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Classification of Wheelchair Commands using Brain Computer Interface: Comparison between Able-Bodied Persons and Patients with Tetraplegia

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***Abstract*— This paper presents a three-class mental task classification for an electroencephalography based brain computer interface. Experiments were conducted with patients with tetraplegia and able bodied controls. In addition, comparisons with different time-windows of data were examined to find the time window with the highest classification accuracy. The three mental tasks used were letter composing, arithmetic and imagery of a Rubik's cube rolling forward; these tasks were associated with three wheelchair commands: left, right and forward, respectively. An eyes closed task was also recorded for the algorithms testing and used as an additional on/off command. The features extraction method was based on the spectrum from a Hilbert-Huang transform and the classification algorithm was based on an artificial neural network with a fuzzy particle swarm optimization with cross-mutated operation. The results show a strong eyes closed detection for both groups with average accuracy at above 90%. The overall result for the combined groups shows an improved average accuracy of 70.6% at 1s, 74.8% at 2s, 77.8% at 3s, 79.6% at 4s and 81.4% at 5s. The accuracy for individual groups were lower for patients with tetraplegia compared to the able-bodied group, however, does improve with increased duration of the time-window.**

I. INTRODUCTION

A Brain Computer Interface (BCI) offers a hands free method for people to communicate by using brain signals only it therefore bypasses the body's natural muscular activity. People with severe disabilities and neurological conditions such as high-level spinal cord injury (SCI) or tetraplegia and amyotropic lateral sclerosis (ALS) could benefit from BCI technology. For example, BCI as a thought controller can be used to improve mobility in this severe disability group when used as a BCI based wheelchair controller. For this application, at least three commands are necessary to control the wheelchair this being, to signal turn left, turn right and move forward [1].

In the current state, non-invasive BCI using electroencephalography (EEG) for measuring electrical brain signals is popular in the BCI research community. Example of EEG based-BCI are P300 [2], the steady state evoked potential (SSVEP) [3], and even-related desyncronization-synchronization (ERD-ERS) [4] that uses sensory motor task and other mental non-motor imagery tasks. P300 and SSVEP are selective attention based BCI methods. For these methods, the user needs to keep focusing on external cues when operating the BCI. This could be cumbersome, as the user is required to control the wheelchair and maintain focus on the external cues at the same time. On the other hand, a BCI using ERD/ERS and other non-motor imagery methods relying on spontaneous intentional mental signals from the user could be a better option for wheelchair control. ERD/ERS method basically concentrates on motor imagery mental tasks by performing hand, foot, tongue and other body parts' movement as describe in the motor homunculus.

There is a case of BCI illiteracy and for people who have been disabled for a long period of time; they may not be able to use the motor imagery based-BCI very well [5]. In this case, we have been used an alternative non-motor imagery based solution as an option [6, 7]. However, most of the results of BCI classification experiments, especially with the mental task non-motor imagery BCI, have reported on the able-bodied only without including individuals with severe disabilities, which are an important target group for BCI technology.

This paper presents the result of three-classes of mental task classification with five able-bodied participants and five patients with tetraplegia. The non-motor imagery mental tasks used are letter composing, arithmetic and figure Rubik's cube rolling forward, which are associated to the three wheelchair movements: left, right and forward. An additional eyes closed task is also recorded for testing. Also, different time-windows of data are investigated to find the best data windowing with an improved result of classification accuracy. The features extraction method was based on the Hilbert-Huang transform (HHT) and the classification algorithm was based on the artificial neural network (ANN) with fuzzy particle swarm optimization using cross-mutated operation (FPSOCM).

II. METHODS

A. Data Collection

This study was approved by the University of Technology, Sydney, Human Research Ethics Committee with five able bodied subjects (S1-S5) aged between 25 and 35 years and five patients with tetraplegia (T1-T5), aged

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between 45 and 80 years who suffer a high-level of SCI in the cervical area at level C3, C4, C5 and C6.

A commercial EEG system (Compumedic-Siesta) with 256 Hz of sampling rate was used for the experiment with the electrodes positioned at locations *C3*, *C4*, *P3*, *P4*, *O1* and *O2*. The left and right earlobes are used as the reference and *GND* electrodes. This configuration uses the international 10-20 montage system. Fig.1 shows the experiment set-up on patients with tetraplegia including electrode locations. During the experiment, the impedance is measured and kept below 5 kΩ and the eye blinks are kept to a minimum. The three mental tasks which are used include: mental letter composing by composing sentences in the mind; mental arithmetic by imagining and solving multiplication problems in the mind and mental figure Rubik's cube rolling by imagining a figure rolling a Rubik's cube in a forward direction. Additional eyes closed and opened tasks were recorded for testing.

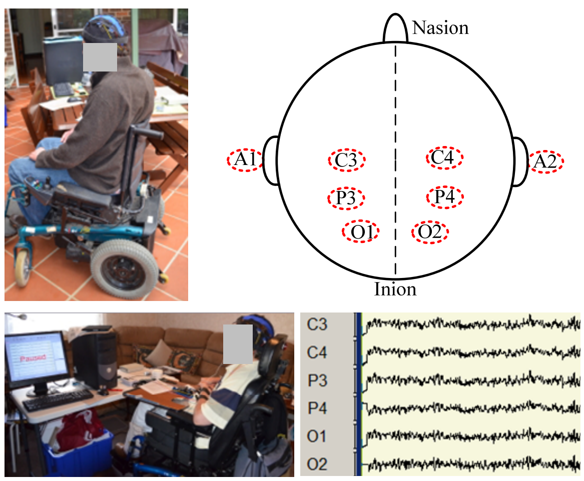

Figure 1. Set-up EEG experiment on patients with tetraplegia

B. Computational Intelligence

The experiment was recorded for 10 sessions for each mental task with 15s of data recording time in each session. The first 3s of data was discarded as preparation time. The rest of data (12s) was used for further computational processing. For signal pre-processing, different moving time-window segmentations of 1s, 2s 3s, 4s and 5s were compared with a quarter second segment of window overlapping. This provided 45 segments for a 1s time-window; 41 segments for a 2s time-window; 37 segments for a 3s time-window; 33 segments for a 4s time-window and 29 segments for a 5s time-window. With a total of 10 sessions, each participant provided data of 450 units for a 1s time-window; 410 units for a 2s time-window; 370 units for a 3s time-window; 330 units for a 4s time-window and 290 units for a 5s time-window in each mental task. This was further processed by applying digital signal processing filters using a Butterworth band-pass filter (0.1-100 Hz) and a Butterworth notch at 50 Hz for signal to noise ratio improvement.

The features extraction method was based on time-frequency analysis of spectrum of a Hilbert Huang transform (HTT). The HHT was used to tackle different non-linear and non-stationary data including EEG signals and provided better results compared to the conventional fast Fourier transform (FFT) [7, 8]. There are two main processes in HHT analysis: empirical mode decomposition (EMD) for decomposing the time series of data into sets of intrinsic mode decomposition (IMF) and Hilbert Transform (HT) to obtain spectrum of Hilbert-Huang transform as follows:

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

where $x(t)$ denotes the segment of EEG data, $c_i(t)$ is the i^{th} extracted IMF and $r_n(t)$ is the residual. The HT provides the amplitude and instantaneous frequency as a function of time as represented as the spectrum of HHT. The amplitude $a_i(t)$, the phase $\varphi_i(t)$ and the instantaneous frequency $\omega_i(t)$ are:

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

$$\varphi_i(t) = \arctan(y_i(t) / c_i(t)) \tag{3}$$

$$\omega_i(t) = d\varphi_i(t) / dt \tag{4}$$

The spectrum of the HHT that was used for the features covered the following EEG frequency bands: δ (1-3Hz), θ (4-7Hz), α (8-13Hz) and β (14-30Hz). The result of input features on each EEG channel was 30 units and with the six EEG channels resulted in 180 units of input features.

For the classification algorithm, artificial neural network (ANN) was employed. ANN is known as a non-linear classification method and has been used for biomedical application including the application of EEG based- BCI [6, 9]. This study used a 3-layers feed forward neural network with one hidden layer network as shown in Fig.2. The features need to be normalized into the range of zero to one as log-sigmoid was used.

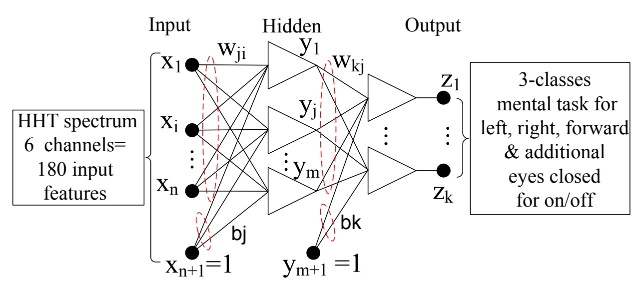

Figure 2. The 3-layers ANN structure for the classification algorithm

$$z_k(x, w) = f_1\left(b_k + \sum_{j=1}^{m} w_{kj} f_2\left(b_j + \sum_{i=1}^{n} w_{ji} x_n\right)\right) \tag{5}$$

$$X^* = (X - X_{min}) / (X_{max} - X_{min}) \tag{6}$$

where f_1 and f_2, denotes the activation functions of ANN, n refers to the number of input nodes, m refers to the number of output nodes, w_{ji} denotes 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 denoted by b_j and b_k. X^* is the input features after normalization. X is the input features before normalization. X_{min} and X_{max} are the minimum and the maximum value of the input features.

Fuzzy particle swarm optimization with cross-mutated operation (FPSOCM) was used to optimize the parameter of ANN. The FPSOCM method has been shown to produce better experimental results compared to other existing methods [10]. A fuzzy inertia weight $\tilde{\omega}(t)$ and a cross-mutated (CM) operation were introduced for performance searching improvement and to tackle the issue of trapping in local minimal.

This was started by the initialization of the particle swarm $X(t)$ with generation number $t = 0$. The particle was evaluated by cost-objective function, $f(X(t))$. Prior to the iterative PSO process, the probability of CM operation (p_{cm}) was defined. The value of $\tilde{\omega}(t)$ is controlled by two inputs of fuzzy inference system, the normalized standard deviation of cost value among all the particles, $||\varsigma(t)||$ and the iteration stage, t/T. After the $\tilde{\omega}(t)$ has been calculated, the velocity ($\mathbf{v}(t)$) was updated.

The next process was to find the control parameter, $\beta(t)$ by using the fuzzy interference system. Here, the velocity of all particle element swarm was evaluated by defined probability of CM (p_{cm}) in the CM process. A random particle (R_{cm}) with the value in the range of 0 and 1 is generated. If the R_{cm} has value more than the p_{cm}, CM operation will be performed on a particular element. The maximum velocity value (v_{max}) was applied to limit the particle velocity. After the CM operation, an updated particle swarm was generated. Another condition was applied to ensure particle elements have value within the range [ρ_{minj} ρ_{maxj}]. The process was repeated until a defined number of iteration (T) was met.

III. Results

During eyes closed task, there was a dominant feature on the alpha band of EEG (8-13Hz). This unique feature can be used for the HHT feature extraction method testing to ensure the method is correctly converting the raw EEG signal into correct features.

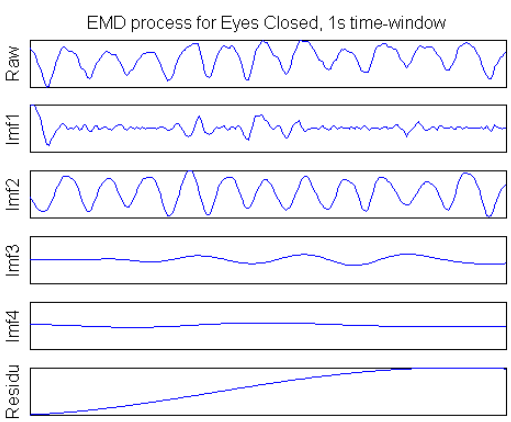

Figure 3. IMFs of eyes closed task in 1s time-window

In HHT, the segmented signal was processed and converted into series of IMF and a residue. Fig.3 shows the tested eyes closed signals that have been converted into a series of IMFs. After the application of the HT to the IMFs, the amplitude and instantaneous frequency was defined as functions of time. The plotting of the HHT results in Fig.4 for the eyes closed task shows a clear dominant feature of the instantaneous frequency of the alpha EEG band (8-13Hz). This proves the features extraction method has correctly converted the eyes closed task into the proper feature.

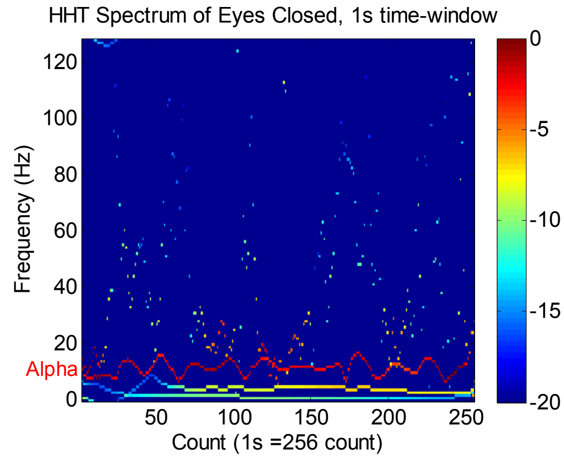

Figure 4. HHT spectrum for eyes closed 1s time-window

The features from different time-windows of data: 1s (450 units), 2s (410 units), 3s (370), 4s (330 units), 5s (290 units) were divided into a training set (50%) and a set for testing (50%) of the ANN with FPSOCM optimization.

TABLE I. ACCURACY OF EYES CLOSED-OPENED TASK WITH ABLE-BODIED (S1-S5) AND PARAPLEGIC (T1-T5) SUBJECTS

Subjects	**Mean of accuracy(%) in different time-windows (1s to 5s) of 5 able-bodied subjects (S1-S5) and 5 patients with tetraplegia (T1-T5)**				
	1s	**2s**	**3s**	**4s**	**5s**
S1	97.4	98.6	99.4	99.8	100
S2	98.9	99.4	99.6	99.7	100
S3	94.5	95	97.8	98.6	99.8
S4	97.9	98.4	98.7	99.3	99.5
S5	98.3	98.8	99.3	100	100
T1	93.6	96.4	98.5	99.2	99.8
T2	96.5	98.6	99.5	99.7	99.8
T3	85.8	90	90.4	94	95.4
T4	80.7	82.9	87.4	93.6	94.3
T5	84.5	92.4	94.2	95.6	98.6
Overall mean % ± std	92.8±6.6	95.1±5.3	96.5±4.4	97.9±2.5	98.7±2.1

The number of hidden neurons was tested with a variation of 4 to 30 units to obtain the best number with the lowest mean square error (MSE) and highest classification accuracy. The training of the neural network was repeated 10 times in each different hidden neuron. The parameters for FPSOCM optimization algorithm were as follows: The population swarm size is 50, number of training iteration is 2000, acceleration constants are 2.05, maximum velocity is 0.2, and probability of CM is 0.0005.

In table I, the overall result of the ANN classification shows the eyes closed and opened experiments resulted in mean accuracies above 90% for able bodied participants and patients with tetraplegia. This accuracy improved as the time-window of EEG signal increased. The high accuracy for eyes closed-opened shows the HHT algorithm was able to generate distinct features for the FPSOCM based neural network for eyes closed-opened classification. The eyes closed task can also be used for the additional on/off command for the purpose of BCI based wheelchair control.

TABLE II. ACCURACY OF THREE MENTAL TASKS CLASSFICATION WITH ABLE-BODIED (S1-S5) AND PARAPLEGIC (T1-T5) SUBJECTS IN DIFFERENT TIME-WINDOWS OF DATA

Subjects	Mean of accuracy(%) in different time-windows (1s to 5s) of 5 able-bodied subjects (S1-S5) and 5 patients with tetraplegia (T1-T5)				
	1s (%±std)	**2s (%±std)**	**3s (%±std)**	**4s (%±std)**	**5s (%±std)**
S1	74.2 ± 1.1	75.9 ± 1.1	77.8 ± 2.3	79.8± 2.4	80.6±1.7
S2	69.5 ± 0.7	71.7 ± 0.9	77.4 ± 0.8	81 ± 0.9	82.7±0.7
S3	78.6 ± 2.3	83.3 ± 1.5	83.9 ± 1.8	86.1 ± 1.4	85.4±2.5
S4	79.2 ± 0.8	81.9 ± 0.9	83.4 ± 0.9	82.1 ± 0.7	82.7±1.2
S5	74.1 ± 1.3	76.9 ± 1.7	79.1 ± 1.5	79.5 ± 1.8	81.1±2.1
Mean (S1-S5) % ± std	**75.1 ± 4.0**	**77.9 ± 4.7**	**80.3 ± 3.1**	**81.7± 2.7**	**82.5±1.9**
T1	64.3 ± 1.8	74.1 ± 1.2	77.3 ± 1.4	77.8 ± 1.0	81.5±1.4
T2	67.4 ± 1.6	69.4 ± 1.5	71.2 ± 1.3	75.6 ± 1.2	79.9±2.7
T3	65.8 ± 1.5	72.8 ± 1.7	78.7 ± 1.1	79.7 ± 1.3	80.1±1.0
T4	68.9 ± 1.9	73.8 ± 1.5	76.9 ± 1.1	79.5 ± 1.5	81.2±0.4
T5	64.2 ± 1.6	68.5 ± 1.7	72.4 ± 1.2	74.8 ± 2.3	78.8±1.5
Mean (T1-T5) % ± std	**66.1 ± 2.7**	**71.7 ± 3.3**	**75.3 ± 3.9**	**77.5 ± 2.2**	**80.3±1.1**
Overall mean % ± std	**70.6 ± 5.9**	**74.8 ± 5.2**	**77.8 ± 4.4**	**79.6 ± 3.2**	**81.4±1.8**

The result classification of three mental tasks (letter composing, arithmetic and Rubik's cube rolling forward) is shown in Table II. For a 1s time-window, the average accuracy of five able-bodied subjects results was 75.1±4.0%. For patients with tetraplegia, the average accuracy is lower at 66.1±2.7%. Compared to the 1s time-window, the accuracy for the 2s time-window for both groups improved. The average accuracy for able-bodied subject was 77.9±4.7% and for the patients group, it was 71.7±3.3%. For the 3s time-window, the average accuracy stays increased for both groups, with the able bodied group result having an average accuracy of 80.3±3.1% and 75.3±3.9% for the patients group. For a 4s time-window, the average accuracy improved for both groups: 81.7±2.7% for able-bodied group and 77.5±2.2% for patients group. The average accuracy was further improved for a 5s time-window compared to previous 1s, 2s, 3s and 4s time-window for both groups: 82.5±1.9% for able-bodied subjects and 80.3±1.1 for patients with tetraplegia.

For overall accuracy for both groups, it can be seen that the average accuracy improved when the time-window of data increased: 1s time-window at 70.6±5.9%, 2s time-window at 74.8± 5.2%, 3s time-window at 77.8±4.4%, 4s time-window at 79.6±3.2 and 5s time-window at 81.4±1.8.

IV. Conclusion

The classification of mental tasks has been applied to able-bodied subjects and patients with tetraplegia by using HHT as the features extraction method and neural network with the fuzzy particle swarm optimization with cross-mutated operation for the classification algorithm. The results showed a high accuracy for both groups for an eyes closed task. This proves the feature extraction method has correctly translated the raw EEG signal into the feature. For a three mental task classification, although the patients group has lower classification accuracy for a 1s time-window input of data, the accuracy is improved upon by increasing the time-window of data to 2s, 3s, 4s and 5s. This three mental tasks (letter composing, arithmetic and Rubik's cube rolling forward) classification can be mapped for three wheelchair movements detection (left, right and forward) with additional eyes closed action for on/off command.

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