A Virtual Individual's Model Based on Facial Expression Analysis: a Non-Intrusive Approach for Wellbeing Monitoring and Self-Management

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***Abstract*—Facial expressions are visible signs of the affective and psychological state of a person, which is strictly correlated with the pathogenesis of clinically relevant diseases and more in general with individuals' wellbeing. The main idea highlighted in this paper is the exploitation of the facial expression analysis for wellbeing monitoring and self-management. This will occur by an innovative multisensory device that will be able to collect images and signals, extract quantitative features of facial expression related to stress, anxiety and fatigue and map them to computational descriptors of an individual's wellbeing. The latter phase will be based on a virtual individual's model conceived to allow the computation and tracing of the daily evolution of individual's wellness. Personalized advices and coaching messages will support the user in keeping a healthy lifestyle and counteract potentially harmful behaviours. The work is part of the FP7 STREP SEMEOTICONS project whose application field will be the prevention of cardio-metabolic risk, for which healthcare systems are registering an exponential growth of social costs.**

I. INTRODUCTION

A big corpus of the medico-clinical literature discusses the strict correlation of psychological alterations with the pathogenesis of some of the most impairing and wide-spread diseases. Negative emotional states, including anxiety, fatigue and depression as well as chronic and acute psychosocial stress, are considered important risk factors for cardiovascular [1]–[2], neuro-degenerative and neurological diseases [3]–[4]. For instance, from the one hand, stress is considered to be itself a risk factor for cardiovascular pathologies [5], and, from the other, high levels of stress elevate other risk factors such as high cholesterol or high blood pressure. Indeed, if an individual is under stress, her/his blood pressure goes up, she/he may overeat, may exercise less, and may be more likely to smoke. In all, the psychological status of an individual is strictly related to her/his quality of life and wellbeing conditions.

Facial expressions are visible signs of the affective and psychological state of a person [6]. The human face can be seen as a multi-signal input-output communicative system capable of tremendous flexibility and specificity [7]. It conveys information via different kinds of signalling mechanisms. For example, rapid facial motions represent temporal changes in neuromuscular activity that lead to visually detectable changes in facial appearance [8]. These signals communicate, among others, messages of affective/attitudinal states and moods (e.g. fear, joy, disbelief, interest, dislike, stress).

The main idea presented in this paper relies on the assessment of a person's psycho-physical status based on the analysis of facial expression so as to identify those facial signs corresponding to psychological risk factors, such as anxiety, fatigue and stress, which heavily impair a person's quality of life and wellbeing. Image and video data, non-intrusively collected during daily life, will be processed to automatically translate relevant facial signs into computational descriptors. These will be used to instantiate a *virtual individual's model*, tailored to individual's characteristics, attitudes and habits, which can be used to assess in-time variations of an individual's wellbeing status. By tracing these variations, warnings about worrying conditions can be provided, thus helping a person to self-relate these with her/his lifestyle. Supportive messages and informative material, automatically provided about nutrition, weight, physical activity, fatigue and stress relief, will further help the person to maintain a good and correct lifestyle, and, possibly, compensate for improper habits leading to increased psychological risk factors. The final goal is to develop an integrated, multisensory *self-monitoring system*, able to easily and unobtrusively fit in people's normal life settings, which will allow people to self-monitor and self-manage their lifestyle and become active actors in keeping their wellbeing status.

The remaining of this article discusses the main concepts behind this idea. More specifically, it is structured as follows: in section II the psycho-physical status evaluation based on facial expression analysis is thoroughly analyzed, while the ideas behind the virtual individual's model are illustrated in section III showing how relevant information can be produced in order to support wellbeing monitoring

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and self-management. Section IV discusses how these concepts will be put in practice.

II. Psycho-physical status evaluation based on facial expressions

Facial expressions give important clues for understanding and identifying the affective state and the psychopathology of a person. The human face can be seen as a multi-message communicative system that can convey information via multiple signals. Among the types of messages conveyed by these signals are emotions, moods and attitudinal states. Hence many applications benefitting from automatic analysis of expressions exist today. Automatic assessment of stress, anxiety and fatigue is e.g. valuable where attention to a crucial but perhaps tedious task, such as air traffic control, surveillance or driving, is essential. Considering a person's wellbeing monitoring and self-management, the automatic assessment of those psycho-physical states provides a highly promising non-intrusive approach.

A. Stress

The term "stress", as it is currently used was defined by Hans Selye, the pioneer of stress response theory, as "the non-specific response of the body to any demand for change" [9]. It does not only occur in negative situations but also in positive ones and it can be helpful and beneficial when it motivates people to higher achievements [10]. A more general definition describes stress as "a generalized stimulation of the autonomic nervous system that alerts a person to the presence of stressors arising from an actual or perceived threat" [11].

Classification models that have been developed from facial feature data have shown that stress can be recognized from facial expressions [12]. Experiments indicate that individual features are sensitive to stress: increase in head and mouth motion, less frequent blinking[1], faster eye closure and more often pupil dilation indicate increase in stress [13] and therefore facial muscle hyper-activity has been used as a stress indicator. Eye gazing and frequent focusing actions can also be considered as sources of information for the assessment of stress. In this case the estimation of gaze spatial distribution and measurement of the percentage of saccadic eye movement have been employed as stress measurement indicators. Pupil dilation has been examined for stress detection by evaluating the mean values for pupil diameters. It has been observed that the growth of these mean values over a time period is coupled with an increase in stress intensity [14].

The facial expression recognition systems that have been used to objectively determine stress are mostly based on machine learning techniques such as Support Vector Machines, Principal Component Analysis and decision tree-based classifiers [14]–[15]. Current affective computing research into stress assessment includes automatic optical facial expression recognition that uses Optical Computer Recognition algorithms for detecting facial changes, while people experience both low and high stress conditions [16]–[17].

B. Anxiety

Anxiety and stress are closely linked and therefore sometimes confused with each other. Anxiety is also sometimes confounded with fear, which is a physiological reaction to an imminent and present threat. In the Encyclopedia of Psychology [18], anxiety is linked with a disorder and defined as "an emotion characterized by feelings of tension, worried thoughts and physical changes like increased blood pressure. People with anxiety disorders usually have recurring intrusive thoughts or concerns. They may avoid certain situations out of worry. They may also have physical symptoms such as sweating, trembling, dizziness or a rapid heartbeat". Therefore, anxiety can be described as behavioural, psychological and physiological state.

While there are many studies that evaluate the capability of a person with anxiety to recognize human facial expressions and emotions [19], the opposite, namely the automatic analysis of facial expressions of persons with anxiety, is sparsely studied. Evidence suggests that anxiety can be determined by detecting features relating to specific affective states such as facial characteristics of fear and arousal [20]. In order to analyze anxiety through facial expressions, there are systems that incorporate implementations of Active Appearance Models, Gabor Wavelet Transforms and Support Vector Machines [21]. The results suggest that the recognition of anxious expressions is possible but becomes more difficult when fearful expressions are also present, similarly to the common misconception.

C. Fatigue

The word "fatigue" is often used interchangeably with the word "sleepiness" although they are not the same phenomenon. Sleepiness and fatigue are interrelated and both observed in a number of psychiatric, medical and primary sleep disorders [22]. Fatigue refers to lack of energy and feeling of exhaustion. It is an overwhelming sense of tiredness that affects both mental and physical functioning. Recent research suggests that fatigue can be triggered by stress, medication, overwork, or mental and physical illness or disease [23]–[24].

Automatic fatigue detection has been intensively studied in the context of preventing accidents when a driver loses attention as a cause of drowsiness. This results in the current existence of a number of commercial products already adopted by the car industry. All vision-based systems are mainly based on eye-tracking and eye-closure detection [25]. The ocular cue known as "percentage eye closure" has

[1]Although some reports suggest that stress is related to a higher frequency of blinks, this difference may be a result of different experimental conditions. Less frequent blinking is usually reported when focusing at a screen is part of the experiment, a task that generally reduces eye blinking.

strong capability in identifying the fatigue state [26]–[27]. The first successful method based on eye-closure detection was reported in 2000, describing a driver monitoring system using edge detection and template matching with accuracy of about 56% [28]. The eye blink rate can also be a measure for fatigue [29]. An increase in 10% of the blink rate, with respect to the person-related normal or base blink rate, signals a state of fatigue [30]. A further eye detection model used an infrared light projection method [31], while the most commonly used method for eye detection is the Hough Transform. Although computationally intensive, the Hough Transform returns high accuracies [32]. For real-time eye blink detection, Graphical Processing Unit-based Scale-Invariant Feature Transform tracking has been reported in combination with Action Units [33]. In 2007, Liang and Houi developed an eye tracking system by combining colour segmentation and Hough Transform techniques [34].

III. Virtual individual's model

Facial expression analysis can be applied to assess facial signs of the main adverse psychological factors as described above. These can be mapped into quantitative, computational descriptors used to appraise the person's wellbeing status. The idea is to integrate such descriptors into a *virtual individual's model* and track their evolution over time. A *wellbeing diary* can be, thus, provided and data about daily conditions can be recorded so as to allow individuals correlate the evolution of their psychological factors to their lifestyle and wellbeing.

In particular, a *wellbeing space* is defined by tracking the facial descriptors. Computational paradigms, including non linear mappings, can be used to extract the most significant information to be conveyed into the wellbeing estimation. Standard psychometric tests can be taken as reference in this estimation. The procedure includes a personalization phase to account for the individuals' variability. Indeed, the virtual individual's model takes into account personal inclinations and preferences and an initial characterization, which corresponds to the baseline starting point for the wellbeing monitoring. In this context, a user profiling approach is conceived to establish a reliable, personalized evaluation of the computational facial descriptors for each subject. User profiling comprehends a specific characterization of face morphological appearance as well as many medical, behavioural and attitudinal data. Actually, people respond in different ways to events and situations. One person may find an event joyful and gratifying, but another person may find the same event miserable and frustrating. Sometimes, people may handle stress in ways that make bad situations worse by reacting with feelings of anger, guilt, fear, hostility, anxiety, and moodiness. Others may face life's challenges with ease.

Similarly, user's profiling serves for personalizing the presentation of the wellbeing evaluation. Since individuals can hear, understand and react differently from one another to an evaluation of their status, the system must visualize its results in accordance to individual's characteristics of being anxious, hypochondriac or sensitive. An expressive and attractive way to represent the user's status is being studied, varying from a very simple and friendly visualization – like a comic or an avatar – to a more 'scientific' one – a sort of augmented subject's photorealistic visualization.

Finally, a user's tailored approach is being conceived for the personalized provision of warning and supportive/ informative messages provided by the system. In this way, such messages can be customized to user's preferences so as to maximize *self-efficacy*, i.e. the person's level of confidence that she or he can perform a specific task or health behaviour in the future. Emerging theories, such as the Self-Determination Theory [35], have to be investigated to supply recommendations in an *autonomy-supportive* style able to stimulate user's adherence and, thus, foster the effectiveness of the support provided.

IV. Discussion and conclusions

In the last years, large attention has been focused on the definition of strategies and technologies to sustain people's wellbeing and to help them keeping a healthy lifestyle.

Information and Communications Technology (ICT) based solutions are, in this context, intended to improve the quality of life, giving people the chance to live uncompromised, comfortable, safe, and active. Smart systems, devices and services are more and more oriented to individual users, instead of healthcare operators, so as to empower common people to become active actors in the management and improvement of their healthy status. A user centric approach is preferred in this respect to improve user's motivation and perception of systems' reliability and effectiveness. Indeed, wellbeing is often related to a healthy lifestyle whose maintenance frequently needs the counselling and supervision of various health professionals, such as dieticians, physical trainers, psychologists and behaviourists. Such a complex strategy is individually tuned and requires an expensive organization of the health systems.

A rationale alternative to this kind of intensive individual coaching is the development of systems for self-learning and self-monitoring. These systems are expected to help people to change and maintain their lifestyle, by providing tailored suggestions about nutrition, weight, physical activity, fatigue, and stress according to daily surveys. Moreover, data collected by such coaching systems could be analyzed and interpreted by health care professionals so as to support decision making targeted to the specific individual conditions. This approach has the potential to result highly cost-effective and might foster the diffusion of self-coaching systems with favourable impact on social, physiological, and environmental factors that, at present, remain barriers for the success of large-scale preventive intervention.

The approach described in the previous sections fits this view since it allows for wellbeing monitoring and self-management, starting from signs acquired non-intrusively through the analysis of facial expression. It is meant to be implemented by using suitable sensors able to provide the raw data (images and video) in a contactless manner and adopting the techniques mentioned.

In particular, the activities described will be carried out as part of a FP7 STREP project titled SEMEOTICONS, "SEMEiotic Oriented Technology for Individual's CardiOmetabolic risk self-assessmeNt and Self-monitoring", whose negotiation is currently being finalized. The project will aim at developing an interactive, multisensory system able to acquire and process multimedia data about a person's face and translate these into an evaluation of an individual's wellbeing conditions with respect to cardio-metabolic risks.

Three main features will characterize such a wellbeing evaluation: (i) non-invasiveness and unobtrusiveness, (ii) natural interaction between the subject and the system, (iii) guidance of individual's personal choices towards improvements and maintenance of a healthy lifestyle. Additional detail about the project activities are to be skipped here since the project is still under negotiation.

REFERENCES

[1] A. Rozanski, J. A. Blumenthal, K. W. Davidson, P. G. Saab and L. Kubzansky, "The epidemiology, pathophysiology, and management of psychosocial risk factors in cardiac practice: the emerging field of behavioral cardiology," *J Am Coll Cardiol,* vol. 45, no. 5, pp. 637-651, 2005.

[2] J. E. Dimsdale, "Psychological stress and cardiovascular disease," *J Am Coll Cardiol,* vol. 51, no. 13, pp. 1237-1246, 2008.

[3] T. Esch, G. B. Stefano, G. L. Fricchione and H. Benson, "The role of stress in neurodegenerative diseases and mental disorders," *Neuro Endocrinol Lett*, vol. 23, no. 3, pp. 199-208, 2002.

[4] R. I. Morimoto, "Stress, aging, and neurodegenerative disease," *N Engl J Med,* vol. 355, no. 21, pp. 2254-2255, 2006.

[5] http://www.euro.who.int/en/what-we-do/health-topics/noncommunicable-diseases/cardiovascular-diseases/facts-and-figures (accessed on July 2013).

[6] G. Donato, M. S. Bartlett, J. C. Hager, P. Ekman and T. J. Sejnowski, "Classifying facial actions," *IEEE Trans Pattern Anal Mach Intell*, vol. 21, no. 10, pp. 974-989, 1999.

[7] P. Ekman and W. V. Friesen, *"Unmasking the face: a guide to recognizing emotions from facial expressions,"* Englewood Cliffs, NJ, Prentice-Hall, 1975.

[8] M. Pantic and M. S. Bartlett, "Machine analysis of facial expressions," *in Face Recognition*, K. Delac and M. Grgic, eds., pp. 377-416, I-Tech Education and Publishing, 2007.

[9] H. Selye, "A syndrome produced by diverse nocuous agents," *Nature*, vol. 138, p. 32, 1936.

[10] H. Selye, *"The stress of life,"* New York, NY, McGraw-Hill, 1956.

[11] J. C. Toth, "Is stress at hospital discharge after acute myocardial infarction greater in women than in men?," *Am J Crit Care*, vol. 2, no. 1, pp. 35-40, 1993.

[12] D. N. Metaxas, S. Venkataraman and C. Vogler, "Image-based stress recognition using a model-based dynamic face tracking system," *in Computational Science – ICCS 2004, Lecture Notes in Computer Science*, M. Bubak, G. D. van Albada, P. M. A. Sloot and J. Dongarra, eds., pp. 813-821, 2004.

[13] W. Liao , W. Zhang , Z. Zhu and Q. Ji, "A real-time human stress monitoring system using dynamic Bayesian network," *in Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshop*, p. 70, 2005.

[14] N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition and classification: a survey," *Comput Methods Programs Biomed*, vol. 108, no. 3, pp. 1287-1301, 2012.

[15] Y. Shi et al., "Personalized stress detection from physiological measurements," *International Symposium on Quality of Life Technology*, 2010.

[16] D. F. Dinges et al., "Optical computer recognition of facial expressions associated with stress induced by performance demands," *Aviat Space Environ Med*, vol. 76, no. 6, pp. B172-B182, 2005.

[17] D. F. Dinges, S. Venkataraman, E. L. McGlinchey and D. N. Metaxas, "Monitoring of facial stress during space flight: optical computer recognition combining discriminative and generative methods," *Acta Astronautica*, vol. 60, no. 4-7, pp. 341-350, 2007.

[18] A. E. Kazdin (Ed.), *"Encyclopedia of psychology,"* (Vols. 1–8). Washington, DC, American Psychological Association and Oxford University Press, 2000.

[19] A. M. Perkins, S. L. Inchley-Mort, A. D. Pickering, P. J. Corr and A. P. Burgess, "A facial expression for anxiety," *J Pers Soc Psychol*, vol. 102, no. 5, pp. 910-924, 2012.

[20] J. A. Harrigan and D. M. O'Connell, "How do you look when feeling anxious? Facial displays of anxiety," *Pers Individ Dif*, vol. 21, no. 2, pp. 205-212, 1996.

[21] G. J. McIntyre, "The computer analysis of facial expressions: on the example of depression and anxiety," PhD Thesis, Australian National University, 2010.

[22] J. Shen, J. Barbera and C. M. Shapiro, "Distinguishing sleepiness and fatigue: focus on definition and measurement," *Sleep Med Rev*, vol. 10, no. 1, pp. 63-76, 2006.

[23] P. Verdonk, W. E. Hooftman, M. J. van Veldhoven, L. R. Boelens and L. L. Koppes, "Work-related fatigue: the specific case of highly educated women in the Netherlands," *Int Arch Occup Environ Health*, vol. 83, no. 3, pp. 309-321, 2010.

[24] E. M. G. Olsson, W. T. Roth and L. Melin, "Psychophysiological characteristics of women suffering from stress-related fatigue," *Stress Health*, vol. 26, no. 2, pp. 113-126, 2010.

[25] R. Senaratne et al., "Comparing two video-based techniques for driver fatigue detection: classification versus optical flow approach," Machine *Vision and Applications*, vol. 22, no. 4, pp. 597-618, 2011.

[26] N. Wright, B. Stone, T. Horberry and N. Reed, "A review of in-vehicle sleepiness detection devices," Technical Report PPR157, QinetiQ, TRL Limited, 2007.

[27] D. F. Dinges, M. M. Mallis, G. Maislin and J. W. Powell, "Evaluation of techniques for ocular measurement as an index of fatigue and the basis for alertness management," Technical Report DOT HS 808 762. National Highway Traffic Safety Administration, 1998.

[28] M. Betke and W. J. Mullally, "Preliminary investigation of real-time monitoring of a driver in city traffic," *in Proceedings of the IEEE Intelligent Vehicles Symposium*, pp. 563-568, 2000.

[29] M. Patel, S. Lal, D. Kavanagh and P. Rossiter, "Fatigue detection using computer vision," *International Journal of Electronics and Telecommunication*s, vol. 56, no. 4, pp. 457-461, 2010.

[30] W.-B. Horng, C.-Y. Chen, Y. Chang and C.-H. Fan, "Driver fatigue detection based on eye tracking and dynamic template matching," *in Proceedings of the 2004 IEEE International Conference on Networking, Sensing and Control*, pp. 7-12, 2004.

[31] T. Ito, S. Mita, K. Kozuka, T. Nakano and S. Yamamoto, "Driver blink measurement by the motion picture processing and its application to drowsiness detection," *in Proceedings of the IEEE 5th International Conference on Intelligent Transportation Systems*, pp. 168-173, 2002.

[32] T. D'Orazio, M. Leo, C. Cicirelli and A. Distante, "An algorithm for real time eye detection in face images," *in Proceedings of the 17th International Conference on Pattern Recognition*, vol. 3, pp. 278-281, 2004.

[33] M. Lalonde, D. Byrns, L. Gagnon, N. Teasdale and D. Laurendeau, "Real-time eye blink detection with GPU-based SIFT tracking," *in Proceedings of the fourth Canadian Conference on Computer and Robot Vision (CVR'07)*, p. 481-487, 2007.

[34] D. B. B. Liang and L. K. Houi, "Non-intrusive eye gaze direction tracking using color segmentation and Hough transform," *in Proceedings of the International Symposium on Communications and Information Technologies (ISCIT'07)*, pp. 602-607, 2007.

[35] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *Am Psychol*, vol. 55, no. 1, pp. 68-78, 2000.