Human Brain Mapping 2007

Abstract Number: 1063
Last Modified: January 7 2007

Bilinear discriminant analysis for ICA component selection in EEG

Mads Dyrholm[1], Robin Goldman[1,2], Marios Philiastides[1], Nelson Wei[2], Truman Brown[2], Paul Sajda[1]
[1]Laboratory for Intelligent Imaging and Neural Computing, Columbia University, USA
[2]Hatch MR Research Center, Columbia University, USA

Background

Unsupervised ICA has been proposed for extracting task-relevant components in EEG (Makeig et al.,1996). Components are typically grouped into different categories, often via visual inspection, in order to describe certain phenomena in the data, for instance ballistocardiogram (BCG) artifacts in simultaneously acquired EEG/fMRI (Srivastava et al., 2005). However in many cases task-relevant components are difficult to extract and group using these unsupervised methods, due to low SNR or because their spatial distribution and time course is completely unknown. In such cases a supervised method can be used, exploiting labels for each trial (e.g. in a auditory oddball paradigm whether the trial was an oddball or a standard). Bilinear discriminant analysis (BDA) is one such supervised methods that has been proposed for classification of EEG (Dyrholm and Parra, 2006). In BDA space and time is combined in a factorial way, with priors separately declared in space and time. Here we extend the concept of BDA, substituting an ICA component matrix for the original data matrix. A sparse prior on the component weights helps prune components that are irrelevant to the classification task and identify "composites" (groups of components) that are discriminative.

Methods

Data:

12 subjects were recorded (simultaneously recording MR and EEG) during an auditory oddball task with button-press. Out of a total of 250 trials 50 were oddballs. Gradient artifacts were removed but BCG was not removed.

Component extraction:

The continuous EEG data was decomposed using Extended Infomax ICA (Lee et al., 1999). A full ICA decomposition was performed yielding 43 components. Matrices of epoched component activation time series was input to BDA.

Classification:

The BDA component weights were given a sparse (Laplace) prior expressing our belief that classification can be based on relatively few components. The temporal prior was smooth (Gaussian) expressing our belief that the evoked time course should be smooth.

Results

The classifiers were validated using cross-validation Receiver Operating Characteristic (ROC) analysis. We first compared the classification performance for our ICA based classifier with our previous BDA approach, which is designed to directly classify on the data. We found both approaches to yield identical classification performance (across subjects, average Az=0.87, max Az = 0.96). For each subject, the ICA based classifier found three composites based on a relatively small number of components. Figure 1 shows the component weights that were learned given one of the subjects. Figure 2 shows the scalp map of the ICA component which had the highest weight for each of the three subjects with the highest classification performances. Note that for two of the subjects (1 and 2) the early motor response was most discriminating, while for subject 3 a component with a P300 scalp topology was most discriminating.

Conclusion

We find that the classifier using the components matrix performed as well as the classifier using the data matrix. Thus, it seems reasonable to model oddball relevant activity by relatively few ICA components, and these components can be identified by the BDA classifier.

Acknowledgement

This work was supported by NIH grant EB004730.

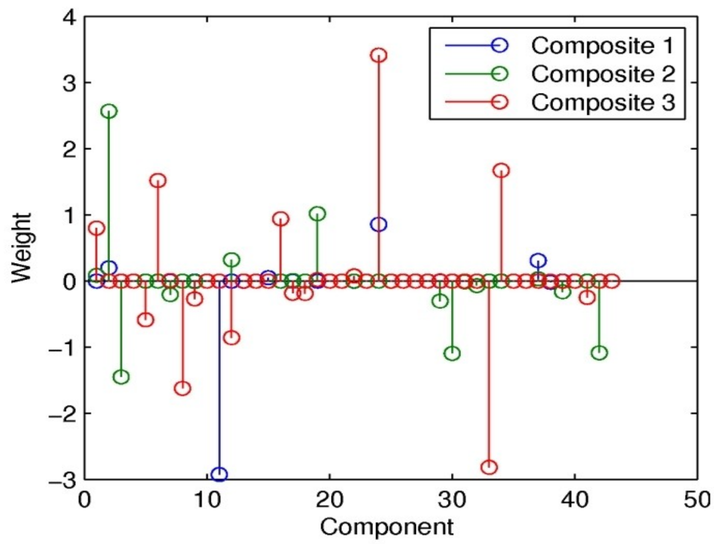

Figure 1: Component weights for subject 1

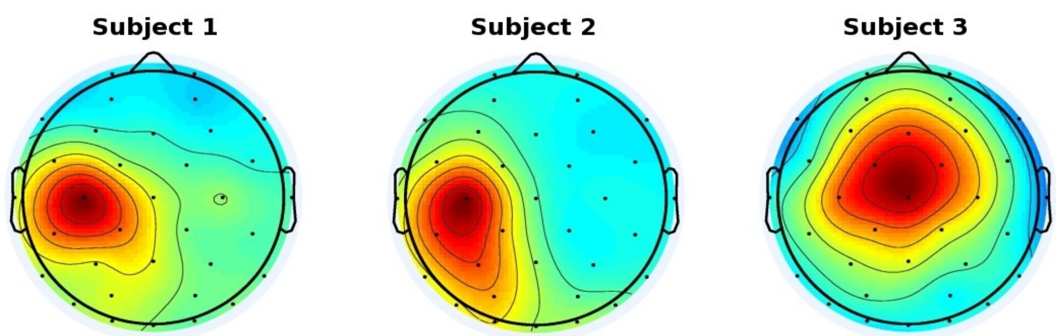

Figure 2: ICA component scalp topographies of the highest weighted component for each of the three best classified subjects.