A USER INDEPENDENT, BIOSIGNAL BASED, EMOTION RECOGNITION METHOD

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Abstract. A physiological signal based emotion recognition method, for the assessment of three emotional classes: *happiness, disgust* and *fear*, is presented. Our approach consists of four steps: (i) biosignal acquisition, (ii) biosignal preprocessing and feature extraction, (iii) feature selection and (iv) classification. The input signals are facial electromyograms, the electrocardiogram, the respiration and the electrodermal skin response. We have constructed a dataset which consists of 9 healthy subjects. Moreover we present preliminary results which indicate on average, accuracy rates of $0.48, 0.68$ and 0.69 for recognition of happiness, disgust and fear emotions, respectively.

Key words: emotion recognition, biosignals, classification.

1 Introduction

Ongoing research efforts focus on empowering computers to understand human emotion. A number of findings from neuroscience, physiology and cognitive science, suggests that emotion plays a critical role in rational and intelligent behavior. Apparently, emotion interacts with thinking in ways that are not obvious but important for intelligent functioning [1]. Furthermore, there are numerous areas in human computer interaction that could efficiently use the capability to understand emotion. For example it is accepted that emotional ability is an essential factor for the next generation of robots [2]. Understanding emotion can also play a significant role in intelligent rooms [3] and affective computer tutoring [4]. To our knowledge, only a small number of studies reported in the literature have demonstrated biosignal based affective recognition that is applicable to multiple users [5]. Apparently, a user independent method is essential for a practical application, so that the users do not have to be bothered with training of the system. Furthermore, current systems require 2-5 minutes signal in order to reach to a decision [6, 7]. In this paper, we present, a biosignal based, user independent emotion recognition method. In this paper we propose a method for emotion recognition, which is fully automated and requires only ten second data acquisition for the signals. The method consists of four steps: (i) biosignal acquisition, (ii) biosignal preprocessing and feature extraction, (iii) feature selection and (iv) classification. The investigated emotional classes are fear, disgust and happiness.

2 Materials and Methods

2.1 Biosignal Acquisition and Dataset

The user's emotional state is defined using information obtained from the following biosignals: facial electromyograms (EMGs), electrocardiogram (ECG), respiration effort and electrodermal activity (EDA). The following set of biosensors are used: (i) for the EMGs signals special thin and flexible surface EMGs grid sensors [8] are placed on the subject's face (a total of 16 EMG channels), (ii) for the ECG, a g.ECG sensor [9] is placed on the subject's thorax, (iii) for the respiration a g.RESP [9] Piezoelectric Respiration Sensor is placed around the subject's thorax and (iv) for the EDA two Ag/AgCl galvanic skin response sensors are attached on the subject's middle and index fingers. We consructed an emotion-specific physiological dataset. We use a set of affective pictures (carefully selected, by an experienced physiologist) drawn from the International Affective Picture System (IAPS) [10], to make the subjects experience the emotional states of interest (fear, disgust and happiness) and simultaneously acquire the various biosignals that accompany them. After being exposed to the outer stimulus the subjects were self annotating their emotional state using the acknowledged technique SAM (Self Assessment Manikin) [11]. SAM has been broadly used for the measurement of the emotional states in a variety of situations including reactions to pictures, images, sounds and advertisements [12]. The obtained dataset consists of 9 subjects and a total number of 118 instances, 30 of them corresponding to happiness, 55 to disgust and 33 to fear.

2.2 Biosignal Pre-Processing and Feature Extraction

The acquired raw biosignals are pre-processed using low-pass filters at 500 Hz and 100 Hz for the facial EMGs and ECG respectively, and smoothing (moving average) filters for the respiration and EDA signals. The resolution used for signal digitization is 12 bit. The extracted features from each signal are shown in Table 1, and described in detail in [13].

2.3 Feature selection

The Simba algorithm [14] is used for feature selection, since it outperforms compared to other well known feature selection algorithms [14]. Having applied the Simba algorithm, from the initial number of 44 features only 9 are selected. These features are shown in Table 2.

Table 1. The features extracted for each of the acquired biosignals (facial EMG, ECG, respiration, and EDA).

EMG	ECG	RESPIRATION	EDA
Mean value Standard deviation	Mean amplitude Rate Means of absolute values of first differences Mean Frequency Median Frequency	Mean amplitude Rate Means of absolute values of first differences	Mean amplitude Rate Means of absolute values of first differences Mean rise duration

Table 2. Selected Features ordered by their significance.

#	Feature	#	Feature
1	Respiration Rate	6	Left Frontalis Standard Deviation
2	Heart Rate	7	Right Frontalis Standard Deviation
3	Right Masseter Standard Deviation	8	Right Nasalis Standard Deviation
4	Means of absolute of first differences of EDA	9	Left Nasalis Standard Deviation
5	Right Masseter Standard Deviation		

2.4 Classification

In order to exploit the proposed method's potential we have employed the K-NN [15] and the Random Forests [16] classifiers.

3 Results

The method is evaluated using the dataset described in Section 2.1. In order to minimize the bias associated with the random sampling of the training and testing data samples, we use 10 fold cross-validation. For our experiments we use the Weka environment [17]. In Table 3, we present for both classifiers the confusion matrix, the True Positive (TP), False Positive (FP) rates and Precisions for each class. Random Forests and K-NN result in statistically similar performance. However, K-NN performs slightly better. To verify that this slight advantage is not due to the feature selection algorithm, we perform an experiment using the Principal Component Analysis (PCA) [18] instead of the Simba feature selection algorithm. PCA is a well known feature reduction method where the features, using a transformation matrix, are projected into a lower dimension space. The results are shown in Table 4. We notice that there is a significant decrease in performance for both K-NN and Random Forests. Thus, using feature selection in our problem we obtain better performance than feature reduction. Moreover, we notice that K-NN does not outperform Random Forest when PCA is used.

Table 3. Results for (a) K-NN, and (b) Random Forests.

Class	Conf. Mat.			TP Rate	FP Rate	Precision
HAPPINESS	14	11	5	0.47	0.19	0.45
DISGUST	10	42	3	0.76	0.32	0.68
FEAR	7	9	17	0.52	0.09	0.68

(a)

Class	Conf. Mat.			TP Rate	FP Rate	Precision
HAPPINESS	13	13	4	0.43	0.16	0.48
DISGUST	10	41	4	0.75	0.38	0.63
FEAR	4	11	18	0.55	0.09	0.69

(b)

Table 4. Results of the K-NN and Random Forest classifiers using the Simba feature selection and PCA approach.

	K-NN (K=1)	Random Forests
Simba	**62.70(14.57)**	62.41(12.58)
PCA	50.64(13.92)	**50.81(12.04)**

4 Discussion-Conclusions

In this work, a user independent emotion recognition method is presented. A 10 second period window has been selected based on the fact that there is a time delay between the instance that the subject experienced an emotion and the corresponding response changes in the selected biosignals [19].

Our initial results are promising, indicating the ability to differentiate the three emotional classes. A direct comparison to related approaches, is not feasible since they are applied in different biosignals, number and type of emotional classes.

It must be noticed that we are well aware that the current form and method of application of the biosensors is anything but intuitive and natural. However, considering the current trend towards wearable computing, it can be expected that the biosensors will be sooner tinny enough to be impended into clothing and jewellery [6]. For research purposes we have chosen the aforementioned sensors since they allow a certain flexibility e.g. in terms of placement of the sensors. This flexibility is important given the fact that many aspects of sensor usage are not completely clear, e.g. which facial muscle EMG signals are the most appropriate in order to manifest an emotional state [5]. An important component of our future work is to increase the number of emotions under investigation and to reduce the set of acquired biosignals which may allow for less complicated sensor arrangements to be developed.

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