Investigation of Artifact Contamination Impact on EEG Oscillations Towards Enhanced Motor Function Characterization

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Abstract: The significant advancements in electroencephalography (EEG) technology have led to its widespread use in assessing stroke-related conditions. While various research studies have explored the potential of EEG oscillatory patterns in neurological research, many have given limited attention to the signal processing methodology. In understanding how artifacts affect EEG oscillatory rhythms, EEG signals were collected from healthy subjects who performed movement tasks, which were processed using automated artifact-attenuation methods. Subsequently, the mu and beta bands in the brain's motor cortex region were extracted using time-frequency analysis and analyzed using relevant metrics. The results revealed that the presence of artifacts in EEG could affect the brain activation strength and response during motor tasks. Notably, signals preprocessed with RELAX_MWF_wICA demonstrated better brain responses and high task classification performance compared to other methods and the raw signal across all tasks. This study's findings revealed that the signal processing methodology could influence its analysis and interpretation, thus highlighting the need for careful consideration and usage.

1 INTRODUCTION

The study of neural oscillations, driven by the coordinated activity of numerous neurons and assessed through techniques functional magnetic resonance imaging (fMRI), electroencephalography (EEG), magnetoencephalography (MEG), and among others, has been a prominent and extensively explored area in neurological research when investigating the mechanisms behind human behavioural activities (Ward, 2015; Gui et al., 2010; Jee, 2021).

Notable advances in EEG technology and other factors have led to it's widely usage in assessing brain function related to strokes. EEG is a non-invasive and safe method with excellent temporal resolution that offers valuable insights into brain activity by directly measuring electrical potentials from the underlying neural tissue through scalp electrodes [Wu et al., 2016; Lin et al., 2017; Asogbon et al., 2021; Anapama et al., 2012]. EEG signals represent recurring patterns resulting from the coordinated activity of neurons firing in synchrony, and they can be observed across a range of frequencies (including delta, theta, alpha, beta, and gamma bands). Brain activities during upper limb movements in these bands have been shown to be affected by stroke (Maura et al., 2023; Bartur et al., 2019). Therefore, they are considered promising predictors that have the potential to offer valuable insights about stroke patients, helping clinicians identify distinct biological subgroups and determine which treatment approach might be more appropriate and effective (Cassidy et al., 2019).

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For instance, in contemporary stroke intervention, these frequency bands are employed as predictors, which are incorporated/combined with intervention techniques. This integration further enhances diagnosis, treatment, and recovery in stroke patients with motor impairments. (Keser et al., 2022). Cassidy et al., 2019 investigated EEG oscillations as a potential predictor of injury and motor function recovery in stroke survivors. Experimenting with EEG recordings from healthy controls and stroke patients, the connection between EEG oscillations with injury and motor condition was examined, utilizing delta and high-beta frequency bands. The study outcome revealed that delta-frequency oscillations reflect both injury and motor function recovery after stroke. In addition, Thibaut et al., 2017 found out in their work that stroke patients' brain activity in lesioned and unlesioned hemispheres measured by EEG provides new insights into the relationship between high-frequency rhythms and motor impairment, highlighting the role of an excess of beta in the affected central cortical region in poor motor function in stroke recovery. A research study conducted by López-Larraz et al., 2018, emphasized the significance of employing suitable techniques for eliminating artifacts in EEG recordings of stroke patients. The study aimed to uncover the real neural activity by eliminating unwanted interference. The findings revealed that during motor tasks, EEG-cortical activation is heightened, and the presence of artifacts can introduce an overly optimistic bias in the performance evaluation of brain-machine interfaces (BMIs).

Unarguably, several works have conducted exploratory investigations on the use of EEG oscillatory rhythms to predict motor function recovery in stroke patients. Given that EEG signal is prone to contamination from various artifacts, it is hypothesized that the influence of these disturbances can significantly affect the resulting signal, potentially causing misinterpretation if a robust cleaning method is not implemented at the signal processing stage. Unfortunately, relatively little attention has been directed towards the methodologies employed for processing EEG signals.

To address this concern, we investigated the role of artifacts on EEG based neural oscillations. The study was conducted using EEG signal recordings of healthy individuals who performed four movement execution (ME) tasks. The recorded signals were individually processed with popularly automated data-driven artifact elimination methods and analyse with EEG quantifier and evaluation metrics.

2 MATERIALS AND METHODS

2.1 Participants Information

In this study, 20 healthy subjects volunteered to participate in the experiment. Specifically, right hand dominated subjects including male and female within the age range of 20 and 35 years were recruited for the experiment. Prior to the experiment, all volunteers were briefed on the study objective and the experimental procedure. Afterward, they all agreed and gave written consent for the publication of their data. The recruitment and experimental process were approved by the Institutional Review Board of Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences.

2.2 Equipment setup and data collection

The experiment was conducted at the Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences. The EEG signals were acquired from the subjects using a 64-channel gel-based AgCl electrode cap combined with a Neuroscan acquisition system. The EEG cap was positioned on each of the volunteer's head following international 10–20 electrode placement configuration. The ground electrode was positioned at AFz and referenced to CPz during signal recording. All electrode channels were sampled at 1000Hz and based on based on the volunteer's tolerance level, the impedance varies between 5-8kΩ.

Before the commencement of the experiment, the subjects were trained on the experimental procedure and instructed them on what to do during each of the ME task performances. In this study, ME tasks, including key grip (KGME), power grip (PGME), wrist extension (WEME), and wrist flexion (WFME), as shown in Figure 1, were performed by each person. All volunteers were told to sit on a comfortable high-back chair and watch a visual display unit (VDU) placed in front of them 1m away. To ensure the tasks were performed correctly, pre-recorded video containing an active (say wrist extension) and non-active task (rest) was developed. The VDU was used to display the video of each task to guide them during the experiment. The participants performed each ME tasks for two consecutive sessions with each containing 10 active and 10 non-active tasks.

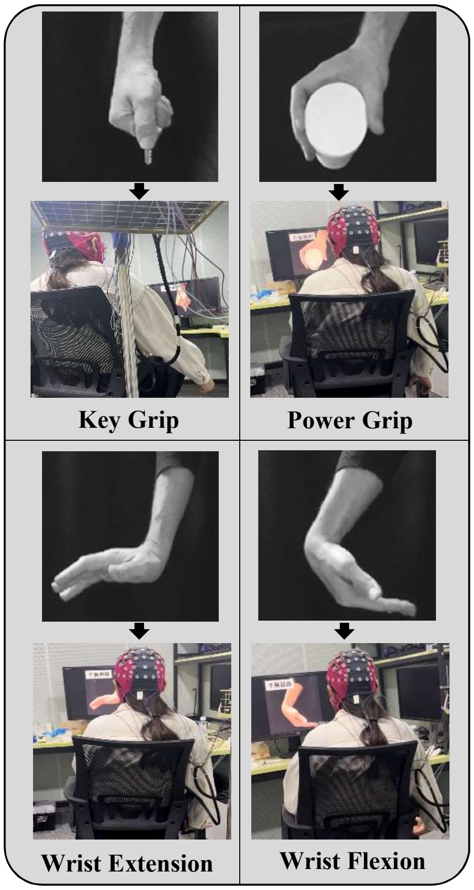


Figure 1: A representation of a participant during the motor execution tasks which includes key grip , power grip ,wrist extension and wrist flexion .

2.2 Data Processing

The signal recorded for each participant underwent offline processing and analysis utilizing the EEGLAB and MATLAB toolkits. Towards understanding the relevance of artifacts on EEG oscillatory patterns five popularly used automatic data-driven EEG artifact attenuation methods were applied to the recorded signals. The procedure for the signal processing is described as follows:

1. Utilizing EEGLAB, each of the ME tasks of the recorded signals trials/session were merged and then filtered with a low pass filter of 30Hz and a high pass filter of 1Hz.
2. Afterward, automated EEG artifacts elimination methods including:

   (a) Independent Component Analysis based Extended Information-maximization (INFOMAX) (Jutten & Herault, 1991; Comon, 1994).
   (b) Artifact Subspace Reconstruction (ASR) (Bloniasz, 2022; Chang et al., 2019, blum et al., 2019).
   (c) ICA based Automated Artifact Removal (CCACCA) (Gómez-Herrero et al., 2006; De Clercq et al., 2006).
   (d) Reduction of Electroencephalographic Artifacts based on Multi Weiner Filter and Enhanced Wavelet ICA (RELAX_MWF_wICA) (Bailey et al., 2022; Somers et al., 2018; Castellanos et al., 2006).
   (e) Reduction of Electroencephalographic Artifacts based on Multi Weiner Filter (RELAX_MWF) (Bailey et al., 2022; Somers et al., 2018).

   was individually applied to the filtered signal.

3. The IC components of the artifact-free signals were computed using ICA decomposition method.
4. The IC_Label classifier (Pion-Tonachini et al., 2019) was applied to detect or flag artefactual ICs based on some thresholding parameters. Then, the flagged artefactual ICs are subtracted from the signals.
5. The resulting continuous EEG signals is epoched by extracting data epochs that are time-locked to a specified ME task.
6. To study the task related EEG dynamics of the signals, each individual task was epoched choosing a window from -1s to 5s.
7. The epoched datasets are saved for time-frequency analysis and other analyses in MATLAB using a custom built script.

It is worth stating that the signal processing steps presented above were performed on each subject's recording signal. The Mu (μ) and Beta (β) EEG oscillatory pattern in the motor cortex region of the brain during ME tasks were considered in this study. Specifically, the μ-band in the range of 10-14Hz and β-band in the range of 16-26Hz were extracted from the cleaned/processed signal from the 18 electrodes at the motor cortex region (excluding the midline electrodes) using a time-frequency analysis-based approach.

2.3 Feature Extraction and Task Decoding

In gaining insights into how various methods for reducing artifacts affect brain activation strength, the z-score power-based EEG quantifier was utilized to evaluate the degree of brain activation response with respect to each task using Z-score power.

For motor task recognition, the preprocessed EEG signals were divided into smaller windows using a sliding segmentation approach. Subsequently, a feature extraction method based on wavelet analysis was employed to extract pertinent features from each segment.

Each resulting feature matrix was used to construct individual machine-learning models using three different algorithms: Linear Discriminant Analysis (LDA), k-nearest Neighbors (kNN), and Random Forest (RF). A five-fold cross-validation technique was applied to partition the extracted feature matrices into training and testing datasets to ensure optimal data utilization.

The performances of the models were assessed using classification accuracy (CA; eqn. 3), positive predictive value (PPV; eqn. 2), negative predictive value (NPV; eqn. 3), and false positive rate (FPR; eqn. 4)

$$CA_{ave} = \frac{\sum_{i=1}^{N}\left(\frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i}\right)}{N} \tag{1}$$

$$PPV_{ave} = \sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i} \tag{2}$$

$$NPV_{ave} = \sum_{i=1}^{N} \frac{TN_i}{TN_i + FN_i} \tag{3}$$

$$FPR_{ave} = \sum_{i=1}^{N} \frac{FP_i}{FP_i + TN_i} \tag{4}$$

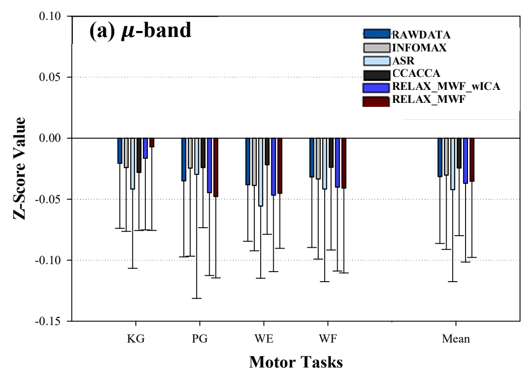
where N denotes the number of ME classes, TP_i: true positive, FP_i: false positive, FN_i: false positive, and TN_i: true negative.

The Friedman test was employed to check the statistically significant effect between the preprocessed signals with the artifact attenuation methods and the original EEG signal recordings.

3 RESULTS

3.1 Analysis of Cortical Activation via Z-score Power

A Short-time Fourier transform was individually applied to each of the pre-processed signals for both frequency bands (μ and β). After the time-frequency decomposition, the data was z-scored and normalized. Figure 2a-b depicts the μ and β bands' average z-score results during movement across all participants. In the figures, each color bar represents the raw signal and different elimination methods. In addition, the z-score power varies for all the methods task by task.



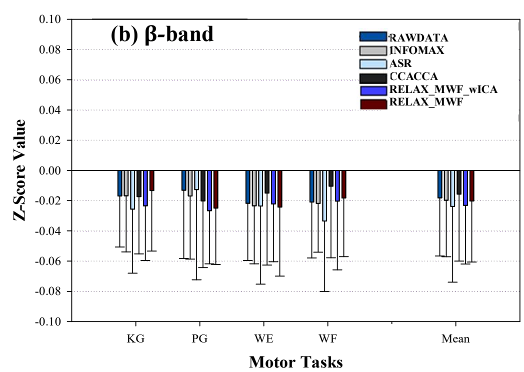


Figure 2 Average z-score power for healthy subjects for the (a) μ (b) and β frequencies band across all participant.

Generally, It is expected that the z-score value increases (more negative) after artifacts are eliminated from the signals. That is, high negative z-score value indicates a stronger brain signal or activation. Through careful examination, ASR obtained increased z-score value for all tasks compared to the raw data in both bands.

Similarly, RELAX_MWF_wICA and RELAX_MWF achieved better z-scores than others did for all tasks except for KGME. However, the CCACCA method recorded the lowest z-score value, followed by INFOMAX, compared to other methods. The performance of these methods may likely be due to more brain signals being removed during pre-processing. It could also be because of their inability to remove other artifacts that are not related to ocular or muscular artifacts. Across all tasks and bands, the RELAX_MWF_wICA and ASR recorded consistently higher average z-score values. At the same time, some artifact removal methods showed an increment in the z-score values; there is no statistical significance between the raw data and the artifacts attenuation methods (μ : p = 0.1815 and β: p = 0.6126).

3. 2 Performance Estimation of Attenuation Methods using FPR, PPV and NPV

The effectiveness of the classifier's performances with respect to the attenuation methods was validated using false positive rate (FPR), positive predictive value (PPV), and negative predictive value (NPV) metrics. The FPR measures the proportion of negative instances that are inaccurately identified as positive instances, while PPV is the percentage chance that a positive result is a true positive, and NPV is the percentage chance that a negative result is a true negative.

The scatter box plot group shown in Figure 4a-b presents the average FPR, PPV, and NPV results for HG across tasks. Each of the plots consists of average (i) FPR, (ii) PPV, and (iii) NPV (partitioned with a black dotted line) for the classifiers (including LDA, KNN, and RF). Observing the plots for the) μ and β bands, the effectiveness of the raw data and the attenuation methods based on the RF classifier for three metrics are also relatively the same compared to other LDA and KNN classifiers.

An obvious difference is noticeable between the artifact attenuation methods and the raw signal for the three metrics, especially PPV. Overall, RELAX_MWF_wICA based on the LDA classifier achieved the lowest FPR value (μ: 0.0108, β: 0.0026), highest PPV (μ: 0.9679, β: 0.9923), and NPV (μ: 0.9892, β: 0.9974)values than other methods.

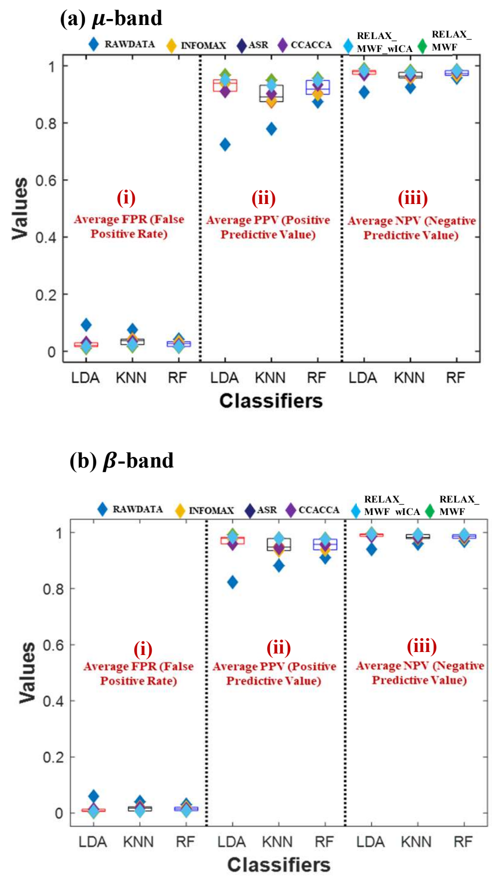


Figure 3: Evaluation of artifact performance in relation to FPR, PPV and NPV for HG (a) μ and (b) β bands.

3.2 Evaluation of Individual Task Decoding Performance

This section examined individual ME task recognition rate using an LDA classifier based on its performance. The obtained result for HG in the μ and β bands is presented in Figure 6a-b using a bar plot graph. The error bar on each preprocessing method bar represents the standard deviation across HG. From the results, the β band performs better than the μ band, and it is clear that all artifact removal methods were able to eliminate artifacts from the signals yielding varying classification performance.

Looking at the performance of each method, the RELAX_MWF_wICA (p-value: 0.0022 for μ and β bands) yielded the best average accuracies. Specifically, μ: 96.98 ± 8.40%, 95.91 ± 6.05%, 96.49 ± 5.00%, and 97.27 ± 4.70% for KGME, PGME, WEME and WFME respectively. For β band, accuracies of KGME: 99.63 ± 1.02%, PGME: 98.77 ± 2.54%, WEME: 98.97 ± 2.75% and WFME: 98.49 ± 3.46%.

On the other hand, the least performance was obtained by the raw signal with mean accuracies of 78.13 ± 10.68%, 71.62 ± 10.92%, 69.66 ± 10.60%, 71.79 ± 10.58%, for μ band. The β band recorded 87.14 ± 7.76%, 80.94 ± 10.79%, 79.30 ± 10.15%, 81.68 ± 10.29% KGME, PGME, WEME and WFME respectively.

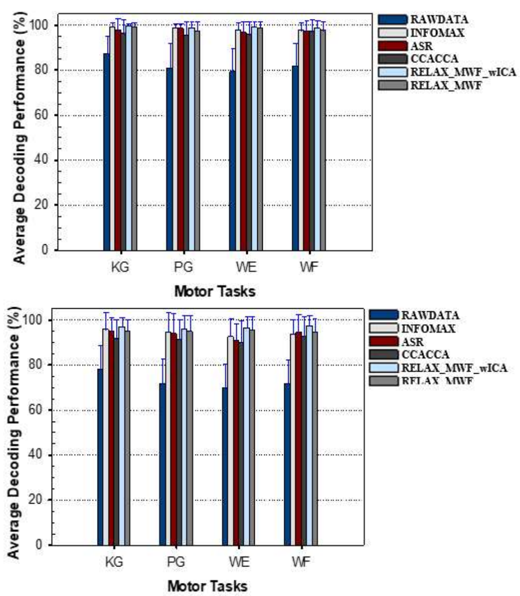


Figure 5 Class-wise task decoding performance for (a) μ (b) and β bands.

4 CONCLUSIONS

In this study, we demonstrated the impact of artifacts on EEG oscillatory rhythms. It was hypothesized that the presence and removal of various kinds of artifacts could result in the biasedness of signal analysis and interpretation. The investigation was conducted using EEG signal from the μ and β bands, which were extracted using time-frequency analysis from signal recordings from healthy volunteers who performed ME tasks.

The obtained experimental results show that the attenuation methods influence the z-score power values in both the μ and β bands. All methods except CCACCA and INFOMAX recorded increased z-score values compared to the raw data for most of the tasks in the μ and β bands. In other words, these methods enhanced the brain response through the mitigation of artifacts. Besides, the μ band achieved better z-score values in comparison to β bands.

The outcome from the FDR and PPV NPV validation metric shows that the based RELAX_MWF_wICA method is an accurate and effective model for processing EEG signals compared to other methods. Similarly, in the individual task classification performance, the RELAX_MWF_wICA method outperformed other methods and the raw data for both bands.

Considering all the methods, RELAX_MWF_wICA demonstrated consistent performance for all the metrics, and this could be because it's a hybrid artifact attenuation method developed based on the advantages of MWF and wICA. In addition, it can simultaneously remove multiple artifacts from possibly because of its ability to remove multiple artifacts from the signals.

The outcome of this work provides valuable insight on the need of using appropriate methodology in the EEG signal processing pipeline to avoid biased signal analyses and interpretation. It is worth mentioning that this is a preliminary study using signal recordings from healthy subjects. In our future work, we will conduct an extensive investigation using stroke patient datasets to validate the findings from this study.

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