## Effectiveness of Advanced ECG Noise Reduction Filters

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***Abstract*—The study examined various filtering methods applied to ECG signals; the MIT-BIH Arrhythmia dataset included two channels to reduce noise and artifacts while maintaining critical waveform characteristics. Initial filtering included a notch filter and a bandpass filter. Advanced filters such as Savitzky-Golay, Wavelet, Kalman, Wiener, and combined Wiener-Golay were used for noise reduction. Results showed that the Kalman filter performed best with an average SNR of 21.40 dB, while the Wavelet method worked well on channel 2. The Wiener filter was less effective due to its limited adaptability to changing noise. The combined Wiener-Savitzky-Golay filter showed a balanced performance but did not outperform the Kalman filter. Visual inspections of ECG signals from five patients revealed that the Kalman and Wavelet filters successfully maintained crucial morphological characteristics. The Savitzky-Golay filter offered effective smoothing but sometimes dampened the QRS complex, while the Wiener filter introduced high-frequency artifacts.**

***Index Terms*—ECG, Noise reduction, Filtering techniques, MIT-BIH Arrhythmia dataset, Golay filter, Wavelet, Kalman, Wiener, SDG 3**

## I. Introduction

Electrocardiography (ECG) is a pivotal diagnostic tool for monitoring the heart's electrical activity, offering crucial insights into cardiac health by detecting various conditions like arrhythmias. Timely ECG assessments are increasingly vital given the rising global prevalence of heart-related issues, as they enable swift medical interventions, thereby enhancing patient outcomes and quality of life. In healthcare, preprocessing ECG datasets is paramount for accurate analysis. Raw ECG signals often contain noise and artifacts that can obscure important patterns. Techniques like filtering, normalization, and segmentation are essential for data cleaning, ensuring subsequent analyses are reliable. By refining ECG datasets, healthcare professionals can leverage advanced algorithms and machine learning models to pinpoint anomalies precisely, facilitating early intervention and improved cardiac health management.

This study employs the MIT-BIH Arrhythmia database to implement and compare denoising methods using MATLAB. Each technique's efficacy in isolating the pure ECG signal from diverse noise sources was evaluated through visual inspections and signal-to-noise ratio (SNR) measurements to determine the most effective method. The paper's structure includes a literature review in Section II, materials and methodologies in Section III, results and discussions in Section IV, and concluding remarks in Section V.

## II. Literature review

Various denoising techniques have been proposed to enhance signal quality in ECG. Podder et al. [1] explored using Butterworth band-pass filters for noise reduction in ECG signals. Their research demonstrated that the Butterworth filter's flat frequency response minimized distortion and improved signal clarity compared to Chebyshev and elliptic filters, effectively preserving essential signal components critical for accurate cardiac diagnosis. Additionally, Psychalinos and Elwakil [2] investigated a generalized fractional-order Butterworth band-stop filter to eliminate 50/60Hz power line interference from ECG recordings. Their novel filter design enhanced the attenuation of unwanted frequencies, offering precise control over the frequency response to safeguard vital ECG features such as the QRS complex. Qassim et al. [3] utilized a 4-level discrete wavelet transform (DWT) to decompose ECG data into different frequency bands to enhance noise removal through wavelet coefficient thresholding. Their study on ECG signals from the MIT-BIH database showed that wavelet families such as Daubechies and Symlets yielded optimal outcomes, notably improving the signal-to-noise ratio (SNR) and reducing Mean Square Error (MSE). Moreover, Aljuaid and Malik [4] introduced a hybrid method to address baseline drift and power line interference in ECG signals. Combining lifting wavelet transform with iterative filtering led to increased SNR and better preservation of crucial ECG features, resulting in significant denoising enhancements. Additionally, Jenkal et al. [5] investigated a real-time hardware implementation of an adaptive dual-threshold filter employing wavelet-based strategies for ECG denoising. Their study illustrated the efficacy of wavelet techniques in real-time ECG monitoring scenarios, demonstrating their capacity to suppress noise while maintaining essential ECG signal characteristics.

The Savitzky-Golay (SG) filter has become a prominent denoising method in ECG signal processing for its ability to smooth noisy signals while preserving crucial features. Raheja and Manoacha [6] combined wavelet transforms with the SG filter for ECG denoising, showing the hybrid approach's effectiveness in maintaining key ECG characteristics like QRS complexes while efficiently removing high-frequency noise and baseline drift. Compared to traditional techniques such as low-pass filtering, the SG filter significantly preserved the integrity of the ECG waveform. In another study, Awal et al. [7] improved noise suppression in ECG denoising by integrating adaptive wavelet thresholding with SG filtering. They highlighted baseline drift distortion as a common issue in ECG signal acquisition, noting the SG filter's substantial mitigation of this distortion across different ECG datasets. Furthermore, Yadav and Sinha [8] explored enhancing the signal-to-noise ratio (SNR) in ECG signals by combining non-local wavelet techniques with SG filtering. Their research underscored the potential of incorporating Golay filtering into comprehensive signal-processing frameworks to enhance the accuracy of clinical diagnoses.

One prevalent noise interference in ECG signal acquisition is 60Hz power line noise, significantly impacting signal quality and diagnostic accuracy in cardiac assessments. Notch filters are commonly utilized to effectively eliminate this interference while preserving the overall integrity of the ECG signal. Mahmoud et al. [9] introduced a cascaded 60Hz notch filter architecture tailored for ECG detection systems, employing a programmable circuit for precise filter adjustment. This method successfully reduced power line noise without compromising essential ECG features. Similarly, Piskorowski [10] developed a variable-Q notch filter to target 60Hz frequencies, allowing for quality factor adjustments to enhance noise removal and maintain waveform structure and Signal-to-Noise Ratio (SNR), making it ideal for ECG monitoring applications. In another approach, Alzaher et al. [11] detailed a fully integrated power line notch filter optimized for biopotential acquisition systems, focusing on its application in ECG signals. Their technique featured variable center frequencies, enabling adaptation to diverse noise conditions while upholding high diagnostic precision, which is crucial for modern wearable and portable ECG systems' ineffective cardiac monitoring.

The Kalman filter stands out as a widely adopted algorithm for ECG denoising due to its ability to estimate a dynamic system's state from noisy observations, making it particularly effective for biological signals like ECGs. Kalman filtering frameworks have evolved to improve noise reduction while preserving crucial ECG features such as the QRS complex and T-waves. Sayadi et al. [12] introduced a model-based Bayesian approach that leverages Kalman filters for segmenting and denoising ECG beats. Their method utilized prior knowledge of cardiac cycles to reduce noise while effectively retaining clinically significant features. This approach proved highly successful for applications in beat segmentation and arrhythmia detection. Expanding on this work, Sarafan et al. [13] proposed a more advanced framework using ensemble Kalman filters to enhance ECG data quality. Utilizing ensemble-based methodologies, their approach is particularly potent for real-time ECG analysis as it addresses stationary and non-stationary noise, thereby improving the potential for accurate cardiac monitoring.

The Wiener filter is a prominent tool in signal processing known for its optimal noise reduction capabilities, particularly effective for signals afflicted by stationary noise. Its ability to minimize the mean square error between estimated and actual signals makes it advantageous for preserving critical ECG features like the QRS complex and T-waves, leading to its widespread application in ECG signal denoising. Mihăilă et al. [14] utilized the Wiener filter to address various noise types, including baseline drift and power line interference, showcasing its adaptability in managing high-frequency artifacts and low-frequency noise. They found that combining the Wiener filter with techniques like wavelet transforms significantly improved the signal-to-noise ratio (SNR), enhancing clarity in ECG data. Similarly, Lascu and Lascu [15] concluded that the Wiener filter effectively reduced noise while preserving ECG signal diagnostic integrity, outperforming conventional filters, especially in environments with significant muscle noise and power line interference. Recent advancements highlighted by Velayudhan and Peter [16] propose integrating Wiener filters with adaptive filtering techniques to enhance performance in real-time ECG monitoring systems, particularly beneficial for wearable medical devices requiring high signal quality and computational efficiency. In their research, Manju et al. [17] explored the synergy of Wiener and Kalman filters, demonstrating that this hybrid approach improved denoising by leveraging the Wiener filter's efficient suppression of stationary noise alongside the Kalman filter's dynamic noise-tracking capabilities. This combined technique effectively preserves essential ECG features while ensuring robust noise removal.

## III. Materials and Methodology

The study aims to enhance ECG signal quality by reducing noise and artifacts while preserving essential morphological features crucial for accurate arrhythmia detection. Various preprocessing steps and filtering methods were applied to

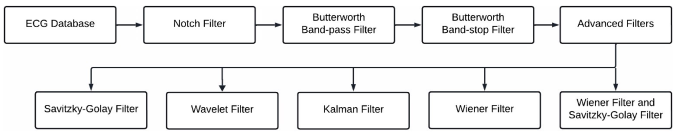


Fig. 1. The block diagram of the proposed system.

ECG data. The block diagram in Figure 1 visually illustrates the proposed system, outlining how preprocessing steps and filtering methods are integrated to enhance signal quality and support precise arrhythmia detection.

### A. Dataset

The MIT-BIH Arrhythmia dataset consists of 48 records, with 23 representing common clinical cases and 25 focusing on complex arrhythmias and conduction abnormalities. Notable cases include records 102 and 104 using a modified lead V5 and records 114 with reversed leads. Signal processing involved analog bandpass filtering (0.1-100 Hz) and digitization to 12-bit signed integers. Technical considerations included analog tape skew, pacemaker artifacts, and 60 Hz noise. Frequency-domain artifacts were linked to specific components of recording equipment, such as recorder pressure wheel and capstans. These details offer insights into the recording process and potential artifacts within the dataset [18].

### B. Methodology

*1) Preprocessing:* Filtering techniques were applied to minimize noise and artifacts while preserving key features of the ECG waveform. Raw ECG signals were initially obtained from ".dat" files featuring two channels corresponding to distinct lead setups. Each file included interleaved 11-bit samples saved as unsigned integers. The raw integer values, spanning 0 to 2047, were converted to millivolt (mV) values within a $\pm 10$ mV range using Eq. (1).

$$mV = \frac{\text{digital value}}{2^{n-1}} \cdot \text{range} + \text{offset} \tag{1}$$

The second ECG channel (Channel 2) is often inverted due to electrode configuration, requiring a correction by multiplying the signal by -1 for proper orientation. To address the interference of the 60 Hz frequency, a 60 Hz notch filter with a quality factor of 30 was applied to each ECG channel independently. Subsequently, a 4th-order Butterworth bandpass filter ranging from 0.1 Hz to 100 Hz was employed to maintain a flat frequency response within the passband. This filter effectively preserved crucial ECG components like the P, QRS, and T waves while reducing baseline drift and high-frequency noise. Furthermore, specific mechanical artifacts at 0.167 Hz, 0.090 Hz, and 0.083 Hz originating from recording equipment were targeted using band-stop filters. These filters were designed to attenuate these artifacts without compromising the physiological information present in the ECG signals, ensuring accurate signal interpretation.

This study employed five advanced filtering techniques to evaluate their efficacy in noise reduction for ECG signals. These methods were selected based on their suitability for the distinctive characteristics of ECG signals, emphasizing their ability to preserve essential features while mitigating noise. The compared techniques included the Savitzky-Golay filter, wavelet denoising, the Kalman filter, the Wiener filter, and a hybrid approach combining the Wiener and Savitzky-Golay filters. Parameters for each filter were meticulously adjusted using a combination of trial and error and grid-search optimization to enhance the signal-to-noise ratio (SNR) to optimal levels.

*2) Savitzky-Golay Filter:* The Savitzky-Golay (Golay) filter [19] smooths the ECG signal while preserving its significant features, such as the QRS complex, which is essential for ECG analysis. It operates by fitting a polynomial to a window of data points as in Eq. (2). A specific window of ECG samples, typically comprising 5 or 7 data points, is initially chosen. Subsequently, a polynomial, frequently of a modest degree like quadratic, is tailored to these samples. This polynomial affords a refined approximation for each segment within the window, aiding in mitigating high-frequency noise, such as power-line interference, all the while preserving the distinct and sharp transitions found in the QRS complex.

$$y_i = \sum_{j=-m}^{m} c_j x_{i+j} \tag{2}$$

where $y_i$ is the smoothed value at point $i$, $x_{i+j}$ are the data points within the window centered around $i$, $c_j$ are the filter coefficients, which are derived by performing a least-squares fit of a polynomial of degree $m$ over a window of width $2m+1$.

*3) Wavelet Filter:* The wavelet transform [20] decomposes the ECG signal into different frequency components, which can be used to separate noise from the signal. The ECG signal is decomposed into approximation and detail coefficients at each level. Low-frequency components and high-frequency noise are separated across different levels. After decomposition, the detail coefficients corresponding to noise (high-frequency components) are thresholded or discarded. The signal is then reconstructed from the approximation coefficients, yielding a denoised ECG signal. A 4-level wavelet decomposition provides a multi-resolution analysis of the signal, as in Eq. (3), with a level-4 decomposition in Eq. (4).

$$\begin{aligned} A_n[n] &= k * x_k * h[k-2n] \\ D_n[n] &= k * x_k * g[k-2n] \end{aligned} \tag{3}$$

$$\begin{aligned} x_n = {} & k(A_4 * h_{k-2n} + D_4 * g_{k-2n}) \\ & + k(D_3 * g_{k-2n}) + k(D_2 * g_{k-2n}) \\ & + kD_1 * g_{k-2n} \end{aligned} \tag{4}$$

$A_n$ are the approximation coefficients at level $n$ (low-frequency content). $D_n[n]$ are the detail coefficients at level $n$ (high-frequency content). $h_k$ is the low-pass filter (scaling function). $g[k]$ is the high-pass filter (wavelet function).

*4) Kalman Filter:* The Kalman filter [21] is an adaptive filter that estimates the true signal from noisy measurements by recursively updating its predictions. The Kalman filter models the ECG signal as a dynamic system. It continuously updates its estimate of the ECG signal based on previous data and the current noisy measurement. This is particularly useful for filtering out low-frequency noise and tracking the QRS complex over time. The predicted state estimate is in Eq. (5).

$$x_{k|k-1} = Ax_{k-1|k-1} + Bu_k \tag{5}$$

where $x_{k|k-1}$ is the predicted state estimate at time step $k$, $A$ is the state transition matrix, $x_{k-1|k-1}$ is the previous state estimate, $B$ is the control input matrix, and $u_k$ is the control input. The predicted covariance Estimate is in Eq. (6).

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{6}$$

where $P_{k|k-1}$ is the predicted error covariance matrix at time step $k$, $P_{k-1|k-1}$ is the previous error covariance matrix, $Q$ is the process noise covariance matrix, and $A^T$ is the transpose of the state transition matrix. Kalman gain, updated state estimate, and updated covariance estimate are in Eq. (7), (8), and (9) respectively.

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1} \tag{7}$$

$$x_{k|k} = x_{k|k-1} + K_k(z_k - Hx_{k|k-1}) \tag{8}$$

$$P_{k|k} = (I - K_kH)P_{k|k-1} \tag{9}$$

*5) Wiener Filter:* The Wiener filter [22] is an optimal linear filter for minimizing the mean square error between the noisy ECG signal and the clean signal. It assumes that both the signal and noise are stationary processes with known statistics. It computes the power spectral density of the ECG signal and noise. It then applies a frequency-domain filter to suppress the noise while retaining the signal. Its frequency and time representation are in Eq. (10).

$$\begin{aligned} H(f) &= \frac{S_{xx}(f)}{S_{xx}(f) + S_{nn}(f)} \\ x(t) &= x(t) + x^2 + n^2y(t) - x(t) \end{aligned} \tag{10}$$

where $H(f)$ is the Wiener filter in the frequency domain, $S_{xx}(f)$ is the power spectral density of the clean signal, and $S_{nn}(f)$ is the power spectral density of the noise. $x(t)$ is the estimate of the clean signal, $x(t)$ is the original signal, $y(t)$ is the noisy observation of the signal, $x^2$ is the variance of the clean signal, and $n^2$ is the variance of the noise.

*6) Combined Wiener and Golay Filter:* In this approach, the Wiener filter was applied first to perform initial noise reduction, followed by the Savitzky-Golay filter for additional smoothing. This combination leverages the strengths of both filters: the Wiener filter's ability to handle Gaussian noise and the Savitzky-Golay filter's capacity to smooth the signal while preserving the morphology of the ECG. The window size for the Wiener filter was set to [3, 1], and the Savitzky-Golay filter was applied with a window length of 5 and 4th order polynomial. These parameters were optimized through grid-search optimization to achieve a good compromise between noise reduction and signal preservation.

### C. Evaluation Metrics

In the evaluation of filtering techniques applied to ECG signals, two important metrics are Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR). The Mean Squared Error (MSE) quantifies the average squared difference between the filtered signals and the original signals. It is defined in (11).

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{11}$$

where $N$ is the total number of samples, $x_i$ represents the original signal, and $\hat{x}_i$ denotes the filtered signal. A lower MSE value indicates better performance of the filtering technique.

Signal-to-Noise Ratio (SNR) measures the ratio of the power of the signal to the power of the noise. It is commonly expressed in decibels (dB) and is calculated as in (12). In addition, it can be expressed in terms of the mean and variance of the signal and noise.

$$\begin{aligned} \text{SNR} &= 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \\ &= 10\log_{10}\left(\frac{\mu^2}{\sigma^2}\right) \end{aligned} \tag{12}$$

where $P_{signal}$ is the average power of the signal, $P_{noise}$ is the average power of the noise, $\mu$ is the mean of the signal, and $\sigma^2$ is the variance of the noise. A higher SNR indicates a clearer signal with less noise interference.

## IV. Results and Conclusion

Table I presents the essential statistics of SNR (dB) for each filtering type, displaying the mean, minimum, and maximum values for each channel, along with the average_average value across channels. Furthermore, Fig. 2 illustrates these results, facilitating a direct comparison of SNR values across methods and patients.

The results of all 48 recordings revealed that the Kalman filter achieved the highest average SNR of 21.40 dB across both channels, consistently outperforming other techniques. The wavelet denoising method was particularly effective on channel 2, where its SNR occasionally matched the Kalman filter. In contrast, the Wiener filter showed limited effectiveness, likely due to its inability to adapt to dynamic ECG noise.

TABLE I
SNR RESULTS FOR DIFFERENT FILTERING METHODS, IN dB.

| **Method** | **Mean Channel 1** | **Mean Channel 2** | **Min Channel 1** | **Min Channel 2** | **Max Channel 1** | **Max Channel 2** | **Average the 2 channels** |
|---|---|---|---|---|---|---|---|
| Savitzky-Golay Filter | 16.761 | 19.264 | 19.259 | 13.249 | 13.232 | 16.770 | 18.013 |
| Wavelet Denoising | 15.717 | 21.940 | 21.830 | 10.899 | 10.806 | 15.736 | 18.829 |
| Kalman Filter | 20.317 | 22.491 | 22.486 | 18.312 | 18.255 | 20.323 | 21.404 |
| Wiener Filter | 12.762 | 16.393 | 16.364 | 9.181 | 9.142 | 12.775 | 14.578 |
| Wiener-Savitzky-Golay Filter | 15.682 | 19.103 | 19.098 | 13.128 | 13.081 | 15.692 | 17.393 |

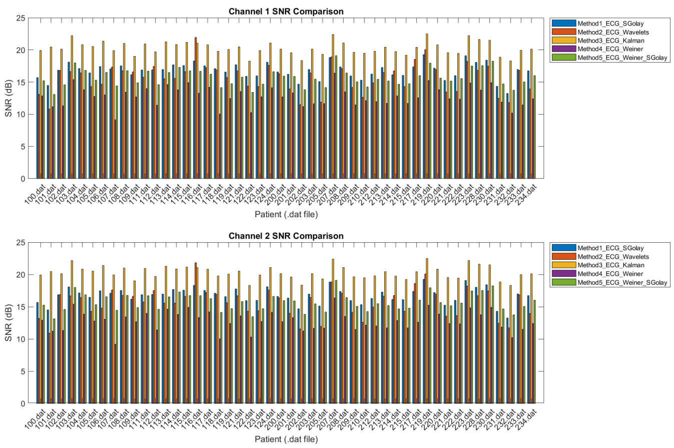


Fig. 2. SNR, all patients, through the two channels.

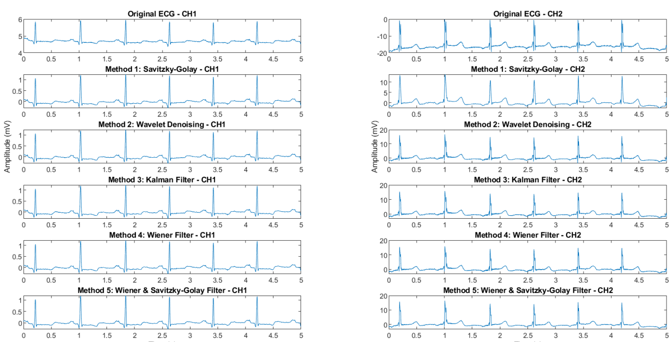


Fig. 3. 5-sec. of all denoising filters for patient 100.

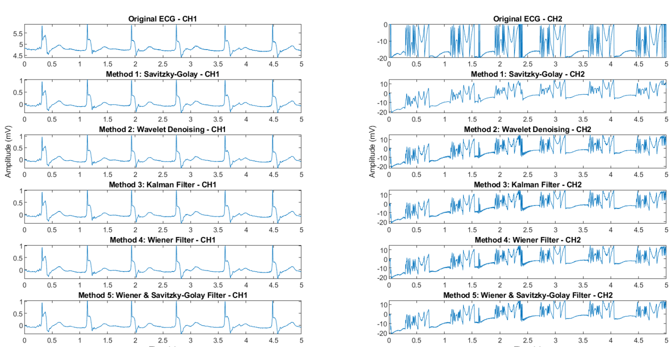


Fig. 4. 5-sec. of all denoising filters for patient 102.

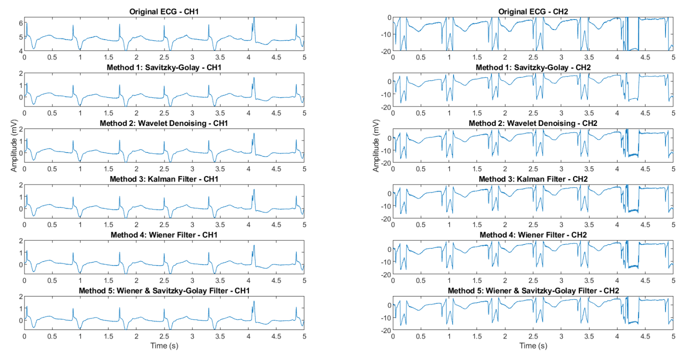


Fig. 5. 5-sec. of all denoising filters for patient 104.

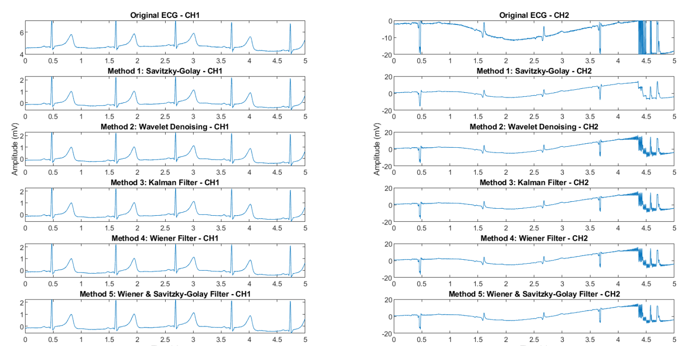


Fig. 6. 5-sec. of all denoising filters for patient 113.

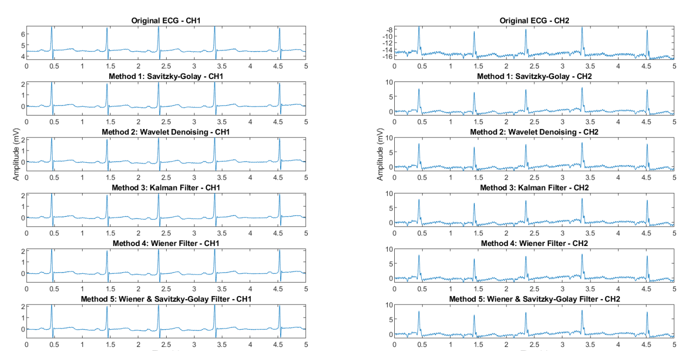


Fig. 7. 5-sec. of all denoising filters for patient 115.

The combined Wiener-Savitzky-Golay filter provided balanced performance, enhancing both SNR and signal smoothness; it did not surpass the Kalman filter.

Besides the SNR analysis, ECG signals from five randomly chosen patients were visually inspected pre and post each filtering method's application, as shown in Fig. 3 to 7. This qualitative evaluation provided further insights into the filters' efficacy, particularly in preserving crucial morphological features like the QRS complex, P wave, and T wave while reducing noise. As expected, both the Kalman filter and Wavelet denoising techniques exhibited outstanding performance with minimal distortion of ECG morphology. The Savitzky-Golay filter effectively smoothed the signal, occasionally causing slight attenuation in QRS complex amplitude. On the other hand, the Wiener filter successfully reduced noise but left behind some residual high-frequency artifacts.

## V. Conclusion

This study evaluated five advanced filtering techniques applied to ECG signals from the MIT-BIH Arrhythmia dataset to assess noise reduction effectiveness while preserving critical morphological features. The methods tested were the Savitzky-Golay filter, Wavelet denoising, Kalman filter, Wiener filter, and a combined Wiener-Savitzky-Golay filter. Both quantitative and qualitative analyses were used to evaluate each technique's impact on SNR enhancement and signal integrity maintenance.

The SNR analysis highlighted the Kalman filter's superiority, achieving the highest average SNR across ECG channels due to its adaptability to varying noise types, making it ideal for real-time clinical monitoring. The Wavelet denoising method also showed promise in handling non-stationary noise components commonly found in ECG signals. Both Kalman and Wavelet methods excelled in noise reduction and signal preservation, as evidenced by SNR metrics and visual assessments of filtered ECG signals. Despite effectively smoothing signals and removing high-frequency noise, the Savitzky-Golay filter struggled with complex noise patterns, occasionally leading to feature attenuation. The Wiener filter, the least effective method in this study, may be more suited for scenarios with predictable noise, struggling with dynamic noise in ECG recordings. The combined Wiener-Savitzky-Golay filter offered a balanced approach but did not surpass the Kalman or Wavelet filters. Visualizations of ECG signals pre and post filtering from randomly selected patients provided qualitative insights, confirming the Kalman and Wavelet filters as the most effective in noise reduction while preserving ECG signal morphology.

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