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Toward Fewer EEG Channels and Better Feature Extractor of Non-Motor Imagery Mental Tasks Classification for a Wheelchair Thought Controller

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Abstract— **This paper presents a non-motor imagery tasks classification electroencephalography (EEG) based brain computer interface (BCI) for wheelchair control. It uses only two EEG channels and a better feature extractor to improve the portability and accuracy in the practical system. In addition, two different features extraction methods, power spectral density (PSD) and Hilbert Huang Transform (HHT) energy are compared to find a better method with improved classification accuracy using a Genetic Algorithm (GA) based neural network classifier. The results from five subjects show that using the original eight channels with three tasks, accuracy between 76% and 85% is achieved. With only two channels in combination with the best chosen task using a PSD feature extractor, the accuracy is reduced to between 65% and 79%. However, the HHT based method provides an improved accuracy between 70% and 84% for the classification of three discriminative tasks using two EEG channels.**

I. Introduction

A Brain Computer Interface (BCI) provides an alternative solution for hands free wheelchair control to assist severely disabled individuals who are unable to move their body or head. Basically, to drive a wheelchair using a thought controller, at least three mental commands are needed to provide wheelchair steering control of turning left, turning right and moving forward [1, 2]. The backward command is not used here for safety reasons.

In the current BCI state of the art, the EEG based system is popular due the advantages of being non-invasive, portable, low cost and having better temporal resolution. However, it has the disadvantage of a higher sensitivity to noise including ocular, muscular and electromagnetic noises. The noise problem can be reduced and the classification accuracy can be improved by using better computational intelligent methods in both features extraction and classification algorithms to extract high dimensional EEG features [3, 4].

Current BCI-EEG technologies focus on selective attention and spontaneous mental signal methods. P300 and steady state visual evoked potential (SSVEP) [5, 6] are examples of the selective attention method in which the user needs to pay attention to external stimuli whilst controlling the wheelchair. Concentrating on the control of the wheelchair and the stimuli at the same time may prove difficult. This is not the case for a BCI system based on spontaneous mental signals given by the user without any external cues. A BCI based on event related desynchronization-synchronization (ERD/ERS) is an example of the spontaneous mental signal method which focuses on the motor imagery area by imagining hand, feet and tongue movement [7].

There is a possibility that individuals who are amputees or have been paralyzed for years may not be able to perform motor imagery mental tasks competently, so as an alternative solution, other non-motor imagery mental tasks could be used [8]. Several researchers have used mental imagery tasks such as imagination of non-trivial arithmetic multiplication, letter composing, figure 3-D rotation and visual counting [1, 9]. In addition, the non-motor imagery cognitive tasks of auditory imagery and spatial navigation have been found to provide good results for classification in pairs [8]. Variability in the EEG signal patterns across different subjects is another additional issue. Therefore the study of combining of non-motor imagery mental tasks needs to be explored. Furthermore, for practical application, a system with less EEG electrodes is preferable to provide more portability and convenience.

This paper presents the development of classifications of non-motor imagery tasks for three wheelchair steering movements using only two EEG channels and a genetic algorithm based neural network. Two features extraction methods, power spectral density (PSD) and Hilbert Huang transform (HHT) energy are compared to yield the best features extraction method with improved accuracy.

II. Methods

A. Data Collection

This study was approved by the University of Technology, Sydney, Human Research Ethics Committee. Five able bodied subjects (3 males and 2 females) aged between 22 and 40 years participated in the experiment. Initially, a mono-polar EEG system from Compumedic with the sampling rate set to 256 Hz was used for the measurement with the electrodes positioned as shown in Fig. 1 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 as referred to the standard of international 10-20 system.

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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 eye blinks were kept to a minimum. A total of six mental non-motor imagery tasks were used in the study including: arithmetic (*math*) by imagining and solving simple multiplication; letter composing (*letter*) by mentally composing simple words; Rubik's cube rolling (cube) by imagining a Rubik's cube being rolled forward; visual counting (*count*) by mentally counting numbers from one to nine while visualizing each number appearing and disappearing on a blackboard; ringtone (*tone*) by imagining a familiar mobile ringtone; and spatial navigation (*navigate*) by moving around and scanning the surroundings in a familiar location in the mind.

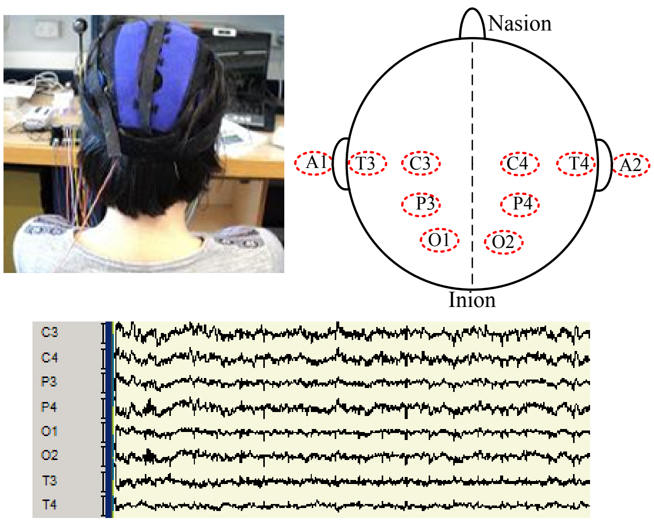

Figure 1. EEG system set-up for data collection

B. Pre-Processing

A moving window segmentation of one second is used with 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.

B. Features Extraction

For the features extraction, two methods are compared to provide a suitable features extractor for non-motor imagery task BCI. The first method is based on power spectral density (PSD). This is computed by squaring the fast Fourier transform (FFT) of each one second segment signal to convert the time based data into the EEG frequency bands.

For the second feature extractor, the Hilbert Huang transform (HHT) [10] spectral density is used. This is based on a time-frequency analysis algorithm and is a good candidate for analyzing non-linear and non-stationary data as recorded by EEG. Basically, the HHT consists of two main 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). Each IMF should satisfy two conditions: the extrema and zero crossings numbers should equal or differ by one and each have a zero-mean envelope of local maxima and minima. The EEG signal can be reconstructed as follows:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

where $x(t)$ is EEG data, $c_i(t)$ denotes the i^{th} extracted empirical mode and $r_n(t)$ the residual, which is a monotonic function without extrema and can be the mean trend or constant. The EMD algorithm is summarized as follows: 1) identify extrema (minima and maxima) of $x(t)$; 2) generate the upper and lower envelope based on interpolation between maxima and minima; 3) compute the average of the two envelopes, $m(t)$; 4) extract the IMF component by $c(t) = x(t) - m(t)$; 5) if $c(t)$ does not satisfy the properties of IMF, replace $x(t)$ with $c(t)$ and repeat from step 1, and if it does, take $c(t)$ as a IMF and evaluate the residue $r(t) = x(t) - c(t)$; 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) as follows:

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{c_i(\tau)}{t-\tau} d\tau \tag{2}$$

Where P indicates the Cauchy principal value and i = 1: n. The amplitude $a_i(t)$, the phase $\varphi_i(t)$ and the instantaneous frequency $\omega_i(t)$ as shown as follows :

$$a_i(t) = \sqrt{y_i(t)^2 + c_i(t)^2} \tag{3}$$

$$\varphi_i(t) = \arctan(y_i(t)/c_i(t)) \tag{4}$$

$$\omega_i(t) = d\varphi_i(t)/dt \tag{5}$$

The signal, after calculating the HT on each IMF component can be expressed as follows:

$$H(\omega, t) = \sum_{i=1}^{n} a_i(t) \exp(j \int \omega_i(t) dt) \tag{6}$$

Equation (6) 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.

Each spectrum calculated from PSD and HHT is used in the range of EEG bands: δ (0-3Hz), θ (4-7Hz), α (8-13Hz) and β (14-30Hz). Next, the total energy of each frequency band is calculated by numerical integration of the spectrums 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 levels are made available for 8 channels and 8 total power levels if two channels are used. Additionally, the power difference of the asymmetry ratio in each spectral band [9] is also calculated with the equation as follows:

$$P_{dif} = (P_R - P_L)/(P_R + P_L) \tag{7}$$

where P_{dif} is the power difference on each band, P_R is the power level of a particular band on the right channel and P_L

is the power level of a particular band on the left channel. The total of 64 spectral power differences (4 pairs of channel × 4 combinations on channel x 4 bands) is calculated for an 8 channel EEG. As a result, a total of 96 units of features are extracted on each one second segment. For a two channel EEG, 4 spectral power differences are calculated resulting in a total of 12 units of features.

B. Classification

The artificial neural network (ANN) as a classification method, is a widely used tool in biomedical applications [11]. This study utilizes a 3-layer feed forward neural network with one hidden layer network as shown in Fig. 2. In this study, a log-sigmoid function is assigned as the activation function which provides data values between one and zero. As a result, prior to the ANN the feature data value needs to be scaled to within a zero to one range.

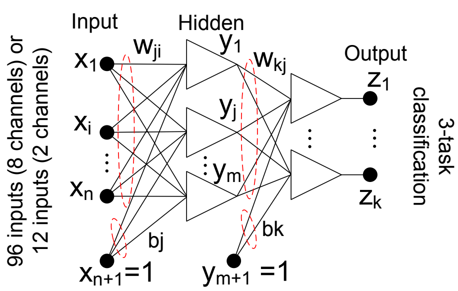

Figure 2. Neural network architecture

The Genetic Algorithm (GA), one of the evolutionary algorithms (EA) is use 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: 1) two parents are selected from the population of chromosomes based on the selection operation with the probability of selection proportional to their fitness value; 2) 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; 3) the population generated replaces the current population. These procedures are repeated until a termination condition is satisfied such as a predefined number of iteration [12].

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 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 that provides the highest fitness value to achieve the highest 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 iterations. 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.

At first, neural network training with the GA optimization is applied to an 8 channel EEG (C3, C4, P3, P4, O1, O2, T3 and T4) with the 96 input features derived from the PSD energy method. Fig. 3 shows the results of accuracies of five subjects for the three tasks classification of any combination from six non-motor imagery tasks (math, letter, cube, count, tone and navigate).

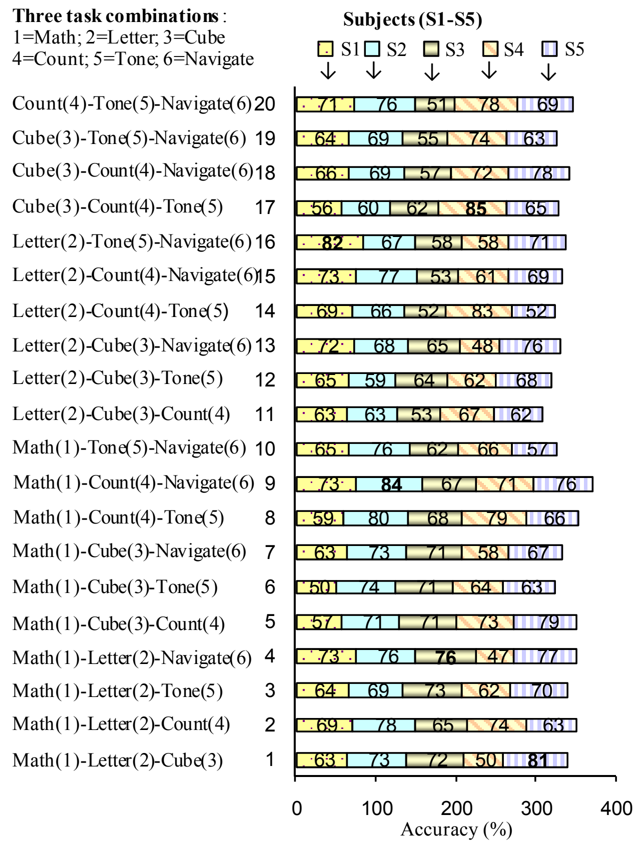

Figure 3. Accuracies of 8 channels EEG classifications for 5 subjects based on PSD features extractor

The result indicates a variation in the value of the classification accuracy across different subjects as the inter subject variability changes. Each subject has its own favorite triplet mental task combination which yields the highest classification accuracy between 76% and 85% using the PSD energy features extraction method. Subject 1 has the best accuracy at 82% with the combination of mental letter composing, ring-tone and spatial navigation. Subject 2 has the highest accuracy at 84% with the combination of arithmetic, counting and spatial navigation. Subject 3 archived accuracy at 76% of best triplet tasks with arithmetic, letter composing and spatial navigation. Subject 4 has the best classification accuracy between mental Rubik's cube rolling, visual counting and familiar ring tone imagery with accuracy at 85%. Subject 5 has the best accuracy at 81% between mental arithmetic, letter composing and Rubik's cube rolling.

Next, the number of EEG channels is reduced from eight to two channels. GA-NN training is performed based on the chosen mental task for each subject. Two features extraction method, PSD and HHT are compared to give a better features extraction algorithm. The result for the two channels combination of the chosen subject specific task is provided in Table I. To give the best accuracy, each preferable task on different subjects has the difference of the best two channels.

TABLE I. ACCURACIES OF 2 CHANNELS EEG CLASIFICATIONS FOR 5 SUBJECTS BASED ON PSD AND HHT FEATURES EXTRACTOR

Subjects	Chosen Subject Combination	Features Extractor	Two channels Combination															
			C3-C4	C3-P4	C3-O2	C3-T4	P3-C4	P3-P4	P3-O2	P3-T4	O1-C4	O1-P4	O1-O2	O1-T4	T3-C4	T3-P4	T3-O2	T3-T4
S1	Letter(2) - Tone (5) - Navigate (6)	PSD	53	53	48	56	51	51	53	59	55	59	57	65	57	58	57	70
		HHT	54	56	56	72	57	57	56	73	56	61	58	**77**	57	59	58	**75**
S2	Math(1) - Count (4) - Navigate (6)	PSD	48	51	54	67	43	48	57	65	47	51	59	67	52	51	60	66
		HHT	48	52	54	**71**	47	52	54	**70**	49	56	58	68	51	55	58	68
S3	Math(1) - Letter (2) - Navigate (6)	PSD	44	45	45	69	48	47	46	64	45	43	46	65	48	49	52	67
		HHT	52	52	49	**70**	51	52	49	66	46	48	46	64	51	53	53	66
S4	Cube(3) - Count (4) - Tone (5)	PSD	51	50	61	68	52	57	64	72	61	67	58	77	53	50	64	68
		HHT	51	49	60	**72**	54	55	65	**73**	68	68	68	**79**	50	51	63	**70**
S5	Math(1) - Letter (2) - Cube (3)	PSD	48	49	69	62	47	49	71	60	65	64	73	79	47	52	68	58
		HHT	54	56	**74**	**71**	51	55	**75**	66	69	69	**78**	**84**	53	55	**75**	64

In detail, subject 1 with the chosen triplet task (letter-tone-navigate) has the best accuracy using O1-T4 pair with improved accuracy from 65% (PSD) to 77% (HHT). Other option is at T3-T4 with improved accuracy at 75 % (HHT). Subject 2 with the chosen task (math-count-navigate) also provided an improvement of best accuracy from 67% (PSD) to 71% (HHT) using C3-T4 and optional P3-T4 with improved accuracy to 70% (HHT) from 65 % (PSD). Subject 3 with chosen triplet task (math-letter-navigate) has best improved accuracy if using HHT with pairs: C3-T4 at 71% from 69% (PSD). Subject 4 has more channel pairs with accuracies above 70% including C3-T4, P3-T4, O1-T4 and T3-T4. The best pair is O1-T4 location with improved accuracy at 79% using the HHT compared to PSD at 77%. Subject 5 also has more channel pairs and an improved accuracy using HHT method such as: C3-O2, C3-T4, P3-O2, O1-O2, O1-T4 and T3-O2 with the best accuracy at 84% (HHT) improving from 79% (PSD) using O1-T4 channel.

Generally, the resulting accuracies with only two channels for five subjects using PSD is lower than the original 8 channels classification at values between 65 % and 79%. However, by using the HHT based feature extractor, these accuracies are improved with values between 70% and 84% across five subjects with two channels.

IV. CONCLUSION

Two-channel mono-polar EEG classification has been successfully applied as a replacement to the original eight channels to discriminate three mental non-motor cognitive tasks tested for five subjects. As a result, two EEG channels with fewer electrodes provide more portability and more convenient setting-up in the practical BCI wheelchair control especially for severely disabled individuals. The original eight channels classification resulted in accuracies between 76% and 85%. With two channels, the accuracy using PSD features was between 65% and 79%. Moreover, the HHT based feature extraction method provides a better performance compared to the PSD-FFT based method with an improved accuracy between 70% and 84%.

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