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# CLASSIFYING MENTAL ACTIVITIES FROM EEG-P300 SIGNALS USING ADAPTIVE NEURAL NETWORKS

Arjon Turnip[1] and Keum-Shik Hong[1,2,*]

[1]School of Mechanical Engineering
[2]Department of Cogno-Mechatronics Engineering
Pusan National University
30 Jangjeon-dong, Geumjeong-gu, Busan 609-735, Republic of Korea
turnip@pusan.ac.kr; *Corresponding author: kshong@pusan.ac.kr

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Abstract. *In this paper, a new adaptive neural network classifier (ANNC) of EEG-P300 signals from mental activities is proposed. To overcome an overtraining of the classifier caused by noisy and non-stationary data, the EEG signals are filtered and their autoregressive (AR) properties are extracted using an AR model before being passed to the ANNC. For evaluation purposes, the same data in Hoffmann et al. (2008) were used. With and without the AR property extraction, the proposed ANNC could achieve 100% accuracy for all the subjects. To verify the performance improvement of the proposed classification scheme, a comparison of the ANNC and the conventional back-propagation neural network classifier was performed as well.*
**Keywords:** Adaptive high order neural network, EEG-P300 potentials, Feature extraction, Classification, Brain computer interface

## 1. Introduction.

A Brain Computer Interface (BCI) is a direct communication pathway between a user's brain and an external device [1]. The BCI system utilizes what are already known about brain signals to detect the messages that the user has chosen to communicate. These systems operate on the principle that the brain reacts differently to different stimuli based on the level of attention given to the stimuli. Thus, brain activities must be monitored. Today there exist various techniques by which this can be accomplished. Among these, EEG is preferred for BCI, owing to its non-invasiveness, cost effectiveness, easy implementation, and superior temporal resolution [1-7]. The current BCI schemes typically incorporate five main steps as shown in Figure 1. Brain signals are acquired and analyzed in segments (trials) for a given duration, according to the operation modes and the types of mental tasks or activities. The acquired signals are preprocessed to reduce external noises and detected artifacts. The filtered signals are then sent to the feature extraction and classification steps, respectively.

An event-related potential (ERP), which can be generated in the EEG during a stimulation paradigm, is a brain response directly resulted from a perception or a thought. Particularly, the P300 component refers to the wave peaking around 300 ms after a task-relevant stimulus [7-9]. While the P300 is elicited in many different ways, the most common factors influencing it are two stimulus-discrimination tasks presented to the subject in an unknown fashion. One occurs infrequently (i.e., target) and the other frequently (i.e., non-target). The P300 has been shown to be fairly stable in locked-in patients. The reappearance of P300s involves a brainstem structure [10]. Farwell and Donchin [11] first

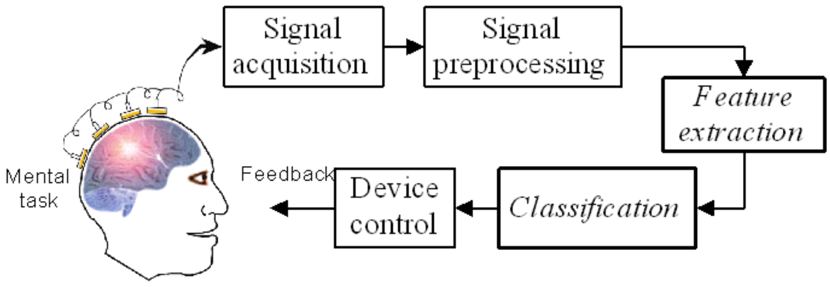


FIGURE 1. Basic five key steps in BCI (the feature extraction and classification steps are focused in this paper)

showed that this signal could be successfully used in BCI applications. Other applications of the EEG-P300 for BCI also have been proposed [1,12]. However, the P300, as a cognitive component, is known to vary with a subject's fatigue level [5].

Since the signal level of a P300 potential compared with the signal level of noises is very small, an efficient method of extracting and classifying the P300 component from the EEG signal is desirable. The most important task for BCI is to classify relevant information from artifacts-contaminated and stochastic EEG signals. Indeed, since an incorrect classification can lead to poor accuracy and low transfer rate, an adaptive neural network classifier (ANNC) for a number of mental activities herein is proposed. To overcome the classifier's lengthy training caused by noisy and non-stationary data, the key features of P300 signals are extracted using an autoregressive (AR) method before being passed to the proposed ANNC. Comparative experiments are conducted to examine the performance (i.e., accuracy and transfer rate) improvement of the ANNC. The contributions of this paper are the following: (i) enhancement and strengthening of artifacts-contaminated and stochastic EEG signals utilizing the small-amplitude of the EEG-P300, (ii) assurance of the tracking error to a small value around zero while guaranteeing the closed-loop stability, (iii) improvement of the classification accuracy and transfer rate by the application of the proposed AR and ANNC method, even when subjects are in a fatigued condition.

The structure of the paper is as follows. Section 2 discusses the EEG data set and its preprocessing. Section 3 explains feature extraction and classification by the AR method and the ANNC, respectively. Results are discussed in Section 4, and conclusions are drawn in Section 5.

2. **Data Set and EEG Preprocessing.** Since the purpose of this paper is to demonstrate the performance of the proposed method (i.e., the ANNC) in comparison with the work of Hoffmann et al. [5], the present study utilizes the same raw data used in their work. Also, only the data of 8 out of 32 channels (i.e., Fz, Cz, Pz, Oz, P7, P3, P4, and P8) placed at the standard positions described in the 10-20 International System [5,13] are used, which is claimed to be sufficient, by Hoffmann et al. [5], in that a good compromise between the sufficiency of accuracy and the computational complexity in handling multiple channels is achieved. Specifically, the used raw EEG data correspond to the signal $s_j(t)$ in Figure 2.

For the completion of this paper, how the data in [5] were made is briefly summarized. A six-choice signal paradigm was used to test a population of five disabled and four able-bodied subjects. According to [5], the data sets for subject 5 were not included in the analysis, since the subject misunderstood the pre-experiment instructions. In their test, four seconds after a warning tone, six different images (a television, a telephone, a lamp, a door, a window, and a radio) flashed in an unknown way to the subjects (one image at a

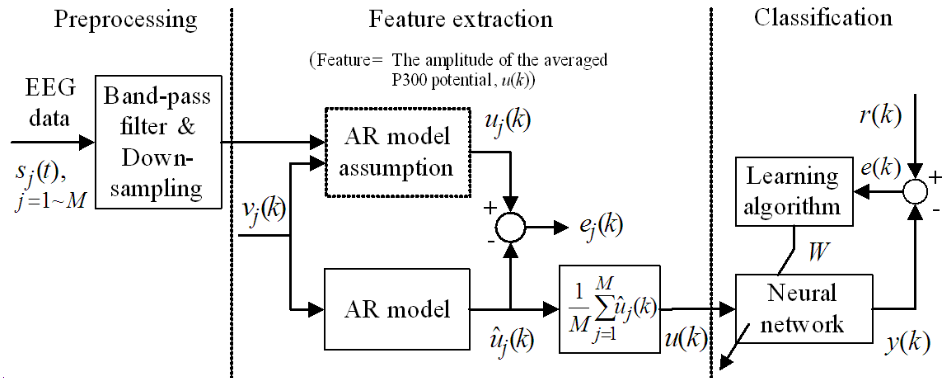


Figure 2. Structure of the proposed feature extraction and classification algorithm

time), and the subjects were asked to count silently the number of times of the flashes of a preselected image on the screen. The EEG signals were recorded, at 2048 Hz sampling rate, with 32 electrodes. The duration of each image flash was 100 ms, followed by a 300 ms blank screen (i.e., the inter-stimulus interval was 400 ms). Each subject completed four recording sessions. The first two sessions were performed on a day, whereas the last two sessions were carried out on a second day. The lapse between the first and the last sessions, for all of the subjects, was less than two weeks. Each of the sessions consisted of six runs, one run for each image as a target. The duration of one run was approximately one minute and that of one session, including the time required for electrode setup and short breaks between runs, was about 30 min.

Summarizing the above, one trial takes about 400 ms; six trials make one segment; about 20 $\sim$ 25 segments make one run; six runs make one session and four sessions are designed for individual subject. Therefore, one session involves an average of 810 trials, and the entire data for one subject, therefore, consist of an average of 3240 trials. Prior to feature extraction, several preprocessing operations including filtering and down-sampling were carried out. To filter the data, a 6th-order band-pass filter (BPF) with cutoff frequencies of 1 Hz (i.e., to remove the trend from low frequency bands) and 12 Hz (i.e., to remove unimportant information in high frequency bands) was used. Then, the signal was down-sampled from 2048 Hz to 32 Hz (i.e., the discrete time is 0.03125 sec, which satisfies the Shannon-Nyquist sampling theorem criterion) by selecting the first data of each 64th sample from the filtered data, which was considered sufficient to reduce unimportant information from high frequency bands.

3. **Feature Extraction and Classification.** The goal of feature extraction is to find the relevant information from the brain signals in order to perform the desired task according to the mental activities. The extracted signals should encode the commands made by the subject but should not contain noises or other interfering patterns (or at least should reduce their strength) that can impede classification or increase the difficulty of analyzing EEG signals. For this reason, the estimation of statistical measurements (or feature extraction) from the EEG trials delivered by the preprocessing module is explored. The AR model is built upon two hypotheses: the signals are stationary and ergodic, and a linear prediction model [14,15] exists. In Figure 2, $s_j(t)$, $j = 1 \sim M$, denote the raw data of 2048 Hz, $u_j(k)$ be the output of the BPF after down-sampling where $k$ denotes the discrete time of 32 Hz, and $\hat{u}_j(k)$ be the output of the AR model through the estimated coefficients that will be discussed below. Let $U(k)$ be an $M$ dimensional multivariable stochastic EEG signal of length $N$composed of random vectors $\{U(k) =$

$[u_1(k) \ldots u_M(k)]^T | \, k = 0, \ldots, N-1\}$ where $u_1, \ldots, u_M$ are the univariate components of $U(k)$. The output of the AR model is generated by a linear prediction model in the following form [14,16]

$$U(k) = \sum_{i=1}^{L} A(k,i)U(k-i) + \nu_1(k), \tag{1}$$

where $L$ is the model order (in this paper, $L = 8$), $A(k,i)$ are $M \times N$ matrices (here, $M$ denote the number of electrodes, that is $M = 8$, and $N$ the number of temporal samples per one segment (i.e., six trials) of EEG channel), and $\nu_1(k)$ is the zero-mean input noise vector. Thus, $U(k)$ is determined entirely by the parameters of the model. It has been shown in [14] that if $U(k)$ is stationary and ergodic, the matrices $A(k,i)$ are time-independent, that is, $\forall k$, $A(k,i) = A(i)$. Since the coupling between channels is ignored, Equation (1) can be split into linear prediction models $u_j(k)$ corresponding to individual components. Accordingly, the $j$th univariate component of $U(k)$ is written in the following form

$$u_j(k) = \sum_{i=1}^{L} a_j(k,i)u_j(k-i) + \nu_j(k), \quad j = 1, 2, \ldots, M \tag{2}$$

where $a_j(k,i)$ are the AR coefficients, and $\nu_j$ is the noise in the $j$th channel. Furthermore, because stationarity and ergodicity are assumed, the AR model for the $j$th channel becomes

$$u_j(k) = \sum_{i=1}^{L} a_j(i)u_j(k-i) + \nu_j(k). \tag{3}$$

The estimated coefficients $\hat{a}_j(1), \ldots, \hat{a}_j(L)$ for every segment can be determined by minimizing the following averaged squared estimation error

$$E_j = \frac{1}{N}\sum_{k=0}^{N-1} e_j^2(k) = \frac{1}{N}\sum_{k=0}^{N-1}\left(u_j(k) - \sum_{i=1}^{L} a_j(i)u_j(k-i)\right)^2, \tag{4}$$

in which the samples prior to $u_j(0)$ are assumed to be zero. Through the estimated coefficients, the estimated output, $\hat{u}_j(k)$, of the AR model were obtained.

It is difficult to compare the performances of BCI systems, because the pertinent studies have derived and presented the results in different ways. Notwithstanding, in the present study, a comparison was made regarding accuracy and transfer rate. Accuracy is perhaps the most important measure of any BCI. Particularly if a BCI is to be used in control applications (environmental controls, hand prosthetics, wheelchairs, etc.), its accuracy is obviously crucial: think about a wheelchair lacking controllability on the street. Besides accuracy, the transfer rate is also very important. The transfer rate (bits per minute) or the speed of a particular BCI is affected by its trial length, that is, the time required for one selection. This time should be shortened in order to enhance the BCI's effectiveness. When considering a BCI as a communication (or control) tool then, it is important to know how long it will take to make one selection. Although a classification can be made in a short time interval, one selection cannot necessarily be made in that same time.

Artificial neural networks have been employed in the fields of information and neural sciences for the conduct of research into the mechanisms and structures of brains. This has led to the development of new computational models for solving complex problems involving pattern recognition, rapid information processing, learning and adaptation, classification, identification and modeling, speech, vision and control systems [17-22]. Here, we are concerned with the problem of an adaptive classification of EEG-P300 components represented by the nonlinear discrete-time system that can be transformed into the following form [20,23]

$$y(k+1) = f^*\left(y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-m+1)\right) \\ + g^*\left(y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-m+1)\right) u(k), \quad (5)$$

or in a state space description

$$\begin{aligned} x_1(k+1) &= x_2(k), \\ x_2(k+1) &= x_3(k), \\ &\vdots \\ x_n(k+1) &= f\left(x(k), \bar{u}(k)\right) + g\left(x(k), \bar{u}(k)\right) u(k), \\ y(k) &= x_1(k), \end{aligned} \quad (6)$$

where $n$ and $m$ are the orders in the system and input, respectively, $m \le n$ $y(k) \in R$ is the estimated output, $u(k) \in R$ is the network input, $x(k) = [x_1(k), \ldots, x_n(k)]^T \in R^n$ are the state variables, and

$$\begin{aligned} \bar{u}(k) &= [u(k), \ldots, u(k-m+1)]^T, \\ f\left(x(k), \bar{u}(k)\right) &= f^*\left(y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-m+1)\right), \\ g\left(x(k), \bar{u}(k)\right) &= g^*\left(y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-m+1)\right). \end{aligned} \quad (7)$$

For simplification, define $f(k) = f\left(x(k), \bar{u}(k)\right)$ and $g(k) = g\left(x(k), \bar{u}(k)\right)$, which are functions of states $x(k)$ and past inputs in (5). The $f(k)$ and $g(k)$ are unknown nonlinear functions which may not be linearly parameterized. As shown in Figure 2 (here, $r(k)$ represents the desired reference sequence in association with the given stimuli). The classifier system attempts to make the network output $y(k)$ match the reference $r(k)$ asymptotically, so that $\lim_{t\to\infty} \|r(k) - y(k)\| < \varepsilon$ for some specified constant $\varepsilon \ge 0$. If $f(k)$ and $g(k)$ are known, the following classifier $c(k)$ can be used to precisely track the reference

$$c(k) = g^{-1}(k)\left(r(k) - f(k)\right). \quad (8)$$

Since $f(k)$ and $g(k)$ are unknown, neural networks can be used to learn to approximate these functions and generate suitable classifiers. Although the function $g(k)$ is not known, it can be assumed that $g(k) > 0$. Neural network is a general modeling tool that can approximate any continuous or discrete nonlinear function to any desired accuracy over a compact set [20,23-25]. In the present study, a new adaptive neural network classifier for nonlinear systems (6) is developed using a high-order neural network (HONN). HONN was first introduced by Giles and Maxwell [25]. With this HONN classifier, mental activities corresponding to the given stimuli can be classified with a high degree of accuracy. It should be noted that although the new states $x_2(k)$, $x_3(k)$, …, $x_n(k)$ are not available in practice, they can be predicted, as will be discussed subsequently. Let $x_r(k) = [r(k),\ r(k+1),\ \ldots,\ r(k+n-1)]^T$ be the reference system states. Let the error be $e(k) = x(k) - x_r(k) = [e_1(k), \ldots, e_n(k)]^T$. Then, the $e(k)$ equation can be rewritten as

$$\begin{aligned} e_1(k+1) &= e_2(k), \\ e_2(k+1) &= e_3(k), \\ &\vdots \\ e_n(k+1) &= f(k) + g(k)u(k) - r(k+n). \end{aligned} \quad (9)$$

In order to develop the adaptive classifier clearly, the following new variables $\bar{y}(k) = [y(k),\ \ldots,\ y(k-n+1)]^T$, $\bar{u}(k-1) = [u(k-1),\ \ldots,\ u(k-m+1)]^T$, and $\bar{z}(k) = [\bar{y}^T(k),\ \bar{u}^T(k-$

$1)]^T \in R^{n+m-1}$ are defined. According to the definition of the new states, $\bar{y}(k) = [x_1(k), \ldots, x_1(k-n+1)]^T$ and from Equation (6), the following holds

$$\begin{aligned} y(k+1) &= x_2(k) = x_3(k-1) = \cdots = x_n(k-n+2) \\ &= f(\bar{y}(k)) + g(\bar{y}(k))\, u(k-m+1) \\ &=: \phi_2(\bar{z}(k)), \end{aligned} \tag{10}$$

where $x_2(k)$ is a function of $y(k)$ and $u(k-m+1)$. From (6), the following equations

$$\begin{aligned} y(k+2) &= x_3(k) = f(\bar{y}(k+1)) + g(\bar{y}(k+1))\, u(k-m+2) \\ &=: \phi_3(\bar{z}(k)), \\ &\vdots \\ y(k+n-1) &= x_n(k) = f(\bar{y}(k+n-2)) + g(\bar{y}(k+n-2))\, u(k-1) \\ &=: \phi_n(\bar{z}(k)) \end{aligned} \tag{11}$$

are similarly obtained. This proves that $x_n(k)$ is a function of $\bar{z}(k)$. By substituting the predicted states into the last equation in (6), we obtain

$$y(k+n) = x_n(k+1) = f(\bar{z}(k)) + g(\bar{z}(k))\, u(k), \tag{12}$$

where

$$f(\bar{z}(k)) = f\left([x_1(k), \phi_2(\bar{z}(k)), \ldots, \phi_n(\bar{z}(k))]^T\right), \tag{13}$$

$$g(\bar{z}(k)) = g\left([x_1(k), \phi_2(\bar{z}(k)), \ldots, \phi_n(\bar{z}(k))]^T\right). \tag{14}$$

Then, if $e(k) = y(k) - r(k)$ is the defined tracking error, its dynamics are given by

$$e_k(k+n) = -r(k+n) + f(\bar{z}(k)) + g(\bar{z}(k))\, u(k). \tag{15}$$

Suppose that the nonlinear functions $f(\bar{z}(k))$ and $g(\bar{z}(k))$ are exactly known. Then, the desired classifier, such that the output follows the reference trajectory, is written as

$$c^*(k) = -g^{-1}(\bar{z}(k))\left(f(\bar{z}(k)) - r(k+n)\right). \tag{16}$$

Substituting (16) into (15) (i.e., $u(k) = c^*(k)$), the convergence of the error dynamics to zero is achieved. This means that after $n$ steps, we have $e(k) = 0$. Therefore, $c^*(k)$ is an $n$-step deadbeat classifier. Since the nonlinear functions $f(\bar{z}(k))$ and $g(\bar{z}(k))$ are unknown, the nonlinearity $c^*(k)$ is not available. The following HONN is introduced to construct the unknown nonlinear functions $f(\bar{z}(k))$ and $g(\bar{z}(k))$ for approximation of the desired signal $c^*(k)$.

It has been proven that a neural network has the function approximation ability [23]. Consider the following HONN [20,23,25]

$$\varphi(W, z) = W^T H(z), \;\; W \text{ and } H(z) \in R^l, \tag{17}$$

$$H(z) = [h_1(z), h_2(z), \ldots, h_l(z)]^T, \tag{18}$$

$$h_i(z) = \prod_{j \in l_i} [h(z_j)]^{d_j(i)}, \;\; i = 1, 2, \ldots, l, \tag{19}$$

where $z = [z_1, z_2, \ldots, z_n]^T \in R^n$, the positive integer $l$ indicates the neural network node number, $d_j(i)$ stands for non-negative integers, $W$ is an adjustable synoptic weight vector, and $h(z_j)$ is a hyperbolic tangent function such that

$$h(z_j) = \frac{e^{z_j} - e^{-z_j}}{e^{z_j} + e^{-z_j}}. \tag{20}$$

According to Girosi and Poggio [24], there exists an estimate weight $\hat{W}$ such that the function $\varphi(z)$ can be approximated by an ideal neural network as

$$\varphi(z) = W^{*T} H(z) + \varepsilon_z, \tag{21}$$

where $\varepsilon_z$ is the neural network approximation error. The ideal neural network weight $W^*$ is not known and needs to be estimated. Let $\hat{W}$ be the estimate of $W^*$ and $\hat{c}(k)$ be the estimate of $\varphi(z)$. Therefore the classifier and the updating law for the estimate of weight $\hat{W}$ are chosen as [20]

$$\hat{c}(k) = \hat{W}^T H\left(\bar{z}(k)\right), \tag{22}$$

$$\hat{W}(k+1) = \hat{W}(k_1) + \Gamma\left[H\left(\bar{z}(k_1)\right)\left(y(k+1) - r(k+1)\right) + \rho\hat{W}(k)\right], \tag{23}$$

where $k_1 = k - n + 1$, diagonal gain matrix $\Gamma > 0$, and $\rho > 0$. In this paper, the following parameters are chosen: the number of neurons $l = 40$, $\hat{W}(0) = 0$, $\Gamma = 0.06I$, and $\rho = 0.008$. Thereby, by increasing the approximation accuracy of the neural network, the tracking error is made to converge to a small neighborhood of zero.

4. **Results and Discussions.** Most EEG research seeks to understand the brain's dynamic processes that are the basis of physical and mental activities. If the information in a mental task is accurately extracted and classified from EEG signals, a user can compose the sequence of the task to indicate commands that can operate a computer display or other devices. In this paper, a new method using adaptive neural network for classification of EEG-P300 signals was proposed. This method is supported by the AR model in extracting features and reducing artifacts contained within EEG signals. Figures 3 and 4 show, respectively, EEG-P300 signals preprocessed using the BPF and extracted using the AR method as a feature extractor and artifacts remover. Although Figure 4 evidences some improvement, classification of the signals with respect to the P300 component remains difficult. Hence, the need for the new adaptive neural network classifier was herein demonstrated. Dealing with the typical low-amplitude and low signal-to-noise ratio (SNR) potentials, the removal of other biological signals becomes one of the major challenges in the study of ERPs. To resolve this problem, the averaging method of extracted EEG signals before classification was applied. Figure 5 shows the average of the eight electrode data in Figure 4.

The tracking errors with and without the application of the AR model before the neural network training processes are compared in Figure 6. The results indicate that, with the AR model, the convergence was attained after about 250 iterations. Contrastingly, when the feature extraction method was not used (i.e., without the AR model), the same level of accuracy was attained only after 1800 iterations. These results show clearly that the introduction of an AR model accelerates the training processes, in which the convergence of the tracking error to a small value around zero is faster. To test the EEG

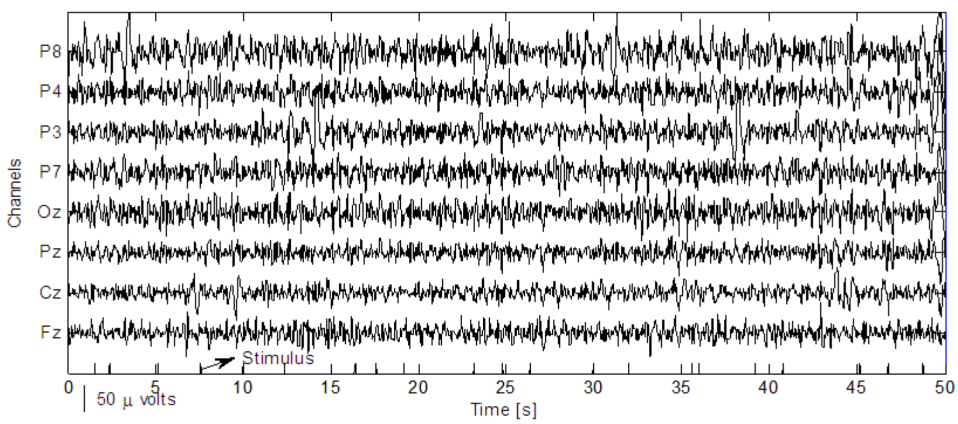


FIGURE 3. The EEG signals preprocessed using the BPF

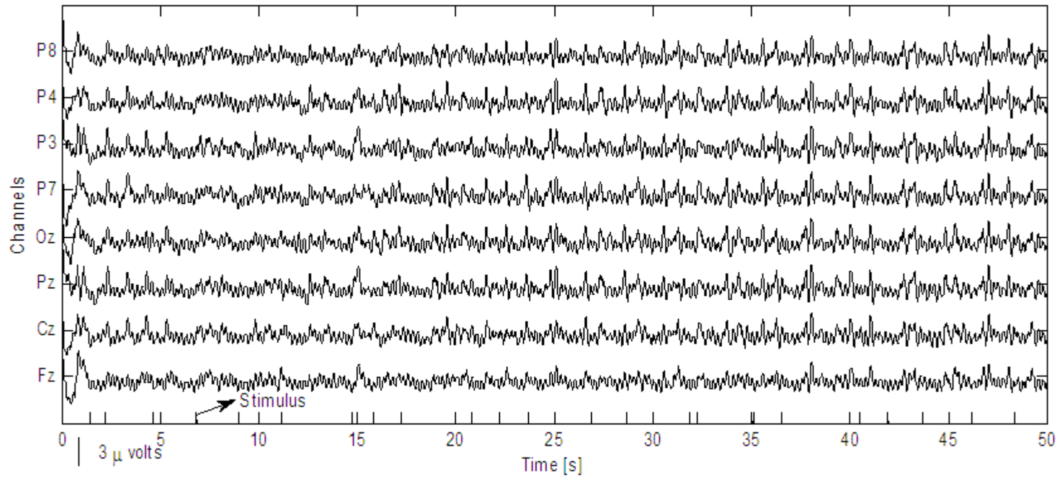


FIGURE 4. The EEG signals extracted using the AR model in (3)

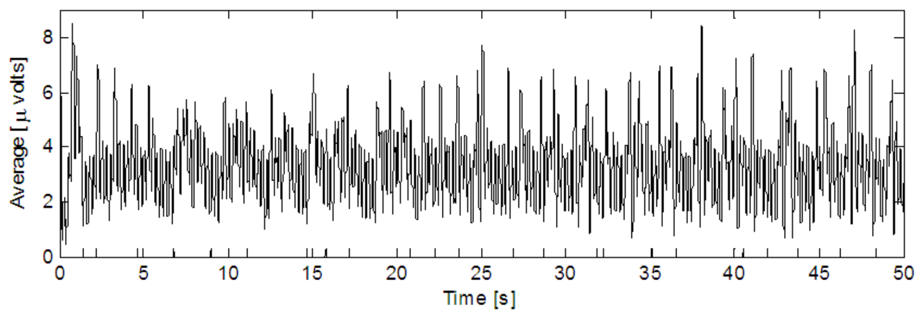


FIGURE 5. The average of the eight extracted signals in Figure 4

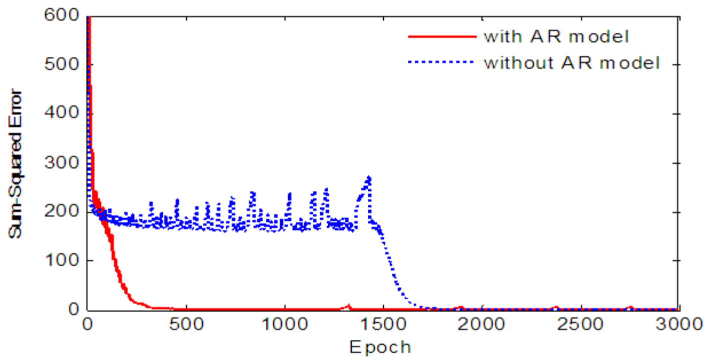


FIGURE 6. Reduction of the classifier training time by using the extracted signals

classification performance improvement effected with the proposed method, comparative experiments were also conducted using back-propagation neural network (BPNN) [26-28]. Comparative plots of the classification accuracies and transfer rates (obtained with the BPNN, the ANNC, the combination of the ANNC with AR model, and the averaged over the subjects) for the disabled subjects (subjects $1 \sim 4$), for the able-bodied subjects (subjects $6 \sim 9$), for the results averaged over all of the disabled subjects, for the results averaged over all of the able-bodied subjects, and for the results averaged over all of the subjects, are shown in Figures 7-11, respectively.

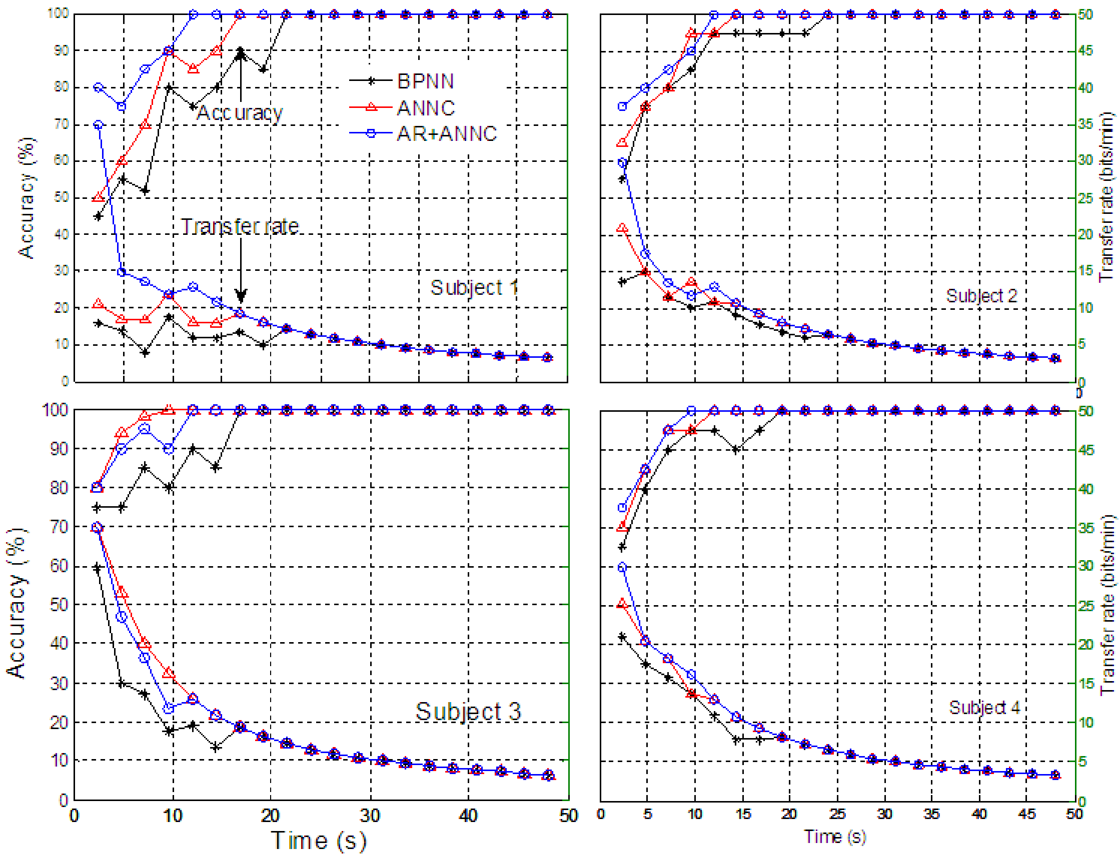


FIGURE 7. Comparison of classification accuracy and transfer rate obtained with BPNN, ANNC, and the ANNC with the AR model for disabled subjects

All of the subjects (with the combination of the AR model and the ANNC method) except subjects 6 and 9 achieved an average classification accuracy of 100% after five blocks of stimulus presentations were averaged (i.e., 14 seconds). However, subjects 6 and 9, compared by means of the BPNN, still achieved an average classification accuracy of 100% after nine blocks of stimulus presentations were averaged, respectively. Moreover, even without the introduction of the AR method, a significant improvement was achieved. This results indeed show the performance of the proposed method and a significant improvement compared with the results presented in [5] (i.e., obtained using the Bayesian linear discriminant analysis (BLDA)), in which subject 6 and subject 9 failed to achieve the average 100% classification accuracy. This confirms that the introduction of the AR method and application of the proposed classifier enabled the BCI to accurately extract and classify information from a fatigued subject. Shown alongside the ANNC classification accuracies for all of the subjects, in Table 1, are the corresponding 95% and 94% confidence intervals with and without AR model, respectively. Looking at the individual subject performances, subject 1 had the best improvement (8.2% and 7.5% with and without AR model, respectively) of average classification accuracy over all of the experiments. Moreover, this subject showed an improvement for all of the configurations. Contrastingly, subjects 7 had the worst improvement (2.1% and 1.8% with and without AR model, respectively) of average classification accuracy over all of the experiments. For all subjects (see Table 1), the improvement with AR model are only slightly better

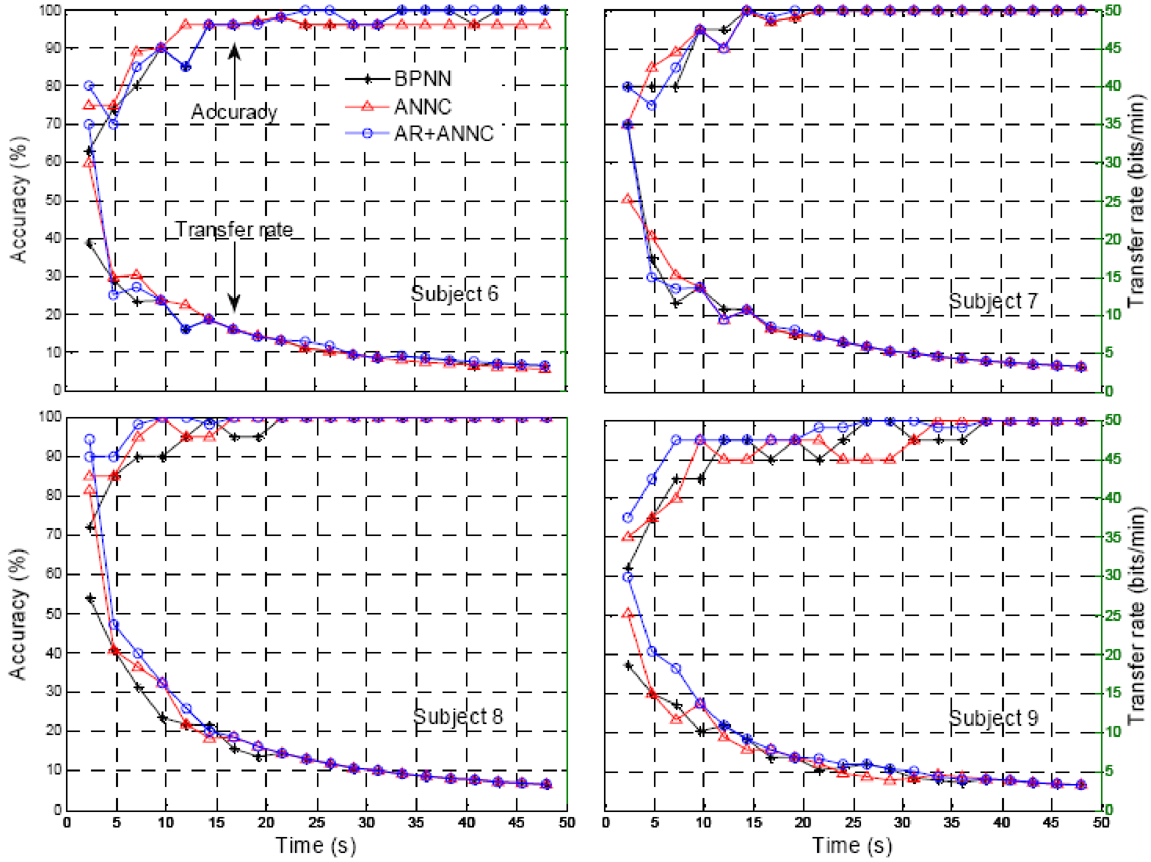


FIGURE 8. Comparison of classification accuracy and transfer rate obtained with BPNN, ANNC, and the ANNC with the AR model for able-bodied subjects

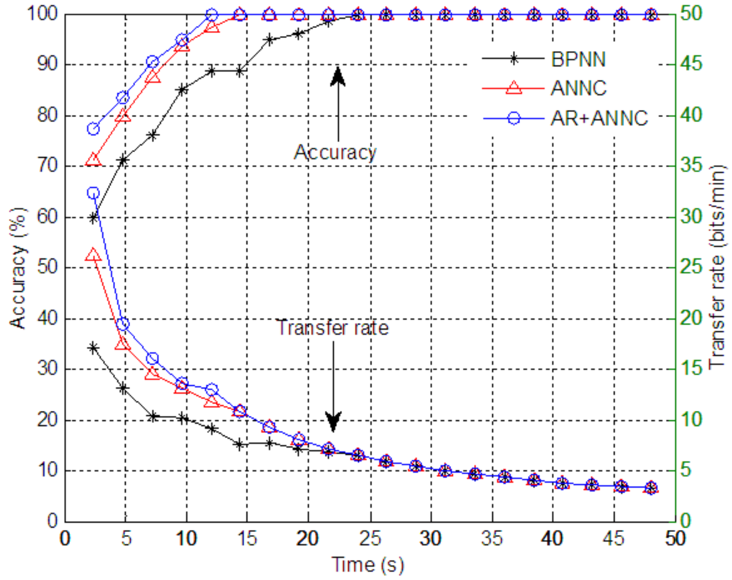


FIGURE 9. Classification accuracy and transfer rate obtained with BPNN, ANNC, and the ANNC with the AR model, averaged over all disabled subjects

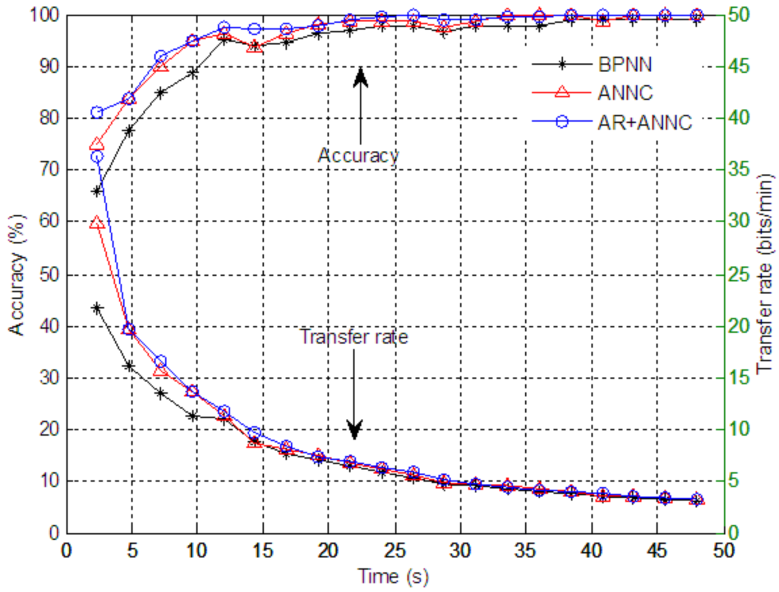


FIGURE 10. Classification accuracy and transfer rate plots obtained with BPNN, ANNC, and the ANNC with the AR model, averaged over all able-bodied subjects

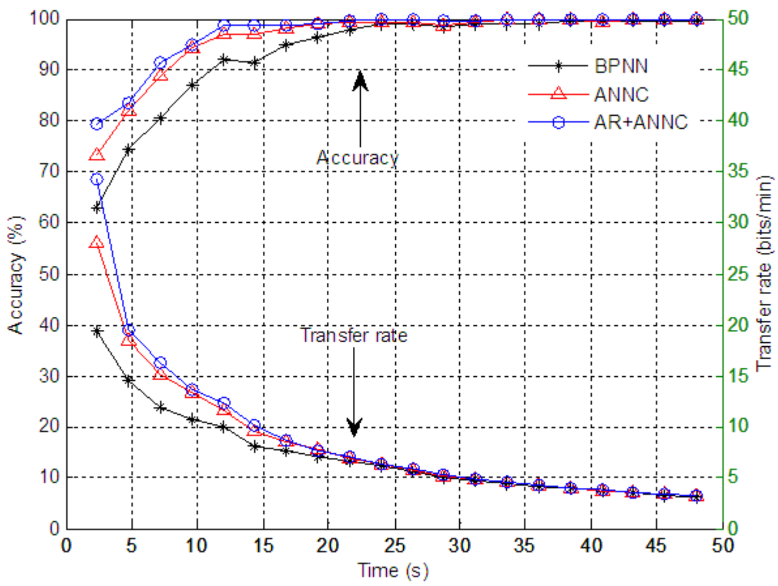


FIGURE 11. Classification accuracy and transfer rate plots obtained with BPNN, ANNC, and the ANNC with the AR model, averaged over all subjects

than without AR model. These results indicate that the classifier performance was highly affected by the proposed method.

The transfer rate (in other words, the amount of information communicated per time unit) is a standard measure of a communication system. The transfer rate is a function of both the speed and the accuracy of selection. Discussions of transfer rate in BCIs can be found in [5,13,29-33]. Current BCIs have maximum information transfer rates of

TABLE 1. Average classification accuracy (%)

| Subject | BPNN | ANNC | | Improvement | |
|---|---|---|---|---|---|
| | | (−) AR | (+) AR | (−) AR | (+) AR |
| S1 | 88.2 | 95.8 | 96.5 | 7.5 | 8.2 |
| S2 | 93.5 | 95.5 | 96.5 | 2.0 | 3.0 |
| S3 | 94.7 | 97.5 | 98.6 | 2.8 | 3.8 |
| S4 | 95.5 | 97.3 | 97.7 | 1.8 | 2.2 |
| S6 | 92.9 | 94.4 | 95.4 | 1.9 | 2.9 |
| S7 | 95.5 | 96.8 | 97.2 | 1.8 | 2.1 |
| S8 | 95.6 | 98.3 | 98.8 | 2.7 | 3.2 |
| S9 | 91.8 | 94.5 | 96.1 | 2.7 | 4.2 |
| Average (S1-S4) | $93.0 \pm 3.2$ | $96.5 \pm 1.0$ | $97.3 \pm 1.0$ | $3.5 \pm 2.7$ | $4.3 \pm 2.7$ |
| Average (S6-S9) | $93.9 \pm 1.8$ | $96.0 \pm 1.9$ | $96.8 \pm 1.4$ | $2.2 \pm 0.5$ | $3.1 \pm 0.8$ |
| Average (all) | $93.5 \pm 2.5$ | $96.2 \pm 1.4$ | $97.1 \pm 1.2$ | $2.9 \pm 1.9$ | $3.7 \pm 1.9$ |

TABLE 2. Maximum average transfer rate (bits/min)

| Subject | BPNN | ANNC | | Improvement | |
|---|---|---|---|---|---|
| | | (−) AR | (+) AR | (−) AR | (+) AR |
| S1 | 8.7 | 25.2 | 34.9 | 16.4 | 26.2 |
| S2 | 14.9 | 21.0 | 29.8 | 6.0 | 14.9 |
| S3 | 29.8 | 35.0 | 35.0 | 5.1 | 5.1 |
| S4 | 20.9 | 25.2 | 29.8 | 4.2 | 8.8 |
| S6 | 20.9 | 29.8 | 35.0 | 8.8 | 14.0 |
| S7 | 20.9 | 25.2 | 35.0 | 4.2 | 14.0 |
| S8 | 26.9 | 40.7 | 47.1 | 13.7 | 20.1 |
| S9 | 18.6 | 25.2 | 29.8 | 6.6 | 11.2 |
| Average (S1-S4) | $18.6 \pm 8.9$ | $26.6 \pm 5.9$ | $32.4 \pm 2.9$ | $7.9 \pm 5.7$ | $13.7 \pm 9.2$ |
| Average (S6-S9) | $21.8 \pm 3.5$ | $30.2 \pm 7.3$ | $36.7 \pm 7.3$ | $8.3 \pm 4.0$ | $14.8 \pm 3.7$ |
| Average (all) | $20.2 \pm 6.5$ | $28.4 \pm 6.4$ | $34.5 \pm 5.6$ | $8.1 \pm 4.6$ | $14.3 \pm 6.5$ |

10-29 bits/min [5]. This limited capacity option, compared with conventional augmentative communication tools, might be appropriate for people who are severely disabled. However, many possible applications of BCI technology might or will require higher classification accuracy and information transfer rates. In the present study, the transfer rates corresponding to the classification accuracies using both classification algorithms (ANNC and BPNN) combined were tested. The maximum average transfer rate, the mean transfer rate, and the standard deviations for all of the combinations of classification algorithms and electrode configurations are listed in Table 2. As is apparent, the maximum average transfer rates obtained with the ANNC algorithm were better those obtained with the BPNN algorithm. In the work of Hoffmann et al. (2008), the maximum average transfer rate (i.e., obtained using the BLDA) was about 15.9 bits/min for disabled subjects and 29.3 bits/min for able-bodied subjects. In the present study, the following improvements of the maximum average transfer rates for the same electrode configurations were achieved: about 35.0 bits/min for disabled subjects and 47.1 bits/min for able-bodied subjects. These results indicate that the system allowed several disabled users to achieve communication rates significantly beyond those reported previously in the literature. The transfer rates obtained on the basis of the ANNC with the AR model were found to be only slightly superior to those achieved without the AR model, but it was found to be marginally superior to those achieved the BPNN approach, which means that the transfer rates performance were highly effected by the proposed method and the former approach may not be good enough for BCI applications. Therefore, the classification accuracies and transfer rates achieved with or without the combined ANNC and AR model were far superior to those obtained with the BPNN approach, and thus are considered to be more adequate for BCI applications.

Factors that definitely are important to obtaining a good classification accuracy and transfer rate, both in communication systems and in BCI systems for disabled subjects, are the sequences of the given stimulus. When applying the AR model to extract the features of the EEG signals corresponding to a given stimulus, it was found that any two sequential target stimuli excite just one P300 component peak, and are extracted in that form. However, in order that EEG signals be classified with 100% accuracy, such stimuli must excite two peaks of amplitude. Therefore, in order to obtain a good classification accuracy and transfer rate, the given stimulus must be inputted randomly with no subsequent target. In other words, two targets should not be flashed sequentially.

5. **Conclusions.** The results presented in this study show that compared with the BPNN algorithm, a better extraction result can be obtained when using the adaptive neural networks classifier (ANNC) algorithm for EEG-P300 from specific brain regions. A 100% average classification accuracy was achieved after four blocks for disabled subjects. The data indicate that a P300-based BCI system can communicates at the rate of 35.0 bits/min and 47.1 bits/min for disabled and able-bodied subjects, respectively. The ANNC-based classification and transfer rate accuracies, obtained with and without the AR models approach, were found to be far superior to those obtained with both the BPNN and the BLDA approach, which means that this approach much more suitable for BCI applications.

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## REFERENCES

[1] J. J. Vidal, Toward direct brain-computer communication, *Annual Review of Biophysics and Bioengineering*, vol.2, pp.157-180, 1973.

[2] T. Yamaguchi, K. Nagala, P. Q. Truong, M. Fujio, K. Inoue and G. Pfurtscheller, Pattern recognition of EEG signal during motor imagery by using SOM, *International Journal of Innovative Computing, Information and Control*, vol.4, no.10, pp.2617-2630, 2008.

[3] M. Hamalainen, R. Hari, R. J. Ilmoniemi, J. Knuutila and O. V. Lounasmaa, Magnetoencephalography – Theory, instrumentation, and applications to noninvasive studies of the working human brain, *Reviews of Modern Physics*, vol.65, no.2, pp.413-497, 1993.

[4] B. E. Hillner, B. A. Siegel, D. Liu, A. F. Shields, I. F. Gareen, L. Hanna, S. H. Stine and R. E. Coleman, Impact of positron emission tomography/computed tomography and positron emission tomography (pet) alone on expected management of patients with cancer: Initial results from the national oncologic pet registry, *Journal of Clinical Oncology*, vol.26, no.13, pp.2155-2161, 2008.

[5] U. Hoffmann, J.-M. Vesin and T. Ebrahimi, An efficient P300-based brain-computer interface for disabled subjects, *Journal of Neuroscience Methods*, vol.167, no.1, pp.115-125, 2008.

[6] C. R. Hema, M. P. Paulraj, R. Nagarajan, S. Taacob and A. H. Adom, Brain machine interface: A comparison between fuzzy and neural classifiers, *International Journal of Innovative Computing, Information and Control*, vol.5, no.7, pp.1819-1827, 2009.

[7] A. Turnip, K.-S. Hong and M.-Y. Jeong, Real-time feature extraction of P300 component using adaptive nonlinear principal component analysis, *BioMedical Engineering OnLine*, vol.10, no.83, 2011.

[8] R. M. Chapman and H. R. Bragdon, Evoked responses to numerical and nonnumerical visual stimuli while problem solving, *Nature*, vol.203, no.12, pp.1155-1157, 1964.

[9] S. Sutton, M. Braren, E. R. John and J. Zubin, Evoked potential correlates of stimulus uncertainty, *Science*, vol.150, no.700, pp.1187-1188, 1965.

[10] M. Onofrj, D. Melchionda, A. Thomas and T. Fulgente, Reappearance of event-related P3 potential in locked-in syndrome, *Cognitive Brain Research*, vol.4, no.2, pp.95-97, 1996.

[11] L. A. Farwell and E. Donchin, Talking off the top of the head: Toward a mental prosthesis utilizing event-related brain potentials, *Electroenceph. Clin. Neurophysiol.*, vol.70, no.6, pp.510-523, 1988.

[12] J. Kronegg, G. Chanel, S. Voloshynovskiy and T. Pun, EEG-based synchronized brain-computer interfaces: A model for optimizing the number of mental tasks, *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol.15, no.1, pp.50-58, 2007.

[13] B. Obermaier, C. Neuper, C. Guger and G. Pfurtscheller, Information transfer rate in a five-classes brain-computer interface, *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol.9, no.3, pp.282-288, 2001.

[14] P. J. Brockwell and R. A. Davis, *Time Series: Theory and Methods*, 2nd Edition, Springer Science, Business Media, LLC, New York, 2006.

[15] X.-S. Hu, K.-S. Hong, S. S. Ge and M.-Y. Jeong, Kalman estimator- and general linear model-based on-line brain activation mapping by near-infrared spectroscopy, *BioMedical Engineering OnLine*, vol.9, no.82, 2010.

[16] S. Erla, L. Faes, E. Tranquillini, D. Orrico and G. Nollo, Multivariate autoregressive model with instantaneous effects to improve brain connectivity estimation, *International Journal of Bioelectromagnetism*, vol.11, no.2, pp.74-79, 2009.

[17] A. Adam, M. I. Shapiai, Z. Ibrahim, M. Khalid and L. W. Jau, Development of a hybrid artificial neural network – Naive bayes classifier for binary classification problem of imbalanced datasets, *ICIC Express Letters*, vol.5, no.9(A), pp.3171-3176, 2011.

[18] A. Jaffar, B. Ahmed, N. Naveed, A. Hussain, F. Jabeen and A. M. Mirza, Multi domain features based classification of mammogram images using SVM and MLP, *ICIC Express Letters*, vol.4, no.3(B), pp.937-942, 2010.

[19] G. Onishi, S. Ishimitsu, K. Sakamoto, T. Yoshimi, Y. Fujimoto and K. Kawasaki, Automatic evaluation of button sound impressions using a neural network, *ICIC Express Letters*, vol.4, no.3(A), pp.683-689, 2010.

[20] S. S. Ge, T. H. Lee and T. Zhang, Adaptive neural network control for a class of discrete-time non-linear systems, *International Journal Control*, vol.76, no.4, pp.334-354, 2003.

[21] E. B. Kosmatopoulos, M. M. Polycarpou, M. A. Christodoulou and P. A. Ioannou, High-order neural network structures for identification of dynamical systems, *IEEE Trans. Neural Netw.*, vol.6, no.2, pp.422-431, 1995.

[22] X.-S. Hu, K.-S. Hong and S. S. Ge, Recognition of stimulus-evoked neuronal optical response by identifying chaos levels of near-infared spectroscopy time series, *Neuroscience Letters*, vol.504, no.2, pp.115-120, 2011.

[23] M. Wang, S. S. Ge and K.-S. Hong, Approximation-based adaptive tracking control of pure-feedback nonlinear systems with multiple unknown time-varying delays, *IEEE Transactions on Neural Networks*, vol.21, no.11, pp.1804-1816, 2010.

[24] F. Girosi and T. Poggio, *Networks and the Best Approximation Property, Artificial Intelligence Laboratory Memorandum*, no.1164, MIT, Cambridge, 1989.

[25] L. Giles and T. Maxwell, Learning, invariance and generalization in high order neural networks, *Applied Optics*, vol.26, no.23, pp.4972-4978, 1987.

[26] Y. Nishihara, J. Irie, T. Yamaguchi, T. Yamazaki and K. Inoue, The statistical estimation method of muscle activity based on surface EEG, *ICIC Express Letters, Part B: Applications*, vol.2, no.3, pp.603-608, 2011.

[27] B. You, H. Wang and L. Zhou, The study of BP neural network classification based on extension, *ICIC Express Letters*, vol.5, no.9(B), pp.3411-3416, 2011.

[28] J. Wang, N. Chen and K. Zhang, Music emotional classification research based on BP neural network, *ICIC Express Letters*, vol.4, no.6(A), pp.2075-2079, 2010.

[29] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson and T. M. Vaughan, Brain-computer interface technology: A review of the first international meeting, *IEEE Trans. Rehabil. Eng.*, vol.8, no.2, pp.164-173, 2000.

[30] D. J. McFarland, W. A. Sarnacki and J. R. Wolpaw, Brain-computer interface (BCI) operation: Optimizing information transfer rates, *Biological Psychology*, vol.63, no.3, pp.237-251, 2003.

[31] X.-S. Hu, K.-S. Hong and S. S. Ge, Recognition of stimulus-evoked neuronal optical response by identifying chaos levels of near-infrared spectroscopy time series, *Neuroscience Letters*, vol.504, no.2, pp.115-120, 2011.

[32] X.-S. Hu, K.-S. Hong and S. S. Ge, fNIRS-based online deception decoding, *Journal of Neural Engineering*, vol.9, no.2, pp.1-8, 2012.

[33] M. Aqil, K.-S. Hong, M.-Y. Jeong and S. S. Ge, Cortical brain imaging by adaptive filtering of NIRS signals, *Neuroscience Letters*, vol.514, no.1, pp.35-41, 2012.