Detection of Error Potentials during a Car-Game with Combined Continuous and Discrete Feedback

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Abstract

This work describes an experiment designed to use continuous feedback in terms of a car game with additional discrete feedback to record error potentials (ErrPs). The game feedback allowed free movement of a car from the left to the right side of a street while moving forward with constant speed. Randomly appearing coins and barriers were required to be picked up or avoided. In case of successful collections or unwanted collisions visual and acoustic signals were presented as discrete feedback. An offline analysis was conducted to evaluate time periods after these discrete feedback events to investigate ErrPs after collisions with barriers. The found detection rates were above chance level for most of the subjects.

1 Introduction

Error potentials (ErrPs) [1], specifically interaction ErrPs [2], provide a promising possibility to increase the performance of brain-computer interfaces (BCIs). By detecting specific reactions to errors that differ from reactions to correct events, false actions can be inhibited and therefore the accuracy of BCI-driven systems can be increased. If an ErrP classifier detects a possibly false reaction it allows users to redo commands instead of picking another command automatically. Several studies already mentioned the technical capabilities of error correction for various paradigms [3, 2]. The paradigms used in these experiments have in common that they are designed to work well for ErrP processing, i.e., due to a discrete setup of the feedback ErrPs can be detected easily by evaluating time periods following discrete events. This study aimed to show that ErrPs can also be recorded during continuous feedback which might be useful in real-life applications. The difficulty here is, however, that ErrPs are time- and phase-locked, i.e., they need specific discrete events to facilitate detection. Also, processing of errors needs definite triggers to know when to look for eventual errors. The study introduced here is a follow-up to [4] where a continuous feedback was already coupled with additional discrete events and ErrPs were successfully found in offline analysis. However, the accuracy for single trial detection of these ErrPs was not enough to be feasible in online applications.

A new paradigm was designed to find a better solution for the integration of ErrPs into online, continuous feedback. A game-like feedback, controlled with motor imagery (MI) [5], was set up to deliver information about the current state in two ways: (i) continuously by a movable car; (ii) discretely by applying distinct flashes/sounds in case of encounters with objects. The main goal of the study was to show that ErrPs could be evoked after presentation of negative discrete feedback after collision with a barrier on top of the constantly active continuous feedback. Another interesting point was whether the modality of the feedback type for discrete events has a positive or negative effect on the evoked ErrPs. Therefore, half of the conducted runs were recorded with visual and acoustic discrete feedback whereas the other half was only using the visual kind.

2 Methods

2.1 Subjects, Hardware, and Recording

Five female and five male subjects (24.9±2.3 years) participated in the study. Data was recorded with two g.USBamps (Guger Technologies OEG, Graz, Austria). The 32 Ag/AgCl-electrodes were placed on the scalp of the subjects following the international 10-20 system. Therefore, all of the important regions for MI (C3, Cz, C4) and ErrP detection (the area over the anterior cingulate cortex (ACC) [6] at channels Fz and Cz) were covered. All channels were recorded monopolarly with a reference electrode at the left mastoid. The ground electrode was mounted on the right mastoid. The sample rate was set to 512 Hz with a high-pass filter at 0.5 Hz, a low-pass filter at 100 Hz, and a notch filter at 50 Hz.

2.2 Experiment Setup

The first part of the experiment consisted of two training runs with the standard Graz-BCI paradigm [5] where subjects were asked to perform MI of the two required classes (right hand vs. both feet), in total 40 trials per class. The low number of trials was possible because all subjects, minus one exception, had previous experience in MI BCI. The person without experience was asked to perform 80 trials per class. ERD/S maps [7] were calculated after common average reference (CAR) was applied on channels C3, Cz, and C4. According to these maps, features (band powers in frequency bands of the three channels) were selected manually to generate a classifier based on linear discriminant analysis (LDA).
The second part consisted of six runs with 20 trials left versus 20 trials right. The LDA classifier was constantly active, letting the subjects move the car all the time. However, actual control of the car was only required when coins were able to be collected on either one side of the street. During every trial four coins could be collected, accompanied by exactly the same number of barriers on the opposite side. Both objects appeared in intervals of one second. In total, a trial lasted 10 s from the appearance of a starting line to the collection of the last object. This setup allowed a maximum collection of 960 coins after all six runs. Half of the runs were recorded with sound (short beeps with different frequencies) and visual (increased size and change of color of the car) feedback combined, the other half used only visual feedback. The discrete feedback events were chosen to be neutral for coin and barrier collisions: instead of linking a bright/positive flashing color and an encouraging sound to coins, the sounds and flashes were merely depending on the side of the street where the current collision occurred.

2.3 Analysis

For offline analysis all channels were spatially filtered with CAR and a bandpass between 0.5 and 8 Hz was applied. Only data within a one-second window following discrete events (collisions with coins and barriers) was evaluated. Here, the data was split into two different classes, the time windows containing either reactions to correct events or to errors. A 10x10 crossvalidation was applied to test the classification accuracy. For each crossvalidation cycle, features were selected with a discriminant power algorithm.

3 Results

3.1 Motor Imagery BCI

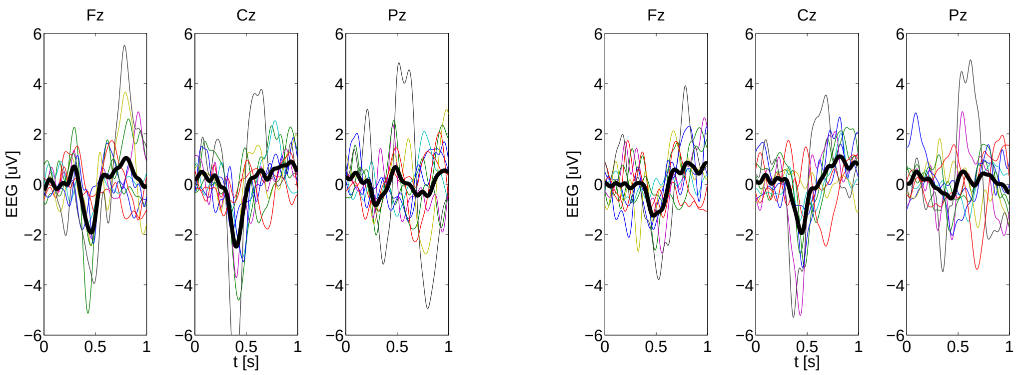
Online performance was measured in terms of scoring points. The score was increased by collecting a coin and reduced after collisions with barriers. Subjects could also miss coins within trials; in this case the score was not altered and neither a positive nor a positive feedback occurred. Further, a negative score was not possible. Table 1 shows the performance for each participant.

Subject	Total Score	Coins:Barriers	Subject	Total Score	Coins:Barriers
S1	409	599:192	S6	202	489:310
S2	718	782:65	S7	703	774:72
S3	588	709:127	S8	751	823:72
S4	189	367:185	S9	100	404:349
S5	722	797:75	S10	265	541:302

Table 1: Online performance in terms of total score out of 960 maximum points and coin:barrier collection rate for each participant which is also the correct:erroneous trial rate for ErrP analysis.

3.2 Error Potential Detection

The performance depending occurrences of errors evoked differently strong ErrPs for the 10 subjects. The error-minus-correct waveform for all the participants can be observed in Figure 1. Three channels, Fz, Cz, and Pz, are shown for the two different modalities 'Sound' and 'No Sound'. The greatest effect is visible over Fz and Cz, the channels directly over the ACC. On average there is a measurable negativity about 400 ms after the moment of a collision with a barrier (event of an error). An offline analysis of the recorded data yielded detection rates for correct and erroneous



(a) Sound

(b) No Sound

Figure 1: Recorded ErrPs for all individual subjects and averaged waveforms, shown specifically for 'Sound' and 'No Sound' modality. Here, point in time zero is the time of the collision with an object on the street. Three subplots demonstrate the measured ErrPs on three different channel locations: Fz, Cz, and Pz.

trials above random for all subjects except S10 in at least one modality ('Sound','No Sound', or all trials combined). The chance level was on average 53 % (all trials combined), 54.4 % ('Sound'), and 54.3 % ('No Sound') according to [8]. The particular values can be seen in Table 2. Feature extraction and cross validation was performed individually for each modality. The comparison of detection rates for feedback with and without sound brought forth following results: the average accuracy for correct detections of correct and erroneous trials was 61.4 % for the two modalities combined, 61.9 % for only runs with sound, and 59.2 % for runs without sound feedback. A performed t-test showed no significant differences in terms of timing and shape of the waveforms.

4 Discussion & Conclusion

The measured ErrPs were different to the interaction ErrPs described in [2] (with a negative peak followed by a positive and another negative peak) but showed an error-related negativity (ERN) about 400 ms after objects were picked up. Addition of sound feedback had a beneficial effect for 7 out of 10 subjects when compared to trials with only visual feedback but did not alter the resulting

Subject	Accuracy [%]			Subject	Accuracy [%]		
	Sound	No Sound	Combined		Sound	No Sound	Combined
S1	64.3	61.1	60.2	S6	59.4	56.0	52.8
S2	75.8	66.5	71.1	S7	79.2	68.7	76.0
S3	56.0	51.1	54.0	S8	58.1	61.0	64.6
S4	64.5	55.6	59.4	S9	53.1	59.8	57.7
S5	56.3	60.7	63.7	S10	52.3	51.6	54.0

Table 2: Offline detection rates for correct and erroneous trials. The results for 'Sound', 'No Sound', and 'Combined' are shown to demonstrate the difference between the feedback modalities.

waveform of the ErrPs significantly. Considering that the paradigm was not optimized to trigger ErrPs, e.g., by giving only discrete feedback and artificially setting a fixed error rate of 20 %, it was still possible to find the ERN after collisions with barriers. Still, for future experiments it will be necessary to find a practical compromise of optimization and applicable feedback systems. A feasible daily life application for the type of feedback used in the study would be to present discrete feedback during continuous states. As an example, users could control a wheelchair continuously but during particular states (e.g., moving forward, turning left/right) visual and/or acoustic events could be added to inform about the current state. Events during unintended states could then be used to evoke ErrPs and alter decisions that can support moving to another state which should be the initially intended one.

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