FEATURE EXTRACTION OF ELECTROENCEPHALOGRAPHY SIGNALS USING FAST FOURIER TRANSFORM

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***Abstract*—This article discusses a method within the area of brain-computer interface. The proposed method is to use the features extracted from the Electroencephalograph signal and a three-hidden-layer artificial neural network to map the brain signal features to the computer cursor movement. The evaluated features are the root mean square and the average power spectrum. The empirical evaluation using 200 records taken from 2003 BCI Competition dataset shows that the current approach can accurately classify a simple cursor movement within 92.5% accuracy in a short computation time.**
***Keywords:* Electroencephalography (EEG); Brain Computer Interface (BCI); Fast Fourier Transform (FFT)**

I. INTRODUCTION

Brain Computer Interface (BCI) is a communication system that translates the direct action of the user's brain activity into signals. BCI can be used to spell, browsing the Internet, controlling robotic devices, or perform other tasks with thoughts alone [1–3]. BCI that there is often used to present information in the signal to assess the state of the brain of subjects with different categories of EEG signals.

Feature extraction methods and an accurate identification corresponding specific users and specific application requirements might be a problem for EEG-based communication in order to be efficient. Slow Cortical Potential (SCP) by using the mu and beta rhythm is used as input for BCI [4–6].

EEG signals from a person, generally, consist of the wave components that can be differentiated according to their frequency ranges, i.e., alpha waves in the range of 8–13 Hz and often appear in the waking state, eyes closed, and relaxed conditions, beta waves in the range of 14–30 Hz and often arises when the person is thinking, theta waves in range of 4–7 Hz and usually occurs when someone is in a light sleep, sleepy or stressed, delta waves in the range of 0.5–3 Hz and often present in the person in a state of deep sleep. EEG signal analysis has been widely represented in the frequency domain and this has been done by researchers. Representation in the frequency domain, among others, for the identification of the waves on the EEG signals using Fourier Transform and Neural Network to distinguish between normal and epilepsy [7].

Reference [8] studied BCI by using only two electrode channels, Channel 4 and 6, four features from the combination of the slow cortical potentials (SCPs), the wavelet transform for the feature extractions, and the neural network for classification. They were able to classify the BCI 2003 competition data at 92% of the level of accuracy. Using the same dataset and classification methods, but different feature extraction method, that was the wavelet packet decomposition, Ref. [9] was able to classify the brain signals at 91% of the level of accuracy.

In this study, the first to present is method of Fast Fourier Transform (FFT) to measure the level of violence EEG signal. Signal was approached by calculating the Root Mean Square (RMS) and use the Average Power Spectrum. The pattern of EEG signals that are recognized are subject of imagine cursor movement upward and downward movement of the cursor.

This article is decomposed into four sections. Section II presents the data used in the current study and the data feature extraction methods. Section III discusses the developed artificial neural network model,

Received: August 1, 2016; received in revised form: August 16, 2016; accepted: August 18, 2016; available online: August 19, 2016.

and shows some examples of the EEG features, and the performance of the current brain-computer interface method. Finally, Section IV briefly restates the research problem and summarizes the current findings.

II. RESEARCH METHOD

A. Data

The data for the current investiation are obtained from 2003 BCI competition. They were taken from healthy subjects from the University of Tuebingen in Germany [10, 11]. During the data acquition, the subjects were asked to move cursor using their brain signals. Each experiment lasted for 6 s. Each channel contained 896 sample data.

During recording, the subjects were asked to move the cursor upward and downward. Each experiment lasted for 6 s. There are 896 samples in each channel. The training data for the experiments contained 135 records of Class 0 and 135 records of Class 1. The testing data data are 293 records.

B. Feature Extraction using Fast Fourier Transformation

1) Root Mean Square: The Root Mean Square (RMS) is used to measure the signal strength. The RMS average is a statistical description to measure the magnitude of a varying signal. The RMS is useful when the signal contains positive and negative variations, e.g., the sinusoid signal. The RMS is widely used in the signal processing for various applications. The RMS is defined by

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{M} |X_i|^2}{M}}, \tag{1}$$

where $|\square|$ denotes the modulus, X_i is the ith component of the signal $x(t)$ in the frequency domain. Figure 2 shows the example of the spectra of the signal $x(t)$.

2) Average Power Spectrum: In addition RMS, the EEG signal is also featured with its average power spectrum. The quantity is denoted by P and is computed by

$$P_x = \frac{1}{2T} \lim_{T\to\infty} \int_{-T}^{T} [x(t)]^2 \, \mathrm{d}t. \tag{2}$$

Prior computing its average power spectrum, the signal is passed through the Hamming window, which is defined by:

$$w(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N-1}\right), \tag{3}$$

where N is the signal length and n is the index within the range of $[0, N-1]$.

III. RESULTS AND DISCUSSION

A backpropagation neural network model is established to map the features reduced from the EEG signal to the cursor movement in upward or downward directions. In the current work, the features are the signal root mean square obtained by using Eq. (1) and the average power spectrum obtained by using Eq. (2). The neural network consists of three hidden layers having 8, 17, and 15 units of neurons, respectively. Figure 3 shows the neuron architecture.

The current study evaluates 200 EEG signals of single channel (C3) splitted equally into two datasets for the training and testing phases. Each signal contains 1409 data point. Some examples of the EEG signal features and the cursor movements are shown in Tables I and II.

TABLE I
SOME EXAMPLES OF THE ROOT MEAN SQUARE (RMS) VALUES OF EEG SIGNALS AND THE RELATED CURSOR MOVEMENTS.

Cursor Movement	RMS of Some Signals				
	1	2	3	4	5
Upward	1876	1824	2009	2718	2716
Downward	3524	3525	4245	5495	5516

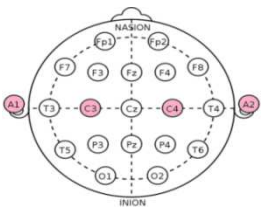

Fig. 1. The montage of Electroencephalograph electrode following international system of 10-20.

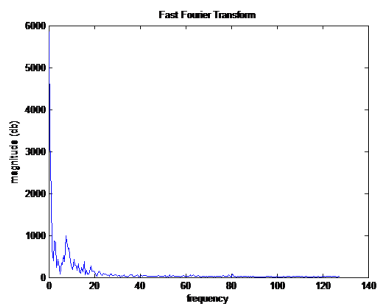

Fig. 2. The example of the spectra of the EEG signal.

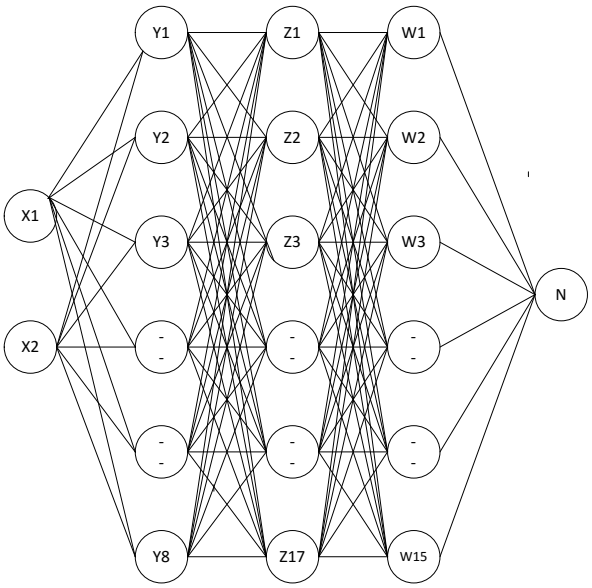

Fig. 3. The backpropagation neural network architecture that receives the input data of the EEG signal root mean square and average power spectrum and produces the output of the cursor directions: upward or downward. The network consists of three hidden layers with 8, 17, and 15 units of neurons.

TABLE II
SOME EXAMPLES OF THE AVERAGE POWER SPECTRA (APS) VALUES OF THE EEG SIGNALS AND THE RELATED CURSOR MOVEMENTS.

Cursor Movement	APS of Some Signals				
	1	2	3	4	5
Upward	8.78	9.03	8.15	7.15	8.65
Downward	6.33	8.88	5.60	3.38	7.81

The data for the EEG features and cursor movements are used to train the ANN model. During the training process, the learning rate parameter was set to 0.1 and the optimal model was concluded when the model mean-squared error (MSE) reached a value below 1.0×10^{-3}. The number of hidden layers was also optimized.

The analysis results are presented in Table III. The results suggest that the highest classification accuracy is obtained by using three-hidden-layer ANN model. The accuracy can reach the level of 92.5%. The model also has very low mean square error in order of 1.0×10^{-3}. However, it requires a slightly longer computational time.

IV. CONCLUSIONS

This study discusses a method to control the computer cursor movement using a brain-computer interface. It uses the data of the brain signal and a three-hidden-layer neural network to map the signal features and the cursor movement. Only a simple cursor movement is studied, upward and downward. The brain signal is extracted for their unique features and is represented using the root mean square and the average power spectrum. The method is evaluated empirically using the data of BCI 2003 competition. The work also studies the optimum number of the hidden layer. The empirical evaluation suggests that the use of the three-hidden-layer neural network is the most optimum where the classification accuracy can reach the level of 92.5% within a short computation time and a low mean square error.

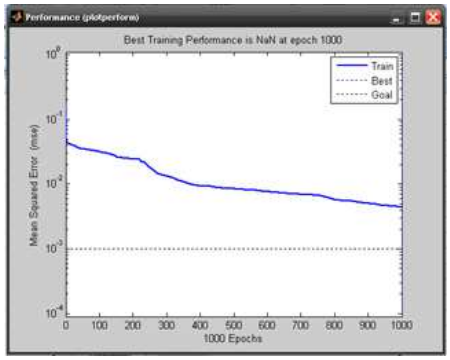

Fig. 4. The reduction of the mean-squared error during iteration for the ANN model having three hidden layers.

TABLE III
A COMPARISON OF THE PERFORMANCE OF THE NEURAL NETWORK FOR VARIOUS NUMBER OF HIDDEN LAYERS.

Indicator	The Number of Hidden Layers		
	1	2	3
Time (s)	32	60	65
Iteration	1000	1000	563
MSE	1.48×10^{-1}	2.80×10^{-2}	1.00×10^{-3}
Accuracy (%)	79.0	83.0	92.5

REFERENCES

[1] B. Z. Allison, C. Brunner, C. Altstätter, I. C. Wagner, S. Grissmann, and C. Neuper, "A hybrid erd/ssvep bci for continuous simultaneous two dimensional cursor control," *Journal of neuroscience methods*, vol. 209, no. 2, pp. 299–307, 2012.

[2] L. J. Trejo, R. Rosipal, and B. Matthews, "Brain-computer interfaces for 1-d and 2-d cursor control: designs using volitional control of the eeg spectrum or steady-state visual evoked potentials," *IEEE transactions on neural systems and*

rehabilitation engineering, vol. 14, no. 2, pp. 225–229, 2006.

[3] J. S. Brumberg, A. Nieto-Castanon, P. R. Kennedy, and F. H. Guenther, "Brain–computer interfaces for speech communication," *Speech communication*, vol. 52, no. 4, pp. 367–379, 2010.

[4] L. Defebvre, J. Bourriez, P. Derambure, A. Duhamel, J. Guieu, and A. Destee, "Influence of chronic administration of l-dopa on event-related desynchronization of mu rhythm preceding voluntary movement in parkinson's disease," *Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control*, vol. 109, no. 2, pp. 161–167, 1998.

[5] B. D. Mensh, J. Werfel, and H. S. Seung, "Bci competition 2003-data set ia: combining gamma-band power with slow cortical potentials to improve single-trial classification of electroencephalographic signals," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1052–1056, 2004.

[6] B. Kotchoubey, D. Schneider, H. Schleichert, U. Strehl, C. Uhlmann, V. Blankenhorn, W. Fröscher, and N. Birbaumer, "Self-regulation of slow cortical potentials in epilepsy: A retrial with analysis of influencing factors," *Epilepsy Research*, vol. 25, no. 3, pp. 269–276, 1996.

[7] P. Pramanick, "Classification of electroencephalogram (eeg) signal based on fourier transform and neural network," Bachelor Thesis, Department of Electrical Engineering, National Institute of Technology, Rourkela National Institute of Technology, 2013.

[8] B. Wang, L. Jun, J. Bai, L. Peng, G. Li, and Y. Li, "Eeg recognition based on multiple types of information by using wavelet packet transform and neural networks," in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, 2006, pp. 5377–5380.

[9] W. Ting, Y. Guo-zheng, Y. Bang-hua, and S. Hong, "Eeg feature extraction based on wavelet packet decomposition for brain computer interface," *Measurement*, vol. 41, no. 6, pp. 618–625, 2008.

[10] B. Blankertz, K.-R. Muller, G. Curio, T. M. Vaughan, G. Schalk, J. R. Wolpaw, A. Schlogl, C. Neuper, G. Pfurtscheller, T. Hinterberger *et al.*, "The bci competition 2003: progress and perspectives in detection and discrimination of eeg single trials," *IEEE transactions on biomedical engineering*, vol. 51, no. 6, pp. 1044–1051, 2004.

[11] A. Kübler, N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N. P. Birbaumer, "Brain-computer communication: self-regulation of slow cortical potentials for verbal communication," *Archives of physical medicine and rehabilitation*, vol. 82, no. 11, pp. 1533–1539, 2001.