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SAVITZKY-GOLAY AND WIENER FILTERING PERFORMANCE ANALYSIS IN ELECTROENCEPHALOGRAPHY SIGNAL PROCESSING OF AUTISTIC CHILDREN

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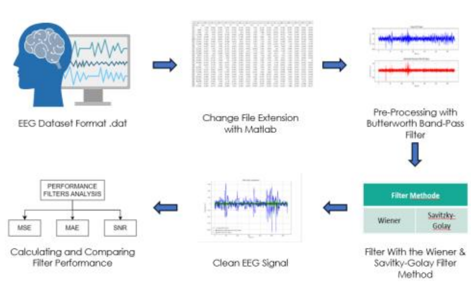
Graphical abstract



Abstract

Electroencephalography (EEG) measures electrical activity in the brain area by placing several electrodes on the scalp that can be used to diagnose autism spectrum disorder (ASD) and various abnormalities in the brain nerves. During the EEG signal recording process, the measured signal is often contaminated by various types of noise, which causes difficulties in analyzing the signal. Therefore, an effective method is needed to reduce these artifacts. This research applied wiener filter (WF) and savitzky-golay filter (SG) methods in reducing noise in the EEG signals of autistic people. This method will be combined with another method, namely Butterworth Band-Pass Filter, to concentrate the frequency in the range of 0.5-40 Hz. Based on the comparison of performance accuracy values using three calculation parameters, namely mean square errors (MSE), Mean absolute errors (MAE), and signal to noise ratio (SNR), this study proves that WF is superior to SG in producing EEG signals of autistic and normal people free from noise. WF shows an SNR value of 34.773 "dB" compared to 22.157 "dB" in SG, as well as lower MAE and MSE values of 0.521 µV and 0.616 μV^2 compared to 1.875 µV and 16.990 μV^2 in SG. These results confirm that WF is more effective in reducing noise interference and producing more accurate signal estimation in EEG data analysis.

Keywords: Autism spectrum disorder, electroencephalography, wiener filter, savitzky-golay, butterworth band-pass filter

Abstrak

Electroencephalography (EEG) mengukur aktiviti elektrik di kawasan otak dengan meletakkan beberapa elektrod pada kulit kepala yang boleh digunakan untuk mendiagnosis gangguan spektrum autisme (ASD) dan pelbagai kelainan pada saraf otak. Semasa proses rakaman isyarat EEG, isyarat yang diukur sering tercemar oleh pelbagai jenis bunyi, yang menyebabkan kesukaran untuk menganalisis isyarat. Oleh itu, kaedah yang berkesan diperlukan untuk mengurangkan artifak ini. Penyelidikan ini menggunakan kaedah penapis wiener (WF) dan penapis savitzky-golay (SG) dalam mengurangkan bunyi bising dalam isyarat EEG orang autistik. Kaedah ini akan digabungkan dengan kaedah lain iaitu Butterworth Band-Pass Filter untuk menumpukan frekuensi dalam julat 0.5-40 Hz. Berdasarkan perbandingan nilai ketepatan prestasi menggunakan tiga parameter pengiraan iaitu mean square errors (MSE), mean absolute errors (MAE), dan signal to noise ratio (SNR), kajian ini membuktikan bahawa WF lebih unggul daripada SG dalam menghasilkan isyarat EEG. orang autistik dan normal bebas daripada bunyi bising. WF menunjukkan nilai SNR sebanyak 34.773 "dB" berbanding 22.157 "dB" dalam SG, serta nilai MAE dan MSE yang lebih rendah iaitu 0.521 µV dan 0.616 µV2 berbanding 1.875 µV dan 16.990 µV2 dalam SG. Keputusan ini mengesahkan bahawa WF lebih berkesan dalam mengurangkan gangguan hingar dan menghasilkan anggaran isyarat yang lebih tepat dalam analisis data EEG.

Kata kunci: Gangguan spektrum autisme, electroencephalography, penapis Wiener, savitzky-golay, butterworth band-pass filter

1.0 INTRODUCTION

Electroencephalography (EEG) records brain electrical activity via scalp electrodes [1–6]. EEG research traces back to the 19th century when Carlo Matteucci and Emil Du Bois-Reymond first recorded nerve signals with a galvanometer [7]. Hans Berger, a German psychiatrist, is regarded as the EEG pioneer, initiating research in 1920 and publishing it in 1929 [7–9]. Medical applications of EEG include detecting neurological disorders like epilepsy, autism, brain tumors, memory loss, hearing damage, and other abnormalities [7,9–11].

EEG detects neural signals via voltage fluctuations from ionic currents [8]. The brain's five lobes (frontal, parietal, occipital, temporal, cerebellum) produce electrical potentials [12,13]. Surface EEG uses scalp electrodes, while intracranial electrodes require surgery [10]. The 1958 international EEG federation protocol, later endorsed by the American Clinical Neurophysiology Society [14], standardizes electrode placement.

The 10 - 20 system is an internationally recognized standard for EEG electrode placement. Electrode placement according to the standard is Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2 (Figure 1) [15].

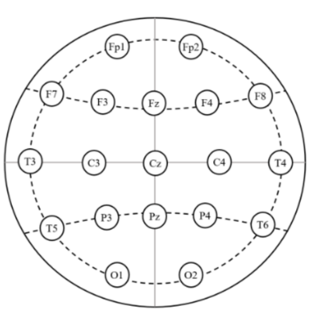


Figure 1 Electrode placement (10 - 20 system [15]

EEG is measured as voltage in the time domain and displayed as frequency in sinusoidal waves [16,17]. Frequency and amplitude are important in analyzing abnormalities in EEG signals. This signal has a frequency range from 0.5 Hz to 100 Hz with amplitude from 1 µV to 100 µV [8,10].

Brain waves are categorized into five primary frequency bands: delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz), beta (13 - 30 Hz), and gamma (30 - 100 Hz). Hans Berger introduced alpha and beta waves in 1929, while gamma waves were introduced by Jasper and Andrews in 1936. Delta waves were first described by Walter in 1936, and theta waves were initially defined by Walter as having a frequency range of 4 - 7.5 Hz, with further elaboration by Wolter and Dovey in 1944 [8,10,13,18]]. Higher frequency bands typically correspond to conscious states, while lower frequencies indicate synchronized activities like relaxation and sleep [10].

EEG signal measurement results are often contaminated by various types of noise (artifacts), which causes difficulties in the process of analyzing the signal [2,4,5,19]. The international federation of clinical neurophysiology (IFCN) explains that all types of potential differences found in EEG signals are referred to as artifacts. Sometimes, artifacts have the same frequency and rhythm parameters as the electrical potential from the brain source, so it becomes a challenge to know the difference between them [13].

EEG signals can have two types of artifacts: internal (biological) and external (environmental). Internal artifacts result from activities like eye movements, blinks (EOG), heartbeats (ECG), and muscle activity (EMG), affecting the EEG signal due to electrical potentials. External artifacts originate from various sources, including electrode placement, recording equipment, and cable movements, causing signal interference [6,12]. These artifacts are common and pose challenges in obtaining noise-free EEG signals in both autistic and typical individuals [4,10,19]. Effective noise reduction methods are essential to improve signal quality in such cases.

Various methods are used to address EEG signal artifacts, including DWT, FIR, Butterworth bandpass filter, Kalman filter, PCA, and ICA [2,4,10,19,20]. This study focuses on comparing the effectiveness of the wiener filter (WF) and savitzky-golay filter (SGF) in reducing artifacts in EEG signals from autistic children when combined with the Butterworth bandpass filter (0.5 - 40 Hz).

Various studies have applied the Wiener and Savitzky-Golay filters to signals other than EEG. One such study, "Adaptive Filtering for Noise Reduction in Speech Signals," [40] uses the Wiener filter to enhance speech clarity by reducing background noise. Additionally, in the study "Application of the Savitzky-Golay Filter for Spectral Data Smoothing," [41] the Savitzky-Golay filter is used to process infrared spectroscopy data, improving peak detection accuracy. In the field of image processing, the research "Image Restoration Using the Wiener Filter" demonstrates the effectiveness of the Wiener filter in restoring images distorted by noise. The Savitzky-Golay filter is also applied in "Noise Reduction in ECG Signals Using Savitzky-Golay Filtering" to smooth electrocardiogram (ECG) signals, facilitating arrhythmia detection. Lastly, the study "Performance Analysis of Wiener Filter in MIMO Wireless Systems" evaluates the use of the Wiener filter in reducing interference in MIMO wireless communication systems, enhancing signal quality and data rates.

This study stands out by using Python for EEG signal processing instead of MATLAB, which was commonly used in previous research [2,4,10,19,21]. Python offers flexibility, user-friendliness, and widespread accessibility. It also supports powerful libraries for signal analysis, including EEG processing.

This research will obtain the results of signal processing and performance comparison between the WF and SGF methods in producing EEG signals of autistic people that are free of artifacts/noise. Analysis of the performance comparison between the two filters is carried out using three calculation parameters, namely mean square errors (MSE), mean absolute errors (MAE), and signal noise ratio (SNR). This research is also expected to contribute to autistic EEG research and support the development of wiener and SG signal filter methods on the EEG signals of autistic people. The main contribution of this paper are as follows:

1. Being the first to use Savitzky Golay and Wiener filtering in EEG signal processing for autistic children.
2. Obtain comparative analysis results on the performance of SGF and WF using MSE, MAE, and SNR.
3. Improve the quality of EEG data analysis more effectively and efficiently through noise reduction. So as to obtain more accurate EEG data information for autistic children.

2.0 METHODS

This section describes the methods used throughout the study. The stages of the research will be carried out as in Figure 2, starting with collecting the ASD and normal EEG signal datasets and then performing the pre-processing stage by changing the extension of the dataset—the pre-processing stage using a band-pass filter. After passing through the band-pass filter, the signal will then be processed using a wiener filter and a SGF and become a signal free from noise. Then, the performance of the two filters will be compared using three calculation parameters, namely MSE, MAE, and SNR.

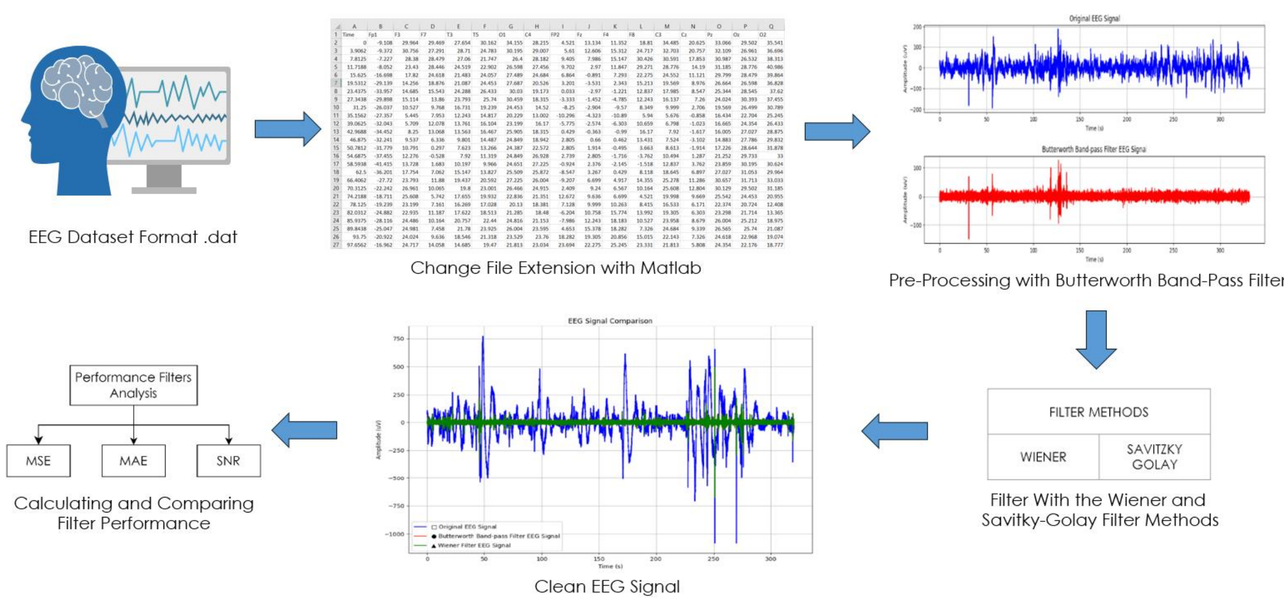


Figure 2 The proposed framework

2.1 Material

In this study, an EEG dataset was used as secondary data provided by King Abdul-Aziz University (KAU), Jeddah, Saudi Arabia. This dataset was recorded in a relaxed condition utilizing a g.tec EEG cap with Ag/AgCl electrodes, G.tech USB amplifiers, and BCI2000 software to generate 16-channel EEG data at a sampling rate of 256 Hz and contains recordings of 8 EEG signals from autistic children and 8 EEG signals from normal children. [22,23]. This data set is stored in a file with the extension .dat. DAT files usually contain binary text, and programs that use this data often create these files automatically. In its original format, this file may not be readable or contain a large amount of data that can support various program functions. Therefore, in this research dataset must be converted to a file with the extension. xlxs to make the process easier.

The following is an example of an EEG signal image generated by BCI2000Viewer (Figure 3). The figure typically displays the standard 10-20 electrode placement system, which includes electrodes positioned at specific locations on the scalp. Common electrodes in this setup include:

- **Frontal (F)**: Fp1, Fp2, F3, F4
- **Central (C)**: C3, C4, Cz
- **Temporal (T)**: T3, T4, T5, T6
- **Parietal (P)**: P3, P4, Pz
- **Occipital (O)**: O1, O2

Each electrode records electrical activity from different brain regions, allowing for a comprehensive view of brain function. The diverse signals from each electrode provide valuable data for further analysis, particularly in understanding conditions like autism.

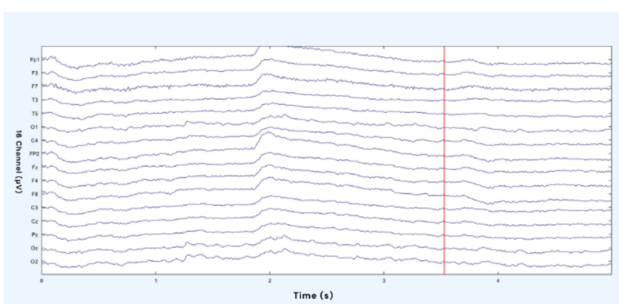


Figure 3 EEG dataset with 16 channel

2.2 Butterworth Band-Pass Filter

Butterworth bandpass filter is commonly employed to eliminate noise from EEG signals. It maintains a consistent frequency response within the desired range while attenuating frequencies outside it. Past experiments have demonstrated the effectiveness of this method in preserving the specified frequency range as per the filter's design parameters [21,24,25].

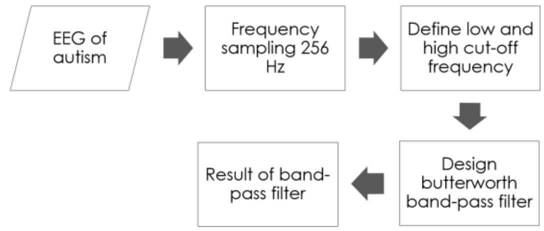


Figure 4 Butterworth band-pass filter method

Figure 4 illustrates the signal pre-processing using a butterworth band-pass filter. The EEG signal data, stored in a NumPy array within the "EEG" variable, undergoes a sampling frequency of 256 Hz (meeting Nyquist criteria). This ensures a minimum of 2 times the maximum frequency contained in the signal dataset. A 4th-order butterworth bandpass filter with a cutoff frequency range of 4 Hz to 40 Hz is applied to process the EEG signal, similar to prior experiments [21].

2.3 Wiener Filter

The wiener filter (WF) is widely used in signal processing and communications engineering to estimate the desired signal from signals containing artifacts or noise [26]. In signal processing, the WF minimizes the mean square error between the estimated and original signals [27].

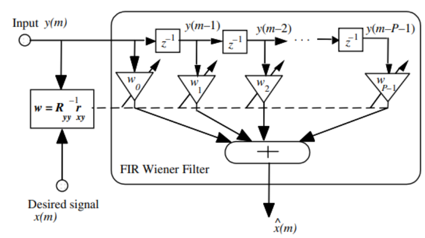


Figure 5 Illustration of wiener filter structure [28]

In the above structure (Figure 5), it can be seen that the wiener filter is illustrated with the symbol *w*. The filter has an input signal $y(m)$ and produces an output x^m where the value of x^m is the estimated value of the least squared error of the desired signal or target signal $x(m)$. The input and output relationship of the filter can be seen from the following equation:

$$\hat{x}(m)=\sum w_k y(m-k)=w^T y \qquad (1)$$

Where *m* is the discrete time index, y^T: $[y(m), y(m-1), \ldots, y(m-P-1)]$ is the input signal to the filter. And vector parameters w^T: $[w_0, w_1, \ldots, w_{(P-1)}]$ is the WF coefficient. From equation 1, the filtering operation is expressed in two forms, namely the alternative and equivalent of convolutional sum and inner vector multiplication. The error signal of a WF $[e(m)]$ is defined as the difference between the desired signal $x(m)$ and the filter output signal $\hat{x}(m)$.

$$e(m) = x(m) - \hat{x}(m) = x(m) - w^T y \qquad (2)$$

Figure 6 depicts the signal filtering process with the WF. It utilizes the eeg_filtered EEG signal from the butterworth band-pass filter as input, with a design parameter (order or window_size) set to 15. The WF is applied via the Wiener function from the scipy.signal module, generating a denoised EEG signal used for performance analysis.

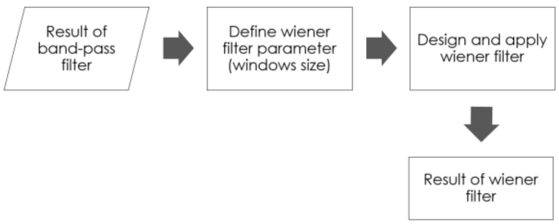


Figure 6 Wiener filter method

The implementation of the Wiener filter (WF) begins with noise estimation, where the noise power spectrum is derived from segments of the signal. Following this, filter design involves calculating the filter coefficients based on the estimated signal and noise spectra, optimizing the balance between noise reduction and signal preservation. The actual filtering process occurs in the frequency domain; the signal undergoes a Fourier transform, the Wiener filter is applied, and then the signal is transformed back to the time domain. One of the key strengths of the WF is its effectiveness in reducing noise while preserving important signal features, particularly in environments with significant background noise. However, a notable limitation is that it requires accurate estimation of noise characteristics, which can be challenging in highly variable environments.

2.4 Savitzky-Golay Filter

The savitzky–golay filter (SGF) reduces noise in polynomial signals while preserving their key features [19,28–30]. It was introduced by Savitzky and Golay 31]. In EEG signals, it helps extract low-frequency eye blinks, leaving the original higher-frequency brain signal [2]. The SGF employs a linear least squares technique to enhance the SNR while maintaining signal integrity. It works by calculating values for *2N+1* central points, with the sequence's center at *N=0*, representing each polynomial with degree "*a*".

$$SG_i = \sum_{j=-(\frac{d-1}{2})}^{j=(\frac{d-1}{2})} A_j B_i + 1 \; \frac{d+1}{2} \leq i \leq n - \frac{d-1}{2} \qquad (3)$$

Equation 3 represents convolutional coefficients, where A and B are convolutional coefficients. Implementing the SGF requires three conditions: the noisy input signal (x), the polynomial sequence (k), and the frame size (f). The choice of k and f values often involves trial and error based on previous research [31,32].

Figure 7 illustrates the SGF's signal-filtering process, using the pre-processed signal (eeg_filtered) from the band-pass filter as input. The filter design includes a window_size of 47 and an order of 4, as seen in prior studies [7]. The implementation of the Savitzky-Golay filter (SGF) begins with polynomial fitting, where a polynomial is fitted to each window of data using least squares fitting, with the coefficients calculated based on the specified order. Following this, the smoothing process involves evaluating the fitted polynomial at the center of the window to produce a smoothed value, effectively replacing the original data point. This process is iteratively applied across the entire dataset, resulting in a smoothed signal that retains important features. One of the strengths of the SGF is its effectiveness in preserving signal features and shapes, making it particularly useful for signals characterized by low-frequency noise. However, a limitation of this method is that it may not perform as well in removing high-frequency noise and can introduce artifacts if the window size is not chosen appropriately.

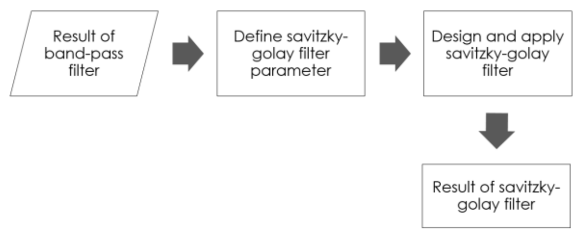


Figure 7 Savitzky-golay filter method

Once designed, the filter is applied using the Savgol function from the scipy.signal module. This function applies a SGF to the eeg_filtered signal to produce an EEG signal that has been noise-denoised. The filtered signal is then stored and used as input in the performance accuracy analysis process.

The comparative analysis between the Wiener filter (WF) and the Savitzky-Golay filter (SGF) highlights several key differences. The WF is notable for its adaptability, as it adjusts to the changing characteristics of the signal and noise, making it particularly suitable for non-stationary signals like EEG. In contrast, the SGF employs a fixed window and polynomial fitting, which may not respond as effectively to varying noise conditions. Both filters aim to preserve signal integrity, but SGF excels in maintaining the shape of the signal, while WF prioritizes minimizing noise while balancing signal preservation. Additionally, the complexity of the two methods differs; the WF involves more intricate calculations, including spectral estimations, whereas the SGF is simpler to implement, relying primarily on polynomial fitting for its smoothing process.

2.5 Filter Performance Accuracy Analysis

The results of processing EEG signals that have passed the filter stage using Wiener and SGF will be calculated, analyzed, and compared using 3 parameters, namely mean squared error (MSE), mean absolute error (MAE), and signal to noise ratio (SNR).

a. MSE

MSE gauges error estimation quality by averaging squared differences between actual and forecasted values. Lower MSE, closer to zero, signifies reliable forecasts from actual data, typically used in regression and forecasting models [33,34].

The MSE method formula is as follows:

$$MAE=\frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \quad (4)$$

x_i is the original value in the experiment or the EEG signal recording value, and y_i is the forecasting value or signal value obtained after filtering with n which is the number of samples or data used.

b. MAE

MAE is a model performance evaluation metric used to measure the average value of the absolute difference between actual and predicted values. MAE is used to measure the accuracy of a statistical model in making predictions or forecasting [33,34].

$$MSE=\frac{\sum_{i=1}^{N}[(x_i)-(y_i)]^2}{N} \quad (5)$$

x_i represents the *i*-th actual data, y_i is the *i*-th forecasted data or the filtered signal value using "n" data samples. In EEG signal analysis, MAE measures a model's accuracy in predicting EEG signal values. It calculates the absolute differences between predicted and actual values, averaging these differences based on the data count. A lower MAE indicates better model performance.

c. SNR

SNR, in decibels (dB), assesses signal quality by comparing the desired signal power to the noise power. It is a common metric for communication systems, including EEG recordings, which often contain various artifacts that degrade signal quality. Higher SNR values indicate better signal quality[33].

$$SNR=10\log_{10}\left\{\frac{\sum_{n=1}^{N}[x(n)]^2}{\sum_{n=1}^{N}[x(n)-\hat{x}(n)]^2}\right\} \quad (6)$$

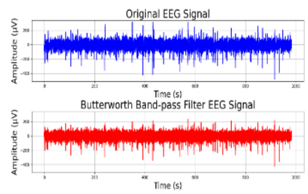
$x(n)$ is the original value in the experiment or the recorded value of the EEG signal, and $\hat{x}(n)$ is the forecasting value or signal value obtained after filtering with the number of samples *n*.

3.0 RESULTS AND DISCUSSION

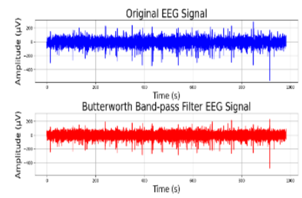
There are three discussion results from the three methods used (butterworth band-pass filter, WF, and SGF) to produce EEG signals for autistic and normal children free of artifacts by conducting a comparative analysis of filter performance.

3.1 Butterworth Band-Pass Filter Result

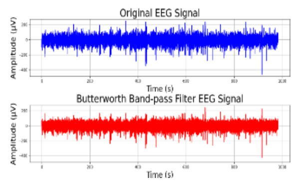
The butterworth bandpass filter retains the EEG signal within the desired frequency range (0.5 Hz to 40 Hz) while eliminating components outside this range. This ensures that only the signal within the specified frequency range is preserved.



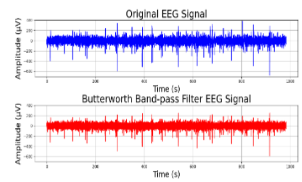
(a) Channel C3



(b) Channel C4



(c) Channel Cz



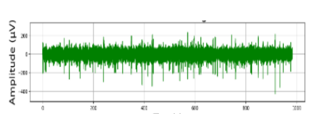
(d) Channel F4

Figure 8 Result of butterworth band-pass filter of autism

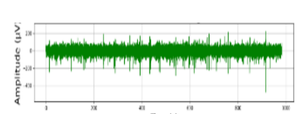
Figure 8 shows the Butterworth bandpass filter applied to a 16-channel EEG signal from individuals with autism. Initially, the signal (in blue) exhibited significant fluctuations due to artifacts, causing instability. After filtering (in red), the signal improved in terms of frequency and amplitude, maintaining a range of 0.5 - 40 Hz while reducing amplitudes outside this range.

3.2 Wiener Filter Result

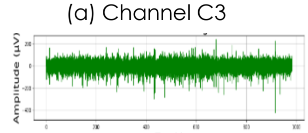
After passing through the butterworth band-pass filter, the filtered EEG signal undergoes further processing using a WF. The WF process involves calculating adaptive filter coefficients that minimize the mean squared error between the original and filtered signals.



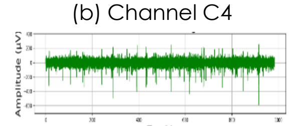
(a) Channel C3



(b) Channel C4



(c) Channel Cz



(d) Channel F4

Figure 9 Result of wiener filter of autism EEG

Figure 9 demonstrates the improvement in EEG signal quality for individuals with autism following WF processing. The processed EEG signals on each channel exhibit enhanced clarity and noise reduction.

3.3 Savitzky-Golay Filter Result

After passing through the butterworth bandpass filter process, the filtered EEG signal also goes through a further process using the SGF.

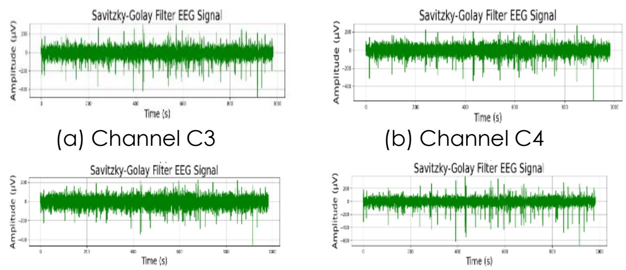
Figure 10 demonstrates the enhancement of EEG signal quality in individuals with autism using the SGF. The SGF process substantially improves signal quality across each channel. By applying SGF following the band-pass filter, any remaining small fluctuations or noise in the EEG signal are further filtered out.

3.4 Results of Filter Performance Accuracy Analysis

To obtain filter performance on EEG signals, the authors used MSE, MAE, and SNR. The analysis show the effectiveness of the applied filters, including the Butterworth band-pass filter, WF, and SGF, in noise reduction within the EEG signal.

a. Butterworth Band Pass Filter

Figures 11, Figure 12, and Figure 13 display MAE, MSE, and SNR comparisons for butterworth band pass filter in performance analysis. The graphs show varying MAE values (highest in red, lowest in green). MSE highlights significant differences between filter results and the original signal, with the highest at 127241.94 µV² and the lowest at 961.61 µV². SNR varies, with the highest at 4.375 dB and the lowest at 0.595 dB.



(a) Channel C3 (b) Channel C4

(c) Channel Cz (d) Channel F3

Figure 10 Result of savitzky-golay of autism EEG

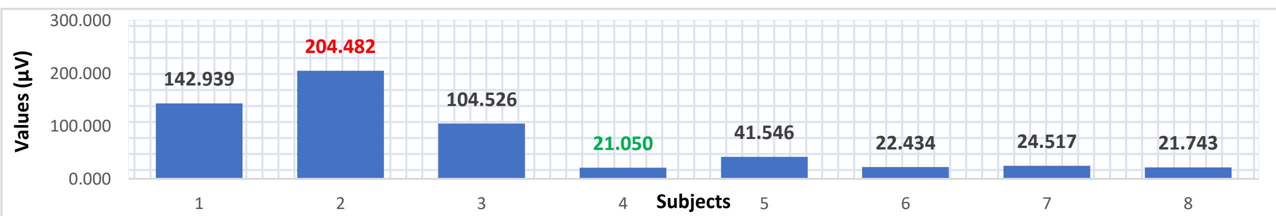


Figure 11 Butterworth bandpass filter MAE average value

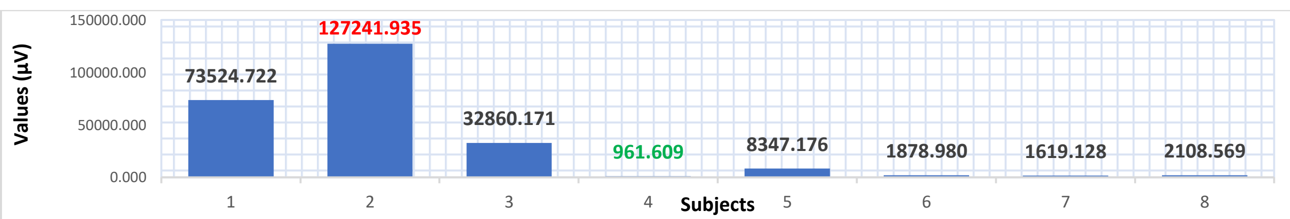


Figure 12 Butterworth bandpass filter MSE average value

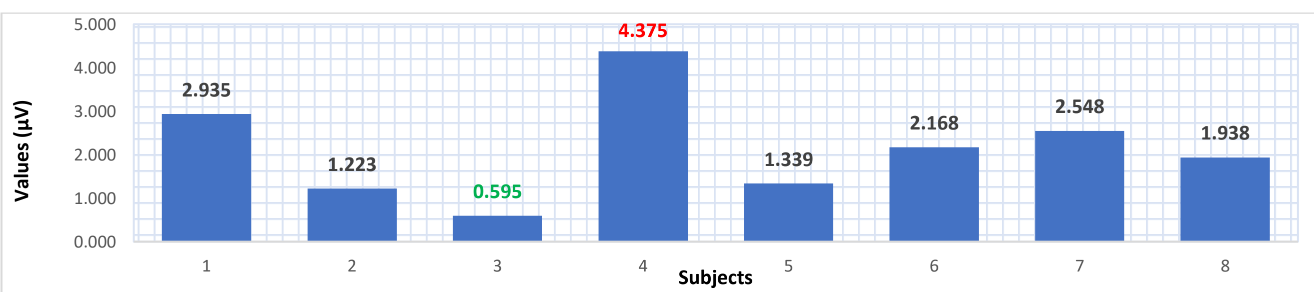


Figure 13 Butterworth bandpass filter SNR average value

Figures 11, 12, and 13 collectively underscore the effectiveness of the Butterworth bandpass filter in processing EEG signals. Figure 11, which presents the Mean Absolute Error (MAE) values, highlights the filter's capability to maintain signal integrity while minimizing errors across different subjects. A lower MAE indicates a successful reduction of noise, essential for accurate signal interpretation. Figure 12 further emphasizes this point by showcasing the Mean Square Error (MSE) values, where lower MSE values reflect the filter's precision in enhancing the quality of the filtered signals. Finally, Figure 13 illustrates the improvement in Signal-to-Noise Ratio (SNR), demonstrating that the Butterworth filter significantly enhances the clarity of EEG signals, as evidenced by higher SNR values across subjects.

In conclusion, using the butterworth bandpass filter on EEG signals from autistic children leads to varying filter accuracy. Some subjects closely approximate the original signal with low MAE, MSE, and high SNR, while others show different results with higher MAE, MSE, and lower SNR, indicating subject-specific variations in filter response.

b. Comparison Results of Wiener and Savitzky-Golay Filter Performance Analysis

Figure 14, Figure 15, and Figure 16 depict comparisons of MAE, MSE, and SNR values in the performance assessments of WF and SGF. Figure 14 consistently illustrates that WF maintains a lower average MAE compared to SGF, indicating that the WF provides more accurate EEG data estimation after butterworth bandpass filtering (0.5-40 Hz), while SGF has a slightly higher error rate. The average MSE value, as shown in Figure 15, reaffirms the effectiveness of WF, with a lower average MSE compared to SGF. This suggests that, overall, WF is more proficient in minimizing errors and distortions in estimating the true EEG signal across the same subjects, resulting in a closer alignment with the actual EEG data.

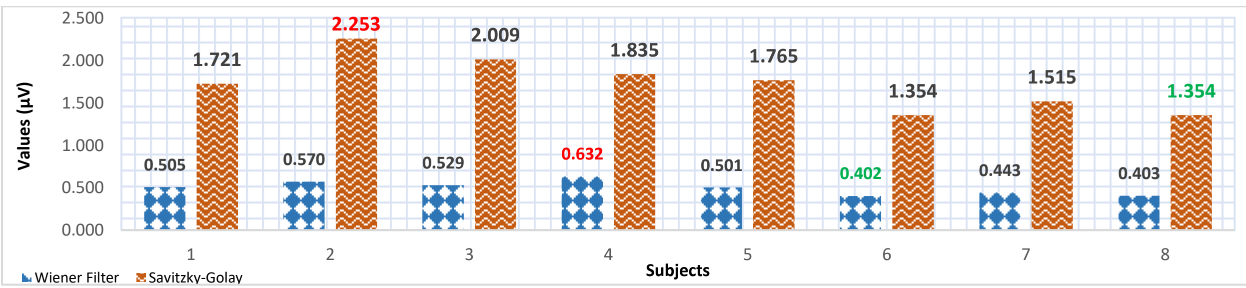


Figure 14 Comparison of average MAE values

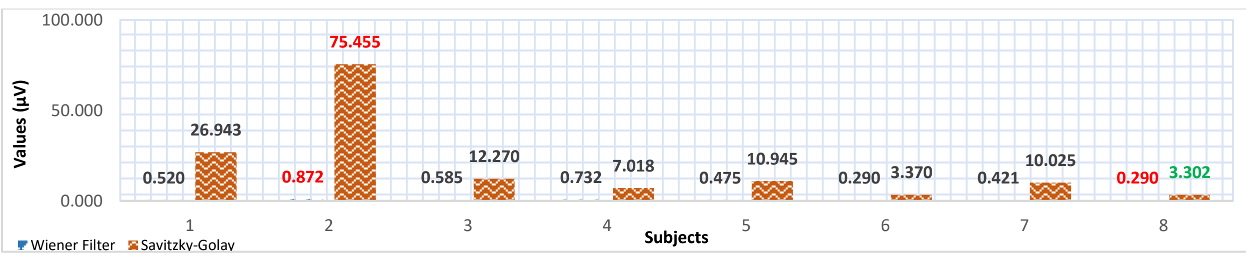


Figure 15 Comparison of average MSE values

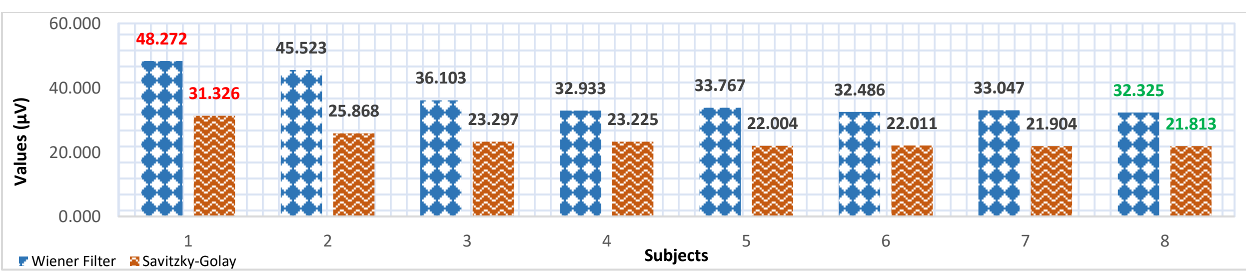


Figure 16 Comparison of average SNR values

Figure 16 shows that the average SNR value from the performance analysis of the Wiener filter and SGF on 8 EEG signal subjects shows differences in the quality of performance of the two filters in processing EEG signals. From the SNR values obtained, the WF (blue) is more effective in reducing noise levels and maintaining relevant signal strength in EEG data, compared to the SGF (orange) on the same subjects. The WF produces higher SNR values, indicating better performance in processing EEG signals.

c. Comparison of Overall Results of Filter Performance Analysis

Figure 17 presents a comprehensive comparison of the Mean Absolute Error (MAE), Mean Square Error

(MSE), and Signal-to-Noise Ratio (SNR) values for the Savitzky-Golay filter and Wiener filter, providing a clear overview of their performance in processing EEG signals. The Savitzky-Golay filter exhibits an average MAE of 1.726 µV, while the Wiener filter significantly outperforms it with a lower average MAE of 0.498 µV, indicating better preservation of signal integrity. In terms of MSE, the Savitzky-Golay filter shows an average value of 18.666 µV², compared to the Wiener filter's average MSE of 0.523 µV², further highlighting the Wiener filter's effectiveness in minimizing errors. Additionally, the SNR values reveal that the Wiener filter achieves an average of 36.807 dB, whereas the Savitzky-Golay filter only reaches 23.931 dB. This substantial difference in SNR underscores the Wiener filter's superior capability in enhancing signal clarity and distinguishing the desired signal from noise. Overall, Figure 17 clearly illustrates the advantages of the Wiener filter in achieving optimal noise reduction and signal preservation when processing EEG data.

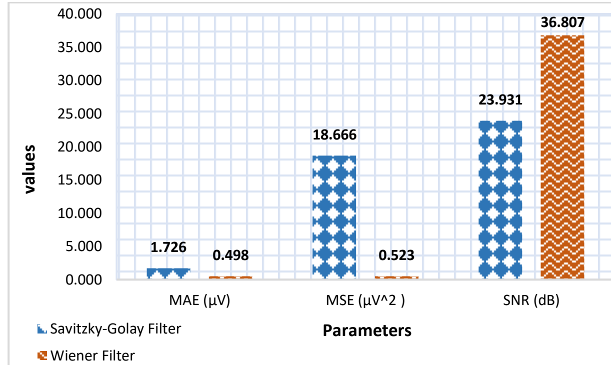


Figure 17 Comparison of MAE, MSE, and SNR

Table 1 The advantages and the drawbacks of our work

Authors	Dataset	Methods	Advantages	Drawbacks
Li, Feng., *et al.* 2020 [35]	• ALS patients • Healthy subjects	• XDAWN spatial filter	• Development of potential transfer learning methods for BCI applications. • Supports generalization between subjects.	• Requires a large dataset for better results. • Accuracy depends on the quality of the initial signal. • Requires significant time and computing resources.
Pise, A. W., *et al.* 2021 [36]	• Epilepsy • Healthy subjects	• LPF Butterworth • LMS • Wavelet	• Utilizes varied wavelet types for tailored denoising to specific conditions.	• Lacks MAE statistical analysis. • Excessive decomposition may omit vital original data.
Tsuchimoto, S., *et al.* 2021 [37]	• Healthy subjects	• CAR • LLSF	• Evaluate spatial-filtering for better SNR in sensorimotor EEG.	• Complexity and electrode sensitivity. • CAR eliminates spatial data.
Alturki, F. A., *et al.* 2021 [38]	• ASD • Epilepsy • Healthy subjects	• CSP	• Enhance diagnostic accuracy using advanced CSP methods.	• Complex EEG signal processing. • Accuracy hinges on initial data quality, affecting CSP results with noise or artifacts.
Melinda, *et al.* 2023 [39]	• ASD • Healthy subjects	• DWT	• DWT extracts varied frequency features for comprehensive EEG analysis.	• Selecting an appropriate wavelet type is necessary for signal characteristics.
Proposed Method	• ASD • Healthy subjects	• SGF • WF	• Enhanced EEG signal analysis. • Improve the quality of EEG signal analysis in ASD • WF yields denoised signals closely matching the original with low error rates.	• Results are ASD-specific; further analysis needed for generalization to other disorders. • SG requires precise parameter matching for optimal performance.

Various studies in EEG signal processing have employed diverse approaches and techniques, as summarized in Table 1. These studies utilized different datasets, ranging from amyotrophic lateral sclerosis (ALS) patients to children with ASD and healthy individuals. They employed various feature extraction methods, including XDAWN spatial filter [35], LPF butterworth filter [36], adaptive LMS [36], wavelet functions, common average reference (CAR), large-laplacian spatial-filter (LLSF) [37], common spatial pattern (CSP) [38], and discrete wavelet transform (DWT) [39].

In our study, we focused on the SGF and WF techniques, which demonstrated effectiveness in efficiently removing noise and artifacts from EEG signals of children with ASD. However, generalizing these results to other neurological disorders may require further analysis, considering the initial signal characteristics and noise variations.

Comparing filter accuracy with other related studies, the WF outperforms the Kalman filter, displaying lower MSE and higher SNR values (5.30 dB and 7.195x1-5 for WF, 4.34 dB and 0.067 for Kalman filter) [20]. The adaptive filter and SGF also exhibit high SNR values and reduce MSE values by an average of 85%, with an average MSE value of 1.50 and SNR value of 0.92 dB [2]. In our proposed method, the WF proves more effective than SGF, with lower MSE and MAE values (0.521 μV and 0.616 μV^2 for WF, 1.875 μV and 16.990 μV^2 for SGF) and a higher SNR value (22.157 dB for WF, 34.773 dB for SGF).

4.0 CONCLUSION

In conclusion, this study demonstrates that the combination of Butterworth, Wiener Filter (WF), and Savitzky-Golay (SG) bandpass filters effectively reduces artifacts, minimizes noise, and preserves signal quality in EEG signal analysis. The WF and SG methods successfully attenuated noise in the EEG signals of both autistic and normal subjects. Notably, the Wiener filter produced a cleaner denoised signal that closely resembles the original, achieving a lower error rate compared to the Savitzky-Golay filter. Additionally, the WF maintained superior signal clarity and reduced noise interference, as evidenced by its higher Signal-to-Noise Ratio (SNR) values. While the Savitzky-Golay filter is also effective in artifact reduction, its performance was found to be slightly less optimal than that of the Wiener filter.

Looking ahead, future research could benefit from exploring additional filter parameters, such as filter order, window size, and polynomial order, to further enhance filtering outcomes. Investigating the impact of these parameters on the quality of the filtered signals will be crucial for optimizing filter performance and achieving even better results in EEG signal processing. This approach could lead to advancements in both research and clinical applications, ultimately improving the analysis and interpretation of EEG data.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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