Abstract

A smart sensor based emotion recognition method is shown. The approach consists of four steps: biosignals acquisition, biosignals preprocessing and feature extraction, feature selection and classification. The input signals are facial electromyograms, the electrocardiogram, the respiration and the electrodermal skin response. We use a dataset which consists of 50 healthy subjects. Moreover we present preliminary results which indicate on mean square error of 1.1936 and 6.5081 for recognition of happiness, sad and angry emotions in two datasets.

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. Understanding emotion can also play a significant role in intelligent rooms and affective computer tutoring. 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 [2]. 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. In this paper, we present, a biosignals based, user independent emotion recognition method. 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 happiness, sadness and anger.

2 Methods

2.1 Building Dataset

The user’s emotional state is defined using information obtained from the following biosignals: (i) Heart rate monitoring: In an average adult, the heart goes through a full cardiac cycle 70 times a minute [3].This means that a healthy heart rate at rest is 60-80 beats per minute (BPM). There are a number of factors that cause irregularities in heart rate. The most common heart rate variability at rest can be due to serious heart problems, respiratory problems and emotional imbalance i.e. stress, panic attacks, anxiety and depression. In this project we are interested in finding relationship between heart rate and emotions. (ii) Skin Temperature Monitoring: Continuous monitoring of body temperature is very important. Generally human skin temperature is between 32-35°C [4]. However, there are many causes of variation from these values. The most common reasons for changes in skin temperature at room temperature include fever, malnutrition, physical exertion and physiological changes. In this project we wanted to observe the changes in skin
temperature and find the relationship between these changes and emotions. (iii) Skin Conductance
Response: Human skin has electrical properties that change relatively quickly and are closely
related to psychological and physiological processes [5]. Changes in electro-dermal activity (EDA)
and skin conductance are related to changes in eccrine sweating gland which, in turn, are related to
activity in the sympathetic branch of the autonomic nervous system (ANS). Therefore, skin
conductance has become an important tool to help find human emotions and motivation which is
why we decided to choose skin conductance response as one of our signals for emotion
recognition.

The dataset is offered by Professor S.C. Mukhopadhyay. In his research, an emotion
recognition system is developed using physiological signals. These signals are obtained from a
heart rate sensor, a skin temperature sensor and a skin conductance sensor and stored for data
analysis and feature extraction using LabView.

![Figure 1: LabView from panel](image1)

Figure 2: BPM of a healthy elderly male resting.

2.2 Preprocessing, Feature Extraction and Selection

The acquired raw biosignals are pre-processed using low-pass filters at 500 Hz and 100 Hz for the
three datasets respectively, and smoothing (moving average) filters for the 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 [6]. Simba Algorithm is used for feature selection, since it outperforms
compared to other well known feature selection algorithms [7].

Table 1: The feature extracted for each of the acquired biosignals

<table>
<thead>
<tr>
<th>BPM</th>
<th>ST</th>
<th>SCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of value</td>
<td>Mean of value</td>
<td>Mean of value</td>
</tr>
<tr>
<td>Mean of Absolute</td>
<td>Mean of Absolute</td>
<td>Mean of Absolute</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>Standard Deviation</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Median</td>
<td>Median</td>
<td>Median</td>
</tr>
</tbody>
</table>

2.3 Classification

We looked into a classification method called k-means clustering technique where we grouped the data into three clusters. Figure 3 and 4 below show the output after applying k-means clustering technique.

In data mining, k-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. Given a set of observations \(\{x_1, x_2, \ldots, x_n\}\), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets \(k \leq n\)

\[ S = \{S_1, S_2, \ldots, S_k\} \] so as to minimize the within-cluster sum of squares (WCSS):

\[ \arg\min_S \sum_{i=1}^k \sum_{x_j \in S_i} \|x_j - \mu_i\|^2 \]

where \(\mu_i\) is the mean of points in \(S_i\) [8].

The data collected from subjects showing four emotions (happy, sad, and angry) were combined together and grouped into four clusters using k-means clustering method. The data points from each cluster were studied back and showed that these clusters represented the four emotions.

3 Result

In order to minimize the bias associated with the random sampling of the training and testing data samples, we use 10 fold cross-validation. As the author pointed out, 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) 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.
Figure 1: Clusters formed using k-means for BPM Data

Figure 2: Clusters formed using k-means for SCR Data
Table 1: Result of the MSE for BPM and SCR

<table>
<thead>
<tr>
<th></th>
<th>BPM</th>
<th>SCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>1.1936</td>
<td>6.5081</td>
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</table>

4 Conclusion

In this work, a user independent emotion recognition method is presented. 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 jewelry. For research purposes the aforementioned sensors can be chosen 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. 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.

Acknowledgments

The dataset is offered by Professor S.C. Mukhopadhyay. In his research, an emotion recognition system is developed using physiological signals. These signals are obtained from a heart rate sensor, a skin temperature sensor and a skin conductance sensor and stored for data analysis and feature extraction.

References

Appendix I

160 Code for K-NN Algorithm
161
162 from pylab import plot,show
163 from numpy import vstack, array
164 from numpy.random import rand
165 from scipy.cluster.vq import kmeans, vq
166
167 import numpy as np
168 from numpy import *
169 from numpy.linalg import *
170 from pylab import *
171
172 X = np.loadtxt('heart.txt')
173 Y = np.loadtxt('skin.txt')
174
175 m, n = X.shape
176 U, S, Vt = svd(X)
177 S = resize(S, [m, 1]) * eye(m, n)
178 k = 2
179 Z = dot(U[:, :k], dot(eye(k), S[:k]))
180 Ph = Z[:, :2]
181
182 m, n = Y.shape
183 U, S, Vt = svd(Y)
184 S = resize(S, [m, 1]) * eye(m, n)
185 k = 2
186 Z = dot(U[:, :k], dot(eye(k), S[:k]))
187 Ps = Z[:, :2]
188
189 centroids1, error1 = kmeans(Ph, 3)
190 idx1, _ = vq(Ph, centroids1)
191
192 centroids2, error2 = kmeans(Ps, 3)
193 idx2, _ = vq(Ps, centroids2)
194
195 figure(1)
196 title('Clusters formed using k-means for BPM data')
197 plot(Ph[idx1 == 0, 0], Ph[idx1 == 0, 1], 'ob',
198      Ph[idx1 == 1, 0], Ph[idx1 == 1, 1], 'or',
199      Ph[idx1 == 2, 0], Ph[idx1 == 2, 1], 'og')
200 plot(centroids1[:, 0], centroids1[:, 1], 'sm', markersize=8)
201
202 figure(2)
203 title('Clusters formed using k-means for SCR data')
204 plot(Ps[idx2 == 0, 0], Ps[idx2 == 0, 1], 'ob',
205      Ps[idx2 == 1, 0], Ps[idx2 == 1, 1], 'or',
206      Ps[idx2 == 2, 0], Ps[idx2 == 2, 1], 'og')
207 plot(centroids2[:, 0], centroids2[:, 1], 'sm', markersize=8)
208
209 show()
**Appendix II**

Biosignals monitored from the left hand

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**Fig: BPM of a healthy elderly male resting.**

**Fig: SCR of a healthy elderly male resting.**

**Fig: d(BPM)/dt**
Fig: First derivative test showing minimal changes in BPM of a healthy elderly male resting.

Fig: BPM of an adult male in an excited (happy) state.

Fig: SCR of an adult male in an excited (happy) state