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Estimation of Interferences in Magnetoencephalography (MEG) Brain Data Using Intelligent Methods for BCI-based Neurorehabilitation Applications

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Abstract: *Brain-Computer Interface (BCI) neurorehabilitation offers the potential to improve recovery and quality of life for stroke survivors. It aims to restore lost physical and mental abilities through motor and cognitive therapies. Magnetoencephalography (MEG) signals are a major advancement in BCI technology as they provide accurate and consistent assessments of brain activity for control and interaction applications. MEG is indispensable for recording the magnetic fields produced in the brain during motor imagery tasks due to its capability to evaluate cerebral activity with remarkable temporal resolution. However, one of the major challenges associated with MEG recording is the loss of signal quality due to physiological artifacts and ambient noise. Additionally, the head movement of the individual during the recording process can result in the introduction of artifacts into the recorded data, which can distort the spatial mapping of brain activity. This, in turn, can jeopardize the reliability and accuracy of the results obtained. This study aims to identify the most effective technique for removing artifacts from MEG signals by conducting a comparative performance analysis of prominent denoising algorithms, such as Infomax, FastICA, SOBI, and SWT. The findings conclude that Infomax is the most effective algorithm for removing physiological artifacts from a signal while maintaining the integrity and essential features of the original data. FastICA was found to be the second most effective algorithm. Infomax outperformed FastICA in Power Spectral Density (PSD) and Percentage Root mean square error Difference (PRD) measurements.*

Keywords: *magnetoencephalography; signal acquisition; artifacts; denoising; ICA*

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1. Introduction

Stroke is still one of the most prevalent causes of long-term disability globally (Avan & Hachinski, 2021). It impairs motor function and makes it difficult for victims to carry out daily tasks on their own. To enhance patient outcomes, there is a need for innovative approaches to neurorehabilitation. Thus, the integration of magnetoencephalography (MEG) with brain-computer interface (BCI) technology has emerged as a potential avenue (Tedesco et al., 2019). MEG is a non-invasive neuroimaging method that measures magnetic fields produced by brain neuronal activity. With its great temporal resolution and millisecond precision in capturing brain activity, MEG has shown itself to be an invaluable tool in neuroscience research (Mellinger et al., 2007). However, MEG data are frequently tainted by a variety of artifacts generated by measurement systems and human subjects (Medvedovsky et al., 2007). These artifacts include environmental noise, as well as physiological signals like muscle activity, heartbeat (Puce, & Hämäläinen, 2017), and eye movements (Carl et al., 2012). If not properly addressed, these artifacts have the potential to mask the relevant neural signals, potentially leading to inaccurate interpretations of brain activity.

The primary obstacle encountered in the acquisition of MEG signals is the sensitivity of MEG systems to artifacts. Ambient noise, a non-physiological artifact that includes electromagnetic interference from electrical power lines, devices, and even the Earth's magnetic field, is one type of noise or artifact in signal capture. Controlling these artifacts can be achieved through strict experimental procedures and precise recording equipment up to a certain point. The MEG signal may also be distorted by the magnetic fields created by biological artifacts such as cardiac activity, eye movements, and muscle activity (Fred et al., 2022). Moreover, the MEG signal can become distorted even by slight head movements made by the patient. It can be challenging to differentiate these artifacts from real brain activity because they can seem like transient bursts or rhythmic oscillations in the MEG signal. The removal of artifacts from MEG data is an essential step in the preprocessing stage. This strives to separate the real brain signals from the interfering artifacts, improving the data's quality and interpretability.

Powerline interference is a high-frequency noise in the 50–60 Hz range that is a non-physiological artifact and is typically caused by power supply lines. These can appear as periodic spikes in the MEG signal that mask the underlying brain activity and reduce the signal-to-noise ratio (Dattatraya et. al, 2008). The movement of the head while recording might skew the spatial localization of neural signals making it difficult to pinpoint the precise locations of brain activity. The eye movements and cardiac activity might add spurious signals to the MEG data, resulting in inaccurate interpretations of neural activity (Zhang et al., 2021). In recordings that require motor tasks, muscle activity such as clenching of the jaw or movements of the face may also interfere with the MEG signal. To ensure accurate interpretation of brain signals during data analysis, it is crucial to properly address the artifacts that occur during the signal acquisition process. Researchers employ various advanced techniques to overcome these challenges in MEG data analysis.

The accuracy of ensuing analysis and interpretations is improved by increasing the signal-to-noise ratio of MEG data, which is made possible by denoising methods. Some of the well-known denoising algorithms used in MEG research are the Stationary Wavelet Transform (SWT), InfoMax, FastICA, and SOBI (Second Order Blind Identification) (Peksa et al., 2023; Teng et al., 2021). SWT is a multiresolution analysis method that divides MEG signals into distinct frequency bands using wavelet functions. Reconstructing the denoised signal by thresholding the wavelet coefficients to reduce noise is the main step in signal decomposition using SWT. This method is effective for adaptively denoising signals with non-stationary features and efficiently capturing both temporal and frequency information. The importance of Independent Component Analysis (ICA) in data preprocessing lies in its ability to extract sources of interest even in the absence of reference signals (Albera et al., 2012; Haumann et al., 2016). ICA makes use of the non-Gaussian structure of the data by assuming that the sources are statistically independent. Although the methods used in the many ICA variations vary, their main objective is to isolate the underlying independent sources (Mäkelä, 2022).

In the field of MEG research, the development of effective methods for removing artifacts is still crucial. In this work, we evaluated the effectiveness of the wavelet decomposition technique in conjunction with three ICA algorithms: FastICA, Infomax, and SOBI, in minimizing artifacts. The basic concept of the SWT is its fixed time-frequency resolution and simultaneous analysis of signals in the frequency and time domains. It is especially helpful for analyzing non-stationary MEG signals because of this stationary characteristic. The fundamental idea behind the ICA technique used here is that signals collected on the scalp are a combination of temporally independent neurological and artifactual sources (Phothisonothai et al., 2012). This method is predicated on the idea that potentials from different parts of the brain, the scalp, and other sources combine linearly. This approach avoids the requirement for reference channels for each artifact source by utilizing spatial filters developed from ICA techniques (Naresh Kumar, et al. 2012). The resulting MEG signals are generated by successfully reducing the contributions of the identified artifacts after independent time courses associated with both brain and artifact sources have been extracted.

The main objective of the proposed study is to conduct a comprehensive comparison of the most widely utilized MEG denoising techniques. In addition to evaluating their performance, we also analyze the impact of these methods on signal quality, aiming to determine the optimal approach for preserving the integrity of neural data while effectively minimizing artifacts.

2. Proposed Methodology

A typical computational structure for choosing the best MEG signal denoising method is displayed in Figure 1. In this study, MEG signals from the MEG-based BCI dataset acquired at the Intelligent Systems Research Centre, Ulster University are used as input in this work (Rathee et al., 2021). A traditional BCI pattern that involves cognitive imagery (CI) and motor imagery (MI) activities is used to record the data. These MEG data were recorded from 17 healthy subjects using a 306-channel Elekta Neuromag system which includes 102 magnetometers and 204 planar gradiometers. Since the MEG signals are provided in unprocessed form, it is presumed that they are clean and normalized.

The MEG signals are obtained from a multi-channel system where there is a possibility that some of the channels may contain bad data. It becomes essential to identify faulty channels in data processing because failing to do so can negatively impact analysis further down the pipeline. The process of rejecting faulty data segments involves manually establishing a threshold value. Data is classified as bad when its peak-to-peak amplitude surpasses this threshold (Gramfort et al., 2014). To reduce or eliminate power line noise in signal processing, a notch filter operating at a frequency of 50 Hz is used. Some denoising techniques, including the Stationary Wavelet Transform (SWT), FastICA, Infomax, and SOBI ICA algorithms, are applied to the preprocessed input signals after which their efficacy is determined by computing several parameters, such as Power Spectral Density (PSD), Signal to Noise Ratio (SNR) and Percentage Root mean square Difference (PRD). The ideal denoising technique is selected based on performance. The denoising methods utilized in this work will be described in the section that follows.

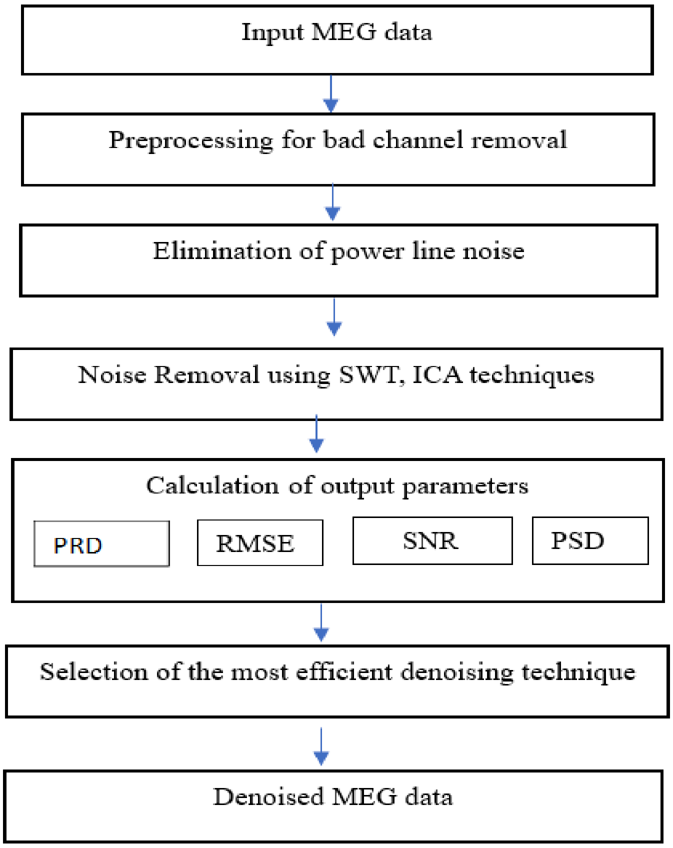


Figure 1. Block diagram of proposed methodology

3. Methodology and Explanation

In this section, we outline our approach through three key subsections: Removal of power line interference, which details techniques for eliminating noise from power lines. Removal of physiological artifacts, which focuses on methods to identify and remove interference from physiological sources such as muscle activity and eye movements; and finally, Performance evaluation, where the criteria and metrics used to assess the effectiveness of the denoising techniques in preserving signal quality and minimizing artifacts are presented.

3.1 Removal of Power line interference

Power lines, that operate at frequencies of about 50 or 60 Hz, have the potential to interfere with MEG signals. MEG signals usually carry information over a large range of frequencies, even those in proximity to the power line interference frequency. To properly assess the brain activity recorded by the MEG, it is necessary to eliminate this interference. Specifically, a notch filter mechanism is made to remove power line interference from MEG signals (Leske et al., 2019). Since the power line operates at the frequency of 50 Hz, a notch filter is specifically made to target this frequency (Kumar et al., 2021). The notch filter attenuates signals within the range of interest while maintaining the rest of the frequency spectrum unaltered. In this work, the power line noise frequencies are selectively suppressed by passing the MEG data via a notch filter. All of the original frequency content of the filtered signal is retained, except the frequencies that the notch filter attenuates or eliminates.

3.2 Removal of Physiological Artifacts

3.2.1 Wavelet-based denoising technique

Decomposing artifactual components using wavelet transform is a frequently used method for reducing undesired artifacts. The Stationary Wavelet Transform (SWT) effectively removes artifacts due to its translation invariance making it preferable to both Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) (Zangeneh Souroush et al., 2022). Non-stationary data can be processed and analyzed mathematically using the SWT approach. It offers a more versatile representation by accommodating various time-frequency resolutions at various sizes. Instead of doing decimation, SWT carries out a multiresolution analysis, after which filters are adjusted to carry out thresholding. The signals generated by the highpass and lowpass filters have the same length. The signal is split into precise and approximative coefficients at each level (Kumar et al., 2021).

The original signal is subjected to several high-pass and low-pass filters, obtaining detailed and approximation coefficients at each level.

The signal is filtered and then downsampled to the next level to provide a multiresolution representation.

Repetitively applying the steps of filtering, and downsampling to n decomposition levels.

The denoised MEG signal is eventually rebuilt by applying the inverse of SWT after the noise has been removed.

3.2.2 Blind Source Separation

The term "blind" in signal processing refers to the absence of prior knowledge about the source signals or the mixing process. Independent component analysis (ICA) is the most commonly used technique for blind source separation (BSS). The statistical independence of the mixed signals is a concept that is used by ICA algorithms. By using ICA, the combined signals are divided into additive, maximally independent subcomponents, each of which represents a different brain source.

A linear relationship can be used to define the ICA model if X is the collected signal mixture of dimension n and S is taken to be the genuine source signals of the same dimension.

$$X = AS \tag{1}$$

Here A is the unknown mixing matrix. The primary problem with this approach is that S and A are not known. The task is to identify W, the unmixing matrix, such that

$$Y = WX \tag{2}$$

An n-channel data array is thus converted into an n-dimensional component space using the ICA. Every temporal component in Y is maximally independent since it contains the least amount of mutual information (Breuer et al., 2014).

The MEG data in this study was processed using three different ICA algorithms: runica, FastICA, and Second Order Blind Identification (SOBI). These algorithms have the same goal and are identical mathematically but the methods used by each algorithm to estimate independence differ (Sahonero-Alvarez, & Calderon, 2017). Infomax uses a parametric technique to estimate component probability distributions whereas FastICA optimizes neg-entropy of component distributions. SOBI is a second-order technique that depends on temporal correlations in the source data and makes use of them (Delorme, Sejnowski, & Makeig, 2007).

a) Infomax ICA

Using the Infomax principle, the runica method produces stable decompositions by arbitrarily separating mixes of independent sources (Popescu, 2021). In Infomax the learning rate is an important component and it fluctuates during the learning process. The aim is to determine a learning rate that achieves a balance between precise estimation accuracy and rapid learning.

The following steps are involved in the Infomax ICA algorithm:

Data preprocessing: After centering the data, X by deducting the mean, the data is transformed to accomplish whitening, resulting in an identity matrix for the covariance matrix.
Iterations of ICA: A nonlinearity function is applied to the whitened data. Then to facilitate independence and non-Gaussianity, iteratively modify the weight matrix by applying a learning rule.
Normalize the weight matrix.
Examine if the weight matrix has changed between iterations to determine whether convergence has occurred. The resultant weight matrix should then be used to translate the whitened data back into the source space.

b) FastICA

FastICA uses a fixed-point iteration strategy, and orthogonal rotation of pre-defined data to maximize a metric of non-Gaussianity for the rotated components. It is simple to use because it lacks a learning rate or additional configurable settings (Tharwat, 2018).

The procedures in the FastICA algorithm involve:

- Data Centering: The data matrix X reflecting the observed mixed signals is centered by subtracting the mean from each column.
- Whitening: Apply whitening to the centered data to create a space where the components are statistically uncorrelated. This entails determining the eigenvalue decomposition of the covariance matrix and utilizing a transformation to produce decorrelation.
- Initialize a square weight matrix A with random values that will be adjusted iteratively to find the independent sources.
- For a predetermined number of iterations or until convergence:
    - ☐ Determine the weight matrix A multiplied by the data that has been whitened.
    - ☐ The product should be subjected to a non-linear function, usually the hyperbolic tangent (tanh). Its non-linearity encourages a non-Gaussian behaviour.
    - ☐ To maximize non-Gaussianity and independence, adjust the weight matrix using the computed values.
- Normalize the weight matrix A.
- The unmixing matrix W is composed of the independent components.

c) Second-order Blind Identification (SOBI)

The second-order statistics-based SOBI approach operates by diagonalizing matrices concurrently that are connected to a significant spatial representation of the sequences that must be separated. It seeks to separate the components by jointly diagonalizing several correlation matrices (Frederic, Rouijel, & Elghazi, 2021).

Estimate the covariance matrix for the data matrix: For the MEG data matrix, X has N number of sensors, and T samples in each trial. The covariance matrix is calculated as

$$P = \frac{1}{T} XX^T \tag{3}$$

Form the whitening matrix: The whitening matrix, W is obtained by multiplying the square root inverse of the eigenvalues, $A^{-1/2}$ by the matrix of eigenvectors, R where A and R are decomposed from P. The whitened data is calculated from this whitened matrix, W, and is given by

$$D = WX \tag{4}$$

Estimation of Source Matrix: Multiply the matrix that results from calculating the cross-products of the whitened data with the whitening matrix, W, to form the source matrix, S.

3.3. Performance Evaluation

The effectiveness of the various denoising methods is qualitatively examined through visual examination. Furthermore, we employed four parameters to measure the performance: Percentage Root mean squared Difference (PRD), Signal-to-noise ratio (SNR), and Power Spectral Density (PSD).

A measurement of the average difference between the values of the input signal and the denoised signal is provided by Root Mean Square Error (RMSE). It is often used to assess how accurate denoising methods are; a lower RMSE denotes greater performance (Mannan, Kamran, & Jeong, 2018).

$$\text{RMSE} = \sqrt{\sum_{i=1}^{N} \frac{(x_i - y_i)^2}{N}} \quad (5)$$

where x_i is the i^{th} input signal, y_i is the corresponding denoised signal and N is the number of channels.

PRD evaluates how similar the input and denoised signals are to one another. It indicates the total variation between the two signals and is expressed as a percentage.

$$\text{PRD} = \frac{\sqrt{\sum_{i=1}^{N} \frac{(x_i - y_i)^2}{N}}}{\tilde{x}} \quad (6)$$

where $\tilde{x}$ is the mean of the input signal.

SNR is used to measure how good a signal is in comparison to the amount of background noise (Gonzales-Moreno et al., 2014; Jaiswal et al., 216). The power difference between the signal and noise is commonly used to express it. SNR can be defined mathematically as:

$$\text{SNR} = \frac{P(s)}{P(n)} \quad (7)$$

where P(s) and P(n) denote the power of the signal and the noise respectively.

Since there is no information about noise in our dataset, the SNR of the input signal is approximated using the standard deviation. The theoretical noise standard deviation is computed assuming Gaussian noise, which results in an uncorrelated signal and noise.

$$\text{SNR(input)} = \frac{SD(i)^2}{SD(nt)^2} \quad (8)$$

where SD(i) and SD(nt) denote the standard deviation of the input signal and theoretical noise respectively. In the case of output SNR, the noise power is calculated as the mean square error (MSE) between the input and output signals.

PSD is very helpful in determining the effects of denoising on a signal's frequency characteristics (Seymour et al., 2022). It is possible to compare the frequency content of the input and denoised signals by computing the PSD for each. It is estimated by dividing the signal into overlapping segments, the periodogram for each segment is calculated, and the resultant periodograms are averaged.

These parameters provide an extensive evaluation of denoising performance by considering the amplitude, accuracy, symmetry, and frequency properties of the signals.

4. Experimental Results and Discussions

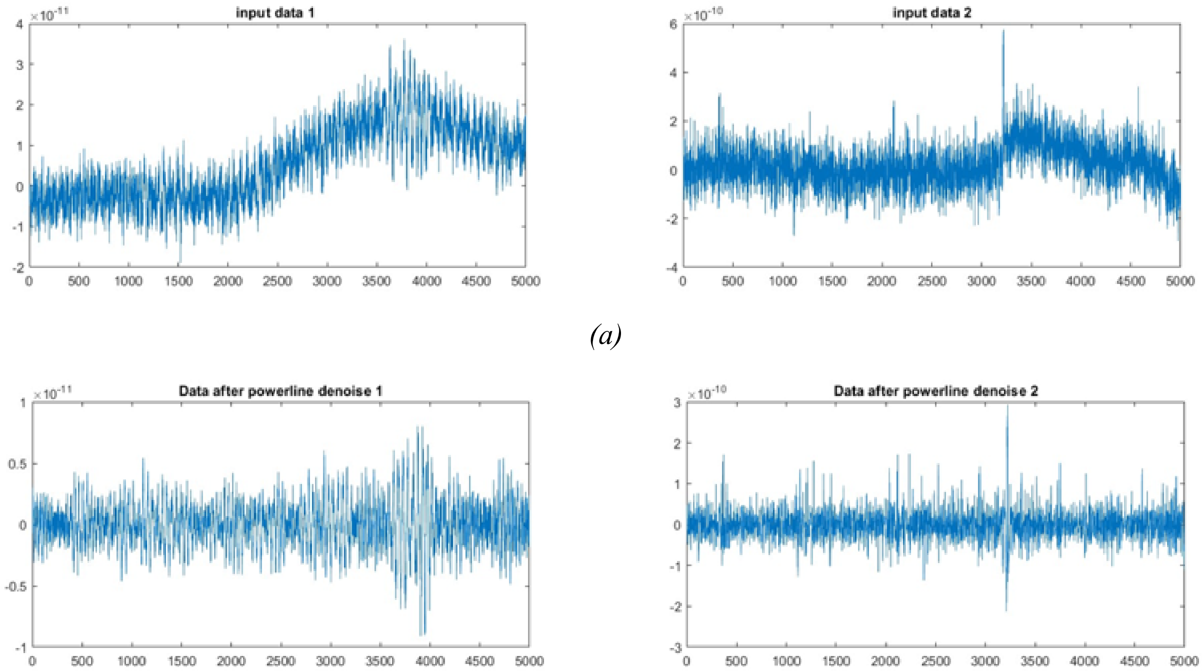
The experiments were performed with the publicly available dataset that included information from 17 different participants. Every subject completed 200 trials, which consisted of four different tasks, and the data was gathered from 306 channels for every trial. Each trial is of 7s duration encompassing both a rest period of 2s and a task period of 5s. These channels yielded 7000 consecutive samples per trial. The dataset comprised a total of two sessions from each participant. (Rathee et al., 2021). The neural activity captured concurrently from several brain areas is

October 2024
Volume 15, Issue 3

represented by these samples. Initially, we looked for defective channels since this dataset was not preprocessed. After that, notch filters set at a frequency of 50Hz were applied to eliminate any power line interference present in the signal. This study includes input data from all individuals and provides sample data for visualization.

4.1 Qualitative Analysis

The signal is qualitatively analyzed after notch filtering, as well as on the preprocessed signals using signal processing algorithms. Additionally, the PSD of the signals is examined to evaluate the effectiveness of the denoising and preprocessing techniques. This comprehensive analysis enables a deeper understanding of the improvements in signal quality and noise reduction, offering insights into the performance of each signal processing method.



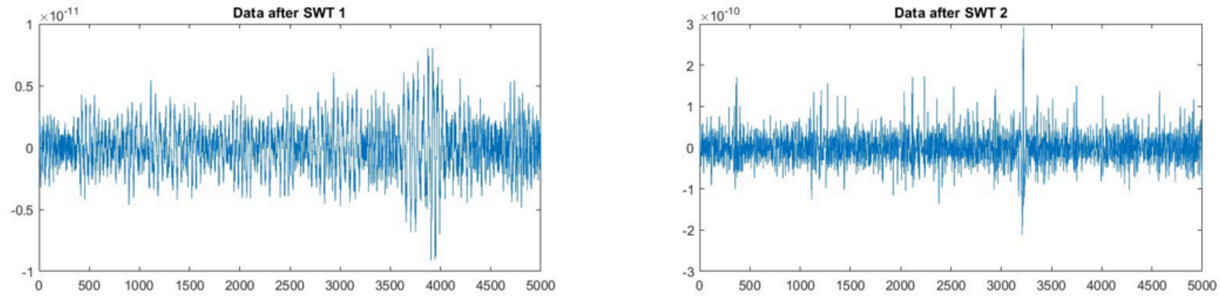
(a)

(b)

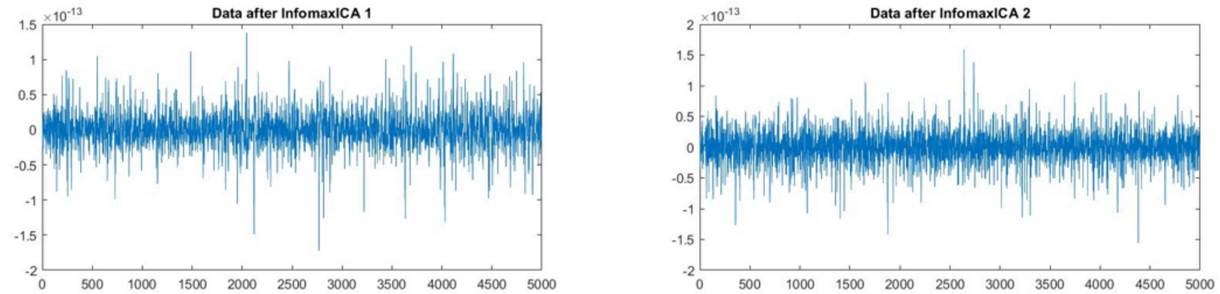
Figure 2. (a) Sample input data from channel 1 and channel 2 (of one trial),
(b) corresponding data after post-notch filtering channel 1, channel 2

Figure 2 shows sample input data from two channels and the corresponding filtered data using a notch filter. A notable observation is that the input data was much more irregular than the filtered data. The plot of the data seems to be more consistent across different samples after being filtered. Notch filtering produces a clearer signal free of 50 Hz noise by efficiently attenuating the powerline interference that is present in the raw MEG signal. It is possible that the filtering process eliminated certain signal components, such as noise or high-frequency fluctuations, which caused a decrease in the total signal amplitude. This is demonstrated by the reduction in amplitude observed when comparing the signal amplitude after filtering to the amplitude before filtering.

The signal following notch filtering is utilized as input for four algorithms—SWT, Infomax, FastICA, and SOBI—to effectively eliminate physiological artifacts such as cardiac signals, muscle activity, and eye movements. Figure 3 depicts the processed signals resulting from the application of the aforementioned denoising algorithms.



(a)



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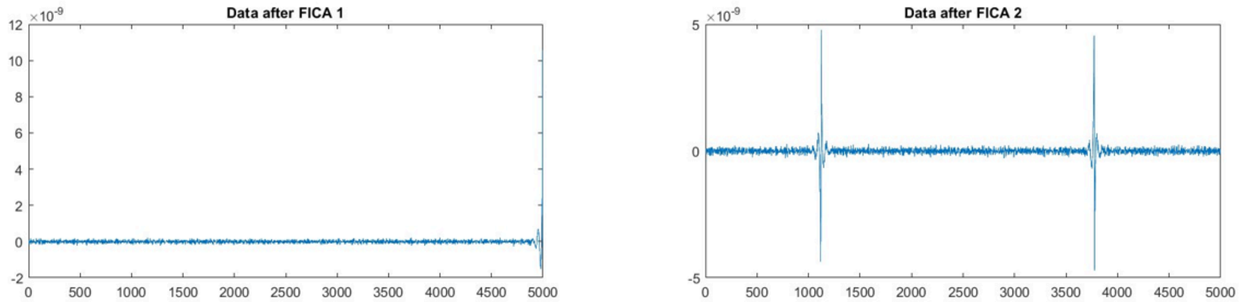
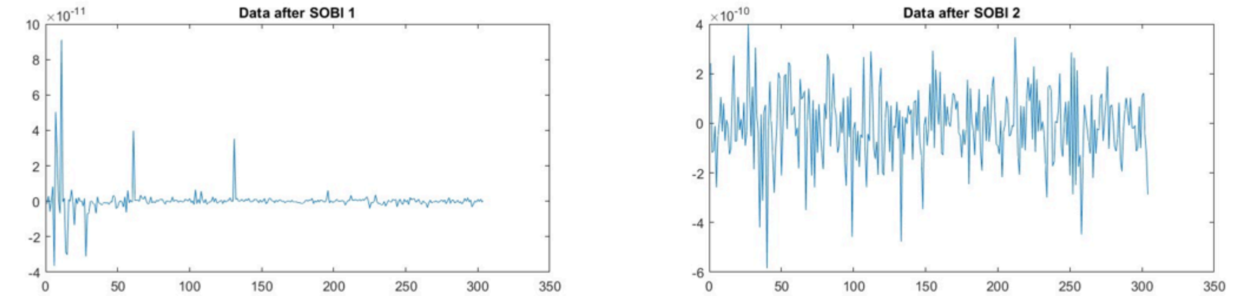


(c)



(d)

Figure 3. Plots of output signals from two channels- channel 1 and channel 2 (a) after SWT processing (b) after InfomaxICA (c) after FastICA (d) after SOBI processing

The output graphs of the denoised algorithms indicate that each technique reduces the amplitude of the input signal to a varying degree. The SWT and SOBI algorithms show an amplitude reduction in a comparable range whereas FastICA exhibits the least amount of decrease. Infomax, when compared to the input signal feed, achieves a greater reduction, with amplitudes in the e-13 range. The output waveform also appears more regular, suggesting that Infomax is particularly effective at eliminating physiological artifacts and producing a clear signal with low residual noise.

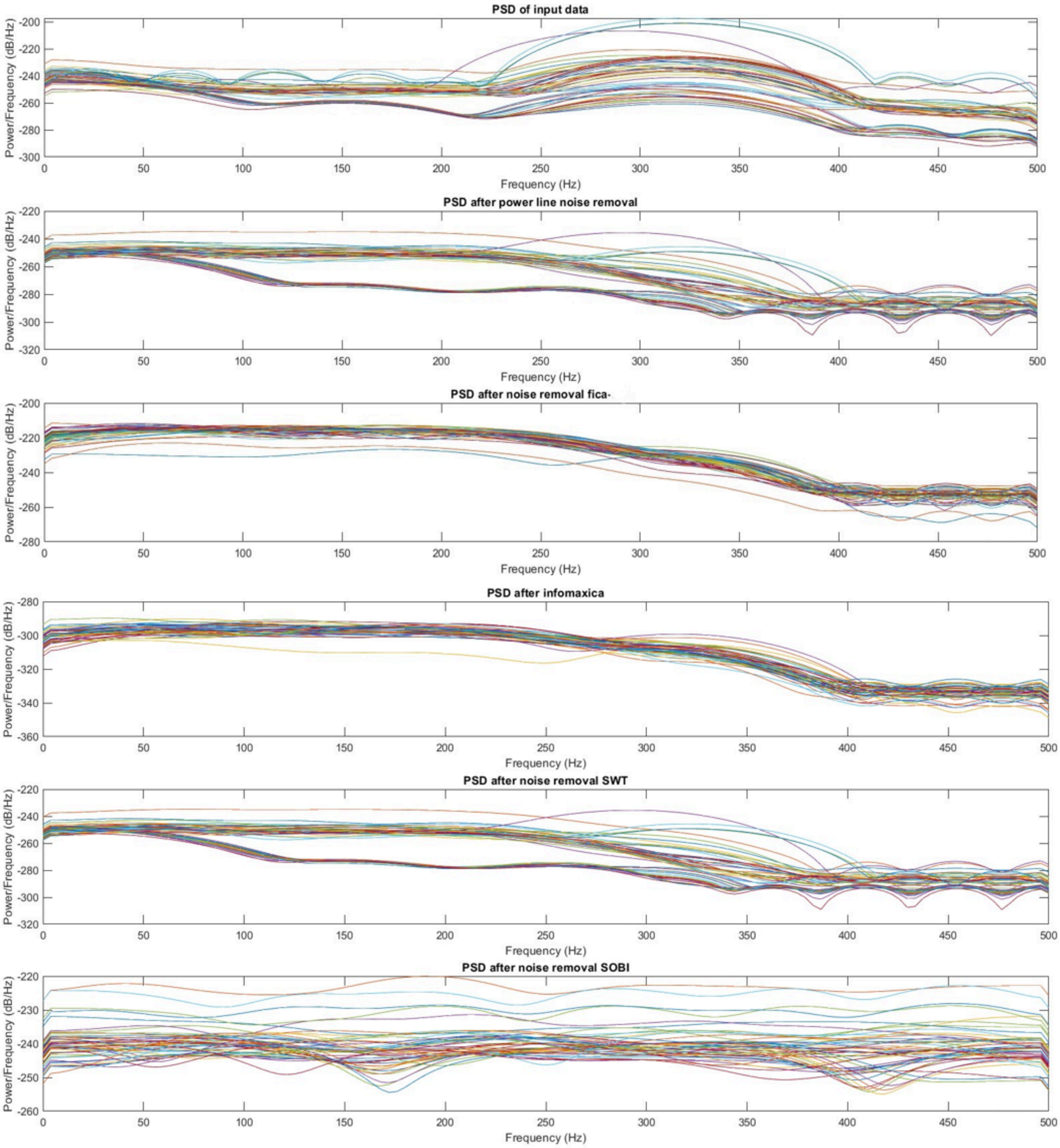


Figure 4. Graphical representation of PSD of input MEG signal, signal after applying notch filter, FastICA, Infomax, SWT, and SOBI processing

The Power Spectral Density (PSD) graph illustrates the distribution of power in the signal across various frequencies. The denoising algorithm should ideally reduce or minimise the power associated with noise, while it should preserve or have minimal effect on the power connected with the signal. At the relevant frequencies, lower PSD values indicate less power.

Figure 4 is a visual representation of a PSD plot, showcasing the frequency-domain data of a single trial for which a few channels and a limited number of samples are chosen to facilitate clearer visualization and a better understanding of the data. In the graph, frequency is depicted on the x-axis, usually measured in hertz (Hz), and power/frequency is represented on the y-axis, measured in dB/Hz. For a PSD plot to be considered ideal, it should have a smooth and continuous distribution with clear peaks that correspond to the frequencies of interest. Additionally, it should have low power levels in frequency areas that are not relevant to the signal of interest and have minimal noise and artifacts. The aim is to minimise any unwanted noise and artifacts to obtain an accurate representation of the signal. Figure 4 demonstrates that Infomax produces smoother plots compared to other algorithms when considering all channels, with FastICA following closely. Moreover, the Infomax algorithm tends to show lower power levels over the frequency spectrum.

4.2. Quantitative Analysis of the Algorithms

Table 1 summarizes the results of the performance evaluation, focusing on the Power Spectral Density (PSD). This table compares the average PSD values from ten trials for each signal processing algorithm. Additionally, Figure 5 gives a plot of SNR values of the different algorithms, and Table 2 provides a summary of the Percentage Root mean square error Difference (PRD) evaluations. These metrics are essential for quantitatively assessing the effectiveness of the algorithms in improving signal quality and reducing errors during preprocessing.

Table 1. Power Spectral Density evaluated for four denoising algorithms

SlNo.	Trial	Input Signal	Powerline denoising	SWT	Infomax	fastICA	SOBI
1	1	4.436e-22	7.278e-25	7.228e-25	1.299e-30	1.413e-22	6.173e-24
2	5	4.366e-22	6.991e-25	6.939e-25	1.349e-30	1.413e-22	7.037e-24
3	10	4.215e-22	7.239e-25	7.234e-25	1.295e-30	1.413e-22	6.991e-24
4	15	4.178e-22	6.840e-25	6.837e-25	1.267e-30	1.413e-22	7.604e-24
5	25	4.065e-22	7.427e-25	7.423e-25	1.276e-30	1.413e-22	5.936e-24
6	50	3.840e-22	7.157e-25	7.153e-25	1.404e-30	1.413e-22	7.153e-24
7	100	3.612e-22	7.216e-25	7.213e-25	1.126e-30	1.413e-22	7.397e-24
8	125	3.833e-22	7.985e-25	7.981e-25	1.184e-30	1.413e-22	6.851e-24
9	150	3.825e-22	7.886e-25	7.882e-25	1.276e-30	1.413e-22	5.944e-24
10	200	3.668e-22	7.860e-25	7.856e-25	1.264e-30	1.413e-22	6.511e-24
Average		4.00e-22	7.39e-25	7.37e-25	1.27e-30	1.41e-22	6.76e-24

Based on the average PSD value following the SWT application, it seems that there is still a considerable amount of power remaining in the frequency domain. This implies that physiological artifacts may not have been eliminated by SWT. The Infomax method has the least amount of power in the frequency domain and is the most successful method for eliminating physiological artifacts, as evident by the PSD value of 1.27e-30. Although the PSD value following the application of FastICA is higher than that of Infomax, it is still much lower than that of SWT. This means that FastICA is still successful to an extent in reducing artifacts while significantly reducing power as compared to SWT. SOBI is probably not as successful in lowering artifacts, perhaps not as effective as Infomax, as it falls between the PSD values for Infomax and SWT. In conclusion, based on the PSD values, Infomax seems to be the best method for eliminating physiological artifacts, resulting in the lowest power in the frequency domain.

The SNR of the input signal is calculated using mean and standard deviation and the value obtained is 2.00. However, the SNR of the signal after notch filtering is dropped, suggesting that the filtering process may have greatly attenuated by removing certain frequencies or signal components but it likely eliminated the noise. The significantly higher SNR following SWT indicates that the signal may have been successfully denoised, or separated from the noise. Infomax was found to have the lowest SNR value, indicating that it struggled to maintain signal quality while reducing noise. FastICA and SOBI have SNR ratings near 1, indicating that while some noise may still exist, signal to noise ratio has been roughly balanced after processing. Although the SNR value of SWT is higher than that of Infomax, it is still very low, indicating that noise may remain a significant effect even after optimization. The SNR value that has been calculated is visually represented in Figure 5. The SNR values indicate that different algorithms may have different levels of challenges when efficiently distinguishing the signal from the noise.

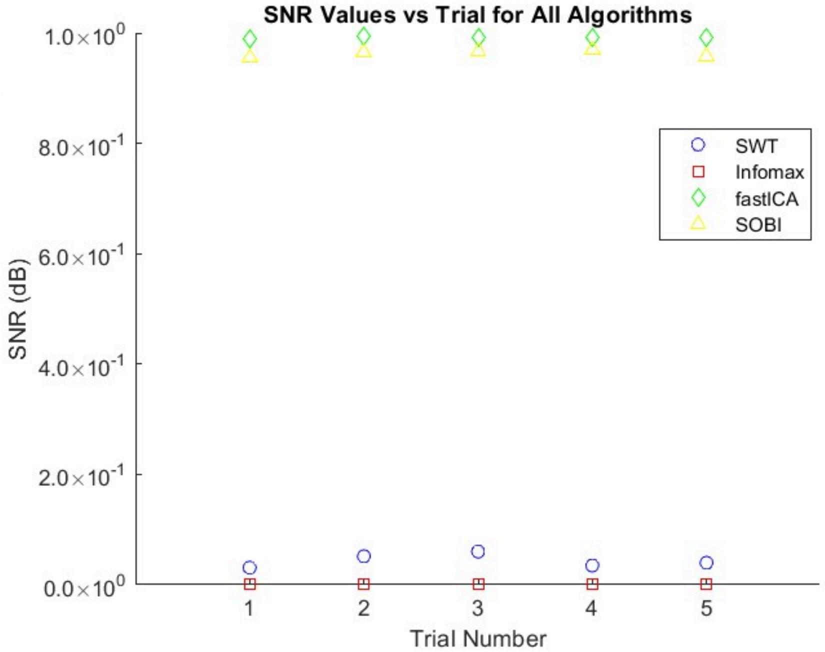


Figure 5. Plot of SNR values Vs Trial of Four algorithm

Table 2. Estimation of PRD from RMSE values

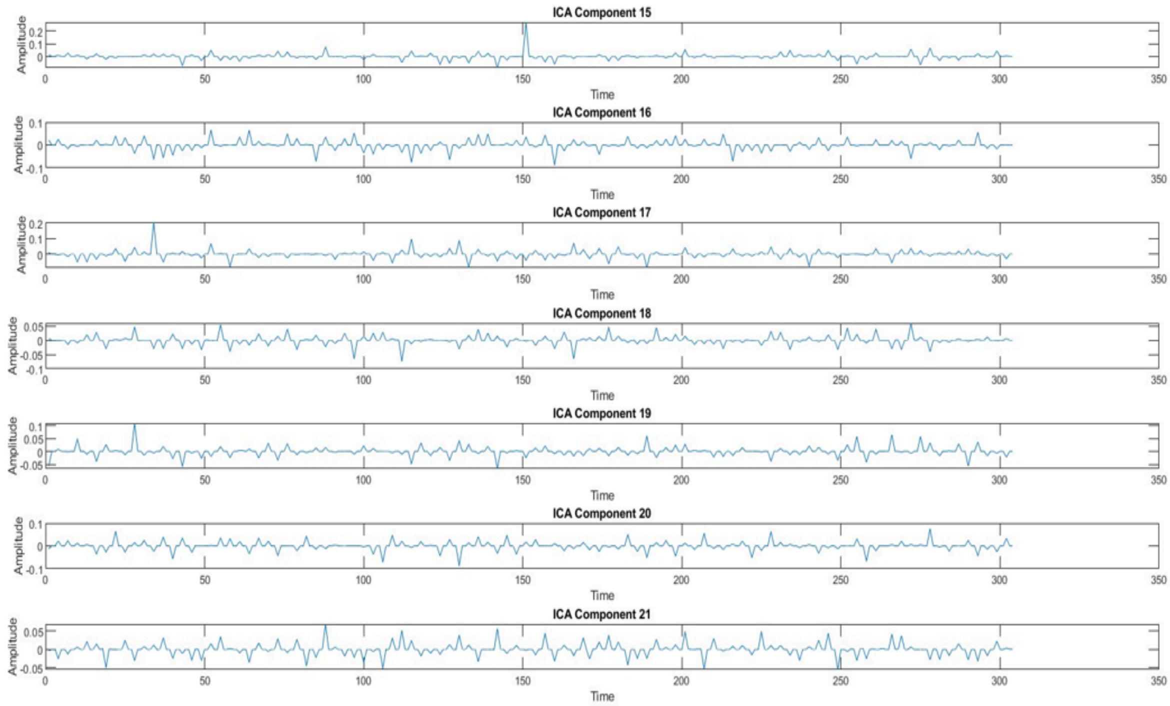
Parameters	SWT	Infomax	fastICA	SOBI
RMSE1	1.413	1.415	1.415	1.420
RMSE2	1.415	1.414	1.415	1.411
PRD(%)	0.14	0.07	0	0.63

The PRD provides an alternative perspective on how effectively the algorithms eliminate physiological artifacts. The relatively low percentage of RMSE inconsistencies between Infomax and FastICA indicates that both methods perform similarly in minimizing the RMSE. SWT performs well, with an RMSE difference of only 0.14 percent, but slightly worse than InfoMax, which is still relatively low. Infomax, on the other hand, outperforms all other methods, whereas SOBI is the least efficient among them.

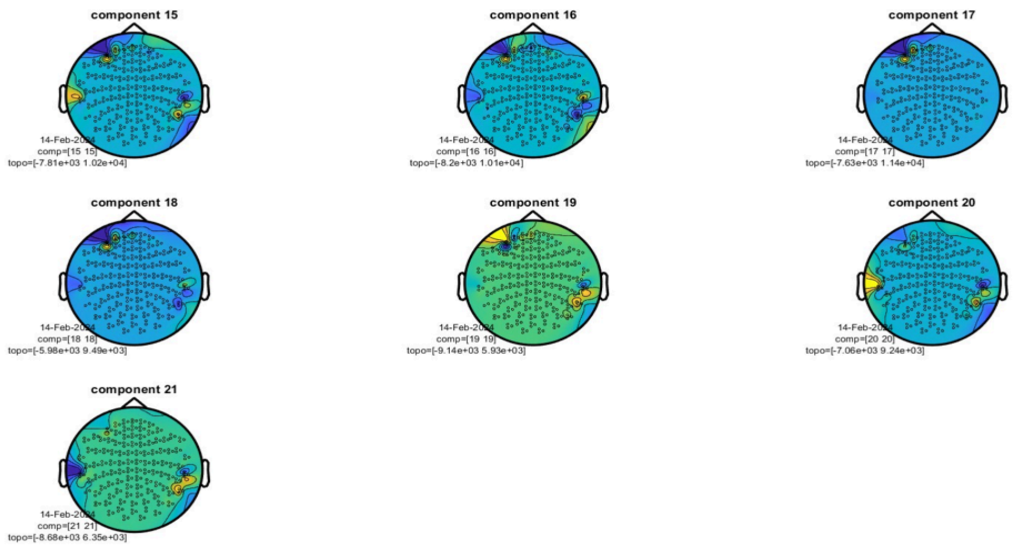
4.3. Signal Reconstruction from Individual Components

The Reconstruction of signals from individual components is a crucial part of signal processing, especially after using techniques like ICA or other decomposition methods. During this process, the original signal is reconstructed from its individual components, each representing different sources of information or noise. It is important to reconstruct the signal properly to preserve its meaningful features while reducing the effects of artifacts or noise.

Infomax successfully separates the mixed signals into their statistically independent sources; a component plot is used to visualize the results in Figure 6. To achieve this separation, Infomax modifies the mixing matrix iteratively, aiming to maximize the non-Gaussianity of the separated signals. This process helps identify statistically independent components and extract as much information as possible from the mixed MEG signals.



(a)



(b)

Figure 6. Plot of independent components after InfomaxICA – Component15 to Component 21 visualization (a) Graphical (b) topographic view

Figure 7 gives the visual representation of the reconstructed signal. This gives researchers a means of verifying the separation of mixed signals into relevant sources and evaluating the accuracy of the reconstruction. Furthermore, it facilitates additional examination and investigation of the fundamental mechanisms guiding the observed data.

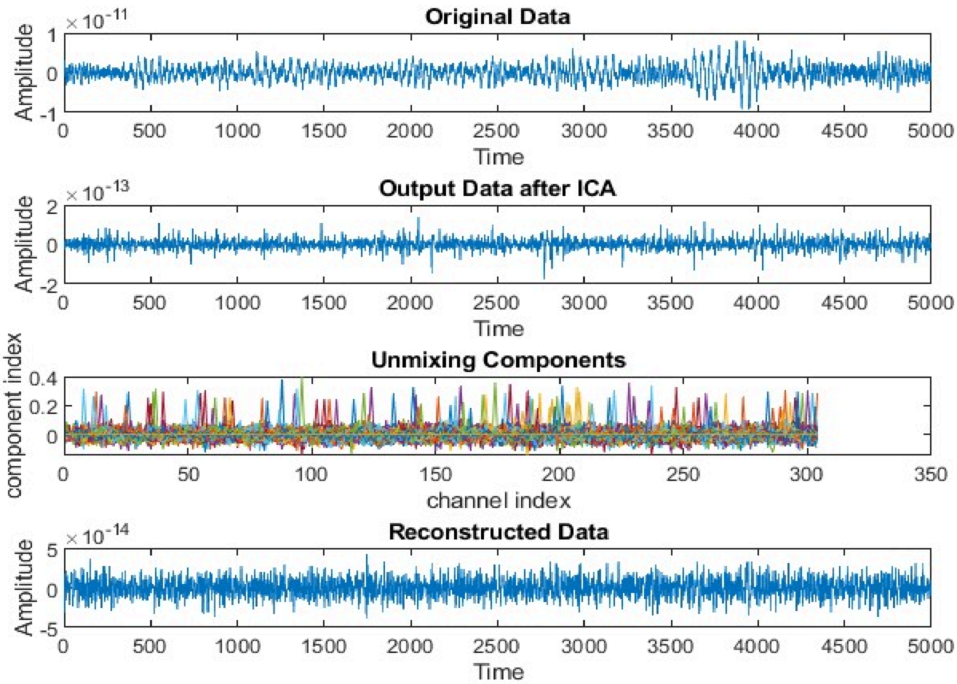
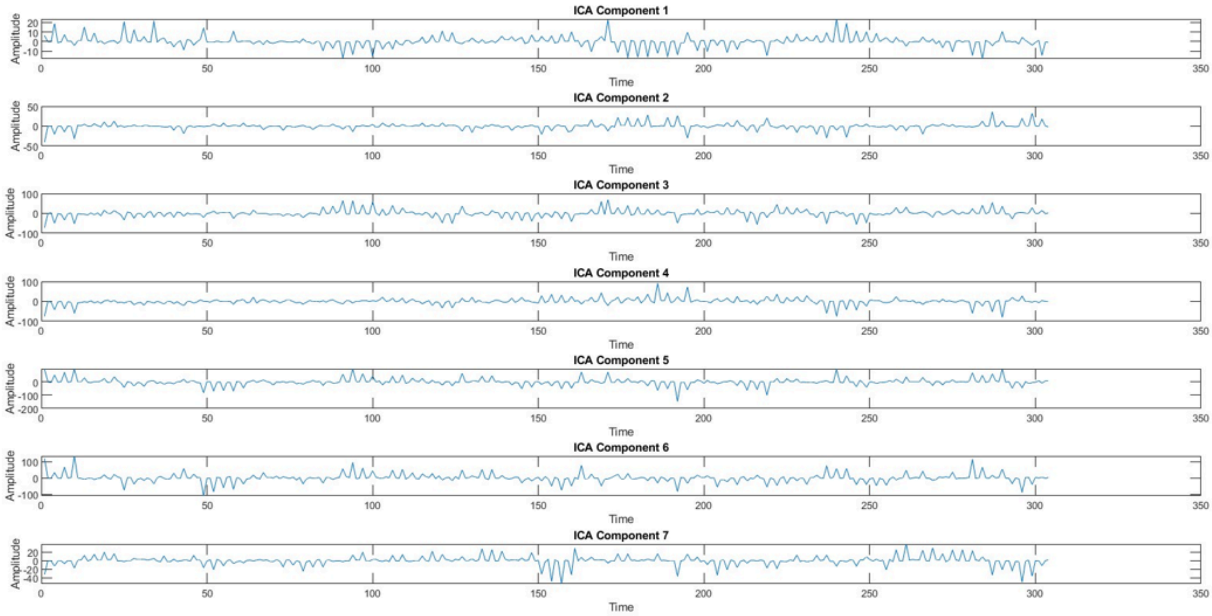


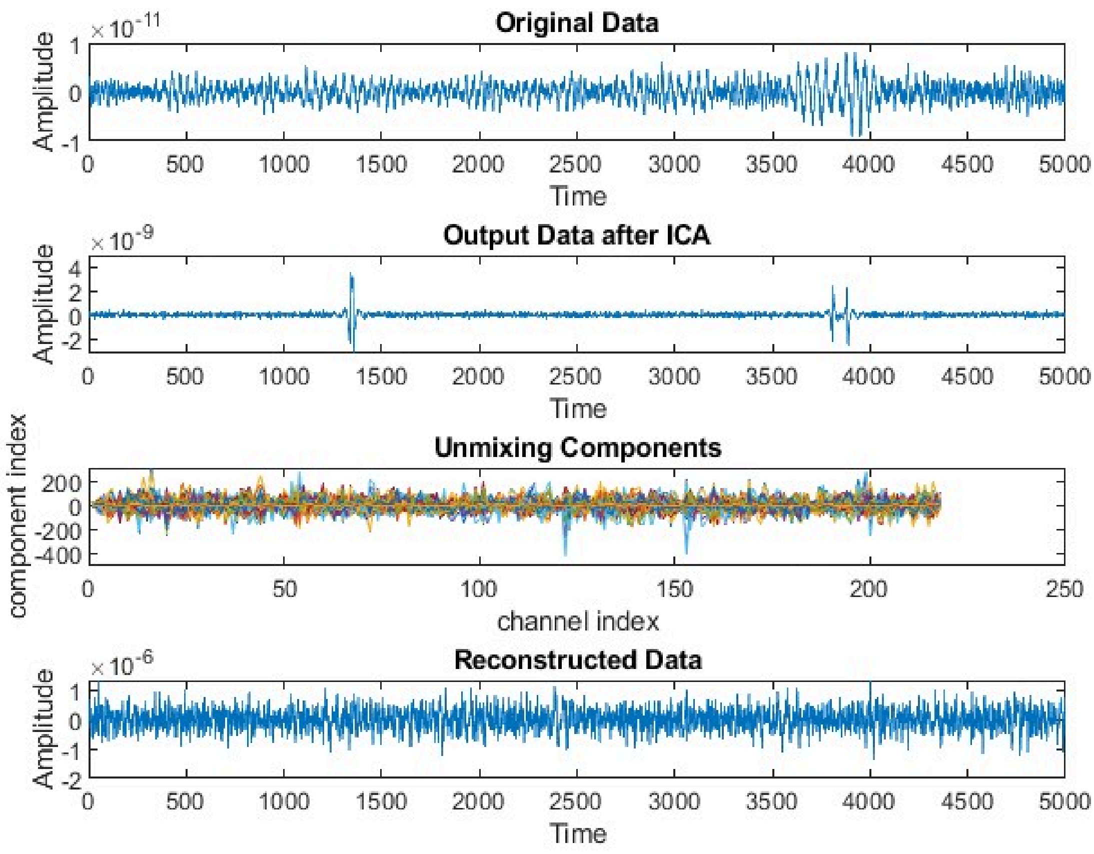
Figure 7. Graphical illustration of raw data alongside output data, unmixing components, and reconstructed MEG data after Infomax processing of one trial

Reconstructed MEG signals using Infomax have graphs with smoother transitions and greater signal characteristic preservation than the original MEG signals. This is so because the goal of Infomax is to maximise the quantity of information, which frequently leads to a more precise separation of separate components.

FastICA separates mixed MEG signals into independent components by iteratively calculating the directions of the components in the feature space. The algorithm works by assuming that the sources have non-Gaussian distributions and maximising the non-Gaussianity of the projections. To recover the original MEG signals, the mixing matrix obtained during the separation process is inverted, and its independent components are multiplied, similar to the Infomax. The independent components obtained from the FastICA decomposition are shown in Figure 8, together with a graphic depiction of the signal that has been reconstructed.



(a)



(b)

Figure 8. (a) Plot of independent components from Component 1 to Component 7 acquired through FastICA (b) graphical representation of output data, unmixing components, and reconstructed MEG data following one trial's FastICA processing

Figure 8 displays that FastICA can potentially recreate MEG signals effectively but the resulting signals may have more noticeable fluctuations or artifacts compared to the original signals. The accuracy of the reconstruction is slightly lower with FastICA than with Infomax. Infomax has excelled in situations where noise reduction and clean component isolation are vital.

4.4. Computational Complexity Analysis

The computational complexity of an algorithm measures the amount of computational resources, such as time or space, needed for the quantity of its input. It enables the evaluation of various signal processing algorithms to determine the best fit for real-time processing or large dataset applications.

Table 3. Comparison of the computational complexity of the signal processing algorithms used

Signal Processing Algorithm	Computational Complexity
SWT	O (K.T)
SOBI	O (n3 + D.n2.T + D.I.n3)
FastICA	O (n3 + I.n2.T)
InfomaxICA	O (n3 + I.n2.T)

where K: Number of decomposition levels
T: Number of samples
n: Number of channels
D: Number of time delays
I: Number of iterations

The computational cost of SOBI will increase significantly with a large number of channels or time delays, whereas SWT has a linear complexity to the number of decomposition levels, K, and the signal length, T. The FastICA and Infomax ICA algorithms have similar computational complexity, but FastICA usually runs faster in real-world applications due to its more efficient fixed-point iteration technique. Infomax ICA is particularly effective in handling complex signal separation because it can improve the statistical independence of the predicted components.

After accounting for all variables, the following conclusions may be drawn:

- Infomax is excellent at eliminating physiological artifacts while maintaining the original signal since it consistently performs well across PSD and Percentage RMSE difference measurements.
- Additionally, FastICA is a formidable competitor because it demonstrated a solid balance between SNR and Percentage RMSE difference.
- Comparing SWT to the other algorithms, it performed comparatively inferior across all parameters.
- Despite having a somewhat balanced SNR, SOBI's performance was inferior to Infomax and FastICA in terms of PSD and Percentage RMSE difference.

As a result, Infomax seems to be the most effective algorithm among the four, closely followed by FastICA, based on the entirety of the analysis. The algorithms demonstrated excellent performance in removing physiological artifacts while maintaining the integrity of the original signal.

4. Conclusion

MEG is a useful method for tracking the changing activity of brain functions. However, many artifacts can deteriorate signal quality. To mitigate the loss of important information when these components are removed, the denoising process aims to reduce the neural information present in artifactual components. Our analysis compared different denoising techniques based on Power Spectral Density (PSD), percentage Root Mean Square Error difference (PRD), and Signal-to-Noise Ratio (SNR) to determine their effectiveness at improving signal quality. Our results showed that

Independent Component Analysis (ICA) methods, particularly Infomax and FastICA, performed better than other approaches. This work efficiently reduces physiological and environmental noise, thereby improving signal quality and facilitating further processing for neurorehabilitation applications.

In the future, there are plans to address the significant issue of head motion estimate and correction while acquiring MEG data. This challenge poses a crucial barrier to understanding brain dynamics and creating efficient rehabilitation strategies for neurological disorders. By improving this aspect of data collection, we aim to offer a more robust basis for future research.

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