



## THE PERFORMANCE OF EEG-P300 CLASSIFICATION USING BACKPROPAGATION NEURAL NETWORKS

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### Abstract

Electroencephalogram (EEG) recordings signal provide an important function of brain-computer communication, but the accuracy of their classification is very limited in unforeseeable signal variations relating to artifacts. In this paper, we propose a classification method entailing time-series EEG-P300 signals using backpropagation neural networks to predict the qualitative properties of a subject's mental tasks by extracting useful information from the highly multivariate non-invasive recordings of brain activity. To test the improvement in the EEG-P300 classification performance (i.e., classification accuracy and transfer rate) with the proposed method, comparative experiments were conducted using Bayesian Linear Discriminant Analysis (BLDA). Finally, the result of the experiment showed that the average of the classification accuracy was 97% and the maximum improvement of the average transfer rate is 42.4%, indicating the considerable potential of the using of EEG-P300 for the continuous classification of mental tasks.

Keywords: EEG-P300 classification, backpropagation neural networks, BLDA, accuracy, transfer rate.

### I. INTRODUCTION

For several years, people have sought for a non muscular channel between the brain and the out world so that they can control peripherals by thinking. With the production of advanced bio-instruments for recording and amplifying the signals as well as cheap and powerful personal computers, this dream was realized and Brain-Computer Interface (BCI) was developed. Signals from the brain are acquired by electrodes on the scalp and be processed to extract specific features that reflect the user's intentions. The BCI must select and extract features that can be controlled by the user and translate those features into device commands correctly and efficiently. For this purpose, brain activity must be monitored. Today there existed various techniques to accomplish these problems [1-8]. Among these methods, almost all BCIs reported the data having been based on EEG. There are two main approaches to detect the user's commands from EEG. In the first approach the

subject concentrates on a few mental tasks. The different concentration on each mental task will produce a different EEG pattern. The BCI (especially the classifier) can then be trained to classify those patterns. Several BCIs system (e.g. [1, 9-14]) are based on the type of the pattern recognition approach. In the second approach the user has to learn the self-regulation of his or her EEG responses, for example to change the-rhythm amplitude [12].

There are various properties in EEG that can be used as a base for BCI such as rhythmic brain activity (i.e., delta, theta, alpha, and beta) [7], event-related potentials (ERPs), event-related desynchronization (ERD) and event-related synchronization (ERS) [1, 9, 13]. However, the present study is focused on the using of ERP properties. The ERP most commonly utilized is P300. P300, as noted in the journal Science, was discovered originally by Samuel Sutton, et al. [15], and represented the unpredictable stimuli presented in an oddball paradigm, in which low-probability targets were mixed with high-probability ones. For this paradigm, the subject is

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told to respond a rare stimulus that occurs randomly and infrequently among other, frequent stimuli [7]. The presence, magnitude, topography, and time of the response signal are often used as metrics of cognitive function in the decision of making processes. In this paper we propose a classification method for time series EEG signals that incorporates with a backpropagation neural network (BPNN), which has been well developed in the field of speech recognition. In order to examine the performance (i.e., accuracy and transfer rate) improvements of the proposed EEG classification method, comparative experiments were conducted using Bayesian Linear Discriminant Analysis (BLDA).

The structure of the paper is as follows. In Section 2, the subject population, the experiments that were conducted, and the methods used for data preprocessing are described. Classification using the BPNN model is explained in Section 3. Results and discussions are presented in Section 4. Conclusions are drawn in Section 5.

## II. METHODS

The data set used in this study was obtained from the website of the EPFL BCI group (<http://bci.epfl.ch/p300>) [6]. The data have been recorded according to the 10-20 international standards from the 32 electrode configurations [13]. Each recorded signal has a length of 820 samples with a sampling rate of 2048 Hz. A six-choice signal paradigm was tested using a population of five disable- and four able-bodied subjects. The subjects were asked to count silently the number of times a prescribed image flashed on a screen. Four seconds after a warning tone, six different images (a television, a telephone, a lamp, a door, a window, and a radio) were flashed in a random order [6]. Each of the image flash lasted for 100 ms, and for the following 300 ms no image was flashed (i.e., the inter-stimulus interval was 400 ms). Each subject completed four recording sessions. Each of the sessions consisted of six runs with one run for each of the six images. The duration of one run was approximately one minute and the duration of one session, including set up of electrodes and short breaks between runs, was approximately 30 min. Our goal is to discriminate all possible combinations of the pairs of mental tasks from each other using the corresponding EEG signals.

Before the classification and validation are performed, several preprocessing operations, including down sampling, windsorizing, scaling, feature vector construction, and desired output construction, were applied to the data. The EEG was down sampled from 2048 Hz to 32 Hz by

selecting each 64th sample from the band pass-filtered data. Not all of the measured EEG signals are electrical activity of the brain. Many potential changes detected in EEG are from other sources. These changes are called artifacts, and their sources can be the equipment or the subject. The data sets consist of the data matrix, events matrix, stimuli, targets, and targets counted. The data matrix contained the raw EEG. The events matrix contained the time-points at when the flashes (events) occurred. The stimulus is an array containing a sequence of flashes. The entries had value between 1 and 6, and each entry corresponded to a flash of one image on the screen. The variable target contained the index of the image in which the user focusing on. For example, if a target equaled three, the user counted the number of the flashes of the lamp. Together with the number of events, this variable can be used to determine if the user was actually concentrating. The extracted features then were fed into the recurrent multilayered perceptron neural networks with decent optimization algorithm. For the test, the hold out method was used, in which 75% of the data is used for training and 25% for test.

It is difficult to compare the performances of the BCI systems, because the pertinent studies present the results in different ways. However, in the present study, the comparison is made based on the accuracy and the transfer rate. Perhaps, accuracy is the most important aspect in any BCI. If a BCI will be used in control applications, the accuracy is obviously crucial. Furthermore, the transfer rate is also very important. The speed of a particular BCI is affected by the trial length, how long one selection will take. This time should be short to enhance a BCI's communication effectiveness. The amount of information communicated per time unit (the transfer rate) is a standard measure of a communication system. The transfer rate depends on both the speed and the accuracy of the selection. If a trial has  $N$  possible selections and each selection has the same probability to be the desired selection, and if  $P$  denotes the probability that the desired choice is actually selected, the probability for the remaining (undesired) selections being selected will be  $(1-P)/(N-1)$ . The bit rate (bits/trial) of each selection then can be expressed as [6, 12, 14, 16]:

$$b = \log_2(N) + P \log_2(P) + (1 - P) \log_2 \frac{1-P}{N-1} \quad (1)$$

The transfer rate (bits per minute) is equal to  $b$  multiplied by the average speed of selection  $S$  (trial per minute, which is equal to the reciprocal

of the average time required for one selection). Therefore, based on the data sets information, the desired output signal is developed. In the present study, the algorithm developed using the BPNN model was used for classification. For four of the disabled subjects and four of the able-bodied subjects, classification accuracies and transfer rates obtained are significantly beyond those reported previously by Hoffmann, Vesin, and Ebrahimi [6], Sellers, et al. [12], and Wolpaw, et al. [14].

### III. BACKPROPAGATION NEURAL NETWORKS

Artificial neural networks have been proposed in the fields of information and neural sciences following the research in the mechanisms and structures of the brain. This has led the development of new computational models for solving complex problems such as pattern recognition, rapid information processing, learning and adaptation, classification, identification and modeling, speech, vision and control systems [17-21]. The network architecture includes statistical and dynamical, single and multilayer as well as feedback (recurrent) networks has been presented. One of the most difficult problems that still take great scientists interest is learning. Special attention has been paid to the most efficient learning algorithm for multilayer networks, namely backpropagation.

The backpropagation algorithm allows exponential acquisition of input-output mapping knowledge within multilayer networks. If a pattern is submitted and its classification is determined to be erroneous, the current least mean-square classification error is reduced. The error is expressed as [22]:

$$E_j = \frac{1}{2} \sum_{i=1}^n (d_j - y_j(x_i, w_{ij}))^2 \quad (2)$$

Where  $d_j$  denotes the desired output of node  $j$  corresponding to input  $x_i$ ,  $n$  is the number of training patterns and  $y_j(x_i, w_{ij})$  denotes the vector output of the networks corresponding to input  $x_i$  and weight matrix  $w = \{w_{ij}\}$ . During the association or classification phase, the trained neural network itself operates in a feed-forward manner. Therefore the error will be a function of the weights of the input and the output layers. The backpropagation algorithm is a gradient descent method minimizing the mean square error between the actual and target outputs of a

multilayer perceptron. Using the sigmoid non linearity:

$$f(net_i) = \frac{1}{1 + e^{-net}} \quad (3)$$

the backpropagation algorithm consists of some steps. First, initialize all weights and node offsets to small random values. Second, present continuous input vector  $x_i$  and specify desired output  $d_j$ . The output vector elements are set to zero values except for the vector that correspond to the class of the current input. Third, calculate the actual output vector  $y$  using the sigmoid non linearity. Fourth, adjust the weights by the following equation:

$$w_{ij}(t + 1) = w_{ij}(t) + \eta \delta_j x_i \quad (4)$$

where  $d_j$  is the sensitivity of node  $j$ . Fifth, repeat the steps from the second step. A better approach is a cross-validation technique, which stops training when the error on a separate validation set reaches a minimum. Figure 1 shows the structure of the BPNN-based classification algorithm. We observe records a vector of EEG signals  $x(t) = [x_1(t), x_2(t), \dots, x_m(t)]^T$  from a multiple-input/multiple-output nonlinear dynamical system. The objective is to find an inverse system, termed a reconstruction system with backpropagation neural networks (BPNN), in order to estimate the primary input source of brain signals  $s(t) = [s_1(t), s_2(t), \dots, s_n]^T$  corresponding to particular stimulus, which are represented by  $y(t) = [y_1(t), y_2(t), \dots, y_n(t)]^T$ .

This program is used to train a set of prototypes from the recorded data. Each prototype corresponds to one particular stimulus. The classifier then will use these prototypes in the classification of the EEG signals. In order to train a new set of prototypes, the processed data of one recording is loaded into the program. The stimuli are labeled in the data. The data is then divided into training and validation sets in such a way that the three first sessions go to the training set and the one remaining session goes to the validation set. The thresholds will affect how

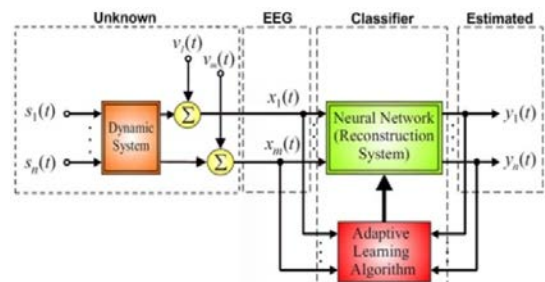


Figure 1. Structure of BPNN-based classification algorithm

easily the signals (data sets) are classified as belonging to one of the stimuli and how easily they are rejected. The classifier computes probability values for a signal belonging to each of the stimuli included in the data set. Then the highest probability value is chosen, and this value is compared to the probability threshold. If the value exceeds the threshold, the sample is classified to the corresponding stimuli, otherwise it is rejected. After the number of the iterations and the thresholds are adjusted, the training of the new prototypes can begin. During the training, a new set of prototypes are trained in each iteration. After the training finished, the weight matrices corresponding to each iteration are reviewed. The best prototypes then can be saved to be used later in the validation set.

#### IV. RESULT AND DISCUSSION

The ability to measure and classify single-trial responses from specific brain regions has important theoretical and practical implications for both basic and applied research. For brain research, the ability to measure single-trial ERPs is one of the important steps toward the understanding of how the relative timing of neuronal activity can affect learning and how memory of a particular experience can be encoded rapidly with a single or very few exposures.

In clinical applications, the ability to obtain such measures in a computationally efficient manner could allow functionally meaningful brain signals to be extracted and used to generate better input and feedback signals for brain computer interfaces. In the present study, a BPNN classifier was used. In order to cope with nonlinearly separable problems, additional layers of neurons placed between the input layer and the output neuron are needed, leading to the multilayer perceptron architecture. At the outset, the structure of the network is chosen, after the validation pattern appears in the graph window, and the network initialization values are introduced. Each subsequent layer has a weight coming from the previous layer. The performance is measured according to the specified performance function such as mean square error. The convergence of the mean square errors to zero, shown in Figure 2, verifies the performance of the network. The data sets for subject 5 were not included in the simulation since the subject misunderstood the instructions given before the experiment. Comparative plots of the classification accuracies and transfer rates (obtained with the BPNN and BLDA methods and averaged over four sessions based on the

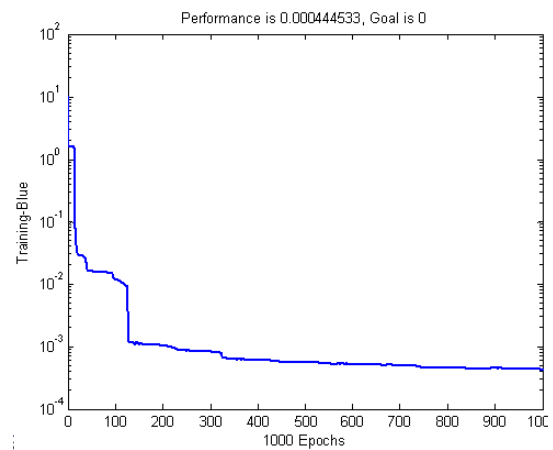


Figure 2. Network's performance according to mean squares errors

eight electrode configurations) for the disable- (S1 - S4) and able-bodied subjects (S6 - S9) are respectively depicted in Figure 3 and Figure 4.

All of the subjects (with BPNN), except the subjects 6 and 9, achieved an average classification accuracy of 100% after eight blocks of stimulus presentations are averaged (i.e., 19.2 s). However, subject 9, compared with BLDA, still achieved an average classification accuracy of 100% after sixteen blocks of stimulus presentations are averaged. The reason for the poorer performance of subject 9 might be fatigue. Subject 6 reported that he accidentally concentrated on the wrong stimulus during one run in session 1 [6]. Shown alongside the classification accuracies using BPNN for all of the subjects, in Table 1, are the corresponding 95% confidence intervals. According to the individual subject performances in Table 2, subject 1 had the best improvement (4.9%) of the average classification accuracy over all of the experiments. Moreover, this subject showed an improvement for all of the configurations. However, subject 8 had the worst improvement (0.3%) of average classification accuracy over all of the experiments (Table 2).

The transfer rates corresponding to the classification accuracies for the different electrode configurations (i.e. consisting of 4, 8, 16, and 32 electrodes) using both classification algorithms (BPNN and BLDA) combined, were tested. The results showed that a significant improvement in classification accuracy (for all of the configurations) and average transfer rate (except for configuration IV with 32 electrodes) was obtained. The maximum average transfer rate, mean transfer rate, and standard deviations for all of the combinations of classification algorithms and electrode configurations are listed in Table 3.

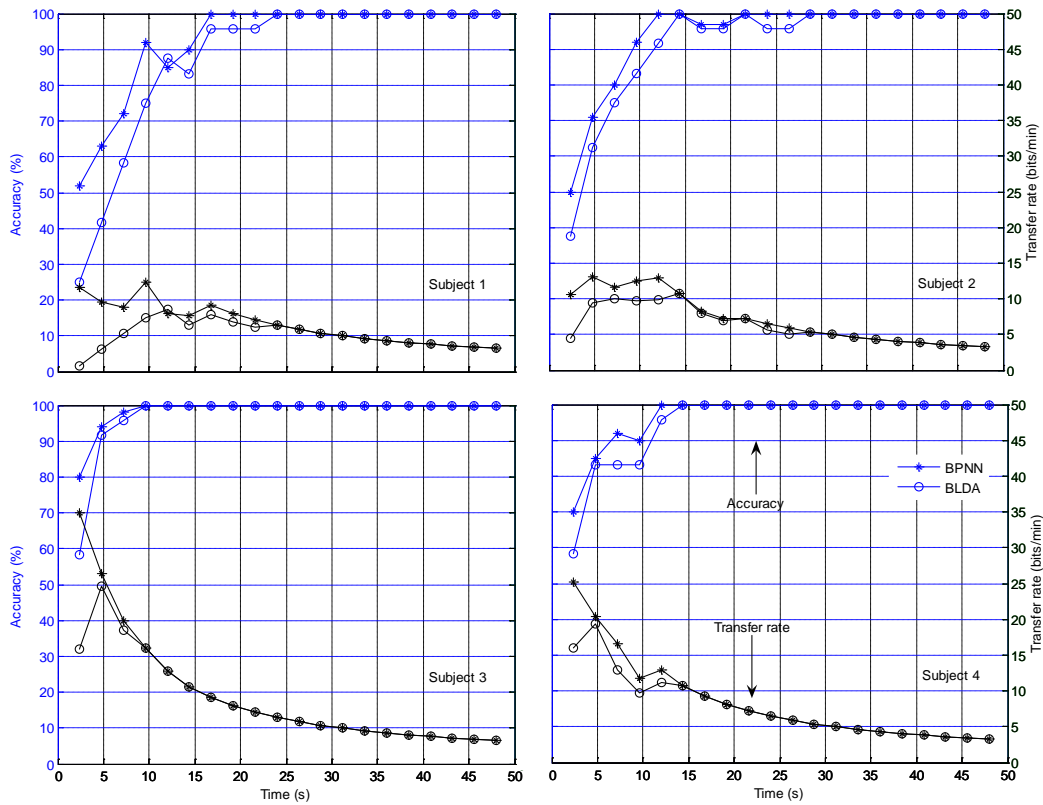


Figure 3. Comparison of classification accuracy and transfer rate plots (averaged over four sessions based on eight electrode configurations) obtained with BPNN and BLDA for disabled subjects (subjects 1- 4)

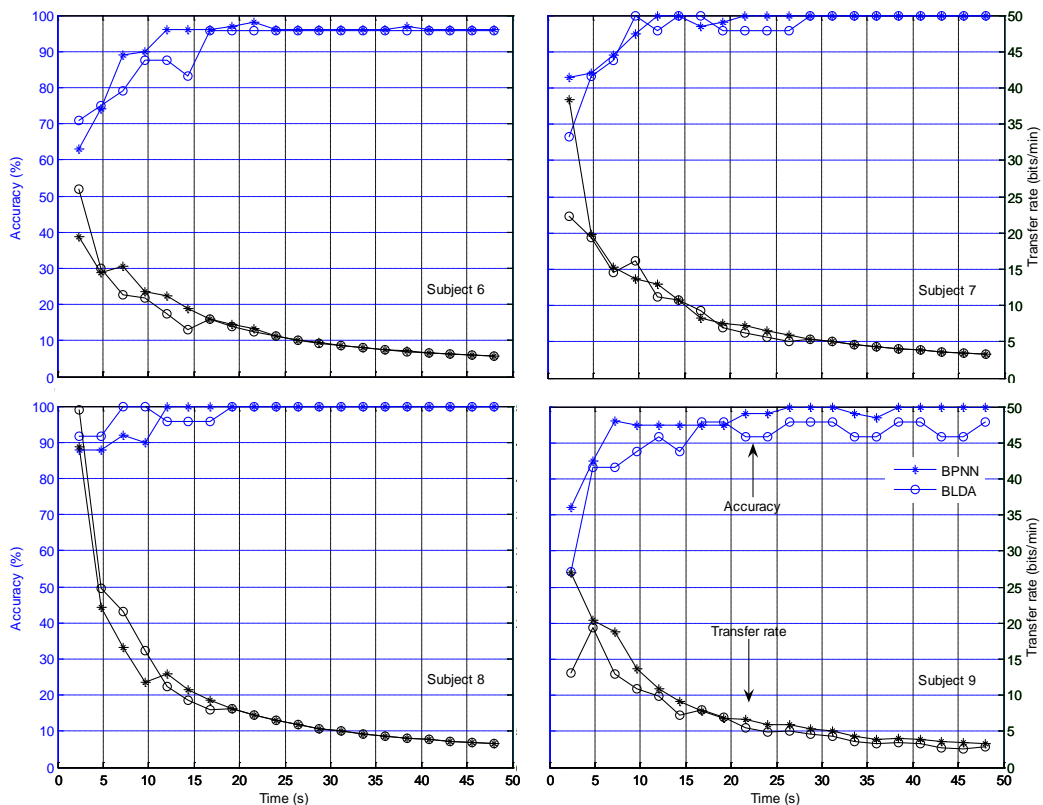


Figure 4. Comparison of classification accuracy and transfer rate plots (averaged over four sessions based on eight electrode configurations) obtained with BPNN and BLDA for able-bodied subjects (subjects 6- 9)

Table 3 shows that the maximum average transfer rates for subjects 6 and 7 in configuration III, obtained with the BLDA algorithm, were better than those obtained with the BPNN

algorithm. However, the maximum average transfer rates (i.e., S1-S4, S6-S9, and all of the subjects) obtained with the BPNN algorithm were better than those obtained with the BLDA

Table 1.  
Average classification accuracy (%)

Subject	BPNN-4	BPNN-8	BPNN-16	BPNN-32	BLDA-4	BLDA-8	BLDA-16	BLDA-32
S1	89.8	92.7	93.7	92.1	82.3	87.9	87.2	91.3
S2	90.8	94.3	95.6	92.1	80.0	91.7	91.7	92.1
S3	97.5	98.6	98.8	97.7	95.8	97.3	97.3	97.3
S4	96.9	96.9	97.2	97.6	93.5	95.2	97.1	97.9
S6	92.5	92.8	94.2	92.7	90.6	91.3	91.9	92.7
S7	98.5	97.3	97.4	99.1	93.5	95.8	98.8	98.8
S8	98.8	97.9	98.7	99.8	95.8	98.5	99.6	100
S9	94.1	95.9	96.8	95.2	85.6	90.2	96.3	95.6
Average (S1-S4)	93.8±4.0	95.6±2.6	96.3±2.2	94.9±3.2	87.9±7.9	93.0±4.1	93.3±4.8	94.6±3.5
Average (S6-S9)	96.0±3.1	95.9±2.3	96.8±1.9	96.7±3.3	91.4±4.4	94.0±3.9	96.6±3.5	96.8±3.3
Average (all)	94.9±3.5	95.8±2.3	96.5±1.9	95.8±3.2	89.7±6.2	93.5±3.8	95.0±4.3	95.7±3.3

Table 2.  
Improvement of average classification accuracy (%)

Subject/ Configuration	I	II	III	IV	Average (I-IV)
S1	7.5	4.8	6.5	0.8	4.9
S2	10.8	2.6	3.9	0.0	4.3
S3	1.7	1.3	1.5	0.4	1.2
S4	3.4	1.7	0.1	-0.3	1.2
S6	1.9	1.5	2.3	0.0	1.4
S7	5.0	1.5	-1.4	0.3	1.4
S8	3.0	-0.6	-0.9	-0.2	0.3
S9	8.5	5.7	0.5	-0.4	3.6
Average (S1-S4)	6.7	2.8	3.2	0.2	3.2
Average (S6-S9)	5.0	2.2	0.1	-0.1	1.8
Average (all)	5.8	2.5	1.6	0.1	2.5

Table 3.  
Maximum average transfer rate

Subject	BPNN-4	BPNN-8	BPNN-16	BPNN-32	BLDA-4	BLDA-8	BLDA-16	BLDA-32
S1	11.2	12.5	14.3	14.9	8.8	8.8	7.7	13.0
S2	9.7	13.0	15.4	12.4	6.8	10.8	11.4	11.2
S3	25.0	35.0	38.3	24.7	21.9	24.7	24.7	21.9
S4	19.0	25.2	28.9	31.3	14.9	19.3	21.9	29.8
S6	26.0	27.0	24.3	34.1	25.9	25.9	25.9	34.1
S7	32.3	38.3	35.0	41.1	22.3	22.3	38.7	38.7
S8	43.8	51.4	57.1	64.6	38.7	49.4	56.0	64.6
S9	18.7	27.0	30.8	26.5	17.0	19.3	22.3	17.0
Average (S1-S4)	16.2±7.2	21.4±10.8	24.2±11.5	20.8±8.8	13.1±6.8	15.9±7.5	16.4±8.2	19.0±8.6
Average (S6-S9)	30.2±10.6	35.9±11.6	36.8±14.2	41.6±16.5	26.0±9.2	29.3±13.7	35.7±15.2	38.6±19.7
Average (all)	23.2±11.2	28.7±13.0	30.5±13.7	31.2±16.5	19.5±10.2	22.6±12.5	26.1±15.3	28.8±17.6

algorithm. These improvements can be seen in Table 4. In the work of Hoffmann, et al. (2008), the maximum average transfer rate was about 15.9 bits/min for the disabled subjects and 29.3 bits/min for the able-bodied subjects.

In the present study, improvements of the maximum average transfer rates for the same electrode configurations are achieved (i.e. about 21.4 bits/min for the disabled subjects and 35.9 bits/min for the able-bodied subjects).

Table 4.  
Improvement of maximum average transfer rate (%)

Subject/ Configuration	I	II	III	IV	Average (I-IV)
S1	27.3	42.0	85.7	14.6	42.4
S2	42.6	20.4	35.1	10.7	27.2
S3	14.2	41.7	55.1	12.8	30.9
S4	27.5	30.6	32.0	5.0	23.8
S6	0.4	4.2	-6.2	0.0	-0.4
S7	44.8	71.7	-9.6	6.2	28.3
S8	13.2	4.0	2.0	0.0	4.8
S9	10.0	39.9	38.1	55.9	36.0
Average (S1-S4)	23.9	34.7	47.7	9.6	29.0
Average (S6-S9)	16.2	22.6	3.1	7.7	12.4
Average (all)	19.0	26.9	16.9	8.3	17.8

## V. CONCLUSIONS

The results presented in this study show that, compared with the BLDA algorithm, a better extraction result can be obtained by using the backpropagation neural networks (BPNN) algorithm for single-trial ERPs based on the P300 component from specific brain regions. With BPNN, the data indicate that a P300-based BCI system can communicate for the disable-and able-bodied subjects respectively at the rate of 21.4 bits/min and 35.9 bits/min. The average of 100% classification accuracy is achieved after eight blocks for disabled subjects and after five blocks for able-bodied subjects. These results indicate that the system allowed several disabled users to achieve transfer rates significantly beyond those reported previously in the literatures. However, if in the future many subjects are going to be tested and computation time is an issue, the BPNN model will appear to be the best choice. To improve our results, we are currently investigating the effect of averaging the output of the classifier over the consecutive windows as well as the effects of other preprocessing methods in artifact-effect reduction.

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