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Efficient Adaptive Stimulus Sequencing for Improved P300 Speller Performance

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Abstract. In the quest for ever higher information transfer rates to aid communication through a Brain Computer Interface, an often overlooked method is the adaptation of stimulus sequences based on early acquired data. Consequent stimulations are constrained based on the already obtained information to increase information transfer. We investigate a novel algorithm targeting the ubiquitous P300 speller, although the theory is applicable in many Brain Computer Interface paradigms. The proposed implementation of adaptive stimulation is based on a model of experimental stimulus responses. Simulations show a reduction of required stimuli by 27.4 % compared to a reference P300 speller in selecting a target out of 6 items. The computational efficiency of the algorithm allows scaling to more items, where it shows increasing performance benefits.

Keywords: adaptive algorithm, stimulus sequencing, visual speller, P300 optimization, BCI

1. Introduction

The development of brain computer interfaces is motivated by the prospect of efficient non-muscular communication for people suffering from severe neurodegenerative diseases [Wolpaw et al., 2002]. The P300 speller [Farwell and Donchin, 1988] in particular relies on the interaction between attention and stimulus presentation. A P300 event related potential is observed in the EEG signals of a subject when an item is highlighted while being attended to by the subject [Polich, 2007]. This correlation between attention and detectable EEG changes allows subjects to make a voluntary choices between several sequentially presented items.

Each item selection requires multiple presentations for adequate accuracy. The adaptive algorithm discussed here uses early obtained information to predict beneficial stimuli later in the sequence. This allows a higher information throughput, enabling faster and more accurate use of the speller interface.

2. Materials and Methods

In the P300 speller, the response of each stimulus is classified as belonging to the target class with a certain probability. A belief state is continuously updated during speller use, estimating the probability of each item being a target item:

$$b_{x,n} \sim \prod_{i=1}^{n} \begin{cases} P(+ \mid r_i), & x \in s_i \\ 1 - P(+ \mid r_i), & x \notin s_i \end{cases}, \tag{1}$$

where $b_{x,n}$ is the belief at iteration n if x is the target item, as function of the target probability $P(+ \mid r_i)$ given response r_i and stimulus s_i at iteration i. The item x with highest belief $b_{x,n}$ is selected as the believed target at iteration n.

The proposed algorithm estimates the probability of reaching a future belief state from the current state, assuming a future stimulus. For each combination of a stimulus and an assumed target, either a target– or non-target response is expected. Probability density functions (PDF's) of response probabilities are modeled after experimental data obtained from [Geuze et al., 2012] (20300 classified responses among 10 subjects). These are approximated by Beta distributions, and assumed symmetric between target– and non-target responses. Considering a PDF of future responses, a belief state update yields a PDF of future belief states.

Assuming a desired outcome is one where the believed target matches the assumed target, the probability of a desired future belief state given a future stimulus is described by:

$$P(t_x, b_x \mid s_y) = P(b_x \mid t_x, s_y) \cdot P(t_x \mid s_y), \tag{2}$$

where t_x indicates x being the assumed target, and b_x our belief that x is the target, given s_y, a stimulus of item y. $P(b_x \mid t_x, s_y)$ is the integral of the future belief state PDF for t_x, s_y over the subspace where the belief in item x is

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highest. We assume that the prior probability $P(t_x \mid s_y)$ is uniform. The best future action is the stimulus s_y which maximizes the probability of desired outcomes $\sum_x P(t_x, b_x \mid s_y)$ over all items x.

In implementing this algorithm, several practical issues are taken into account. First of all, there is an observed processing delay of around 4 stimulations (800 ms at a rate of 5 Hz) between presentation of an item and the corresponding belief state update. Furthermore, due to a P300 refractory period [Martens et al., 2009; Polich, 2007], target stimuli within a short period after each other do not evoke as strong a P300 response, and are often incorrectly classified. To minimize inaccurate classification, no repeated stimuli are allowed within a window of 600 ms (3 stimulations).

3. Results

Simulation results stimulating individual items out of 6 total (5000 trials) and 36 total (1000 trials) are shown in Fig. 1, using response Beta distributions with $\alpha = 3.599, \beta = 2.022$ for target responses and inverted for non-target ones.

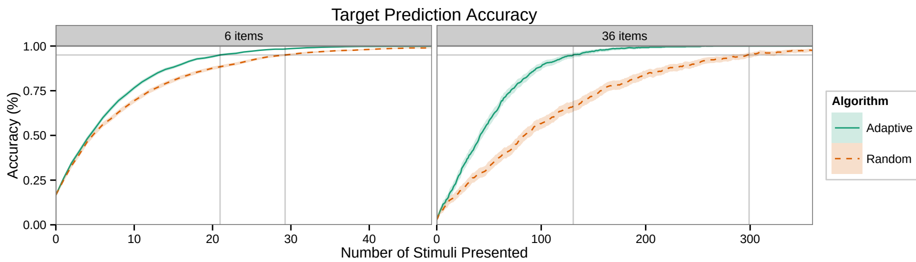

Figure 1: *Accuracy as function of the number of stimuli comparing the adaptive algorithm to the reference random algorithm. Results from a simulation with 6 items and 36 items. 95 % CI indicated as shaded area. Gray lines indicate 95 % accuracy.*

Similar performance is observed for a range of model parameters covering individual subject observations. Additionally, the behavior is not sensitive to inaccuracy in the response model (offset of up to $\pm 2\sigma$ of the inter-subject variation), or to overestimation of the P300 refractory period by up to 400 ms.

4. Discussion

With the current implementation, the required stimuli to attain an accuracy of 95 % are decreased by 27.4 % (95 % CI: 19.9 %–32.4 %) compared to random stimulation with 6 items. Similar improvements are expected using the common 6×6 grid layout [Farwell and Donchin, 1988], where stimuli consist of either rows or columns. When stimulating individual items, relative improvements increase with more items. The algorithm, as implemented in MATLAB and without significant optimization, is able to process 1500 trials per second (6 items) on regular equipment.

An alternative method is proposed by [Park et al., 2011], where partially observable Markov decision processes are used to select the most beneficial future action. Performance is similar to our approach (stimulations at 95 % accuracy compared to random decrease by 22.7 %, 95 % CI: 15.6 %–31.2 %) for the same parameters and constrains (6 items, target response distribution $\alpha = 1.228, \beta = 0.625$). Importantly, our approach does not require pre-computations.

While care has been taken to faithfully reproduce an experimental environment, it is important to experimentally verify the simulation results. [Martens et al., 2009] suggests that P300 refractory effect affects responses even for intervals of over 1 s, therefore it would be beneficial to accurately measure such effects and incorporate them into the response model. This would allow for an accurate handling of the decreased classification accuracy.

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