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A Comprehensive Approach to ECG Signal Enhancement Using Multi-Filter SNR Improvement and Baseline Shift Correction

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This study presents an approach to enhancing ECG signals by improving signal-to-noise ratio (SNR) and correcting baseline shifts using various filters. We evaluated four filters—Butterworth, Chebyshev, Elliptic, and Savitzky-Golay—on ECG signals, finding that the Savitzky-Golay filter consistently achieved the highest SNR improvements across multiple databases. Unlike the other filters, its performance remained stable regardless of filter order. Additionally, a low-order polynomial filter effectively corrected baseline drift, aligning it close to 0 volts. The results highlight the superior performance of the Savitzky-Golay filter for ECG signal preprocessing and the importance of effective baseline correction.

Keywords: ECG Signal Processing, Signal-to-Noise Ratio (SNR), Savitzky-Golay Filter, Baseline Shift Correction, Butterworth Filter, Chebyshev Filter, Elliptic Filter, Noise Reduction, Filter Order Impact, ECG Preprocessing.

1. Introduction

Electrocardiography (ECG) is a critical tool in diagnosing and monitoring cardiovascular diseases, providing a non-invasive method to assess the heart's electrical activity. However, the accuracy and reliability of ECG analysis can be significantly compromised by noise and baseline shifts, which are commonly introduced during signal acquisition. These artifacts can stem from various sources, including power line interference, muscle contractions, and electrode motion, making it challenging to obtain clean signals for accurate interpretation [1],[2].

Signal-to-noise ratio (SNR) is a vital metric in ECG signal processing, representing the ratio of the desired signal to the background noise [3]. A low SNR can obscure crucial features of the ECG, such as the P, QRS, and T waves, leading to misinterpretations and potential misdiagnoses. Therefore, enhancing the SNR is a fundamental step in the preprocessing of ECG signals [4]. Baseline shift, another common issue in ECG signals, refers to the gradual drift of the signal's baseline level, which can distort the overall shape of the ECG waveform. This shift is particularly problematic in long-term monitoring, where small drifts can accumulate over time, further complicating signal interpretation.

Mian Qaisar S [5], presents an efficient signal-piloted filtering method for eliminating baseline wander and power-line interference in ECG signals. The proposed approach significantly enhances ECG signal quality by selectively targeting noise components while preserving essential cardiac features, making it highly suitable for clinical environments. In another approach, Gupta P, et. al [6] explore using multivariate empirical mode decomposition (MEMD) to remove baseline wander from ECG signals effectively. Ji, T.Y., et. al [7], investigated a hybrid method combining empirical mode decomposition (EMD) with mathematical morphology for ECG baseline normalization. This methodology effectively isolates and corrects baseline drift, providing a normalized ECG signal that enhances diagnostic accuracy. Similarly, Weng, B., et. al [8] have demonstrated the application of empirical mode decomposition (EMD) for baseline wander correction in ECG signals. Xu, Y., et. al [9] discussed a combined approach using complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and wavelet thresholding to effectively de-noise ECG signals and correct baseline wander. This method provides a robust solution for real-time ECG monitoring applications. Zhang, D.[10], introduced a wavelet-based method for correcting baseline wander and reducing noise in ECG signals. This wavelet-based approach performs better in preserving signal fidelity while eliminating unwanted baseline shifts. Singh, P., et. al [12], have explored the application of Fourier decomposition methods for the removal of baseline wander and power-line interference in ECG signals. The authors have highlighted the method's efficiency in enhancing signal clarity and facilitating accurate ECG interpretation in their research paper. Sharma, R.R., & Pachori, R.B. [13], have introduced an eigenvalue decomposition-based technique for eliminating baseline wander and power-line interference from ECG signals. The proposed method shows promise in maintaining the integrity of ECG signal features while reducing noise.

Bachi, L., et. al [14] discusses a QRS detection method that utilizes medical knowledge and cascades of moving average filters to improve the accuracy of ECG signal analysis. Malik, S.A., et. al [15], proposed an iterative filtering technique using lifting wavelet transform for ECG denoising. This method efficiently reduces noise while preserving crucial ECG signal characteristics, enhancing diagnostic accuracy. B'charri, O.E., et. al [16], assesses ECG signal de-noising performance using dual-tree wavelet transform with optimized threshold tuning. The method significantly improves the signal-to-noise ratio (SNR) while correcting baseline drift. Hesar, H.D., & Mohebbi, M. [17], have demonstrated the use of an adaptive Kalman filter bank for denoising ECG signals, with a particular focus on eliminating baseline wander and power-line interference. The adaptive nature of the filter enhances its effectiveness across different signal conditions.

To address these challenges, this study proposes a comprehensive preprocessing framework that involves the application of multiple filters—namely, Butterworth, Chebyshev, Elliptic, and Savitzky-Golay—to enhance the SNR of ECG signals. Each filter offers distinct characteristics that can be leveraged to improve signal quality. Additionally, the study examines the effect of filter order on SNR performance, providing insights into the optimal configurations for ECG signal enhancement. Finally, a low-order polynomial filter is employed to correct the baseline shift, ensuring that the processed signals are aligned to a consistent baseline, facilitating more accurate analysis.

In this paper, we have presented a comprehensive comparison of various filters to improve the SNR of the ECG signal. The proposed filters are tested on ECG signals from multiple databases, including the MIT-BIH Arrhythmia Database (MITDB), the Creighton University Ventricular Tachyarrhythmia Database (CUDB), and the VFDB. The results demonstrate significant improvements in SNR, particularly with the Savitzky-Golay filter, and effective baseline correction, underscoring the potential of this approach for improving the quality and reliability of ECG signal analysis.

FILTERS FOR IMPROVING SNR AND BASELINE SHIFT REMOVAL

A. Data Acquisition

A total of 104 ECG signals are used in this study and are sourced from three well-established databases: CUDB, MIT-BIH Arrhythmia Database (MITDB), and VFDB. These databases provide a comprehensive set of ECG recordings that are widely recognized in the field of biomedical signal processing. The ECG signals were acquired at a sampling rate of 360 Hz, which is typical for detailed ECG analysis. This sampling rate ensures that the critical components of the ECG waveform, including the P wave, QRS complex, and T wave, are accurately captured for subsequent analysis. The raw ECG signals were initially subjected to noise, primarily due to muscle activity, electrode motion, and baseline wander, necessitating the need for preprocessing to enhance signal quality.

B. Signal-to-noise ratio (SNR) Calculation

The Signal-to-Noise Ratio (SNR) is a crucial metric in assessing the quality of the ECG signal before and after filtering [3], [18]. In this study, SNR was calculated using the following method:

- Pre-filtering SNR Calculation: The initial SNR was calculated directly from the raw ECG signals. This involved estimating the power of the signal component and the noise component. The noise power was estimated by identifying segments of the ECG signal that predominantly contained noise, such as the isoelectric line segments between heartbeats.

- Post-filtering SNR Calculation: After applying each filtering technique, the SNR was recalculated to assess the improvement in signal quality. The formula used for SNR calculation is:

$$\text{SNR (dB)} = 10\log_{10}\left(\frac{\text{Signal Power}}{\text{Noise Power}}\right) \quad \dots (1)$$

This method allows for a quantitative comparison of the effectiveness of each filter in enhancing the ECG signal by reducing noise.

C. Filtering Techniques

In this study, four different filtering techniques were applied to the ECG signals to improve the SNR: Butterworth, Chebyshev, Savitzky-Golay, and Elliptic filters [19] - [22]. Each filter was chosen based on its unique characteristics and ability to address specific aspects of the noise present in the ECG signals.

- Butterworth Filter: The Butterworth filter can be chosen for its smooth frequency response in the passband, which minimizes distortion of the ECG signal's important components. This filter is characterized by a maximally flat magnitude response, meaning that it avoids ripples in the passband and provides a gradual transition to the stopband. This property makes the Butterworth filter particularly useful for preserving the overall shape of the ECG waveform while removing high-frequency noise.

- Chebyshev Filter: The Chebyshev filter can be selected due to its sharper cutoff characteristics compared to the Butterworth filter. This sharper transition allows for more aggressive noise reduction, particularly in cases where the noise frequencies are close to the signal frequencies. However, this filter introduces a ripple in the passband, which can slightly distort the signal. The trade-off between sharper cutoff and ripple was carefully considered in this study.

- Elliptic Filter: The Elliptic filter, known for providing the sharpest transition between passband and stopband, can be utilized for cases requiring precise cutoff frequencies. However, this filter's increased complexity and the introduction of ripples in both passband and stopband require careful design and implementation. Despite these challenges, the Elliptic filter's ability to achieve the desired frequency separation made it a valuable tool in this study.

- Savitzky-Golay Filter: The Savitzky-Golay filter can be employed to reduce noise while preserving the important features of the ECG signal [23], such as the peaks and valleys corresponding to the QRS complex, P wave, and T wave. This filter works by fitting successive subsets of adjacent data points with a low-degree polynomial, effectively smoothing the signal while maintaining the integrity of its key features. The Savitzky-Golay filter is particularly advantageous in applications where maintaining the shape of the ECG waveform is critical.

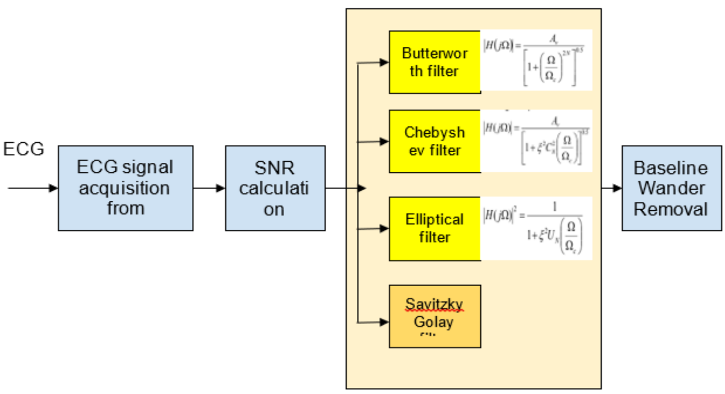


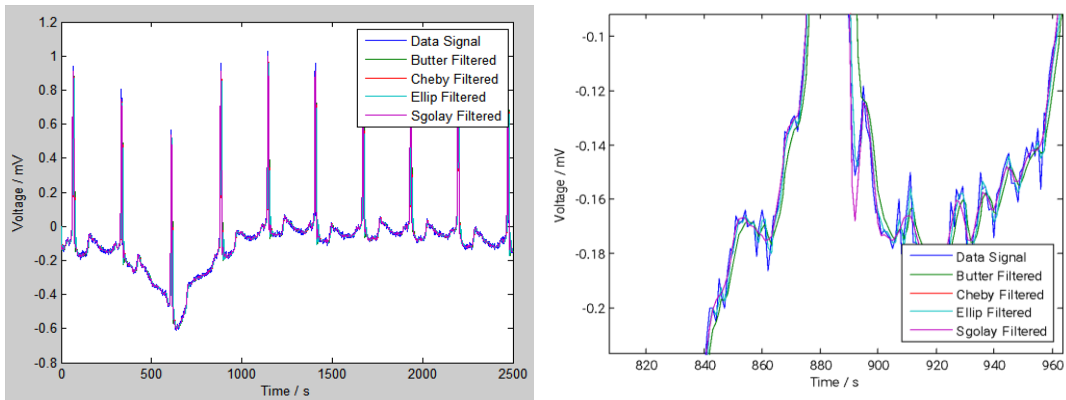
Fig. 1 Block Diagram of proposed ECG signal preprocessing system

D. Baseline Shift Removal

Baseline drift, a common artifact in ECG signals, was addressed using a low-order polynomial filter. Baseline drift typically arises due to slow changes in the signal's baseline level, often caused by respiration, movement, or electrode impedance changes. In this study, a low-order polynomial filter was implemented to model and subtract the baseline drift from the ECG signal. The polynomial fitting was performed by selecting a low-degree polynomial that best fits the slowly varying baseline of the ECG signal. The fitted polynomial was then subtracted from the original ECG signal, effectively removing the baseline drift while preserving the critical components of the ECG waveform. This approach ensures that the baseline is stabilized around zero, facilitating more accurate interpretation and analysis of the ECG data.

RESULTS AND DISCUSSION

A. SNR Improvement



(a) (b)

Fig. 2 (a) Original Data Signal Vs All four filtered signals (b) Zoomed version of Fig. 2(a) over the interval 800 - 980 secs

Table I: Average SNR values before filter application and after filter application

Sr. No.	Database	ASNR before filter application	ASNR Values after application of various filter			
			Butterworth	Chebyshev	Elliptic	Savitzky-Golay
1	CUDB	0.199	0.20	0.21	0.19	0.22
2	MITDB	17.79	18.58	17.80	18.22	21.23
3	VFDB	0.174	0.174	0.176	0.174	0.19

We have used four different types of filters namely Butterworth, Chebyshev, Savitzky-Golay, and Elliptic filters for improving SNR. Fig. 2 shows the comparison of the original ECG data signal and the ECG signal filtered using various filters. As observed from Fig. 2 (b), the Savitzky-Golay filter offers more smoother ECG signal as compared to other filters. We have done a comparative study between SNR before filtering and SNR after filtering. Table I shows the mean SNR values obtained for all four designed filter implementations in this research work. From simulation experiments carried out, it can be easily concluded that the Savitzky-

Golay filter offers improved SNR of the noisy ECG signal as compared to the other filter implementations.

B. Effect of Filter Order on SNR

Additionally, it is observed that although the order of the Savitzky-Golay filter is increased, the SNR is found to not affect SNR. Whereas, in the case of other filter implementations the performances of the other filter implementations decrease as the filter order increases. Hence from Tables I and II, it is concluded that the designed Savitzky-Golay filter outperforms all the rest of the other designed filter implementations in the context of mean SNR.

Table II. Mean SNR ratio of the entire filter for order 1 to 6.

Filter	Order 1	Order 2	Order 3	Order 4	Order 5	Order 6	Mean SNR
Butterworth	6.61	6.04	5.67	5.38	5.14	4.94	5.6366
Chebyshv	6.63	5.99	5.66	5.14	4.96	4.59	5.4997
Elliptic	6.63	5.99	5.70	5.27	5.25	5.02	5.6484
Savitzky-Golay	6.94	6.94	6.94	6.94	6.94	6.94	6.9419

C. Baseline Shift Correction

Fig. 2(a) shows a baseline shift in the filtered ECG signal and therefore does not represent the true amplitude. To remove the trend, fit a low-order polynomial to the signal sig and use the polynomial to detrend it. It shows the baseline drifting of the filtered signal. It can also be noticed from Fig. 3 that the original data signal plotted as a blue line has one peak base below -0.6 voltage and after baseline modulation figure base is approximately around 0 volts.

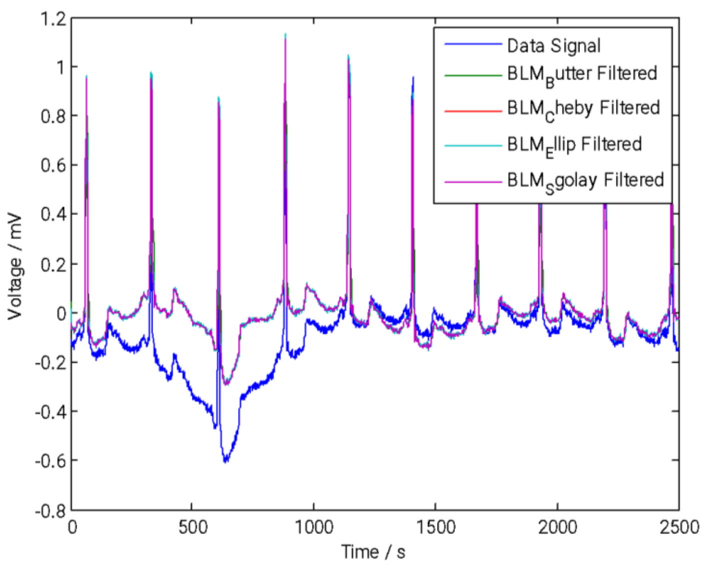
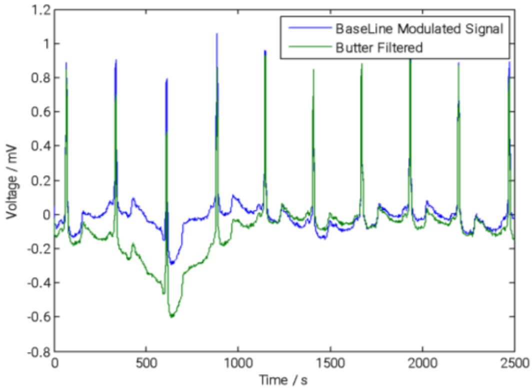
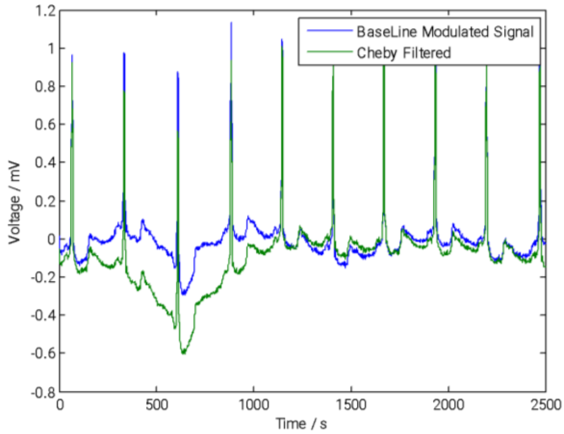
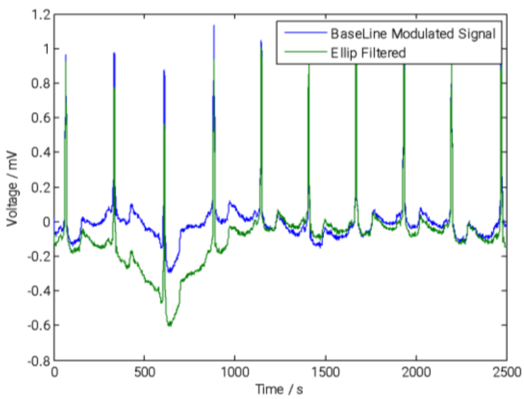


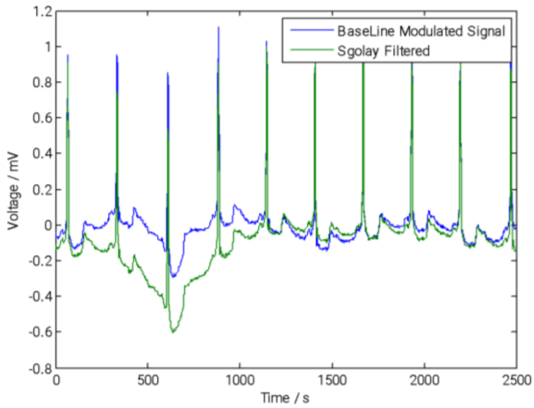
Fig. 3 Baseline wander removal using fit a low-order polynomial





(a) (b)





(c) (d)

Fig. 4 Original versus (a) baseline modulated Butterworth filter (b) baseline modulated Chebyshev filter (c) baseline modulated Elliptical filter (d) baseline modulated Sgolay filter

CONCLUSION

This study presents a comprehensive approach to enhancing ECG signals through the application of multiple filtering techniques and baseline shift correction. The primary objective was to improve the Signal-to-Noise Ratio (SNR) of ECG signals, which is crucial for accurate analysis and diagnosis and is done by employing four different filters—Butterworth, Chebyshev, Savitzky-Golay, and Elliptic. The results indicate that the Savitzky-Golay filter is effective in preserving the important features of the ECG signal while significantly improving the SNR as compared to the other filters. An additional key finding of this study was the minimal impact of the filter order on SNR when using the Savitzky-Golay filter, suggesting that it is robust across different configurations. In contrast, increasing the order of the Butterworth, Chebyshev, and Elliptic filters led to a decline in performance, highlighting the importance of selecting an appropriate filter order based on the specific characteristics of the

ECG signal.

The study also addressed baseline shift, a common artifact in ECG signals, by implementing a low-order polynomial filter. This method effectively corrected baseline drift, bringing the baseline of the ECG signal close to zero, thus improving the overall accuracy of ECG interpretation. In conclusion, the combination of advanced filtering techniques and baseline shift correction presented in this study offers a robust framework for enhancing ECG signal quality. The findings have significant implications for the development of more accurate and reliable ECG analysis tools, particularly in clinical settings where precise signal interpretation is critical.

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