Life Science Informatics Publications

Research Journal of Life Sciences, Bioinformatics, Pharmaceutical and Chemical Sciences

Journal Home page http://www.rjlbpcs.com/

RJLBPCS
ISSN 2454-6348

Original Research Article DOI: 10.26479/2019.0502.63

EMOTION RECOGNITION VIA PHYSIOLOGICAL SIGNALS USING HIGHER ORDER CROSSING AND HJORTH PARAMETER

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ABSTRACT: Emotion plays an important role in human-computer interaction, it can be expressed verbally through emotional vocabulary, or by non-verbally like voice intonation, facial expressions, and gestures. In this paper, an automatic emotion recognition system has been designed based on three biosignals signals: (EEG, EMG, and GSR). Two techniques, higher order crossing (HOC) and Hjorth parameter, have been used to extract the features which have been proposed to three supervised classifiers: (kNN, SVM, Decision Tree) to classify these biosignals into three groups along two dimensions: Valence and arousal. The achieved accuracy rate is 94.2% for HOC and 93.2% for Hjorth parameter.

KEYWORDS: Emotion Recognition, Higher order crossing, Hjorth parameter.

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1.INTRODUCTION

Affective computing, that develops systems for detecting the human emotions, is a growing research area that helps assistive technology research in improving the neglected area of affective communication for disabled people [1] . There are several sets of emotion recognition applications including human-robot interaction, emotion aware interactive games, computer-aided tutoring, socially intelligent software apps neuro-marketing, computers should consider the emotions of their human conversation partners. Emotion can be detected from many modalities like facial expression, speech recognition, analyzing handwriting, body language, and physiological signals, all these modalities are not reliable to detect emotion except physiological signals, as it records the internal cognitive and emotional changes of users [2, 3]. There are several studies that handled emotion recognition from a facial expression like [4], [5], [6]. Although of the spread of these studied but facial expressions can be faked so emotion recognition using physiological signals has become more reliable, that appears in increasing number of studies that handled physiological signals like A study for Koelstra and others who have extracted 106 statistical features from EEG and other peripheral signals to classify human emotions into low/ high arousal, low/high valence and low/high liking using Naïve Bayes classifier, they have achieved 62% for EEG, 57% for peripheral signals, and 65% for MCA in arousal dimension, and 57% for EEG, 62% for peripheral signals, and 61% for MCA in valence dimension, and 55% for EEG, 59% for peripheral signals, and 67% for MCA in Liking dimension [7]. Deep Neural Network has been used to classify EEG signals into two classes in both arousal and valence dimension using Power spectral density (PSD) and frontal asymmetry features, the classification accuracy was 82.0% [8]. Another experiment has been done to evaluate audio and visual stimuli and compare the result with DEAP dataset in which audio-visual stimuli has been used, the result of this study has shown that DEAP dataset with audiovisual stimuli has recorded higher accuracy rate than audio and visual experiment [9]. Multiwavelet transform has been applied to classify EEG signals into four emotional groups, they have achieved 84.79 % with ten-fold cross-validation [10]. Another study for N. Ramzan and others who have tested five classifiers to evaluate the extracted features from EEG and ECG, they have achieved 71.6% for two states in valence classification and 54.0% for three states in arousal classification [11]. In this study, emotion recognition has been performed based on three biosignals (EEG, EMG, and GSR) Where Electroencephalography (EEG) [12] captures the changes occur in brain activity. Electromyography (EMG) [13] records the changes in muscle activity. Galvanic skin response (GSR) which is known also as Electro Dermal Activity (EDA) [14] captures the generated reactions in the skin during excitation. Two linear techniques higher order crossing (HOC) and Hjorth parameter have been used to classify these signals into three cases in both arousal and valence dimension. The study has compared the accuracy rate for three machine learning algorithms k-Nearest Neighbors (kNN), Support vector machine (SVM), and Decision Tree (DT).

2. MATERIALS AND METHODS

Different biosensors can monitor the physiological attributes of the human body that are controlled directly by the autonomic nervous system. In this study, the designed automatic emotion recognition system is shown in (Figure 1):

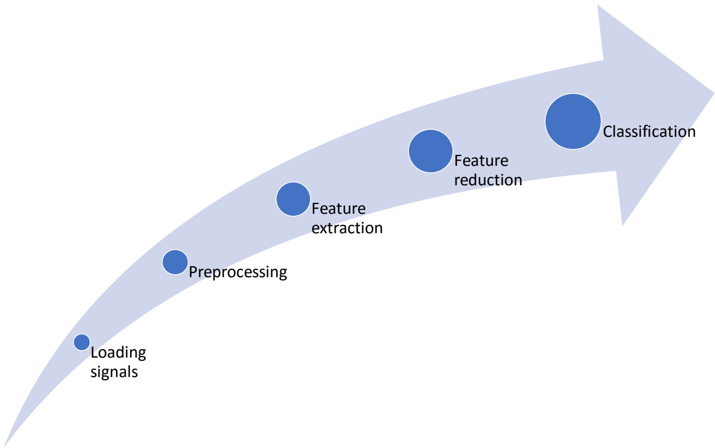

Figure 1 Block diagram for automatic emotion recognition system

In EEG signals, six channels have been selected (Fp1, Fp2, F3, F4, Fz, Cz) [15] to cover both brain side (left and right) and the central line. All these channels have been selected on Gamma band according to A study for Zhen [16] which has proved that Gamma band is the frequency band that related more to emotions. For EMG signals two-channels have been selected the first on facial muscle and the second on the left shoulder (zygomaticus major and trapezius muscles), and one-channel for GSR signal on the ring finger of right hand.

2.1. Dataset

In this study, the DEAP dataset [17], Database for Emotion Analysis Using Physiological Signals, has been used for acquiring the three physiological signals (EEG, EMG, and GSR). This dataset contains 32 subjects who have watched to 40 one-minute video clips to evoke their emotions, then they have asked to rate their emotions into five level of emotions (valence-arousal-dominance-liking- familiarity). Different physiological signals have been recorded like EEG, EOG, EMG, GSR, Respiration, Blood pressure, and temperature. This study has focused on three biosignals (EEG, EMG, and GSR) which are the most common signals used in emotion recognition.

2.2. Preprocessing

Butter worth bandpass filter has been used with different cutoff frequencies according to the signal; in EEG five-order bandpass filter has been used with cutoff frequency (30:75) Hz, wherein EMG three-order filter has been used with cutoff frequency (40:100) Hz, and in GSR second-order bandpass filter has been used with cutoff frequency (0.05:1.5) Hz. Then this filtered raw data has been normalized using the formula:

$$x = \frac{x - \mu}{\sigma} \quad (1)$$

2.3. Feature extraction

Two techniques have been used; higher order crossing (HOC) and Hjorth parameters:

2.3.1. Higher order crossing (HOC)

It is a technique that gives information about the oscillatory pattern of the signals [18]. When the time passes, the signal shows many up and down movements. These movements can be analyzed by calculating the count of zero crossings around the x-axis [19]. It can be calculated as the following:

The difference operator $\nabla$is a high-pass filter.

$$\nabla z_t \equiv z_t - z_{t-1} \quad (2)$$

The sequence of high-pass filters is defined as:

$$\mathrm{S_k} = \nabla^{\mathrm{k}-1}, \mathrm{k} = 1,2,3, \ldots \quad (3)$$

Then the corresponding HOC will be:

$$\mathrm{D_k} = \mathrm{NZC}\{\mathrm{S_k}(\mathrm{z_t})\} \quad (4)$$

Where: NZC- the number of zeros crossing

In this study, different k-values have been tested and the optimum k is at k=10.

This sequence of zero-crossing has been considered the feature vector that has proposed to classifiers.

2.3.2. Hjorth parameters

These are three statistical properties that have introduced by Bo Hjorth [20]. These parameters measure the signal complexity. The Hjorth parameters are [21]:

a. Activity parameter represents the signal power.
b. Mobility (μ) is the ratio of standard deviation of the first derivative of signal and the standard deviation of the original signal.

$$\mu = \sqrt{(}\frac{var(y'(t))}{var(y(t))} \quad (5)$$

c. Complexity parameter represents the change in frequency.

$$complexity = \frac{\mu(y'(t))}{\mu(y(t))} \quad (6)$$

2.4. Feature reduction

DEAP dataset contains more than 1000 samples as each subject from 32 subjects have watched to 40 video clips, so after extracting features from HOC technique the feature vector contains 60 features (10 values of HOC sequence for six channels) for EEG signal, and 20 features for EMG signal, and 10 features for GSR signal. This number could enlarge classification time and decrease classification accuracy. So, we must reduce it by selecting the features which are more significant than others. One-way ANOVA test [22] has been applied in this study; this technique is a collection of statistical models which used to analyze the variation among and between the groups producing p-value, the smallest p-value refers to significant features [23].

2.5. Classification

Three supervised classifiers [24] have been used in this study: k-nearest neighbor [25], support vector machine (SVM) [26], and Decision tree (DT) [27].

3. RESULTS AND DISCUSSION

In this study, an automatic emotion recognition system has been proposed based on three biosignals: EEG, EMG, and GSR using two linear techniques: HOC and Hjorth parameters. The extracted featured from both techniques have been optimized using the one-way ANOVA test. Three supervised classifiers have been tested: KNN, SVM, and DT. The achieved accuracies have been validated using 10-fold cross-validation. Table 1 shows the average accuracies for each signal individually and after combining the three signals together along three classifiers.

Table 1: The average accuracies for the three signals through HOC analysis

	EEG (Gamma)		EMG		GSR		EEG+EMG+ GSR	
	VA	AR	VA	AR	VA	AR	VA	AR
RT	93.3	92	91.3	88	90.7	85	90.3	93.7
SVM	91.3	92.3	92.7	87.5	86	83.7	92	92.8
KNN	92.4	93.7	92.3	90.3	91.1	89.4	93.7	94.2

Table 2: The average accuracies for the three signals through Hjorth parameters

	EEG (Gamma)		EMG		GSR		EEG+EMG+GSR	
	VA	AR	VA	AR	VA	AR	VA	AR
RT	91.7	91.3	89.3	85.3	90	92	93.2	93.2
SVM	88.3	88	82.3	84	80.3	81.5	90.3	89.3
KNN	86.8	88.7	85.6	88.5	82.6	85.6	92	92.7

Then the features extracted from HOC and Hjorth parameters have been combined and the average accuracies have been summarized in the following figure (Figure 2):

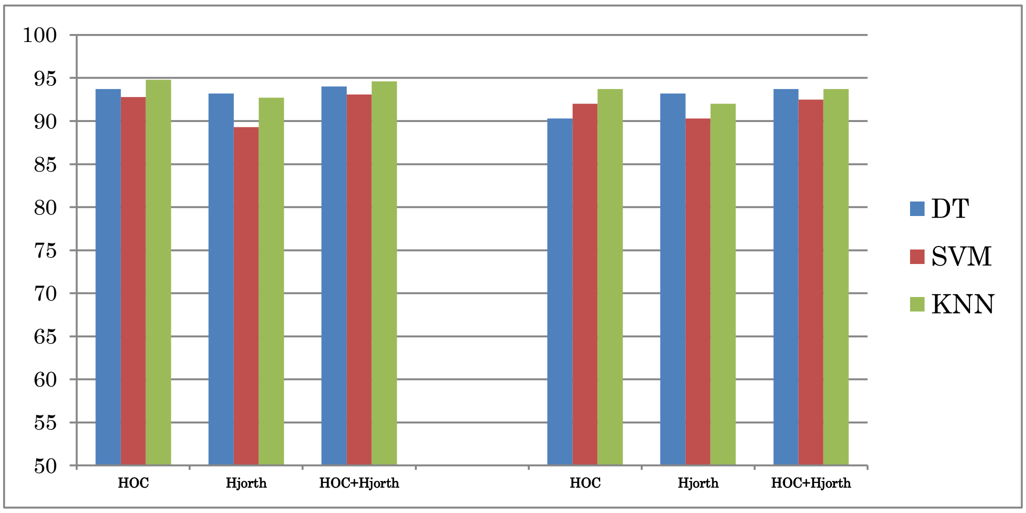

Figure 2: Average accuracy rate from the Combination between HOC and Hjorth parameters

Figure 2 shows the achieved accuracies for the three biosignals along the two techniques: HOC and Hjorth parameters; it is obvious that HOC records higher accuracy rate than Hjorth parameters and after combining both techniquess together the overall accuracy have enhanced with a little percentage.

To evaluate this study, the results have been compared with other studies in the same field as in the following table (Table 3):

Table 3: Comparing the result of this study with other studies

Technique	Database	Achieved accuracy
Fractal dimension and Higher Order Crossings (HOC)[28]	DEAP EEG	90.35 %
Hjorth parameters [29]	Experiment	70%
Higher order crossings (HOC) and cross-correlation(CC) [9]	Experiment	94.4%
Multi-wavelet transform[30]	DEAP -EEG	84.79%
This study	DEAP	94.2% for HOC and 93.2% for Hjorth parameter

4. CONCLUSION

In this paper, an automatic emotion recognition system has been proposed based on three biosignals EEG, EMG, and GSR. It has shown that the extracted features from HOC and Hjorth parameters were promising in recognizing human emotion. Results show that HOC technique has achieved a classification accuracy of 94.2% where Hjorth parameters have achieved 93.2%. This promising accuracy enables us to use this system in different applications that depend on emotion recognition. After comparing our proposed system to other systems who have applied the same technique and the same dataset as in [28], it is shown that our proposed system Superiority on it. Then we have compared our results with the same techniques but with the different dataset, our proposed system is the largest accuracy except in one study [9] with difference accuracy rate of 0.2%.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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