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

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Abstract: The significant advancements in electroencephalography (EEG)-driven technology have led to its widespread use in assessing stroke-related conditions. Over the years, various studies have explored the potential of EEG oscillatory patterns in neurological research, with several of them giving limited attention to the signal processing techniques employed, precluding a proper understanding of EEG oscillatory patterns under various conditions. To resolve this issue, we systematically investigated how artifacts impact EEG oscillatory rhythms associated with upper limb movement-related tasks. Thus, the EEG signals of motor tasks were acquired non-invasively from healthy subjects and processed using automated artifact-attenuation methods. Subsequently, the Mu and Beta bands in the brain's motor cortex region were extracted through time-frequency analysis and analyzed using relevant metrics. Experimental results revealed that artifacts in EEG would substantially influence the brain activation strength and response during motor tasks. Notably, signals preprocessed with Reduction of Electroencephalographic Artifacts based on Multi Wiener Filter and Enhanced Wavelet Independent Component Analysis (RELAX_MWF_wICA) showed better brain responses and high task classification performance compared to other methods and the raw signal across motor tasks. This study's findings revealed that the choice of signal processing technique is crucial, as it would 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 such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magneto-encephalography (MEG), among others, has been a prominent and extensively explored area in neurological research (Ward, 2015; Gui et al., 2010; Jee, 2021).

Notable advances in EEG technology have led to its wide usage in assessing stroke-related brain function. EEG is a non-invasive and safe method with an excellent temporal resolution that offers valuable insights into brain activity through direct measurement of electrical potentials from the underlying neural tissue (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 are affected by stroke (Maura et al., 2023; Bartur et al., 2019). Therefore, they are considered promising predictors that can offer valuable insights into stroke patients' status, 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 therapeutic treatment, EEG oscillations are utilized as predictive indicators, incorporated with clinical intervention techniques. This integration further enhances diagnosis, treatment, and recovery in stroke patients with motor impairments (Keser et al., 2022). In 2019, Cassidy et al. investigated EEG oscillations as a potential predictor of injury and motor function recovery in stroke survivors. By experimenting with EEG recordings from both healthy controls and stroke patients, the study examined the connection between EEG oscillations and injury and motor condition, utilizing delta and high-beta frequency bands. The study's outcome revealed that delta-frequency oscillations reflect both injury and motor function recovery after a stroke.

In addition, Thibaut et al. (2017) found, in their work, that brain activity in both lesioned and unlesioned hemispheres of stroke patients, as measured by EEG, provides new insights into the relationship between high-frequency rhythms and motor impairment. Their findings highlight the role of an excess of beta activity in the affected central cortical region, contributing to poor motor function during stroke recovery.

A research study conducted by López-Larraz et al. (2018) emphasized the significance of employing suitable techniques to eliminate artifacts in EEG recordings of stroke patients. The study aimed to uncover the true 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 using EEG oscillatory rhythms to predict motor function recovery in stroke patients. Considering that the EEG signal is susceptible to contamination from various artifacts, these disturbances can significantly influence the resulting signal, potentially leading to 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 oscillations in relation to upper limb motor tasks, representing a fundamental drawback in the field.

In addressing this concern, we systematically investigated the influence of artifacts on cortical activation and the recognition of motor tasks using EEG-based neural oscillations, with a specific focus on the Mu (μ) and Beta (β) bands. The study involved the analysis of non-invasively collected EEG signals from healthy individuals participating in four distinct movement execution (ME) tasks.

These signals were individually processed using five automated data-driven methods capable of removing either single or multiple artifacts. These methods were selected from widely used EEG artifact attenuation techniques based on performance criteria evident in existing works.

The ICA decomposition method is applied to the processed signal, and an automated independent component (IC) classification method was used to detect or flag artefactual ICs based on specific thresholding parameters. After that, the signal segment that is time-locked to a specific event was epoched and analysed using time-frequency analysis.

2 MATERIALS AND METHODS

2.1 Participants Information

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

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 the volunteer's tolerance level, the impedance varies between 5-8kΩ.

Before commencing the experiment, the subjects were trained on the experimental procedure and instructed on how to perform the ME tasks. The ME tasks, including key grip (KGME), power grip

(PGME), wrist extension (WEME), and wrist flexion (WFME), shown in Figure 1, were performed by each subject. The subjects were instructed to sit on a comfortable high-back chair and watch a visual display unit (VDU) placed 1m in front of them. 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 throughout the experiment. Each active task (ME) was performed for a duration of 5s, followed by 5s of non-active task (rest) to mitigate fatigue. In total, participants completed two consecutive sessions, each comprising 10 active tasks 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 .

2.3 Data Processing

The signal recorded for each participant underwent offline processing and analysis utilizing the EEGLAB (Delorme and Makeig 2004) and MATLAB (The MathWorks Inc. 2019) 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. Subsequently, the signals were filtered using a passband edge frequency of 1Hz and 30Hz. The 1Hz signifies the upper limit of the lower frequency range, and 30Hz represents the lower limit of the higher frequency range that can pass through the filter.
2. Afterward, the following automated EEG artifacts elimination methods were individually applied to the filtered signal:
   (a) Independent Component Analysis (ICA) 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 Wiener 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 Wiener Filter (RELAX_MWF) (Bailey et al., 2022; Somers et al., 2018).

Importantly, the single and multiple automated artifact reduction methods were chosen from commonly used EEG artifact removal techniques based on their superior performance. The detail description of each method can found in the provided references above.

3. Next, ICs of the individually processed signals were computed using the ICA decomposition method.
4. The IC_Label, an accurate and computationally efficient classifier compared to other commonly used automated IC component classification method (Pion-Tonachini et al., 2019), was applied to detect or flag artefactual ICs based on thresholding parameters. Thereafter, the flagged artefactual ICs were subtracted from the processed signals.

5. The resulting continuous EEG signals are epoched by extracting data epochs that are time-locked to a specified ME task.
6. In examining the task-related EEG dynamics of the signals, each 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 EEG recording.

2.4 Feature Extraction and Task Decoding

In gaining insights into how the automated methods for reducing artifacts affect brain activation strength, the z- The μ and β oscillatory pattern in the brain's motor cortex region during ME tasks were considered. As demonstrated in existing works, these bands were selected based on their modulation characteristics during movement. In addition, alterations in these bands during ME tasks have been found to correspond with motor impairment in stroke patients. (Bartur et al., 2019; Leonardi et al., 2022).

Apply a time-frequency analysis-based approach, the μ and β bands in the range of 10-14Hz and 16-26Hz were extracted from the cleaned/processed signal from the 18 electrodes at the motor cortex region (excluding the midline electrodes).

The short-time Fourier transform analysis was performed on each processed signal within the designated frequency bands (μ and β). Following the time-frequency decomposition, the data were z-scored (eqn. 1). A statistical comparison of the z-scored power in both frequency bands during rest and movement task was conducted across all EEG channels using the Wilcoxon rank-sum test, and the results were subsequently topographically mapped. In cases where no significant difference was observed between rest and movement for a channel, the value was set to 0.

$$X^{\wedge} = \frac{X - \mu}{\sigma} \quad (1)$$

where X^ is the Z-scored signal, X denotes the processed signal, μ and σ is the mean and standard deviation of the signal during rest time for each trial.

For the 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, including 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 five-fold cross-validation involves randomly dividing the entire dataset into five subsets, and this process is repeated five times. During each iteration, the model is trained on four of the folds, while the remaining one is used for testing the model.

The performances of the models were assessed using classification accuracy (CA; eqn. 2), positive predictive value (PPV; eqn. 3), negative predictive value (NPV; eqn. 4), and false positive rate (FPR; eqn. 5). PPV is the percentage chance that a positive result is a true positive. NPV is the percentage chance that a negative result is a true negative. The FPR measures the proportion of negative instances that are inaccurately identified as positive instances.

$$CA_{ave} = \frac{\sum_{i=1}^{N}\left(\frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i}\right)}{N} \quad (2)$$

$$PPV_{ave} = \sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i} \quad (3)$$

$$NPV_{ave} = \sum_{i=1}^{N} \frac{TN_i}{TN_i + FN_i} \quad (4)$$

$$FPR_{ave} = \sum_{i=1}^{N} \frac{FP_i}{FP_i + TN_i} \quad (5)$$

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

Figure 2a-b depicts the average z-score results for the μ and β bands during motor execution (ME) across all participants. In the figures, each color bar represents the raw signal and different artifact reduction methods, with the z-score power varying for all methods task by task.

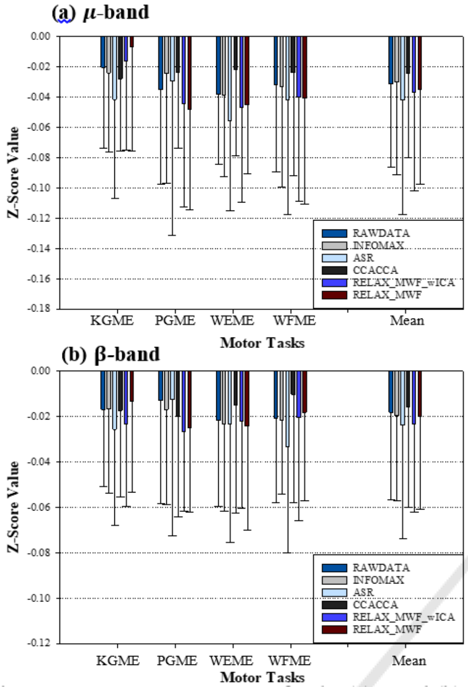

Figure 2: Average z-score power for the (a) μ and (b) β frequencies band across all participants.

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

Similarly, RELAX_MWF_wICA and RELAX_MWF methods achieved better z-scores than others for all tasks except for KGME. However, the CCACCA method recorded the lowest z-score value, followed by INFOMAX. The performance of INFOMAX and CCACCA methods may be due to removing more brain signals during pre-processing. It could also be because of their inability to remove other artifacts unrelated to ocular or muscular artifacts. Across all tasks and bands, the RELAX_MWF_wICA and ASR methods 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 artifact attenuation methods (μ : p = 0.1815 and β: p = 0.6126).

3.2 Performance Estimation 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 average FPR, PPV, and NPV results for the bands across tasks are presented in Figure 3a-b using a scatter plot by group graph.

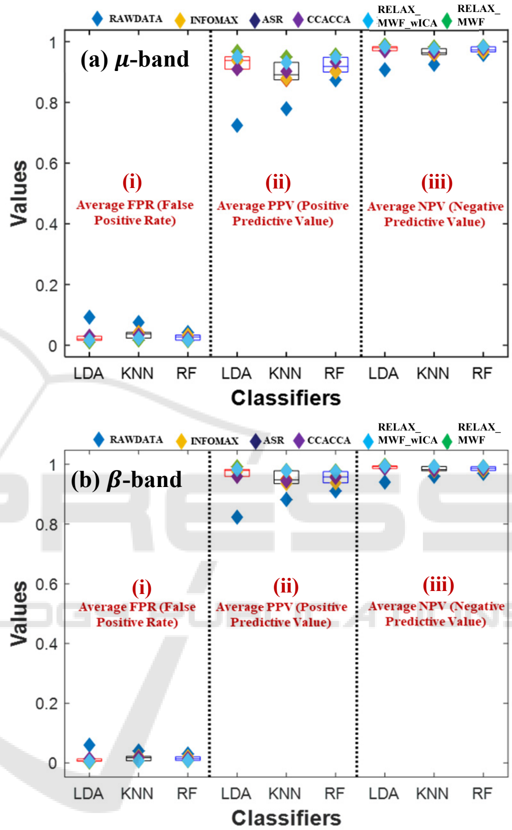

Figure 3: Performance evaluation of the methods for FPR, PPV and NPV (a) μ and (b) β bands.

Each plot 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 the metrics are also relatively the same compared to LDA and KNN classifiers.

However, an obvious difference is noticeable between the artifact attenuation methods and the raw signal for all the 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 compared to other methods.

3.3 Evaluation of Individual Task Decoding Performance

This section presents the individual ME task recognition rate for LDA classifier because of its performance in section 3.2. The obtained result in the μ and β bands is presented in Figure 4a-b using a bar plot graph.

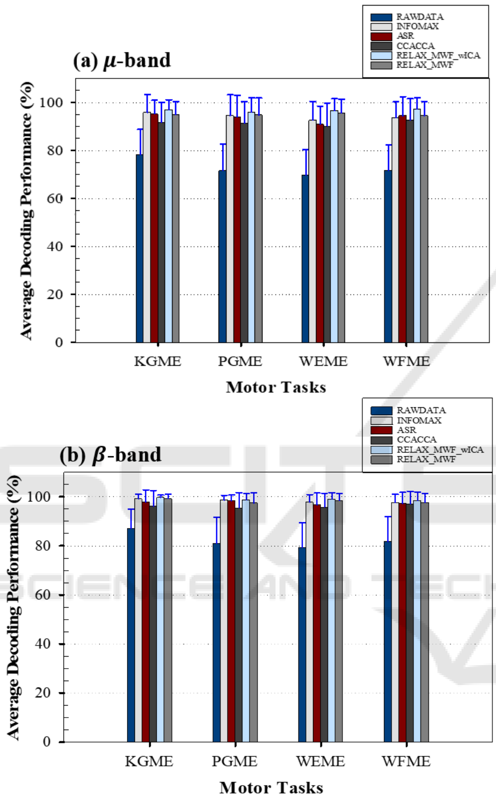

Figure 4: Class-wise task decoding performance for (a) μ (b) and β bands using LDA classifier.

The error bar on each preprocessing method represents the standard deviation across participants. 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 the 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.

4 DISCUSSION AND CONCLUSION

In this study, we demonstrated the impact of artifacts on μ and β oscillations detected in the motor cortex region of the brain during the execution of upper limb motor tasks. Five automated artifact removal methods, including single (INFOMAX) and multiple artifact removal capabilities (ASR, CCACCA, RELAX_MWF_wICA, and RELAX_MWF), were individually employed to attenuate the artifacts present in both bands. After the Independent Component Analysis (ICA) decomposition of the processed signal, an automated IC classifier, namely IC_LABEL (Pion-Tonachini et al., 2019), was utilized to detect and flag artifact-contaminated ICs for removal from the processed signal.

The impact of artifacts were considered on cortical activation strength and motor task recognition. The brain activation response was evaluated using z-score power. From the obtained results, the average z-score values across participants varied from task to task and between methods. Table 1 presents the average z-score power values across participants and tasks for μ and β frequency bands. When comparing the values between the bands, the μ band showed better brain activation during the tasks for all the methods compared to the β band. The ASR

Table 1: Average z-score power values all across participants and tasks for the μ and β bands.

Methods	μ Band	β Band
RAWDATA	-0.0314	-0.0182
INFOMAX	-0.0302	-0.0197
ASR	-0.0421	-0.0238
CCACCA	-0.0244	-0.0157
RELAX_MWF_wICA	-0.0370	-0.0231
RELAX_MWF	-0.0353	-0.0202

method exhibited the highest z-score values in both bands, followed by RELAX_MWF_wICA. CCACCA recorded the least z-score value compared to the raw data and other methods in the μ and β bands. In other words, these methods, except CCACCA, enhanced the brain response through the mitigation of artifacts.

The outcome from the False Discovery Rate (FDR) and Positive Predictive Value (PPV) and Negative Predictive Value (NPV) validation metrics shows that the RELAX_MWF_wICA-based method is an accurate and effective model for processing EEG signals compared to other methods. Similarly, in individual task classification performance, the RELAX_MWF_wICA method outperformed other methods and the raw data in both bands.

Examining the performance of CCACCA, though it has a low z-score power value compared to the raw data, it recorded better decoding performance compared to the raw data. One possible reason for this could be that a strong brain response during the ME task may not necessarily correlate with high classification performance.

Overall, considering the impact of artifacts on brain activation response and motor task classification, the RELAX_MWF_wICA demonstrated better performance, albeit with no significant difference when compared with ASR and RELAX_MWF methods. It performance could be attributed to its status as a hybrid artifact attenuation method that incorporates the advantages of MWF and wICA.

The outcome of this work provides valuable insights into the significance of using appropriate methodology in the EEG signal-processing pipeline to obtain precise estimations of motor brain activity, thereby avoiding biased signal analyses and interpretation.

It's important to note that this study is preliminary and confined to a dataset consisting solely of healthy subjects. The analysis utilized Z-score power quantifier and statistical metrics. In our forthcoming research, we plan to recruit stroke patients and acquire EEG signals from them to validate our findings. Furthermore, we will employ noteworthy quantifiers to thoroughly investigate and analyze EEG oscillatory rhythms.

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