ANALYSIS PHYSIOLOGICAL SIGNALS FOR EMOTION RECOGNITION

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ABSTRACT

The emotion recognition is one of the great challenges in human-human and human- computer interaction. In this paper, an approach for the emotions recognition based on physiological signals is proposed. Six basic emotions: joy, sadness, fear, disgust, neutrality and amusement are analysed using physiological signals. These emotions are induced through the presentation of IAPS pictures (International Affecting Picture System) to the subjects. Also, the physiological signals of interest in this analysis are: electromyogram signal (EMG), respiratory volume (RV), skin temperature (SKT), skin conductance (SKC), blood volume pulse (BVP) and heart rate (HR). These are selected to extract some characteristic parameters, which will be used for classifying the emotions. The SVM (support vector machines) technique is used for classifying these parameters. The experimental results show that the proposed methodology provides a recognition rate of 85% for different emotional states.

1. INTRODUCTION

Emotion is a psychophysiological process, produced by the limbic system activity in response to a stimulus, which in turn leads to activation of the somatosensory system [1].

Furthermore, different peripheral physiological changes lead to different emotions, and a corporal feed-back is necessary for the emergence of emotion [2]. We can represent this theory succinctly as follows:

Stimulus → physiological responses → peripheral changes sensation → emotion.

Some psychologists consider affective states as categories, but others consider them as a multidimensional construct. The First consider the emotions characteristics as universal and episodic, but the second proposed to model all the emotional states with several dimensions [3]. The two dimensions most known are valence (positive, negative) and activation (active / passive).

In our work, we are interested in six emotions that will be used for emotional recognition: joy, fear, sadness, amusement, neutrality, and disgust.

The six physiological signals, which are used for the emotions recognition are:
The skin conductance (SKC) , heart rate (HR), blood volume pulse (BVP), respiratory volume (RV), electromyographic activity (EMG), skin temperature (SKT).

The remainder of this paper is organized as follows. In section 2, physiological signals collection using multimodal sensors is described. The design of emotion recognition system using SVM is presented in section **3.** Section 4 is concerned with the presentation of the results obtained by the system. Finally, in section 5, the conclusion is provided.

2. EMOTION DATA COLLECTION

2.1. Emotion Induction

The experiment has been carried out in the LASC (cooperative automatic system laboratory) in METZ University, France. Four subjects aged from 25 to 28 years; two men (subject 2 and 4) and two women (subject 1 and 3); have been asked to carry out the experiment.

The different physiological signals have been detected from these subjects as they tested the different emotional states. The tests were carried out with an incentive system controlled by computer, scrolling images IAPS (International Affective Picture System).

These images are supposed to induce the expression of the six emotional states (amusement, joy, disgust, fear, neutrality and sadness).

2.2. Experimental equipment

This experiment consists in collecting data of physiological signals acquired by the Procomp hardware.

In fact, physiological signals related to emotional states are detected by means of five sensors: skin conductance (SKC), blood volume pulse (BVP), respiratory volume (RV), electromyogram signal (EMG), skin temperature (SKT) and heart rate (HR) estimated from the BVP signal.

Each of these detected signals is initially processed before it was used for extracting characteristic parameters in order to recognize the emotions.

2.2.1. Skin Conductance (SKC)

This response is the phenomenon in which the skin becomes momentarily a better conductor of electricity when external or internal stimuli occur, that are physiological arousals. The SKC signal is filtered by a low pass optimum Finite impulse response filter given by the equation 1 with a cut off frequency of 4 HZ.[4]

$$\mathbf{H(e^{jw}) = \sum_{n=0}^{N-1} b_n\, e^{-jwn}} \quad \textbf{(1)}$$

2.2.2. Blood Volume Pulse (BVP)

The blood volume measurement device may provide information on changes in sympathetic activation. This activity, acting on the blood vessels diameter, leads to changes in blood volume and blood flow [2]. For this reason, it is taken into account when studying the emotional context influence. The BVP signal is filtered by a low pass optimum Finite impulse response filter given by the equation 1 above with a cut off frequency of 40 HZ.

2.2.3. Respiratory Volume (RV)

Rest and relaxation lead to slower and more superficial breaths. Emotional excitement and physical activities generate more deep breaths [3]. A stress state will be detectable by frequent breaths. Generally, the emotions with negative valence cause irregular breathing. The energy of this signal is in the range of [0.1-10] Hz. [5]

2.2.4. Electromyogram Signal (EMG)

The emotional tone is an involuntary, permanent and moderate contraction of muscle fueled by nervous energy [6]. It is shown that frontal facial muscle activity increases during stress and emotions with negative valence [2].

EMG signal is filtered by band pass optimal Finite impulse response filter given by the equation 1, with a band pass frequency of [20-125] HZ. [7]

2.2.5. Skin Temperature (SKT)

Changes in skin temperature are related to vaso-dilatation of peripheral blood vessels induced by increased activity of the sympathetic nervous system [2]. If the person is stressed the temperature of the body extremities decreases because, blood is redirected to vital organs, as a protection measure. The dominant energy of SKT signal is in the band [0,1] HZ. [7]

2.2.6. Heart Rate (HR)

The cardiovascular changes induced changes of necessary tone to prepare for action and likely reflect the emotional experiences [2]. Particularly, it was found that the emotional valence is predicted by the heart rate. In this study the heart rate is determined through the measurement of the successive peaks in the BVP signal.

3. FEATURE EXTRACTION

Feature extraction is concerned with the extraction from the physiological signals described above of some parameters which are considered as pertinent in emotion recognition. These parameters are of two types: temporal parameters and frequency parameters.

3.1. Temporal Parameters

Let $\mathbf{s(n)}$ the filtered physiological signal, and N the number of samples: The temporal parameters are defined as follows:

a. Mean of the physiological signal

$$\boldsymbol{\mu_s} = \frac{1}{N} \sum_{n=1}^{N} \mathbf{s(n)} \quad \textbf{(2)}$$

b. Standard deviations of the physiological signal

$$\boldsymbol{\sigma_s} = \left(\frac{1}{N-1} \sum_{n=1}^{N} (\mathbf{s(n)} - \boldsymbol{\mu_s})^2\right) \quad \textbf{(3)}$$

c. Mean of the absolute values of the first differences of the physiological signal

$$\boldsymbol{\delta_s} = \frac{1}{N-1} \sum_{n=1}^{N-1} |\mathbf{s(n+1)} - \mathbf{s(n)}| \quad \textbf{(4)}$$

d. Means of the absolute values of the first differences of the normalized signal

$$\tilde{\boldsymbol{\delta}}_s = \frac{1}{N-1} \sum_{n=1}^{N-1} |\,\tilde{\mathbf{s}}(\mathbf{n+1}) - \tilde{\mathbf{s}}(\mathbf{n})| = \frac{\delta_s}{\sigma_s} \quad \textbf{(5)}$$

e. Means of the absolute values of the second differences of the physiological signal

$$\boldsymbol{\gamma_s} = \frac{1}{N-2} \sum_{n=1}^{N-2} |\mathbf{s(n+2)} - \mathbf{s(n)}| \quad \textbf{(6)}$$

f. Means of the absolute values of the second differences of the normalized signal

$$\tilde{\boldsymbol{\gamma}}_s = \frac{1}{N-2} \sum_{n=1}^{N-2} |\,\tilde{\mathbf{s}}(\mathbf{n+2}) - \tilde{\mathbf{s}}(\mathbf{n})| = \frac{\gamma_s}{\sigma_s} \quad \textbf{(7)}$$

The six parameters from a to f are called the Picard parameters [8].

g. Ratio max/min of the physiological signal

$$\boldsymbol{R} = \mathbf{max}(\boldsymbol{s(n)})\,/\mathbf{min}\,(\boldsymbol{s(n)}) \quad \textbf{(8)}$$

h. Euclidian Distance

Let $\mathbf{S_{Neu}(n)}$ the signal to the neutral emotion. The Euclidean distance between the signal to such an emotion and the signal $\mathbf{S_{Neu}(n)}$ is calculated as follows:

$$\mathbf{D_s} = \left(\frac{1}{N-1} \sum_{n=1}^{N} |(\mathbf{s(n)} - \mathbf{s_{Neu}(n)})|^2\right)^{\frac{1}{2}} \quad \textbf{(9)}$$

3.2. Frequency parameters

As frequency parameter evaluation considered in this study the mean and the standard deviation of the Spectral coherence function.

Let $\mathbf{Sq\ (\omega)}$ and $\mathbf{S_{Neu}\ (\omega)}$ are respectively the signal spectrum to such an emotion and the signal spectrum to the neutral emotion. The spectral coherence function is given [9]:

$$\boldsymbol{\gamma^2_{xy}} = \frac{|\mathbf{S_{xy}(\omega)}|^2}{\mathbf{S_{xx}(\omega)\, S_{yy}(\omega)}} \leq \mathbf{1} \quad \textbf{(10)}$$

Then, we extract the mean $\mathbf{mean_{coh}}$ and the standard deviation $\boldsymbol{\sigma_{coh}}$ of the spectral coherence function.

4. EMOTION RECOGNITION

For the recognition of emotion using the stated above parameters, the support vector machine (SVM) method is used. SVM is a binary classification method by supervised learning [10]. The aim is to learn the **h(x)** function through a training set given below:

$$\{(x_1, l_1), (x_2,l_2)\ldots\ldots(x_p,l_p)\} \in R^N \times \{-1,1\} \quad (11)$$

Where l_k are the labels, x_k are input vectors, being in a space R^N and **p** is the size of the training set. The technique seeks a separating hyperplane $h(x)=wx+w_0$ Which minimises the number of errors through the introduction of variable spring ξ_k, which can relax the constraints on the training vectors [11].

$$l_k\,(w\,x_k+ w_0) \geq 1- \xi_k\ ,\xi_k > 0,\ \ 1 \leq k \leq p \quad (12)$$

With the previous constraints, the optimization problem is modified by a penalty term which penalises high variables, spring ξ_k.:

$$\text{Minimiser } \frac{1}{2}||w||^2 + C\sum_{k=1}^{p} \xi_k\ ,\ C > 0 \quad (13)$$

Where **C** is a constant that controls the compromise between the number of classifications errors and the margin width. Different kernel functions can be used. Such functions can be as cited below [12].

a. Linear kernel

$$K(x_i, x_j) = (x_i . x_j) \quad (14)$$

b. Polynomial kernel

$$K(x_i, x_j) = (x_i . x_j + c)^n \quad (15)$$

c. Gaussian kernel

$$K(x_i\,, x_j) = \exp\left(\frac{||x_i-x_j||^2}{\sigma^2}\right) \quad (16)$$

The SVM method is applicable for binary classification tasks, but there are extensions to the multiclass classification [13].
The one against all method consist of constructing **M** binary classifiers by assigning the label 1 to samples of one class and the label -1 to all others [13]. In the test phase, the classifier, which gives the highest margin, wins the vote.

4.1. Computational Emotion Recognition Experiments

The data classification is carried out by programming the SVM method one against all SVM multiclass. This has been experimented considering respectively the kernel functions linear, polynomial and Gaussian. Also in this experiment, and for every emotion, eight samples are used for training and two samples for testing. After several tests, it was found empirically that:

For the polynomial kernel, the most appropriate degree is n=2 and c= 1000 and for the Gaussian kernel σ = 1.

To study the efficiency of each pertinent parameter on the recognition rate relating each kernel type of kernel function, we extract the latter for several combinations of pertinent parameters and for the 4 subjects (see table 1 to table 4).

kernel / Pertinent param	Linear	poly	Gauss
Picard parameters	**50%**	41.67%	16.67%
Picard parameters R	**75%**	66.67%	58.33%
Picard parameters D_s	**66.6%**	66.67%	25%
Picard parameters $mean_{coh}$, σ_{coh}	**75%**	75%	50%
All the parameters	**83.3%**	75%	25%

Table 1. Recognition rate for different combinations of pertinent parameters for subject 1

kernel / Pertinent param	Linear	poly	Gauss
Picard parameters	**66.67%**	58.33%	33.33%
Picard parameters R	**75%**	41.67%	25%
Picard parameters D_s	**58.33%**	50%	25%
Picard parameters $mean_{coh}$, σ_{coh}	**66.67%**	75%	33.33%
All the parameters	**83.33%**	66.67%	16.67%

Table 2. Recognition rate for different combinations of pertinent parameters for subject

Kernel / Pertinent param	linear	poly	Gauss
Picard parameters	**75%**	66.67%	41.67%
Picard parameters R	**83.33%**	75%	50%
Picard parameters D_s	**66.67%**	50%	25%
Picard parameters $mean_{coh}$, σ_{coh}	**91.67%**	91.67%	41.67%
All the parameters	**91.67%**	83.33%	25%

Table 3.Recognition rate for different combinations of pertinent parameters for subject 3

From the tables presented above, we remark that for the four subjects, linear and polynomial kernels generate improved recognition rates compared to the Gaussian kernel. Similarly, using the linear kernel, we obtain recognition rates relatively improved compared to the polynomial kernel.

This means that pertinent parameters extracted from physiological data are relatively separable.

The four tables show that if we combine the six Picard parameters with the ratio R or the six Picard parameters with the coherence function, the recognition rate is improved compared to the results found using only six Picard parameters. The tables show also, that the distance D decreases the recognition rate.

kernel / Pertinent param	linear	poly	Gauss
Picard parameters	**50%**	41.33%	16.67%
Picard parameters R	**75%**	50%	33.33%
Picard parameters D	**50%**	58.33%	16.67%
Picard parameters $mean_{coh}$, σ_{coh}	**75%**	66.67%	33.33%
All the parameters	**83.33%**	75%	16.67%

Table 4. Recognition rate for different combinations of pertinent parameters for subject 4

Thus, we conclude that the six Picard parameters, coherence function and the ratio R characterize well the six emotions.

5.CONCLUSION

In this paper, an approach of emotion recognition has been proposed, studied and evaluated. This approach based on first the analysis and processing of physiological signals such as SKC, BVP, RV, EMG, SKT; HR estimated from the BVP signal then the emotion recognition through the multiclass SVM technique showed a high performance in recognizing the six emotions considered in this study. The obtained results showed that the recognition rates vary according to several criteria: Selection of physiological signals associated with emotions induced; selection of characteristic parameters to be extracted from physiological signals and selection of the multiclass SVM kernel.

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