ANALOGUE P300-BASED BCI POINTING DEVICE

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SUMMARY: We propose a P300-based BCI mouse. The system is analogue: the pointer is controlled by directly combining the amplitudes of the outputs produced by a filter in the presence of different stimuli. The system is optimised by a genetic algorithm.

INTRODUCTION

We present a P300-based system for the two-dimensional control of a pointer on a computer screen, inspired by Donchin's Speller [1]. In our BCI mouse, four unobtrusive rectangles are superimposed on the screen, near its edges, and are used to represent the directions up, right, down and left (Figure 1). The rectangles are flashed in random order at 180 ms intervals. To limit the risk of perceptual errors [2], the same rectangle is not allowed to flash twice in a row.
By focusing their attention to one particular rectangle, users produce P300s when the rectangle flashes. The system processes responses and moves the mouse pointer in the appropriate direction. The approach is similar to that used in [3] but with a substantial difference: logically *our BCI mouse is an analogue device*, since the responses for the four directions directly affect the movement of the pointer without requiring any binary classification.
Unlike previous approaches, we use a genetic algorithm (GA) to optimise the parameters of the system for each user and each session – a technology which provided promising results in our earlier work in medical signal processing [4, 5] and BCI [6].
The system makes it possible for a person with no previous training and within 15 minutes of wearing the electrode cap, to move a pointer to any location of a computer screen.

SYSTEM

We used the 19 channels corresponding to the 10-20 international system to acquire EEG. The analysis of the P300 components is preceeded by a preprocessing phase in which: a) each channel is low-pass filtered using a FIR filter (order 30, $f_{pass} = 34$ Hz, $f_{stop} = 47$ Hz), b) the signal is decimated to a sampling rate of 128 Hz, c) the Continuous Wavelet Transform (CWT) of each EEG channel is performed. CWT was done at 30 different scales between 2 and 40 and for a temporal window from 235 ms and 540 ms after the presentation of stimuli. So, the ERP response to each stimulus gives us a 3–D array $\mathbf{V}(c, s, t)$ of features, where c indexes the channel, s the scale and t the time corresponding to a feature. In total we have $19 \times 30 \times 40 = 22,800$ components.
Because of the large numbers of features we performed feature selection using a wrapper approach where the selection of features and the training of a classifier are performed jointly.
Computer mice are fundamentally analogue devices. So, it seemed inappropriate to turn analogue brain activity recorded in the EEG into binary form, as it is done traditionally in P300-based BCI by thresholding the output of classifiers, to later turn the signal in analogue form again. So, we felt that an analogic BCI approach would offer the potential to better use the information present in P300s.
To obtain this, the motion of the pointer is directly determined by the output of a filter. More precisely, the vertical motion of the pointer is proportional to the difference between the output produced by the filter when processing an epoch where the "up" rectangle was flashed and the output produced by the filter when processing an epoch where the "down" rectangle was flashed. Horizontal motion is determined similarly.
Therefore, the task of the GA is not just selecting features and designing detectors to best discriminate between P300 and non-P300 responses, but also to do so in such a way that the responses to pairs of stimuli provide the fastest and most precise way of moving the pointer in the desired direction.
To control the motion we used the output of the following filter which combines a subset of elements of the feature matrix $\mathbf{V}$:

$$O(\mathbf{V}) = \arctan\left(a_0 + \sum_{j=1}^{N} a_j \cdot \mathbf{V}(c_j, s_j, t_j)\right) \quad (1)$$

where N is the number of terms in the filter, the coefficients c_j, s_j, t_j identify which component of $\mathbf{V}$ is used as the j-th feature, and finally the values a_j are coefficients weighing the relative effect of each term.
We take a *single trial* approach. This allows our mice to move approximately once per second.
Each individual in the GA represents a tentative solution to the problem, i.e., it is a collection of the parameters a_j, c_j, s_j and t_j that need optimising. In the GA runs we used tournament selection, blend crossover, headless-chicken mutation, populations of size 50,000, and 40 generations.
The problem of evolving a mouse is multi-objective: we want to obtain both maximum motion in the desired direction *and* minimal motion in the orthogonal

direction. To achieve this we used the following fitness function:

$$f = \alpha \left(\sum_{t=1}^{N} \sum_{i=1}^{30} (v_d^{i,t} - 0.2|v_o^{i,t}|) - 0.2 \left| \sum_{t=1}^{N} \sum_{i=1}^{30} v_o^{i,t} \right| \right)$$

where $\alpha = 1/(30N)$, N is the number of groups of 30 repetitions of a command (up, down, left or right), $v_d^{i,t}$ represents the motion in the target direction produced at repetition i in the t-th group of 30, while $v_o^{i,t}$ represents the motion produced in the direction orthogonal to the desired direction.

RESULTS

We report results with 3 participants: A (male, age 25), B (male, age 28) and C (female, age 35). During the phases of acquisition of training and validation sets, the experimenter selected one of the rectangles on the screen as a target, and participants were asked to count the number of flashes of the target. During testing, participants are asked to perform the same task, except the trajectory of the mouse pointer produced by their efforts was also shown. Each run of our experiment involved presenting a full series of 4 flashing rectangles for 30 times. The process was repeated multiple times for each direction. For participant A, 12 runs were recorded while B and C performed 16 runs.
3- and 4-fold cross-validation was used to train the filters and test their performance and generalisation ability. For each participant a total of 12 different classifiers have been evolved.

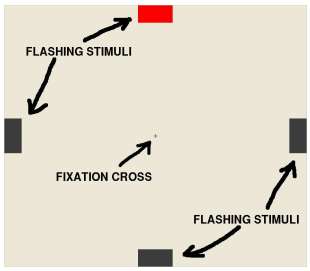

Figure 1: The stimuli used for BCI mouse control.

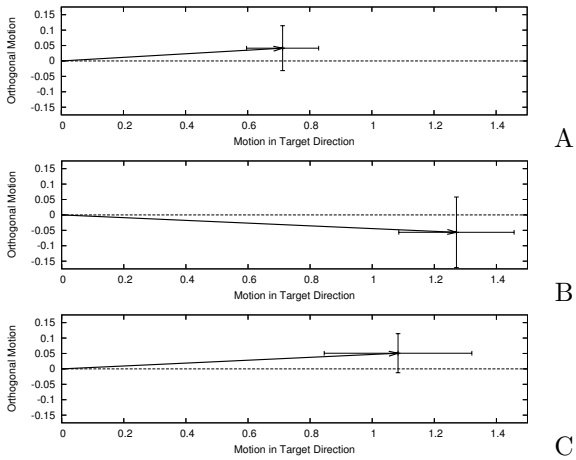

Figure 2: Performance on validation set.

The accuracy results for the validation set are depicted in Figure 2. The arrows represent the average distance travelled in the direction of the target and in a direction orthogonal to the target. The crosses represent standard deviations over the performance of different classifiers. Clearly users were able to move the mouse pointer in the desired direction with only minor inaccuracies.

CONCLUSIONS

In this paper we have proposed a BCI mouse based on the manipulation of P300s. The system is analogue, in that at no point a binary decision is made as to whether or not a P300 was actually produced in response to a particular stimulus. Instead, the motion of the pointer on the screen is controlled by directly combining the amplitudes of the output produced by a filter in the presence of different stimuli. The performance of our BCI mouse is very encouraging. Control in testing was accurate and all participants were able to use the system within 15 minutes of wearing the electrode cap.
The hardest part of the design in this system (i.e., the feature selection and the selection of the order and parameters of the controller) was entirely left to a genetic algorithm. We only provided carefully designed stimuli, a rich set of features (wavelet coefficients) and a simple combination mechanism (a squashed linear filter) through which we thought a solution to the problem of controlling a pointer via EEG could be found.
The GA has been very effective and efficient at finding good designs for the system. Indeed, it succeed in every run, suggesting that we had chosen a good infrastructure and feature set for the system.

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