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Adaptive EEG Thought Pattern Classifier for Advanced Wheelchair Control

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***Abstract*— This paper presents a real-time Electroencephalogram (EEG) classification system, with the goal of enhancing the control of a head-movement controlled power wheelchair for patients with chronic Spinal Cord Injury (SCI). Using a 32 channel recording device, mental command data was collected from 10 participants. This data was used to classify three different mental commands, to supplement the five commands already available using head movement control. Of the 32 channels that were recorded only 4 were used in the classification, achieving an average classification rate of 82%. This paper also demonstrates that there is an advantage to be gained by doing adaptive training of the classifier. That is, customizing the classifier to a person previously unseen by the classifier caused their average recognition rates to improve from 52.5% up to 77.5%.**

I. INTRODUCTION

Assistive technologies for people who are severely disabled is a fast growing research field. Much work has been done to enable those members of the community who suffer from conditions like tetraplegic spinal injury, cerebral palsy and head trauma to enjoy improved quality of life. One of the key areas for possible improvement, especially from spinal cord injury (SCI) sufferers, is in the area of mobility assistance. The key university research centre for health technologies at the University of Technology, Sydney (UTS) has been investigating methods to allow the control of a power wheelchair without the use of the hands or shoulders. These methods allow the control of the wheelchair by all except the most seriously injured of SCI sufferers. Of course, there is a large body of work in this field already, with numerous attempts being made to allow hands-free control of a power wheelchair. Some of these methods include eye gaze control [1], [2], eye wink control [3] and voice control [4]–[6].

All of these methods have their own unique drawbacks which prevents them being used in a standalone setting for wheelchair control. The favoured method of wheelchair control within the health sciences group at UTS is control via head movement. This is a flexible control technique, which has its own set of disadvantages, but these are relatively easily overcome. Systems have been built which utilise this technique quite successfully [7]–[9]. One of the major drawbacks of this particular approach is that the user of the system is required to have good neck and head movement. This precludes SCI sufferers with injuries to the spinal cord above the C_3 vertebrae from using one of the head movement systems [10].The reason for this was to try to make the data as close to 'real-world' data as possible.

Consequently, the feasibility of using a brain computer interface (BCI) for the control of the wheelchair has been under recent investigation at UTS. Initial work involved using a simple 2 channel EEG recorder, attempting to classify 3 different classes of mental commands in order to allow the control of the wheelchair [11]. The main advantage of this method is that it requires no motor skills whatsoever in order to achieve wheelchair control. However it also has some rather key disadvantages when used as the sole method of wheelchair control, for instance a 2 second classification window makes the eventual control quite slow.

In order to attempt to address these disadvantages, the approach has been taken that further wheelchair development will occur in a shared-control environment; that is, the user has the option of either using head movement control, thought control, or a combination of the two. This should allow us to use the BCI system to supplement the head movement system for users with injuries above C_3, perhaps customising the system to allow the replacement of a troublesome head movement command with a thought based command instead.

II. METHODS

A. Data Acquisition

The data from this study was recorded entirely on a BioSemi^{TM}Active-Two System. The system was setup to acquire 32 channels of EEG data, as well as one channel for each ear lobe. The data was recorded at a sampling rate of 1024Hz, and had 24-bit resolution. The Active-Two System uses active electrodes (Ag-AgCl Pin-type) which are held in place by being plugged into the BioSemi head cap. To enable better electrical contact with the scalp, a high-conductivity gel is applied to the scalp underneath the electrode.

The 32 channels recorded were chosen from the extended 10-20 electrode system, and the recording was conducted in a dedicated EEG laboratory. Whilst participants were requested to avoid any unnecessary movements such as eye-blinks during the recording session, when these artifacts did occur, they were not removed from the EEG data. The reason for this was to try to make the data as close to 'real-world' data as possible.

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Fig. 1. The BioSemi™ Active-Two System

B. Mental Tasks

Participants in this study were asked to perform a total of four different mental tasks, which were chosen so as to evoke changes in brain activity as observed as electronic signals on the scalp. The tasks were intended to generally give results which tended to favour one hemisphere over the other, as the intention of the research is to use the differences in EEG over the two hemispheres to help with the classification [12]. Each participant was recorded doing each task a total of ten times. All of these recordings were taken in a single sitting. Each 10 second recording period was interspersed with 10 seconds of baseline recording.

The mental tasks that the participants were asked to perform were as follows:

- *Mental Arithmetic (MA)*: This task involves performing a non-trivial multiplication problem (such as 73x17) mentally. Each sample involved solving a different problem.
- *Figure Rotation (FR)*: The subjects were given time to study a complex three dimensional block figure, and then asked to visualise the object being rotated around an axis.
- *Mental Counting (MC)*: The counting of numbers as the subject visualised them appearing on a blackboard, then disappearing. This happens with sequential numbers.
- *Letter Composition (LC)*: The subject was instructed to mentally compose a letter to a friend or relative without vocalising.

In addition, each subject was also recorded alternating between eyes open and eyes closed, to attempt to capture the 'mind-switch' of the subject (a signal evoked when the user closes their eyes) [13]. While not strictly a mental task, this was investigated to allow another potential binary command to be used in the control of the wheelchair.

C. Data Pre-processing and Feature Selection

The raw data for this experiment is recorded at 1024Hz, and is 32 channels, as discussed above. This presents far too much redundant information to be efficiently classified by a learning technique such as artificial neural networks. Furthermore, such a system is no use in the real world for actual system control; primarily because of the large amount of setup required. Setup of the entire 32 channel system by experienced research assistants often takes in excess of half an hour. So in order to more closely model the equipment that will be used in the real-time version, we have reduced the data used by the neural network.

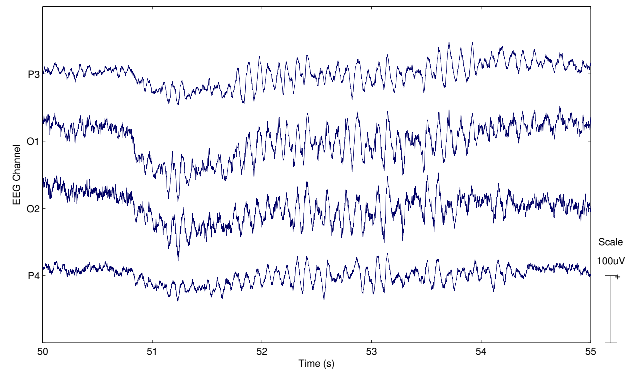

Fig. 2. P_3, P_4, O_1 and O_2 during 'Eyes Closed' event

The data is initially reduced from 32 channels down to 4 channels. These channels were chosen symmetrically as a subset of the six channels that were used by Keirn [12]. The four channels chosen for this research are P_3, P_4, O_1 and O_2. The data is then downsampled to a sampling rate of 256Hz. A band pass filter from 0.1 to 100Hz is then applied to the data.

Each ten second sample is then reduced down to a six second sample, by removing two seconds of data from both the beginning and the end of the sample. By doing this we remove any transitional effects, and hopefully any lag in between the issuing of the command, and the beginning of the corresponding thought process. This six second sample is then split into 2s fragments for frequency based analysis, to increase the amount of data available for training.

Furthermore, the first 2 attempts at each mental command by each user were discarded as 'learning attempts' for the subject. This left a total of 240 input samples, which were split evenly into the training and validation sets - giving 60 samples of each command in each set.

It should be noted that the data for the training of the eyes closed classifier was organised slightly differently. In this classifier only the 2s-4s and 6-8s windows were used of the 10s sample. No 'learning attempts' were deemed necessary for this activity, giving a total of 100 eyes-closed input samples split evenly between both sets.

Then the FFT power spectrum of the data is calculated of each sample, using a 512-point FFT. As has been observed, most EEG activity can be characterised as being within four distinct frequency bands: delta (0.1 - 3Hz), theta (4 - 7Hz), alpha (8 - 13Hz) and beta (14 - 20Hz). The total power within each frequency band was estimated using a numerical integration technique (the trapezoidal rule) to produce a power value for each band and each channel. These power values are used as the first set of inputs to the neural network.

The channels are then compared in pairs to one another using the asymmetry ratio, given in Equation 1. The asymmetry ratio compares the hemispheric difference in EEG signals located on opposite sides of the head. Thus P_3 and P_4 were compared with one another, as were O_1 and O_2. This results in a further eight inputs to the neural network (four bands for each pair of channels).

$$A = \frac{(R - L)}{(R + L)} \tag{1}$$

The final input vector then has a size of 24 input nodes: 16 frequency power band sums, and 8 asymmetry ratio values.

D. Adaptive Neural Network Training

Artificial neural networks is a powerful artificial intelligence based technique, which is very strong at classifying non-linear problems. The classification of EEG signals is a very good candidate for artificial neural networks, because EEG as a whole is still very poorly understood, and is non-linear in nature, thus is difficult to classify using traditional, statistical based, means.

One of the problems that we have noted in our previous EEG work is that the signals can tend to be difficult to generalise from person to person - unlike for example, in a head-movement system, where eventually a user can learn which response elicits the best reaction from the system, this sort of feedback is much harder in an EEG based system. To overcome this, we believe that the final system must display some adaptive learning traits, which will allow the customisation of the control system to an individual user over time.

The system was initially trained with data from the first five participants, and after network training the three mental commands that were best classified were selected. The resulting neural network was then tested with the data from a participant unseen by the classifier, to test the true generality of the system. In order to show that our system can improve adaptively, the final network was then further trained with data from the same participant.

III. Results

A. Classifier Training

The first artificial neural network classifier to be trained was to recognise the eyes closed (or mind switch [13]) command. This classifier was trained separately because this command is an override command, used to start and stop the wheelchair.

As illustrated in Figure 3, the training was successful, and the classifier should generalise sufficiently.

The other classifier that was trained in this study was designed to classify two further mental commands. This classifier is intended to be run in parallel with the first classifier, with the 'eyes-closed' classifier taking precedence.

As illustrated in Figure 4 the training appears to have been somewhat successful, although the classifier has not achieved the same accuracy as the stop-start classifier.

As illustrated in Table I we have achieved quite acceptable overall results. The 'stop-start' classifier has achieved a total accuracy of 94%, while the 'left-right' classifier has achieved approximately 77.5% accuracy. We believe that these results are reasonable, however it was noticed in the training process that there is a general trend towards a decrease in classifier accuracy as it is trained to recognise the data of more participants. To test how well these results generalise to an entirely new person's data, we carried out a further set of training and testing.

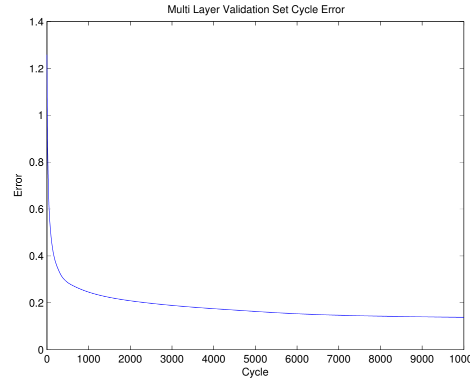

Fig. 3. Validation cycle error of Eyes Closed classifier training

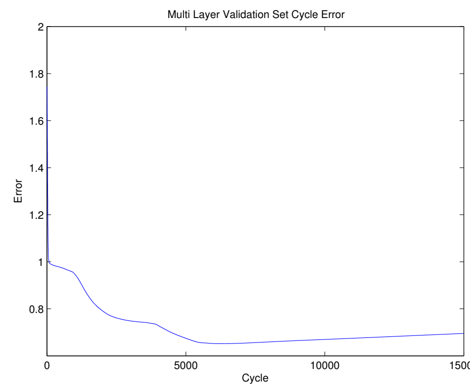

Fig. 4. Validation cycle error of MA vs. LC

B. Adaptive Training

The first test we carried out to see how well both classifiers generalise was to simply test the available classifier on some entirely new data, from new subjects. Data from the training set has been omitted from this table. The approach of dropping the first 2 samples of each subject as 'learning attempts' was not used for this testing, due to the lack of overall data available. Table II summarises these results.

TABLE I
FINAL NETWORK CLASSIFICATION

Command	Total	Correctly Identified	% Identified
Eyes Closed	50	47	94%
Mental Arithmetic	60	48	80%
Letter Composition	60	45	75%
Totals	**170**	**140**	**82.4%**
Overall Success Rate			**82.4%**

TABLE II

GENERALISATION TESTING

Command	Total	Correctly Identified	% Identified
Eyes Closed	10	5	50%
Letter Composing	15	6	40%
Mental Arithmetic	15	10	66%
Totals	**40**	**21**	**52.5%**

As illustrated in Table II, the classification rates have dropped significantly once the classifier is shown data from a new subject. The overall classification rate has dropped to 52.5%, while the 'start-stop' classifier has shown a large drop in classification accuracy as compared to Table I. Neither of these results are acceptable, so in an attempt to increase classification accuracy, the classifiers were further trained using the new data. Table III summarises the results of the adaptive training.

TABLE III

ADAPTIVELY TRAINED CLASSIFIER RESULTS

Command	Total	Correctly Identified	% Identified
Eyes Closed	10	10	100%
Letter Composing	15	11	73%
Mental Arithmetic	15	10	67%
Totals	**40**	**31**	**77.5%**

The adaptive training increases the accuracy of the system for a new user significantly. As seen in Table III, the overall classification accuracy rose from 52.5% to 77.5% for the new user while on the 'start-stop' classifier accuracy rose from 50% up to 100% for the given set of samples. All of the commands rose from their prior low levels to around or above the actual test set results initially gained after training.

IV. CONCLUSION

This paper has shown that it is possible to achieve good results classifying at least three different signals from EEG, generated by mental commands. The classifier was able to generalise the results from five different people, and learned to recognise them with an overall success rate of 82.4%. The most important findings in this paper, however, related to the overall generalisation of our classifier. We found that the results classifying data on a person previously unseen by the classifier were markedly worse than expected at about 52.5%. It could be theorised that the EEG signals we are classifying are significantly different from person to person to prevent a neural network based classifier from ever achieving generalisation to an acceptable level.

To overcome this problem, adaptive training of the classifier was simulated. When the classifier was subsequently trained with the data of the new subject that it was originally shown to test it's generalisation, the overall classification rates increased markedly, up to 77.5% from 52.5%. This brought the data from this subject back into line with what was being achieved initially. If these findings can be verified, they present implications to the area of BCI research.

The primary implication is to the assumption that mental command data (and EEG responses as a whole) remain common enough between different people that they can be classified successfully by a pattern recognition technique, such as artificial neural networks. The data from this study would seem to imply that some level of individual training is necessary to achieve good results with a system of this type.

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