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Asynchronous detection of error potentials

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Abstract

Recent developments in brain-machine interfaces (BMIs) have proposed the use of error-related potentials as cognitive signal that can provide feedback to control devices or to teach them how to solve a task. Due to the nature of these signals, all the proposed error-based BMIs use discrete tasks to classify a signal as correct or incorrect under the assumption that the response is time-locked to a known event. However, during the continuous operation of a robotic device, the occurrence of an error is not known a priori and thus it is required to be constantly classifying. Here, we present an experimental protocol that allows to train a decoder and detect errors in single trial using a sliding window.

1 Introduction

EEG-measured error-related potentials (ErrPs) are one class of event-related potential (ERP) elicited in the user brain when the outcome of an event differs from the user expected one. These potentials have been observed, in particular, when a user observes a machine committing incorrect actions or operations. Recent works have proposed the incorporation of these signals into brain-machine interfaces (BMI) to correct the classifier or as rewards to control or to teach devices [5]. As with all event-related potentials, the neural response associated to ErrPs is triggered in response to an exogenous event. Consequently, most of the developed works try to distinguish whether an action is correct or erroneous based on the knowledge of the time of its occurrence[1, 4]. On the other hand, real applications (such as executing a trajectory with a robotic arm or a mobile robot) imply the use of continuous actions where the classifier has to asynchronously differentiate between erroneous events and the background EEG.

This works presents a method to detect error potentials during the continuous operation of a device. Showing that using events introduced as abrupt changes of direction, it is possible to train a classifier to later on asynchronously classify among a complete trajectory achieving detection rates comparable to those obtained in discrete tasks.

2 Methods

2.1 Experimental Protocol

Two healthy subjects (mean age 28 years) participated in the study. The experimental setup consisted of a virtual cursor that had to reach a target position by moving at a fixed speed towards it. The initial cursor and target positions of each trial were randomly generated. One trial consisted of a trajectory performed by the device and lasted between 3 and 5 seconds. Trajectories were correct in 70% of the trials, which consisted in a straight line between the start and goal locations, Figure 1a. The remaining 30% of the trials were erroneous trajectories that started as the correct ones but executed an abrupt change of direction in a random instant between the 20% and 80% of the path, Figure 1b. Six rounds composed of 40 trials each were recorded, obtaining around 70 erroneous and 170 correct trials per participant.

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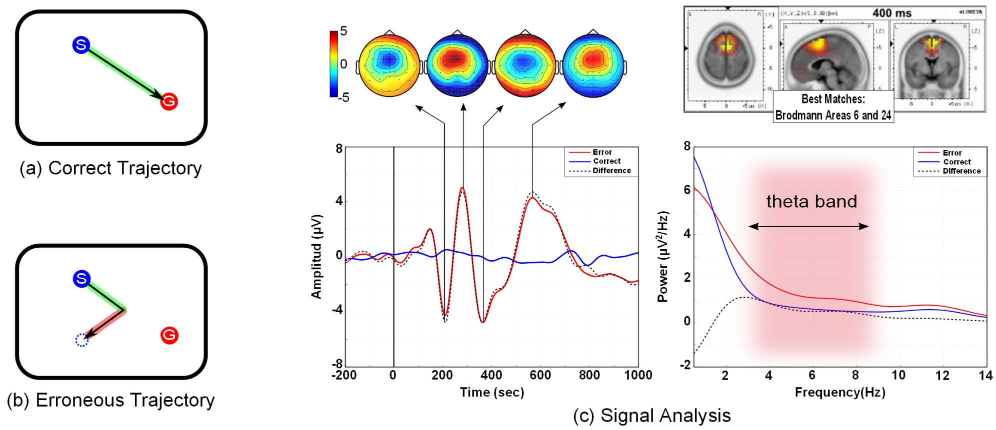

Figure 1: (a-b) Designed experimental setup. Starting (S) and goal (G) positions of the device are marked in blue and red respectively. Correct and wrong directions of movements are shadowed in green and red respectively. (c) Neurophysiology Analysis: grand averages in temporal (bottom,left) and frequency (bottom,right) domain, topographical representation (top,left) and source localization(top,right).

EEG and EOG activity were recorded at 256 Hz using a gTec system with 32 electrodes according to the 10/20 international system (including 8 fronto-central channels), with the ground on FPz and the reference on the left earlobe; for the EOG, 6 monopolar electrodes were recorded [3], with the ground on FPz and the reference on the left mastoid. Recorded data were power-line notch filtered, and band-pass filtered at $[1, 10]$ Hz. The EEG was also common-average-reference (CAR) filtered. Additionally, EOG was removed from the EEG using a regression algorithm, and those trajectories where EOG magnitude higher than 40 μV was detected, were rejected.

2.2 Single-trial continuous classification

Temporal domain features have been widely used to detect ErrPs under discrete tasks. However, for continuous detection, temporal features result in a large number of false positives as EEG oscillations resemble ErrP patterns. On the other hand, it has been shown that frequency features can be more robust under specific changes in the ErrP signals [7]. In this work, we propose the combination of temporal and frequency features extracted from the most relevant common spatial patterns associated (CSPs) for the continuous detection of ErrPs. To train a classifier, the onset of the erroneous events was selected at the instant in which the device performed the abrupt change of direction. On the other hand, onsets of correct trials were selected at random instants of time within the execution of a correct trajectory. Training data from error and correct conditions was used to extract the CSPs, and the two first CSPs were retained. For each retained CSP, the temporal features were the EEG voltages within a time window of $[0, 1000]$ ms downsampled to 64 Hz, forming a vector of 128 features. The power spectral density (PSD) was computed taking a window interval from 0 to 1000 ms as it gave the best trade-off between frequency resolution and capturing the signal of interest. Frequency features were selected as the power values of each channel from the theta band ($[4, 8]$ Hz) $\pm$ 1 Hz [2] leading to a vector of 14 features. Finally, both set of features were concatenated and normalized within the range $[0, 1]$.

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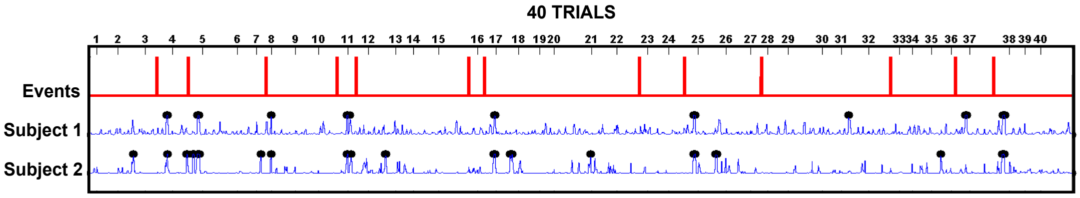

Figure 2: Representative example of the sliding window results. The error events are plotted as red spikes indicating a change in direction, while the probability of detecting an error (p_e) for each of the 2 subjects is plotted in blue. Black dots over the probability values indicate the time instant when the classifier detected an error ($p_e > 0.8$).

After balancing the error and correct datasets, a RBF-SVM was trained using the previous features [6]. During classification, we retained the classifier output for each window evaluation as the probability estimate that the current EEG was an error, p_e. For the asynchronous classification we performed a 6-fold cross-validation where each fold was composed by a complete recorded round. We continuously classified every 62.50ms over the testing set using a sliding window of one-second width. To ensure a low false positive rate, the detection of error events was only considered when $p_e > 0.8$, value selected through cross-validation. For the sliding window, all inter-trial data was removed. Classification performance was computed as follows: the erroneous trials where the classifier detected an error, in a one second window after the direction change, were considered as true positives. When an error was not detected the trial was a false negative. True negatives were those correct trials where no error was detected. And, when an error was detected on correct trials, they were considered false positives.

3 Results

Figure 1(c) shows the error, correct and difference grand averages for channel FCz averaged for the two subjects in temporal and frequency domain, next to topographic interpolation of 4 representative peaks and the source localization for the most prominent negative deflection. Regarding to the results of applying the sliding window, Figure 2 displays the detection level obtained for both subjects in a representative round of the experimental condition. Here, the 40 trials that compose the round are concatenated removing the inter-trial resting periods. It can be seen that most of the trials are properly classified. Also notice that the correctly detected ErrPs are delayed with respect the onset of the event. This delay was on average 867.13 ± 99.33 ms after the onset of the erroneous action, corresponding to the time needed for the appearance of the most relevant peaks and the maximum spectral power activation used as features.

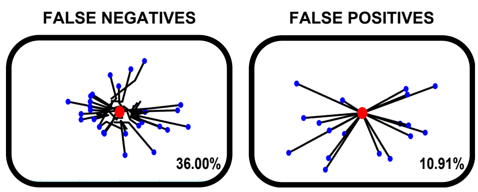

Figure 3: Trajectories of false positives and false negatives reprojected to have the goal at center of the image (red dot). The starting position is marked in blue.

The performance rates achieved for the entire test set reached an 89.09% of true negative and 64% of true positives. At the same time, the number of false positives and false negatives hovered the 11% and 36% respectively. On average, these values were around 10% less performance

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than those obtained with standard ErrP protocols that only classify in the window of the event [1]. This decay is reasonable considering that classifying with a sliding window conveys a higher chance of detecting a false positive during non event intervals. Trajectories executed by the device according to their classification as false positives or false negatives are depicted in Figure 3. Furthermore, it can be seen that correct trials are mostly well detected independently of the direction and distance covered by the device, and only few of them are detected as erroneous. However, the number of erroneous trials not detected was higher, since it was preferable to miss the detection of an error than detect errors where was not intended. Also, notice that most of the true negatives ended up very close to the goal. Indeed, 40% of them ended less than 50 pixels from it, which lead us to think that the subjects may have not interpreted them as erroneous.

4 Conclusions and future work

This paper studies the on-line asynchronous detection of error potentials during continuous trajectories. The results obtained for the proposed experimental protocol show that the error potentials appear when the user monitors a continuous target reaching task and that they can be detected in single trial using a sliding window, obtaining results comparable to those achieved in discrete tasks. These promising results are a first step towards the use of this type of cognitive information to control or teach robotic devices in realistic and complex tasks. There exist several opportunities for future work. Currently, we are extending the study to more users and more types of trajectories containing errors. Also we are testing the usage of this kind of events on real devices obtaining promising results.

5 Acknowledgments

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