# Utilizing Gamma Band to Improve Mental Task Based Brain-Computer Interface Design

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***Abstract*—A common method for designing brain–computer Interface (BCI) is to use electroencephalogram (EEG) signals extracted during mental tasks. In these BCI designs, features from EEG such as power and asymmetry ratios from delta, theta, alpha, and beta bands have been used in classifying different mental tasks. In this paper, the performance of the mental task based BCI design is improved by using spectral power and asymmetry ratios from gamma (24–37 Hz) band in addition to the lower frequency bands. In the experimental study, EEG signals extracted during five mental tasks from four subjects were used. Elman neural network (ENN) trained by the resilient backpropagation algorithm was used to classify the power and asymmetry ratios from EEG into different combinations of two mental tasks. The results indicated that 1) the classification performance and training time of the BCI design were improved through the use of additional gamma band features; 2) classification performances were nearly invariant to the number of ENN hidden units or feature extraction method.**

***Index Terms*—Asymmetry ratio, brain–computer interface (BCI), gamma band, mental task.**

## I. Introduction

BRAIN–COMPUTER Interface (BCI) designs are very useful for individuals to communicate with their external surroundings. This is especially true for the paralyzed. They could also be used in designing "hands off" controls. In the last decade, BCI research has grown tremendously due to these useful applications [1]. There are several common methods of designing a BCI. Electroencephalogram (EEG) signals recorded at the scalp during particular mental tasks have been used by some of the research groups [2]–[4]. Some others have utilized single-trial visual evoked potential (VEP) signals where the subjects gaze at a screen full of alphanumeric characters [5]. Synchronization and desynchronization of micrometer rhythms and beta rhythms extracted during sensory motor tasks are another method for BCI design [6]. Reviews of some of these technologies and developments are given in [1].

The advantage of using mental task based BCI method over the other existing BCIs is that it does not require any in-between interface. The "in-between interface" is for example the screen of alphanumeric characters used in the VEP-based BCI. Several different feature extraction methods for the mental task-based BCI design have been developed. Some of these are band and asymmetry ratios [2], autoregressive coefficients [2], [3], and spectral power densities [2]–[4]. In the method that used band and asymmetry ratios [2], the total power in four spectral bands namely delta (0–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), and beta (14–20 Hz) were summed up and used together with asymmetry ratios as representative features for classifying mental tasks. Asymmetry ratios are especially useful for recognizing mental tasks that elicit interhemispheric differences. Here, an attempt is made to show that the performance of the BCI design could be improved by using additional gamma band (24–37 Hz) spectral power and asymmetry ratios. Gamma band is closely associated with integrative functions and awareness [8], [9] and it has been used in evoked potential based BCI design [10]. The spectral range of 24–37 Hz is obtained based on the studies in [10].

## II. Methodology

### A. EEG Data

The EEG data used in this study were collected by Keirn and Aunon [2]. The subjects were seated in a sound controlled booth with dim lighting and noiseless fan (for ventilation). An electro-cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1, and O2, defined by the 10–20 system of electrode placement. The impedances 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 bandpass analog filters were set at 0.1–100 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 ten seconds during each task and each task was repeated for ten sessions held on separate weeks.

In this paper, EEG signals from four subjects performing five different mental tasks were used. The data is available online.[1] In the original dataset, there were seven subjects in the study but only four subjects were chosen here as the other three had fewer than ten sessions or some errors in the recording. These mental tasks were as follows.

*Geometrical Figure Rotation*: The subject was instructed to study a complex three-dimensional block diagram for 30 s. The diagram was then removed and the subject was asked to visualize the object being rotated about an axis.

*Mathematical Multiplication Task*: The subject was given a nontrivial multiplication problem. No subject completed the task before the end of the 10-s recording.

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[1]http://www.cs.colostate.edu/eeg/index.html#Data

*Mental Letter Composing Task*. The subject was instructed to mentally compose a letter to a friend or relative. Since the task was repeated numerous times, the subject was asked to pick up the writing from where it was left off in the previous time.

*Visual counting task*. The subject was asked to imagine numbers being written sequentially on a blackboard, with the previous number erased before the next number was written.

*Baseline-resting task*. There was no mental task to be performed here. The subject was told to relax and try to think of nothing in particular.

In all the tasks, the subjects were instructed not to verbalize or vocalize and not to make any overt movement. Keirn and Aunon [2] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). Here, the EEG signal for each mental task was segmented into 20 segments with length 0.5 s, so each EEG segment was 125 samples in length.

### *B. Feature Extraction*

The EEG segments were filtered twice (once forward and once reverse to remove phase distortion effects) using Elliptic filters into the respective bands with passband spectral range of 0–3 Hz (delta), 4–7 Hz (theta), 8–13 Hz (alpha), 14–20 Hz (beta), and 24–37 Hz (gamma). Order five was sufficient to obtain a minimum of 30-dB attenuation at frequencies $\pm 0.5$ Hz beyond the passbands. The powers of the specific spectral bands were computed using the variance of the filtered output.

Next, the asymmetry ratios [2] for each spectral band were computed using

$$\mathrm{Asym}(i,j) = \frac{(\mathrm{Power}(i) - \mathrm{Power}(j))}{(\mathrm{Power}(i) + \mathrm{Power}(j))} \tag{1}$$

where the indices $i$ and $j$ are the electrodes from left and right hemispheres, respectively, *power(i)* and *power (j)* are spectral band powers in these electrodes. Asymmetry ratio (as used in this paper) gives an indication on the ratio of brain activity in the left and right hemispheres. That is, it is useful in the detection of tasks that dominate the left hemisphere more than the right and vice versa. This procedure was repeated for all the spectral bands. Each spectral band gave 15 features (six band powers and nine asymmetry ratios), thereby giving a total of 75 features. To compare the performance of these features, power of spectral bands and asymmetry ratios from four bands excluding gamma band were also stored, totaling 60 features.

### *C. Classification*

Elman neural network (ENN) [11] with single hidden layer trained by the resilient backpropagation (RBP) algorithm [12] was used to classify different combinations of two mental tasks represented by the different EEG features as the output of the BCI design was bi-state. The ENN architecture and RBP training algorithm were chosen after some preliminary experiments. The preliminary experiments (using a small subset of the dataset) were conducted to decide the suitable training algorithm (fastest with available memory) among different types of backpropagation (BP) algorithms—standard BP, BP with momentum, BP with adaptive learning, Levenberg–Marquardt BP, and resilient BP, which showed that resilient BP to be suitable. The preliminary experiments were also conducted with a simple classifier (linear discriminant), the standard three layer perceptron, and ENN, which showed that ENN gave best classification performance. Both the hidden and output layers used hyperbolic tangent function as activation function. The inputs were normalized from $-1$ to 1 using the minimum and maximum value of each feature as this would improve the ENN training. As mentioned earlier, for experiments involving the standard spectral band powers and asymmetry ratios (Method A), the number of features (i.e., inputs to ENN) was 60. For the proposed method (Method B), the number of features was 75. The output units were set at two so that the ENN could classify into either of the two categories representing the mental tasks. Weights and biases were initialized according to the Nguyen–Widrow algorithm, which chooses values in order to distribute the active region of each neuron in the unit evenly across the unit's input space. The ENN-RBP training and testing were repeated for hidden unit (HU) sizes of 20, 40, 60, 80, and 100.

A total of 200 EEG patterns (20 segments for each EEG signal $\times$ ten sessions) were used for each subject for each mental task in all the experiments. Therefore, for each experiment, there were 400 EEG patterns from two mental tasks, where half of the patterns were used in training and the remaining half in testing. A modified ten-fold cross-validation technique was used to increase the reliability of the results. In this method, the entire data for an experiment (i.e., 400 EEG patterns) were split into ten parts. Training and testing were conducted for five times where for each time, five randomly selected parts were used for training, and the rest five parts for testing. So for each HU size, the ENN-RBP training and testing were repeated for five times. Overall, training and testing were conducted for 2000 times (five HU sizes $\times$ ten mental task combinations $\times$ two features extraction methods $\times$ five cross-validation repetitions $\times$ four subjects). Training was conducted until the ENN mean square error fell below 0.0001. 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 other category, it was set to 0.

## III. Results and Discussions

Tables I–IV show the ENN-RBP averaged classification performance (%) using modified ten-fold cross validation for methods A and B for the four subjects. From the average and maximum values, it is obvious that the classification performances are improved by using the additional gamma band features, which is also true for most of the classification performances of different HU sizes. This result is more clearly indicated in Fig. 1(a)–(d), which shows the results that have been averaged from all HU sizes from Tables I–IV. Another interesting property is that the best mental task combinations were invariant for different hidden unit sizes (for all subjects) and invariant to Methods A and B (except for subject four). It could also be noted that different subjects had different best mental task combinations. This could be because the thought

TABLE I
ENN-RBP CLASSIFICATION RESULTS FOR SUBJECT 1

| HU | 20 | 40 | 60 | 80 | 100 | 20 | 40 | 60 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mental tasks | Method A (60 features) | | | | | Method B (proposed 75 features) | | | | |
| Bas, Cou | 63.7 | 60.9 | 62.0 | 62.3 | 63.9 | 75.8 | 76.0 | 76.7 | 75.1 | 76.7 |
| Bas, Let | 50.3 | 51.5 | 52.3 | 53.7 | 53.9 | 67.5 | 67.6 | 67.1 | 66.3 | 68.8 |
| Bas, Mat | 66.9 | 67.5 | 69.9 | 70.0 | 68.9 | 82.0 | 82.8 | 81.9 | 82.8 | 82.1 |
| Bas, Rot | 68.3 | 70.6 | 68.9 | 69.7 | 71.0 | 90.7 | 91.7 | 91.7 | 91.2 | 91.5 |
| Let, Cou | 54.7 | 56.8 | 55.6 | 55.9 | 55.9 | 63.9 | 63.4 | 61.7 | 63.9 | 64.2 |
| Let, Rot | 62.1 | 65.2 | 64.5 | 64.7 | 63.9 | 77.2 | 76.6 | 78.3 | 78.4 | 78.0 |
| Mat, Cou | 77.5 | 76.6 | 78.6 | 77.9 | 78.1 | 87.3 | 85.6 | 86.0 | 87.1 | 87.2 |
| Mat, Let | 76.9 | 77.7 | 74.9 | 76.2 | 76.9 | 90.6 | 90.8 | 90.8 | 90.9 | 90.6 |
| Mat, Rot | **81.1** | **80.3** | **82.2** | **80.9** | **82.0** | **93.9** | **94.3** | **94.1** | **94.3** | **94.4** |
| Rot, Cou | 57.5 | 56.8 | 56.2 | 60.2 | 58.6 | 65.5 | 65.5 | 67.1 | 66.0 | 64.4 |
| Average | 65.9 | 66.3 | 66.5 | 67.1 | 67.3 | 79.4 | 79.4 | 79.5 | 79.6 | 79.8 |
| Max | 81.1 | 80.3 | 82.2 | 80.9 | 82.0 | 93.9 | 94.3 | 94.1 | 94.3 | 94.4 |
| Best tasks | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot | Mat, Rot |

Bas=Baseline, Cou=Count, Let=Letter, Mat=Maths, Rot=Rotation.

TABLE II
ENN-RBP CLASSIFICATION RESULTS FOR SUBJECT 2

| HU | 20 | 40 | 60 | 80 | 100 | 20 | 40 | 60 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mental tasks | Method A (60 features) | | | | | Method B (proposed 75 features) | | | | |
| Bas, Cou | 52.5 | 52.8 | 54.2 | 53.8 | 53.3 | 65.7 | 64.2 | 65.3 | 66.2 | 66.4 |
| Bas, Let | 53.1 | 57.9 | 55.8 | 54.0 | 55.2 | 69.9 | 70.9 | 70.9 | 71.9 | 72.5 |
| Bas, Mat | 58.6 | 59.4 | 61.7 | 59.7 | 57.5 | 71.4 | 72.1 | 72.0 | 71.8 | 72.4 |
| Bas, Rot | 56.6 | 56.9 | 57.6 | 54.4 | 55.0 | 65.9 | 65.4 | 65.7 | 67.1 | 68.1 |
| Let, Cou | 51.2 | 53.2 | 52.4 | 50.0 | 51.7 | 74.1 | 76.4 | 77.7 | 75.3 | 75.3 |
| Let, Rot | 56.9 | 59.4 | 61.4 | 61.3 | 59.3 | 69.2 | 68.9 | 71.5 | 70.4 | 72.1 |
| Mat, Cou | 54.8 | 56.3 | 56.1 | 55.7 | 56.1 | 61.9 | 63.6 | 61.0 | 63.4 | 63.5 |
| Mat, Let | **63.0** | **65.2** | **66.1** | **64.8** | **64.9** | **78.4** | **78.4** | **78.4** | **79.6** | **80.1** |
| Mat, Rot | 51.3 | 51.6 | 52.9 | 53.9 | 53.7 | 63.4 | 63.8 | 62.6 | 63.0 | 62.0 |
| Rot, Cou | 51.3 | 51.6 | 50.4 | 52.1 | 54.6 | 55.8 | 59.1 | 61.1 | 59.3 | 59.1 |
| Average | 54.9 | 56.4 | 56.9 | 56.0 | 56.1 | 67.6 | 68.3 | 68.6 | 68.8 | 69.1 |
| Max | 63.0 | 65.2 | 66.1 | 64.8 | 64.9 | 78.4 | 78.4 | 78.4 | 79.6 | 80.1 |
| Best tasks | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let | Mat, Let |

Bas=Baseline, Cou=Count, Let=Letter, Mat=Maths, Rot=Rotation.



patterns from different individuals were not the same and, therefore, different mental tasks resulted in varying classification performance.

When the mental tasks from all four subjects are considered (using results from Method B), it is evident that mental multiplication (maths) task is the most important task followed by object rotation and letter writing tasks (equal importance), and finally, counting task (least important). The good performances given by asymmetry ratios from mental multiplication and object rotation tasks conform the basic neuroscience knowledge that one hemisphere of the brain (i.e., left) is dominant for calculation while the other hemisphere (i.e., right) of the brain is dominant for visual tasks (though the object rotation task is imagined visual activity).

When comparing all the subjects and all the HU sizes, the ENN training required an average of 94.4 iterations which took 2.06 s when features from Method A was used, while only an average of 63.6 iterations which took 1.41 s were required when features from Method B were used. The codes were written in MATLAB (Mathworks, Inc.) and run on a Pentium IV 2.8-GHz PC with 1-GB RAM.

These results show that with the inclusion of additional gamma band features, less iterations were required and this resulted in reduced training time. Though there would be some additional computation required for the gamma band features,

TABLE III
ENN-RBP CLASSIFICATION RESULTS FOR SUBJECT 3

| HU | 20 | 40 | 60 | 80 | 100 | 20 | 40 | 60 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mental tasks | Method A (60 features) | | | | | Method B (proposed 75 features) | | | | |
| Bas, Cou | 56.5 | 56.5 | 59.1 | 57.7 | 57.7 | 58.9 | 61.2 | 58.5 | 58.9 | 57.6 |
| Bas, Let | 63.0 | 64.8 | 64.3 | 63.9 | 66.2 | 65.9 | 69.1 | 69.7 | 67.9 | 68.0 |
| Bas, Mat | 60.3 | 60.2 | 60.6 | 62.0 | 61.1 | 64.0 | 65.4 | 64.5 | 65.6 | 64.9 |
| Bas, Rot | 65.4 | 65.1 | 66.4 | 66.3 | 66.2 | 73.0 | 72.0 | 73.3 | 73.8 | 71.7 |
| Let, Cou | 66.3 | 66.6 | 66.6 | 67.9 | 66.8 | 68.2 | 69.3 | 69.4 | 70.5 | 68.3 |
| Let, Rot | **76.7** | **75.0** | **76.4** | **76.3** | **75.4** | **79.7** | **80.9** | **81.1** | **81.2** | **81.6** |
| Mat, Cou | 57.4 | 55.7 | 56.2 | 57.6 | 59.2 | 60.5 | 63.3 | 61.6 | 62.0 | 63.4 |
| Mat, Let | 69.9 | 68.9 | 70.7 | 68.9 | 70.0 | 78.4 | 75.7 | 76.9 | 76.8 | 77.0 |
| Mat, Rot | 60.4 | 62.4 | 61.9 | 61.8 | 62.4 | 72.1 | 73.6 | 71.4 | 73.7 | 74.6 |
| Rot, Cou | 63.6 | 63.9 | 62.8 | 62.8 | 62.9 | 73.2 | 72.3 | 74.3 | 74.8 | 75.3 |
| Average | 63.9 | 63.9 | 64.5 | 64.5 | 64.8 | 69.4 | 70.3 | 70.1 | 70.5 | 70.2 |
| Max | 76.7 | 75.0 | 76.4 | 76.3 | 75.4 | 79.7 | 80.9 | 81.1 | 81.2 | 81.6 |
| Best tasks | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot | Let, Rot |

Bas=Baseline, Cou=Count, Let=Letter, Mat=Maths, Rot=Rotation.

TABLE IV
ENN-RBP CLASSIFICATION RESULTS FOR SUBJECT 4

| HU | 20 | 40 | 60 | 80 | 100 | 20 | 40 | 60 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mental tasks | Method A (60 features) | | | | | Method B (proposed 75 features) | | | | |
| Bas, Cou | 61.6 | 61.6 | 60.3 | 60.6 | 61.9 | 72.3 | 76.7 | 73.9 | 75.4 | 74.5 |
| Bas, Let | 59.1 | 58.0 | 59.3 | 58.6 | 58.6 | 64.7 | 66.0 | 64.6 | 66.1 | 65.2 |
| Bas, Mat | 77.7 | 77.4 | 78.2 | 78.5 | 78.7 | 85.6 | 85.8 | 85.4 | 85.2 | 84.4 |
| Bas, Rot | **85.0** | **87.6** | **85.0** | **85.6** | **85.1** | 85.8 | 86.5 | 87.3 | 87.3 | 87.7 |
| Let, Cou | 57.6 | 56.8 | 57.1 | 59.7 | 60.4 | 66.3 | 69.2 | 67.2 | 66.6 | 67.5 |
| Let, Rot | 83.1 | 84.3 | 83.1 | 84.0 | 83.4 | 84.2 | 83.8 | 84.5 | 84.0 | 83.6 |
| Mat, Cou | 65.1 | 63.0 | 64.7 | 65.1 | 63.0 | **88.9** | **88.9** | **89.9** | **89.4** | **89.5** |
| Mat, Let | 70.7 | 71.1 | 70.8 | 73.0 | 71.0 | 85.4 | 84.1 | 83.6 | 85.9 | 84.3 |
| Mat, Rot | 74.5 | 76.3 | 76.1 | 76.6 | 77.0 | 81.0 | 79.1 | 81.3 | 81.4 | 81.1 |
| Rot, Cou | 75.4 | 74.7 | 73.5 | 75.8 | 75.5 | 84.0 | 83.4 | 84.7 | 84.7 | 84.9 |
| Ave | 71.0 | 71.1 | 70.8 | 71.7 | 71.5 | 79.8 | 80.3 | 80.2 | 80.6 | 80.3 |
| Max | 85.0 | 87.6 | 85.0 | 85.6 | 85.1 | 88.9 | 88.9 | 89.9 | 89.4 | 89.5 |
| Best tasks | Bas, Rot | Bas, Rot | Bas, Rot | Bas, Rot | Bas, Rot | Mat, Cou | Mat, Cou | Mat, Cou | Mat, Cou | Mat, Cou |

Bas=Baseline, Cou=Count, Let=Letter, Mat=Maths, Rot=Rotation.

it was negligible (for both the methods, the computation of features for each EEG segment took 0.046 s). The differences in ENN testing times for Methods A and B were also negligible (both methods took 0.031 s on average to classify 200 EEG patterns).

## IV. CONCLUSION

In this paper, it has been shown that the classification performance and training time of a bistate mental task based BCI design could be improved by including gamma band in addition to delta, theta, alpha, and beta bands in the computation of spectral powers and asymmetry ratios. The computational complexities incurred by including the additional gamma band features were negligible. The results showed that in most cases, the mental task pair that gave the best classification performance is invariant to the ENN HU sizes and feature extraction methods. As such, it is equally important to choose suitable mental task pairs for each individual as compared to the feature extraction method for a successful BCI design.

For future work, the effect of each spectral band or combination of spectral bands on the classification performance could be studied in contrast to using all five spectral bands as in the current study. It would also be very useful to check for other suitable ranges for gamma band. In addition, it is probable that

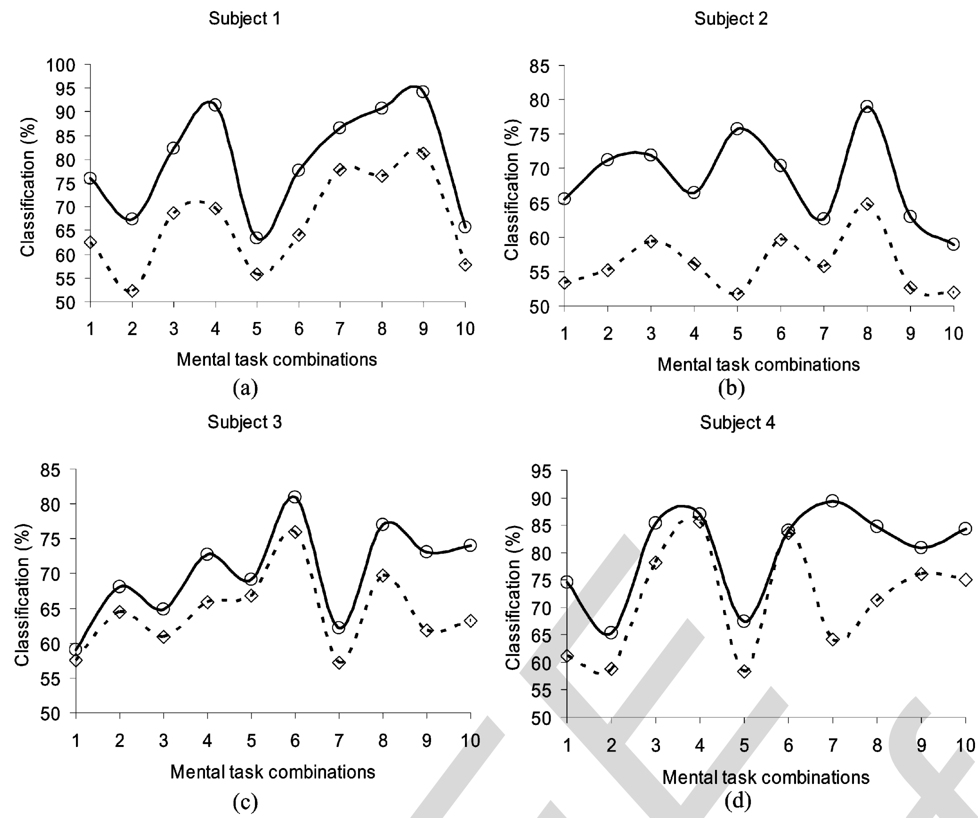


Fig. 1. Comparison of results (using average from all HUs sizes from Tables I–IV) for methods A and B for (a) subject 1, (b) subject 2, (c) subject 3, and (d) subject 4. Refer to Tables I–IV for the mental task combinations. Legend: Method A: – –◇– – and Method B: —○—. Mental task combination numbers relates to the mental task rows inTables I–IV.

the suitable gamma band range could be different for different subjects, which is hoped to be verified in future studies. Also, the inclusion of frontal electrodes could be explored in future as gamma band is evoked easily in this part of the brain.

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## References

[1] J. R. Wolpaw, N. Birbaumer, W. J. Hectderks, D. J. McFarland, P. H. Pecleham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: A review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, Jun. 2000.

[2] Z. A. Keirn and J. I. Aunon, "A new mode of communication between man and his surroundings," *IEEE Trans. Biomed. Eng.*, vol. 37, no. 12, pp. 1209–1214, Dec. 1990.

[3] C. W. Anderson, E. A. Stolz, and S. Shamsunder, "Multivariate autoregressive models for classification of spontaneous electroencephalogram during mental tasks," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 3, pp. 277–286, Mar. 1998.

[4] R. Palaniappan, R. Paramesran, S. Nishida, and N. Saiwaki, "A new brain-computer interface design using fuzzy ARTMAP," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 10, no. 3, pp. 140–148, Sep. 2002.

[5] E. Donchin, K. M. Spencer, and R. Wijesinghe, "The mental prosthesis: Assessing the speed of a P300-based brain-computer interface," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 174–179, Jun. 2000.

[6] G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoses, A. Schlogl, B. Obermaier, and M. Pregenzer, "Current trends in graz brain-computer interface (BCI) research," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 216–219, Jun. 2000.

[7] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 1, pp. 70–85, Mar. 2003.

[8] K. V. R. Ravi and R. Palaniappan, "Neural network classification of late gamma band electroencephalogram features," *Soft Comput.*, vol. 10, no. 2, pp. 163–169, 2006.

[9] E. Basar, C. B. Eroglu, T. Demiralp, and M. Schurman, "Time and frequency analysis of the brain's distributed gamma-band system," *IEEE Eng. Med. Biol. Mag.*, vol. 14, no. 4, pp. 400–410, Jul./Aug. 1995.

[10] 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 Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1052–1056, Jun. 2004.

[11] J. L. Elman, "Finding structure in time," *Cognit. Sci.*, vol. 14, pp. 179–211, 1990.

[12] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm," in *Proc. IEEE Int. Conf. Neural Netw.*, 1993, vol. 1, pp. 586–591.

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