

# BRAIN COMPUTER INTERFACE DESIGN USING MENTAL TASK CLASSIFICATION

<sup>1</sup>Nai-Jen Huan and <sup>2</sup>Ramaswamy Palaniappan

<sup>1</sup>Faculty of Information Science and Technology, Multimedia University, Melaka, Malaysia.

<sup>2</sup>Biomedical Engineering Research Centre, Nanyang Technological University, Singapore.

**Abstract-** In this paper, a bi-state Brain Computer Interface (BCI) using neural network (NN) classification of electroencephalogram (EEG) signals extracted during mental tasks has been designed. The output of the BCI design could be used with a translation scheme such as Morse Code for paralysed individuals to communicate with their external surroundings. In the experimental study, EEG signals from 5 mental tasks were recorded from 4 subjects and combinations of 2 different mental tasks were studied for each subject. Three different feature extraction methods were employed in the BCI design: 6<sup>th</sup> order autoregressive (AR) coefficient computed with Burg's algorithm, power and asymmetry ratio from delta, theta, alpha, beta spectral bands, and power spectral density (PSD) values. The NN utilised for classifying the features were Multilayer Perceptron architecture with Back-propagation training (MLP-BP) and Simplified Fuzzy ARTMAP (SFAM). Comparisons of classification performances were made among the 3 different feature extraction methods and the NNs. The results indicated that 6<sup>th</sup> order AR coefficients gave the best performance, in addition to requiring the least amount of time to train and test. In general, MLP-BP performed better than SFAM. The results also showed the importance of selecting suitable mental task combinations to maximise the BCI output for each subject because of the varying NN classification performances for different mental tasks.

**Key words:** Asymmetry Ratio, Autoregressive, Brain Computer Interface, Electroencephalogram, Mental Tasks, Neural Network, Power Spectral Density

## 1. INTRODUCTION

Over the last ten years, the volume and pace of BCI research have grown tremendously [1]-[2]. In 1995 there were no more than six active BCI research groups, and in the year 2000, there were more than 20 [2]. BCI design is very useful for completely paralysed

individuals<sup>1</sup> to communicate with their external surroundings using their brain thoughts. These individuals could have become completely paralysed after being involved in an accident or due to some diseases. BCI design is also suitable for use in simple hands off menu selection on the screen.

There are a few non-invasive methods for obtaining these brain signals to be utilised in a BCI design. EEG signals recorded at the scalp during some mental tasks have been used by some of the research groups [3]-[8]. Some others utilise single-trial visual evoked potential (VEP) signals where the subjects gaze at a screen full of alphabets or menus. Synchronisation and desynchronisation of  $\mu$ -rhythm extracted during sensory motor tasks is another method for BCI design [9]-[11]. Reviews of some of these technologies and developments in this area are given by Vaughan *et al* [1], Wolpaw *et al* [2] and Mason and Birch [6].

Besides all these, there are some invasive BCI designs. These designs make use of the recent developed technologies such as magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) to improve in-patient evaluation and preliminary identification of sites for implantation of invasive BCI recording electrodes. However, these are not very common due to their invasive nature and it will not be discussed further since it is not the focus of the paper.

The main problem in BCI design is the accuracy of classification the EEG signals. At present, no one single method of both feature extraction and classification could achieve a one hundred percentage accuracy. As a result studies must be conducted in order to achieve at least a better percentage such as above 90.00% in terms of accuracy, so that the output of the BCI could be considered as a reliable results. These reliable results are crucial to those individuals that are unable to communicate with the external world due to nerves system failure or lost of muscle control. This is because accurately interpret their EEG signals will play an precious role for them to express their feeling and demands since they could not communicate verbally.

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<sup>1</sup> Individuals who have lost all forms of control over their peripheral nerves and muscles

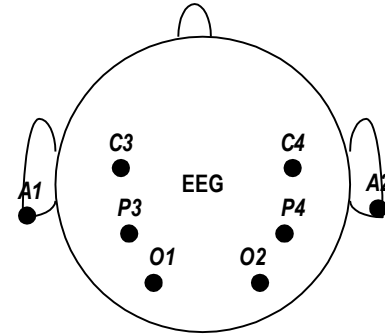
In this paper, we design a bi-state BCI using three different methods to extract features from EEG signals that are recorded during five different mental tasks from four different healthy subjects. These mental tasks are: geometrical figure rotation, mathematical multiplication, mental letter composing, visual counting and a baseline-resting task. The BCI designs are individual BCIs, that is those that are suitable for use by a particular individual. We show through simulation results that we cannot expect to build universal BCIs because the thought patterns from different individuals are not the same. The three different feature extraction methods are

- 6<sup>th</sup> order autoregressive (AR) coefficient computed with Burg's algorithm
- Power and asymmetry ratio from delta, theta, alpha, and beta spectral bands
- Power spectral density (PSD) values computed with AR Burg's coefficients

These features are then used by a MLP-BP NN to classify different combinations of two mental tasks. Two mental tasks are chosen because the output of the BCI design is bi-state. The output of this BCI design could be used with some translation schemes like Morse Code or to control the movement of a cursor to select a target on a computer screen, which would provide a communication channel for paralysed individuals to communicate with others.

## 2. METHODOLOGY

The EEG data used in this study were collected by Keirn and Aunon [5]. 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 [12] of electrode placement. The impedance of all electrodes were kept below 5 K $\Omega$ . 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 10 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.



**Figure 1: Electrode placement**

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

- a) Baseline task. 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.
- b) Math task. The subjects were given nontrivial multiplication problems, such as 42 times 18 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.
- c) 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.
- d) 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.
- e) 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.

Keirn and Aunon [5] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). For example, it was shown by Osaka [13] 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 [5] and later Anderson *et al* [3] proposed that these tasks are suitable for brain-computer interfacing.

In this paper, we have used three different feature extraction methods to extract the features from the EEG signals. In the first method, AR coefficients were computed using Burg's method [14]-[16]. Model order 6 was used for this AR process based on the suggestions in [3]-[5]. The second method used PSD computed using AR method. The third method used power and asymmetry ratios from four spectral bands: delta (0-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), and beta (14-20 Hz).

The following discussion details the three different feature extraction processes.

### 2.1 6<sup>th</sup> order AR coefficients

A real valued, zero mean, stationary, nondeterministic, autoregressive process of order  $p$  is given by

$$x(n) = -\sum_{k=1}^p a_k x(n-k) + e(n), \quad (1)$$

where  $p$  is the model order,  $x(n)$  is the signal at the sampled point  $n$ ,  $a_k$  are the real valued AR coefficients and  $e(n)$  represents the error term independent of past samples. The term autoregressive implies that the process  $x(n)$  is seen to be regressed upon previous samples of itself. The error term is assumed to be a zero mean noise with finite variance,  $\sigma_p^2$ . In applications, the values of  $a_k$  and  $\sigma_p^2$  have to be estimated from finite samples of data  $x(1), x(2), x(3), \dots, x(N)$ .

In this paper, we used Burg's method [14-16] to estimate the AR coefficients. The method is more accurate as compared to other methods like Levinson-Durbin as it uses the data point directly. Furthermore, Burg algorithm uses more data points by minimising both forward error and backward error. This algorithm is given in the appendix. Order 6 was used for the AR process because other researchers [3, 5] have suggested the use of order 6 for AR process for mental task classification. Therefore, we had a total of 6 AR

coefficients for each channel, giving a total of 36 features for each EEG segment from a mental task.

### 2.2 PSD

After the AR coefficients were calculated by using Burg's algorithm, we obtained the PSD values by using the equation

$$S(f) = \frac{\sigma_p^2 T}{\left| \sum_{k=0}^p a_k e^{-i2\pi f k T} \right|^2}, \quad (2)$$

where  $S(f)$  represents the PSD function,  $T$  is the sampling period and  $\sigma_p^2 T$  represents the power spectrum of the error sequence. The PSD values from 1-20 Hz (in intervals of 0.5 Hz) were used. The cut-off was chosen at 20 Hz because most of the mental task related EEG signals are below this frequency [6]. Therefore, we had a total of 40 PSD values for each channel, giving a total of 240 features for each EEG segment from a mental task.

### 2.3 Power and asymmetry ratios

In this method, the total power in each spectral band (i.e. delta, theta, alpha and beta) were summed using the PSD values in the specific spectral band ranges. Next, asymmetry ratios [5] were computed using  $(R-L)/(R+L)$  where R was the total spectral power in a specific band in one of the right hemispheric leads and L was the total spectral power in a specific band in one of the left hemispheric leads. These features were especially useful for recognising mental tasks that elicit interhemispheric differences. The features for this method included the individual spectral band power values in addition to the asymmetry ratios. Since we had 6 channels (3 on each hemisphere) and 4 spectral bands, we had a total of 24 spectral band power values. In addition, the asymmetry ratio calculation resulted in 36 values giving a total of 60 features for each EEG segment from a mental task.

## 3. MLP-BP NEURAL NETWORK

A MLP NN with single hidden layer trained by the BP algorithm [17] was used to classify different combinations of two mental tasks represented by the three different EEG features. Figure 2 shows the architecture of the MLP-BP NN used in this study. The output nodes were set at two so that the NN could classify into one of the two categories representing the mental task. The hidden layer nodes were varied from 10 to 100 in steps of 10.

A total of 200 EEG patterns (20 segments for EEG each signal x 10 sessions) were used for each subject for each mental task in this experimental study. Therefore, for each simulation, there were 400 EEG patterns from two mental tasks, where half of the patterns were used in training and the remaining half in testing. The selection of the parts for training and testing were chosen randomly. Training was conducted until the average error falls below the error limit of 0.01 or reaches a maximum iteration limit of 10000. The 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.

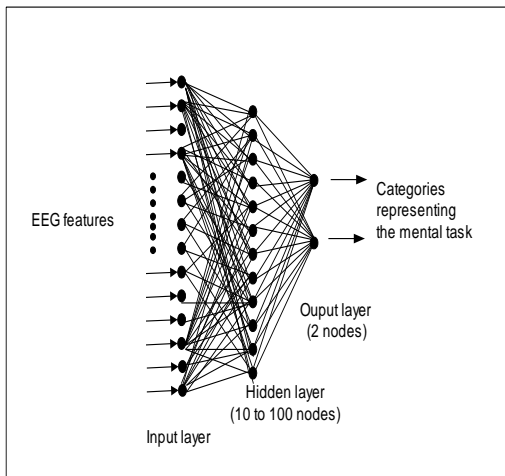


Figure 2: MLP-BP NN architecture

#### 4. SIMPLIFIED FUZZY ARTMAP NN

Classifications using SFAM NN were also experimented in addition to MLP-BP NN due to its high speed training ability in fast learning modes and its incremental supervised learning ability [18].

It consists of a Fuzzy ART module linked to the category layer through an Inter ART module. During supervised learning, Fuzzy ART receives a stream of input features representing the pattern and the output classes in the category layer are represented by a binary string with a value of 1 for the particular target class and values of 0 for all the rest of the classes. Inter ART module works by increasing the vigilance parameter (VP),  $\rho$  of Fuzzy ART by a minimal amount to correct a predictive error at the category layer. Parameter  $\rho$  calibrates the minimum confidence that Fuzzy ART must have in an input vector in order for Fuzzy ART to accept that category, rather than search for a better one through an automatically controlled process of hypothesis testing. Lower values of  $\rho$  enable larger categories to form and

lead to a broader generalisation and higher code compression.

The testing stage works similar to the training (i.e. learning) stage except that there will be no match tracking. This is because the input presented to Fuzzy ART will output a category in layer  $F_2$ , which will be used by the Inter ART module to trigger the corresponding category layer node that refers to the predicted class. Figure 3 shows the SFAM network architecture as used in the experimental study. For further details on SFA, refer to [18].

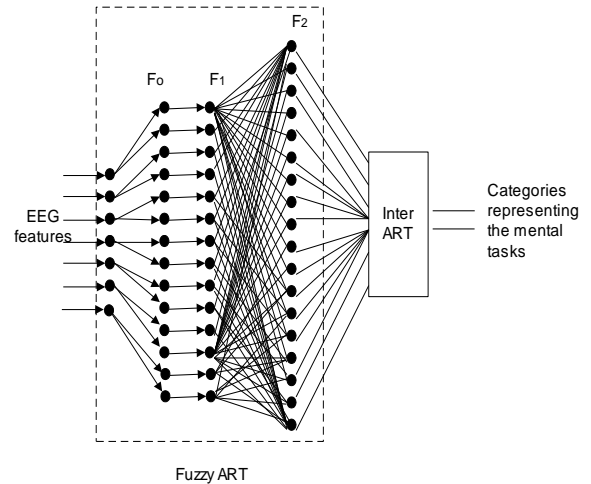


Figure 3: SFAM network as used in the study

#### 5. RESULTS AND DISCUSSION

Table 1 shows the result of NN classifications for different combinations of two mental tasks using 6<sup>th</sup> order AR coefficients computed using Burg's algorithm. The NN classification accuracies are shown in terms of average, maximum and minimum percentages for the 10 different numbers of hidden units ranging from 10 to 100 in intervals of 10. It could be seen that for different subjects, the best mental task combinations were not similar. The highest classification percentage for subjects 1, 2, 3 and 4 were 83.20%, 88.80%, 76.65% and 92.70% respectively for the combination of multiplication-rotation, letter-counting, letter-rotation and multiplication-counting mental tasks. For these cases, it could be noted that none of the best mental task combinations involved baseline task. This shows that the baseline task was not as suitable as the other four tasks for mental task classification using 6<sup>th</sup> order AR coefficients.

**TABLE 1: MLP-BP NN CLASSIFICATION RESULTS USING 6<sup>th</sup> ORDER AR COEFFICIENTS**

Task	Subject 1			Subject 2			Subject 3			Subject 4			Overall average
	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	
Baseline, Count	82.20	78.73	85.67	71.30	67.97	74.63	57.60	54.96	60.24	76.40	74.18	78.62	
Baseline, Letter	76.80	74.97	78.63	80.60	78.39	82.81	59.85	57.45	62.25	63.30	59.42	67.18	
Baseline, Maths	80.20	78.37	82.03	74.50	71.58	77.42	67.85	64.60	71.10	86.10	83.87	88.33	
Baseline, Rotation	76.25	73.88	78.62	70.90	67.44	74.36	74.25	72.04	76.46	80.95	78.41	83.49	
Letter, Count	68.80	66.15	71.45	88.80	86.87	90.73	61.85	58.92	64.78	71.35	68.77	73.93	
Letter, Rotation	72.30	69.08	75.52	73.90	71.33	76.47	76.65	74.76	78.54	72.55	70.36	74.74	
Maths, Count	83.10	80.50	85.70	72.95	70.19	75.71	63.40	61.19	65.61	92.70	91.38	94.02	
Maths, Letter	82.65	79.99	85.31	74.30	72.05	76.55	71.15	68.82	73.48	78.20	75.42	80.98	
Maths, Rotation	83.20	81.65	84.75	68.85	66.69	71.01	71.55	69.16	73.94	75.20	72.13	78.27	
Rotation, Count	72.05	69.44	74.66	66.00	64.09	67.91	69.90	67.97	71.83	73.75	70.84	76.66	
Average	77.76			74.21			67.41			77.05			74.11
Maximum	83.20			88.80			76.65			92.70			85.34
Best Combination	Maths, Rotation			Letter, Count			Letter, Rotation			Maths, Count			

Table 2 shows the classification results using PSD features, while Table 3 shows the classification results using power and asymmetry ratio features. It can be seen that even though the highest percentage for each subject differed, the best mental task combinations were the same for each subject for the two feature extraction methods. This could most probably be the result of the partial similarity in the feature extraction procedures. For subject 1, the best mental task combination was multiplication-rotation, subject 2:

baseline-multiplication, subject 3: letter-rotation and subject 4: baseline-rotation. It could also be seen that the combination of baseline-rotation lead in terms of percentage for both methods, follow by multiplication-rotation, letter-rotation and baseline-multiplication.

**TABLE 2: MLP-BP NN CLASSIFICATION RESULTS USING PSD VALUES**

Task	Subject 1			Subject 2			Subject 3			Subject 4			Overall average
	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	
Baseline, Count	70.60	63.09	78.11	60.25	56.30	64.20	56.70	52.47	60.93	65.30	54.68	75.92	
Baseline, Letter	62.00	58.68	65.32	59.05	55.26	62.84	59.55	55.41	63.69	64.60	59.22	69.98	
Baseline, Maths	81.15	80.04	82.26	64.65	59.29	70.01	59.95	52.98	66.92	79.65	69.05	90.25	
Baseline, Rotation	75.85	62.19	89.51	59.15	55.06	63.24	72.10	63.84	80.36	86.65	73.74	99.56	
Letter, Count	59.70	55.88	63.52	56.20	52.47	59.93	60.15	53.22	67.08	57.60	53.19	62.01	
Letter, Rotation	71.65	70.03	73.27	56.30	52.43	60.17	75.20	73.43	76.97	80.35	69.60	91.10	
Maths, Count	79.15	77.43	80.87	60.15	55.79	64.51	59.75	54.77	64.73	64.05	56.45	71.65	
Maths, Letter	80.95	79.33	82.57	61.25	57.07	65.43	68.90	62.35	75.45	69.65	62.50	76.80	
Maths, Rotation	81.65	70.49	92.81	60.30	54.68	65.92	59.60	56.07	63.13	75.35	66.25	84.45	
Rotation, Count	64.40	62.69	66.11	51.30	49.81	52.79	66.30	54.99	77.61	68.10	58.38	77.82	
Average	72.71			58.86			63.82			71.13			66.63
Maximum	81.65			64.65			75.20			86.65			77.04
Best Combination	Maths, Rotation			Baseline, Maths			Letter, Rotation			Baseline, Rotation			

**TABLE 3: MLP-BP NN CLASSIFICATION RESULTS USING POWER AND ASYMMETRYRATIO VALUES**

Task	Subject 1			Subject 2			Subject 3			Subject 4			Overall average
	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	Average	Mini	Max	
Baseline, Count	70.60	63.09	78.11	60.25	56.30	64.20	56.70	52.47	60.93	65.30	54.68	75.92	
Baseline, Letter	62.00	58.68	65.32	59.05	55.26	62.84	59.55	55.41	63.69	64.60	59.22	69.98	
Baseline, Maths	81.15	80.04	82.26	64.65	59.29	70.01	59.95	52.98	66.92	79.65	69.05	90.25	
Baseline, Rotation	75.85	62.19	89.51	59.15	55.06	63.24	72.10	63.84	80.36	86.65	73.74	99.56	
Letter, Count	59.70	55.88	63.52	56.20	52.47	59.93	60.15	53.22	67.08	57.60	53.19	62.01	
Letter, Rotation	71.65	70.03	73.27	56.30	52.43	60.17	75.20	73.43	76.97	80.35	69.60	91.10	
Maths, Count	79.15	77.43	80.87	60.15	55.79	64.51	59.75	54.77	64.73	64.05	56.45	71.65	
Maths, Letter	80.95	79.33	82.57	61.25	57.07	65.43	68.90	62.35	75.45	69.65	62.50	76.80	
Maths, Rotation	81.65	70.49	92.81	60.30	54.68	65.92	59.60	56.07	63.13	75.35	66.25	84.45	
Rotation, Count	64.40	62.69	66.11	51.30	49.81	52.79	66.30	54.99	77.61	68.10	58.38	77.82	
Average	72.71			58.86			63.82			71.13			66.63
Maximum	81.65			64.65			75.20			86.65			77.04
Best Combination	Maths, Rotation			Baseline, Maths			Letter, Rotation			Baseline, Rotation			

From both Tables 2 and 3, it could be noted that none of the best mental task combination involved counting task. So, if PSD and PSD derived values (like power and asymmetry ratios) are used, one could avoid counting task. It is also noticeable that the average percentages for both methods were very close to each other (power and asymmetry ratio features: 66.55% and PSD features: 66.63%) but these results were not as good as 6<sup>th</sup> order AR coefficient features, which gave 74.11%. Furthermore, the time for NN training for 6<sup>th</sup> order AR coefficient features was the shortest (0.12 hours per mental task combination) as compared to 0.42 hours per mental task combination for power and asymmetry ratio features and 1.2 hours per mental task combination for PSD features. The NN training time was proportional to the number of features. This was also true for classification time of test patterns. It took around 0.004 s, 0.007 s and 0.03 s to classify a test pattern using 6<sup>th</sup> order AR coefficient features, power and asymmetry ratio features and PSD features, respectively.

Therefore, for designing a bi-state BCI using mental tasks, it is proposed that 6<sup>th</sup> order AR coefficients is the best choice among the three different feature extraction methods. Another important result, which could be obtained from Tables 1,2 and 3 is that, the best mental task combination was different for

different subjects. Therefore, it is important to complete some preliminary simulation for the particular individual using different mental task combinations, in order to maximize the bi-state BCI design output. As stated earlier, these results show that designing individual BCIs are more appropriate than universal BCIs using the signal processing and classification methods available currently.

Table 4 shows the result of SFAM NN classification for different combinations of two mental tasks using 6<sup>th</sup> order AR coefficients estimated using Burg's algorithm. Overall, the average percentage for this method was 62.60%. The results shown are the average performance for the 10 different values of vigilance parameter ranging from 0.0 to 0.9 in intervals of 0.1. It could be seen that the best mental tasks combinations were not similar from one subject to another. The highest classification percentages for subjects 1, 2, 3 and 4 were 72.00%, 69.00%, 73.50% and 71.50% respectively for the combination of baseline-counting, multiplication-counting, baseline-rotation and baseline-multiplication mental task. None of the best combinations involved letter composing task. As a result, it could be said that letter composing task was not suitable to be used for this method with SFAM NN.

**TABLE 4: SFAM NN USING 6<sup>th</sup> ORDER AR COEFFICIENTS**

	Subject 1	Subject 2	Subject 3	Subject 4	Overall
Task	Average	Average	Average	Average	Average
Baseline, Count	72.00	62.50	58.00	64.50	
Baseline, Letter	63.50	64.00	60.50	48.00	
Baseline, Maths	60.50	63.50	64.50	71.50	
Baseline, Rotation	61.50	58.50	73.50	68.50	
Letter, Count	61.00	64.50	61.00	56.50	
Letter, Rotation	56.50	60.00	64.00	62.50	
Maths, Count	65.00	69.00	53.50	66.00	
Maths, Letter	66.50	62.00	63.00	65.50	
Maths, Rotation	64.00	57.00	57.50	60.50	
Rotation, Count	64.50	61.00	62.50	65.50	
Average	63.50	62.20	61.80	62.90	62.60
Maximum	72.00	69.00	73.50	71.50	71.50
Best Combination	Baseline, Count	Maths, Count	Baseline, Rotation	Baseline, Maths	

**TABLE 5: SFAM NN USING PSD VALUES**

	Subject 1	Subject 2	Subject 3	Subject 4	Overall
Task	Average	Average	Average	Average	Average
Baseline, Count	72.00	54.00	60.50	63.50	
Baseline, Letter	55.00	61.50	60.00	53.50	
Baseline, Maths	77.00	61.00	54.50	81.00	
Baseline, Rotation	82.00	58.50	65.50	80.50	
Letter, Count	56.00	61.50	67.50	63.00	
Letter, Rotation	60.00	65.50	70.50	75.00	
Maths, Count	80.50	60.50	54.00	61.00	
Maths, Letter	70.50	58.00	66.50	61.50	
Maths, Rotation	82.50	59.00	59.50	71.50	
Rotation, Count	62.50	60.00	60.00	61.00	
Average	69.80	59.95	61.85	67.15	64.69
Maximum	82.50	65.50	70.50	81.00	82.50
Best Combination	Maths, Rotation	Letter, Rotation	Letter, Rotation	Baseline, Maths	

**TABLE 6: SFAM NN CLASSIFICATION RESULTS USING POWER AND ASYMMETRY RATIO VALUES**

	Subject 1	Subject 2	Subject 3	Subject 4	Overall
Task	Average	Average	Average	Average	Average
Baseline, Count	68.00	58.00	62.50	63.00	
Baseline, Letter	52.00	57.50	59.00	57.00	
Baseline, Maths	77.50	65.50	60.00	79.00	
Baseline, Rotation	79.50	57.50	63.00	80.00	
Letter, Count	56.50	51.50	69.00	56.50	
Letter, Rotation	73.00	59.50	73.50	75.00	
Maths, Count	80.00	59.00	56.50	58.50	
Maths, Letter	83.50	62.00	67.50	65.00	
Maths, Rotation	87.50	50.00	63.00	68.00	
Rotation, Count	67.50	52.50	63.00	66.00	
Average	72.50	57.30	63.70	66.80	65.08
Maximum	87.50	65.50	73.50	80.00	76.63
Best Combination	Maths, Rotation	Baseline, Maths	Letter, Rotation	Baseline, Rotation	

Table 5 shows the classification result using PSD features, while Table 6 shows the classification results using power and asymmetry ratio features. It could be seen that these two methods performed slightly better than Burg's algorithm with average percentages of 64.69% and 65.08% respectively. In terms of highest percentage for the best combination, 82.50% was obtained for multiplication-rotation of Subject 1 using PSD features and 87.50% using asymmetry ratio features. It could also be noticed that the best combinations for each subject and method differed from each other except Subject 2 and 3 using PSD features, which were similar with letter-rotation task. In addition, none of the best combinations from these two methods involved counting task, which means it was not a suitable task to consider when PSD features and asymmetry ratio features were used for SFAM NN classification.

It took around 0.006 s, 0.01 s and 0.04 s to classify a test pattern using 6<sup>th</sup> order AR coefficient features, power and asymmetry ratio features and PSD features, respectively. From Tables 4, 5 and 6, it could be seen that there was no best combination task common for all the subjects and methods. However, in terms of single mental task, it could be seen that for subjects 3 and 4, all the best combinations involved rotation and baseline, respectively.

From Tables 1 and 4, it can be said that MLP-BP NN classification performed better than SFAM NN. The average percentage for each individual is higher for MLP-BP NN with a difference of 14.26% for subject 1, 12.01% for subject 2, 5.61% for subject 3, 14.15% for

subject 4 and 11.51%. Furthermore, in terms of highest percentage for each subject, none of the percentage from SFAM NN was better than MLP-BP NN. When comparison is conducted between Tables 2 and 5, it can be seen that MLP-BP NN classification achieves higher percentage than FA NN classification for all the subjects except subject 2 and average percentage for MLP-BP NN classification is 1.94% higher than FA NN classification. None of the best combinations were similar for these two classifiers except for Subject 3 with Letter-Rotation for both. In terms of best combination, both classification results suggest multiplication-rotation as the best combination for subject 1 and Letter composing-Rotation for subject 3. It can be noticed that the best combination for both NNs do not involve counting task.

From Tables 3 and 6, the best combinations for all subjects were similar for both classifications except MLP-BP NN classification performed better than SFAM NN classification with a difference of 1.47% in terms of average. Overall, MLP-BP NN classification suggested that feature extraction using Burg's algorithm (74.11%) to be the best method, followed by PSD values (66.63%) and Asymmetry Ratio (66.55%), but SFAM NN classification suggested in reverse: Asymmetry Ratio (65.08%), PSD values (64.69%) and Burg's algorithm (62.60%). However, MLP-BP NN classification performed better in terms of accuracy and consistency. So, it is suggested that in future works, MLP-BP NN could be used for mental task classification even though it took longer time than SFAM NN. But testing time was faster for MLP-BP NN as compared to SFAM NN, which is another advantage.

## 6. CONCLUSION

In this paper, a bi-state BCI using MLP-BP and SFAM NN classification of EEG features recorded during mental tasks was designed. We analysed combination of two mental tasks from four subjects and compared the NN classification performances for each subject using three different methods to extract the features from the EEG signals. Our results indicated that the performances using 6<sup>th</sup> order AR coefficients with Burg's algorithm performed better than the other two methods: PSD values, and power and asymmetry ratio values. The training and testing times were also the lowest for the 6<sup>th</sup> order AR coefficients, which is another advantage that should be considered when designing online BCI systems. Comparing the two NN performances, MLP-BP gave better performance than SFAM NN. MLP-BP also required lower testing time although it required longer time during training as compared to SFAM NN. The results also indicated that to maximise the output of the BCI design, suitable

combination of mental tasks must be pre-determined and to design individual BCIs would be more appropriate than universal BCIs. As a future work, we plan to improve the classification performance further by enhancing the signal processing aspects of the EEG signals.

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### Appendix

The steps for implementing Burg's algorithm are as follows:

#### Step 1:

Initial conditions:

$$\hat{\pi}_0 = r(0)$$

The forward prediction errors,  $\varepsilon_0^f(n) = y(n)$ , where  $n = 1, 2, 3, \dots, N-1$

The backward prediction errors,

$$\varepsilon_0^b(n) = y(n), \text{ where } n = 0, 1, 2, \dots, N-2$$

$N$  is the data size.

#### Step 2:

Reflection coefficients. For  $p = 1, 2, 3, \dots, P$  where  $P$  is the required model order

$$\hat{\pi}_p = \frac{-2 \sum_{n=p}^{N-1} \varepsilon_{p-1}^f(n) \varepsilon_{p-1}^b(n-1)}{\sum_{n=p}^{N-1} \{[\varepsilon_{p-1}^f(n)]^2 + [\varepsilon_{p-1}^b(n-1)]^2\}}$$

$$s_p^2 = (1 - |\hat{\pi}_p|^2) s_{p-1}^2$$

For  $p = 1$ ,

$$\hat{a}_1(1) = \hat{\pi}_1$$

For  $p > 1$ ,

$$a_p(i) = \begin{cases} a_{p-1}(i) + \hat{\pi}_p a_{p-1}(p-i) & \text{for } i = 1, 2, 3, \dots, p-1 \\ \hat{\pi}_p & \text{for } i = p \end{cases}$$

#### Step 3:

Prediction errors for next orders:

$$\varepsilon_p^f(n) = \varepsilon_{p-1}^f(n) + \hat{\pi}_p \varepsilon_{p-1}^b(n-1) \quad \text{for } n = k+1, k+2, \dots, N-1$$

$$\varepsilon_p^b(n) = \varepsilon_{p-1}^b(n-1) + \hat{\pi}_p \varepsilon_{p-1}^f(n) \quad \text{for } n = k+1, k+2, \dots, N-2$$

Note:  $k$  = the first  $n$  in the previous step to determine errors

#### Step 4:

Repeat step 2 and 3 (with  $p$  incremented by 1) until the selected model order  $p$  is reached.