In Proceedings of the *Eleventh International Conference on User Modeling UM2007* Corfu, Greece (June 25th to 29th 2007)

A User Model of Psycho-Physiological Measure of Emotion

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Abstract. The interpretation of physiological signals in terms of emotion requires an appropriate mapping between physiological features and emotion representations. We present a user model associating psychological and physiological representation of emotion in order to bring findings from the psychophysiology domain into User-Modeling computational techniques. We discuss results based on an experiment we performed based on bio-sensors to get physiological measure of emotion , involving 40 subjects.

1 Introduction

Affective computing systems based on psychophysiology aim at interpreting user's physiological activity (e.g. heart rate -HR- and skin conductance -SC-) as discrete emotions or affective dimensions toward near to real time recognition of emotion [1–4]. Main approaches to perform emotion recognition use user-independent data (with a common training database for different subjects) and enable to build user-models including the user's emotions from that recognition process. Indeed, existing litterature point to the existence of relation between physiological signals and their psychological emotional meaning (e.g. heart rate acceleration and fear are usually positively correlated across subjects [5]. However emotional specificity of subjects [6] suggests that we should take into account in a user model specifity for a particular user. Other existing approaches to emotion recognition are single-subject based and are therefore not fully generalizable but allow precise user's model.

2 Psycho-Physiological Emotion Map as a U.M. representation

Our proposed User Model (UM) aim at mapping physiological emotional measures with associated psychological emotional measures in a emotional given situation, for a specific user (but using both user-dependent and user-independent

** The authors would like to acknowledge that this work was partially founded by ST Microelectronics in the framework of the Region Provence-Alpes-Côte-d'Azur (PACA) PACALab.

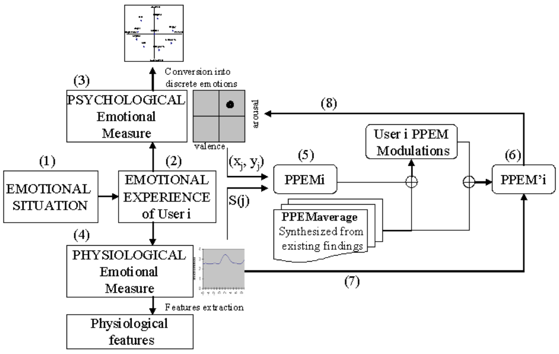

Fig. 1. Psycho Physiological Emotional Map construction and use.

data) : the Psycho Physiological Emotional Map (**PPEM**, see figure 1) [7]. *In a UM learning phase*, we provide a set of emotional situations to the user (1), which elicit affective experiences (2). We perform psychological (3) and physiological (4) measures associated to the affective experience. The psychological measure can be converted into different representations (discrete and dimensional). A set of features extraction is performed from the physiological measure. Then, the user model called PPEM (single subject form) is built from the association of psycho-physiological measure (5), for the user i. Then, from a PPEMaverage (user-independent data : synthesis of existing findings in terms of psycho-physiological maps), we build the modulations from this average for this subject. Finally, by combining these modulations with the PPEMaverage, we build the PPEM'i (parametric form combining user-independent and user-dependent data) which will be used to recognize emotion. *In a UM use phase*, we continuously measure physiological signal from the user and extract features related to emotion (7). By comparing the current features values, with the contents of the PPEM'i, we estimate the emotion representation actually felt by the user (8).

3 Experiment and Results

3.1 Materials and Methods

We performed an experiment to test the possibilities to build the proposed user model. 40 subjects participated (21 men and 19 women, average 32 years old). A set of 61 stimuli (31 images, 5 videos, 25 sounds)was selected to be varied regarding the type of media (audio, visual et video), the contents and the intented emotional characteristic (i.e. pre validated by a population, e.g. 31 images from the International Affective Picture System [8] and 2 videos from [9]), to try to cover the most extended range of emotion. Figure 2 shows the three steps exposure and emotional measure of the same stimuli, performed by each subject. Phase (1) was a slideshow of stimuli and recording of physiological measure (heart rate and skin conductance, using Bodymedia armband used on the left

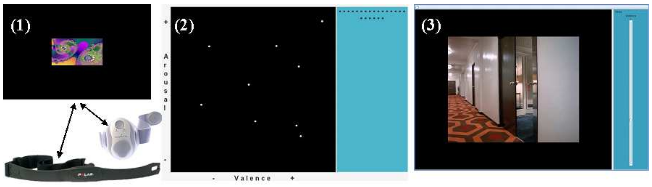

Fig. 2. The three steps of emotion measures for the experiment.

hand and an adapted polar T31 transmitter). Phase (2) was a *static* classification of the same stimuli in the emotional space of expression made of valence*arousal dimensions. Phase (3) was a *dynamic* measure of the valence, during a slideshow of the dynamic stimuli.

3.2 Data preprocessing and statistical analysis

Psychological data. For each subjects, we estimated the position in the valence arousal space as discrete emotion (using the Circumplex model [10] and by dividing the valence and arousal space into five regions), to study the compatibility of both representations into our user model (see figure 3 for an example of clustering).

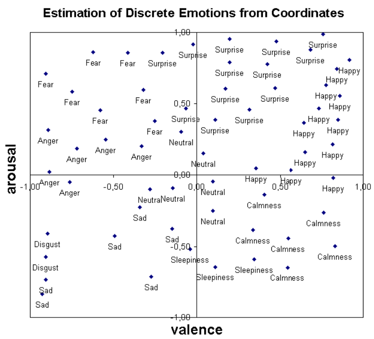

Fig. 3. Estimation of Discrete Emotion from the valence and arousal coordinates expressed by a subject.

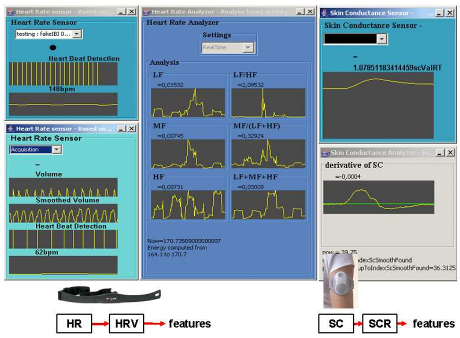

Fig. 4. Designed Real Time Heart Rate and Skin Conductance Emotional Feature Analyzer

Physiological features. We extracted from the physiological signals 28 features related to emotion (detailled in table 1 with our implementation shown in figure 4). Skin conductance (SC), Skin Conductance level (SCL, the tonic signal in SC), and Skin Conductance Responses (SCRs, the phasic signal in SC, considered as discrete events) were extracted for each stimulus. Heart Rate (HR) and Heart Rate Variablity (the variability in different frequency bands,

Table 1. SC-related and HR-related features calculated for each multimedia stimulus.

SC-related Features	Description	**HR-related Features**	Description
SC (raw)	SCAverage	HR (raw)	HRAverage
	SCMaxAmplitude		HRMin
SCL	SCLOnsetOffsetDiff		HRMax
SCR	SCRsRelativeNb	HRV, in each Freq. bands : with i =LF, MF or HF)	meanE_i
	timeStart		minE_i
	meanRiseTime		maxE_i
	meanAmplitude		meanDerivativeE_i
			sympathovagalBalance
			relativeMFPower
			totalVariability

based on FFTs) were extracted. **Analysis at intra-individual level.** Figure 6 plots the number of subjects which presented a significant linear correlation ($p < 0.05$) between physiological features and psychological representation of emotion expressed in the provided valence and arousal space. This results confirm the general population trend that heart rate could be used as an indicator of valence, while skin conductance could be used as an indicator of arousal. Moreover, the different number of significant correlations for each subject is an indicator of inter individual differences.

	a_0	a_1	a_2
PPEMaverage	0.143	0.05	-0.113
subject 1	0.029	-0.128	0.158
dx_1	0.029	0.151	-0.054
subject 2	0.258	0.236	-0.384
dx_2	-0.199	-0.213	0.488

Fig. 5. Built PPEM'_i from $\text{PPEM}_{\text{average}}$ and PPEM_i for two subjects.

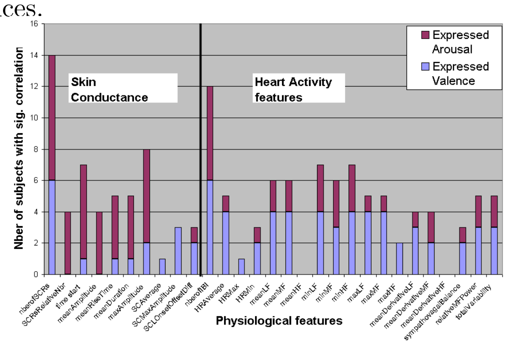

Fig. 6. Number of subjects for which we found a significant linear correlation, for each feature.

Using dynamic emotional measure for user modeling. Intra-individual dynamic expression of valence could be considered for a user modeling of psychophysiology. Psychological features performed on the slider values (e.g. averaged rigth derivative of slider movement) analyzed with phyiological features lead in signficant results (a maximum of 63% of significants correlations was found, $p < 0.05$). Thus, the (a_j, b_j) components of PPEM could be taken into consideration. **Combining different emotion representations.** We tested statistically discrete emotion representation with physiological values. Results showed that the mean of 64% of physiological features in each emotion class statistically changes according to classes (One-way ANOVAs with F(1,63) and $p < 0.01$). This validates the possibility to combine dimensional and discrete psychological representations.**Psycho-physiological mappings, from PPEMi to PPEM'i.** We built PPEM'i using multilinear regression model based on least squares method. For example, $valence = a_0 + a_1x_1 + a_2x_2$, with x_1 and x_2 two features values, and a_0, a_1 and a_2 the associated coefficients, could be the model of a subject. Differences between the coefficients provide differences between the psychophysiological mappings. We provide in table 5 an example of models we built for two subjects (PPEMi, user-dependent model) and their equivalent as PPEM'i (combination of user-dependent and user-independent data) using the population average (PPEMaverage, user-independent data) with valence as output. The PPEM'_i combines user-dependent and user-independent data, and allows to compare model among subjects.

4 Discussion

We provided a user model (PPEM) which may help computer sensing of emotion by embedding average psychophysiological rules as well as what we learn from each user. Our results shows that (1) Combining different emotion representations (dimensional and discrete, dynamic and static) into one User Model is suitable ; (2) Considering the average population psychophysiological mappings could be taken into account to facilitate the user modeling. The PPEM'_i, which combines user-dependent and user-independent data, may help to model psychophysiological mappings of users, and thus increase the emotion recognition efficiency from physiological signals.

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