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Design of a Multimodal Interface based on Psychophysiological Sensing to Identify Emotion

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Abstract **–This work proposes a design of a multimodal interface to classify or estimate emotion states. Thus, 7emotions are considered such as:anger, boredom, disgust, anxiety/fear, happiness, sadness and normal.A couple of sensing technologies such as: galvanic skin response (GSR), heart rate (HR), electrocardiography (ECG), oxygen saturation (SpO2) and electroencephalography (EEG)are used to collect psychophysiological signals in relation with emotion state estimation. The International Affective Picture System (IAPS) dataset is used to design the classifier system. Regarding the classification task, a comparison between artificial neural networks (ANN-MLP) and support vector machine (SVM) is presented. The tests were carried out for 20 healthy volunteers ($N_v = 20$) of both genders with age from 23-50 years old. The proposed classifier presents accuracies of 85.71% when using ANN-MLP and 77.14% when using SVM.**

Keywords **– Multimodal interface, signal analysis, emotion classification, psychophysiological signals.**

I. INTRODUCTION

Emotion is an important part of the human behavior and is organized in two primary categories – conscious and unconscious. Conscious emotion relates the emotional response based on some cognitive processes and the unconscious emotion is based on the autonomic process from nervous system [1, 2]. The interactions with pleasant places [3], hazards situations or by the judgment that it requires [4], memory bias and societal influences [2] are some situations that may determine the emotional state of an individual.

The emotions studies and its effects may beused for several purposes, researches and applications such as:detection of the relation among emotion and the regulation of lifestyle behavior [5]; analysis of its positives effects in individuals when they are in green and natural city's places [3]; analysis of suicides notes to avoid recurrent occurrences [6]; developments of tools of meaning detection of language to understand, identifyand recognize emotions [7];developments of interfaces to detect emotions from facial expressions to helps anxious individuals [8]; also to give support in healthcare, based in smart city context and internet of things (IoT) [9].

Automatic emotion classifiicationis a complex and important task that also can be used to improve the health and the life's quality. Different techniques may be used on the automatic emotion prediction or identification task, such as:salivary cortisol analysis [3], Hilbert-Huang transform [10], electrocardiography (ECG) [10-12], fuzzy logic, galvanic skin response (GSR) [13]and electroencephalography (EEG) [14]. Other researches present the importance of the multimodal sensing interfaces to acquire and identify emotions as for instance: identification of cognitive states of aircraft pilots while they are using flightsimulators [15]; to exam of the usefulness of psychophysiological measurements in a biocooperative feedback loop to adjusts the difficulty of an upper extremity rehabilitation task [16]; and to harmonizes robotic devices and emotion states as frustration and boredom [17].

The proposed design of a multimodal sensing interface is used to gives support to emotion acquisition, processing and identification tasks using several sensing devices and identification techniques. The emotions considered are: anger, boredom, disgust, anxiety/fear, happiness, sadness and normal. Moreover, to give support to the acquisition system, the International Affective Picture System (IAPS) dataset is used, which its pictures have been rated by both male and female volunteers [18].

II. DATASET PICTURES SELECTION

The International Affective Picture System (IAPS) dataset is considered in this work to provoke emotions in the vonlunteers. The IAPS dataset folder "test images artphoto" with 807 pictures was initially analyzed. Itspictures are labeled as amusement, anger, awe, contentment, disgust, excitement, fear and sad.

These pictures were valued by 5 healthy volunteers (they were not part of the main experiment) to select the most representative pictures according with the emotions: anger, boredom, disgust, anxiety/fear, happiness, sadness and normal. To reduce the dataset from 807 to 14 pictures (2 pictures representing each emotion),these volunteers first selected visually a subset of 40 pictures related to the

7 emotions used in this work.With this subset, a voting by each vonlunteer was based on two questions: “What emotion you felt when saw this picture?” and “What is the intensity of it (ranging from 0-10)?”.

All voting results are joined in a subset of 70 pictures (10 by each emotion). A final statistical analysis of the emotion intensities with means and standard deviations are applied to finally determine the final subset as shown in Figure 1.

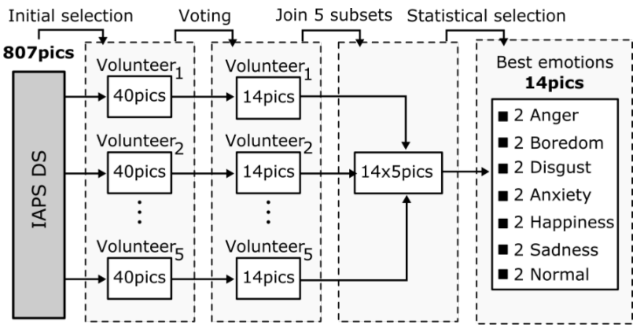

Fig. 1. Flow diagram of the pictures selection from IAPS.

III. INTERFACE DESCRIPTION

The present work focusses on emotion acquisition and emotion identification. Several psychophysiological signals are acquired, processed and identified to try to match to a specific emotion with acceptable accuracy. The multimodal interface have two parts: the real time software developed in MATLAB to show the input signals,and thehardwares based on the external sensorialdevices, responsible by the signal acquisition.

The communication between the sensorial devices and the MATLAB software is based on the universal serial bus (USB), using the Arduino Uno to receive all external signals. The computer used is an Asus AIO Transformer, characterized by a BaseTegra3+i7 and 18.4” touch panel.

The interface considers 7 emotions such as, anger, boredom, disgust, anxiety/fear, happiness, sadness and normal, where each emotion is labelled from 1 (anger) to 7 (normal), andthree main aspects such as, multimodal sensing (signal acquisition), signal processing and emotion identification (classification).

A. Real Time Interface

Figure 2 shows the realtime interfacebased on MATLAB to show the input signals. It has two main panels:the configuration panel, used to set the serial port number, baudrate, learning method, log enablings, framerate and max samplesmethod; and the real time signalpanel,used to plot all inputs signals from sensing devices.

The volunteers have no contact with this graphical interface,but only with the emotional pictures.

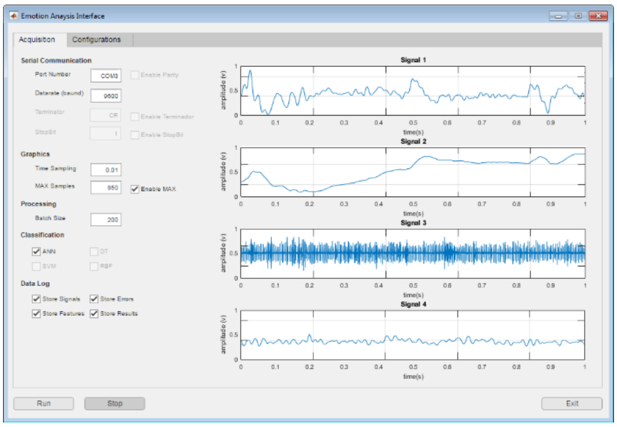

Fig. 2. Snapshot of the real time interface with the configuration panel (left) and real time signal panel (right).

B. Multimodal Sensing and Additional Information

Multimodal sensing includes the signal acquisition and the pre-processing. More than one technique (mode)of acquisition [10-14]are usedwhile the volunteers see the dataset pictures. Their signals are acquired based on galvanic skin response (GSR), heart rate (HR), electrocardiography (ECG), oxygen saturation (SpO2) and electroencephalography(EEG).

The devices used to the signal acquisition were: MedLab Pearl-100, Shimmer3and Neuroelectrics Enobio 8 (NE8/BCI). It wereapplied in a non-invasive mannerthough a couple of wet and dry electrodes.These devices also execute the analog filtering and amplifications (pre-processing) before the signal processing phase.

Beside of the multimodal sensing, an additional information (i.e. subjective questionnaires) are acquired after each picture presentation. With these questionnaires the volunteers should select the emotion (ranging from 1-7) and the intensity (ranging from 0-10)that they think that felt when saw the picture.

C. Electrodes Positions

Were used 20Ag/AgCl electrodes and one fingerclip. The electrodes positions change according to each acquisition technique.

Figure 3shows theelectrodes positionsapplied in this work.The EEG techniqueis based on 8 channels (Fp1, Fp2, T7, T8, C3, C4, O1 and O2)using the international10-20 system positioning [19];the frontal, temporal, central and occipital lobes are used.The positions of EEG electrodes is based on past research that indicated that the frontal lobes are responsible for emotional regulations [20] as such as for the emotional face processing [21]. Although, the other EEG electrodes are used to give auxiliary brain information.

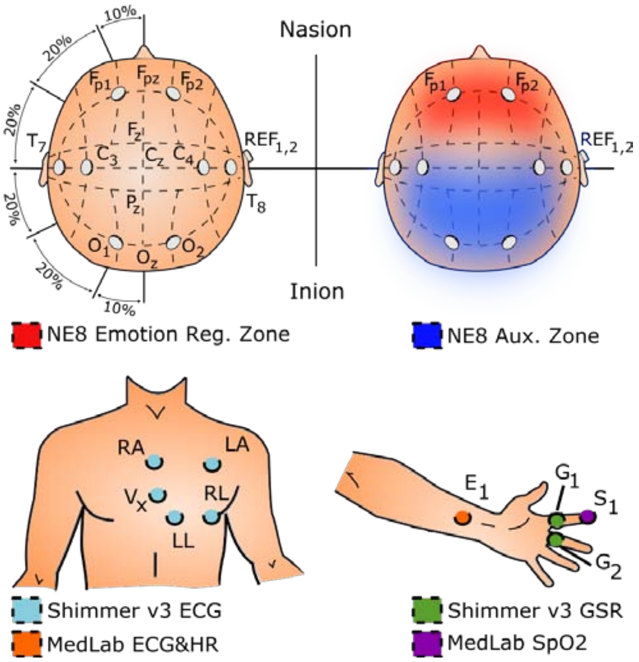

Fig. 3. *Electrode positions for EEG (up); main and auxiliary electrodes for emotion detection (up-right); ECG, GSR and SpO2 (bottom).*

For ECG, four channels are considered using the bipolar limb lead electrodes such as: LA (left-arm), RA (right-arm), LL (left -leg), RL (right-leg), and one channel unipolar lead electrode Vx (chest position). The HR uses three dry electrodes placed on both arms and left ankle. The SpO2 uses one fingerclip sensor and the GSR uses two dry electrodes placed on the right finger.

The amounts N_e (according to each technique) of theelectrodes and fingerclip as such as its types and positionsare presented in Table 1.

Table 1.Electrodes/fingerclip positions, types and its amounts.

Technique	**Electrodes/Fingerclip positions**	**Type**	N_e
EEG	-Scalp	Dry	10
GSR	-Fingers	Dry	2
SpO2	-Fingers (fingerclip)	Dry	1
ECG&HR	-Chest	Wet	5
	-Pulses	Dry	2
	-Ankle	Dry	1
	Total of electrodes:	**21**	

D. Signal Processing

The signal processing is used to to improve signal to noise ratio, to perform the spectral analysis and to extract features for the emotion identificationtask.

The considered features are: peaks of ECG, PPG and eye moviments; RR peaks distances; QRS complex; 1-D detail coefficients from the wavelet decomposition; and statistical analisys(i.e. variances, means and standard deviations).

Table 2 presents the amounts of features N_f and its characteristics.

Table 2. Sensing techniques and features description.

Technique	**Features**	N_f
EEG	-Eye movements peaks	1
	-Wavelets decomposition	2 x 8/CHs
	-Statistical analysis	3 x 8/CHs
GSR	-Peaks detection	1
	-Statistical analysis	3
SpO2	-Statistical analysis	3
ECG&HR	-Peaks detection	1
	-Statistical analysis	3
	-Wavelets decomposition	2
	Total of features:	**54**

E. Emotion Identification Task

This work usestwoidentification methodsto produce an emotion identificationanalysis and comparison of results. These methods are:artificial neural networkbased onmultilayer perceptron and backpropagation (ANN/MLP), and support vector machine (SVM).Since the emotion identification task is not in real time then, after the features extraction using MATLAB, the WEKA software was used on the identification task with its default configuration, batch size of 10 and split dataset of 50%.

A total of 54 features from the signal processing phase were applied as inputs for the considered classifiers. The emotions selected by the questionnaire were used as desired output from the classifier reference,the valuesas presented in Section IV.

IV. INTERFACE EXPERIMENT

The experiments were carried out for 20 volunteers ($N_v = 20$) of both genders with age from23-50 years old. All participants signed a consent term. For each experiment (i.e. volunteer)were used 14 different pictures ($N_p = 14$), 2 pictures by each emotion (desired emotion) as presented in Section II.Since 20 volunteers see 14 different pictures it result on 280 emotions ($S_e = 280$) selected and felt during all experiments.

Each picture (selected according to Section II)is presented during 15s ($t_{pp} = 15s$). All sensing acquisition and questionnaires were executed in laboratory with the same conditions of light and temperature (Figure 4).

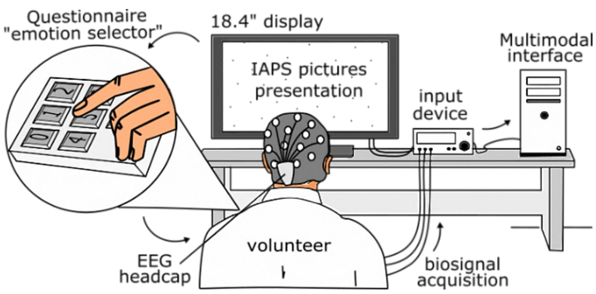

Fig. 4. Setup of sensing experiment in laboratory.

Before start each picture presentation, was recommended for all volunteers to close their eyes for 1 minute and open for another minute torecord the baseline reference [14];afterwards, the picture presentation begins.

Immediately after each picture presentation, the volunteers should select an emotion (ranging from 1-7) and the intensity of it (ranging from 0-10) felt when they saw the picture on display. Was considered an interval of 15-20s to the volunteers select these informationinto the questionnaires. After that, thebaseline recording process restarts for another experiment or picture presentation.

All psychophysiological datacollected during allpicture presentationswere locally recorded andsampledusing the emotions previoulsy selected into the questionnairesas a split reference, as shown in Figure 5.

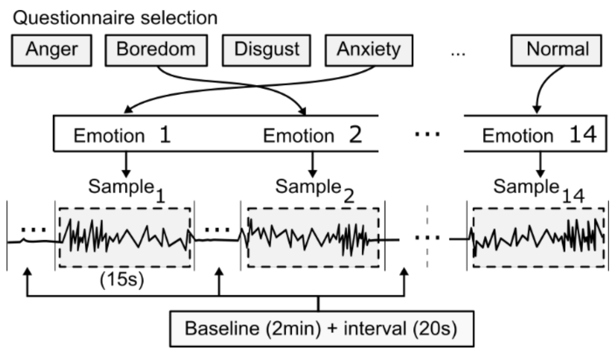

Fig. 5. Flow diagram of the emotions sampling process.

Part of all sampled signals, i.e. 50%, were used as "local" dataset of emotions references (desired emotions)to trains both emotion classifiers;the last 50%of the samples were used to test the classifier (offline emotion identification).

V. RESULTS AND DISCUSSIONS

The proposed design of a multimodal interface was able to capture, process and identifyseveral emotions.

Two groups of volunteers were considered in this work. One group with 5 volunteers was responsible to selects 14 pictures from IAPS dataset; and the another 20 volunteers participatedin the experiment.

The results of the emotion identificationtask are presented below and were based on two identification methods such as:ANN-MLP and SVM.

A. Results Analysis from Acquisition and Processing

Considering the EEGexperiments,it were analysedwith 500 samples/s(sampling rate) using the theta (4-8Hz) and alpha (8-13Hz) bands (waves), due it be correlated with the emotional experiences [14].

Figures 6-7 show an experiment example from a baseline based on EEG (no picture presentation).It present some signal fragments (half-time) and scalp map of the theta and alpha bands from the frontal lobe (Fp1 and Fp2 positions) during the baseline process with the first 30s representing eyes closed and the last 30s representing the eyes open.

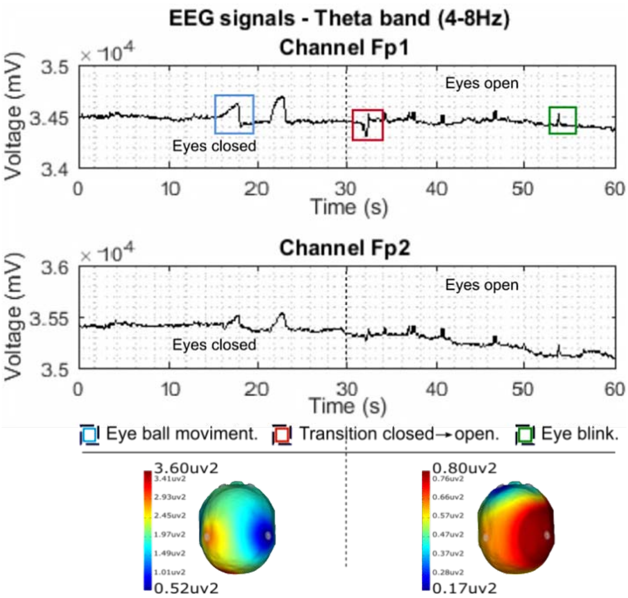

Fig. 6. Fragment (up) and scalp map (bottom) of the theta band from the frontal lobe during the baseline process.

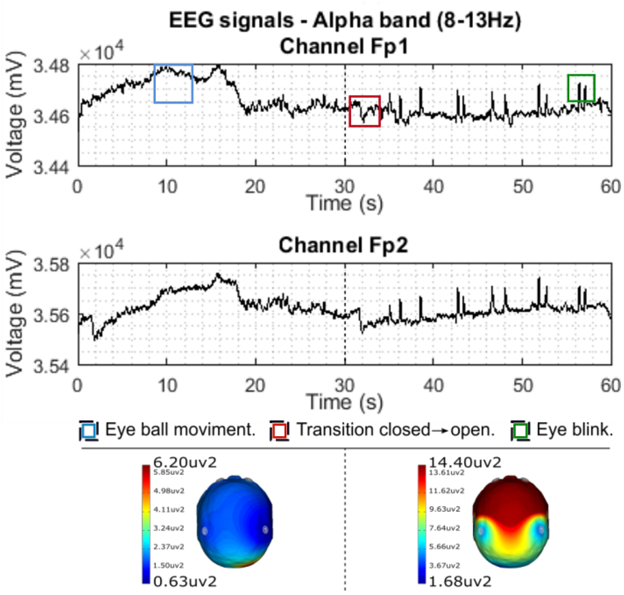

Fig. 7. Fragment (up) and scalp map (bottom) of the alpha band from the frontal lobe during the baseline process.

B. Results Analysis from Emotion Identification

Were executed 20 experiments with 20 volunteers ($V_1 - V_{20}$), where 280 emotions were selected through of the questionnaires (Section IV) at same time that 280 signals were collected by the sensing devices. Table 3 presents all emotions selected by each volunteer.

Table 3. Emotions selected by the volunteers.

Emotion selection by the volunteers ($N_v = 20$) using the questionnaire	Pictures selected from IAPS dataset (Emotions 1-7)														
		ang_0024 (1)	ang_0259 (1)	exc_0238 (2)	sad_0388 (2)	dis_0764 (3)	dis_0803 (3)	ang_0272 (4)	ang_0819 (4)	amu_0744 (5)	exc_0164 (5)	sad_0297 (6)	sad_0330 (6)	exc_0215 (7)	sad_0328 (7)
	V_1	1	1	7	2	4	3	4	4	5	5	6	6	5	6
	V_2	1	1	2	2	4	3	4	4	5	5	6	6	7	2
	V_3	1	1	2	2	3	3	4	4	5	5	6	6	7	2
	V_4	1	1	2	3	3	3	4	5	4	5	6	6	7	2
	V_5	1	1	2	2	3	3	4	4	5	5	6	1	5	7
	V_6	1	1	7	3	3	3	4	4	5	5	6	6	5	7
	V_7	1	1	7	4	3	3	4	4	5	5	6	1	5	7
	V_8	1	1	2	2	3	3	4	4	5	5	6	1	5	6
	V_9	1	1	2	2	4	3	4	1	5	5	6	1	7	7
	V_{10}	1	1	2	2	4	3	4	4	5	5	6	6	7	7
	V_{11}	1	1	7	2	4	3	3	4	5	5	6	6	7	6
	V_{12}	1	1	2	2	3	3	4	4	5	5	6	6	7	6
	V_{13}	1	1	2	3	3	4	4	4	5	5	6	6	7	6
	V_{14}	1	1	2	2	3	3	4	4	5	5	6	6	7	6
	V_{15}	1	1	2	2	3	3	4	4	5	5	6	6	7	6
	V_{16}	1	1	2	2	3	4	4	4	5	5	6	1	7	6
	V_{17}	1	1	2	2	3	3	4	4	5	5	6	6	5	2
	V_{18}	1	1	7	2	3	3	4	4	5	5	6	6	5	7
	V_{19}	1	1	2	4	3	3	4	5	5	5	6	6	5	7
	V_{20}	1	1	2	2	4	3	4	1	5	5	6	1	7	6

From the questionnaires used to select emotionsin a subjetive manner, were possible to collect 48 emotions answeared as "anger", 34 "boredom", 36 "disgust", 46 "anxiety/fear" 49 "happiness", 43 "sadness" and 24 "normal".

Results of the basic emotion identification task based on ANN and SVM are presented through a classification matrix in Tables 4-5, where E_1 to E_7 represent the emotions from anger to normal as presented in Section III.

Table 4.Emotion identification using ANN-MLP.

	Identified emotions ($50\%\ of\ S_e = 140$)							
	E_1	E_2	E_3	E_4	E_5	E_6	E_7	Accur.
E_1	**21**	0	0	3	0	0	0	0.875
E_2	0	**15**	2	0	0	0	0	**0.882**
E_3	0	1	**15**	1	0	0	1	0.833
E_4	2	2	0	**19**	0	0	0	0.826
E_5	1	0	0	2	**22**	0	0	0.880
E_6	0	2	1	0	0	**19**	0	0.863
E_7	0	3	0	0	0	0	**9**	0.666
Total accuracy: $^{120}/_{140}$ **=85.71%**								

Table 5.Emotion identification using SVM.

	Identified emotions ($50\%\ of\ S_e = 140$)							
	E_1	E_2	E_3	E_4	E_5	E_6	E_7	Accur.
E_1	**19**	0	0	4	0	1	0	0.791
E_2	0	**12**	3	0	0	2	0	0.705
E_3	0	1	**13**	2	0	1	1	0.722
E_4	4	2	0	**17**	0	0	0	0.739
E_5	1	0	0	2	**21**	0	1	**0.840**
E_6	1	3	1	0	0	**17**	0	0.772
E_7	0	1	2	0	0	0	**9**	0.750
Total accuracy: $^{108}/_{140}$ **=77.14%**								

Considering the small "local" database used to identify emotions (i.e. 140 emotions for training and 140 for test), the SVM identificationreached a total accuracy of 77.14%, and the best emotion identification was happiness (E_5) with 84% of accuracy.The ANN-MLP identification reached a total accuracy of 85.71% and the best emotion identification was boredom (E_2) with 88.20% of accuracy.

Thus, the experiment shown that the identification of emotions from psychophysiological signals reached better results when using ANN-MLP.

VI. CONCLUSIONS AND FUTURE WORKS

This work presents a framework that can be succesfully used as support for the emotion identification task. Experimental results shown that the proposed interface is able to capture, process and identify several emotions.

The tests were caried out with 20 volunteers, that visualised a set of 14 pictures selected from IAPS dataset. These volunteers aswered also a subjective questionnaire and selected one emotion and corresponding intensity for each visualised picture. A total of 280 emotions were selected and the correspondent signals were used for the emostion identification task.

As the future workwill be considered the usage of this interface for emotion study in the administration(i.e. secretaries and public service), in the fields of smart city, aviation context but also will be considered the possibility to estimated emotions during the physical rehabilitation based on virtual reality serious games.

VII. ACKNOWLEDGMENT

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