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A BCI Using MEGvision and Multilayer Neural Network - Channel Optimization and Main Lobe Contribution Analysis -

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***Abstract*— Multilayer neural networks (MLNN) and the FFT amplitude of brain waves have been applied to 'Brain Computer Interface' (BCI). In this paper, a magnetoencephalograph (MEG) system, 'MEGvision' developed by Yokogawa Corporation, is used to measure brain activities. MEGvision is a 160-channel whole-head MEG system. Channels are selected from 8 main regions, a frontal lobe, a temporal lobe, a parietal lobe and a occipital lobe, located in the left and the right sides of the brain. The 8 channels, located at the central point in the 8 lobes, are initially selected. Optimum channels are searched for in the same lobe as the initial channels in order to achieve high classification accuracy. Two subjects and four mental tasks, including relaxed situation, multiplication, playing sport and rotating an object, are used. The brain waves are measured 10 times for one subject and one mental task. Among them, 8 data sets are used for training the MLNN, and the remaining 2 data sets are used for testing. 5 kinds of combinations of 2 data sets are selected for testing. Rates of correct classification by using the initial channels are $82.5 \sim 90\%$. By optimizing the channels, the accuracy is improved up to $85.0 \sim 97.5\%$, which is very high accuracy. Furthermore, contributions of the brain waves in the 8 lobes are analyzed.**

I. Introduction

Among man-machine interfaces, Brain Computer Interface (BCI) has been recently attractive [1], [2]. 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, the FFT amplitude of the brain waves and a multilayer neural network (MLNN) have been applied to BCI. Efficient pre-processing techniques have been proposed to achieve highly accurate classification of mental tasks [12]. Furthermore, the generalization methods have been applied to the MLNN based BCI. The method of adding small random numbers to the MLNN input data can improve classification performance [13].

In this paper, the BCI system based on the FFT amplitude and the MLNN is employed [12], [13]. The magnetoencephalograph (MEG) system, 'MEGvision' developed by Yokogawa Corporation, is used to measure brain activities. MEGvision is a 160-channel whole-head MEG system, which has very high time and spatial resolution [14]. The channels are selected from 8 main lobes located in the left and the right sides of the brain. Effects of selecting 8 channels from 160 channels will be investigated. Two subjects and four mental tasks, including relaxed situation, multiplication, playing sport and rotating some object, are used. The MLNN based BCI is applied to the MEG brain data, and mental task classification accuracy will be evaluated. Furthermore, contributions of the brain waves in the 8 lobes on the mental task classification will be investigated.

II. MEGvision

The MEG is a measurement instrument specifically designed to measure electrophysiological cerebral nerve activities, featuring high time and spatial resolution performance [14]. The key technology of the MEG is the SQUID fluxmeters, which detect the extremely weak magnetic field generated by the brain. MEGvision places the SQUID fluxmeters at 160 locations to cover the entire head, so that the complex magnetic field source generated by the activity of the brain can be recorded at a high spatial resolution.

III. Mental Tasks and MEG Brain Wave Measurement

A. Mental Tasks

In this paper, the following four mental tasks are used.

- Baseline: Staying in relaxed condition (B)
- Multiplying a 3-digit number by a 1-digit number (M)
- Playing some sport (S)
- Rotating some object (R)

B. MEG Brain Wave Measurement

Locations of 160 sensors of MEGvision are shown in Fig.1. Blue points indicate the sensors, which are also called 'channels' in this paper. Activity of the brain can be measured by these 160 channels simultaneously. Among them, we will select appropriate 8 channels for classifying the mental tasks.

The subjects imagine the mental task during 30sec, and the brain activities are measured by the MEGvision. The brain waves of 10sec at the middle part of the 30sec interval are extracted, and are used for the BCI. The brain waves are sampled by 1,200Hz. Therefore, $10\text{sec} \times 1,200\text{Hz} = 12,000$ samples are obtained for each channel and each mental task.

The brain waves are measured 10 times for one subject and one mental task. Therefore, 10 trials$\times$4 mental tasks=40

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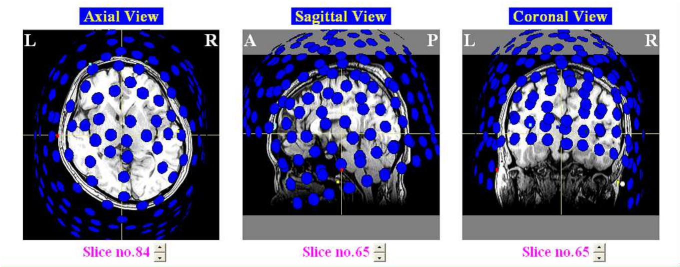

Fig. 1. Location of 160 sensors of MEGvision.

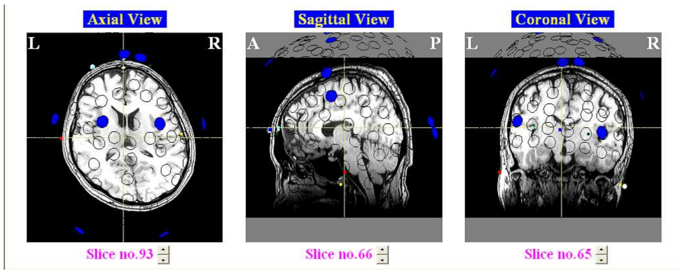

Fig. 3. Optimum channels searched for in the same lobes.

data sets are measured for one subject. One data set includes 8 channels×12,000 samples=96,000 samples. Among 40 data sets, 8 trials×4 mental tasks=32 data sets are used for training the MLNN, and the remaining 2 trials×4 mental tasks=8 data sets are used for testing the MLNN. 5 kinds of combinations of 8 test data sets are selected, and classification accuracy is evaluated by averaging the results for the above 5 test data sets.

C. Channel Selection and Optimization

A purpose of this paper includes analysis of contributions of the brain waves in the main 8 lobes on the mental task classification. The main 8 lobes includes a frontal lobe, a parietal lobe, a temporal lobe and a occipital lobe, located in the left and the right sides of the brain. 8 channels are selected from these lobes. The channels, which are located at the central point of each lobe, are selected as the initial channels. Optimum channels will be searched for in the same lobe as the initial channels taking classification accuracy into account.

In this paper, representative channel numbers are assigned for convenience as follows: Ch1: a frontal lobe(left), Ch2: a frontal lobe(right), Ch3: a parietal lobe(left), Ch4: a parietal lobe(right), Ch5: a temporal lobe(left), Ch6: a temporal lobe(right), Ch7: a occipital lobe(left), Ch8: a occipital lobe(right). For example, Ch1 represents the initial channel and also the optimum channel in the frontal lobe(left).

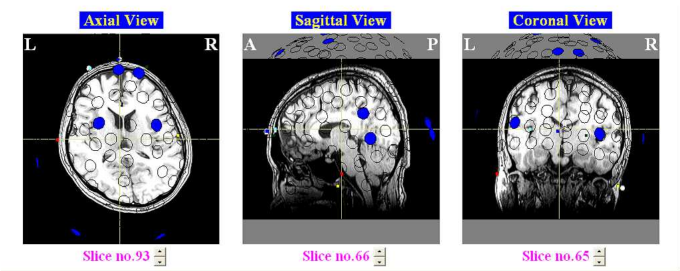

Fig. 2. Initial channels selected from 8 lobes. Blue points indicate selected channels.

Figure 2 shows the 8 initial channels for Subject 1. Blue points indicate the selected channels.

The optimum channel is first searched for in the frontal lobe(left), that is Ch1, in order to maximize the classification accuracy. Next, it is searched for in the frontal lobe(right), that is Ch2, in the same way. Like this, the optimum channels are successively searched for individually in each lobe in the order of Ch1, Ch2, $\cdots$, Ch8. In each lobe, the near optimum channel is searched for around the initial channel. After that, the optimum channel is further searched for around the near optimum channel. Figure 3 shows the optimum channels.

Figure 4 shows the brain waves for the initial 8 channels measured by MEGvision. The brain waves correspond to Ch1 through Ch8 in this order from the top to the bottom.

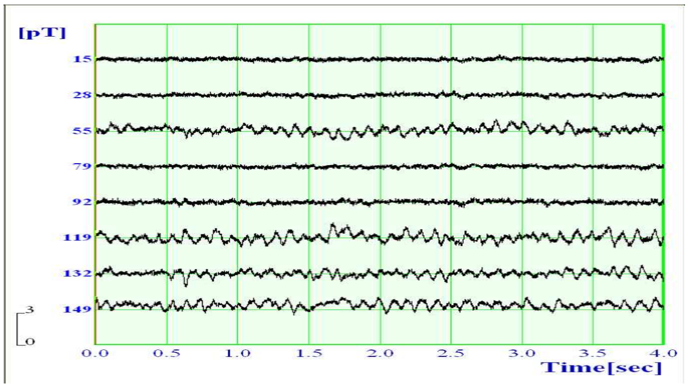

Fig. 4. Brain waves for initial 8 channels measured by MEGvision.

IV. Pre-Processing of MEG Data

Several techniques for pre-processing the brain waves proposed in [12] are also employed in this paper, and are briefly described here.

A. Amplitude of FFT

In order to avoid effects of brain wave shifting along the time axis, which is not essential, the brain waves are first Fourier transformed and their amplitude are used for the MLNN input data.

B. 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. By this averaging, the number of samples is reduced from 12,000 to 20. Since the brain waves are real numbers, their FFT amplitude are symmetrical, a half of 20 samples, that is 10 samples, can express all information.

C. Nonlinear Normalization

The nonlinear normalization as shown in Eq.(1), introduced in [12], is also applied in this paper. x is the FFT 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 in all channels.

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

D. Input of Multilayer Neural Network

The amplitude response of the 8 channels are simultaneously applied to the MLNN. An example of the MLNN input is shown in Fig.5. It includes 8 channels, and 10 samples are assigned for each channel. Thus, 80 nodes are used for the MLNN input. Ch1 through Ch8 are arranged in this order from the left side to the right side. Each 10 samples in the horizontal axis are frequencies ranging from 0 to 600Hz, and the vertical axis is the FFT amplitude.

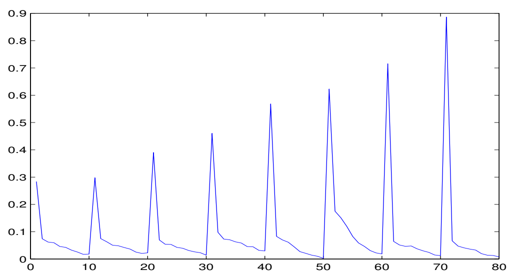

Fig. 5. Input data of multilayer neural network for a single mental task.

V. Mental Task Classification by Using Multilayer Neural Network

A. Multilayer Neural Network

An MLNN 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$\times$8 channels=80. The number of hidden units is 20. Four output neurons are used for four mental tasks. The targets $(1, 0, 0, 0)$, $(0, 1, 0, 0)$, $(0, 0, 1, 0)$, $(0, 0, 0, 1)$ are assigned to the mental tasks B, M, S, R, respectively. In the testing phase, the maximum output becomes the winner and the corresponding mental task is assigned. The error back-propagation algorithm is employed for adjusting the connection weights. A learning rate is 0.02.

B. Rates of Correct and Error Classifications

Estimation of the mental tasks is evaluated based on rates of correct classification (P_c) and error classification (P_e) as follows:

$$P_c = \frac{N_c}{N_t} \times 100\% \tag{2}$$

$$P_e = \frac{N_e}{N_t} \times 100\% \qquad N_t = N_c + N_e \tag{3}$$

N_c and N_e are the numbers of correct and incorrect classifications, respectively.

C. Mental Task Classification

Table I shows rates of the mental task classification by using the initial channels and the optimum channels. From these results, we can recognize the classification rates depend on the channel locations. By selecting the optimum channels, the correct classification rates can be improved from $82.5 \sim 90.0\%$ up to $85.0 \sim 97.5\%$. Especially, in Subject 1, the correct classification can be drastically improved.

TABLE I
RATE OF MENTAL TASK CLASSIFICATION FOR INITIAL AND OPTIMUM CHANNELS.

Channel conditons	Subject 1	Subject 2
Initial channels	$P_c = 90.0\%$ $P_e = 10.0\%$	$P_c = 82.5\%$ $P_c = 17.5\%$
Optimum channels	$P_c = 97.5\%$ $P_e = 2.5\%$	$P_c = 85.0\%$ $P_c = 15.0\%$

Table II shows rates of classification for Subject 1 in more detail. In this case, the brain waves are almost correctly classified. Only one data set in 'Sport' is mis-classified into 'Baseline'.

TABLE II
RATE OF MENTAL TASK CLASSIFICATION FOR 'SUBJECT 1' BY USING OPTIMUM CHANNELS.

Mental tasks	B	M	S	R	$P_c[\%]$	$P_e[\%]$
Baseline	10	0	0	0	100	0
Multiplication	0	10	0	0	100	0
Sport	1	0	9	0	90	10
Rotation	0	0	0	10	100	0
				Av	97.5	2.5

Table III shows rates of classification for Subject 2. In this case, the classification rates are lower than those of Subject 1. Estimating 'Sport' is also weak in Subject 2, which is mis-classified into all the other mental tasks one time.

TABLE III
RATE OF MENTAL TASK CLASSIFICATION FOR 'SUBJECT 2' BY USING OPTIMUM CHANNELS.

Mental tasks	B	M	S	R	$P_c[\%]$	$P_e[\%]$
Baseline	9	1	0	0	90	10
Multiplication	1	9	0	0	90	10
Sport	1	1	7	1	70	30
Rotation	0	0	1	9	90	10
				Av	85.0	15.0

VI. Analysis of Contributions of Brain Waves in 8 Lobes

Contributions of the brain waves in the 8 lobes are analyzed based on the connection weights of the MLNN after learning. In this case, all data sets are used in learning the MLNN. Figure 6 shows the connection weights from the hidden layer to the output layer. The horizontal axis indicates the hidden unit number, and the vertical axis means the mental tasks, B, M, S and R arranged in this order from the bottom to the top.

Red color means positive large value and blue color means negative large value. From this figure, we can recognized that specific hidden units are strongly related to one of the mental tasks. For example, the hidden units 16 and 30 have positive large weights connected to 'Baseline'. They are important hidden units for this mental task. The hidden units 2, 4, 24 and 27 are important for 'Multiplication'. These important hidden units are listed in Table IV. Therefore, by investigating the connection weights from the input layer to these important hidden units, contributions of the brain waves in the 8 lobes can be analyzed.

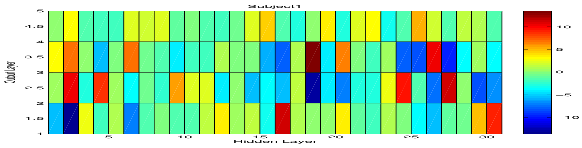

Fig. 6. Connection weights from hidden layer to output layer for Subject 1.

Figure 7 shows the connection weights from the input layer to the hidden layer. The horizontal axis indicates the input node number. 10 nodes are included in one channel. The channels Ch1 through Ch8 are arranged in this order from the left side to the right side. The vertical axis means the hidden unit number. The channel numbers, whose weights are connected to the important hidden units, are summarized in Table IV. In this table, the numbers $1 \sim 8$ in the first row indicate the channel numbers. Furthermore, 'H', 'M' and 'L' mean that contribution level is 'High', 'Middle' and 'Low', respectively. For example, in 'Baseline', the brain waves in Ch5, that is a temporal lobe(left), play an important role. Furthermore, in 'Sport', Ch4, that is a parietal lobe(right), is very important. On the other hand, in 'Rotation', there is no specific channel, rather, weak contributions are distributed over Ch1, 2, 6.

These properties are a little different from subject by subject.

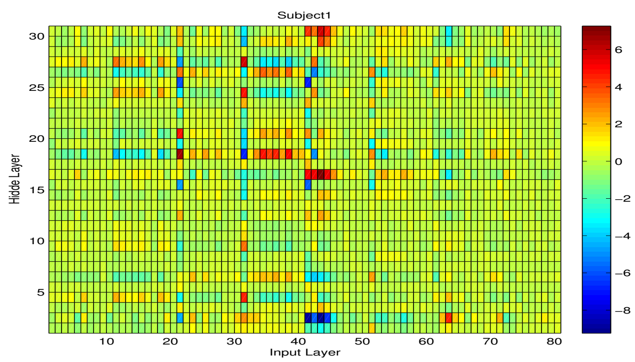

Fig. 7. Connection weights from input layer to hidden layer for Subject 1.

VII. Conclusion

In this paper, the BCI based on the FFT amplitude and the MLNN is dealt with. The brain waves are measured by using 'MEGvision'. Two subjects and four mental tasks are examined. 8 channels are selected from the 8 main lobes. In the same lobe, the optimum channels are searched in order to maximize the classification accuracy. By using the optimum channels, the classification accuracy can be improved from 90.0% up to 97.5% and from 82.5% up to 85.0% for Subject 1 and Subject 2, respectively. Furthermore, contributions of brain waves in the 8 main lobes are investigated. In 'Baseline' and 'Sport', the brain waves in some specific lobes play an important role. On the other hand, in 'Multiplication' and 'Rotation', the important lobes are not specified, rather weak contributions are distributed over several lobes.

TABLE IV

Contributions of brain waves in 8 lobes to mental tasks (Subject 1). Optimum channels are used.

M-tasks	H-units	1	2	3	4	5	6	7	8
Baseline	16, 30		L			H	L		
Multipli	2, 4, 24, 27		M		L			M	
Sport	18, 26			M	H				
Rotation	15, 25	L	L				L		

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