigue occurrence due to sleep deprivation or directed attention. In addition to these features head pose and yawning behavior in facial video is used in [5]. A review of facial video based fatigue detection methods can be found in [2]. However, all of these methods address the detection of mental fatigue occurred from prolonged directed attention activity or sleep deprivation, more specifically known as driver fatigue, instead of physical fatigue occurred from maximal or sub-maximal muscle activity, as shown in Figure 6-1(b, c). Most of the available technologies for detecting physical fatigue occurrence (in terms of fatigue time offsets and/or fatigue level) use contact-based sensors such as force gauge, Electromyogram (EMG), and Mechanomyogram (MMG). Force gauge is minimally invasive, but it requires a device like a hand grip dynamometer [6]. EMG uses electrodes which requires wearing adhesive gel patches [7]. MMG is based on an accelerometer or goniometer that requires direct skin contact and is sensitive to noise [8].

(a) Driver's mental fatigue experiment (image taken from [5])

(b) Physical fatigue experiment using dumbbell

(c) Physical fatigue experiment using hand dynamometer

Figure 6-1 Analyzing facial video for different fatigue scenarios.

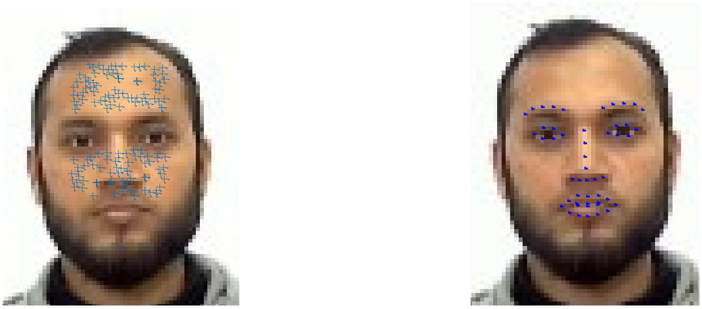
To the best of our knowledge, the only video-based non-invasive system for non-localized (i.e., not restricted to a particular muscle) physical fatigue detection in a maximal muscle activity scenario (as shown in Figure 6-1(c)) is the one introduced in [9] which uses head-motion (shaking) behavior due to fatigue in video captured by a simple webcam. It takes into account the fact that muscles start shaking when fatiguing contraction occurs in order to send extra sensation signal to the brain to get enough force in a muscle activity and this shaking is reflected in the face. Inspired by [10] for heartbeat detection from Ballistocardiogram, in [9] some feature points on the ROI (forehead and cheek) of the subject's face in a video are selected and tracked to generate trajectories of the facial feature points, and to calculate the energy of the vibration signal, which is used for measuring the onset and offset of fatigue occurrence in a non-localized notion. Though both physical fatigue and mental fatigue can occur simultaneously during a physical activity, the physiological mechanisms are not same. While mental fatigue represents the temporary reduction of cognitive performance, physical fatigue represent temporary reduction of force induced in muscle to accomplish a physical activity [2]. Unlike driver mental fatigue, physical fatigue for maximal muscle activity does not necessarily require a prolonged period. Thus, the visual clues found in the case of driver fatigue cannot be found in the case of physical fatigue from maximal muscle contraction. Changes in facial features in these two different types of fatigue are very different: in the driver mental fatigue eye blinking, yawning, varying head pose and degree of mouth openness are used (as shown in Figure 6-1(a)), while in the non-localized maximal muscle contraction based physical fatigue *head motion behavior from shaking* is used. Consequently, physical fatigue occurred from maximal muscle activity cannot be detected or quantized by the computer vision methods used for detecting driver mental fatigue.

The previous facial video based method in [9] for non-localized physical fatigue detection extracts some facial feature points as shown in Figure 6-2(a). Depending upon imaging scenario, the number of feature points and their position can vary. The method then employs signal processing techniques to detect head motion trajectories from feature points in the video frames and estimates energy escalation to detect fatiguing contraction. However, the work in [9] assumes that there is neither internal facial motion, nor external movement or rotation of the head during the data acquisition phase. We denote internal motion as facial expression and external motion as head pose. In real life scenarios there are, of course, both internal and external head motion. The current method, therefore, fails due to an inability to detect and track the feature points in the presence of internal and external motion, and low texture in the facial region. Moreover, real-life scenarios challenge current methods due to low facial quality in video because of motion blur, bad posing, and poor lighting conditions [11]. The proposed system in this chapter extends [9] by addressing the abovementioned shortcomings and thereby allows for automatic and more reliable detection of fatigue time offsets from facial video captured by a simple webcam. To address the shortcomings, we introduce a Face Quality Assessment (FQA) method that prunes the captured video data so that low quality face frames cannot contribute to erroneous results [12], [13]. Following [10], [14], we track feature points (Figure 6-2(a)) through a method Good Feature to Track (GFT) with Kanady-Lucas-Tomasi (KLT) tracker, and then combine these trajectories with 49 facial landmark trajectories (Figure 6-2(b)), tracked by a Supervised Descent Method (SDM) of [15], [16]. The idea of combining these two types of features has been developed in our paper [17], which was applied to heartbeat estimation from facial video. Here we look at another application of this idea for physical fatigue estimation. The experiments are conducted on realistic datasets collected at the lab and a commercial fitness center for fatigue measurement. The chapter's contributions are as follows:

- We identify the limitations of the GFT-based tracking used in previous methods for physical fatigue detection and propose a solution using SDM-based tracking.

- We provide evidence for the necessity of combining the trajectories from the GFT and the SDM, instead of using the trajectories from either the GFT or the SDM.
- We introduce the notion of FQA in the physical fatigue detection context and demonstrate empirical evidence for its effectiveness.

The rest of the chapter is organized as follows. Section three describes the proposed method. The results are summarized in section four. Finally, section five concludes the chapter.



(a) (b)

Figure 6-2 (a) Facial feature points (total numbers can vary) in a face obtained by GFT-based tracking [9], (b) 49 facial landmarks in a face obtained by SDM-based tracking [15].

6.3. THE PROPOSED METHOD

The block diagram of the proposed method is shown in Figure 6-3. The steps are explained in the following subsections.

6.3.1. FACE DETECTION AND FACE QUALITY ASSESSMENT

The first step of the proposed motion-based physical fatigue detection system is face detection from facial video, which has been accomplished by Viola and Jones object detection framework using Haar-like features obtained from integral images [18].

Facial videos captured in real-life scenarios can be subject to the problems of pose variation, varying levels of brightness, and motion blur. When the intensity of these problems increases, the face quality decreases. A low quality face produces erroneous results in detecting facial features using either GFT or SDM [11]. To solve this problem, we pass the detected face to a FQA module. The FQA module assesses the quality of the face in the video frames. As investigated in [17], [19], four quality metrics can be critical for facial geometry analysis and detection of landmarks: resolution, brightness, sharpness, and out-of-plan face rotation (pose). Thus, the low quality faces can be discarded by calculating these quality metrics and employing thresholds to check whether the face needs to be discarded. The formulae to obtain these quality scores from a face are listed in [11]. Resolution score is calculated in terms of number of pixels, pose score is calculated by detecting the center of mass in the binary image of the face region, sharpness is calculated by employing a low-pass filter to detect motion blur or unfocused capture, and brightness is calculated from the average of the illumination component of all the pixels in the face region. When we obtain the quality scores, following [17], we discard the low quality faces by the thresholds as follows: face resolution- 150x150, brightness- 0.80, sharpness- 0.80, and pose- 0.20 by following [11]. As we detect the fatigue time offsets over a long video sequence (e.g. 30 secs to 180 secs) for maximum muscle activity, discarding few frames (e.g. less than 5% of the total frames) does not affect much the regular characteristic of the trajectories, but removes the most erroneous segments coming from low quality faces. In fact, no frames are discarded if the quality score is not less than the thresholds. Missing points in the trajectory are removed by concatenating trajectory segments. The effect of employing FQA will be illustrated in the experimental evaluation section.

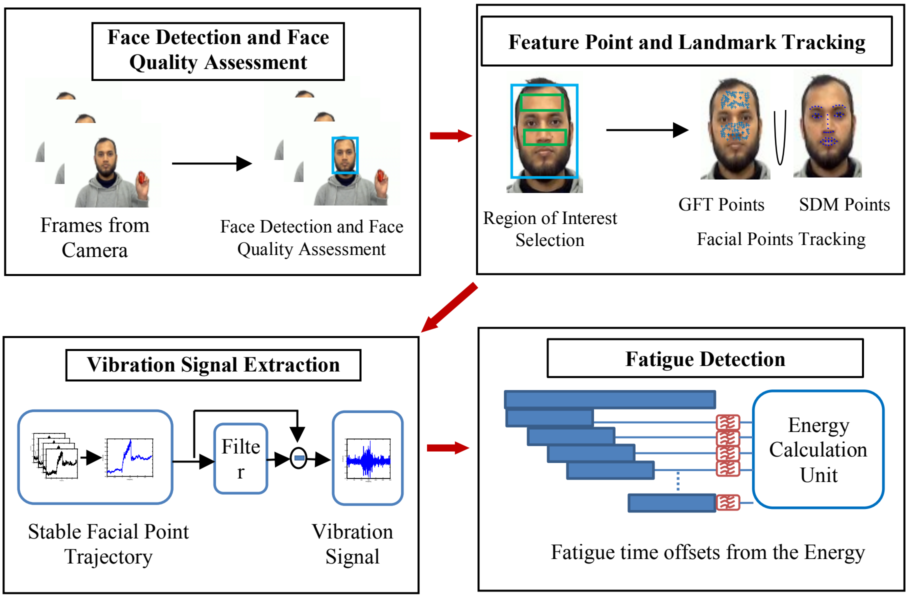


Figure 6-3 The block diagram of the proposed system.

6.3.2. FEATURE POINTS AND LANDMARKS TRACKING

As mentioned earlier, muscles start shaking when a subject becomes tired physically (the occurrence of physical fatigue from maximal muscle activity) [20]. The energy dispersed from this shaking is distinctively intense then the other types of head motion and is reflected in the face. Thus, physical fatigue can be determined from head motion by estimating the released shaking energy. Tracking facial feature points and generating trajectory help to record the head motion in facial video. This task was accomplished in [9] using merely a GFT-based method (utilizes KLT tracker). In order to detect and track facial feature points in consecutive video frames, the GFT-based method uses an affine motion model to express changes in the intensity level in the face. It defines the similarity between two points in two frames using a so called 'neighborhood sense' or window of pixels. Tracking a window of size $w_x \times w_y$ in the frame I to the frame J is defined on a point velocity parameter $\boldsymbol{\delta} = [\delta_x \; \delta_y]^T$ for minimizing a residual function f_{GFT} as follows:

$$f_{GFT}(\boldsymbol{\delta}) = \sum_{x=p_x}^{p_x+w_x} \sum_{y=p_y}^{p_y+w_y} \big(I(\mathbf{x}) - J(\mathbf{x}+\boldsymbol{\delta})\big)^2 \qquad (1)$$

where $(I(\mathbf{x}) - J(\mathbf{x}+\boldsymbol{\delta}))$ stands for $(I(x,y) - J(x+\delta_x, y+\delta_y))$, and $\mathbf{p} = [p_x, p_y]^T$ is a point to track from the first frame to the second frame. According to the observations in [14], the quality of the estimate by this tracker depends on three factors: the size of the window, the texture of the image frame, and the amount of motion between frames. The GFT-based fatigue detection method assumes that the head does not have voluntary head motion during data capture. However, voluntary head motion (both external and internal) and low-texture in facial videos are usual in real life scenarios. Thus, the GFT-based tracking of facial feature points exhibits four problems. **First problem** arises due to low texture in the tracking window. This difficulty can be overcome by tracking feature points in corners or regions with high spatial frequency content, instead of forehead and cheek. **Second problem** arises by losing track in long video sequences due to point drifting in long video sequences. **Third problem** occurs in selecting an appropriate window size (i.e. $w_x \times w_y$ in (1)). If the window size is small, a deformation matrix to find the track is harder to estimate because the variations of motion within it are smaller and therefore less reliable. On the other hand, a bigger window is more likely to straddle a depth discontinuity in subsequent frames. **Fourth problem** comes when there is large optical flow in consecutive video frames. When there is voluntary motion or expression change in a face, the optical flow or face velocity in consecutive video frames is very high and GFT-based method misses the track due to occlusion [21]. Higher video frame rate may able to address this problem, however this will require specialized camera instead of simple webcam. Due to these four problems, the GFT-based trajectory for fatigue detection leads to erroneous result in realistic scenarios where lighting changes and voluntary head motions exist.

A viable way to enable the GFT-based systems to detect physical fatigue in a realistic scenario is to track the facial landmarks by employing a face alignment system. Face alignment is considered as a mathematical optimization problem and a number of methods have been proposed to solve this problem. The Active Appearance Model (AAM) fitting [22] and its derivatives [23] were some of the early solutions in this area. The AAM fitting works by estimating parameters of an artificial model that is sufficiently close to the given image. In order to do that AAM fitting was formulated as a Lukas-Kanade (LK) problem [24], which could be solved using Gauss-Newton optimization [25]. A fast and effective solution to this was proposed recently in [15], which develops a Supervised Descent Method (SDM) to minimize a non-linear least square function for face alignment. The SDM first uses a set of manually aligned faces as training samples to learn a mean face shape. This mean shape is then used as an initial point for an iterative minimization of a non-linear least square function towards the best estimates of the positions of the landmarks in facial test images. The minimization function can be defined as a function over Δx as:

$$f_{SDM}(x_0 + \Delta x) = \left\| g\big(d(x_0 + \Delta x)\big) - \theta_* \right\|_2^2 \qquad (2)$$

where x_0 is the initial configuration of the landmarks in a facial image, $d(x)$ indexes the landmarks configuration (x) in the image, g is a nonlinear feature extractor, $\theta_* = g(d(x_*))$, and x_* is the configuration of the true landmarks. The Scale Invariant Feature Transform (SIFT) [11] is used as the feature extractor g. In the training images Δx and θ_* are known. By utilizing these known parameters the SDM iteratively learns a sequence of generic descent directions, $\{\partial_n\}$, and a sequence of bias terms, $\{\beta_n\}$, to set the direction towards the true landmarks configuration x_* in the minimization process, which are further applied in the alignment of unlabelled faces [15]. This working procedure of SDM in turns addresses the four previously mentioned problems of the GFT-based approach for head motion trajectory extraction by as follows. **First**, the 49 facial landmark point tracked by SDM are taken only around eye, lip, and nose edges and corners, as shown in Figure 6-2(b). As these landmarks around the face patches have high spatial frequency and do not suffer from low texturedness, this eventually solves the problem of low texturedness. We cannot simply add these landmarks in the GFT based tracking, because the GFT based method has its own feature point selector. **Second**, SDM does not use any reference points in tracking. Instead, it detects each point around the edges and corners in the facial region of each video frame by using supervised descent directions and bias terms. Thus, the problems of point drifting do not occur in long videos. **Third**, SDM utilizes the 'neighborhood sense' on a pixel-by-pixel basis instead of a window. Therefore, window size is not relevant to SDM. **Fourth**, the use of supervised descent direction and bias terms allows the SDM to search selectively in a wider space and look after it from large optical flow problem. Thus, large optical flow cannot create occlusion in the SDM-based approach.

As in realistic scenarios the subjects are allowed to have voluntary head motion and facial expression change in addition to the natural cyclic motion, the GFT-based method results to either of the two consequences for videos having challenging scenarios: i) completely missing the track of feature points and ii) erroneous tracking. We observed more than 80% loss of feature points by the system in such cases. The GFT-based method, in fact, fails to preserve enough information to estimate fatigue from trajectories even though the video have minor expression change or head motion voluntarily. On the other hand, the SDM does not miss or erroneously track the landmarks in the presence of voluntary facial motions or expression change or low texturedness as long as the face is qualified by the FQA. Thus, the system can find enough trajectories to detect fatigue. However, the GFT-based method uses a large number of facial points to track when compared to SDM. This matter causes the GFT-based method to generate a better trajectory than SDM when there is no voluntary motion or low texturedness. Following the above discussions Table 6-1 summarizes the behavior of GFT, SDM and a combination of these two methods in facial point tracking. We observe that a combination of trajectories obtained by GFT and SDM-based methods can produce better results in cases where subjects may have both motion and non-motion periods. We thus propose to combine the trajectories. In order to generate combined trajectories, the face is passed to the GFT-based tracker to generate trajectories from facial feature points and then appended with the SDM trajectories.

6.3.3. VIBRATION SIGNAL EXTRACTION

To obtain vibration signal for fatigue detection, we take the average of all the trajectories obtained from both feature and landmark points of a video by as follows:

$$T(n) = \frac{1}{M}\sum_{m=1}^{M}(y_m(n) - \bar{y}_m) \tag{3}$$

where $T(n)$ is the shifted mean filtered trajectory, $y_m(n)$ is the n-th frame of the trajectory m, M is the number of the trajectories, N is the number of the frames in each trajectory, and $\bar{y}_m$ is the mean value of the trajectory m given by:

$$\bar{y}_m = \frac{1}{N}\sum_{n=1}^{N} y_m(n) \tag{4}$$

The vibration signal that keeps the shaking information is calculated from T by using a window of size R by:

$$V_s(n) = T(n) - \frac{1}{R}\sum_{r=0}^{R-1} T(n-r) \tag{5}$$

The obtained signal is then passed to the fatigue detection block.

Table 6-1 Behaviour of the GFT, SDM and a combination of both methods for facial points tracking in different scenarios

Scenario	Challenge	GFT	SDM	Combination
Low texture in video	Number of facial points available to effectively generating motion trajectory	*Bad*	*Good*	*Better*
Long video sequence	Facial point drifting during tracking	*Bad*	*Good*	*Better*
Appearance of voluntary head motion in video	Optical occlusion and depth discontinuity of window based tracking	*Bad*	*Good*	*Better*
Perfect scenario	None of the aforementioned challenges	*Good*	*Good*	*Better*

6.3.4. PHYSICAL FATIGUE DETECTION

To detect the released energy of the muscles reflected in head shaking we need to segment the vibration signal V_s from (5) with an interval of Δt_{sec}. Segmenting the signal V_s helps detecting the fatigue in temporal dimension. After windowing, each block is filtered by a passband ideal filter. Figure 6-4(a) shows the power of the filtered vibrating signal with a cut-off frequency interval of *[3-5]* Hz. The cutoff frequency was determined empirically in [9]. We observe that the power of the signal rises when fatigue happens in the interval of *[16.3–40.6] seconds* in this figure. After filtering, the energy of i-th block is calculated as:

$$E_i = \sum_{j=1}^{M} \left|Y_{ij}\right|^2 \tag{6}$$

where E_i is the calculated energy of the i-th block, Y_{ij} is the FFT of the signal V_s, and M is the length of Y. Finally, fatigue occurrence is detected by:

$$F_i = k \frac{E_i}{\frac{1}{N}\sum_{j=1}^{N} E_j} \tanh\left(\gamma\left(\frac{E_i}{\frac{1}{N}\sum_{j=1}^{N} E_j} - 1\right)\right) \tag{7}$$

where F_i is the fatigue index, N is the number of the initial blocks in the normal case (before starting the fatigue), K is the amplitude factor, and γ is a slope factor. Experimentally, we obtained reasonable results with k = 10 and γ = 0.01. As observed in [9], employing a bipolar sigmoid (tangent hyperbolic) function to E_i in (7) suppresses the noise peaks out of fatigue region that appear in the results because of the facial expression and/or the voluntary motion. Figure 6-4(b, c) illustrates the effect of the sigmoid function on the output results and Figure 6-4(d, e) depicts the effect in values. To realize the effect of such noise suppression in percentage, by following [26] we use the following metric:

$$SUP_i = \frac{F_i}{F_{max}} \times 100\% \tag{8}$$

where SUP_i is the ratio of the noise to the released fatigue energy. If we employ (8) on Figure 6-4(d, e), we obtain values 8.94%, 11.65% and 0.77%, 1.38%, respectively, for the noise datatips shown in the figures. It can be noticed that before employing the suppression the noise to fatigue energy were ~10%, however reduced to ~1% after employing the suppression. When we obtain the fatigue index, the starting and ending time of fatigue occurrence in a subject's video are detected by employing a threshold with value: 1.0 to the normalized fatigue index, as the bipolar sigmoid suppresses the signal energy out of fatigue region to less than 1.0 by (7). Fatigue starts when the fatigue index exceeds the threshold upward and fatigue ends when fatigue index exceeds the threshold downward.

6.4. EXPERIMENTAL RESULTS

6.4.1. EXPERIMENTAL ENVIRONMENT

The proposed method was implemented using a combination of Matlab (2013a) and C++ environments. We integrated the SDM [15] with the GFT-based tracker from [9], [11] to develop the system as explained in the methodology section. We collected four experimental video databases to generate results: a database for demonstrating the effect of FQA, a database with voluntary motions in some moments for evaluating the performance of GFT, SDM and the combination of GFT and SDM, a database collected from the subjects in a natural laboratory environment, and a database collected from the subjects at a real-life environment in a commercial fitness center. We named the databases as "FQA_Fatigue_Data", "Eval_Fatigue_Data" "Lab_Fatigue_Data" and "FC_Fatigue_Data" respectively. All the video clips were captured in VGA resolution using a Logitech C310 webcam. The videos were collected from 16 subjects (including both male and female from different ethnicities with the ages between 25 to 40 years) after adequately informing the subjects about the concepts of maximal muscle fatigue and the experimental scenarios. Subjects exposed their face in front of the cameras while performing maximal muscle activity by using a handgrip dynamometer for about 30-180 seconds (varies from subject to subject). Subjects were free to have natural head motion and expression variation due to activity prompted by using the dynamometer. Both setups (in the laboratory and in the fitness center) used indoor lighting for video capturing and the dynamometer reading to measure ground truth for fatigue. The FQA_Fatigue_Data has 12 videos, each of which contains some low quality face in some moments. The Eval_Fatigue_Data has 17 videos with voluntary motion, Lab_Fatigue_Data has 54 videos and the FC_Fatigue_Data has 11 videos in natural scenario.

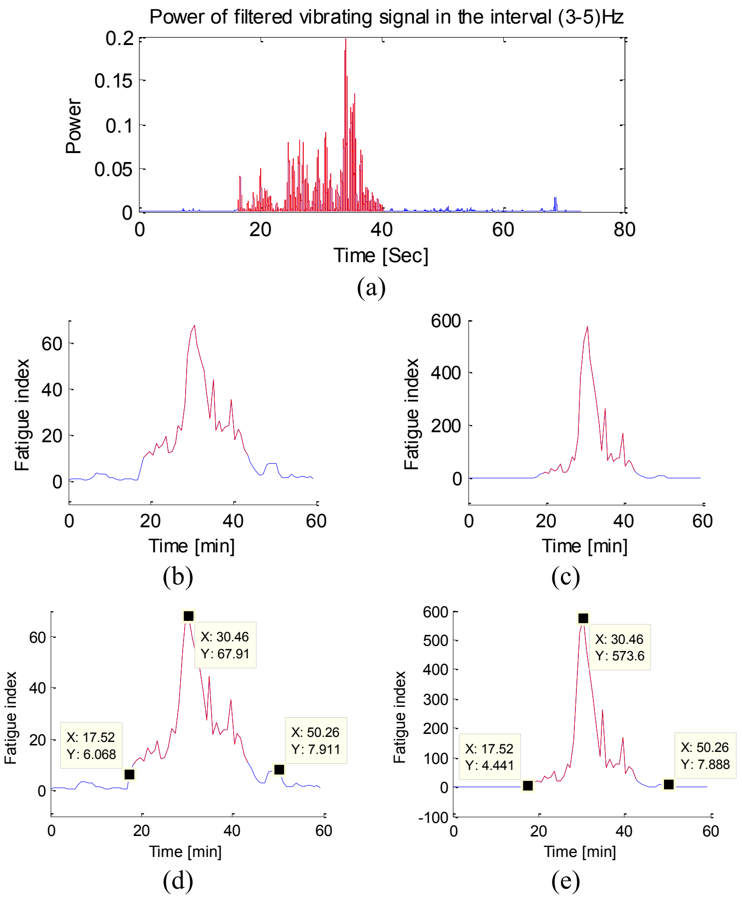


Figure 6-4 Analyzing trajectory for fatigue detection: (a) The power of the trajectory where the blue region is the resting time and the red region shows the fatigue due to exercise in the interval (16.3–40.6) seconds, (b) and (c) before and after using a bipolar sigmoid function to suppress the noise peaks, respectively, and (d) and (e) depicts the effect of bipolar sigmoid in values corresponding to (b) and (c), respectively.

As physical fatigue in a video clip occurs between a starting time and an ending time, the starting and ending times detected from the video by the experimental methods should match with the starting and ending times of fatigue obtained from the ground truth dynamometer data. Thus, we analyzed and measured the error between the ground truth and the output of the experimental methods for starting and ending time agreement by defining a parameter μ. This parameter expresses the average of the total of starting and ending point distances of fatigue occurrence for each subject in the datasets, and is calculated as follows:

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\left(\left|G_S^i - R_S^i\right| + \left|G_E^i - R_E^i\right|\right) \quad (9)$$

where, n is the number of video (subjects) in a dataset, G_S^i is the ground truth of the starting point of fatigue, G_E^i is the ground truth of the ending point of fatigue, R_S^i is the calculated starting point of fatigue, and R_E^i is the calculated ending point of fatigue.

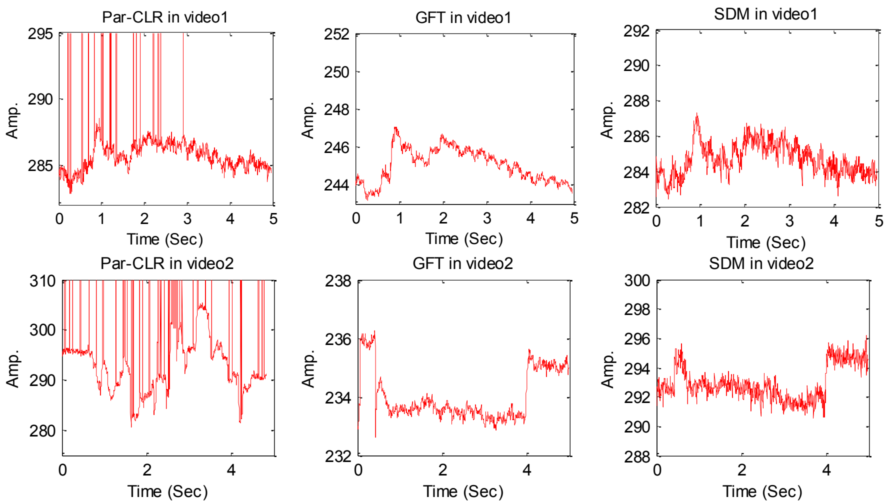


Figure 6-5 Trajectories of tracking points extracted by Par-CLR [27], GFT [14], and SDM [15] from 5 seconds of two experimental video sequences with continuous small motion (for video1 in the first row) and large motion at the beginning and end (for video2 in the second row).

6.4.2. PERFORMANCE EVALUATION

The proposed method used a combination of the SDM- and GFT-based approaches for trajectory generation from the facial points. Figure 6-5 shows the calculated average trajectories of tracked points in two experimental videos. We depicted the trajectories obtained from GFT-based tracker, SDM and another recent face alignment algorithm Par-CLR [27] for two facial videos with voluntary head motion. As observed from the figure, the GFT and SDM-based trackers provide similar trajectories when there is little head motion (video1, first row of Figure 6-5). On the other hand, Par-CLR provides a trajectory very different than the other two because of tracking on false positive face in the video frames. When the voluntary head motion is sizable (beginning of video2, second row of Figure 6-5), GFT-based method fails to track the point accurately and thus produces an erroneous trajectory. However, SDM provides stable trajectory in this case. Thus, lack in proper selection of method(s) for trajectory generation can contribute to erroneous results in estimating fatigue time offsets, as we observe for the GFT-based tracker and the recently proposed Par-CLR in comparison to SDM.

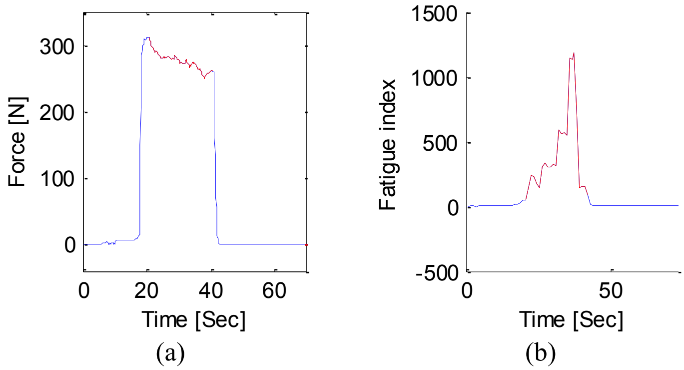


Figure 6-6 Detection of physical fatigue due to maximal muscle activity: a) dynamometer reading during fatigue event, and b) fatigue time spectral map for fatigue time offset measurement. The blue region is the resting time and the red region shows the fatigue due to exercise.

For the fatigue time offset measurement experiment we asked the test subjects to squeeze the handgrip dynamometer as much as they could. As they did this we recorded their face. The squeezed dynamometer provides a pressure force, which is used as the ground truth data in fatigue detection. Figure 6-6(a) displays the data recorded while using the dynamometer, where the part of the graph with a falling force indicates the fatigue region. The measured fatigue level from the dynamometer reading is shown in Figure 6-6(b). Fatigue in this figure happens when the fatigue level sharply goes beyond a threshold defined in [9]. Comparative experimental results for fatigue detection using different methods are shown in the next section.

We conducted experiments to evaluate the effect of employing FQA, and a combination of GFT and SDM in the proposed system. Figure 6-7 shows the effect of employing FQA on a trajectory obtained from a subject's video. It is observed that low quality face region (due to pose variation) shows erroneous trajectory and contributed to the wrong detection of fatigue onset (Figure 6-7(a)). When, FQA module discarded this region, the actual fatigue region was detected as shown in Figure 6-7(b). Table 6-2 shows the results of employing FQA on the FQA_Fatigue_Data, and evaluating the performance of GFT, SDM and the combination of these two on the Eval_Fatigue_Data. From the results it is observed that when videos have low quality faces (which are true for all the videos of the FQA_Fatigue_Data), automatic detection of fatigue time stumps exhibited very high error due to wrong place of detection. When we employed FQA the fatigue was detected in the expected time with minor error. While comparing GFT, SDM and the combination of these two, we observe that the SDM minimally outperformed the GFT, however the combination worked better. These observations came with the agreement of the characteristics we listed in Table 6-1.

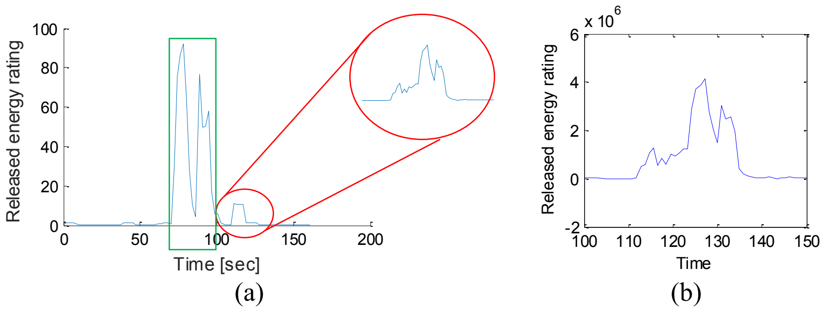


Figure 6-7 Analyzing the effect of employing FQA on a trajectory obtained from an experimental video: (a) without employing FQA (red circle presents the real fatigue location and green rectangle presents the moments of low quality faces), (b) employing FQA (presenting the area within the red circle of (a)).

Table 6-2 Analysing the effect of the FQA and evaluating the performance of GFT, SDM, and the combination of GFT and SDM in fatigue detection

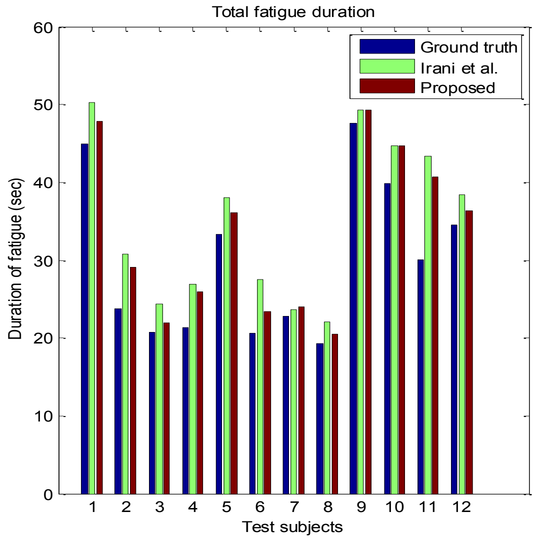
Dataset	**Scenario**	**Average of the total of the starting and ending point distance of fatigue occurrence for each subject in a dataset (μ)**
FQA_Fatigue_Data	Without FQA	65.32
	With FQA	3.79
Eval_Fatigue Data	GFT	6.81
	SDM	6.35
	Combination of GFT and SDM	5.16

6.4.3. PERFORMANCE COMPARISION

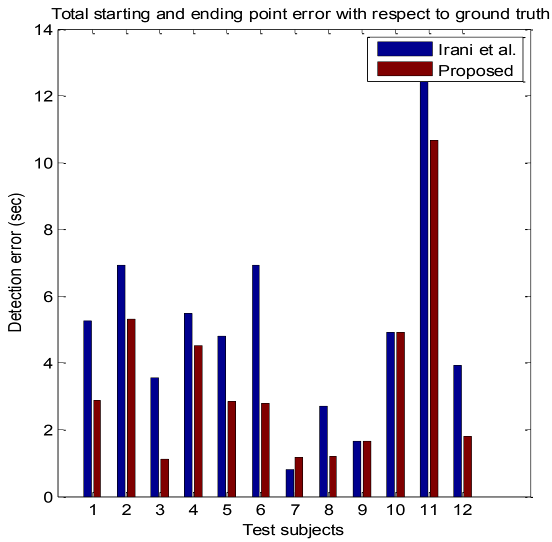
To the best of our knowledge, the method of [9] is the first and the only work in the literature to detect physical fatigue from facial video. Other methods for facial video based fatigue detection work for driver mental fatigue [2], and use different scenarios than what is used in physical fatigue detection environment. Thus, we have compared the performance of the proposed method merely against the method of [9] on the experimental datasets. Figure 6-8(a) shows the physical fatigue detection duration for a subset of database Lab_Fatigue_Data in a bar diagram. The height of the bar shows the duration of fatigue in seconds. Figure 6-8(b) shows the total detection error in seconds for starting and ending points of fatigue in the videos. From the result it is observed that the proposed method detected the presence of fatigue (expressed by fatigue duration) more accurately than the previous method of [9] in comparison to the ground truth as shown in Figure 6-8(a) and demonstrated better agreement with the starting and ending time of fatigue with the ground truth as shown Figure 6-8(b). Table 6-3 shows the fatigue detection results on both Lab_Fatigue_Data and FC_Fatigue_Data, and compares the performance between the state of the art method of [9] and the proposed method. While analyzing the agreement with the starting and ending time of fatigue with the ground truth, we observed that the proposed method shows more consistency than the method of [9] both in the Lab_Fatigue_Data experimental scenario and the FC_Fatigue_Data real-life scenario. However, the performance is higher for Lab_Fatigue_Data than FC_Fatigue_Data. We believe the realistic scenario of a commercial fitness center (in terms of lighting and subject's natural behavior) contributes to lower performance. The computational time of the proposed method suggest that the method is doable for real-time application, because it requires only 3.5 milliseconds (app.) processing time for each video frame in a platform with 3.3 GHz processor and 8GB RAM.

6.5. CONCLUSIONS

This chapter proposes a physical fatigue detecting system from facial video captured by a simple webcam. The proposed system overcomes the drawbacks of previous facial video based method of [9] by extending the application of SDM over GFT based tracking and employing FQA. The previous method works well only when there is neither voluntary motion of the face nor change of expression, and when the lighting conditions help keeping sufficient texture in the forehead and cheek. The proposed method overcomes these problems by using an alternative facial landmarks tracking system (the SDM-based system) along with the previous feature points tracking system (the GFT-based system) and provides competent results. The performance of the proposed system showed very high accuracy in proximity to the ground truth not only in a laboratory setting with controlled environment, as considered in [9], but also in a real-life environment in a fitness center where faces have some voluntary motion or expression change and lighting conditions are normal.



a)



b)

Figure 6-8 Comparison of physical fatigue detection results of the proposed method with the Irani's method [9] on a subset of the Lab_Fatigue_Data: (a) total duration of fatigue, and (b) total starting and ending point error in detection.

The proposed method has some limitations. The camera was placed in close proximity to the face (about one meter away) because the GFT-based feature tracker in the combined system does not work well if the face is far from the camera during video capture. Moreover, the fatigue detection of the proposed system does not take into account the sub-maximal muscle activity due to lack of reliable ground truth data for fatigue from sub-maximal muscle activity. Future work should address these points.

Table 6-3 Performance comparison between the proposed method and the state of the art method of contact-free physical fatigue detection (in the case of maximal muscle activity) on experimental datasets

No	**Dataset name**	**Average of the total of the starting and ending point distance of fatigue occurrence for each subject in a dataset (μ)**	
		Irani et al. [9]	**The proposed method**
1.	Lab_Fatigue_Data	*7.11*	*4.59*
2.	FC_Fatigue_Data	*3.35*	*2.65*

6.6. REFERENCES

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CHAPTER 7. MULTIMODAL ESTIMATION OF HEARTBEAT PEAK LOCATIONS AND HEARTBEAT RATE FROM FACIAL VIDEO USING EMPIRICAL MODE DECOMPOSITION

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The layout has been revised.

7.1. ABSTRACT

Available systems for heartbeat signal estimations from facial video only provide an average of Heartbeat Rate (HR) over a period of time. However, physicians require Heartbeat Peak Locations (HPL) to assess a patient's heart condition by detecting cardiac events and measuring different physiological parameters including HR and its variability. This chapter proposes a new method of HPL estimation from facial video using Empirical Mode Decomposition (EMD), which provides clearly visible heartbeat peaks in a decomposed signal. The method also provides the notion of both color- and motion-based HR estimation by using HPLs. Moreover, it introduces a decision level fusion of color and motion information for better accuracy of multi-modal HR estimation. We have reported our results on the publicly available challenging database MAHNOB-HCI to demonstrate the success of our system in estimating HPL and HR from facial videos, even when there are voluntary internal and external head motions in the videos. The employed signal processing technique has resulted in a system that could significantly advance, among others, health-monitoring technologies.

7.2. INTRODUCTION

Heartbeat signals represent Heartbeat Peak Locations (HPLs) in a temporal domain and help physicians assess the condition of a human cardiovascular system by detecting cardiac events and measuring different important physiological parameters such as Heartbeat Rate (HR) and its variability [1]. Until now the most popular standard device for heartbeat signal acquisition has been the "Electrocardiogram (ECG)". Use of an ECG requires the patient to wear electrodes or chest straps, which are obtrusive and fail in cases where patients/users get upset about the use of the sensors and in cases where patients'/users' skin is sensitive to the sensors. Thus, technologies with contact-free sensors have emerged. Some of the contact-free systems are the Radar Vital Sign Monitor (RVSM) [2], Laser Doppler Vibrometer (LDV) [3], and Photoplethysmography (PPG) [4]. However, the availability of low cost multimedia hardware including webcam and cell phone cameras has made it possible to carry out research that involves extracting heartbeat signals and estimating HR from facial video acquired by an ordinary camera.

When the human heart pumps blood, subtle chromatic changes in the facial skin and slight head motion occur periodically. These changes and motion are associated with the periodic heartbeat signal and can be detected in a facial video [5]. Takano et al. first utilized the subtle color changes as heartbeat signals from facial video acquired by a camera to estimate HR [6]. Subsequently a number of methods have been proposed to extract heartbeat signal from color change or head motion due to heartbeat in facial video. However, all of these methods drew attention to the idea of simply obtaining HR from the signal by employing filters and frequency domain decomposition. In view of these previous methods, here are the demands/challenges that we address in this chapter:

i. Previous methods provide an average HR over a certain time period, e.g. 30-60 seconds. Average HR alone is not sufficient to reveal some conditions of the cardiovascular system [7]. Health monitoring personnel often ask for a more detailed view of heartbeat signals with visible peaks that indicate the beats. However, employing frequency domain decompositions along with some filters on the extracted color or motion traces from the facial video does not provide visible HPLs for further analysis.
ii. The accuracy of HR estimation from facial video has yet to reach the level of ECG-based HR estimation. This compels investigations of a more effective signal processing method than the methods used in the literature to estimate HR.
iii. When a facial video is available, the beating of a heart typically shows in the face through changing skin color and head movement. Thus, merely estimating HR from color or motion information may be surpassed in accuracy by a fusion of these two modalities extracted from the same video.
iv. Most of the facial video-based fully automatic HR estimation methods, including color-based [6], [8]–[10] and motion-based [7], assume that the head is static (or close to) during data capture. This means that there is neither internal facial motion nor external movement or rotation of the head during the data acquisition phase. We ascribe internal motion to facial expression and external motion to head pose. However, in real life scenarios there are, of course, both internal and external head motion. Current methods, therefore, provide less accuracy in HR estimation and no results for HPL.

In this chapter we address the aforementioned demands/challenges by proposing a novel Empirical Mode Decomposition (EMD)-based approach to estimate HPL and then HR. Unlike previous methods, the proposed EMD-based decomposition of raw heartbeat traces provides a novel way to look into the heartbeat signal from facial video and generates clearly visible heartbeat peaks that can be used in, among others, further clinical analysis. We estimate the HR from both the number of peaks detected in a time interval and inter-beat distance in a heartbeat signal from HPLs obtained by employing the EMD. We then introduce a multimodal HR estimation from facial video by fusion of color and motion information and demonstrate the effectiveness of such a fusion in estimating HR. We report our results through a publicly available challenging database MAHNOB-HCI [11] in order to demonstrate the success of our system in estimating HR from facial videos, even when there are voluntary internal and external head motions in the videos.

The rest of the chapter is organized as follows. Section three is a literature review. Section four describes the proposed system for EMD-based HPL estimation. Section five describes HR estimation from HPLs, and an approach to fusing color and motion information for HR estimation. Section six presents the experimental environment and the obtained results. Section seven contains the conclusions.

7.3. RELATED WORKS

Takano et al. first utilized the trace of skin color changes in facial video to extract heartbeat signal and estimate HR [6]. They recorded the variations in the average brightness of the Region of Interest (ROI) – a rectangular area on the subject's cheek – to estimate HR. This method was further improved by Verkruysse et al., who separated color channels (R, G and B) of ROI in captured video frames, tracked each channel independently, and extracted HR by filtering and analyzing the average color traces of pixels [12]. About two years later, Poh et al. proposed a method that used ROI mean color values as color traces from facial video acquired by a simple webcam, and employed Independent Component Analysis (ICA) to separate the periodic signal sources and a frequency domain analysis of an ICA component to measure HR [8]. The authors later improved their method by employing some filters before and after ICA [9]. Kwon et al. improved Poh's method in [8] by using merely green color channel instead of all three Red-Green-Blue (RGB) color channels [10]. Wei et al. employed a Laplacian Eigenmap (LE), rather than ICA, to obtain the uncontaminated heartbeat signal and demonstrated better performance than the ICA-based method [13]. Other articles contributed a peripheral improvement of the color-based HR measurement by using a better estimation of ROI [14], adding a supervised machine learning component to the system [15], and analyzing the distance between the camera and the face during data capture [16].

Color-based methods suffer from tracking sensitivity to color noise and illumination variation. Thus, Balakrishnan et al. proposed a method for HR estimation which was based on invisible motion in the head due to pulsation of the heart muscles, which can be obtained by a Ballistocardiogram [7]. In this approach, some feature points were automatically selected on the ROI of the subject's facial video frames. These feature points were tracked by the Kanade–Lucas–Tomasi (KLT) feature tracker [17] to generate some trajectories, and then a Principle Component Analysis (PCA) was applied to decompose trajectories into a set of orthogonal signals based on Eigen values. Selection of the heartbeat rate was accomplished by using the percentage of the total spectral power of the signal, which accounted for the frequency with the maximum power and its first harmonic. In contrast to color-based methods, Balakrishnan's system was not only able to address the color noise sensitivity but also to provide similar accuracy without requiring color video. However, Balakrishnan's assumption of selecting maximal frequency of the chosen signal as pulse frequency is not very precise. Thus, a semi-supervised method in [18] was proposed to improve the results of Balakrishnan's method by using the

Discrete Cosine Transform (DCT) along with a moving average filter rather than the Fast Fourier Transform (FFT) employed in Balakrishnan's work. The method in [19] also utilized motion information; however, unlike [7] it used ICA (previously used in color-based methods) to decompose the signal, but demonstrated the results on a local database.

7.4. THE PROPOSED SYSTEM

The proposed HPL estimation method extracts the color and motion traces from facial video as the raw heartbeat signal. As heartbeats are cyclic, the raw signal is passed through a filter to discard extraneous trends and cyclical components. The resultant signal is then decomposed into some Intrinsic Mode Functions (IMF) by employing a decomposition method. We then select the IMF that keeps the heart-beat peaks and employ a peak detection method to estimate the HPLs. This section describes the steps of the proposed EMD-based HPL estimation method from color or motion traces as shown in Figure 7-1.

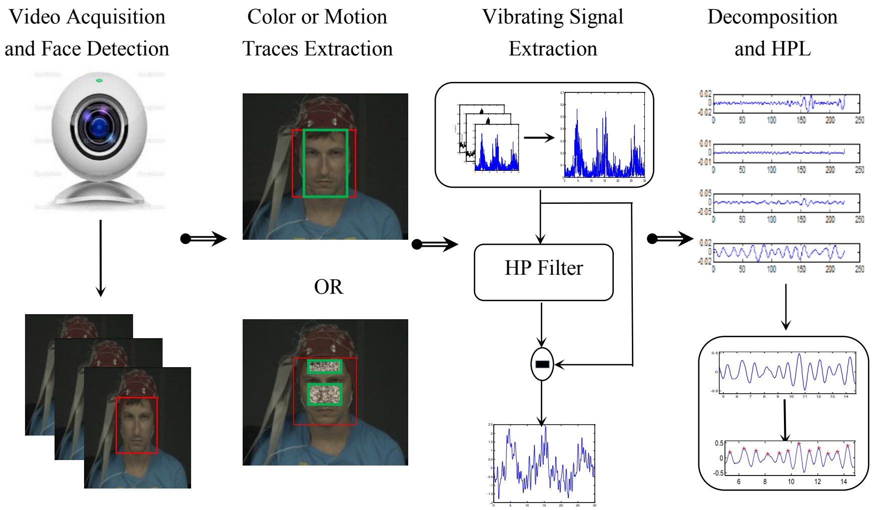

Figure 7-1 Steps of the proposed HPL estimation method using skin color or head motion information from facial video.

7.4.1. VIDEO ACQUISITION AND FACE DETECTION

The first step of the proposed HPL estimation system is face detection from facial video acquired by a simple RGB camera. We employ the well-known Haar-like feature-based Viola and Jones object detection framework [20] for face detection. Examples of face detection results in a video frame are shown by the red rectangles in Figure 7-2.

7.4.2. FACIAL COLOR AND MOTION TRACES EXTRACTION

As mentioned earlier, periodic circulation of the blood from the heart through the body causes facial skin to change color, and the head to move or shake in a cyclic motion. The proposed system for HPL estimation can utilize either of the modalities (skin color variations and head motions) as shown in Figure 7-1. Recoding RGB values of pixels in facial regions to generate the color trace and tracking some facial feature points to generate the motion trace help to record such skin color variation and head motion from facial video, respectively. In order to obtain the traces of either of the two modalities, we first select a ROI in the detected face. For the color-based approach, the ROI contains 60% of the facial area width (following [5]) detected by the automatic face detection method, as shown by the green rectangle in Figure 7-2(a). We take the average of the RGB values of all pixels in the ROI in each frame and obtain a single color trace as follows:

$$\bar{S}_{color}(t) = \frac{1}{n}\sum_{i=1}^{n} \mu_i(R, G, B) \quad (1)$$

where, $\bar{S}_{color}$ is the color trace, n is the total number of pixels in the ROI, μ_i is the grayscale value of the i-th pixel obtained from R, G and B values, and t is the frame index.

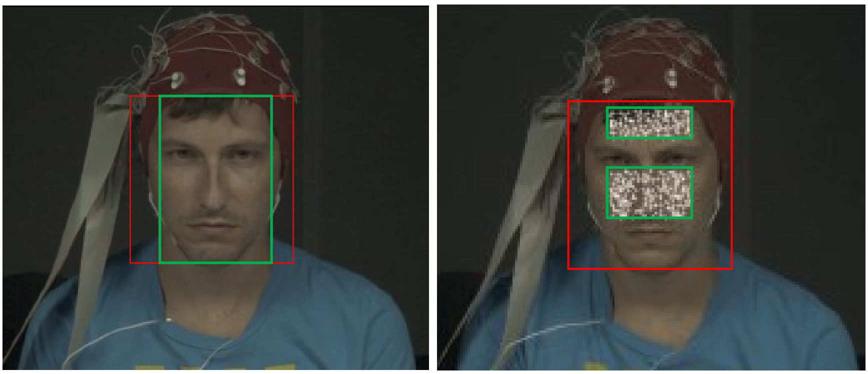

Figure 7-2 Selected ROIs (green rectangles) and tracked feature points (inside the green rectangles) in a face of a subject's video for the color trace (left) and the motion trace (right).

For the motion-based approach the ROI (following [18]) contains two areas of forehead and cheek, as shown by the green rectangles in Figure 7-2(b). We divide the ROI into a grid of rectangular regions of pixels and detect some feature points in each region by employing a method called Good Features to Track (GFT) [21]. The GFT works by finding corner points from the minimal Eigen values of the windows of pixels in the ROI. An example of all the feature points detected by GFT in the ROI is shown by white markers in Figure 7-2(b). When the head moves due to heart pulse, the feature points also move in the pixel coordinates. We employ a KLT tracker to track the feature points in consecutive video frames and obtain a single trajectory of each feature points in the video by measuring Euclidian distance of the point-locations in consecutive frames. We then fuse all trajectories into a single motion trace as follows:

$$\bar{S}_{motion}(t) = \frac{1}{n}\sum_{i=1}^{n} S_i(t) \tag{2}$$

where, $S_i(t)$ is the trajectory of i-th feature point in the video frame t and n is the total number of trajectories.

Both color and motion traces ($\bar{S}_{color}$ and $\bar{S}_{motion}$, respectively) are one dimensional raw heartbeat signals with lengths equivalent to the number of video frames and values that represent the color variation and head motion, respectively. The next steps of the proposed method follow the same procedure for both color and motion and hereafter we refer to the raw heartbeat signal as $\bar{S}$.

7.4.3. VIBRATING SIGNAL EXTRACTION

The raw heartbeat signal ($\bar{S}$) contains other extraneous high and low frequency cyclic components than heart beat due to ambient color and motion noise induced from the data capturing environment. It also exhibits non-cyclical trendy noise due to voluntary head motion, facial expression, and/or vestibular activity. Thus, to remove/reduce the extraneous frequency components and trends from the signal we decompose it using Hodrick-Prescott (HP) filter [22]. The filter breaks down the signal into the following components with respect to a smoothing penalty parameter, τ:

$$S_{\tau}^{log}(t) = T_{\tau}(t) + C_{\tau}(t) \tag{3}$$

where S_{τ}^{log} is the logarithm of $\bar{S}$, T_{τ} is the trend component, and C_{τ} denotes the cyclical component of the signal with t as the time index (video frame index). We follow two times the decomposition of the trajectory by using two smoothing parameter values $\tau = \infty$ and $\tau = 400$ to obtain all of the cyclic components (C_{∞}) and high frequency cyclic components (C_{400}), respectively. A detailed description of the HP filter can be obtained from [22]. We completely overlook the trend components (T_{τ}) because these are not characterized by cyclic pattern of heartbeat. We then obtain the difference between the cyclical components to get the vibrating signal as follows:

$$V(t) = C_{\infty}(t) - C_{400}(t) \tag{4}$$

We will show how a signal evolves by employing the aforementioned phases in the experimental evaluation section. The obtained vibrating signal (V) is then passed to the next step of the system.

7.4.4. EMD-BASED SIGNAL DECOMPOSITION FOR THE PROPOSED HPL ESTIMATION

The vibrating signal (V) cannot clearly depict the heartbeat peaks (which will be shown in the experimental evaluation section). This is because of the contamination of heartbeat information by the other lighting and motion sources, which the HP filter alone cannot restore for visibility. Previous methods in [7]–[10], [14], [18] moved to the frequency domain and filtered the signal by different bandpass filters and/or calculating the power spectrum of the signal to determine the HR in the frequency domain. However, this cannot provide a heartbeat signal with visible peaks, i.e. no possible HPL estimation, and thus cannot be useful for clinical applications where inter-beat intervals are necessary or signal variation needs to be observed over time. Thus, we employ a derivative of EMD to address the issue. EMD usually decomposes a nonlinear and non-stationary time-series into functions that form a complete and nearly orthogonal basis for the original signal [23]. The functions into which a signal is decomposed are all in the time domain and of the same length as the original signal. However, the functions allow for varying frequency in time to be preserved. When a signal is generated as a composite of multiple source signals and each of the source signals may have individual frequency band, calculating IMFs using EMD can provide illustratable source signals.

In the case of processing the heart signal obtained from skin color or head motion information from facial video, the obtained vibrating signal (V) is a nonlinear and nonstationary time-series that comes as a composite of multiple source signals from lighting change, and/or internal and external head motions along with heartbeat. The basic EMD, as defined by Huang [24], breaks down a signal into IMFs satisfying the following two conditions:

i. In the whole signal, the number of extrema and the number of zero-crossings cannot differ by more than 1.
ii. At any point, both means of the envelopes defined by the local maxima and local minima are zero.

The decomposition can be formulated as follows:

$$V(t) = \sum_{i=1}^{m} M_i + r \quad (5)$$

where M_i presents the mode functions satisfying the aforementioned conditions, m is the number of modes, and r is the residue of the signal after extracting all the IMFs. The procedure of extracting such IMFs (M_i) is called shifting. The shifting process starts by calculating the first mean ($\mu_{i,0}$) from the upper and lower envelopes of the original signal (V in our case) by connecting local maxima. Then a component is calculated as the first component ($I_{i,0}$) for iteration as follows:

$$I_{i,0} = V(t) - \mu_{i,0} \tag{6}$$

The component $I_{i,0}$ is then considered the data signal for an iterative process, which is defined as follows:

$$I_{i,j} = I_{i,j-1} - \mu_{i,j} \tag{7}$$

The iteration stops when a predefined value exceeds the following parameter (δ) calculated in each step:

$$\delta_{i,j} = \sum_{k=1}^{l} \frac{(I_{i,j-1}(k) - I_{i,j}(k))^2}{I_{i,j-1}^2(k)} \tag{8}$$

where l is the number of samples in I (in our case, the number of video frames used).

The basic model of EMD described above, however, exhibits some problems such as the presence of oscillations of very disparate amplitudes in a mode and/or the presence of very similar oscillations in different modes. In order to solve these problems an enhanced model of EMD was proposed by Torres et al. [25], which is called Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). CEEMDAN adds a particular noise at each stage of the decomposition and then computes residue to generate each IMF. The results reported by Torres showed the efficiency of CEEMDAN over EMD. Therefore, we decompose our vibrating signal (V) into IMFs (M_i) by using the CEEMDAN. The total number of IMFs depends on the vibrating signal's nature. As a normal adult's resting HR falls within the frequencies $[0.75 - 2.0]$ Hz (i.e. $[45 - 120]$ bpm) [7] and merely 6-th IMF falls within this range, we selected the 6-th IMF as the final uncontaminated (or less contaminated) form of the heartbeat signal of all experimental cases.

We employ a local maxima-based peak detection algorithm on the selected heartbeat signal (the 6-th IMF) to estimate the HPL. The peak detection process was restricted by a minimum peak distance parameter to avoid redundant peaks in nearby positions. The obtained peak locations are the HPLs estimated by the proposed system.

7.5. HR CALCULATION USING THE PROPOSED MUTLI-MODAL FUSION

The HPLs we obtained in the previous section can be utilized to measure the total number of peaks and peak distances in a heartbeat signal. These can be obtained for either case of the color and motion information from facial video. We calculate the HR in bpm for both approaches in two different ways – from the total number of peaks and average peak distance – as follows:

$$HR_{numPeak} = \left(\frac{N \times F_{rate}}{F_{total}}\right) \times 60 \tag{9}$$

$$HR_{distPeak} = \left(\frac{F_{rate}}{\frac{1}{(N-1)}\sum_{k=1}^{(N-1)} d_k}\right) \times 60 \tag{10}$$

where N is the total number of peaks detected, F_{rate} is the video frame rate per second, F_{total} is the total number of video frames used to generate the heartbeat signal, and d_k is the distance between two consecutive peaks.

As we stated in the first section of this chapter, facial video contains both color and motion information that denote heartbeat. Along with the proposed EMD-based method, the applications of color information for HR estimation were shown in [8]–[10], [14], [15], and the applications of motion information were shown in [7], [18]. None of these methods exploited both color and motion information. We assume that, since color and motion information have different notions of heartbeat representation, a fusion of these two modalities in estimating HR can include more deterministic characteristics of heart pulses in the heartbeat signal.

There are three levels that can be considered for the fusion of modalities: raw-data level, feature level, and decision level [26]. Although the extracted raw heartbeat signals in color and motion-based approaches have the same dimensions, they are mismatched due to the nature of the data they present. Thus, instead of raw-data level and feature level fusion, we propose a rule-based decision level (HR estimation results) fusion in this chapter for exploiting the HR estimation results from both modalities. For each of the modalities, we obtain two results using the total number of peaks and average peak distance. Thus, we have four different estimates of the HR: $HR_{numPeak}^{color}$, $HR_{distPeak}^{color}$, $HR_{numPeak}^{motion}$, and $HR_{distPeak}^{motion}$. We employed four feasible rules, listed in Table 7-1, to find the optimal fusion.

7.6. EXPERIMENTS AND OBTAINED RESULTS

This section first describes the experimental environment used to generate the results and then describes the performance evaluation and comparison against state of the art similar systems. In the performance evaluation section we first show how the raw heartbeat signal extracted from facial video evolves to the signal with clearly visible HPLs after the application of EMD. We also show the HR estimation results of the EMD-based method for color, motion, and fusion of color and motion. In the performance comparison section we first show the results of HPL estimation and then the overall HR comparison between the proposed method and the state of the art methods.

Table 7-1 Fusion rules invested

Rule parameter	**Definition**
$HR_{numPeak}^{Fuse}$	$mean\left(HR_{numPeak}^{color}, HR_{numPeak}^{motion}\right)$
$HR_{distPeak}^{Fuse}$	$mean\left(HR_{distPeak}^{color}, HR_{distPeak}^{motion}\right)$
HR_{all}^{Fuse}	$mean\begin{pmatrix} HR_{numPeak}^{color}, HR_{distPeak}^{color}, \\ HR_{numPeak}^{motion}, HR_{distPeak}^{motion} \end{pmatrix}$
$HR_{nearestTwo}^{Fuse}$	$mean_{nearest\ two}\begin{pmatrix} HR_{numPeak}^{color}, HR_{distPeak}^{color}, \\ HR_{numPeak}^{motion}, HR_{distPeak}^{motion} \end{pmatrix}$

7.6.1. EXPERIMENTAL ENVIRONMENT

The proposed methods (the EMD-based methods for color and motion and the multimodal fusion method) were implemented in Matlab (2013a). Most of the previous methods provided their results on local datasets, which makes the methods difficult to compare with the other methods. In addition, most of the previous methods did not report the results on a challenging database that includes realistic illumination and motion changes. In order to overcome such problems and show the competency of our methods, we used the publicly available MAHNOB-HCI database [11] for the experiment. The database is recorded in realistic Human-Computer Interaction (HCI) scenarios, and includes data in two categories: 'Emotion Elicitation Experiment (EEE)' and 'Implicit Tagging Experiment (ITE)'. Among these, the video clips from EEE are relevant to HR measurement because they are frontal-face video data with ECG ground truth for HR. Some snapshots of the MAHNOB-HCI EEE database taken in different facial states are shown in Figure 7-3.

The EEE data was treated as a realistic and highly challenging dataset in the literature [14] because it contains facial videos recorded in realistic scenarios, including challenges from illumination variation and internal and external head motions. It contains videos of 491 sessions with 25 subjects that are longer than 30 seconds, and subjects who consent attribute 'YES'. Both males and females participated; they were between 19 and 40 years of age. Among the sessions, 20 sessions of subject '12' do not have ECG ground truth data and 20 sessions of subject '26' are missing video data. Excluding these sessions, we used the remainder as the dataset for our experiment. In this database, the ground truth ECG signals were acquired using three sensors and listed as EXG1, EXG2 and EXG3 channels in the data files. As the original videos are of different lengths, we use 30 seconds (frame 306 to 2135) of each video and the corresponding ECG from EXG3 for the ground truth.

(a) Video acquisition environment

(b) Faces in normal (leftmost column) and challenging states (rest of the columns)

Figure 7-3 Video acquisition environment and example faces of five subjects from the MAHNOB-HCI database [11].

We show the experimental results for HPL estimation in a qualitative manner and HR estimation through four statistical parameters used in the previous literature [8], [14]. The first one is mean error, defined as follows:

$$M_E = \frac{1}{N}\sum_{k=1}^{N}\left(HR_k^{video} - HR_k^{groundTruth}\right) \quad (11)$$

where HR_k^{video} is the calculated HR from the k-th video of a database, $HR_k^{groundTruth}$ is the corresponding HR from the ECG ground truth signal, and N is the total number of videos in the database. The second parameter is the standard deviation of M_E, defined as follows:

$$SD_{M_E} = \sqrt{\left(\frac{1}{N}\sum_{k=1}^{N}\left(HR_k^{video} - M_E\right)^2\right)} \quad (12)$$

The third parameter is the root mean squared error, defined as follows:

$$RMS_E = \sqrt{\left(\frac{1}{N}\sum_{k=1}^{N}\left(HR_k^{video} - HR_k^{groundTruth}\right)^2\right)} \quad (13)$$

The fourth statistical parameter is the mean of error rate in percentage, defined as follows:

$$M_{ER} = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{HR_k^{video} - HR_k^{groundTruth}}{HR_k^{groundTruth}}\right) \times 100 \quad (14)$$

7.6.2. EXPEIMENTAL EVALUATION

The proposed method tracks color change and head motion due to heartbeat in a video. Figure 7-4 shows four head motion trajectories of two feature points from a video in MAHNOB-HCI. The location trajectories show variation in both horizontal ((a) and (b)) and vertical ((c) and (d)) directions. Figure 7-5 shows the average trajectory ($\bar{S}$ in eq. (2)) calculated from the individual trajectories of the feature points and corresponding vibrating signal (V in eq. (4)) obtained after employing the HP filter for the video used for Figure 7-4. We observe that the vibrating signal is less noisy than the previous signal due to the application of the HP filter. We obtain similar results in the color-based approach.

The CEEMDAN, a derivative of EMD, decomposes the vibrating signal into IMFs (M_i) to provide an uncontaminated form of heartbeat signal. Figure 7-6 shows first eight IMFs obtained from the signal by eq. (5)-(8). The IMFs are separated by different frequency components as discussed in Section III(D), and we selected M_6 as the final heartbeat signal to employ the peak detection algorithm. The result of peak detection on M_6 of Figure 7-6 is shown in Figure 7-7. One can observe that the final heartbeat signal has more clearly visible beats than the raw heartbeat signal obtained from motion traces. After employing peak detection we obtained all HPL that can be used in further medical analysis. The qualitative and quantitative comparison of the estimated HPL with the beat locations in ground truth ECG is shown in the performance comparison section.

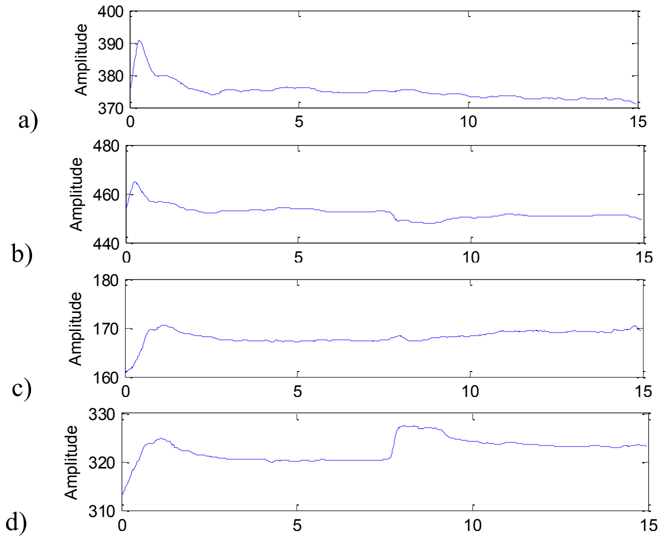

Figure 7-4 Trajectories of two feature points (both horizontal and vertical trajectories) in a video of the MAHNOB-HCI database.

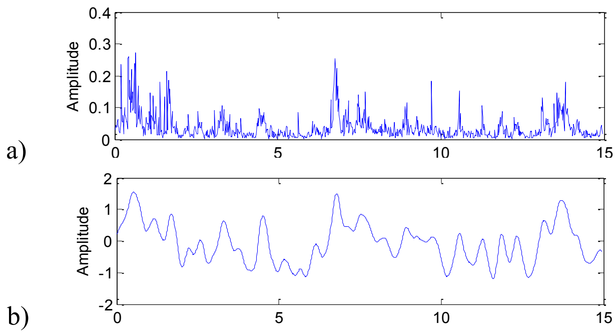

Figure 7-5 Vibrating signal extraction by HP filtering: a) average signal from motion trajectories and b) filtered vibrating signal.

We count the number of peaks and measure average peak distance from HPLs. These two measures have been used to measure four parameters $HR^{color}_{numPeak}$, $HR^{color}_{distPeak}$, $HR^{motion}_{numPeak}$, and $HR^{motion}_{distPeak}$ in bpm. These results and the results of four fusion rules defined in Table 7-1 have been shown in Table 7-2. From the results we observe that counting the number of peaks provides better results than measuring peak distance for both color and motion information. This is because, unlike counting peaks, heartbeat rate variability in the signal can contribute negatively to the average peak distance. The overall error rates (M_{ER}) are less than 10% for HR estimation by counting the number of peaks for both motion and color signals. The fusion results show that, similar to the individual use of motion or color information, the number of peaks fusion generates the best results out of the four fusion rules. Simple arithmetic mean in decision level fusion, as we used, shows a strong correlation with the corresponding color and motion-based results. While comparing the results to the individual motion and color-based estimations, the fusion shows greater accuracy.

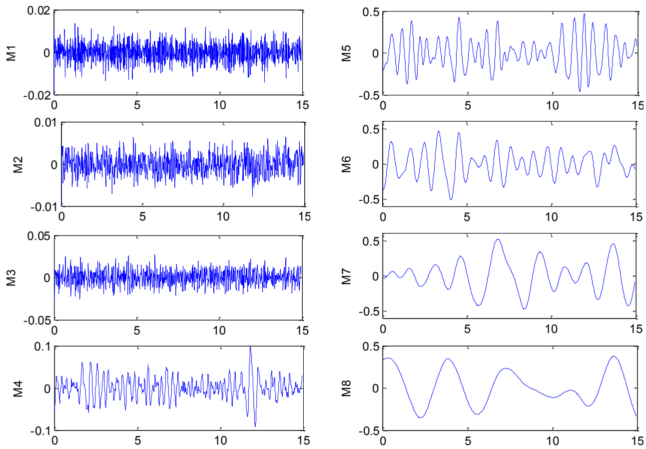

Figure 7-6 Obtained IMFs (M_i) after employing CEEMDAN on the vibrating signal (V).

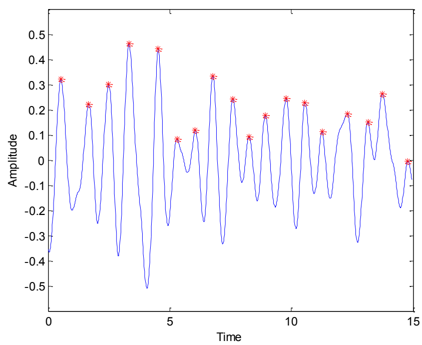

Figure 7-7 Heartbeat peak detection in the 6-th IMF.

We have also depicted in Figure 7-8 the HR estimation performance of the proposed approaches in a scatter plot by plotting the estimated HR against the ground truth HR for all the experimental videos of the MAHNOB-HCI database. From the figure one can observe that most of the estimation was highly consistent with the ground truth. However, there are cases where the estimations were not good (outlier points in the plot) due to contamination of noise from extraneous face movement in the video. It is important to note that the points in the scatter plot are much closer to the line through the origin of the plot for the fusion of chromatic and motion information than the merely chromatic or motion information-based estimations. This means the values are more accurately estimated in this case.

Table 7-2 HR estimation results of the proposed EMD-based methods using color, motion and fusion

No.	Method	M_E (bpm)	SD_{M_E} (bpm)	RMS_E (bpm)	M_{ER} (%)
1.	$HR_{numPeak}^{motion}$	**-0.90**	**8.28**	**8.32**	**8.65**
2.	$HR_{distPeak}^{motion}$	-1.33	10.77	10.84	11.51
3.	$HR_{numPeak}^{color}$	**0.21**	**8.55**	**8.54**	**9.26**
4.	$HR_{distPeak}^{color}$	0.95	10.25	10.29	11.59
5.	$HR_{distPeak}^{Fuse}$	-0.19	10.08	10.07	11.00
6.	HR_{all}^{Fuse}	-0.27	9.04	9.03	9.79
7.	$HR_{nearestTwo}^{Fuse}$	-0.29	8.47	8.46	8.92
8.	$HR_{numPeak}^{Fuse}$	**-0.35**	**8.08**	**8.08**	**8.63**

7.6.3. PERFORMANCE COMPARISON

The performance of the proposed method has been compared with the relevant state of the art methods in two respects: i) presentation of visible heartbeat peaks in the extracted heartbeat signal in time domain (HPL estimation performance) and ii) accuracy of HR estimation.

As we mentioned in Section I, the most important demand addressed in the proposed method is obtaining an uncontaminated form of heartbeat signal with visible heartbeat peaks. To the best of our knowledge, all the previous methods employ some filter to the color or motion traces of noisy heartbeat signal and then transform the signal from time domain to the frequency domain. While this can provide an estimate of HR, it cannot provide clearly visible heartbeat peaks for clinical analysis. However, the proposed methods can obtain the visible heartbeat peaks in the final estimated signal. Figure 7-9 shows the extracted heartbeat signals using the proposed EMD-based method from motion trajectories of two videos (subject ID-1, session 14 and subject ID-20, session 26) from the MAHNOB-HCI database next to the extracted signals using the motion-based method of [7]. The second video represents the case of voluntary facial motions. We have also included ground truth ECG for these videos. From the figures we observe that the final time domain signal extracted by [7] is clearly impossible to comprehend for visual analysis. This is also true for the other state of the art methods because of similar filters and ICA/PCA/DCT-based decomposition. On the other hand, the final time domain signal generated by the proposed EMD-based method not only shows heartbeat peaks but also preserves a correspondence to the ECG ground truth.

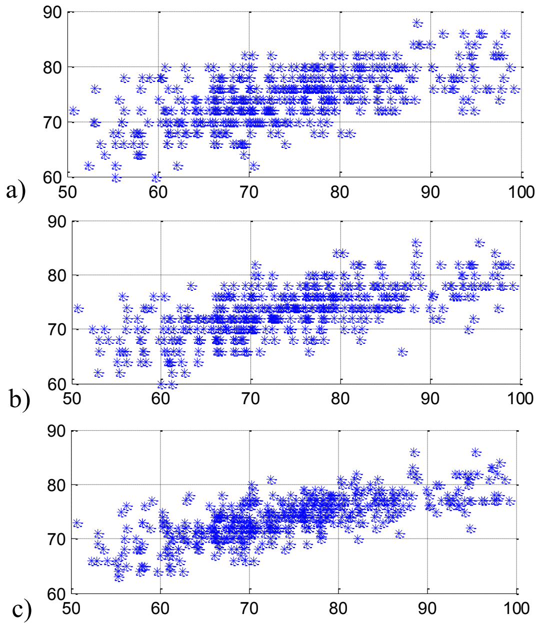

Figure 7-8 Scatter plots of the HR obtained from video (y-axis) against HR obtained from the ECG ground truth for the videos of MAHNOB-HCI database by employing: a) color-based method ($HR_{numPeak}^{color}$), b) motion-based method ($HR_{numPeak}^{motion}$) and c) fusion of color and motion ($HR_{numPeak}^{Fuse}$).

The proposed method used HPLs (number of HPLs and distance between HPLs) to estimate HR. Thus, the statistical parameters used to present HR estimation accuracy in turns show the consistency of estimating HPLs with respect to the heartbeat peaks in ground truth ECG. This provides a quantification of the qualitative presentation of HPL in Figure 7-9. We use this quantification to compare the accuracy of the proposed method with state of the art color and the motion-based methods of [7]–[10]. We overlooked some other recently proposed methods from [14]–[16], [18], [27] in the comparison. We did this because some of the methods provide a peripheral contribution in data capturing and facial region selection for HR estimation instead of providing novel methodology of better estimation (which is our one of the major contributions), and other methods need prior training for HR estimation; we believe that comparing an unsupervised fully automatic method with supervised or semi-automatic methods is not reasonable. The results of the accuracy comparison are summarized in Table 7-3. From the results, it is clear that the proposed EMD-based methods for both color and motion provide a better estimation of HR than the other state of the art methods in a less constrained data acquisition environment of the MAHNOB-HCI EEE database. The proposed methods outperformed the other methods in both RMS_E and M_{ER} because EMD can decompose the signal in a better way than the filters and ICA/PCA-based decomposition used in the previous methods. The results of the proposed method demonstrate a high degree of consistency in estimating HR in comparison to the other methods. This, in turn, validates our peak location estimation as well because the peak locations have been used to estimate HR.

Table 7-3 Performance comparison of the proposed methods with the previous methods of HR estimation

No.	Method	M_E (bpm)	SD_{M_E} (bpm)	RMS_E (bpm)	M_{ER} (%)
1.	Poh2010 [8]	*-8.95*	*24.3*	*25.90*	*25.00*
2.	Kwon2012 [10]	*-7.96*	*23.8*	*25.10*	*23.60*
3.	Guha2013 [7]	*-14.4*	*15.2*	*21.00*	*20.70*
4.	Poh2011 [9]	*2.04*	*13.5*	*13.60*	*13.20*
5.	**Proposed_color**	***0.21***	***8.55***	***8.54***	***9.26***
6.	**Proposed_motion**	***-0.90***	***8.28***	***8.32***	***8.65***
7.	**Proposed_Fusion**	***-0.35***	***8.08***	***8.08***	***8.63***

7.7. DISCUSSIONS AND CONCLUSIONS

This chapter proposed methods for estimating HPL and HR from color and motion information from facial video by a novel use of an HP filter and EMD decomposition. The chapter also proposed a fusion approach to exploit both color and motion information together for multi-modal HR estimation. The contributions of these methods are as follows: i) provided the notion of visually analyzing heartbeat signal in time domain with clearly visible heartbeat peaks for clinical applications, ii) provided better estimations of HR for separate color and motion traces, iii) a decision level fusion further improved the result, and iv) provided a highly accurate HPL and HR estimations method from facial video in the presence of challenging situations due to illumination change and voluntary head motions.

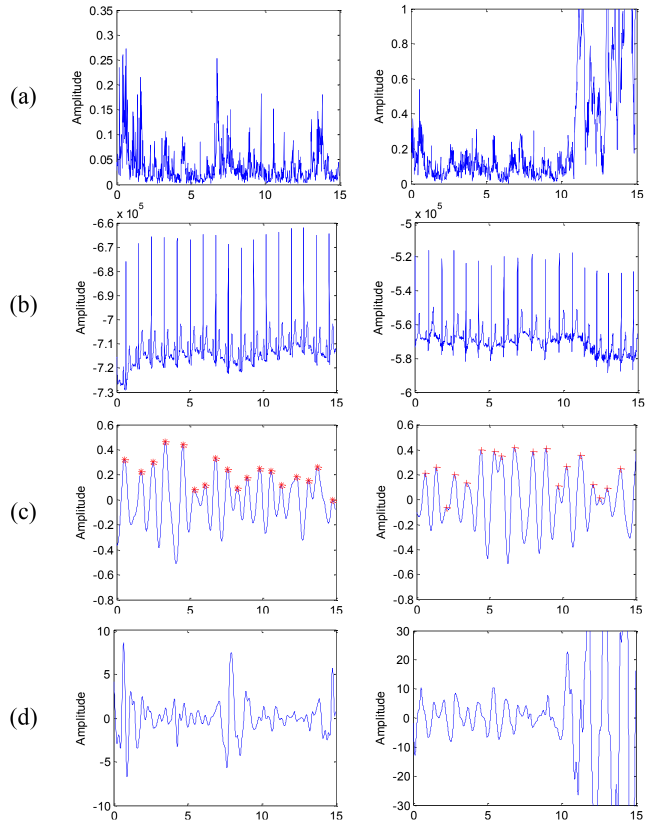

Figure 7-9 Illustrating heartbeats obtained by different methods for two facial videos from two different subjects for normal case (left) and challenging case with voluntary motion (right): a) raw heartbeat signals from motion trajectories, b) ECG ground truth, c) Final heartbeat signal obtained by the proposed method and detected peak locations, and d) Final heartbeat signal obtained by Guha2013 [7] after PCA, which cannot produce clear peak locations.

The proposed method, however, also imposed some limitations when generating the results. We assume that the camera will be placed in close proximity to the face (about one meter away). Moreover, we did not employ any sophisticated ROI detection and tracking methods, illumination rectification methods, or extraneous motion filtering before final decomposition. Instead of these peripheral fine-tuning notions, our contribution focused on a core signal processing technique for heartbeat extraction. The system is not adapted yet to the real-time application for HR measurement due to the high volume of computation required for CEEMDAN decomposition. In addition, instead of instant estimation of the peak location and intensity, the system estimates the heartbeat peaks in a time period (30 seconds in our experiment). Future work should address these points.

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PART V

CONTACT-FREE HEARTBEAT BIOMETRICS

CHAPTER 8. HEARTBEAT SIGNAL FROM FACIAL VIDEO FOR BIOMETRIC RECOGNITION

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8.1. ABSTRACT

Different biometric traits such as face appearance and heartbeat signal from Electrocardiogram (ECG)/Phonocardiogram (PCG) are widely used in the human identity recognition. Recent advances in facial video based measurement of cardio-physiological parameters such as heartbeat rate, respiratory rate, and blood volume pressure provide the possibility of extracting heartbeat signal from facial video instead of using obtrusive ECG or PCG sensors in the body. This chapter proposes the Heartbeat Signal from Facial Video (HSFV) as a new biometric trait for human identity recognition, for the first time to the best of our knowledge. Feature extraction from the HSFV is accomplished by employing Radon transform on a waterfall model of the replicated HSFV. The pairwise Minkowski distances are obtained from the Radon image as the features. The authentication is accomplished by a decision tree based supervised approach. The potential of the proposed HSFV biometric for human identification is demonstrated on a public database.

8.2. INTRODUCTION

Human identity recognition using biometrics is a well explored area of research to facilitate security systems, forensic analysis, and medical record keeping and monitoring. Biometrics provides a way of identifying a person using his/her physiological and/or behavioral features. Among different biometric traits iris image, fingerprint, voice, hand-written signature, facial image, hand geometry, hand vein patterns, and retinal pattern are well-known for human authentication [1]. However, most of these biometric traits exhibit disadvantages in regards to accuracy, spoofing and/or unobtrusiveness. For example, fingerprint and hand-written signature can be forged to breach the identification system [2], voice can be altered or imitated, and still picture based traits can be used in absence of the person [3]. Thus, scientific community always searches for new biometric traits to overcome these mentioned problems. Heartbeat signal is one of such novel biometric traits.

Human heart is a muscular organ that works as a circulatory pump by taking deoxygenated blood through the veins and delivers oxygenated blood to the body through the arteries. It has four chambers and two sets of valves to control the blood flow. When blood is pumped by the heart, some electrical and acoustic changes occur in and around the heart in the body, which is known as heartbeat signal [4]. Heartbeat signal can be obtained by Electrocardiogram (ECG) using electrical changes and Phonocardiogram (PCG) using acoustic changes, as shown in Figure 8-1.

Both ECG and PCG heartbeat signals have already been utilized for biometrics recognition in the literature. ECG based authentication was first introduced by Biel et al. [5]. They proposed the extraction of a set of temporal and amplitude features using industrial ECG equipment (SIEMENS ECG), reduced the dimensionality of features by analyzing the correlation matrix, and authenticated subjects by a multivariate analysis. This method subsequently drew attention and a number of methods were proposed in this area. For example, Venkatesh et al. proposed ECG based authentication by using appearance based features from the ECG wave [6]. They used Dynamic Time Wrapping (DTW) and Fisher's Linear Discriminant Analysis (FLDA) along with K-Nearest Neighbor (KNN) classifier for the authentication. Chetana et al. employed Radon transformation on the cascaded ECG wave and extracted a feature vector by applying standard Euclidean distance on the transformed Radon image [7]. They computed the correlation coefficient between such two feature vectors to authenticate a person. Similar to [5], geometrical and/or statistical features from ECG wave (collected from ECG QRS complex) were also used in [8]–[10]. Noureddine et al. employed the Discrete Wavelet Transformation (DWT) to extract features from ECG wave and used a Random Forest approach for authentication [11]. A review of the important ECG-based authentication approaches can be obtained from [12]. The common drawback of all of the above mentioned ECG based methods for authentication is the requirement of using obtrusive (touch-based) ECG sensor for the acquisition of ECG signal from a subject.

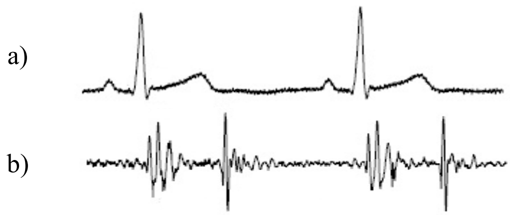

Figure 8-1 Heartbeat signal obtained by a) ECG and b) PCG.

The PCG based heartbeat biometric (i.e. heart sound biometric) was first introduced by Beritelli et al [13]. They use the *z*-chirp transformation (CZT) for feature extraction and Euclidian distance matching for identification. Puha et al. [14] proposed another system by analyzing cepstral coefficients in the frequency domain for feature extraction and employing a Gaussian Mixture Model (GMM) for identification. Subsequently, different methods were proposed, such as a wavelet based method in [15] and marginal spectral analysis based method in [16]. A review of the important PCG-based method can be found in [17]. Similar to the ECG-based methods, the common drawback of PCG-based methods for authentication is also the requirement of using obtrusive PCG sensor for the acquisition of ECG signal from a subject. In another words, for obtaining heart signals using ECG and PCG the required sensors need to be directly installed on subject's body, which is obviously not always possible, especially when subject is not cooperative.

A recent study at Massachusetts Institute of Technology (MIT) showed that circulating the blood through blood-vessels causes periodic change to facial skin color [18]. This periodic change of facial color is associated with the periodic heartbeat signal and can be traced in a facial video. Takano et al. first utilized this fact in order to generate heartbeat signal from a facial video and, in turns, calculated Heartbeat Rate (HR) from that signal [19]. A number of other methods also utilized heartbeat signal obtained from facial video for measuring different physiological parameters such as HR [20], respiratory rate and blood pressure [21], and muscle fatigue [20].

This chapter introduces Heartbeat Signal from Facial Video (HSFV) for biometric recognition. The proposed system uses a simple webcam for video acquisition, and employs signal processing methods for tracing changes in the color of facial images that are caused by the heart pulses. Unlike ECG and PCG based heartbeat biometric, the proposed biometric does not require any obtrusive sensor such as ECG electrode or PCG microphone. Thus, the proposed HSFV biometric has some advantages over the previously proposed biometrics. It is universal and permanent, obviously because every living human being has an active heart. It can be more secure than its traditional counterparts as it is difficult to be artificially generated, and can be easily combined with state-of-the-art face biometric without requiring any additional sensor. This chapter proposes a method for employing this new biometric for person's identity recognition by employing a set of signal processing methods along with a decision tree based classification approach.

The rest of this chapter is organized as follows. Section three describes the proposed biometric system and section four presents the experimental results. Section fine concludes the chapter and discusses the possible future directions.

8.3. THE HSFV BASED BIOMETRIC IDENTIFICATION SYSTEM

The block diagram of the proposed HSFV biometric for human identification is shown in Figure 8-2. Each of the blocks of this diagram is discussed in the following subsections.

8.3.1. FACIAL VIDEO ACQUISITION AND FACE DETECTION

The proposed HSFV biometric first requires capturing facial video using a RGB camera, which was thoroughly investigated in the literature [21]–[23]. As recent methods of facial video based heartbeat signal analysis utilized simple webcam for video capturing, we select a webcam based video capturing procedure. After video capturing, the face is detected in each video frame by the face detection algorithm of [22].

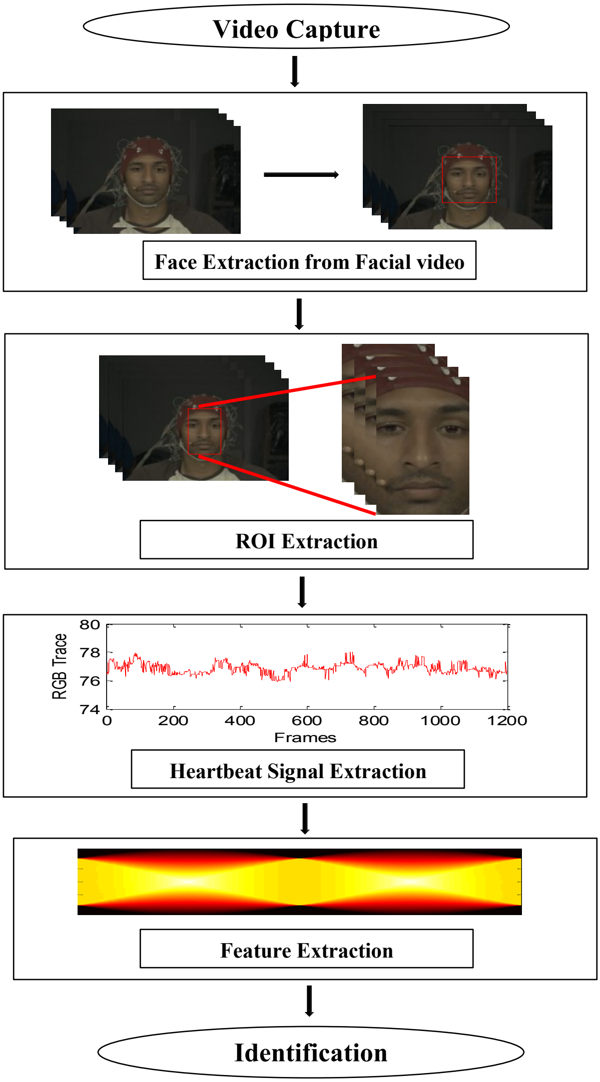

Figure 8-2 The block diagram of the proposed HSFV biometric for human identification.

8.3.2. ROI DETECTION AND HEARTBEAT SIGNAL EXTRACTION

The heartbeat signal is extracted from the facial video by tracing color changes in RGB channels in the consecutive video frames using the method explained in [21]. This is accomplished by obtaining a Region of Interest (ROI) from the face by selecting 60% width of the face area detected by the automatic face detection method. The average of the red, green and blue components of the whole ROI is recorded as the RGB traces of that frame. In order to obtain a heartbeat signal from a facial video, the statistical mean of these three RGB traces of each frame is calculated and recoded for each frame of the video.

The heartbeat signal obtained from such a video looks noisy and imprecise compared to the heartbeat signal obtained by ECG, for example that in Figure 8-1. This is due to the effect of external lighting, voluntary head-motion, and the act of blood as a damper to the heart pumping pressure to be transferred from the middle of the chest (where the heart is located) to the face. Thus, we employ a denoising filter by detecting the peak in the extracted heart signal and discarding the outlying RGB traces. The effect of the denoising operation on a noisy heartbeat signal obtained from RGB traces is depicted in Figure 8-3. The signal is then transferred to the feature extraction module.

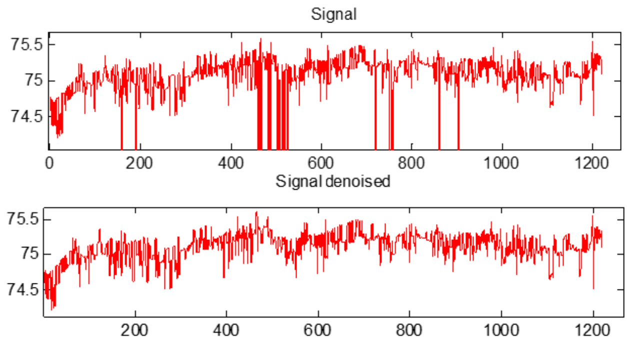

Figure 8-3 A heartbeat signal containing outliers (top) and its corresponding signal obtained after employing a denoising filter (bottom).

8.3.3. FEATURE EXTRACTION

We have extracted our features from radon images, as these images are shown in the ECG based system of [7] to produce proper results. To generate such images we need a waterfall diagram which can be generated by replicating the heartbeat signal obtained from a facial video. The number of the replication equals to the number of the frames in the video. Figure 8-4 depicts an example of a waterfall diagram obtained from the heartbeat signal of Figure 8-3. From the figure, it can be seen that the heartbeat signal is replicated and concatenated in the second dimension of the signal in order to generate the waterfall diagram for a 20 seconds long video captured in a 60 frames per second setting. In order to facilitate the depiction on the figure we employ only 64 times replication of the heartbeat signal in Figure 8-4. The diagram acts as an input to a transformation module in order to extract the features.

The features used in the proposed system are obtained by applying a method called Radon transform [24] to the generated waterfall diagram. Radon transform is an integral transform computing projections of an image matrix along specified directions and widely used to reconstruct images from medical CT scan. A projection of a two-dimensional image is a set of line integrals. Assume $f(x, y)$ is a two-dimensional image expressing image intensity in the (x, y) coordinates. The Radon transform (R) of the image, $R(\theta)[f(x, y)]$, can be defined as follows:

$$R(\theta)[f(x,y)] = \int_{-\infty}^{\infty} f(\acute{x}\cos\theta - \acute{y}\sin\theta, \acute{x}\sin\theta - \acute{y}\cos\theta)\, d\acute{y} \qquad (1)$$

where θ is the angle formed by the distance vector of a line from the line integral with the relevant axis in the Radon space, and

$$\begin{bmatrix} \acute{x} \\ \acute{y} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad (2)$$

When we apply Radon transform on the waterfall diagram of HSFV a two-dimensional Radon image is obtained, which contains the Radon coefficients for each angle (θ) given in an experimental setting. An example Radon image obtained by employing Radon transform on the waterfall diagram of Figure 8-4 is shown in Figure 8-5.

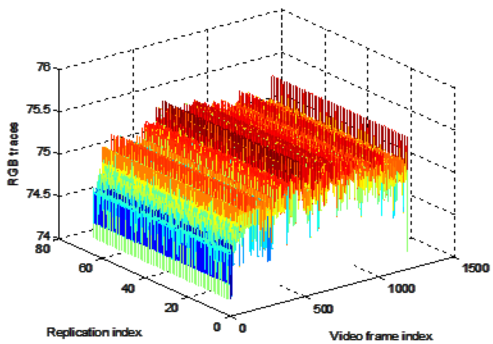

Figure 8-4 Waterfall diagram obtained from an extracted heartbeat signal of a given video.

In order to extract features for authentication, we employ a pairwise distance method between every possible pairs of pixels in the transformed image. We use the well-known distance metric of Minkowski to measure the pairwise distance for a $m \times n$-pixels of the Radon image R by:

$$\mathrm{d}_{st} = \sqrt[p]{\sum_{i=1}^{n} |R_{si} - R_{ti}|^{p}} \qquad (3)$$

where R_s and R_t are the row vectors representing each of the $m(1 \times n)$ row vectors of R, and p is a scalar parameter with $p = 2$. The matrix obtained by employing the pairwise distance method produces the feature vector for authentication.

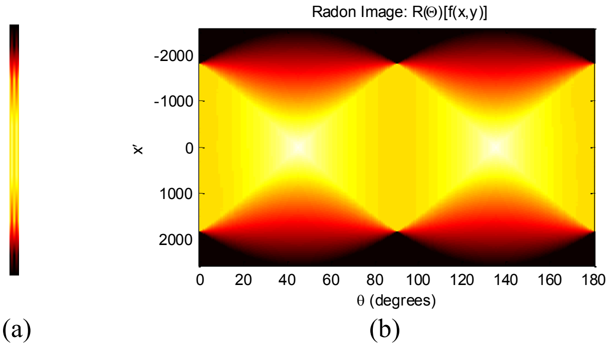

Figure 8-5 Radon image obtained from the waterfall diagram of HSFV: (a) without magnification, and (b) with magnification.

8.3.4. IDENTIFIATION

We utilize the decision tree based method of [25] for the identification. This is a flowchart-like structure including three types of components: i) Internal node- represents a test on a feature, ii) Branch- represents the outcome of the test, and iii) Leaf node- represents a class label coming as a decision after comparing all the features in the internal nodes. Before using the tree (the testing phase), it needs to be trained. At the training phase, the feature vectors of the training data are utilized to split nodes and setup the decision tree. At the testing phase, the feature vector of a testing data passes through the tests in the nodes and finally gets a group label, where a group stands for a subject to be recognized. The training/testing split of the data is explained in the experimental results.

8.4. EXPERIMENTAL RESULTS AND DISCUSSIONS

8.4.1. EXPERIMENTAL ENVIRONMENT

The proposed system has been implemented in MATLAB 2013a. To test the performance of the system we've used the publicly available database of MAHNOB-HCI. This database has been collected by Soleymani et al. [26] and contains facial videos captured by a simple video camera (similar to a webcam) connected to a PC. The videos of the database are recorded in realistic Human-Computer Interaction (HCI) scenarios. The database includes data in two categories: 'Emotion Elicitation Experiment (EEE)' and 'Implicit Tagging Experiment (ITE)'. Among these, the video clips from EEE are frontal face video data and suitable for our experiment

[20], [27]. Thus, we select the EEE video clips from MAHNOB-HCI database as the captured facial videos for our biometric identification system. Snapshots of some video clips from MAHNOB-HCI database are shown in Figure 8-6. The database composes of 3810 facial videos from 30 subjects. However, not all of these videos are suitable for our experiment. This is because of short duration, data file missing, small number of samples for some subjects to divide these into training and testing set, occluded face (forehead) in some videos, and lack of subject's consent. Thus, we selected 351 videos suitable for our experiment. These videos are captured from 18 subjects (16-20 videos for each subject). We used the first 20 seconds of each video for testing and 80 percent of the total data for training in a single-fold experiment.

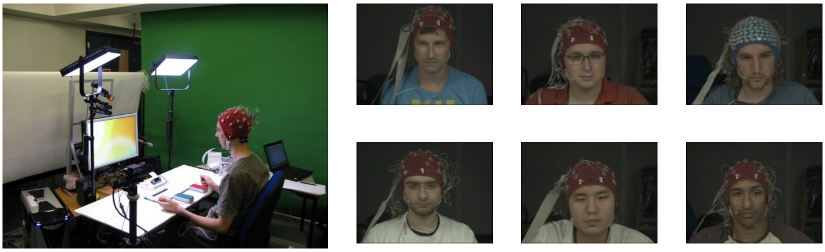

Figure 8-6 Snapshots of some facial video clips from MAHNOB-HCI EEE database [26].

8.4.2. PERFORMANCE EVALUATION

After developing the decision tree from the training data, we generated the authentication results from the testing data. The features of each test subject obtained from the HSFV were compared in the decision tree to find the best match from the training set. The authentication results of 18 subjects (denoted with the prefix 'S-') from the experimental database are shown in a confusion matrix (row matrix) at Table 8-1. The true positive detections are shown in the first diagonal of the matrix, false positive detections are in the columns, and false negative detections are in the rows. From the results it is observed that a good number of true positive identifications were achieved for most of the subjects.

The performance of the proposed HSFV biometric was evaluated by the parameters defined by Jain et al. in [28], which are False Positive Identification Rate (FPIR) and False Negative Identification Rate (FNIR). The FPIR refers to the probability of a test sample falsely identified as a subject. If TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative identifications among N number of trials in an experiment, then the FPIR is defined as:

$$FPIR = \frac{1}{N}\sum_{n=1}^{N}\frac{FP}{TP+TN+FP+FN} \quad (4)$$

The FNIR is the probability of a test sample falsely identified as different subject which is defined as follows:

$$FNIR = \frac{1}{N}\sum_{n=1}^{N}\frac{FN}{TP+TN+FP+FN} \qquad (5)$$

From FNIR we can calculate another metric called True Positive Identification Rate (TPIR) that represents the overall identification performance of the proposed biometric as:

$$TPIR = 1 - FNIR \qquad (6)$$

Table 8-1 Confusion matrix for identification of 351 samples of 18 subjects using the proposed HSFV biometric

Subjects	***S1***	***S2***	***S3***	***S4***	***S5***	***S6***	***S7***	***S8***	***S9***	***S10***	***S11***	***S12***	***S13***	***S14***	***S15***	***S16***	***S17***	***S18***
S1	**16**	2	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
S2	0	**17**	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0
S3	1	1	**16**	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
S4	0	0	0	**18**	0	0	0	1	0	0	0	0	0	0	1	0	0	0
S5	0	0	0	0	**19**	0	1	0	0	0	0	0	0	0	0	0	0	0
S6	4	1	0	0	0	**15**	0	0	0	0	0	0	0	0	0	0	0	0
S7	0	0	0	0	0	0	**18**	0	0	0	0	0	0	2	0	0	0	0
S8	1	0	0	0	0	0	0	**10**	0	0	1	0	1	0	2	1	0	0
S9	0	0	0	0	0	0	0	0	**20**	0	0	0	0	0	0	0	0	0
S10	0	0	0	0	0	0	0	0	0	**18**	0	1	0	1	0	0	0	0
S11	2	2	0	0	0	1	0	1	0	0	**13**	0	0	0	0	0	0	0
S12	0	0	0	0	0	0	2	0	0	0	0	**16**	0	0	0	0	0	0
S13	1	2	0	0	0	0	1	2	0	0	0	0	**12**	0	2	0	0	0
S14	0	0	0	0	0	0	0	0	0	3	0	0	0	**17**	0	0	0	0
S15	0	1	2	0	0	0	0	1	0	0	0	0	1	0	**15**	0	0	0
S16	3	2	0	0	0	0	0	0	0	0	1	0	2	0	1	**11**	0	0
S17	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	**16**	0
S18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	**16**

Besides the aforementioned metrics, we also calculated the system performance over four other metrics from [29]: precision, recall, sensitivity and accuracy. Precision and recall metrics present the ratio of correctly identified positive samples with total number of identification and total number of positive samples in the experiment, respectively. The formulations of these two metrics are:

$$Precision = \frac{1}{N}\sum_{n=1}^{N}\frac{TP}{TP+FP} \tag{7}$$

$$Recall = \frac{1}{N}\sum_{n=1}^{N}\frac{TP}{TP+FN} \tag{8}$$

Specificity presents the ratio of correctly identified negative samples with total number of negative samples and sensitivity presents the ratio of correctly identified positive and negative samples with total number of positive and negative samples. The mathematical formulations of these two metrics are:

$$Specificity = \frac{1}{N}\sum_{n=1}^{N}\frac{TN}{TN+FP} \tag{9}$$

$$Sensitivity = \frac{1}{N}\sum_{n=1}^{N}\frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Table 8-2 summarized the overall system performance in the standard terms mentioned above. From the results it is observed that the proposed HSFV biometric can effectively identify the subjects with a high accuracy.

Table 8-2 Performance of the proposed HSFV biometric based authentication system

Parameters	**Results**
FPIR	1.28%
FNIR	1.30%
TPIR	98.70%
Precision rate	80.86%
Recall rate	80.63%
Specificity	98.63%
Sensitivity	97.42%

One significant point can be noted from the results that the TPIR and precision rate have a big difference in values. This is because the true positive and true negative trials and successes are significantly different in numbers and the system achieved high rate of true negative authentication as indicated by specificity and sensitivity metrics. This implies that the proposed biometric, though is of high potential may need improvement in both the feature extraction and the matching score calculation.

To the best of our knowledge, this chapter is the first to use HSFV as a biometric, thus, there is not any other similar systems in the literature to compare the proposed system against. Though touch based ECG [12] and PCG [14] biometrics obtained more than 90% accuracy on some local databases, we think their direct comparison against our system is biased towards their favor, as they use obtrusive touch-based sensors, which provide precise measurement of heartbeat signals, while we, using our touch-free sensor (webcam), get only estimations of those heartbeat signals that are obtained by touch based sensors. This means that it makes sense if our touch-free system, at least in this initial step of its development, does not outperform those touch-based systems.

The observed results of the touch-free HSFV definitely showed the potential of the proposed system in human identification and it clearly paves the way for developing identification systems based on heartbeat rate without a need for touch based sensors. Reporting the results on a publicly available standard database is expected to make the future studies comparable to this work.

8.5. CONCLUSIONS AND FUTURE DIRECTIONS

This chapter proposed heartbeat signal measured from facial video as a new biometric trait for person authentication for the first time. Feature extraction from the HSFV was accomplished by employing Radon transform on a waterfall model of the replicated HSFV. The pairwise Minkowski distances were obtained from the Radon image as the features. The authentication was accomplished by a decision tree based supervised approach. The proposed biometric along with its authentication system demonstrated its potential in biometric recognition. However, a number of issues need to be studied and addressed before utilizing this biometric in practical systems. For example, it is necessary to determine the effective length of a facial video viable to be captured for authentication in a practical scenario. Fusing face and HSFV together for authentication may produce interesting results by handling the face spoofing. Processing time, feature optimization to reduce the difference between precision and acceptance rate, and investigating different metrics for calculating the matching score are also necessary to be investigated. The potential of the HSFV as a soft biometric can also be studied. Furthermore, it is interesting to study the performance of this biometric under different emotional status when heartbeat signals are expected to change. These could be future directions for extending the current work.

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CHAPTER 9. CAN CONACT-FREE MEASUREMENT OF HEARTBEAT SIGNAL BE USED IN FORENSICS?

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9.1. ABSTRACT

Biometrics and soft biometrics characteristics are of great importance in forensics applications for identifying criminals and law enforcement. Developing new biometrics and soft biometrics are therefore of interest of many applications, among them forensics. Heartbeat signals have been previously used as biometrics, but they have been measured using contact-based sensors. This chapter extracts heartbeat signals, using a contact-free method by a simple webcam. The extracted signals in this case are not as precise as those that can be extracted using contact-based sensors. However, the contact-free extracted heartbeat signals are shown in this chapter to have some potential to be used as soft biometrics. Promising experimental results on a public database have shown that utilizing these signals can improve the accuracy of spoofing detection in a face recognition system.

9.2. INTRODUCTION

Forensic science deals with techniques used in criminal scene investigation for collecting information and its interpretation for the purpose of answering questions related to a crime in a court of law [1]. Such information is usually related to the human body or behavioral characteristics that can (or help to) reveal the identity of criminal(s). Such characteristics are extracted either from traces that are left in the crime scene, like DNA, handwritings, and fingerprints [2], or devices like cam-eras and microphones, if any, that have been recording visual and audio signals in the scene during the crime. Recorded visual signals as well as audio signals can be of great help as many different characteristics can be extracted from them, characteristics that can directly be used for identification (bio-metrics), or can help the identification process (soft biometrics).

Forensics investigations have long been utilizing such human characteristics. For example, the importance of DNA in [3], fingerprint in [4], facial images and its related soft bio-metrics in [5], [6], gait in [7] have been discussed for forensics applications. However, most of these biometric/soft biometric traits exhibit disadvantages in regards to accuracy, spoofing and/or unobtrusiveness. For example, fingerprint can be forged to breach the identification system, gait can be imitated, and facial image can be used in absence of the person. Thus, further investigations for new biometric traits are of interest of many applications. Human heartbeat signal is one of such emerging biometric traits.

Human heart is a muscular organ that works as a circulatory blood pump. When blood is pumped by the heart, some electrical and acoustic changes occur in and around the heart in the body, which is known as heartbeat signal [8]. Heartbeat signal can be obtained by Electrocardiogram (ECG) using electrical changes and Phonocardiogram (PCG) using acoustic changes. Both ECG and PCG heartbeat signals have al-ready been used as biometrics for human identity verification in the literature. A review of such important ECG-based approaches can be obtained from [9]. On the other hand, a re-view of the important PCG-based identification methods can be found in [10]. The common drawback of all of the above mentioned ECG and PCG based methods for identity verification is the requirement of using obtrusive (contact-based) sensors for the acquisition of ECG or PCG signals from a subject. In another words, for obtaining heart signals using ECG and PCG the required sensors need to be directly installed on subject's body, which is obviously not always possible. There-fore, after an introductory work in [11] for heartbeat signal based human authentication, in this chapter we look at contact-free measurement of the Heartbeat Signal from Facial Videos (HSFV) and investigate its distinctiveness potential in forensics. It is shown in this chapter that such signals have distinctive features, however, their distinctiveness capability are not that high to use them as biometrics. Instead, it is shown that they can help improving the detection accuracy of a face spoofing detection algorithm in face recognition system, and hence can be used as a soft biometric in forensics applications, for example, with video-based face recognition algorithms.

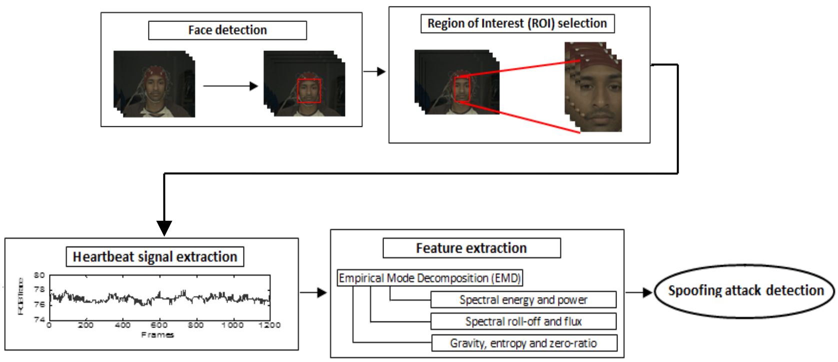


Figure 9-1 The block diagram of the proposed system.

The proposed system obtains HSFV signals from video sequences that are captured by a simple webcam, by tracing changes in the color of facial images that are caused by the heart pulses. Then, it extracts some distinctive features from these signals. Unlike ECG and PCG based heartbeat biometric, the proposed HSFV soft biometric does not require any obtrusive sensor such as ECG electrode or PCG microphone. It is universal and permanent, obviously because every living human being has an active heart. It can be more secure than its traditional counterparts as it is difficult to be artificially generated, and can be easily combined with state-of-the-art face biometric without requiring any additional sensor.

The rest of this chapter is organized as follows: the proposed system for detecting spoofing attacks in a face recognition system and its sub-blocks (including the heartbeat signals measurement and feature extraction) are explained in the next section. The experimental results are given in section four. Finally the chapter is concluded in section five.

9.3. THE PROPOSED SYSTEM

The block diagram of the proposed system is shown in Figure 9-1. Each of these sub-blocks of the system is described in the following subsections.

9.3.1. FACIAL VIDEO ACQUISITION

The first step is capturing the facial video using a RGB cam-era, which is thoroughly investigated in the literature [12–14]. As recent methods of facial video based heartbeat signal analysis utilized simple webcam for video capturing, we select a webcam based video capturing procedure.

9.3.2. FACE DETECTION

Face detection is accomplished by the well-known Haar-like features based Viola and Jones method of [15]. The face region is expressed by a rectangular bounding box in each video frames.

9.3.3. REGION OF INTEREST (ROI) SELECTION

As the face area detected by the automatic face detection method comprises some of the surrounding areas of the face including face boundary, it is necessary to exclude the sur-rounding area to retain merely the area containing facial skin. This is accomplished by obtaining a Region of Interest (ROI) from the face by selecting 60% width of the face area detected by the automatic face detection method.

9.3.4. HEARTBEAT SIGNAL EXTRACTION

The heartbeat signal is extracted from the facial video by tracing color changes in RGB channels in the consecutive video frames. The average of the red, green and blue components of the whole ROI is recorded as the RGB traces of that frame. In order to obtain a heartbeat signal from a facial video, the statistical mean of these three RGB traces of each frame is calculated and recoded for each frame of the video. The resulting signal represents the heartbeat signal.

The heartbeat signal obtained from facial video by following the aforementioned approach is, however, noisy and imprecise. This is due to the effect of external lighting, voluntary head-motion, induced noise by the capturing system and the act of blood as a damper to the heart pumping pressure to be transferred from the middle of the chest (where the heart is located) to the face. Thus, we employ a de-noising filter by detecting the peak in the extracted heart signal and discarding the out-lying RGB traces. The effect of the de-noising operation on a noisy heartbeat signal obtained from RGB traces is depicted in Figure 9-2. The signal is then passed through a Hodrick-Prescott filter [16] with a smoothing parameter (value = 2 in our case) in order to decompose it into trend and cyclic components. As heartbeat is a periodic vibration due to the heart pulse, we assume that the trend component comprises the noise in the heartbeat signal induced by voluntary head-motion. Thus, we obtain the denoised heart-beat signal from the cyclic component.

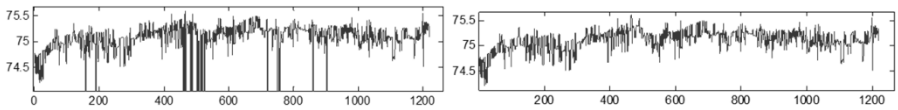


Figure 9-2 An example of heartbeat signal before (left) and after (right) employing a de-noising filter. On the x-axis is the frame number and on the y-axis is the RGB trace.

9.3.5. FEATURE EXTRACTION

The feature extraction from the denoised HSFV is accomplished by employing a decomposition method called Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) from [17]. The CEEMDAN decom-poses the HSFB into a small number of modes called Intrinsic Mode Functions (IMFs). The number of IMFs can vary, but not less than 6 in this case. Thus, we considered first 6 IMFs. An example of first 6 IMFs for a HSFV in the case of a real face are shown in Figure 9-3. We then calculated some spectral features of the original HSFV and each of the 6 IMFs for feature extraction. The extracted features from the one dimensional HSFV are the statistical mean and variance of the spectral energy, power, low-energy, gravity, entropy, roll-off, flux, zero-ratio as stated in [18–21] for one dimensional audio signal. As a whole, we extracted a feature vector of 112 elements for each facial video.

9.3.6. SPOOFING ATTACK DETECTION

We employ the Support Vector Machines of [22], with a tangent hyperbolic kernel function, as the classifier to discriminate between real facial video and spoofing attack.

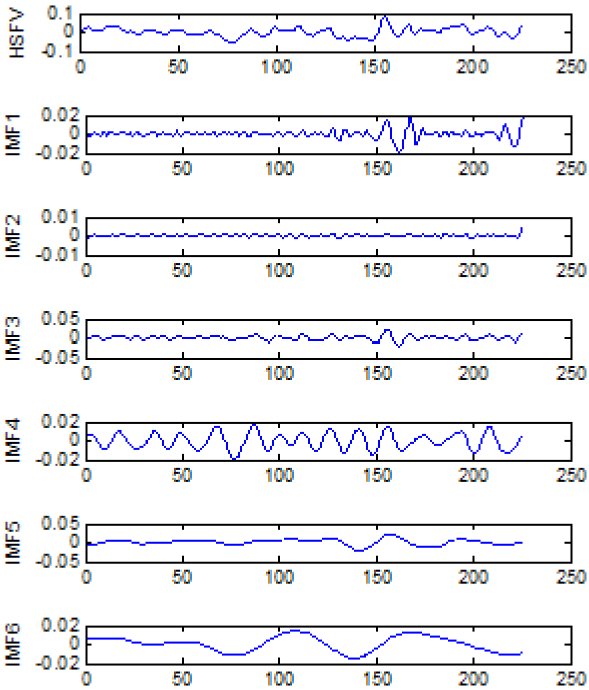


Figure 9-3 An example of first 6 IMFs with obtained for a HSFV of a real face.

9.4. EXPERIMENTAL RESULTS AND DISCUSSIONS

9.4.1. EXPERIMENTAL ENVIRONMENT

The performance of spoofing detection using the HSFV was evaluated in a system implemented in a combination of MAT-LAB and C++ environment by following the methodology of the previous section. We used the publicly available PRINT-ATTACK database [23] for spoofing attack detection. This database was collected by Anjos et al. and contains facial videos (each about 10 seconds long) captured by a simple webcam. The videos of the database are recorded in three scenarios. These are: video of real face, video of printed face held by operator's hand, video of printed face held by a fixed support. All these videos were then categorized into three sets: *train*, *devel*, and *test*. The details are given in Table 9-1. However, some of these videos are too dark to automatically detect face and extract heart signal. Thus, we discarded 2 videos from the *train* set and 4 videos from the *devel* set. The rest of the videos were used in the experiment.

9.4.2. PERFORMANCE EVALUATION

A spoofing detection system exhibits two types of errors: accepting a spoofed face and rejecting a real face. First error is measured by False Acceptance Rate (FAR) and the second one is measured by False Rejection Rate (FRR). The performance can be depicted on a Receiver Operating Characteristics (ROC) graph where FAR and FRR are plotted against a threshold to determine the membership in true groups of real access and spoofed access. The ROC of the different combinations of datasets, after the training using *train* set, is shown in Figure 9-4. From the results it is observed that the Equal Error Rates (EER), where FAR and FRR curves intersect, are different for different settings. When a printed face was shown in front of the camera by holding it in a fixed place the periodic variation in the heart signal of a real face can be discriminated with higher accuracy as shown in Figure 9-4(a) and (d). But, when the printed face was held by hand, the hand shaking behavior affects the result. However, the results show that HSFV can retrieve the difference between real face and print attack moderately accurately.

Table 9-1 The Numbers of videos in different groups of the PRINT-ATTACK database [23]

Type	***train***	***devel***	***test***	**Total**
Real face	60	60	80	200
Printed face in hand	30	30	40	100
Printed face in a support	30	30	40	100
Total	120	120	160	400

9.4.3. PERFORMANCE COMPARISON

We compare the performance of the HSFV with the baseline results for the test set of the PRINT-ATTACK database provided in [23]. The results are shown in Table 9-2.

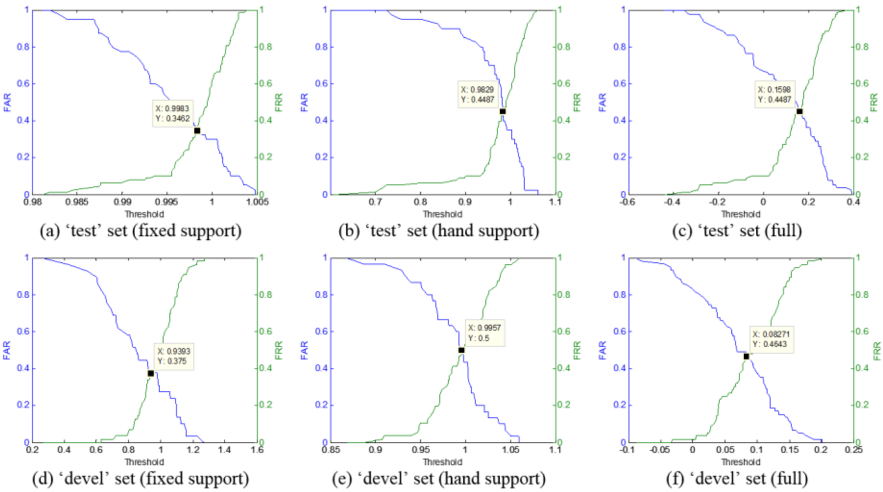
From the results it is observed that the HSFV alone cannot outperform the baseline approach. However, the experiment reveals that the HSFV is able to unveil some clues between real face and printed face shown to a biometric system, and can be a potential soft biometric to be used along with other features to achieve a doable result in face spoofing detection. This notion is shown in the last three rows of Table 9-2, where the features extracted from HSFV is fused with four background features (maximum, minimum, average and standard deviation of the signal obtained from the video frames background by following [23]), hereafter referred as BG. We employ a score-level fusion of probability estimates of classifier outputs obtained for HSFV and BG features. We observe that the fusion of HSFV and BG features improves the performance in face spoofing detection. One significant point to mention is that when BG features were fused with HSFV features in score-level, the spoofing detection system showed reduced performance than the baseline as indicated by the third-last row of Table 9-2. We believe that this is because of sensitivity of HSFV to the periodic noise induced by the camera capturing system.

Table 9-2 Performance of HSFV in spoofing detection in comparison to a baseline for PRINT-ATTACK database [23]

Type	***test*-dataset**
HSFV (fixed)	66,10
HSFV (hand)	66,10
HSFV (all)	61,39
Baseline (fixed)	77,94
Baseline (hand)	85,47
Baseline (all)	82,05
HSFV (fixed)+BG	75,64
HSFV (hand)+BG	91,03
HSFV (all)+BG	85,90

9.4.4. DISCUSSIONS ABOUT HSFV AS A SOFT BIOMETRIC FOR FORENSIC INVESTIGATIONS

Face recognition systems need to be robust against spoofing attacks. As printed face spoofing attack is very common in this regard, we investigate the potential of HSFV as a soft biometric for printed face spoofing attack detection in a face recognition system. Though from the results it is observed that the HSFV alone cannot provide very high accuracy, it is able to unveil some clues between real face and printed face shown to a biometric system. When HSFV was fused with some other features (BG features in our experiment), the results were considerably improved in most of the cases. Thus, we can infer that the HSFV carries some distinctive features and can be considered as a soft biometric. Hence, one could answer the question raised by the chapter by a *Yes* answer, i.e., heartbeat signals extracted from facial images have some distinctive properties and might be useful for forensics applications.



(a) 'test' set (fixed support) (b) 'test' set (hand support) (c) 'test' set (full)

(d) 'devel' set (fixed support) (e) 'devel' set (hand support) (f) 'devel' set (full)

Figure 9-4 ROC curves for employing the HSFV based spoofing detection on different combinations of the experimental datasets.

9.5. CONCLUSIONS

This chapter investigated the potential of the heartbeat signal from facial video as a new soft biometric. To do that, the distinctive properties that are carried in a heartbeat signal have been utilized to improve the accuracy of spoofing attack detection in a face recognition system. A description of the procedure of heartbeat signal extraction from facial video was provided and experimental results were generated by using a publicly available database for printed face spoofing attack detection in a face recognition system. The experimental results revealed that the contact-free measured heartbeat signal has the potential to be used as a soft biometric.

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CHAPTER 10. CONTACT-FREE HEARTBEAT SIGNAL FOR HUMAN IDENTIFICATION AND FORENSICS

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10.1. ABSTRACT

The heartbeat signal, which is one of the physiological signals, is of great importance in many real-world applications, for example, in patient monitoring and biometric recognition. The traditional methods for measuring such this signal use contact-based sensors that need to be installed on the subject's body. Though it might be possible to use touch-based sensors in applications like patient monitoring, it won't be that easy to use them in identification and forensics applications, especially if subjects are not cooperative. To deal with this problem, recently computer vision techniques have been developed for contact-free extraction of the heartbeat signal. We have recently used the contact-free measured heartbeat signal, for bio-metric recognition, and have obtained promising results, indicating the importance of these signals for biometrics recognition and also for forensics applications. The importance of heartbeat signal, its contact-based and contact-free extraction methods, and the results of its employment for identification purposes, including our very recent achievements, are reviewed in this chapter.

10.2. INTRODUCTION

Forensic science deals with collecting and analyzing information from a crime scene for the purpose of answering questions related to the crime in a court of law. The main goal of answering such questions is identifying criminal(s) committing the crime. Therefore, any information that can help identifying criminals can be useful. Such information can be collected from different sources. One such a source, which has a long history in forensics, is based on human biometrics, i.e., human body or behavioral characteristics that can identify a person, for example, DNA [1], fingerprints [2], [3], and facial images [4]. Besides human biometrics, there is another closely related group of human features/characteristics that cannot identify a person, but can help the identification process. These are known as soft biometrics, for instance, gender, weight, height, gait, race, and tattoo.

The human face, which is of interest of this chapter, is not only used as a biometric, but also as a source for many soft biometrics, such as gender, ethnicity, and facial marks and scars [5], [6], [8]. These soft biometrics have proven great values for forensics applications in identification scenarios in unconstrained environments wherein commercial face recognition systems are challenged by wild imaging conditions, such as off frontal face pose and occluded/covered face images [7], [8]. The mentioned facial soft-biometrics are mostly based on the physical features/characteristics of the human. In this chapter, we look into heartbeat signal which is a physiological feature/characteristic of the human that similar to the mentioned physical ones can be extracted from facial images in a contact-free way, thanks to the recent advances in computer vision algorithms. The heartbeat signal is one of the physiological signals that is generated by the cardiovascular system of the human body. The physiological signals have been used for different purposes in computer vision applications. For example, in [9] electromyogram, electrocardiogram, skin conductivity and respiration changes and in [10] electrocardiogram, skin temperature, skin conductivity, and respiration have been used for emotion recognition in different scenarios. In [11] physiological signals have been used for improving communication skills of children suffering from Autism Spectrum Disorder in a virtual reality environment. In [12], [13], and [14] these signals have been used for stress monitoring. Based on the results of our recent work, which are reviewed here, the heartbeat signal shows promising results to be used as a soft biometric.

The rest of this chapter is organized as follows: first, the measurements of heartbeat signal using both contact-based and contact-free methods are explained in the next section. Then, employing these signals for identification purposes is discussed in section four. Finally, the chapter is concluded in section five.

10.3. MEASUREMENT OF HEARTBEAT SIGNAL

The heartbeat signal can be measured in two different ways: contact-based and contact-free. These methods are explained in the following subsections.

10.3.1. CONTACT-BASED MEASUREMENT OF HEARTBEAT SIGNAL

The heartbeat signal can be recorded in two different ways using the contact-based sensors:

- By monitoring electrical changes of muscles during heart functioning, by a method that is known as Electrocardiogram which records ECG signals.
- By listening to the heart sounds during its functioning, by a method that is known as Phonocardiogram which records PCG signals.

The main problem of the above mentioned methods is obviously the need for the sensors to be in contact (touch) with the subject's body. Depending on the application of the measured heartbeat signal, this requirement may have different consequences, for example, for:

- Constant monitoring of patient, having such sensors on the body may cause some skin irritation.
- Biometric recognition, the subjects might not be cooperative to wear the sensors properly.

Therefore, contact-free measurement of heartbeat signals can be of great advantage in many applications. Thanks to the recent advances in computer vision techniques, this has been possible recently to measure heartbeat signals using a simple webcam. Methods developed for this purpose are reviewed in the following subsection.

10.3.2. CONTACT-FREE MEASUREMENT OF HEARTBEAT SIGNAL

The computer vision techniques developed for heartbeat measurement mostly utilize facial images. The reason for this goes back to this fact that heart pulses generate some periodic changes on the face, as well as other parts of the human body. How-ever, since the human face is mostly visible, it is usually this part of the body that has been chosen by the researchers to extract the heartbeats from. The periodic changes that are caused by the heartbeat on the face are of two types:

- Changes in head motion which is a result of periodic flow of the blood through the arteries and the veins for delivering oxygenated blood to the body cells.
- Changes in skin color which is a result of having a specific amount of blood under the skin in specific periods of time.

None of these two types of changes are visible to the human eyes, but they can be revealed by computer vision techniques, like Eulerian magnification of [16] and [17]. The computer vision techniques developed for heartbeat measurement are divided into two groups, depending on the source (motion or color) they utilize for the measurement. These two types of methods are reviewed in the following subsections.

10.3.2.1 Motion for Contact-Free Extraction of Heartbeat Signal

The first motion-based contract-free computer vision method was just recently released by [18]. This system utilizes the fact that periodic heart pules, through aorta and carotid arteries, produce periodic subtle motions on the head/face which can be detected from a facial video. To do that, in [18] some stable facial points, known as good features to track, are detected and tracked over time. The features they track are located on the forehead area and the region between the mouth and then nose are as these areas are less affected by internal facial expressions and their moments should thus be from another source, i.e., heart pules. Tracking these facial points' results in a set of trajectories, which are first filtered by a Butterworth filter to remove the irrelevant frequencies. The periodic components of these trajectories are then extracted by PCA and considered as the heartbeat rate. Their system has been tested on video sequences of 18 subjects. Each video was of resolution of 1280x720 pixels, at a frame rate of 30 with duration of 70-90 seconds.

To obtain the periodicity of the results of the PCA (applied to the trajectories), in [18] a Fast Fourier Transform (FFT) has been applied to the obtained trajectories from the good features to track points. Then, a percentage of the total spectral power of the signal accounted for by the frequency with the maximal power and its first harmonic is used to define the heartbeat rate of the subject [18]. Though this produces reasonable results when the subjects are facing the camera, it fails when there are other sources of motion on the face. Such sources of motion can be for instance, changes in facial expressions and involuntary head motion. It is shown in [19] that such motions makes the results of [18] far from correct. The main reason is because the system in [18] uses the frequency with the maximal power as the first harmonic when it estimates the heartbeat rate. However, such an assumption may not always be true, specifically when the facial expression is changing [19]. To deal with these problems [19] has detected good features to track Figure 10-1(right) from the facial regions shown in Figure 10-1(left).

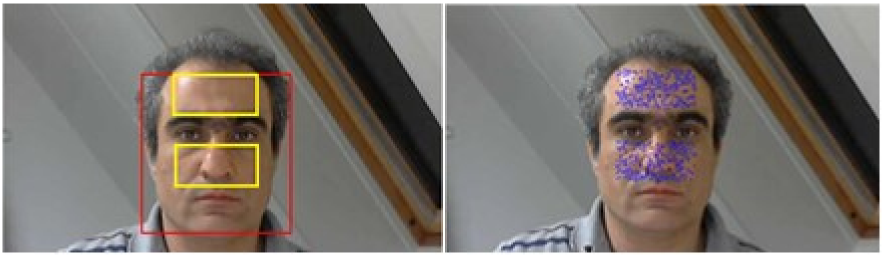

Figure 10-1 The facial regions (yellow areas in the left image) that have been used for detecting good feature to track (blue dots in the right image) for generating motion trajectories in [19].

Then, [19] tracks the good features to track to generate motion trajectories of these features. Then, it replaces the FFT with a Discrete Cosine Transform (DCT), and has employed a moving average filter before the Butterworth filter of [18]. Figure 10-2 shows the effect of the moving average filter employed in [19] for reducing the noise (resulting from different sources, e.g., motion of the head due to facial expression) in the signal that has been used for estimating the heartbeat rate.

Experimental results in [19] show that the above mentioned simple changes have improved the performance of [19] compared to [18] in estimating the heartbeat signal, specifically, when there are changes in facial expressions of the subjects. The system in [19] has been tested on 32 video sequences of five subjects in different facial expressions and poses with duration about 60 seconds.

To the best of our knowledge, the above two motion based systems are the only two methods available in the literature for contact-free measurement of the heartbeat rate using motion of the facial features. It should be noted that these systems do not report their performance/accuracy on estimating the heartbeat signal, but do so only for the heartbeat rate. The estimation of heartbeat signals are mostly reported in the color based systems which are reported in the next subsection.

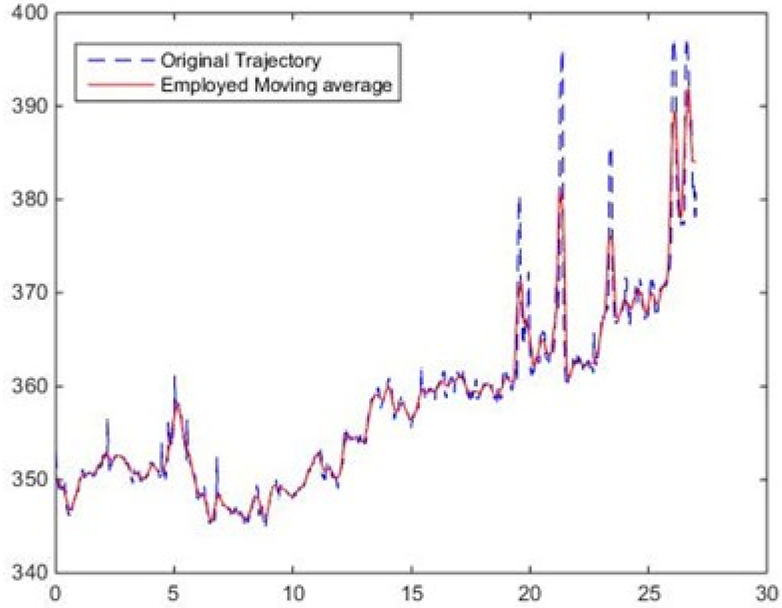

Figure 10-2 The original signal (red) vs. the moving averaged one (blue) used in [19] for estimating the heartbeat rate. On x and y-axis are the time (in seconds) and the amplitude of a facial point (from (good features to track)) that has been tracked, respectively.

10.3.2.2 Color for Contact-Free Extraction of Heartbeat Signal

Using expensive imaging techniques for utilizing color of facial (generally skin) regions for the purpose of estimating physiological signal has been around for decades. However, the interest in this field was boosted when the system of [20] reported its results on video sequences captured by simple webcams. In this work, [20], Independent Component Analysis (ICA) has been applied to the RGB separated color channels of facial images, which are tracked over time, to extract the periodic components of these channels. The assumption here is that periodic blood circulation makes subtle periodic changes to the skin color, which can be revealed by Eulerian magnification of [16]. Having included a tracker in their system, they have measured heartbeat signals of multiple people at the same time [20]. Furthermore, it has been discussed in [20] that this method is tolerant towards motion of the subject during the experiment as it is based on the color of the skin. They have reported the results of their systems on 12 subjects facing a webcam that was about 0.5 meters away in an indoor environment. Shortly after in [21] it was shown that besides heartbeat, the methods of [20] can be used for measuring other physiological signals, like respiratory rate.

The interesting results of the above systems motivated others to work on the weakness of those systems, which had been tested only in constrained conditions. Specifically,

- In [22], it has been discussed the methods of [20] and [21] are not that efficient when the subject is moving (questioning the claimed motion tolerance of [20] and [21]) or when the lightning is changing, like in an outdoor environment. To compensate for these they have performed a registration prior to calculating the heartbeat signals. They have tested their system in an outdoor environment in which the heartbeat signals are computed for subjects driving their vehicles.
- In [23] auto-regressive modelling and pole cancellation have been used to reduce the effect of the aliased frequency components that may worsen the performance of a contact-free color based system for measuring physiological signals. They have reported their experimental results on patients that are under monitor in a hospital.
- In [24] normalized least mean square adaptive filtering has been used to reduce effect of changes in the illumination in a system that tracks changes in color values of 66 facial landmarks. They reported their experimental results on the large facial database of MAHNOB-HCI [25] which is publicly available. The re-ported results show that the system of [24] outperforms the previously published contact-free methods for heartbeat measurement including the color-based meth-ods of [20] and [21] and the motion-based of [18].

10.4. USING HEARTBEAT SIGNAL FOR IDENTIFICATION PURPOSES

Considering the fact the heartbeat signals can be obtained using the two different methods explained in the previous section, different identification methods have been developed. These are reviewed in the following subsections.

10.4.1. HUMAN IDENTIFICATION USING CONTACT-BASED HEARTBEAT SIGNAL

The heartbeat signals obtained by contact-based sensors (in both ECG and PCG forms) have been used for identification purposes for more than a decade. Here we only review those methods that have used ECG signals as they are more common than PCG ones for identification.

There are many different methods for human identification using ECG signals: [27]-[44], to mention a few. These systems have either extracted some features from the heart signal or have used the signal directly for identification. For example, it has been discussed in [27] that the heart signal (in an ECG form) composes of three parts: a P wave, a QRS complex, and a T wave (Figure 10-3). These three parts and their related key points (P, Q, R, S, and T, known as fiducial points) are then found and used to calculate features that are used for identification, like the amplitude of the peaks or valleys of these point, the onsets and offsets of the waves, and the duration of each part of the signal from each point to the next. Similar features have been combined in [29] with radius curvature of different parts of the signal. It is discussed in [38] that one could ultimately extract many fiducial points from an ECG signal, but not all of them are equally efficient for identification.

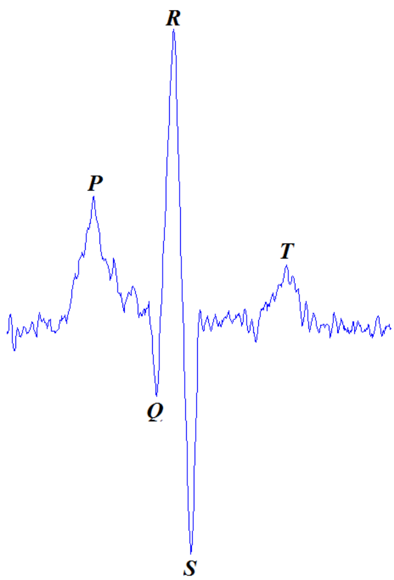

Figure 10-3 A typical ECG signal in which the important key points of the signal are labeled.

In [30], [31], [35], [37], and [39] it has been discussed that fiducial points detection based methods are very sensitive to the proper detection of the signal boundaries, which is not always possible. To deal with this, in:

- [30] the ECG signals have directly been used for identification in a Principal Component Analysis (PCA) algorithm.
- [31] the ECG signal has been first divided into some segments and then the coefficients of the Discrete Cosine Transform (DCT) of the autocorrelation of these segments have been obtained for the identification.
- [35] a ZivMerhav cross parsing method based on the entropy of the ECG signal has been used.
- [37], [40], [43] the shape and morphology of the heartbeat signal has been directly used as feature for identification.

- [39] sparse representation of the ECG signal has been used for identification.
- [33], [34], [36] frequency analysis methods have been applied to ECG signals for identification purposes. For example, in [33] and [36] wavelet transformation has been used and it is discussed that it is more effective against noise and outliers.

10.4.2. HUMAN IDENTIFICATION USING CONTACT-FREE HEARTBEAT SIGNAL

The above mentioned systems use contact-based (touch-based) sensors for measuring heartbeat signals. These sensors provide accurate, however sensitive to noise, measurements. Furthermore, they suffer from a major problem: these sensors need to be in contact with the body of the subject of interest. As mentioned before, this is not always practical, especially in identification context if subjects are not cooperative. To deal with this, we in [45] have developed an identification system that uses the heartbeat signals that are extracted using the contact-free technique of [21]. To the best of our knowledge this is the first system that uses the contact-free heartbeat signals for identification purposes. In this section we review the details of this system and its findings.

Having obtained the heartbeat signals, in form of RGB traces, from facial images using the method of [21] in [45] first a denoising filter is employed to reduce the effect of the external sources of noise, like changes in the lightning and head motions. To do that, the peak of the measured heartbeat signal is found and used to discard the outlying RGB traces. Then, the features that are used for the identification are extracted from this denoised signal. Following [26] the features that are used for identification in [45] are based on Radon images obtained from the RGB traces. To produce such images from the RGB traces, in [45] first the tracked RGB traces are replicated to the same number as the number of the frames that is available in the video sequence that is used for the identification, to generate a waterfall diagram. Figure 10-4 shows an example of such a waterfall diagram obtained for a contact-free measured heartbeat signal.

The Radon image, which contains the features that are going to be used for the recognition in [45], is then generated from the waterfall by applying a Radon transform to the waterfall diagram. Figure 10-5 shows the obtained Radon image from the waterfall diagram of Figure 10-4. The discriminative features that are used for identification purposes from such a Radon image are simply the distance between every two possible pixels of the image.

The experimental results in [45] on a subset of the large facial database of MAHNOB-HCI [25] shown in Table 10-1 indicate that the features extracted from the Radon images of the heartbeat signals that were collected using a contact-free computer vision technique carries some distinctive properties.

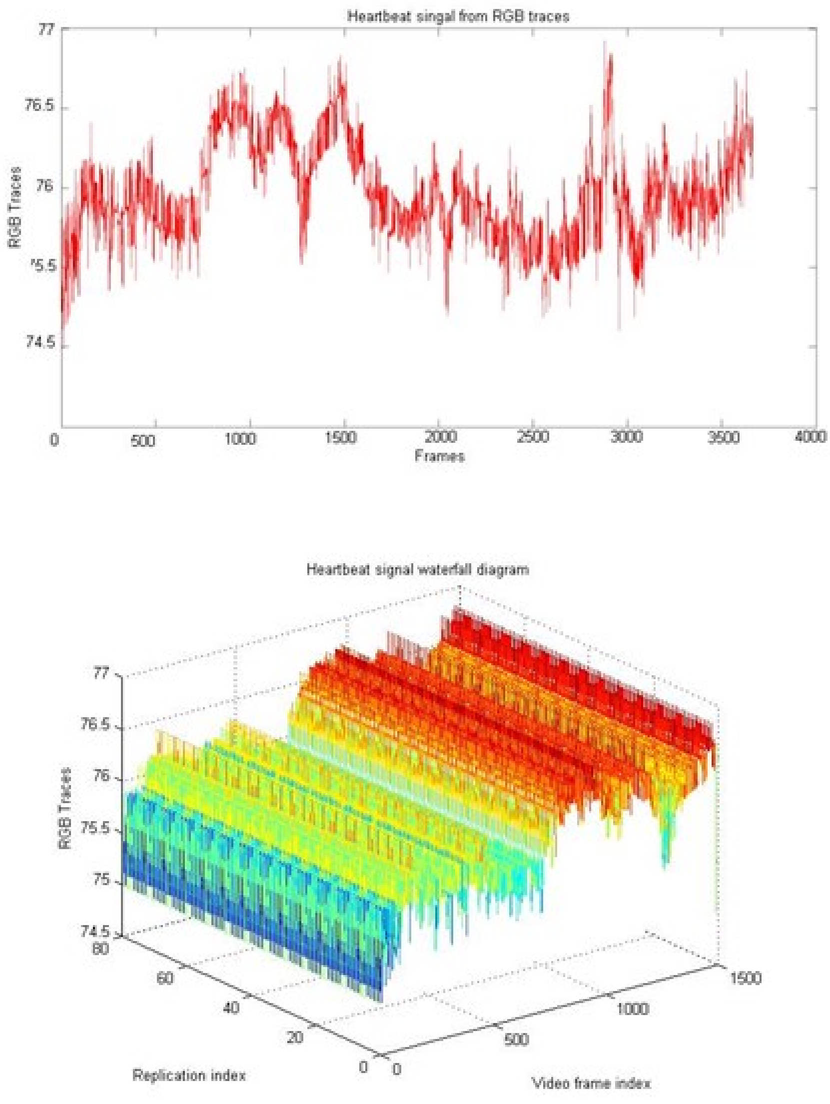

Figure 10-4 A contact-free measured heartbeat signals (on the top) and its waterfall diagram (on the bottom).

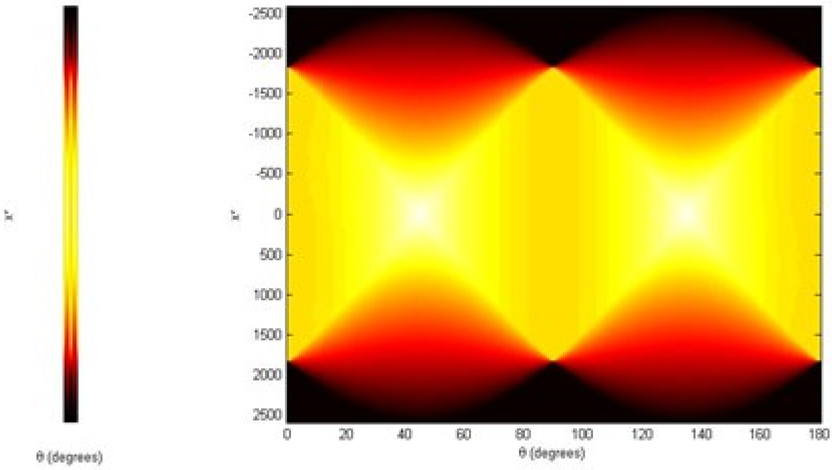

Figure 10-5 The Radon image obtained from the waterfall diagram of Figure 10-4. The discriminative features for the identification purposes are extracted from such Radon images [45]. The image on the right is the zoomed version of the one on the left.

Table 10-1 The identification results using distance features obtained from Radon images of contact-free measured heartbeat signals from [45] on a subset of MAHNOB-HCI [25] containing 351 video sequences of 18 subjects

Measured Parameter	Results
False positive identification rate	1.28 %
False negative identification rate	1.30%
True positive identification rate	98.70 %
Precision rate	80.86%
Recall rate	80.63%
Specificity	98.63%
Sensitivity	97.42%

10.5. DISCUSSIONS AND CONCLUSIONS

If the heartbeat signals are going to be used for identification purposes, they should serve as a biometric or a soft-biometric. A biometric signal should have some specific characteristics, among others, it needs to be:

- Collectible, i.e., the signal should be extractable. The ECG-based heartbeat signal is obviously collectible, though one needs to install ECG sensors on the body of subjects, which is not always easy, especially when subjects are not cooperative.
- Universal, i.e., everyone should have an instance of this signal. An ECG heartbeat signal is also universal as every living human has a beating heart. This also high-lights another advantage of heartbeat signal which liveness. Many of the other biometrics, like face, iris, and fingerprints, can be spoofed by printed versions of the signal, and thus need to be accompanied by a liveness detection algorithm. Heartbeat signal however does not need liveness detection methods [35] and is difficult to disguise [29].
- Unique, i.e., instances of the signal should be different from one subject to an-other.
- Permanent, i.e., the signal should not change over time [15].

Regardless of the method used for obtaining the heartbeat signal (contact-free or contact-based), such a signal is collectible (according to the discussions in the previous sections) and obviously universal. The identification systems that have used the contact-based sensors (like ECG), [27]-[44] have almost all reported recognition accuracies that are more than 90% on datasets of different sizes from 20 people in [27] to about 100 subjects in the others. The lowest recognition rate, 76.9 %, has been reported in [34]. The results here are however reported on a dataset of 269 subjects for which the ECG signals have been collected in different sessions. Some of the sessions are from the same day and some are form different days. If both the training and the testing samples are from the same day (but still different sessions) the system report 99% recognition rate, but when the training and testing data is coming from different sessions recorded in different days, the recognition rate drops to 76.9% for the rank-1 recognition, but still as high as 93.5% for rank-15 recognition. This indicates that an ECG based heartbeat signal might be considered as a biometric, though there is not that much study on the permanent dimensions of such signals for the identification purposes, reporting their results on very large databases.

On the other hands, due to the measurement techniques that contact-free methods provide for obtaining the heartbeat signals, the discriminative properties of contact-free obtained heartbeat signals is not as high as their peer contact-based ones. However, it is evident from the results of our recent work, which was reviewed in the previous section, that such signals have some discriminative properties that can be utilized for helping identification systems. In another words, a contact-free obtained heartbeat signal has the potential to be used as soft-biometric.

To conclude, the contact-free heartbeat signals seem to have promising applications in forensics scenarios. First of all, because according to the above discussions they seem to carry some distinguishing features, which can be used for identification purposes. Furthermore, according to the discussion presented in [18] the motion based methods, which do not necessarily need to extract these signals from a skin region, can extract the heartbeat data from the hairs of the head, or even from a masked face. This will be of great help in many forensics scenarios, if one could extract a biometric or even a soft-biometric from a masked face because in many such scenarios the criminals are wearing a mask to hide their identity from, among others, surveillance cameras.

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PART VI

DECISION SUPPORT SYSTEM FOR HEALTHCARE

CHAPTER 11. CONSTRUCTING FACIAL EXPRESSION LOG FROM VIDEO SEQUENCES USING FACE QUALITY ASSESSMENT

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11.1. ABSTRACT

Facial expression logs from long video sequences effectively provide the opportunity to analyse facial expression changes for medical diagnosis, behaviour analysis, and smart home management. Generating facial expression log involves expression recognition from each frame of a video. However, expression recognition performance greatly depends on the quality of the face image in the video. When a facial video is captured, it can be subjected to problems like low resolution, pose variation, low brightness, and motion blur. Thus, this chapter proposes a system for constructing facial expression log by employing a face quality assessment method and investigates its influence on the representations of facial expression logs of long video sequences. A framework is defined to incorporate face quality assessment with facial expression recognition and logging system. While assessing the face quality a face-completeness metric is used along with some other state-of-the-art metrics. Instead of discarding all of the low quality faces from a video sequence, a windowing approach has been applied to select best quality faces in regular intervals. Experimental results show a good agreement between the expression logs generated from all face frames and the expression logs generated by selecting best faces in regular intervals.

11.2. INTRODUCTION

Facial analysis systems now-a-days have been employed in many applications including surveillance, medical diagnosis, biometrics, expression recognition and social cue analysis (Cheng, 2012). Among these, expression recognition received remarkable attention in last few decades after an early attempt to automatically analyse facial expressions by (Suwa, 1978).

In general, human facial expression can express emotion, intension, cognitive processes, pain level, and other inter- or intrapersonal meanings (Tian, 2011). For example, Figure 11-1 depicts five emotion-specified facial expressions (neutral, anger, happy, surprise, and sad) of a person's image from a database of (Kanade, 2000). When facial expression conveys emotion and cognitive processes, facial expression recognition and analysis systems find their applications in medical diagnosis for diseases like delirium and dementia, social behaviour analysis in meeting rooms, offices or classrooms, and smart home management (Bonner, 2008, Busso, 2007, Dong, 2010, Doody, 2013, Russell, 1987). However these applications often require analysis of facial expressions acquired from videos in a long time-span. A facial expression log from long video sequences can effectively provide this opportunity to analyse facial expression changes in a long time-span. Examples of facial expression logs for four basic expressions found in an example video sequence are shown in Figure 11-2, where facial expression intensities (0-100), assessed by an expression recognition system, are plotted against the video sequence acquired from a camera.

Figure 11-1 Five emotion-specified facial expressions for the database of (Kanade, 2000): (left to right) neutral, anger, happy, surprise, and sad.

Recognition of facial expressions from the frames of a video is essentially the primary step of generating facial expression log. As shown in Figure 11-3, a typical facial expression recognition system from video consists of three steps: face acquisition, feature mining, and expression recognition. Face acquisition step find the face from video frames by a face detector or tracker. Feature mining step extracts geometric and appearance based features from the face. The last step, i.e., expression recognition employs learned classifiers based on the extracted features and recognizes expressions.

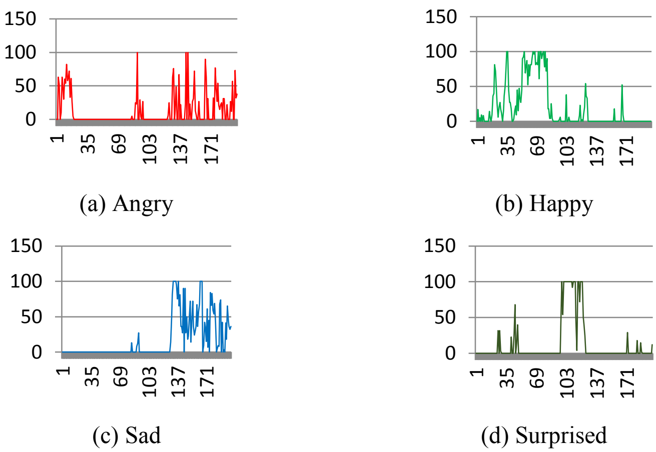


Figure 11-2 An illustration of facial expression log for four basic expressions found in a video, where vertical axis presents the intensities of expression corresponding to the sequence in the horizontal axis.

Generating facial expression log from a video sequence involves expression recognition from each frame of the video. However, when a video based practical image acquisition system captures facial image in each frame, many of these images are subjected to the problems of low resolution, pose variation, low brightness, and motion blur (Feng, 2008). In fact, most of these low quality images rarely meet the minimum requirements for facial landmark or expression action unit identification. For example, a face region with size 96x128 pixels or 69x93 pixels can be used for expression recognition. However, a face region with size 48x64 pixels, 24x32 pixels, or less is not likely to be used for expression recognition (Tian, 2011). This state of affairs can often be observed in scenarios where facial expression log is used from a patient's video for medical diagnosis, or from classroom video for social cue analysis. Extracting features for expression recognition from a low quality face image often ends up with erroneous outcome and wastage of valuable computation resource.

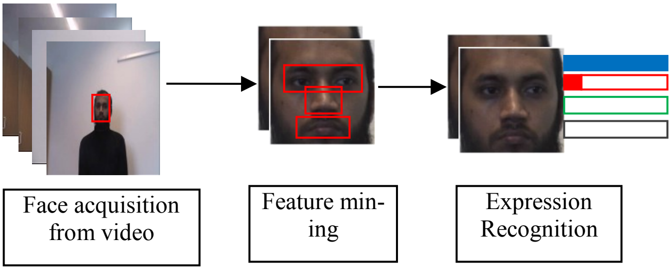


Figure 11-3 Steps of a typical facial expression recognition system.

In order to get rid of the problem of low quality facial image processing, a face quality assessment technique can be employed to select the qualified faces from a video. As shown in Figure 11-4, a typical face quality assessment method consists of three steps: video frame acquisition, face detection in the video frames using a face detector or tracker, face quality assessment by measuring face quality metrics (Mohammad, 2013). Face quality assessment in video before further application reduces significant amount of disqualified faces and keeps the best faces for subsequent processing. Thus, in this chapter, we propose a facial expression log construction system by employing face quality assessment and investigate the influence of Face Quality Assessment (FQA) on the representation of facial expression logs of long video sequences.

The rest of the chapter is organized as follows: Section three presents the state-of-the-art and Section four describes the proposed approach. Section five states the experimental environment and results. Section six concludes the chapter.

11.3. STATE-OF-THE-ARTS

The first step of facial expression recognition is facial image acquisition, which is accomplished by employing a face detector or tracker. Real-time face detection from video was a very difficult problem before the introduction of Haar-like feature based Viola and Jones object detection framework (Viola, 2001). Lee et al. and Ahmed et al. proposed two face detection methods based on saliency map (Lee, 2011, Ahmad, 2012). However, these methods, including the Viola and Jones one, merely work real-time for low resolution images. Thus, few methods address the issues of high resolution face image acquisition by employing high resolution camera or pan-tilt-zoom camera (Chang, 2012, Dinh, 2011). On the other hand, some methods addressed the problem by speeding up the face detection procedure in a high resolution image (Mustafa, 2007, 2009). When a face is detected in a video frame, instead of detecting the face in further frames of that video clip, it can be tracked. Methods for tracking face in video frames from still cameras and active pan-tilt-zoom cameras are proposed in (Corcoran, 2007) and (Dhillon, 2009, and Dinh, 2009), respectively.

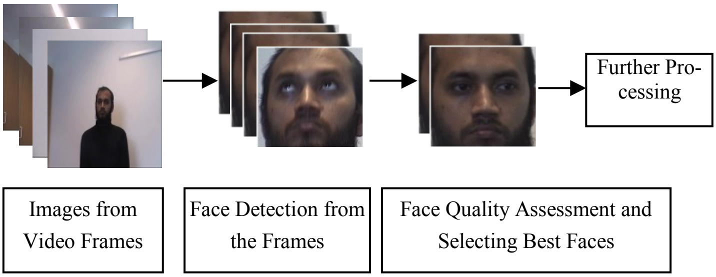


Figure 11-4 Steps of a typical facial image acquisition system with face quality measure.

A number of methods proposed for face quality assessment and/or face logging. Nasrollahi et al. proposed a face quality assessment system in video sequences by using four quality metrics: resolution, brightness, sharpness, and pose (Nasrollahi, 2008). Mohammad et al. utilized face quality assessment while capturing video sequences from an active pan-tilt-zoom camera (Mohammad, 2013). In (Axnick, 2009, Wong, 2011), two face quality assessment methods have been proposed in order to improve face recognition performance. Instead of using threshold based quality metrics, (Axnick, 2009) used a multi-layer perceptron neural network with a face recognition method and a training database. The neural network learns effective face features from the training database and checks these features from the experimental faces to detect qualified candidates for face recognition. On the other hand, Wong et al. used a multi-step procedure with some probabilistic features to detect qualified faces (Wong, 2011). Nasrollahi et al. explicitly addressed posterity facial logging problem by building sequences of increasing quality face images from a video sequence (Nasrollahi, 2009). They employed a method which uses a fuzzy combination of primitive quality measures instead of a linear combination. This method was further improved in (Bagdanov, 2012) by incorporating multi-target tracking capability along with a multi-pose face detection method.

A number of complete facial expression recognition methods have been proposed in the literature. Most of the methods, however, merely attempt to recognize few most frequently occurred expressions such as angry, sad, happy, and surprise (Tian, 2011). In order to recognize facial expressions, some methods merely used geometric features (Cohn, 2009), some methods merely used appearance features (Bartlett, 2006), and some methods used both (Wen, 2003). While classifying the expressions from the extracted features, most of the well-known classifiers have been tested in the literature. These include neural network (NN), support vector machines (SVM), linear discriminant analysis (LDA), K-nearest neighbour (KNN), and hidden Markov models (HMM) (Tian, 2011).

11.4. THE PROPOSED APPROACH

A typical facial expression logging system from video consists of four steps: face acquisition, feature mining, expression recognition, and log construction. On the other hand, a typical FQA method in video consists of three steps: video frame acquisition, face detection in the video frames using a face detector or tracker, FQA by measuring face quality metrics. However, as discussed in introduction section, the performance of feature mining and expression recognition highly depends on the quality of the face region in video frames. Thus, in this chapter, we proposed an approach to combine a face quality assessment method with a facial expression logging system. The overall idea of combining these two approaches into one is depicted in Figure 11-5. Before passing the face region of video frames to the feature extraction module, the FQA module discards the non-qualified faces. The architecture of the proposed system is depicted in Figure 11-6 and described in the following subsections.

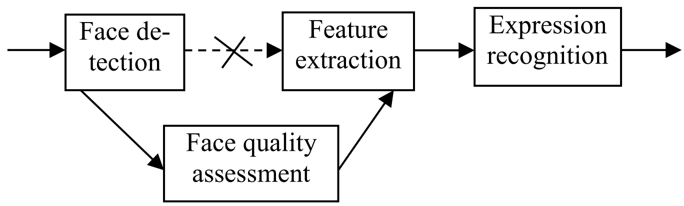


Figure 11-5 Face quality is assessed before feature extraction is attempted for expression recognition.

11.4.1. FACE DETECTION MODULE

This module is responsible to detect face in the image frames. The well-known Viola and Jones face detection approach has been employed from (Viola, 2001). This method utilizes so called Haar-like features in a linear combination of some weak classifiers to form a strong classifier to perform a face and non-face classification by using an adaptive boosting method. In order to speed up the detection process an evolutionary pruning method from (Jun-Su, 2008) is employed to form strong classifiers using fewer classifiers. In the implementation of the proposed approach, the face detector was empirically configured using the following constants:

- Minimum search window size: 40x40 pixels in the initial camera frames
- The scale change step: 10% per iteration
- Merging factor: 2 overlapping detections

The face detection module continuously runs and tries to detect face in the video frames. Once a face is detected, it is passed to the Face Quality Assessment (FQA) module.

11.4.2. FACE QUALITY ASSESSMENT MODULE

FQA module is responsible to assess the quality of the extracted faces. Four parameters that can effectively determine the face quality have been selected in (Nasrollahi, 2008) for surveillance applications. These parameters are: out-of-plan face rotation (pose), sharpness, brightness, and resolution. All these metrics have remarkable influence in expression recognition. However, the difference between a typical surveillance application and an expression logging system entails exploration of some other face quality metrics. For example, face completeness can be an important measure for face quality assessment before expression recognition. This is because features for expression recognition are extracted from different components of a face, more specifically from eyes and mouth. If a facial image doesn't clearly contain these components, it is difficult to measure expressions. Thus, we calculate a face completeness parameter, along with four other parameters from (Nasrollah, 2008), by detecting the presence of the eyes and the mouth in a facial image. A normalized score is obtained in the range of *[0:1]* for each quality parameter and a linear combination of scores has been utilized to generate single score.

The basic calculation process of some FQA parameters is described in (Mohammad, 2013). We, however, include a short description below for the readers' interest by incorporating necessary changes to fit these mathematical models with the requirement of constructing facial expression log.

- Pose estimation - Least out-of-plan rotated face: The face ROI (Region of Interest) is first converted into a binary image and the center of mass is calculated using:

$$x_m = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} ib(i,j)}{A} \qquad (1)$$

$$y_m = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} j b(i,j)}{A} \tag{2}$$

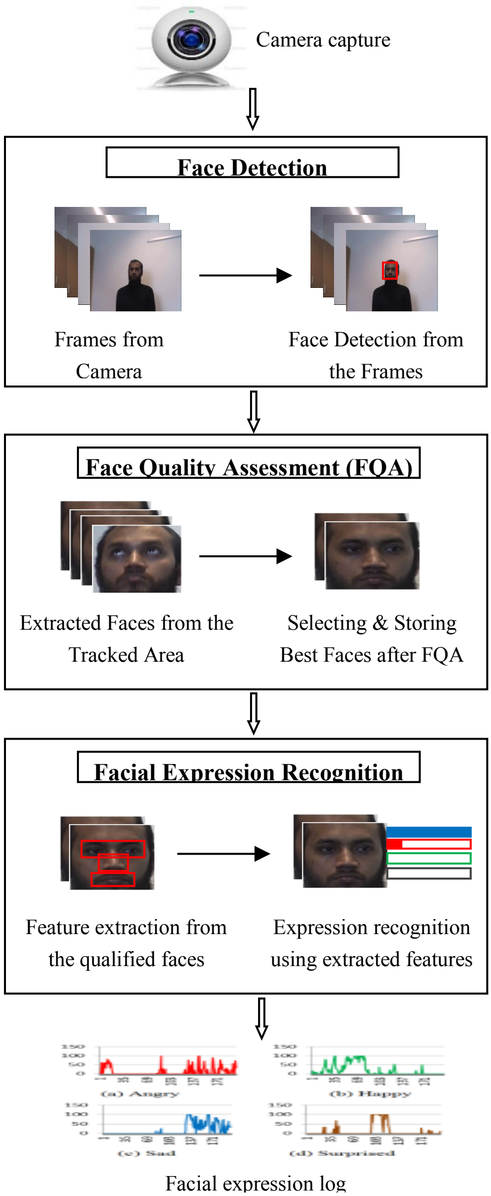


Figure 11-6 The block diagram of the proposed facial expression log construction system with face quality assessment.

Then, the geometric center of face region is detected and the distance between the center of region and the center of mass is calculated by:

$$Dist = \sqrt{(x_c - x_m)^2 + (y_c - y_m)^2} \tag{3}$$

Finally the normalized score is calculated by:

$$P_{Pose} = \frac{Dist_{Th}}{Dist} \tag{4}$$

Where (x_m, y_m) is the center of mass, b is the binary face image, m is the width, n is the height, A is the area of the image, x_1, x_2 and y_1, y_2 are the boundary coordinates of the face, and $Dist_{Th}$ is an empirical threshold used in (Mohammad, 2013).

- Sharpness: Sharpness of a face image can be affected by motion blur or an unfocused capture. This can be measured by:

$$Sharp = abs(A(x, y) - lowA(x, y)) \tag{5}$$

Sharpness's associated score is calculated by:

$$P_{Sharp} = \frac{Sharp}{Sharp_{Th}} \tag{6}$$

Where, *lowA(x,y)* is the low-pass filtered counterpart of the image *A(x,y)*, and $Sharp_{Th}$ is an empirical threshold used in (Mohammad, 2013).

- Brightness: This parameter measures whether a face image is too dark to use. It is calculated by the average value of the illumination component of all pixels in an image. Thus, the brightness of a frame is calculated by (6), where *I(i,j)* is the intensity of pixels in the face image.

$$Bright = \left(\sum_{i=1}^{n} \sum_{j=1}^{m} I(i,j) \Big/ (m * n) \right) \tag{7}$$

Brightness's associated score is calculated by:

$$P_{Bright} = \frac{Bright}{Bright_{Th}} \tag{8}$$

Where, $Bright_{Th}$ is an empirical threshold used in (Mohammad, 2013).

- Image size or resolution: Depending upon the application, face images with higher resolution may yield better results than lower resolution faces (Axnick, 2009, Long, 2011). The score for image resolution is calculated by (10), where w is image width, h is image height, $Width_{th}$ and $Height_{th}$ are two thresholds for expected face height and width, respectively. From the study of (Nasrollahi, 2008), we selected the values of the thresholds 50 and 60, respectively.

$$P_{Size} = \min\left\{1, \frac{w}{Width_{th}} \times \frac{h}{Height_{th}}\right\} \tag{9}$$

- Face completeness: This parameter measures whether the key face components for expression recognition can be detected automatically from the face. In this study, we selected eyes and mouth region as the key components of face and obtain the score using the following rule:

$$P_{Completeness} = \begin{cases} 1, if\ components are identifiable \\ 0, if\ components are not identifiable \end{cases} \tag{10}$$

The final single score for each face is calculated by linearly combining the abovementioned 5 quality parameters with empirically assigned weight factor, as shown in (10):

$$Quality_{Score} = \frac{\sum_{i=1}^{4} w_i P_i}{\sum_{i=1}^{4} w_i} \tag{11}$$

Where, w_i are the weight associated with P_i, and P_i are the score values for the parameters pose, sharpness, brightness, resolution, and completeness consecutively. Finally, the best quality faces are selected by observing the $Quality_{Score}$. The detail procedure of selection the best faces for expression logging is described in the following section.

11.4.3. FACIAL EXPRESSION RECOGNITION AND LOGGING

This module recognizes facial expressions from consecutive video frames and plots the expression intensities against time in separate graphs for different expressions. In this chapter, we use an off-the-shelf expression recognition technique from (Kublbeck, 2006), which is implemented in SHORE library (Fraunhofer IIS, 2013). An appearance based modified census transformation is used in this method for face detection and expression intensity measurement. In fact, the eye-region, nose-region and mouth region represent the expression variation in face appearance, as shown in Figure 11-6. Changes in patterns of these regions are obtained by employing the transformation. Four frequently occurred expressions are measured by this system: angry, happy, sad, and surprize.

The next step after expression recognition is the construction of facial expression log. Four graphs are created for four expressions from a video sequence. As generating expression log from the faces of consecutive frames of a video suffers significantly due to erroneous expression recognition from low quality faces from the video frames, generating log by merely using the high quality faces can be a solution. However, discarding low quality face frames from video generate discontinuity in the expression log, especially if a large number of consecutive face frames contain low quality face. Thus, we employed a windowing approach in order to ensure continuity of the expression log while assuring an acceptable similarity with the expression log from all faces and expression log from qualified faces. The approach works by selecting the best face among *n* consecutive faces, where *n* is the window size indicating the number of video frames in each window. When plotting the expression intensities into the corresponding graphs of the expressions, instead of plotting values for all face frames, the proposed approach merely plots the value for the best face frame in each window. The effect of discarding the expression intensity score for other frames of the window is shown in the experimental result section.

11.5. EXPERIMENTAL RESULTS

11.5.1. EXPERIMENTAL ENVIRONMENT

The underlying algorithms of the experimental system were implemented in a combination of Visual C++ and Matlab environments. As the existing online datasets merely contain images or videos of good quality faces rather than mixing of good and bad quality faces, to evaluate the performance of the proposed approach we recorded several video sequences from different subjects by using a camera setup. Faces were extracted from the frames of 8 experimental video clips (named as, *Sq1, Sq2, Sq3, Sq4, Sq5, Sq6, Sq7,* and *Sq8*) having 1671 video frames, out of which 950 frames contain detectable faces with different facial expressions.

Face quality assessment and expression recognition were performed to generate the results. Four basic expressions were used for recognition: happy, angry, sad, and surprise. Two types of facial expression logs were generated: first type shows the facial expression intensities of each face frames of video (Type1), and the other type shows the facial expression intensities of the best faces in each consecutive window with *n*-frames of the video (Type2). In order to compare Type1 and Type2 representations, we calculate normalized maximum cross-correlation magnitudes of both graphs for each expression (Briechle, 2001). Higher magnitude implies more similarity between the graphs.

11.5.2. PERFORMANCE EVALUATION

The experimental video clips were passed through the face detection module and face quality metrics were calculated after detecting faces. As an example, Figure 11-7 shows the $Quality_{Score}$ for each face frames of the video sequence *Sq1*, where the score is plotted against the video frame index. From the figure it is observed that some of the faces may exhibit poor quality score as low as 40%. If these low quality faces are sent to the expression recognition module the recognition performance will be significantly suffered.

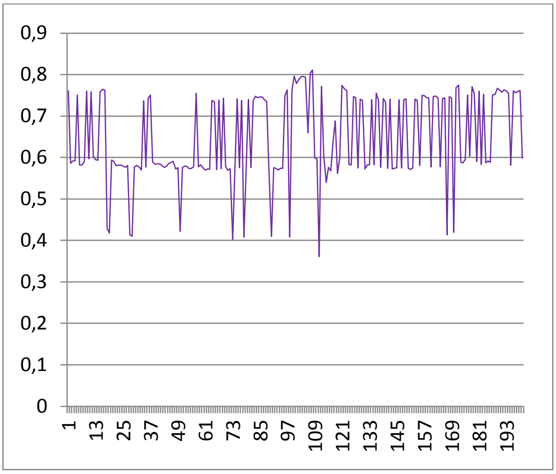
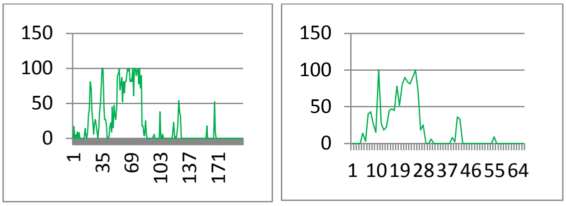


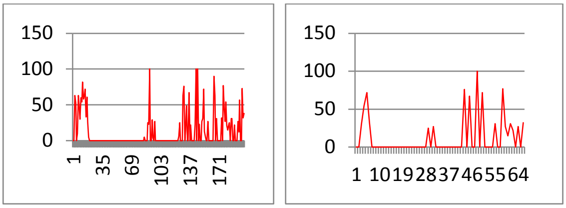
Figure 11-7 Face quality score calculated by the FQA module for 200 face frame of experimental video sequence Sq1.

Facial expression recognition module measures the intensity of each facial expression for each face of the frames of a video, and then facial expression logs were generated. Figure 11-8 illustrates two types of expression logs for the experimental video sequence *Sq1*, where the window size *n* was set to 3 for selecting best faces. The graphs at the left of each rows of Figure 11-8 present the Type1 graph and the graphs at the right presents corresponding Type2 graph. When we visually analysed and compared Type1 and Type2 graphs, we observed temporal similarity between these two facial expression logs from the same video sequence due to the application of windowing approach.

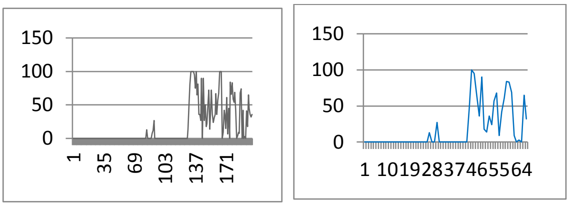
In order to formalize this observation, we showed a normalized maximum cross-correlation magnitude similarity measure between these two representations of the video sequences for all four expressions by varying the window size *n*. The results are summarized in Table 11-1 and Table 11-2 for window sizes 3 and 5, respectively.



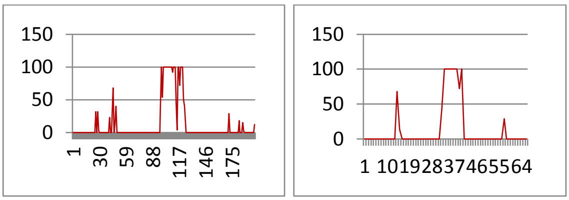
a) Happy



b) Angry



c) Sad



d) Surprise

Figure 11-8 Facial expression log for the experimental video sequence Sq1 (the left graphs are from all face frames, and the right graphs are from selected best quality face frame by the windowing method with 3-frames per window)

From the results, it is observed that discarding more faces decreases similarity between Type1 and Type2 graphs. For some sequences, changing the window size doesn't have much effect for some expression modalities. This is due to nonvariable expression in these video sequences. However, in order to keep agreement with other modalities, the window size should be kept same. For example, in *Sq3* the results for the expressions of happiness, sadness and surprise aren't affected much by the change of window size. Moreover, some expression exhibited very high dissimilarity even for a very small window size. This is because the expression in that video sequence changed very rapidly, and thus discarding face frame discards expression intensity values too. On the other hand, discarding more faces by setting a higher window size reduces the computational power consumption geometrically. Thus, the window size should be defined depending upon the application the expression log is going to be used.

Table 11-1 Similarity between Type1 and Type2 graphs, when window size is 3 (higher value implies more similarity).

	Angry	**Happy**	**Sad**	**Surprise**	**Average**
Sq1	0.60	0.94	0.80	0.90	0.81
Sq2	0.81	0.97	1.00	0.77	0.89
Sq3	0.70	0.99	1.00	1.00	0.92
Sq4	0.52	0.97	1.00	1.00	0.87
Sq5	0.62	0.99	1.00	1.00	0.90
Average similarity for *n*=3					0.88

Table 11-2 Similarity between Type1 and Type2 graphs, when window size is 5 (higher value implies more similarity).

	Angry	**Happy**	**Sad**	**Surprise**	**Average**
Sq1	0.31	0.54	0.49	0.53	0.47
Sq2	0.44	0.50	1.00	0.46	0.60
Sq3	0.57	1.00	1.00	1.00	0.89
Sq4	1.00	0.46	1.00	1.00	0.86
Sq5	1.00	0.46	1.00	1.00	0.86
Average similarity for *n*=5					0.73

11.6. CONCLUSIONS

This chapter proposed a facial expression log construction system by employing face quality assessment and investigated the influence of face quality assessment on the representation of facial expression logs of long video sequences. A step by step procedure was defined to incorporate face quality assessment with facial expression recognition system and finally the facial expression logs were generated. Instead of discarding all of the low quality faces, a windowing approach was applied to select best quality faces in a regular interval. Experimental results shows a good agreement between expression logs generated from all face frames and expression logs generated by selecting best faces in a regular interval.

As the future works, we will analyse the face quality assessment metrics individually and their impact on facial expression recognition. In the construction of facial expression log, a formal model needs to define by addressing the questions such as how to address discontinuity of face frame while making the log, how to improve face quality assessment, how to select optimum window size for discarding non-qualified face frames, how to include motion information for missing face frames while generating face log.

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