Proceedings of the 6th International Brain-Computer Interface Conference 2014 DOI:10.3217/978-3-85125-378-8-76

Automatic Pause Detection during P300 Web Browsing

A. Pinegger[1], L. Deckert[1], S. Halder[2], J. Faller[1], I. Käthner[2], S. C. Wriessnegger[1], A. Kübler[2] and G. R. Müller-Putz[1]

[1] Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria
[2] Institute of Psychology, University of Würzburg, Würzburg, Germany
a.pinegger@tugraz.at

Abstract

Brain-computer interfaces (BCI) have been investigated for more than 40 years. P300-based BCIs can nowadays control very complex applications such as spelling applications and even web browsers. To do this in a practical way, it is essential to have the possibility to pause the command selection of the BCI. We implemented and evaluated an automatic pause detection system for P300-based BCIs based on artifact detection with an inverse filtering method. Experimental results of an offline study (9 healthy participants) demonstrate the feasibility of the proposed approach and its high performance.

1 Introduction

The electroencephalogram (EEG) can be used to establish a noninvasive communication/control channel between the human brain and a computer, a so-called brain-computer interface (BCI). A very prominent BCI application is the P300 speller [1]. This system enables healthy as well as severely impaired users to communicate [2, 4]. However, a standard P300 speller is designed to work in synchronous mode, i.e., after defined stimulation sequences one item of all selectable items will be selected. This is not an issue as long as the user just wants to write a text without making a pause. However, if the user wants to make a pause during spelling a text or because she/he wants to look at the content of a web page it becomes a substantial problem. A very simple approach to avoid unintended selections is to include a pause element into the spelling matrix. This approach has two main disadvantages: First, you have to select two correct elements to go into and leave the pause mode and second, there is a certain probability that the pause-end element is selected by chance.

In this study, we introduce an automatic pause detection method on the basis of artifact detection with inverse filtering. Originally, the inverse filtering method was introduced in [5] to detect muscle and movement artifacts in the EEG of a sensorimotor rhythm (SMR)-based BCI. The main idea behind our approach is that a user produces more EEG artifacts during a pause than when she/he is actively engaged with the BCI. We use this difference to distinguish between the pause and the control state, i.e., when the user wants to select something.

2 Methods

2.1 Participants, Data Acquisition, and Experimental Design

Ten volunteers participated in this study. All participants stated that they have no history of neurological or psychiatric disorders. Due to a technical problem the data of one participant was not useable for this study. The final sample comprised 9 participants (3 female; mean age

Published by Graz University of Technology Publishing House Article ID 076-1

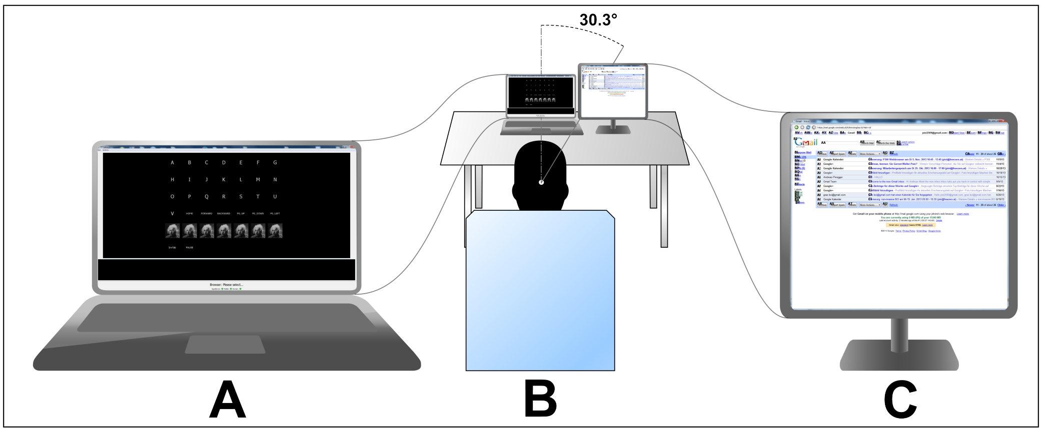

Figure 1: (A) Laptop displaying the user interface for feedback and P300 stimulation. (B) Sketch of the experimental design. The angle between the participant, the laptop, and the monitor was 30.3^o. (C) Monitor for the web browser.

23.9 ± 1.3 years).
EEG was acquired with a wireless EEG amplifier with dry electrodes (g.Nautilus, Guger Technologies OG, Graz, Austria). Signals from Fz, Cz, Pz, PO7, PO8, and Oz were used in this study with a sampling rate of 250 Hz. The channels were referenced to the right mastoid and grounded at the left mastoid. The raw signal of the Wi-Fi headset was filtered with a 0.5–30 Hz bandpass.
The participants were seated in a comfortable chair approximately 65 cm away from two screens (39.5 cm and 43 cm diameter), see Figure 1 (B). One screen was centered in front of the participants. At this screen a P300 matrix was displayed to control a special web browser (see Halder et al., in preparation), which was shown on a second screen placed right beside the first one, see Figure 1 (A) and (C).
The P300 user interface and signal processing in Matlab (MathWorks, Natick, USA) was presented in [3].
Calibration was performed with fifteen highlightings per row and column and ten letters as described in [3]. The online task for the participants was to write an email to a given address and reply to an automatically generated email. The whole task needed a minimum of 52 selections and was aborted if the goal was not reached within 78 regular selections.

2.2 Manual Pause

A “PAUSE/RUN” element was selectable with the matrix. If the user selected this element, no further selections were sent to the web browser until the same element was selected again. The participants had to select the “PAUSE/RUN” element in the study when they were waiting for the reply of the first email and they could select it whenever they needed a pause.

2.3 Automatic Pause Detection

The automatic pause detection was performed on the offline data by detecting artifacts in the EEG during the flashing time periods. The principle of inverse filtering was applied to detect the artifacts, cf. [5]. For this method autoregressive filter model parameters have to be estimated

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out of clean (i.e., artifact free) EEG data. Our assumption was that the participants generated few artifacts during the P300 calibration period. Consequently, we used the data of the P300 calibration to estimate autoregressive filter model parameters (model order $p = 10$) by using the Burg method.
The created filter model was applied inversely to the EEG data of every online task selection. An artifact detection threshold was set to three times the standard deviation of values calculated with this inverse filter from the calibration EEG data. If in more than 1 percent of the online task data artifacts were detected, the selection was marked as pause state related.

3 Results

The participants needed on average 11.8 (SD 2.9) highlighting sequences to select a command. Eight participants completed the task within the maximum allowed value of 78 selections. Only participant S7 did not complete the task. They had an average selection accuracy of 88.7% (SD 9.4) and needed an average time of 63.1 (SD 16.4) minutes including pauses to complete the whole task.

3.1 Manual Pause

Two selections were necessary to go manually into pause mode and leave the pause mode. The time the participants needed to perform these two selections was between 58 and 100 seconds depending on the number of highlighting sequences and the actual number of rows and columns. Seven participants had no problem to switch between pause and control mode. Two participants (S6, S7) needed more than one attempt to leave the pause mode. The probability that the pause mode was left by chance was $1/N$ with N being the actual number of matrix elements. This occurred once (S7) in this study.

3.2 Automatic Pause Detection

Participant	All Selections[a]	Pause Detection TP	TN	FP	FN	TPR	TNR	Cohen's κ
S1	61	5 (6)	52	4 (3)	0	100.0%	92.9%	0.68
S2	62	7 (7)	46	9 (9)	0	100.0%	83.6%	0.54
S3	61	3 (5)	56	2 (0)	0	100.0%	96.6%	0.73
S4	66	2 (2)	63	1 (1)	0	100.0%	98.4%	0.79
S5	93	26 (29)	63	4 (1)	0	100.0%	94.0%	0.90
S6	101	8 (9)	92	1 (0)	0	100.0%	98.9%	0.94
S7	94	9 (12)	74	6 (3)	5	64.3%	92.5%	0.55
S8	73	10 (12)	60	3 (1)	0	100.0%	95.2%	0.85
S9	64	6 (6)	64	0 (0)	0	100.0%	100.0%	1.00

[a] incl. selections during pause.

Table 1: Automatic pause state detection results. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) detections as well as the true positive rate (TPR) and the true negative rate (TNR) are presented for every subject. Values in parentheses indicate prevented wrong item selections during the control state. Cohen's Kappa was calculated to give a measure of agreement.

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In Table 1 the offline simulation results of the automatic pause detection are shown. The number of selections of some participants was higher than 78 because selections during the pause were also counted for evaluation. The sensitivity (TPR) of the automatic pause detection was 100 % for eight participants and 64.3 % for one participant. Consequently, the overall mean TPR was 96.0% (SD: 11.9). The specificity (TNR) was between 83.6 % and 100% with a mean of 94.7 % (SD: 4.9). At eight participants no false negative (FN) detections were made, see 6^{th} column in Table 1. This is very important because false negative detections would result in unintended, random selections. The measured Cohen's Kappas for our results were between 0.54 and 1.00, indicating moderate to strong agreement.

4 Discussion

In this study we provide evidence that our suggested automatic pause detection method works comparable to the manual pause selection method without its disadvantages.
The introduced automatic pause detection method detected the pause state with 100% accuracy at eight participants and the control state with an accuracy between 83.64% and 100%. Unintended selections in the pause state are almost non-existent and the number of prevented selections in the control state is low and acceptable. Considering the prevented wrong selections during the voluntary control periods by the automatic pause detection the number of wrong classifications would be even lower (numbers in parentheses beside the TPs and FPs in Table 1). In conclusion, this study shows that detecting artifacts in a P300-based BCI can be used as a very reliable and effective automatic P300 pause state detection method.

Acknowledgments

This work is supported by the FP7 research project BackHome (No. 288566). This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.

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