Online BCI with Stable Sources

Mohit Kumar Goel, Ricardo Chavarriaga, J. del R. Millán
EPFL , Lausanne, Switzerland

Correspondence: M. K. Goel, Ecole Polytechique Fédérale de Lausanne, 1015, Lausanne, Switzerland. E-mail: mohitkumar.goel@epfl.ch

Abstract. In this paper, we show that the estimated intra-cranial sources using source localization on EEG signals can be used for online Brain Computer Interation (BCI) and the discriminant sources remain stable over days. Classifiers are trained on discriminant sources obtained for Error-related Potential (ErrP) based BCI on day 1 and then tested online on day 2. The results for nine subjects show that the source localization with discriminant sources can be used for online detection of ErrPs. Furthermore, the number of common sources among the discriminant sources for different days is above chance which shows that the discriminant sources remain stable over days.

Keywords: Online BCI, discriminant sources, Error-related Potentials

1. Introduction

Inverse solution is used to localize and estimate the activity of intra-cranial sources that are responsible for generating scalp EEG. Previously, in an offline analysis, we have shown that these localized sources could be used for single trial classification of Error-related Potential (ErrP) signals [Goel et. al, 2011]. In this paper we extended the use of intra-cranial sources to online Brain-Computer Interaction (BCI) where the error potentials were detected to undo the error moves performed by the cursor in ErrP protocol [Chavarriaga and Millán, 2010]. In addition, we report the consistency in localization of discriminant sources that are obtained during offline and online sessions of the BCI experiment. A high number of common discriminant sources suggest that these sources are stable over different days and hence information from these sources can be used for online sessions.

2. ErrP Experiment

The protocol and experimental setup for measuring ErrPs is similar to the procedure presented in [Chavarriaga and Millán, 2010]. Nine healthy subjects (6 males, 3 females) took part in the experiment on two different days. The subjects were asked to monitor movement of a cursor which was moving in discrete steps towards a fixed target on the screen. The cursor movement is termed erroneous whenever it moves away from the target. For online experiment, the movements were reverted based on the detection of error-potential in the brain signals. Six offline sessions on day one and four online sessions on day two were performed with 64 electrodes (10/10 international system) EEG system. Online error detection on day 2 was done by classifiers trained for each subject from the sources obtained on day 1.

3. Source Localization

To estimate intra-cranial source activity, the cortical current density (CCD) based distributed inverse method was used to estimate values for 3013 vertexes on the cortical surface of a 3-dimensional head model, with each vertex corresponding to a source [Cincotti et al., 2008]. The EEG data was common average referenced, filtered in a frequency range [1 10] Hz and down-sampled to 32 Hz. After estimating values for intra-cranial sources, a discriminant power (DP) was computed (using Fisher score for class separation) for each source and each time point within time window [0.3 0.8]s after cue presentation. We selected top 100 discriminant sources at each time point. We trained likelihood classifiers for the entire selected sources and then combined individual classification outputs using naïve Bayes method. This classifier was used for detecting ErrPs for online BCI on day 2. To quantify stability, we identify the number of discriminant sources that intersects over two days. The stability score is computed by finding the number of common sources and then dividing it with all the above selected sources. Furthermore, for source localization analysis, the common sources are visualized on a topographic map of 3D head model (Fig. 1), where higher intensity of a source suggests that it is selected more often with respect to other sources in the above mentioned time window.

4. Results

The classification results obtained using discriminant sources for online ErrP-based BCI are shown with area under the curve (AUC) values for nine subjects (Fig. 1). There are six subjects (c2, c9, b2, d6, c5, e7) who have AUC values above 80%, two subjects (a6, e4) between 60 and 80% and one subject (g3) close to 50%. Overall the AUC values represent good classification with discriminant sources for most of the subjects.

For the stability analysis, we found that the percentage of common sources among the selected discriminant sources lie above chance for all the subjects (chance level for obtaining common sources in a random selection of 100 out of 3013 sources is below 7 %) (Fig.1). Higher number of common sources suggests that they are stable and are not an outcome of random selection.

We also analyzed the localization of these sources for two subjects: e7 with highest percentage of common sources (47.7%) and e4 with minimum percentage of common sources (8.4%). We found that the highest number of sources selected for subject e7 is localized as a big compact cluster over the central cortex. However, for subject e4, we found the sources are distributed across smaller clusters and very few of them are over the central cortex.

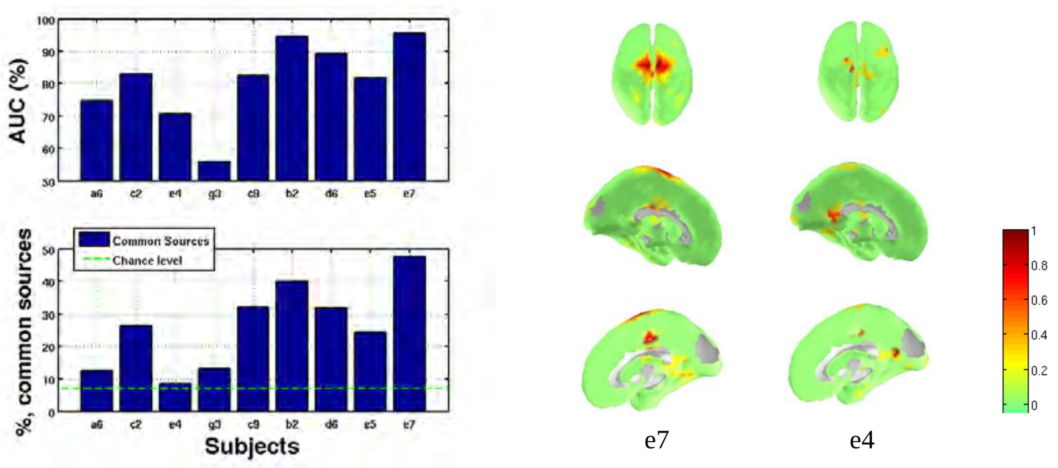

Figure 1. *Figure (Left) AUC for the online experiment of day 2 and percentage of common source selected during the time window [0.3 0.8]s for 9 subjects and. (Right) Localization of stable sources on CCD head model. From top to bottom, nose is on top, right and left.*

5. Discussion

In this paper we presented the use of estimated intracranial sources for online detection of ErrPs in a BCI experiment to undo error movements of the cursor on a screen. We obtained good online classification results for most of the subjects. This is an extension to our previous offline single trial classification of ErrPs [Goel et. al, 2011]. Furthermore, we have shown that the selected discriminant sources for classification remain stable over days by comparing the number of common sources among the discriminant sources for two days of recording.

Acknowledgements

This work is supported by Swiss National Science Foundation, Project 200021-120293.

References

Chavarriaga R, Millán J del R. Learning from EEG error-related potentials in noninvasive brain-computer interfaces. IEEE Transactions on Neural Systems and Rehabilitation, 18(4):381-388.

Cincotti F, Mattia D, Aloise F, Bufalari S, Astolfi L, Falani FDV, Tocci A, Bianchi L, Marciani MG, Gao S, Millán J del R, Babiloni F. High-resolution EEG techniques for brain–computer interface applications. *Journal of Neuroscience Methods*. 167(1):31-42, 2008.

Goel MK, Chavarriaga R, Millán J del R. Cortical Current Density vs. Surface EEG for Event-Related Potential-based Brain-Computer Interface. In 5th International IEEE EMBS Conference on Neural Engineering, 2011, 430-433