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Emotion Assessment for Affective Computing Based on Physiological Responses

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***Abstract*—Information about a user's emotional state is a very important aspect of affective interaction with embodied conversational agents. Most research work aims at identifying emotions through speech or facial expressions. However, facial expressions and speech are not continuously available. Furthermore, in some cases, bio-signal data are also required in order to fully assess a user's emotional state. We aimed to recognize the six, basic, primary emotions proposed by Ekman, using a widely-available and low-cost brain-computer interface (BCI) and a biofeedback sensor that measures heart rate. We exposed participants to sets of 10 IAPS images that had been partially validated through a subjective rating protocol. Results showed that the collected signals allowed us identifying user's emotional state. In addition, a partial correlation between objective and subjective data can be observed.**

I. Introduction

Scientific research in the area of emotion extends back to the 19^{th} century when Charles Darwin [10] and William James [26] proposed theories of emotion that continue to influence thinking today. During most of the 20^{th} century, research in emotion assessment has found increasing importance since feelings are present in many situations where humans are involved [55] [62] [54].
One of the main problem in emotion recognition is related to the definition of emotions and the types of emotions that can be distinguished. Ekman proposed a model which relies on universal emotional expressions to differentiate between six primary emotions (joy, sadness, anger, fear, disgust, surprise) [12] [9].

Most research work has aimed at identifying emotions through different modalities such as speech or facial expression analysis [52]. However, it is rather easy to mask a facial expression or to simulate a particular tone of voice [6]. In addition, these channels are not continuously available since users are not always facing the camera or speaking. We believe that the use of physiological signals such as EEG, EMG, ECG, among others, allows solving these problems to be solved. For example, heart rate has been shown to effective to differentiate among anger, fear, disgust, and sadness in young and elderly participants [38].

Psychological researchers used many diverse methods to investigate emotion expression or perception in their laboratory, ranging from imagery inductions to film clips and static pictures. The International Affective Picture System (IAPS) is one of the most widely-used stimulus sets [34]. This set of static images is based on a dimensional model of emotion. It contains various pictures depicting mutilations, insects, attack scenes, snakes, accidents, among others. IAPS-based experiments have also shown that discrete emotions (disgust, sadness, fear, among others.) have different valence and arousal ratings, and can be distinguished by facial electromyography, heart rate, and electrodermal measures [3].
The propose of our work is to recognize the six basic primary emotions proposed by Ekman using a widely-available and low-cost, brain-computer interface (BCI) (Emotiv Epoc [22]) and a biofeedback sensor (Nonin Oxymeter [23]) that measures heart rate. The Epoc allows to be recorded EEG signals from 14 electrodes positioned on the user's head, and provides high-level expressive and affective data. An experimental protocol based on IAPS pictures has been conducted to elicit and identify emotion through high-level data from Epoc and the heart-rate sensor. The IAPS image sets have been validated using a rating protocol of the user's perceived emotional states. The results of this work will contribute to the development of a job interview simulator allowing face-to-face communication between a human being and an Embodied Conversational Agent (ECA) [17], [18], [21]. This simulator will be used to train candidates (students, job hunters, among others.) to better master their emotional states and behavioral skills. In this context, we will take into account the six, basic, primary emotions as well as the secondary emotions (excitement, concentration and stress).
The remainder of the paper is organized as follows : in the next section, we survey the related work concerning the modeling and classification of emotions with a particular emphasis on emotion assessment from physiological signals. In Section 3, we present the experimental study along with the data acquisition procedure and the experimental protocol used to extract emotions from IAPS images. The results are presented and discussed in Section 4. The paper ends with a conclusion and provides some ideas for future research.

TABLE I
LISTS OF BASIC EMOTIONS FROM DIFFERENT AUTHORS [50].

Reference	Basic emotions
Ekman et al. [13]	Anger, disgust, fear, joy, sadness, surprise
Izard [24]	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
Plutchik [57]	Acceptance, joy, anticipation, anger, disgust, sadness,surprise, fear
Tomkins [64]	Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise
Gray [14]	Rage and terror, anxiety, joy
Panksepp [51]	Expectancy, fear, rage, panic
McDougall [42]	Anger, disgust, elation, fear, subjection, tender-emotion, wonder
Mower [44]	Pain, pleasure
James [26]	Fear, grief, love, rage
Oatley, Johnson-Laird [49]	Anger, disgust, anxiety, happiness, sadness

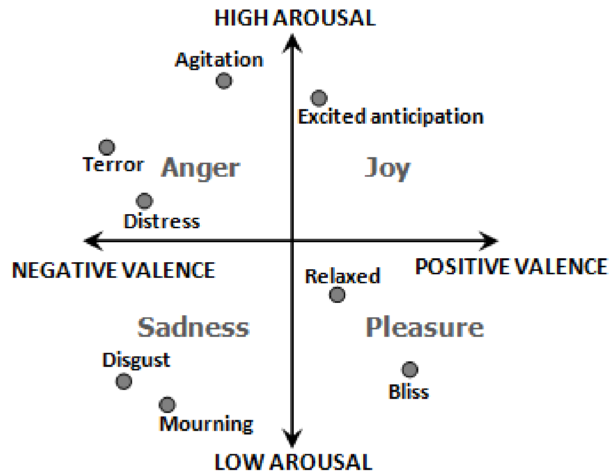

Fig. 1. Illustration of the two-dimensional model based on valence and arousal [60].

II. RELATED WORK

A. The modeling and classification of emotions

Theories of emotion are now recognized as involving other components such as cognitive and physiological changes, and trends in action and motor expressions. Each of these components has various functions. Darwin postulated the existence of a finite number of emotions present in all cultures and that they have an adaptation function [10]. Although several theoretical models of emotions exist, the most commonly used are the dimensional and categorical models of emotions [41]. One approach is to label the emotions in discrete categories, i.e. humans have to select emotions from a prescribed list of word labels, e.g. joy, sadness, surprise, anger, love, fear. This postulate was subsequently confirmed by Ekman who divided emotions into two classes: the primary emotions (joy, sadness, anger, fear, disgust, surprise) which are natural responses to a given stimulus and ensure the survival of the species, and the secondary emotions that evoke a mental image which correlates with the memory of primary emotions [11]. However, several lists of basic emotions have been adopted during the years by different researchers (see Table I from Ortony and Turner [50]).

Another way of classifying emotions is to use multiple dimensions or scales based on arousal and valence (Figure 1). This approach was advocated by Russell [60]. The arousal dimension ranges from 'not-aroused' to 'excited', and the valence dimension ranges from negative to positive. The different emotional labels can be plotted at various positions on a two-dimensional plane spanned by two axes to construct a 2D-emotion model. For example, happiness has a positive valence, whereas disgust has a negative valence: sadness has low arousal, whereas surprise triggers high arousal [33].

However, each approach, in discrete or continuous dimensions, has its advantages and disadvantages. In the discrete approach, where each affective display is classified into a single category, complex mental/affective states or blended emotions may be too difficult to handle [68]. Despite exhibiting such advantages using a dimensional approach, whereby each stimulus may be present on several continuous scales, this approach has received a number of criticisms. Firstly, the theorists working on discrete emotions, such as Silvan Tomkins, Paul Ekman, and Carroll Izard, have challenged the usefulness of these approaches by arguing that the reduction of emotional space to two or three dimensions is extreme and results in a loss of information. Secondly, some emotions may lie outside the space of two or three dimensions (e.g., surprise) [15].

In our study, we aim to identify the six basic emotions proposed by Ekman and Friesen [12] (disgust, joy, anger, surprise, disgust, fear, sadness) because this classification of emotions is widely used for the study of human emotional states. In addition, discrete categorical models have provided numerous empirical insights. Thus, the set of IAPS images used in this work has shed light on discrete emotions, showing that different discrete emotions have distinct valence and arousal ratings. For example, heart rate analysis allows to differentiation among anger, fear, disgust, and sadness [38].

B. Emotion recognition using physiological signals

The analysis of physiological signal is a possible approach for emotion recognition [56]. Thus, several types of physiological signals have been used to measure emotions, based on the recordings of electrical signals produced by the brain (EEG), the muscles (EMG), and the heart (ECG).

These measures include the signals derived from the Autonomic Nervous System (ANS) of the human body (fear, for example, increases heartbeat and respiration rate) [29], the Electromyogram (EMG) that measures muscle activity, the Electrocardiogram (EKG or ECG) that measures heart activity, Electrodermal Activity (EDA) that measures electrical

TABLE II

PHYSIOLOGICAL SIGNALS FOR AFFECT RECOGNITION. IN ADDITION, THE SEMINAL WORK OF PICARD ET AL. [56] AND EGON ET AL. [65] IS PROVIDED AS A BASELINE.

Study	**Year**	**Signal**	**Part.**	**Classifiers**	**#classes**	**S&E**	**Result**
[56]	2001	CA, EA , R , M	1	LDA, KNN	8 Es.	Self elicited	81.25%
[47]	2004	EA, HRV, ST	14	KNN, DFA, MBP	6 Es.	Movie clips selected by panel	KNN: 71%, DFA: 74%, MBP: 83%
[16]	2004	EKG, EMG, EA, ST, BVP, RESP	1	MLP	Dimensional model	IAPS	V: 90-97%, A: 63-90%
[32]	2004	EKG, ST, EA	50	SVM	3&4 Es.	Audio-bisual, self evaluation	78% for 3 and 62% for 4
[8]	2005	EA	1	MPL	4 Es.	Self elicited	75%
[19]	2005	CA, EA , R , M	9	LDA	3 stress levels	Self elicited	97%
[25]	2005	CA , EA , R , M	1	kNN, LDA, MLP	4 Es.	Self-selected songs	92%
[67]	2005	CA, EA	6	MPL	4 Es.	video clips	80%
[58]	2006	CA, EA, M, ST, P	15	KNN, SVM, FT, BN	3 Es.	Self elicited	86%
[40]	2006	CA , EA , M , ST	14	FT	3 anxiety levels	basketball game	70%
[69]	2006	CA, EA, ST, P	32	SVM	2 stress levels	Self elicited	90%
[20]	2007	EEG	17	NN, DT, Bagging	3 dimensions	IAPS	75%
[36]	2007	CA , EA	8	ANN	3 Es.	IAPS	71%
[2]	2008	ECG, SC, Face	151	Chi-square/SVM	2 Es.	3rd & Films	–
[27]	2008	CA, EA, R, M	10	SVM, ANFIS	4 affect states	Self elicited	79%
[31]	2008	CA, EA, R, M	3	LDA, DC	4 Es.	musical induction	70/95%
[39]	2008	ECG, EA, EMG, ST	6	SVM	3 Es.	Pong game and anagram	83%
[66]	2008	CA, EA	72	SVM, MLP	2 fun levels	Physical Game	70%
[1]	2009	EEG	3	SVM, NB, KNN	10 Es.	Self elicited	33-55%
[5]	2009	EKG, EA, EMG	3	NB, FT, BN, MLP, LLR, SVM	8 Es.	Self elicited	68-80% for individual subjects, 42% for all subject
[7]	2009	CA, EA, R	13	ANN	3 Es.	Self elicited	51%
[28]	2009	EEG, GSR, ST, R, M	13	QFA	Dimensional model	Self elicited	–
[29]	2010	EEG	26	KNN	4 Es.	IAPS	84.5%
[53]	2010	EEG	16	SVM, QDA, KNN	6 Es.	60 pictures	QDA: 62%, SVM: 83%
[63]	2011	EEG, GSR, ECG, ST	30	HMMs, SVM	Dimensional model	Movie clip [59]	73.2% to 75%
[45] [46]	2011	EEG, ECG, HRV	24	ANOVA	2 dimensions	IAPS and IADS [4]	–
[48]	2011	EEG, EMG	100 and 50	SVM	2 dimensions	Movie clip	89% and 84%

Signals: EKG; Electrodermal activity (EA), Skin Temperature (ST); Cardiovascular activity (CA); Respiration (R); electromyogram (M); Pupil diameter (P); Heart Rate Variability (HRV); galvanic skin response (GSR). **Classifiers**: Naive Bayes (NB), Function Trees (FT), BNs, Multilayer Perceptron (MLP), Linear Logistic Regression (LLR), Support Vector Machine (SVM), Discriminant Function Analysis (DFA), and Marquardt Backpropagation (MBP); BN: Bayesian Network; ANN: Artificial Neural Network; Linear Discriminant Analysis (LDA); quadratic Discriminant Analysis (QDA); k-Nearest Neighbors (kNN); Adaptive Neuro-Fuzzy Inference System (ANFIS); Dichotomous Classification (DC); Nearest Neighbours (NN); Decision tree (DT); Hidden Markov Models (HMMs). **Additional abbreviations**: Number of (#); Participants (part.); Stimulus and Evaluation (S&E); Emotions (Es.) and classification result (result).

conductivity as a function of the activity of sweat glands on the skin, the Electrooculogram (EOG) that measures eye movement, and the Electroencephalogram (EEG) [28] [29]. Table II summarizes some of the studies where physiological signals, including EEG, have been used to recognize emotions. Some of these studies combine multiple signals, each with advantages and drawbacks for laboratory and real-world applications. Feature selection techniques and the model used (categorical or dimensional) for each study are also included in the Table, and it appears that most studies use categorical models.

The stimulus or elicitation technique used in most of these studies was 'self-enactment' where subjects use personal mental images to trigger (or act out) their emotions. Psychophysiologists have also performed many studies using databases of photographs, videos, and text (Table II).

III. EXPERIMENTAL STUDY

We collected data from sixteen participants with a mean age of 26.4 years (ranging from 21 to 35 years). The group consisted of 6 females and 10 males. All of them were employees or students of Angers University (France). They

TABLE III
CHARACTERISTICS OF IAPS PICTURES USED FOR EMOTION INDUCTION.

Emotion	Valence Mean (std)	Arousal Mean (Std)
Disgust	2.72 (1.65)	5.40 (2.32)
Joy	7.29 (1.54)	4.34 (2.28)
Surprise	4.75 (1.89)	6.39 (1.98)
Sadness	2.83 (1.59)	4.66 (2.00)
Fear	3.82 (1.84)	5.99 (2.14)
Anger	2.44 (1.69)	6.46 (2.31)

had perfect or corrected-to-perfect vision and had not taken any medication that could affect EEG signals, and they stated that they felt healthy.

A. Stimulus Material

Gathering emotional data that corresponds to a particular emotional state is a difficult problem. Self-assessment by a person can differ in many different factors. Consequently, we needed a consistent and valid emotion induction-method with the possibility of reproducing the experiment. For this reason we decided to use images from the International Affective Picture System (IAPS for emotion induction) [4] [35]. Each of these images has been extensively evaluated by north-American participants, providing valence and arousal values on nine-point scales (ranging from 1 to 9). Some previous experiments showed a 0.8 correlation with evaluations performed by Europeans [61]. Each image was associated with the average arousal μ_A and the valence μ_V computed from these evaluations as well as with their standard deviations σ_A and σ_V [7]. Moreover, Mikels [43] provided a more complete characterization of the categorical structure of the IAPS stimulus set, with the objective of identifying images that elicit one discrete emotion more than other emotions. He defined a subset of 390 pictures. Each image is associated with an average value for each basic emotion. A total number of 60 pictures [1] were selected from this subset. The images were divided into six, randomly-ordered subsets (10 pictures per emotion). The subset order was counterbalanced across participants. Table III shows the mean values and standard deviations of the IAPS ratings for the selected pictures.

B. Experimental set-up

The devices used for the acquisition of physiological signals are the Emotiv Epoc headset [22], and the Nonin biofeedback (ECG) sensor [23]. The Epoc headset is quite non-intrusive, as it is enabled by a wireless connection and is very light. It consists of 14 electrodes labeled according to the international 10-20 system. This headset comes with preprogrammed features, which can be quickly employed in evaluation (high-level data). They offer real-time feedback about the emotional reactions of a user. It can retrieve data from affective and expressive suites. The expressive suite identifies a user's facial expression (smile, clench, right/left smirk, and laugh), whereas the affective suite analyzes a user's emotional state (engagement, frustration, meditation, instantaneous and long-term excitement). Sadly, the algorithms for this are proprietary. As such, the owners of an Epoc device have to rely on the manufacturer's encoding, without much proof about the correctness of the detection. To overcome this and to validate the output of the high-level, data headset, we compared the results of the Epoc headset against the results through a subjective rating protocol. Indeed, we compared objective and subjective data. Nonin WristOx2^{TM} is a pulse oximeter that can retrieve heart rate (HR) and pulse oximetry (SPO2). Figure 2 shows a subject wearing both an Emotiv Epoc headset and a biofeedback sensor.

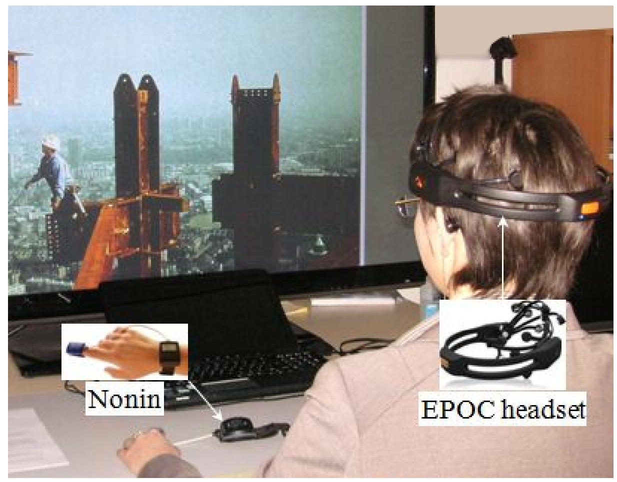

Fig. 2. Illustration of the experimental set-up.

C. Procedure and design

The participants were asked to read and sign a consent form to participate in the study. Each participant then received a copy of the instructions and a rating booklet. The participants were informed that the purpose of the study was to determine how people respond to pictures. They were further informed that the study would take about 45 minutes and that they would have to look at a series of 60 pictures projected onto a screen. A calibration procedure is necessary for the user to train the Emotiv Epoc headset by performing the desired action before it can be detected (Fig. 3). As the user supplies more training data, the accuracy of expressive detection typically improves. After looking at each image, they had to rate it on the following dimensions: joy, anger, surprise, disgust, fear, sadness.

The computing of the temporal window length in the attempt of the automatic affect analysis is based on the modality and the target emotion. A study published by Levenson and co-workers [37] showed that the duration of emotions varies from 0.5 to 4 seconds. However, some researchers proposed to use a different window size that depend on modality, e.g., 2-6 seconds for speech, and 3-15 seconds for bio-signals [30]. In our experiment, each trial included a 5-second rest period

[1] The following pictures were used for emotion induction: Joy: 7325, 1463, 2091, 2341, 1920, 2560, 2655, 1340, 2070, 2092. Sadness: 9415, 3300, 6838, 9530, 2205, 2490, 2141, 2590, 2276, 9470. Fear: 5972, 1110, 1052, 1301, 1302, 5970, 1113, 1930, 3280, 1321. Disgust: 7361, 9405, 2352.2, 9290, 7360, 9830, 9300, 9490, 9320, 7380. Anger: 6560, 6830, 6212, 6360, 9800, 9810, 3500, 6540, 6550, 6313. Surprise: 8192, 1726, 1022, 5920, 8475, 5940, 8160, 7640, 1114, 1931.

between IAPS images presentation, a 6-second picture presentation and a 15-second rating interval in which the picture was not displayed on the screen (Fig. 4). In this interval, the participants answered on a 10-point scale according to the degree to which they felt each emotion by pressing a visual analogue scale (0-10) with 0 indicating not at all and 10 indicating a great amount. This procedure allowed the participants to indicate multiple labels for a given image. The IAPS images were presented randomly to the subjects. hints

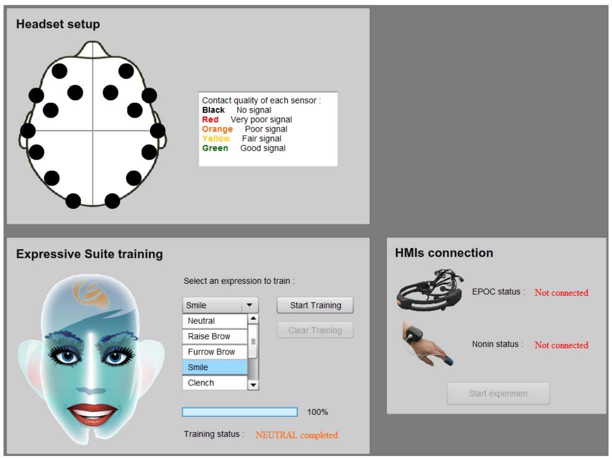

Fig. 3. Expressive Suite Training Panel.

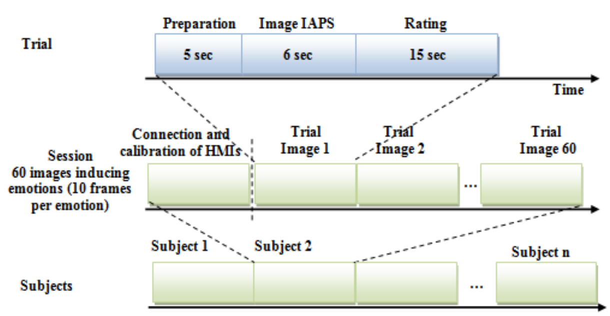

Fig. 4. IAPS picture presentation process.

IV. Results

A. Affective rating of IAPS images

Table IV illustrates the level of participants' perceived emotions from IAPS image sets. For example, the participant rated the 10 IAPS pictures related to joy, on average, as 84.61% joy, 2.67% sadness, among others. Similarly, IAPS images related to anger were rated as 64% anger, 12% disgust, among others. However, we observed that some participants were unable to correctly rate surprise images sets. Thus, these results partially validated the selected IAPS images used in our experiment. In addition, they are consistent with the results found by Mikels [43].

B. Objective data analysis

After checking the correctness of the results of the subjective evaluation by the participants, we turned our attention to

TABLE IV
Confusion matrix obtained as a result of the classification of the IAPS pictures regarding each emotion.

in \ out	Joy	Sadness	Disgust	Anger	Surprise	Fear
Joy	**84,61%**	2,67%	2,04%	0,68%	8,26%	1,74%
Sadness	0,64%	**74,17%**	11,21%	11,03%	0,95%	2,00%
Disgust	0,00%	4,31%	**64,44%**	20,58%	2,90%	7,77%
Anger	2,18%	14,48%	12,01%	**63,93%**	1,50%	5,89%
Surprise	10,13%	11,08%	13,44%	4,41%	**36,95%**	23,98%
Fear	0,00%	8,18%	10,70%	14,36%	28,60%	**38,15%**

evaluate the capacity of correctly assessing the emotional state of the user. The subjects were given tasks that should trigger emotional reactions. These emotional responses, measured by the Epoc headset and Nonin biofeedback, were compared with the results of the subjective evaluation of the participants. If the results from the high-level data headset/Nonin biofeedback and the subjective analysis rating are found to be nearly identical, then we can argue that the Epoc device is a viable alternative or supportive method in evaluation.

1) Epoc expressive data: The main goal of this work is to express the different expressive signals according to Ekman's six listed emotions (joy, fear, surprise, disgust, anger and sadness). Emotiv Epoc allows the recording of different facial expressions such as left and right smirk, laugh, smile and clench. An ANOVA was used to analyze the emotional effect of the IAPS image sets on participants. We observed a significant difference of expressive data for right smirk ($F(5,15) = 17,31$ $P < 0.05$), laugh ($F(5,15) = 12,65$ $P < 0.05$), smile ($F(5,15) = 6,1$ $P < 0.05$) and clench ($F(5,15) = 21,50$ $P < 0.05$). However, no significative difference have been observed for left smirk ($F(5,15) = 0.4$ $P > 0.05$).

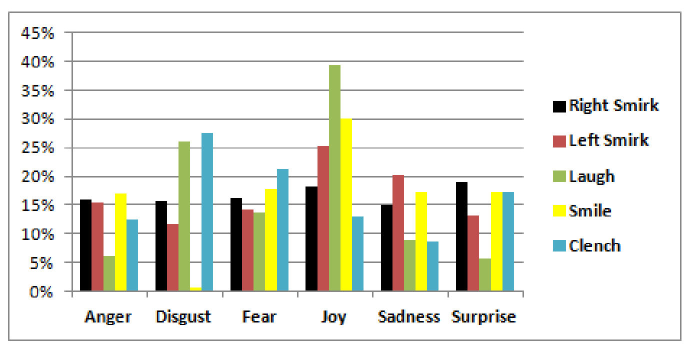

Fig. 5. Histogram of related Epoc expressive data.

The histogram (Fig. 5) shows an example of five EMG physiological signals (corresponding to left and right smirk, laugh, smile and clench) recorded during the induction of the six emotions. We observed that each physiological signal varied widely among emotions and subjects. According to the histogram assigned to the right smirk, the mean of this physiological signal has an average of 19% for surprise, and 18% for joy respectively. For left smirk, the mean was 25.36% for joy which is greater than sadness (average 20.30%). For the laugh, the average is 39.35% for joy and 11.70% for disgust respectively. For the smile, the expressive signal has a mean average of 30% for joy which is the highest score compared to other emotions. Finally, the mean of the clench signal is 27.68% for disgust, 21.15% for fear and 17.18% for surprise respectively. As expected, our results are congruent with those found by Ekman, except for the left smirk that failed to give an acceptable meaning.

2) Epoc affective data: High-level data related to both excitement and frustration were collected using the Epoc BCI and analyzed using ANOVA. For both high-level emotional states, no significant differences among the 6 emotions was observed (Figures 6(a) and 6(b)). ANOVA gave $F(5,15) = 0.47$ $(P > 0.05)$ for excitement, and $F(5,15) = 0.13$ $(P > 0.05)$ for frustration. This result can be explained by the low-level engagement of the participants.

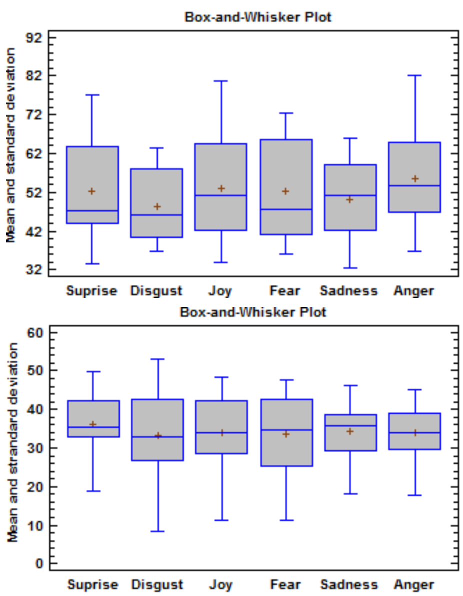

Fig. 6. Illustration of the results concerning (a) frustration and (b) excitement.

3) Heart rate: We used with Nonin biofeedback sensor data to record heart rate. An ANOVA test was used to analyze the emotional effect of the IAPS image sets on participants. We observed a significant difference between the means of the image sets at the 95.0% confidence level $(F(5,15) = 32.30; P < 0.05)$. Figure 7 A reveals three phases of the participants' heart rate: in the first one, the heart rate increase by 1bpm (beat per minute) within the first three seconds, then it remained constant up to seven seconds. Finally, the heart rate decreased slightly. The first phase could be associated with reaction time, the second one shows the natural level of the human heart rate in the case of joy (Figure 7(c). In the second test, related to surprise, the curve of the heart rate shows a peak at the third second. This illustrates a sudden increase of the heart rate (Figure 7 (c)). Figure 7 (b) illustrates a slight decrease of the heart rate that can be explained by the continuity of the response according to sadness and disgust. Figure 7 (a) shows a slight increase in heart rate that has the same explanation as the previous Figures related to anger and fear.

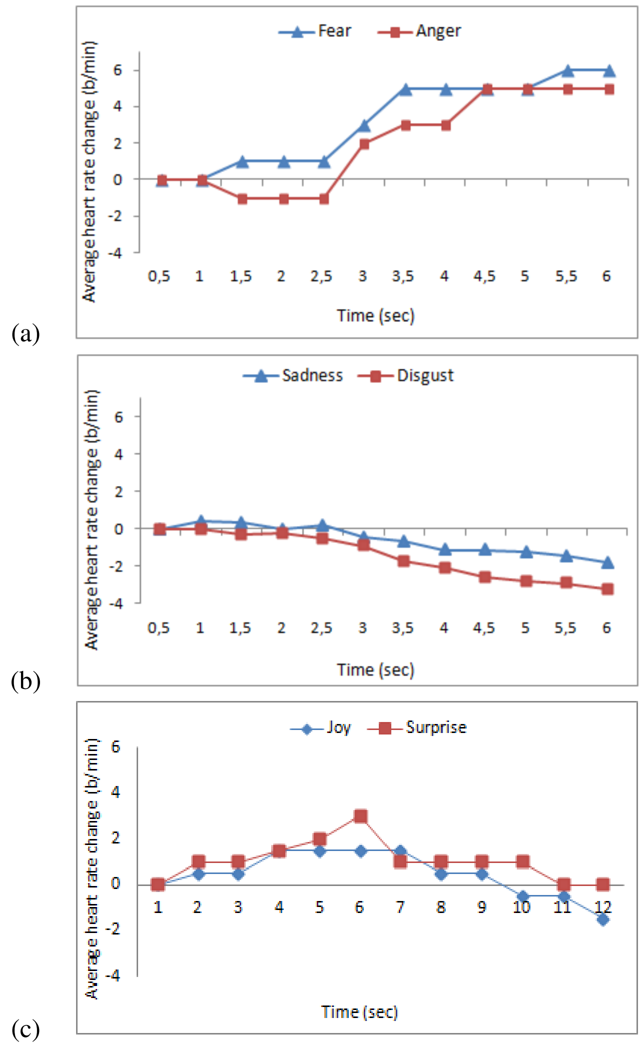

Fig. 7. Relative variation of heart rate responses to (a) anger/fear, (b) disgust/sadness and (c) joy/surprise stimuli.

V. Discussion

A. Perceived emotional states from IAPS images

The selected IAPS pictures were validated by the work of Mikels [43] and classified according to the six basic emotions. Each image is associated with an average value for each basic emotion. However, several problems regarding the emotion rating procedure were encountered. First, the main drawback of the proposed induction technique was the difficulty of distinguishing between close emotional states such as surprise and fear. Secondly, according to the participant, the induction of emotions with IAPS pictures is not pertinent. Third, the same picture may have a different influence depending upon the participant. For example a picture of animals will have a negative influence on a person who worries, whereas a person who is not interested in animals might perceive this picture as neutral. Moreover, the IAPS images are static and don't induce a high level of emotion; it is therefore necessary to find an alternative inducer in order to avoid these problems.

B. Classification of emotions from Epoc-based, high-level data

An ANOVA test was applied on the different types of physiological signal features (high-level data headset and a biofeedback sensor) to check for a difference in mean between the six emotional states. In the Epoc Emotiv expressive data, we observed that each physiological signal varied widely across both emotions and subjects. As expected, our results are congruent with those found by Ekman, except for the left smirk that failed to give an acceptable meaning. In the Epoc Emotiv affective data, contrary to what was expected, no significant differences were found in the six emotional states. This could be due to the lower signal-to-noise ratio. Another explanation could be that the IAPS images are static and don't induce a high-enough level of emotion.

VI. CONCLUSION AND FUTURE WORK

The areas of emotion recognition are nowadays considered interesting alternatives for the discrimination of different human feelings via a set of physiological signals that can be recorded through easy-to-handle, embedded, electronic equipment. In this paper, we have reported on the use of different types of physiological signals to assess emotions. High-level data signals were collected using a brain computer interface (Epoc headset), and heart activity was measured through a biofeedback sensor (Nonin). A preliminary experiment involving 16 subjects was carried out to identify the physiological signals corresponding to the six basic emotions proposed by Ekman (joy, sadness, fear, surprise, anger, disgust). Participants were exposed to sets of 10 IAPS (International Affective Picture System) pictures for each emotion. IAPS image sets were partially validated through a subjective rating protocol. In our future work, we will carry out other experiments based on the use of video sequences involving both real and virtual humans, with the aim of following the evolution of emotions during more realistic situations. Furthermore, we will conduct experiments with children and elderly, particularly people with Huntington's disease. This work contributes to the development of a job-interview simulator allowing face-to face communication between a human being and an Embodied Conversational Agent. Collected data will be used to extract a model for real-time behavioral analysis.

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