A Ten-Channel Brain-Computer Interface System Based on Six Mental Tasks

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Abstract— **In brain-computer interfaces (BCI), choosing small number of recording channels and also suitable mental tasks play an important role. The chosen mental tasks must be selected in a way that they can be easily imagined by users and also do not lead to users' fatigue. In addition, the more the number of these tasks, the more complexity will be involved in designing such systems, but users would have more degree of freedom to communicate with their surroundings. In this study, a noninvasive BCI system by using 10 EEG channels and based on six imagery movements has been proposed. The EEG signals of 4 subjects have been recorded during a predetermined session. After removing noises and artifacts, proper feature extraction methods have been implemented in time and frequency domains. Then Linear Discriminant Analysis (LDA) has been applied on the features in order to remove the linear dependency exists between them. Finally, in average, the correct classification result of 88.42% has been achieved using Bayesian classifier.**

Keywords- Brain-computer interface (BCI); Linear discriminant analysis (LDA); Electroencephalogram (EEG); Baysian classifier

I. INTRODUCTION

Brain-Computer Interface (BCI) can be considered as a means of communication between the human brain and his surroundings. In BCI systems, usually Electroencephalographic (EEG) signals are recorded from the skull in a noninvasive way. The recording take place during performing different mental activities by a subject, and the recorded signals are then analyzed in a computer or any other suitable processing unit. After pre-processing stages, the EEG signal is classified where each class corresponds to one of the mental tasks [1].

A BCI system can help users to control their real or virtual environment via brain signals, by establishing a communication link between them and computer. This would especially help disable people who are unable to move their limbs. Preliminary works in this context have been done in 1990 by Aunon and Keirn in Colorado University [1]. After them, many researchers have attempted to develop new strategies for achieving this goal by defining new specific tasks, using smaller number of recording channels or applying innovative processing techniques.

One essential step to achieve a proper BCI system is determining suitable mental tasks. These mental tasks must be easily imaginable, should not cause fatigue, and also must have enough separability from each other. In order to reach the appropriate separability, selected mental tasks should lead to different brain patterns. In this study, we have proposed a brain-computer interface system which is capable to classify six different mental activities, by using only 10 EEG channels.

The remaining of the paper is as follows: In section II, signal acquisition and processing are discussed in detail. The results are reported and also discussed in section III. Finally, in section IV, the conclusion is drawn.

II. METHODS

A. *signal acquisition*

We used NRSIGN3840 EEG recording system with 500 Hz sampling rate at the School of Electrical and Computer Engineering, University of Tehran for recording our dataset. These data were recorded from four subjects (two males and two females; all right-handed; 23 to 25 years old). By considering topographic map of brain [2], we have selected six mental tasks, which are imagery movements of right hand, left hand, face, feet, tongue and head. One advantage of using imagery movement as mental task is that the subjects have usually reported ease of performing such mental activities comparing to some other types of mental activities (e.g. arithmetic calculation).

In human, the preparation of both physical movement and imagery movement changes the so-called sensorimotor rhythms (SMR), which refers to oscillations in brain activity recorded from somatosensory and motor areas [3]. That is why it has been proposed to process the signals recorded from electrodes which are in contact with these areas. By considering this issue, we have used ten electrodes of C3, C4, Cz, F3, F4, P3, P4, Pz, T3 and T4 referenced to an electrode placed on forehead (according 10-20 international standard).

All subjects, whose EEG were to be recorded, sat on a chair in front of a monitor and tried to control their brain activity in accordance with some cues given on the monitor. Data collection from each subject included ten runs and lasted about half an hour. Each run was consisted of three 10-seconds-trials of each mental task (see Fig. 1). Between each run, the subjects could have one or two minutes break.

As it can be seen in Fig. 1, at first (0-2 s), a cross symbol accompanying with a short “beep” tone is shown on the screen. This symbol is used for informing the subject about the beginning of the trial. Then, a cue appears on the screen to inform the subject about the desired motor imagery. Between second 3 and 8, the user imagines the mentioned mental activity.

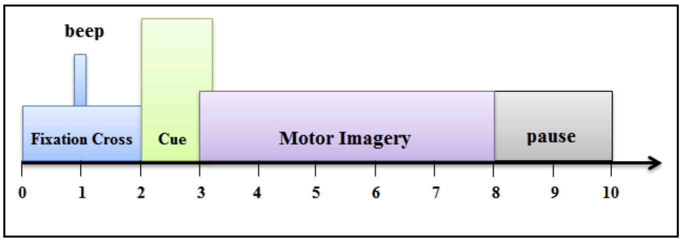

Figure 1. Timing of each trial

B. Preprocessing

The recorded brain signals contain several disturbances originating from surroundings, inside body or recording machine. Preprocessing is all the processes that are performed for removing these undesirable noises and artifacts.

Brain signals, generally, have a frequency range between 0.5 and 100 Hz [4] which includes alpha and beta bands. These bands are considered as the most important bands for imagery movements [3]. For removing unwanted components of the signals (out of 0.5-100 Hz), the raw signals have been filtered by using 50^{th} order linear-phase FIR filter. In addition, a 50 Hz Notch filter has been applied on the signals in order to remove the electrical power line interference.

Independent Component Analysis (ICA) is a statistical technique for transforming data from various channels into independent and non-Gaussian distributed components [5], [6]. ICA has been applied on our date for removing the artifacts related to eyes, which includes eyes movements and blinking. The algorithm that we have used is FastICA which is based on a fixed-point iteration scheme for maximizing the non-gausssianity which is measured by estimating negentropy [5].

After removing noises and artifacts, the signal has been divided into 1 second long segments, where each segment has 50% overlap with its adjacent segments. Due to the size of each segment (which is below 2 seconds) the stationary problem of EEG signals can be neglected [7].

C. Feature Extraction

Seventy two features, explained as follows, have been extracted from each of the ten mentioned channels (totally 720 features).

Using spectral analysis is very common in BCI, because of providing effective features. We have applied an autoregressive method for estimating the power spectral density (PSD) of the signals [8]. Then we have divided the spectrum into ten frequency sub-bands. These sub-bands are represented in TABLE I. For each sub-band, the ratio between the sub-band spectral power (BSP) and the total spectral power, called the relative spectral power (RSP), has been computed.

TABLE I. SPECTRAL SUB-BANDS USED IN RSP COMPUTATION [9]

Bands	Sub-bands	Bandwidth $\{f_L, f_H\}$ (Hz)
Delta	Delta 1 Delta 2	{0.5,2.0} {2.0,4.0}
Theta	Theta 1 Theta 2	{4.0,6.0} {6.0,8.0}
Alpha	Alpha 1 Alpha 2	{8.0,10.0} {10.0,12.0}
Sigma	Sigma 1 Sigma 2	{12.0,14.0} {14.0,16.0}
Beta	Beta 1 Beta 2	{16.0,25.0} {25.0,35.0}

For highlighting some spectral bands over slow wave bands, delta-slow-wave index (*DSI*), theta-slow-wave index (*TSI*) and alpha-slow-wave index (*ASI*), defined by the following ratios, have been extracted from the signals [9].

$$DSI = BSP_{Delta} / (BSP_{Theta} + BSP_{Alpha}) \tag{1}$$

$$TSI = BSP_{Theta} / (BSP_{Delta} + BSP_{Alpha}) \tag{2}$$

$$ASI = BSP_{Alpha} / (BSP_{Delta} + BSP_{Theta}) \tag{3}$$

The other features extracted from the EEG signals are harmonic parameters, which are center frequency (f_c), bandwidth (f_σ) and spectral value at center frequency (S_{fc}) [10]. These three parameters are defined in (4), (5) and (6). In these equations $P_{xx}(f)$ denotes the PSD of the desired frequency band.

$$f_c = \sum_{f_L}^{f_H} f P_{xx}(f) / \sum_{f_L}^{f_H} P_{xx}(f) \tag{4}$$

$$f_\sigma = \left(\sum_{f_L}^{f_H} (f - f_c)^2 P_{xx}(f) / \sum_{f_L}^{f_H} P_{xx}(f) \right)^{1/2} \tag{5}$$

$$S_{f_c} = P_{xx}(f_c) \tag{6}$$

The Hjorth parameters of the EEG signals, defined in (7), (8) and (9), have been considered as our other features [11].

$$Activity(x) = \mathrm{var}(x) = \frac{1}{N} \sum_{n=1}^{N} (x(n) - \bar{x})^2 \tag{7}$$

$$Mobility = \sqrt{\mathrm{var}(x') / \mathrm{var}(x)} \tag{8}$$

$$Complexity = \sqrt{\mathrm{var}(x'') \times \mathrm{var}(x) / \mathrm{var}(x')^2} \tag{9}$$

where x is a EEG segment with length of N. x' and x'' are the first and second derivatives of x, respectively.

We computed *skewness* and *kurtosis* for characterizing probability distribution of our data. These measures can be calculated by using (10) and (11), in which m_k is the k^{th} order momentum [12].

$$skewness = m_3 / m_2 \times \sqrt{m_2} \tag{10}$$

$$kurtosis = m_4 / m_2 \times m_2 \tag{11}$$

The last features that have been extracted from our EEG signals are coefficients of discrete cosine transform (DCT) and Autoregressive (AR) model [7], [13], [14].

D. Dimension Reduction and Classification

Linear Discriminant Analysis (LDA) is a linear transformation technique used for dimension reduction. In fact, in LDA new features are constructed by combining previous features. In addition to dimension reduction, applying LDA reduces linear dependency between the features [15]. By applying LDA on our extracted features, 95% of separability could be saved by selecting only the first 5 combined features (components). Therefore the total number of the extracted features (i.e. 72 features * 10 channels) has been reduced to 5, for each 1 second trial.

We have used Bayesian classifier with Gaussian distribution assumption [16] for classifying our final dimensionally reduced features into six different classes. Seventy percent of the data (for all classes) has been chosen randomly for training the classifier, and the other thirty percent has been left for testing.

III. RESULTS & DISCUSSION

For evaluating the performance of our ten-channel based BCI system, we have calculated Correct Classification Rate (CCR) for the test data, considering all 6 classes. The resulted CCRs for all subjects are presented in TABLE II. The random selection of training and testing data has been repeated 5 times. Thus, the presented CCRs in TABLE II are average of these values (considering all the random selections). The standard deviation of the calculated CCRs is also shown in TABLE II.

TABLE II. CCR AND IT'S STANDARD DEVIATION FOR ALL SUBJECTS

Subject	1	2	3	4
CCR %	91.33	88.59	88.55	85.19
STD	1.35	1.12	0.40	0.59

It can be observed that in average the system is able to recognize all 6 classes correctly for 88.41% of cases (with appropriately low standard deviation). For studying the suitability of each imagery movement, the diagonal elements of confusion matrix, which are related to the number of correct data classification in each class, have been evaluated (see TABLE III). Each class has 90 test samples. The class numbers stated in TABLE III are related to imaginary movements of right hand, left hand, face, legs, tongue, and head, respectively.

TABLE III. CORRECT CLASSIFICATION RATE (%) OF EACH CLASS (FOR ONE OF THE RANDOM SELECTIONS)

	Class Numbers					
	1	2	3	4	5	6
Subj. 1	93.33	93.33	87.78	88.89	90.00	93.33
Subj. 2	86.67	84.44	92.22	91.11	92.22	86.67
Subj. 3	92.22	88.89	91.11	90.00	81.11	87.78
Subj. 4	84.44	91.11	82.22	80.00	81.11	93.33
Mean	89.17	89.44	88.33	87.50	86.11	90.28

According to TABLE III, all classes show proper performance. In other words, we cannot say that a specific class has a better or worse performance. If we consider their average value, the best performance is for the sixth class (head imagery movement) and the worst performance is for the fifth class (tongue imagery movement). Finally, we can conclude that resultant combined features of LDA show appropriate performance and show the distinction among these six imaginary movement classes. To further evaluate this issue, the histogram of first three combined features are shown in Fig. 2 with blue, red and green colors respectively for the first subject, considering all classes. All of these features have been normalized in the [-1, 1] interval.

As it is clear in Fig. 2, each of these features has different distributions and values for six classes. For example, the first feature (blue color) for the first class has positive value in [0, 0.5] interval in most of the cases, whereas it has the most negative values and near zeroes values for the second and the fourth classes, respectively. Moreover, in Fig. 3 the scattering plots of the four subjects are shown. Due to the difficulty of plotting the effect of all 5 combined features (output of LDA), we have illustrated the scattering plot of the best 3 combined features in Fig. 3. Yet, by considering only 3 combined features (instead of 5), it can be seen in Fig. 3 that these features are capable of separating 6 imagery movements.

IV. CONCLUSION

In this paper, we have proposed a synchronous BCI system based on 10 EEG channels and 6 imagery movements. This system was custom-designed and mental task-based. Different time and frequency domain methods have been applied to extract necessary features from the EEG signals and Bayesian classifier has been used as a classifier. By using 5 combined features extracted from 10 EEG channels, the subjects' mental tasks could be recognized correctly in 88.41% of the cases (in average).

It should be mentioned that separating all 6 simple mental tasks by using only 10 EEG channels and 5 combined features can be considered as an important achievement. In fact, the capability of giving 6 different orders (many research is based on 2 or 3 mental tasks) and avoiding using all the recording channels can be helpful for designing effective and practical BCI systems. In brief, the results are promising and make BCI systems more appealing devices for those who would be able to benefit from them.

As a future work, other methods of pattern recognition can be applied for evaluating the possibility of reducing number of extracted features and/or channels, while maintaining an acceptable rate of correct classification.

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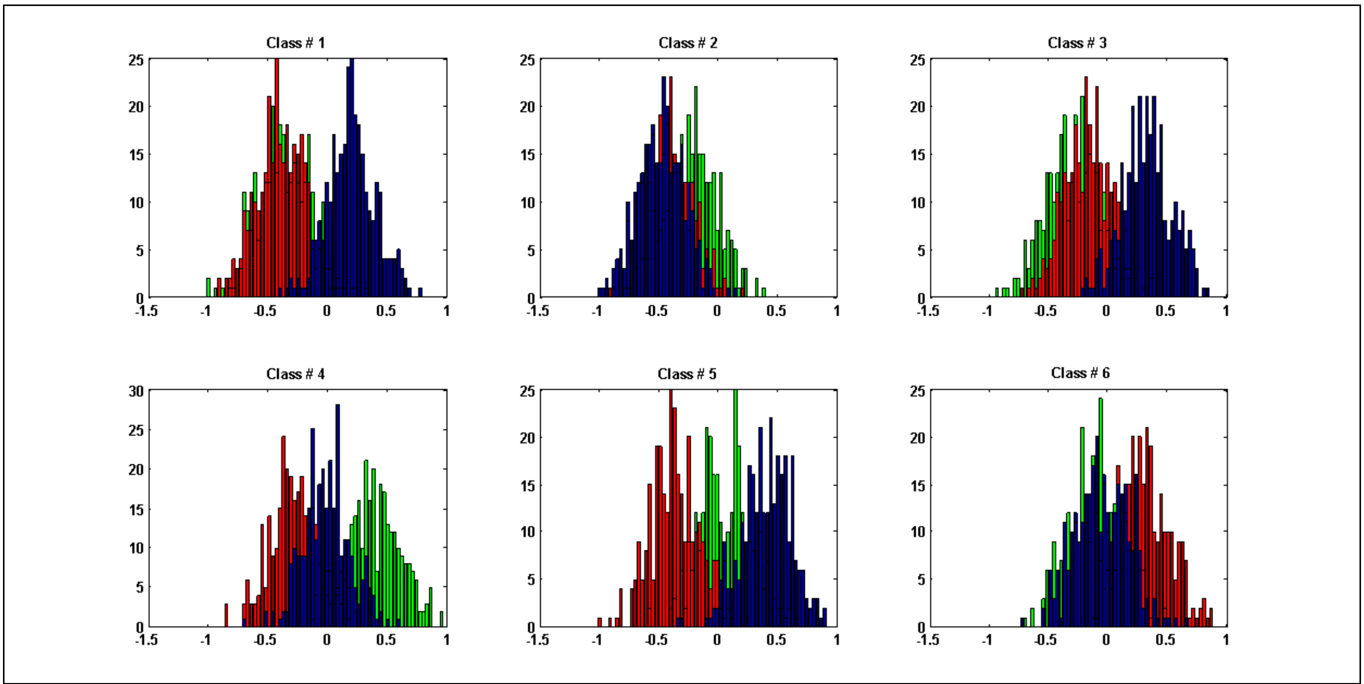

Figure 2. Distribution (histogram) of the first three combined features for the first subject (considering all 6 classes)

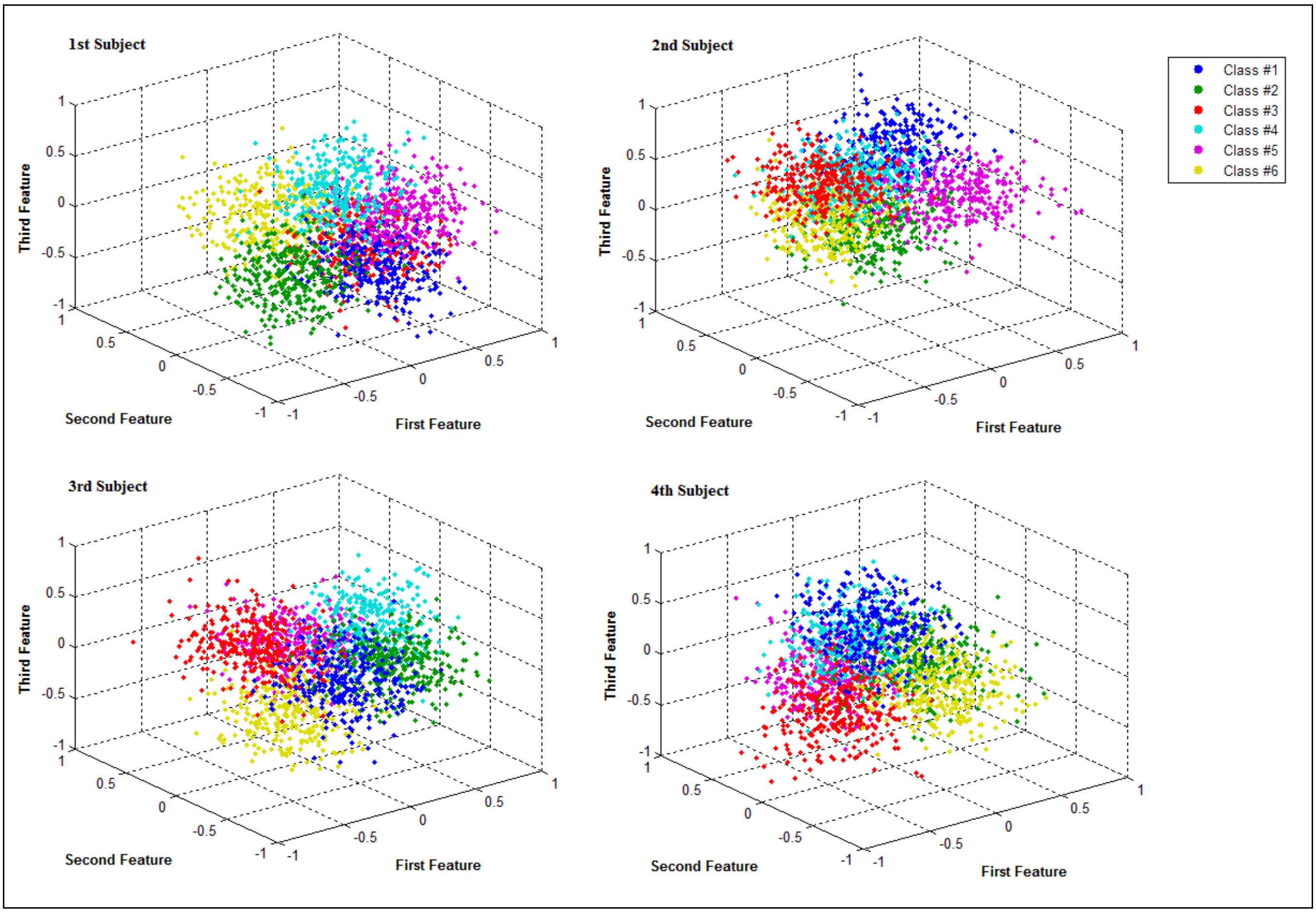

Figure 3. 3D scatter plot of the first three combined features for all subjects (considering all 6 classes)