Analogue P300-based BCI pointing device

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Abstract

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.

1 Introduction

In this paper a P300-based BCI mouse – a system for the two-dimensional control of a pointer on a computer screen – is presented. In building our system we drew inspiration from Donchin Speller [6, 5], where P300s were used to determine on which stimulus, out of a large set of stimuli concurrently presented, an observer's attention was focused. In our BCI mouse, four unobtrusive squares are superimposed on the screen, near its edges, and are used to represent the directions up, right, down and left (see Figure 1). The squares are flashed in random order at 180 ms intervals. To limit the risk of perceptual errors [3], the same rectangle is not allowed to flash twice in a row.

By focusing their attention to one particular square, users produce P300s when the square flashes. The system processes responses and moves the mouse pointer in the appropriate direction. The approach is similar to that used in [1] 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.

At the core of the control system for the mouse is well-established technology. However, 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 [9, 8, 2] and BCI [4].

The system makes it possible for a person having undergone no previous training and within 15 minutes of wearing the electrode cap, to move a pointer to any location of a computer screen.

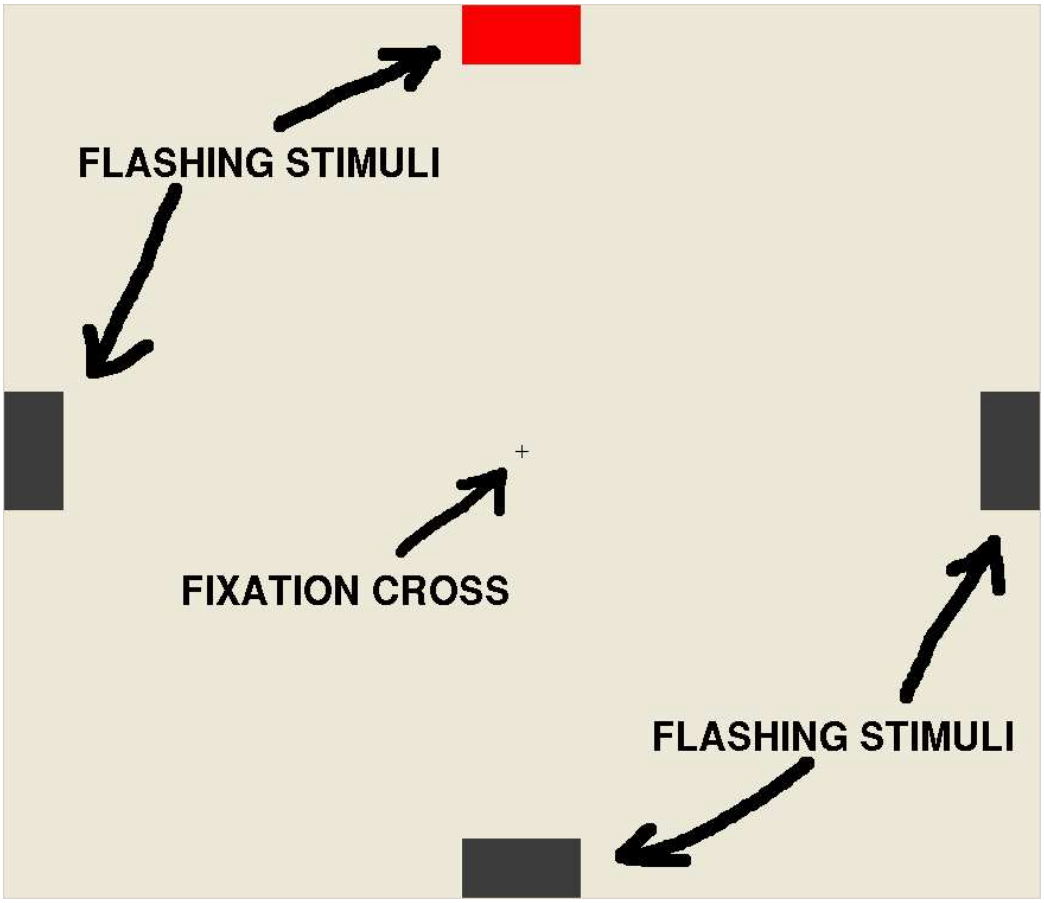


Figure 1: The stimuli used for BCI mouse control.

2 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.

In the presence of large numbers of features, adaptive classifiers tend to have a very hard time, and it is usually necessary to perform some form of selection to identify the most informative features. In this work we take a *wrapper* approach to feature selection [7] where the selection of features and the training of a classifier are performed jointly.

Computer mice are fundamentally analogue devices (the more you move the mouse the more the pointer on the screen moves). 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. Given the limited information available in EEG, we felt that an analogic BCI approach would limit any further losses introduced by the detection process and would offer the potential to use the information present in any analogue variations 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. The horizontal motion of the pointer 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.

This, in principle, allows the full exploitation of all information present in P300s.

To control the motion we used the output of the following filter which combines a subset of elements of the feature matrix $\mathbf{V}$:

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

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.

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. Individuals are selected for mating using tournaments, where the individual with the highest fitness in a group of 3 is declared the winner and is used for breeding. Crossover, which has the purpose of combining the genetic material of two parent individuals to create new individuals, was performed using the blend method where the offspring $(a_1^s, \ldots, a_n^s)$ is obtained, component by component, as $a_i^s = a_i^1 + c_i(a_i^2 - a_i^1)$, where the c_i's are drawn from the interval $[-0.1, 1.1]$. We also used a mutation method which involves performing crossover between a parent individual and a randomly generated individual. Given the complexity of the task we used very large populations including $50,000$ individuals, evolved for 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:

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

where N_r 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.

3 Results

Here we report preliminary 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 for our filter, the experimenter selected one of the rectangles on the screen as a target, and participants were asked to focus their attention only on the target stimulus. To facilitate the task, they were instructed to count the number of flashes of the target. During testing, participants are asked to perform the same task with the same stimuli, except, that at this stage we show participant the trajectory of the mouse pointer produced by their efforts. 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.

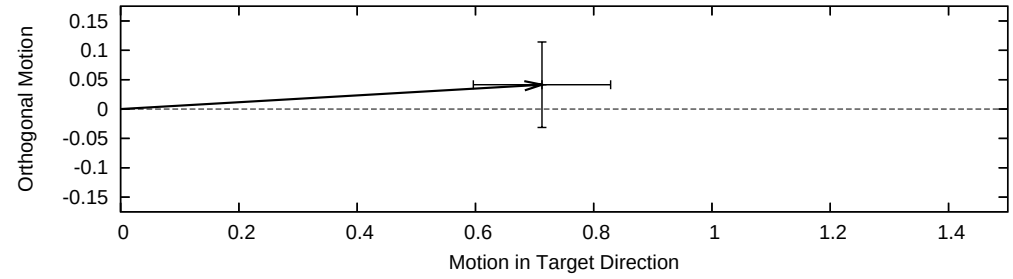
3- and 4-fold cross-validation was used to train the filters and test their performance and generalisation ability. For each participant a total of 12 different classifiers have been evolved.

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, which could easily be corrected by focusing on other stimuli. For reproducibility, corrections, however, were not allowed during validation.

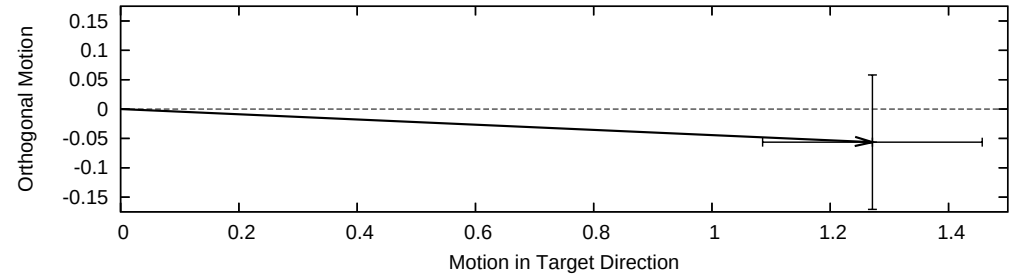
4 Conclusions

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.

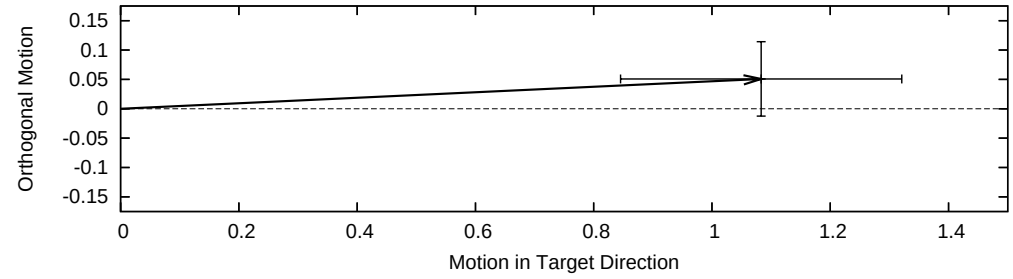
The performance of our BCI mouse is very encouraging. Control in testing was accurate and all participants were able to use the system within 15 minutes of wearing the electrode cap.



A



B



C

Figure 2: Performance on validation set.

Beyond providing 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, we actually did not do any other design. The biggest part of the design in this system (i.e. the feature selection, the selection of the order and parameters of the controller) was entirely left to a genetic algorithm.

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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