Unobtrusive Physiological and Gesture Wearable Acquisition System: A Preliminary Study on Behavioral and Emotional Correlations

Nicola Carbonaro, Alberto Greco, Gaetano Anania, Gabriele Dalle Mura,
Alessandro Tognetti, Pasquale Scilingo, Danilo De Rossi and Antonio Lanatà
Interdepartmental Research Centre ”E. Piaggio”, Faculty of Engineering, University of Pisa, Pisa, Italy
Email: nicola.carbonaro@centropiaggio.unipi.it, alberto.greco@centropiaggio.unipi.it, g.anania@ing.unipi.it,
gabrieledallemura@gmail.com, a.tognetti@centropiaggio.unipi.it, e.scilingo@centropiaggio.unipi.it, d.deross@centropiaggio.unipi.it,
a.lanata@centropiaggio.unipi.it

***Abstract*—This study proposes an integrated wireless wearable system, that provides relevant information on gesture and electrodermal responses for affective communication investigations. The system is designed to be comfortable and unobtrusive to be used in immersive virtual realities as well as in actual scenarios in order to acquire implicit and explicit affective information. The system is comprised of a glove where textile electrodes, deformation sensors, and an inertial motion unit are integrated. The glove simultaneously acquires electrodermal activity and gesture, providing pre-elaborated signals that will be used for feature extraction purpose in emotion recognition filed. Preliminary results are reliable and promising for the complete integration of affective motion and physiological signal contents. This prototype is useful to investigate how humans perceive and produce affective interactions. Moreover, this prototype could be used for designing novel emotional models based on high-level and largely-comprehensive affective information.**

***Index Terms*—Gesture; electrodermal activity; affective recognition; textile-based systems; signal processing; features extraction; statistics;**

I. Introduction

In recent years, research on emotions [1], [2] increased, dramatically. In particular, the aspects related to how emotions can be elicited, measured and recognized are still open issues to be solved. One of the most interesting concepts under study is how a person can communicate an emotion non-verbally either alone or in a social scenario, where two or more people are interacting. Indeed, the evaluation and interpretation of physiological signals, facial expressions, body movements and postures present a strong challenge because of the many ambiguities related to affect definition, communication, and interpretation. Classical methods for evaluating affects tend to focus on questionnaires, in which the subjects are interviewed for reporting what they felt during the experiment, sometimes showing them a video of their performance, or asking them to recall what they felt at each moment during the earlier tasks [3]. Despite the promising results, in the majority of cases physiological signals and body movements are studied, separately. As matter of fact, previous studies showed that human movement is a visual stimulus and that we have experience of both perceiving and producing [4]. Concerning physiological signal evaluation for emotions recognition, many works have attempted to study physiological signals in order to extract parameters able to identify patterns which are related to specific emotions. Moreover, physiological reactions are one of the most reliable signs of an implicit affective response since they are controlled by the Autonomous Nervous System (ANS). In the literature, many works have provided evidence of the strong relationship between physiological reactions and emotional/affective states of humans [2], [5], [6]. In particular, the physiological signals used in the affect computing research are Heart Rate Variability (HRV), Respiration (Resp) and ElectroDermal Activity (EDA). Previous works in physiological signal-based emotion recognition are summarized in [7]. In our study, we propose the first integrated prototype for the simultaneous acquisition of gesture and physiological signals in the form of a textile glove that can acquire EDA, finger movements and that can also determine forearm orientation. Since EDA is the measurement of the sweat gland activity and is directly controlled by Sympathetic Nerve Activity (SNA), [8]–[10], it is considered an ideal way to monitor the ANS. EDA can be acquired at the palmar and fingers surface, because they are suitable anatomical sites of sweat eccrine glands. In the presented prototype, EDA is acquired by using textile electrodes placed on the index and medium fingers. Finger movements are collected by using textile deformation sensors placed on the glove metacarpophalangeal area and forearm orientation is acquired by employing an Inertial Measurement Unit (IMU) embedded in the glove electronics.

This works is split into two big sessions, as follows: the first one is named ”Materials and Methods” and the second one is the ”Conclusion”. Material and Methods is structured as follows: at the beginning, a description of the textile platform is reported in detail, afterwards, the study exposes through several sub sessions the principles and the methodologies of analysis for both the hand gesture detection (e.i., the first and second sub sessions) and the EDA (e.i. the third and fourth sub sessions). Afterwards, there are two sub sessions that

 ISBN: 978-1-61208-243-1

are dedicated of reporting the experimental results on textile deformation sensors and wearable EDA tests. Finally, in the Conclusion session, the study results and improvements are underlined and a discussion is open on where and how these data could be integrated and used to improve the knowledge on the emotional communication system from a more high-level approach.

II. Materials and Methods

In this study, the first prototype of a multi-parameter sensing glove for the simultaneous acquisition of hand gestures and EDA is presented. EDA is acquired through dedicated textile electrodes integrated in the index and medium fingertip areas (see Fig. 1a). Finger movement is tracked by using five textile deformation sensors integrated in the glove metacarpophalangeal area (see Fig. 1b). Both EDA and deformation signals are acquired and elaborated on-line by using a dedicated wearable and wireless (i.e., ZigBee [11]) electronic unit. Moreover, forearm orientation is measured by an Inertial Measurement Unit (HMC6343 [12] by Honeywell) embedded in the glove electronics and fixed in the dorsal part of the forearm close to the wrist.

(a) EDA electrodes

(b) Textile deformation sensors

Fig. 1: Multi-sensing glove prototype

A. Textile deformation sensors for hand gesture recognition

Textile deformation sensors and,more specifically conductive elastomer (CE) smeared sensors have been widely used for movement and gesture detection in neurorehabilitation [13]. Previous studies demonstrated the possibility of using a CE-based sensing glove to measure hand joint angles by using algorithms based on multivariate interpolation or neural networks. The drawbacks of these techniques was the high calibration effort, which limitated the use of such devices in practical situations [13]. Despite promising performances, CE-based prototypes showed several limitations such as non negligible relaxation time, non linearities and hysteresis [14]. Here, the gestural interface consists of five textile deformation sensors made of a particular conductive and elastic yarn. The same sensors were previously used for respiration monitoring in [15]. With respect to CE materials, this new sensor configuration was chosen for the better long term stability, the lower hysteresis and the faster relaxation time. The sensors have piezoresistive properties. Local fabric deformations due to user hand movements modify the sensor electrical resistance, and each sensor resistance is closely correlated with the single finger degree of flexion.

1) Processing methods: The sensor signal is characterized by a slow baseline drift due to the intrinsic characteristics of textile substrate (i.e., hysteresis and relaxation time are improved but they still exist). For this reason, an ad hoc algorithm for hand gesture recognition was conceived. The algorithm follows in real time signal local maximum and minimum levels through a peak detection routine that works without empiric thresholds. This continuous update of signal maximum/minimum allows for recognizing the condition of single finger opening or closing independently from the baseline variation (see Fig. 2). The combination of the described procedure on the five fingers enables a rapid recognition of the current hand gesture. With respect to previous methodology, no initial calibration is needed. This last point makes the algorithm flexible towards different hand physical configurations and glove sizes. In Fig. 2, the results of the developed

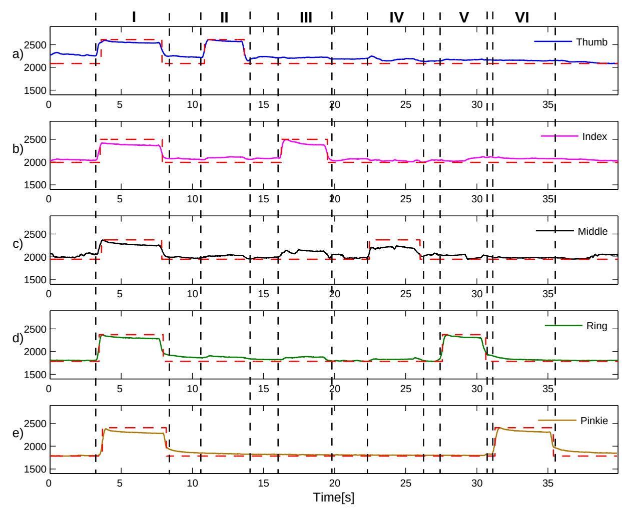

Fig. 2: Raw signals (solid lines) and algorithm results (dotted lines)

algorithm are shown. In each figure is represented the finger sensor signal (solid line) and the algorithm result (dotted line). In the case of high dotted line, the respective finger is flexed and vice versa. In this example, the user was asked to close the hand (Phase I) and then to flex one finger while the others are extended (Phase II to VI).

B. Textile electrodes for EDA monitoring

EDA is acquired by integrated textile electrodes placed at the fingertips. The use of textile electrodes as opposed to standard Ag/AgCl electrodes has already proven to be equivalent, as we reported in our study [16], where we performed the electrode characterization calculating the voltage-current characteristics and the electric impedance and found that their behaviors are comparable with standard electrodes. Moreover, the use of a wearable textile system exhibits several advantages in terms of portability and usability for long-term monitoring, and gives minimal constraints. In this prototype, the EDA is obtained as the ratio between an imposed continuous voltage of $0.5V$ between the two fingers and the passing current. Hereinafter, we refer to this EDA measurement as Skin Conductance (SC).

1) SC processing and features extraction: The SC signal is characterized by a tonic (i.e., Skin Conductance Level, SCL) and a phasic component (Skin Conductance Response, SCR). SCL is the slowly varying baseline level of skin conductance, while SCR arises within a predefined response window ($1-5s$ after stimulus onset), and is directly related to a given stimulus [17]. The signal division into its phasic and tonic components can be complicated by an overlapping of consecutive SCRs, in case of an inter-stimulus interval shorter than the SCR recovery time. In order to overcome this issue, we analyzed the SC by means of a modeling technique based on the deconvolution process [18]. The SC signal is the result of a convolution between the SNA and an Impulse Response Function (IRF). The IRF is a biexponential function the so-called Bateman function [19], which is the result of a diffusional model of the dynamics of sweat concentration in the corneum, assuming that it is governed by the laws of diffusion [20]. The decomposition of the SC in its components was performed by means of Ledalab 3.2.2. software package for MATLAB [21]. The row SC signal is pre-filtered by a lowpass filter with a cut-off frequency of $2Hz$. After this phase, a deconvolution between the filtered SC data and the IRF is performed. The deconvoluted signal was analyzed by a peak detection algorithm. A significant peak was detected if a local maximum had a difference greater than $0.2\mu S$ from its preceding or following local minimum [18]. The points under the threshold was considered part of the tonic driver signal. The tonic driver was estimated over the experiment duration time by an interpolation algorithm, and, consequentially, the tonic SC activity was achieved by a convolution between the tonic driver and the IRF. The phasic driver component was obtained by subtracting the tonic driver signal from the deconvoluted SC. In Fig. 3, an example of the original SC signal and the two deconvoluted tonic and phasic driver signals are shown. The extracted features from both phasic and tonic driver signals were the Number of Peak (NP), the MEAN value of the AMPlitude (MeanAmp), the MAXimum value of the AMPlitude (MaxAmp) and the MEAN value of the first derivative AMPlitude (DMeanAmp). The features were calculated within a window response of $5s$.

C. Textile deformation sensors tests

A set of experiments were carried out in order to test the performance of the sensor response and new algorithms of the sensing glovSeven participants were asked to perform different combinations of hand postures by performing finger flexion-extension movements while wearing the glove. Once a posture position was recognized (e.g., close thumb and open other fingers), the system generated the results of the finger combination. This operation was replicated three times for each user.

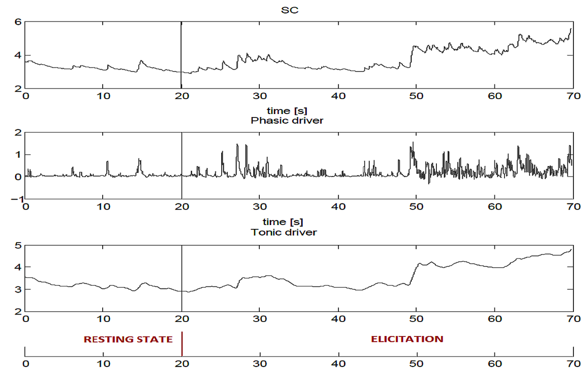

Fig. 3: Example of decomposition analysis. In the upper figure the row SC signal is shown. The lower figures report the deconvoluted tonic and phasic driver signals during resting and elicitation phase.

TABLE I: HAND POSTURE RECGNITION

Task	N Test	Recognized	No Recognized	Success
zero fingers	21	21	0	100
one finger	105	102	3	97.14
two fingers	210	199	11	94.76
three fingers	210	195	15	92.8
four fingers	105	97	8	92.38
five fingers	21	21	0	100

The results of this test are shown in the Table I. In this table, column*Task* represents the different configurations performed by the user, considering how many fingers are closed in that particular posture. Taking into account the first row of the table, *zero fingers* means that the user was performing the flat hand posture. Positive and negative recognition is reported in the third and fourth columns respectively. In the last column, the percentages are presented that represent the algorithms' capability of recognizing a particular posture.

D. Wearable EDA test

A preliminary test was carried out to evaluate the performances of the glove for affective evaluation. Seven patients were recruited and an affective stimulating protocol was administered. Affective elicitation was performed by projecting a set of images selected from the International Affective Picture System (IAPS) database [22], which consists of hundreds of pictures with an associated specific emotional rating in terms of valence and arousal. The valence and arousal ratings are based on several studies where subjects were requested to rank these images using the Self Assessment Manikin [23]. The protocol was divided into two sessions: basal, lasting 20 seconds and arousal, lasting 50 seconds. The first was a resting state phase in order to record the baseline of the subjects; the second session was characterized by a slideshow of images with an arousal level between $[5-6]$. The features extracted from the two sessions were compared by using statistical analysis. The statistical inference analysis was performed by means of a nonparametric test due to the non-gaussianity of the sample set. In particular, the data of subjects derived from the

TABLE II: P-VALUE RESULTING OF A MANN WHITNEY TEST BETWEEN THE NEUTRAL AND AROUSAL SESSION

	NP	MeanAmp	MaxAmp	DMeanAmp
phasic	< 0.05	< 0.05	< 0.05	< 0.05
tonic	< 0.05	0.34	0.42	0.2

basal and the arousal session were compared by using Mann Whitney test [24]. The results of the analysis are shown in the Table II.

III. CONCLUSION

In this study, a preliminary test on the performance of a first integrated prototype for the simultaneous acquisition of gesture and physiological signals is reported. The novelty of the prototype lies on the use of a wearable textile glove integrated with different technologies enrolled in monitoring EDA and hand posture. Unlike previous textile-based sensing gloves for posture recognition, this glove employs new strategies using sensor integration into textile substrates. Moreover, the new implemented algorithm was able to distinguish the xconfiguration of each finger without any calibration stage or empiric threshold. Referring to EDA results, the textile electrodes integrated in the glove showed optimal capacity in detecting reliable signals (see Fig. 3). The results of the statistical analysis applied to the features extracted from the phasic SC component showed that calculated affective information was statistically significant for differentiating basal and arousal session. On the contrary, most of the features of the tonic signal did not show a statistical difference, which is most likely due to the short duration of the experiment, not allowing enough time for significant changes to be made in the slowly varying skin conductance level. These revelations create and interesting basis and open up promising novel research applications. The integration of gestural and physiological data could enable the use of EDA signal in real environments, allowing for the possibility of implementing innovative algorithms for the automatic filtering of movement artifacts that usually corrupt the electrodermal signals. Currently, it is well-known that EDA signals can only be used in strongly controlled conditions. Furthermore, the analysis of affective body language jointly to physiological signal interpretation can offer the possibility of both understanding how humans process emotional stimuli, [25], and allowing the implementation of innovative emotional models. It is worthwhile noting that, the integration of information coming from non verbal emotional expressions and physiological signals is widely advocated but rarely implemented [2]. It is a matter of fact that physiological and body language convey information about emotional states. However, current literature lacks the exact informational values given from these channels as emotional indicators. Even if oldest emotional expression research was focused on body language and posture, state-of-the-art affect detection systems have disregarded this information preferring facial expressions and acoustic-proposed features. However, it is a common experience that human body language is commonly used as a emotional communicative channel, therefore, gesture and posture together with direct sympathetic information, such as EDR, can offer a kind of integrated information that is often unavailable from the conventional nonverbal measures such as the face and paralinguistic features of speech. Although physiological signal interpretation is thoroughly studied in this field it is well know, that their emotional content is not sufficient enough in order to understand emotional communicative system. In this view, the recent advances in gestural interfaces, as that presented in this study, present an opportunity to study how advocate emotions, e.g., expressions and embodiments, activate physiological and behavioral responses during an emotional episode. According to our results we believe that new methodologies could hypothesize how these information cold be represented in specific models arising from the collaboration of affective and human-etology sciences giving weighted importance to all variables that can be simultaneously monitored by the wearable platform.

ACKNOWLEDGMENT

This research has been partially funded by the European Commission through CEEDs (FP7 FET 258749) project.

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