MIRROR MIRROR ON THE WALL…
AN INTELLIGENT MULTISENSORY MIRROR FOR WELL-BEING SELF-ASSESSMENT

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ABSTRACT

The face reveals the healthy status of an individual, through a combination of physical signs and facial expressions. The project SEMEOTICONS is translating the semeiotic code of the human face into computational descriptors and measures, automatically extracted from videos, images, and 3D scans of the face. SEMEOTICONS is developing a multisensory platform, in the form of a smart mirror, looking for signs related to cardio-metabolic risk. The goal is to enable users to self-monitor their well-being status over time and improve their life-style via tailored user guidance. Building the multisensory mirror requires addressing significant scientific and technological challenges, from touch-less data acquisition, to real-time processing and integration of multimodal data.

***Index Terms*—** Cardio-metabolic risk, unobtrusive health monitoring, 3D face detection and tracking, 3D morphometric analysis, multispectral imaging, breath analysis, psycho-somatic status recognition, multimodal data integration

1. INTRODUCTION

The face is the preeminent channel of communication among humans: it is a mirror of status, emotions, and mood. As such it is the base of medical semeiotics, revealing the healthy status of an individual through a combination of physical signs (e.g., skin color, subcutaneous fat) and facial expressions.

This paper describes how the EU FP7 project SEMEOTICONS (http://www.semeoticons.eu/) is moving medical semeiotics to the digital realm, translating the semeiotic code of the face into computational descriptors

Fig. 1. The Wize Mirror is a multisensory platform which collects videos, images, 3D scans of the human face and gas concentration signals, looking for signs correlated with cardio-metabolic risk.

and measures extracted from videos, images, and 3D scans of the human face. A multisensory platform in the form of a smart mirror, called the Wize Mirror, is developed. It detects and monitors over time facial signs correlating with cardio-metabolic risk — the leading cause of mortality worldwide — and gives personalized advice to users on how to improve their habits.

The Wize Mirror seamlessly integrates contactless sensors and a user-friendly interface (Figure1). The sensors collect heterogeneous data: 3D scans, videos, (multispectral) images, and gas concentration signals of the subject in front of the mirror. The data are processed by dedicated algorithms, extracting biometric, morphometric, colorimetric, and compositional descriptors of facial signs. According to a semeiotic model of the face for cardio-metabolic risk [1], the descriptors include:

• 3D morphological face descriptors, related e.g. to overweight, obesity, swelling, and asymmetry, computed on a reconstructed 3D face model;
• facial descriptors revealing stress, fatigue and anxiety, captured via 3D and 2D expression analysis on video sequences, and skin face colorimetry descriptors, such as pallor, redness, jaundice;
• physiological parameters such as heart rate, heart rate variability, and respiratory rate, all estimated from videos by detecting face color changes and cyclic movements actions;
• descriptors associated with diabetes, cholesterol, and endothelial dysfunction, evaluated through a novel multi-spectral imaging system assessing the skin tissue including the microcirculation;
• exhaled gas composition, measured through a novel gas sensing device, which gives feedback about noxious habits such as smoke and alcohol intake.

The descriptors will be integrated to define a Virtual Individual Model and an individual Wellness Index. The index will enable common people to self-assess and self-monitor their well-being status over time. The Wize Mirror will also offer personalized suggestions and coaching messages, up to truly personalized user guidance, towards the achievement and the maintenance of a correct life-style.

Building the Wize Mirror requires addressing significant scientific and technological challenges. Indeed, the Wize Mirror promises touch-less data acquisition and real-time processing of multimodal data to extract reliable computational measures correlated with clinical risk factors.

Below, we report on the data acquisition and synchronization (Section 2), the multimedia processing (Sections 3-6) and finally the Virtual Individual Model definition (Section 7).

2. 3D/2D MEASUREMENT FACILITATION

The vast majority of the measurements performed by the Wize Mirror are based on the data acquired from multiple imaging devices. To facilitate an unobtrusive data acquisition and synchronisation of the different Mirror sensors, there is a need for user detection, 3D head pose tracking and subsequent face image segmentation (Subsection 2.1). Moreover, to detect and monitor over time facial changes due to weight, swelling, local growth, facial asymmetry or preform other bio-morphometric analysis, the Wize Mirror is going to be equipped with a 3D scanner for 3D face reconstruction (Subsection 2.2).

2.1 Face detection, tracking and segmentation

The proposed face detection and 3D head pose estimation is based on the approach described in [2]. A random forest framework is used to classify depth image patches between two different classes (head and no head) and perform a regression in the continuous spaces of head position and orientation. detection noise [3] and use of a personalized 3D mask, to improve the spatial accuracy. Subsequently the user personalized and labeled face mask is projected into the corresponding image domain enabling face segmentation and partition. The proposed processing pipeline has been tested against number of the state-of-the-art solutions ([4][5][6])as shown in Figure 2. A comparison between the several methods is summarized in Table 1. The personalized face mask used in this case is shown on the right in Fig. 3.

Fig. 2. Sample of results using different methods, from left to right: [4],[5],[6], and the proposed method. Extreme head poses are not detected by all approaches. For the last three methods, the automatic face partition is demonstrated using differently colored dots to indicate position of eyes and nose.

Table 1. Summary results of face detection accuracy obtained for the tested methods. TP and FP denote True and False Positive rates respectively.

[4]		[5]		[6]		Proposed	
TP	FP	TP	FP	TP	FP	TP	FP
81 %	1 %	93 %	5 %	58 %	**0 %**	**100 %**	**0 %**

2.2 3D face reconstruction

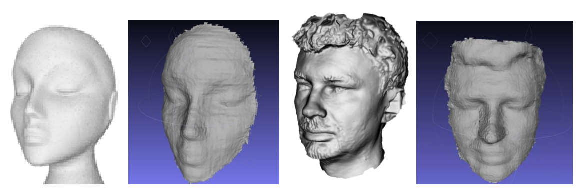

Fig. 3. A sample of preliminary 3D reconstructions (blue background) and corresponding scans obtained from FaroArm laser scanner for the head model, and DI scanner for the real face.

The currently implemented approach is based on the method proposed in [7]. Originally, the reconstruction method was designed to reconstruct static scenes of rigid objects by moving a range sensor and capturing different points of view of the area. The reconstruction requirements for the Mirror are different, as the sensor is in a fixed position and a subject is moving. In the proposed algorithm the reversed relative motion of the head with respect to the sensor is calculated for each depth frame in order to estimate the point of view. Then, only the segmented face regions and the camera parameters are used as input for the reconstruction. The output is provided as a triangulated 3D point cloud. A sample of the preliminary results is shown in Fig. 3, alongside corresponding 3D scans obtained by the commercial reference scanners. The whole reconstruction process, using the developed inexpensive compact scanner, is taking just couple of seconds. It should be noted that the use of the reference scanners on the Wize Mirror is not possible as these scanners are too big and expensive for that.

3. 3D FACE ANTHROPOMETRIC QUANTIFICATION

Anthropometry is the discipline which deals with facial morphology. One of the pioneers of modern craniofacial morphology was Leslie G. Farkas, who gathered a set of measurements of the face based on anatomical landmarks across different ethnic groups. Landmark-based measures, which are called morphometric, usually consist of distances, angles, areas etc. that involve more than one landmark. Farkas also examined the effects of some syndromes on these measures [8].

Up to now, the recording and analysis of morphometric measures was generally performed in 2D, that is on images. Nevertheless, 2D measures suffer from the sensory gap and cannot represent fully surface information. With the recent technological advancements of the devices for 3D acquisition and modeling, the measurements of morphometric properties on 3D models started gaining momentum [9]. Nonetheless, up to our knowledge, effective solutions to the 3D analysis of facial morphology have not been demonstrated in clinical settings yet.

In SEMEOTICONS, 3D face data are analysed to monitor and quantify temporal facial shape changes related with cardio-metabolic risk. One of the main causes of such face changes are overweight and obesity: the face is involved in the process of fat accumulation, which often produces an increase in some facial dimensions [10]. Some studies demonstrate that some geometrical facial features are strictly related to Body Mass Index and Waist Circumference [11].

Computational topology, an emerging field of research in Computer Graphics [12], gives accurate descriptors of 3D data, which can be used to study morphological face changes. One of these descriptors, which has been investigated in SEMEOTICONS, is Persistent Homology [13]. It is a technique which grows a space incrementally and analyses the placement of topological events within the history of this growth: for example, the birth of a connected component and its death when it merges into another component. The lifespan of topological attributes is encoded in a simple and compact representation called persistence diagram. The aim is to furnish a scale to assess the relevance of topological attributes, under the assumption that longevity is equivalent to significance. Persistent homology can be useful in analysing 3D shape data and shape changes in particular: comparing faces by using a metric on the space of their persistence diagrams can provide information about the variability within the data, and help to identify interesting features. Similar ideas were used with success in orthodontics, for the study of the outcome of clinical procedures [14].

In our contest, Persistent Homology was tested on different configuration of soft-tissue face landmarks. The input of the algorithm is the 3D Delaunay triangulation, whose nodes correspond to anthropometric landmarks, and edge lengths to their Euclidean or geodesic distances; note that distances are computed on the surface mesh, which retains complete information about the face morphology, as compared with linear measurements on images. The output is the shape descriptor (a persistence diagram) giving information on the geometry and topology of the landmark structure. As persistence diagrams can be efficiently compared using suitable distances, evaluating face changes boils down to comparing the persistence diagrams computed on 3D face scans taken at different times. Then, dimensionality reduction techniques are applied to the matrices of similarities between persistent diagrams, followed by an analysis of variance to make inference about landmark data and check if the proposed technique helps discovering 3D features which are well-related to overweight and obesity. As a longitudinal study on real subjects to monitor weight and 3D face changes is not available, a dataset of synthetic 3D faces simulating weight changes was generated using a parametric morphable model [15] and used for the first experiments (Fig. **4**).

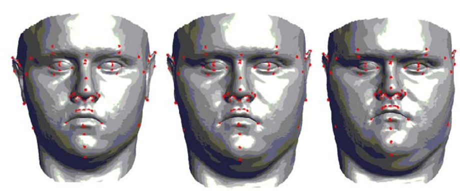

Fig. 4. A synthetic 3D face deformed to simulate weight gain. Red dots label anthropometric landmarks.

4. EMOTIONAL AND PSYCHOPHYSICAL STATUS

The Wize Mirror includes methods to detect and analyze facial expressions that are related to fatigue, stress and anxiety (Subsection 4.1). It also monitors some physiological signs (heart rate, heart rate variability, respiratory rate) and skin colour (Subsection 4.2).

4.1 Stress, anxiety and fatigue detection

Table 2 lists the signs that are the most representative of stress, anxiety and fatigue, according to the literature. The Wize Mirror uses a high resolution camera at a maximum frame rate of 90 fps for a non-obtrusive detection of those signs. Advanced algorithms process the captured frame sequence and produce a set of signs that represent the psychophysical status as expressed through the face. The algorithms rely on face detection, tracking and segmentation of appropriate regions of interest (ROIs) based on the techniques described in Section 2.

Table 2. Signs of stress, anxiety, fatigue monitored by the WM.

Status	Signs
Stress	Heart rate (HR), heart rate variability (HRV) and respiratory rate (RR), blood pressure, galvanic skin response, gaze spatial distribution, saccadic eye movement, pupil dilation, blink rate
Anxiety	HR, HRV, RR, Blinks, eye opening, eyebrows movement, reddening, lip deformations, strained face, facial pallor, pupil dilation, and eyelid twitching
Fatigue	Percentage eye closure, eye blink rate, speed (or duration), and amplitude, head motion, yawning

For head motion estimation, a ROI defining the face region between eyes and mouth is initially set and points on the four edges of the ROI are tracked. To retain the most stable feature points, the maximum distance traveled by each point between consecutive frames is used as a measure to discard points with a distance exceeding the mode of distribution of distances. Then, the feature point trajectories are analyzed to extract motion signals in different directions.

For eyebrows motion, a ROI that includes the eyes and eyebrows is defined. Eyebrow segmentation is based on the observation that facial features differ from the rest of the face due to their low brightness [16]. A skin filter helps in removing areas covered with hair. Minima in the x and y image projections indicate the position of eyebrows feature points [17]. This information is used for the evaluation of eyebrow lowering and eyebrow raising.

Mouth and lips motion are analyzed in terms of dense optical flow [18] in order to get a description of the motion pattern of the lips. Eye and mouth related parameters can also be studied using deformable models that are fitted to an image or to a video sequence. A combined model of shape and texture appearance like Active Appearance Models [19] is considered more appropriate.

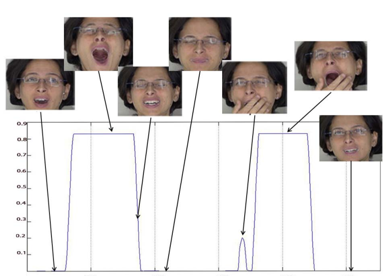

Fig. 5. Yawn probability in a video sequence. The method is robust against occlusions.

The analysis of specific landmarks of the face and their relational position can characterize action units and facial movements such as yawning. The Wize Mirror detects yawns by matching landmark-based geometric features of each frame in a video sequence with templates representing yawning and neutral expressions. Fig. 5 shows the probability of each frame in a sequence to represent a yawn: peaks are correctly located in correspondence of the yawns.

All the methodologies above were tested on different datasets ([20],[21]), and a project reference dataset collected during an acquisition campaign. Tests showed that the methods are promising, and indicated directions for improving robustness and performance.

4.2 Other signs

Besides facial expressions, other signs and biometrics of facial regions like heart rate (HR), heart rate variability (HRV) and respiratory rate (RR) can be used to get information [22]. Facial pallor and reddening are significant signs of the psychophysical status of the user, therefore also a colorimetric analysis of the face is carried out. In addition to videos, thermal imaging and near infrared spectroscopy are considered quite promising as a non-invasive techniques in cardiac pulse estimation [23].

5. MULTISPECTRAL MEASUREMENTS

The multispectral imaging (MSI) of facial skin aims to determine endothelial function [24], cholesterol concentration [25], and advanced glycation end-product (AGE) accumulation [26]. These parameters are measured in facial skin including its microcirculation, either directly or indirectly, emphasizing reproducibility for longitudinal health assessment.

The principle for measuring endothelial function is to evaluate skin hyperemia during local heating. Skin cholesterol determination is based on characterizing spectral features during controlled illumination. AGE accumulation is measured using UV induced auto-fluorescence.

The MSI hardware is based on compact cameras with filters at selected wavelengths controlled by a computer. It consists of five small monochrome 3.2 MP USB 3.0 CMOS cameras, computer controllable light sources (a bright white-LED and UV-LED, respectively), and a remote skin heater. Specification of the wavelength regions was deduced from theoretical analysis, simulations and hyperspectral data acquired by a line scanning diffraction grating based camera or cameras with liquid crystal or acousto-optical tunable filters. Among the skin tissue parameters also hemoglobin concentration and saturation can be measured.

The experimental tests indicate that the best candidate for assessing microcirculation parameters is hemoglobin saturation. This parameter typically increases from 35% to 92% in forearm skin indicating a shunt flow in larger vessels [27]. The facial skin has a baseline oxygenation of about 65%, which could be due to a different vascular structure.

Facial skin spectra recorded using white light illumination showed that spectral features correlated with lipid accumulation can be identified in skin regions below the eyes. These features correlate with blood cholesterol levels. In addition, numerical simulations indicated that small lipid depositions, microxanthelasmas, can be detected.

For AGE detection, the UV-induced auto-fluorescence in the visible wavelength range was registered. The corresponding MSI data is strongly correlated with the reference method recordings from forearm skin (a commercial AGE reader).

Remotely heating facial skin at a controlled temperature is not trivial. Experiences from local forearm heating indicate that temperatures in-between 39 ^{o}C – 42 ^{o}C are preferred for endothelial function assessment by determining the skin hyperemia, while heating to 44 ^{o}C provides a measure of the maximal hyperemia response [28]. We have tested full face heating based on IR heat sources. However, full facial heating including deep tissue, at higher than 42 ^{o}C is not well tolerated. Heating with visible light is feasible but interferes with the camera recordings. A promising solution based on a temperature-controlled fan with heated air is being developed.

6. BREATH ANALYSIS

Breath gases are good indicators of the presence of diseases and clinical conditions. This motivates the idea to develop a portable, cheap, and easy-to-use device able to detect breath gases and analyse them in real time: the Wize Sniffer. The Wize Sniffer captures breath samples, and thanks to a chemical gas sensors array, detects a selected number of molecules (carbon dioxide, oxygen, hydrogen, ethanol, carbon monoxide, ammonia) related to cardio-metabolic risk or to noxious habits for cardio-metabolic risk. The Wize Sniffer uses eight gas sensors, six placed in a store chamber, and two which work in flow thanks to a sampling circuit. The signals from the sensors are read by Arduino Mega 2560 platform and sent to the principal board of the Wize Mirror by Ethernet connection (protocol).

Tests showed that the device is able to provide reliable outputs. We plan in the future to improve the sensitivity of the sensors using nano fibers as sensing element, increasing surface/volume ratio (the sensitivity strongly depends on it). Such materials, as well as their selectivity, will be evaluated in order to develop, possibly, an hybrid platform.

7. VIRTUAL INDIVIDUAL MODEL

The final aim of the Wize Mirror is to monitor the individual well-being with respect to the cardio-metabolic risk, and foster healthier lifestyle. Besides the data acquisition and processing functionalities described above, the platform has to include three other modules for *(i)* user profiling; *(ii)* building of a Virtual Individual Model and definition of the Wellness Index; *(iii)* tailored user guidance.

The user profiling has a twofold objective: assessing the page-zero health status of users at their starting point,; and identifying users', attitudes, habits and preferences, so as to select the best strategy to provide customized suggestions and coaching messages. We define a baseline profile and an action profile. According to the semeiotic model of cardio-metabolic risk, the *baseline profile* is built up on the base of a minimum set of descriptors, collected by the Wize Mirror, able to assign the user to a cardio-metabolic risk cluster. The *action profiling* aims to identify user's *targets* (that is, objectives of lifestyle intervention), and *modulators* (which pertain the way the intervention is managed).

The complete set of computational descriptors of face signs are gathered into the Virtual Individual Model day-bay-day, in order to build a representation of the individual's status consistent with his/her cardio-metabolic risk. By means of data fusion techniques, the Virtual Individual Model is exploited to synthesize the Wellness Index, a non-diagnostic estimation for self-assessment and self-monitoring of cardio-metabolic risk. Most of the existing wellness or well-being indices [29] are designed for statistics about large populations, rather than for individual monitoring, and are often based on subjective components only, rather than on measured biophysical data. Conversely, our Wellness Index is based on both subjective criteria (e.g., perceived physical and mental status recorded via properly selected questionnaires) and objective data, i.e. the parameters measured on the sensed data described in the previous section. Conceptually, the values of monitored parameters can be seen as the components of a state vector moving in a multidimensional *well-being space.* In particular, the Virtual Individual Model is mapped into three separate wellness sub-spaces, which relate to physical wellness, emotional wellness, life-style habit wellness respectively. This allows to reduce the dimensionality of the problem and introduces a semantic characterization of data. The Wellness Index lives in this space and the analysis of its trajectories characterize the user's health status over time. Well-established cardio-metabolic risk charts (HEART SCORE, Fatty-Liver index, HOMA index, FINRISK index) are the ground-truth for the index validation [1].

The Wize Mirror will provides customized and personalized suggestions and messages, in accordance with the estimated WI and its variation over time, the user's profile in terms of attitudes, habits and preferences, and contextual information about the user's life circumstances. To promote health education, ad-hoc information and educational messages will be provided to users. The messages will be tailored to users' characteristics so as to increase information intake and user engagement. The presentation, visualization and linguistic style of suggestions are studied to be in accordance with users' peculiarities, since they are important moderators in communication modalities. Indeed, techniques used in recommender system are under investigation. A proactive decision support system is being studied, exploiting both computational models and procedural knowledge through ontologies and open standards provided by Semantic Web community.

8.CONCLUSIONS

This paper described the ongoing work in the European project SEMEOTICONS, which is developing a multisensory platform which detects and monitors over time facial signs correlated with cardio-metabolic risk, and gives personalized guidance towards lifestyle changes. SEMEOTICONS brings medical semeiotic analysis close to everyday life: from the office of medical doctors to the home, the gym, the pharmacy. The empowerment of individuals, in terms of their ability to self-monitor their status and improve their life-style, is expected to have a great impact on the reduction of disease burden and health expenditure. Indeed, it is well-known that the cost of health systems grows exponentially with the aging of the population, together with the widespread use of complex diagnostic procedures. Currently prevention is the best strategy to limit the spread of cardio-metabolic diseases, and SEMEOTICONS offers a fresh, ICT-driven perspective on educational programs and lifestyle intervention.

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