CHAPTER 6

Computer Vision for Ambient Assisted Living

Monitoring Systems for Personalized Healthcare and Wellness That Are Robust in the Real World and Accepted by Users, Carers, and Society

Sara Colantonio[*], **Giuseppe Coppini**[†], **Daniela Giorgi**[*], **Maria-Aurora Morales**[†], **Maria A. Pascali**[*]

[*]National Research Council, Institute of Information Science and Technologies, Pisa, Italy
[†]National Research Council, Institute of Clinical Physiology, Pisa, Italy

Contents

Abstract

The Ambient Assisted Living (AAL) paradigm proposes advanced technologies and services to improve the quality of life, health, and wellbeing of citizens by making their daily-life activities easier and more secure, by monitoring patients under specific treatment, and by addressing at-risk subjects with proper counseling. The challenges brought by AAL range from robust, accurate, and nonintrusive data acquisition in daily-life settings to the development of services that are easy to use and appealing to the

Computer Vision for Assistive Healthcare.
DOI: https://doi.org/10.1016/B978-0-12-813445-0.00006-X

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 1

users and that support long-term engagement. This chapter offers a brief survey of existing vision-based monitoring solutions for personalized healthcare and wellness, and introduces the Wize Mirror, a multisensory platform featuring advanced algorithms for cardiometabolic risk prevention and quality-of-life improvement.

Keywords

Ambient assisted living (AAL), Self-monitoring, Unobtrusiveness, User engagement, Physiological monitoring, Wellness index

6.1 INTRODUCTION

The term Ambient Assisted Living (AAL) concerns ICT[1] solutions embedded in the living environment to monitor the setting and the behavior of its occupants in real time. AAL solutions can go beyond observing; they can move towards interacting by communicating with the user via prompts, triggering assistance from emergency services, and providing up-to-date information to families and caregivers.

AAL technologies trace their roots back to home automation and assistive domotics; they are now applied in many different scenarios, from telecare to pervasive wellness [1,2]. The main aim is improving the quality of life, health, and wellbeing of citizens; making their daily-life activities easier and more secure; monitoring and curing ill or at-risk subjects; and even performing primary prevention in healthy subjects.

The three main targets of AAL solutions are

- monitoring (and acting on) environmental conditions (e.g. lights, temperature, opening of doors, gas detection) for the occupants' safety and comfort;
- monitoring human activity and behavior, from basic motion tracking and human activity recognition up to long-term behavioral analysis;
- monitoring human physiological signs (physical, clinical, vital, emotional parameters) for personalized healthcare and wellness, including telerehabilitation, cure management, and prevention.

The general scheme of AAL solutions is to enrich the environment with a distributed sensor system. The sensors include *ambient sensors* (e.g. magnetic switches, photosensors) as well as *body* or *wearable sensors* that are fixed to the human body or clothing (e.g. gyroscopes, pulse oximeters). A large network of sensors are often needed to gather enough data to accomplish the complex tasks required for AAL applications; therefore, systems may be

[1] Information and Communication Technology.

B978-0-12-813445-0.00006-X, 00006

costly to maintain, highly sensitive to a sensor's performance, and obtrusive. Obtrusiveness is an issue especially for wearable sensors, due to their weight, effects on the skin, and burden on the subject during daily-life activities.

Recently, video cameras (including standard and depth cameras) and computer vision techniques came into the spotlight as alternative solutions for AAL applications [3,4]. Video-based AAL solutions benefit from the maturity of the research in computer vision: decades of studies, boosted by needs in domains such as security and surveillance, have brought robust techniques for interpreting the rich information provided by cameras. Also, video-based solutions can favor the acceptability of AAL systems: video cameras are expected to reduce the possible anxiety towards new technologies, even for the elderly, as they are familiar objects. Moreover, cameras may be perceived as less invasive than other sensors as they do not require any physical contact with the subject, they do not have to be worn (with the exception of wearable cameras), and they can be fitted in the home setting by taking aesthetics into account.

Another main advantage of video and depth cameras is that they can register a great deal of information compared to other sensors, and allow the analysis of complex scenarios. A single camera can capture most of the activities performed in a room; therefore, in principle, it could replace many sensors. This would cut costs, also thanks to the fact that high-quality cameras are now available at affordable prices. Moreover, the same hardware setup can serve for multiple applications by just changing the software analyzing the visual data. Therefore, computer vision supports flexible and adaptive solutions, which can be easily extended and updated on demand.

6.1.1 Chapter Scope

There is a huge corpus of work on the use of computer vision for ambient monitoring and navigation and for activity recognition [5]. These topics are also covered in other chapters of this book. Therefore, after a brief introduction to the field of computer vision for AAL (Section 6.2), this chapter focuses on the use of computer vision techniques for monitoring human physiological signs in AAL solutions for personalized healthcare and wellness. In Section 6.3, we discuss the monitoring through videos, images, and 3D data, of

- vital signs (heart rate and respiratory rate);

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 3

- posture and movement, especially for rehabilitation;
- morphological parameters (e.g. body mass index);
- emotional state (e.g. stress and anxiety).

Subsequently, in Section 6.4, we identify barriers and challenges for vision-based AAL solutions to reach their full maturity and applicability, especially within the healthcare domain.

Finally, as a possible solution, we introduce the Wize Mirror, a multisensory platform for health and wellbeing monitoring (Section 6.5). The Wize Mirror features advanced computer vision algorithms for cardiometabolic risk assessment through facial analysis.

Our target audience includes researchers and healthcare professionals, who will find information about the aspects that may affect their practice.

6.2 COMPUTER VISION FOR AAL

The traditional three-step pipeline for video-based AAL solutions includes image/video acquisition, preprocessing (segmentation of the region of interest, filtering for noise reduction, or contrast enhancement), and feature extraction and interpretation. The acquisition devices include traditional RGB cameras (including omnidirectional cameras and wearable cameras for egocentric vision); thermal cameras that acquire the infrared radiation of the scene; MultiSpectral Imaging (MSI) systems [6]; and depth sensors, based either on time of flight or on structured light [7]. Depth sensors in particular have became very popular lately because of their decreasing cost and the advantages they provide, including robustness to changing lighting conditions and protection of privacy since the appearance of a person is not recognized in depth images.

The architecture of a video-based AAL solution traditionally consists of a set of cameras for data capture connected to a server; processing modules for data processing and analysis; and an alert/decision module, which may or may not include a human operator. This solution can ease the integration of data from different sources, but usually requires high bandwidth for data transmission, unless compressed video is used for transmission. An alternative band-saving solution is given by distributed smart camera networks that analyze the data locally and only transmit the alert/decision [8].

One of the main challenges of video-based AAL systems is the robustness with respect to the operating conditions in real-life settings. A first issue for robust data acquisition is what cameras are able to see, which

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 4

depends on the viewing angle and user positioning with respect to the camera, but also on occlusions and clutter. The problem of the viewing angle of the scene can be solved via hardware or software solutions. A solution often adopted in ambient surveillance systems is based on omnidirectional cameras which can capture virtually a 360 degree viewing angle of data. Alternatively, view-invariant computer vision algorithms are required, based either on single cameras or on image fusion strategies from multiple cameras. Multiple cameras and image fusion strategies may also help to solve the problem of occlusions that are likely to occur in a room. Finally, face recognition and the ability to track (multiple) people are needed in case of multiple occupants of the monitored space.

Another major concern for video-based assistive technologies is privacy. AAL systems imply the collection of information in private spaces about individual subjects and their lives. With image and video recordings, the privacy protection issue becomes even more prominent since the occupants' identities are shown. Privacy protection is considered urgent especially if image data are stored and transmitted to a server, and if they are expected to be analyzed by designated carers. The consequences can be low acceptance by the end users, and even techniques for avoiding the camera to sabotage the monitoring [9]. Striking a happy medium between the benefits of image and video recording and the potential privacy loss requires focusing on the perspective of the end user. Some studies [10,11] have suggested that people would be willing to accept video-based activity monitoring systems, in principle, if they felt that the technology would make a real difference to their lives, and if they were really in need of assistance. Also, improving the reliability of systems so that they do not require images to be analyzed by humans could improve confidentiality. Again, a possible solution is given by smart cameras, which can perform a part of the image and video processing locally, and either only transmit decision information to carers or filter the data to obscure individual identities [8].

6.3 MONITORING IN PERSONALIZED HEALTHCARE AND WELLNESS: THE STATE OF THE ART

The home can be a focal point for ensuring healthy living if it is equipped with the right infrastructure: AAL systems based on computer vision solutions can support health status monitoring for the management of chronic diseases and rehabilitation therapies, but also for the prevention of disease

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 5

B978-0-12-813445-0.00006-X, 00006

and improvement of individual wellbeing through the achievement and maintenance of a healthy lifestyle. These systems may become part of the medical toolbox for healthcare professionals, who could benefit from innovative communication and monitoring facilities.

The parameters to be monitored include vital signs such as heart rate and respiratory rate (Section 6.3.1); measures related to posture and movement, especially during rehabilitation (Section 6.3.2); morphological parameters of the body and face related to risk factors such as overweight and obesity (Section 6.3.3); and descriptors of the affective state, such as cues about the onset and progression of different diseases (Section 6.3.4).

6.3.1 Vital Signs

The monitoring of vital signs includes the estimation of

- heart rate (HR);
- heart rate variability (HRV);
- respiratory rate (RR).

Heart Rate

Heart rate monitoring is important by virtue of the significance of this vital sign in both health and disease. Physiological changes in HR can be assessed during exercise or during sleep when a reduction in HR may occur due to prevalence of vagal drive. In disease, there is an association between HR and outcome in heart failure patients, and a baseline HR is considered a cardiovascular risk factor. A special application of HR monitoring can be reported in the aging population as HR can also be a sign of improper movements. Since an increasing number of older subjects wish to live in their home environments rather than moving into care facilities, the opportunity to unobtrusively monitor HR is challenging. Therefore, several studies have been performed to evaluate whether the HR can be assessed from video streams [12], thus avoiding the use of wearable sensors.

A commonly adopted approach to HR assessment is based on the processing of RGB video images acquired by RGB cameras or webcams. Blood Volume Pulses (BVPs) are expected to produce changes of the intensity of spectral components of the video signal [13]. In analogy with standard PhotoPlethysmoGraphy (PPG), the term video PhotoPlethysmoGraphy (vPPG) has been introduced. The basic steps of vPPG are

- acquiring the video signal, possibly in a specific wavelength band, and averaging it in a region of interest to produce a time sequence reflecting BVP changes;

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 6

B978-0-12-813445-0.00006-X, 00006

- enhancing BVPs by specific processing, and locating them, e.g. by peak detection.

Concerning the signal acquisition, webcams [14–18] and standard video cameras [19,13,20,21] are both used. Webcams provide low-cost and easily available setups, while standard cameras are expected to produce better quality signals, due to higher spatial and temporal resolution, along with multispectral imaging capabilities.

For the processing methods, a common framework is based on Blind Source Separation (BSS) techniques modeling the video signal as a mixture of contributions including BVP propagation, the various motion sources, and external illumination changes. Poh et al. [14] process the RGB component by Independent Components Analysis (ICA) to separate BVP from other contributions. An alternative approach based on BSS by Principal Components Analysis (PCA) was suggested by Lewandowska et al. [18]. The limitations of BSS (ICA- and PCA-based) have led several researchers to investigate more robust processing methods able to cope with motion artifacts. Wang et al. [19] exploit image redundancy to counteract the effects of facial movements. Feng et al. [17] adopted a simplified model of skin optical properties to compensate for head motion. Tarassenko et al. [20] proposed a vPPG system exploiting autoregressive modeling of video time series to compute HR together with RR and oxygen saturation.

In general, HR estimation from vPPG is in good agreement with reference techniques (usually standard PPG or ECG in a few studies), high correlation coefficients being reported by most authors. It is worth noting that, to date, experimental results have been from small populations of volunteers.

Though video signal intensity is the most utilized source of information, an alternative method based on head motion related to BVP propagation and recorded by video is reported in [22].

Heart Rate Variability

In addition to heart rate, the temporal variation of Heart Rate Variability (HRV) is an indicator of health status in the general population, of adaptation to stress in athletes [23], and of fatigue in drivers [24].

The assessment of HRV from video is usually more demanding than simply assessing HR. In fact, while HR estimation only requires BVP detection to compute the average number of pulses per minute, a precise temporal localization of pulses is needed for HRV assessment. Most methods for HR assessment from video can be adapted to estimate HRV. For

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 7

example, in [14] vPPG is used to compute the related tachogram (i.e. the time series of inter-beat interval duration) and to compute standard HRV indices both in time and frequency domain. A high correlation with the parameters derived by standard PPG on 15 subjects is reported. An alternative solution based on zero-phase component analysis has been reported by Iozzia et al. [25] to evaluate the suitability of vPPG for assessing autonomic response.

Respiratory Rate

Computer vision may support the assessment of RR and related breathing disorders. A recent application that may have important clinical impact is the assessment sleep apnea. Obstructive Sleep Apnea (OSA) is a sleep breathing disorder characterized by partial or complete obstruction of the upper airway during sleep. Left untreated, OSA has been linked to an increase in motor vehicle and occupational accidents, hypertension, cardiovascular disease, and diabetes. Since present diagnostic methods are complicated and require in-hospital stay, computer vision technologies offer a novel and interesting solution for diagnosing OSA [26]. Monitoring RRs has been approached by computer vision systems also related to positions in bed. This aspect is particularly important for the aging population since posture changes in bed may reflect sleeping disorders; disturbances of sleep rhythm could be related to nocturnal falls, one of the most important causes of morbidity in elderly subjects.

A direct approach to video-based RR estimation is based on the analysis of chest movements. Benetazzo et al. [27] used a RGB camera equipped with a depth sensor to evaluate RR from depth data. As already mentioned, Tarassenko et al. [20] proposed a direct RR estimation from video streams by autoregressive models of video time series. Indirect approaches to RR estimation are based on the power spectrum of HRV signals: indeed, respiration introduces a peak in the high-frequency region of the spectrum [14].

6.3.2 Posture and Movement

In recent decades, studies of quantitative analysis of human posture and movements have been stimulated by several fields, including rehabilitation, sports, children's motor skills, and aging. We focus in particular on

- gait analysis and fall detection;
- movement for rehabilitation.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 8

B978-0-12-813445-0.00006-X, 00006

Gait Analysis and Fall Detection

A relation exists between gait, cognitive decline, and risk of falls [28]. In older people, higher stages of cognitive impairment were associated with reduced ability to increase speed and walk quickly [29]. In particular, preventing falls in the elderly is a challenging task currently being investigated by many researchers [30]. Wearable sensors are mostly used in gait studies [31]; however, in recent years vision-based solutions have been introduced to improve unobtrusive monitoring. In this perspective, several researchers have proposed vision based systems to assist the elderly at home and reduce the risk of falls. The vast majority of reported approaches exploit standard single-view cameras with a wide field of view able to image the entire person [32–35], multiview camera-based systems [36], or omnidirectional surveillance cameras [37]; the use of depth sensors is also reported [38].

In general, the idea underlying most of these systems is predicting/recognizing falls by dynamic analysis of image sequences of the monitored subject. This usually relies on a model of the observed motion coupled with the classification of the inferred activities. To obtain a compact motion description, a common choice is based on the silhouette of the monitored subject. It is usually extracted following some sort of background suppression so as to reduce interference from the surrounding scene. Even though this operation can dramatically simplify the motion description, it can be prone to noise and can lead to false alarms, a matter that needs to be dealt with to achieve a reasonable system acceptability. Subject motion can be described by features extracted from the bounding box of the silhouette tracked over time.

Various solutions have been proposed which include: Hidden Markov Models [39] or Layered Hidden Markov Models [36], Finite State Models [35], and the use of Historical Motion Image [32,33] computed by time integration of image features possibly using eigenspace methodology to reduce dimensionality [33]. Falls can be recognized by standard machine learning methods such as multilayer perceptrons [33], algorithms based on distance between feature histograms of the silhouette bounding-box [40], and specific motion quantification coefficients [32]. As some processing steps can be prone to structured and nonstructured noise (e.g. background suppression), attempts to reduce possible inaccuracies have been faced [40]. The integration of visual and nonvisual cues (e.g. acoustic signals) has been proposed to improve fall detection accuracy [39].

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 9

Movement for Rehabilitation

Rehabilitation is a dynamic process which allows persons to restore or at least improve their functional capability to normal. Physiotherapy exercise is a medical treatment aimed at returning patients to a normal life. During rehabilitation plans, patients may encounter difficulties such as time and cost of traveling, waiting for the availability of specialists, and ineffective personal exercise. These difficulties could be greater for those patients living in the areas that are distant from medical centers or that lack medical staff and experts, and for the frail elderly. Therefore, the concept of telephysiotherapy has been developed to allow patients and medical experts to carry on their sessions through telecommunication networks as if they were in the same place. In general, the implementation of home-based rehabilitation interventions is an emerging area of scientific interest and where the use of sensors plays a fundamental role.

Computer vision-based approaches in particular are expected to ease the optimization of rehabilitation strategies at home. In fact, they enable objective and quantitative monitoring of physiotherapy exercises: the user's motion can be accurately tracked in 3D and compared to the planned therapy, thus enabling the fine-tuning of the therapeutic feedback on an individual basis. Also, the combination of sensing technology and interactive gaming or virtual reality can facilitate the implementation of rehabilitation exercise programs [41].

One of the main fields of interest is represented by stroke survivors. Approximately 800,000 new cases of stroke are reported each year in the United States. About 80% of acute stroke survivors lose arm and hand movement skills [42]. Movement impairment after a stroke typically requires intensive treatment. Due to resource reduction in healthcare all over the world, in-hospital rehabilitation tends to be limited. Thus, stroke rehabilitation in home environments is an appealing solution. Computer vision systems that allow individuals with stroke to practice arm movement exercises at home with periodic interactions with a therapist have been developed by different research groups [43,44].

It has been demonstrated that combining telemedicine with in-home robot-assisted therapy (telerehabilitation) for people with residual impairment following stroke is able to reduce barriers. Moreover, it is cost-effective, providing high-quality treatment to patients with limited access to rehabilitation centers. Interestingly, patients and caregivers report overall satisfaction and acceptance of telerehabilitation intervention, with a marked reduction in drop-outs [45].

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 10

B978-0-12-813445-0.00006-X, 00006

6.3.3 Anthropometric Parameters

Anthropometry is the branch of anthropology dealing with the quantitative measurement of the human body, including size, proportions, and composition [46]. The most often used anthropometric body parameters are weight, height, skin-fold thickness, mass, triceps skin-fold, neck circumference, waist circumference, hip circumference, and mid-arm circumference. Derived indices such as Body Mass Index (BMI) [47], waist-to-hip circumference ratio, and waist-to-height ratio are also commonly used. Anthropometric measurements are used by the World Health Organization to describe physical trends in large-scale population studies [48,49]. Cut-off values and ranges, inferred on the basis of these statistics, are used to classify the individual status. Recently, many works have focused on correlating anthropometric parameters or derived indices with risk factors of cardiovascular and metabolic risk, such as overweight, obesity, and body fat distribution [50–58].

Manually collected anthropometric measurements are intrinsically affected by inter- and intra-observer variability; instead, computer vision technologies may support the automation and standardization of the acquisition, analysis, and recording of the physical parameters. Therefore, vision-based AAL solutions for the automatic computation and monitoring over time of anthropometric parameters may offer great support to longitudinal health studies.

Nowadays, there are many devices that can acquire people's 3D shape and appearance, including low-cost depth sensors (e.g. Microsoft Kinect, Asus Xtion), whole-body scanners (e.g. Cyberware, TC^2), mixed solutions (e.g. the turnable station designed by Styku for fitness and health), portable scanners (e.g. Artec3D). These 3D scanners can capture highly accurate 3D body maps, including size, shape, and skin-surface area, in 1 to 10 seconds [59–63]. Standard photogrammetry has also been used to obtain a 3D reconstruction of a human body from a sequence of RGB images [64]. The above technologies provide the automatic extraction of hundreds of measurements from a body or facial reconstruction, avoiding manual measurement and transcription errors, and ensuring the repeatability of the measurements. Also, the use of acquired 3D data overcomes the 1D nature of tape measurements, by supporting volume and surface measurements, potentially meaningful with respect to the subject's overall health status.

Additional resources for 3D digital anthropometry include publicly or commercially available datasets. For example, the Civilian American and European Surface Anthropometry Resource project (CAESAR) [65]

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 11

B978-0-12-813445-0.00006-X, 00006

dataset contains thousands of full-body textured 3D scans, labeled with anthropometric landmarks, and supporting the study of shape spaces in [66]. Also, several databases of human faces are available, the face being a rich source of information about an individual's psycho-physical status. The repositories of 3D facial data include CASIA HFB [60], FRGC v2.0 [67], Magna Database [68], USF Human ID 3-D [69], EURECOM Kinect Face dataset [70], and the Basel Face Morphable model [71].

In the following, we revised main methods to assess

- body parameters,
- face parameters.

Body Parameters

The analysis of reconstructed 3D bodies includes the surface skeleton extraction; the location of feature points; the analysis of local properties (such as curvature); and the measurement of lengths, areas, and volumes of specific curves or regions. The registration and alignment of 3D reconstructions with reference models is either based on the location of a very few feature points characterized by local shape descriptors (e.g. curvature maps [72], auto diffusion function [73], integral invariants [74], salient geometric features [75]) or on dense correspondence (e.g. multidimensional scaling methods based on geodesic distances [76]).

The correlation between 3D shape measurements of the human body and health issues has been studied in [77–81] in comparison with classical anthropometric measures and indices. The use of body landmarks to perform shape measurements requires the precise location of the body landmarks themselves [82], which can be difficult, especially in the case of points that are poorly geometrically characterized. Therefore, many *digital* anthropometry methods have focused on overcoming the precise location of body landmarks. Recent works have focused on finding relevant correlations between geometric parameters automatically computed and body fat estimates, or cardiovascular and metabolic risk factors. Among these, Giachetti et al. presented in [83] a pipeline for processing heterogeneous 3D body scans (skeletonization and body segmentation) and extracting geometric parameters which are independent of pose and robust against noise. Another representative example of an automatic system for the extraction of a health-related index is described in the 2009 US patent [84], where the *Barix* index is introduced and is defined as

$$Barix = \frac{\text{Torso Height} * \text{Torso Surface Area}}{\text{Torso Volume}}.$$

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 12

The clinical value of the index was assessed through a study of hundreds of human scans, showing significant correlation with body fat composition.

Face Parameters

The face has always been a very rich source of information, for example in studies on Human Computer Interaction, automatic detection of user's feelings, and early detection of numerous diseases, such as obstructive sleep apnea.

A number of studies have focused on using 2D images to detect morphological facial correlates of body fat. In [85], Ferrario et al. observed an increase in some facial dimensions in a study on facial morphology of obese adolescents. Djordjevic et al. [86] reported an analysis of facial morphology of a large population of adolescents under the influence of confounding variables: though the statistical univariate analysis showed that four principal components of the face (face height, asymmetry of the nasal tip and columella basis, asymmetry of the nasal bridge, depth of the upper eyelids) correlated with insulin levels, the regression coefficients were weak and no significance persisted in the multivariate analysis. In [87], Lee et al. proposed a prediction method, based on BMI, of normal and overweight for adult females using geometrical facial features extracted from 2D images. The features include Euclidean distances, angles, and facial areas defined by selected soft-tissue landmarks. The study was extended in [88] focusing on the association of visceral obesity with several facial characteristics. The authors determined statistically the best predictor of normal waist and visceral obesity among the considered facial characteristics. Cross-sectional data were obtained from a population of over 11 thousand adult Korean men and women, aged between 18 and 80 years.

Recently, 3D data have started to be used. One of the first results concerning the relation between 3D facial shape and a syndrome was presented by Banabilh et al. in [89]: the authors showed that craniofacial obesity, assessed via 3D stereo-photogrammetry, is correlated with obstructive sleep apnea syndrome. In [90], Giorgi et al. defined a shape descriptor based on the theory of persistent homology, and tested it on a synthetic dataset of 3D faces to assess the relation of facial morphology with obesity and overweight.

6.3.4 Emotions, Expressions, and Individual Wellness

The intertwining of emotional states and the onset and progression of diseases has been under investigation for a long time [91]. Studies in modern

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 13

B978-0-12-813445-0.00006-X, 00006

neuroscience have shed new light on the topic, leading to an extended reconsideration of the classical view of the interaction of soma and psyche [92]. On the one hand, chronic adverse emotional states, such as stress, anxiety, and tiredness, are among the main risk factors of serious illnesses, including metabolic syndrome and cardiovascular diseases [93–95]; conversely, the effect of positive states may reduce the incidence of cardiovascular disease [96]. On the other hand, chronic illness is coupled with an emotional dimension that can affect therapy outcome; for example, distress, depression, and anxiety may reduce one's motivation to access medical care and follow treatment plans [97]. Also, many studies have investigated the relation between adverse affective states (stress and depression) and the response of the immune system [98,99]. It is therefore not surprising that there is a great deal of interest in the medical community for novel tools that can assist the individual in self-managing stressful and anxiogenic situations and reducing disease risks.

Computer vision may support the implementation of unobtrusive, continuous monitoring systems of the emotional state of an individual, not only by supporting the estimation of emotion-related physical parameters (e.g. HR and RR; see Section 6.3.1), but also by analyzing facial expressions and body language evoked by emotions [100]. Indeed, assessing individual psychological wellness implies the recognition of complex mental states such as fatigue, frustration, pain, depression, and mood, which require the integration of multiple cues: physiological, acoustic, and visual cues. The combined use of physiological parameters computed by sensors and expressive features is documented in [101].

The visual clues to the affective state include general facial expression, micro-expressions, and other features such as eye gaze and head orientation. In general, the interpretation of facial codes in terms of underlying emotional states remains an open problem. Coding schemes such as the Facial Action Coding Scheme (FACS) [102] are generally related to primary affective states (e.g. anger, fear, happiness) rather than to complex states. Additional information about complex states may derive from micro-expressions, which are brief (lasting between 1/25 and 1/3 of a second) low-intensity facial expressions believed to reflect repressed feelings [103]. Due to their subtlety, they are hard to detect; for this reason the use of local dynamic appearance representations extracted from high-frequency video is usually reported [104]. The video-based analysis of multiple visual clues, including head, eyebrows, eye, and mouth movements, led in [105] to a technique for the identification of stress and anxiety.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 14

B978-0-12-813445-0.00006-X, 00006

For a detailed analysis of computer vision techniques for affective state recognition, we point the reader to Chapter 10 of this book. Here we confine ourselves to observing how moving emotional analysis in AAL settings is an exciting though extremely challenging task, which can pursue the objective of assessing emotional wellness. In particular, at-home monitoring can be implemented to evaluate stress, fatigue, and anxiety in different conditions, including resting states and a wide variety of everyday tasks (e.g. watching TV, listening to music, using a PC, or doing homework), which should ensure a detailed and possibly complete description of the individual responses to many external stimuli. In addition, AAL favors the correlation of monitoring data with life-style habits. This can be the key towards a true holistic representation of individual wellbeing in naturalistic contexts.

6.4 METHODOLOGICAL, CLINICAL, AND SOCIETAL CHALLENGES

We have seen how computer vision holds the potential to boost a new generation of noninvasive, effective systems for continuous health monitoring. The possibility of close follow-up by means of technological solutions at home would be an additional time-saving support to busy health professionals. These tools could help physicians not only in managing chronic diseases, but also in counseling on risk factors in the general population, especially for primary prevention. To make this scenario come true, some methodological, technological, clinical, and societal challenges still need to be faced.

Computational Demand

In physiological monitoring, high computational demand could result from the need to acquire and process data in real time, including real-time tracking, data alignment, and data analysis. Also, the spatial and temporal resolution of the acquisition may be high, depending on the parameters to be computed; the resolution requirements should be balanced with complexity and cost requirements, depending on the application at hand.

Acquisition Robustness in Real-Life Scenarios

Acquiring physiological parameters in uncontrolled settings requires methods that are robust to occlusions, clutter, or pose, for example the presence of a beard or make-up while analyzing the facial skin, or slight movements of the user while recording vital signs. Also, robustness to lighting

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 15

B978-0-12-813445-0.00006-X, 00006

conditions can be an issue in several applications, and computer-controlled external light sources may be required.

To operate in real-life scenarios, it is also mandatory to capture data without requiring too much effort from the subject, i.e. without asking the subject to stay still in front of a camera for several minutes. The challenge here is how to automate the acquisition process so that data are captured when the environmental conditions are most favorable.

Reliability of Measurements for Clinical Purposes

It is mandatory that physiological monitoring systems provide a description of the individual status coherent with the clinical view. In particular, a crucial requirement is the reliability of measurements and their usability by doctors and health professionals. Even though it is not expected that monitoring systems produce results in the form of validated clinical tests, the data provided must be adequate to properly drive the physician's reasoning and action planning. This requires intelligent image processing algorithms, ensuring high repeatability, adequate sensitivity, and specificity in measuring data in comparison to standard reference methods used in clinical practice.

Clinical Evaluation

Evaluating and validating in-home monitoring systems is a nontrivial task that requires an interdisciplinary team and a close involvement of the medical experts. The validation issue also calls for shared benchmark datasets.

The literature reports few and small case studies, which means that new studies involving a greater number of subjects become mandatory. In the particular case of physiological monitoring, satisfactory clinical evidence should be provided regarding the reliability of measurements, and also regarding the improvement in the quality of life, wellness, and health conditions brought by technological solutions.

Acceptability and Long-Term Engagement

To be applicable on a large scale, video-based assistive technologies must be accepted by the end users, including monitored subjects, their families, and carers.

Stimulating initial adoption of the technology and long-term engagement is the key to making a true impact in real-life scenarios. To this end, the monitoring system design should adapt to different scenarios that range from primary prevention for healthy youngsters to the management of

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 16

B978-0-12-813445-0.00006-X, 00006

chronic diseases in the elderly. While the physiological parameters computed could be the same in these scenarios, the best way to acquire data, interact, and communicate should be tailored to the specific needs of the users and their carers.

Privacy and Security

The monitoring of sensitive physiological data bears with it the issue of privacy. On the one hand, people should be made aware of a functioning system in order to augment their sense of trust and confidence and the feeling that they are retaining control of their data. On the other hand, cross-age and cross-gender studies are needed to assess individual levels of user acceptance since the concept of privacy is evolving as technology evolves [106] and the perception of privacy shows cultural, gender, and age differences. The goal is to support the development of privacy-by-design video-based systems, which take into account user privacy requirements from the very beginning [107].

Another issue is that sensitive data can be intercepted by third parties and used for malicious purposes. The recording of images and video data makes preventing sensitive data from attacks especially urgent. The problem of cyber-security calls for solutions from different fields, including cryptography, data management, data mining, and related areas.

6.5 A POSSIBLE SOLUTION: THE WIZE MIRROR

The European Community's Seventh Framework Programme Project SEMEOTICONS developed an innovative AAL solution that extensively leverages computer vision methods into a noninvasive device for wellbeing monitoring. The multisensory device, which looks like a common mirror and is called the Wize Mirror, was conceived as an effective technology-assisted intervention to prevent cardiometabolic diseases.

Cardiometabolic diseases (i.e. cardiovascular diseases and type 2 diabetes) are the leading causes of mortality worldwide and their spread on a global scale is putting a strain on social resources and health systems. An estimated 17.7 million people died from cardiovascular diseases in 2015, corresponding to 31% of all global deaths [108]. This figure is expected to increase in the coming years due to population aging and the increasing incidence of obesity and diabetes [109]. Clinical evidence has demonstrated that the majority of cardiometabolic diseases can be prevented by limiting exposure to the main risk factors; by exercising regularly, eating well,

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 17

B978-0-12-813445-0.00006-X, 00006

controlling stressful conditions, avoiding smoking, and moderating alcohol intake, about 90% of type 2 diabetes, 80% of coronary heart disease, and 70% of strokes could be prevented [110]. This awareness has fostered the promotion of educational and guidance programs for lifestyle improvement that call for assistive and personal technologies as a powerful ally to address large shares of the population.

The Wize Mirror responds to this call coming as a self-monitoring device able to blend seamlessly into life's daily routines. The guiding principle was to have a device able to minimize invasiveness, obtrusiveness, and attention theft, while maximizing usability, trustfulness, and user acceptance. This appears, in fact, to be the most promising way to address and engage various shares of the at-risk population, who have assorted needs and expectations and have diverse digital skills. The Wize Mirror implements an AAL solution based on a virtuous cycle underpinning three main elements:

- self-measurement;
- education and coaching;
- user experience, with particular emphasis on contact with healthcare professionals.

Combining together these features into a loop has demonstrated to be the key to ensuring the acceptance, effectiveness, and long-term impact of self-monitoring AAL interventions [111]. The Wize Mirror blends together these functionalities by taking into account the diverse challenges reported in Section 6.4.

6.5.1 Self-Measurement

The Wize Mirror seamlessly integrates a contactless sensing framework, including different types of cameras, and a data processing platform able to scan the person in front of it and assess physiological markers of cardiometabolic risk. The main cardiometabolic risk factors include hypertension; dyslipidemia; glucose dysmetabolism; obesity and overweight; noxious habits such as smoking and alcohol abuse; and adverse psychological states such as chronic conditions of stress, anxiety, and fatigue [108]. Stemming from the principles of medical semeiotics [112], the Wize Mirror analyzes physical and expressive traits of the face and the composition of the breath to detect both perceptible and subtle signs correlated to the factors listed above. The sensing framework relies on

- an inexpensive 3D scanner based on depth cameras;

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 18

B978-0-12-813445-0.00006-X, 00006

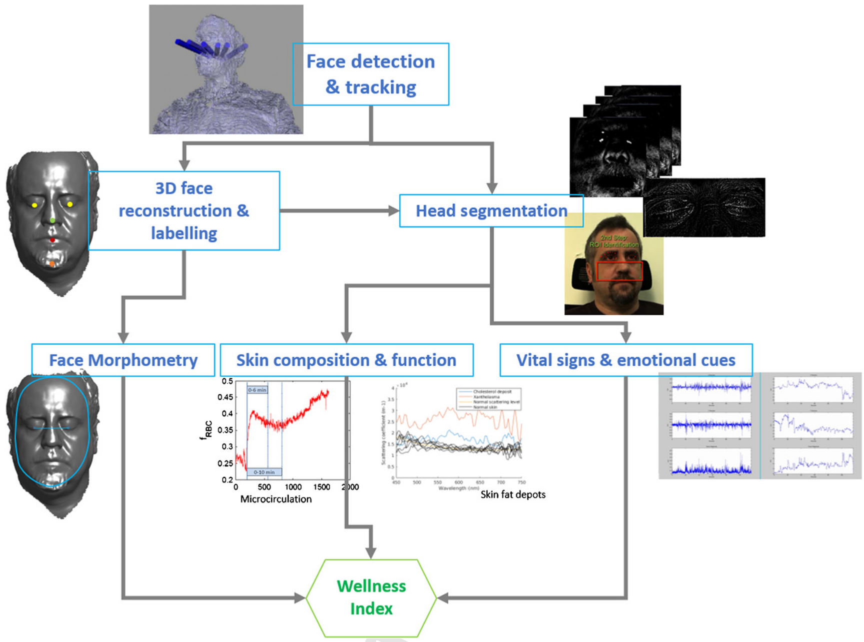

Figure 6.1 Scheme of the Wize Mirror workflow. Data from sensors are preprocessed, analyzed, and finally integrated in the virtual individual model.

- a MSI system, made up of five compact monochrome cameras with band-pass filters at selected wavelengths, and two computer-controlled LED strips (white and UV light sources);
- high-resolution RGB cameras;
- and a portable gas-sensor device connected to the Wize Mirror.

The sensors acquire depth and multispectral images, videos, and breath signals that are processed with cutting-edge computer vision and data-processing methods to evaluate anthropometric and morphometric parameters, facial skin compositional and functional markers, vital signs and emotional cues, and breath composition. The data workflow in the Wize Mirror is summarized in Fig. 6.1.

Details on the methods developed have been reported in other publications [113,7]. Here we report and discuss their main features with respect to the challenges introduced in Section 6.4. It is worth noting that the technological development of the Mirror required a careful organization of the sensory framework to meet data quality and robustness requirements. Position, displacement, and tilt of the cameras resulted from several tests

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 19

B978-0-12-813445-0.00006-X, 00006

and prototyping trials that explored several options with respect to the user position in front of the Mirror. This was done to achieve the best view and overcome disturbances. Similarly, the lighting system was devised to counteract ambient light disturbances and ensure the homogeneous illumination of the face during data acquisitions.

3D Data

The 3D scanner data are processed to enable

- face detection and recognition, used to detect and recognize the user in front of the Mirror, as reported in [114];
- 3D head pose tracking, facial segmentation, and labeling;
- 3D reconstruction.

These are core functionalities that serve as a common asset for the other data processing facilities of the Mirror. The 3D data are in fact used to enable face detection and labeling on the 2D data obtained from the other camera systems. This choice responds to the need for robustness and efficiency of data processing methods. Face detection and tracking is performed on the data from the depth sensors only once rather than several times on the various data streams: this ensures robustness to varying illumination conditions and optimizes the processing time. The user is first detected in the 3D space; then, by fitting a face mask on the depth sensor data, the position and the orientation of the user's face are detected. After that, selected facial landmarks are localized and their 3D coordinates are projected into the 2D frames of the other camera streams. This is done by using the intrinsic and extrinsic parameters of the cameras within a camera calibration and registration procedure done at system setup [113]. The camera's synchronization procedure allows the system to meet the requirement for real-time processing.

The 3D model of the face serves the anthropometric and morphometric analyses. It results from a reconstruction algorithm adapted from the Kinect fusion method to meet the needs posed by the fact that in the Mirror the depth sensors remain in a fixed position while the face is moving [7]. A re-meshing algorithm runs on the 3D point cloud to ensure producing a manifold, without holes and degenerate elements [115].

Facial Morphometry

Facial morphometry analyzes the 3D face model to detect signs related to overweight and obesity. Four shape parameters are computed on the 3D

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 20

B978-0-12-813445-0.00006-X, 00006

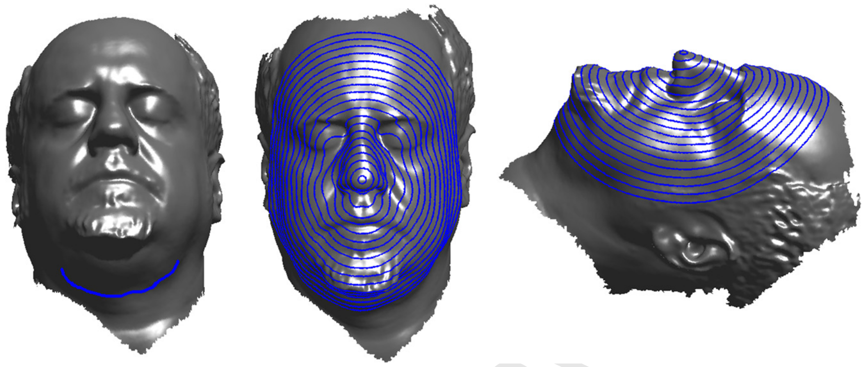

Figure 6.2 Facial morphology description in the Wize Mirror.

manifold as strictly correlated to weight, BMI, waist circumference, hip circumference, and neck circumference [116]. They correspond to

- the length of the maximal curve among those resulting from the intersection of a family of concentric Euclidean spheres centered on the nose tip and the face manifold (see the left panel in Fig. 6.2);
- the geodesic analogue of the previous length;
- the area of an annulus computed at the border of the face manifold (see the mid panel in Fig. 6.2);
- the length of the geodesic path in the neck area that connects two points under the ears (see the right panel in Fig. 6.2).

In addition to their relevance with respect to risk factors, these parameters represent a good trade-off between processing time and accuracy. Indeed, their estimation does not require the detection of a large number of landmarks, which can be cumbersome and time-consuming, and their value is invariant to rotation, translation, and scale, and robust to noise and pose estimation errors.

Skin Compositional and Functional Markers

Multispectral imaging data enable the analysis of skin composition and function to detect signs correlated to dyslipidemia, glucose dysmetabolism, and endothelial dysfunction. These are completely innovative techniques, developed for the first time in SEMEOTICONS, which rely on noninvasive, contactless data acquisition through a camera system.

The analysis of skin composition focuses on the detection of fat depots and the accumulation of Advanced Glycation End-products (AGEs). Skin fat depots turned out to be anti-correlated to low levels of HDL cholesterol

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 21

B978-0-12-813445-0.00006-X, 00006

in the blood, which is one of the signs of dyslipidemia. In the Mirror, they are detected and measured on images acquired on a single wavelength (560 nm or 580 nm) by estimating the droplets with higher skin reflection in an area underneath the eye (where fat accumulates most) [113].

AGE-products are linked to the metabolism of glucose. Their accumulation in the skin increases with aging, but when above a certain threshold, it signals an increased risk of cardiometabolic disorders. In the Mirror, AGE accumulation is estimated during UV exposure from a 365 nm LED as the ratio of the fluorescence intensity (evaluated on a 475 nm image) to the illumination intensity (evaluated on a 360 nm image). See [117] for further details.

The analysis of skin function aims to assess endothelium function. The endothelium regulates vasodilation in response to different blood-flow needs. A dysfunction of this tissue may be a consequence or a cause of several pathologies, such as hypertension, hypercholesterolemia, and diabetes. In the Mirror, endothelial function is measured on MSI data by assessing the response of facial skin microcirculation after heating the cheek via a computer-controlled remote skin heater. An index of the function is defined based on two parameters calculated on 475–650 nm images: hemoglobin oxygenation and the fraction of red blood cells in the skin before and after heating [113].

Vital Signs and Emotional Cues

By processing 2D videos, the Mirror estimates vital signs and emotional cues connected to adverse psychological statuses. Vital signs include HR, RR, and HRV, which are indeed the most informative parameters associated with the psycho-physical status of an individual. In the Mirror these parameters are analyzed through video-processing methods based on blind source separation through Independent Component Analysis, as described in [118].

Cues of emotional status derive from the analysis of short video recordings processed to spot micro-expressions and facial gestures typical of stress, anxiety, and fatigue. For stress and anxiety, these cues generally correspond to facial-muscle hyperactivity, which may be discretized in head movements, eye movements (in terms of eye gazing and frequent focus, pupil dilation, and blinking rates), and mouth movements (in terms of jaw clenching, lip trembling, and biting). Fatigue is here intended as a sense of tiredness, lack of energy, and a feeling of exhaustion. Signs of fatigue are mainly yawing and saccadic movements. In the Mirror, all these signs

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 22

are extracted from the videos though different feature extraction methods and are fed into an Artificial Neural Network model trained to classify emotional traits [113,105]. Considering how challenging and complex a proper recognition is, the neural model also takes in vital signs (i.e. HR and RR) and uses as reference a video shot at baseline during the user's registration when the user is shown a video to induce a relaxed condition.

Breath Analysis

The gas sensing device connected to the Mirror analyzes the composition of the breath and supplies feedback about the effect of noxious habits. The device, called the Wize Sniffer, detects molecules such as carbon monoxide, ethanol, hydrogen, oxygen, and carbon dioxide. The presence and variation of these substances can be correlated to smoking, alcohol consumption, and metabolic disorders. The Sniffer acquires a breath sample through a corrugated tube connected to the Mirror, analyzes its composition and provides the Mirror with a grading of the risk the users are exposed to due to their habits (no risk, moderate risk, or high risk) [119].

Acquisition Timing

The Mirror requires just a few seconds without requiring too much effort to scan the faces of the users while they are standing or sitting in front of it as part of their daily routine. Overall, facial morphometry, skin composition, vital signs, and emotional analyses all together take one minute of data acquisition. Breath analysis takes the time of a deep breath and it entails the simple interaction of breathing into a mouthpiece. Thanks to a parallel implementation on a multiprocessor board, results are provided in real time, in only a few seconds. Only HRV and endothelial function require a five- and six-minute acquisition, respectively. This time is unavoidable and is necessary to ascertain the dynamics of the underlying physiological phenomenon.

It is worth underlining that unlike the breath analysis, all the other analyses rely on image and video processing. This means that they can be integrated, with proper customization, into any device or equipment that already hosts or is able to host some of the sensors behind the Mirror such as a TV set, a mobile phone or tablet, a personal computer, etc. This flexibility increases the potential of the Wize Mirror to address users with different needs and preferences.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 23

B978-0-12-813445-0.00006-X, 00006

6.5.2 Education and Coaching

The Wize Mirror is an interactive device with a touchscreen Graphical User Interface (GUI) that conveys information to and from the users. Through the GUI, the Mirror trains on and guides the users through the self-measurement procedure and informs them about the significance of the parameters measured. It also provides the users with high-quality educational materials on cardiometabolic risks and the importance of primary prevention. In the current implementation, during data acquisition, the Mirror displays some short and sharp messages promoting behavioral changes, complementing them with captivating and instructive images or short videos.

Although properly explained, the set of measurements that the Mirror is able to assess covers a wide range of psycho-physiological parameters that if displayed separately may overwhelm the users and mislead their understanding of their own status. To avoid this, the Mirror integrates the measurements into a Wellness Index, which measures the users' wellness with respect to the risk of a cardiovascular disease on a scale from 1 to 100. The Index results from the application of a Structural Equation Model [120] to the measurements taken by the device and other data inputted by the users through validated questionnaires on their habits and attitudes [113]. The Index is displayed on the Mirror (see Fig. 6.3), organized in three main components that cover the main facets of individual wellness: (i) the physical component summarizes the physical conditions of the user as the outcome of physiological measurements (i.e. facial morphometry and skin composition and function); (ii) the emotional component measures psychological conditions as a combination of the emotional cues and the vital signs; and (iii) the lifestyle component scores the users' habits in terms of noxious habits, diet, and physical activity by leveraging outcomes from the Sniffer and the data provided by the questionnaires. The approach behind the WI is highly innovative, since it merges objective measures (obtained by the device) with subjective information provided by the users on their perceived status. Other solutions currently in use, such as the WHO-5 index [121], use only the subjective evaluation and this can obviously hide potential biases.

As shown in Fig. 6.4, the Wellness Index is traced over time and stored in the Mirror in a diary to be consulted by the users. Its evolution over time is the basis of the personalized guidance that counsels the users on lifestyle improvements that increase their WI and ameliorate their physical and emotional health. The guidance relies on the definition of the user profile in

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 24

B978-0-12-813445-0.00006-X, 00006

Figure 6.3 The Wellness Index as presented in the Wize Mirror GUI.

Figure 6.4 The Wellness Index can be traced over time and stored in a personal diary.

terms of attitudes, habits, and preferences. These pieces of information are gathered through the questionnaires the users answer when registering the first time or whenever they want via a dedicated mobile app connected to the Mirror. The guidance addresses the major lifestyle targets, including diet, physical activity, smoking, alcohol consumption, sleep, and stress and anxiety management. Recommendations are tailored to the users' traits, in terms of frequency, intensity, and linguistic style. Tailoring relies on a set of modulators that estimate initial health conditions, reported self-efficacy, and emotional strength via the set of standardized questionnaires [113].

Education and guidance are essential ingredients of AAL solutions to drive a long-term effect. In the era of doctor Google, the provision of high-

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 25

B978-0-12-813445-0.00006-X, 00006

quality information based on scientific evidence is becoming more and more urgent and mandatory. Overall, educational and counseling messages contribute to improving users' knowledge and risk perception, ameliorating their health literacy, and increasing their involvement and degree of comfort in making healthy choices [122].

The approach adopted by the Wize Mirror stems from these considerations and is meant to captivate the users by offering a holistic approach to wellness. As a matter of fact, more and more people are seeking ways not only to lose weight or look better, but also to improve their quality of life and overall sense of wellness.

6.5.3 User Experience

A pleasant user experience is crucial to stimulating the initial adoption and periodic utilization of self-monitoring devices. The Wize Mirror features a touchscreen and an intuitive interface that makes it usable and appealing to people with different digital skills. It also offers a range of user applications and services that span from sharing data with healthcare professionals and general practitioners to playing music, social network connections, email consultation, and web surfing. The Wize Mirror can indeed be seen as a big tablet integrated into the bathroom mirror. Future extensions include the connection to wearable devices or mobile apps to automatically upload data on physical activity, sleep, and diet.

Among the different services, the link with healthcare professionals is of paramount importance: on the one hand, it reinforces the impact of the device by making the users feel more secure and cared about; on the other hand, it enables care providers to gather data and insight never available before.

To meet privacy and security requirements, the Mirror features an authentication facility that is based on the automatic user recognition, but it always requires a confirmation code. A privacy-by-design approach was adopted to design the storage system along with data encryption. The data shared with care professionals mainly consist of the Wellness Index and measurement values. Images and videos are never transferred from the Mirror over the Internet.

6.5.4 Wize Mirror Validation

The Wize Mirror underwent a validation campaign to verify the accuracy, repeatability, reproducibility, and effectiveness of its measurements and to

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 26

B978-0-12-813445-0.00006-X, 00006

check acceptability by the users. Three prototypes were deployed in three clinical sites in Italy and France between July and October 2016. A human study involved 72 volunteers who underwent Mirror scans every 15 days for three months. Reference data were acquired contextually with diagnostic devices used in clinical practice to measure body composition and metabolic, homeostatic, and vital parameters. A comparison showed a statistically significant correlation of Mirror measurements and standard clinical measures. Moreover, it was observed that both originally motivated and unmotivated volunteers were able to significantly modify their physiological conditions, and that there was an evident decrease in their BMI. Details on these outcomes are being reported in a dedicated paper to be published within the medical literature.

Overall, the validation demonstrated the reliability of the Mirror's measurements and interventions. This is key to nurturing the device acceptance by both the end users and the clinical professionals. In particular, the clinicians' trust in the device plays a key role in the promotion of the Mirror among the at-risk population.

6.6 CONCLUSION

In recent decades healthcare systems have experienced an exponential growth in costs that is related to different social, cultural, and economic factors. The need for sustainable healthcare systems translates into challenges in ICT for the implementation of autonomous and proactive healthcare services. We believe the synergy between AAL technologies and computer vision may support moving medical and healthcare services from hospitals to home environments, thus cutting down healthcare costs.

As observed in [2], AAL systems could support the third generation of telecare systems. The first generation was the panic-alarm gadgets used to summon help in case of emergency, and the second was sensor-based monitoring systems used to support medical decisions; the third generation of systems shifts from a reactive approach to a proactive strategy for anticipating emergency situations. Computer vision can help embark on this revolutionary path. Science and technology and research are mature, though further research is needed to solve a number of open issues, including robustness, accuracy, and nonintrusiveness of data acquisition; clinical validity of the output delivered by existing techniques; and attention to the needs and demands of real end users in terms of acceptability and long-term engagement.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 27

With the Wize Mirror, we have seen how we can begin to think of a fourth generation of telecare systems, which are explicitly designed to influence human behavior and persuade people to act upon their lifestyles and their health. We believe the convergence of different disciplines, from information technology (including computer vision) to cognitive science, is the way forward.

ACKNOWLEDGMENTS

This work has been partially supported by the European Community's Seventh Framework Programme (FP7/2013–2016) under grant agreement number 611516 (SEMEOTICONS). The authors would like to acknowledge the SEMEOTICONS project partners (Centre de Recherche en Nutrition Humaine Rhone–Alpes, COSMED SRL, DRACO SYSTEMS SL, FORTH – Foundation for Research and Technology, Hellenic Telecommunications & Telematics Applications Company, INTECS SPA, Linkóping University, Norwegian University of Science and Technology, University of Central Lancashire) for their valuable contributions to the development of the Wize Mirror.

REFERENCES

[1] R. Al-Shaqi, M. Mourshed, Y. Rezgui, Progress in ambient assisted systems for independent living by the elderly, SpringerPlus 5 (624) (2016).

[2] G. Acampora, D.J. Cook, P. Rashidi, A.V. Vasilakos, A survey on ambient intelligence in health care, Proceedings of the IEEE 101 (12) (2013) 2470–2494.

[3] F. Cardinaux, D. Bhowmik, C. Abhayaratne, M.S. Hawley, Video based technology for ambient assisted living: a review of the literature, Journal of Ambient Intelligence and Smart Environments 3 (3) (2011) 253–269.

[4] R. Planinc, A.A. Chaaraoui, M. Kampel, F. Florez-Revuelta, Computer vision for active and assisted living, in: F. Florez-Revuelta, A.A. Chaaraoui (Eds.), Active and Assisted Living: Technologies and Applications, IET, 2016, pp. 57–79.

[5] T. Subetha, S. Chitrakala, A survey on human activity recognition from videos, in: Proceedings of IEEE International Conference on Information Communication and Embedded Systems (ICICES), 2016.

[6] A. Danielis, D. Giorgi, M. Larsson, T. Strömberg, S. Colantonio, O. Salvetti, Lip segmentation based on Lambertian shadings and morphological operators for hyperspectral images, Pattern Recognition 63 (2017) 355–370.

[7] Y. Andreu, F. Chiarugi, S. Colantonio, G. Giannakakis, D. Giorgi, P. Henriquez, et al., Wize Mirror: a smart, multisensory cardio-metabolic risk monitoring system, Computer Vision and Image Understanding 148 (2016) 3–22.

[8] S. Fleck, W. Strasser, Smart camera based monitoring system and its application to assisted living, Proceedings of the IEEE 96 (10) (2008) 1698–1714.

[9] K. Caine, S. Šabanović, M. Carter, The effect of monitoring by cameras and robots on the privacy enhancing behaviors of older adults, in: Proceedings of the 7th ACM/IEEE International Conference on Human–Robot Interaction (HRI), 2012, pp. 343–350.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 28

B978-0-12-813445-0.00006-X, 00006

[10] S.T. Londei, J. Rousseau, F. Ducharme, A. St-Arnaud, J. Meunier, J. Saint-Arnaud, An intelligent videomonitoring system for fall detection at home: perceptions of elderly people, Journal of Telemedicine and Telecare 15 (8) (2009) 383–390.
[11] M. Mataric, J. Eriksson, D. Feil-Seifer, C. Winstein, Socially assistive robotics for post-stroke rehabilitation, Journal of NeuroEngineering and Rehabilitation 4 (5) (2007).
[12] C. Brüser, C.H. Antink, T. Wartzek, M. Walter, S. Leonhardt, Ambient and unobtrusive cardiorespiratory monitoring techniques, IEEE Reviews in Biomedical Engineering 8 (2015) 30–43.
[13] W. Verkruysse, L.O. Svaasand, J.S. Nelson, Remote plethysmographic imaging using ambient light, Optics Express 16 (26) (2008) 21434–21445.
[14] M.Z.Z. Poh, D.J. McDuff, R.W. Picard, Advancements in noncontact, multiparameter physiological measurements using a webcam, IEEE Transactions on Biomedical Engineering 58 (1) (2011) 7–11.
[15] H. Monkaresi, R. Calvo, H. Yan, A machine learning approach to improve contactless heart rate monitoring using a webcam, IEEE Journal of Biomedical and Health Informatics 18 (4) (2013) 2168–2194.
[16] L. Wei, Y. Tian, Y. Wang, T. Ebrahimi, T. Huang, Automatic webcam-based human heart rate measurements using Laplacian Eigenmap, in: K.M. Lee, Y. Matsushita, J.M. Rehg, Z. Hu (Eds.), Computer Vision – ACCV 2012, ACCV 2012, in: Lecture Notes in Computer Science, vol. 7725, Springer, Berlin, Heidelberg, 2013, pp. 281–292.
[17] L. Feng, L.M. Po, X. Xu, Y. Li, R. Ma, Motion-resistant remote imaging photoplethysmography based on the optical properties of skin, IEEE Transactions on Circuits and Systems for Video Technology 25 (5) (2015) 879–891.
[18] M. Lewandowska, J. Ruminski, T. Kocejko, J. Nowak, Measuring pulse rate with a webcam; A non-contact method for evaluating cardiac activity, in: 2011 Federated Conference on Computer Science and Information Systems (FedCSIS), 2011, pp. 405–410.
[19] W. Wang, S. Stuijk, G. De Haan, Exploiting spatial redundancy of image sensor for motion robust rPPG, IEEE Transactions on Biomedical Engineering 62 (2) (2015) 415–425.
[20] L. Tarassenko, M. Villarroel, A. Guazzi, J. Jorge, D.A. Clifton, C. Pugh, Non-contact video-based vital sign monitoring using ambient light and auto-regressive models, Physiological Measurement 35 (5) (2014) 807–831.
[21] G. De Haan, V. Jeanne, Robust pulse rate from chrominance-based rPPG, IEEE Transactions on Biomedical Engineering 60 (10) (2013) 2878–2886.
[22] G. Balakrishnan, F. Durand, J. Guttag, Detecting pulse from head motions in video, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2013, pp. 3430–3437.
[23] L. Capdevila, J. Moreno, HRV based health&sport markers using video from the face, in: 34th Annual International Conference of the IEEE EMBS, 2012, pp. 5646–5649.
[24] S.J. Jung, W.Y. Chung, B.G. Lee, Real-time physiological and vision monitoring of vehicle driver for non-intrusive drowsiness detection, IET Communications 5 (17) (2011) 2461–2469.
[25] L. Iozzia, L. Cerina, L. Mainardi, Relationships between heart-rate variability and pulse-rate variability obtained from video-PPG signal using ZCA, Physiological Measurement 37 (11) (2016) 1934–1944, http://stacks.iop.org/0967-3334/37/i=11/a=1934?key=crossref.c843764ea2967b599a70a9124fef61c3.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 29

[26] M.H. Li, A. Yadollahi, B. Taati, Non-contact vision-based cardiopulmonary monitoring in different sleeping positions, IEEE Journal of Biomedical and Health Informatics (2016) 2194, http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7468522.

[27] F. Benetazzo, A. Freddi, A. Monteriù, L. Sauro, Respiratory rate detection algorithm based on RGB-D camera: theoretical background and experimental results, Healthcare Technology Letters 1 (3) (2014) 81–86.

[28] G. Allali, C.P. Launay, H.M. Blumen, M.L. Callisaya, A.M.D. Cock, R.W. Kressig, et al., Falls, cognitive impairment, and gait performance: results from the GOOD initiative, Journal of the American Medical Directors Association 18 (4) (2017) 335–340.

[29] M.L. Callisaya, C.P. Launay, V.K. Srikanth, J. Verghese, G. Allali, O. Beauchet, Cognitive status, fast walking speed and walking speed reserve – the Gait and Alzheimer Interactions Tracking (GAIT) study, GeroScience (2017), http://link.springer.com/10.1007/s11357-017-9973-y.

[30] R. Kenny, C.N. Scanaill, M. McGrath, Falls prevention in the home, in: Intelligent Technologies for Bridging the Grey Digital Divide, IGI Global, 2010, pp. 46–64, http://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-61520-825-8.ch004.

[31] A. Muro-de-la Herran, B. García-Zapirain, A. Mendez-Zorrilla, Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications, Sensors 14 (2) (2014) 3362–3394.

[32] C. Rougier, J. Meunier, A. St-Arnaud, J. Rousseau, Fall detection from human shape and motion history using video surveillance, in: Advanced Information Networking and Applications Workshops, 2007.

[33] H. Foroughi, A. Naseri, A. Saberi, H. Sadoghi Yazdi, An eigenspace-based approach for human fall detection using Integrated Time Motion Image and Neural Network, in: 9th International Conference on Signal Processing, 2008, pp. 1499–1503.

[34] T. Lee, A. Mihailidis, An intelligent emergency response system: preliminary development and testing of automated fall detection, Journal of Telemedicine and Telecare 11 (4) (2005) 194–198.

[35] J. Tao, M. Turjo, M.-F. Wong, M. Wang, Y.-P. Tan, Fall incidents detection for intelligent video surveillance, in: 5th International Conference on Information Communications & Signal Processing, IEEE, 2005.

[36] N. Thome, S. Miguet, S. Ambellouis, A real-time, multiview fall detection system: a LHMM-based approach, IEEE Transactions on Circuits and Systems for Video Technology 18 (11) (2008) 1522–1532.

[37] Y. Xiang, Y.P. Tang, B.Q. Ma, H.C. Yan, J. Jiang, X.Y. Tian, Remote safety monitoring for elderly persons based on omni-vision analysis, PLoS ONE 10 (5) (2015) 1–16.

[38] C. Rougier, J. Meunier, A. St-Arnaud, J. Rousseau, Monocular 3D head tracking to detect falls of elderly people, in: Proceedings, Annual International Conference of the IEEE Engineering in Medicine and Biology, 2006, pp. 6384–6387.

[39] B.U. Töreyin, Y. Dedeoğlu, A.E. Çetin, HMM based falling person detection using both audio and video, in: N. Sebe, M. Lew, T.S. Huang (Eds.), Computer Vision in Human–Computer Interaction, HCI 2005, in: Lecture Notes in Computer Science, vol. 3766, Springer, Berlin, Heidelberg, 2005, pp. 1–4.

[40] C.W. Lin, Z.H. Ling, Automatic fall incident detection in compressed video for intelligent homecare, in: Proceedings, International Conference on Computer Communications and Networks, ICCCN, 2007, pp. 1172–1177.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 30

B978-0-12-813445-0.00006-X, 00006

[41] C.Y. Chang, B. Lange, M. Zhang, S. Koenig, P. Requejo, N. Somboon, et al., Towards pervasive physical rehabilitation using Microsoft Kinect, in: 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops, 2012, pp. 159–162.
[42] S.S. Rathore, A.R. Hinn, L.S. Cooper, H.A. Tyroler, W.D. Rosamond, Characterization of incident stroke signs and symptoms, Stroke 33 (2002) 2718–2721.
[43] L.E. Sucar, F. Orihuela-Espina, R.L. Velazquez, D.J. Reinkensmeyer, R. Leder, J. Hernández-Franco, Gesture therapy: an upper limb virtual reality-based motor rehabilitation platform, IEEE Transactions on Neural Systems and Rehabilitation Engineering 22 (2014) 634–643.
[44] K.M. Vamsikrishna, D.P. Dogra, M.S. Desarkar, Computer-vision-assisted palm rehabilitation with supervised learning, IEEE Transactions on Biomedical Engineering 63 (2016) 991–1001.
[45] T. Johansson, C. Wild, Telerehabilitation in stroke care – a systematic review, Journal of Telemedicine and Telecare 17 (1) (2011) 1–6.
[46] K. Norton, T. Olds, Anthropometrica: A Textbook of Body Measurements for Sports and Health Courses, UNSW Press, 1996.
[47] A. Keys, F. Fidanza, M. Karvonen, N. Kimura, H. Taylor, Indices of relative weight and obesity, Journal of Chronic Diseases 25 (1972) 329–343.
[48] World Health Organization, Obesity and overweight – fact sheet n. 311, http://www.who.int/mediacentre/factsheets/fs311/en/, 2016.
[49] World Health Organization, Physical activity – fact sheet n. 385, http://www.who.int/mediacentre/factsheets/fs385/en/, 2017.
[50] M.K. Tulloch-Reid, D.E. Williams, H.C. Looker, R.L. Hanson, W.C. Knowler, Do measures of body fat distribution provide information on the risk of type 2 diabetes in addition to measures of general obesity?, Diabetes Care 26 (9) (2003) 2556–2561.
[51] A. Onat, G. Hergenc, H. Yuksel, G. Can, E. Ayhan, Z. Kaya, D. Dursunoglu, Neck circumference as a measure of central obesity: associations with metabolic syndrome and obstructive sleep apnea syndrome beyond waist circumference, Clinical Nutrition 28 (1) (2009) 46–51.
[52] C. Stabe, A. Vasques, M. Lima, M. Tambascia, J. Pareja, A. Yamanaka, B. Geloneze, Neck circumference as a simple tool for identifying the metabolic syndrome and insulin resistance: results from the Brazilian Metabolic Syndrome Study, Clinical Endocrinology 78 (6) (2013) 874–881.
[53] L. Ben-Noun, A. Laor, Relationship between changes in neck circumference and cardiovascular risk factors, Experimental and Clinical Cardiology 11 (1) (2006) 14–20.
[54] D. Brenner, K. Tepylo, K. Eny, L. Cahill, A. El-Sohemy, Comparison of body mass index and waist circumference as predictors of cardiometabolic health in a population of young Canadian adults, Diabetology & Metabolic Syndrome 2 (1) (2010) 1–8, https://doi.org/10.1186/1758-5996-2-28.
[55] I. Janssen, P. Katzmarzyk, R. Ross, Body mass index, waist circumference, and health risk: evidence in support of current national institutes of health guidelines, Archives of Internal Medicine 162 (18) (2002) 2074–2079.
[56] A. Liese, et al., Development of the multiple metabolic syndrome in the ARIC cohort: joint contribution of insulin, BMI, and WHR. Atherosclerosis risk in communities, Annals of Epidemiology 7 (6) (1997) 407–416.
[57] B. Heitmann, et al., Hip circumference and cardiovascular morbidity and mortality in men and women, Obesity Research 12 (2004) 482–487.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 31

[58] R. Huxley, S. Mendis, E. Zheleznyakov, S. Reddy, J. Chan, Body mass index, waist circumference and waist: hip ratio as predictors of cardiovascular risk—a review of the literature, European Journal of Clinical Nutrition 64 (2009) 16–22, https://doi.org/10.1038/ejcn.2009.68.

[59] R. Newcombe, S. Izadi, O. Hilliges, D. Molyneaux, D. Kim, A. Davison, et al., Kinectfusion: real-time dense surface mapping and tracking, in: Proceedings of the 10th IEEE International Symposium on Mixed and Augmented Reality (ISMAR), Basel, Switzerland, 2011, pp. 127–136.

[60] S. Li, Z. Lei, M. Ao, The HFB face database for heterogeneous face biometrics research, in: 6th IEEE Workshop on Object Tracking and Classification Beyond and in the Visible Spectrum (OTCBVS, in conjunction with CVPR 2009), Miami, Florida, 2009.

[61] H. Li, E. Vouga, A. Gudym, L. Luo, J. Barron, G. Gusev, 3D self-portraits, ACM Transactions on Graphics 32 (6) (2013) 1–9, https://doi.org/10.1145/2508363.2508407.

[62] J. Tong, J. Zhou, L. Liu, Z. Pan, H. Yan, Scanning 3D full human bodies using Kinects, IEEE Transactions on Visualization and Computer Graphics 18 (2012) 643–650, https://doi.org/10.1109/TVCG.2012.56.

[63] A. Weiss, D. Hirshberg, M. Black, Home 3D body scans from noisy image and range data, in: 2011 IEEE International Conference on Computer Vision (ICCV), IEEE, pp. 1951–1958, 2011.

[64] F. Remondino, 3-D reconstruction of static human body shape from image sequence, Computer Vision and Image Understanding 93 (1) (2004) 65–85, https://doi.org/10.1016/j.cviu.2003.08.006.

[65] K. Robinette, H. Daanen, E. Paquet, The CAESAR project: a 3-D surface anthropometry survey, in: IEEE Second International Conference on 3-D Digital Imaging and Modeling, IEEE, 1999, pp. 380–386.

[66] L. Pishchulin, S. Wuhrer, T. Helten, C. Theobalt, B. Schiele, Building statistical shape spaces for 3D human modeling, Pattern Recognition (2017).

[67] P. Phillips, P. Flynn, T. Scruggs, K. Bowyer, K. Hoffman, J. Marques, Jaesik Min, W. Worek, Overview of the face recognition grand challenge, in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2005, pp. 947–954.

[68] M.P. Evison, R.W.V. Bruegge, The Magna database: a database of three-dimensional facial images for research in human identification and recognition, Forensic Science Communications 10 (2) (2008).

[69] V. Blanz, T. Vetter, A morphable model for the synthesis of 3D faces, in: SIGGRAPH 1999, ACM, 1999, pp. 187–194.

[70] T. Huynh, R. Min, J. Dugelay, An efficient LBP-based descriptor for facial depth images applied to gender recognition using RGB-D face data, in: ACCV Workshop on Computer Vision with Local Binary Pattern Variants, Springer, 2012, pp. 133–135.

[71] P. Paysan, R. Knothe, B. Amberg, S. Romdhani, T. Vetter, A 3D face model for pose and illumination invariant face recognition, in: 6th IEEE International Conference on Advanced Video and Signal Based Surveillance for Security, Safety and Monitoring in Smart Environments, IEEE, 2009, pp. 296–301.

[72] T. Gatzke, C. Grimm, M. Garland, S. Zelinka, Curvature maps for local shape comparison, in: Proceedings of the International Conference on Shape Modeling and Applications 2005, SMI '05, IEEE Computer Society, Washington, DC, USA, 2005, pp. 246–255.

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 32

B978-0-12-813445-0.00006-X, 00006

[73] K. Gębal, J.A. Bærentzen, H. Aanæs, R. Larsen, Shape analysis using the auto diffusion function, Computer Graphics Forum 28 (5) (2009) 1405–1413, https://doi.org/10.1111/j.1467-8659.2009.01517.x.

[74] N. Gelfand, N.J. Mitra, L.J. Guibas, H. Pottmann, Robust global registration, in: Proceedings of the Third Eurographics Symposium on Geometry Processing, SGP '05, Eurographics Association, ISBN 3-905673-24-X, 2005.

[75] R. Gal, D. Cohen-Or, Salient geometric features for partial shape matching and similarity, ACM Transactions on Graphics 25 (1) (2006) 130–150, https://doi.org/10.1145/1122501.1122507.

[76] A. Elad, R. Kimmel, On bending invariant signatures for surfaces, IEEE Transactions on Pattern Analysis and Machine Intelligence 25 (10) (2003) 1285–1295, https://doi.org/10.1109/TPAMI.2003.1233902.

[77] B.K. Ng, B.J. Hinton, B. Fan, A.M. Kanaya, J.A. Shepherd, Clinical anthropometrics and body composition from 3D whole-body surface scans, European Journal of Clinical Nutrition 70 (11) (2016) 1265–1270, https://doi.org/10.1038/ejcn.2016.109.

[78] A. Tahrani, K. Boelaert, R. Barnes, et al., Body volume index: time to replace body mass index?, Endocrine Abstracts 15 (2008) 104.

[79] A. Romero-Corral, V. Somers, F. Lopez-Jimenez, Y. Korenfeld, S. Palin, K. Boclaert, et al., 3-D body scanner, body volume index: a novel, reproducible and automated anthropometric tool associated with cardiometabolic biomarkers, Obesity Research Journal 16 (1) (2008) 266-P.

[80] N.Y. Krakauer, J.C. Krakauer, A new body shape index predicts mortality hazard independently of body mass index, PLoS ONE 7 (7) (2012) 1–10, https://doi.org/10.1371/journal.pone.0039504.

[81] C.Y. Yu, C.H. Lin, Y.H. Yang, Human body surface area database and estimation formula, Burns 36 (5) (2010) 616–629, https://doi.org/10.1016/j.burns.2009.05.013.

[82] M. Kouchi, M. Mochimaru, Errors in landmarking and the evaluation of the accuracy of traditional and 3D anthropometry, Applied Ergonomics 42 (3) (2011) 518–527, https://doi.org/10.1016/j.eswa.2010.08.048.

[83] A. Giachetti, C. Lovato, F. Piscitelli, C. Milanese, C. Zancanaro, Robust automatic measurement of 3D scanned models for the human body fat estimation, IEEE Journal of Biomedical and Health Informatics 19 (2) (2015) 660–667, https://doi.org/10.1109/JBHI.2014.2314360.

[84] D.B. Stefan, D.A. Gilbert, Method for determining a subject's degree of adiposity, 2009, US Patent 7,599,537.

[85] V.F. Ferrario, C. Dellavia, G.M. Tartaglia, M. Turci, C. Sforza, Soft-tissue facial morphology in obese adolescents: a three-dimensional noninvasive assessment, Angle Orthodontist 74 (1) (2004) 37–42.

[86] J. Djordjevic, D.A. Lawlor, A.L. Zhurov, et al., A population-based cross-sectional study of the association between facial morphology and cardiometabolic risk factors in adolescence, BMJ Open 3 (2013) 1–10, e002910.

[87] B.J. Lee, J.H. Do, J.K. Kim, A classification method of normal and overweight females based on facial features for automated medical applications, Journal of Biomedicine and Biotechnology 2012 (2012) 1–9, 834578, https://doi.org/10.1155/2012/834578.

[88] B.J. Lee, J.K. Kim, Predicting visceral obesity based on facial characteristics, BMC Complementary and Alternative Medicine 14 (248) (2014) 1–9, https://doi.org/10.1186/1472-6882-14-248.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 33

B978-0-12-813445-0.00006-X, 00006

[89] S.M. Banabilh, A.H. Suzina, S. Dinsuhaimi, A.R. Samsudin, G.D. Singh, Craniofacial obesity in patients with obstructive sleep apnea, Sleep and Breathing 13 (2009) 19–24, https://doi.org/10.1007/s11325-008-0211-9.

[90] D. Giorgi, M.A. Pascali, P. Henriquez, B.J. Matuszewski, S. Colantonio, O. Salvetti, Persistent homology to analyse 3D faces and assess body weight gain, The Visual Computer 33 (5) (2017) 549–563.

[91] S. Cohen, D. Janicki-Deverts, G.E. Miller, Psychological stress and disease, JAMA: the Journal of the American Medical Association 298 (2007) 1685–1687.

[92] A. Damasio, G.B. Carvalho, The nature of feelings: evolutionary and neurobiological origins, Nature Reviews. Neuroscience 14 (2013) 143–152.

[93] M.F. Piepoli, A.W. Hoes, S. Agewall, et al., European Guidelines on cardiovascular disease prevention in clinical practice, European Heart Journal 2016 (37) (2016) 2315–2381.

[94] J.E. Dimsdale, Psychological stress and cardiovascular disease, Journal of the American College of Cardiology 51 (2008) 1237–1246.

[95] M. Bagherniya, S.S. Khayyatzadeh, A. Avan, M. Safarian, M. Nematy, G.A. Ferns, et al., Metabolic syndrome and its components are related to psychological disorders: a population based study, Diabetes & Metabolic Syndrome: Clinical Research & Reviews (2017), http://linkinghub.elsevier.com/retrieve/pii/S1871402117300784.

[96] K.W. Davidson, E. Mostofsky, W. Whang, Don't worry, be happy: positive affect and reduced 10-year incident coronary heart disease: The Canadian Nova Scotia Health Survey, European Heart Journal 31 (2010) 1065–1070.

[97] J. Turner, Emotional dimensions of chronic disease, Western Journal of Medicine 172 (2000) 124–128.

[98] M.E. Kemeny, M. Schedlowski, Understanding the interaction between psychosocial stress and immune-related diseases: a stepwise progression, Brain, Behavior, and Immunity 21 (2007) 1009–1018.

[99] E.M.V. Reiche, S.O.V. Nunes, H.K. Morimoto, Stress, depression, the immune system, and cancer, Lancet Oncology 5 (2004) 617–625.

[100] H. Gunes, M. Piccardi, Bimodal face and body gesture database for automatic analysis of human nonverbal affective behavior, in: Proceedings, vol. 1, International Conference on Pattern Recognition, 2006, pp. 1148–1153.

[101] M. Soleymani, M. Pantic, T. Pun, Multimodal emotion recognition in response to videos, IEEE Transactions on Affective Computing 3 (2012) 211–223.

[102] P. Ekman, W.V. Friesen, Facial Action Coding System: A Technique for the Measurement of Facial Movement, ISBN 0931835011, 1978.

[103] M. Shreve, S. Godavarthy, V. Manohar, D. Goldgof, S. Sarkar, Towards macro- and micro-expression spotting in video using strain patterns, in: 2009 Workshop on Applications of Computer Vision (WACV), IEEE, 2009, pp. 1–6.

[104] X. Li, X. Hong, A. Moilanen, X. Huang, T. Pfister, G. Zhao, M. Pietikainen, Towards reading hidden emotions: a comparative study of spontaneous micro-expression spotting and recognition methods, IEEE Transactions on Affective Computing 1 (2017), arXiv:1511.00423.

[105] G. Giannakakis, M. Pediaditis, D. Manousos, E. Kazantzaki, F. Chiarugi, P.G. Simos, et al., Stress and anxiety detection using facial cues from videos, Biomedical Signal Processing and Control 31 (2017) 89–101.

[106] C. Hayes, E. Poole, G. Iachello, S. Patel, A. Grimes, G. Abowd, et al., Physical, social, and experiential knowledge in pervasive computing environments, IEEE Pervasive Computing 6 (4) (2007) 56–63.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 34

B978-0-12-813445-0.00006-X, 00006

[107] M. Langheinrich, Privacy by design principles of privacy-aware ubiquitous systems, in: Proceedings of Ubiquitous Computing (Ubicomp), in: Lecture Notes in Computer Science, vol. 2201, 2001, pp. 273–291.

[108] World Health Organization, Cardiovascular diseases, Fact sheet, updated May 2017, http://www.who.int/mediacentre/factsheets/fs317/en/.

[109] A. Pandya, T.A. Gaziano, M.C. Weinstein, D. Cutler, More Americans living longer with cardiovascular disease will increase costs while lowering quality of life, Health Affairs 32 (10) (2013) 1706–1714, NIHMS150003.

[110] F. Sassi, J. Hurst, The Prevention of Lifestyle Related Chronic Disease: An Economic Framework, OECD Health Working Papers 32, 2008.

[111] A.M. Ward, C. Heneghan, R. Perera, D. Lasserson, D. Nunan, D. Mant, P. Glasziou, What are the basic self-monitoring components for cardiovascular risk management?, BMC Medical Research Methodology 10 (2010) 105.

[112] G. Coppini, R. Favilla, A. Gastaldelli, S. Colantonio, P. Marraccini, Moving medical semeiotics to the digital realm: SEMEOTICONS Approach to face signs of cardiometabolic risk, in: Proceedings, HEALTHINF 2014 – 7th International Conference on Health Informatics, Part of 7th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2014, 2014, pp. 606–613.

[113] P. Henriquez, B.J. Matuszewski, Y. Andreu-Cabedo, L. Bastiani, S. Colantonio, G. Coppini, et al., Mirror mirror on the wall... an unobtrusive intelligent multisensory mirror for well-being status self-assessment and visualization, IEEE Transactions on Multimedia 19 (7) (2017) 1467–1481.

[114] S. Klemm, Y. Andreu, P. Henriquez, B.J. Matuszewski, Robust face recognition using key-point descriptors, in: Proceedings of the 10th International Conference on Computer Vision Theory and Applications, SCITEPRESS – Science and Technology Publications, 2015, pp. 447–454.

[115] M. Kazhdan, M. Bolitho, H. Hoppe, Poisson surface reconstruction, in: Proceedings of the Fourth Eurographics Symposium on Geometry Processing, SGP '06, 2006, pp. 61–70.

[116] M.A. Pascali, D. Giorgi, L. Bastiani, E. Buzzigoli, P. Henríquez, B.J. Matuszewski, et al., Face morphology: can it tell us something about body weight and fat?, Computers in Biology and Medicine 76 (2016) 238–249, https://doi.org/10.1016/j.compbiomed.2016.06.006.

[117] M. Larsson, R. Favilla, T. Strömberg, Assessment of advanced glycated end product accumulation in skin using auto fluorescence multispectral imaging, Computers in Biology and Medicine 85 (2015) 106–111.

[118] E. Christinaki, G. Giannakakis, F. Chiarugi, M. Pediaditis, G. Iatraki, D. Manousos, et al., Comparison of blind source separation algorithms for optical heart rate monitoring, in: Proceedings of the 4th International Conference on Wireless Mobile Communication and Healthcare – Transforming Healthcare Through Innovations in Mobile and Wireless Technologies, MOBIHEALTH 2014, 2015, pp. 339–342.

[119] D. Germanese, M. Righi, M. Guidi, M. Magrini, M. D'Acunto, O. Salvetti, A device for self-monitoring breath analysis, in: The Seventh International Conference on Sensor Device Technologies and Applications, SENSORDEVICES 2016, 2016, pp. 77–82.

[120] D. Kaplan, Structural Equation Modeling: Foundations and Extensions, Sage, Newbury Park, CA, USA, 2000.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:17 p. 35

B978-0-12-813445-0.00006-X, 00006

[121] WHO European Regional Office, Who-Five Well-being Index (WHO-5), https://www.psykiatri-regionh.dk/who-5/Pages/default.aspx.

[122] R. Adams, Improving health outcomes with better patient understanding and education, Risk Management and Healthcare Policy 3 (2010) 61.

MARCO, 978-0-12-813445-0

MARCO[monography] model: a07a • color: 1c • ref-style: Numbered (Style 1) • lang: en-US • docsubty: CHP •
file: marco06.tex (Alicija) Prn: 2017/12/22;09:21:18 p. 36