Classification of error-related potentials in EEG during continuous feedback

Conference Paper · September 2014

DOI: 10.3217/978-3-85125-378-8-6

4 authors:

Martin Spüler
Hain Lifescience GmbH

Christian Laßmann
University of Tuebingen

Wolfgang Rosenstiel
University of Tuebingen

Martin Bogdan
University of Leipzig

 DOI:10.3217/978-3-85125-378-8-6

Classification of error-related potentials in EEG during continuous feedback

Martin Spüler[1], Christian Niethammer[1], Wolfgang Rosenstiel[1] and Martin Bogdan[1,2]

[1] Wilhelm-Schickard-Institute for Computer Science, University of Tübingen, Tübingen, Germany
[2] Computer Engineering Department, University of Leipzig, Leipzig, Germany

Abstract

When a Brain-Computer Interface (BCI) delivers erroneous feedback, an error-related potential (ErrP) can be measured as response of the user recognizing that error. Classification of ErrPs has been previously used in BCIs with time-discrete feedback to correct errors or to improve adaptation of the classifier for more robust BCI feedback. In this study we investigated if ErrPs can be measured in electroencephalography (EEG) recordings during continuous feedback and if ErrPs can be classified. We recorded EEG data from 10 subjects during a video game task and investigated two different types of error (execution error, due to inaccurate feedback; outcome error, due to not achieving the goal of an action). ErrPs could be measured in the EEG for both types of errors and we were able to classify both types of errors using a Support Vector Machine (SVM).

1 Introduction

If a subject makes or perceives an error, an error-related potential (ErrP) can be detected in the EEG due to the subject recognizing the error [1]. That an ErrP can also be detected when a Brain-Computer Interface (BCI) delivers erroneous feedback has been shown in several publications and it has further been shown that the detection of ErrPs can be utilized to correct errors [2, 3] or improve adaptation of the BCI [4, 5]. For the analysis of ErrPs it is necessary to have stimulus-locked data and therefore the previous studies have only investigated time-discrete feedback, in which feedback is given once at the end of a trial.

Kreilinger et al. [6] studied ErrPs during continuous arm movement and tried to classify ErrPs by mapping the continuous feedback to time-discrete feedback and additionally displaying the discrete feedback. That a discretisation of the feedback is not needed was shown by Milekovic et al. [7] in a study using Electrocorticography (ECoG) instead of EEG. They could show that an error-related response during continuous feedback can be observed in the ECoG signal and also classified [8]. For this paper we evaluated if ErrPs can also be measured in the EEG during only continuous feedback and if two different types of errors can be discriminated.

2 Methods

2.1 Task description

The experimental task was similar to the one described by Milekovic et al. [7] in which the subject had to play a simple video game. The subject used the thumbstick of a gamepad to control the angle in which the cursor on the screen moved. The task was to avoid collisions of the cursor with blocks dropping from the top of the screen with a constant speed. The speed of the falling blocks was set to a level that the game was challenging and the player collided with a

 DOI:10.3217/978-3-85125-378-8-6

block from time to time. In case of a collision, the game resumed for 1 second and then stopped. The delay of 1 second was introduced to make sure that the reaction measured in the EEG originates from the subject recognizing the collision (outcome error) and not from the game stopping or restarting. To study the execution error, which is happening when the interface delivers erroneous feedback, the angle of the cursor movement was modified for the duration of 2 seconds. The degree of modification was randomized (45 °, 90 °, 180 ° to either the left or the right side). The time between two execution errors was randomized to be between 5 and 8 seconds.

2.2 Experimental setup

10 healthy subjects (mean age: 24.1 ±1.1 years) were recruited for this study. EEG was measured with two g.tec g.USBamp amplifiers and a Brainproducts Acticap System. 29 electrodes were placed on the scalp of the subject to measure EEG, while 3 electrodes where placed below the outer canthi of the eye and above the nasion for electrooculogram (EOG) recordings. The data was recorded with a sampling rate of 512 Hz and a 50 Hz notch filter was applied to filter out power line noise, as well as an additional bandpass filter between 0.5 Hz and 60 Hz. The position of the thumbstick as well as information about outcome or execution errors was transmitted to the recording software using the parallel port of the computer.

2.3 Signal processing and classification

The data was segmented into different trials with a length of 1 second: execution errors, time-locked to the start of an angle modification; outcome errors, time-locked to the collision event; and noError trials, where neither a collision nor an angle modification has happened during the trial or in the 1 second before or after the trial. For each subject about 1 hour of EEG was recorded resulting on average in 597 ±22 execution errors, 86 ±30 outcome errors and 475 ±39 noError trials.

An EOG-based regression method was used to reduce the effect of eye artifacts. To estimate classification accuracies we used a 10-fold cross-validation. For classification we used a Support Vector Machine (SVM) with a linear kernel. For all channels the samples in the time range 0.2 s to 0.9 s were used for classifiation and the signal was rereferenced to the common average. To investigate how well the error can be classified, outcome error and execution error, respectively, were classified against noError trials. To see if the two types of errors can be discriminated, we also classified execution errors against outcome errors. Since the number of trials were different for each class, the dataset was balanced to obtain an even amount of trials for each class.

To test if the subject's movements (due to gamepad control) or eye movements influence classification, classification was also done on the EOG data and on the recorded position of the thumbstick.

3 Results

Averaged over all subjects, execution errors and noError trials could be classified with an average accuracy of 65.0 % based on EEG, 50.9 % based on EOG and 52.5 % based on the thumbstick position. For outcome error against noError trials, average accuracies of 73.9 % (EEG), 54.9 % (EOG) and 56.0 % (thumbstick) could be reached. For the classification of the two error types, execution error and outcome error, we obtained average accuracies of 75.3 % (EEG), 56.4 % (EOG) and 55.3 % (thumbstick). Detailed results of the classification on the EEG data is shown

 DOI:10.3217/978-3-85125-378-8-6

in table 1. For the classification results of the EEG data we performed a permutation test (1200 permutations) to test for significance and all EEG results were found to be significantly above chance level.

Table 1: Classification accuracies based on EEG data obtained by 10-fold cross-validation. Classes were balanced and therefore the chance level is at 50 %. All results are significantly above chance level.

subject	Execution vs. Outcome	Outcome vs. noError	Execution vs. noError
S01	77.9 %	74.4 %	69.7 %
S02	76.3 %	78.5 %	65.4 %
S03	69.6 %	68.2 %	59.9 %
S04	72.1 %	75.0 %	60.1 %
S05	70.2 %	60.3 %	64.3 %
S06	67.7 %	76.5 %	63.4 %
S07	73.6 %	76.3 %	62.8 %
S08	85.0 %	80.4 %	68.6 %
S09	78.1 %	71.3 %	64.5 %
S10	82.1 %	78.0 %	71.2 %
mean	75.3 %	73.9 %	65.0 %

Figure 1 shows the average waveform of the execution error at electrode Cz for all subjects as well as the topographic distribution of the potential. Although the waveform of the two error potentials differed strongly, the topographic distribution was very similar for both errors and all subjects with the maximum around electrode FCz and Cz.

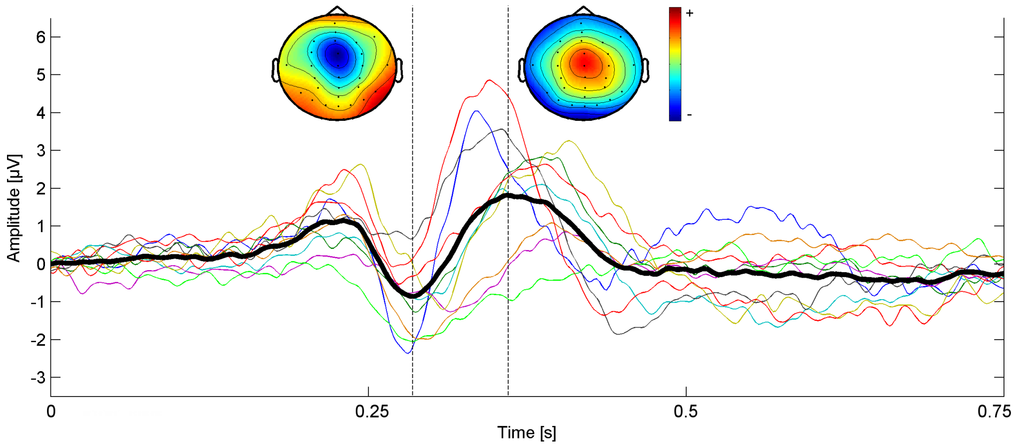

Figure 1: Execution error-related potential at electrode Cz. The colored lines depict the ErrP for the different subjects, while the bold black line is the average over all subjects. The topographic distribution of the potential averaged over all subjects at 285 ms and 360 ms is shown at the top. For display of the ErrPs, the difference between the error trials and noError trials was calculated.

Since the angle of the movement was randomly modified with different degrees, we also tested if execution errors with a different degree can be classified, e.g. 45 ° against 180 °, but did not achieve significant results.

4 Discussion and Conclusion

In this study we could show that ErrPs can be measured in the EEG, due to an erroneous response during continuous feedback. While we have further shown that two different types of errors can be discriminated in EEG (outcome error vs. execution error), we could not detect the severity of an execution error (e.g. 45 ° or 180 °). When looking at the shape and topographic distribution of the execution error, it is similar to the results of earlier studies [2, 6], thereby showing that classification is based on an electrophysiological response and not on artifacts. This is supported by the lower classification accuracies obtained on EOG and gamepad data, which are not significantly above chance level for most subjects.

Although we were able to classify both types of error, the classification accuracy needs to be improved to be useable for adaptation or error correction in a BCI application. Therefore it needs to be tested if the power spectrum of the EEG yields additional information to classify those ErrPs. While we could show that ErrPs are elicited during continuous feedback and we are able to classify them based on the EEG, the classification itself is still event-locked and it needs to be tested in a further study how well classification works if it is done continuous [8].

Acknowledgements

The authors would like to thank Johannes Anufrienko for programming the experimental task. This study was funded by by the German Federal Ministry of Education and Research (BMBF, BFNT F*T, Grant UTü 01 GQ 0831) and the *Deutsche Forschungsgemeinschaft* (DFG, Grant RO 1030/15-1, KOMEG).

References

[1] Pierre W Ferrez and José del R Millan. Error-related eeg potentials generated during simulated brain–computer interaction. *Biomedical Engineering, IEEE Transactions on*, 55(3):923–929, 2008.

[2] Martin Spüler, Michael Bensch, Sonja Kleih, Wolfgang Rosenstiel, Martin Bogdan, and Andrea Kübler. Online use of error-related potentials in healthy users and people with severe motor impairment increases performance of a P300-BCI. *Clinical Neurophysiology*, 123(7):1328–1337, 2012.

[3] Nico M Schmidt, Benjamin Blankertz, and Matthias S Treder. Online detection of error-related potentials boosts the performance of mental typewriters. *BMC neuroscience*, 13(1):19, 2012.

[4] Martin Spüler, Wolfgang Rosenstiel, and Martin Bogdan. Online adaptation of a c-VEP Brain-Computer Interface (BCI) based on Error-related potentials and unsupervised learning. *PloS one*, 7(12):e51077, 2012.

[5] Alberto Llera, Marcel AJ van Gerven, Vicenç Gómez, Ole Jensen, and Hilbert J Kappen. On the use of interaction error potentials for adaptive brain computer interfaces. *Neural Networks*, 24(10):1120–1127, 2011.

[6] Alex Kreilinger, Christa Neuper, and Gernot R Müller-Putz. Error potential detection during continuous movement of an artificial arm controlled by brain–computer interface. *Medical & biological engineering & computing*, 50(3):223–230, 2012.

[7] Tomislav Milekovic, Tonio Ball, Andreas Schulze-Bonhage, Ad Aertsen, and Carsten Mehring. Error-related electrocorticographic activity in humans during continuous movements. *Journal of neural engineering*, 9(2):026007, 2012.

[8] Tomislav Milekovic, Tonio Ball, Andreas Schulze-Bonhage, Ad Aertsen, and Carsten Mehring. Detection of Error Related Neuronal Responses Recorded by Electrocorticography in Humans during Continuous Movements. *PLoS ONE*, 8(2):e55235, 02 2013.