WCCI 2012 IEEE World Congress on Computational Intelligence
June, 10-15, 2012 - Brisbane, Australia IJCNN

Mental Non-motor Imagery Tasks Classifications of Brain Computer Interface for Wheelchair Commands Using Genetic Algorithm-Based Neural Network

Rifai Chai, *Student Member, IEEE,* Sai Ho Ling, *Member, IEEE*
Gregory P. Hunter, *Member, IEEE and* Hung T. Nguyen, *Senior Member IEEE*
Centre for Health Technologies, Faculty of Engineering and Information Technology
University of Technology, Sydney, NSW, Australia
E-mail: Rifai.Chai@student.uts.edu.au, (Steve.Ling, Greg.Hunter, Hung.Nguyen)@uts.edu.au

***Abstract*—A genetic algorithm (GA)-based neural network classification in the application of brain computer interface (BCI) for controlling a wheelchair is presented in this paper. This study uses an electroencephalography (EEG) as a non-invasive BCI approach to discriminate three non-motor imagery mental tasks for disabled individuals who may have difficulty in using BCI based motor imagery tasks. The three tasks classification is mapped into three wheelchair movements: left, right and forward and the relevant combination mental tasks used in this study are mental arithmetic, letter composing, Rubik's cube rolling, visual counting, ringtone imagery and spatial navigation. The results show the proposed system provides good classification performance after selecting the most effective of three discriminative tasks across combination of the different non-motor imagery mental tasks for the five subjects tested. The average classification accuracy is between 76% and 85 %, with information transfer rates varies from 0.5 to 0.8 bits per trial.**

Keywords- genetic algorithm (GA); artificial neural network (ANN); brain computer interface (BCI); electroencephalography (EEG); evolutionary algorithm (EA);

I. INTRODUCTION

There are some alternative hands-free technologies used to replace the joystick control of a wheelchair for people with disabilities including eye movement, voice recognition, chin controller, tongue controller, head movement, and sip-and-puff systems. These technologies have their own benefits and drawbacks. In practical situations, the operation of a chin or tongue controller or a sip-and-puff system may discomfort the users. Noisy environments can be problematic for voice recognition system. An alternative technology for disabled individuals who are still able to move their head properly is a real-time telemetric head movement controller using a tilt sensor and embedded system [1].

There is a requirement of other method for severely disabled or locked-in syndrome individuals who are unable to move their body and head but whose brain is still capable. A brain computer interface (BCI) could be used as an alternative solution for these disabled individuals by converting brain activities to provide a control for the three wheelchair steering commands: left, right and forward [2, 3, 4].

The acquisition techniques which are available in BCI systems basically can be classified into invasive and non-invasive brain measurements. The invasive method, although it could provide a better signal resolution and quality, the main drawbacks include the risk of infection, scarring of post-surgery and other possible long term side effects. On the other hand, the electroencephalography (EEG) base non-invasive method has the advantages of portability, low cost, better temporal resolution although it suffers from low spatial-frequency resolution and high sensitivity to noise contamination including ocular –muscular artifacts and external electromagnetic noise [5, 6].

So far, from a mental strategy point of view, BCI-EEG methods could be divided into either selective attention or spontaneous mental signal methods. The P300 technique [7, 8] and the steady state visual evoked potential (SSVEP) technique [9] are examples of the selective attention method. This BCI method relies on external stimuli which might prove difficult for the user when controlling a wheelchair as they need to focus on the external stimuli, environment and wheelchair at the same time. This is not the case for BCI system relying on spontaneous mental signals generated voluntarily by the user which may include self regulation of the slow cortical potential (SCP) [10], control of the sensory motor rhythm (SMR) [11, 12] and motor imagery tasks as so called event-related desynchronization/synchronization (ERD/ERS) [13, 14] which focuses on the motor imagery area such as by imagining hand, foot or tongue movement.

Although the motor imagery method is concentrated mostly in BCI research and provides a good option for wheelchair control, there is a possibility that individuals who have been paralyzed or are amputated for a number of years may not be able to perform motor imagery mental tasks very well [15, 16]. Variability in the EEG signal patterns across different subjects is another additional issue. Therefore other non-motor imagery mental tasks need to be explored as an alternative solution.

Several researchers have used mental imagery tasks such as imagination of non-trivial arithmetic multiplication, letter composing, figure 3-D rotation and visual counting [17, 18, 19, 20]. Also, the non-motor imagery cognitive tasks of auditory imagery and spatial navigation have been found to provide a good result of classification in pairs [16, 21]. Therefore the study of combination classification for these non-motor imagery tasks all together is provided in this paper especially for targeting the three commands needed for controlling movement of a wheelchair.

From the classification algorithm point of view, the linear and non-linear methods have been explored in the BCI-EEG signal classification. Both have their own advantages and disadvantages [22, 23, 24]. Because the EEG signal is a multi dimensional, in this paper a non-linear method is preferred. The method used is based on the genetic algorithm (GA) optimization of an artificial neural network (ANN) to classify any combination of three tasks out of six non-motor imagery mental tasks. The best triplet combination provides the effective tasks for three wheelchair steering commands.

This paper is organized as follows: the details of the method are discussed in Section II where the general structure of BCI system, data collection, signal pre-processing, feature extraction, classification system with GA based ANN, and performance measurement, are discussed. Results are given in Section III. A conclusion for this study is drawn in Section IV.

II. METHODS

A. General Structrure of BCI System

The model of the BCI system is illustrated in Fig. 1 and consists of several elements. First the data is collected from the mental cognitive tasks, followed by signal pre-processing methods which include window segmentation and digital signal processing (DSP) filters. Next, features extraction transforms the signals into useful features that are associates with the related mental task. The features are fed into neural network training, optimization and classification processes. The result provides three outputs classification which associates to the three wheelchair steering commands (left, right and forward).

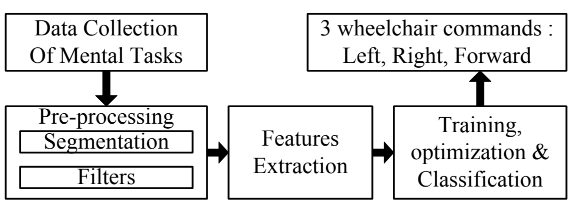

Figure 1. *Flow of general process diagram*

B. Data Collection and Experiment Procedure

This study was approved by the university human research ethics committee. A total of five able bodied subjects (3 males and 2 females) aged between 22 and 40 years participated in the experiment. A mono-polar 32 channels EEG system from Compumedic with the sampling rate set to 256 Hz was used but only ten channels were attached on the scalp for the measurement as shown in Fig 2 with the electrodes positioned at locations C3, C4, P3, P4, O1, O2, T3, and T4. A reference electrode was placed at location A2 and location A1 as GND electrode. The electrode placement is referred to the standard of international 10-20 system.

To keep the impedance level low and good electrical contact, prepping and EEG gels were applied on the scalp. The impedance was measured and maintained below 5 kΩ. Unnecessary movements and eyes blinks were kept as minimum as possible during data collection in each session with the total of six mental non-motor imagery tasks used in the study are as follows:

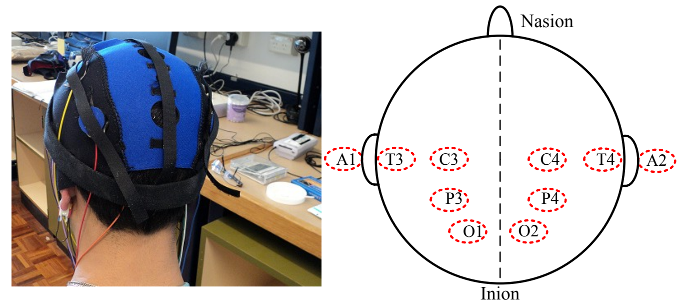

Figure 2. *EEG Electrodes placement*

1) Arithmetic calculation (math): Participants were instructed to imagine solving a series of one by one digit multiplication.

2) Letter composing (letter): Participants were asked to mentally compose a simple letter in mind without vocalizing through their mouth.

3) Rubik's cube rolling (cube) : Participants were asked to imagine a figure of Rubik's cube being rolled forward.

4) Visual counting (count): Participants performed mentally counting number from one to nine repeatly by visualize the number appearing and disappearing on a blackboard in their mind.

5) Ringtone (tone): Participants were asked to imagine a familiar mobile ringtone in their head without moving their mouth.

6) Spatial navigation (navigate): Participants were asked to imagine moving around and scanning the surroundings in a familiar environment. This task is not using motor imagery because the imagination involved examining the surroundings rather than foot walking as in motor imagery mental task.

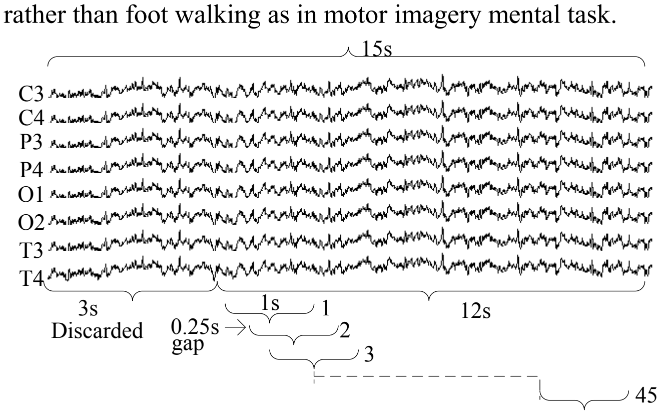

Figure 3. *Data segmentation proceses*

C. *Signal Pre-Processing*

Each subject performs a recording session of ten sub-sessions on each particular mental task with the duration of 15 seconds on each sub-session as illustrated in Fig. 3. The first three seconds is discarded as preparation time. The remaining 12 seconds is processed for further signal pre processing techniques. First, a moving window segmentation of one second is used with overlapping every quarter second segments to give a result in 45 overlapping segments for the remained 12 seconds data. Therefore each subject provides data around 45×10 or 450 units. 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. Fig. 4 shows the alpha wave raw data during eyes closed action and result after the filters were applied.

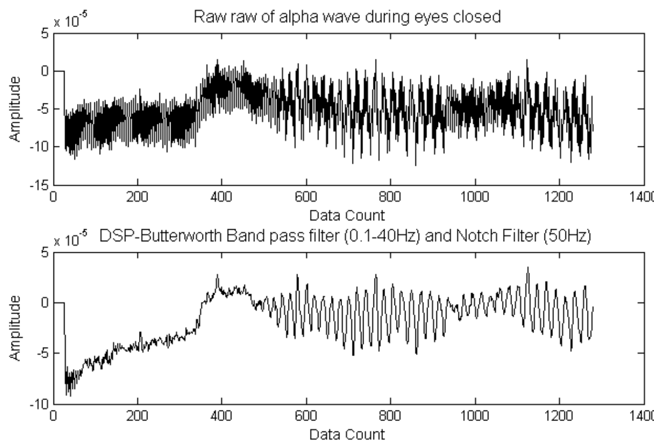

Figure 4. *Result of the applied DSP filters*

D. *Features Exraction*

For the features extraction process, the power spectral density (PSD) is first computed by squaring the fast Fourier transform (FFT) of each one second segment signal to convert the time base data into the following frequency bands of EEG rhythms: δ (0-3Hz), θ (4-7Hz), α (8-13Hz) and β (14-30Hz). Next, the total energy each frequency band was calculated by numerical integration of the PSD over that band using the trapezoidal rule method. With the energy over four bands calculated for each of the 8 channels (C3, C4, P3, P4, O1, O2, T3 and T4), 32 total power are made available. Finally, power difference as the asymmetry ratio in each spectral band was also calculated with the equation as follows:

$$P_{dif} = (P_R - P_L)/(P_R + P_L) \qquad (1)$$

where P_{dif} is the power different on each band, P_R is the power of particular band on right channel and P_L is the power of particular band on left channel. The total of 64 spectral power differences (4 pairs of channel × 4 combinations on channel x 4 bands) is calculated. As the result, the overall of 96 units of features are extracted on each one second segment.

E. *Classification*

1) *Artificial Neural Network*

The neural network as a non-linear classification method is popular tool used in biomedical and brain computer interface applications especially for the pattern recognition and classification algorithms [25]. This study utilizes a 3-layer feed forward neural network with one hidden layer network as shown in Fig. 5. The output vector z and the k-th component z_k are computed as follows:

$$z = f(\mathbf{W}\mathbf{x} + b) \qquad (2)$$

$$z_k(x,w) = f_1\left(b_k + \sum_{j=1}^{m} w_{kj} f_2\left(b_j + \sum_{i=1}^{n} w_{ji} x_n\right)\right) \qquad (3)$$

where f, f_1, f_2 is the activation function, x represents the input vector, $\boldsymbol{W}$ 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, 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.

In this study, a log-sigmoid function was assigned as the activation function which provides data values between one and zero. As the result, prior to the ANN the feature data value needs to be scaled to within the range zero to one as follows:

$$X^* = (X - Xmin) / (Xmax - Xmin) \qquad (4)$$

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

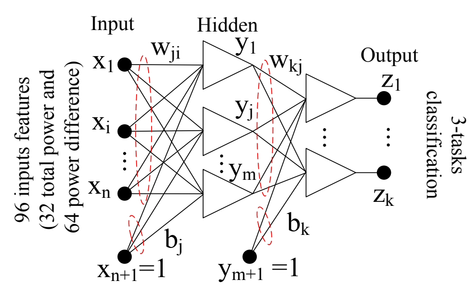

Figure 5. *Architecture of ANN*

```
begin
    τ→0                  // τ: iteration number
    initialize P(τ)      // P(τ): population for iteration τ
    evaluate f(P(τ))  // f(P(τ)): fitness function
    while (not termination condition) do
        begin
            τ→ τ+1
            select 2 parent p1 and p2 from P(τ-1)
            perform crossover and mutation operations
            reproduce a new P(τ)
            evaluate f(P(τ))
        end
    end
end
```

Figure 6. *Procedure of GA*

2) Genetic Algorithm optimization

The conventional ANN by using the gradient-descent (GD) technique as the back-propagation algorithm for the parameter training of the feed-forward neural networks has both convergence to the local minima and sensitivity problems. Genetic algorithm (GA), a widely used global search method for the optimization problem may solve these problems.

To optimize the parameters of the neural network, a GA is used. The GA process is shown in Fig. 6. First, a set of population of chromosomes P is created. Each chromosome $\mathbf{p}$ contains a set of genes p_{ij}, where $i = 1, 2, \ldots, n_p$, $j = 1, 2, \ldots, n_g$, n_p and n_g denote the population size (number of chromosome) and the number of gene respectively. Second, the chromosomes are evaluated by a defined fitness function which is written as,

$$fitness = f(\mathbf{p}_i) \tag{5}$$

The form of the fitness function depends on the application. The better chromosomes return higher fitness values in this process. Third, some of the chromosomes are selected to undergo genetic operations for reproduction by the method of normalized geometric ranking [26]. This is a selection process based on a non-stationary penalty function which is a function of the generation number. As the number of generations increases, the penalty increases putting more and more selective pressure on the GA to find a feasible solution. In general, a higher-rank chromosome will have a higher chance to be selected. Fourth, the genetic operation of crossover is performed. The crossover operation is mainly for exchanging information from the two parents, chromosomes $\mathbf{p}1$ and $\mathbf{p}2$, obtained in the selection process with a defined probability of crossover μc. This probability gives an expected number of chromosomes that undergo the crossover. In this paper, Blend-α [27] is selected as the operation of crossover as it has a good searching ability for handling multimodal and separability problems effectively. For Blend-α crossover, the resulting offspring is chosen randomly from the interval $\left[X_j^1, X_j^2\right]$ following the uniform distribution,

$$X_j^1 = \min(p_{1j}, p_{2j}) - \alpha d_j \tag{6}$$

$$X_j^2 = \max(p_{1j}, p_{2j}) + \alpha d_j \tag{7}$$

where $d_j = |p_{1j} - p_{2j}|$, p_{1j} and p_{2j} are the j-th elements of $\mathbf{p}_1$ and $\mathbf{p}_2$, respectively, and α is a positive constant. After the crossover operation, the mutation operation follows. The mutation operation changes the genes of the chromosomes in the population such that the features inherited from their parents can be changed. A probability of mutation μ_m is defined to govern the operation and it gives an expected number of genes that undergo the mutation. Non-uniform mutation [28] is investigated in this paper and it is an operation with a fine-tuning capability. The mutated gene is given by,

$$\hat{p}_{ij} = \begin{cases} p_{ij} + \Delta\left(\tau, \delta_{\max}^j - p_{ij}\right) \text{if } r_d = 0 \\ p_{ij} - \Delta\left(\tau, p_{ij} - \delta_{\min}^j\right) \text{if } r_d = 1 \end{cases} \tag{8}$$

where r_d is a random number equal to 0 or 1 only. The function $\Delta(\tau,y)$ return a value in the range $[0,y]$ and approaches 0 as τ increases. It is defined as follows:

$$\Delta(\tau, y) = y\left(1 - r^{\left(1-\tau/T\right)^{\zeta}}\right) \tag{9}$$

where r is a random number in the range of [0,1], τ represents the current generation number, T represents the total iteration number and ζ is a system parameter that determines the degree of non-uniformity. After going through the mutation operation, the new offspring are evaluated using the fitness function. The new population is formed when the new offspring replaces the chromosome with the smallest fitness value. After the operations of selection, crossover and mutation, a new population is generated. The same process is then repeated with this new population. This iterative process is terminated when a defined condition is met.

Here the ANN is employed to learn the input-output relationship of an application using a GA with arithmetic crossover and non-uniform mutation. The input-output relationship is described as follows:

$$\mathbf{y}^d(t) = \mathbf{g}(x^d(t)), t = 1, 2, \ldots, n_d \tag{10}$$

where $\mathbf{x}^d(t) = \left[x_1^d(t) \quad x_2^d(t) \quad \cdots \quad x_{n_{in}}^d(t)\right]$ and $\mathbf{y}^d(t) = \left[y_1^d(t) \quad y_2^d(t) \quad \cdots \quad y_{n_{out}}^d(t)\right]$ are the given inputs and the desired outputs of an unknown nonlinear function $\mathbf{g}(\cdot)$ respectively and n_d denotes the number of input-output data pairs. The fitness function is defined as,

$$fitness = \frac{1}{1 + err} \tag{11}$$

where

$$err = \sum_{k=1}^{n_d} \frac{\sum_{t=1}^{n_d}\left(y_k^d(t) - y_k(t)\right)^2}{n_{out} n_d} \tag{12}$$

is the mean square error (MSE). The objective is to maximize the fitness value of (11) using the improved GA by setting the chromosome to be $\left[w_{ji} \quad b_j \quad w_{kj} \quad b_k\right]$ for all i, j and k. The range of the fitness value (11) is [0, 1]. It can be seen from (11) and (12) that a larger *fitness* implies a smaller MSE *err*.

F. Performance Measurement

This study provides two important ways to measure the performance of the BCI system: classification accuracy and information transfer rate (ITR). Classification accuracy refers to the percentage of correctly classified tasks. ITR or sometimes called as bit rate refers to the amount of reliable information received [29] ,with function as follows:

$$B = log_2 N + P log_2 P + (1 - P) log_2 \left[\frac{1 - P}{N - 1}\right] \tag{13}$$

where B is bit rate (bits/trial), N is number of mental task and P is to the classification accuracy. Equation (13) shows for a trial of N possible mental task has equally probability of being the true detection of mental task that the user imagines. The probability P that the desired target task will be selected is the same for each user desired mental task, and each other undesired mental task selections ha the same probability of being selected (i.e., $(1-P)/(N-1)$).

III. RESULTS

The features dataset per subject consists of 450 units for each mental task and 1350 for the total of 3-tasks classification. This is divided into half portion for the training set and the same amount for the testing set. The GA is employed to optimize the parameter of the neural network. The number of hidden neurons is changed using value varying from 4 to 40 per training session of neural network for each subject in order to find the best number that provides highest fitness value or lowest MSE to achieve the highest classification accuracy. The population size used for the GA is 50 and the training is stopped when the training of the neural network reaches up to 2000 iteration. The probability for crossover is set at 0.8 and the probability of mutation is set at 0.1 for the GA based neural network training. Figure 7 shows the selected best fitness value plotting which has steady increasing value toward highest point for five subjects involved in the study.

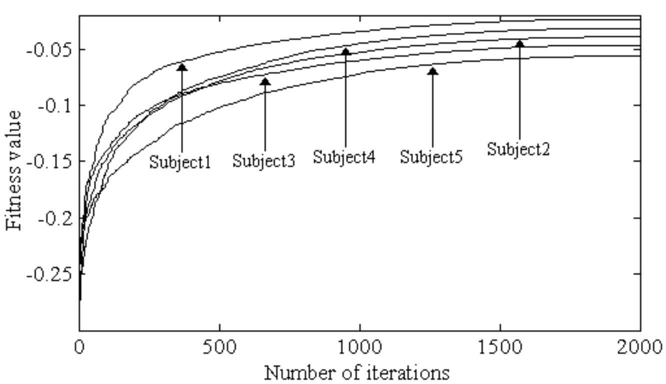

Figure 7. *Plotting of fitness value*

The training of the genetic algorithm based neural network is done in combination of any three tasks classification of six mental cognitive tasks (math, letter, cube, count, tone and navigate), providing 20 combinations of training sets in total. In each combination, the training of the neural network was repeated ten times. This provided ten network weight parameters. As a result each mental task is the averaging of ten classifications value as shown in Table I and Table II. The mean value of triplet mental tasks classification is provided in the table as the average classification accuracy.

The result classification accuracy as shown in Table I indicates a variety value of classification accuracy across different subjects as the inter subject variability changes. With total of 20 combinations of result, each subject has its own favorite triplet mental task combination which yields the highest classification accuracy between 76% and 85%. In detail, subject 1 has best 3-tasks classification between mental letter composing, ringtone imagery and spatial navigation with classification accuracy around 82%. Subject 2 archived highest accuracy based on combination of mental arithmetic, visual counting and spatial navigation with accuracy at 84%. Subject 3 archived accuracy at 76% of best triplet tasks with mental arithmetic, letter composing and spatial navigation. Next, subject 4 has best classification accuracy between mental Rubik's cube rolling, visual counting and familiar ring tone imagery with accuracy at 85%. Subject 5 has best classification accuracy at 81% between mental arithmetic, letter composing and Rubik's cube rolling.

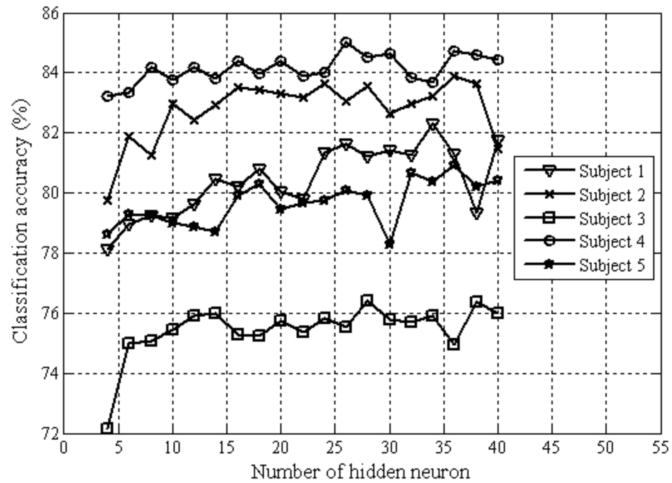

Figure 8. *Number of hidden neuron versus accuracy*

There are also shown in the table other alternative combination tasks on each subject with average classification accuracy result above 70%. This could be used as the additional chosen combination.

Figure 8 shows the plotting of the number of hidden neuron versus classification accuracy. Each hidden neuron value provides a different result. The best chosen hidden neuron value gives the highest classification accuracy for five subjects is between 24 and 36. Figure 9 and Table II provide a summary of the favorite triplet tasks for each individual. This provides the best suitable combination task and matching their circumstances and background. Generally, with user preferable three tasks classification, a satisfactory higher accuracy is achieved at between 76% and 85%. This is enough to be used in application for three steering wheelchair control system (left, right and forward).

The information transfer rate of the classification is also provided in Table II which has value between 0.5 to 0.8 bits per trial. The bit rate can also be illustrated as the number of bits per minutes by multiplying the bit rate (bits/trials) by system speed (trials/min). For example the speed classification of the system is set every second which means 60 times in a minute. Therefore the value bit rate 0.5- 0.8 bit/trial is corresponded to 30-48 bits/min. A faster bit rate could be implemented by increasing the speed of the system to classify each mental task.

TABLE I. CLASSIFICATION ACCURACY RESULTS FOR FIVE SUBJECTS

Number Combination	Triplet tasks combinations of 1= Math; 2 =Letter; 3=Cube; 4=Count; 5= Tone; 6=Navigate	Percentage of correctly classified task; classification accuracy (%)																			
		Subject 1				Subject 2				Subject3				Subject 4				Subject 5			
		1^{st} task	2^{nd} task	3^{rd} task	Mean	1^{st} task	2^{nd} task	3^{rd} task	Mean	1^{st} task	2^{nd} task	3^{rd} task	Mean	1^{st} task	2^{nd} task	3^{rd} task	Mean	1^{st} task	2^{nd} task	3^{rd} task	Mean
1	Math(1)-Letter(2)-Cube(3)	51	86	51	63	81	75	63	73	83	84	50	72	48	38	63	50	73	94	77	81
2	Math(1)-Letter(2)-Count(4)	61	83	63	69	85	67	82	78	93	55	47	65	63	61	96	74	78	49	64	63
3	Math(1)-Letter(2)-Tone(5)	54	84	54	64	84	67	56	69	85	90	45	73	50	67	70	62	74	100	35	70
4	Math(1)-Letter(2)-Navigate(6)	60	76	83	73	77	80	71	76	88	77	64	76	56	35	50	47	66	99	65	77
5	Math(1)-Cube(3)-Count(4)	53	44	76	57	95	49	70	71	97	53	62	71	55	69	94	73	75	86	77	79
6	Math(1)-Cube(3)-Tone(5)	45	56	49	50	94	68	60	74	90	77	45	71	43	71	78	64	71	84	34	63
7	Math(1)-Cube(3)-Navigate(6)	62	56	71	63	85	56	78	73	90	61	63	71	53	59	64	58	59	80	62	67
8	Math(1)-Count(4)-Tone(5)	53	71	51	59	98	86	54	80	89	67	47	68	60	99	77	79	69	92	35	66
9	Math(1)-Count(4)-Navigate(6)	64	81	75	73	87	83	81	84	90	55	57	67	68	87	58	71	67	93	69	76
10	Math(1)-Tone(5)-Navigate(6)	52	59	83	65	88	61	79	76	85	43	58	62	48	78	72	66	63	46	62	57
11	Letter(2)-Cube(3)-Count(4)	78	62	48	63	71	48	70	63	68	45	45	53	43	65	93	67	44	84	57	62
12	Letter(2)-Cube(3)-Tone(5)	83	58	53	65	58	66	54	59	92	50	49	64	40	67	80	62	94	67	43	68
13	Letter(2)-Cube(3)-Navigate(6)	84	63	70	72	74	51	79	68	78	46	71	65	37	61	48	48	94	55	78	76
14	Letter(2)-Count(4)-Tone(5)	79	58	70	69	68	81	50	66	63	46	46	52	72	98	79	83	50	61	44	52
15	Letter(2)-Count(4)-Navigate(6)	80	64	74	73	68	80	81	77	52	43	64	53	49	87	45	61	49	63	93	69
16	Letter(2)-Tone(5)-Navigate(6)	84	79	84	82	66	53	83	67	80	44	49	58	35	85	55	58	100	35	80	71
17	Cube(3)-Count(4)-Tone(5)	57	57	55	56	57	67	55	60	51	80	54	62	73	95	87	85	76	76	42	65
18	Cube(3)-Count(4)-Navigate(6)	54	76	67	66	47	68	91	69	45	55	71	57	66	89	61	72	67	76	90	78
19	Cube(3)-Tone(5)-Navigate(6)	58	63	72	64	61	58	89	69	55	45	64	55	62	90	68	74	78	35	76	63
20	Count(4)-Tone(5)-Navigate(6)	73	65	73	71	82	52	95	76	54	46	52	51	88	88	56	78	92	35	80	69

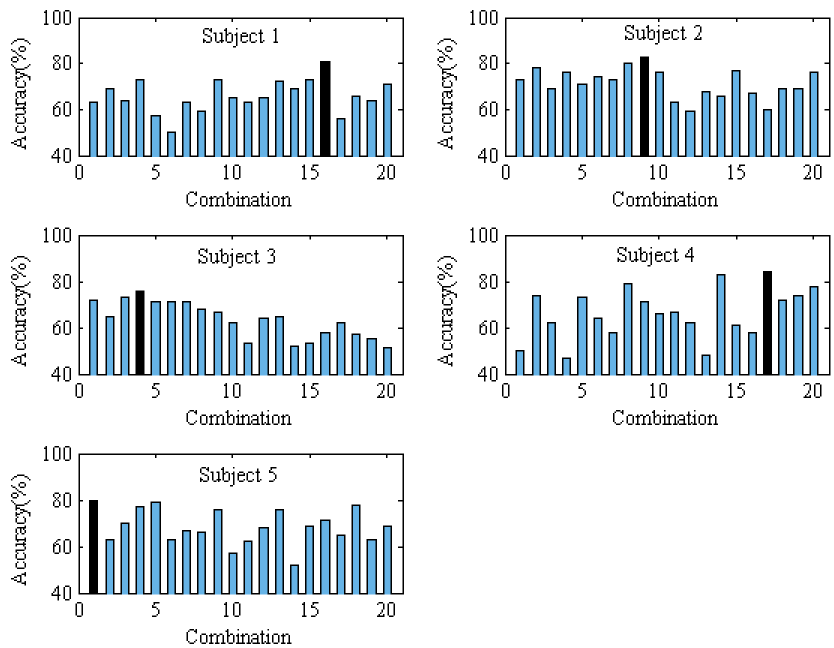

Figure 9. *Graphics of classification result for five subjects*

TABLE II. RESULT CHOSEN MENTAL TASKS AND BIT RATE

Subject	Chosen tasks	Best hidden neuron	Mean of accuracy (%)	Bit rate (bits/trial)
1	Letter(2)-Tone(5)-Navigate(6)	34	82	0.7
2	Math(1)-Count(4)-Navigate(6)	24	84	0.8
3	Math(1)-Letter(2)-Navigate(6)	28	76	0.5
4	Cube(3)-Count(4)-Tone(5)	26	85	0.8
5	Math(1)-Letter(2)-Cube(3)	36	81	0.7

IV. CONCLUSION

A genetic algorithm has been successfully applied for the optimal training of the neural networks to provide classification outputs of three mental non-motor imagery tasks for application of wheelchair movement control. The results show that each subject who participated in the study was able to have their own best triplet of mental task combination with classification mean accuracy is between 76% and 85% and with a bit rate value of around 0.5 to 0.8 bits per trial. This would give more flexibility to select a suitable combination of non motor imagery mental tasks as an alternative solution for disabled individuals who could not perform well using motor imagery tasks of a BCI system.

REFERENCES

[1] H. T. Nguyen, L. M. King, and G. Knight, "Real-time head movement system and embedded Linux implementation for the control of power wheelchairs," in *Proc. of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2004, vol. 2, pp. 4892-4895.

[2] D. A. Craig and H. T. Nguyen, "Adaptive EEG Thought Pattern Classifier for Advanced Wheelchair Control," in *Proc. of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* 2007, pp. 2544-2547.

[3] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C. L. Teo, Q. Zeng, C. Laugier, and M. H. Ang Jr, "Controlling a Wheelchair Indoors Using Thought," *IEEE Intelligent Systems,* vol. 22, pp. 18-24, 2007.

[4] J. d. R. Millan, F. Galan, D. Vanhooydonck, E. Lew, J. Philips, and M. Nuttin, "Asynchronous non-invasive brain-actuated control of an intelligent wheelchair," in *Proc. of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2009, pp. 3361-3364.

[5] 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.

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

[7] 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.

[8] E. W. Sellers and E. Donchin, "A P300-based brain–computer interface: Initial tests by ALS patients," *Clinical Neurophysiology,* vol. 117, pp. 538-548, 2006.

[9] 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.

[10] N. Birbaumer, T. Hinterberger, A. Kubler, and N. Neumann, "The thought-translation device (TTD): neurobehavioral mechanisms and clinical outcome," *IEEE Trans. Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 120-123, 2003.

[11] 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.

[12] A. Kubler, F. Nijboer, J. Mellinger, T. M. Vaughan, H. Pawelzik, G. Schalk, D. J. McFarland, N. Birbaumer, and J. R. Wolpaw, "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface," *Neurology,* vol. 64, pp. 1775-1777, 2005.

[13] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proceedings of the IEEE,* vol. 89, pp. 1123-1134, 2001.

[14] G. Pfurtscheller, C. Brunner, A. Schlogl, and F. Lopes da Silva, "Mu rhythm (de) synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage,* vol. 31, 153-159, 2006.

[15] G. E. Birch, Z. Bozorgzadeh, and S. G. Mason, "Initial on-line evaluations of the LF-ASD brain-computer interface with able-bodied and spinal-cord subjects using imagined voluntary motor potentials," *IEEE Trans. Neural Systems and Rehabilitation Engineering,* vol. 10, pp. 219-224, 2002.

[16] E. Curran, P. Sykacek, M. Stokes, S. J. Roberts, W. Penny, I. Johnsrude, and A. M. Owen, "Cognitive tasks for driving a brain-computer interfacing system: a pilot study," *IEEE Trans. Neural Systems and Rehabilitation Engineering,* vol. 12, pp. 48-54, 2004.

[17] 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.

[18] C. W. Anderson, S. V. Devulapalli, and E. A. Stolz, "EEG signal classification with different signal representations," in *Neural Networks for Signal Processing [1995] V. Proceedings of the 1995 IEEE Workshop*, 1995, pp. 475-483.

[19] 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.

[20] F. Faradji, R. K. Ward, and G. E. Birch, "Design of a mental task-based brain-computer interface with a zero false activation rate using very few EEG electrode channels," in *Proc. of the 4th International IEEE/EMBS Conference on Neural Engineering*, 2009, pp. 403-406.

[21] A. F. Cabrera and K. Dremstrup, "Auditory and spatial navigation imagery in Brain-Computer Interface using optimized wavelets," *Journal of Neuroscience Methods,* vol. 174, pp. 135-146, 2008.

[22] D. Garrett, D. A. Peterson, C. W. Anderson, and M. H. Thaut, "Comparison of linear, nonlinear, and feature selection methods for EEG signal classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 141-144, 2003.

[23] A. Bashashati, M. Fatourechi, R. Ward, and G. Birch, "A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals," *J. Neural engineering,* vol. 4, p. R32, 2007.

[24] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," *J. Neural engineering,* vol. 4, p. R1, 2007.

[25] 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.

[26] J. A. Joines and C. R. Houck, "On the use of non-stationary penalty functions to solve nonlinear constrained optimization problems with GA's," in *Proc. of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence*, 1994, pp. 579-584.

[27] L. J. Eshelman and J. D. Schaffer, "Real-coded genetic algorithms and interval-schemata," in *Foundation of Genetic Algorithms 2*, 1993, pp. 187-202.

[28] Z. Michalewicz, "Genetic algorithms + data structures = evolution programs," *2nd, extended edition, Springer-Verlag,* 1994.

[29] J. R. Wolpaw, H. Ramoser, D. J. McFarland, and G. Pfurtscheller, "EEG-based communication: improved accuracy by response verification," *IEEE Trans. Rehabilitation Engineering,* vol. 6, pp. 326-333, 1998.