Removing ballistocardiographic noise in combined EEG-fMRI using soft constrained PLS method

Siamak Salari Sharif[1], Michael D. Noseworthy[2], James P. Reilly[3], and Daniel J. Bosnyak[4]

[1]*MR Innovations Inc., Detroit, MI, United States,* [2]*Electrical and computer engineering, school of biomedical engineering, McMaster University, Hamilton, ON, Canada,* [3]*Electrical and computer engineering, McMaster University, Hamilton, ON, Canada,* [4]*Department of Psychology, Neuroscience and Behaviour, McMaster University, Hamilton, ON, Canada*

Introduction: An essential step prior to the analysis of electroencephalographic (EEG), during combined EEG-fMRI analysis, is the removal of a specific type of noise artifact known as ballistocardiographic noise (BCG) induced by the movement of body and blood in the static field of MRI. This type of artifact appears as structured noise affecting many channels. We propose the use of a soft constrained PLS algorithm (SC-PLS)[1] for removal of this noise. The method makes use of additional knowledge about the event related potentials (ERPs) and uses latent variable methods (LVM) to extract EEG components that are noise free. We applied the SC-PLS algorithm to EEG data contaminated with BCG artifacts and compared the results to those obtained by conventional methods.

Algorithm and theory: SC-PLS is a constrained LVM which inherits the properties of PLS[2] such as accommodating low rank data structures and missing data elements. In addition, it incorporates additional knowledge about the noise or signal to improve component selection. In general SC-PLS algorithm can be presented as a maximization problem in which the objective is to find a linear combination of $\boldsymbol{X}$ ($\boldsymbol{t=Xw}$) which has maximum covariance with a matrix of signal $\boldsymbol{Y}$, but at the same time penalizes any covariance with noise subspace ($\boldsymbol{Z}$). Overall the equation can be written as: $max_{w}\ \boldsymbol{w'X'YY'X\ w}\text{-}\lambda\boldsymbol{w'X'ZZ'Xw}$, where λ is a regularizing coefficient, and $\boldsymbol{w}$ is the eigenvector associated with the largest eigenvalue of matrix $\mathbf{X'YY'X}\text{-}\lambda\mathbf{X'ZZ'X}$. One interesting property of this method is that the sign of $\boldsymbol{w}$ can determine whether the eigenvector is in the direction of noise or signal, allowing identification of noise and signal subspaces. For this study we proposed an iterative algorithm in which an estimate of ERPs was initially generated using the noisy signal and used as a constraint in the SC-PLS algorithm to estimate the noise subspace, .where $\boldsymbol{Y = X\text{-}Z}$. During each iterative step of the algorithm a better estimate of the noise and ERP's were found by removing noise from EEG data, by projecting EEG onto the orthogonal complement of noise subspace, and re-calculating the ERP values and reusing the new ERP in SC-PLS to find a better estimate of the noise subspace again. The noise subspace consists of the extracted components that have negative eigenvalues associated with them.

Methods: The study was approved by our local research ethics board and performed on 6 healthy volunteers.. The EEG experiment involved exposition to a simple flashing checker board experiment outside and inside an MRI (GE 3T) using a 64 channel MR compatible EEG system (Brain Products GMBH). We performed the experiments with and without fMRI scanning (gradient echo EPI TE/TR=30/3000ms, flip angle=90^{o}, matrix=64×64, 30 slices, 24cm FOV, 180 temporal points over 9 minutes). We used the EEG collected outside the MRI as a BCG noise-free reference. We compared our results to the optimal basis sets (OBS)[3] . Root mean squared error (RSME) between reference ERP and extracted ERP, signal to noise ratio (SNR) and the correlation coefficient before and after noise removal for both the SC-PLS and OBS algorithms were compared. In the cases where the fMRI was running the gradient artifacts were removed using the built-in GA removal toolbox from EEGLAB[4] software before further processing of data.

Results and Discussion: Figure 1 (left) shows the ERP estimates at the occipital lobe (OZ) when EEG was collected inside and outside the MRI. It can be seen that the BCG artifacts can severely distort the ERP estimates. Figure 1 (middle and right) shows the EEG after removing BCG artifacts using OBS and SC-PLS method in one of the patients compared to the patient's reference EEG ERP, collected outside of MRI. It can be seen that the results from OBS and SC-PLS were both satisfactory, with SC-PLS having less overall noise. Figure 2 shows the overall quality parameters calculated for each subject. It can be seen that SC-PLS provides better overall results compared to OBS. Overall we can conclude that our method is a very effective way of removing BCG especially when ECG data is corrupt or not available. Furthermore, one major advantage of our method is that it does not require the finding of QRS peaks (nor requires collection of ECG data) which is often problematic.

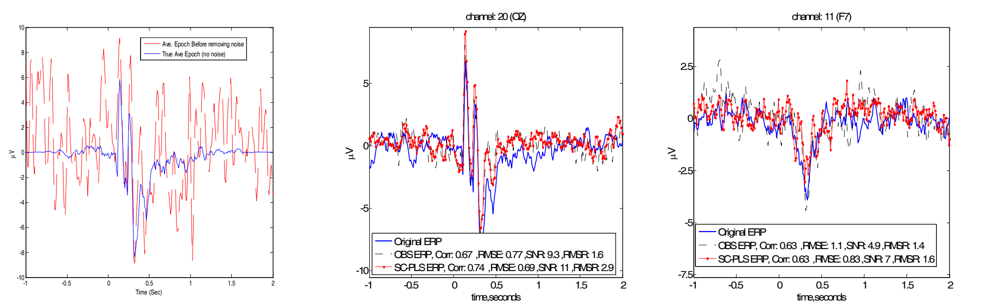

Figure 1: Left: ERP from EEG collected outside (blue) and inside MRI (red). Middle and right: ERP signal obtained after cleaning the noisy EEG using OBS method (dashed) and SC-PLS (red) compared to the reference ERP (Black) for channels OZ and F7.

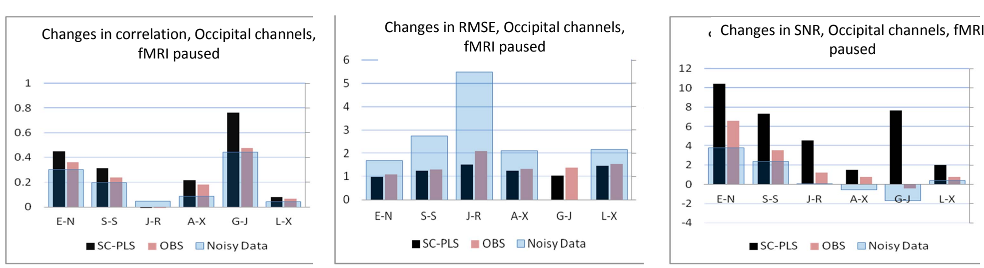

Figure 2: Quality parameters for EEG data before and after removal of BCG noise, for each individual subject, using SC-PLS and OBS methods, with fMRI paused. Overall, SC-PLS provides higher quality results compared to OBS. Each individual subject is plotted separately.

[1] Salari Sharif, Siamak. *Ph.D. Thesis, McMaster University,* 2012.
[2] Burnham, Alison J, et al. *Journal of Chemometrics* 13, no. 1 (January 1, 1999): 49–65.
[3] Niazy, R et al. *Neuroimage* 2005, *28*, 720–737.
[4] EEGLAB V10 Swartz Center for Computational Neuroscience