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Cortically-Derived Error-Signals During BCI Use

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Abstract. Standard training regimens for decoders used in brain-computer interfaces (BCI) typically involve a calibration phase where training data is collected a priori within the context of a known task. Such a paradigm is not applicable in the general case of BCI use where the tasks are not known a priori. A potential solution to this problem is to derive a "reward" or "punishment" signal from the neural data itself. One example of such a signal is an error signal generated whenever the BCI fails to reach a goal the subject seeks to achieve. In this study we trained five human subjects to use a simple, one-dimensional electrocorticographic (ECoG). We demonstrate that invariant to multiple task parameters, there exist robust cortical signals that are correlated with failure to successfully complete the task. Further, we show that these error signals can be used to infer the outcome of new executions of the task. Our results suggest that such signals could potentially be utilized as reinforcement signals in the general case where task structure is unknown.

Keywords: Error potentials, adaptive classification, reinforcement learning, performance

1. Introduction

During the initial phases of use of a brain-computer interface (BCI), the standard procedure is to calibrate a feature selection algorithm and/or decoder based on training data collected during a known task structure. While this is a suitable method for operation of BCIs that will be used within tightly constrained structures (e.g., P300 speller), it may not be appropriate for abstract task environments. One proposed solution to handle the latter case is to derive information from the users themselves to serve as a positive or negative reinforcement signal to the BCI. Previous work using electroencephalography (EEG) has demonstrated that there exist neural responses that can be used to classify trial success, both in use of a BCI [Buttfield, 2006] as well as non-BCI paradigms [Blankertz, 2003], however these responses develop on timescales of up to 550 ms, limiting their potential use in a real-time BCI. As an alternative to EEG, electrocorticography (ECoG) is a signal modality that may allow for extraction of similar error signals on faster time scales. Recent work has shown that outcome-related error signals can be derived from frontal and parietal cortices during an overt motor task [Milekovic, 2012], and that these signals can be classified on a single trial basis [Milekovic, 2013]. It has yet to be shown that there exists a neural correlate of errors in BCI tasks that can be derived from ECoG data and whether such a signal can be detected on a single-trial basis.

2. Material and Methods

Five subjects with intractable epilepsy were implanted with platinum sub-dural ECoG electrodes for the purpose of seizure focus localization at Harborview Medical Center and Children's Hospital in Seattle, Washington. Data were sampled at either 1000 Hz or 1200 Hz.

All subjects performed variants of the standard right-justified box task. BCI paradigms were driven by spectral power changes in the high-gamma (HG, 70-100 Hz) frequency band of a single electrode, selection of which was done with an initial screening task. Subjects were instructed to conduct/imagine movement or rest to control the cursor. The vertical extent of any given target was determined by the current task difficulty (i.e., the number of different potential targets). A cursor travelled from left to right across the screen at a fixed horizontal velocity, while its vertical velocity was updated every 40 ms based on spectral changes in the control feature.

Trials and electrodes containing obvious artifacts were hand-identified and discarded. Signals were common average re-referenced and spectral power was estimated by band pass filtering and finding the envelope of the resultant signal. All samples from successful trials were compared to those of failed trials and clusters were formed by grouping all significant (two-sample t-test, $p < 0.05$) contiguous samples. To correct for multiple comparisons, clusters generated by this method were then tested for significance against distributions generated through 1000 repeated random regroupings of trials ($p < 0.01$). Resultant features of greater than 150 ms were then used as learning features for subsequent classification analyses, which were performed using a linear discriminant analysis classifier and a standard 5-fold validation procedure.

3. Results

Subjects performed a number of variants of the BCI task, using overt and or imagined movements and attempting to select from between two and seven targets (occupying 50% and 14.3% of the total target area, respectively). Performance varied with movement type and target count. The mean number of trials performed by each subject was 358.6 (s.d. 124.2) with a mean overall accuracy of 76% (s.d. 9.5%).

In four of the five subjects we found statistically robust ($p < 0.01$, see methods) neural correlates of error trials (missed target), the majority of which occurred in the time period immediately after trial ended ($t > 3$ s). Generally, there was an increase in HG during the post-trial period in missed trials relative to successful trials, though this was not exclusively the case.

To verify that these error signals could be detected in real-time, we trained an LDA classifier on subsets of the data. For the four subjects in whom we found error signals, the classifier obtained a mean peak classification accuracy of 77% (s.d 8.0%). We performed these classification analyses on subsets of the error signal features to test the sensitivity of the classifier to feature count (see Fig. 1b).

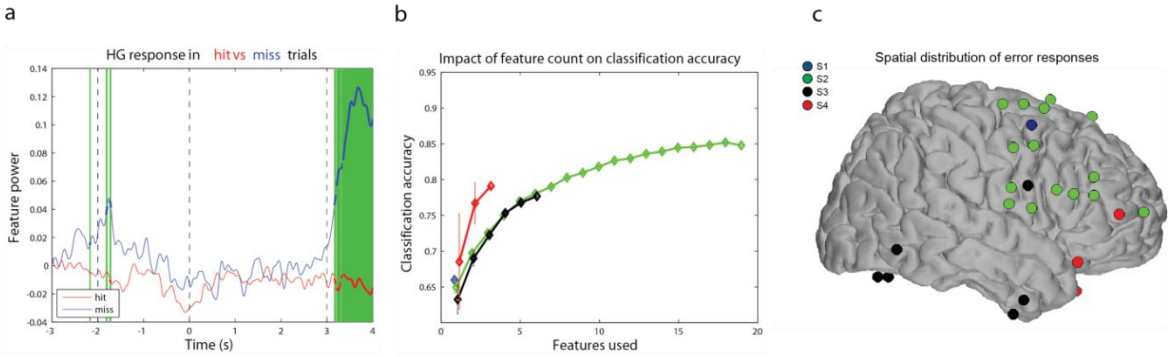

Figure 1. *(a) mean HG response of an example electrode. Online control begins at t = 0 and the trial ends at t = 3. Significant differences between successful (red) and failed (blue) trials are highlighted in green (b) Classification accuracy as a function of feature count. Error bars represent SEM. (c) Spatial distribution of electrodes exhibiting error potentials, different subjects are shown in distinct colors.*

4. Discussion

In this study we demonstrated that, in ECoG, there exist neural correlates of BCI trial outcome that have predictive value in evaluating the success or failure of a specific trial. These error signals typically occur directly after the trial has concluded, though we found some in-trial and even pre-trial indicators of trial outcome, though similar to EEG based studies, maximal classifier performance is obtained when error response latencies of 500 ms or greater are considered. Our findings indicate that it would be feasible to train a classifier to detect these error signals in real-time. This has significant implications for the design of co-adaptive BCIs as such an error signal could serve as a neurally-derived reinforcement signal for adapting a BCI in real-world applications.

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