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	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	37

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1 users and that support long-term engagement. This chapter offers a brief survey of 1  
2 existing vision-based monitoring solutions for personalized healthcare and wellness, and 2  
3 introduces the Wise Mirror, a multisensory platform featuring advanced algorithms for 3  
4 cardiometabolic risk prevention and quality-of-life improvement. 4

## 5 Keywords 5

6 Ambient assisted living (AAL), Self-monitoring, Unobtrusiveness, User engagement, 6  
7 Physiological monitoring, Wellness index 7  
8 8

## 9 6.1 INTRODUCTION 9

10 10  
11 The term Ambient Assisted Living (AAL) concerns ICT<sup>1</sup> solutions embed- 11  
12 ded in the living environment to monitor the setting and the behavior of its 12  
13 occupants in real time. AAL solutions can go beyond observing; they can 13  
14 move towards interacting by communicating with the user via prompts, 14  
15 triggering assistance from emergency services, and providing up-to-date 15  
16 information to families and caregivers. 16

17 AAL technologies trace their roots back to home automation and 17  
18 assistive domotics; they are now applied in many different scenarios, from 18  
19 telecare to pervasive wellness [1,2]. The main aim is improving the quality 19  
20 of life, health, and wellbeing of citizens; making their daily-life activities 20  
21 easier and more secure; monitoring and curing ill or at-risk subjects; and 21  
22 even performing primary prevention in healthy subjects. 22

23 The three main targets of AAL solutions are 23

- 24 • monitoring (and acting on) environmental conditions (e.g. lights, tem- 24  
25 perature, opening of doors, gas detection) for the occupants' safety and 25  
26 comfort; 26
- 27 • monitoring human activity and behavior, from basic motion tracking 27  
28 and human activity recognition up to long-term behavioral analysis; 28
- 29 • monitoring human physiological signs (physical, clinical, vital, emo- 29  
30 tional parameters) for personalized healthcare and wellness, including 30  
31 telerehabilitation, cure management, and prevention. 31

32 The general scheme of AAL solutions is to enrich the environment with 32  
33 a distributed sensor system. The sensors include *ambient sensors* (e.g. mag- 33  
34 netic switches, photosensors) as well as *body* or *wearable sensors* that are fixed 34  
35 to the human body or clothing (e.g. gyroscopes, pulse oximeters). A large 35  
36 network of sensors are often needed to gather enough data to accomplish 36  
37 the complex tasks required for AAL applications; therefore, systems may be 37  
38 38

39 <sup>1</sup> Information and Communication Technology. 39

1 costly to maintain, highly sensitive to a sensor's performance, and obtru- 1  
2 sive. Obtrusiveness is an issue especially for wearable sensors, due to their 2  
3 weight, effects on the skin, and burden on the subject during daily-life 3  
4 activities. 4

5 Recently, video cameras (including standard and depth cameras) and 5  
6 computer vision techniques came into the spotlight as alternative so- 6  
7 lutions for AAL applications [3,4]. Video-based AAL solutions benefit 7  
8 from the maturity of the research in computer vision: decades of stud- 8  
9 ies, boosted by needs in domains such as security and surveillance, have 9  
10 brought robust techniques for interpreting the rich information provided 10  
11 by cameras. Also, video-based solutions can favor the acceptability of 11  
12 AAL systems: video cameras are expected to reduce the possible anxi- 12  
13 ety towards new technologies, even for the elderly, as they are familiar 13  
14 objects. Moreover, cameras may be perceived as less invasive than other 14  
15 sensors as they do not require any physical contact with the subject, 15  
16 they do not have to be worn (with the exception of wearable cameras), 16  
17 and they can be fitted in the home setting by taking aesthetics into ac- 17  
18 count. 18

19 Another main advantage of video and depth cameras is that they can 19  
20 register a great deal of information compared to other sensors, and al- 20  
21 low the analysis of complex scenarios. A single camera can capture most 21  
22 of the activities performed in a room; therefore, in principle, it could 22  
23 replace many sensors. This would cut costs, also thanks to the fact that 23  
24 high-quality cameras are now available at affordable prices. Moreover, the 24  
25 same hardware setup can serve for multiple applications by just changing 25  
26 the software analyzing the visual data. Therefore, computer vision supports 26  
27 flexible and adaptive solutions, which can be easily extended and updated 27  
28 on demand. 28

### 29 6.1.1 Chapter Scope 29

30 There is a huge corpus of work on the use of computer vision for ambient 30  
31 monitoring and navigation and for activity recognition [5]. These topics 31  
32 are also covered in other chapters of this book. Therefore, after a brief 32  
33 introduction to the field of computer vision for AAL (Section 6.2), this 33  
34 chapter focuses on the use of computer vision techniques for monitoring 34  
35 human physiological signs in AAL solutions for personalized healthcare and 35  
36 wellness. In Section 6.3, we discuss the monitoring through videos, images, 36  
37 and 3D data, of 37

- 38 • vital signs (heart rate and respiratory rate); 38
- 39 39

- 1 ● posture and movement, especially for rehabilitation; 1
- 2 ● morphological parameters (e.g. body mass index); 2
- 3 ● emotional state (e.g. stress and anxiety). 3

4 Subsequently, in Section 6.4, we identify barriers and challenges for 4  
5 vision-based AAL solutions to reach their full maturity and applicability, 5  
6 especially within the healthcare domain. 6

7 Finally, as a possible solution, we introduce the Wize Mirror, a multisen- 7  
8 sory platform for health and wellbeing monitoring (Section 6.5). The Wize 8  
9 Mirror features advanced computer vision algorithms for cardiometabolic 9  
10 risk assessment through facial analysis. 10

11 Our target audience includes researchers and healthcare professionals, 11  
12 who will find information about the aspects that may affect their practice. 12

13 13

14 14

## 15 **6.2 COMPUTER VISION FOR AAL** 15

16 The traditional three-step pipeline for video-based AAL solutions includes 16  
17 image/video acquisition, preprocessing (segmentation of the region of in- 17  
18 terest, filtering for noise reduction, or contrast enhancement), and feature 18  
19 extraction and interpretation. The acquisition devices include traditional 19  
20 RGB cameras (including omnidirectional cameras and wearable cameras 20  
21 for egocentric vision); thermal cameras that acquire the infrared radiation 21  
22 of the scene; MultiSpectral Imaging (MSI) systems [6]; and depth sensors, 22  
23 based either on time of flight or on structured light [7]. Depth sensors in 23  
24 particular have become very popular lately because of their decreasing cost 24  
25 and the advantages they provide, including robustness to changing lighting 25  
26 conditions and protection of privacy since the appearance of a person is not 26  
27 recognized in depth images. 27

28 The architecture of a video-based AAL solution traditionally consists of 28  
29 a set of cameras for data capture connected to a server; processing modules 29  
30 for data processing and analysis; and an alert/decision module, which may 30  
31 or may not include a human operator. This solution can ease the integra- 31  
32 tion of data from different sources, but usually requires high bandwidth 32  
33 for data transmission, unless compressed video is used for transmission. 33  
34 An alternative band-saving solution is given by distributed smart camera 34  
35 networks that analyze the data locally and only transmit the alert/dec- 35  
36 sion [8]. 36

37 One of the main challenges of video-based AAL systems is the robust- 37  
38 ness with respect to the operating conditions in real-life settings. A first 38  
39 issue for robust data acquisition is what cameras are able to see, which 39

1 depends on the viewing angle and user positioning with respect to the 1  
2 camera, but also on occlusions and clutter. The problem of the viewing an- 2  
3 gle of the scene can be solved via hardware or software solutions. A solution 3  
4 often adopted in ambient surveillance systems is based on omnidirectional 4  
5 cameras which can capture virtually a 360 degree viewing angle of data. Al- 5  
6 ternatively, view-invariant computer vision algorithms are required, based 6  
7 either on single cameras or on image fusion strategies from multiple cam- 7  
8 eras. Multiple cameras and image fusion strategies may also help to solve 8  
9 the problem of occlusions that are likely to occur in a room. Finally, face 9  
10 recognition and the ability to track (multiple) people are needed in case of 10  
11 multiple occupants of the monitored space. 11

12 Another major concern for video-based assistive technologies is pri- 12  
13 vacy. AAL systems imply the collection of information in private spaces 13  
14 about individual subjects and their lives. With image and video record- 14  
15 ings, the privacy protection issue becomes even more prominent since the 15  
16 occupants' identities are shown. Privacy protection is considered urgent es- 16  
17 pecially if image data are stored and transmitted to a server, and if they 17  
18 are expected to be analyzed by designated carers. The consequences can 18  
19 be low acceptance by the end users, and even techniques for avoiding the 19  
20 camera to sabotage the monitoring [9]. Striking a happy medium between 20  
21 the benefits of image and video recording and the potential privacy loss 21  
22 requires focusing on the perspective of the end user. Some studies [10,11] 22  
23 have suggested that people would be willing to accept video-based activ- 23  
24 ity monitoring systems, in principle, if they felt that the technology would 24  
25 make a real difference to their lives, and if they were really in need of 25  
26 assistance. Also, improving the reliability of systems so that they do not 26  
27 require images to be analyzed by humans could improve confidentiality. 27  
28 Again, a possible solution is given by smart cameras, which can perform 28  
29 a part of the image and video processing locally, and either only transmit 29  
30 decision information to carers or filter the data to obscure individual iden- 30  
31 tities [8]. 31

### 32 33 **6.3 MONITORING IN PERSONALIZED HEALTHCARE AND** 33 34 **WELLNESS: THE STATE OF THE ART** 34 35

36 The home can be a focal point for ensuring healthy living if it is equipped 36  
37 with the right infrastructure: AAL systems based on computer vision solu- 37  
38 tions can support health status monitoring for the management of chronic 38  
39 diseases and rehabilitation therapies, but also for the prevention of disease 39

1 and improvement of individual wellbeing through the achievement and 1  
2 maintenance of a healthy lifestyle. These systems may become part of the 2  
3 medical toolbox for healthcare professionals, who could benefit from inno- 3  
4 vative communication and monitoring facilities. 4

5 The parameters to be monitored include vital signs such as heart rate and 5  
6 respiratory rate (Section 6.3.1); measures related to posture and movement, 6  
7 especially during rehabilitation (Section 6.3.2); morphological parameters 7  
8 of the body and face related to risk factors such as overweight and obesity 8  
9 (Section 6.3.3); and descriptors of the affective state, such as cues about the 9  
10 onset and progression of different diseases (Section 6.3.4). 10

11 11

### 12 6.3.1 Vital Signs 12

13 The monitoring of vital signs includes the estimation of 13

- 14 ● heart rate (HR); 14
- 15 ● heart rate variability (HRV); 15
- 16 ● respiratory rate (RR). 16

17 17

#### 18 Heart Rate 18

19 Heart rate monitoring is important by virtue of the significance of this vital 19  
20 sign in both health and disease. Physiological changes in HR can be as- 20  
21 sessed during exercise or during sleep when a reduction in HR may occur 21  
22 due to prevalence of vagal drive. In disease, there is an association between 22  
23 HR and outcome in heart failure patients, and a baseline HR is considered 23  
24 a cardiovascular risk factor. A special application of HR monitoring can 24  
25 be reported in the aging population as HR can also be a sign of improper 25  
26 movements. Since an increasing number of older subjects wish to live in 26  
27 their home environments rather than moving into care facilities, the op- 27  
28 portunity to unobtrusively monitor HR is challenging. Therefore, several 28  
29 studies have been performed to evaluate whether the HR can be assessed 29  
30 from video streams [12], thus avoiding the use of wearable sensors. 30

31 A commonly adopted approach to HR assessment is based on the process- 31  
32 ing of RGB video images acquired by RGB cameras or webcams. 32  
33 Blood Volume Pulses (BVPs) are expected to produce changes of the in- 33  
34 tensity of spectral components of the video signal [13]. In analogy with 34  
35 standard PhotoPlethysmoGraphy (PPG), the term video PhotoPlethys- 35  
36 moGraphy (vPPG) has been introduced. The basic steps of vPPG are 36

- 37 ● acquiring the video signal, possibly in a specific wavelength band, and 37  
38 averaging it in a region of interest to produce a time sequence reflecting 38  
39 BVP changes; 39

- 1 • enhancing BVPs by specific processing, and locating them, e.g. by peak 1  
2 detection. 2

3 Concerning the signal acquisition, webcams [14–18] and standard video 3  
4 cameras [19,13,20,21] are both used. Webcams provide low-cost and eas- 4  
5 ily available setups, while standard cameras are expected to produce better 5  
6 quality signals, due to higher spatial and temporal resolution, along with 6  
7 multispectral imaging capabilities. 7

8 For the processing methods, a common framework is based on Blind 8  
9 Source Separation (BSS) techniques modeling the video signal as a mixture 9  
10 of contributions including BVP propagation, the various motion sources, 10  
11 and external illumination changes. Poh et al. [14] process the RGB com- 11  
12 ponent by Independent Components Analysis (ICA) to separate BVP from 12  
13 other contributions. An alternative approach based on BSS by Principal 13  
14 Components Analysis (PCA) was suggested by Lewandowska et al. [18]. 14  
15 The limitations of BSS (ICA- and PCA-based) have led several researchers 15  
16 to investigate more robust processing methods able to cope with motion 16  
17 artifacts. Wang et al. [19] exploit image redundancy to counteract the effects 17  
18 of facial movements. Feng et al. [17] adopted a simplified model of skin 18  
19 optical properties to compensate for head motion. Tarassenko et al. [20] 19  
20 proposed a vPPG system exploiting autoregressive modeling of video time 20  
21 series to compute HR together with RR and oxygen saturation. 21

22 In general, HR estimation from vPPG is in good agreement with ref- 22  
23 erence techniques (usually standard PPG or ECG in a few studies), high 23  
24 correlation coefficients being reported by most authors. It is worth not- 24  
25 ing that, to date, experimental results have been from small populations of 25  
26 volunteers. 26

27 Though video signal intensity is the most utilized source of information, 27  
28 an alternative method based on head motion related to BVP propagation 28  
29 and recorded by video is reported in [22]. 29

### 30 31 Heart Rate Variability 31

32 In addition to heart rate, the temporal variation of Heart Rate Variability 32  
33 (HRV) is an indicator of health status in the general population, of adapta- 33  
34 tion to stress in athletes [23], and of fatigue in drivers [24]. 34

35 The assessment of HRV from video is usually more demanding than 35  
36 simply assessing HR. In fact, while HR estimation only requires BVP de- 36  
37 tection to compute the average number of pulses per minute, a precise 37  
38 temporal localization of pulses is needed for HRV assessment. Most meth- 38  
39 ods for HR assessment from video can be adapted to estimate HRV. For 39

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

### 9 Respiratory Rate

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

24  
25 A direct approach to video-based RR estimation is based on the analysis  
26 of chest movements. Benetazzo et al. [27] used a RGB camera equipped  
27 with a depth sensor to evaluate RR from depth data. As already mentioned,  
28 Tarassenko et al. [20] proposed a direct RR estimation from video streams  
29 by autoregressive models of video time series. Indirect approaches to RR  
30 estimation are based on the power spectrum of HRV signals: indeed, respi-  
31 ration introduces a peak in the high-frequency region of the spectrum [14].

### 33 6.3.2 Posture and Movement

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

- 37 ● gait analysis and fall detection;
  - 38 ● movement for rehabilitation.
- 39



## 1 Gait Analysis and Fall Detection 1

2 A relation exists between gait, cognitive decline, and risk of falls [28]. 2  
3 older people, higher stages of cognitive impairment were associated with 3  
4 reduced ability to increase speed and walk quickly [29]. In particular, pre- 4  
5 venting falls in the elderly is a challenging task currently being investigated 5  
6 by many researchers [30]. Wearable sensors are mostly used in gait studies 6  
7 [31]; however, in recent years vision-based solutions have been introduced 7  
8 to improve unobtrusive monitoring. In this perspective, several researchers 8  
9 have proposed vision based systems to assist the elderly at home and reduce 9  
10 the risk of falls. The vast majority of reported approaches exploit standard 10  
11 single-view cameras with a wide field of view able to image the entire 11  
12 person [32–35], multiview camera-based systems [36], or omnidirectional 12  
13 surveillance cameras [37]; the use of depth sensors is also reported [38]. 13  
14

15 In general, the idea underlying most of these systems is predicting/rec- 15  
16 ognizing falls by dynamic analysis of image sequences of the monitored 16  
17 subject. This usually relies on a model of the observed motion coupled 17  
18 with the classification of the inferred activities. To obtain a compact motion 18  
19 description, a common choice is based on the silhouette of the monitored 19  
20 subject. It is usually extracted following some sort of background suppres- 20  
21 sion so as to reduce interference from the surrounding scene. Even though 21  
22 this operation can dramatically simplify the motion description, it can be 22  
23 prone to noise and can lead to false alarms, a matter that needs to be dealt 23  
24 with to achieve a reasonable system acceptability. Subject motion can be 24  
25 described by features extracted from the bounding box of the silhouette 25  
26 tracked over time. 26  
27

28 Various solutions have been proposed which include: Hidden Markov 28  
29 Models [39] or Layered Hidden Markov Models [36], Finite State Mod- 29  
30 els [35], and the use of Historical Motion Image [32,33] computed by 30  
31 time integration of image features possibly using eigenspace methodology 31  
32 to reduce dimensionality [33]. Falls can be recognized by standard machine 32  
33 learning methods such as multilayer perceptrons [33], algorithms based on 33  
34 distance between feature histograms of the silhouette bounding-box [40], 34  
35 and specific motion quantification coefficients [32]. As some processing 35  
36 steps can be prone to structured and nonstructured noise (e.g. background 36  
37 suppression), attempts to reduce possible inaccuracies have been faced [40]. 37  
38 The integration of visual and nonvisual cues (e.g. acoustic signals) has been 38  
39 proposed to improve fall detection accuracy [39]. 39

1 **Movement for Rehabilitation** 1

2 Rehabilitation is a dynamic process which allows persons to restore or at 2

3 least improve their functional capability to normal. Physiotherapy exercise 3

4 is a medical treatment aimed at returning patients to a normal life. During 4

5 rehabilitation plans, patients may encounter difficulties such as time and 5

6 cost of traveling, waiting for the availability of specialists, and ineffective 6

7 personal exercise. These difficulties could be greater for those patients liv- 7

8 ing in the areas that are distant from medical centers or that lack medical 8

9 staff and experts, and for the frail elderly. Therefore, the concept of tele- 9

10 physiotherapy has been developed to allow patients and medical experts to 10

11 carry on their sessions through telecommunication networks as if they were 11

12 in the same place. In general, the implementation of home-based rehabili- 12

13 tation interventions is an emerging area of scientific interest and where the 13

14 use of sensors plays a fundamental role. 14

15 Computer vision-based approaches in particular are expected to ease the 15

16 optimization of rehabilitation strategies at home. In fact, they enable ob- 16

17 jective and quantitative monitoring of physiotherapy exercises: the user's 17

18 motion can be accurately tracked in 3D and compared to the planned 18

19 therapy, thus enabling the fine-tuning of the therapeutic feedback on an in- 19

20 dividual basis. Also, the combination of sensing technology and interactive 20

21 gaming or virtual reality can facilitate the implementation of rehabilitation 21

22 exercise programs [41]. 22

23 One of the main fields of interest is represented by stroke survivors. 23

24 Approximately 800,000 new cases of stroke are reported each year in the 24

25 United States. About 80% of acute stroke survivors lose arm and hand 25

26 movement skills [42]. Movement impairment after a stroke typically re- 26

27 quires intensive treatment. Due to resource reduction in healthcare all over 27

28 the world, in-hospital rehabilitation tends to be limited. Thus, stroke re- 28

29 habilitation in home environments is an appealing solution. Computer 29

30 vision systems that allow individuals with stroke to practice arm move- 30

31 ment exercises at home with periodic interactions with a therapist have 31

32 been developed by different research groups [43,44]. 32

33 It has been demonstrated that combining telemedicine with in-home 33

34 robot-assisted therapy (telerehabilitation) for people with residual impair- 34

35 ment following stroke is able to reduce barriers. Moreover, it is cost- 35

36 effective, providing high-quality treatment to patients with limited access 36

37 to rehabilitation centers. Interestingly, patients and caregivers report overall 37

38 satisfaction and acceptance of telerehabilitation intervention, with a marked 38

39 reduction in drop-outs [45]. 39

### 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]. Cutoff 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]

1 dataset contains thousands of full-body textured 3D scans, labeled with 1  
2 anthropometric landmarks, and supporting the study of shape spaces in 2  
3 [66]. Also, several databases of human faces are available, the face being a 3  
4 rich source of information about an individual's psycho-physical status. The 4  
5 repositories of 3D facial data include CASIA HFB [60], FRGC v2.0 [67], 5  
6 Magna Database [68], USF Human ID 3-D [69], EURECOM Kinect Face 6  
7 dataset [70], and the Basel Face Morphable model [71]. 7

8 In the following, we revised main methods to assess 8

- 9 • body parameters, 9
- 10 • face parameters. 10

### 11 12 Body Parameters 12

13 The analysis of reconstructed 3D bodies includes the surface skeleton ex- 13  
14 traction; the location of feature points; the analysis of local properties 14  
15 (such as curvature); and the measurement of lengths, areas, and volumes 15  
16 of specific curves or regions. The registration and alignment of 3D recon- 16  
17 structions with reference models is either based on the location of a very 17  
18 few feature points characterized by local shape descriptors (e.g. curvature 18  
19 maps [72], auto diffusion function [73], integral invariants [74], salient ge- 19  
20 ometric features [75]) or on dense correspondence (e.g. multidimensional 20  
21 scaling methods based on geodesic distances [76]). 21

22 The correlation between 3D shape measurements of the human body 22  
23 and health issues has been studied in [77–81] in comparison with clas- 23  
24 sical anthropometric measures and indices. The use of body landmarks 24  
25 to perform shape measurements requires the precise location of the body 25  
26 landmarks themselves [82], which can be difficult, especially in the case of 26  
27 points that are poorly geometrically characterized. Therefore, many *digital* 27  
28 anthropometry methods have focused on overcoming the precise location 28  
29 of body landmarks. Recent works have focused on finding relevant correla- 29  
30 tions between geometric parameters automatically computed and body fat 30  
31 estimates, or cardiovascular and metabolic risk factors. Among these, Gia- 31  
32 chetti et al. presented in [83] a pipeline for processing heterogeneous 3D 32  
33 body scans (skeletonization and body segmentation) and extracting geo- 33  
34 metric parameters which are independent of pose and robust against noise. 34  
35 Another representative example of an automatic system for the extraction 35  
36 of a health-related index is described in the 2009 US patent [84], where 36  
37 the *Barix* index is introduced and is defined as 37

$$38 \quad \text{Barix} = \frac{\text{Torso Height} * \text{Torso Surface Area}}{\text{Torso Volume}}. \quad 38$$

39

1 The clinical value of the index was assessed through a study of hundreds of 1  
2 human scans, showing significant correlation with body fat composition. 2

3  
4 Face Parameters 4

5 The face has always been a very rich source of information, for example 5  
6 in studies on Human Computer Interaction, automatic detection of user's 6  
7 feelings, and early detection of numerous diseases, such as obstructive sleep 7  
8 apnea. 8

9 A number of studies have focused on using 2D images to detect mor- 9  
10 phological facial correlates of body fat. In [85], Ferrario et al. observed an 10  
11 increase in some facial dimensions in a study on facial morphology of obese 11  
12 adolescents. Djordjevic et al. [86] reported an analysis of facial morphology 12  
13 of a large population of adolescents under the influence of confounding 13  
14 variables: though the statistical univariate analysis showed that four prin- 14  
15 cipal components of the face (face height, asymmetry of the nasal tip and 15  
16 columella basis, asymmetry of the nasal bridge, depth of the upper eyelids) 16  
17 correlated with insulin levels, the regression coefficients were weak and no 17  
18 significance persisted in the multivariate analysis. In [87], Lee et al. pro- 18  
19 posed a prediction method, based on BMI, of normal and overweight for 19  
20 adult females using geometrical facial features extracted from 2D images. 20  
21 The features include Euclidean distances, angles, and facial areas defined 21  
22 by selected soft-tissue landmarks. The study was extended in [88] focus- 22  
23 ing on the association of visceral obesity with several facial characteristics. 23  
24 The authors determined statistically the best predictor of normal waist and 24  
25 visceral obesity among the considered facial characteristics. Cross-sectional 25  
26 data were obtained from a population of over 11 thousand adult Korean 26  
27 men and women, aged between 18 and 80 years. 27

28 Recently, 3D data have started to be used. One of the first results con- 28  
29 cerning the relation between 3D facial shape and a syndrome was presented 29  
30 by Banabilh et al. in [89]: the authors showed that craniofacial obesity, as- 30  
31 sessed via 3D stereo-photogrammetry, is correlated with obstructive sleep 31  
32 apnea syndrome. In [90], Giorgi et al. defined a shape descriptor based 32  
33 on the theory of persistent homology, and tested it on a synthetic dataset 33  
34 of 3D faces to assess the relation of facial morphology with obesity and 34  
35 overweight. 35

### 36 6.3.4 Emotions, Expressions, and Individual Wellness 37

38 The intertwining of emotional states and the onset and progression of dis- 38  
39 eases has been under investigation for a long time [91]. Studies in modern 39

1 neuroscience have shed new light on the topic, leading to an extended 1  
2 reconsideration of the classical view of the interaction of soma and psy- 2  
3 che [92]. On the one hand, chronic adverse emotional states, such as 3  
4 stress, anxiety, and tiredness, are among the main risk factors of serious ill- 4  
5 nesses, including metabolic syndrome and cardiovascular diseases [93–95]; 5  
6 conversely, the effect of positive states may reduce the incidence of cardio- 6  
7 vascular disease [96]. On the other hand, chronic illness is coupled with 7  
8 an emotional dimension that can affect therapy outcome; for example, dis- 8  
9 tress, depression, and anxiety may reduce one’s motivation to access medical 9  
10 care and follow treatment plans [97]. Also, many studies have investigated 10  
11 the relation between adverse affective states (stress and depression) and the 11  
12 response of the immune system [98,99]. It is therefore not surprising that 12  
13 there is a great deal of interest in the medical community for novel tools that 13  
14 can assist the individual in self-managing stressful and anxiogenic situations 14  
15 and reducing disease risks. 15

16 Computer vision may support the implementation of unobtrusive, con- 16  
17 tinuous monitoring systems of the emotional state of an individual, not only 17  
18 by supporting the estimation of emotion-related physical parameters (e.g. 18  
19 HR and RR; see Section 6.3.1), but also by analyzing facial expressions 19  
20 and body language evoked by emotions [100]. Indeed, assessing individ- 20  
21 ual psychological wellness implies the recognition of complex mental states 21  
22 such as fatigue, frustration, pain, depression, and mood, which require the 22  
23 integration of multiple cues: physiological, acoustic, and visual cues. The 23  
24 combined use of physiological parameters computed by sensors and expres- 24  
25 sive features is documented in [101]. 25

26 The visual clues to the affective state include general facial expression, 26  
27 micro-expressions, and other features such as eye gaze and head orienta- 27  
28 tion. In general, the interpretation of facial codes in terms of underlying 28  
29 emotional states remains an open problem. Coding schemes such as the 29  
30 Facial Action Coding Scheme (FACS) [102] are generally related to pri- 30  
31 mary affective states (e.g. anger, fear, happiness) rather than to complex 31  
32 states. Additional information about complex states may derive from micro- 32  
33 expressions, which are brief (lasting between 1/25 and 1/3 of a second) 33  
34 low-intensity facial expressions believed to reflect repressed feelings [103]. 34  
35 Due to their subtlety, they are hard to detect; for this reason the use of local 35  
36 dynamic appearance representations extracted from high-frequency video 36  
37 is usually reported [104]. The video-based analysis of multiple visual clues, 37  
38 including head, eyebrows, eye, and mouth movements, led in [105] to a 38  
39 technique for the identification of stress and anxiety. 39

1 For a detailed analysis of computer vision techniques for affective state 1  
2 recognition, we point the reader to Chapter 10 of this book. Here we con- 2  
3 fine ourselves to observing how moving emotional analysis in AAL settings 3  
4 is an exciting though extremely challenging task, which can pursue the 4  
5 objective of assessing emotional wellness. In particular, at-home monitor- 5  
6 ing can be implemented to evaluate stress, fatigue, and anxiety in different 6  
7 conditions, including resting states and a wide variety of everyday tasks (e.g. 7  
8 watching TV, listening to music, using a PC, or doing homework), which 8  
9 should ensure a detailed and possibly complete description of the individual 9  
10 responses to many external stimuli. In addition, AAL favors the correlation 10  
11 of monitoring data with life-style habits. This can be the key towards a true 11  
12 holistic representation of individual wellbeing in naturalistic contexts. 12

#### 13 14 **6.4 METHODOLOGICAL, CLINICAL, AND SOCIETAL** 15 **CHALLENGES** 16

17 We have seen how computer vision holds the potential to boost a new gen- 17  
18 eration of noninvasive, effective systems for continuous health monitoring. 18  
19 The possibility of close follow-up by means of technological solutions at 19  
20 home would be an additional time-saving support to busy health profes- 20  
21 sionals. These tools could help physicians not only in managing chronic 21  
22 diseases, but also in counseling on risk factors in the general population, 22  
23 especially for primary prevention. To make this scenario come true, some 23  
24 methodological, technological, clinical, and societal challenges still need to 24  
25 be faced. 25

#### 26 27 **Computational Demand** 28

28 In physiological monitoring, high computational demand could result from 28  
29 the need to acquire and process data in real time, including real-time 29  
30 tracking, data alignment, and data analysis. Also, the spatial and tempo- 30  
31 ral resolution of the acquisition may be high, depending on the parameters 31  
32 to be computed; the resolution requirements should be balanced with com- 32  
33 plexity and cost requirements, depending on the application at hand. 33

#### 34 35 **Acquisition Robustness in Real-Life Scenarios** 36

36 Acquiring physiological parameters in uncontrolled settings requires meth- 36  
37 ods that are robust to occlusions, clutter, or pose, for example the presence 37  
38 of a beard or make-up while analyzing the facial skin, or slight move- 38  
39 ments of the user while recording vital signs. Also, robustness to lighting 39

1 conditions can be an issue in several applications, and computer-controlled 1  
2 external light sources may be required. 2

3 To operate in real-life scenarios, it is also mandatory to capture data 3  
4 without requiring too much effort from the subject, i.e. without asking the 4  
5 subject to stay still in front of a camera for several minutes. The challenge 5  
6 here is how to automate the acquisition process so that data are captured 6  
7 when the environmental conditions are most favorable. 7  
8 8

### 9 Reliability of Measurements for Clinical Purposes 9

10 It is mandatory that physiological monitoring systems provide a description 10  
11 of the individual status coherent with the clinical view. In particular, a cru- 11  
12 cial requirement is the reliability of measurements and their usability by 12  
13 doctors and health professionals. Even though it is not expected that moni- 13  
14 toring systems produce results in the form of validated clinical tests, the data 14  
15 provided must be adequate to properly drive the physician's reasoning and 15  
16 action planning. This requires intelligent image processing algorithms, en- 16  
17 suring high repeatability, adequate sensitivity, and specificity in measuring 17  
18 data in comparison to standard reference methods used in clinical practice. 18  
19 19

### 20 Clinical Evaluation 20

21 Evaluating and validating in-home monitoring systems is a nontrivial task 21  
22 that requires an interdisciplinary team and a close involvement of the med- 22  
23 ical experts. The validation issue also calls for shared benchmark datasets. 23  
24 24

25 The literature reports few and small case studies, which means that 25  
26 new studies involving a greater number of subjects become mandatory. 26  
27 In the particular case of physiological monitoring, satisfactory clinical ev- 27  
28 idence should be provided regarding the reliability of measurements, and 28  
29 also regarding the improvement in the quality of life, wellness, and health 29  
30 conditions brought by technological solutions. 30  
31 31

### 32 Acceptability and Long-Term Engagement 32

33 To be applicable on a large scale, video-based assistive technologies must be 33  
34 accepted by the end users, including monitored subjects, their families, and 34  
35 carers. 35

36 Stimulating initial adoption of the technology and long-term engage- 36  
37 ment is the key to making a true impact in real-life scenarios. To this end, 37  
38 the monitoring system design should adapt to different scenarios that range 38  
39 from primary prevention for healthy youngsters to the management of 39



1 chronic diseases in the elderly. While the physiological parameters com- 1  
2 puted could be the same in these scenarios, the best way to acquire data, 2  
3 interact, and communicate should be tailored to the specific needs of the 3  
4 users and their carers. 4

## 5 Privacy and Security 6

7 The monitoring of sensitive physiological data bears with it the issue of 7  
8 privacy. On the one hand, people should be made aware of a functioning 8  
9 system in order to augment their sense of trust and confidence and the 9  
10 feeling that they are retaining control of their data. On the other hand, 10  
11 cross-age and cross-gender studies are needed to assess individual levels 11  
12 of user acceptance since the concept of privacy is evolving as technology 12  
13 evolves [106] and the perception of privacy shows cultural, gender, and age 13  
14 differences. The goal is to support the development of privacy-by-design 14  
15 video-based systems, which take into account user privacy requirements 15  
16 from the very beginning [107]. 16

17 Another issue is that sensitive data can be intercepted by third parties 17  
18 and used for malicious purposes. The recording of images and video data 18  
19 makes preventing sensitive data from attacks especially urgent. The problem 19  
20 of cyber-security calls for solutions from different fields, including cryptog- 20  
21 raphy, data management, data mining, and related areas. 21

## 22 6.5 A POSSIBLE SOLUTION: THE WIZE MIRROR 23

24 The European Community's Seventh Framework Programme Project SE- 24  
25 MEOTICONS developed an innovative AAL solution that extensively 25  
26 leverages computer vision methods into a noninvasive device for wellbeing 26  
27 monitoring. The multisensory device, which looks like a common mirror 27  
28 and is called the Wize Mirror, was conceived as an effective technology- 28  
29 assisted intervention to prevent cardiometabolic diseases. 29  
30

31 Cardiometabolic diseases (i.e. cardiovascular diseases and type 2 dia- 31  
32 betes) are the leading causes of mortality worldwide and their spread on a 32  
33 global scale is putting a strain on social resources and health systems. An 33  
34 estimated 17.7 million people died from cardiovascular diseases in 2015, 34  
35 corresponding to 31% of all global deaths [108]. This figure is expected to 35  
36 increase in the coming years due to population aging and the increasing 36  
37 incidence of obesity and diabetes [109]. Clinical evidence has demonstrated 37  
38 that the majority of cardiometabolic diseases can be prevented by limit- 38  
39 ing exposure to the main risk factors; by exercising regularly, eating well, 39

1 controlling stressful conditions, avoiding smoking, and moderating alcohol  
2 intake, about 90% of type 2 diabetes, 80% of coronary heart disease, and  
3 70% of strokes could be prevented [110]. This awareness has fostered the  
4 promotion of educational and guidance programs for lifestyle improvement  
5 that call for assistive and personal technologies as a powerful ally to address  
6 large shares of the population.

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

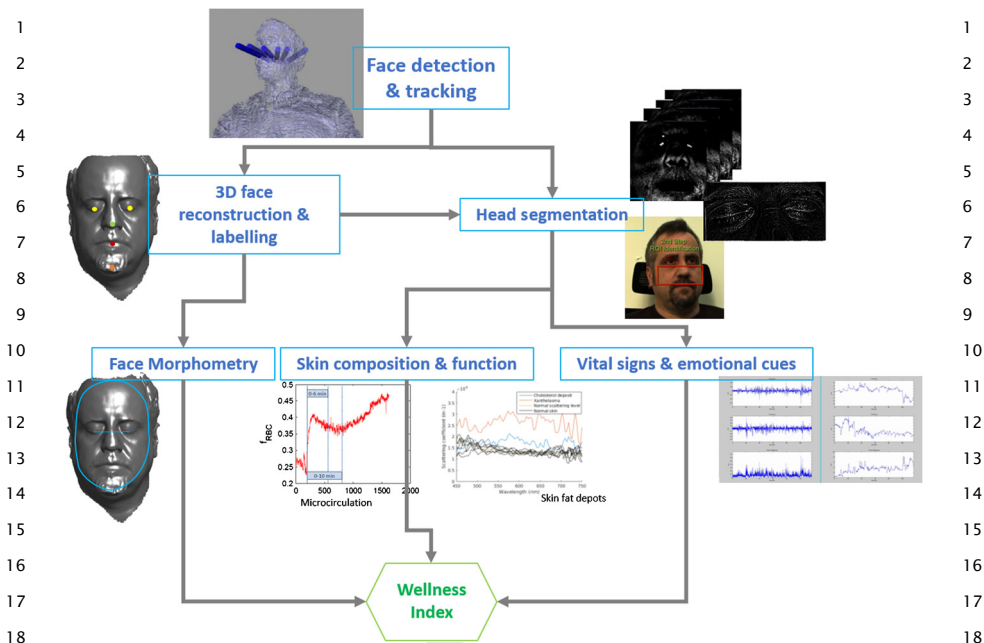
- 15 • self-measurement;
- 16 • education and coaching;
- 17 • user experience, with particular emphasis on contact with healthcare  
18 professionals.

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

### 24 6.5.1 Self-Measurement

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

- 36 • an inexpensive 3D scanner based on depth cameras;



**Figure 6.1** Scheme of the Wise 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 Wise 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 Wise 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

1 and prototyping trials that explored several options with respect to the user 1  
2 position in front of the Mirror. This was done to achieve the best view and 2  
3 overcome disturbances. Similarly, the lighting system was devised to coun- 3  
4 teract ambient light disturbances and ensure the homogeneous illumination 4  
5 of the face during data acquisitions. 5  
6

### 7 3D Data 7

8 The 3D scanner data are processed to enable 8  
9 • face detection and recognition, used to detect and recognize the user in 9  
10 front of the Mirror, as reported in [114]; 10  
11 • 3D head pose tracking, facial segmentation, and labeling; 11  
12 • 3D reconstruction. 12

13 These are core functionalities that serve as a common asset for the 13  
14 other data processing facilities of the Mirror. The 3D data are in fact used 14  
15 to enable face detection and labeling on the 2D data obtained from the 15  
16 other camera systems. This choice responds to the need for robustness and 16  
17 efficiency of data processing methods. Face detection and tracking is per- 17  
18 formed on the data from the depth sensors only once rather than several 18  
19 times on the various data streams: this ensures robustness to varying illu- 19  
20 mination conditions and optimizes the processing time. The user is first 20  
21 detected in the 3D space; then, by fitting a face mask on the depth sensor 21  
22 data, the position and the orientation of the user's face are detected. After 22  
23 that, selected facial landmarks are localized and their 3D coordinates are 23  
24 projected into the 2D frames of the other camera streams. This is done by 24  
25 using the intrinsic and extrinsic parameters of the cameras within a camera 25  
26 calibration and registration procedure done at system setup [113]. The cam- 26  
27 era's synchronization procedure allows the system to meet the requirement 27  
28 for real-time processing. 28  
29

30 The 3D model of the face serves the anthropometric and morphometric 30  
31 analyses. It results from a reconstruction algorithm adapted from the Kinect 31  
32 fusion method to meet the needs posed by the fact that in the Mirror 32  
33 the depth sensors remain in a fixed position while the face is moving [7]. 33  
34 A re-meshing algorithm runs on the 3D point cloud to ensure producing a 34  
35 manifold, without holes and degenerate elements [115]. 35  
36

### 37 Facial Morphometry 37

38 Facial morphometry analyzes the 3D face model to detect signs related to 38  
39 overweight and obesity. Four shape parameters are computed on the 3D 39

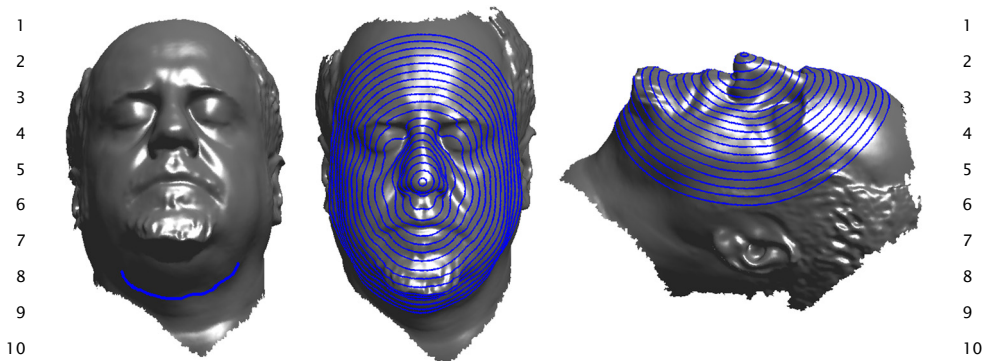


Figure 6.2 Facial morphology description in the Wize Mirror.

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

1 in the blood, which is one of the signs of dyslipidemia. In the Mirror, 1  
2 they are detected and measured on images acquired on a single wavelength 2  
3 (560 nm or 580 nm) by estimating the droplets with higher skin reflection 3  
4 in an area underneath the eye (where fat accumulates most) [113]. 4

5 AGE-products are linked to the metabolism of glucose. Their accumu- 5  
6 lation in the skin increases with aging, but when above a certain threshold, 6  
7 it signals an increased risk of cardiometabolic disorders. In the Mirror, AGE 7  
8 accumulation is estimated during UV exposure from a 365 nm LED as the 8  
9 ratio of the fluorescence intensity (evaluated on a 475 nm image) to the 9  
10 illumination intensity (evaluated on a 360 nm image). See [117] for further 10  
11 details. 11

12 The analysis of skin function aims to assess endothelium function. 12  
13 The endothelium regulates vasodilation in response to different blood-flow 13  
14 needs. A dysfunction of this tissue may be a consequence or a cause of 14  
15 several pathologies, such as hypertension, hypercholesterolemia, and di- 15  
16 abetes. In the Mirror, endothelial function is measured on MSI data by 16  
17 assessing the response of facial skin microcirculation after heating the cheek 17  
18 via a computer-controlled remote skin heater. An index of the function 18  
19 is defined based on two parameters calculated on 475–650 nm images: 19  
20 hemoglobin oxygenation and the fraction of red blood cells in the skin 20  
21 before and after heating [113]. 21

## 22 23 Vital Signs and Emotional Cues 23

24 By processing 2D videos, the Mirror estimates vital signs and emotional 24  
25 cues connected to adverse psychological statuses. Vital signs include HR, 25  
26 RR, and HRV, which are indeed the most informative parameters associ- 26  
27 ated with the psycho-physical status of an individual. In the Mirror these 27  
28 parameters are analyzed through video-processing methods based on blind 28  
29 source separation through Independent Component Analysis, as described 29  
30 in [118]. 30

31 Cues of emotional status derive from the analysis of short video record- 31  
32 ings processed to spot micro-expressions and facial gestures typical of stress, 32  
33 anxiety, and fatigue. For stress and anxiety, these cues generally corre- 33  
34 spond to facial-muscle hyperactivity, which may be discretized in head 34  
35 movements, eye movements (in terms of eye gazing and frequent focus, 35  
36 pupil dilation, and blinking rates), and mouth movements (in terms of jaw 36  
37 clenching, lip trembling, and biting). Fatigue is here intended as a sense 37  
38 of tiredness, lack of energy, and a feeling of exhaustion. Signs of fatigue 38  
39 are mainly yawning and saccadic movements. In the Mirror, all these signs 39

1 are extracted from the videos though different feature extraction methods 1  
2 and are fed into an Artificial Neural Network model trained to classify 2  
3 emotional traits [113,105]. Considering how challenging and complex a 3  
4 proper recognition is, the neural model also takes in vital signs (i.e. HR 4  
5 and RR) and uses as reference a video shot at baseline during the user's 5  
6 registration when the user is shown a video to induce a relaxed condi- 6  
7 tion. 7

### 9 Breath Analysis 9

10 The gas sensing device connected to the Mirror analyzes the composition 10  
11 of the breath and supplies feedback about the effect of noxious habits. The 11  
12 device, called the Wize Sniffer, detects molecules such as carbon monoxide, 12  
13 ethanol, hydrogen, oxygen, and carbon dioxide. The presence and variation 13  
14 of these substances can be correlated to smoking, alcohol consumption, 14  
15 and metabolic disorders. The Sniffer acquires a breath sample through a 15  
16 corrugated tube connected to the Mirror, analyzes its composition and 16  
17 provides the Mirror with a grading of the risk the users are exposed to due 17  
18 to their habits (no risk, moderate risk, or high risk) [119]. 18  
19

### 20 Acquisition Timing 20

21 The Mirror requires just a few seconds without requiring too much effort 21  
22 to scan the faces of the users while they are standing or sitting in front of 22  
23 it as part of their daily routine. Overall, facial morphometry, skin composi- 23  
24 tion, vital signs, and emotional analyses all together take one minute of data 24  
25 acquisition. Breath analysis takes the time of a deep breath and it entails 25  
26 the simple interaction of breathing into a mouthpiece. Thanks to a paral- 26  
27 lel implementation on a multiprocessor board, results are provided in real 27  
28 time, in only a few seconds. Only HRV and endothelial function require 28  
29 a five- and six-minute acquisition, respectively. This time is unavoidable 29  
30 and is necessary to ascertain the dynamics of the underlying physiological 30  
31 phenomenon. 31  
32

33 It is worth underlining that unlike the breath analysis, all the other 33  
34 analyses rely on image and video processing. This means that they can 34  
35 be integrated, with proper customization, into any device or equipment 35  
36 that already hosts or is able to host some of the sensors behind the Mirror 36  
37 such as a TV set, a mobile phone or tablet, a personal computer, etc. This 37  
38 flexibility increases the potential of the Wize Mirror to address users with 38  
39 different needs and preferences. 39

## 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





Figure 6.3 The Wellness Index as presented in the Wise 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-

1 quality information based on scientific evidence is becoming more and 1  
2 more urgent and mandatory. Overall, educational and counseling messages 2  
3 contribute to improving users' knowledge and risk perception, ameliorat- 3  
4 ing their health literacy, and increasing their involvement and degree of 4  
5 comfort in making healthy choices [122]. 5

6 The approach adopted by the Wize Mirror stems from these consider- 6  
7 ations and is meant to captivate the users by offering a holistic approach to 7  
8 wellness. As a matter of fact, more and more people are seeking ways not 8  
9 only to lose weight or look better, but also to improve their quality of life 9  
10 and overall sense of wellness. 10  
11 11

### 12 6.5.3 User Experience 12

13 A pleasant user experience is crucial to stimulating the initial adoption and 13  
14 periodic utilization of self-monitoring devices. The Wize Mirror features a 14  
15 touchscreen and an intuitive interface that makes it usable and appealing to 15  
16 people with different digital skills. It also offers a range of user applications 16  
17 and services that span from sharing data with healthcare professionals and 17  
18 general practitioners to playing music, social network connections, email 18  
19 consultation, and web surfing. The Wize Mirror can indeed be seen as a 19  
20 big tablet integrated into the bathroom mirror. Future extensions include 20  
21 the connection to wearable devices or mobile apps to automatically upload 21  
22 data on physical activity, sleep, and diet. 22  
23 23

24 Among the different services, the link with healthcare professionals is 24  
25 of paramount importance: on the one hand, it reinforces the impact of the 25  
26 device by making the users feel more secure and cared about; on the other 26  
27 hand, it enables care providers to gather data and insight never available 27  
28 before. 28

29 To meet privacy and security requirements, the Mirror features an au- 29  
30 thentication facility that is based on the automatic user recognition, but 30  
31 it always requires a confirmation code. A privacy-by-design approach was 31  
32 adopted to design the storage system along with data encryption. The data 32  
33 shared with care professionals mainly consist of the Wellness Index and 33  
34 measurement values. Images and videos are never transferred from the Mir- 34  
35 ror over the Internet. 35  
36 36

### 37 6.5.4 Wize Mirror Validation 37

38 The Wize Mirror underwent a validation campaign to verify the accuracy, 38  
39 repeatability, reproducibility, and effectiveness of its measurements and to 39

1 check acceptability by the users. Three prototypes were deployed in three 1  
2 clinical sites in Italy and France between July and October 2016. A human 2  
3 study involved 72 volunteers who underwent Mirror scans every 15 days 3  
4 for three months. Reference data were acquired contextually with diag- 4  
5 nostic devices used in clinical practice to measure body composition and 5  
6 metabolic, homeostatic, and vital parameters. A comparison showed a statis- 6  
7 tically significant correlation of Mirror measurements and standard clinical 7  
8 measures. Moreover, it was observed that both originally motivated and 8  
9 unmotivated volunteers were able to significantly modify their physiologi- 9  
10 cal conditions, and that there was an evident decrease in their BMI. Details 10  
11 on these outcomes are being reported in a dedicated paper to be published 11  
12 within the medical literature. 12

13 Overall, the validation demonstrated the reliability of the Mirror's mea- 13  
14 surements and interventions. This is key to nurturing the device acceptance 14  
15 by both the end users and the clinical professionals. In particular, the clin- 15  
16 icians' trust in the device plays a key role in the promotion of the Mirror 16  
17 among the at-risk population. 17

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## 6.6 CONCLUSION

21 In recent decades healthcare systems have experienced an exponential 21  
22 growth in costs that is related to different social, cultural, and economic fac- 22  
23 tors. The need for sustainable healthcare systems translates into challenges 23  
24 in ICT for the implementation of autonomous and proactive healthcare 24  
25 services. We believe the synergy between AAL technologies and computer 25  
26 vision may support moving medical and healthcare services from hospitals 26  
27 to home environments, thus cutting down healthcare costs. 27

28 As observed in [2], AAL systems could support the third generation 28  
29 of telecare systems. The first generation was the panic-alarm gadgets used 29  
30 to summon help in case of emergency, and the second was sensor-based 30  
31 monitoring systems used to support medical decisions; the third genera- 31  
32 tion of systems shifts from a reactive approach to a proactive strategy for 32  
33 anticipating emergency situations. Computer vision can help embark on 33  
34 this revolutionary path. Science and technology and research are mature, 34  
35 though further research is needed to solve a number of open issues, includ- 35  
36 ing robustness, accuracy, and nonintrusiveness of data acquisition; clinical 36  
37 validity of the output delivered by existing techniques; and attention to the 37  
38 needs and demands of real end users in terms of acceptability and long-term 38  
39 engagement. 39

1 With the Wize Mirror, we have seen how we can begin to think of 1  
2 a fourth generation of telecare systems, which are explicitly designed to 2  
3 influence human behavior and persuade people to act upon their lifestyles 3  
4 and their health. We believe the convergence of different disciplines, from 4  
5 information technology (including computer vision) to cognitive science, 5  
6 is the way forward. 6  
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