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Two Channel EEG Thought Pattern Classifier

D.A. Craig, H.T. Nguyen, H.A. Burchey
Key University Research Centre for Health Technologies, Faculty of Engineering,
University of Technology, Sydney, NSW, AUSTRALIA

Abstract— **This paper presents a real-time Electro-Encephalogram (EEG) identification system with the goal of achieving hands free control. With two EEG electrodes placed on the scalp of the user, EEG signals are amplified and digitised directly using a ProComp+ encoder and transferred to the host computer through the RS232 interface. Using a real-time multilayer neural network, the actual classification for the control of a powered wheelchair has a very fast response. It can detect changes in the user's thought pattern in 1 second. Using only two EEG electrodes at positions O_1 and C_4 the system can classify three mental commands (forward, left and right) with an accuracy of more than 79%.**

I. Introduction

In recent years, there has been a growing demand for hands-free powered wheelchair as assistive systems. The number of people in need of mobility assistance is increasing due to longer life expectancy and improved resuscitation techniques. Conventional electrical wheelchairs are not always sufficient to compensate for mobility disabilities such as cerebral palsy, tetraplegia or head trauma. To overcome the problems associated with joystick control, a new variety of interfaces have been designed to replace the joystick. Some of the more novel of these include eye gaze control [1], [2], eye wink control [3] and voice control [4]–[6].

One of the more promising hands-free control techniques is head-movement, based on embedded systems which process data from a multi-axis accelerometer worn in a cap on the user's head [7]. This technique, while useful, is not applicable to all potential users of a power wheelchair. Sufferers with Injuries to the spinal cord above the C_3 vertebrae [8] will find it difficult to operate a head-movement based system. This work attempts to address this problem through the development of a control system which uses classification of different thought patterns as a method of controlling a power wheelchair in real-time.

The brain has long been sought after as a method of directly controlling devices. There have been many attempts at designing function brain computer interfaces (BCIs) [9]–[11]. There have also been succesful BCIs applied to problems, for example a BCI has been designed which allows control of a mouse-pointer [12]. A feature of our work is that in contrast to this previous work, we have focused on creating a classifier which is both simpler to set up and is able to be analysed by a low powered computer (an embedded system).

The development of a fully embedded, real-time BCI will be a defining point in the technology, because it will enable people without any bodily movement to control many types of devices, thus giving a more autonomous lifestyle, and consequentially, a better quality of life. The goal of this project is to bring the state of BCI one step closer to this goal by realising an embedded, real-time power wheelchair control system which relies only on mental tasks for control signals.

II. Methods

A. High Level System Design

The system contains three main logical groupings - input, data processing and output. The system inputs are two EEG channels, processed by the Procomp+ encoder from Thought Technology Ltd. The encoder is connected via RS232 to a laptop computer running custom software written on the Linux operating system, which processes the data, recognising different thought patterns. The laptop is connected to a National Instruments USB-6008 DAC, which can then to be used to control a device, for example a power wheelchair.

B. EEG Electrode Placement & Mental Tasks

In work on a similar mental task based BCI, an EEG system with the capability of recording 6 EEG channels was used [13]. This system achieved better than 80% classification accuracy, using a Bayes quadratic classifier. The 6 channels used in the study were - as defined by the 10-20 system of electrode placement - C_3, C_4, P_3, P_4, O_1 and O_2. In contrast to this, the Procomp+ is able to process only two channels at once.

This design decision was taken primarily because this project is focusing on an EEG classifier for control purposes. Current systems being developed are too unwieldy, and require too much computing power to process to be viable as a control method for an assistive device - one recent project uses 13 electrodes, and a desktop PC to process data [14].

Thus we chose a 2 channel system because it would be much more practical in terms of everyday setup for a real-life user, and secondly because we wish to limit the data coming in to the system in real time so that we can process it easily on an embedded platform. In order to choose the locations for our two electrodes, we have assumed that the optimal location for such a two electrode system would be a subset of these 6 locations.

Furthermore, the system described above used a total of 5 different mental tasks [13]. These tasks were:

- Task 1 - Baseline measurements: The subjects were told to relax and think of nothing in particular
- Task 2 - Complex problem solving: The subject was given a nontrivial multiplication problem to solve

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- Task 3 - Geometric figure rotation: The subjects were given 30s to study a complex three dimensional block figure, and then asked to visualise the object being rotated around an axis.
- Task 4 - Mental letter composing: The subject was instructed to mentally compose a letter to a friend or relative without vocalising.
- Task 5 - Visual counting: The subject was asked to imagine a blackboard and to visualise numbers being written on the board sequentially, with the previous number being erased before the next is written.

In order to achieve control a device such as a power wheelchair, our system needs to be able to use a minimum of 3 different commands, and will do so through the classification of data from the simultaneous recording of 2 EEG channels.

To determine which 2 EEG channels give us the optimum in terms of classification strengths and which 3 commands would be best for wheelchair control, we have extensively analysed data made available by a previous group of researchers [13].

To perform the analysis, a small shell script was written to run neural network software repeatedly, creating a neural network for each set of mental tasks and for each pair of electrode locations. The software recorded the selection strength G of the final validation cycle. Since there are 36 combinations of electrodes and 25 combinations of mental tasks, this resulted in the creation of 900 different neural networks. A summary of these results as applicable to channel selection is shown in Fig. 1 and Fig. 2.

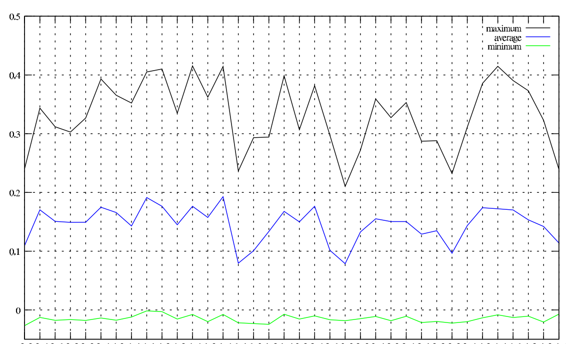

Fig. 1. neural network selection strength versus channel

As we can see in Fig. 1, the optimal positioning of the two EEG electrodes was found to be O_1 and C_4, for the three best wheelchair tasks which were identified in Fig. 2. The final tasks which will be used by the system are Task 2 (complex problem solving), Task 3 (geometric figure rotation) and Task 4 (mental letter composing). It is interesting to note that EEG signals at O_1 are generally related to visual processing, procedural memory and dreaming, while the signals at C_4 relate to sensory and motor functions, as well as short term memory.

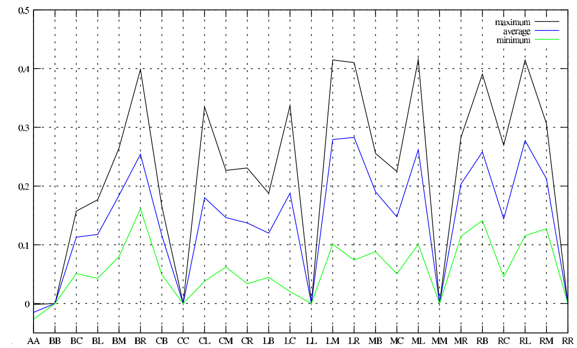

Fig. 2. neural network selection strength versus task

C. EEG-based Thought Recognition

EEG is recorded using EEG electrodes and sensors from Thought Technology, Ltd. These sensors are connected to a ProComp+ encoder (SA7008P, Thought Technology, Fig. 3) which digitises the signals and transmits them using RS232 via a fibre-optic cable, electrically isolating the Procomp+ from the host computer. The encoder samples both EEG channels at 256Hz.

Fig. 3. The Procomp+ encoder

A total of three mental tasks is the minimum required in order to successfully provide a hands-free control system for a power wheelchair. These three commands correspond to a start / stop signal, turn left, and turn right. The mental tasks that were chosen to correspond to these tasks are a subset of those tasks which have been previously investigated [13]. The commands used by the system are:

- Forward command (**F**igure rotation): The subjects were asked to focus on an object in their line of sight, and to visualise the object being rotated around an axis.
- Left command (**L**etter composing): The subject mentally composes a letter to a friend or relative without vocalising.
- Right command (a**R**ithmetic solving) : The subject mentally solves a non-trivial multiplication problem.
- Stop command - Eyes closed: The subject closes their eyes, relaxing.

D. Neural Network Classifier Design

EEG is a notoriously difficult signal to analyse correctly. Artificial neural networks was used as the primary analysis method for this problem for their well known property of learning to recognise complex signals and patterns which are not well known or well described quantitatively. Nevertheless, the EEG data needed some preprocessing before it became useful in the neural network analysis.

The EEG data for each location (O_1 and C_4) is transformed into the frequency domain using a discrete Fast Fourier Transform, and then broken up into the Delta, Theta, Alpha, Beta and Gamma frequency bands. In order to find the total power of the signal in each frequency band, the integral of the frequency power spectrum is taken. These areas are combined with the raw frequency spectrum of each sample. Finally, this is combined with the Left - Right Asymmetry Ratio for each frequency band [13].

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

To use Equation 1, we take R as the area under the power spectrum on the right electrode in a given frequency band, and we take L as the area under the power spectrum on the other electrode in the same frequency band. This is repeated for each of the 5 frequency bands described above.

This results in an input layer with 273 input neurons, 134 for each channel plus 5 for each asymmetry ratio. A dual layer neural network was used, and it was decided to use 10 hidden nodes in this network, after extensive experimentation with various numbers of hidden nodes. The network has four output nodes, each of which corresponds to one mental command.

E. Wheelchair Control

The eventual goal of this project was to achieve control of a power wheelchair using only thought patterns as the control stimuli. The wheelchair used for this project is an M1 Roller Chair. The features of the M1 Roller Chair include a mid-wheel drive motor, which gives the chair the ability to turn on the spot, which makes control with more limited control schemes much more feasible.

In order to control this wheelchair in real-time, software was written for the Linux operating system. This software included a shared library to allow simple interpretation of the Procomp+ data stream, which has been reverse-engineered as a part of this project. In addition to this, software was written in the C programming language to allow the analysis of the signal. In order to make the system as portable to other hardware architectures as possible - especially embedded platforms, we have chosen to use the FFTW library for our numerical FFT - which is the single most CPU intensive aspect of this project.

Connected to the real-time controller is a National Instruments USB digital to analogue converter (USB-6008). This digital to analogue converter was chosen for its convenience and for the fact that the device is usable under Linux and is supplied with a C API.

III. RESULTS

A. Neural Network

The success of this project depends on the most part on the system's ability to correctly identify the different thought patterns presented in this paper. The complexity of EEG analysis as a whole, coupled with the fact that we have access to only two EEG channels means that this is quite a challenging task. It follows that the most crucial part of the system as a whole is the classifier itself.

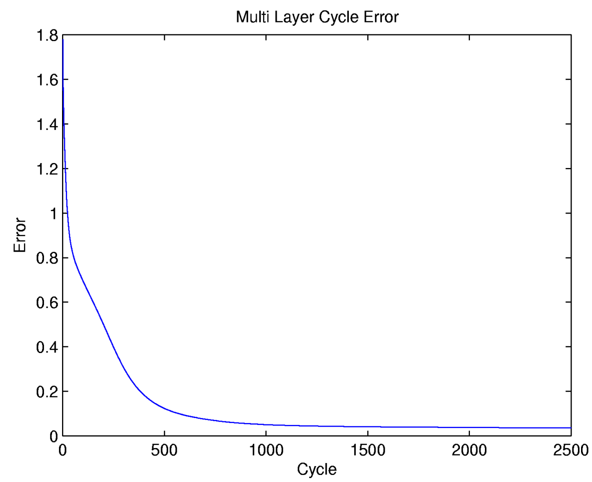

Fig. 4. Training Cycle Error of Neural Network Classifier

Training of the Neural Network classifier was undertaken using the delta learning rule and standard back propagation with a fixed learning constant. A total of 300 samples from 5 people were collected for the training of the classifier. These samples were divided up into three sets, a training set, a validation set and a test set. The training set was allocated 200 samples, whilst the test and validation sets were each allocated 50 samples.

Fig. 4 shows the cycle error curve of the training data set, as it is trained. This figure shows a smooth curve, without sharp changes or discontinuities, which indicates that the ten hidden nodes that have been used in the network are sufficient. We can also see that the training set itself has very little final error. However, this alone is not an indication of how well the system has been trained - it does not tell us if our network will still recognise data on which it has not been directly trained. The best way to get an indication of whether the system has been over-trained is by looking at the Validation cycle error curve.

Fig. 5 shows the cycle error curve of the validation set, throughout the training process. Again, this curve is quite smooth, and follows the same basic shape as the training set. It is important to note that Fig. 5 does not show any signs of over-training, as at no point does the validation cycle error begin to rise again. Thus the final weights for this neural network were taken to be the weights after the 2500th training cycle.

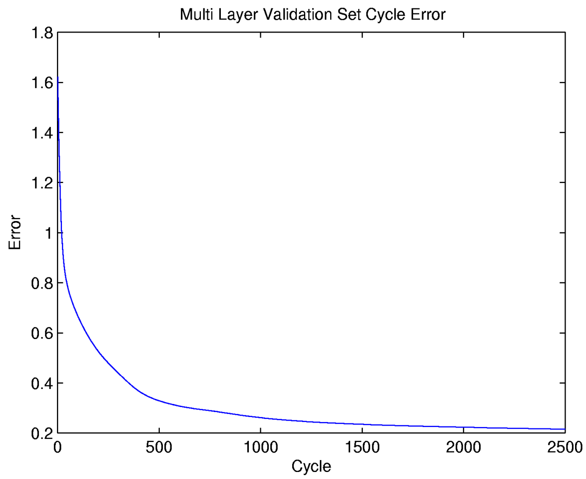

Fig. 5. Validation Cycle Error of Neural Network Classifier

TABLE I

FINAL NETWORK CLASSIFICATION

Command	**Total**	**Correctly Identified**
Mental Arithmetic	12	7
Letter Composing	13	12
Figure Rotation	13	11
Totals	**38**	**30**
Success Rate		**79%**

Following the completion of the training, the network was analysed using the test set. Table I shows us the final results of the system, having undergone training. As we can see, the overall accuracy achieved in the test set was 79% for the four different commands used in the system. Mental arithmetic was the weakest of the commands to be trained, with just over 50% being recognised, while letter composing and figure rotation both had recognition rates of about 85% - 90%.

IV. CONCLUSION

This project has successfully shown that a system utilising a two channel EEG encoder can successfully classify thought pattern commands. It is quite feasible that this classifier could be used for control purposes. as the simple two electrode EEG system has achieved both high accuracy (around 80%) and low latency (one second). It needs to be acknowledged that the individual classification strengths of two of the mental tasks is lower, however, we believe that this is a problem that can be worked around - and have already begun the process of improving the network classification. We will also be looking migrate the system purely to real-time, in order to achieve control of the powered wheelchair. Finally, any real-time control system especially with severely disabled subjects.

ACKNOWLEDGEMENT

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