Removal of Ultra-Fast MR-gradient and Ballistocardiogram Artifacts in High-Density EEG Data to Detect Sleep

Anders Olsen[1], Sebastian C Holst[1], Claus Svarer[1], Morten Mørup[2]

[1] Neurobiology Research Unit, Copenhagen University Hospital Rigshopitalet

[2] Cognitive Systems, Department of Applied Mathematics and Computer Science , Technical University of Denmark

Introduction

A research team at Neurobiology Research Unit (NRU) is set to investigate several aspects of sleep using simultaneous Electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI). EEG measures electrical activities in the cortex of the brain using electrodes on the scalp, and is well established as the preferred method of sleep observation and classification. Its spatial resolution is exceeded by fMRI, which measures functional activities in the brain. It is the hope that using EEG to classify sleep, the research team can observe changes in the cardiovascular physiology of the brain using fMRI. However, this multimodality setup has a major drawback: The presence of artifacts in the EEG-signal.

Artifacts

Two major artifacts corrupt EEG-signals recorded inside an MR-scanner: The Gradient Artifact (GA) and the Ballistocardiogram (BCG). Both of these artifacts corrupt the signal enough to disrupt the sleep characteristics of EEG-signals.

The GA is a high amplitude spike with amplitude more than 100 times what is normally seen in EEG. It is caused by the switching of magnetic gradients of the MR-scanner, i.e. whenever an image is taken. The morphology of the artifact changes according to the imaging sequence being used and varies from channel to channel. Within each channel the artifact shows little fluctuation over time. An example is shown in Fig. 1

The Ballistocardiogram (BCG) originates from the heart beat and is an artifact heavily amplified by the presence of the strong constant magnetic field of the MR-scanner. The BCG-artifact is time-variant to a higher degree than the GA, meaning that both the shape and scale of the artifact suffers from temporal variations and is not dependent on MR sequence. Likewise, the time from heartbeat to BCG also vary from channel to channel depending on the distance from the heart. The approximate delay is 200ms. An example is shown in Fig. 2

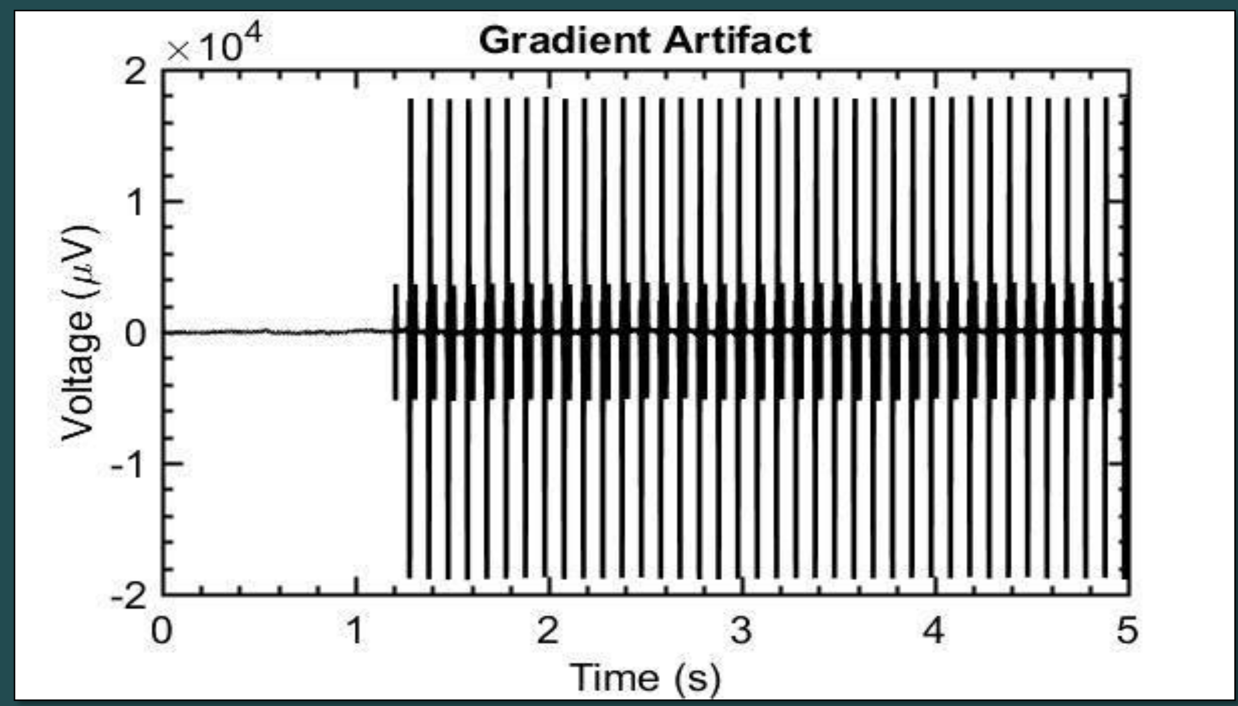


Fig. 1: The Gradient artifact during 5 seconds, of which an imaging sequence is running during the last 4

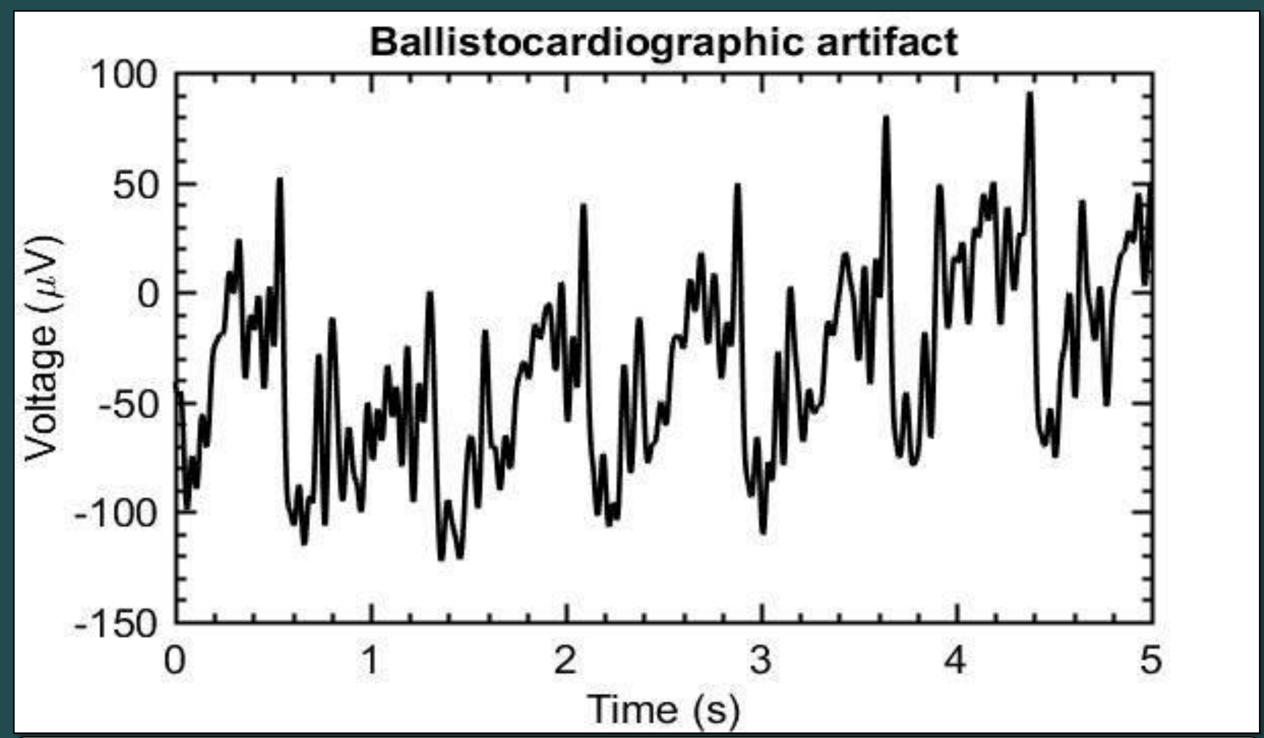
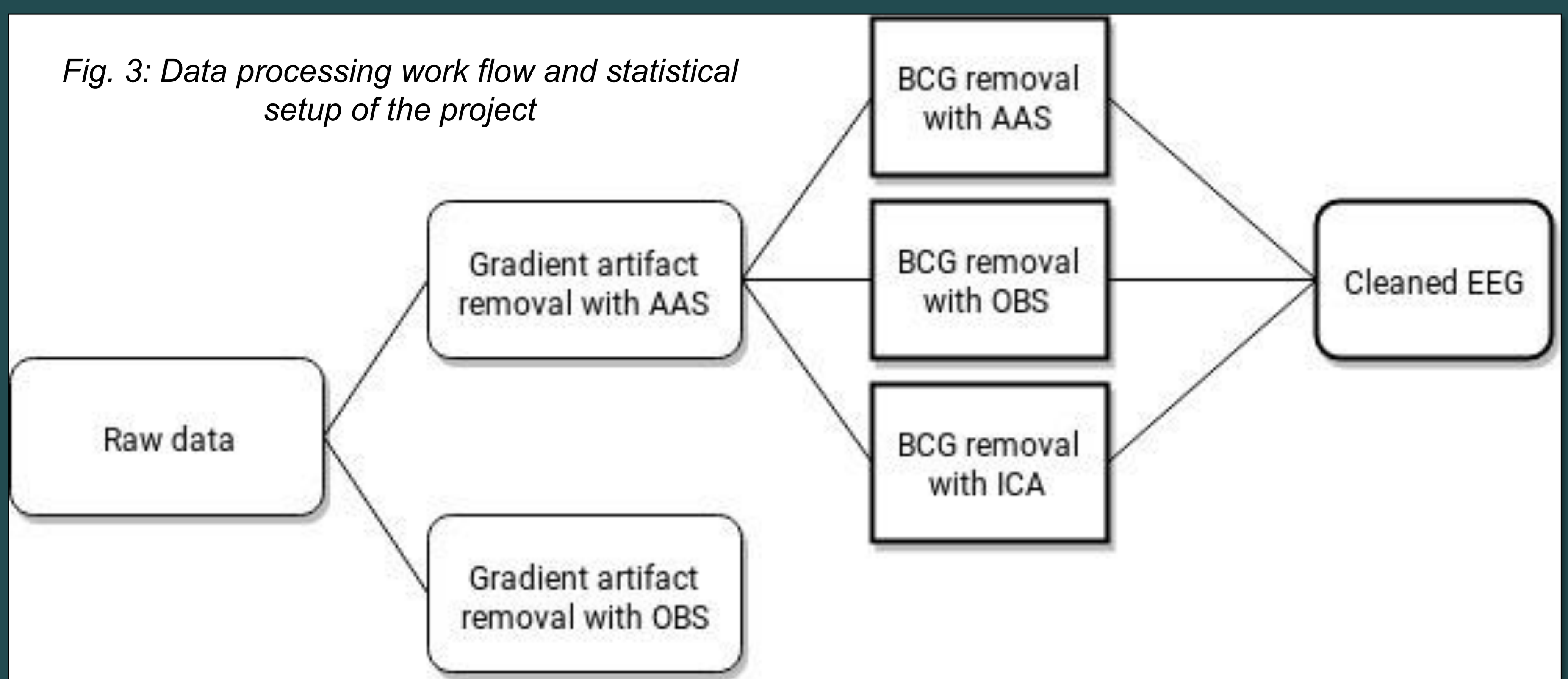


Fig. 2: The ballistocardiogram during 5 seconds of EEG data recorded inside scanner but without imaging sequence running

Fig. 3: Data processing work flow and statistical setup of the project



Methods

In this project, different methods are tested for the removal of the two artifacts. Due to the exogenous nature of the GA, it makes more sense to remove this artifact before correcting for BCG.

For GA-removal, Average Artifact Subtraction (AAS)[**1**] and Optimal Basis Sets (OBS)[**2**] are tested. AAS is an algorithm that computes and subtracts a moving average template artifact. OBS extends this algorithm with a principal component analysis on the residuals after template artifact subtraction.

Three methods are tested for BCG-removal: AAS, OBS and Independent component analysis[**3**]. All algorithms rely on stable QRS-detection, for which the k-Teager Energy Operator[**4**] is used. The latter is an algorithm that takes all EEG-channels as input and computes statistically independent components that are present to different extent in all. The hope of using this method is that heart beat contributions to the EEG-signals will be captured in one single component. This method assumes that the morphology of the BCG in different channels is scalably related and that there is equal delay between heart beat and artifact in all channels. These assumptions do not hold true in reality and in fact the algorithm computes many components with visible heart beat contributions. An example is shown in Fig. These components have to be manually identified.

We therefore propose a stepwise procedure that automatically selects the components that have heart beat contributions. The procedure is outlined below:

- First, each component is divided into N segments, where N is the number of detected QRS-complexes. Each segment has a length of an average R-R interval in the recording period.
- The N segments are then averaged.
- The averaged heart beat contribution is then repeated at each time point of an R-peak.
- The Pearson correlation between the repeated averaged heart beat segment and the corresponding independent component is computed.
- Components with coefficient above threshold, r=0.05, are determined to contain heart beat contribution and can thus be removed from the signal.

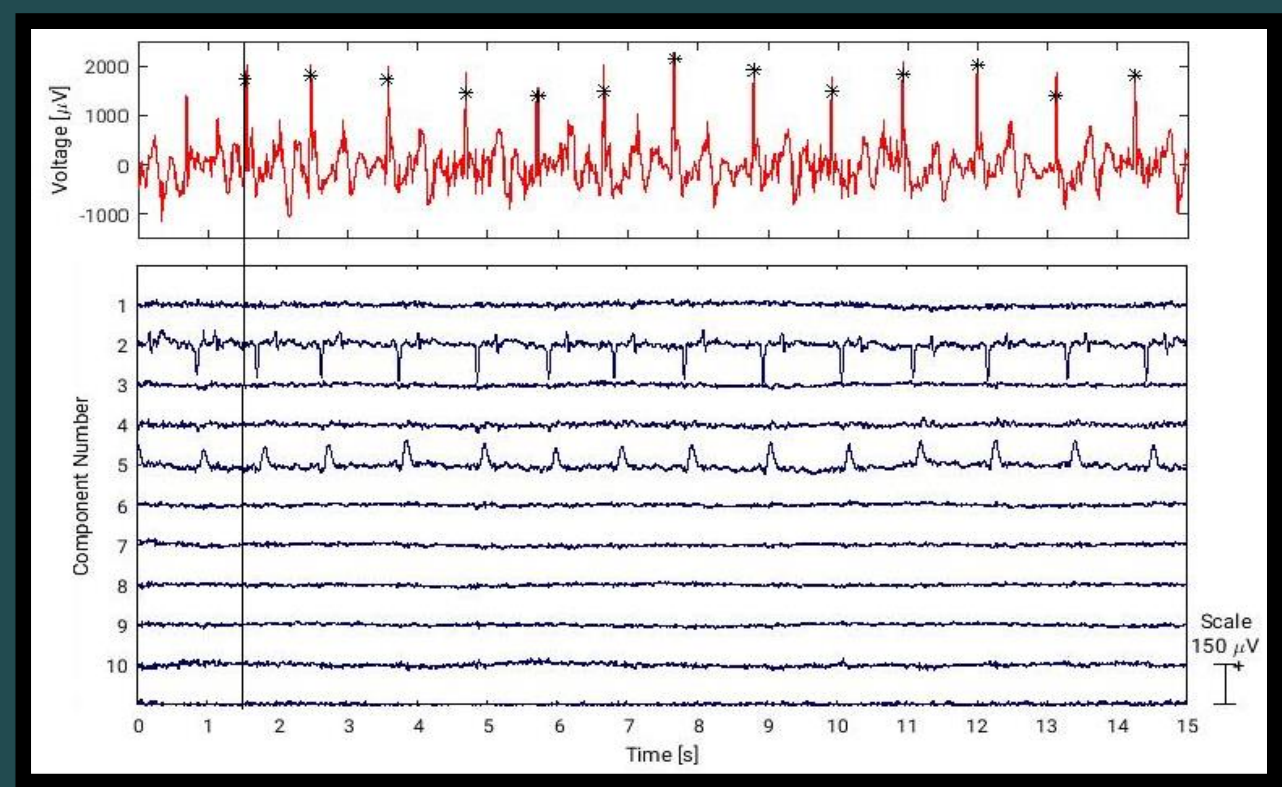


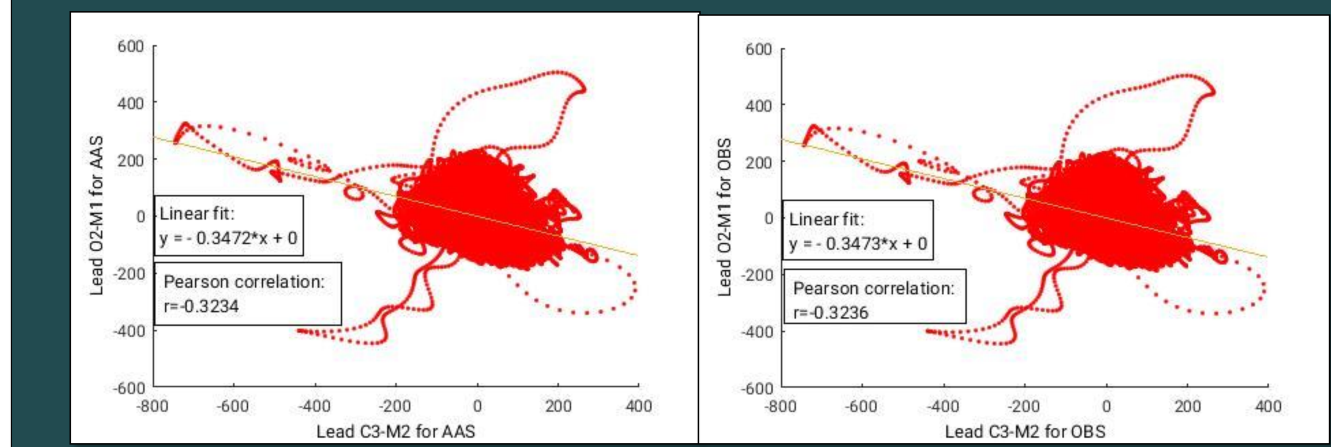
Fig. 4: The first 10 independent components after performing independent component analysis on GA-free EEG data recorded inside MR-scanner. Top shows the corresponding ECG signal

Results

No ground truth is available for evaluation of the algorithms. Only statistical comparisons between the output of the methods was possible within the time limit of this project. For comparison, 6 standard leads were selected. We then computed the Pearson correlation between two combinations of leads in data, where artifact had been removed using the same method. This was repeated for all combinations of leads. Fisher's r-to-z transformation was then computed on the difference between two correlation coefficients that come from the same data set, the same combination of leads but different artifact removal algorithms.

For GA-removal, the two algorithms AAS and OBS did not show any statistical significant differences in the Fisher's r-to-z transformation comparison of correlation coefficients.

For BCG-removal, all three methods showed statistically significant differences between each other.



Conclusion

This purpose of this project was to test current methods of artifact removal in simultaneous EEG-fMRI setting. Both methods for GA-removal showed promising results, and it was not possible to find any statistical significant difference between the two.

For BCG-removal, all three methods showed visually promising results. Statistically, all three methods were individually different from each other. Further analyses have to be made to determine which method is superior in removing artifacts. Further, the proposed extension to ICA can also be expanded and edited much further to enhance the accuracy of the algorithm.

References

[**1**] Allen et al., "*A method for removing imaging artifact from continuous EEG recorded during functional MRI* " (Neuroimage, 2000)

[**2**] Niazy et al., "*Removal of FMRI environment artifacts from EEG data using optimal basis sets*" (Neuroimage, 2005)

[**3**] Makeig et al., "*Independent component analysis of electroencephalographic data*" (Advances in neural information processing systems, 1996)

[**4**] Christov et al., "*Real-time electrocardiogram QRS detection using combined adaptive threshold*" (biomedical Engineering online, 2004)

Contact

Anders Stevnhoved Olsen
s154043@student.dtu.dk
20 86 86 03