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Autism EEG Signal Pre-Processing: Performance Evaluation of MS-ICA and Butterworth Filter

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Abstract

Autism Spectrum Disorder (ASD) is a neurological condition characterized by challenges in communication and social interaction, accompanied by the development of repetitive behavioral patterns. Electroencephalography (EEG) is primarily used to assess brain function in children with Autism Spectrum Disorder (ASD), mainly due to its non-invasive nature and superior temporal resolution compared to other neuroimaging methods. However, EEG signals are often contaminated by biological artifacts, such as eye movements and muscle contractions, which can significantly distort analysis outcomes. Pre-processing is therefore required to increase the accuracy of the EEG signal before additional analysis. The goal of this study was to compare and evaluate the performance of two pre-processing techniques, the Butterworth Band-Pass Filter and Multiscale Independent Component Analysis (MS-ICA), using four different performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Signal-to-Noise Ratio (SNR). The Butterworth method has an MAE of 227.57, which is acceptable. However, it produced an MSE of 160,653.22, an RMSE of 394.49, and a maximum SNR of only 1.33 dB. MS-ICA performs far better with a best MAE of only 0.44, an MSE of 3.33, an RMSE of 1.76, and an SNR of 30.88 dB. Paired t-test ($p < 0.05$) was employed to determine statistical significance, while Cohen's d was used to assess the practical significance of the results. The effect sizes of MAE (d = 1.60), MSE (d = 1.02), RMSE (d = 1.54), and SNR (d = -9.50) were all calculated as large. These findings demonstrate that MS-ICA offers both statistical advantages and strong practical usefulness for noise removal while preserving the structural integrity of the original EEG signals. Therefore, MS-ICA proves to be the best approach for pre-processing EEG signals to be used for analysis in children with ASD.

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I. Introduction

Autism or Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that can be defined by several types of impairments, such as communication, socialization, and repetitive behaviors. ASD consists of a spectrum of symptoms that reflect the disorder, with severity varying from mild impairment to severe [1]. Electroencephalography (EEG) is a non-invasive neuroimaging technique that measures the brain's electrical activity by placing several electrodes on the scalp. It is widely used to diagnose various abnormalities in the brain nerves [2]. The resulting electrical signals are composed of a mixture of various frequencies with different correlations according to certain brain conditions [3]. These frequencies are classified as Delta (0.5-3.5 Hz), Theta (4-7 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (>30 Hz) bands [4]. Results from EEG recordings have driven research and clinical applications in neuroscience and neurology for nearly a century [2].

EEG signal recordings require pre-processing before further analysis because EEG signals can easily be contaminated with other biological potentials, such as EOG, ECG, and EMG [5]. These noisy signals can produce higher energy than the original EEG signal, thus affecting the quality of the information obtained and reducing the accuracy in further analysis [6]. Therefore, an effective pre-processing stage is essential to minimize noise and improve the quality of the signal obtained.

Pre-processing stage is one of the most crucial stages before analyzing EEG signals because the quality of the analysis results depends on the quality of the cleaned signal at this stage. Various methods have been developed for the pre-processing stage, including the Discrete Wavelet Transform (DWT), Finite Impulse Response (FIR), and Kalman Filter. [7], [8], [9]. However, this research focuses on the Butterworth Band-Pass filter and Multiscale Independent Component Analysis (MS-ICA). Multiscale Independent Component Analysis (MS-ICA) is an extension of the Independent Component Analysis (ICA) method commonly used to separate EEG signals from noise sources, such as eye movements or muscle activity. MS-ICA combines this technique with multiscale analysis, where the signal is split into different temporal scales using wavelets [10].

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This research will present the pre-processing results obtained by passing the filtering process through the Butterworth Band-Pass method and denoising using Multiscale Independent Component Analysis (MS-ICA) to produce EEG signals free of artifacts (noise). The two stages of the process are compared by looking at four calculation parameters, namely Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (MSE), and Signal Noise Ratio (SNR). This research is expected to significantly contribute to the development of EEG-related studies and support the advancement of MS-ICA denoising methods.

II. Materials and Method

In this study, Fig. 1 illustrates the flow of the research method, which utilizes a dataset of EEG signals from children with Autism Spectrum Disorder (ASD), obtained from King Abdulaziz University (KAU). These signals undergo two main pre-processing stages: the Butterworth Band-Pass Filter and Multiscale Independent Component Analysis (MS-ICA). The filtering process is performed using a 4th-order Butterworth Band-Pass Filter with a cut-off frequency range of 4–40 Hz to remove low-frequency noise (such as DC drift and respiratory artifacts) and high-frequency interference. This filter is designed using the scipy.signal.butter library and applied using the zero-phase method via scipy.signal to prevent phase distortion in the signal.

The next stage involves the application of the MS-ICA method, which is implemented with the help of the PyWavelets library for multiscale decomposition using the Daubechies 4 (db4) wavelet and the sci-kit-learn library for independent component separation using FastICA. This process aims to remove non-neural artifacts such as eye blinks and muscle activity. After artifact removal, the clean signal is reconstructed using inverse DWT, and the entire process is developed in Python 3.13 with a modular code structure for easy replication. Data processing is performed on a laptop equipped with an AMD Ryzen 7 processor and 16 GB of RAM. Performance evaluation is conducted using MAE, MSE, RMSE, and SNR parameters, along with signal visualization per channel, to facilitate a comprehensive analysis of the results.

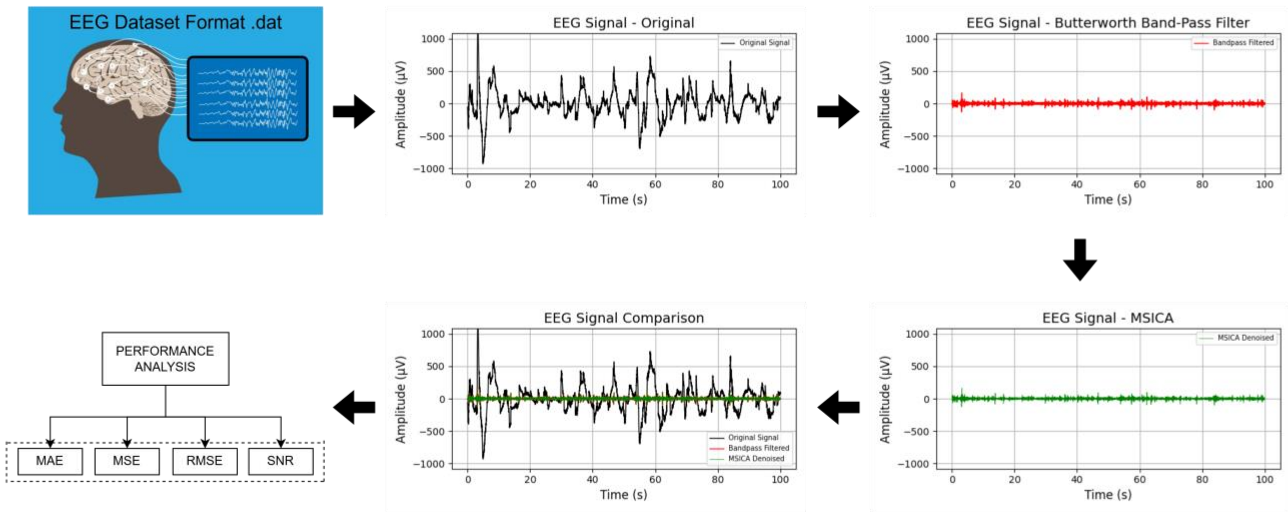

Fig. 1. FlowChart Of EEG Signal Pre-Processing with Butterworth Band-Pass Filtering and Multi Scale Independent Component Analysis

A. Dataset

This research utilizes EEG datasets obtained from King Abdul-Aziz University (KAU) in Jeddah, Saudi Arabia [11]. This dataset has also been used in previous studies such as [12], [13]. The dataset is publicly available and can be accessed by making an official request via email to Dr. Mohammed Jaffer Alhaddad, as described in the reference [14]. This study followed a predetermined procedure while maintaining participant confidentiality by excluding any personally identifiable information..

The participants' EEG signals were recorded under relaxed conditions using an EEG cap device from g.tec equipped with Ag/AgCl electrodes, a USB amplifier from G.tec, and BCI2000 software. The EEG dataset taken consists of 16 channels with a sampling frequency of 256 Hz, with eight male subjects with an ASD diagnosis, aged 10–16 years, resulting in an accumulated signal duration of 4104.2 seconds [15], [16].

The data was obtained in a .dat file format, containing numbers in binary form or text generated automatically by the software. The recording utilizes 16 channels, following the international provisions of 10-20 channels, where electrodes are placed at specific points on the scalp.

Electrode placement is divided into several parts, namely, in the front of the head. The electrodes used include Fp1, Fp2, Fp3, and Fp4. The center of the head includes C3, C4, and Cz. The side of the head (temporal) includes T3, T4, T5, and T6. The head's parietal area, or the head and the upper back of the head, includes P3, P4, and Pz. Finally, the lower back of the head (occipital) includes O1 and O2 [17], [18]. The function of each electrode is to record electrical activity in each part of the

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brain, providing an overview that is useful for further analysis. Fig. 2 shows the results of reading a dataset in .dat format with 16 channels following the international standard of 10-20 channels.

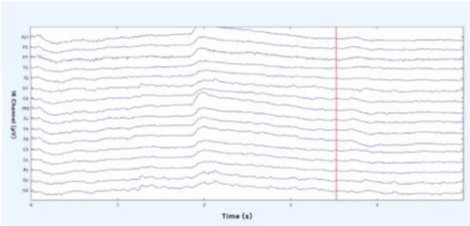

Fig. 2. Visualization of EEG Signal Patterns Over Time from 16 Channels in Microvolts.

B. Butterworth Band-Pass Filter

The Butterworth Band-Pass Filter is a widely used signal processing technique often designed to cut frequencies within a specific range. The Butterworth Band-Pass Filter has two types of cut-off frequencies: lower cut-off (Cutting at the lower limit) and upper cut-off (Cutting at the upper limit). The lower cut-off type utilizes a low-pass filter (LPF), while the upper cut-off type employs a high-pass filter (HPF). Furthermore, the two functions are multiplied to obtain a band-pass function that aims to separate signals with frequencies between the two cut-offs [19].

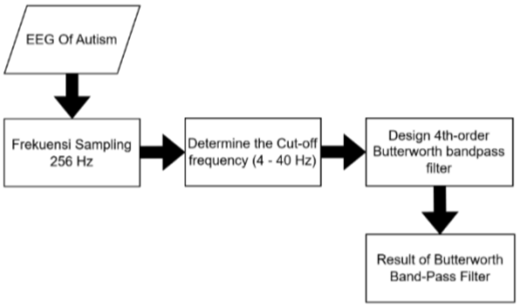

Fig. 3. Schematic Representation of EEG Filtering Using Butterworth Band-Pass in 4–40 Hz Band

In the initial processing stage, the EEG signal is filtered through a 4th order Butterworth Band-Pass Filter with a cut-off frequency between 4 Hz and 40 Hz. Filtering is performed to purify the signal by removing low-frequency components less than 4 Hz, which are generally termed noise, such as effects of DC drift or respiratory artifacts. At the same time, frequency components higher than 40 Hz are filtered out to prevent intrusions from extraneous noises, e.g., power line interference. The reason the range 4–40 Hz is utilized is that it encompasses the principal spectrum of brain activity, namely, theta, alpha, beta, and a part of gamma waves, which are commonly regarded as being the best for the analysis of EEG signals. This filter is designed in a bidirectional manner to minimize phase distortion. It is realized as an Infinite Impulse Response (IIR) filter to achieve a continuous and effective frequency response. The efficacy of this frequency spectrum has been corroborated through several preceding researches [20], [21], [22], which demonstrates that this frequency range is the most indicative of pertinent neurophysiological activity. Fig. 3 provides a general overview of the workflow associated with this filtering process.

C. Multiscale Independent Component Analysis (MS-ICA)

MS-ICA is an EEG signal processing technique that combines multiscale approaches such as Discrete Wavelet Transform (DWT) and Independent Component Analysis (ICA). MS-ICA aims to separate independent components of the signal at each frequency scale, which helps to reduce noise or remove artifacts, such as eye movement artifacts or muscle activity, so that the EEG signal becomes cleaner and ready for further analysis [23], [24], [25].

1. Discrete Wavelet Transform (DWT)

DWT is a signal decomposition method that combines both low-pass and high-pass filters. In this process, DWT analyzes the signal at various frequency bands, allowing the decomposition of the signal into two types of coefficients: approximate coefficients ($A[n]$), which contain low-frequency components, and detail coefficients ($D[n]$), which include high-frequency components. DWT provides a more detailed signal representation with varying resolutions according to its frequency characteristics [26], [27]. In mathematical equations, the Discrete Wavelet Transform (DWT) can be defined in the following formula:

$$A[n] = \sum_{n} S\,[k] \cdot g[2n-k] \tag{1}$$

$$D[n] = \sum_{n} S\,[k] \cdot h[2n-k] \tag{2}$$

Based on Eq. (1) and Eq. (2), the coefficients A[n] represent the low-frequency information, while D[n] captures the high-frequency components of the signal. Each time the signal passes through the low-pass and high-pass filters, its frequency will be halved, resulting in multilevel decomposition

$$A_j[n] = \sum_{k} A_{j-1}\,[k] \cdot g[2n-k] \tag{3}$$

$$D_j[n] = \sum_{k} A_{j-1}\,[k] \cdot h[2n-k] \tag{4}$$

Based on Eq. (3) and Eq. (4), the DWT decomposition process is performed in stages. The approximation signal from the previous level $A_{j-1}[k]$ is used as input to obtain the approximation coefficients $A_j[n]$and details $D_j[n]$ at the j decomposition level. The inverse DWT is used to recombine the components into the original signal.

$$s(t) = \sum_{k} c_k \phi_j(t) + \sum_{j=0}^{N} \sum_{k} d_{j,\kappa} \psi_{j,k}(t) \tag{5}$$

Based on Eq. (5), the Inverse DWT is used to reconstruct the original signal $s(t)$ from the decomposed coefficients. This reconstruction process incorporates the approximation coefficients c_k, which are multiplied by the scale function $\phi_j(t)$, and the detailed coefficients $d_{j,\kappa}$,

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which are multiplied by the wavelet function $\psi_{j,k}(t)$ at various j levels. This approach enables accurate signal recovery from multi−resolution representations, which N denotes the maximum decomposition level.

2. Independent Component Analysis (ICA)

ICA assumes that the recorded EEG signal X results from several independent signals sourced from brain activity and artifacts [27], [28]. This modeling is expressed in linear Eq. (6):

$$x = As \tag{6}$$

where x is the observed mixed signal matrix, A is the mixing matrix that combines the original signal with other sources, and s is the original signal vector consisting of the independent components to be separated. To get the independent components s, the inverse matrix W of matrix A must be computed. In the ICA formula, if W is the inverse of A, then (Eq. (7)):

$$W = A^{-1} \tag{7}$$

The independent components are separated from the mixed signal using the following equation (Eq. (8)):

$$S = WX \tag{8}$$

In the context of EEG, an independent signal S will consist of the original component of brain activity and other separate artifact components. The original artifact-free signal can be reconstructed once the artifacts are identified and removed. To restore the desired independent components into a mixed signal form, the reconstruction algorithm used is (Eq. (9)):

$$X_C = W^{-1}A_C \tag{9}$$

where X_C is the corrected and reconstructed signal after removing the artifact components. The matrix W^{-1} is the inverse of the unmixing matrix W, which returns the signal to the observation domain. It A_C is the mixture matrix of the corrected independent components, i.e., it only consists of relevant (artifact-free) sources. The steps of using MS-ICA in the EEG Pre-Processing Stage include:

a. The subject's multi-channel EEG signal is input. These signals are represented as $x = [x_1, x_2, \dots, x_n]$, where each xi is one EEG channel. This EEG data is the original signal, which may contain noise and artifacts.

b. Each EEG channel xi is decomposed using DWT up to a certain level, thus obtained (Eq. (10) and Eq. (11)):

$$D_i = [D_{i,1}, D_{i,2}, \dots, D_{i,n}], \quad i = 1,2,\dots,L \tag{10}$$

$$A_L = [A_{L,1}, A_{L,2}, \dots, A_{L,n}] \tag{11}$$

where $D_{i,j}$ is the detail coefficient at the i scale for the j channel, and $A_{L,j}$ is the approximation coefficient at the highest scale (L) for the j channel. This process extracts time-frequency information from the EEG signal.

c. Each detail coefficient is thresholded with a soft-thresholding method to reduce noise (artifacts). This process is written in the form (Eq. (12)):

$$d_i = f_i + \varepsilon \cdot z_i, \quad i = 1,2,\dots,n \tag{12}$$

Where f_i is the original signal and z_i is the noise. The threshold is used to subtract $\varepsilon \cdot z_i$ from the observed signal.

d. Separation of independent components using ICA, after thresholding, ICA is performed on each set of noise-reduced detail coefficients Di. This process aims to separate independent signals (both from the brain and artifacts) (Eq. (13)):

$$X = A \cdot S \Rightarrow S = W \cdot X \tag{13}$$

The relevant independent components (without artifacts) are selected as the ICA output.

e. Signal reconstruction using Inverse DWT. The corrected ICA output coefficients ($\widehat{D}_i$) replace the detail coefficients in the initial DWT structure. IDWT is then performed for each EEG channel to obtain a clean signal (Eq. (14)):

$$\hat{x} = IDWT(A_L, \widehat{D}_1, \widehat{D}_{2,\dots,}\widehat{D}_L) \tag{14}$$

Here, only the detail coefficients have been processed with ICA while A_L retained.

f. The final output is $\hat{x}$ is the reconstructed EEG signal that has undergone the entire process of the above stages.

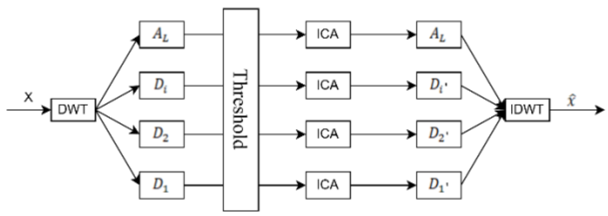

Fig. 4. Structural Diagram of Multiscale Independent Component Analysis (MS-ICA) Method

In the application of the MS-ICA method in this study (Fig. 4), the detection and removal of artifacts were performed automatically, without manual inspection. The Daubechies 4 (db4) wavelet basis was employed with one-level decomposition (level = 1) to preserve high-frequency details while maintaining important temporal structures. The Thresholding process was carried out softly (soft Thresholding) with a threshold value of 2. Furthermore, the FastICA algorithm was applied with 16 components, adjusted to the number of EEG channels. The denoising process was carried out on the detail coefficients of the DWT results and then reconstructed using the inverse DWT function. All parameters were determined based on initial experiments and related literature references.

D. Filter Performance Analysis

EEG signals that have undergone the filtering process using the MS-ICA filter are evaluated, analyzed, and compared based on four parameters: MAE, MSE, RMSE, and SNR.

1. Mean Absolute Error (MAE)

Mean Absolute Error is a simple equation for calculating model evaluation measures, representing the average

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absolute error between observed and predicted values. This equation is used to evaluate the average residuals of a data set [29]. The following is the mathematical equation for MAE.

$$MAE = \frac{\Sigma_i |x_i - y_i|}{n} \tag{15}$$

Based on the mathematical Eq. (15), x_i is the actual data value i, y_i is the predicted value i, and n is the total number of samples. In the context of EEG, MAE is used to measure model accuracy by calculating the average absolute difference between the predicted value and the actual signal value. A smaller MAE value indicates better model performance in preserving signal accuracy..

2. Mean Squared Error (MSE)

Mean Squared Error is one of the methods often used to determine the error value when making predictions. This method measures the average value of the squared error between the actual value and the predicted value. A low MSE value or one that is close to zero indicates that the prediction results are close to the actual data [30]. The formula is

$$MSE = \frac{\Sigma_i (x_i - y_i)^2}{n} \tag{16}$$

Based on the mathematical Eq. (16), x_i represents the actual data value i, y_i is the predicted data value i, and n indicates the total number of samples. The use of MSE in the context of EEG aims to measure the accuracy or quality of signal reconstruction after it has undergone pre-processing stages. A low MSE value indicates that the difference between the original signal and the reconstructed result is increasingly tiny, thereby assessing the pre-processing method as more effective in preserving important information from the EEG signal.

3. Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a method used to evaluate the average error between actual and predicted values. RMSE is obtained by calculating the square root of the MSE value, so this method places more emphasis on significant errors due to the square operation [29]. The formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{17}$$

Based on this mathematical Eq. (17), x_i represents the actual data value i, y_i is the predicted data value i, and nnn indicates the total number of samples. RMSE is used to assess how well the reconstructed signal retains the characteristics of the original signal.

4. Signal-to-Noise Ratio (SNR)

Signal-to-noise ratio is a method used to measure signal quality by comparing the strength of the primary signal to the strength of the noise. The quality of a signal that experiences interference can be determined using the SNR method, which has a measurement unit in decibels (dB) [30]. The following is the mathematical equation for the SNR.

$$log_{10}\left(\frac{\sum_{i=1}^{n} {x_i}^2}{\sum_{i=1}^{n}(x_i - y_i)^2}\right) \tag{18}$$

Based on this, Eq. (18), x_i is the value of the original signal i, y_i is the value of the reconstructed or predicted signal i, and nnn is the number of samples. A higher SNR value indicates that the signal energy is dominant compared to the error or noise energy, so the pre-processing method used is considered successful in retaining important information from the EEG signal and effectively reducing interference components.

5. Test Statistics

When evaluating methods of denoising EEG signals, statistical inference methods often employ paired t-tests to determine if observed differences in performance between the two methods are statistically significant. Essentially, this test compares the differences in metric values (e.g., MAE, MSE, or SNR) obtained for each paired observation recorded with both methods. The formula for the paired t-test is as follows in Eq. (19):

$$t = \frac{\bar{d}}{s_d \,/\, \sqrt{n}} \tag{19}$$

In this case, $\bar{d}$ is the average difference between the data pairs from the two methods, s_d is the standard deviation of the difference, and n is the number of sample pairs. These three values are used to calculate the t-value in the significance test. The t-value obtained is then compared with the critical value of the t-distribution (with degrees of freedom $df = n - 1$) to calculate the p-value, which represents the probability that the observed difference occurred by chance. Mathematically, this p-value is formulated in Eq. (20):

$$p = 2\big(1 - T(|t|, df)\big) \tag{20}$$

where T is the cumulative distribution function (CDF) of the t distribution, which shows the cumulative probability under the t distribution curve [31].

6. Effect Size Estimation

Cohen's d is one of the effect sizes commonly used in inferential statistical analysis, especially to measure the magnitude of the difference between two groups in standard deviation units. This measure provides additional information beyond the results of significance tests (such as p-values) by emphasizing the practical significance of the difference rather than just whether the difference is statistically significant [32]. Mathematically, Cohen's d is formulated as follows Eq. (21):

$$d = \frac{M_1 - M_2}{SDpooled} \tag{21}$$

This value is calculated by dividing the difference in means divided by the pooled standard deviation. Its interpretation is 0.2 for a small effect, 0.5 for a medium effect, and ≥0.8 for a significant effect. This measure is used to assess the practical significance of differences in data, complementing the results of significance tests such as the p-value.

III. Results

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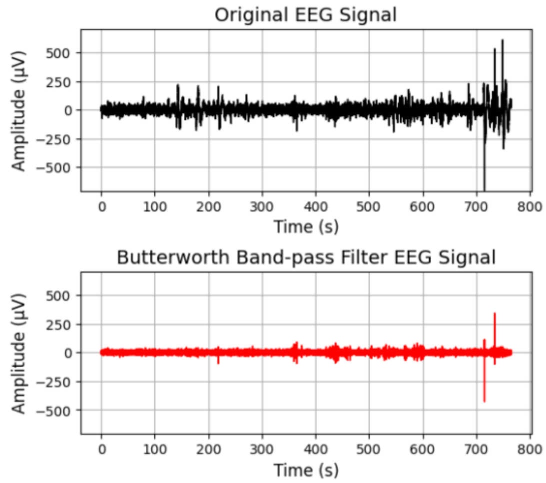
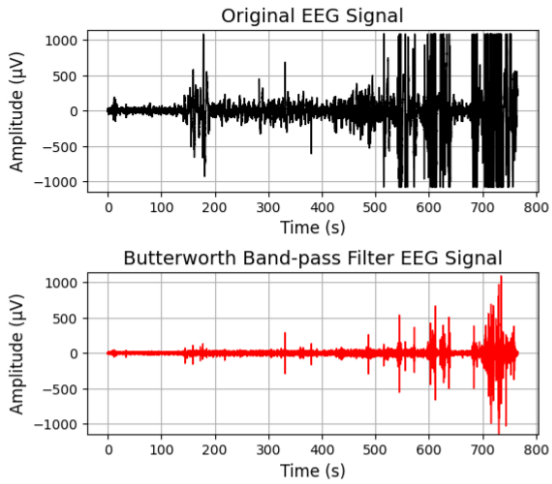
The raw EEG signals used in this study were obtained from eight subjects with ASD, each recorded for varying durations depending on the circumstances during data acquisition. All signals from the eight subjects were analyzed in their entirety without segmentation, resulting in a total cumulative duration of 4104.2 seconds. Before entering the primary analysis stage, the EEG signals were first processed through an initial preprocessing stage by applying a Butterworth Band-Pass Filter. This filter was applied to eliminate frequency components outside the range relevant to brain activity, such as very low frequencies (drift) and high-frequency noise. After the filtering process, the filtered signals were then analyzed using the MS-ICA method. This method can separate complex EEG signals into multiple independent components based on their multiscale characteristics. The resulting components are then reconstructed into a refined signal that is expected to maintain the main information of the original signal while minimizing unwanted artifacts. To evaluate the quality of the decomposition and signal reconstruction results, four quantitative parameters were used, namely Mean Absolute Error (Eq. 15), Mean Squared Error (Eq. 16), Root Mean Squared Error (Eq. 17), and Signal-to-Noise Ratio (Eq. 18).

A. Butterworth Band-Pass Filter Result

The application of a Butterworth band-pass filter to EEG signals aims to preserve important frequency components within the range of 4 Hz to 40 Hz while reducing interference from frequencies outside this range. This range is chosen because the most relevant brain activity, such as theta, alpha, beta, and some gamma waves, typically falls within this range. At the same time, frequencies below 4 Hz often contain artifacts such as eye movements or DC drift. The Butterworth filter was chosen due to its smooth frequency response characteristics in the passband region, which lack sharp ripples, allowing it to preserve the original signal shape better and minimize distortion during the filtering process. Filtering was performed on a 16-channel EEG signal from an individual with autism spectrum disorder. As shown in Fig. 5, two example channels (T5 and T6) demonstrate the effect of filtering. Before filtering, the raw signal (shown in black) exhibited intense fluctuations due to artifacts, with the highest amplitude reaching 700 µV and the lowest at -750 µV at channel T5 and at channel T6, extreme amplitude fluctuations reaching more than ±1000 µV, which disrupt the stability of the signal. After being filtered by a Butterworth band-pass filter (shown in red), the signal is cleaner, with the highest amplitude reaching 300 µV and the lowest at -400 µV at channel T5 and at channel T6 It can be seen that the signal amplitude becomes more controlled, with the fluctuation range mostly being within ±500 µV. However, some noise and prominent peaks are still present, especially at the end (around 700th second), where more stable frequency and amplitude patterns are found. This filtering effectively keeps frequency components within the 4–40 Hz range and removes interference from frequency components outside this range, which are not relevant.



a) Channel T5



b) Channel T6

Fig. 5. Result Filtered EEG Signal of Autism Using Butterworth Band-Pass Method

B. Multiscale Independent Component Analysis (MS-ICA) Result

After undergoing pre-processing, the EEG signals were further analyzed using the MS-ICA method. As shown in Fig. 6, the application of MS-ICA was proven to improve the quality of EEG signals in subjects with ASD. The method is adept at minimizing the residual noise present in each channel, thus cleansing the signal of undesirable artifacts. Thus, MS-ICA plays a key role in enhancing the clarity of EEG signals and, hence, in enabling a more accurate and stable representation of cerebral activity. Filtering was performed on the 16-channel EEG signal from an individual with autism spectrum disorder. Fig. 6 shows two examples of EEG channels after processing using MS-ICA. In channel T5, the signal amplitude primarily falls within the range of ±100 µV, with some spikes reaching ±400 µV near the 700th second, indicating effective noise and outlier reduction. In channel T6, fluctuating amplitudes are still visible up to ±900 µV after the 700th second. However, the overall signal pattern appeared more structured,

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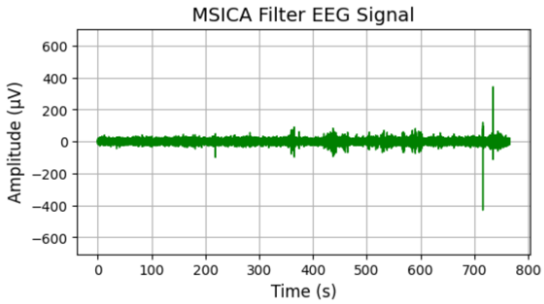
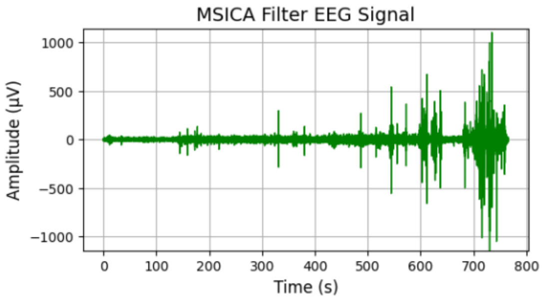
indicating the partial success of MS-ICA in reducing artifacts while preserving relevant brain activity components.



a) Channel T5



b) Channel T6

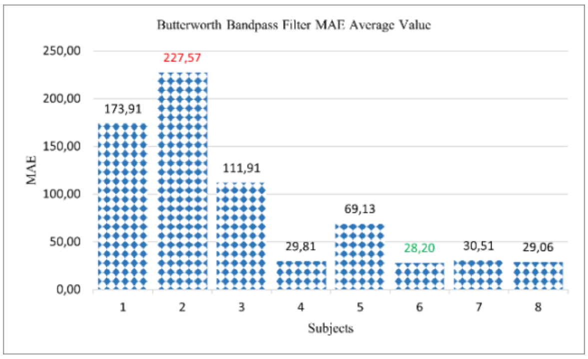
Fig. 6. Result EEG Signal of Autism After Applying MS-ICA Method

C. Filter Performance Analysis Result

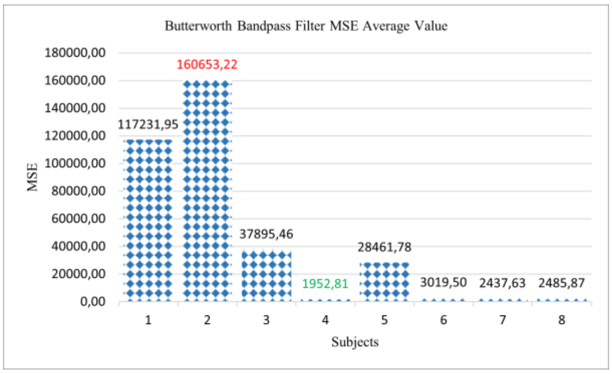
To assess the performance of the EEG signal filtering process, this study employed four primary evaluation parameters: MSE, MAE, RMSE, and SNR. These four metrics were used to evaluate the effectiveness of the filtering method in reducing interference while retaining important information from the signal. Based on the analysis results, the combination of the Butterworth band-pass filter and the MS-ICA method demonstrates optimal performance in improving EEG signal quality. The Butterworth band-pass filter plays a role in preserving relevant frequency components within the EEG signal range. At the same time, MS-ICA effectively performs denoising by separating independent components across various scales, thereby reducing artifacts and producing a cleaner signal that more accurately represents actual brain activity.

1. Butterworth Band-Pass Filter

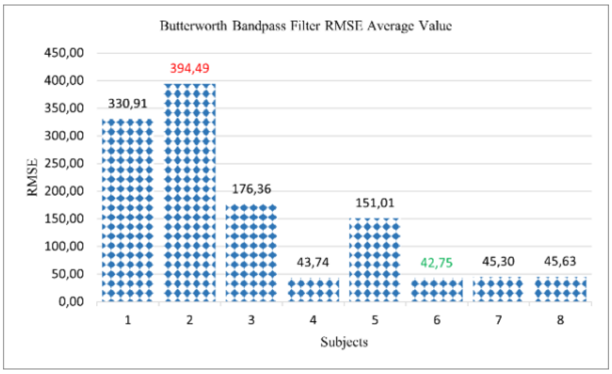
Fig. 7 shows that the evaluation of the Butterworth Band-Pass Filter method reveals significant variations in the four evaluation parameters. The highest MAE value was observed in subject 2, at 227.57, while the lowest value was found in subject 6, at 28.20. The MSE parameter also showed notable differences, with the highest value of 160,653.22 (Subject 2) and the lowest value of 1,952.81 (Subject 4). For the RMSE, the highest value was obtained in Subject 2 at 394.49, while the lowest value of 42.75 was recorded in Subject 6. Meanwhile, the highest SNR value was 1.33 dB (Subject 4), and the lowest value was 0.03 dB (Subject 3), indicating low signal quality in that subject after processing with the Butterworth filter.



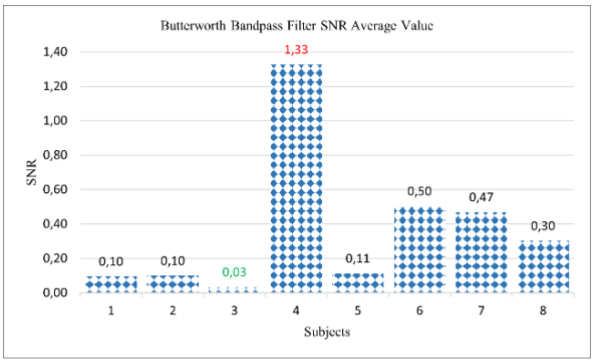
a) Mean Absolute Error (MAE)



b) Mean Squared Error (MSE)



c) Root Mean Squared Error (RMSE)



d) Signal-to-Noise Ratio (SNR)

Fig. 7. Performance Evaluation Results of EEG Filtering Using Butterworth Band-Pass Method

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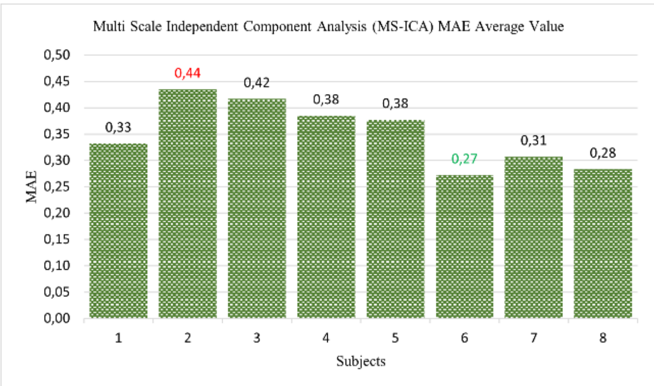
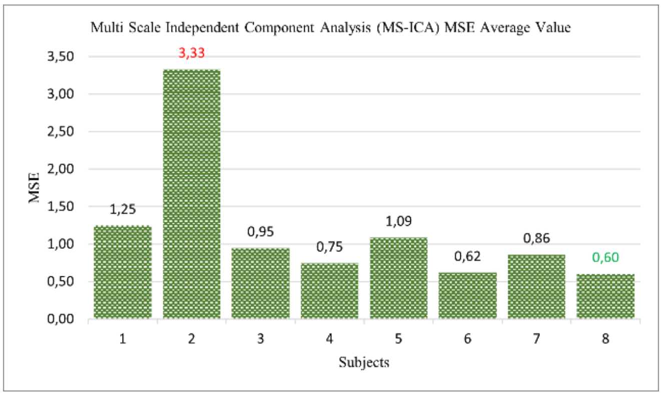
2. Multiscale Independent Component Analysis

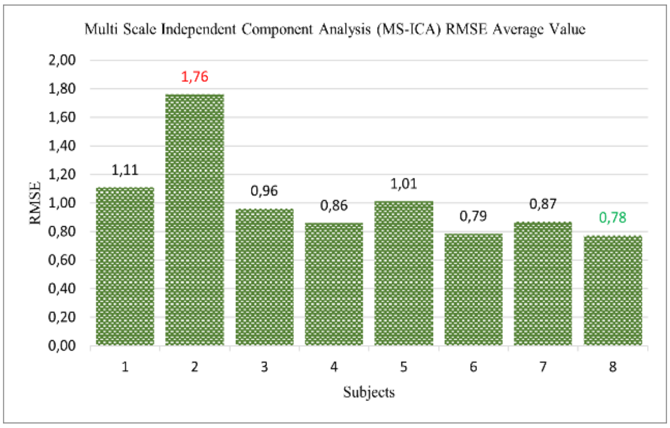
Fig. 8 shows that the Multiscale Independent Component Analysis (MS-ICA) method yields MAE values ranging from 0.27 (Subject 6) to 0.44 (Subject 2). The lowest MSE value of 0.60 was obtained in Subject 8, while the highest value of 3.33 was observed in Subject 2. The RMSE values ranged from 0.78 to 1.76, with Subject 8 recording the lowest value and Subject 2 the highest. For the SNR parameter, MS-ICA produced significantly higher values than Butterworth, with the highest value of 30.88 dB in Subject 1 and the lowest value of 21.77 dB in Subject 8. Visualization of the average MAE, MSE, RMSE, and SNR values of the eight subjects showed striking differences between individuals, reflecting the inhomogeneity of the artifact levels in the EEG signal. For example, Subject 2 recorded the highest values in MAE (0.44), MSE (3.33), and RMSE (1.76), accompanied by a reasonably high SNR of 29.18 dB, indicating the presence of dominant signal interference that was successfully suppressed by the MS-ICA method. In contrast, Subjects 6 and 8 showed much lower and more stable metric results (MAE between 0.27 and 0.28; MSE between 0.62 and 0.64), indicating the signals produced had a minimal level of interference or were obtained under more optimal recording conditions. This variation is a challenge in EEG analysis because the presence of artifacts is highly dependent on individual factors, recording sessions, and device quality, which can affect the accuracy of pre-processing.



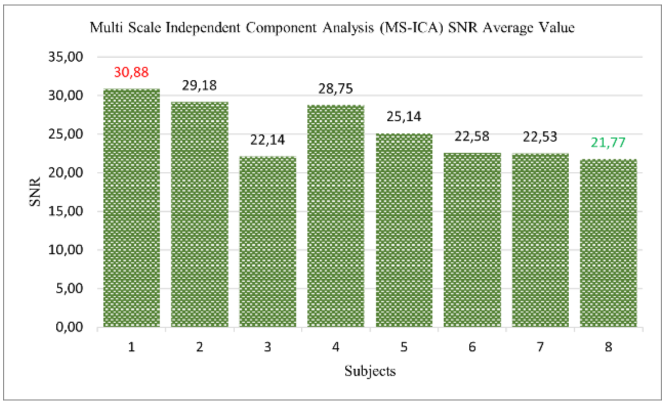
a) Mean Absolute Error (MAE)



b) Mean Squared Error (MSE)



c) Root Mean Squared Error (RMSE)



d) Signal-to-Noise Ratio (SNR)

Fig. 8. Performance Evaluation Results of EEG Filtering Using MS-ICA Method

Therefore, this study employs a paired comparison approach, comparing the Butterworth and MS-ICA methods within the same signal time range for each subject. This enables a fair performance evaluation of each technique, ensuring that differences in signal characteristics between individuals do not influence the results.

3. Comparison Between Butterworth Band-Pass Filter Method and MS-ICA

Fig. 9 presents a comparison of the performance between the Butterworth Band-Pass Filter method and Multiscale Independent Component Analysis (MS-ICA) in EEG signal processing, revealing contrasting results in four evaluation parameters: MAE, MSE, RMSE, and SNR.

In the Butterworth method, the highest average MAE value was recorded in Subject 2 at 227.57, while the lowest value of 28.20 was found in Subject 6. For the MSE parameter, Subject 2 also recorded the highest value of 160,653.22, with the lowest value of 1,952.81 in Subject 4. RMSE values ranged from 42.75 (Subject 6) to 394.49 (Subject 2), while the highest SNR value was 1.33 (Subject 4) and the lowest was 0.03 (Subject 3), indicating the Butterworth method's limited ability to improve signal quality.

In contrast, the MS-ICA method demonstrated more

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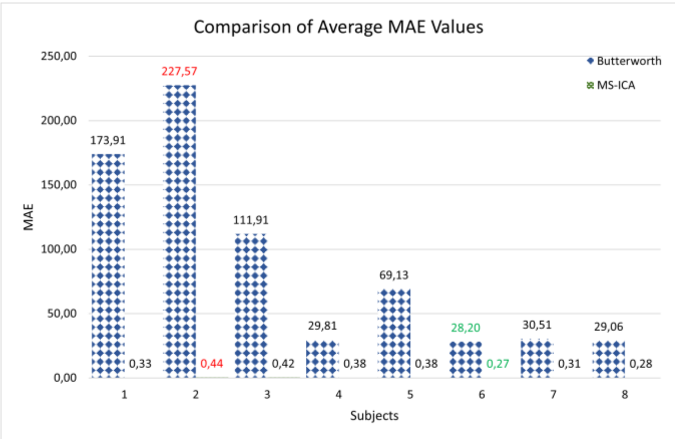
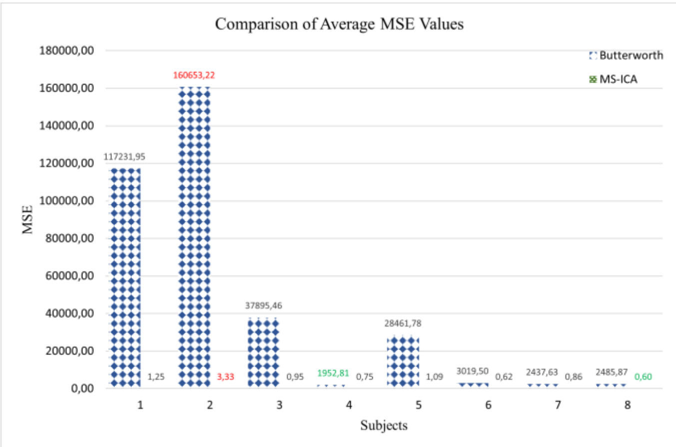
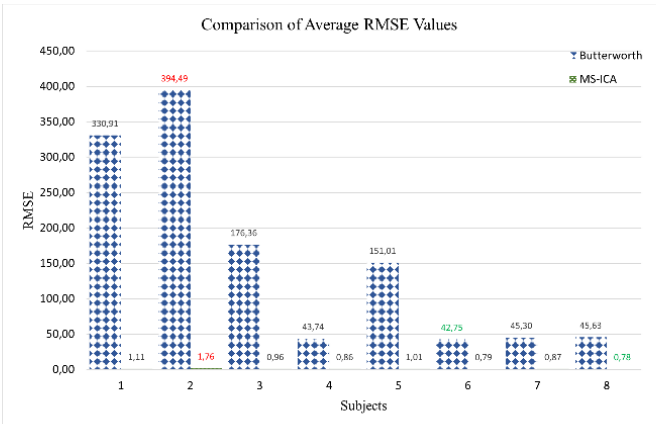
consistent and superior performance. The highest MAE value was 0.44 (Subject 2), and the lowest was 0.27 (Subject 6). The highest MSE was recorded at 3.33 (Subject 2), which is significantly lower than the MSE obtained using the Butterworth method. The highest RMSE value was 1.76, and the lowest was 0.78. Most notably, the SNR values for MS-ICA ranged from 21.77 to 30.88, indicating a very significant improvement in signal quality compared to the Butterworth method.



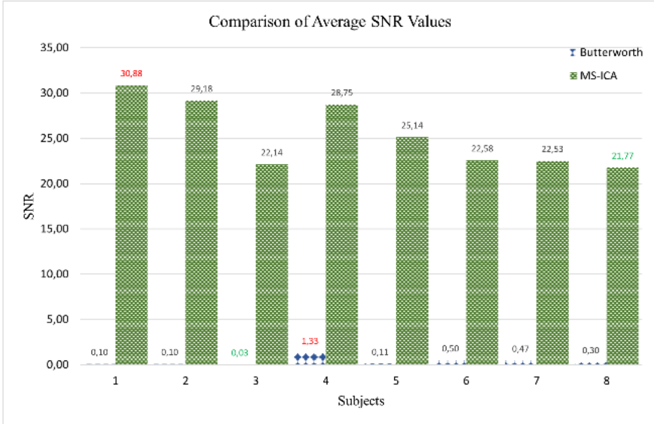
a) Comparison of Mean Absolute Error (MAE)



b) Comparison of Mean Squared Error (MSE)



c) Comparison of Root Mean Squared Error (RMSE)



d) Comparison of Signal-to-Noise Ratio (SNR)

Fig. 9. Comparison of Performance Evaluation Results of EEG Filtering Between Butterworth Band-Pass Filter and MS-ICA Method

IV. Discussion

A. Performance of Butterworth Filters and MS-ICA

This study aims to evaluate the performance of two EEG signal denoising methods, namely Butterworth Band Pass Filter and MS-ICA, using four main evaluation parameters: MAE, MSE, RMSE, and SNR. Based on the analysis results, the Butterworth method yields relatively high MAE values and shows a fairly significant level of variation between subjects, with a range between 28.20 and 227.57. This variation reflects the dependence of Butterworth's performance on the individual characteristics of the EEG signal and its inability to eliminate noise consistently across subjects. In addition, the MSE value, which reaches up to 160,653.22, strengthens the suspicion of significant distortion in the filtered signal, in line with the high RMSE value (maximum 394.49) and very low SNR (maximum 1.33 dB), indicating the overall low quality of the resulting signal.

In comparison with the Butterworth method, the MS-ICA method has superior and more stable performance in EEG signal denoising. The superiority of the method is evident from the low value of MAE, ranging from 0.27 to 0.44, indicating that the denoised signal is very close to the reference signal. In addition, the MSE value recorded is comparatively low, ranging from 0.60 to 3.33, and is accompanied by a lower value of RMSE (0.78–1.76), indicating a very low amount of distortion. Apart from this, the output signal quality is enhanced by a high SNR with a max value of 30.88 dB, which signifies that the signal has been purified very efficiently and has an ideal signal-to-noise ratio. This consistency confirms the superiority of MS-ICA in reducing artifacts without sacrificing important information from the EEG signal.

However, it is essential to acknowledge that each evaluation metric exhibits varying sensitivity to noise and artifacts. MSE and RMSE, which involve calculating the square of the signal difference, are very susceptible to the presence of outliers or extreme artifacts, which can significantly increase the error value. In contrast, MAE is more stable in the face of noise spikes because it only

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calculates the absolute difference between the actual and predicted values. Meanwhile, the SNR value can be distorted if there is a channel with extreme artifact contamination, which causes the noise estimation to be excessive. This variability is important to note in the context of EEG analysis, especially in subjects with neurophysiological disorders such as ASD, which generally show high and uneven noise levels between channels and between individuals.

B. Butterworth vs MS-ICA Performance Comparison

The implementation and analysis results demonstrate that the MS-ICA method consistently outperforms the Butterworth Band-Pass Filter approach in the EEG signal preprocessing stage. MS-ICA integrates two techniques, namely the DWT and ICA, which work adaptively across various time scales, allowing them to separate signal components from non-stationary artifacts more efficiently. In contrast, Butterworth only filters signals based on a fixed frequency range, making it less effective in handling dynamic artifact variations. The quantitative evaluation results demonstrate that the MS-ICA method is highly effective in enhancing the quality of EEG signals. This improvement is indicated by an increase in the average SNR value, as well as a decrease in the MAE, MSE, and RMSE values in most of the subjects studied. For example, in the third subject, MS-ICA produced an MAE value of 0.42 and an MSE of 0.95. In contrast, the Butterworth method demonstrated significantly lower performance, with an MAE value of 111.91 and an MSE of 37895.46. The most significant difference was seen in the SNR parameter, where MS-ICA recorded a value of 22.14 dB, far exceeding the value of 0.03 dB obtained through the filtering process using the Butterworth filter.

To determine whether the difference in performance between the two methods is statistically significant, a paired t-test and effect size measurement using Cohen's d were performed. Results confirmed that the MS-ICA method showed statistically and practically superior performance compared to Butterworth in most evaluation metrics. Based on the results of the t-test analysis, the MAE and RMSE parameters showed significance values of 0.015 and 0.017 ($p < 0.05$), indicating a statistically significant difference between the two methods being compared. The MS-ICA method was shown to produce a lower error rate than the other methods in both parameters. Meanwhile, for the MSE parameter, a p-value of 0.079 ($p > 0.05$) was obtained, indicating that the difference between the two methods was not statistically significant. However, the results still indicate a tendency for MS-ICA to have superior performance in reducing errors compared to the comparison method. The most significant improvement was seen in the SNR metric with a p-value < 0.0001, indicating that MS-ICA consistently provides higher signal quality. Cohen's d values further support this finding, showing large to substantial effects on all metrics, specifically +1.60 for MAE, +1.54 for RMSE, +1.02 for MSE, and -9.50 for SNR. The negative value for SNR indicates a direction of difference in favor of MS-ICA. Overall, the combination of the t-test and Cohen's d results strengthens the finding that MS-ICA is substantially more effective in improving the accuracy and stability of EEG signals than the conventional Butterworth approach.

This study shows that the MS-ICA approach can significantly improve the quality of EEG signals compared to the Butterworth method, especially in children with Autism Spectrum Disorder (ASD). Unlike the combination of wavelet and ICA approaches previously used on ECG signals, such as in the WICA study by Calcagno et al. [27], no publication has applied MS-ICA specifically to EEG signals until now. Thus, this study makes an initial contribution to applying MS-ICA to EEG, particularly for the ASD population, by combining the advantages of DWT and ICA in a single preprocessing series.

Support for this advantage is also evident in similar studies, such as the use of the Savitzky-Golay filter, which only recorded the lowest MAE value of 1.35 [13]. Meanwhile, in this study, MS-ICA achieved a minimum MAE value of 0.27, indicating a significant improvement in accuracy. These results indicate that MS-ICA excels in preserving EEG signals integrity and effectively reducing errors caused by artifacts.

C. Research Limitation

Although MS-ICA shows superior performance compared to the Butterworth Band-Pass Filter based on MAE, MSE, RMSE, and SNR values, several technical and practical limitations still need to be considered in its application. MS-ICA has higher computational complexity because it involves multiple stages, including decomposition using the Discrete Wavelet Transform (DWT), a soft threshold process, signal separation via Independent Component Analysis (ICA), and signal reconstruction through the inverse DWT. This process results in an average processing time of 1 to 2 minutes per EEG subject (16 channels), whereas the Butterworth method takes less than a minute for the same dataset. This shows a clear trade-off between increasing denoising accuracy and computational time efficiency. In addition, MS-ICA performance is greatly influenced by the selection of parameters, such as the number of components and decomposition level, which can affect the consistency of the results, especially in EEG signals with complex and overlapping artifacts. The variability of signal characteristics between subjects also affects the effectiveness of this method, as evident from the fluctuation in evaluation results across several subjects. The limited sample size further limits the generalization of the results of this study to a broader population. Therefore, further studies with larger sample sizes and exploration of more computationally efficient adaptive or hybrid approaches are highly recommended to improve the validity and practical applicability of MS-ICA in clinical contexts.

D. Implications and Potential Use of MS-ICA in Signal Denoising

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The Multiscale Independent Component Analysis (MS-ICA) method was discovered to significantly enhance the quality of EEG signals by embracing a more adaptive and discriminatory denoising process compared to other conventional techniques, such as the Butterworth technique. MS-ICA consistently reduces the error metrics, i.e., MAE, MSE, and RMSE, while augmenting SNR measures, resulting in cleaner, more information-rich signals. The aforementioned technical merits are not only applicable to signal analysis; they also bear important implications in clinical settings, particularly in the detection and diagnosis of Autism Spectrum Disorders (ASD). High-fidelity signals facilitate more precise feature extraction process, effectively capturing the normative brain activity patterns of individuals with ASD, thereby enhancing the effectiveness of classification algorithms in detecting the neurophysiological features indicative of ASD. Additionally, there is a compelling need for EEG signals to contain minimal artifacts in the context of long-term monitoring and evaluation of EEG-based therapies. Through the preservation of functional signal component integrity, MS-ICA is fundamental in improving the precision and trustworthiness of diagnosis systems. Consequently, it provides access to a series of applications ranging from the monitoring of brain development in the pediatric population to the implementation in Brain Computer Interface (BCI) systems that necessitate high-fidelity signals.

V. Conclusion

This study examines the effectiveness of two EEG signal pre-processing methods, the Butterworth Band-Pass Filter and MS-ICA, in processing EEG signals from children with ASD. When we examine the results of the evaluation against four main factors, MAE, MSE, RMSE, and SNR, we observe that the MS-ICA technique consistently outperforms. MS-ICA exhibits significantly lower error values (MAE: 0.27–0.44; MSE: 0.60–3.33; RMSE: 0.78–1.76) and superior signal quality, as indicated by high SNR values (21.77–30.88 dB). The Butterworth technique, on the other hand, was less than ideal, with MAE values of 227.57, MSE of 160,653.22, RMSE of 394.49, and the highest SNR of only 1.33 dB.

The paired t-test statistical test showed statistically significant differences in all parameters ($p < 0.05$), indicating that MS-ICA consistently provided better results than Butterworth. To strengthen the practical interpretation, an effect size analysis was performed using Cohen's d. The results showed a large effect size for MAE ($d = 1.60$), MSE ($d = 1.02$), RMSE ($d = 1.54$), and a very large effect size for SNR ($d = -9.50$), indicating a substantial practical impact of using MS-ICA on improving EEG signal quality. These findings suggest that MS-ICA is not only statistically superior but also offers real benefits in clinical applications, particularly in enhancing the accuracy of identifying typical ASD brain activity patterns.

Thus, MS-ICA is recommended as a more reliable and accurate pre-processing method in EEG signal processing in children with ASD. The application of this method can significantly contribute to improving the validity of EEG-based diagnosis results and lay the foundation for the development of an automatic classification system based on artificial intelligence. For further research, it is recommended to examine the integration of MS-ICA with a hybrid approach or advanced machine learning algorithms to improve the overall system performance.

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