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EEG SIGNAL IDENTIFICATION BASED ON ROOT MEAN SQUARE AND AVERAGE POWER SPECTRUM BY USING BACKPROPAGATION

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ABSTRACT

The development of user interface for game technology has currently employed human centered technology researches in which EEG signal that utilizes the brain function has become one of the trends. The present research describes the identification of EEG Signal by segmenting it into 4 different classes. The segmentation of these classes is based on Root Mean Square (RMS) and Average Power Spectrum (AVG), employed in feature extraction. Both Root Mean Square (RMS) and Average Power Spectrum (AVG) are employed to extract features of EEG signal data and then used for identification, by which a BackPropagation method is employed. The experiment,done with 200 tested signal data file, demonstrates that the identification of the signal is 91% accurate.

Keywords : *Root Mean Square, Average Power Spectrum, BackPropagation, EEG signal.*

1. INTRODUCTION

ElectroEncephaloGraphy (EEG) is a recording of electrical activity along the scalp. EEG voltage fluctuation is resulted from ionic stream in the neuron of the brain [1]. The response of the brain to external and internal stimulus can be recognized in classical EEG, Event Related Potential phase-locked (ERP), non-locked phase (induction) reactivity. ERP can be clearly seen in the average response EEG time which is properly synchronized; however, non-locked phase activity is cancelled from the average. Then, the classical induced by desynchronization (ERD) and Event Related Synchronized (ERS) were calculated throughout the following procedures : the most reactive frequency bands are selected throughtrial-and-error procedure; furthermore, the signal and band-pass were filtered in the bands; and then, the results of the calculation were squared then calculated to yield the average [2].

Brain-Computer Interface (BCI) is a communication system that translates the direct action of user's brain activity into signal and control command. BCI is able to spell, browse in the internet, control robotic devices, and/or perform other tasks by using thoughts [3][4][5][6][7][8][9]. By using appropriate design, input combined with extractor feature and classifier is a suitable framework for motor imagery. Different attribute of EEG signal has been used as BCI input, such as rhythm (8-12 Hz) and beta rhythm (18-25 Hz), while ERP, for instance P300, established visual evoked response and or Slow Cortical Potential (SCP) [10][11][12].

The present research attempts to focus on the discussion of two major points namely: first, Fast Fourier Transform (FFT) method used to measure the strength level of each signal of EEG sample data, and Signal estimated by using Root Mean Square (RMS); second, Average Power Spectrum (AVG) that is employed, and signal pattern of EEG identified as the subjects would be inquired to imagine the movement of left finger, left arm and right arm. The paper would be organized in the following sequences, as the following; section 1 is the introduction, section 2 describes the materials and methods, Section 3 contains the result and discussion, and the last section would be the conclusion.

2. MATERIALS AND METHODS

2.1. Description of dataset

This present study was carried out by doing an experiment involving ten subjects of the study who were coming from General Laboratory for Biomedical Engineering, Experimental Department of Informatics, University of Kyushu. The selected subjects were those who really found to have good health condition as they would be involved in an

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experiment that required them to imagine the movements of left finger (up cursor), right finger (down cursor), left arm (left cursor) and right arm (right cursor) in front of computer screen. During the process of imagining the movement, the Slow Cortical Potential (SCP) was recorded. The activity of the brain was also recorded from two different channels by applying a sampling frequency of 256 Hz. Two EEG electrodes were placed accordingly based on the international 10-20 system as shown in figure 1 and referred to the point of Cz electrode as follow: Line 1: C3 (Central Lobe3), Line2: C4 (Central Lobe4). Overall process would be undertaken within 9 seconds: however, the process of recording the sample of the material needed for the experiment just took only 4 seconds.

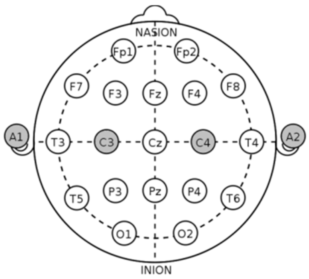

Figure 1: EEG Electrode Montage as The International 10-20 System

2.2. Fast Fourier Transform (FFT)

FFT is an optimal computational algorithm that implements Discreet Fourier Transform (DFT) with a rapid calculation technique and utilizes the periodical nature of Fourier transformation. FFT is a mathematical operation that aims to decompose a time domain signal to frequency domain signal. DFT was employed by applying a transformation in which the length of N vector was acounted using the following formula::

$$F(u) = 1/N \sum_{\chi=0}^{Z=N-1} f(x) \exp[-2\pi ux/N] \quad (1)$$

$$F(u) = 1 \sum_{\chi=0}^{Z=N-1} x) (\cos (2\pi x/N) - \sin (2\pi ux/N)) \quad (2)$$

The calculation of FFT employs multiple reflection transformation in order that DFT result is derived from counting the half value of signal data, thus the calculation process became faster. Then, the other half values were counted through conjugate value method calculated by DFT. To divide the data signal, this study uses the following formula:

$$b = (N + 1) \text{ div } 2 \quad (3)$$

2.3 Feature Extraction

2.3.1 Feature Extraction by Using FFT

To attain a feature extraction, the research used acoustic analysis method to reduce EEG signal into several sets of parameter and statistic technique to take EEG signal. By quantifying the values of acoustic feature parameters of various EEG signal, each of them has been taken from the feature extraction and has been used as introduction sample of EEG signal.

The strength of EEG signal is taken from the signal to measure the strength level of each EEG signal sample data. The signal was calculated by applying Root Mean Square (RMS). In mathematics, RMS is known as the quadratic mean. It is the statistics to measure the magnitude of varying quantity. RMS is useful tobe used when there are positive and negative variations, for instance sinusoid. RMS is used in various fields and most often used in the field of signal. RMS in this feature calculates RMS in frequency domain/FFT as the following formula:

$$\sqrt{\frac{\sum_{i=1}^{M} | uij | 2}{M}} \leq M \quad (4)$$

The EEG signals that have been selected based on subjects imagination movements of their left finger, right finger, left arm and right arm. Then, the performance of each EEG signal is processed by using FFT. Each signal is tested to find the feature of EEG signal. The results of FFT process is shown by Figure 2.

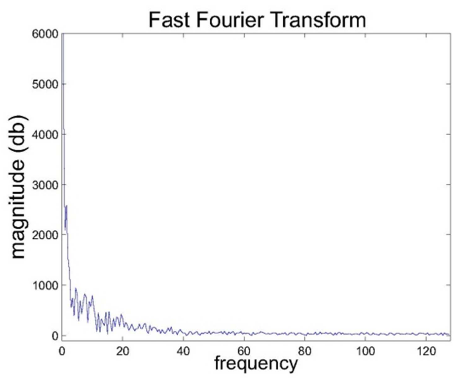

Figure 2: Left Finger of FFT

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Based on the result of FFT, then the strength level of each EEG signal data sample has been measured by RMS as shown by Figure 3.

Figure 3:The Chronology of EEG Signal Input after FFT Process

2.3.2 Feature Extraction by Using AVG

AVG is a process to measure the average power of a deterministic periodical signal. The type of signal is time domain signal, however, it has resulted discrete power spectrum. A signal consists of sinusoid, for instance electrical signal that has unlimited energy, but the average power is limited. To measure the average power of spectrum, it uses periodogram spectrum object and window hamming method. The formula for window hamming method as follow:

$$W(n) = 0.54 - 0.46 \cos (2\pi n/N\text{-}1),\ 0 \leq n \leq N\text{-}1 \quad (5)$$

After the process of windowing, then the values will be converted into logarithmic value by using the following formula:

$$\text{Avg power} = 10 \times \log (W(n)/2) \quad (6)$$

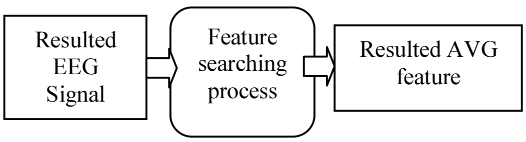
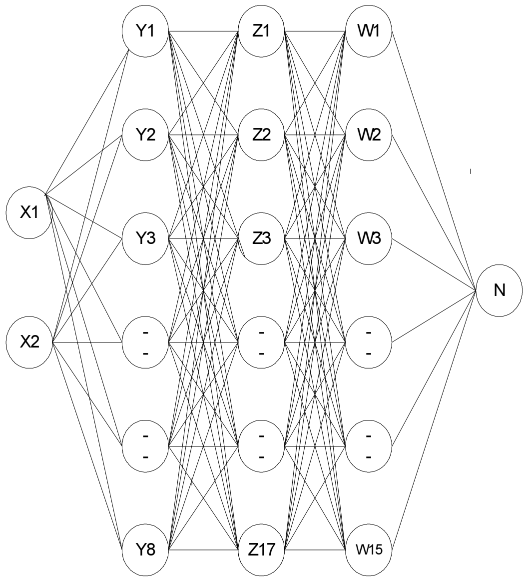


Figure 4: The Chronology of EEG Signal Input to Result AVG Feature

2.3.3 Back Propagation Neural Network

Backpropagation is one of the developments of a Single Layer Neural Network architecture. This architecture consists of input layer, hidden layer and output layer, and each layer is composed by one or more artificial neurons.



Note:
X1, x2 = Input (Result of RMS and result of AVG)
Y1, Y2, Y3… Y8 = Neuron-neuron hidden layer 1
Z1, Z2, Z3… Z17 = Neuron-neuron hidden layer 2
W1, W2, W3… W15 = Neuron-neuron hidden layer 3
N = Output

Figure 5: Architecture of BackPropagation Network 3 Hidden Layer

This research uses BackPropagation (2-8-17-15-1) method, i.e. 2 inputs are derived from the characteristic of EEG signal and 3 hidden layer in which each of them consist of 8 units, 17 units, and 15 units and 1 target (the movements of left finger, right finger, left arm and right arm).

Table 1: Pattern of Input and Target Designed from BackPropagation Method

Input Pattern	Input data (RMS = x1 and AVG = x2)	Output Target
Signal of right finger imagination	Characteristic of EEG signal for imagination of right finger movement	0.2
Signal of left finger imagination	Characteristic of EEG signal for imagination of left finger movement	0.4
Signal of left arm imagination	Characteristic of EEG signal for imagination of left arm movement	0.6
Signal of right arm imagination	Characteristic of EEG signal for imagination of right arm movement	0.8

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The design of the system in this research is made through three processes, namely taking process of EEG signal, feature searching process and identification as shown in figure 6.

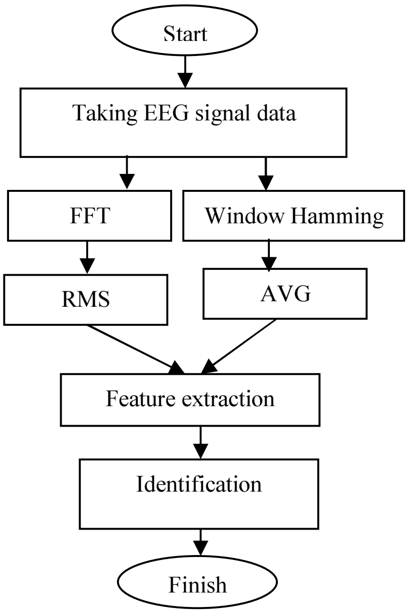

Figure 6: Planning System for The Identification Process of EEG Signal Data

3. RESULT AND DISCUSSION

In this research, Root Mean Square (RMS) and Average Power Spectrum (AVG) were employed to extract features from EEG signal data and then for identification, a BackPropagation method was employed. The total data taken in this research were comprised from 200 data *file* of EEG signal derived from 10 subjects by using 1 channel (C3). One file of EEG signal has 1409 data point. This research divides one EEG signal into 2 features. The first feature uses FFT to take the value of its MRS, and then the second feature uses the value of AVG.

The result values of MRS and AVG are shown in the table 2 by taking 5 examples for the values of MRS and AVG of each signal for each movement imagination.

Input Data of RMS and AVG values are used in the process of identification by using BackPropagation Neural Network method. There are two steps in the identification process, namely learning process and mapping process. The learning process uses the learning rate parameter of 0.1, yet the errors are found to be 0.001. The initial weight values are determined randomly by the range of -1 to 1.

Table2: Results of RMS and AVG from EEG Signal for Each Signal Channel C3

Signal Data	1		2		3		4		5	
	VALUE		VALUE		VALUE		VALUE		VALUE	
	MRS	A VG	MRS	AVG	MRS	A VG	MRS	A VG	MRS	A VG
Left Finger	1876	-8.78	1824	-9.03	2009	-8.15	2718	-7.15	2716	-8.65
Right Finger	3524	-6.33	3525	-8.88	4245	-5.60	5495	-3.38	5516	-7.81
Left Arm	1631	-8.91	1650	-8.87	1651	-8.67	2174	-8.53	4171	-7.57
Right Arm	3742	-5.70	3715	-9.03	3685	-8.84	5476	-5.19	5477	-8.63

To find the optimal parameter that results the best performance from Neural Network, it has been done according to the magnitude of Mean Squared Error (MSE) and the number of optimal hidden unit during training process. The result of performance has been shown in the table 3 and figure 7 – 9.

As seen in figure7 by using one hidden layer, MSE value of 0.0366 was obtained 1000 times Iteration. The desired error for the identification process of 0.001 level, then the identification is not expected to meet the target of 100%.

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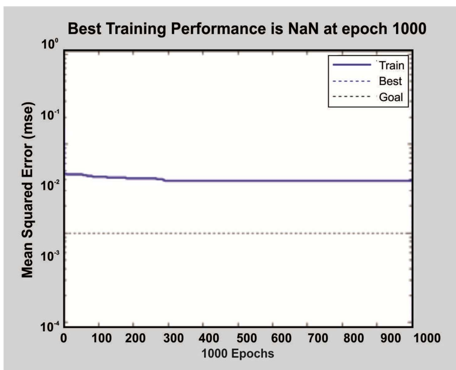

Figure7: Prosess of Trainning of 1 Hidden Layer

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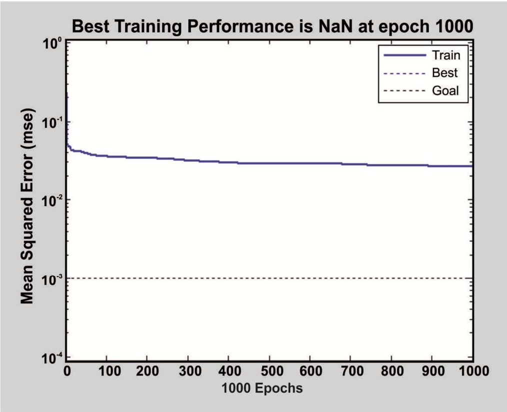

Figure 8: Process of Trainning of 2 Hidden Layer

In figure 8, the number of hidden layer is 2 and the value of MSE in process of identification has yet to meet the target. Figure 8 with 2 hidden layers using values has obtained MSE of 0.0211 to 1000 times Iteration. The desired error for the identification process by 0.001, then the identification is not expected to meet the target of 100%.

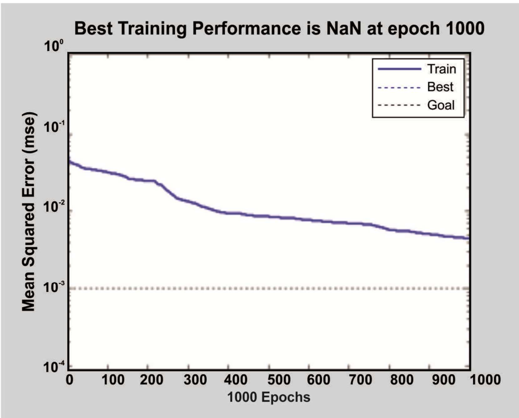

Figure 9: Process Trainning of 3 Hidden Layer

In the figure 9, the number of hidden layer is 3 and the value of MSE in process of identification has yet to meet the target. Figure 9 with 3 hidden layer using MSE values obtained for 0.003 to 1000 times Iteration. The desired error for the identification process by 0.001, then the identification is not expected to meet the target of 100%. By using 3 hidden layer of its MSE by using less than 1 or 2 hidden layers.

Table 3:The Performance of Neural Network on Different Number of Hidden Layer

	MSE of 1 Hidden Layer	MSE of 2 Hidden Layer	MSE of 3 Hidden Layer
Time	29 second	35 second	46 second
Iteration	1000	1000	1000
MSE	0.0366	0.0211	0.003
Accuracy	56 %	87.75 %	91 %

Table 3 shows that by using 3 hidden layer MSE is getting smaller, so that the process of identifying the level of accuracy by using 3 hidden layer is better, as that is equal to 91%.

4. CONCLUSION

In this research, the researchers introduced FFT by taking the values of RMS and AVG from EEG signal to extract the feature and to identify of BackPropagation neural Network. This research uses 100 data file of EEG signal for training, then in step of identification, it is classified into four classes. The data file of EEG has been added to 100 data from testing data EEG signal. Thus, the total data in the research is 200 EEG data signal. The accuracy to identify BackPropagation is 91% to examine the data using 3 hidden layer.

This research has shown that the number of hidden layer at BackPropagation affects the magnitude of MSE. In the future, the researcher should examine the appropriate search technique to extract the feature and to identify EEG signal, so that the accuracy level would be better. The result obtained will be compared to the method that has been studied.

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