

Noise-Specific Hybrid Wavelet-Kalman Framework for Electrocardiogram Signal Denoising

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How to cite this paper: Madalngué, M.L., Jérôme, M., Cherif, A.O., Natebaye, N. and Jonas, M. (2026) Noise-Specific Hybrid Wavelet-Kalman Framework for Electrocardiogram Signal Denoising. *Open Journal of Applied Sciences*, **16**, 3721-3744.
<https://doi.org/10.4236/ojapps.2026.1610205>

Received: August 20, 2026

Accepted: September 27, 2026

Published: September 30, 2026

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Abstract

Electrocardiogram (ECG) signals are frequently contaminated by noise, which degrades signal quality and may compromise the clinical interpretation of the P-QRS-T morphology. This paper proposes a noise-specific hybrid Wavelet-Kalman framework in which the processing strategy is configured according to the considered disturbance characteristics. The proposed approach was evaluated using ECG records 103, 105, and 121 from the MIT-BIH Arrhythmia Database under representative noise conditions. Its performance was assessed using signal-to-noise ratio (SNR), mean squared error (MSE), and percent root-mean-square difference (PRD), and compared with conventional Wiener, Kalman, and Wavelet-based filtering methods. Experimental results show that denoising performance depends on the disturbance characteristics: Wavelet-based processing is particularly effective for high-frequency and non-stationary interference, whereas Kalman-based estimation provides additional benefits for low-frequency and narrowband disturbances. Under the evaluated conditions, the proposed framework achieved SNR improvements of up to 26.97 dB and PRD values as low as 2.45%, while preserving ECG morphology. These findings support the use of noise-specific processing configurations for ECG denoising, while computational complexity and real-time suitability require further quantitative evaluation.

Keywords

Electrocardiogram, Signal Denoising, Wavelet Transform, Kalman Filter, Hybrid Filtering

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 19.8 million deaths annually [1] [2]. Early detection and continuous monitoring are therefore essential for improving cardiovascular care. Among available clinical tools, the electrocardiogram (ECG) is a widely used, noninvasive method for assessing cardiac electrical activity and detecting cardiovascular abnormalities [3]-[5]. However, ECG signals are often contaminated by noise during acquisition or transmission, which may obscure clinically relevant features and compromise visual or automated interpretation. Common disturbances include additive white Gaussian noise (AWGN), baseline wander, electromyographic (EMG) interference, and power-line interference [6]. These artifacts can distort the P-QRS-T morphology and reduce the reliability of subsequent diagnostic analysis.

Effective ECG denoising therefore requires a careful balance between noise suppression and preservation of clinically relevant morphology [7]. Conventional approaches exhibit complementary strengths and limitations. Wiener filtering is effective for Gaussian and stationary noise [8] [9], whereas Kalman filtering provides adaptive state estimation and is particularly useful for slowly varying disturbances and dynamic signal tracking [10]-[12]. Wavelet-based methods offer multiresolution time-frequency analysis and are well suited to nonstationary ECG components and transient noise [13]-[15]. However, no single method performs optimally across all noise conditions, and excessive filtering may distort the P, QRS, or T waves, whereas conservative filtering may leave substantial residual noise.

Other adaptive decomposition techniques, including empirical mode decomposition (EMD), variational mode decomposition (VMD), and empirical wavelet transform (EWT), have also been investigated for isolating intrinsic signal components [16] [17]. Although these methods can improve noise separation, their performance may depend strongly on decomposition settings and signal characteristics, leading to trade-offs between noise attenuation and morphological preservation [17] [18]. More recently, hybrid approaches have combined time-frequency decomposition with adaptive filtering or learning-based methods to exploit complementary denoising capabilities [19]-[23]. Nevertheless, existing hybrid strategies may still face challenges related to relevant sub-band selection, parameter tuning, computational requirements, and robustness across heterogeneous noise conditions.

To address these challenges, this study proposes a noise-specific hybrid Wavelet-Kalman framework for ECG denoising. Rather than applying a fixed Wavelet-Kalman cascade to all disturbance conditions, the framework exploits the complementary characteristics of wavelet decomposition and Kalman filtering through processing configurations tailored to the considered noise type. Depending on the disturbance characteristics, Wavelet and Kalman filtering are applied individually, sequentially, or jointly, with appropriate wavelet components, Kalman models, and

processing order. The main contributions of this study are:

- The development of a noise-specific Wavelet-Kalman framework that avoids imposing a single processing chain across heterogeneous ECG disturbances;
- The design of dedicated processing configurations for AWGN, baseline wander, EMG-like interference, and power-line interference; and
- A comparative evaluation against conventional Wiener, Wavelet, and Kalman filtering using quantitative, spectral, and time-frequency analyses on ECG recordings from the MIT-BIH Arrhythmia Database.

Experimental results show improved denoising performance across different noise conditions while preserving the morphological integrity of the P-QRS-T complexes. Beyond algorithmic performance, the proposed framework provides a basis for further investigation toward practical ECG monitoring applications, including wearable devices, telemedicine platforms, and embedded healthcare systems.

The remainder of this paper is organized as follows. Section 2 describes the materials, methods, and evaluation framework. Section 3 presents and discusses the experimental results obtained under the different noise conditions, including comparisons with conventional methods and recent studies. Finally, Section 4 concludes the paper by summarizing the main findings, highlighting the practical implications of the proposed approach, and outlining future research directions.

2. Materials and Methods

2.1. Database and ECG Signal Selection

ECG recordings 103, 105, and 121 from the MIT-BIH Arrhythmia Database were used in this study. Each recording contains 650,000 samples per channel acquired at a sampling frequency of 360 Hz, corresponding to approximately 30 min of ECG data. The first channel, corresponding to the modified limb lead II (MLII), was selected for all three recordings.

The complete MLII signal from each recording was used for the experiments, without temporal truncation. Before noise addition, each ECG signal was mean-centered and normalized by its maximum absolute amplitude. To reduce boundary and filtering transient effects, the first and last 2 s of each recording were excluded from quantitative performance evaluation. The reported SNR, MSE, and PRD values were therefore computed over the remaining portion of each complete recording.

2.2. Synthetic Noise Modeling

Four controlled noise conditions were considered: additive white Gaussian noise (AWGN), baseline wander, electromyographic (EMG)-like interference, and power-line interference. For AWGN, EMG-like noise, and power-line interference, input SNR levels of 5, 10, and 15 dB were investigated. For stochastic noise generation, the pseudorandom number generator was initialized with a fixed seed of 7 to ensure reproducibility.

AWGN: Zero-mean, unit-variance Gaussian noise $v(t)$ was generated and scaled to the prescribed input SNR. For a target SNR S (dB), the noise power was defined as

$$P_n = \frac{P_x}{10^{S/10}} \quad (1)$$

where P_x is the mean power of the reference ECG. The corrupted signal was then obtained as

$$y(t) = x(t) + \sqrt{P_n} v(t) \quad (2)$$

Baseline wander: Low-frequency baseline drift was modeled as

$$b(t) = A_{BW} \sin\left(2\pi f_{BW} \frac{n}{f_s}\right) \quad (3)$$

with $f_{BW} = 0.33$ Hz and $A_{BW} \in \{0.05, 0.10, 0.12\}$. The amplitudes are expressed relative to the normalized ECG amplitude, and the contaminated signal was

$$y(t) = x(t) + b(t) \quad (4)$$

These three amplitude levels were used instead of SNR-controlled scaling for the baseline-wander experiments.

EMG-like interference: Synthetic muscle interference was generated from zero-mean, unit-variance Gaussian noise using an eighth-order IIR band-pass filter with half-power frequencies of 20 and 100 Hz. Zero-phase forward-backward filtering was applied, and the resulting band-limited noise was scaled according to the reference ECG power to achieve the prescribed input SNR before addition to $x(t)$.

Power-line interference: Power-line contamination was modeled by combining a 50 Hz sinusoidal fundamental with its second harmonic at 100 Hz:

$$p(t) = \sin(2\pi f_0 t) + 0.2 \sin(4\pi f_0 t), \quad f_0 = 50 \text{ Hz} \quad (5)$$

Thus, before global SNR scaling, the second-harmonic amplitude was 20% of the fundamental amplitude. No frequency drift was introduced. The composite interference $p(t)$ was subsequently scaled according to the reference ECG power to achieve the prescribed input SNR before addition to $x(t)$.

2.3. Denoising Methods

2.3.1. Wavelet-Based Denoising (DWT)

The ECG signal $x(t)$ was decomposed using the discrete wavelet transform (DWT), which separates the signal into approximation coefficients A_j and detail coefficients D_j at different resolution levels:

$$x(t) = A_J + \sum_{j=1}^J D_j \quad (6)$$

where J denotes the decomposition level.

The Daubechies 6 (db6) mother wavelet was selected due to its suitability for ECG morphology.

Soft thresholding based on the Stein's Unbiased Risk Estimator (SURE) criterion was applied to the selected coefficients before signal reconstruction. Within the proposed framework, the approximation or detail components to be processed are selected according to the considered disturbance characteristics.

2.3.2. Kalman Filter

The Kalman filter was applied to the selected wavelet components according to the processing configuration associated with the considered disturbance. The process and observation models are defined as:

$$x_k = Ax_{k-1} + w_k \quad (7)$$

$$y_k = Cx_k + v_k \quad (8)$$

where A is the state transition matrix, C is the observation matrix, $w_k \sim N(0, Q)$ represents the process noise, and $v_k \sim N(0, R)$ represents the measurement noise.

The filter recursively estimates the signal state through prediction and correction steps, providing adaptive noise suppression while preserving the morphological characteristics of the ECG signal.

2.3.3. Proposed Noise-Specific Hybrid Wavelet-Kalman Framework

The proposed method is formulated as a unified noise-specific Hybrid Wavelet-Kalman framework for ECG signal denoising. Unlike conventional hybrid approaches employing a fixed processing sequence, the proposed framework preserves a common architecture while configuring the processed wavelet components, Kalman state model, covariance parameters, and filtering sequence according to the characteristics of the considered disturbance. This strategy exploits the complementary capabilities of multiresolution wavelet decomposition and Kalman recursive estimation while preserving ECG morphology.

1) General Framework

Figure 1 presents the general workflow of the proposed framework. A reference ECG signal is first corrupted through noise modeling to generate the noisy ECG signal. The noisy signal is then decomposed using the discrete wavelet transform (DWT), followed by a noise-specific Wavelet-Kalman processing stage. According to the considered disturbance, appropriate wavelet components, Kalman models, and processing sequences are selected before signal reconstruction. Finally, the denoised ECG signal is evaluated using quantitative, spectral, and time-frequency performance metrics.

In the present controlled experiments, the disturbance type was known *a priori* because each noise condition was synthetically generated. The corresponding processing configuration was therefore selected using the known noise label rather than through an automatic noise-classification stage. Accordingly, the present study constitutes an oracle-configured evaluation of the proposed noise-specific framework. Automatic disturbance identification and subsequent configuration selection from unknown ECG recordings are beyond the scope of the present study.

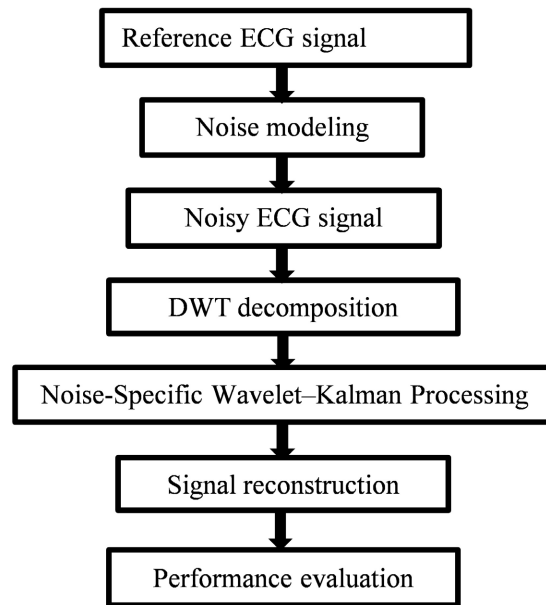


Figure 1. General workflow of the proposed noise-specific Hybrid Wavelet-Kalman framework for ECG signal denoising.

2) Noise-Specific Processing Configurations

Although the proposed framework follows a common processing architecture, its internal configuration is adapted according to the spectral characteristics of the considered noise. Depending on the disturbance, different wavelet components, Kalman state models, covariance parameters, and filtering sequences are employed to maximize noise suppression while preserving ECG morphology. The adopted processing configurations are summarized in **Table 1**.

Table 1. Noise-specific processing configurations adopted in the proposed framework.

Noise type	Wavelet processing	Kalman configuration	Processing strategy
AWGN	Selective detail sub-bands	Local-level Kalman with optimized Q and R	Selection Kalman filtering followed by weighted Wavelet-Kalman fusion
Baseline wander	Approximation component (cA_7)	Local-level Kalman	Baseline estimation and subtraction
EMG interference	Wavelet thresholding (SURE, Soft)	Not applied	Wavelet denoising only
Power-line interference	Wavelet decomposition	Harmonic Kalman	Sequential Wavelet-Kalman or Kalman-Wavelet processing

The adopted configurations were selected according to the dominant spectral characteristics of each disturbance. Broadband Gaussian noise benefits from selective Wavelet-Kalman processing, whereas low-frequency baseline wander is estimated through the approximation component using a local-level Kalman model.

Because EMG interference mainly occupies a broadband high-frequency range, wavelet thresholding alone is employed. For narrowband power-line interference, a harmonic Kalman model is combined with wavelet processing using two sequential configurations to evaluate the influence of the filtering order.

3) Implementation and Parameter Configuration

All wavelet-based configurations used the Daubechies 6 (db6) mother wavelet with SURE-based soft thresholding and level-dependent noise estimation. The decomposition level was set to 5 for AWGN and EMG-like interference, 7 for baseline wander, and 4 for power-line interference. Symmetric boundary extension was explicitly applied in the baseline-wander, EMG-like, and power-line implementations.

For AWGN, the candidate detail-band sets were $D_3 - D_5$, $D_2 - D_5$, and $D_3 - D_4$, with the approximation coefficients left unchanged. The Kalman parameters were searched over $Q = \{5 \times 10^{-7}, 10^{-6}, 2 \times 10^{-6}, 5 \times 10^{-6}, 10^{-5}\}$ and $R = \{8 \times 10^{-3}, 10^{-2}, 1.2 \times 10^{-2}, 1.5 \times 10^{-2}, 2 \times 10^{-2}\}$. The configuration maximizing output SNR relative to the clean ECG reference was retained. The final estimate used fixed fusion weights of 0.95 and 0.05 for the Wavelet and Wavelet-Kalman outputs, respectively.

For baseline wander, the local-level Kalman filter used $Q = 5 \times 10^{-6}$ and $R = 2 \times 10^{-2}$ in the hybrid configuration, with initial covariance $P_0 = 1$ and the first processed sample as the initial state. The Kalman stage was bypassed for EMG-like interference. For power-line interference, the harmonic Kalman model used $Q = 10^{-6} I_2$, $R = 5 \times 10^{-3}$, $P_0 = I_2$, and the state-transition matrix

$$F(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}, \quad \theta = 2\pi f T_s \quad (9)$$

with the observation matrix $H = [1 \ 0]$, which maps the two-dimensional harmonic state vector to the estimated sinusoidal interference. The model was applied to the 50 Hz fundamental and its 100 Hz second harmonic. The AWGN parameter search used the clean reference ECG from each evaluated experiment to maximize output SNR and therefore represents reference-guided oracle optimization rather than independent training/validation tuning.

2.4. Evaluation Metrics

The performance of the denoising methods is evaluated using the signal-to-noise ratio (SNR), mean squared error (MSE), percent root-mean-square difference (PRD), low-frequency energy ratio (LF), and morphology preservation. The latter is assessed through visual comparison of ECG waveforms before and after filtering, as well as frequency-domain analyses, including time-frequency spectrograms, power spectra, and power spectral density (PSD). This comprehensive evaluation framework enables an accurate assessment of the trade-off between effective noise suppression and preservation of clinically relevant spectral and morphological information.

The signal-to-noise ratio (SNR) quantifies the improvement in signal quality

after denoising and is defined as:

$$\text{SNR}_{\text{out}} = 10 \log_{10} \left(\frac{\sum_{i=1}^N (x(i))^2}{\sum_{i=1}^N (x(i) - \hat{x}(i))^2} \right) \quad (10)$$

where $x(i)$ and $\hat{x}(i)$ denote the reference clean ECG and denoised ECG, respectively, and N is the number of evaluated samples.

Higher SNR values indicate better noise suppression and improved signal quality.

To evaluate the improvement achieved by the denoising process, the SNR gain (ΔSNR) is computed as:

$$\Delta\text{SNR} = \text{SNR}_{\text{out}} - \text{SNR}_{\text{in}} \quad (11)$$

A positive ΔSNR value indicates an improvement in signal quality after filtering.

The mean squared error (MSE) measures the average squared difference between the reference and denoised signals:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (x(i) - \hat{x}(i))^2 \quad (12)$$

Lower MSE values indicate better preservation of the original ECG waveform.

The percent root-mean-square difference (PRD) is used to assess the distortion introduced by the denoising process:

$$\text{PRD}(\%) = 100 \sqrt{\frac{\sum_{i=1}^N (x(i) - \hat{x}(i))^2}{\sum_{i=1}^N (x(i))^2}} \quad (13)$$

Lower PRD values correspond to smaller deviations from the reference ECG signal.

To quantify baseline wander suppression, the low-frequency energy ratio (LF < 0.5 Hz) is calculated as:

$$\text{LF}(\%) = 100 \frac{\sum_{i=1}^{K_c} |X_{\text{freq}}(i)|^2}{\sum_{i=1}^{K_c} |Y_{\text{freq}}(i)|^2} \quad (14)$$

where X_{freq} and Y_{freq} represent the frequency spectra of the denoised signal $\hat{x}(i)$ and the noisy signal $y(i)$, respectively, and K_c denotes the cutoff frequency index. The spectra are obtained using the Fast Fourier Transform (FFT).

A reduction in LF energy indicates more effective attenuation of low-frequency baseline fluctuations.

3. Results and Discussion

3.1. Results

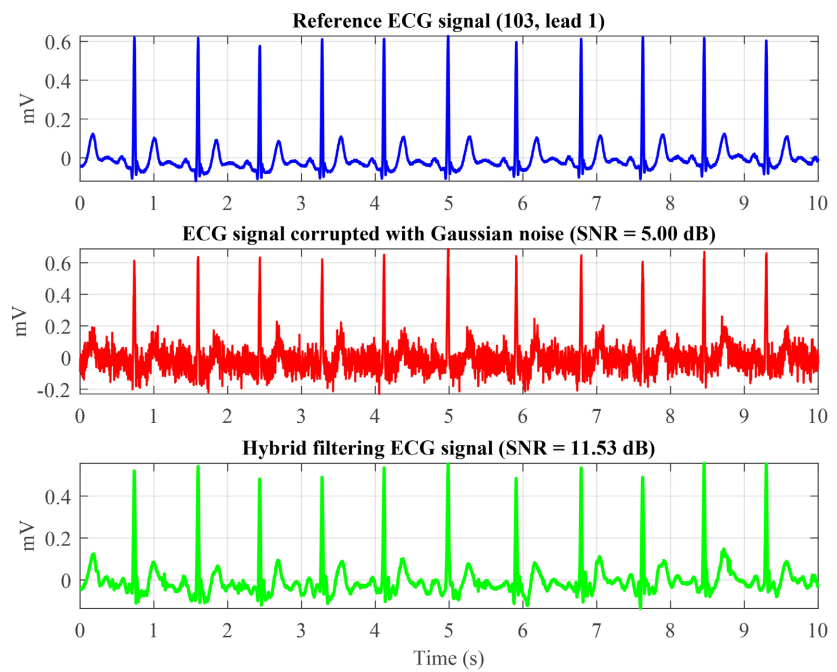
3.1.1. Experimental Framework

The performance of the Wiener, Kalman, wavelet-based (Wavelet), and hybrid (Wavelet-Kalman) filters was evaluated using three ECG signals extracted from the MIT-BIH Arrhythmia Database (recordings 103, 105, and 121).

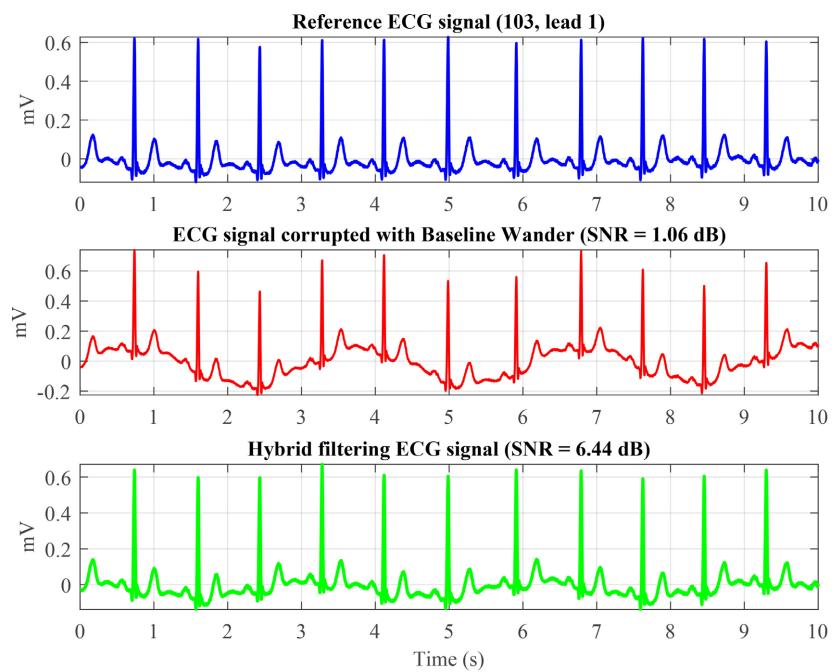
Each signal was corrupted with four types of noise commonly encountered in clinical environments:

- Additive white Gaussian noise (AWGN);
- Baseline wander (BW);
- Electromyographic (EMG) noise;
- Power-line interference (50 Hz).

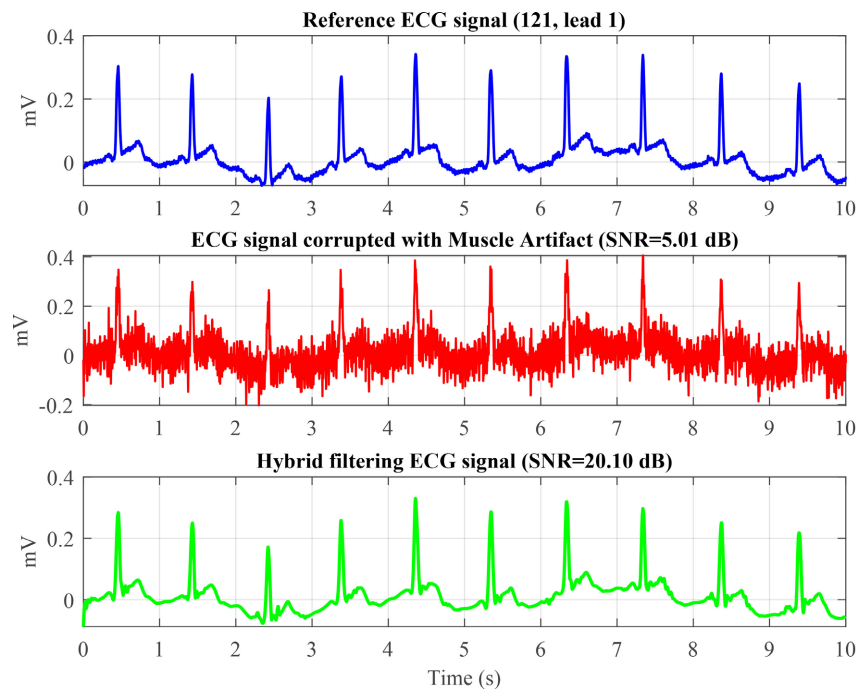
This experimental configuration ensures a comprehensive and controlled comparison of denoising performance across heterogeneous noise conditions (see **Figure 2**).



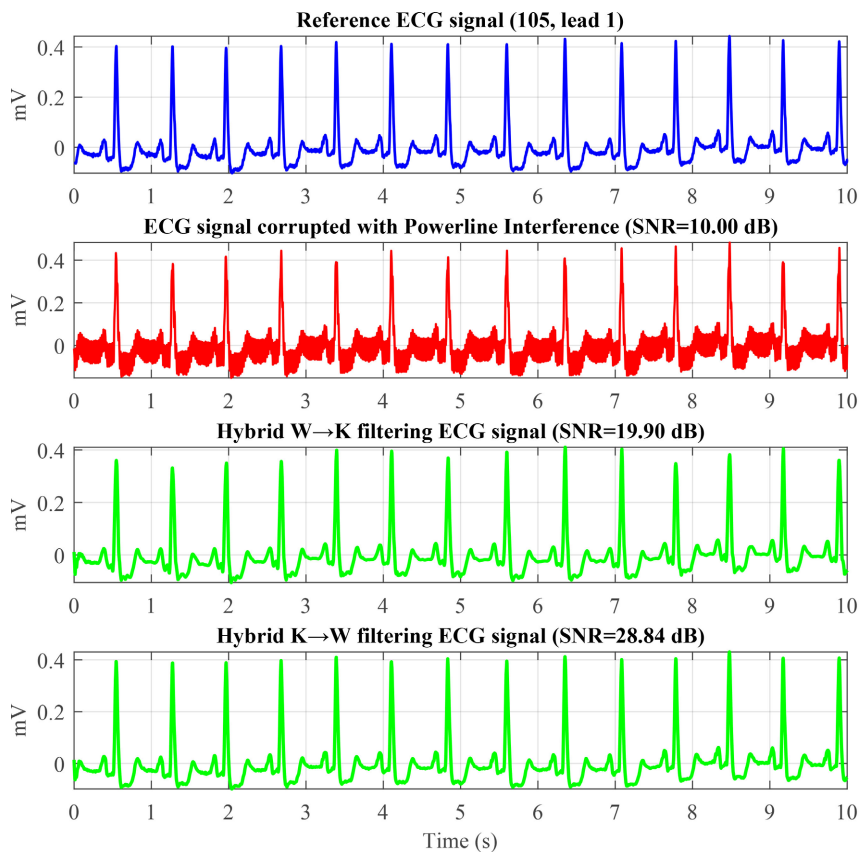
(a)



(b)



(c)



(d)

Figure 2. ECG denoising results obtained with the proposed hybrid Wavelet-Kalman method under different noise conditions: (a) Additive white Gaussian noise (AWGN); (b) Baseline wander; (c) Electromyographic (EMG) interference; and (d) Power-line interference.

For each scenario, performance was quantified using signal-to-noise ratio (SNR), SNR gain, mean squared error (MSE), and percent root-mean-square difference (PRD). In the case of baseline wander, the proportion of low-frequency energy ($LF < 0.5$ Hz) was additionally evaluated.

3.1.2. Additive White Gaussian Noise (AWGN)

The analysis of recordings 103, 105, and 121 from the MIT-BIH Arrhythmia Database reveals a significant increase in signal-to-noise ratio (SNR) after filtering (see **Table 2** and **Figure 3**). The wavelet-based method demonstrates clear superiority in terms of SNR and percent root-mean-square difference (PRD). It achieves an SNR gain ranging from 0.7 to 9.93 dB, with optimized reconstruction characterized by minimal information loss (PRD as low as 8.78%). The hybrid (Wavelet-Kalman) approach closely follows, maintaining performance comparable to standalone wavelet decomposition for input SNR values ($SNR_{in} \geq 10$ dB), while exhibiting enhanced stability across all recordings. This behavior is expected because the proposed framework assigns the main denoising task to wavelet-domain processing for broadband Gaussian noise, whereas Kalman filtering provides only complementary refinement. Consequently, the hybrid approach naturally converges toward the performance of standalone wavelet denoising under AWGN conditions. For the Wiener filter, an SNR gain ranging from 0.33 to 7.24 dB is observed. In contrast, the Kalman filter proves ineffective under this type of broadband noise condition.

Table 2. AWGN denoising results for the three recordings.

Record	SNR_IN (dB)	Method	SNR_OUT (dB)	Gain SNR (dB)	MSE	PRD (%)
103	5	Wiener	10.01	5.01	9.18e−04	31.6
		Kalman	5	0	2.91e−03	56.23
		Wavelet	11.69	6.69	6.23e−04	26.03
		Hybrid	11.53	6.53	6.47e−04	26.51
	10	Wiener	13.21	3.21	4.39e−04	21.86
		Kalman	10	0	9.20e−04	31.63
		Wavelet	14.03	4.03	3.64e−04	19.88
		Hybrid	13.89	3.89	3.75e−04	20.2
	15	Wiener	15.65	0.65	2.51e−04	16.51
		Kalman	15	0	2.91e−04	17.79
		Wavelet	15.69	0.7	2.48e−04	16.42
		Hybrid	15.58	0.58	2.55e−04	16.64
105	5	Wiener	9.72	4.72	1.44e−03	32.65
		Kalman	5	0	4.27e−03	56.24
		Wavelet	12.17	7.17	8.19e−04	24.64
		Hybrid	12.19	7.19	8.14e−04	24.57

Continued

121	10	Wiener	12.92	2.91	6.88e-04	22.59
		Kalman	10.01	0	1.35e-03	31.58
		Wavelet	14.84	4.82	4.43e-04	18.12
		Hybrid	14.85	4.84	4.42e-04	18.1
	15	Wiener	15.33	0.33	3.95e-04	17.12
		Kalman	15	0	4.26e-04	17.77
		Wavelet	16.57	1.57	2.97e-04	14.84
		Hybrid	16.63	1.62	2.93e-04	14.74
	5	Wiener	12.24	7.24	4.10e-04	24.44
		Kalman	5	0	2.17e-03	56.25
		Wavelet	14.92	9.93	2.21e-04	17.94
		Hybrid	14.88	9.89	2.23e-04	18.02
	10	Wiener	15.81	5.81	1.80e-04	16.2
		Kalman	10	0	6.85e-04	31.61
		Wavelet	18.29	8.28	1.02e-04	12.18
		Hybrid	18.24	8.24	1.03e-04	12.25
	15	Wiener	19.21	4.21	8.22e-05	10.95
		Kalman	15	0	2.17e-04	17.78
		Wavelet	21.13	6.13	5.29e-05	8.78
		Hybrid	21.04	6.04	5.41e-05	8.88

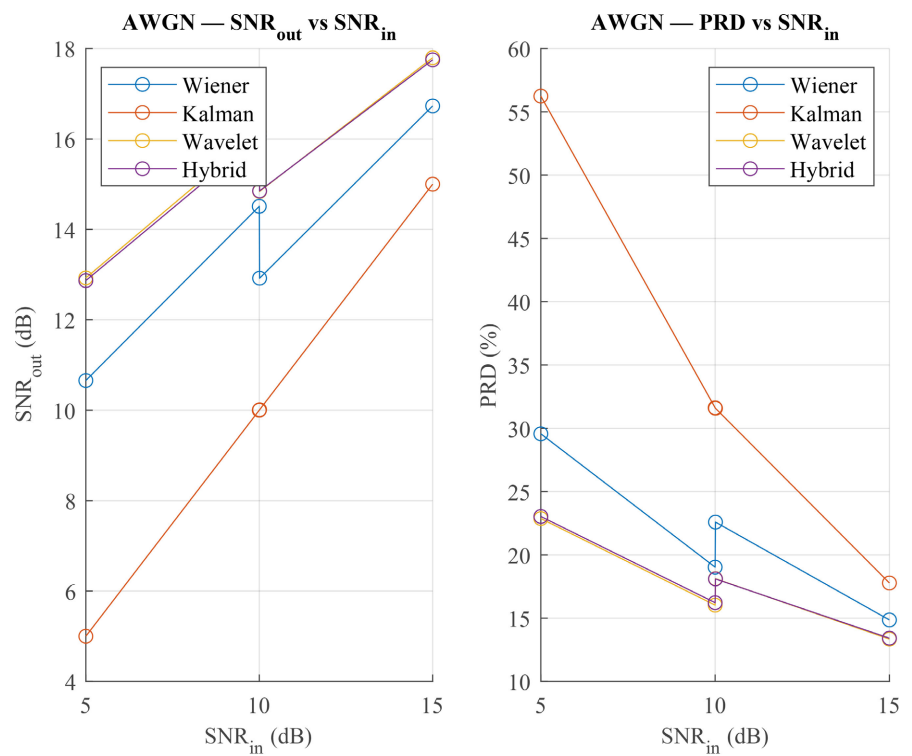


Figure 3. Evolution of SNR_{out} and PRD (%) as a function of SNR_{in}.

Simulation results, based on the performance indicators of the denoising techniques, show that the wavelet-based and hybrid methods are the most suitable for AWGN conditions. This trend supports recent findings [18] [24] which demonstrate the effectiveness of hybrid approaches integrating wavelet transforms to mitigate the impact of additive Gaussian noise affecting the entire ECG signal bandwidth.

3.1.3. Baseline Wander (BLW)

The results presented in **Table 3** indicate that the Kalman filter, combined with low-frequency modeling (<0.5 Hz), is particularly effective for removing baseline drift. Signals processed using either the Kalman filter or the hybrid approach exhibit a reduction in low-frequency energy exceeding 80% for baseline drift amplitudes ranging from 0.05 to 0.12. These findings confirm the relevance of adaptive state-space estimation for suppressing slowly varying disturbances while limiting distortion of clinically relevant ECG components.

Table 3. Results for different baseline drift amplitudes ($bw_{amp} = 0.05, 0.10, 0.12$).

Record	bw_{amp} (dB)	Method	SNR (dB)	Gain SNR (dB)	MSE	PRD (%)	LF < 0.5 Hz (%)
103	0.05	Wiener	7.84	-0.83	1.51e-03	40.57	13.09
		Kalman	7.33	-1.34	1.70e-03	43	0.62
		Wavelet	4.15	-4.52	3.54e-03	62.03	16.16
		Hybrid	8.21	-0.46	1.39e-03	38.86	1.09
	0.10	Wiener	2.46	-0.18	5.22e-03	75.32	23.61
		Kalman	6.77	4.12	1.93e-03	45.86	2.08
		Wavelet	1.01	-1.64	7.29e-03	89.02	27.43
		Hybrid	7.01	4.37	1.83e-03	44.6	3.57
	0.12	Wiener	0.95	-0.12	7.39e-03	89.66	27.38
		Kalman	6.47	5.41	2.07e-03	47.45	2.89
		Wavelet	-0.14	-1.2	9.49e-03	101.57	31.12
		Hybrid	6.44	5.38	2.09e-03	47.63	4.9
105	0.05	Wiener	9.48	-0.85	1.52e-03	33.56	13.05
		Kalman	4.45	-5.88	4.84e-03	59.9	0.93
		Wavelet	4.33	-6	4.98e-03	60.76	18.58
		Hybrid	5.89	-4.44	3.47e-03	50.75	1.46
	0.10	Wiener	4.11	-0.2	5.24e-03	62.32	21.15
		Kalman	4.27	-0.04	5.05e-03	61.19	2.22
		Wavelet	1.89	-2.42	8.73e-03	80.45	27.53
		Hybrid	5.41	1.1	3.88e-03	53.66	3.46
	0.12	Wiener	2.59	-0.13	7.42e-03	74.18	24.44
		Kalman	4.16	1.43	5.18e-03	61.96	2.95

Continued

121	0.05	Wavelet	0.91	-1.81	1.09e-02	90.01	30.73
		Hybrid	5.14	2.42	4.13e-03	55.32	4.55
		Wiener	7.33	-0.06	1.27e-03	42.98	36.04
		Kalman	1.25	-6.14	5.15e-03	86.6	3.15
		Wavelet	6.38	-1.01	1.58e-03	47.95	38.47
		Hybrid	1.46	-5.94	4.90e-03	84.54	4.95
	0.10	Wiener	1.39	0.01	4.99e-03	85.25	40.57
		Kalman	1.06	-0.31	5.37e-03	88.51	8.34
		Wavelet	1.1	-0.28	5.33e-03	88.12	42.33
		Hybrid	1.09	-0.28	5.34e-03	88.2	12.29
	0.12	Wiener	-0.19	0.02	7.17e-03	102.2	42.11
		Kalman	0.95	1.16	5.51e-03	89.6	10.88
		Wavelet	-0.4	-0.19	7.53e-03	104.75	43.59
		Hybrid	0.89	1.1	5.59e-03	90.27	15.58

With very low percentages (0.62% - 10.88%) of residual LF energy after de-noising (see **Figure 4**), the Kalman filter clearly stands out as the most effective method for suppressing undesirable low-frequency components, as baseline drift is almost entirely removed. This demonstrates strong preservation of the clinical integrity of the ECG signal, particularly the ST segments and T waves, whose components also partially lie within the low-frequency range.

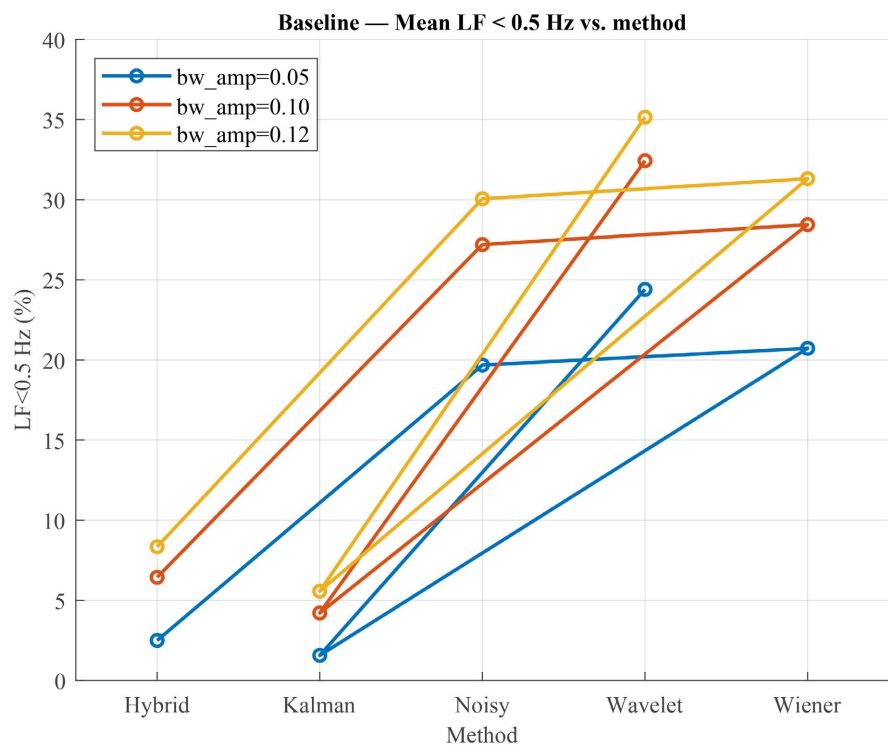


Figure 4. Residual low-frequency energy rate (LF < 0.5 Hz) for $bw_{amp} = 0.05, 0.10, \text{ and } 0.12$.

The hybrid Wavelet-Kalman approach achieves comparable low-frequency attenuation while providing improved preservation of QRS waveform morphology. These findings are consistent with previous studies [19] [25], which highlight the relevance of adaptive state-space models for slowly varying and quasi-deterministic components. Moreover, the spectral analyses confirm strong attenuation of frequencies below 0.5 Hz, supporting the effectiveness of Kalman-based modeling for baseline wander suppression.

3.1.4. Electromyographic (EMG) Noise

EMG noise, which is nonstationary and distributed over the 20 - 100 Hz frequency band, is particularly well handled by the wavelet-based method. For the three recordings (see **Table 4**), the wavelet approach achieves SNR gains ranging from 0.91 to 15.09 dB and yields the lowest PRD (7.24%), indicating minimal information loss and superior ECG signal reconstruction. The Wiener filter appears less effective under these conditions, while the hybrid approach essentially reduces to the performance of the standalone wavelet method. This result is consistent with the proposed noise-specific framework, in which Kalman filtering is intentionally omitted for EMG interference because its local-state model is not well suited to broadband high-frequency disturbances. Therefore, the hybrid configuration naturally converges to the standalone wavelet solution. The Kalman filter, designed for slow dynamics, remains ineffective against broadband high-frequency noise.

Table 4. Performance results for EMG noise (20 - 100 Hz).

Record	SNR_IN (dB)	Method	SNR_OUT (dB)	Gain SNR (dB)	MSE	PRD (%)
103	5	Wiener	13.06	8.06	4.55e-04	22.24
		Kalman	5	0	2.91e-03	56.22
		Wavelet	12.59	7.58	5.07e-04	23.48
		Hybrid	12.59	7.58	5.07e-04	23.48
	10	Wiener	17.63	7.62	1.59e-04	13.14
		Kalman	10	0	9.20e-04	31.62
		Wavelet	14.73	4.73	3.10e-04	18.35
		Hybrid	14.73	4.73	3.10e-04	18.35
	15	Wiener	21.55	6.55	6.43e-05	8.36
		Kalman	15	0	2.91e-04	17.78
		Wavelet	15.92	0.91	2.36e-04	16
		Hybrid	15.92	0.91	2.36e-04	16
105	5	Wiener	12.74	7.73	7.18e-04	23.07
		Kalman	5.01	0	4.26e-03	56.2
		Wavelet	15.08	10.08	4.19e-04	17.62
		Hybrid	15.08	10.08	4.19e-04	17.62

Continued

121	10	Wiener	16.71	6.71	2.87e-04	14.6
		Kalman	10	0	1.35e-03	31.61
		Wavelet	16.24	6.24	3.20e-04	15.41
		Hybrid	16.24	6.24	3.20e-04	15.41
	15	Wiener	20.55	5.54	1.19e-04	9.39
		Kalman	15	0	4.26e-04	17.77
		Wavelet	17.36	2.35	2.48e-04	13.56
		Hybrid	17.36	2.35	2.48e-04	13.56
	5	Wiener	13.63	8.63	2.97e-04	20.81
		Kalman	5.01	0	2.17e-03	56.2
		Wavelet	20.1	15.09	6.71e-05	9.89
		Hybrid	20.1	15.09	6.71e-05	9.89
	10	Wiener	17.62	7.62	1.19e-04	13.15
		Kalman	10.01	0	6.85e-04	31.6
		Wavelet	21.76	11.75	4.58e-05	8.17
		Hybrid	21.76	11.75	4.58e-05	8.17
	15	Wiener	21.54	6.53	4.81e-05	8.37
		Kalman	15.01	0	2.17e-04	17.77
		Wavelet	22.8	7.8	3.60e-05	7.24
		Hybrid	22.8	7.8	3.60e-05	7.24

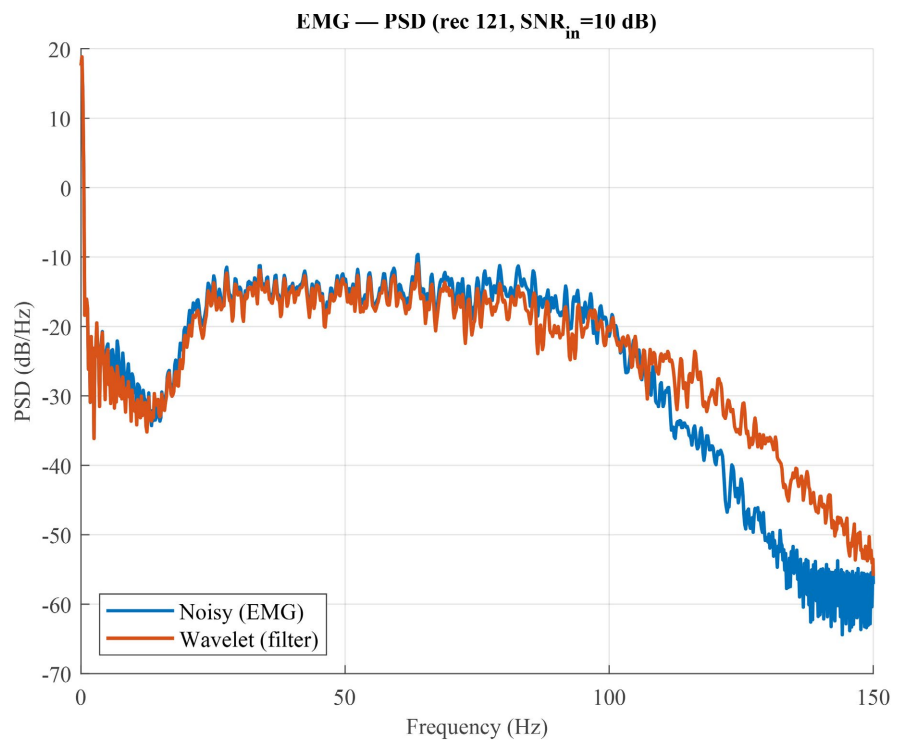


Figure 5. Power spectral density (PSD) of EMG noise before and after filtering.

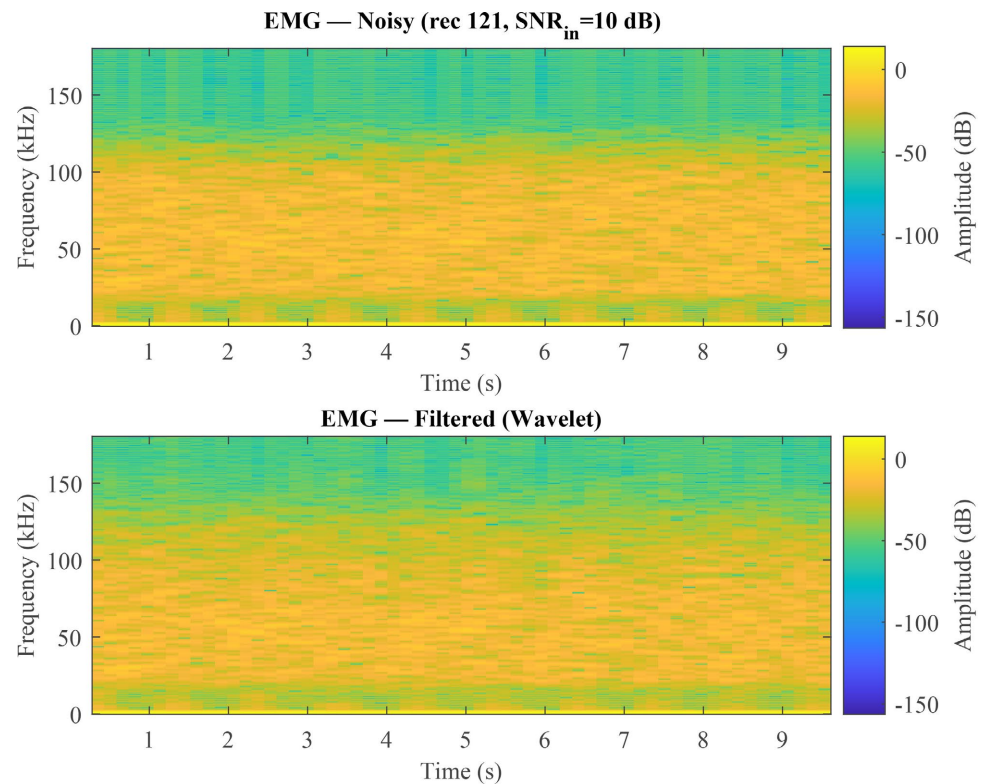


Figure 6. Time-frequency spectrogram of the contaminated and subsequently filtered ECG signal.

The time-frequency analyses (spectrograms and power spectral densities) presented in **Figure 5** and **Figure 6** reveal a significant reduction in energy within the 20 - 100 Hz frequency band. These findings are consistent with the studies of [13], [26] and [27], which emphasize that morphology-guided time-frequency approaches (P-QRS-T-oriented) constitute state-of-the-art references for electromyographic (EMG) noise suppression.

3.1.5. Power-Line Interference (50 Hz)

Power-line interference at 50 Hz (including its second harmonic) was simulated and effectively corrected using a sinusoidal Kalman filter specifically designed for this purpose. The results presented in **Table 5** indicate a substantial SNR gain (ranging from 14.62 to 16.1 dB) following Kalman filtering, with further improvement observed in the hybrid K → W configuration. The latter demonstrates superior performance compared with the W → K hybrid strategy (see **Figure 7** and **Figure 8**).

Table 5. Results for power-line interference.

Record	SNR_IN (dB)	Method	SNR_OUT (dB)	Gain SNR (dB)	MSE	PRD (%)
103	5	Wiener	13.91	8.91	3.74e-04	20.17
		Kalman	21.01	16.01	7.29e-05	8.9
		Wavelet	15.49	10.48	2.60e-04	16.82

Continued

105	10	Hybrid W → K	15.42	10.41	2.64e−04	16.95
		Hybrid K → W	26.1	21.1	2.26 e−05	4.95
		Wiener	17.3	7.3	1.71e−04	13.65
		Kalman	25.64	15.63	2.51e−05	5.23
		Wavelet	18.42	8.41	1.32e−04	12
		Hybrid W → K	18.27	8.27	1.37e−04	12.2
	15	Hybrid K → W	27.52	17.52	1.63e−05	4.21
		Wiener	20.51	5.51	8.18e−05	9.43
		Kalman	29.62	14.62	1.00e−05	3.3
		Wavelet	21.14	6.13	7.08e−05	8.77
		Hybrid W → K	20.88	5.88	7.51e−05	9.04
		Hybrid K → W	28.22	13.21	1.39e−05	3.88
	5	Wiener	12.89	7.89	6.93e−04	22.66
		Kalman	21.05	16.05	1.06e−03	8.86
		Wavelet	19.11	14.1	1.66e−04	11.09
		Hybrid W → K	19.01	14	1.70e−04	11.21
		Hybrid K → W	28.25	23.25	2.02e−05	3.87
	10	Wiener	16.19	6.19	3.24e−04	15.5
		Kalman	25.75	15.75	3.59e−05	5.16
		Wavelet	20.02	10.02	1.34e−04	9.97
		Hybrid W → K	19.9	9.89	1.38e−04	10.12
		Hybrid K → W	28.84	18.83	1.76e−05	3.61
	15	Wiener	19.51	4.5	1.51e−04	10.59
		Kalman	29.91	14.91	1.38e−05	3.19
		Wavelet	21.7	6.69	9.12e−05	8.22
		Hybrid W → K	21.51	6.5	9.53e−05	8.41
		Hybrid K → W	29.23	14.22	1.61e−05	3.46
121	5	Wiener	15.46	10.46	1.95e−04	16.87
		Kalman	21.11	16.1	5.32e−05	8.81
		Wavelet	24.79	19.78	2.28e−05	5.76
		Hybrid W → K	24.56	19.55	2.40e−05	5.92
		Hybrid K → W	31.97	26.97	4.36e−06	2.52
	10	Wiener	18.68	8.68	9.29e−05	11.64
		Kalman	25.9	15.9	1.76e−05	5.07
		Wavelet	24.79	14.78	2.28e−05	5.76
		Hybrid W → K	24.56	14.56	2.40e−05	5.91
		Hybrid K → W	32.04	22.03	4.29e−06	2.5
	15	Wiener	21.9	6.89	4.43e−05	8.04
		Kalman	30.33	15.32	6.36e−06	3.05

Continued

Wavelet	24.8	9.8	2.27e-05	5.75
Hybrid W $\rightarrow$ K	24.57	9.57	2.39e-05	5.91
Hybrid K $\rightarrow$ W	32.2	17.2	4.13e-06	2.45

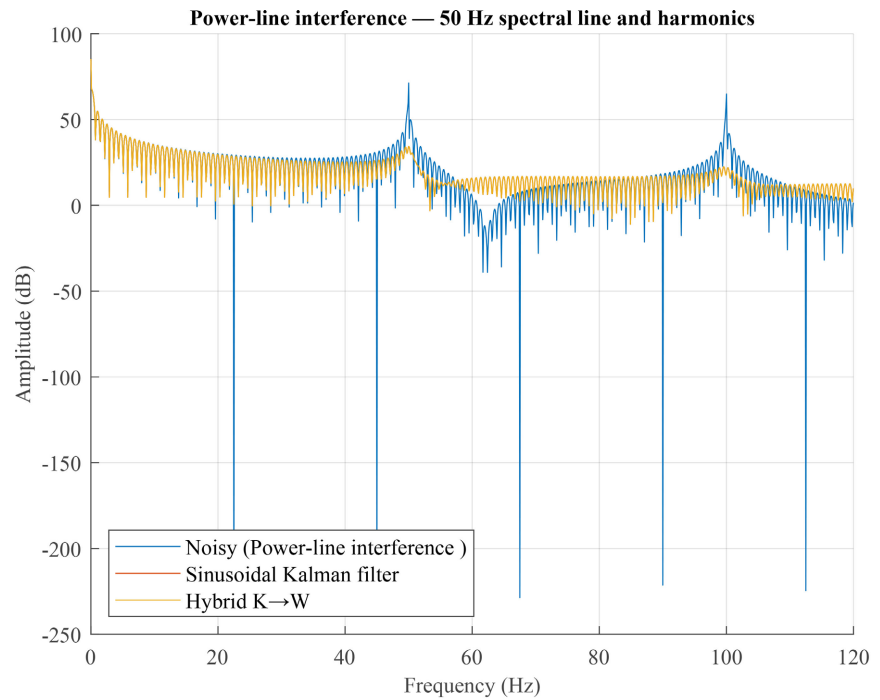


Figure 7. Power spectrum around 50 Hz before and after filtering.

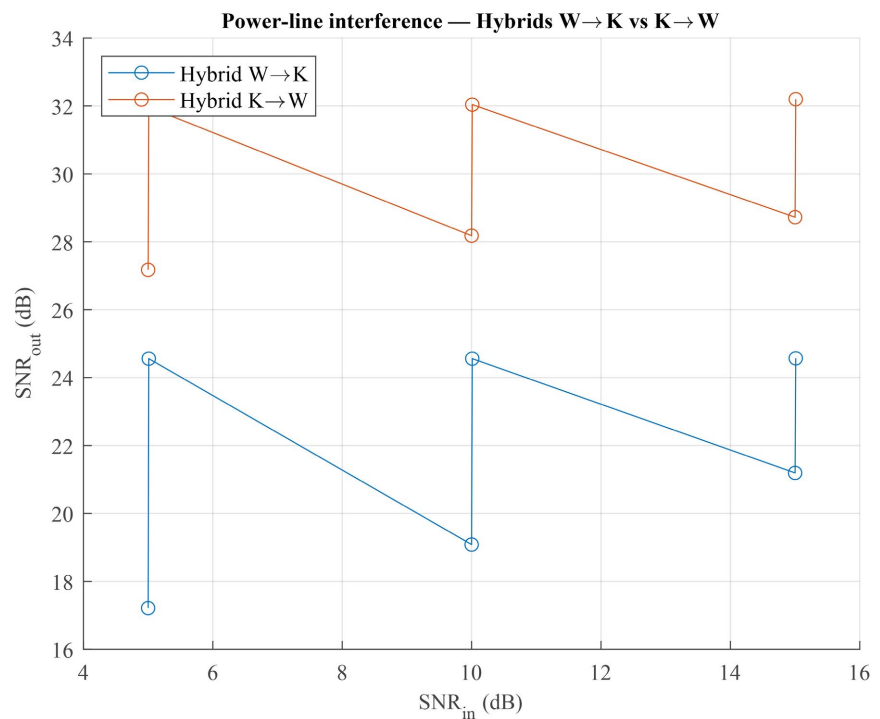


Figure 8. Comparison between hybrid strategies W $\rightarrow$ K and K $\rightarrow$ W.

The results indicate that the $K \rightarrow W$ hybrid approach is more effective in attenuating power-line interference than the standalone Kalman filter, as it first suppresses the harmonic component before applying wavelet-based smoothing. These findings are consistent with recent studies [16] [25] which highlight the superiority of adaptive filters over notch filters in the presence of frequency drifts, particularly when combined with Kalman filtering. The spectra shown in **Figure 7** demonstrate the near-complete removal of the 50/100 Hz peaks.

3.1.6. Comparative Synthesis

The four investigated scenarios, additive white Gaussian noise (AWGN), baseline wander (BLW), electromyographic interference (EMG), and power-line interference (50 Hz) enabled a comprehensive evaluation of the robustness and complementarity of the tested filtering methods: Wiener, Kalman, Wavelet, and Hybrid (W-K and K-W). The results show that:

- Wavelet-based filtering performs well for high-frequency noise such as EMG;
- Kalman filtering is effective for low-frequency noise such as baseline wander;
- The proposed hybrid method provides more consistent performance across different noise types.

The hybrid approach achieves a good balance between noise reduction and signal preservation.

3.2. Discussion

The experimental results indicate that no single denoising method is optimal for all considered noise conditions. Wavelet-based methods are particularly effective for non-stationary high-frequency noise, such as EMG-like interference, owing to their time-frequency localization capabilities. In contrast, Kalman filtering provides greater benefits for low-frequency disturbances, such as baseline wander, through recursive estimation and dynamic signal modeling.

Quantitative results confirm this complementarity. For example, the Wavelet method achieves an SNR gain of 9.93 dB in the presence of high-frequency noise, whereas Kalman filtering achieves a gain of 5.41 dB for low-frequency disturbances. The proposed noise-specific framework exploits these complementary properties by tailoring the processing configuration to the considered disturbance. These findings are consistent with recent hybrid ECG denoising studies [13] [19] [26] based on DWT, VMD, and adaptive filtering, which also reported improved robustness under heterogeneous noise conditions.

The performance of the proposed framework can be attributed to the selective use of wavelet-domain processing and Kalman-based estimation according to the spectral and temporal characteristics of the considered disturbance. However, the framework does not systematically outperform standalone Wavelet filtering in the presence of predominantly high-frequency noise, indicating that the benefit of hybrid processing depends on the disturbance characteristics and model configuration. This behavior is particularly evident under AWGN and EMG-like interference, for which wavelet-domain processing provides the primary denoising

mechanism owing to its multiresolution representation of non-stationary signals. Conversely, for low-frequency baseline wander and narrowband power-line interference, Kalman-based state estimation provides additional benefits by exploiting the temporal dynamics of these disturbances. These observations support the use of noise-specific processing configurations rather than a fixed Wavelet-Kalman filtering sequence.

Although computational complexity was not quantitatively benchmarked, the individual processing stages rely on finite-level wavelet decomposition and recursive Kalman estimation. Moreover, the noise-specific configurations activate different processing stages according to the considered disturbance. Nevertheless, because runtime, memory consumption, processing latency, and embedded implementation were not evaluated in the present study, the computational suitability of the framework for real-time wearable applications remains to be experimentally established.

Despite these findings, the present study has several limitations. The evaluation was conducted using selected recordings from a public ECG database under controlled synthetic noise conditions and did not include validation on real-time embedded hardware or wearable ECG acquisition systems. A further limitation is that the disturbance type was known *a priori* in the present controlled experiments; therefore, the noise-specific processing paths were evaluated under an oracle-configured setting rather than being selected by an automatic noise-identification module. Future work will extend the evaluation to real-world and mixed-noise conditions, investigate automatic noise characterization and configuration selection for ECG signals affected by unknown or mixed real-world disturbances, and assess computational cost and real-time feasibility on embedded and wearable ECG monitoring systems.

4. Conclusions

This study proposed a noise-specific Wavelet-Kalman framework for ECG denoising under AWGN, baseline wander, EMG-like interference, and power-line interference. The results demonstrate that the relative effectiveness of Wavelet and Kalman filtering depends on the characteristics of the disturbance. Wavelet-based processing was particularly effective for high-frequency and non-stationary interference, whereas Kalman-based estimation provided additional benefits for low-frequency and narrowband disturbances. Consequently, hybrid processing did not systematically outperform standalone methods under all noise conditions, but provided advantages when the complementary properties of Wavelet and Kalman filtering were appropriately exploited.

The proposed framework achieved SNR improvements of up to 26.97 dB and PRD values as low as 2.45% under the evaluated controlled conditions. However, its computational suitability for real-time ECG monitoring has not yet been established. Future work will therefore investigate automatic noise identification, real-world and mixed-noise conditions, and quantitative evaluation of runtime,

memory requirements, and processing latency on embedded and wearable ECG systems.

Data Availability

The data that support the conclusions of this study are freely available in Physio-Net at <https://physionet.org/content/mitdb/>, reference numbers (103, 105 and 121).

Author Contributions

Conceptualization, M.L.M., M.J., A.O.C., N.N. and M.J.; methodology, M.L.M., M.J., A.O.C., N.N. and M.J.; software, M.L.M.; validation, M.L.M., M.J. and M.J., formal analysis, M.L.M.; investigation, M.L.M.; resources, M.L.M.; data curation, M.L.M.; writing—original draft preparation, M.L.M. and M.J.; writing—review and editing, M.L.M.; visualization, M.L.M., M.J. and A.O.C.; supervision, M.J. and A.O.C. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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