34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

# Mental Task Classifications using Prefrontal Cortex Electroencephalograph Signals

Rifai Chai, *Student Member, IEEE*, Sai Ho Ling, *Senior Member, IEEE*, Gregory P. Hunter, *Member, IEEE* and Hung T. Nguyen, *Senior Member, IEEE*

*Abstract*—**For an electroencephalograph (EEG)-based brain computer interface (BCI) application, the use of gel on the hair area of the scalp is needed for low impedance electrical contact. This causes the set up procedure to be time consuming and inconvenient for a practical BCI system. Moreover, studies of other cortical areas are useful for BCI development. As a more convenient alternative, this paper presents the EEG based-BCI using the prefrontal cortex non-hair area to classify mental tasks at three electrodes position: Fp1, Fpz and Fp2. The relevant mental tasks used are mental arithmetic, ringtone, finger tapping and words composition with additional tasks which are baseline and eyes closed. The feature extraction is based on the Hilbert Huang Transform (HHT) energy method and the classification algorithm is based on an artificial neural network (ANN) with genetic algorithm (GA) optimization. The results show that the dominant alpha wave during eyes closed can still clearly be detected in the prefrontal cortex. The classification accuracy for five subjects, mental tasks vs. baseline task resulted in average accuracy is 73% and the average accuracy for pairs of mental task combinations is 72%.**

## I. INTRODUCTION

A brain computer interface (BCI) system offers an option for people with severe disability issues by converting their brain activities into communication and control [1]. A BCI system using invasive surgery methods, such as electrocorticogram (ECoG) and intra-cortical recording, although providing a better signal resolution, frequency range, and better quality of signal, has serious drawbacks, which include: risk of infection, scarring of post-surgery, and long term effects which still remain unclear for a safe and stabile operation. On the other hand, noninvasive BCI technologies, including functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and positron emission tomography (PET) are not mobile and are expensive. An electroencephalograph (EEG) is still a popular tool for BCI in terms of portability and cost benefits [2, 3].

From the mental strategy viewpoint, the most common BCI-EEG technologies focus on selective attention and spontaneous mental signal methods. P300 [4] and steady state visual evoked potential (SSVEP) [5] are examples of the selective attention BCI in which the user needs to concentrate on external stimuli and which might become uncomfortable to user. An event related desynchronization-synchronization (ERD/ERS) is an example of the spontaneous mental signal method. It focuses on the motor cortex area by imagining the left hand, right hand, feet and tongue [6, 7]. Other researchers have focused on different mental tasks such as baseline, multiplication, letter composing, 3-D rotation, and counting task [8, 9, 10]. These studies use electrodes on the cortex areas such as central, parietal, and occipital.

However, these EEG methods require electrodes to be placed on hair covered of the scalp which creates some problems in ensuring good low impedance electrode contact. The use of conductive gel is needed for reducing the impedance and for proper electrical contact. This causes an inconvenient and time consuming set up procedure in a practical BCI system. The prefrontal cortex has the advantage of being located in the non-hair fore head area compared to other scalp areas. The electrode placement using prefrontal area could be used as an alternative solution for a practical BCI system. In addition, this is a useful as an option when disease or injury damages the other cortices.

This paper presents the classification of the pairs combination of mental tasks by using EEG based-BCI with three electrodes positioned on the non-hair prefrontal cortex area at locations Fp1, Fpz, and Fp2. The mental tasks used in this experiment are based on the function of the prefrontal cortex in emotion and cognition which include mental arithmetic, ring tone, finger tapping and word association. From the brain functioning point of view, the parietal lobe shows significant activity during mental arithmetic calculation. The left prefrontal cortex also activates the working memory during arithmetic calculation [11, 12]. Next, the music imagery task has correlated to emotional responses as part of the prefrontal function [13]. The motor imagery task is dominant in the motor cortex region, but it also has a correlation with the prefrontal cortex as the execution task [14, 15]. Finally, word association induces activation more on the left prefrontal cortex [16].

## II. METHODS

### A. Data Collection

The Human Research Ethics Committee from the University of Technology, Sydney approved this study. Five able-bodied and right handed subjects (3 males and 2 females) aged between 25 and 35 years participated in the experiment. An EEG system from Compumedic with the sampling rate set to 256 Hz was used. The EEG electrodes were positioned as shown in Fig. 1 at locations: Fp1, Fpz, and Fp2. The location A2 was used for a reference electrode and the location A1 was used as a GND electrode. This

Manuscript received June, 2012. Rifai Chai, Sai Ho Ling, Gregory P. Hunter and Hung T. Nguyen are with Centre for Health Technologies, Faculty of Engineering and Information Technology, University of Technology, Sydney, Broadway NSW 2007, Australia.
E-mail contacts: Rifai.Chai@student.uts.edu.au, Steve.Ling@uts.edu.au, Greg.Hunter@uts.edu.au, and Hung.Nguyen@uts.edu.au

placement refers to the international 10-20 system standard. The impedance was measured and kept below 5kΩ. Unnecessary movements and eye blinks were kept to a minimum. The mental tasks used in the study include:

- Baseline (*base*): Participants were asked to relax with open eyes and not to think of any other tasks.
- Arithmetic calculation (*math*): Participants were instructed to imagine solving a series of simple one digit multiplications.
- Ringtone (*tone*): Participants were asked to imagine a familiar mobile ringtone in their head without moving their mouth.
- Finger tapping (*finger*): Participants were asked to imagine tapping their right index finger without actual movement.
- Word association (*words*): Participants were asked to compose words in their mind without vocalizing.

An additional eyes closed action was also collected to check the level of alpha wave activity. Each subject performed a recording session of ten sub-sessions for each particular mental task with the duration of 15 seconds on each sub-session. The first 3 seconds are removed to allow for the preparation time which results in 12 seconds being used.

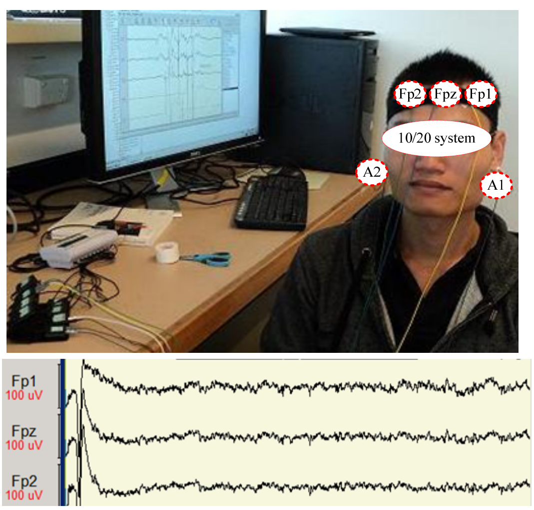


Figure 1. EEG system setup

## B. *Feature Extraction Algorithm*

Prior to feature extraction, a moving window segmentation of one second is applied, with an overlap of every quarter second segment, to give a result in 45 overlapping segments for 12 seconds data in 10 session recordings for each mental task. Therefore, each subject provides data around 45×10 or 450 units per task. Next, digital signal processing (DSP) filters are employed to improve raw signal quality. These consist of a Butterworth band-pass filter with a bandwidth of 0.1 Hz to 40 Hz followed by a Butterworth notch filter at 50 Hz.

For the feature extractor, the Hilbert Huang transform (HHT) [17] energy as the time-frequency analysis algorithm is used. The HHT has two processes: empirical mode decomposition (EMD) and Hilbert Huang transform. The EMD decomposes a time series data into amplitude and frequency modulated signals which are sets of intrinsic mode functions (IMF). In each set, each IMF needs to satisfy two conditions: first, the extrema and the zero crossings numbers should be equal or differ by one; second, it is a zero-mean value of the envelope. The EMD algorithm is summarized as follows: 1) identify extrema (minima and maxima) of the EEG signal; 2) generate the upper and lower envelope based on interpolation between maxima and minima; 3) compute the average of the two envelopes. 4) Extract the IMF component; 5) if the candidate IMF does not satisfy the properties of IMF replace the EEG data signal with candidate IMF and repeat from step 1, and if it does, take as an IMF and evaluate the residue; 6) repeat from step 1 to 5 by shifting the residual until the stopping criterion is satisfied.

The Hilbert transform (HT) is applied to each IMF to obtain the Hilbert Huang amplitude spectrum (HHS). The signal, after calculating the HT on each IMF component, can be expressed as follows:

$$H(\omega,t)=\sum_{i=1}^{n}a_i(t)\exp(j\int\omega_i(t)dt) \qquad (1)$$

where $H(\omega,t)$ is Hilbert Huang spectrum, $a_i(t)$ is amplitude of the transform and $\omega_i(t)$ is the instantaneous frequency and $n$ is the number of input. Equation (1) provides the amplitude and the frequency of each component as a function of time. This frequency-time distribution of the amplitude is represented as the HHS.

Spectrum calculated from the HHT is used in the range of EEG bands: δ (0-3Hz), θ (4-7Hz), α (8-13Hz) and β (14-30Hz). Next, numerical integration of the trapezoidal method is used to calculate the total energy on each frequency band, as a result with the energy over four bands calculated from 3 channels (Fp1, Fpz, and Fp2), twelve power levels are made available.

## B. *Classification Algorithm*

The artificial neural network (ANN) as a classification method is a popular pattern recognition tool in biomedical applications [18]. This study uses a 3-layer feed forward neural network with one hidden layer network as shown in Fig. 2. The output vector $z$ and the $k$-th component $z_k$ are computed as follows:

$$z_k(x,w)=f_1\left(b_k+\sum_{j=1}^{m}w_{kj}f_2\left(b_j+\sum_{i=1}^{n}w_{ji}x_n\right)\right) \qquad (2)$$

where $f_1$, $f_2$ is the activation function, $x$ represents the input vector, $w$ is the weight matrix vector, $b$ is the scalar bias, $n$ is the number of input nodes, $m$ is the number of output nodes, $w_{ji}$ is the weight to the hidden unit $y_j$ from input unit $x_i$ and $w_{kj}$ represents the weights to output unit $z_k$ from hidden unit $y_j$. The biases are represented by $b_j$ and $b_k$. A log-sigmoid function was assigned as the activation function which provides data values between one and zero. Therefore, prior to the ANN the feature data value needs to be scaled to within the range zero to one as follows:

$$X^* = (X - Xmin) / (Xmax - Xmin) \tag{3}$$

where $X$ is the input features value, $X^*$ is the value after scaling, $Xmin$ is the minimum and $Xmax$ is the maximum value of the input feature values.

The Genetic Algorithm (GA) is used to optimize the neural network training. A population of chromosomes is initialized at the beginning and evolves with each generation of iteration in the following procedure: first, two parents are selected from the population of chromosomes based on the selection operation with the probability of selection proportional to their fitness value; second, after applying the crossover and mutation operation, a new offspring is generated from these parents. This is governed by the probabilities of crossover and mutation; third, the population generated replaces the current population. These procedures are repeated until a termination condition is satisfied such as a predefined number of iteration [19].

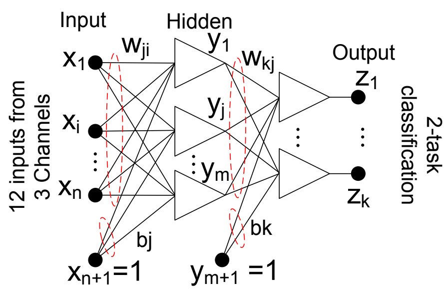


Figure 2. Neural network architecture

## III. RESULTS

The alpha wave during eyes closed action has the dominant value in the occipital cortex area. Figure 3 shows the comparison alpha wave during eyes closed and opened using the prefrontal cortex area. The alpha wave with a frequency band between 8-13Hz during eyes closed on the prefrontal cortex (Fp1, Fpz, and Fp2) also clearly shows the dominant frequency compared to the eyes opened action. Therefore, the eyes closed action as the mind switch [20] is still also available for the BCI operation.

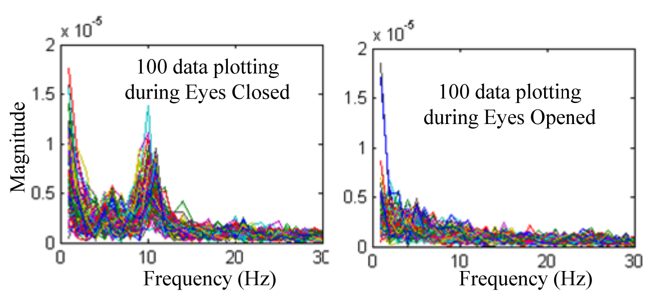


Figure 3. Detection of the dominant alpha wave during eyes closed in the prefrontal cortex

The features data set per subject consists of 450 units for each mental task and 900 for the total of 2-tasks classification. This is divided equally between the training set and the testing set. The number of hidden neurons used for each subject is varied in order to find the best number which provides the highest fitness value to achieve the highest accuracy. The population size used for the GA is 50, and training is stopped when the training of the neural network reaches up to 2000 iterations. The probability of crossover is set at 0.8, and the probability of mutation is set at 0.1 for the GA based-neural network training.

Because there is a difference in the EEG signals across different subjects, so called inter-subject variability, the ANN training and classifications are performed on each subject.

TABLE I. ACCURACIES OF TWO TASKS COMBINATION CLASSIFICATION FOR 5 SUBJECTS

| **Task combination: Base(1), Math(2), Tone(3), Finger(4), Words(5)** | ***Accuracy (%) for 5 subjects (S1-S5)*** | | | | | |
|---|---|---|---|---|---|---|
| | ***S1*** | ***S2*** | ***S3*** | ***S4*** | ***S5*** | ***Average*** |
| Base(1)-Math(2) | 65 | 71 | 75 | 69 | 77 | 71 |
| Base(1)-Tone(3) | 84 | 60 | 91 | 61 | 60 | 71 |
| Base(1)-Finger(4) | 79 | 78 | 89 | 80 | 64 | 78 |
| Base(1)-Words(5) | 74 | 64 | 94 | 69 | 60 | 72 |
| Average | | | | | | **73** |
| | | | | | | |
| Math(2)-Tone(3) | 78 | 72 | 80 | 67 | 74 | 74 |
| Math(2)-Finger(4) | 75 | 88 | 75 | 89 | 74 | 80 |
| Math(2)-Words(5) | 69 | 78 | 77 | 86 | 73 | 77 |
| Tone(3)-Finger(4) | 58 | 70 | 69 | 85 | 68 | 70 |
| Tone(3)-Words(5) | 59 | 55 | 70 | 81 | 62 | 65 |
| Finger(4)-Words(5) | 58 | 59 | 57 | 95 | 60 | 66 |
| Average | | | | | | **72** |

Table I shows the results of any two mental task combinations for 5 subjects. First, all mental tasks (math, tone, finger, words) are compared to the baseline task. This comparison is necessary to make sure of any unique differences between mental task imagination and non-metal task imagination (baseline). The resulting comparison with the baseline shows a variation of accuracies across different subjects. Subject 1 has the best mental task when performing ringtone (tone) imagination with accuracy at 84%. Subject 2 performs best the result in mental motor imagery of finger tapping (finger) with accuracy around 78%. Subject 3 has the best accuracy during mental word association (words) with accuracy above 94%. Subject 4 has the best accuracy around 80% when performing mental motor imagery of finger tapping (finger). The best mental task for subject 5 is mental arithmetic calculation with the accuracy at 77%.

As a result, the chosen mental task has provided accuracy between 77% and 94% compared to the baseline task. The average accuracy of the baseline vs. mental task combination classification is around 73%.

Next, the training and classification are done for any combinations of two mental tasks on each subject. The results show that each subject has at least two pairs of mental task combination with accuracy above 70%. Subject 1 has the best two pairs: mental arithmetic vs. ringtone with accuracy at 78% and arithmetic vs. finger tapping with accuracy at 75%. Subject 2 has the best two pairs: arithmetic vs. finger tapping with accuracy at 88% and arithmetic vs. word association with accuracy at 78%. Subject 3 has mental arithmetic vs. ringtone and arithmetic vs. words as the best two pair combination with accuracy 80% and 77%. Subject 4 has best two combination pairs: mental arithmetic vs. finger tapping with accuracy at 89% and finger tapping vs. words association with accuracy at 95%. Subject 5 has the best two pairs when performing mental arithmetic vs. ringtone and arithmetic vs. finger tapping with accuracy of around 74%.

The average accuracy of all mental tasks in pair combinations classification is around 72%. In general, this result of mental tasks classifications shows the prefrontal cortex area could be used as the alternative location for the EEG based BCI with the advantage of being more practical and convenient.

## IV. Conclusion

The EEG-BCI, based on prefrontal cortex with only three electrodes position at Fp1, Fpz and Fp2, has been successfully used to classify pairs of mental task combinations. Moreover, the dominant alpha wave during eyes closed still can be detected on the prefrontal cortex area. This could be used as an additional command for the BCI. The resulting classification shows variation accuracies of the best mental task on different subjects. Classification between chosen best mental task and baseline task resulted in accuracy at between 77% and 94% with the different best mental task on each subject. The average accuracy of all baseline and mental task combinations are at around 73%. This shows a distinct feature difference between subjects performing a particular mental task compared to those who are not performing mental task (baseline state). In mental task pair classifications, each subject is able to have at least two best pairs with accuracy between 74% and 95%. The average accuracy for pairs of mental task combinations is around 72%.

## References


[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology,* vol. 113, pp. 767-791, 2002.

[2] J. R. Wolpaw, G. E. Loeb, B. Z. Allison, E. Donchin, O. F. do Nascimento, W. J. Heetderks, F. Nijboer, W. G. Shain, and J. N. Turner, "BCI meeting 2005-workshop on signals and recording methods," *IEEE Trans. Neural Systems and Rehabilitation Engineering,* vol. 14, pp. 138-141, 2006.

[3] G. Schalk, "Brain–computer symbiosis," *J. Neural engineering,* vol. 5, pp. 1-14, 2008.

[4] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology,* vol. 70, pp. 510-523, 1988.

[5] B. Z. Allison, D. J. McFarland, G. Schalk, S. D. Zheng, M. M. Jackson, and J. R. Wolpaw, "Towards an independent brain-computer interface using steady state visual evoked potentials," *Clinical Neurophysiology,* vol. 119, pp. 399-408, 2008.

[6] G. Pfurtscheller, G. R. Muller, B. Graimann, R. Scherer, R. Leeb, C. Brunner, C. Keinrath, G. Townsend, M. Naeem, F. Y. Lee, D. Zimmermann, and E. Hofler, "Graz-Brain-Computer Interface: State of Research," in *Toward Brain-Computer Interfacing*, G. Dornhege, J. R. Millan, T. Hinterberger, D. J. McFarland, and K.-R. Muller, Eds.: The MIT Press, 2007, pp. 66-84.

[7] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc. of the National Academy of Sciences of the United States of America,* vol. 101, pp. 17849-17854, Dec 2004.

[8] Z. A. Keirn and J. I. Aunon, "A new mode of communication between man and his surroundings," *IEEE Trans. Biomedical Engineering,* vol. 37, pp. 1209-1214, 1990.

[9] D. A. Craig, H. T. Nguyen, and H. A. Burchey, "Two Channel EEG Thought Pattern Classifier," in *Proc. of the 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2006, pp. 1291-1294.

[10] F. Faradji, R. K. Ward, and G. E. Birch, "Plausibility assessment of a 2-state self-paced mental task-based BCI using the no-control performance analysis," *Journal of Neuroscience Methods,* vol. 180, pp. 330-339, 2009.

[11] H. Kondo, M. Morishita, N. Osaka, M. Osaka, H. Fukuyama, and H. Shibasaki, "Functional roles of the cingulo-frontal network in performance on working memory," *NeuroImage,* vol. 21, pp. 2-14, 2004.

[12] N. De Pisapia, J. A. Slomski, and T. S. Braver, "Functional specializations in lateral prefrontal cortex associated with the integration and segregation of information in working memory," *Cerebral Cortex,* vol. 17, pp. 993-1006, 2007.

[13] S. D. Power, T. H. Falk, and T. Chau, "Classification of prefrontal activity due to mental arithmetic and music imagery using hidden Markov models and frequency domain near-infrared spectroscopy," *Journal of Neural engineering,* vol. 7, p. 026002, 2010.

[14] E. Gerardin, A. Sirigu, S. Lehéricy, J. B. Poline, B. Gaymard, C. Marsault, Y. Agid, and D. Le Bihan, "Partially overlapping neural networks for real and imagined hand movements," *Cerebral Cortex,* vol. 10, pp. 1093-1104, 2000.

[15] T. Hanakawa, M. A. Dimyan, and M. Hallett, "Motor planning, imagery, and execution in the distributed motor network: a time-course study with functional MRI," *Cerebral Cortex,* vol. 18, pp. 2775-2788, 2008.

[16] R. J. Zatorre, A. C. Evans, E. Meyer, and A. Gjedde, "Lateralization of phonetic and pitch discrimination in speech processing," *Science,* vol. 256, pp. 846-849, 1992.

[17] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences,* vol. 454, pp. 903-995, 1998.

[18] H. T. Nguyen, "Intelligent technologies for real-time biomedical engineering applications," *Int. J. Automation and Control,* vol. 2, Nos.2/3, pp. 274-285, 2008.

[19] F. H. F. Leung, H. K. Lam, S. H. Ling, and P. K. S. Tam, "Tuning of the structure and parameters of a neural network using an improved genetic algorithm," *IEEE Trans. Neural Networks,* vol. 14, no. 1, pp. 79-88, 2003.

[20] A. Craig, P. Moses, Y. Tran, P. McIsaac, and L. Kirkup, "The effectiveness of a hands-free environmental control system for the profoundly disabled," *Archives of physical medicine and rehabilitation,* vol. 83, pp. 1455-1458, 2002.