A Brain Computer Interface Based on FFT and Multilayer Neural Network
- Feature Extraction and Generalization -

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Abstract— In this paper, a multilayer neural network is applied to 'Brain Computer Interface' (BCI), which is one of hopeful interface technologies between humans and machines. Amplitude of the FFT of the brain waves are used for the input data. Several techniques have been introduced for pre-processing the brain waves. They include segmentation along the time axis for fast response, nonlinear normalization to emphasize important information, averaging samples of the brain waves to suppress noise effects, reduction in the number of the samples to realize a small size network, and so on. In this paper, two kinds of generalization techniques, including adding small random noises to the input data and decaying connection weight magnitude, are applied. Their usefulness are analyzed and compared based on correct and error classifications. Simulation is carried out by using the brain waves, which are available from the web site of Colorado State University. The number of mental tasks is five. Some data sets are used for training the multilayer neural network, and the remaining data sets are used for testing. In our previous work, classification accuracy of 64%~74% for the test data have been achieved. In this paper, by applying the generalization techniques, the accuracy can be improved up to 80%~88%.

I. INTRODUCTION

Nowadays, several kinds of interfaces between humans and computers or machines have been proposed and developed. For persons being in a healthy condition, keyboards and mouses are useful and practical interfaces. On the other hand, for handicapped persons, several interface techniques, which use available organs and functions, have been studied and developed.

Among the interfaces developed for the handicapped persons, Brain Computer Interface (BCI) has been attractive recently. A subject imagines some mental tasks, and the brain waves are measured. The brain waves are analyzed and the mental tasks are estimated. Furthermore, based on the estimated mental task, computers and machines are controlled [1].

It can be expected that severely handicapped persons, who cannot control any parts of their own body, can control a wheelchair, computers and other machines through the BCI [2]. Furthermore, in the virtual reality (VR) technology, it may be possible to control a person in the VR world, and to have many kinds of experiences in the VR world. For instance, training how to move in danger situations may be possible by using the BCI technology.

Approaches to the BCI technology includes nonlinear classification by using spectrum power, adaptive auto-regressive model and linear classification, space patterns and linear classification, hidden Markov models, and so on [3],[4]. Furthermore, application of neural networks have been also discussed [5],[6],[7],[8],[9],[10]. In our works, FFT of the brain waves and a multilayer neural network have been applied to the BCI. Efficient pre-processing techniques have been also employed in order to achieve a high probability for correct classification of the mental tasks [15].

In this paper, features of the brain waves, which are extracted by the multilayer neural network, are analyzed. Furthermore, two kinds of generalization techniques are applied to increasing accuracy of classification. Simulations are carried out by using the brain waves, which are available from the web site of Colorado State University [11]. Estimation results of the proposed method are compared to the conventional methods.

II. MENTAL TASKS AND BRAIN WAVE MEASUREMENT

A. Mental Tasks

In this paper, the brain waves, which are available from the web site of Colorado State University [11], are used. The following five kinds of mental tasks are used as imaging.

- Baseline (B)
- Multiplication (M)
- Letter-composing (L)
- Rotation of a 3-D object (R)
- Counting numbers (C)

B. Brain Wave Measurement

Location of the electrodes to measure brain waves is shown in Fig.1. Seven channels including C3, C4, P3, P4, O1, O2, EOG, are used. EOG, which does not appear in this figure, is used for measuring movement of the eyeballs.

The brain waves are measured for a 10sec interval and sampled by 250Hz for each mental task. Therefore, $10sec \times 250Hz = 2,500$ samples are obtained for one channel and one
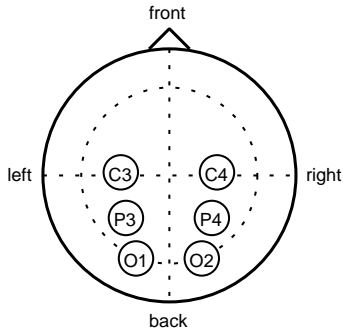
Fig. 1. Location of electrodes measuring brain waves.

mental task. Therefore, one data set includes 2,500 samples for each channel and each mental task. Five mental tasks and seven channels are included in one data set.

III. PRE-PROCESSING OF WAVE FORMS [15]

A. Segmentation along Time Axis

In order to make the BCI response fast, the brain wave measured during 10sec is divided into the segments of a 0.5sec length. The segmentation is shifted by 0.25sec. This means the segment of a 0.5sec length can be obtained every 0.25sec. The brain wave segment in a 0.5sec length is used to classify the mental tasks.

B. Amplitude of FFT of Brain Waves

What kinds of features of the brain waves should be used to classify the mental tasks is very important. In order to avoid effects of brain wave shifting along the time axis, which is not essential, the brain wave is first Fourier transformed and its amplitude is used. The segment of the brain wave of a 0.5sec length includes $2,500 \times 0.5/10 = 125$ samples.

C. Reduction of Samples by Averaging

In order to make the neural network size to be compact and to reduce effects of the noises added to the brain waves, the FFT samples in some interval are averaged. The average value is used to express the representative sample in this interval, and is used for the neural network input. By this averaging, the number of samples is reduced from 125 to 20.

D. Nonlinear Normalization

The amplitude of the FFT is widely distributed. Small samples also contain important information for classifying the mental tasks. However, in the neural networks, large inputs play an important role. If large samples do not include important information, correct classification will be difficult. For this reason, the nonlinear normalization as shown in Eq.(1) is introduced in this paper. x is the amplitude before normalization and $f(x)$ is the normalized amplitude. In Eq.(1), x_{min} and x_{max} mean the minimum and the maximum values of x. The small samples are expanded and the large samples are compressed.

$$f(x) = \frac{\log(x - x_{min})}{\log(x_{max} - x_{min})} \quad (1)$$

E. Input of Neural Network

Since the amplitude response is symmetrical in the frequency range from 0 to f_s, which is a sampling frequency, only the right hand side is used. Furthermore, the amplitude response of the seven channels are simultaneously applied to the neural network. An example of the neural network input is shown in Fig.2.
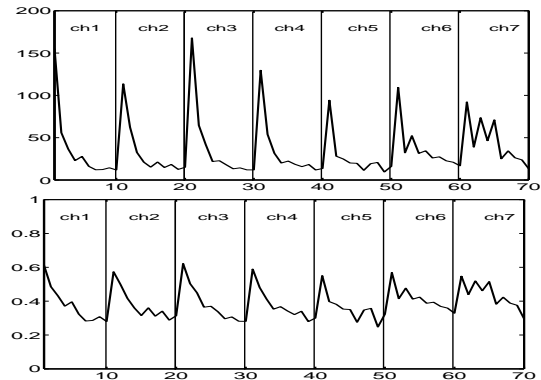

Fig. 2. Input of neural network including 7-channels for one mental task. (Upper) Before normalization. (Lower) After normalization.

IV. MENTAL TASK CLASSIFICATION BY USING MULTILAYER NEURAL NETWORK

A multilayer neural network having a single hidden layer is used. Activation functions used in the hidden layer and the output layer are a hyperbolic tangent and a sigmoid function, respectively. The number of input nodes is 10 samples×7 channels=70. Five output neurons are used for five mental tasks. The target for the output has only one non-zero element, such as $(1, 0, 0, 0, 0)$. In the testing phase, the maximum output becomes the winner and the corresponding mental task is assigned. However, when the winner have small value, estimation becomes incorrect. Therefore, the answer of the neural network is rejected, that is any mental task cannot be estimated. The error back-propagation algorithm is employed for adjusting the connection weights.

V. GENARALIZATION

The brain waves are very sensitive, which easily change depending on health conditions of the subjects and the measuring environment. The data sets measured for the same subject, have different features. Therefore, generalization is very important for the BCIs. The generalization is equivalent to make a boundary at the middle point between the different mental task regions in the input space, taking a probability of the input data into account.

In this section, two kinds of the generalization techniques, which are adding random noise to the neural network input [12] and a weight decay technique [13], are applied to learning the neural network.

A. Adding Random Noise to NN Input Data

By adding small and different random noises to the neural network input data at each epoch of the learning process, the region, where the input data of a mental task are distributed, can be expanded. The boundary between the different mental tasks in the input space can be set at the middle point of their regions.

B. Weight Decay Method

When the magnitude of the connection weights of the neural network are large, slopes of the hyperbolic tangent and the sigmoid function become steep. When the slope is steep, the boundary can locate at any point between the different mental task regions in the input space. By suppressing the magnitude of the connection weights in a learning process, the slope can be controlled to be gentle. As a result, the boundary can be set at the middle point between the different mental task regions [13],[14].

VI. SIMULATIONS AND DISCUSSIONS

A. Simulation Setup

1) Training and Testing Brain Waves: The brain waves with 10sec length for five mental tasks were measured 10 times. Therefore, 10 data sets are available. Among them, 9 data sets are used for training and the remaining one data set is used for testing. Five different combinations of 9 data sets are used for the training. As a result, five different data sets are used for testing. Thus, five independent trials are carried out. Classification accuracy is evaluated based on the average over five trials [3].

2) Probability of Correct and Error Classifications: Estimation of the mental tasks is evaluated based on probabilities of correct classification (P_c) and error classification (P_e), and a correct classification rate (R_c).

$$P_c = \frac{N_c}{N_t} \times 100\%, P_e = \frac{N_e}{N_t} \times 100\%, R_c = \frac{N_c}{N_c + N_e} \quad (2)$$
$$N_t = N_c + N_e + N_r \quad (3)$$

N_c, N_e and N_r are the numbers of correct and error classifications and rejections. N_t is the total number of the training data or the testing data. P_c can express probability of correct classifications, and P_e expresses mis-classifications for all data. R_c is used to evaluate a correct classification rate except for 'Rejection'.

3) Parameters in Neural Network Learning:

- Activation functions:
    Hidden layer: Hyperbolic tangent
    Output layer: Sigmoid function
- The number of hidden neurons: 20
- A learning rate: 0.2
- Initial weights: Random numbers in -0.1~+0.1
- The threshold for rejection: 0.8

B. Probabilities of Classification

Effects of the nonlinear normalization given by Eq.(1) on the mental task classification accuracy is investigated. For reference, linear normalization, by which the sample values are linearly normalized from 0 to 1, is also used. The segmentation is used, and 125 samples are reduced to 20 samples by averaging. The probability of correct and error classifications and their rate are shown in Table I. From these results, the nonlinear normalization can make convergence of the learning fast, and the probability can be also improved.

TABLE I
PROBABILITY OF CLASSIFICATIONS FOR LINEAR AND NONLINEAR
NORMALIZATION.

Normalization	Training data			Testing data		
	P_c	P_e	R_c	P_c	P_e	R_c
Linear	81.8	1.9	0.98	68.4	9.8	0.88
Nonlinear	99.7	0.1	0.99	79.7	10.5	0.88

C. Feature Extraction

The connection weights of the trained multilayer neural network are investigated in order to analyze feature extracted by the neural network in the learning process. Magnitude of the connection weights from the hidden layer to the output layer are shown in Fig.3. The horizontal axis indicates the hidden unit number and the vertical axis is the output unit number. 20 hidden units and 5 output units, which correspond to the 5 mental tasks, are used. Red color means large magnitude and blue color is small magnitude. For example, the 4th and the 9th hidden units have large connection weights for the 1st mental task. Furthermore, the 1st, 7th and 17th hidden units have large connection weights for the 3rd mental task. The connection weights from these hidden units to the other output units do not have large magnitude. Thus, they play an important role for the 1st and the 3rd mental tasks. Therefore, it can be recognized that these hidden units extract the features for these mental tasks. The feature of the FFT of the brain waves for these mental tasks can be expressed by using the connection weights from the input layer to these hidden units, as shown in Fig.4. In this figure, the horizontal axis indicates the input unit number and the vertical axis means the hidden unit number.
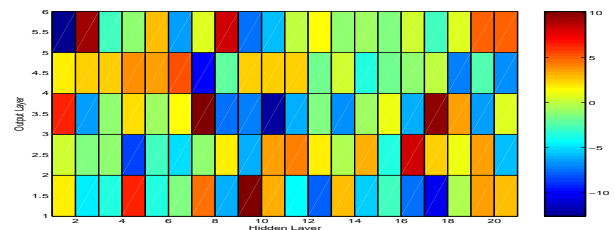

Fig. 3.   Connection weights from hidden layer to output layer.

D. Effects of Generalization Techniques

1) Adding Random Noise: The input data of the multilayer neural network are distributed from 0 to 1 by the nonlinear
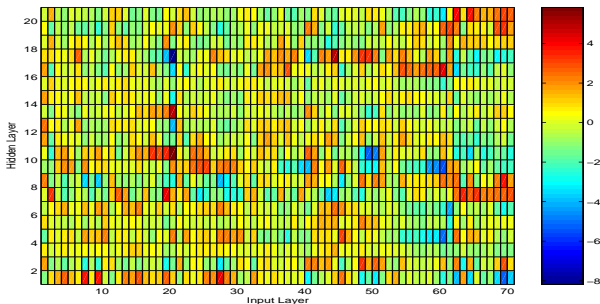
Fig. 4.   Connection weights from input layer to hidden layer.

normalization. One example is shown in Fig.2, in which the input data are distributed from 0.25 to 0.6. In this simulation, random numbers, which are uniformly distributed in the $-0.1 \sim 0.1$ interval, are added to the input data. This range is determined by experience. Actually, it should be optimized for each problem.

The probability of correct and error classifications and their rate for the testing data are listed in Table II. In Subject 1, P_c is increased from 74% to 88% and P_e is decreased from 6% to 2%. Thus, R_c is increased from 0.925 to 0.978. In Subject 2, P_c is increased from 64.0% to 80.0%. P_e is decreased from 8.0% to 4%. Therefore, R_c is also well improved from 0.889 to 0.952. As a result, efficiency of generalization of adding random noises to the input data can be recognized.

TABLE II

IMPROVEMENT OF CLASSIFICATIONS BY GENERALIZATION.

Methods	Subject 1			Subject 2		
	P_c	P_e	R_c	P_c	P_e	R_c
No generalization	74.0	6.0	0.925	64.0	8.0	0.889
Adding random noises	88.0	2.0	0.978	80.0	4.0	0.952
Weight decay	82.0	4.0	0.954	60.0	4.0	0.938
Weight decay & Scaling	88.0	12.0	0.88	84.0	16.0	0.84

2) Generalization by Weight Decay: The connection weights are compressed at each epoch by multiplying the following variable factor $g(n)$.

$$g(n) = g_0 + (1 - g_0)\frac{1 - e^{2\pi an}}{1 + e^{2\pi an}}, \quad n \geq 0 \quad (4)$$

$$\hat{\boldsymbol{w}}(n) = g(n)\boldsymbol{w}(n) \quad (5)$$

$g_0 = 0.99 \sim 0.994$ and $a = 0.5 \sim 1$ are used, which are determined by experience. $\hat{\boldsymbol{w}}(n)$ will be used in the next epoch. The probabilities of the classification are also listed in Tabel II, denoted 'Weight decay'. In the case of Subject 1, P_c, P_e and R_c are all improved from thoese of 'No generalization'. However, the improvements are inferior to 'Adding random noises'. In the case of Subject 2, even though P_c is decreased from 'No generalization', P_e and R_c can be improved. In this case, 'Adding random noises' still can provide good performances.

In the weight decay method, the boundary can be controlled at the middle point between different classes. However, the

outputs of the multilayer neural network gradually change from one class to the other class. In order to emphasize the outputs, that is to make the outputs more clear, all connection weights are scaled up by multiplying $1.5 \sim 2$. Probabilities of classification are also listed in Table II denoted 'Weight decay & Scaling'. In this case, P_c can be improved from 82% to 88% and from 60% to 84% for Subject 1 and 2, respectively. However, P_e is also increased from 4% to 12% and from 4% to 16%, resulting in lower R_c.

VII. CONCLUSION

A multilayer neural network has been applied to the BCI problem. Probabilities of correct classification of $64\% \sim 74\%$ have been obtained. In this paper, two kinds of generalization techniques are applied. The accuracy is more increased to $80\% \sim 88\%$. Compared to the conventional methods, the higher probability of correct classification can be obtained. Furthermore, features, which are used to classify the mental tasks, are analyzed.

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