Emotion Investigation Based on Biosignals

E. Lupu, S. Emerich, and R. Arsinte

Technical University of Cluj-Napoca, Communications dept., Cluj-Napoca, Romania

Abstract— **In this paper a physiological signal-based emotion recognition approach is presented. The input biosignals are electromyogram, electrocardiogram, skin conductivity and respiration change. The feature vector is extracted from each signal type by using the same technique based on wavelets and TESPAR DZ method. A Support Vector Machine (SVM) classifier was employed to distinguish among four emotional states: joy, anger, sadness and pleasure. The database employed in our experiments is the AuBT corpus.**

Keywords— **emotional states, TESPAR DZ, biosignals, feature selection, SVM.**

I. Introduction

”Everyone knows what an emotion is, until asked to give a definition” [Beverly Fehr and James Russell]. Emotions play an important role in: motivation, perception, cognition, coping, creativity, attention, planning, reasoning, learning, memory and decision making. Research in emotions is pursued in several scientific disciplines, such as neuroscience, cognitive sciences and psychology. The progress in the aforementioned sciences determines much of the success in the development of affective multimodal systems. In advanced human-machine interaction, emotion recognition is one of the key steps towards emotional intelligence. One way to differentiate emotions is by their being short-term (seconds /minutes), whereas moods are long-term (some days) emotional states, typically global and very variable over the time, dominating the intensity of each short-term emotional state. Moreover, temperaments and personalities are very long-term (months/years/a lifetime) and are much more complex by their including personality factors and moods (Jenkis & et al., 1998).

Various experiments on human judgment on still photographs of posed facial behavior were conducted by Ekman and his colleagues who concluded that there are six basic emotions which can be recognized universally, respectively: happiness, sadness, surprise, fear, anger and disgust (Ekman, 1982). This theory of universality is the most widely used theory in affect sensing by machines [1]. The human communication modes are affected by emotional states through facial expression, body gestures, tone of voice, respiration rate, skin temperature, skin conductance etc.

Biosignals

Physiological signals or biosignals refer to: brain signals measured via functional Near Infrared Spectroscopy (fNIRS), scalp signals measured via electroencephalogram (EEG), and peripheral signals: cardiovascular activity (ECG); electrodermal activity or galvanic skin response (GSR), electromyogram activity (EMG) (Changchun& et al., 2005; Savran& et al., 2006). While visual modalities such as facial expressions and body gestures provide a visible/external understanding of one’s emotional state, biosignals such as EEG, ECG and fNIRS provide an invisible/internal understanding of the emotion phenomenon [1].

Psychophysiology establishes the relation between physiological signals and arousal/valence and argues that the activation of the autonomic nervous system changes while emotions are elicited (Levenson, 1988). Consequently, different emotional expressions produce different changes in autonomic activity (for instance, happiness: decreased heart rate, no change in skin temperature; anger: increased heart rate and skin temperature; fear: increased heart rate, decreased skin temperature [6].

However, in general, an optimal set of bio-potential cues that can assist in reliably discriminating among various affective states has not yet been identified.

II. Methods and tools

A. TESPAR DZ Approach

In this approach the signal waveform is divided into periods or epochs determined by successive passes through zero of the signal. The time information is thus maintained combined with a simple approximation of the waveform between two successive passes through zero. An overview of TESPAR coding method can be found in [3], [4].

This paper employs a version of the described method based on the TESPAR DZ matrices, by using three descriptors so as to describe each epoch:

- ***duration (D)*** between two successive zero crossings of the signal, expressed in samples;
- ***shape (S)*** of the signal between two successive zero crossings, expressed in number of minima;
- ***amplitude (A)*** which represents the maximum value found amongst the samples of an epoch [5].

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A comparison is made between pairs of epochs by using the TESPAR DZ coding procedure. The descriptors from each epoch pair are compared and symbols are produced. The symbol indicates the differences between the individual D, S and A, features of the two epochs under testing. Different lags can be considered when performing the epochs' descriptors comparison. For example, for a lag=1, comparisons will be made between epoch E and epoch E-1, and for a lag=2, comparisons will be performed between epoch E and epoch E-2. The flowchart of the entire coding procedure or symbol assignation can be found in Fig 1.

For each epoch descriptor, a three-stage vector comparison is generated in the case of each individual epoch pair comparison. Hence, for a lag = 1, when comparing D, S and A, for epochs E1 and E2, the following value results are provided. For D2 versus D1: if D2=D1, the resulted value is 0, if D2<D1, the resulted value is -1 or if D2>D1, the resulted value is +1. In the case of the other descriptors (S, A), the procedure is the same.

From any paired descriptors comparison of D, S and A, one of the 27 possible difference options may be derived by using this algorithm, this indicating the nature of the difference between the pair of epochs being tested The symbols were arbitrarily assigned to the numbers 1 to 27 of the 27 symbol DZ TESPAR alphabet. The TESPAR coder issue represents a string of symbols provided by the comparison of the three descriptors corresponding to each epoch. By converting this simple series of symbols, fixed length structures can be obtained.

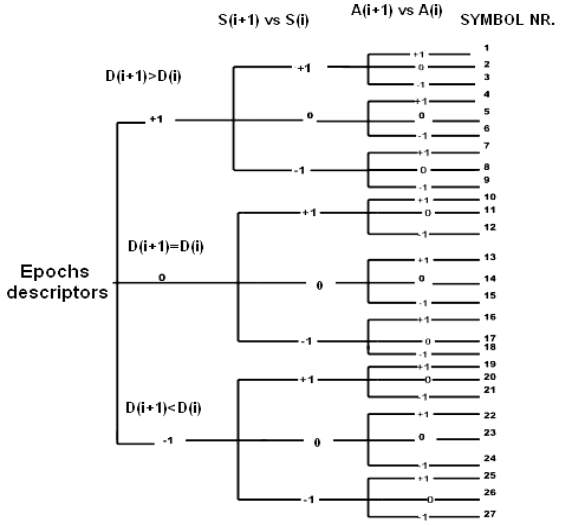

Fig. 1 TESPAR DZ symbols assignation

A one-dimensional vector which counts the number of occurrences of alphabet symbols in an instance can be used, this leading to a histogram [5]. Symbols may be found missing in the coding process, depending on the type of processed signal. Consequently, the alphabet may be redefined with a lower number of symbols.

B. *Classification Method*

The technique of SVM, developed by Vapnik [10], is a powerful, widely used technique for solving supervised classification problems due to its generalization ability. In this study, the LIBSVM software is used. LIBSVM is an integrated software package for support vector classification, regression and distribution estimation [9]. From the available kernels, the radial basis function was selected for our experiments.

C. *AuBT Corpus (Augsburger Database of Biosignal)*

The AuBT corpus contains physiological data taken from a single user in four different emotional states: joy, anger, sadness and pleasure. It was recorded while the subject was listening to four music songs, which were previously picked by the user himself according to the four targeted emotion classes. The subject had been advised to select songs which could trigger special memories to him and he was also asked to make an effort to enter the particular needed affective state. Criteria for song selection:

- song1: enjoyable, harmonic, dynamic, moving;
- song2: noisy, loud, irritating, discord ;
- song3: melancholic, reminding of sad memory;
- song4: blissful, slow beat, pleasurable, slumberous.

In order to record electromyogram, electrocardiogram, skin conductivity (SC) and Respiration change (RSP), four-channel biosensors were used. 25 recordings (in 25 days) for each emotion were overall collected.

The length of the recordings is dependent on the length of the songs, but it was later cropped to a fixed length of 2 minutes per session and per emotion. ECG was sampled at 256 Hz, while the other signals were sampled at 32 Hz [7].

III. Experiments and Results

A. *Feature Extraction and Selection*

The emotional status of a person is inherently reflected in the activity of the nervous system. In psychophysiology, traditional tools for the investigation of human emotional status are based on the recording and on the statistical analysis of biosignals.

This paper proposes a new feature extraction method, based on wavelets and on the TESPAR DZ techniques.

Further, different waveforms extracted from ECG and RSP signals are presented, in the case of the emotional states of joy and, respectively, sadness. The waveforms can be divided into epochs whose dimension, amplitude and

shape is variable in time. Consequently, TESPAR DZ algorithm can be applied, this providing the first 27 coefficients of the feature vector.

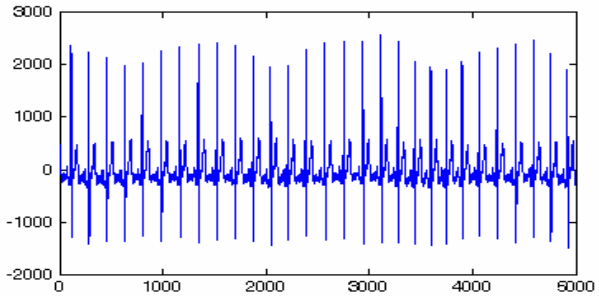

Fig. 2 The first 5000 samples from an ECG signal, emotional state of joy

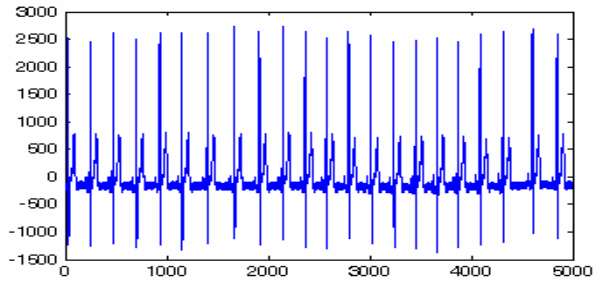

Fig. 3 The first 5000 samples from an ECG signal, emotional state of sadness

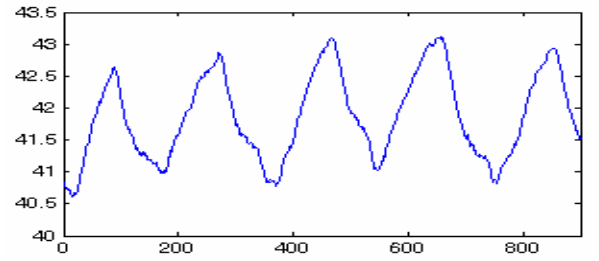

Fig. 4 The first 900 samples from a RSP signal, emotional state of joy

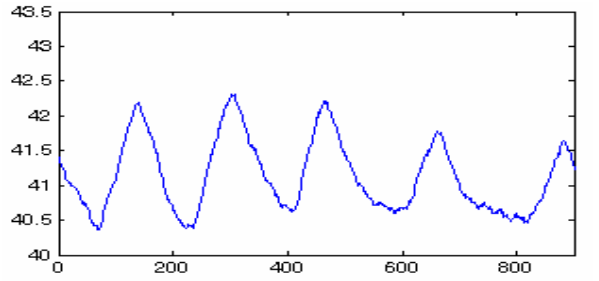

Fig. 5 The first 900 samples from a RSP signal, emotional state of sadness

The signal under test is also decomposed in up to 4 levels, by using the Discrete Wavelet Transform (DWT) and Db4 (Daubechies) as mother function. By passing a signal x through a series of filters, its DWT can be calculated. First, the samples are passed through a low pass filter with impulse response g, while the signal is being decomposed simultaneously using a high-pass filter h. The outputs are giving the detail coefficients (from the high-pass filter) and the approximation coefficients (from the low-pass). The two filters must be related to each other, hence they are known as a quadrature mirror filter. The decomposition is repeated to further increase the frequency resolution and the approximation coefficients are decomposed with high and low pass filters and then down-sampled. The process is represented as a binary tree with nodes representing a sub-space with different time-frequency localization. The tree is known as a filter bank, Fig. 6. The energy content of the approximation and details is then computed, resulting into the next 5 coefficients of the feature vector.

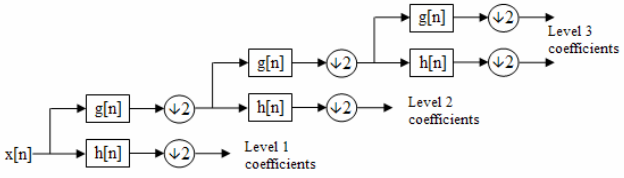

Fig. 6 Wavelet decomposition tree

Finally, the obtained feature vector for each employed biosignal has a fixed dimension equal with 32 coefficients.

$$\underbrace{v1, v2, \ldots, v27}_{\substack{\text{TESPAR DZ} \\ \text{coefficients}}}, \underbrace{v28, \ldots, v32}_{\substack{\text{Wavelet Energy} \\ \text{coefficients}}} \quad (1)$$

The goal of feature selection is that of reducing the dimensionality of input patterns to make the computation feasibl and to meanwhile retain the most relevant features which would reflect the emotional state changes.

Table 1 Feature selection

Feature vector	TESPAR DZ	Wavelet Energy
ECG6	v1,v6, v12	v30,v31
EMG12	v1,v3,v4,v6,v22,v24,v25	v28,v29,v30,v31,v32
SC4	v1,v27	v28,v29
RSP7	v1,v3,v7,v21,v25	v32

The ChiSquaredAttribute Evaluation method was used for this purpose. It evaluates the worth of an attribute by computing the value of the chi-squared statistic with respect to the class. In the next table, the reduced feature vector is described for each biosignal category.

B. AuBT Experiments

The AuBT GUI supports four different signals by default, thier being SC, EMG, RSP and ECG. For each signal, a number of preprocessing steps are applied, such as low pass filtering and normalization. Several statistical features such as mean and standard deviation are then calculated from the preprocessed signals, along with different transformations of the signals, e.g. respiration rate and heart rate variability. The approximation of the first and second derivation is used so as to obtain the same statistical features. 81 features were extracted from the ECG signal, 65 features were extracted from the RSP signal, 19 features were extracted from the SC signal and 21 features were extracted from each of the EMG signals. The complete list of the features extracted can be consulted in [6], [7].

C. Results

Figure 7 shows the results generated by our system. Based on the four selected biosignals, we classified four emotional states: joy, anger, sadness and pleasure. The vectors coresponding to the selected signals are fused at the feature level and provide a 128 coefficients vector. After the feature selection step the vector became shorter, with a length of 29 coefficients, and the resulted acurracy was 89.33%, for the SVM classifier, RBF kernel (C=100 and γ =0.01). By comparing our results with the ones obtained by using AuBT toolbox [7], one can notice that for the AuBT final vector (resulted after feature level fusion and selection – Aubt_40), the classification rate was equal to merely 76.66%, in the case of the same classifier.

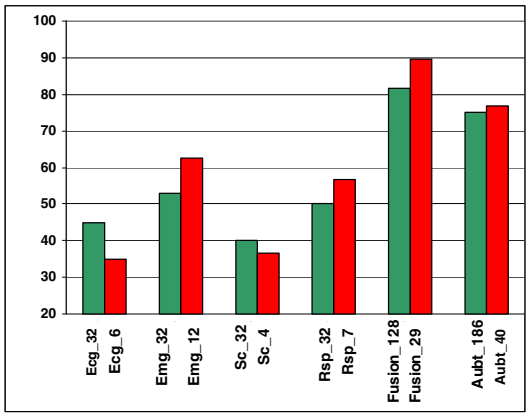

Fig. 7 Classification rates provided by experiments

The results are promising and support the general conclusions in the automatic recognition of emotions that distinguishing emotional states is not an easy task. At this point, experiments have distinguished four emotional classes with good accuracy, compared with the current results found in references.

IV. Conclusions and Outlook

The approach we propose offers a better performance than that provided by the AuBT attempt, experiments being made on the same database. Also, SVMs based classification methods represents a major support in pattern recognition research.

Future work will be concentrated on including the validation of the performance on a much larger population of test subjects, on comparing/combining with other biosignals and also on extending the range of emotions under study.

Furthermore, we are aware that recognizing emotions very accurately using one signal source only is a difficult task. Therefore, we also plan on pursuing research in this area by employing the fusion of visual modalities such as facial expressions, body gestures and speech, which provide an external understanding of the emotions phenomenon.

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Author: EUGEN LUPU
Institute: TECHNICAL UNIVERSITY OF CLUJ-NAPOCA
Street: 26-28 BARITIU
City: CLUJ-NAPOCA
Country: ROMANIA
Email: eugen.lupu@com.utcluj.ro