EEG-based communication: a pattern recognition approach

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Abstract— **The overall aim of this research is to develop an EEG-based computer interface for use by people with severe physical disabilities. The work focuses on using EEG signals to drive one-dimensional cursor movements on a computer screen and our approach is characterised by our emphasis on the computer adapting to the user rather than the user adapting to the computer.**

Keywords— **Pattern Recognition, Cognitive Tasks, EEG.**

I. Introduction

THE ultimate aim of this research is to develop an EEG-based computer interface for use by people with severe physical disabilities. This would, for example, facilitate interaction with a wordprocessor package or manipulation of various environmental controls.

Our approach relies less on biofeedback training [8] and more on the use of pattern recognition methods, the idea being that the burden of communication be met by the user adapting to the computer *and* the computer adapting to the user. In this type of scheme, cursor movements are generated by the output of a pattern classifier such as a neural network.

Our approach is novel in two important technical respects. Firstly, we infer not just the parameters of our classifiers (eg. weights in a neural net) but also the uncertainty on those parameters. This allows us to estimate the uncertainty associated with each subsequent classification. Secondly, we use dynamic classifiers such that the cursor movement at a given time step is dependent on cursor movements at previous time steps. Both of these features lead to more robust cursor control [7].

A further aspect of our work is an exploration of the cognitive tasks used to generate the signals which provide a starting point for communication. To date, we have investigated motor imagery and mental arithmetic tasks.

II. Offline studies

Our research into EEG-based communication began in 1996. At that time, whilst there was some anecdotal evidence from biofeedback experiments [8] to suggest that motor imagery can be identified from the background EEG, there were no formal experiments to suggest that this is indeed the case. Or indeed, any information on what proportion of subjects these patterns could be detected in or with what accuracy.

To clarify the situation we recorded EEG from seven subjects performing cued imagined hand movements [5]. Control recordings were also made to ensure we were not picking up stimulus-related activity. The EEG was recorded using a single reference electrode and two 11-electrode arrays placed over the left and right sensorimotor cortex (a total of 23 electrodes).

Laplacian operators were applied to estimate local activity at three sites over left and right sensorimotor cortex. Analysis of mu-rhythm power in the resulting signals showed that imagined hand movements could be identified in six out of seven subjects with a typical accuracy of 70%. The most discriminative electrode positions were found to be 3cm posterior to the C3 and C4 positions in the 10/20 system. Extraction of complexity features [6] showed that, in four out of seven subjects, imagined hand movements could be discriminated from background EEG activity with a typical accuracy of 80%.

This research was useful in concretely establishing that motor imagery signals could be detected by spectral and complexity features and that, in principle, they could be used to drive cursor movements. It also identified the best position to place a smaller number of electrodes.

III. Online system

The above research informed the design of our 'online' EEG-based computer interface. It uses only three electrodes, a single isolation amplifier and a 266MHz PC. The electrodes are placed 3cm behind C3 and C4 and a reference electrode is placed over the right mastoid.

Subjects move a cursor up or down a computer screen by performing different cognitive tasks. We have also carried out experiments in which the cursor does not move. We have tried two different pairs of cognitive tasks; (i) motor imagery versus a baseline task and (ii) motor imagery versus a maths task. For the motor imagery tasks, subjects were asked to imagine opening and closing their hand (right or left according to handedness), and for the maths tasks subjects were asked to serially subtract seven from a large number. Further experimental details are available in [4].

Cursor movements were generated by extracting autoregressive (AR) features from the EEG and classifying them using a Bayesian logistic regression model.

A. Handling uncertainty

The AR features are classified using a logistic regression model trained using the Bayesian evidence framework [7]. This procedure estimates both the classifier weights and the distribution of those weights. The distribution captures the fact that the classifier is not entirely certain as to how to classify some inputs. If this uncertainty is taken

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into account when making a new prediction (as it should be) then the correct predictive output to use is the 'moderated' output. Moderation in a two-class problem changes the output to a value nearer to 0.5 (the class prior) by an amount which is proportional to the uncertainty on the weights. It is possible to make more robust cursor movements by choosing not to move the cursor if the classifier output is not sufficiently different to 0.5. This is known as 'rejection'.

B. Dynamic models

For EEG data, averaging classifier outputs over a number of consecutive data segments is known to significantly increase classification accuracy. This is known as 'temporal smoothing'. One approach to temporal smoothing is to average classifier responses not in the output space, but in the space of activations, or the 'latent' space. This scheme arises from considerations of how to make optimal decisions in a 'committee' of classifiers [3] where each committee member makes a prediction from a different time point. Optimal smoothing periods can be established via cross-validation; a typical period is two seconds.

C. Results

We report results from online experiments by analysing the EEG data on a segment-by-segment basis. In the stationary cursor trials, the imagery versus maths pairing was more easily discriminated than the imagery versus baseline pairing, and this difference was significant in four of the subjects. In the moving cursor trials, however, the two different task pairings were equally well discriminated.

An analysis of the spectra associated with each cognitive task showed that, for most subjects, the majority of differential activity is in the mu-band (8-13 Hz) whilst some subjects also showed differences in the beta (14-20 Hz) band and, for the maths tasks, also in the theta (4-7 Hz) band.

Overall, in the moving cursor trials, four out of seven subjects achieved at least 75% accuracy. The average accuracy over all seven subjects was 61% which could, however, be increased to 87% with the use of a reject option [7]. These figures correspond to bit rates of 0.02, without a reject option, and 0.12 with a reject option; a six-fold increase in communication rate [4]. This upper bit rate corresponds to communicating 2 to 3 letters of the English language per minute. A further benefit of using a reject option is that sections of EEG containing irrelevant cognitive components (eg. during lapses of concentration) do not result in spurious cursor movement. This greatly enhances the robustness of the system.

IV. Discussion and future plans

Firstly, we intend to persevere with methods involving little or no biofeedback training and focus on other ways of improving classification accuracy. One method might be to also use slow cortical potentials (SCPs) [1]. Recent research shows that SCPs and spectral changes are uncorrelated. The SCPs would therefore provide an additional source of information. A second method is to look at using additional features such as complexity [6] or to pre-process the signals in more adventurous ways eg. using an Independent Component Analysis embedding. A third method is to use hidden Markov models which have so far been applied to data from one subject with positive results.

Secondly, we will train subjects using a biofeedback approach. This involves the interaction of two adaptive controllers; the user and the computer. One promising approach for handling this interaction is to use nonstationary classification algorithms [2] which acknowledge that the statistics of each class (ie. how the user moves the cursor up or down) can change with time.

Thirdly, we will continue to investigate the choice of cognitive tasks appropriate for use in a BCI system and will also study the implicit learning process involved in biofeedback training. We will investigate the tasks themselves with a view to improving instructions for subjects and possibly cutting down on the considerable training time that has been necessary in previous BCI research. We will also consider other cognitive and psychological factors, including patients' needs and the effects of concentration, attention, distractions, emotions and fatigue, which may influence the accuracy and effective control of the system.

We plan to incorporate all of the more recent developments into a new version of the interface and to evaluate it on a large population of normal subjects and people with severe physical disabilities.

Acknowledgements

The authors would like thank Nahid Haque, EEG Research Assistant at the Royal Hospital for Neuro-disability, and the subjects who took part in the experiment. W. D. Penny was supported by the UK Engineering and Physical Sciences Research Council (EPSRC), grant number GR/K79062, and equipment and technical support were funded by the Neuro-disability Research Trust.

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