Automatic Quantitative Evaluation of Emotions in E-learning Applications

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***Abstract*— The long term goal of our research is to develop a tool for recognizing human emotions during e-learning processes. This could be accomplished by combining quantitative indexes extracted from non-invasive recordings of four physiological signals: namely skin conductance, blood volume pulse, electrocardiogram and electroencephalogram. Wearable, non-invasive sensors, communicating with a PC, were applied to 30 students and data were collected during exposure to three different computer-mediated content stimuli designed to evoke specific emotional states: stress, relaxation and engagement. In this paper we describe both the general emotion evaluation algorithm, and present a preliminary results suggesting that some of the quantitative indexes may be successful in characterizing and distinguishing between the three different emotional states.**

I. Introduction

THE importance of affective states in influencing learning processes has been noted out in previous research. For example, reference [1] reported that affective mechanisms and emotional experience in humans play a significant and useful role in learning. Since learning processes are becoming increasingly mediated by the burgeoning impact of computers and the internet in the everyday environment, the integration of emotion into a computer mediated communication (CMC) system may result in significant improvements to learning behavior. Several studies have aimed to deduce affective states by means of body signal monitoring, with the ultimate goal of utilizing human emotions as input for an innovative computer human interaction [2]-[6]. The end goal of our research is to design and develop an automatic tool that is able to detect and classify different affective patterns during e-learning by means of four physiological variables that we assume are modulated by the emotions of interest. More concretely, by e-learning we mean situations where users are seated down in front of an (a)synchronous terminal in order to gain specific knowledge. In particular, 3 emotions have been considered to characterize the e-learning process along the activation/non activation channel of arousal: e-stress (frustrating situation), e-engagement (situation of optimal involvement) and e-relax (easy subject). We refer to the experimental conditions by using the prefix "e-" to focus attention on the context (e.g. distance learning) in which we are developing human emotion recognition. Since the study of emotion is tightly coupled to the context [7], it is important that their automated evaluation should take into account the specific context under which the emotions were aroused.

We begin by hypothesizing that an automatic evaluation of emotional states can be obtained through acquisition and processing of four physiological signals, measured by means of the following non-invasive sensors: Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), Electrocardiogram (EKG) and Electroencephalogram (EEG). We then perform a series of quantitative analyses to characterize the affective states of interest and compare the derived indexes to previously validated psychological findings. The emotional states are induced by means of realistic distance learning stimuli simulated in Laboratory. A combination of these indexes is expected to provide a prediction of the emotional state of the subject in question. These results will provide us the basis to achieve automatic emotion state recognition by virtue of the statistical multimodal model depicted in Figure 1. In principle, such a characterization of the three emotional states facilitates a

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(real-time) feedback loop between subject and tutor throughout the e-learning process. In the future, we envisage that these set of indexes will be the core of a "traffic light" interface program, developed with Java

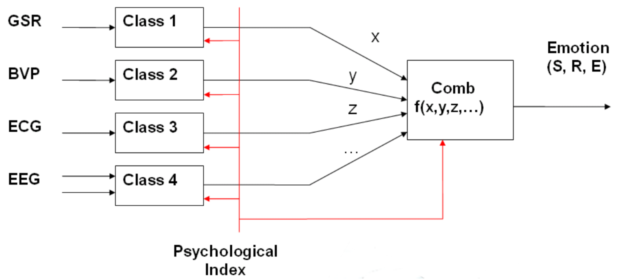

Fig. 1. Methodology flow chart.

technology, to give a visual performance feedback of the student's emotional state during learning, as showed in Figure 2.

II. Hardware Description

Data acquisition has been performed using Procomp Infinity, an 8 channel USB PC peripheral by Thought

Fig. 1. The figures show the student affective states and the real-time interface by means of biological signal computation and "translation" using a traffic light interface: tutor will be allowed to know if student is e-stressed, e-relaxed or e-engaged by lesson contents.

Technology. Every channel was acquired at a 256 Hz sampling rate. The Emotion Lab is equipped with two portable PCs, one for delivering the stimuli and the other for data acquisition. Two web cams are used to monitor, during the whole experiment, both the students' facial expression and the contents of the stimuli he/she is watching on the PC screen; these video inputs are fundamental, in order to correctly analyze the student affective response to stimuli and to detect the occurrence of undesired influences (such as those induced by the environment).

III. Experimental Design

The design methodology consists of three phases. During the first phase the experimental protocol is defined, taking into account distance learning objective, available physiological data, processing methodologies and the need to evaluate students from a psychological point of view. The protocol is applied (second phase or "pre-test phase") to a small number of students, in order to preliminarily tune the extent and the efficiency of the psychological stimuli. During the pre-test phase several stimuli are studied and evaluated, in order to shape and select the best affective inducers of emotions. Finally, in the third "laboratory phase", the pre-test findings are validated in a larger population of students. In our experimental design, we use four conditions as independent variables (e-relax, e-engagement, e-relax and e-performance) that are randomly exposed to all subjects (within subject design). We then analyze as dependent variables two measurements of students' affective reactions: by means of psychological self-report scores (STAI scores) and physiological activation (GSR, BVP, EKG and EEG signal processing).

IV. E-Learnig Objects, Protocol and Procedure

A series of digital affective stimuli are at the core of the e-learning protocol definition. Stimuli are created ad hoc to trigger specific emotions in 30 students (age ranged from 20 to 25 years) of the Polytechnic of Milan. The METID Centre methodology, described in [8], has been the template for our procedure and the structure of the Learning Object interface. Furthermore, the studies in [9] [10] constitute a key point in helping us to enrich stimuli with particular components to trigger specific psychological reactions in the subjects. The protocol is composed of five epochs: baseline, relax induction, stress induction, engagement induction and performance evaluation. To avoid stress caused by the lack of familiarity with the experimental situation, every student is briefed in the Laboratory in order to adapt him/herself with the new environment. Signals are first acquired during a baseline phase, followed by the four digital randomized stimuli: stress, relax, engagement and performance. Biological signals (GSR, BVP, EKG and EEG) are continuously recorded through sensors opportunely placed on the student. In addition, student facial expressions and student-content interactions are recorded for eventual future analysis. Physiological data acquisition has been made in the Emotion Lab at METID, the e-learning Center of Polytechnic of Milan

V. Psychological Self-Reports and Physiological Acquisitions

In order to score the affective state, the student was asked to complete a psychological self-report after each digital stimulus. During the pre-test phase, several questionnaires were evaluated to choose the best one. They are: EMAS (Endler Multidimensional Anxiety Scales), STAI (State Trait Anxiety Iventory), and PANAS (Positive Affect Negative Affect Scale). The STAI scale was selected as the most responsive according to the correlation among physio/psycho data.

VI. Statistical Analysis

Data have been analyzed both at the Polytechnic of Milan and at MGH/HMS/MIT in Boston. Mean and

Standard Error were computed for the group, for each index considered, for each epoch (Baseline, Relax, Stress, Engagement, and Performance). Statistical analysis was performed to compare the three emotional states (Relax, Stress, Engagement) using a t-student test with Bonferroni multiple comparison correction.

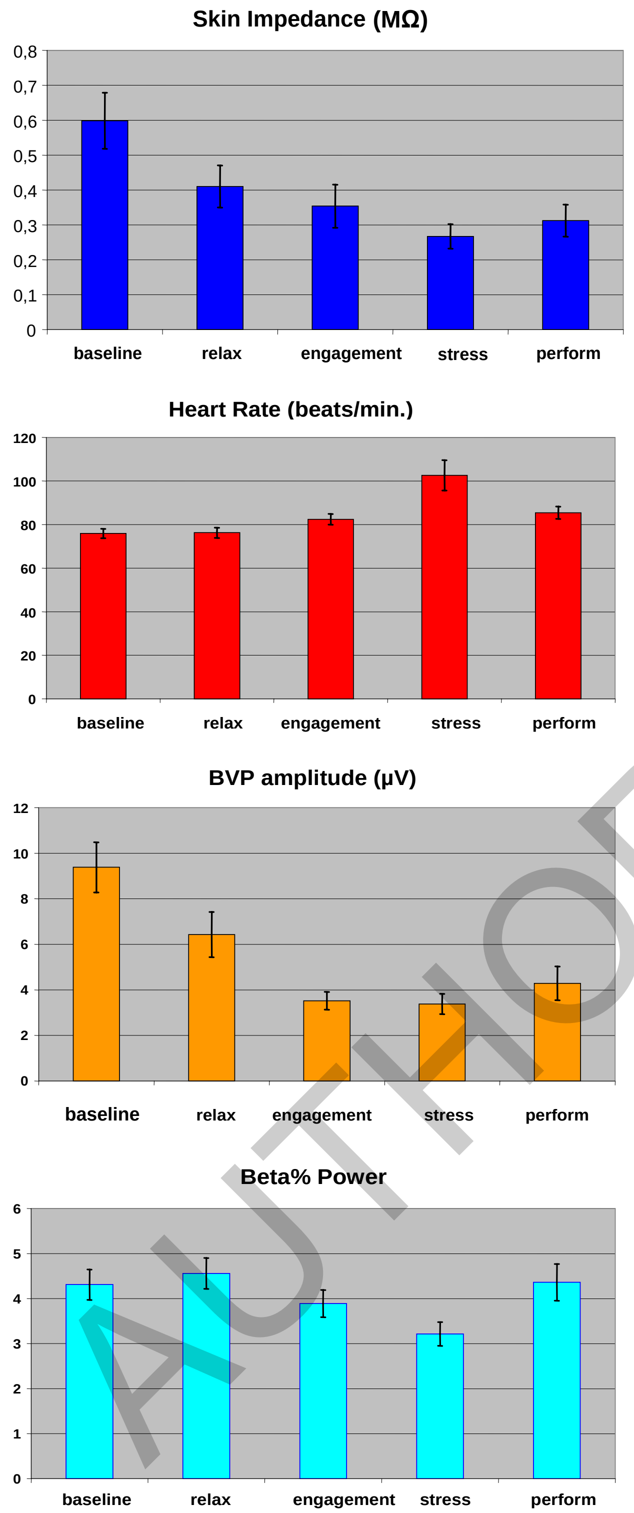

Fig. 3. From the top, the histograms of 4 physiological indexes extracted from GSR, EKG, BVP and EEG respectively: Skin Impedance (MΩ), Heart Rate (Beats/min.), BVP Amplitude (µV), EEG β Power (%). Results are averaged for the group for each epoch. Bars indicate Standard Errors.

VII. Results

Our results are aimed at illustrating that a collection of indexes extracted from the biological signals considered are able to characterize the three investigated emotional states (relax, engagement and stress). Performance could then be classified by relating the indexes computed during the specific tasks to the respective values from the emotional states of reference. Baseline epoch has not to be considered since it is just a reference point for the acquisition. Figure 3 shows results from four indexes averaged for the group in each epoch. These are: skin impedance, mean heart rate, BVP mean amplitude, β % Power; extracted from GSR, EKG, BVP, and EEG respectively. The first index (skin impedance) is able to separate significantly the three states,

TABLE I Units for Magnetic Properties

	Relax-Stress	***Relax-Eng***	***Stress-Eng.***
GSR	**0.000431**	**0.026057**	**0.025764**
	P<0.005	*0.005<P<0.05*	*0.005<P<0.05*
HR	**0.0008483**	**0.002038**	**0.014468**
	P<0.005	*P<0.005*	*0.005<P<0.05*
BVP Amplitude	**0.0022954**	**0.002346**	**Not sign.**
	P<0.005	*P<0.005*	*p>0.05*
EEG Beta % P.	**0.002067**	**Not sign.**	**Not. sign.**
	P<0.005	*p>0.05*	*p>0.05*
LF/HF Balance	**0.007667**	**Not sign.**	**0.027800**
	0.005<P<0.05	*p>0.05*	*0.005<P<0.05*

Statistical analysis showing the degree of confidence for each physiological index in differentiating the 3 main affective states examined: relax-stress, relax-engagement, stress-engagem. Green when p<0.005; Yellow when 0.005<p<0.05; Red when p>0.05.

with a maximum value of statistical confidence for relax and a minimum value for stress. In this case, the value of performance falls somewhere between engagement and stress. The second index (heart rate) is also able to separate significantly all three states, with a maximum value for stress, and a minimum value for relax. Also in this case, the value of performance for this index is located between engagement and stress values. The BVP amplitude index [11] was chosen as the best discriminator of relax from the other two states, whereas the β % Power index [12] is minimum in case of stress and maximum in case of relax, engagement and performance fall somewhere in between. Indexes that can discriminate a single state are potentially crucial in determining an orthogonal base in an abstract multidimensional emotional state space. Table 1 shows statistical significance for each index in differentiating the

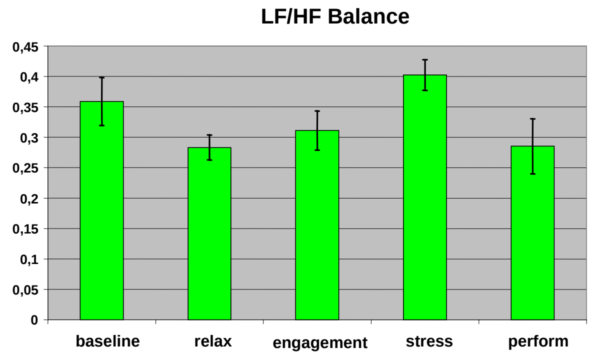

Fig. 4. The sympatho-vagal balance averaged for the group for each epoch. Bars indicate Standard Errors

three emotional states. The green histograms in Figure 4 represent results for the simpatho-vagal balance index [13] obtained by processing the EKG and averaged for the group for each epoch: also this index is able to separate significantly between relax and stress, as well as between stress and engagement. Figure 5 shows the mean STAI measurements averaged for the group, divided in four psychological contributions. In violet and purple are the

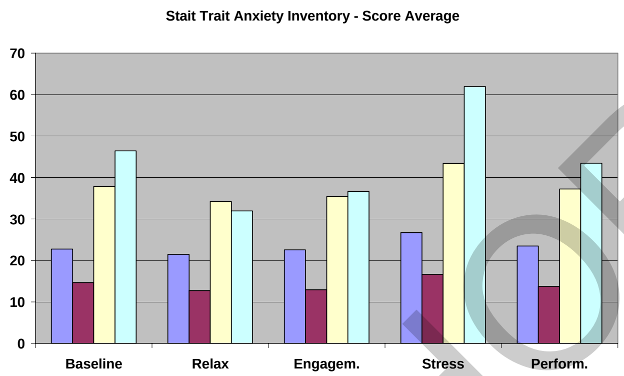

Fig. 5. The histograms show the Score Averages derived form the self-reports (State Trait Anxiety Inventory).

STAI subscales. The first is the STAI positively stated (i.e., Factor 1) items, whereas the second is the STAI negatively worded (i.e., Factor 2) items. In yellow is the total score, obtained by adding the scores of the two subscales. The light blue histograms indicate the transformation of the total score into a percentage score. Comparison of the histograms in figure 5 with results obtained for our indexes shows a significant correlation between *psychological stress* and the indexes obtained from *GSR and BVP*. The highest value of heart rate are related to psychological stress rate, while relax stimuli are diminishing these values; the inverse is true when skin impedance is considered. Finally, performance stimuli bring these values in the middle, coherently as indicated in the psycho histograms. and the same reasoning, comparing the simpatho-vagal balance with STAI mean measures, shows similar results.

VIII. Conclusion

In this paper we illustrate how specific quantitative indexes extracted from non-invasive recordings of multiple physiological variables may be successful in characterizing and distinguishing simple defined emotional states. We presented preliminary results are preliminary and further investigation is required to establish the most appropriate choice of affective patterns of reference, an optimal set of indexes, and the most effective criterion for combining them in a single reliable detector of the individual emotional state. Nevertheless, our results demonstrate that by combining information from multiple biological signals it is possible to achieve a significant classification of basic emotional states. This important achievement will be used as the basis to construct a computational algorithm for recognizing human emotions during e-learning activities.

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