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A User-Modeling Approach to Build User's Psycho-Physiological Maps of Emotions using Bio-Sensors

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***Abstract*— Near to real-time emotion recognition is a promising task for Human-Computer Interaction (HCI) and Human-Robot Interaction (HRI). Using knowledge about the user's emotions depends upon the possibility to extract information about users' emotions during HCI or HRI without explicitely asking users about the feelings they are experiencing.**

To be able to sense the user's emotions without interrupting the HCI, we present a new method applied to the emotional experience of the user for extracting semantic information from the Autonomic Nervous System (ANS) signals associated with emotions. We use the concepts of *1 st person* - where the *subject* consciously (and subjectively) extracts the semantic meaning of a given lived experience, e.g. 'I felt amused') - and *3rd* person approach - where the *experimenter* interprets the semantic meaning of the subject's experience from a set of externally (and objectively) measured variables (e.g. galvanic skin response measures) -

Based on the 3rd person approach, our technique aims at psychologically interpreting physiological parameters (skin conductance and heart rate), and at producing a continuous extraction of the user's affective state during HCI or HRI. We also combine it with the 1 st person approach measure which allows a tailored interpretation of the physiological measure closely related to the user own emotional experience.

I. INTRODUCTION

A. *Definitions*

Emotion is a mind-body phenomenon. We can access this phenomenon with different views from cognitive science depending on the level of organisation we are considering (social, psychological, cerebral, cellular). This paper studies two opposite kind of observables of emotion : (1) an expression of consiouss aspect of this phenomenon (psychological level), and (2) some peripheral expression of the Autonomic Nervous System (ANS) activity, modulated by the emotion through the control from sub-cortical structures (physiological level). The topic of this paper is to manipulate theses two measures of emotion, confronted by the concepts of 1 st and 3rd person approach, using measure from the psychophysiology research field. In the case of the 1 st person approach, the interpretation of the subject's emotional experience is done by the subject himself. It correspond here to a psychological approach, as we explicitely request the subject to express the affective state (s)he's feeling. In the case of the 3 rd person approach, its an external observer (the experimenter) who produce the meaning associated with the measured signals. In this case, such signals are the physiological one.

B. *Objectives*

Including affect sensing in Human Computer Interaction (HCI, e.g. in teaching application), Human-Robot Interaction (HRI, e.g. for assisting tele-healthcare patients in remaining autonomous), and Computer Mediated Communication (CMC, like mailing, artistic collaborative systems), are dependent on the possibility of extracting emotion in a continuous way, independent from the explicit user request of his(her) affective state. Actually, an interruption in HCI, with the purpose to explicitly ask user about his (her) current feeling could modify true feeling of user. Such interruption should be avoided by a suitable third person approach, i.e. a continuous extraction of actual affective state of user by a mechanism of interpretation and thus without explicit asking for consciously experienced emotion. Motivated by the possibility to extract user emotion, the aim of this paper is (1) to show how the psychological and the physiological cues are related, and (2) propose a method and a system to infer psychological meanning from measured physiological cues, in near to real-time. Our approach is generic and aims at permit the use of psychophysiology in HCI, HRI (incorporating psychophysiological research into HRI could be found in [1]), and CMC. This paper is organized as following. After an overview of the methodolgy used, we present the litterature related to the Autonomic Nervous System (ANS), and the possibilities to extract information from it, especially emotional one. Then, we propose what we call Psycho Physiological Emotional Map (PPEM) as default emotional mapping between psychological responses and affective space, from previous experiments. Then, we presents the hardware system and software algorithms for heart rate and skin condcutance extraction and analysis, including design and software implementation, which we will use in our experiment.

II. METHODOLOGICAL OVERVIEW

Several physiological peripheral activities have been found to be related to emotional processing of situations. The physiological parameters studied here are the heart beat rate and the skin conductance.

A. *Framework*

The **proposed framework** consists on extracting in real time heart beat rate and skin conductance, and, using the

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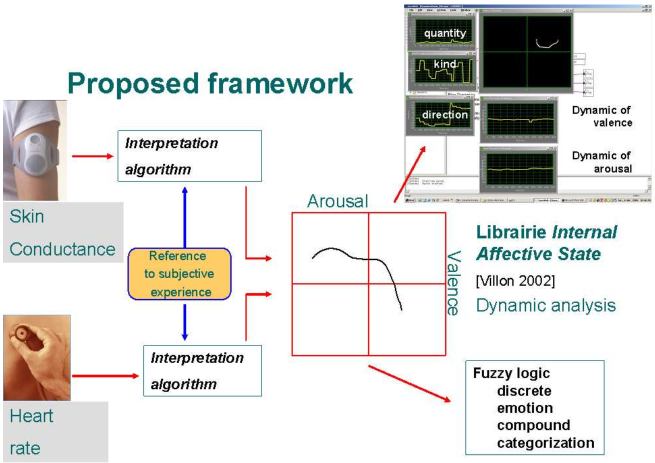

Fig. 1. Proposed Framework to extract affective state, in continuous and discrete emotion representation.

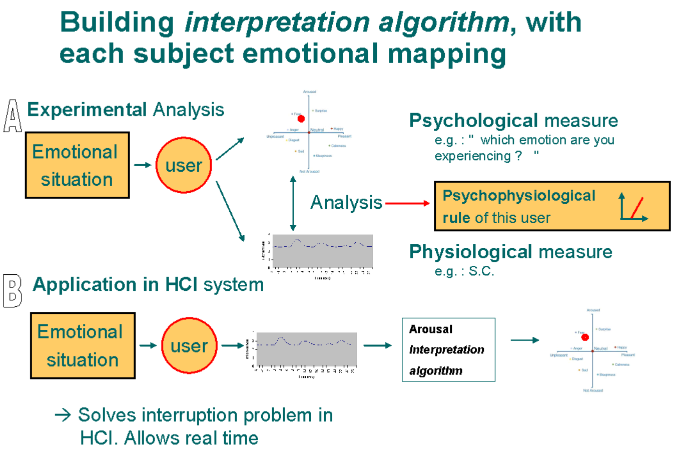

Fig. 2. Proposed Methodology to build interpretation algorithms.

appropriate PPEM, extracts current emotion of the user (see figure 1).

B. Proposed methodology

The **proposed methodology** consists on two steps, illustrated in figure 2. The first is the experimental one, based on the 1 st and 3 rd person approaches. We propose an emotional situation to the subject, and measure its emotional evaluation with both psychological method (e.g. explicit emotion expression as valence and arousal scales) and physiological measures (using cues related to emotion). The relations between theses two types of data are analyzed to extract a semantic of physiological measure (which we call Psycho Physiological Emotional Map - PPEM, see section below). The second step is the applicative one, using a 3 rd person approaches, with a reference to the results of the previous 1 st person approach. We continuously extract physiological parameters from the user, and try to extract in real-time the affective state his feeling, according to the semantic interpretation of the measures, done with the previously assessed PPEM.

C. Psycho Physiological Emotional Map (PPEM) definition

The PPEMs are the mode of representation of the psychological link to physiological features. The above-mentionned methodology assumes the hypothesis that the *static* measures (post presentation of stimuli, i.e. an emotionnal resultant) and *dynamic* (while the subject his experiencing the stimuli) are closely related. Actually the idea is that an expressed static evaluation of an emotional stimulus (i.e. with discrete emotion questionnaire, or with continuous representation using emotion scale) is produced from the analysis of the felt affective dynamics during the stimulus experience. Thus, we should be able to find some rules whithin the dynamics of affective experiences of each stimulus, linking the dynamic measures (here the physiological measure), with the static measures (here the psychological ones) of stimulus affective evaluation. As if dynamic psychological measures are supported within the PPEM, we focus on static one due to the experimental difficulty to mesure 1st person accurate dynamic measure. Such rules will be stored into PPEMs.

Indeed, at the opposite of [2] who set up a "user-independant emotion recognition based on physiological signal" , the notion of PPEM corresponds to the aim of our approach which is to tailor the interpretation of physiological measure, refering to psychological measure, on the same person.

As mentionned in section II, the objective is to be able to create a mapping of physiological onto psychological measures, what we call the Psycho Physiological Emotional Map (**PPEM**). Because we want such mapping to be suitable for, and so tailored to, several user, we decided to model the PPEMs as a sum of *common* processes to the population, *modulated* for each individual, and which could be *modulated within* an individual due to specific reasons.

We define the link exhibited by a subject between the physiological and psychological measures of a given emotional situation as a PPEM. Let be $PPEM_i$ the PPEM associated to the subject i. Let be S a group of specific physiological patterns, represented as sets of features values derived from the physiological signal.
Each set of features values, is denoted by $S^f_{n_f}(j)$,$j = 1, \ldots, s$ where s is the number of sets. $S^f_{n_f}$, $f = 1, \ldots, F_j$ is a set of F_j features (denoted by f) values (ranged from $n_f = 1, \ldots, N_{f,j}$ for each feature f) computed from the physiological signal.
For example, let's considering the pattern $S^f_{n_f}(1)$, defined by a succession of 3 SCR amplitude values represented in $S^1_{n_1}(1)$, with $N_{1,1} = 3$ and the succession of 10 energy values in MF Bands of Heart rate PSD represented in $S^2_{n_2}(1)$, with $N_{2,1} = 10$).

Let be (x, y) a coordinate in valence*arousal space. Let be (x_j, yj) the coordinate of a point j in the valence*arousal space, and (a_j, bj) a value to add to current coordinate of the (x, y) point.

The *single subject* form of $PPEM_i$ is a set of psycho physiological associations. The psychological part is denoted by a coordinate (x_j, y_j) (see equation 1), or by a dynamic, i.e. a change from a state to an other, (a_j, b_j) (see equation 2) :

$$PPEM_i = \{(x_j, y_j), S(j)\} \quad \text{with} \quad j = 1, \ldots, N \tag{1}$$

$$PPEM_i = \{(a_j, b_j), S(j)\} \quad \text{with} \quad j = 1, \ldots, N \tag{2}$$

where N is the number of PPEM element

Once created, a PPEM is used as following by a recognition system. Let be V a set of feature values, in the form of $S(j)$. Let be $PPEM_i(V)$ the function associated to the $PPEM_i$, which returns a specific coordinate (x, y) or dynamic (a, b), see equations 3 and 4 :

$$(x, y) = PPEM_i(V) \tag{3}$$

$$(a, b) = PPEM_i(V) \tag{4}$$

Let be t a threshold. The $PPEM_i(V)$ is defined by (see equation 5) :

$$PPEM_i(V) = \begin{cases} (x_1, y_1) & \text{if } |V - S(1)| < t \\ (x_2, y_2) & \text{if } |V - S(2)| < t \\ \ldots & \text{if } \ldots \\ (a_3, b_3) & \text{if } |V - S(3)| < t \\ \ldots & \text{if } \ldots \end{cases} \tag{5}$$

The PPEM have here the status of simulation and not machine learning (i.e. the pairs made of psychological and physiological components are descriptive). Actually, it is interesting as we could retrieve psychophysiological relationship qualitatively. However, each user should have a unique PPEM, which is difficult to compare user, and to relie on previous findings.

We defined the *single subject* form of $PPEM_i$. We define now the *parametric* form of PPEM : $PPEM_i'$, which should return the same result as the $PPEM_i$, but with a different internal process. In this form, the psychological output is based on the PPEM of a virtual subject ($PPEM_{\text{average}}$), which represent the prevous findings in the litterature, i.e. the pshychophysiological links of the average population. To exhibit the inter-individual differences, as a modulation of $PPEM_{\text{average}}$ output, we introduce $dx_{j,i}$ and $dy_{j,i}$, which represent the subject i modulation of the average population results, for the pairs $((x_j, y_j), S(j))$. To exhibit the intra-individual differences, as showed with "Day-dependance" phenomenon ([3]), we introduce $dx_{j,i,c}$ and $dy_{j,i,c}$, which correspond to the subject i modulation due to specific conditions c, as day, moment of the day, etc... Let be $j = 1, \ldots, N$ with N the number of PPEM elements. The $PPEM_i'$ is (see equation 6):

$$PPEM_i' = \{((x_j + dx_{j,i} + dx_{j,i,c}, y_j + dy_{j,i} + dy_{j,i,c}), S(j))\} \tag{6}$$

We can make the hypothesis that $dx_{j,i}$ and $dy_{j,i}$ correspond to a personality of the subject, while $dx_{j,i,c}$ and $dy_{j,i,c}$ are more related to mood and body state, and so day changes. The day-dependance changes could be measured with repeated measures. So, the litteral form of $PPEM_i'$, is : averagepopulation + $user_i$ delta + mood of $user_i$ delta. A more detailled use of the PPEM could be found in [4]. The PPEM are not yet implemented with a specific machine learning technique. PPEM are made of a dictionary. A comparison of several implementation techniques for psychophysiology could be found in [5]. Our ongoing work consists on a learning phase followed by a use phase. The learning is done one-time, before the interaction with the system. This learning could be done again, if we want to precisely model short term changes as the day-dependant phenomenon. This learning extracts significant statistical rules between psychological (the valence and arousal positions) and physiological features. Once found, the rules are stored into the PPEM of the current user. The use phase is made of a distance calculation between the current set of features measured on the user and each sets of features (Sj) associated to psychological coordinates in the PPEM of the current user. The physiological features are produced in near to real-time.

III. HOW TO EXTRACT EMOTIONAL SEMANTIC FROM ANS

A. The representation of emotion

Huge debate in emotional modeling is the representation of emotion. The two main opposite approaches are discrete (e.g. labels like joy, anger, fear, etc...) and dimensional (mainly the valence*arousal*dominance space). Both approaches have advantage :

- The affective dimensions are continuous, and so are interesting for real-time monitoring of user emotion. Moreover, this mode of representation allow the computation of dynamics in the state of the user, which is needed to represent emotion as an evolutive process.
- The discrete emotions are interesting when we search to match a specific state of the user, like frustration.

As we should keep advantage of each dimension, the chosen approach is to focus on dimensional representation (i.e. the system will use a dimensional representation) but which easily convertible into discrete representation. The chosen dimension are the valence and the arousal. Valence (pleasure/displeasure) is related to motivational system of approach/withdrawal. Arousal(calm/excited) is the excitation state of the user, the bodily activation, an intensity of emotion. The possibility to convert from one representation to other is given by a discrete-dimensional model of affective space : the Circumplex model [6]. In 1980, Russel provided a valence*arousal space where discrete emotions can be plotted (see 3). emotion.

B. Respect the inter-individual differences using self-report to study emotion

We formalize the elicitor as the situation which elicits emotion (e.g. multimedia content in HCI context, or robot action in HRI), and the affective experience the evaluation,

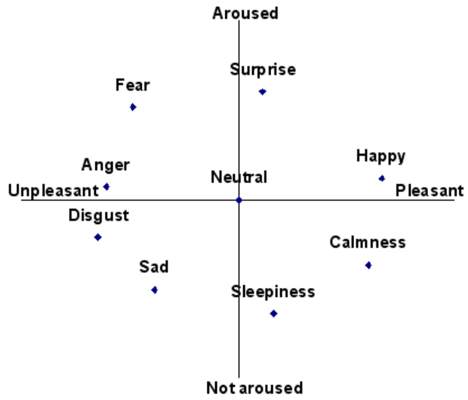

Fig. 3. The circumplex model. From Russel,1980

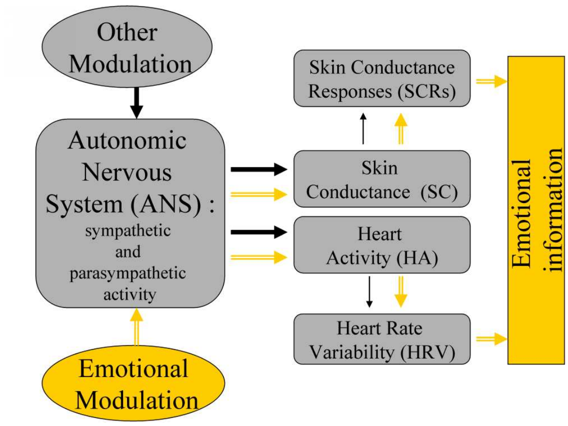

Fig. 4. Emotional modulation of ANS and peripheral measure of this emotional information.

made by an individual of this situation, and made of psychological and physiological components. Theses two components are the expression/measure of the affective experience. Considering the physiological and psychological evaluations as the ouptut of a system evaluating this elicitor, we can isolate two levels of potential inter-individual differences. The first level is the existing differences between the psychological and physiological component according to individuals, which is what this paper aim at adressing, as denoted in section II-C. The second level is the existing differences between the elicitor and the affective experience. As pointed out in [7],[8], the way individuals evaluate elicitors could be considered as an *embodied affective relationship*, thus dependant of the personal history of each individual. This consideration direclty drive our experimental setup, which is based on the self-report evaluation of subject, and its analysis which is based on intra-individual methodology instead of averaging self-report affective responses of several individuals.

C. Autonomic Nervous System (ANS) semantic

1) ANS description and psychological information contents: Autonomic Nervous System (ANS) is driven by brain structure, related to emotional processing. The ANS role is the regulation of the organism. We can access indirectly to it by several measures like heart activity (mainly the rate) and skin electrical properties (conductance). Specific peripheral measures of ANS activity gives information about behavior. For example, [9] and [10] heart rate activity contains breathing information, known as RSA.

So, ANS is modulated by emotional and other factor((see 4). For example, [11] showed that ANS could be modulated by personality trouble. We focus here on the emotional information contained in ANS, and peripherically measured trought the Heart Rate (HR), and the Skin Conductance (SC). These two measures are non-invasive and were found to contains auseful information about ANS activty.

Heart Rate. The heart beats are autonomously controlled by the sinoatrial node, situated at the top of the heart. The parasympathetic and sympathetic branch of nervous system modulates the HR (short term modulation), as well as norepinephrine realeased in the bloodstream by the adrenal glands(long term modulation).

Skin Conductance. The skin conductance (SC) is the electrical conductance measure at the surface of the skin. We apply a tension of reference to the skin, and then measure its variations ([12] and [13]). The modulation of the SC is the result of neurons activity, afferent from the sympathetic system, which controls the sudoripar glands of the skin. The sympathetic system is, as for it, innervated by cortical and sub-cortical structures involved in emotional and motivational system. More precisely, the neural substartes of SC are mainly amygdala and hypothalamus ([14]).

Both HR and SC modulation are thus peripheral measures of cerebral activity.

2) Emotional information in ANS : Psychophysiology: The possibility of measurement of the emotions starting from physiological data such as the skin conductance, had been proven in experiments by many articles. An interesting philosophical review of the suitable inference of a psychological semantics starting from physiology is given in [15] (see page 6-7 for a specific criticism of SC and HR). It is a fundamental problem for the measurement of the emotions, corresponding to the discipline of psychophysiology of emotion. [16] made a review of more than thirty articles having put together expirimentally physiological measurements with their emotional interpretation. This abundant literature legitimates the use of physiological cues for the measurement of the emotions. Recently, [17] and [18], [19] showed that ANS can discriminate affective states, both in dimensional and discrete representations.

Actually, specific cues contained in SC and HR were found to be related to the expressed emotion of subject.

3) Heart Rate Variablity (HRV) and emotional information: Heart activity analysis allow extraction of heart rate (HR) and related heart rate variability (HRV). HR and HRV has been found related to physical efforts, but also to cognitive activities, as meditation ([20]) and emotional processing. Direct analysis of HR, like in [21], showed that HR is involved in emotional valence processing ; [22] showed that an HR acceleration occurs when subject are looking at unpleasant films. HRV analysis is a more difficult task, but gives more precise information about the changes of the heart rate. Mood and emotion influences HRV. For example, [23] found relation between people with depressed mood and their HRV, compare to person with normal mood. [24] showed the effects of picture of emotional faces to HRV. [25] demonstrates that ”anger produces a sympathetically dominated power spectrum”, while ”appreciation produces a power spectral shift toward MF and HF activity”.

HRV could be assesed in time-domain and frequency-domain (see next section). Several studies focused on emotion in the time-domain, and few in the frequency domain. However, the Frequency domain seems to contain a lot of useful uinformation for emotion, as it reflect how the ANS is modulated by emotional factor (see 4). Thus, we will study here the relationship between felt emotion, and the HRV measured in frequency domain.

4) Skin Conductance Responses (SCRs) and emotional information: The SC is an index of subjective arousal, in other words we can say that the psychological semantic of the skin conductance is the arousal. For example, the experiment of [26] showed experimentaly a covariance between amplitude of SC of subjects exposed to stimuli, with the 1 st person evaluation of these same stimuli. We usually distinguish two major information into the raw signal of SC. Firsly, the Skin Conductance Level (SCL) which represent the basal level, the tonic component of arousal. The SCL reflects the general arousal level of the organism. The second signal is the SCRs which are transitional responses, contained into the raw SC signal, with a characteristic form. They are characterized by fast variations of the SC signal, and doesn't take into accounts the slow changes of the raw SC. Theses responses seems to be correlated with uncounsciouss emotional and attentional processes, which interested us.

Morevoer, [27](page 213) and [28](table 3, page 106) showed experimentaly statistical correlation of arousal and SCRs.

In addition, valence couldn't be retrieved systematically from this signal, as if some poor coorelation were found, and without any discrimination of the valence sign. For example, ([29] paragraph *results*, page 1439), found strong correlations from the arousal (subjectvies measures) and the SC signal, while for valence, they only found correlations discriminating 'neutral' and 'pleasant or unpleasant' conditions.

So, we should find intra-individual (within-subject) correlations between SCRs (amplitude, duration, number), and the subjects' affective ratings in arousal.

Nature, duration and elicitation of SCRs. The SCR is a characteristic response obtained from the SC raw signal, with a typical duration of 1 to 3 secondes [13]), which can be extended to 10 secondes between the beginnig and the complete return to the SC former level (before the SCR) ([30]).

SCRs are elicited between 200ms and 1 seconde after the presentation of a new stimulus (see [31], paragraph *Measures of Electrodermal Activity*). The modification of deep sudoripar glands is extremely fast. It is not only a superficial sudation, but actually the skin resistance, modulated by deep skin layer (see [13], who provide an electrical model of deep skin layer electrical modulation).

The SCRs can be elicited by stimuli of really short duration (see a study with subliminal images, i.e. around 30 ms, inferior to liminal level [32]).

The sitmuli which elicits SC reactions could be of different nature, duration and modality. [33] used music, [34] used odours, and [22] used films. The synthesis of [16] presents a collection of studies using different stimuli. However, the stimuli seems to not follow a specific typology. Actually, [35] wrote about this subject, talking about SCRs : The stimuli that elicit these responses are so ubiquitous that it has proved difficult to offer a conceptualization of the features common to these stimuli.

D. Existing system to recognize emotion, and their limitations

Recently, several system closely related to the one proposed were presented. Actually, they use also skin conductance and heart rate, and aims at extracting online, or (near to) real-time, a meaning of physiology in term of psychological parameters. Morevover, they compare psychological and physiological measures.

However, several critics could be adressed to these approaches. Firstly, the choice of feature set from physiological signal is a problematic approach as we know that SC and HR are not only modulated by emotion. For example, [16] and [3] used SC and HR signal with preprocessing as min, max, average, etc... of the signal during the stimulus presentation. The problem with such approach is that features such as SCRs and HRV in spectral domain seems to be cues of emotion (see section III-C.3 and III-C.4), while SCL and HR in time domain contains less specific semantic(as physical activity, or general arousal state, see Fig. 4). Also, a suitable preprocessing is needed, before any machine learning or other means to build what we call the PPEM. This is the approach recently taken by [2],using mainly SCRs and HRV in frequency domain.

Secondly, as if theses systems justify the use of these physiological signals refering to previous psychophysiological experiment in the litterature, they don't re-use these result for the modelisation of links between psychological and physiological measures. Actually, [16] tested different machine learning techniques, [2] used Support Vector Machines, and [3] used SFFS-FP and k-NN, directly between their discrete emotionnal categories and the physiological features (pre-processed or not). Once the machine learning model is created, authors present their recognition scores of emotion, at inter-individual level (i.e. with a common training database for different subjects). This approach underlie two problems : (1) As if such machine learning system are effective and robust to the differences in physiological signal interpretation, the limitation here is that we can't establish a common parametric model (with previous research) to describe precisely the link between psychological and physiological aspect of emotion.

Fig. 5. Bodymedia Armband : hardware device to measure skin conductance.

(2) A machine learning system at inter-individual level couldn't point out qualitatively the differences : we can't model the difference from one subject to other regarding the psychological semantic of a physiological signal, and we can't describe precisely the intra-individual differences (thoses described as "Day-dependance", in [3]).

The PPEM approach, as defined in section II, might allow to establish a common model, taking into accounts and precisely describing inter and intra-individual differences. Our methodology aims at tailor interpretation, to get better recognition score (were 74% for 3 categories of emotions, for [2]), and take a descriptive approach. Finally, another specificity is the system's output both available as discrete and continuous emotion.

IV. Physiological Recordings

We describe in this section the system we use to measure physiological data, and to to design a computer-based system for emotional continuous measurement.

A. Skin Conductance measurement

Hardware device. The bodymedia armband, along with the InnerView Research Software 4.1 from Bodymedia is used to record skin conductance (see figure 5). Despite that this system is designed to work on the arm, we found that the data are more precise and amplified using the armband onto the hand on palmar region, a measurement site recommended since [12]. Thus, indivudals are asked to wear the armband on the left hand, using a bipolar placement (on the forefinger and the middle finger), on medial phalanx.

B. Heart Rate measurement, by adapting a Polar T31 transmitter

Both hardware and software were made for this experiment. The software part is a java class. Hardware components reference and java implementation could be provided. **Hardware device**. The hardware was made from a chip of Polar, the HFUi receiver. Several techniques exist to measure heart activity (i.e. electric Electrocardiogram -ECG-, optic or phonologic). The chosen technique is the ECG one, with the T31 transmitter of Polar. For each found Q-R-S complex signal (which contain the R-wave, the main peak used for heart beat timing), the T31 send a pulse to the HFUi receiver. The HFUi receiver is connected to the serial port of any PC, with an appropriate wiring (see figure 6). As the current delivered by the HFUi was not sufficient to elicit event detection into the serial port, a system with a transistor was

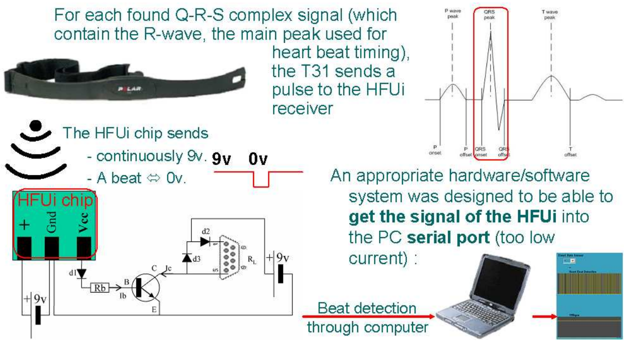

Fig. 6. Our proposed system to measure Heart Beat in real time from a Polar's HFUi receiver, connected to the PC serial port.

designed. The HFUi is continuoulsy set at 9v. The poor current is amplified and the serial port detect the incoming voltage, between pin 1 and 5 which represent the CD signal (carrier detect for modems). When an heart beat is detected by the T31 transmitter, the HFUi receiver down the digital pulse to 0 volt, for $100ms$, which is detected by the serial port as a CD event.

Heart Beat detection. The heart rate detection was implemented in Java 1.5.0. The processing applied on the serial port had to be suitable for real-time processing. An event detection was implemented using the Sun API for javax.comm package. After searching for serial ports, the serial port named "COM1" is searched by our java class. Once done, and EventListener is created and added to this serial port. When an event occurs, we check if this event is the Carrier Detect signal, i.e. if some voltage changes occur between the pin 1 (CD) and pin 5 (signal ground). When the event is detected, we check that the IBI isn't inferior to the minimal duration of an heart period ($300\ ms$, i.e. $200\ beats.min^{-1}$). We should only consider beats inferior to this period as artifacts of the polar/serial system. Then, the class deals with Inter-Beat Interval calculations, graphic plotting. The IBI are stored in IBI buffer, which could be continously recorded to a text file containing the timestamp of the begining of the experiment (for synchronisation purpose), or which could be used by any java based program in real time.

C. HRV extraction in time-frequency domain

The set of detected Inter heart Beats Intervals (IBI), also called R-R intervals, when measured with an ECG, is stored as an interval tachogram (IT), defined by :

$$IBI(i) = t_i - t_{i-1} \text{ for each } i\text{-}th \text{ beat , occurring at time } t_i \quad (7)$$

Starting from the IT, HRV could be measured in time and frequency domain, with several methods [36] and [37] and [38] who presents a tool to compute HRV in matlab, with different techniques (STFT, Wavelet, etc...). The method we chose is based on Short Time Fast Fourier Transform (STFT) applied on a floating window of N beats (N ranged from 8 to 64, according to the allowed delay during the interaction with a system), with an overlap of N-1 beats, as the new

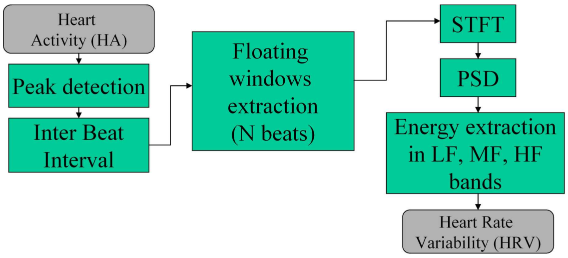

Fig. 7. Measurement of Heart Rate Variablity in frequency domain.

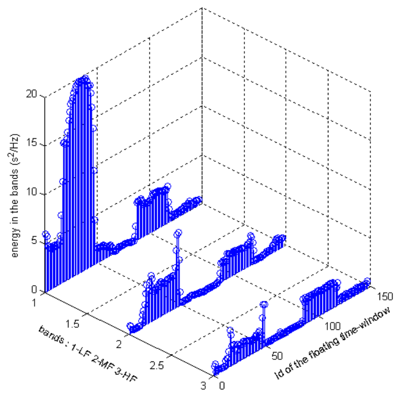

Fig. 8. Power Spectral Density in LF, MF and HF bands. Each value correspond to a time-window of N beats, denoted by the floating time-window id.

HRV measure is applied every new incoming IBI value. Fig. 7 presents the method we detail below.

For each new recorded beat, an N-points FFT is computed on the Inter heart Beat Interval (IBI) values, on a time-window of N beats. Let be $FFT = fft(IBI, N)$ the set of fft values from the IBI. To avoid resampling, which introduces smoothing, the scale of the frequency axis of the FFT is found by averaging the IBI on the N beats time-window. Let be Fs the sampling duration of the signal (in seconds), defined by (8):

$$Fs = \frac{\sum_{i=1}^{N} IBI_i}{N} \tag{8}$$

Then, one point frequency of FFT ($f(i)$, in Hz), where i is the fft's output index, is given by $f(i) = i * Fs/N$

A Power Spectral Density (PSD) is then computed on each FFT, i.e. on each time-window. It represents the amount of power per unit of frequency, as a function of frequency ([39]). It is a useful tool to compute the distribution of IBI variance with frequency. For each $FFT(i)$, the PSD (in s^2/Hz) is computed with (see 9):

$$PSD(i) = |FFT(i)|^2 \tag{9}$$

Finally, for each time-window, the energy is computed in three bands (Hz): LF [0.01,0.08[, MF [0.08,0.15[and HF[0.15,0.5[which had been found to be related to emotion ([25], see section III-C.3 above-mentioned). Let be E_{LF}, E_{MF} and E_{HF} the energy in these three bands. Let l and h be the low and high limits of a band. to compute the energy in one band, let's consider $PSD(m, n)$ the set of PSD values like $f(m) \geq l$ and $f(m-1) < l$, and like $f(n) < h$ and $f(n+1) \leq h$. Energy is computed as a sum of PSD values within the band. For example, the Low Frequency Energy (E_{LF}) is (see 10):

Knowing m, n like $f(m) \geq 0.01, f(m-1) < 0.01$ and $f(n) < 0.08, f(n+1) \leq 0.08$

$$E_{\text{LF}} = \sum_{i=m}^{n} PSD(i) \tag{10}$$

Thus, the energy of the PSD is computed for each time window of N beats, in the three bands (see 8, for an example with an IBI set of 178 values, with $N = 32$) :

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

We provided a new methodology enabling to tailor the interpretation of physiological components of emotion in terms of psychological descriptor of emotion (namely the valence and arousal dimension or affective discrete labels). Moreover, we provided a system to measure skin conductance and heart rate trough computer, and extract the heart rate variability in real time. The proposed system is intented to enhance interaction in HCI, HRI and CMC, by providing an input to system which need an estimation of the emotional state of the user to adapt to the user.

B. Future Works

Remaining work consist on filling what we call the $PPEM_{\text{average}}$, in order to constitute a computational state-of-the-art of psychophysiological rules published. Morevoer, we currently proceeds to the analysis of an experiment based on the presented methodology, involving 40 subjects. The future works include the analysis of this experiment, in order to establish adapted $PPEM$. Then, an API software will be provided, with experimental and applicative mode, in order to quickly build user's $PPEMs$, and then use this maps to produce online emotion recognition adapted to users.

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