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Bispectral Analysis of EEG for Emotion Recognition

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Abstract

Emotion recognition from electroencephalogram (EEG) signals is one of the most challenging tasks. Bispectral analysis offers a way of gaining phase information by detecting phase relationships between frequency components and characterizing the non-Gaussian information contained in the EEG signals. In this paper, we explore derived features of bispectrum for quantification of emotions using a Valence-Arousal emotion model; and arrive at a feature vector through backward sequential search. Cross-validated accuracies of 64.84% for Low/High Arousal classification and 61.17% for Low/High Valence were obtained on the DEAP data set based on the proposed features; comparable to classification accuracies reported in the literature.

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Keywords: Brain Computer Interface; electroencephalogram; emotion; classification; Valence-Arousal model;

1. Introduction

Enabling human-machine interfaces to interpret emotional states paves the path towards emotionally capable machines that offer more natural interactions and better performance in the fields of rehabilitation robotics, multimedia content characterization, personalized recommender systems etc. Several approaches to emotion detection have been proposed. Characterizing emotional data from facial expressions have been explored[1]. However, such methods may be prone to deception as the associated parameters vary easily, subject to different situations. Use of physiological signals (especially electroencephalogram (EEG)) have gained a lot of interest. Time-frequency domain features such as power spectral density (PSD) and frequency power ratios have been employed with relative success[6,7]. Given the non-Guassian nature of EEG signals, it makes sense to explore higher order spectral features. In this paper, we explore derived features of bispectrum for quantification of emotions using a Valence-Arousal emotion model. Classification of emotional states viz. Low/High Arousal (calm/bored to excited/stimulated) and Low/High Valence (unhappy/sad to happy/joyful) have been considered. Classification experiments were performed over EEG signals from the DEAP dataset[2]. The choice of the Valence-Arousal model has been inspired by the circumplex model of affect[3]. Preliminary classification experiments were conducted using EEG pertaining to Fp1 and Fp2 channels. Linear Kernel Least Square Support Vector Machine (LS-SVM) and back-propogation Artificial Neural Networks (ANN) were used. Further experiments were conducted by performing backward sequential feature selection.

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2. Related Work

Modelling Emotions. Emotion is a psychological state or a process that functions in maintaining the balance of information process in the brain and the relevant goals. Every time an event is evaluated as relevant to a goal, an emotion is elicited. A model of emotion can be characterized by two main dimensions called valence and arousal. The valence is the degree of attraction or aversion that an individual feels toward a specific object or event. It ranges from negative to positive. The arousal is a physiological state of being awake or reactive to stimuli, ranging from passive to active. The valence arousal dimensional model, represented in Figure 1(a) is the accepted model.

EEG and Emotion. Emotional data can be captured by means of EEG, acquired by measuring the electrical activities at different electrode positions on the scalp. The 10-20 system of electrode placement is used. See figure 1(b). Brain wave is the composition of five main frequency bands called delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-50 Hz). Soleymani et al.[4] employed EEG and peripheral physiological signals to classify emotions into three levels of valence and arousal. Using a support vector machine (SVM) with PSD Soleymani et al. arrived at accuracy rates of 57.0% and 52.4% for valence and arousal respectively. In another study, 66.05% and 82.46% accuracy rates for valence and arousal respectively was achieved by Huang et. al[5] using an Asymmetrical Spatial Pattern technique to extract features. Other machine learning techniques have also been applied[8,9].

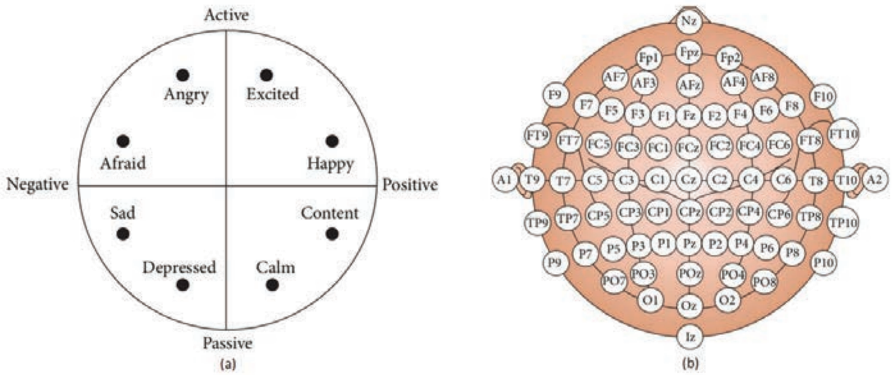

Fig. 1. (a) Valence-Arousal Model; (b) 10-20 system of electrode positions.

3. Materials

EEG Signal. Signals were acquired from the DEAP dataset[2], which is a multimodal dataset for analysis of human affective states. EEG and peripheral physiological signals of 32 subjects were recorded as each subject watched one-minute long excerpts of music videos designed to elicit peak emotional responses (For detailed discussion refer to DEAP dataset[2]). Figure 2 shows the organization of the trials vis-a-vis the section and complete experiment; the protocol followed for elicitation of emotion is marked in the trail.

Valence / Arousal. Each participant went through 40 trials of stimuli presentation (music videos). During the presentation, EEG signals were recorded at a sampling frequency of 512 Hz using 32 active AgCl electrodes, placed in accordance to the international 10-20 system. For self-assessment, the subjects selected values in the continuous scale of 1-9 to indicate their emotion states in each category. This study mapped the scales (1-9) into two levels of each valence and arousal states. The valence/arousal scale rating from 1-5 was mapped to Low valence/arousal state and the valence/arousal scale rating of 5-9 was mapped to High valence/arousal states.The choice of two level mapping (with a threshold of 5 on a scale of 1-9) is based on the analysis carried out by Koelstra et. al[2] on the DEAP dataset. According to the new scale mapping, the system provides 4 state emotion classification: High Valence, Low Valence, High Arousal and Low Arousal. The adopted mapping scheme is illustrated in Figure 3.

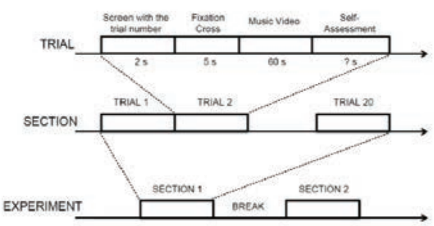

Fig. 2. Protocol of signal acquisition

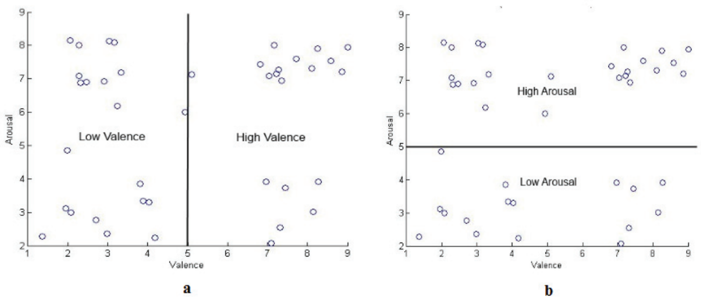

Fig. 3. Mapping of scales. (a)Low/High Valence states. (b)Low/High Arousal states. Each point represents a trial rating given by a subject for an experienced emotion in the valence and arousal dimensions.

4. Methods

Signal Processing. Signals for this research were downsampled from 512 Hz to 128 Hz. Signals were segmented into 60 second trials with a 3-second pre-trial baseline removed. Signals were preprocessed for the removal of Electro-Oculogram (EOG) artifacts using a blind source separation technique[2] and bandpass filtered for the frequency range of 4.0-45.0 Hz. EEG data was averaged to the common reference. Filtering of brain rhythms theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz) was performed using a Butterworth filter.
Feature Extraction. We employed 2-channel EEG signals, without any additional peripheral physiological signals. Fp1 and Fp2 (electrodes over the prefrontal cortex) were used. The bispectrum was calculated using the bispecd function from the **HOSA** (Higher Order Spectral Analysis) toolbox for MATLAB. Derived features of bispectrum of the EEG signals were extracted in 3 frequency bands: theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz).
Bispectrum:. Bispectral analysis is an advanced signal processing technique, first reported by Huber et al.[11], that quantifies quadratic non-linearities (phase coupling) among the components of a signal. The bispectrum is the third order statistics of a signal, denoted by $B(f_1, f_2)$, defined as the Fourier transform of the third order correlation of a signal and is given by the following equation

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

where $X(f)$ represents the Fourier transform of the signal $x(nT)$, n is an integer index, * denotes complex conjugate and $E[]$ denotes the statistical expectation operation. For deterministic sampled signals, $X(f)$ is the discrete-time Fourier transform and is computed using Fast Fourier Transform (FFT) algorithm. The frequency f may be normalized by the Nyquist frequency (half of the sampling frequency) that lies between 0 and 1. The bispectrum given by equation 1, is a complex valued function of two frequencies. The bispectrum exhibits symmetry and needs to be computed in the non-redundant region or in its principal domain. Assuming there is no bispectral aliasing, the bispectrum of a real valued signal is uniquely defined in the triangle $0 \leq f_2 \leq f_1 < f_1 + f_2 \leq 1$. This non-redundant region/principal domain is denoted by Ω.
Derived Features of bispectrum:. Following derived features of bispectrum were used for the feature vector.

- Normalised Bispectral Entropy $BE1 = -\sum_n p_n log p_n;\ \ p_n = \frac{|B(f_1,f_2)|}{\sum_\Omega |B(f_1,f_2)|}$
- Normalised Bispectral Squared Entropy $BE2 = -\sum_n q_n log q_n;\ \ q_n = \frac{|B(f_1,f_2)|^2}{\sum_\Omega |B(f_1,f_2)|^2}$
- Mean-Magnitude of Bispectrum $MMOB = \frac{1}{L}\sum_\Omega |B(f_1, f_2)|$; where L is the number of points within Ω
- First Order Spectral Moment $FOSM = \sum_{k=1}^{N} log|B(f_1, f_1)|$
- Second Order Spectral Moment $SOSM = \sum_{k=1}^{N} (k - FOSM)^2 log|B(f_1, f_1)|$

Classification. To asses the association between EEG and emotional states and for demonstrating the effectiveness of the proposed features, the classification into the pre-defined emotional states was performed by the LS-SVM classifier with the Linear and RBF kernels along with ANN running the Error-back-propagation algorithm.

5. Experimental Results and Discussion

Time Window. Data pertaining to the first 30 seconds and last 30 seconds for each trial of the recorded EEG signals were used. A total of 5 features were calculated for each channel (Fp1, Fp2) resulting in a 10 dimensional feature vector. A linear kernel LS-SVM and an ANN (error back-propagation, 1 hidden layer of 20 neurons) were employed. A total of 180 samples were used with symmetric distribution of labels between the two classes for each classification task. These observations were randomly partitioned into training and testing sets using Holdout partitioning with 80% samples in training and 20% samples in testing set. Observed results are illustrated in Table 1. It is observed that the last 30 seconds of the recorded signals yielded better classification. Furthermore, filtered rhythms of the EEG signals yielded better classification.

Table 1. Classification accuracy with varying time windows

Channels Fp1 and Fp2	Low/High Valence Classification				Low/High Arousal Classification			
	First 30 sec		Last 30 sec		First 30 sec		Last 30 sec	
	SVM	ANN	SVM	ANN	SVM	ANN	SVM	ANN
All Rhythms	52.25	43.33	53.72	45.00	54.47	41.68	58.89	50.49
Theta Rhythm	58.04	45.00	66.67	58.44	63.47	58.98	72.22	64.44
Alpha Rhythm	57.45	47.65	66.67	61.11	58.45	43.33	63.89	59.47
Beta Rhythm	58.00	45.00	63.89	61.11	62.61	57.60	75.00	61.11

Feature Selection. Experiments were conducted using backward sequential selection. This method forms the best feature subset by sequentially removing features (from the original feature vector) until there is no improvement in prediction. This selection method resulted in reduced feature vectors as illustrated in Table 2.

Table 2. Reduced Feature Vectors

Alias	Rhythms	Feature Vector	
		Fp1 Channel	Fp2 Channel
FS1	Theta Rhythm	SOSM, BE2, MMOB	SOSM, BE2, MMOB
FS2	Alpha Rhythm	FOSM, BE1, BE2	SOSM, BE1, BE2
FS3	Beta Rhythm	FOSM, SOSM, BE1	FOSM, SOSM, BE1, MMOB

Hyperparatemer optimization of the LS-SVM RBF kernel parameters was performed using Grid search. Grid search is performed in two stages: a 'coarse' grid search where a better region in the grid space is identified followed by a 'fine' search in that space. The feature vectors calculated in Table 2 were used to report 10-fold cross validation accuracy results on the entire dataset (1280 samples). Results obtained using ANN were significantly lower than those obtained from the LS-SVM RBF kernel. The results obtained from the LS-SVM RBF kernel are illustrated in Tables 3 and 4. The confusion matrices corresponding to Tables 3 and 4 are shown in Tables 5 and 6 respectively.

Table 3. Low/High Arousal Classification

	10- fold Cross Validation Accuracy											Hyperparameters	
Feature Vector	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Avg Acc	C	Gamma
FS1	61.72	53.08	64.84	54.69	68.75	74.22	85.16	58.59	66.41	60.94	64.84 ± 9.56	4.223	1.533
FS2	41.41	59.38	54.69	65.63	62.50	51.56	54.69	55.47	54.69	65.63	56.56 ± 7.25	0.126	1.4224
FS3	57.81	57.03	64.84	56.25	62.50	56.25	70.31	48.44	46.88	56.25	57.65 ± 7.01	5.679	3.004

The focus of this research was to perform emotion classification using EEG via Low/High Valence and Low/High Arousal classification. Accuracies of 61.17% and 64.84% respectively were obtained. The analysis presented by Kolestra et. al[2] on the DEAP dataset quotes (for EEG modality) Low/High Valence classification accuracy of 57.6% and Low/High Arousal classification of 62% using PSD of specific brain rhythms and change in spectral power of symmetrical pair of electrodes on the left and right hemispheres of the brain. The results obtained suggest that derived features of bispectrum may be better discriminants than power spectral features. Also the LS-SVM RBF kernel

Table 4. Low/High Valence Classification

10- fold Cross Validation Accuracy											Hyperparameters	
Feature Vector	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Avg Acc	C	Gamma
FS1	48.44	57.81	60.16	51.56	67.97	61.72	59.38	51.56	57.81	58.59	57.50 ± 5.69	5.057	3.00
FS2	56.25	55.47	64.84	57.81	58.59	64.06	65.63	59.38	67.19	62.50	61.17 ± 4.18	4.023	1.414
FS3	49.22	50.00	57.03	54.69	51.56	54.69	60.16	61.72	58.59	60.94	55.86 ± 4.55	0.0313	2.013

Table 5. Confusion Matrix for Low/High Arousal

Total Test Samples :128		Predicted Labels	
		Low	High
Actual Labels	Low	39	25
	High	20	44

Table 6. Confusion Matrix for Low/High Valence

Total Test Samples :128		Predicted Labels	
		Low	High
Actual Labels	Low	38	26
	High	24	40

outperforms its linear kernel variant and ANNs. Both findings conform with the results presented by Yuvaraj et al.[12], who also use bispectrum as a feature for emotion classification. The higher discriminating power of the last 30 seconds of the signals suggest that emotion peaks for the presented stimuli were generally realized in this time window.

6. Conclusion

In this paper we performed the classification of human emotions using EEG data via two classification tasks resulting in four-state classification of emotions. Initial experiments revealed that a window of the last 30 seconds of the recordings have greater discriminating power. Also filtered brain rhythms (Theta, Alpha and Beta) showed better classification accuracy than unfiltered EEG signals. Experimental results also showed that reduced feature sets obtained by backward feature selection, for the Theta and Alpha rhythm yielded best cross-validated accuracy results for the Low/High Arousal and Low/High Valence classification tasks respectively. The accuracy percentages obtained in this work however are valid for offline classification of emotions. Building predictors for online classification is part of on-going research. A combination of time-frequency domain and bispectrum features from different channels along with ensemble classifiers (Random Forest, AdaBoost etc.) may be explored to achieve higher accuracy rates.

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