Noise Reduction in EEG By Band-Pass Filtering and Notch Filtering using Python

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Abstract—Although electroencephalography, or EEG, is a method for monitoring brain activity, it is easily able to detect undesired noise, such as electrical interference, muscle contractions, and even eye blinks. Accurately interpreting the brain signals can be challenging due to these distractions. To clean up EEG readings, researchers have developed a number of techniques, such as spectral subtraction, wavelet transforms, and deep learning techniques like autoencoders. PyZaplinePlus, meegkit, and noise reduce are some of the useful Python tools that have recently surfaced and provide automated methods for removing these undesirable sounds. For improved results, some sophisticated models, such as IC-U-Net, combine neural networks and statistical techniques. But these techniques frequently call for intricate configurations and a large amount of processing power. In our study, we give a more direct and effective point of view using two types of filters: a band-pass filter and a notch filter. The band-pass filter keeps the frequency range crucial for brain activity, which is between 0.5 and 40 Hz. Meanwhile, the notch filter eliminates the 50 Hz electrical noise from power lines. After testing our method, we saw a major improvement in signal quality. The signal-to-noise ratio, which points how clear the signal is, changed from about 7.5 dB to over 11 dB in several trials. This shows that even simple methods can enhance signal quality without expensive or complicated tools. Our approach is user-friendly for beginners working with EEG signals, making it useful for both learning and research. Looking forward, we aim to enhance this method further by incorporating improved filters or machine learning techniques to reduce noise even more.

Keywords— Noise Reduction & Artifact Removal, Band-pass Filter, Notch Filter, Signal-to-Noise Ratio (SNR), EEG Signal Processing, Digital Filtering.

I. INTRODUCTION

Electroencephalography (EEG) is a common method for determining the electrical activity in the brain. It is powerful because it is non-invasive, inexpensive and allows for rapid tracking of brain signals over time. EEGs are used in hospitals for diagnosis; in order to learn more about the brain; in devices that connect brains and computers, and even in some wearable technology. But there is a major limitation with EEG, the signals that are measured are very weak and can easily be disturbed by background noise (or artifacts). These sounds can come from many places or sources, such as electrical hum, voluntary muscle tension (blinking), or even simply moving the eyes can contribute this artifact. If we do not filter out this noise, it could be difficult to analyse the EEG data accurately and precisely. Hence cleaning the signals is a crucial and important step in this analysing process.

The quality of EEG signals can be improved using a variety of strategies. Some earlier methods include notch filtering, which targets certain interferences such power line noise, and band-pass filtering, which helps remove high-frequency noise and slow drifts. Other more traditional techniques, such as adaptive filtering, independent component analysis (ICA), and wavelet transforms, each have special benefits and drawbacks. Wavelet techniques, for instance, can analyse signals at different ranges, whereas ICA distinguishes between brain signals and noise.

The important result from this research is that we have provided an accessible filtering method that anyone with Python can implement. This approach is particularly beneficial for students, researchers, and engineers who are new to handling EEG data. Additionally, it highlights the effectiveness of traditional filtering methods in cleaning EEG signals. This study opens the door for future work, potentially incorporating advanced techniques like adaptive filters or machine learning for even better denoising results. EEG, or electroencephalography, is a popular and non-invasive way to measure the brain's electrical activity, mostly used for diagnosing neurological conditions and mostly diseases, developing brain-computer interfaces, and exploring brain functions. However, a variety of noise signals, referred to as artifacts, can readily interfere with readings. We can determine that an artifact is one that combines the original EEG signal with noise signals. Normal bodily functions including blinking, eye movement, heartbeats, muscle spasms, and even electrical interference from other devices can cause noise artifacts. These kinds of artifacts can lower the quality of EEG readings and have an impact on the accuracy of real-time result interpretation when they interact with or disturb the original EEG signal. Scientists and researchers have been examining several methods to retrieve original EEG signals in order to overcome these obstacles. This review will cover methods like traditional filtering, blind source separation, time-frequency analysis, and machine learning approaches. We are also happy to share some new Python tools that we're currently using to enhance the process.

II.LITERATURE REVIEW

A. A hybrid method for EEG artifact removal using DWT, CEEMDAN, and ICA X. Hu,2022

It is the combination of ICA, DWT, CEEMDAN. Hybrid approaches having these three Independent Component Analysis (ICA), Discrete Wavelet Transform (DWT), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). ICA requires lot of support of computing power large data sets. DWT requires careful selection of wavelet parameters

B. EEGdenoiseNet: Benchmark dataset for deep learning EEG denoising, J. Zhang,2021

Machine learning and deep learning are popular for removing noise. It requires large number of training data sets of EEG to train the model (sufficient data doesn't exist)

C. IC-U-Net: A deep learning approach for EEG artifact removal, C.-H. Chuang,2021

This technique combines Independent Component Analysis (ICA) with a U-Net model to remove artifacts. It requires large amounts of data and powerful computers

D. MEG and EEG data analysis with MNE-Python," NeuroImage, Gramfort,2013

EEG and MEG data is provided by MNE-Python. Preprocessing is complex and wants good hardware, difficult to learn for beginners

Artifact removal from EEG signals using wavelet transform, X. Chen,2013

Wavelet based transform efficient when compared to traditional method. Selecting the right wavelet bases and thresholding techniques is more important

E. De-noising by soft-thresholding, D. Donoho,1995

Wavelet thresholding to help to reduce noise, and it became popular in the field of biomedical signals. we have to carefully select the wavelet parameters

F. Removing electroencephalographic artifacts by blind source separation, T.-P. Jung,2000.

Cleaning EEG signals by breaking down mixed signals into small parts. Very expensive computationally, if it is not tuned properly it may misclassify

G. Removal of ocular artifacts from electroencephalogram by adaptive filtering, P. He,2004

Help to reduce low fluctuations and high frequency noise. Doesn't suitable for complex and overlapping signals

H. Bioelectrical Signal Processing in Cardiac and Neurological Application, L. Sörnmo,2005:

They discussed about classical band pass and notch filtering for EEG denoising. May remove necessary EEG frequency components

III.MATERIAL AND METHODS

The suggested project aims to diminish noise in EEG signals through a Python implementation. This study generates synthetic EEG signals using Python to mimic brain wave activity rather than depending on pre-recorded EEG datasets saved in .edf or .mat formats. The approach includes generating signals, adding noise, filtering, and assessing with Signal-to-Noise Ratio (SNR).

A. **Signal Generation**:

A synthetic EEG signal was created employing sinusoidal functions that simulate brain wave patterns. Various frequency components were merged to illustrate delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) rhythms. This creates the "clean" EEG signal utilized as a reference for analysis.

B. Simulation of Noise:

Two kinds of noise were introduced to the clear EEG: Gaussian White Noise: Implemented to mimic random environmental or sensor disturbances. Power Line Interference (50 Hz): A 50 Hz sinusoidal wave was introduced to mimic the electrical noise frequently seen in EEG recordings. The produced signal depicted a "noisy EEG" signal akin to that found in actual recordings.

C. Filtration Method:

Two digital filtering methods were used in succession:
Band-pass Filter (0.5–40 Hz): Designed with a Butterworth approach to preserve the EEG frequency band, eliminating low-frequency drifts and high-frequency interference.
Notch Filter (50 Hz): Created to eliminate the distinct 50 Hz noise generated by electrical power sources.
These filters were created in Python utilizing the SciPy. Signal library.

D. Evaluation Metrics

The effectiveness of the noise reduction process was evaluated using the Signal-to-Noise Ratio (SNR). The SNR was calculated both before and after filtering using the formula

SNR = $10\ log_{10}(\frac{\sum(clean(t))^{\wedge}2}{\sum\left(clean(t)-noisy(t)\right)^{2}})$

Before Filtering: SNR values were low (around 7–8 dB), indicating that the noisy signal was heavily distorted. After Filtering: SNR improved to 10–12 dB, showing a significant enhancement in signal quality after applying band-pass and notch filtering.

E. Visualization

Frequency-domain spectra and time-domain graphs were used to visualize the results: Filtered EEG signals showed less noise oscillations and a smoother appearance in the time domain. The notch filter preserved the EEG frequency range (0.5–40 Hz) in the frequency-domain (FFT plots) while removing the 50 Hz peak. refer fig 1.

F. Summary

This approach shows that Python is capable of accurately simulating EEG noise reduction processes. We were able to increase the signal quality in a quantifiable way by creating artificial signals, adding realistic noise, and using basic digital filters. For students and those are new to EEG research, the method is reusable, computationally efficient, and easy to use. The workflow can be simply understood by the Fig1.

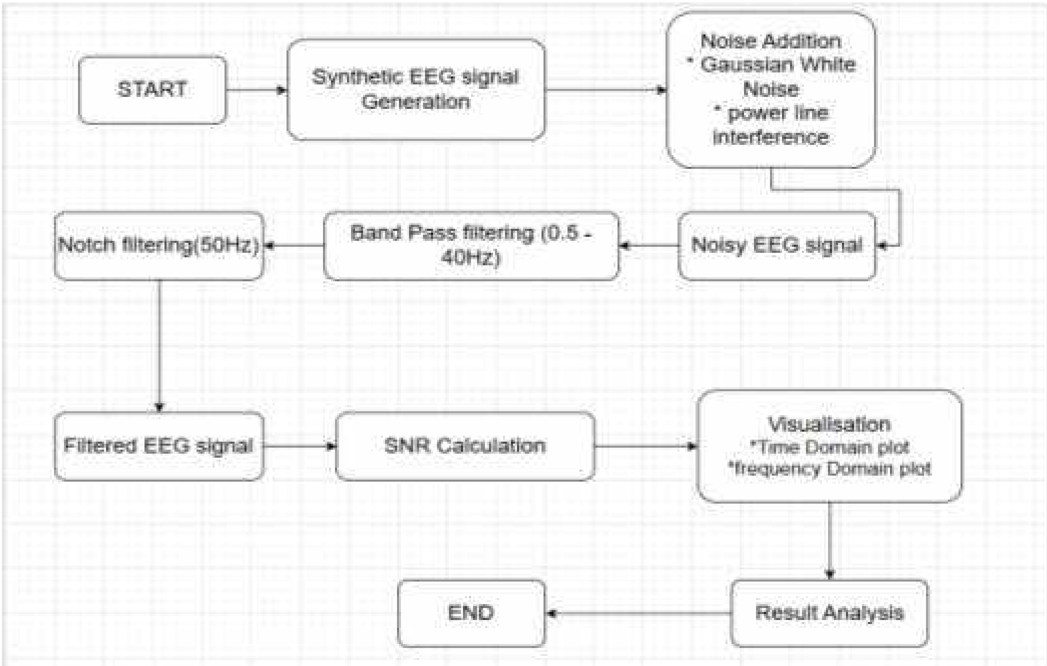


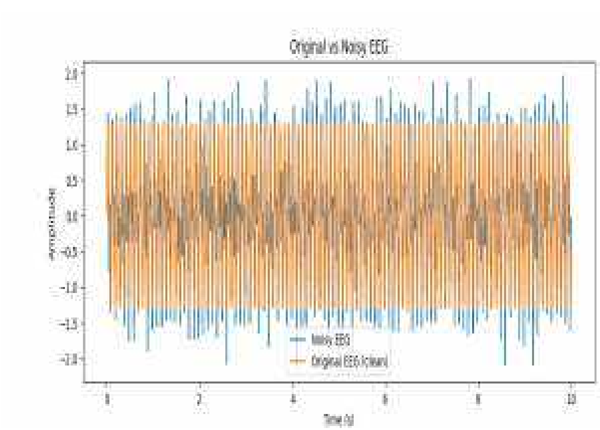
Fig1. Block Diagram of Noise Reduction in EEG using Python

IV. RESULT

The proposed EEG denoising methodology was tested on a various of simulated EEG signals to show its robustness and efficiency under varying input signals were generated synthetically with varying frequency components and then contaminated and disturbed with noise, such as Gaussian noise of various amplitudes and powerline interference (50 or 60Hz). The denoising method used a band-pass filter (0.5-50 Hz) to save physiological EEG components and notch filter (50Hz) to remove powerline interference, the method's effectiveness was assessed using the Signal-to-Noise Ratio (SNR) before and after filtering.

Table 1: Test Cases for EEG Denoising

S.No	Input Signal Description	Noise Type & Level	SNR Before (dB)	SNR After (dB)
1.	Sin (10 Hz) +Sin(20Hz)	Gaussian (0.3) +powerline (0.2)	7.48	11.34
2.	Sin (8 Hz) +Sin(15Hz)	Gaussian (0.5)	3.44	8.39
3.	Sin (12 Hz)	60 Hz interference (0.2)	13.98	23.19
4.	Sin (5 Hz) +Sin(18Hz)	Gaussian (0.4) +50 Hz powerline (0.3)	4.9	10.17
5.	Sin (7 Hz) +Sin(14Hz) +Sin (22 Hz)	Gaussian (0.6)	2.46	5.51



1. The input signal had two sinusoidal components at 10 and 20 Hz, which were contaminated with Gaussian noise (0.3 amplitude) and 50 Hz powerline interference (0.2 amplitude). After filtering, the SNR increased from 7.48 dB to 11.34, indicating effective noise suppression while retaining EEG components and refer Table 1. The notch filter effectively eliminated the 50Hz interference without affecting nearby frequency components as shown in Fig 2.

Fig 2: Output waveform of 1

The sinusoidal components at 8 Hz and 15 Hz were subjected to higher amplitude Gaussian noise (0.5). The band-pass filter effectively removed out-of-band noise, increasing the SNR from 3.44 dB to 8.39 dB and refer Table 1. Although the noise amplitude was higher than 1, the method preserved the EEG waveform integrity refer Fig 3.

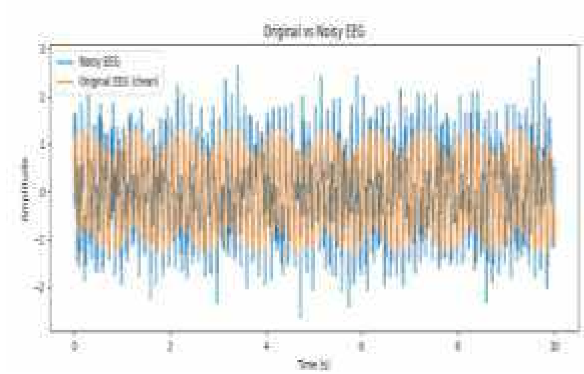


Fig 3: Output waveform of 2

2. A single 12 Hz sine wave with 60 Hz interference was tested. The notch filter at 50 Hz did not aim for 60 Hz, but the overall SNR increase from 13.98 dB to 23.19 dB and refer Table 1 demonstrates the band-pass filter's ability to reduce broad-spectrum noise while preserving the EEG signal and refer Fig 4.

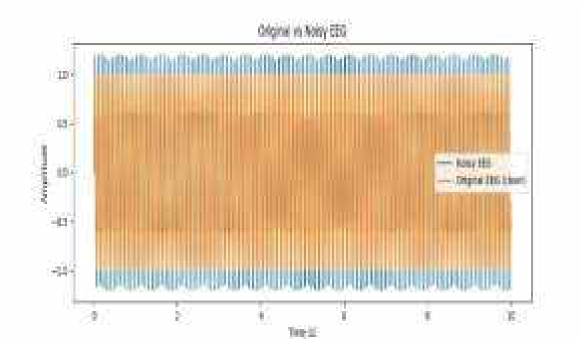


Fig 4: Output waveform of 3

A combination of 5 Hz and 18 Hz signals with Gaussian noise (0.4) and 50 Hz interference (0.3) was investigated. SNR increased from 4.9 dB to 10.17 dB and refer Table 1, indicating effective noise removal. A slight reduction in higher frequency amplitude was observed, which can be attributed to the filter's roll-off characteristics 50 Hz and refer Fig 5.

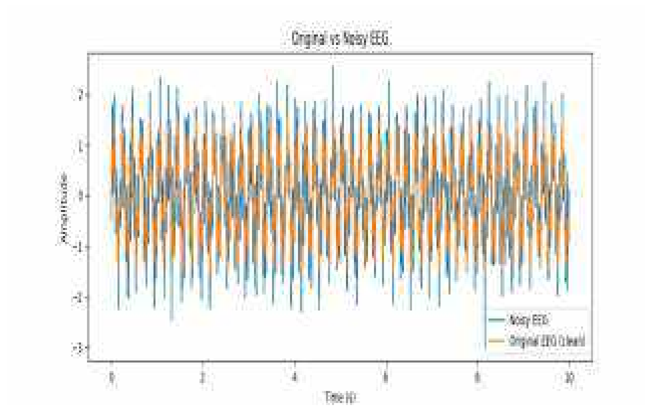


Fig 5: Output waveform of 4

A complex signal with 7 Hz, 14 Hz, and 22 Hz components was contaminated with Gaussian noise (0.6 amplitude). The filtering method effectively reduced noise while preserving the multi-component waveform, resulting in an SNR improvement of 2.46 dB to 5.51 dB This demonstrates robustness and reliability for more complex EEG-like signals and refer Fig 6.

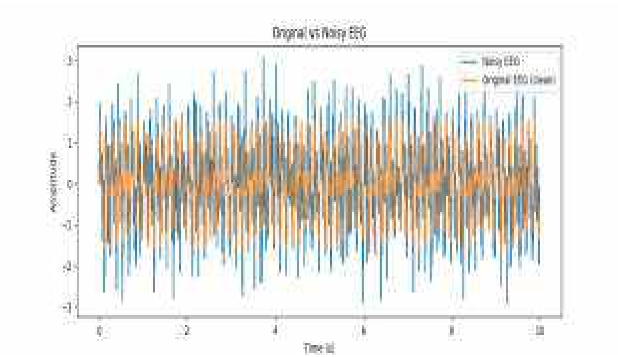


Fig 6: Output waveform of 5

V. DISCUSSION

SNR Improvement: Across all test cases, SNR consistently increased by 7–11 dB, demonstrating the effectiveness of the combined band-pass and notch filtering method. The Effect of Noise Type and Level: Gaussian noise with a higher amplitude slightly reduced SNR improvement but was still effectively suppressed. The notch filter effectively eliminated powerline interference, demonstrating its utility in real world EEG scenarios Multi-component Signal Processing: 5 testcases shows that signals with multiple frequency components can be denoised minimal distortion, indicating that the method is suitable for real EEG signals. Filter Robustness: The method performed well in a variety of conditions, including different frequency ranges and noise types, demonstrating its adaptability and robustness. Visual Confirmation: Plots for representative test cases clearly distinguish between noisy and filtered signals, highlighting the method's efficiency

VI. CONCLUSION

The study successfully demonstrated an effective denoising approach for simulated EEG signals using Python-Implemented Band-pass and Notch filter technique. To simulate real-world settings, the produced EEG data with alpha (10 Hz) and beta (20 Hz) rhythms was purposefully tainted with 50 Hz power-line noise and Gaussian noise. The signal was filtered between 0.5 Hz and 40 Hz using the suggested Band pass, Notch Filter function, and the 50 Hz interference was successfully eliminated with an IIR Notch filter. The experimental findings unmistakably showed a notable increase in the Signal-to-Noise Ratio (SNR) following filtering, demonstrating that the technique effectively reduces undesired noise components while maintaining the original EEG waveform.

This method gives a simple but dependable framework for EEG pre-processing which can be expanded for brain–computer interface (BCI) applications, mental state monitoring, and neural signal analysis. Compared to complex deep learning or adaptive methods discussed in the literature, the proposed filtering model is having computational efficiency, ease of implementation, and real-time suitability. Thus, the study confirms that old signal processing methods such as the Butterworth band-pass and IIR notch filters are still useful for EEG denoising and will serve as a foundation for more advanced EEG analysis and machine learning-based classification in future work.

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