Denoising EEG Signals

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1 Introduction

Electro **E**ncephalo**g**raphy (EEG) is a non-invasive method to measure electrical signals from the brain [1] using electrodes placed on the patient's scalp [2]. EEG signals are widely used in many emerging applications such as brain computer interfaces (BCI) [3], motor imagery (MI) [4], as well as physical/mental ailment detection [5]. One drawback to EEG signals - brain signals with a high temporal resolution [6] is that they are typically vulnerable to noise from various artifacts such as ocular artifacts, cardiovascular artifacts, muscular artifacts, and line noise [7, 8]. Therefore, denoising EEG signals is an important step in ensuring efficient downstream processing for most applications of EEG; in addition to the sample recovery aspect, which maximizes the data that can be used for training and testing. With the understanding that the neural patterns from MI, blinks, and movement are all independent from one another, we will look closely at using ICA to denoise EEG signals [9, 10]. In our study we will be focusing on the Corrmap technique [11] for identifying ICA components associated with noise and reconstructing the EEG signal without those components. With the aid of a unique dataset suited for testing our denoising algorithm, we intend to analyze the effectiveness of our algorithm against several types of artifacts.

2 Related Work

Due to the limited number of electrodes that can be placed on the head in a non-invasive manner, the raw EEG signals captured by the electrodes measure the desired signal mixed with undesirable signals and noise, collectively known as artifacts [12]; the examples of which have been described previously. In addition, both the desirable and undesirable signals are affected by various human and environmental stimuli such as sleep, drugs, and aural stimuli [12]. Finally EEGs are primarily electric field measurements which are smeared and attenuated by the skull [13] which makes the problem of BCI not only a spatial filtering problem, but a source separation problem as well.

Researchers have put forth a variety of EEG signal pre-processing methods such as Principal Component Analysis (PCA) [6], Independent Component Analysis (ICA) [14], Common Spatial Patterns (CSP) [15], and Adaptive Filtering [16]. Among those approaches, ICA is one of the most popular feature extraction algorithms in the field of biomedical engineering [17] along with CSP [18]. There are many different variations and implementations of ICA that can be applied to denoising EEG signals. Albera et. al. [19] compared 15 different ICA-based EEG denoising methods on their performance and numerical complexity. In their experiments, CoM2 [20] has the best trade-off between application task performance and time complexity.

For our classifier we utilized Linear Discriminant Analysis (LDA) and CSP features following our baseline [18, 4].

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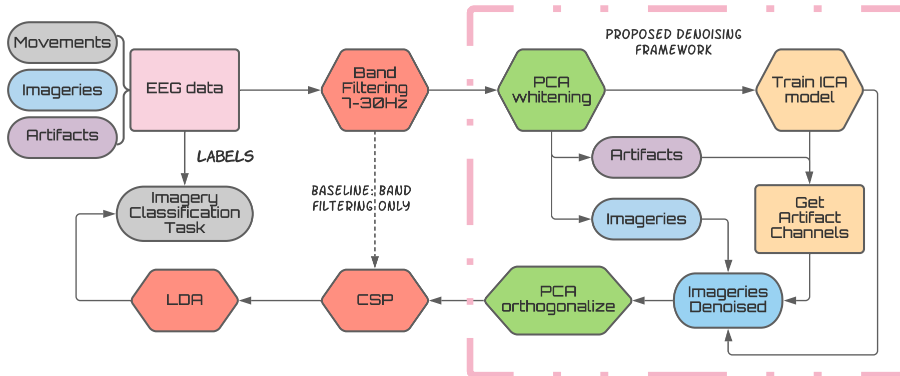


Figure 1: The pipeline diagram of proposed denoising framework.

3 Dataset

We plan to focus on the *GigaScience* dataset [4], which specifically targets MI-BCI applications where EEG signals can be induced by imagining motor movements rather than performing them. Measuring signals from this type of action has widely varying performances from session to session. Thus, Cho et. al. devised a rigorous EEG measurement procedure which includes repeated rest state measurements, repeated MI actions, and results from psychological and physiological questionnaires to test performance of upcoming systems that could achieve good single session and user-to-user performance [4]. Ascenção et. al. ran analysis on this dataset and compared several performance evaluation metrics in distinguishing between the MI-BCI system and the ability level of the users of that system [18].

There are also three corrupted files which we removed before pre-processing the complete data. Further, there are two subjects s29 and s34 which are correlated with EMG over 90%, so these two subjects will identify as bad subjects and will not be included in our EEG analysis [4]. During the pre-processing step, we identified certain imagery data as unusable. Thus, we discarded the same before proceeding with EEG analysis. For each subject, we also discarded inactive trails if the peak-to-peak amplitude of the trail is lower than $100\mu V$.

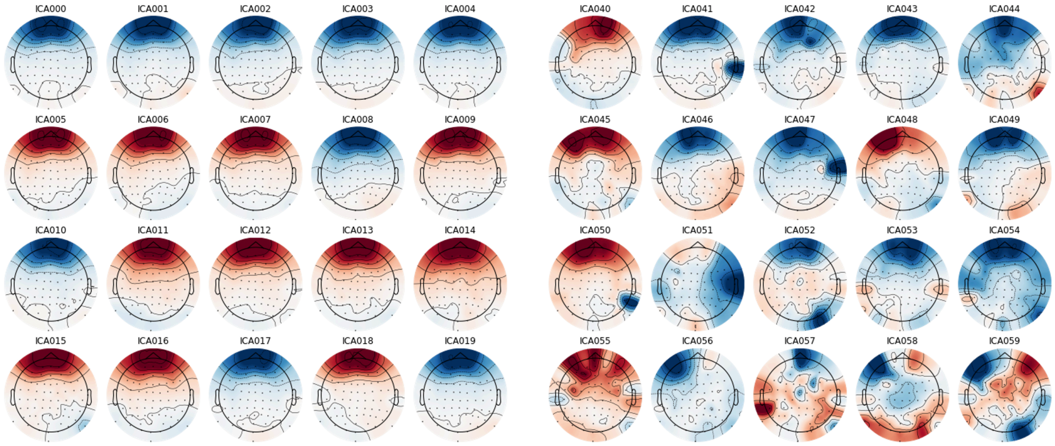
The dataset contains three type of EEG recordings for each subject: 2 7 second trial noise recordings for rest, eye blink, eye movement, jaw movement, and head movement; 20 trails each for both left and right hand movement; 100 to 120 trails for both left and right motor imagery. The input of our experiments are noise and motor imagery EEGs, and the output is the denoised imagery signals as well as the prediction of left or right. We process our data such that each motor imagery trial is broken up in to separate epochs, while the noise trials were broken up in to an epoch for each noise event with a window size of 0.5 to 0.6 seconds depending on the duration of the event. The artifacts were not tagged in the noise trials and were automatically detected by performing a hard threshold on the baseline-corrected EEG signal to detect large amplitude events correlated with such artifacts.

4 Denoising EEG Signals with CorrMap

The proposed denoising approach is shown in the diagram of Figure 1. The left side of the diagram is how we re-implemented the baseline classifier [4, 18]. It consists of band filtering of 7-30 Hz, 4 component CSP, and LDA. The 7-30 Hz band covers alpha, beta, and mu frequency of EEG signals, where most motor imagery activities occur [13, 4].

The right side of the diagram is the pipeline of our denoising framework, which re-implements Viola's Corrmap [11] with modifications on ICA implementation, adding pre- and post-PCA, as well as how we extracted artifacts ICA templates. The ICA implementation we used is FastICA. We experimented with InfoMax, extended InfoMax, Picard, and FOBI ICA, but FastICA gave us the best results.

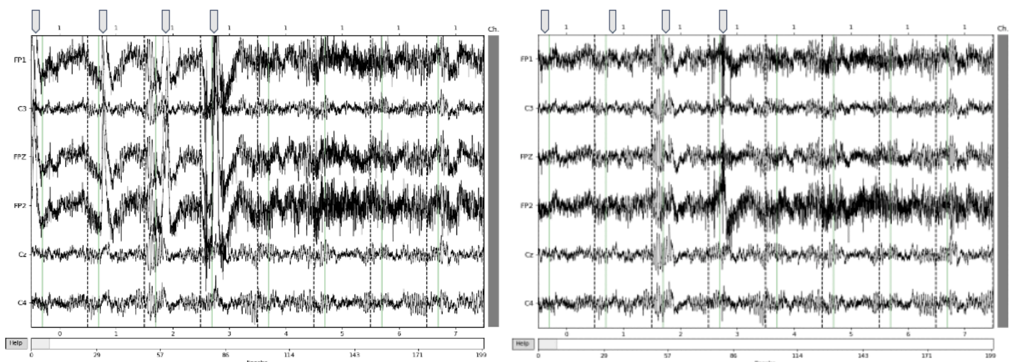
In the denoising process, we fit separate ICA models for imagery signals of each subject, as well as for each artifact category. The ICA components are sorted by R^2 score with respect to the data



(a) The scalp topography shows independent components 0 through 19 for the blinking trial.

(b) The scalp topography shows components 40 through 59 for the same trial.

Figure 2: ICA components selection



(a) Raw EEG from MI Trials

(b) Reconstructed signal with correlated component(s) removed

Figure 3: Denoise via signal reconstruction

they are describing as seen in Figure 2. For the motor imagery ICA, 64 components were extracted to match the number of EEG electrodes, as we expect events in the EEG signals to be independent and highly localized to the location of each electrode. For each artifact type, we pick the first 10 channels which we will take as our noise "templates".

With ICA components for imagery signals and artifacts, we used Viola's CorrMap to find similar Independent Components by computing correlation scores between the noise templates and every ICA component from the motor imagery trials [11]. We drop the channels with a correlation of 0.8 - 0.9 or higher with the noise template in the EEG signal reconstruction. The reconstructed signal is often not full rank, which makes its co-variance matrix non-invertible; this prevents us from using CSP to extract patterns. This was a common problem when removing signals from EEGs and the solution to this was available[1]. The solution was to introduce PCA to orthogonalize the data without reducing its dimension. This trick is really important, enabling us to try many methods and heuristics of removing ICA channels. The rest operations and parameters are kept the same as the baseline.

5 Results

5.1 Denoising Effectiveness

The left side of Figure 2 shows independent components 0 through 19 for the blinking trial. The right side of Figure 2, shows components 40 through 59 for the same trial. Note that these components are sorted by R^2 score with respect to the original data they are describing. For denoising, the first

[1]https://github.com/mne-tools/mne-python/issues/8555

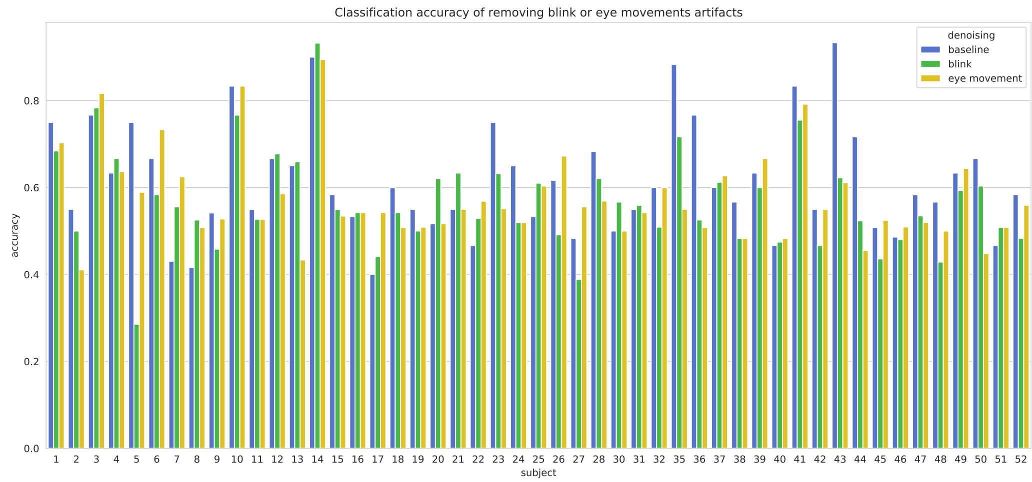


Figure 4: MI classification accuracy by removing eye blinking or eye movement artifacts.

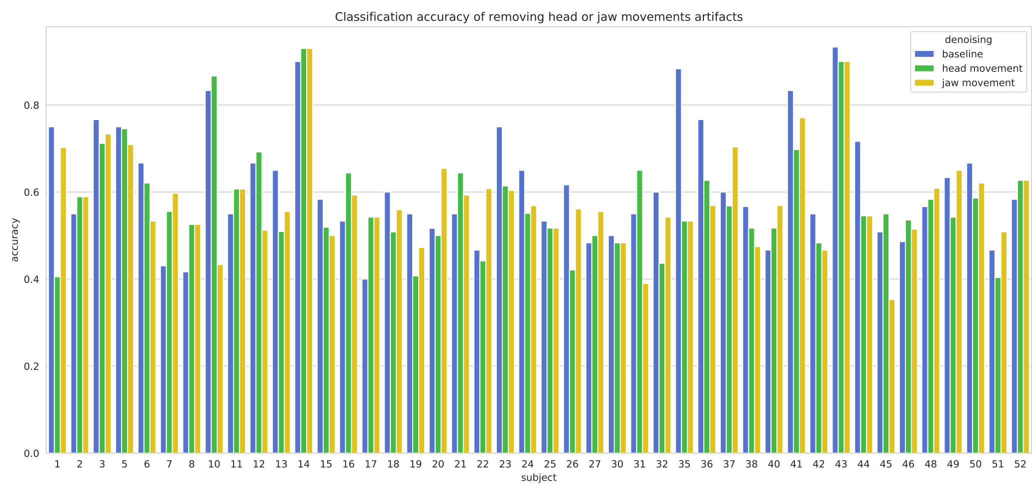


Figure 5: MI classification accuracy by removing head movement or jaw movement artifacts.

10 components were chosen since we observed that empirically the first 10 components sorted by R^2 contained all the artifacts (in most cases, there were only one or two components relating to the artifact and the other components of the 10 were just copies of those components). In the blinking example here, it is clear from the topology plot that they are all describing the same event, a strong positive or negative impulse occurring over the eyes which strongly matches the expected topology plot for this type of artifact [21].

Figure 3 shows the results from the denoising process. The original EEG (with baseline correction applied so they are mean centered and can be more easily visualized) are shown on the left. The denoised EEG is shown on the right. Note the arrows above the two plots which mark the location of blink occurring. Blink artifacts are characterized by a strong, short-duration, discontinuity which increases then decreases due to the fluctuation of charge when the eyelids move over the eyes. In addition, the blink artifacts are highly localized around the eyes which is clearly shown by the change in amplitude from the FP1, FP2, and FPZ electrodes which are located over the pre-frontal area of the brain, extremely close to the eys. The C3, C4, and Cz electrodes located closer to the top of the head further away from the eyes still contain the artifact, albeit at a much smaller amplitude. On the right, we can see in the denoised signal the artifact has been suppressed, but a small trace of the artifact still remains.

5.2 Motor Imagery Classification

We trained our MI classification model by using sklearn ShuffleSplit cross validation with 10 fold to split 20 percent as test set. The classification task is to discriminating between left motor imagery or right motor imagery. Our result for classifying the test set compare with the baseline from Cho's method [4] is shown in Figure 4 and Figure 5. The Figure 4 shows the MI classification result of denoising blinking and eye movement. The Figure 5 shows the MI classification result of denoising jaw and head movement.

We got acceptable results from most of the subjects such as Subject 14 with improvement in accuracy of denoising each artifacts compare to the baseline, and have 0.93 accuracy after removing blinking artifact. However, there are also some extreme results such as Subject 5 with low accuracy 0.28 in removing blinking artifacts and Subject 45 with low accuracy 0.35 in removing jaw movement artifacts compare with other subjects. We conducted further analysis on these extreme cases, we found that the electrodes location of blinking movement ICA components from Subject 5 are all slightly tilt to right, unlike the blinking effects on other subjects are mainly located in the center of two eyes. Likewise, many of the jaw movement ICA components from subject 45 have strong positive or negative impulses covering over 70% of scalp area, different from other subjects such as Subject 14 shows only small area has impulses. These difference might caused some significant signal be removed during the denoising process and contributed to the extreme results.

6 Discussion and Analysis

The challenge is that the EEG signals of same movement may vary from every subjects. It's even different for the same person on different days, and we only have one artifact sample for each subject. Our results, as you can see, is not perfect as we initially expected. We think it will be more convincing if the classification accuracy is higher for more cases. By manually going through the removed ICA channels, we think some of them were not reasonable (e.g. eye blink from back of head is strange). We have one signal segment for each artifact, each subject, so the quality of this single trial is crucial to this subject. Also, overall baseline is performing better than our result, that is because of the low SNR for EEG signals, removing significant artifacts is going to undermine the performance of following task. We attempted multiple implementations of ICA (FastICA, InfoMax, Extended InfoMax, Picard, and our own version of FOBI), but FastICA gave us the best results.

In the field, there are quite a few EEG denoising frameworks that look at spatially filtering EEG signals in order to minimize the impact of noise. In the case of motor-imagery, the electrodes in the C3, C4, and CZ locations are located over the centrotemporal part of the brain which is responsible for MI as it is located between the sections of the brain which deal with vision and muscle movement. The popular CSP (common spatial filters) technique is actually what we used in the final feature extraction stage prior to classification, but it was not robust to noise, hence our project focused on EEG denoising as a preprocessing step to this feature extraction and classification. Other filtering techniques such as bipolar or laplacian montages are similar to CSP in that they are spatial filters which can reduce the amplitude of artifacts by using locality, but can't suppress them directly. Other work that we looked at relating to ICA denoising used Wavelet soft-thresholding and similar time-series techniques, but we found that they were not particularly helpful.

The changes we made to improve the framework dealt primarily with the ICA component selection step. As we learned in class, ICA components have no notion of ordering unlike PCA, so being able to find the ideal number of components to extract in addition to identifying the components containing the artifacts in an unsupervised manner is desirable. All the research we have come across use artifacts detected in-situ and the generality of EEG patterns is believed to be quite low due to their dependence on many external sources (sleepiness, drug use, excitability of the subject, etc.). We expanded on and analyzed the existing Corrmap algorithm to use prerecorded EEG "noise" signals to denoise giving rise to a "general" EEG template.

Conclusion It is feasible to use pre-recorded EEG noise templates for denoising EEG signals either as a stand-alone solution or supporting in-situ denoising of EEG signals which is a more common practice today. Our modified Viola Corrmap technique with the prerecorded templates generally only changed the classification accuracies by a few percent. The change is attributed to the frequency of artifacts in the EEG which is highly dependent on subject.

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