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Comparing BCI performance using scalp EEG- and inverse solution-based features

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Abstract

Several studies have proposed the use of inverse solutions based features to improve the decoding performance of brain-computer interfaces. Most of these studies have compared the performance of inverse solutions features over scalp activity in a small set of electrodes. However, the estimated sources are indeed a linear combination of scalp-wide activity. Therefore, this comparison may be biased against surface EEG. Performance comparison in three ERP-based protocols show that classifiers combining larger sets of EEG electrodes may perform comparably, and previous reports may have overestimated the advantages of using inverse solution based features.

1 Introduction

Brain-Computer interfaces (BCI) rely on the single-trial recognition of neural signals corresponding to different conditions. Currently, the most common BCI implementations use electroencephalography (EEG) signals elicited after presentation of different stimuli (i.e., event-related potentials, ERP). However, EEG-based applications have low spatial resolution of the signals due to poor skull conductivity which smears the electrical activity originated in cortical sources. This reduces the signal-to-noise ratio (SNR) posing serious challenges for BCI use.

Inverse solution methods, allowing to estimate the intra-cranial sources that generate the scalp measured potentials, have been proposed as a potential method to improve classification performance compared to surface EEG [3, 8, 7]. The rationale is to increase the signal spatial resolution by projecting scalp potentials onto a higher dimensional (source) space. The estimated activity of these sources is expected to have better SNR as they represent unmixed scalp potentials captured by the EEG electrodes. Correspondingly, from a classification perspective, the features extracted from the estimated cortical activity are expected to yield better discrimination between the BCI classes.

Previous studies on the use of inverse solutions for BCI typically compared the performance using source-related features against features from individual or a small number of EEG channels. However, since sources are estimated by linearly combining information from all the EEG channels, is not surprising that source-based features provide higher discriminant information compared to individual scalp-electrodes. Therefore, results may be biased against against surface EEG. In this paper we address this issue by comparing source-based classification with features based on linear combination of scalp electrodes aiming to provide a fair assessment of their capabilities in ERP-based BCIs.

2 Methods

We compared the classification performance using scalp- and source-based features. The first classifier, henceforth termed *Cortical*, uses the estimated cortical current density (CCD) of intracranial sources [3]. Features are extracted from the temporal activity of each source within a given time window (see below) and at each time-point the 100 most discriminant CCD features are selected using the Fisher score. We train individual classifiers for each of these selected features that compute the probability of likelihood to the means and covariance computed on the training data. The output of these classifiers are combined using naïve Bayes rule. The motivation for this ensemble method is that using individual classifiers per feature reduces the possibility of overfitting when limited number of training trials are available

In the case of EEG features, we compute the classification performance using a Fisher linear discriminator (*FLD*). This classifier combines linearly the activity from all the electrodes. Thus mathematically, it is comparable to the projection used to compute one intracranial source. However, projection weights in the FLD are optimized for separating the classes while the inverse solution optimize localization capabilities. Since the *Cortical* classifier combines several projections (i.e. sources) at each time point while the FLD only uses one, we also tested two more classifiers that combine multiple linear projections of the scalp activity. In the first one these projections were obtained through bagging, i.e. multiple FLD (N=100) are built from subsets of the training data. Each subset was obtained by randomly selecting 50% of trials from the training set. This classifier is referred to as *EEG N-FLD* to signify multiple FLD projections whereas the earlier classifier is referred to as *EEG 1-FLD*. Furthermore, since the bagging approach may lead to similar projections, we also tested a method, termed *Orthogonal*, that enforces the use of orthogonal FLD projections [5]. Last but not least, as it has been done in previous works on decoding using inverse solutions [3, 8, 4], we also tested classifiers trained on a small subset of electrodes, here referred to as *EEG-Channel* classifier.

These classifiers were compared offline in three standard ERP-based BCI experiments: Rapid Serial Visual Presentation (RSVP) [10], P300-speller [6] and Error-related potentials (ErrP) [2]. In the RSVP study (N=15), sequences of images are rapidly presented (4 images per second) and the evoked EEG activity is decoded looking for signatures of target and distractor images. Training data was acquired during 4 search tasks, each one composed of two sequences of 200 images. The testing phase was performed on three search tasks using different target objects than for training. Both training and test phases were performed on the same day. 64 EEG channels were acquired at 2048 Hz, then filtered in the range 1-10 Hz, spatially filtered using CAR and downsampled to 32Hz. Classification was based on the data in the time window [200-700] ms. Following previous works, channels Cz, Pz and Oz were used for the *EEG-Channel* classifier [9].

The second experiment (N=8) consists on the standard P300 matrix speller. The experiment was performed over two days (average separation of 12 days) and each day an average of 5 runs were performed per subject. Each run requires the writing of 5 characters. Data of the first day was used for training and classifiers were tested on the data for the second day. 61 EEG channels were recorded at 250Hz, then filtered in the [1 20] Hz range, downsampled to 50 Hz and CAR referenced. Signal in the window [100 600] ms was selected for classification. The *EEG-Channel* classifier used channels Fz, Cz and Pz [1].

Finally, in the ErrP (N=6) experiment subjects monitor a cursor that moves horizontally in discrete steps towards a target location. 20% of the time it goes in the opposite direction to the target. The experiment was performed over two days with a separation ranging from 2 months to 2 years. Classifiers were trained on day 1 and tested on the second day. 64 EEG channels were acquired at 2048 Hz, then filtered in the range 1-10 Hz, spatially filtered using CAR and downsampled to 32Hz. Classification was based on the data in the time window [200-450] ms. Features from channels Fz, Cz and Pz were used by the *EEG-Channel* classifier [2].

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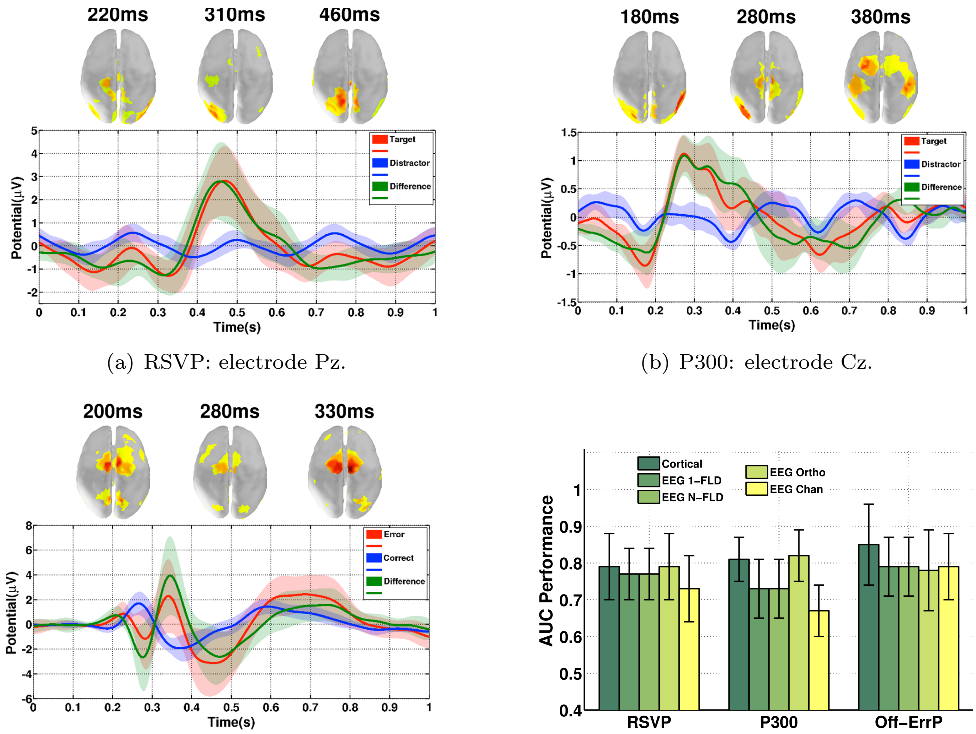

(a) RSVP: electrode Pz.

(b) P300: electrode Cz.

(c) Error-related potential: electrode FCz.

(d) Performance (AUC).

Figure 1: (a-c) Event-related potentials at discriminant electrodes. Topographic Localization of discriminant sources (Top view) at selected time points is shown in the top row. (d) Classification performance on the three ERP protocols.

3 Results

Fig 1(a-c) shows representative ERPs and discrminant intracranial sources for the three protocols. Sources are color coded from green to red to show how often they were found to be discriminant across subjects (red color indicates features that were discriminant in all subjects). Classification performance (area under the ROC curve, AUC) is shown in Figure 1(d). In general *EEG-Channel* classifier exhibits the lowest performance. In the RSVP protocol the *Cortical* classifier outperforms the *EEG-Channel* but failed to show statistically significant differences ($p = 0.08$, Wilcoxon). It also performs comparably to the other three classifiers, all using linear combinations of EEG channels. The performance obtained with inverse solution is similar to a previous study using a full brain head model based inverse solution [9]. In contrast, in the P300 experiment the *Cortical* and *Orthogonal* methods significantly outperform the other three classifiers (p <0.05, Wilcoxon). The results with our classifiers are comparable to previous EEG-based studies [6]. In the case of the ErrP protocol, on average the *Cortical*, *1-FLD*, and *N-FLD* show higher performance. Nonetheless, no significant differences were found with respect to the *Orthogonal* and *EEG-Channel*. Overall, performance of the *1-FLD* and *N-FLD* classifiers was comparable across protocols. This implies that the bagging procedure yielded similar projections and therefore no improvement with respect to the initial classifier.

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4 Conclusion

We found that inverse solution based classifiers have consistent classification performance for all the experimental protocols and the results matches with the state of the art methods. Contrasting with previous reports, most of them on SMR-based BCIs, surface EEG based classifiers yielded similar performance, in particular when multiple channels are considered. There is thus, at least for ERP-based BCIs, the risk of overestimating the advantages of source-based classification if the proper validation is not performed. Noticeably, bar a few exceptions [7], previous works on SMR classification do not report such comparison.

Nevertheless, the *Cortical* classifier outperformed the *FLD* scalp-based classifiers. This suggests that these classifiers can indeed bring some advantages. Remarkably, testing data in two of the experiments were obtained on a different day than for training, suggesting that source estimation can still be reliable despite removal and relocation of the EEG electrodes across sessions. Further studies are required to better identify those cases where the use of inverse solutions may be more suitable for BCI systems than scalp-recorded signals.

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