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Switching Characters between Stimuli improves P300 Speller Accuracy

Thibault Verhoeven, Pieter-Jan Kindermans, Pieter Buteneers and Benjamin Schrauwen

Ghent University, Ghent, Belgium
thibault.verhoeven@ugent.be

Abstract

In this paper, an alternative stimulus presentation paradigm for the P300 speller is introduced. Similar to the checkerboard paradigm it minimizes the occurrence of the two most common causes of spelling errors: adjacency distraction and double flashes. Moreover, in contrast to the checkerboard paradigm, this new stimulus sequence does not increase the time required per stimulus iteration. Our new paradigm is compared to the basic row-column paradigm and the results indicate that, on average, the accuracy is improved.

1 Introduction

The P300 speller, as first described by Farwell & Donchin in [1], is a BCI for spelling text. In the original speller in [1] the six rows and six columns of the grid are highlighted in a random order. The target element is the element on the intersection of the row and the column that elicited a P300 as response when highlighted. A sequence containing every stimulus once is called an 'iteration'. This row-column paradigm (RC) thus has an iteration length of 12 stimuli.

Two common phenomena limit the speller accuracy. In 'adjacency distraction' the patient is distracted by the intensification of a row or column next to the actual target. 'Double flash' (DF) errors occur when the target element is intensified twice in rapid succession. The second P300 wave generated has a lower amplitude [2] which can result in a wrong target selection.

To alleviate these effects, several stimulus sequence paradigms have been examined, for example the checkerboard paradigm [4]. Unfortunately, the improvements to the accuracy were diminished by an increased time required per iteration. New paradigms always seem to make this compromise between accuracy and speed of spelling. The goal of this paper is to present a paradigm that achieves a higher accuracy than RC with a speed of spelling as high as in RC.

In what follows, the new paradigm is explained in detail together with the simulation results. The performance of this paradigm is compared with RC in a first online experiment.

2 The Switching Paradigm

For every character to spell, the new paradigm constructs a pre-determined sequence of stimulus patterns through an optimization algorithm. This algorithm takes a full sequence of stimuli (in this paper: a sequence of 15 iterations constructed by the RC paradigm) as initialisation and tries to reduce the potential causes of spelling errors by swapping the highlighted elements between stimuli. If the initial sequence, for example, contains the subsequence of stimuli S_1-S_2-S_3 in which the sets of characters {A, B, C, D, E, F}, {E, K, Q, W, 3, 9} and {C, I, O, U, 1, 7} are respectively highlighted, there is clearly a DF of character E in the consecutive stimuli S_1 and S_2. Swapping the characters E and U between the stimuli S_2 and S_3 changes the sequence to {A, B, C, D, E, F}-{U, K, Q, W, 3, 9} -{C, I, O, E, 1, 7} and eliminates the DF.

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Double flashes are thus easily avoided by preventing elements to be highlighted twice in rapid succession. Adjacency distraction itself can not be avoided. However, when the target element is simultaneously highlighted with a neighbouring element, the generated P300 wave on this target stimulus is also linked to this neighbour. A single distraction by a following intensification of this neighbour is enough to wrongly select this neighbour as the target. Adjacency distraction errors thus can be partly avoided by preventing an element to be highlighted simultaneously with a neighbouring element in the grid. The subject then needs to be distracted twice to a neighbour before wrong selection, which is less likely to occur. This results in the reported decrease of adjacency distraction errors in the checkerboard paradigm [4].

Not every two elements from every two stimuli can be swapped. If two elements are highlighted in the same set of stimuli in the sequence and these stimuli appear to be target stimuli, then it is impossible to determine which one of the two is the target element. The sequence is said to be 'undecodable'. A swap that does not harm this decodability is a 'legal swap'. Only these swaps will be considered further on.

The algorithm works in two phases. The first phase tries to remove the most severe causes of mistakes, while the second phase optimizes the sequence further on. As each optimization in one phase creates new optimization opportunities in the other, these phases are alternately executed until no more optimizations are found. We allow a maximum of 5 alternate executions to prevent the algorithm from getting stuck in a loop, constantly swapping the same elements.

For every iteration in the sequence separately, every possible pair of stimuli is examined in random order. For every pair of stimuli, every legal swap of highlighted elements between these stimuli is examined in random order. Two criteria are used to verify if the swap is indeed optimizing the sequence. In the first phase these criteria are:

1. For both elements: does the swap reduce the number of DFs? If this number is not altered, does the swap reduce the second order DFs (DFs with one stimulus in between)?

2. For both stimuli: does the swap reduce the number of direct horizontal/vertical neighbouring elements in the grid simultaneously intensified? If this number is not altered, does the swap reduce the number of direct diagonal neighbours?

In the second phase these criteria are:

1. For both elements: does the distance in the sequence to the closest stimulus in which this element is highlighted increase?

2. For both stimuli: is the distance in the grid of the swapped element to the closest highlighted element bigger, i.e. does the spread of highlighted elements in the grid increase?

If at least one of these questions has a strict positive answer and none of the others is strictly negative, then the swap is executed. After considering all legal swaps, the procedure is repeated all over again until no more optimizations are found and the algorithm moves to the next phase.

A total of 500 row-column sequences of 15 iterations each are created and compared to their counterparts after applying the algorithm. The number of target double DFs seen by the subject in a sequence of 15 iterations is shown in the histograms in Figure 1a. On average, 2.71 ($\sigma = 1.49$) double flashes are noticed in a standard RC sequence. After applying the algorithm, this reduces by 98% to only 0.05 ($\sigma = 0.23$) double flashes on average.

The probability of adjacency distraction is reflected in the number of times the subject sees the target being flashed simultaneously with at least one of its direct (horizontal or vertical) neighbours in the grid. In the RC paradigm the target is always flashed with a neighbour. After applying the algorithm only 1.32% of the target intensifications occur together with a neighbour.

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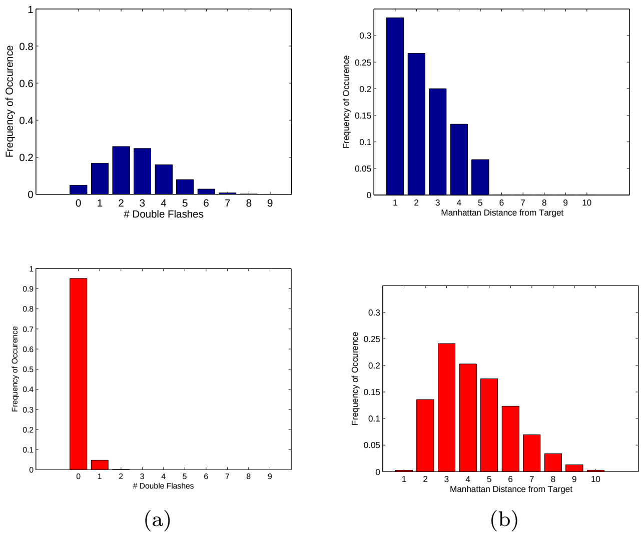

Figure 1: Simulation results. Left: normalized histogram of the number of double flashes seen in the sequence for the RC paradigm (top) and the new paradigm (bottom). Right: normalized histogram of the Manhattan distance in the grid from the target to every other element for RC (top) and the new paradigm (bottom).

Figure 1b gives a histogram of the Manhattan distance in the grid from the target to every other element simultaneously highlighted. After application of the algorithm the highlighted characters are clearly spread more over the grid.

3 Experimental Setup & Online Experiment

After presentation of a stimulus sequence to the subject, the recorded brain signals are preprocessed. A Common Average Reference filter is applied, followed by a bandpass filter with cutoff frequencies 0.5 Hz and 15 Hz. Each EEG channel is normalized to zero mean and unit variance. Dimensionality reduction retains 10 samples per stimulus, centered around the expected time step of the P300 wave and uniformly distributed over the range between $150ms$ and $450ms$ after stimulus onset. Finally, we add a bias term. The stimuli are classified as target/non-target by detecting the presence/absence of a P300 wave in the response. The classifier used in this work is based on the unified probabilistic model proposed by Kindermans et al. in [3].

9 subjects (6 male, 3 female) with an average age of 22.56 ($\sigma = 0.73$) used the original RC paradigm and the switching paradigm (SP) to spell the 36 characters of the grid in random order. Both the order of the characters and the order in which the paradigms are used are altered between subjects. In the calibration procedure, 10 characters are spelled. Calibration is done separately for both paradigms. The stimulus and interstimulus time are 62.5 ms and 125 ms respectively. Every sequence of stimuli contains 15 iterations. Apart from subject 7, the two tests where done on different days. Only subjects 5 and 8 had previous experience with the P300 speller. The Emotiv EPOC headset is used to record the EEG.

The accuracy of the speller is defined as the fraction of characters correctly spelled. Accu-

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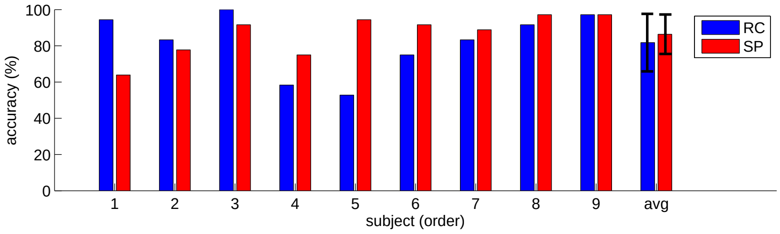

Figure 2: Spelling accuracies obtained with both paradigms for the 9 subjects separately, and their average result. For the first 4 subjects the RC paradigm is used first, for the other 5 SP.

racies for both paradigms can be found in Figure 2. Subject 1 to 4 used the RC paradigm first, the others started with the SP paradigm. A mixed-design ANOVA shows the larger effect of the order in which the paradigms are used ($F_{between-subjects} = 0.81$) compared to the effect of the paradigm itself ($F_{within-subjects} = 0.337$). A possible cause is that, once a subject gets used to a paradigm, it may be harder for him to adapt to a new paradigm. A more thorough examination will be done in the future in which the effect of the order is reduced by letting the subjects get more familiar with the speller and the paradigms before passing on to the actual experiment. The average accuracy over all subjects when using the RC paradigm is 81.79% compared to 86.42% when using SP. This indicates that the newly developed paradigm can potentially achieve a higher accuracy than RC while the time per iteration is still 2.25 s.

4 Conclusion

The first online results with the new paradigm are promising, although not convincing. On average, the accuracy is increased while the iteration length and thus the speed of spelling remain the same. Starting from these pilot tests, extensive testing with real EEG caps will have to show whether the new paradigm significantly improves the accuracy of the classifier.

Acknowledgment

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References

[1] L.A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and clinical Neurophysiology*, 70:510–523, 1988.

[2] C.J. Gonsalvez and J. Polich. P300 amplitude is determined by target-to-target interval. *Psychophysiology*, 39:388–396, 2002.

[3] P. Kindermans, H. Verschore, and B. Schrauwen. A unified probabilistic approach to improve spelling in an event-related potential based brain-computer interface. *ieee transactions on biomedical engineering*, 60(10):2696–2705, 2013.

[4] G. Townsend, B.K. LaPallo, C.B. Boulay, D.J. Krusienski, G.E. Frye, C.K. Hauser, N.E. Schwartz, T.M. Vaughan, J.R. Wolpaw, and E.W. Sellers. A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. *Clinical Neurophysiology*, 121(7):1109–1120, July 2010.