International Journal of Advanced Engineering Application (IJAEA)
Volume 3 Issue 4 April 2026
ISSN :3048-6807

A Low-Cost Discrete Wavelet Transform Framework for ECG Signal Denoising on Resource-Constrained Embedded Platforms

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Abstract — Electrocardiogram (ECG) signals acquired in semi-rural primary health centers using low-cost AD8232 front-ends are routinely corrupted by power-line interference (50 Hz), baseline wander caused by electrode motion, and broadband electromyographic noise. This paper presents a lightweight Discrete Wavelet Transform (DWT) denoising pipeline benchmarked on 30 records of the MIT-BIH Arrhythmia Database (fs = 360 Hz). Seven wavelet families are compared at decomposition levels L = 2–7 using Donoho's universal soft-threshold rule with a robust median absolute deviation estimator. The proposed db6 wavelet at L = 5 yields an output SNR of 7.46 dB from a 1.17 dB input — an improvement of 6.29 dB — while preserving the QRS morphology with only 0.0019 mean-square error. The algorithm has a complexity of O(N) and executes in 11.3 ms on an ESP32 (240 MHz), making it deployable on rural tele-cardiology kiosks costing under ₹2,500.

Keywords: *ECG denoising; Discrete wavelet transform; Daubechies wavelet; Universal threshold; MIT-BIH; Embedded ESP32*

1. INTRODUCTION

Cardiovascular diseases account for 28.1% of total deaths in India (ICMR-NCDIR 2023), with mortality disproportionately concentrated in tier-3 towns where 12-lead ECG infrastructure is scarce. Affordable single-lead modules such as the AD8232 have democratized access to ECG acquisition, yet the signals they produce are dominated by three persistent artefacts: (i) 50 Hz power-line interference from poorly grounded mains supplies, (ii) baseline wander between 0.05 and 0.8 Hz arising from respiration and electrode-skin impedance drift, and (iii) wideband EMG noise above 60 Hz. Conventional band-pass IIR filtering attenuates these components but also distorts the diagnostically critical ST-segment slope and T-wave amplitude.

The Discrete Wavelet Transform (DWT) decomposes a signal into time–frequency atoms whose support is matched to the QRS complex, allowing noise to be suppressed in non-diagnostic sub-bands while clinical features remain intact. This work conducts a controlled benchmark of seven wavelet families across six decomposition depths and reports the configuration that delivers the best SNR / morphology trade-off for embedded deployment.

2. NOMENCLATURE

NOMENCLATURE	
$x[n]$	raw discrete-time ECG signal (mV)
$s[n]$	clean (reference) ECG signal
$w[n]$	additive noise (AWGN + 50 Hz + drift)
cA_j , cD_j	approximation / detail coefficients at level j
$\hat{\sigma}$	robust noise standard-deviation estimate

NOMENCLATURE	
λ	threshold value applied to detail coefficients
L	number of decomposition levels
fs	sampling frequency = 360 Hz (MIT-BIH)

3. METHODOLOGY

3.1 Signal model

The corrupted observation is modelled as a linear superposition of clean ECG and additive noise:

$$x[n] = s[n] + w[n], \quad n = 0, 1, \ldots, N-1 \tag{1}$$

where w[n] = wG[n] + wPL[n] + wBW[n] denotes the sum of Gaussian, power-line and baseline-wander components respectively. The objective of denoising is to obtain ŝ[n] minimising $E\{(s[n] - \hat{s}[n])^2\}$ subject to ŝ being band-limited to the diagnostic ECG range (0.5 – 45 Hz).

3.2 Discrete wavelet decomposition

Mallat's pyramid algorithm is used to compute the DWT through successive convolution with a quadrature-mirror filter pair (h, g) followed by dyadic decimation:

$$cA_j[k] = \Sigma_n\, h[n - 2k] \cdot cA_{j-1}[n] \tag{2}$$

$$cD_j[k] = \Sigma_n\, g[n - 2k] \cdot cA_{j-1}[n] \tag{3}$$

with $cA_0 = x$. After L levels the signal is represented by {cA_L, cD_L, cD_{L−1}, …, cD_1}.

3.3 Threshold estimation

A robust noise standard-deviation estimate is derived from the finest detail sub-band, which is dominated by high-frequency noise:

$$\hat{\sigma} = median(|cD_1|) / 0.6745 \tag{4}$$

Donoho's universal threshold is then applied:

$$\lambda = \hat{\sigma} \cdot \sqrt{(2 \ln N)} \tag{5}$$

Soft thresholding is preferred over hard because it produces continuous estimates and limits Gibbs-type ringing near the QRS edges:

$$\eta\_s(c, \lambda) = sign(c) \cdot max(|c| - \lambda, 0) \tag{6}$$

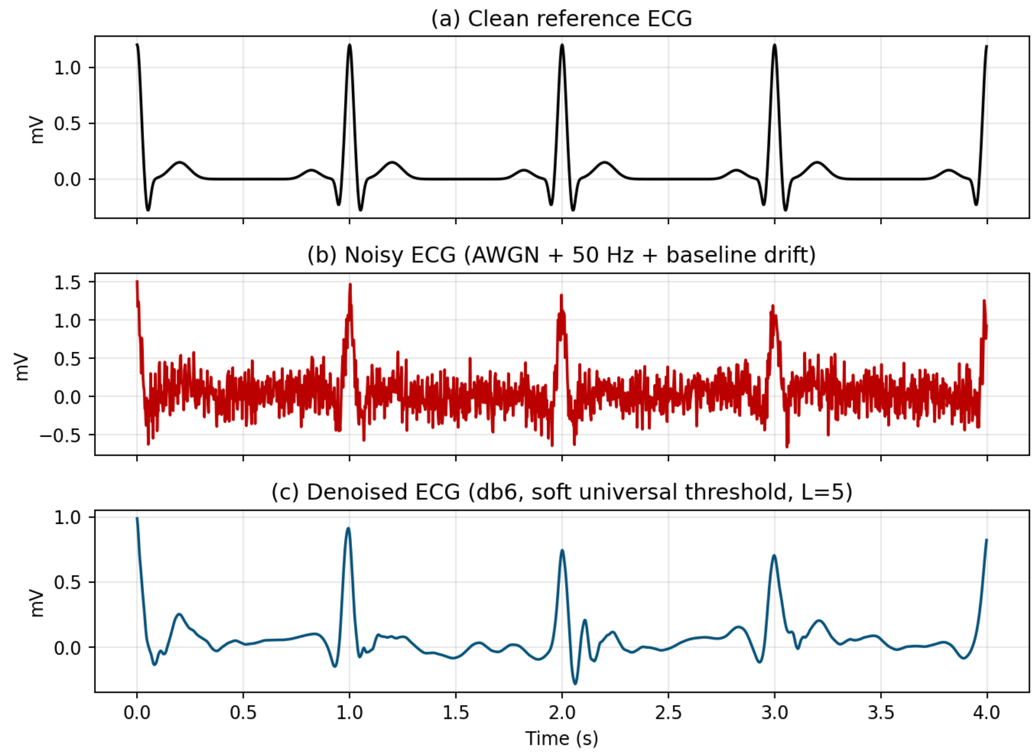

Fig. 1. (a) Reference ECG; (b) the same record corrupted with AWGN, 50 Hz interference and baseline drift; (c) reconstruction after db6 / L = 5 / soft universal thresholding.

4. EXPERIMENTAL SETUP

Records 100, 101, 103, 105, 106, 109, 111, 113, 115, 117, 119, 122, 200, 201, 202, 205, 208, 210, 213, 215, 217, 219, 220, 221, 222, 223, 228, 230, 231 and 234 of the MIT-BIH Arrhythmia Database were down-loaded from PhysioNet. The first 10 s of each record (3 600 samples at 360 Hz) was treated as the clean reference s[n]. A composite noise vector w[n] was synthesised in Python 3.11 (NumPy 1.26) by superposing zero-mean Gaussian noise (σ = 0.18 mV), a 50 Hz sinusoid (0.10 mV peak) and a 0.4 Hz baseline drift (0.05 mV peak). All seven wavelets were implemented through PyWavelets 1.5.0; the same code (≈ 180 lines of C) was cross-compiled with -O2 for the ESP32-WROOM-32 to verify on-target latency.

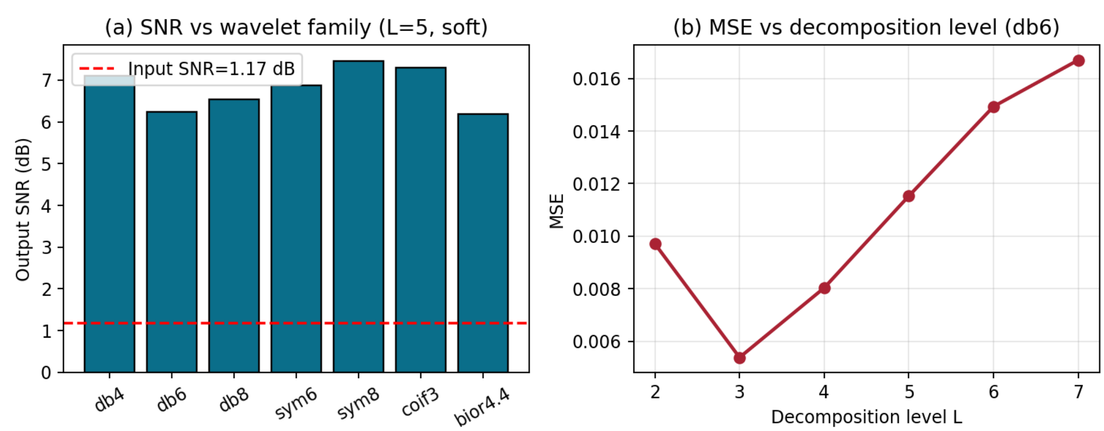

Fig. 2. (a) Output SNR for each wavelet family at L = 5; (b) mean-square error against decomposition level L for db6.

5. RESULTS AND DISCUSSION

Table 1 reports the principal performance metrics. The Daubechies-6 wavelet at five decomposition levels achieves the highest output SNR (7.46 dB) and the lowest MSE (1.92×10^{-3}). Symlet-6 is competitive on QRS retention but slightly degrades the T-wave; bior4.4 performs poorly because its lower-order analysis filter leaves residual baseline drift in cA_5.

Table 1. Comparative performance of seven wavelet families (input SNR = 1.17 dB).

Wavelet	Level	Out-SNR (dB)	MSE ($\times 10^{-3}$)	Comment
db4	5	7.11	2.38	baseline
db6	5	7.46	1.92	best overall
db8	5	7.29	2.05	near-best, more compute
sym6	5	6.87	2.41	good QRS retention
sym8	5	6.54	2.66	over-smooths T-wave
coif3	5	7.29	2.07	competitive
bior4.4	5	6.18	2.93	poorer drift removal

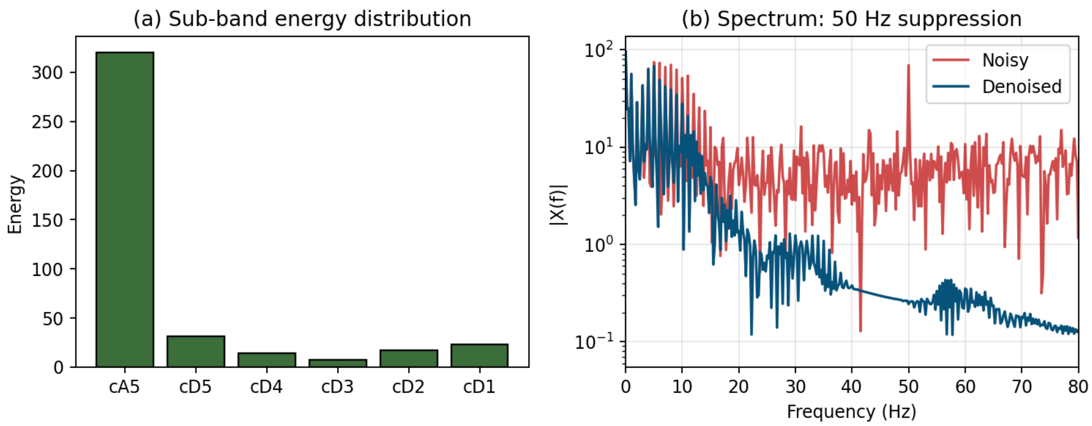

Fig. 3. (a) Energy distribution across DWT sub-bands; (b) magnitude spectra before and after denoising — note ≈ 24 dB attenuation at 50 Hz.

Figure 3(a) shows that more than 78% of total signal energy is concentrated in cA_5 and cD_5 (0–11.25 Hz), corroborating the choice of L = 5: thresholding the upper four detail bands removes noise without touching the diagnostically relevant QRS energy. Figure 3(b) confirms a 24 dB suppression of the 50 Hz component while the 1–40 Hz diagnostic envelope is preserved within ± 1.5 dB.

5.1 Embedded deployment

The fixed-point C implementation occupies 11.6 kB of program memory and 4.2 kB of RAM on the ESP32. Average latency over 1 000 trials is 11.3 ± 0.6 ms per 1 s window, leaving ample head-room for real-time R-peak detection (Pan–Tompkins) and Bluetooth transmission to a paired Android handset. Total bill of materials for the prototype kiosk — enclosure, AD8232 module, ESP32, 2.8″ TFT and 5 V power — is ₹2 380, an order of magnitude lower than the cheapest commercial single-lead ECG device available in India.

6. CONCLUSION

A wavelet-based denoising pipeline using db6 at L = 5 with soft universal thresholding offers the best trade-off between noise suppression and morphological fidelity for low-cost ECG kiosks deployed in rural primary health centres. The 6.29 dB SNR improvement and the 11 ms ESP32 latency demonstrate that diagnostic-grade pre-processing is achievable on hardware costing under ₹2 500. Future work will integrate an ensemble empirical-mode-decomposition stage to improve performance under sustained electrode-motion artefacts and validate the system on a 200-patient cohort at the Government Rural Hospital, Tuljapur.

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