Emotion Recognition based on Heart Rate and Skin Conductance

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Abstract: Information on a customer's emotional states concerning a product or an advertisement is a very important aspect of marketing research. Most studies aimed at identifying emotions through speech or facial expressions. However, these two vary greatly with people's talking habits, which cause the data lacking continuous availability. Furthermore, bio-signal data is also required in order to fully assess a user's emotional state in some cases. We focused on recognising the six basic primary emotions proposed by Ekman using biofeedback sensors, which measure heart rate and skin conductance. Participants were shown a series of 12 video-based stimuli that have been validated by a subjective rating protocol. Experiment results showed that the collected signals allow us to identify user's emotional state with a good ratio. In addition, a partial correlation between objective and subjective data has been observed.

1 INTRODUCTION

Scientific research in the area of emotion extends back to the 19th century when Charles Darwin (Darwin, 1872) and William James (James, 1884) proposed theories of emotion that continue to influence our way of thinking today. During most of the 20th century, research in emotion assessment has gained popularity thanks to the realisation of the presence of feelings in social situations (Picard, 1995) (Croucher and Sloman, 1981) (Pfeifer et al., 1988). One of the major problems in emotion recognition is related to defining emotion and distinguishing emotions. Ekman proposed a model which relies on universal emotional expressions to distinguish six primary emotions (joy, sadness, anger, fear, disgust, surprise) (Friesen and Ekman, 1978) (Cowie et al., n.d.).

The majority of research concentrated on analysing speech or facial expressions in the interest of identifying emotions (Rothkrantz and Pantic, 2003). Nonetheless, it is easy to mask a facial expression or to simulate a particular tone of voice (Pun et al., 2007). Additionally, these channels are not continuously available, meaning that users are not always facing the camera or constantly speaking. We believe that the use of physiological signals, such as electro dermal activity (EDA), electromyography (EMG) or electrocardiography (ECG), grants us the key to solving the previously mentioned problems. For example, heart rate proves to effectively recognise anger, fear, disgust, and sadness in both young and elderly participants (Levenson, 2003).

Psychological researchers applied diverse methods to examine emotion expression as well as perception in their laboratories, ranging from imaginary inductions to film clips and static pictures. A particular set of video stimuli (Bartolini, 2011), developed by the University of Louvain, is the most widely used. It is based on a categorical model of emotion and it contains various videos depicting, among others, mutilations, murders, attack scenes and accidents.

The purpose of our work is to recognize the six basic primary emotions proposed by Ekman, using widely-available and low-cost, biofeedback sensors that measure heart rate (Nonin Oxymeter (I-Maginer, n.d.)) and skin conductance (TEA, n.d.). The latter provides physiological data which reveals stress-related behaviors. We designed an experiment based on video clips from University of Louvain.

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The goal of the experiment is to elicit and identify emotions by studying physiological data collected from the heart-rate and skin conductance sensors. The videos' set has been validated using an evaluation system formerly established by the emotional reaction the viewer had to different clips. The result of this experiment contributes to the development of the real-time platform for emotions recognition by using bio-signals (Hamdi, 2012). This platform is part of the EMOTIBOX project developed between three laboratories: LARIS, GRANEM and LPPL. This platform is to complete a complex system, such as a job interview simulator, which establishes a face-to-face communication between a human being and an Embodied Conversational Agent (ECA) (Saleh et al., 2011), (Hamdi et al., 2011), (Herbelin et al., 2004). In this context, we will take into account the six primary emotions.

The rest of the paper is organized as following: in the next section, we will evaluate the work in the aspect of the modelling and classification of emotions with a particular emphasis on emotion assessment from physiological signals. In Section 3, we will present the experimental study along with the data acquisition procedure and the experimental design used to recognise emotions related to videos. The results are presented and discussed in Section 4. The paper ends with a conclusion and provides ideas for future research.

2 RELATED WORK

2.1 The Modelling and Classification of Emotions

Theories of emotion have integrated other components such as cognitive and physiological changes, as well as trends in action and motor expressions. Each of these components has different functions. Darwin postulated the existence of a finite number of emotions present in all cultures and theorised that they have an adaptation function (Darwin, 1872). Although several theoretical models of emotions exist, the most commonly used are the dimensional and categorical models (Mauss and Robinson, 2009). The second approach is to label the emotions in discrete categories, i.e. experiment participants have to select amongst a prescribed list of word labels, e.g. joy, sadness, surprise, anger, love, fear. The result 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 which ensure the survival of the species, and the secondary emotions that evoke a mental image which correlates with the memory of primary emotions (Ekman, 1999). Later on, several more lists of basic emotions have been adopted by different researchers (see Table 1 (Ortony and Turner, 1990)).

Table 1: Lists of basic emotions from different authors (Ortony & Turner, 1990).

Reference	Basic emotions
(Ekman & Friesen, 1982)	Anger, disgust, fear, joy, sadness, surprise
(Izard, 1971)	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
(Plutchik, 1980)	Acceptance, joy, anticipation, anger, disgust, sadness, surprise, fear
(Tomkins, 1984)	Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise
(Gray, 1982)	Rage and terror, anxiety, joy
(Panksepp, 1982)	Expectancy, fear, rage, panic
(McDougall, 1926)	Anger, disgust, elation, fear, subjection, tender-emotion,
(Mower, 1930)	Pain, pleasure
(James, 1884)	Fear, grief, love, rage
(Oatley & Johnson-Laird, 1987)	Anger, disgust, anxiety, happiness, sadness

Another way of classifying emotions is to use multiple dimensions or scales based on arousal and valence (Figure 1). This method was advocated by Russell (Russell, 1979). The arousal dimension varies from "not-aroused" to "excited", and the valence dimension goes from negative to positive. The different emotional labels can be plotted at numerous positions on a two-dimensional plan 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, while surprise triggers high arousal (Lang, 1995).

Moreover, each approach, in discrete categories or continuous dimensions, has its advantages and disadvantages. In the first, each affective display is classified into a single category, complex mental/affective states or blended emotions may be too difficult to assort (Barreto and Zhai, 2006). Despite exhibiting advantages that cover this blind spot, the dimensional approach, in which each stimulus could be found on several continuous scales, has received a number of criticisms. Firstly, the theorists working on discrete emotions, for example Silvan Tomkins, Paul Ekman, and Carroll Izard, have questioned the usefulness of the theory, arguing that the reduction of emotional space to two or three dimensions is extreme and results a loss of information. Secondly, some emotions may lie outside the space of two or three dimensions (e.g., surprise) (Pantic and Gunes, 2010).

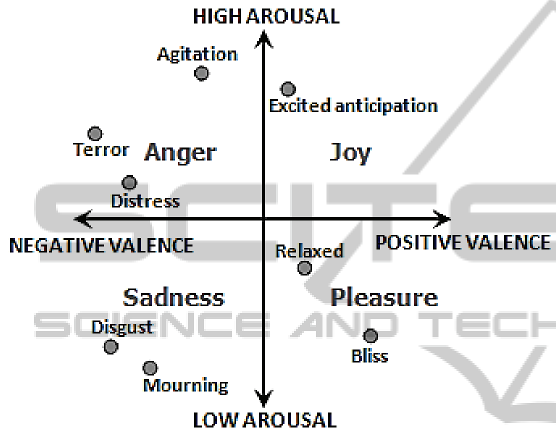

Figure 1: Illustration of the two-dimensional model based on valence and arousal (Russell, 1979).

In our study, we aim to identify the six basic emotions proposed by Ekman and Friesen (Friesen and Ekman, 1978) (disgust, joy, anger, surprise, disgust, fear, sadness) because of universal acceptance on human emotional states study.

2.2 Emotion Recognition by Physiological Signals

The analysis of physiological signal is a possible approach for emotion recognition (Healey et al., 2001). 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 indications include signals derived from the Autonomic Nervous System (ANS) of the human body (fear, for example, increases heartbeat and respiration rate) (Ang et al., 2010), the Electromyogram (EMG) that measures muscle activity, the Electrocardiogram (EKG or ECG) that measures heart activity, Electrodermal Activity (EDA) that measures electrical conductivity that is in charge of organs such as sweat glands on the skin, the Electrooculogram (EOG) that measures eye movement, and the Electroencephalogram (EEG) (Moradi and Khalili, 2009) (Ang et al., 2010).

3 EXPERIMENTAL STUDY

The designed experimentation intended to collect enough data for building models for each of our sensors. We followed a simple concept: one stimulus corresponds to one particular emotion, which is applied on the subject, and the sensors collect physiological activity data of this emotion.

3.1 Stimulus Material

We selected visual and dynamic stimuli for this experimentation in favour of catching and establishing models of the evolution of our signals. Emotions such as “anger” and “fear” surfaces slowly. Dynamic stimuli proved to be more efficient during the experiment. Concretely, video clips stimulate two sensory modalities (visual and auditory), which are close to the system for a job interview simulator, a video game or an interactive virtual reality system.

Given that the majority of our subjects are of French origin, we had to find video clips in French language. Several sets of videos exist in the literature (Carvalho et al., 2012) (Bednarski, March 29, 2012) and the one developed at the University of Louvain (Schaefer et al., 2004) was particularly interesting.

The total length of experimentation was then the most important criterion. At least two videos for each emotion were necessary to assess accurately the signals. Therefore, we had twelve videos plus one neutral video between each emotion category for our six emotions. As we chose to limit the total experimentation to 30 min so that it does not take too much time of our subjects, we selected videos that lasting 30s to 2 min.

The neutral video is supposed to assure the variables independence by giving a break to our subjects between each category of emotions. They were also asked to grade each emotions felt on a scale from 1 to 10 after the video. It helped to qualify our experimentation material according to the inducted emotional stimulus.

3.2 Experimental Set-up

We collected data from 35 participants, mostly between 18 and 30 years old; 11.4% of the subjects were older than 30. Gender parity was positive: with

54% of men and 46% of women. They were either students or employees of the University of Angers. The experimentation took place in a room equipped with nothing other than the screen and the shutters were closed: no distractions were admitted.

Only two sensors were used during the experimentation, one is an EDA sensor (TEA, n.d.) and the other is a heart-rate sensor (Nonin) (I-Maginer, n.d.). Knowing that the Nonin sensor was previously calibrated to be used on the platform, building models with another classifier allowed us to validate the existing models.

The design of the experiment is the following: the subject was first asked to read and sign a consent form to participate in the study. Then he/she received a copy of the instructions. He/she was then informed the purpose of the study and the exact experimentation procedure. Once the person sat in front of the screen, the researcher set up the sensors and checked whether everything was functioning.

As soon as the subject was ready for the experimentation, the program started and the researcher left the room to ensure genuine reaction from the subject. Twelve videos with a neutral one between each emotion category were displayed. After watching each video, the participant had to rate it on the following dimensions: joy, anger, surprise, disgust, fear, sadness.

The duration of the transitory window between two video was to trigger the automatic affect analysis and was decided by the sensory modality and the targeted emotion. A study published by Levenson and his co-workers (Levenson, 1988) demonstrated that the length of emotions display varies from 0.5 to 4 seconds. However, some researchers suggested using a different window length that depends on the modality, e.g., 2-6 seconds for speech, and 3-15 seconds for bio-signals (Kim, 2007). In our experiment, each trial included a 5-second rest between video presentations, and a 15-second rating interval during which time the video was not displayed on the screen. In this interval, the participant answered on a 10-point scale the degree he felt for each emotion, by pressing a visual analogue scale (0-10) with 0 indicating not at all and 10 a great amount. This procedure allowed the participant to specify multiple labels for a certain image.

At the end of the experiment, the researcher came back in the room to check the subject's emotional state, remove the sensors and get a feedback.

4 RESULTS

4.1 Affective Rating of Videos

Table 2 illustrates the level of participants' perceived emotions from the videos. For example, the participants the 2 video related to joy, on average, as 86.9% joy and 8.3% sadness. Similarly, the videos related to anger were rated as 38.9% anger and 30.6% disgust. We can see here that subjects recognised every emotions but Anger (38.9%) and Fear (26.1%). This could be attributed to the general stimulating atmosphere (horrifying, appalling and uneasy) that generates such emotions: it is easy to mix Fear and Anger with Disgust. These results thus partially validated the selected videos as being representative of the studied emotions.

Table 2: Confusion Matrix obtained as the result of the classification of the videos regarding each emotion.

IN	OUT					
	An	Di	Fe	Jo	Su	Sa
An	38,9%	30,6%	6,2%	1,6%	5,2%	17,5%
Di	0,4%	63,5%	15,8%	8,4%	10,4%	1,4%
Fe	1,5%	47,4%	26,1%	5,0%	18,1%	1,9%
Jo	0,0%	1,0%	0,0%	86,9%	3,8%	8,3%
Su	10,8%	6,5%	21,6%	8,4%	51,0%	1,6%
Sa	15,5%	27,9%	2,5%	1,0%	2,8%	50,2%

Abbreviations related: Anger (An), Disgust (Di), Fear (Fe), Joy (Jo), Surprise (Su), Sadness (Sa)

4.2 Objective Data Analysis

After checking the correctness of the results of the subjective assessment by the participants, we turned our attention to evaluate the capacity of correctly estimate the emotional state of the user. The subjects were given tasks that should trigger emotional reactions. The skin conductivity and the heart-rate, measured by the TEA sensor and the Nonin sensor, were recorded respectively at a frequency of 2Hz. Each measure corresponds to one video (and associated emotion), the heart-rate and the skin conductivity. Measures for the neutral video were taken only once.

We decided to process first the collected signals with a Fourier Transform to get the Fourier coefficients, and then classify theses coefficients with the Support Vector Machine (SVM) (Lin and Chang, 2011).

For each recording $i\,(i = 1, \dots, n)$, the function X_i is supposed to belong to $\mathbb{L}^2(\mathbb{R})$.

We introduce then $\mathbb{L}^2(\mathbb{R})$ Fourier Basis, i.e. for $k = 1,2,\ldots$:

$$\varphi_1(t) = 1, \tag{1}$$

$$\varphi_{2k}(t) = \sqrt{2}\cos(2\pi kt), \tag{2}$$

$$\varphi_{2k+1}(t) = \sqrt{2}\sin(2\pi kt). \tag{3}$$

For each i, the function X_i can be decomposed into Fourier series (Bercher & Baudoin, 2001):

$$X_i = \sum_{j=1}^{+\infty} X_{i,j}\varphi_j, \tag{4}$$

$$\text{with} \quad X_{i,j} = \int_{\mathbb{R}} X_i(t)\varphi_j(t)dt \tag{5}$$

In practice, Fourier coefficients $X_{i,j}$ are computed by Fast Fourier Transform (FFT) for $j = 1,\ldots,k$ where k is chosen by the user.

For each of our recordings i, we have $X_i^k = (X_i, 1, \ldots, X_{i,k})$ the vector of the first k Fourier coefficients corresponding to X_i.

By watching the set $\{X_i^k, i = 1,\ldots,n\}$, we wish to build a discriminative rule allowing us to predict the label associated to the next recording X_{n+1}.

We build an input table of size $n \times (k+1)$, with in raw, recordings i and in columns, for each i : emotion Y_i, then the k Fourier coefficients computed by $(X_{i,1},\ldots,X_{i,k})$, i.e.:

$$\begin{pmatrix} Y_1 & X_{1,1} & \cdots & X_{1,k} \\ Y_2 & X_{2,1} & & X_{2,k} \\ & \vdots & \ddots & \vdots \\ Y_n & X_{n,1} & \cdots & X_{n,k} \end{pmatrix}$$

We then used this table as an input for the SVM to build a model. For $C = 1.0, \gamma = 1.0 \times 10^{-12}$, the best classification rate was computed for both signals at $k = 200$ (33% of the whole dataset was put aside for the validation). For the skin conductivity, the computed classification rate was 85.57%. The table 3 is the confusion matrix related.

For the heart rate, the computed classification rate was 89.58%, to which the confusion matrix is shown on table 4. Classification rates (85% and 89%) were sufficient enough for further exploitation. In another word, any model built under a 70% classification rate would direct the exploitation to an incorrect result.

Table 3: Confusion Matrix for the skin conductance data classification.

IN	OUT						
	An	Di	Fe	Jo	Su	Sa	Ne
An	16	0	0	0	0	0	0
Di	7	6	0	0	0	0	0
Fe	8	0	9	0	0	0	0
Jo	0	0	0	14	0	0	0
Su	0	0	0	0	19	0	0
Sa	0	0	0	0	0	19	0
Ne	0	0	0	0	0	0	6

Abbreviations related: Anger (An), Disgust (Di), Fear (Fe), Joy (Jo), Surprise (Su), Sadness (Sa), Neutral (Ne)

Table 4: Confusion Matrix for the heart-rate data classification.

IN	OUT						
	An	Di	Fe	Jo	Su	Sa	Ne
An	22	0	0	0	0	0	0
Di	5	13	0	0	0	0	0
Fe	10	0	12	0	0	0	0
Jo	0	0	0	27	0	0	0
Su	0	0	0	0	19	0	0
Sa	0	0	0	0	0	25	0
Ne	0	0	0	0	0	0	11

Abbreviations related: Anger (An), Disgust (Di), Fear (Fe), Joy (Jo), Surprise (Su), Sadness (Sa), Neutral (Ne)

4.3 Synthesis

This work was directed to add new sensors with an emotions recognition platform. Previous analyses enabled us to integrate an EDA sensor and to improve the efficiency when applying a heart-rate sensor. The SVM let us build new models that are more robust and more accurate to fit our emotions' set. A new C++ plug-in was created for the platform in order to process the data collected by the previous sensors. It works as a solver where the SVM (integrated with the library LibSVM (Lin and Chang, 2011)) classifies the data, according to the previously built model, and output of the emotional state of the subject.

5 DISCUSSION

Several points of this work could be discussed. First of all, the platform targets fields such as marketing and medical research, which means its subject could be the major population. Yet, our experimentations conducted on subjects ageing from 20 to 30 years old. Models built for this population are certainly not accurate for subjects' ageing between 40 and 50 years old. What's more, most of the subjects came because they were intrigued by the experiment: half of the sample has a psychology background, making them interested in research concerning emotions. These people, knowing the research topic, might cause a certain social desirability bias. The experimental conditions also play an important role on how people react: subjects might not have the same physiological reactions at different time of the day.

6 CONCLUSIONS

Today, the areas of emotion recognition are seen as an alternative to the discrimination of different human feelings, thanks to physiological signals collected by easy-to-handle, embedded, electronic equipment. In this paper, we showed the use of different types of physiological signals to assess emotions. Electrodermal activity was collected by an EDA sensor (TEA), and heart activity was measured through a biofeedback sensor (Nonin). An experiment involving 35 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 a set of 12 videos (2 for each emotion). Videos set was partially validated through a subjective rating system. In our future work, we focus on confirming the benefits of multimodality for emotions recognition with bio-signals, as well as on integrating an electrocardiogram sensor (ECG) which could bring more swiftness to the system.

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