Proceedings of the 2nd International IEEE EMBS
Conference on Neural Engineering
Arlington, Virginia · March 16 - 19, 2005

Brain Computer Interface Design Using Band Powers Extracted During Mental Tasks

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***Abstract*-In this paper, a Brain Computer Interface (BCI) is designed using electroencephalogram (EEG) signals where the subjects have to think of only a single mental task. The method uses spectral power and power difference in 4 bands: delta and theta, beta, alpha and gamma. This could be used as an alternative to the existing BCI designs that require classification of several mental tasks. In addition, an attempt is made to show that different subjects require different mental task for minimising the error in BCI output. In the experimental study, EEG signals were recorded from 4 subjects while they were thinking of 4 different mental tasks. Combinations of resting (baseline) state and another mental task are studied at a time for each subject. Spectral powers in the 4 bands from 6 channels are computed using the energy of the Elliptic FIR filter output. The mental tasks are detected by a neural network classifier. The results show that classification accuracy up to 97.5% is possible, provided that the most suitable mental task is used. As an application, the proposed method could be used to move a cursor on the screen. If cursor movement is used with a translation scheme like Morse Code, the subjects could use the proposed BCI for constructing letters/words. This would be very useful for paralysed individuals to communicate with their external surroundings.**

I. INTRODUCTION

Electroencephalogram (EEG) based Brain-Computer Interface (BCI) technology has seen much development in recent years. Specifically, EEG based BCI technologies that do not depend on peripheral nerves and muscles have received much attention as possible modes of communication for the disabled [1,2,4,5,7,8,10,11]. In general, these could be divided into several types: mental task [1,4,7], readiness potential (mu rhythm) [8] and P300 evoked potential [2]. Mental task based BCI is somewhat the least studied among the methods due to the difficulty in obtaining low error rates. Keirn and Aunon [4] proposed a BCI design using classification of pairs of mental tasks represented by spectral power asymmetry ratio in delta, theta, alpha and beta bands using Bayesian classifier. Anderson *et al* [1] studied classification of baseline and multiplication mental tasks using neural network classification of autoregressive features. Palaniappan *et al* [7] studied classification of three mental tasks using Fuzzy ARTMAP classifier. Reviews of some of these technologies and developments in this area are given by Vaughan *et al* [10] and Wolpaw *et al* [11].

In this paper, a technique is proposed using spectral power and power difference in 4 bands from 6 channels to classify into two outputs, where one is baseline and another is a specific mental task. There are some differences in the current work as compared to the earlier studies. The first is the use of gamma band (30-50 Hz) EEG in addition to the commonly used delta, theta, alpha and beta bands (below 30 Hz). The second is the use of spectral power difference from 6 channels instead of the spectral power asymmetry (i.e. difference) between hemispheres studied by Keirn and Aunon [4]. The third is the study of single mental tasks instead of 2 or 3 mental tasks as studied by others [1,4,7]. It is shown that it is possible to construct a simple BCI with subjects either thinking of a single mental task or relaxing.

Elliptic filters have been utilized to extract EEG in 4 bands: delta and theta, beta, alpha and gamma. Delta and theta bands are combined since their frequency range is small. The spectral power of each band is computed and the difference in each band from 6 channels gives the spectral power difference. These spectral power and spectral power differences are then used by a Multilayer Perceptron (MLP-BP) neural network to classify into a baseline state or the mental task state. The EEG data were recorded from 4 subjects during 2 sessions while the subjects were thinking of 4 different mental tasks.

II. METHODOLOGY

The EEG data used in this study were collected by Keirn and Aunon [4]. The subjects were seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noise-less fan (for ventilation). An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 (shown in Figure 1), defined by the 10-20 system [3] of electrode placement. The impedance of all electrodes were kept below 5 KΩ. Measurements were made with reference to electrically linked mastoids, A1 and A2. The electrodes were connected through a bank of amplifiers (Grass7P511), whose band-pass analog filters were set at 0.1 to 100 Hz. The data were sampled at 250 Hz with a Lab Master 12-bit A/D converter mounted on a computer. Before each recording session, the system was calibrated with a known voltage. Signals were recorded for 10s during each task and each task was repeated for 2 sessions where the sessions were held on different weeks. The EEG signal for each mental task was segmented into 20 segments with length 0.5 s. The sampling rate was 250 Hz, so each EEG segment was 125 samples in length.

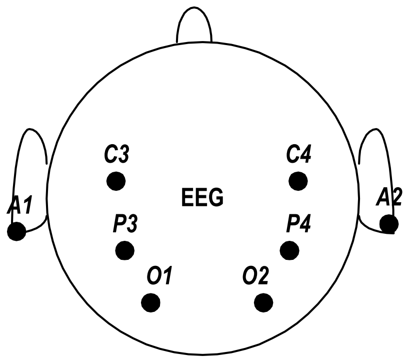

Fig. 1. Electrode placement.

In this paper, EEG signals from 4 subjects performing 4 different mental tasks were used. The data is available online at http://www.cs.colostate.edu/~anderson. These mental tasks are:

Math task. The subjects were given nontrivial multiplication problems, such as 24 times 14 and were asked to solve them without vocalising or making any other physical movements. The tasks were non-repeating and designed so that an immediate answer was not apparent. The subjects verified at the end of the task whether or not he/she arrived at the solution and no subject completed the task before the end of the 10 s recording session.

Geometric figure rotation task. The subjects were given 30 s to study a particular three-dimensional block object, after which the drawing was removed and the subjects were asked to visualise the object being rotated about an axis. The EEG signals were recorded during the mental rotation period.

Mental letter composing task. The subjects were asked to mentally compose a letter to a friend or a relative without vocalising. Since the task was repeated several times the subjects were told to continue with the letter from where they left off.

Visual counting task. The subjects were asked to imagine a blackboard and to visualise numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were instructed not to verbalise the numbers but to visualise them. They were also told to resume counting from the previous task rather than starting over each time.

In addition, the baseline state was used where the subjects were asked to relax and think of nothing in particular. This task was used as a control and as a baseline measure of the EEG signals.

Keirn and Aunon [4] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). For example, it was shown by Osaka [6] that arithmetic tasks exhibit a higher power spectrum in the right hemisphere whereas visual tasks do so in the left hemisphere. As such, Keirn and Aunon [4] and later Anderson *et al* [1] proposed that these tasks are suitable for brain-computer interfacing.

The EEG signals are high pass filtered using Elliptic Finite Impulse Response (FIR) at 0.5 Hz with 3 dB cut-off of 1 Hz, with 30 dB attenuation in the stop-band and 0.5 dB ripple in the pass-band. This is to reduce low frequency noise. Elliptic filter was used because of its low order as compared to other FIR filters like Butterworth. Forward and backward filtering was performed to ensure that there would be no phase distortion. The frequency ranges of each bands are delta and theta (0.5-7 Hz), alpha (8-12 Hz), beta (13-29 Hz) and gamma (30-50 Hz). Spectral power in each band was computed from the filtered output. Next, power difference in each spectral band was computed using

$$Power_{difference} = \left[\frac{P_1 - P_2}{P_1 + P_2} \right] \quad (1)$$

where P_1 is the power in one channel and P_2 is the power in another channel in the same spectral band. Overall, this gave 24 spectral powers and 120 spectral power differences, with a total of 144 features.

MLP NN with single hidden layer trained by the BP algorithm [9] was used to classify different combinations of two states: mental task and baseline represented by the 144 spectral power and power difference features. The output nodes were set at two so that the NN could classify into one of the two states. The hidden nodes were varied from 10 to 50 in steps of 10. This is to investigate the effects of number of hidden nodes on classification accuracies.

A total of 80 EEG patterns (20 segments for EEG each signal x 2 sessions x 2 states) were used for each subject in this experimental study. Half of the patterns were used in training and the remaining half in testing. The selection of the patterns for training and testing were chosen randomly. Training was conducted until the average error fell below 0.01 or reached a maximum iteration limit of 10000. The average error denotes the error limit to stop NN training. The average error is the average of NN target output subtracted by the desired target output from all the training patterns. The desired target output was set to 1.0 for the particular category representing the mental task of the EEG pattern being trained, while for the baseline category, it was set to 0. Figure 2 shows the flow of the methodology. Figure 3 shows the architecture of the MLP-BP NN used in this study.

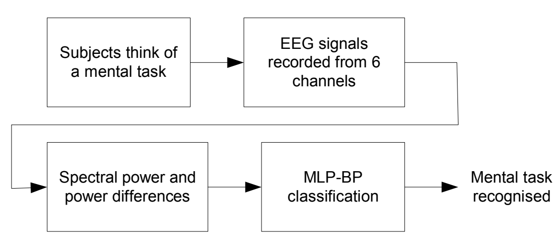

Fig. 2. Methodology Flow.

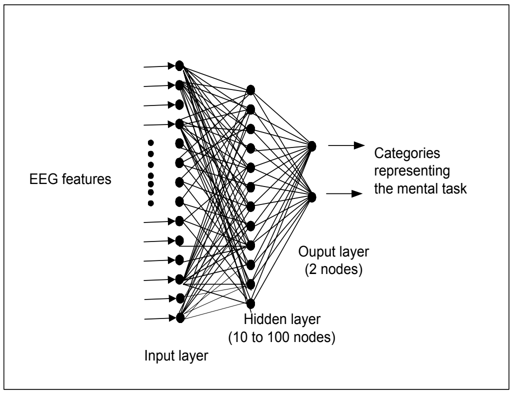

Fig. 3. MLP-BP NN architecture.

An example of possible BCI application using the method is shown in Figure 4. The cursor on a computer screen moves from left to right at a constant and low speed. The cursor moves up if the subject thinks of the particular mental task, else the cursor moves down i.e. when the subject does not think of anything. At the right end of the screen, the cursor will eventually select a dash or dot. Sequence of several dashes or dots will determine the appropriate English letter using some translation schemes like Morse Code [7].

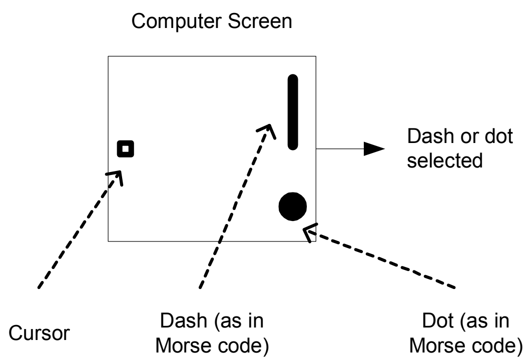

Fig. 4. Example of possible application using the method.

III. RESULTS

Tables 1-4 show the shows of MLP-BP classification results using baseline and a mental task states. It could be seen that different subjects have different suitable mental tasks. The suitable mental task is the one that gives the highest recognition and/or with lowest NN hidden nodes.

For example, for subject 1 the suitable mental task is image rotation. For subjects 2 and 4, the most suitable mental task is maths task, while for subject 3, it is counting task.

Another interesting result is that 10 hidden nodes are sufficient for the BCI design. All the suitable mental task classifications denote this fact.

TABLE 1
MLP-BP CLASSIFICATION RESULT FOR SUBJECT 1

No. of H.U.	Mental tasks			
	Count	Letter	Rotate	Math
10	87.5	85.0	**95.0**	80.0
20	87.5	87.5	95.0	80.0
30	87.5	77.5	95.0	80.0
40	85.0	85.0	95.0	82.5
50	85.0	82.5	95.0	82.5
Average	86.5	83.5	95.0	81.0

TABLE 2
MLP-BP CLASSIFICATION RESULT FOR SUBJECT 2

No. of H.U.	Mental tasks			
	Count	Letter	Rotate	Math
10	70.0	92.5	75.0	**95.0**
20	90.0	75.0	95.0	77.5
30	77.5	95.0	77.5	92.5
40	95.0	77.5	92.5	77.5
50	77.5	92.5	80.0	92.5
Average	82.0	86.5	84.0	87.0

TABLE III
MLP-BP CLASSIFICATION RESULT FOR SUBJECT 3

No. of H.U.	Mental tasks			
	Count	Letter	Rotate	Math
10	**92.5**	70.0	75.0	87.5
20	70.0	75.0	87.5	87.5
30	72.5	87.5	87.5	70.0
40	87.5	90.0	70.0	75.0
50	90.0	70.0	75.0	90.0
Average	82.5	78.5	79.0	82.0

TABLE IV
MLP-BP CLASSIFICATION RESULT FOR SUBJECT 4

No. of H.U.	Mental tasks			
	Count	Letter	Rotate	Math
10	92.5	85.0	90.0	**97.5**
20	82.5	87.5	97.5	92.5
30	85.0	95.0	92.5	85.0
40	95.0	92.5	82.5	90.0
50	92.5	87.5	90.0	95.0
Average	89.5	89.5	90.5	92.0

IV. CONCLUSION

In this paper, it has been shown that a BCI system could be designed where the subject has to think of a single mental task only. The method utilizes EEG features, namely spectral power and power differences in 4 bands from 6 channels. MLP-BP NN classifies these 144 features into the baseline or mental task states. In future, it is planned to expand the work to include more data and more subjects and test the performance on an actual EEG to English letter translation system.

ACKNOWLEDGMENT

The authors would like to acknowledge the assistance of Dr. C. Anderson of Colorado State University, USA for giving permission to use the EEG data.

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