Classification System of EEG Signals During Mental Tasks

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Abstract: We propose accurate classification method of EEG signals during mental tasks. In the experimental task, the tasks of subjects show 3 major measurements; there are mathematical tasks, color decision tasks, and Chinese phrase tasks. The classifier implemented for this work is a feed-forward neural network that trained with the error back-propagation algorithm. The new BCI system is proposed by using neural network. In this system, the architecture of the neural network is composed of three layers with a feed-forward network, which implements the error back propagation-learning algorithm. By applying this algorithm to 4 subjects, we achieved 95% classification rates. The results for BCI mathematical task experiments show performance better than those of the Chinese phrase tasks. The selection time of each task depends on the mental task of subjects. We expect that the proposed detection method can be a basic technology for brain-computer interface by combining with left/right hand movement or yes/no discrimination methods.

1. INTRODUCTION

This research is aimed at studying disabled persons who are unable to communicate via normal physical methods, but who do completely control over their mental faculties. Some success has been achieved in classifying EEG for this purpose, but either evoked responses [1] or biofeedback trainings [2] are included in the data.

The success of this article depends on finding a signal representation that is as small as possible (for speedy processing and improved generalization) and, yet, contains the information needed to accurately classify different mental states. Here, scalar is used to define signal representations. Various features based on these models are classified with a multiplayer, feed-forward neural network using the error back-propagation training algorithm. Discrimination is performed between a single pair of tasks.

2. DATA COLLECTION

Figure 1 shows electrodes placement in the 10-20 systems. The subjects were seated in an Industrial Acoustics Company sound-controlled booth with dim lighting and noiseless fans for ventilation. An Electro-Cap elastic electrode cap was used to record EEG from positions: Fp1, Fp2, T3, T4, T5, T6, C3, C4, P3, P4, O1, and O2 (shown in Fig 1) and defined by the 10-20 system of electrode placement [3][4]. These twelve channels were referenced to electrical-linked mastoids denoted in the figure as A1 and A2. Another channel was added to record eye blinks by placing an electrode on the forehead above the left brow-line and another on the left cheekbone. The impedance of all electrodes was kept below 5 KΩ. The data were recorded at a sampling rate of 250 Hz. The electrodes were connected through a bank of MP100 amplifiers with analogue band-pass filters. The pass-band was from 0.1-100 Hz. The data were recorded for 10 s during each task and each task was repeated. For this paper we analyzed the data from four subjects with the second subject completing only one session. The data recorded during an eye blink were removed in all of our experiments. An eye blink was said to have occurred if a change in magnitude greater than 100 □ occurred within a 10-ms period. Artifacts other than eye blinks were not removed. Artifacts do not necessarily contaminate our data, since our goal is a system for recognizing patterns correlated with tasks. Artifacts, such as those due to muscle movement, are actually helpful if they facilitate the discrimination of various tasks.

Figure 2 shows the process of BCI experiment

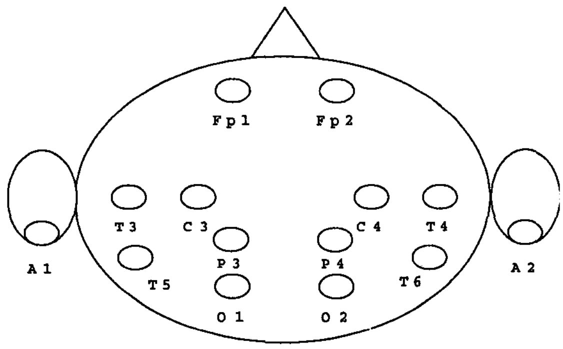


Fig.1. Placement of the electrodes according to the 10-20 system

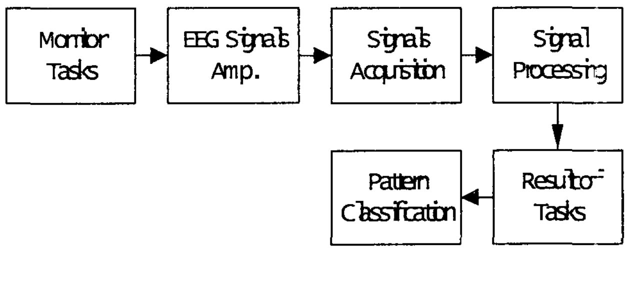


Fig.2. Process of BCI Experiment

3. EXPERIMENTAL CONDITIONS AND TASKS

The mental tasks described here were made from Java Programming and chosen to invoke hemispheric brainwave asymmetry. It was shown through experiments that the peak of the power spectrum in the alpha frequency range (8-13 Hz) increased in the left hemisphere rather than the right during arithmetic tasks, whereas it increased in the right hemisphere rather than the left for visual tasks.

The subjects were not asked to perform a specific mental task, but to relax as much as possible and think of nothing in particular. This task is considered the baseline task for alpha wave production and used as a control measure for the EEG.

The three tasks applied to the experiment are as follows:

1) Math task: The subjects were given calculation problems and were asked to solve them without vocalizing or making any other physical movements. An example is 10 × 15. The problems were not repeated and were designed so that an immediate answer was not attainable. Subjects were asked after each trial whether or not they found the answer.

2) Color decision task: The subjects were given 10s to discriminate a particular color figure.

3) Chinese phrase task: The subjects were asked to mentally compose a Chinese letter to a relative or a friend without vocalizing.

The subject mental statement of each task is shown in Figure3.

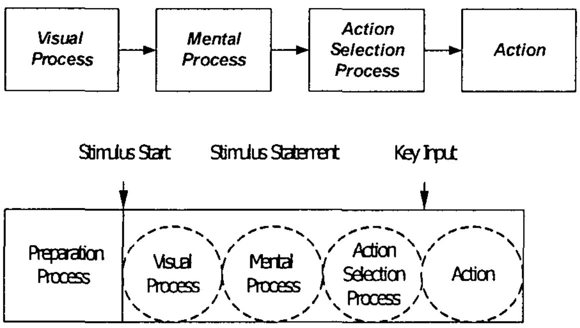


Fig.3. Analysis Process of subject mental statement

4. RESULT

The classifier implemented for this work is a standard, feed-forward neural network, trained with the error back-propagation algorithm.

In the forward pass when an input pattern is applied to input layer, the output values are calculated through the connection weights. In the backward pass, the output values are compared with the desired output values and the error is calculated. The error is back-propagation through the network and the connection weight is changed by the gradient descents of the mean squared error as a function of weights.

$$NET_Z = XV^T, Z = f(NET_Z) \quad (1)$$

$$NET_Y = XV^T, Y = f(NET_Y) \quad (2)$$

Where (1), (2) represent output weights

$$E = \frac{1}{2}(d-y)^2 \quad (3)$$

Where (3) a squared error E from reference d and output y

$$\delta_y = (d-y)y(1-y) \quad (4)$$

$$\delta_z = f'(NET_z)\sum_{i=0}^{m}\delta_y\omega \quad (5)$$

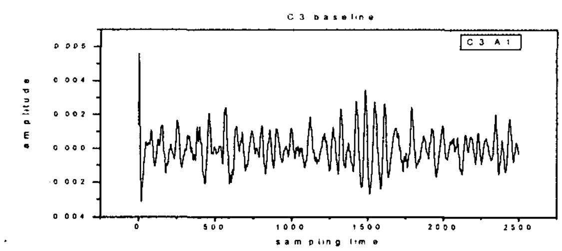
(4) and (5), error signals δ_y of output layer and error signal δ_z of hidden layer

$$\Delta\omega^k = \alpha\delta_y z, \Delta v^k = \alpha\delta z x \quad (6)$$

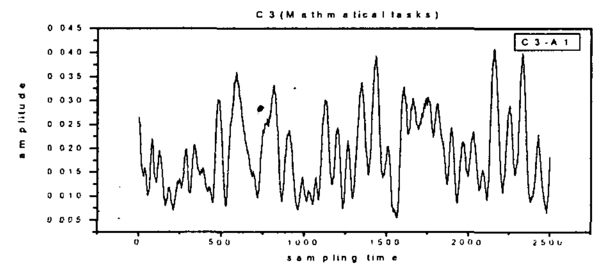
Where the weight $\Delta\omega^k$ of the hidden layer to the output layer, weight Δv^k of input layer to the output layer.

Fig 4 shows a 40-second long data from a subject doing the three tasks described below. An eye blink (open, close) of from the result of our experiment is shown in Fig 5. Wavelet decomposition of mental state is shown in Fig 6. The leaning result of samples and the result of experiment for subjects are shown in fig 7 and Fig 8 respectively.

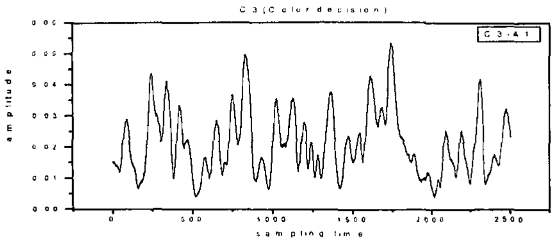
In Table 1, the selection time of each task depends on the mental task of each subject, and Wrong means either the uncompleted problem within 10s or wrong answer.



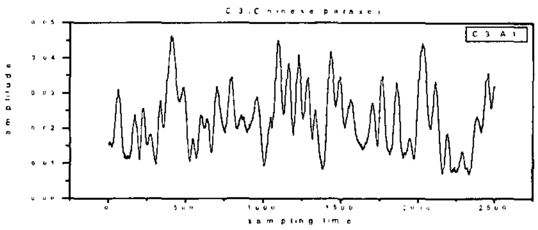
(a)



(b)

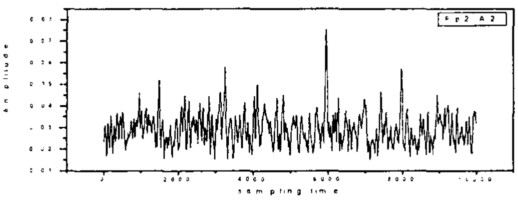


(c)

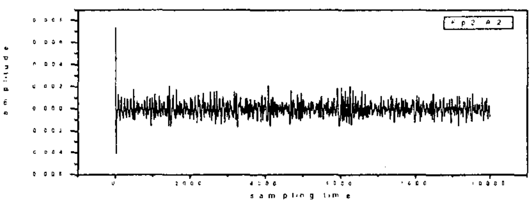


(d)

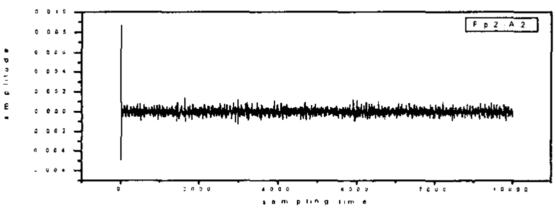
Fig.4. Data from subject 4 performing each task. (a) Mental task (b) Baseline task.



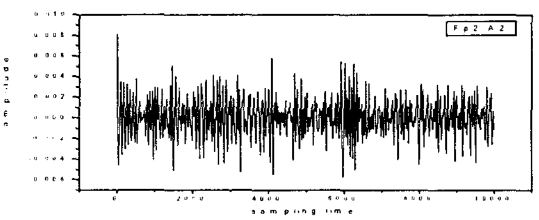
(a) Fp2 source signal



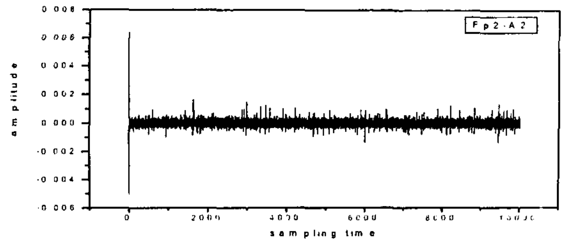
(b) Alpha band frequency



(c) Beta band frequency



(d) Theta band frequency



(e) Gamma band frequency

Fig.5. Eye (open, close) result of experiment ((a) Raw (Fp1, Fp2), (b) Alpha frequency band, (c) Beta frequency band, (d) Theta frequency band and (e) gamma frequency band)

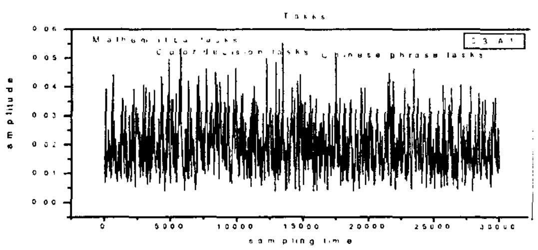
Table 1. Result of BCI Experiment

Subjects	Task	Test Total/Wrong	Time Aver. (sec)
A	Math Tasks	10/0	6.2
B	Chin. Letter Tasks	10/2	7.1
C	Math Tasks	10/1	6.3
D	Color decision	10/0	6.4

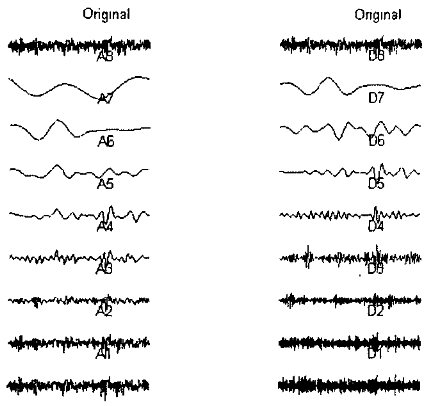
The results of simulation using neural network are shown in table 2.

Table 2. Result of Neural Network Simulations

Subjects	Square Error	Iteration	Recognition (%)
A	0.0013	15,000	88
B	0.0017	21,100	93
C	0.0021	17,130	95
D	0.0019	16,233	92



(a)



(b)

Fig.6. Wavelet decomposition of mental state. (a) Original signal (b) Scaling coefficient and wavelet coefficient.

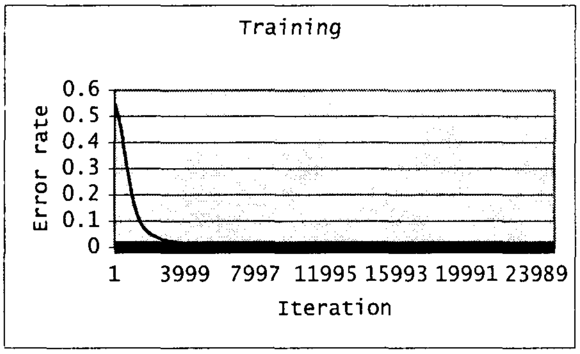


Fig.7. Learning result of examples

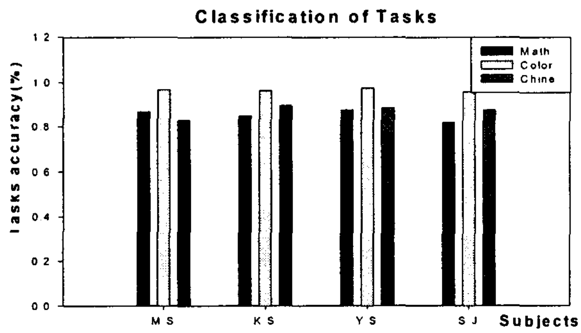


Fig. 8. Result of experiment for subjects

5. CONCLUSION

This paper proposes a new BCI system using neural network. The proposed system shows a little more accurate diagnosis for EEG by analysis of frequency using Wavelet, and by classification using neural network.

From the simulation results of the implemented system, this research demonstrated being reduced doctor's labors.

We are now trying to verify the detailed classification work using algorithm based on EEG data. We hope that more works, developed from the proposed BCI technology, will take place in the near future, and enable the design of a complete working system.

References

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