



Emotional Response using Power Spectrum Approach

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Abstract:

The objective of this study is to detect affective response of children to facial expression based on alpha power density of brain activity. Electroencephalography data were collected from 10 typical children. The alpha power temporal information of active brain regions was extracted. Performance of the power spectrum feature was evaluated in emotion recognition process using K nearest neighbor, a regularized least square and multilayer perceptron classifier. A statistical analysis indicated right alpha activity during negative and calm emotional states. Statistical results showed significant difference between rest conditions and emotional state. The best accuracy we got to detect emotional states is by using regularized least square that is 70%.

Keywords: EEG, Alpha wave, Emotional states, classification.

الكشف عن الاستجابة العاطفية بالتحليل الطيفي للإشارة الكهربائية للدماغ

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الخلاصة:

يقدم البحث دراسة تحليلية عن استجابة العاطفية للأطفال عند النظر الى صور وجوه أطفال تمثل حالات من الحزن والسعادة والخوف والحالة الطبيعية. تم التحليل بسحب إشارة الدماغ من عشرة أطفال أعمارهم بين الخامسة والرابعة. وتم استخدام مصنفات (KNN, RLS, MLP) التحليل الإحصائي بين نشاط موجة ألفا من الجهة اليمنى للدماغ خلال حالة الحزن والطبيعية. وكذلك بين الاختلاف العالي في نشاط ألفا بين حالة الهدوء خلال إغلاق العين أو فتح العين وحالة النظر للصور التي تمثل حالات عاطفية مختلفة. نسبة الدقة لتصنيف الحالة العاطفية باستخدام تقنيات الذكاء الصناعي وصلت الى 70 بالمئة.

الكلمات المفتاحية: الإشارة الكهربائية للدماغ، موجة ألفا، الحالة العاطفية، التصنيف.

1. INTRODUCTION:

Since the early studies of emotion, researches focused on the facial expression of emotion and reported that different facial expressions are related to different emotional state [1-3]. Aboard of studies by cognitive scientists and psychologists have been showing that facial expression is one of the important factors to develop the cognitive process and emotional state of the child. In early age, infants develop their ability to recognize emotion influenced by their parents or caregiver's facial expression [4-6]. However, some children have problem in processing facial information such as autism spectrum disorder and other children with learn disability [7-9]. Therefore, it is important to examine children response to emotional stimuli.

Emotion is psycho-physiological phenomena that can measure based on expressive movement [10] or skin conductance, heart rate and blood pressure [11,12] that present the physiological responses of autonomic nervous system. Further emotion is measured by neurophysiologic measurement such as functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG) which are noninvasive techniques that detect the emotion from the central nervous system (CNS) with respect to spatiotemporal resolution [13,14]. Regarding emotional measurement tools, EEG has used extensively for emotional studies.

Nevertheless, the low spatial resolution of EEG, EEG provides direct measurement of brain activity with high temporal resolution that enables of recording the instantaneous responses to emotional stimuli. EEG is less cost-effective, safe for infants and less physical restriction. These markers make it the most appropriate tool to study neurons activity correlated to brain functions [15,16]. Aboard of studies have done in this area which focusing on EEG asymmetry in the alpha band at the frontal and pre-frontal regions [14, 17-19] following the study of Davidson [20,21]. The left frontal alpha activity is associated with positive response whereas the right frontal alpha activity is related to negative emotion for adults and infants. However, studies on children were inconsistent. Feng et al [22] didn't report a difference in the activation between happy and sad stimuli. Pickens et al [23] reported left frontal activation for both happy and sad stimuli. This may be due to issue in the methodology or may interpret as a lack in stimuli intensity.

Other studies were concern on emotion recognition model to predicate human emotional states. A various feature extraction methods have been implied for emotion recognition including power spectrum [24] , higher order crossing [25], connectivity [26,27], wavelet coefficient [28], fractal dimension [29], statistical features of ERP [30], and EEG asymmetry at the frontal and pre-frontal regions [20]. Studies done on brain connectivity showed great potential for improving emotion recognition system [26, 27]. This can be related to that emotion process integrates among different brain regions. Neuroscience studies reported activation of different brain region during emotional stimuli and there are; amygdale, prefrontal cortex, anterior cingulated cortex, insula , hippocampus and hypothalamus [31]. Further brain imaging studies have shown that there is no specific location of EEG patterns [32,33]. This finding is quite consistent with the distribution theory whereby emotion is produced through interactions among brain regions rather than a specific brain location [34].

In this study we characterize the underlying process of emotion by computed alpha power density (PSD) for left and right brain regions during negative and positive emotional sessions. Further it will be used in a pattern recognition paradigm to recognize brain activity patterns under the emotional states. For this reason three classifiers are used; K-nearest neighbor (Knn) [35] a multilayer perceptron (MLP) with back propagation [36, 37] and regularized least squares (RLS) [38].

2.Method:

A. Emotion Stimuli

In this study we used the data from Othman et al [39]. The experiment was designed to induce positive and negative emotion in two dimensional affective space model [40]. Combinations of pictures with different valence and arousal levels were selected from Radboud database that presented four emotional stimuli, each composed of eight pictures of children faces [41]. The negative emotion is labeled as low valence = -1, and positive emotion are labeled as high valence = 1. Calm emotion is labeled when Arousal = -1, presenting in this study as low arousal (LA) and excited emotion is labeled when Arousal = 1, presenting in this study as high arousal (HA).

B. Data collection

Ten healthy children between 4 to 6 years old participated in this study. The subjects were from several pre-schools in Malaysia. The data was collected by Brain Development Group at the International Islamic university of Malaysia. Prior to data collection, experimental procedure was explained to the subjects and a consent form was signed by the participants' parents. The experiment was started with baseline condition of 1.5-minute closed eyes and 1.5-minute open eyes and then followed by 4 minutes for emotional stimuli. Subjects were seated in a comfortable chair and asked to minimize their body movements. The emotional stimuli were displayed on 15 inches screen, 75 cm away from the subjects. The emotional stimuli consisted of four emotions with different level of valence and arousal. The EEG data was recorded with eight channels BIMEC equipment (Brainmarker BV product, Netherlands). Electrodes were placed according to the international 10-20 system (C3, C4, F3, F4, P5, P6, T7, and T8 with Cz as referenced channel). Data was sampled at 250 Hz and band-pass filtered (0.5-50 Hz). Impedance of each electrode was kept below than 5 ohms. According to age group of children, EEG data was band pass filtered in range (7 to 11.5 Hz) to retain only the interesting band. Data were segmented to 2 second epoch. Each epoch was examined manually for blink eyes movement and muscles artifacts with excluded the epoch of amplitude ± 70 microvolt from all channels. The free-artifact epoch was used for further analysis.

C. Feature extraction

A mean alpha power were computed for each artifact free epoch using Fast Fourier Transform (FFT) with 1 second hanning window and with 1 Hz frequency bin [42]. The mean alpha power was computed from each channel producing feature vector set to examine alpha activity associated with subject's affective states.

D. Classification Process

We used classification process to evaluate the performance of the proposed feature for identifying emotional pattern from EEG. The feature set was divided into training set to learn the classifier and testing set (unseen data), which was not labeled. The high performance was achieved when the classifier maps out the unseen data accurately. Further, the performance of the classification process is based on the classifier and the feature set itself. Three classifiers were used in this study. A K-nearest neighbor classifier is a feed forward learning method that based on computing the standard Euclidean distance of a new instance to the nearest given classes [35]. The second classifier was Regularized least squares classifier which reflects as the Tikhonov regularization problem [38]. The regularized parameter (lambda value) was determined by one-leave out cross validation of the training data set and a Gaussian kernel was considered. The RLS was applied using MIT toolbox [43]. The last classifier was MLP with back propagation. The MLP network consisted of one input layer with number of nodes representing the features set and one output layer to present the predicated value and two hidden layers. Functions of hidden layers were set to a tangent-sigmoid and a linear function was considered for the output layer [44]. In this model, the initial values of the weights were randomly set, and the learning rate was set to 0.01. In addition, 10 nodes were used for each hidden layer and number of iterations was set to 10000. Consequently, leave one out cross validation technique was used to evaluate the performance of each classifier with the training set. The classification process was done with subject independent classification. The extracted features were divided into training and a test set with ratio of 0.8 and 0.2, respectively.

2. Result

In this study we have two purposes of using PSD; (1) to investigate alpha frontal activity on our data set of children and (2) to compare between EEG recognition system based on PSD with different classifiers respectively.

A. Alpha

Regarding Davidson study[45], we computed the mean alpha power for each brain region during affective state. **Figure 1.** presents the mean alpha power with standard derivation for left and right brain regions for negative (LV) and positive emotions (HV). Results indicate alpha right frontal activity during negative emotion. This confirms with previous studies that during negative emotion alpha activity increased in right frontal rather than in left frontal of brain region. However, there is no difference between left and right frontal alpha activity

during positive emotional state. This also confirms with studies by Feng et al [22] and Davdiosn et al [45]. For arousal level, results show alpha right activity in frontal brain regions during low arousal stimuli as demonstrate in Figure 2. However, there is alpha right activity in temporal region responding to high arousal stimuli.

An ANOVAs test was conducted to investigate the difference in PSD value among brain regions for valence and arousal levels. For each domain, we have two classes. For valence level, the electrodes F3, F4, C3, C4 and T7 indicate significant difference between positive and negative emotion ($p < 0.05$). For arousal level, the electrodes F3 and C3 show significant difference between low and high arousal with ($p < 0.05$). These results will be used later in classification process. Further, we examined the changes in mean alpha power during both eyes open and eyes-closed with emotional session. The statistical results indicate that there is a great difference between rest conditions and emotional states ($p < 0.005$) as shown in Table 1. The increase of alpha activity in whole brain region during emotion stimuli indicates the response of participants to emotion stimuli. Figure 3. shows the mean alpha power for rest conditions and emotional state.

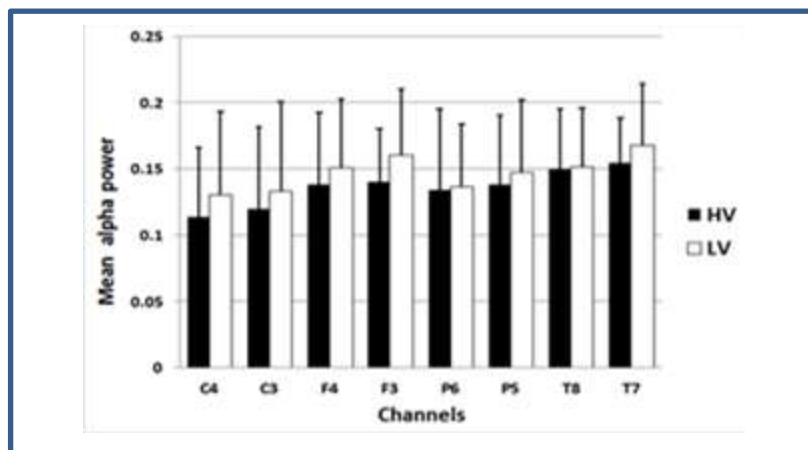


Fig 1. Mean alpha power with standard derivation for different brain regions for high and low valence level.

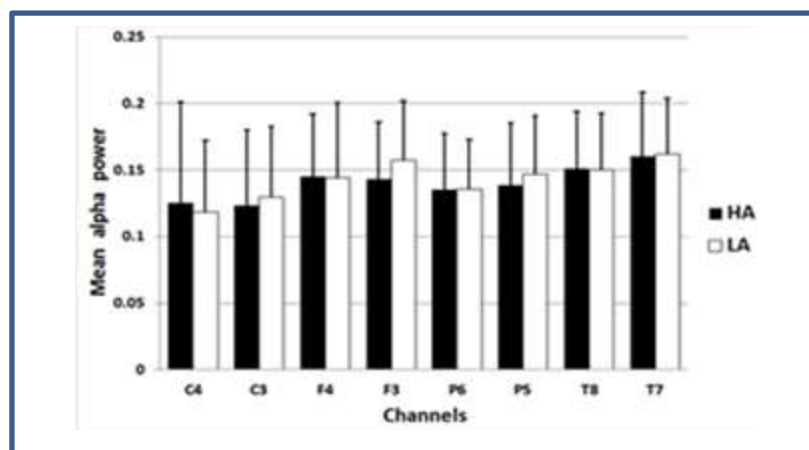


Fig 2. Mean alpha power with standard derivation for different brain regions for high and low arousal level.

Table 1. F test value for different comparison

Channel	HV-LV	HA-LA	EO-emotion	EC-emotion
C3	3.4*	2.6	6**	20**
C4	3.5*	3*	6.5**	19**
F3	4*	0.1	15**	22**
F4	12*	6*	15**	23**
P5	0.16	2	14**	26**
P6	2	0.2	15**	24.5**
T7	3.2*	0.08	14**	22**
T8	0.01	0.04	13**	19**

HV high valence; LV low valence; HA high arousal; LA low arousal; EO eyes-open; EC eyes-closed; *p < 0.05; **p << 0.005

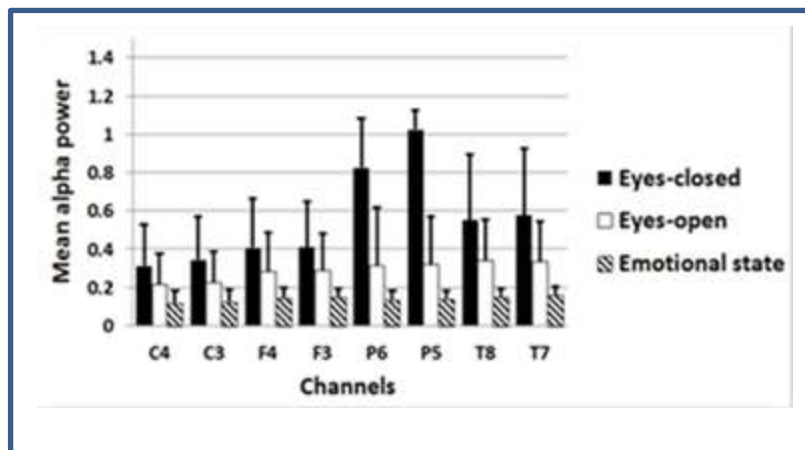


Fig 3. Mean alpha power with standard derivation for eyes closed ,eyes open and emotional state.

B. Classification process of detection emotional states

We evaluated the performance of (PSD) to detect emotional states in affective space domains (valence and arousal). The data was divided into training and testing group with ratios 0.8 and 0.2 respectively as mentioned before. The accuracy was computed using repeated random sub-sampling validation. The highest accuracy was 61 % using Knn for valence and 58 % using RLS for arousal level. **Table 2** summarizes the average accuracy and standard derivation for each class and method.

To find best discriminate between classes, we evaluated the performance of PSD after feature selection. Feature selection was performed based on repeated ANOVAs as mentioned previously with alpha value less than 0.05. The feature selection was done using all population of our dataset. Then the selected features were applied for both training and testing sets. A pair test was applied to compare the accuracy of each method. Table III summarizes the mean classification accuracy without features selection and with features selection. Obviously, there was improvement in classification accuracy using PSD with knn and RLS classifiers ($p < 0.01$).

Classification accuracy for PSD feature was improved with feature selection. The frontal, central and temporal regions are involved in discriminate among affective states. Comparison with other studies has many difficulties though each study has used different emotion stimuli, aged group and modality. However, we compared our results with methods based on using PSD and connectivity among brain regions. Regarding recent studies, Gupta et al [46] got 60% accuracy for detection arousal and valence using PSD and support vector machine (SVM). Soleymain et al [47] reported 50% classification accuracy for valence and 62% for arousal. Khosrowabadi et al [26] got 71.43% and 70.8 % for valence and arousal level respectively using coherence and Lee et al [27] reported 62% using Phase synchronization index (PSI) of alpha band. Our classification results are compatible with the previous studies and indicate the capability of RST feature to identify brain activity. Overall EEG feature based on interaction among brain region such as connectivity and our proposed approach showed high ability to detect emotional state compared to method based on specific brain region.

Table 2. Mean classification accuracy with standard derivation of detection emotional states

Method	HV	LV	HA	LA
PSD-Knn	0.60(0.03)	0.63(0.07)	0.525(0.02)	0.51(0.01)
PSD-RLS	0.58(0.06)	0.60(0.06)	0.595(0.08)	0.585(0.02)
PSD-MLP	0.49(0.37)	0.50(0.34)	0.50(0.1)	0.54(0.3)

HV;High valence ,LV;low valence,HA;high arousal,LA;low arousal

Table 3. classification accuracy with standard derivation of detection emotional states.

Methods	Without feature selection	With feature selection	P
PSD-Knn	0.55(0.018)	0.65(0.019)	2.50E-04**
PSD-RLS	0.58(0.057)	0.70(0.037)	2.00E-04**
PSD-MLP	0.50(0.28)	0.63(0.03)	0.012

HV;High valence ,LV;low valence,HA;high arousal,LA;low arousal

4. Conclusions

This study showed the benefit of characterizes brain activity by spatial temporal information to discriminate different emotional states. This study used 8 channels present different brain region with temporal domain. The power alpha wave has been computed. Different classifiers have been used to detect between high valence and low valence as well as high arousal and low arousal. Our results indicate that EEG of frontal, parietal and cortex region can characterize emotional states. Further RLS classifier show good performance to detect brain activity compared to Knn and MLP classifiers.

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