Brain Computer Interface with Low Cost Commercial EEG Device

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Abstract

In this study, a brain computer interface (BCI) system was explored. Instead of high cost EEG devices, a low cost commercial EEG device (EMOTIV) was used. Raw EEG data was obtained by using research edition SDK of EMOTIV. EMOTIV EEG device has 14 channels (10-20 placement) for EEG and two channels (x and y axis gyro: GYROX, GYROY) for head movements. Head movements and eye-blink can affect the EEG data and are usually referred to as artifacts. In this study, raw EEG data was pre-processed using the x and the y axis gyro data and the two front EEG channels, namely AF4, F8, in order to determine whether the data is artifact free or not. EEG data was collected from subjects that were asked to accomplish two cognitive tasks: pushing a cube and relaxing. Subjects performed each task for a duration of five seconds during 20 trials. The acquired EEG data was divided into 0.25 second epochs. Epochs that were determined to have artifacts were discarded. Power spectral density (PSD) and time domain based features were extracted from artifact free epochs. The features were then used to train a Support Vector Machine (SVM) to determine the corresponding task. The performance of the SVM classifier was compared to that of an Artifical Neural Network (ANN) based one. Experimental results show the efficacy of the SVM based scheme.

Key words: Classification, EEG, Cognitive Task, SVM

1. Introduction

Understanding the human brain has become a scientific endeavor for centuries. In 1929, a German scientist Hans Berger developed a system called electro-encephalo-gram (EEG) for the measurement of the brain electrical activities using electrodes [1]. EEG signals are categorized into five main frequency bands: delta (0-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-60 Hz). These frequency bands are given in Table 1. In the literature, EEG signal analysis was used in various fields such as epilepsy detection [2, 3], sleep research [4, 5], anesthetic depth detection [6] and BCI systems [7].

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Table 1. Brain waves

Brain waves	**Condition**
Delta(0-4 Hz)	Deep sleep
Theta (4-8 Hz)	Deep relaxing
Alpha (8-12 Hz)	Creative visualization
Beta (12-30 Hz)	Consciously alert

BCI systems can interact with and control devices through manipulating the brain activity. They are generally user dependent because of the variability in EEG data among different people. Academic interest still continues on developing user independent BCI systems [8]. The first step in developing a BCI system is the design of the cognitive tasks to be performed by the users. In the literature, generally high cost EEG devices were used for acquiring EEG data in BCI applications. In this study, a low cost commercial EEG device (Emotiv Headset) was used for the proposed BCI system. Emotiv Epoch system has increased the accessibility of EEG systems with its affordable price for researchers. It is a wireless system which does not require an expert assistance for the electrode placement. A lot of research has been performed in the literature using Emotiv Neuro-Headset. O'Connor controlled a robot arm with neuroheadset in real time. He used an SVM model for classifying the pre-defined cognitive tasks [9]. Karolina and her team used steady state visual evoked potentials for their Emotiv Epoc based BCI system. They used a LED display that consists of four fields which flicker in different frequencies. They collected EEG data from the O1 electrode during 4 second intervals. They used the power spectral density as a feature vector and used the classification tree method for the classification task [10]. In this study, two different cognitive tasks, namely pushing a cube and relaxing, were defined. In general, subjects must be trained for each cognitive task to use a BCI system effectively. Therefore, subjects were trained using the cognitive suit software interface of the Emotiv neuroheadset. EEG data was then collected from users who successfully completed the training phase. The acquired EEG data was divided into 0.25 second epochs. Epochs that were determined to have artifacts were discarded. Power spectral density and time domain features were extracted from artifact free epochs. The features were then used to train a Support Vector Machine (SVM) model to determine the corresponding task. Experimental results show the efficacy of the proposed scheme.

2. EEG Data Collection

In this study, Emotiv EEG device was used for EEG data collection. The device has 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) with digital notch filters at 50Hz and 60 Hz for EEG data collection. Emotiv’s electrode placement system is depicted in Fig. 1. The sampling rate and the resolution for the Emotiv EEG system are 128 Hz and 14 bits, respectively.

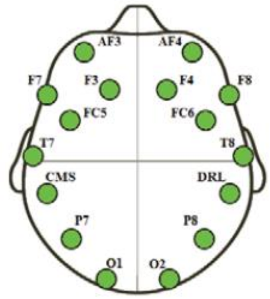

Figure 1. Emotive epoch electrode placement [10]

Emotiv has easier set-up than conventional EEG devices. To improve conductivity, the electrodes were wetted with a commonly used saline solution before the data collection. In Fig.2 Emotiv neuroheadset is shown. In addition to standard EEG channels, EEG Emotiv headset has two channels (x and y axis gyro: GYROX, GYROY) for measuring gyroscopic movement of the head.

Two subjects were asked to perform pre-defined tasks after a training phase. EEG data was obtained from the subjects that tried to perform each task for five seconds during 20 trials. The front 7 channels (AF3; AF4; F7; F3; FC5; FC6; F8) were selected for the analysis after a visual inspection of the data. At the end of the experiments, for each channel 100 seconds of data were acquired for each task performed by a subject.

Figure 2. Emotiv epoch system [11]

2.1. Artifact Elimination

Head movements and eye-blink can affect the EEG data and are usually referred to as artifacts. In this study, captured EEG signals were divided into 0.25 second time windows. Before processing the EEG signal in each window, two kinds of eliminations were applied. Firstly, gyro data based elimination was performed for detecting undesired head movements. The mean value of the first order derivative of gyro data in time domain (GYROX and GYROY) was calculated for each window. Windows which have a mean value lower than a certain threshold, were accepted as artifact free windows. The remaining windows were discarded and not used in the task classification. Sample gyro data and the head movement artifact detection results are given in Fig.3.

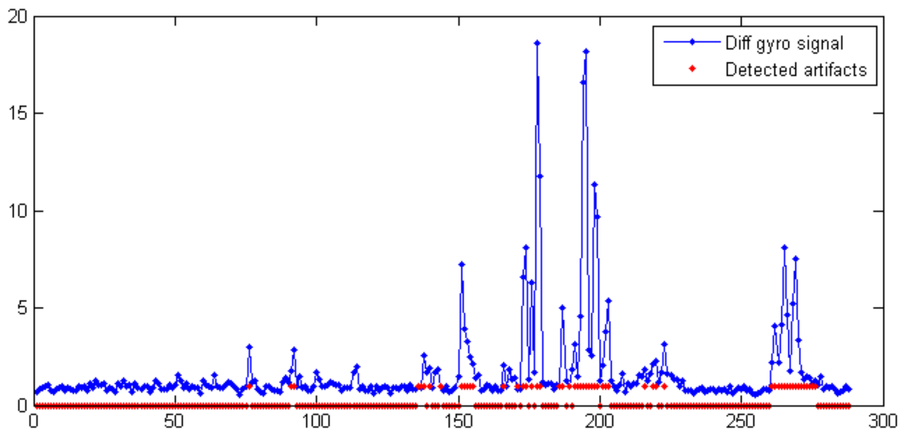

Figure 3. Artifact elimination for head movements

Eye blinks can also affect the EEG data. To detect windows corrupted with eye blinks, energy based elimination method was applied to the two front EEG channels (AF4, F8). For each 0.25 second time window, the energies of the AF4 and F8 channels were computed. Windows which have energy greater than a pre-determined threshold, were discarded. Sample EEG signal collected from the AF4 channel and the eye-blink artifact detection results are given in Fig.4.

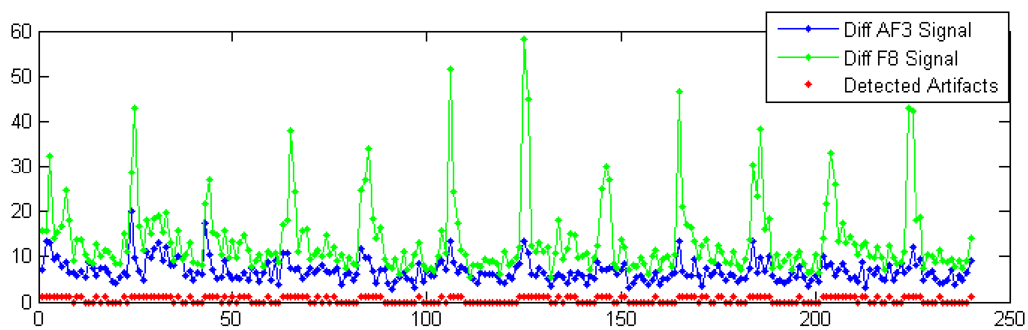

Figure 4. Artifact elimination for eye blinks

3. EEG Signal Processing

The acquired raw EEG data was processed offline by the developed algorithm in MATLAB environment. EEG data was divided into 0.25 epochs (32 samples) resulting in 5600 epochs for each defined task. However, 352 epochs corresponding to the pushing a cube task were discarded due to either head movemenent or eye-blink artifacts.

3.1. Feature Extraction

In this study, energies of pre-defined EEG bands and time domain features like line length and approximate entropy were included in the feature vector. The line-length quantifies the predictability of a signal and can be calculated as follows,

$$L = \sum_{j=1}^{N} \left| x_{j+1} - x_j \right| \tag{1}$$

In addition to line-length, approximate entropy (ApEn) is another way to measure predictability of a signal. ApEn is a widely used feature for EEG analysis [12]. Unpredictable signals have obviously higher ApEn values than predictable signals. EEG data collected during the pushing a cube cognitive task has higher ApEn value as compared to relaxing task. Steps for calculating ApEn of an N point time series y_i, i =1,…, N is given below. First, the state vectors in the embedded space are defined as,

$$X_i = \{y_i, y_{i+\tau}, y_{i+2\tau}, \ldots, y_{i+(m-1)\tau}\}, \quad 1 \le i \le N-(m-1)\tau \tag{2}$$

, where m represents the embedding dimension and τ represents the time delay. For each i, we define

$$C_i^m(r) = \frac{1}{N-(m-1)\tau} \sum_{j=1} \theta(r - d(x(i), x(j))) \tag{3}$$

θ is the standard heavyside function and is defined as,

$$\theta(x) = \begin{cases} 1, & x >= 0 \\ 0, & otherwise \end{cases} \tag{4}$$

r is the vector comparison distance and is defined as,

$$d(x_i, x_j) = \max_{k=1,2\ldots m} \left(\left| y(i+(k-1)\tau) - \right| y(j+(k-1)\tau) \right) \tag{5}$$

Next, $\phi^m(r)$ is be defined as,

$$\phi^m(r) = \frac{1}{N-(m-1)\tau} \sum_{i=1} \log C_i^m(r) \tag{6}$$

Finally, ApEn of a signal for fixed m, r, τ can be calculated as,

$$ApEn = \phi^m(r) - \phi^{m+1}(r) \tag{7}$$

In this study, EEG band energies, line-length and ApEn were used as a feature vector for classification. During the experiments, it was observed that including the delta band energy in the feature vector decreased the classification performance. It was also visually verified that delta waves do not change during the defined tasks. Therefore, theta, alpha and beta band energies were included in the feature vector.

4. SVM and ANN based Classification and Results

SVM, which was developed by Vapnik in 1992, is a supervised learning method which is commonly used in classification tasks. SVM implements the following idea: input vectors are non-linearly mapped into a very high dimensional feature space. A linear decision surface is constructed in this feature space. SVM classification technique is frequently used in EEG signal processing [8]. In this study, EEG signals were classified using SVM. Confusion table for developed classification system is given in Table 2. The sensitivity and the specificity of classification scheme were calculated to be 0.99 and 0.98, respectively.

Table 2. Confusion matrix of proposed SVM classifier

	Pushing Cube	Relaxing
Pushing Cube	5165	83
Relaxing	9	5551

The SVM classification accuracies for the relaxing task, pushing a cube task and total accuracy was calculated as 98.4%, 99.8% and 99.1% respectively.

Besides SVM, ANN is another frequently used classification technique in EEG signal processing [13]. ANNs are computer programs inspired from the biological nervous system. Although first artificial neuron was produced by McCulloh in 1943, the technique was started to be used frequently for classification after the investigation of the back propagation method by Rumelhart in 1986 [14]. ANN based classification scheme was applied to the same EEG data. Confusion table for the ANN classification system is given in Table 3. The sensitivity and the specificity of classification scheme were calculated to be 0.97 and 0.96, respectively.

Table 3. Confusion matrix of proposed ANN classifier

	Pushing Cube	Relaxing
Pushing Cube	5038	210
Relaxing	112	5488

The ANN classification accuracies for the relaxing task, pushing a cube task and total accuracy was calculated as 96%, 98% and 97% respectively. The experimental results show that in both techniques, classification accuracy of the relax task is greater than pushing a cube task. In overall, SVM based classification scheme performed better than the ANN based one.

5. Conclusions and Future Work

In this study, a BCI scheme was developed by processing EEG signals which were captured by a low cost commercial neuroheadset. Two cognitive tasks: pushing a cube and relaxing were performed by each subject. EEG data was processed offline by the developed algorithm in MATLAB. In the future, number of cognitive tasks will be increased to three and the developed program will be modified for real time EEG data processing.

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