Higher Order Spectra Analysis of EEG Signals in Emotional Stress States

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Abstract— **This paper proposes an emotional stress recognition system with EEG signals using higher order spectra (HOS). A visual induction based acquisition protocol is designed for recording the EEG signals in five channels (FP1, FP2, T3, T4 and Pz) under two emotional stress states of participants, Calm-neutral and Negatively exited. After pre-processing the signals, higher order spectra are employed to extract the features for classifying human emotions. We used Genetic Algorithm for optimum features selection for the classifier. Using the SVM classifier, our study achieved an average accuracy of 82% for the two-abovementioned emotional stress states. We concluded that HOS analysis could be an accurate tool in the assessment of human emotional stress states. We achieved to same results compared to our previous studies.**

Keywords- classification; emotional stress; EEG Signals; genetic algorithm; higher order spectra.

I. INTRODUCTION

Our study deals with emotional stress assessment using HOS to analyze the brain signals in emotional stress states both quantitatively and qualitatively. The importance of this view is in its practical application in the assessment of emotional stress state, which is in turn directly related to the quality of life [1].

Understanding the behavior and dynamics of billions of interconnected neurons from the brain signal requires knowledge of several signal-processing techniques, which relates the brain activity to the physiological events.

Most of researches in the domain of emotional states use peripheral physiological signals such as respiratory rate, skin galvanic resistance, and photoplethysmograph [1-4].

Since one important emotion theory is the cognitive theory in which the brain is the onset and center of emotional activity, a few works have used the electroencephalography (EEG) signals, which are a representative of the central nervous system [1]. Brain waves occur during the activity of brain cells and have a frequency range of 1 to 100 Hz. Researchers have found that the following are the frequency bands of interest to interpret EEG signal: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz) [1,2].

In recent years, useful properties of higher order spectra (HOS) in the extraction of phase information have been used in the processing of EEG signal.

In other related studies, different emotional stress recognition systems based on brain signals [1-4] and the application of HOS in biosignal processing have already been studied [1,5-7].

The layout of the paper is as follows: Section II presents briefly the data acquisition protocol and preprocessing. Section III presents the features extracted from the HOS parameters, Hinich's test and the classification system. The results are covered in section IV. Finally, our conclusions based on our results are discussed in section V.

II. DATA AQUISITION

A. Subjects and acquisition protocol

Signals were acquired from fifteen subjects. Most subjects were students from biomedical engineering department of Islamic Azad University of Mashhad. Each participant was examined by a dichotic listening test to identify the dominant hemisphere [1]. Subjects were right-handed males between the age of 20 and 24 years. All subjects had normal or corrected vision; none of them had neurological disorders. We used a Flexcom Infiniti biofeedback device for data acquisition. Data such as skin conductance, photoplethysmograph, respiratory rate and EEG signals were continuously recorded through bio-sensors placed on the participant. The EEG signals, sampled at 256 Hz, were recorded from five channels (FP1, FP2, T3, T4

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and Pz) placed on each subject's scalp according to the international 10-20 system. Each recording lasted about 3 minutes [1,2]. In our study, the stimuli to elicit the target emotions (calm-neutral and negatively excited) were some of the pictures in International Affective Picture System (IAPS) databases [8]. The use of IAPS allows better control of emotional stimuli and simplifies the experimental design.

In order to choose the best emotional correlated EEG signals, we implemented a new emotion-related signal recognition system, which has not been studied so far [1,2]. We recorded psycho-physiological signals concomitantly in order to firstly recognize the correlated emotional state and then label the correlated EEG signal.

More details of the data acquisition protocol can be found in reference [1,2].

B. *Pre-processing*

We need to pre-process EEG signals in order to remove environmental noises and drifts. Therefore, the data was filtered using a band pass filter in the frequency band of 0.5~60 Hz. Although we studied the signals of up to 30 Hz, we included the 30 to 60 Hz bandwidth because we need a double maximum frequency content when analyzing the data using HOS [1]. The signals were filtered using the "filtfilt" function from the signal processing in MATLAB toolbox, which processes the input signal in both forward and reverse directions. This function allows performing a zero-phase filtering. Safety of signal phase information is very important in higher order spectra [1,7].

III. Analysis of EEG signals

A. *Feature extraction using HOS*

In this study, features are characteristics of a signal that are able to distinguish between different emotions. We analyzed the EEG signal using different higher order spectra that are spectral representations of higher order moments or cumulants of a signal [1,7,9-11].

One of important characteristics of HOS is that their second order spectrum (and other higher orders) has the ability to recognize nonlinear couplings between phases. This means that if a frequency factor is composed of two other frequency factors, we can distinguish them. This is called Quadratic Phase Coupling (QPC) detection [1,7].

In particular, this paper studies features related to the third order statistics of the signal, namely the bispectrum. The bispectrum is the Fourier transform of the third order correlation of the signal and is given by

$$Bis(f_1,f_2)=E[X(f_1).X(f_2).X^*(f_1+f_2)] \tag{1}$$

Where * denotes complex conjugate, $X(f)$ is the Fourier transform of the signal $x(nT)$ and $E[.]$ stands for the expectation operation. This method is known as direct Fast Fourier Transform (*FFT*) based method. There is also another indirect method, which is used in our study. For more details on this method please refer to [1,7,11].

If the bispectrum of a signal is zero, none of the component waves are related and or coupled to each other.

Assuming that there is no bispectral aliasing, the bispectral of a real-valued signal is uniquely defined with the triangle $f_2 \geq 0$, $f_1 \geq f_2$ and $f_1+f_2 \leq \pi$. For real processes, since discrete bispectrum has symmetric characteristics, it has 12 symmetry regions in the (f_1, f_2) plane [1,7,11]. Some of these regions can be seen in (2):

$$\begin{aligned} Bis(f_1,f_2) &= Bis(f_2,f_1)=Bis(-f_1-f_2,f_2) \\ &= Bis(-f_1-f_2,f_1)=Bis(f_1,-f_1-f_2) \\ &= Bis(f_2,-f_1-f_2) \end{aligned} \tag{2}$$

The normalized bispectrum (or bicoherence) is defined as

$$Bic(f_1,f_2)=\frac{Bis(f_1,f_2)}{\sqrt{P(f_1).P(f_2).P(f_1+f_2)}} \tag{3}$$

Where $P(f)$ is the power spectrum.

Since bispectrum and bicoherence cannot fully help signal extraction, Hinich has developed algorithms to test for non-skewness (called Gaussianity) and linearity [12]. The basic idea is that if the third-order cumulants of a process are zero, then its bispectrum is zero, and hence its bicoherence is also zero. If the bispectrum is not zero, then the process is non-Gaussian; if the process is linear and non-Gaussian, then the bicoherence is a non-zero constant [1,7].

The Gaussianity test (actually zero-skewness test) involves deciding whether the expected value of the bicoherence is zero, that is, $E\{Bic(f_1,f_2)\}=0$. The test of Gaussianity is based on the mean bicoherence power,

$$S=\sum \left|Bic(f_1,f_2)\right|^2 \tag{4}$$

The squared bicoherence is chi-squared distributed ($\chi 2$ distributed) with two degrees of freedom and non-centrality parameter Lambda (λ) [11]. In (4) the squared bicoherence is the sum of P points in the non-redundant region, S is the estimated statistics for the Gaussianity test with chi-squared distributed and $2P$ degree of freedom, and *Pfa* is the probability of false alarm in rejecting the Gaussian hypothesis. More details can be found in [1,7,11].

In order to calculate these features, we used a 256 sample FFT with a default C parameter of 0.51. Based on these, the $2P$ degree of freedom will be 96.

Blocks of 512 samples of EEG signals (neutral and negative), corresponding to 2 seconds, were used to compute the bispectrum and bicoherence. The analysis was done using the higher order spectral analysis (*HOSA*) toolbox [11]. The bicoherence was computed using the direct FFT method in the toolbox.

For the whole bifrequency plane region, four quantities were calculated: sum of the bispectrum magnitudes, sum of the squares of the bispectrum magnitudes, sum of the bicoherence magnitudes, and sum of the squares of the bicoherence magnitudes.

Since bispectrum and bicoherence are functions of f_1 and f_2, in order to define the features, we will have five frequency intervals on each axis, as can be seen in Fig. 1. We will have 15 distinct regions. Then the defined features will be analyzed in each of these 15 regions and in the whole frequency range.

These and the three other features obtained from Hinich's tests for Gaussian and linearity add up to make 7 features for each channel.

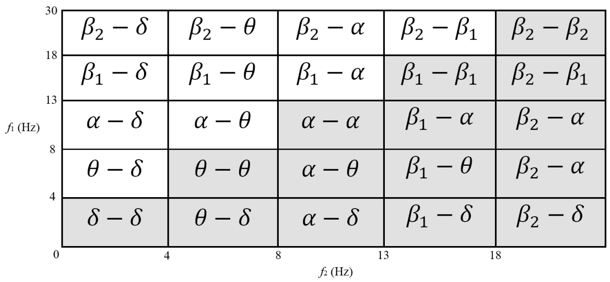

Figure 1. The different regions used for analysis in bifrequency plane

These seven features are excreted for each channel, so the total number of features by this method is: [5×4×(15+1)] + [5×3] = 335. This leads to the problem of dimensionality, which is solved by using Genetic Algorithm (GA) as a feature selection method [13]. This is of interest to improve the computational speed of the classification algorithm.

B. Normalization

In order to normalize the features in the limits of [-1, 1], we used (5).

$$Y_{norm} = \frac{-2Y_s^{'} + Y_{s\max}^{'} + Y_{s\min}^{'}}{Y_{s\min}^{'} - Y_{s\max}^{'}} \tag{5}$$

Here Y_{norm} is the relative amplitude.

C. Features selection with genetic algorithm

The problem of vast number of features is solved by using Genetic Algorithm as a feature selection method. The genetic algorithm is a type of natural evolutionary algorithm that models biological process to optimize complex cost function by allowing a population composed of many individuals to evolve under specific rules to a state that maximizes the fitness. The emphasis on using the genetic algorithm for feature selection is to reduce the computational load on the training system while still allowing near optimal results to be found relatively quickly. The classification performance of the trained network using the whole dataset was returned to the GA as the value of the fitness function, Fig. 2.

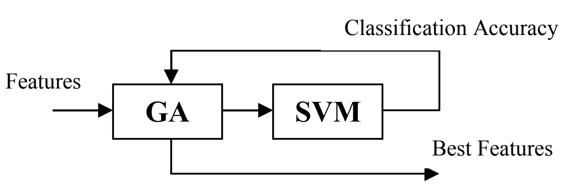

Figure 2. Combination of GA and SVM to achieve the best features

D. Classification with support vector machine

After extracting the obtained good features, we still have to find the related emotional stress state in the EEG. A classifier will do this process. A classifier is a system that divides some data into different classes, and is able to learn the relationship between the features and the different emotional stress states. One very useful classifier is a Support Vector Machine (SVM) [14,15]. Nonlinear support vector machine maps the input space to a high dimensional feature space, and then constructs a linear optimal hyperplane in the feature space, which relates to a nonlinear hyperplane in the input space. The major problem of training a learning machine to perform supervised classification is to find a function (kernel function) that can not only capture the essential properties of the data distribution, but also prevent the over-fitting problem [1]. We used kernel functions including linear kernel, Polynomial kernel and Radial basis function (RBF) kernel. The *LibSVM* MATLAB toolbox (Version 2.9) was used as an implementation of the SVM algorithms [14].

IV. RESULTS

The contour plots of the Indirect Estimate of the bispectrum are shown as examples for T3 channel in Figs. 3 and 4. We used a 2-second rectangular window without overlap for data segmentation. We used around 70% of the data for training, 20% of the data for testing. The last 10% was used for validating the data. The system was tested using the 5-fold cross-validation method, which divides the training data into five parts. One of the parts was used for testing the classifier, and the four others were used for training. The process was repeated five times, every time with another part of the data. This method reduces the possibility of deviations in the results because of the distribution of training and test data, and ensures that the system is tested with different samples from those it has seen for training. Using a 5-fold cross validation error assessment for training and testing, we reached an accuracy of 22.6% for the two categories of emotional stress states using the EEG signals.

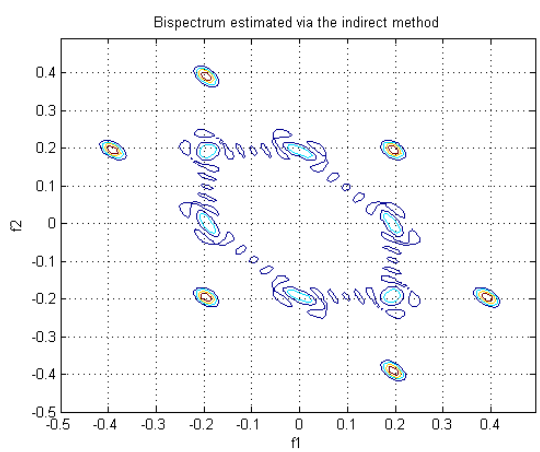

Figure 3. A contour plot of the magnitude of the indirect estimated bispectrum on the bifrequency plane, for T3 in calm state

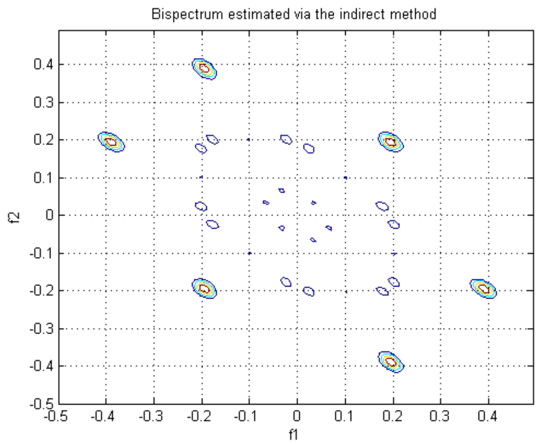

Figure 4. A contour plot of the magnitude of the indirect estimated bispectrum on the bifrequency plane, for T3 in negative emotional stress state

The classification results of the SVM used for classification of the raw EEG signals under two emotional stress states is given in Table 1.

TABLE I. EMOTIONAL STRESS CLASSIFICAION ACCURACY ON EEG SIGNALS USING SVM FOR THE THREE KERNEL FUNCTION

SVM	***Linear***	***Poly***	***RBF***
Classifier accuracy	71.10%	80.67%	82%
5-fold cross validation-error	29%	27.45%	22.6%

Table 2 gives the average classification accuracy in five channels of EEG signals under two emotional stress states with using RBF kernel in SVM classifier.

TABLE II. THE AVERAGE CLASSIFICATION ACCURACY IN DIFFERENT CHANNELS USING RBF KERNEL OF SVM

Channels	***FP1***	***FP2***	***T3***	***T4***	***Pz***
Classifier accuracy	81.1%	78%	82.1%	79.7%	75.5%

V. DISCUSSION AND CONCLUSION

This paper proposes an approach to classify emotional stress states in the two main areas of the valance-arousal space by using EEG signals. As demonstrated in this paper, EEG signals can be used for emotional stress assessment. For the first time in this investigational field, we had done a feature extraction using higher order spectra in emotional stress state assessment. The review of the contour plots of the five channels (FP1, FP2, T3, T4 and Pz) shows that most of the changes are amplification or diminish of the peaks or transfer of the peaks in the bifrequency plane.

The best accuracy was obtained when we used the RBF kernel of SVM, in which case the averaged accuracy was 82%. The analysis of our data shows that the RBF kernel performs better than the other two kernels. The classification of results demonstrated that this recognition method has a good accuracy. We concluded that HOS analysis could be an accurate tool in the assessment of human emotional stress states. A natural result is that it can be a good tool in the assessment of the behavior of human brain in emotional stress states. We achieved to same results compared to our previous studies [2].

Future work to acquire data from more participants is underway to validate the current results. We are pursuing this track, as it should lead to a better identification of emotions.

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