Error Potentials for Brain-Computer Interfaces

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Abstract. The idea to use EEG correlates of errors to correct or reinforce BCI operation has been proposed over a decade ago. Since then a body of evidence has corroborated this approach. In this paper we give an overview of our recent work exploring the possibilities of error-potential applications, involving removing constraints of laboratory paradigms to increase "real-life" validity, and investigating EEG feature-spaces to increase detection robustness.

Keywords: EEG, Error-Related Potentials, Connectivity Analysis, Self-Paced Movements, Driving Simulator

1. Introduction

Non-invasive BCIs recognize user's intentions from EEG features. Mis-classification results in an erroneous command being executed by the BCI. The user's perceptions of such errors have, in turn, their own EEG correlates (error-related potentials, ErrPs). The simple, but ingenious idea to use such ErrPs to correct or reinforce BCI operation has been proposed more than a decade ago [Schalk et al., 2000]. Since then a body of evidence has accumulated, demonstrating the feasibility and usefulness of this approach [e.g. Schmidt et al., 2012]. Nevertheless, integration of these signals into practical BCI requires further characterization in realistic setups. For instance, errors are usually modeled as a binary variable. Here we show how the magnitude of error modulates the resultant ErrPs detectability. We also demonstrate how augmenting ErrP recognition algorithms with more complex EEG features, such as directed connectivity, improves accuracy. In our research we have also investigated ErrPs in several experimental setups, mimicking "real-life" applications, ranging from a driving simulator to robotic platforms. In the last section of this paper we give a brief account of these applications.

2. Error-processing of self-paced movements

Decoding arm kinematics from EEG is receiving empirical support [Bradberry et al., 2010]. However, any on-line BCI application will be prone to errors. The challenge in ErrP recognition here lies in such movements not being discrete sensory events. The onset perception and magnitude of error may vary. We investigated ErrPs induced in subjects operating today's most ubiquitous hand avatar, the computer mouse, in a self-paced reaching task. In some trials we distorted the hand-to-cursor mapping by $\pm 20°$, $40°$ or $60°$ (simulating imperfect BCI). Averaged EEG epochs showed the typical readiness potential preceding movement, followed by the ErrP waveform (Fig. 1A). The ErrP's average amplitude follows the degree of the perturbation. We performed off-line classification of non-perturbed vs. perturbed trials in the spectral domain (tests with time domain features gave inferior results). Distribution of discriminant power – found principally in theta band – is shown in Fig. 1B,C with classification accuracy in Fig. 1D.
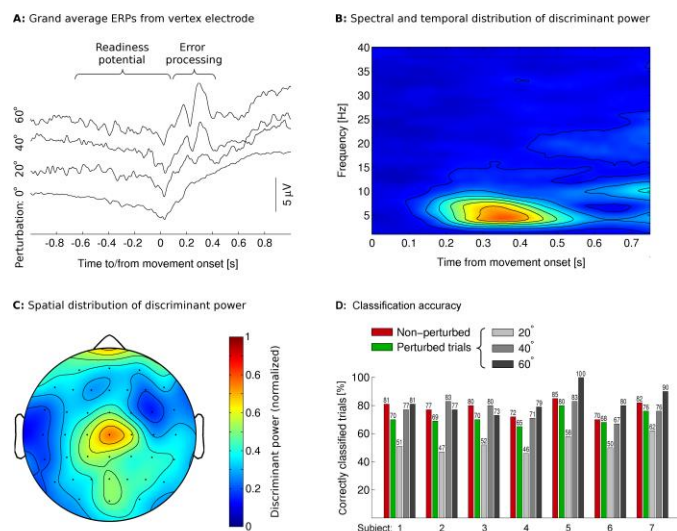

Figure 1. *(A) Group average EEG epochs time locked to movement onset. (B,C) Distribution of discriminant power in the spectral domain between perturbed and non-perturbed trials. (D) Accuracy of classification of perturbed vs. non-perturbed trials.*

3. ErrP recognition with connectivity features

ErrP detection algorithms typically rely on temporal, less often spectral (see above) features. Here we report the results of an off-line study in which we used directed transfer functions (DTF) as a feature extraction method, reflecting information flow between EEG channels at different frequencies [Zhang et al., 2012]. We applied this to data recorded in a performance monitoring experiment, where subjects viewed on a computer screen a rectangular cursor moving in discrete steps either towards a specified target, or away from it – the latter considered errors. We compared classification accuracy afforded by the connectivity features with time domain features; best results were given by combined features, demonstrating the benefit of including connectivity features in ErrP detection (Fig. 2A-C).
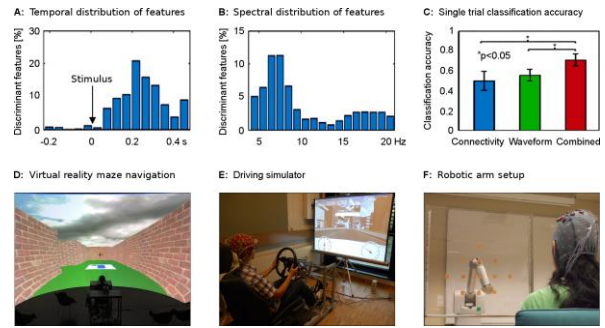

Figure 2. *(A,B) Distribution of discriminant connectivity features in the performance monitoring experiment. (C) Group average classification accuracy of erroneous vs. correct trials. (D) Virtual reality setup used in the maze navigation experiment. (E) Driving simulator. (F) Robotic arm with a subject.*

4. Towards real-life scenarios

We have also tested the laboratory findings on ErrPs in a number of still closely-controlled, but significantly more ecological scenarios. To simulate a BCI-driven telepresence robot (actually deployed in our laboratory) we have devised a virtual reality environment in which the user observes a robot navigating a maze from a first person perspective (Fig. 2D) [Chavarriaga et al., 2012]. At an intersection, the robot suggests a direction via visual or tactile (actuators on user's body) feedback. We found that wrong suggestion elicits an ErrP – regardless of feedback modality – which can be used to guide the robot's path. Another realistic scenario in which we tested usability of ErrPs is a driving task using a car simulator (Fig. 2E). It consists of a BCI system predicting the driver's intended driving direction. As the car approaches the intersection, a cue is displayed instructing the driver which direction to take. This is followed by a probe stimulus (an arrow pointing in one of the possible directions) which - if wrong - also results in a detectable ErrP. Still another scenario employs a robotic arm moving in left, right, up, or down steps (Fig. 2F) [Iturrate et al., 2012]. By setting a goal for the arm to reach and making it known to a human observer, we were able to detect ErrPs evoked by the robot's erroneous movement. Concluding, we believe that reliable usage of ErrP signals could significantly enhance BCI operation, and current research goals should include implementing basic findings into real applications, operating under less and less laboratory constraints.

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