A Comparison among Classification Accuracy of Neural Network, FLDA and BLDA in P300-based BCI System

Ali Bakhshi
Shahrood Branch, Islamic Azad University
Shahrood, Iran

Alireza Ahmadifard
Shahrood University of Technology
Shahrood, Iran

ABSTRACT
In the past decade, many studies focused on communication systems that translate brain activities into commands for a computer or other devices that called brain computer interface (BCI). In this study, we present a BCI system that achieves high classification accuracy with Neural Network (NN), Fisher Linear Discriminant Analysis (FLDA) and Bayesian Linear Discriminant Analysis (BLDA) for both disabled and able-bodies subjects. The system is based on the P300 evoked potential and is tested with four able-bodied and five severely disabled subjects. The effect of different electrode configurations on accuracy of machine learning Algorithms is tested and effect of other factors on classification accuracy in P300-based systems are discussed.

General Terms
Medical Signal Processing

Keywords
Classification, Event Related Potential, P300 Evoked Potential, Neural Network, Bayesian's Linear Discriminant Analysis.

1. INTRODUCTION
The major goal of BCI research is to develop systems that make it possible for disabled users to communicate with others, to control artificial limbs or their environment. To control signals for brain–computer interface (BCI) applications, several different features of EEG signals are being used; most markedly, event-related potentials (Donchin et al., 2000; Farwell and Donchin, 1988; Serby et al., 2005), spontaneous sensory motor rhythms (Wolpaw and McFarland, 2004; Pfurtscheller et al., 1996), and slow cortical potentials (Birbaumer et al., 1999). A comprehensive review is provided by Wolpaw et al. (2002). Many researchers have confirmed BCI accuracy high enough for online communication (Farwell and Donchin, 1988; Kübler et al., 2005; Serby et al., 2005; Wolpaw and McFarland, 2004). Besides, researchers have also reported that patients with amyotrophic lateral sclerosis (ALS) can use BCI systems with accuracy levels acceptable for communication using slow cortical potentials, mu rhythms, or P300 event-related potentials (Birbaumer et al., 1999, 2000; Kübler et al., 2005; Sellers and Donchin, 2006). These findings from ALS patients are very important because people who suffer from ALS and other severe motor disabilities are the most likely candidates for long-term use of BCI systems [1].

In this study, we discuss BCI systems for disabled users based on a noninvasive method to measure brain-activity, namely the electroencephalogram (EEG). Several kinds of mental activities may be used to implement a BCI system; they can be divided into two main groups according to how they are generated; using evoked input (e.g. visual evoked potentials and P300) and spontaneous input (e.g. slow cortical potentials, sensory motor rhythms and Non-motor Cognitive Tasks) [2] . In the present work, a control-signal is used that can be detected reliably and does not require extended subject training: the P300 event-related potential.

The P300 wave is an event-related Potential (ERP) which can be recorded via EEG. The wave corresponds to a positive deflection in voltage at latency of about 300 ms in the EEG. In other words, it means that after an event like a flashing light, a deflection in the signal should occur after 300 ms [3]. The most important applications of the technology are mainly meant for the paralyzed people who are suffering from severe neuromuscular disorders, as BCI potentially provides them with communication, control, or rehabilitation tools to help compensate for or restore their lost abilities [4].

Farwell and Donchin (1988) were the first to employ the P300 as a control-signal in a BCI. They described the P300 speller system, with which subjects were able to spell words by sequentially choosing letters from the alphabet. A 6×6 matrix containing the letters of the alphabet and other symbols was displayed on a computer screen. Rows and columns of the matrix were flashed in random order. To choose a symbol, subjects had to silently count how often it was flashed. Flashes of the row or column containing the desired symbol evoked P300-like EEG signals, while flashes of other rows and columns corresponded to neutral EEG signals. The target symbol could be inferred with a simple algorithm that searched for the row and column which evoked the largest P300 amplitude. Since the work of Farwell and Donchin much of the research in the area of P300 based BCI systems has concentrated on developing new application scenarios (see for example Polikoff et al. (1995), Bayliss (2003)), and on developing new algorithms for the detection of the P300 from possibly noisy data (see for example Xu et al. (2004), Kaper et al. (2004), Rakotomamonjy et al. (2005), Hoffmann et al. (2005), Thulasidas et al. (2006)). Recently, two studies have been published in which P300-based BCI systems were tested with disabled subjects. These studies are described in the following. Piccione et al. (2006) tested a 2D cursor control system with five disabled and seven able-bodied subjects. For cursor control, a four-choice P300 paradigm was used. Subjects had to concentrate on one of four arrows flashing every 2.5 s in random order in the peripheral area of a computer screen. Signals were recorded from one electrooculogram electrode and four EEG electrodes, preprocessed with independent component analysis and classified with a neural network. The results described by Piccione et al. showed that the P300 is a viable control-signal for disabled subjects. However the average communication speed obtained in their study was relatively low when compared to state of the art systems, as for example the systems described by Kaper et al. (2004), Thulasidas et al. (2006). This was the case for the disabled subjects, as well as for able-bodied subjects and can probably be ascribed to the use of signals from only few electrodes, the small number of different stimuli, and long inter stimulus intervals (ISIs). Sellers and Donchin (2006) also used a four-choice paradigm and tested their system with three subjects suffering from ALS and three able-bodied subjects. In their study four stimuli ('YES', 'NO', 'PASS', 'END') were presented every 1.4 s in random order, either in the visual modality, in the auditory modality, or in a combined auditory–visual modality. Signals from three electrodes were classified with a stepwise linear discriminant algorithm. The research of Sellers and Donchin showed that P300 based communication is possible for subjects suffering from ALS. The research also showed that communication is possible in the visual, auditory, and combined auditory-visual modality [5].

In the present work, a six-choice P300 paradigm is tested using a population of five disabled and four able-bodied subjects. Six different images were flashed in random order with an ISI of 400 ms. Electrode configurations consisting of 4, 8, 16 and 32 electrodes were tested. Bayesian Linear Discriminant Analysis (BLDA) and Neural Network (NN) were tested for classification. For four of the disabled subjects and for all the able-bodied subjects communication rates and classification accuracies were obtained that are superior to those of Piccione et al. (2006) and Sellers and Donchin (2006). Factors that are possibly important for obtaining good classification accuracy in BCI systems for disabled subjects are discussed.

2. MLP NEURAL NETWORK

Multilayer perceptron (MLP) neural networks with sufficiently many nonlinear units in a single hidden layer have been established as universal function approximators [5,6]. MLPs have several significant advantages over conventional approximations. First, MLP basis functions (hidden unit outputs) change adaptively during training, making it unnecessary for the user to choose them beforehand. Second, the number of free parameters in the MLP can be clearly increased in small increments by simply increasing the number of hidden units. Third, MLP basis functions are bounded, make round-off and overflow errors unlikely. Disadvantages of the MLP relative to conventional approximations include its long training time and its sensitivity to initial weight values [8].

The network topology used in this study, is composed of three layers, which are themselves composed of several units. The classifier architecture is illustrated in Fig.1. The number of neurons for each layer is presented between brackets.

The two transfer function, 'logsig' and 'tansig' is used for hidden layer and output layer, respectively. The dimensionality of input feature vector is n×m that as represented in Table 1. In multilayer feed-forward networks, each neuron arranged in layers connected to the neuron in subsequent layer with only forward connections. The connections have weights associated with them. Each signal traveling along the link is multiplied by the connection weight.

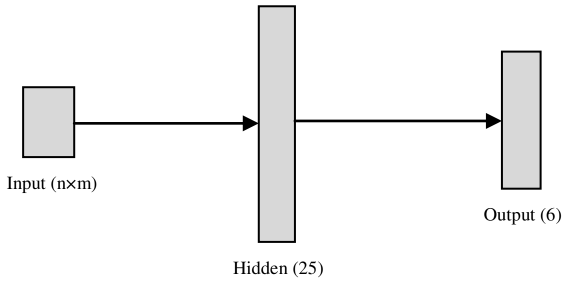

Fig 1: Neural Network Architecture

As presented in Figure 1 the input neurons in first layer, distribute the inputs to neurons in subsequent layers. In the next layers, each neuron sums its inputs and adds a bias or threshold term to the sum and nonlinearly transforms the sum to produce an output.

3. FISHER LINEAR DISCRIMINANT ANALYSIS

The objective in Fisher linear discriminant analysis (FLDA) is to find a linear combination of features to compute a discriminant vector that separates two or more classes as well as possible in statistics, pattern recognition and machine learning.
A potential problem in FLDA is that the within-class scatter matrix can become singular, and the inverse of it can become ill-defined. In particular, this happens when the number of features becomes larger than the number of training Examples [5].

4. BAYESIAN LINEAR DISCRIMINANT ANALYSIS

BLDA can be considered as an extension of Fisher's Linear Discriminant Analysis (FLDA). Here, the main problem in FLDA is solved. In BLDA, to prevent overfitting to high dimensional and possibly noisy datasets, the regularization is used and through this analysis the degree of regularization can be estimated automatically and quickly from training data without the need for time consuming cross-validation.

Algorithms that are closely related to the method used here are the Bayesian least-squares support vector machine (Van Gestel et al., 2002) and the algorithm for Bayesian non-linear discriminant analysis described by Centeno and Lawrence (2006). BLDA is also closely related to the so-called evidence framework for which detailed accounts are given by MacKay (1992) and Bishop (2006) [5].

5. DATABASE

In the present Study, a six-choice P300 paradigm is tested using a population of five disabled and four able-bodied subjects. In every run, six different images were flashed in random order with an inter stimulus interval (ISI) of 400 msec. Electrode configurations consisting of 4, 8, 16 and 32 electrodes were tested [6]. Fisher Linear Discriminant Analysis (FLDA), Bayesian Linear Discriminant Analysis (BLDA) and Neural Network were tested for classification. It should be mentioned that the biological and mental condition of candidate during signal recording and concentration and its motivation through the experiment are very effective on getting high-quality database.

6. RESULTS

In order to achieve more promising results we apply several preprocessing operations prior to learning a classification function and validation stage. These preprocessings are as follows:

(i) Referencing; the average signal from the two mastoids Electrodes were used for referencing.

(ii) Filtering; a six-order forward–backward Butterworth bandpass filter was used to filter the data. Cut-off frequencies were set to 1.0 Hz and 12.0 Hz. The MATLAB function "butter" was used to compute the filter coefficients and the function "filtfilt" was used for filtering.

(iii) Downsampling; the EEG was down sampled from 2048 Hz to 32 Hz by selecting each 64th sample from the bandpass-filtered data.

(iv) Single trial extraction; Single trials of duration 1000 ms were extracted from the data. Single trials started at first stimulus, i.e. at the beginning of the strengthening of an image, and ended 1000 ms after stimulus onset. Due to the ISI of 400 ms, the last 600 ms of each trial were overlapping with the first 600 ms of the following trial.

(v) Windsorizing; eye blinks, environment, muscle activity, or subject movement can cause large amplitude outliers in the EEG. The effects of such outliers can be decreased by windsorizing the data from each electrode. The algorithm described in Hoffmann et al. (2006) was used for preprocessing and the algorithm described in Hoffmann et al. (2004) was used for classification. In this way, the 10th percentile and the 90th percentile from each electrode were computed. Amplitude values lying below the 10th percentile or above the 90th percentile were then replaced by the 10th percentile or the 90th percentile, respectively.

(vi) Scaling; the samples from each electrode were scaled to the interval [−1, 1].

(vii) Electrode selection; four electrode configurations with different numbers of electrodes were tested.

(viii) Feature vector construction:

a) BLDA and FLDA: the samples from the selected electrodes were concatenated into feature vectors. The dimensionality of the feature vectors was $N_e \times N_t$, where N_e denotes the number of electrodes and N_t denotes the number of temporal samples in one trial. Since the trial duration and the downsampling are is 1000 ms and 32 Hz, respectively, N_t would always be equal to 32. Moreover, N_e is equal to 4, 8, 16, or 32 depending on the electrode configurations.

b) Neural Network: the feature vector used for this method was different. In this approach, the target sample and non target sample were extracted separately. Then, with applying some rules, these samples concatenated together and suitable feature vector constructed. The dimensionality of feature vector for each subject represented in Table 1. As can be seen from the below table, number of rows is equal but number of column is different. This is because of difference in number of blocks in each run in used database. Actually, as the accuracy of NN is highly depends on training data, the feature vector is very important. In the present study, in the case of NN used for classification, we consider 90 percent of feature vector for training and 10 percent for testing.

Table 1: The Dimensionality of Feature Vector for NN

Subject No.	Dimensionality
S1	128×11340
S2	128×10962
S3	128×11340
S4	128×11214
S6	128×10962
S7	128×11214
S8	128×11214
S9	128×11088

Now, simulation results for different electrode configuration illustrated in Table 2 to Table 5.

The classification accuracy for considering 4 electrodes are represented in Table 2. As can be seen in this table, the classification accuracy of NN is higher than other subjects only for subject 7. However, in the case of two other methods and other subjects, the subject 8 has higher classification accuracy with BLDA. Also, BLDA has better classification accuracy for all subjects except for subject 7.

Table 2: The Classification Accuracy for 4 Electrodes

Subject No.	NN	FLDA	BLDA
S1	0.904762	0.92147	0.928257
S2	0.903285	0.90508	0.909048
S3	0.893298	0.91327	0.917813
S4	0.899197	0.91348	0.913264
S6	0.903741	0.93324	0.936324
S7	0.9438	0.91275	0.920972
S8	0.888046	0.96785	0.973774
S9	0.898917	0.90969	0.925464

Table 3: The Classification Accuracy for 8 Electrodes

Subject No.	NN	FLDA	BLDA
S1	0.886243	0.94218	0.952375
S2	0.896898	0.91857	0.932649
S3	0.904321	0.93922	0.941576
S4	0.888938	0.94595	0.963706
S6	0.892336	0.92557	0.954272
S7	0.90455	0.92357	0.942854
S8	0.877788	0.97491	0.983003
S9	0.891697	0.93214	0.941419

The classification accuracy for considering 8 electrodes depicted in Table 3. Obviously, the classification accuracy of BLDA is higher than other methods for all subjects and subject 8 gained highest accuracy.

Table 4: The Classification Accuracy for 16 Electrodes

Subject No.	NN	FLDA	BLDA
S1	0.888448	0.91575	0.934218
S2	0.882755	0.92649	0.928157
S3	0.890653	0.91976	0.937922
S4	0.893399	0.90706	0.932595
S6	0.887318	0.90572	0.936557
S7	0.898751	0.92854	0.929357
S8	0.879572	0.90803	0.968491
S9	0.878159	0.91419	0.934174

Similarly, the classification accuracy with this configuration is the same as previous configuration, but in comparison with last mentioned method, the classification accuracy is lower. Actually, this decrease is due to the noise and other environmental or artifact defects that created by additional electrodes. As we know, the quality of signal obtained from each electrode is different and, perhaps, this is the main reason of generating these defects.
Each electrode detects the electric potential of synchronized neuronal activity occurring in that area of the brain. Since the electric potentials must pass through the skull, the EEG signals are inherently very noisy [9].

Table 5: The Classification Accuracy for 32 Electrodes

Subject No.	NN	FLDA	BLDA
S1	0.895503	0.90787	0.926937
S2	0.881387	0.91577	0.937548
S3	0.892857	0.91831	0.927461
S4	0.900535	0.93922	0.943712
S6	0.895073	0.92555	0.936565
S7	0.886262	0.91712	0.921724
S8	0.879572	0.91706	0.93216
S9	0.88583	0.90318	0.914813

Obviously, the classification accuracy with considering 32 electrodes does not have a meaningful difference compared with other configuration.

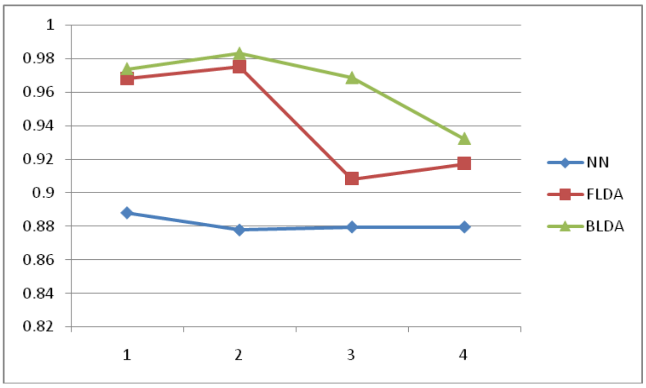

Fig 2: Classification Accuracy for subject 8 for 4, 8, 16, 32 electrodes respectively (Left to Right).

The classification accuracy for subject 8 with different electrode configuration represented in above Figure. Clearly, the classification accuracy for subject 8 for BLDA method is higher than other method and in the case of NN this is lower than others. Actually, the lower accuracy of the NN method is because of the training data and other properties of Neural Network.

Finally, as best results obtained for subject 8 with BLDA approach, the classification accuracy for this method considering all electrode configurations illustrated in Figure 3.

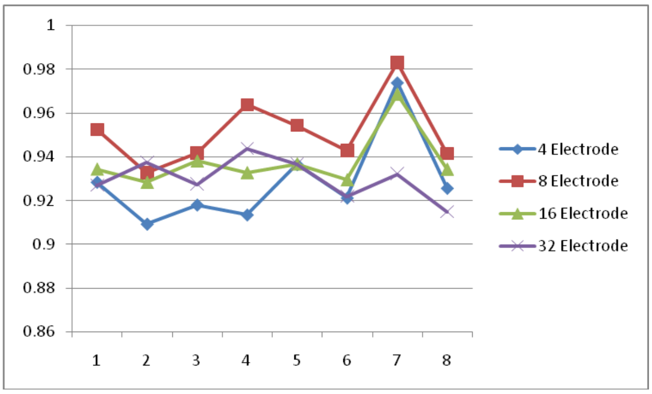

Fig 3: Classification Accuracy for subject 8 for 4, 8, 16, 32 Electrodes

For a precise comparison among three methods with 4 configurations, the mean classification accuracy is depicted on Table 6.

Table 6: The Mean Classification Accuracy for Different Electrode Configuration

Subject No.	NN	FLDA	BLDA
4 Electrode	0.891843	0.938791	0.954606
8 Electrode	0.891745	0.941435	0.954673
16 Electrode	0.889184	0.945008	0.957036
32 Electrode	0.891463	0.939027	0.951843

The mean classification accuracy calculated for all subjects represented in above table. The mean classification accuracy of NN is lower than two other methods but yet this value is higher than classification accuracy of 0.866 achieved by Senthilmurugan et al. [10]. Moreover, we should mention that for better comparison between two methods, using the same database is essential. The database used in this study is different from other comparable work. Actually, most of them used database from BCI competitions.

7. CONCLUSION

In summary, the classification accuracy for 3 methods represented and the simulation results illustrated. Clearly, with regards to simulation results, the classification accuracy for subject 8 was higher than other subject, especially for considering 8 electrodes and FLDA and BLDA methods. Actually, in each method, with setting parameters precisely we can obtain better results and improving the classification accuracy. In addition, as simulation results highly depend on input data and feature vector, suitable selection of this parameter is very important.

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