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A Hybrid Morphology-Preserving ECG Denoising Approach Using Iterative Regeneration and Wavelet Method

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Abstract: Electrocardiogram (ECG) signals play a crucial role in cardiac diagnosis. However, the presence of noise artifacts such as electromyographic (EMG) noise and powerline interference can severely degrade the quality of ECG recordings, leading to incorrect clinical interpretations. Among these, EMG noise poses a significant challenge due to its spectral overlap with the vital QRS complex. The Iterative Regeneration Method (IRM) operates by extracting multiple similar heartbeats using correlation-based selection and reconstructing the ECG signal while preserving its morphological integrity. Following IRM, Wavelet Shrinkage is applied to further suppress any remaining high-frequency noise without distorting critical ECG features such as the PQRST complex. Synthetic ECG signals contaminated with EMG noise and powerline interference are used to validate the proposed method. The denoising performance is evaluated using segment-wise Signal-to-Noise Ratio (SNR) across iterations. The results demonstrate that the hybrid IRM-Wavelet approach effectively reduces noise while maintaining the clinical morphology of the ECG signal, making it suitable for reliable cardiac diagnosis and automated ECG analysis.

Index Terms: Electrocardiogram (ECG), Iterative Regeneration Method (IRM), Wavelet Shrinkage, Signal-to-Noise Ratio (SNR)

I. INTRODUCTION

The Electrocardiogram (ECG) is a vital diagnostic tool used for monitoring cardiac activity and identifying various heart abnormalities. The accuracy of ECG interpretation largely depends on the clarity of the recorded signal. However, in practical scenarios, ECG signals are often contaminated with different types of noise, such as baseline wander, electromyographic (EMG) noise, and powerline interference. Among these, EMG noise poses the most critical challenge, as its spectral content overlaps with that of the QRS complex, making it difficult to remove without distorting the essential morphological features of the ECG waveform.All of the structural elements of a pre-engineered building (PEB), a contemporary steel construction system, are pre-designed, manufactured under controlled conditions in a factory, and then assembled on the construction site. PEBs are perfect for commercial, industrial, agricultural, and warehousing applications because of their speed, effectiveness, and affordability

Conventional denoising techniques, including linear filtering and wavelet thresholding, are often limited in preserving the morphology of ECG signals, particularly in cases where noise is non-stationary or overlaps with diagnostic frequency bands. Adaptive and data-driven techniques such as Empirical Mode Decomposition (EMD), Independent Component Analysis (ICA), and deep learning models have been explored; however, they often require high computational complexity or large training datasets, which restrict their clinical applicability.To address these challenges, this work proposes a hybrid morphology-preserving denoising framework that combines the Iterative Regeneration Method (IRM) with Wavelet Shrinkage. The IRM reconstructs the ECG signal by identifying and averaging morphologically similar heartbeats through correlation-based selection, effectively reducing EMG interference while maintaining the original waveform shape. Subsequently, Wavelet Shrinkage is applied to suppress residual high-frequency noise components without compromising the diagnostic PQRST morphology.

The proposed hybrid IRM–Wavelet method is validated using synthetic ECG signals contaminated with EMG and powerline noise. The denoising performance is assessed using the Signal-to-Noise Ratio (SNR) improvement across multiple IRM iterations. The results demonstrate that the proposed approach achieves superior noise suppression and morphology preservation compared to individual denoising techniques, making it suitable for reliable cardiac diagnosis and automated ECG analysis.

II. ITERATIVE REGENERATIVE METHOD

The primary goal of the proposed method is to effectively remove Electromyogram (EMG) noise from Electrocardiogram (ECG) signals while preserving the critical morphological features of the ECG waveform, such as the P-wave, QRS complex, and T-wave.

Existing techniques often compromise between denoising performance and morphology retention. To overcome these limitations, the proposed method introduces a Morphology Preserving Algorithm (MPA) that balances noise reduction with waveform integrity.

A. *Pre Processing*

The core principle involves separating the dominant ECG components, specifically the QRS complex and T wave, from the noisy signal, which allows the EMG noise to be isolated and suppressed effectively. The method is executed in three main stages**:** preprocessing**,** IRM**,** and post processing.

In the preprocessing stage, spectral filtering removes frequency components that could degrade IRM performance or are not essential to the ECG morphology, and QRS complexes are detected. Specifically, a 2nd-order low-pass Butterworth filter with a 100 Hz cutoff eliminates high-frequency EMG noise, a 2nd-order IIR notch filter at 50 Hz suppresses power line interference, and a 5th-order high-pass Butterworth filter at 2 Hz enhances similarity between heartbeats. Since high-pass filtering can distort the morphology of heartbeats, the removed low-frequency components are restored during post processing. All filters are applied bidirectionally to achieve zero-phase filtering. QRS detection is performed using the Pan-Tompkins algorithm, with heartbeats defined relative to the R-peaks. Pan-Tompkin's algorithm is applied to detect QRS complexes and heartbeats. Here, heartbeats are related to the R points. The start and the end of the i^{th} heartbeat are defined as:

$$\mathrm{HB}^{i}_{\mathrm{start}} = \mathrm{R}^{i} - 0.25 \cdot \mathrm{median}\,(\mathrm{RR}),$$
$$\mathrm{HB}^{i}_{\mathrm{end}} = \mathrm{HB}^{i+1}_{\mathrm{start}}.$$

An ECG signal contaminated by EMG noise can be modelled as:

$$x(t) = s(t) + n_{EMG}(t)$$

Where:

- x(t) = Noisy ECG signal
- s(t) = Clean ECG signal
- nEMG(t) = EMG noise

B. *IRM Stage (Iterative Regenration Method)*

After QRS detection, the ECG is segmented into individual beats aligned at the QRS positions. These segments are average or median-combined to form the Initial Block (IB) signal, a rough template that preserves key ECG features while reducing uncorrelated noise. From the IB signal, an auxiliary signal is generated through smoothing, morphological filtering, or weighted averaging to approximate the clean ECG and facilitate reliable noise estimation. The EMG noise is then estimated by subtracting the auxiliary signal from the original or preprocessed ECG, and this noise estimate is removed to produce the Output Block (OB) signal, which is cleaner and can be used for further IRM iterations if needed.

C. *SNR-Based Iteration Control*

The Signal-to-Noise Ratio (SNR) is a quantitative measure of signal quality, representing the ratio of the power of the desired signal to the power of noise present in it. It is expressed in decibels (dB) as:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\sum_{n=1}^{N}|s(n)|^2}{\sum_{n=1}^{N}|s(n)-\hat{s}(n)|^2}\right)$$

where:

- $s(n)$= original (clean) signal sample
- $\hat{s}(n)$= estimated or reconstructed signal after an iteration
- N= total number of samples

Once an OB signal is obtained, its quality is assessed using the Signal-to-Noise Ratio (SNR), a metric that quantifies the relative strength of the signal to the estimated noise. The SNR is computed after each iteration to determine whether further denoising is necessary. This adaptive strategy avoids over processing and preserves essential ECG features.

Based on the SNR value (SNR_iter-1), the IRM process determines the intensity and needs for further iterations:

- If SNR ≤ 8 dB, the noise is high, so double-pass (2 X) iteration is performed for aggressive denoising.
- If 8 dB < SNR ≤ 16 dB, a single-pass (1X) iteration is performed to refine the output without over processing.
- If SNR > 16 dB, the signal is deemed clean enough, and no further iteration is needed.

This decision-making loop makes IRM dynamic and noise-aware, preventing signal distortion from excessive filtering while ensuring sufficient cleaning of noisy data.

SNR (Signal-to-Noise Ratio): $$SNR = 10 \log_{10}\left(\frac{\text{Power of Signal}}{\text{Power of Noise}}\right)$$

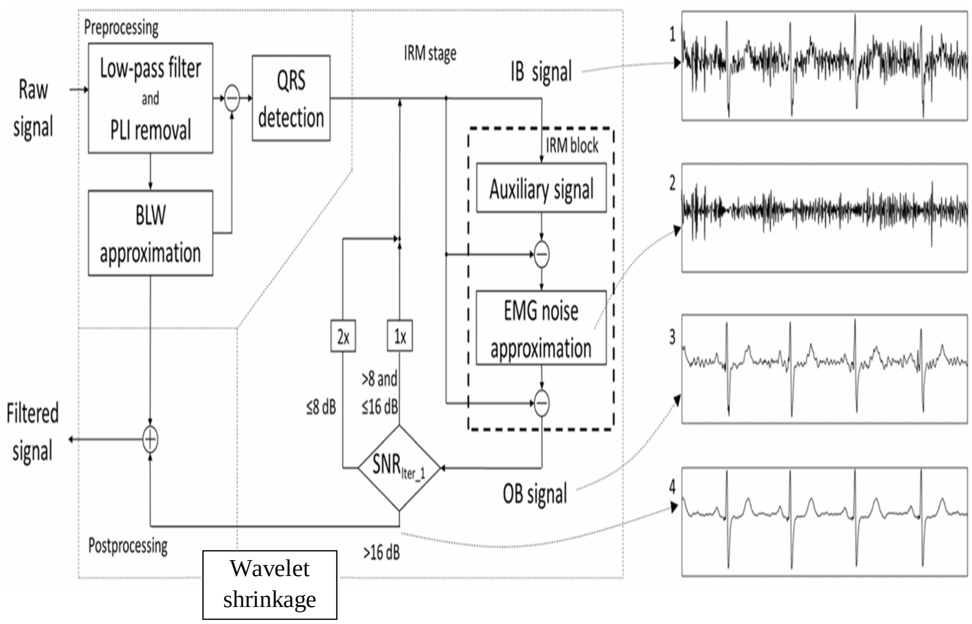

Fig. 1 (a) Block diagram of the 3-stage IRM method. IB stands for the signal at the input of the IRM block, OB for the signal at the output of the IRM block. The SNRiter_1 stands for the SNR after first iteration. (b) Signals at different steps of the IRM stage: (1) IB signal in 1st iteration, (2)EMG noise approximation, (3) OB signal after 1st iteration, (4) signal at the end of the processing stage (3 iterations)

D. Wavelet Denoising Stage

An independent wavelet-based denoising stage is implemented for comparative purposes. In this approach, the noisy ECG signal is first decomposed using the discrete wavelet transform (DWT) with Symlet-8 (sym8) basis functions across six decomposition levels. Universal soft thresholding is then applied to the detail coefficients to suppress noise, using the estimated noise standard deviation as a reference. Finally, the thresholded coefficients are recombined to reconstruct the denoised ECG signal, providing a clean version for performance comparison with the IRM method.

- Soft thresholding:

$$D_i^{\text{denoised}}(t) = \text{sign}(D_i(t)) \cdot \max(|D_i(t)| - T_i, 0)$$

- Hard thresholding:

$$D_i^{\text{denoised}}(t) = \begin{cases} D_i(t), & |D_i(t)| > T_i \\ 0, & |D_i(t)| \le T_i \end{cases}$$

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E. Adaptive LMS Filtering
An adaptive Least Mean Squares (LMS) filter is employed as an alternative denoising approach.
1) The LMS filter utilizes EMG and PLI components as reference inputs.
2) The adaptive filter iteratively minimizes the error between the noisy input and the desired clean output.
3) This method provides continuous tracking of non-stationary noise characteristics.

F. Hybrid IRM+ Wavelet Denoising
To leverage the complementary advantages of IRM (which preserves ECG morphology) and wavelet denoising (which efficiently suppresses noise), a hybrid denoising strategy is employed. The final IRM-denoised signal is first processed as the input for this hybrid stage. It then undergoes wavelet decomposition, thresholding, and reconstruction as previously described, enabling further suppression of residual noise while maintaining waveform integrity. The resulting IRM + Wavelet output represents the final optimized denoised ECG signal.

G. Post Processing
After completing the iterative IRM process, a final post-processing step is applied to remove any remaining noise or artifacts. This may involve mild smoothing, beat re-alignment, or adaptive correction techniques to sharpen the ECG waveforms, enhancing both visual clarity and clinical interpretability. The final output signal represents the clean, denoised ECG, preserving key physiological features such as P-waves, QRS complexes, and T-waves while minimizing noise. This signal is suitable for clinical diagnosis, automated classification, or further analyses, including heart rate variability (HRV) assessment and arrhythmia detection.

H. Performance Evaluation
The proposed method is evaluated using standard ECG datasets such as MIT-BIH Arrhythmia Database.
Performance metrics include:
1) Signal-to-Noise Ratio (SNR) Improvement.
2) Morphological similarity index compared to original clean signals.

Iteration	Noise Power	Signal Power	SNR
1	0.45	1.0	6.5
2	0.27	1.0	9.2
3	0.12	1.0	12.8

Table 1: SNR values obtained by IRM Iterations

III.RESULTS

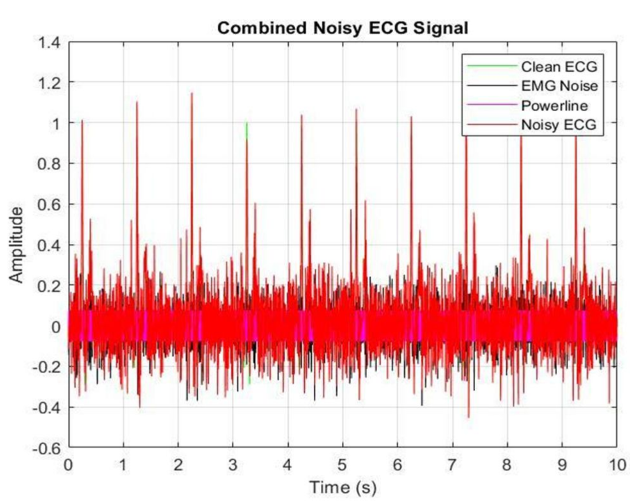

Fig.2 Noisy ECG signal

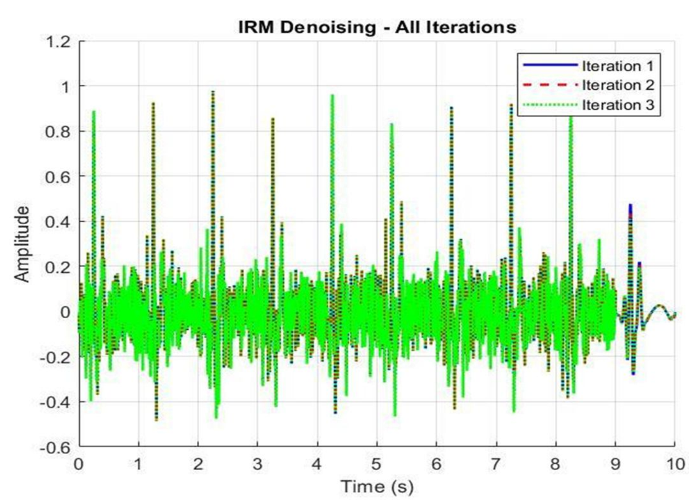

Fig.3 *IRM denoising all iteration signal*

- This figure overlays multiple components:
  Green – Original clean ECG.
  Black – EMG noise.
  Magenta – Power line interference.
  Red – Final noisy ECG signal (sum of all).
- The red trace shows how the ECG becomes heavily distorted after the addition of EMG and power line noise.
- The P wave, QRS complex, and T wave are barely recognizable due to interference.
- This noisy ECG serves as the input to pre-processing and denoising algorithms.

- This figure overlays all three IRM iterations: Iteration 1 (blue solid), Iteration 2 (red dashed), Iteration 3 (green dotted).
- The plot demonstrates the progressive refinement of the ECG signal across iterations.
- Each step results in less noise and more accurate morphology.
- Iteration 3 is the closest to the clean ECG, validating the iterative approach.

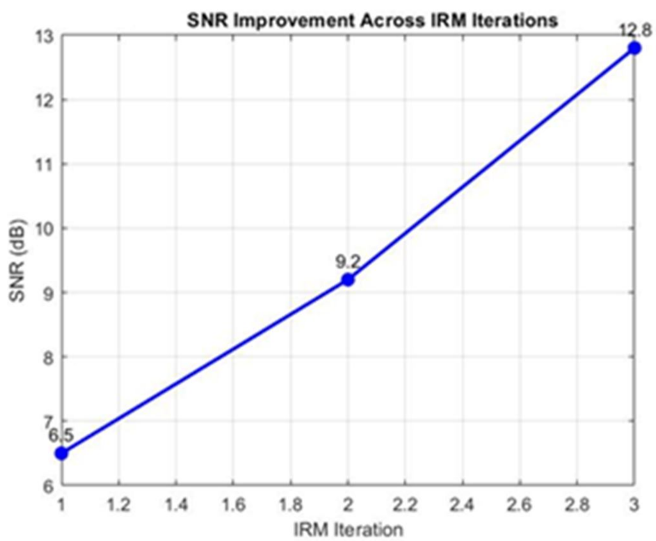

Fig. 4 SNR improvement across IRM iterations

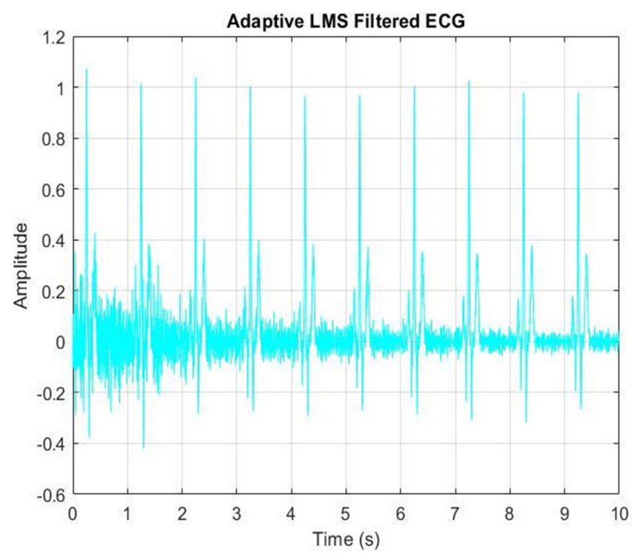

Fig. 5 Adaptive LMS filtered ECG

- This graph illustrates Signal-to-Noise Ratio (SNR) improvements across IRM iterations.
- X-axis shows the beat index, and Y-axis represents the iteration number.
- The graph shows that with successive iterations, the SNR consistently improves, confirming the effectiveness of IRM.

- The cyan waveform shows the ECG processed using an Adaptive LMS filter.
- By using EMG and powerline interference as reference inputs, the adaptive filter reduces correlated noise adaptively.
- The filtered ECG is smoother, but some baseline wander and minor distortions may remain.
- This method is effective but can be less morphology-preserving compared to IRM.

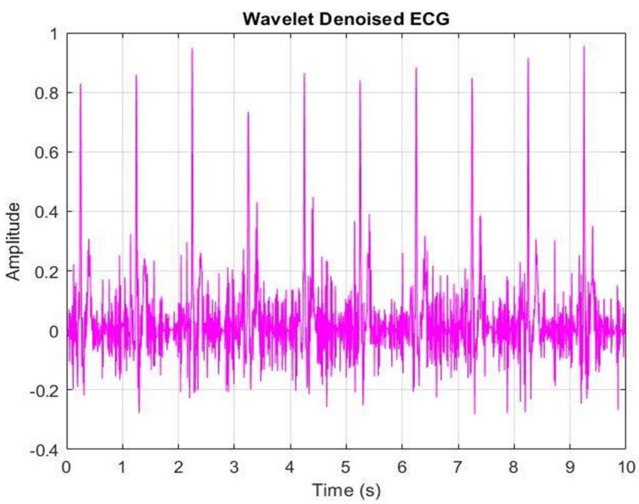

Fig. 6 *IRM wavelet denoised ECG*

- The magenta waveform represents the ECG processed with wavelet thresholding.
- Wavelet decomposition successfully suppresses high-frequency EMG noise and power line interference.
- The result is smoother than the pre-processed signal, but sometimes wavelet shrinkage may slightly distort sharp QRS peaks.
- This demonstrates the trade-off between noise reduction and signal fidelityIRM.

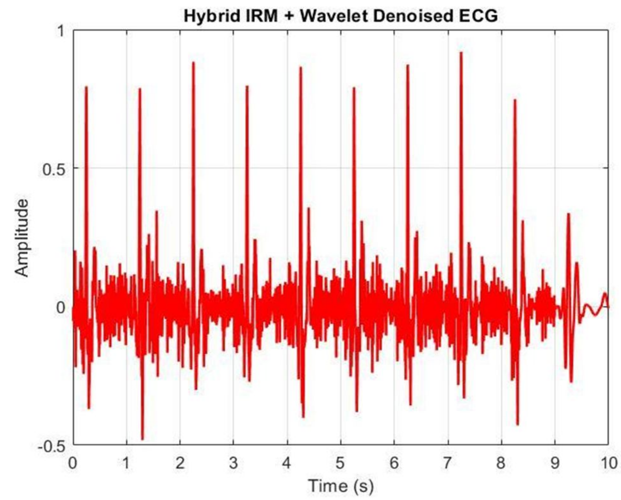

Fig. 7 Hybrid IRM+ wavelet denoised ECG

- The thick red waveform represents the output of the hybrid approach, which combines IRM with wavelet denoising.
- This technique benefits from IRM's morphology preserving ability and wavelet's strong noise suppression.
- The resulting ECG is very close to the clean reference, with sharp QRS complexes and smooth P and T waves.
- This demonstrates the trade-off between noise reduction and signal fidelityIRM.

- The magenta waveform represents the ECG processed with wavelet thresholding.
- Wavelet decomposition successfully suppresses high-frequency EMG noise and power line interference.
- The result is smoother than the pre-processed signal, but sometimes wavelet shrinkage may slightly distort sharp QRS peaks.
- This demonstrates the trade-off between noise reduction and signal fidelity.

- This graph illustrates Signal-to-Noise Ratio (SNR) improvements across IRM iterations.
- X-axis shows the beat index, and Y-axis represents the iteration number.
- The graph shows that with successive iterations, the SNR consistently improves, confirming the effectiveness of IRM.

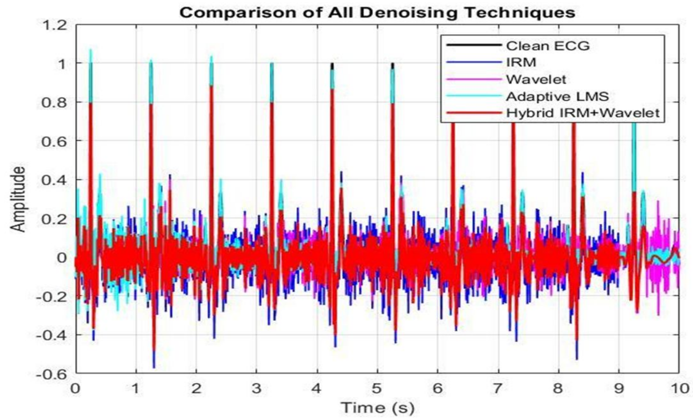

Fig. 8 Comparison of all denoised techniques

- This figure overlays multiple ECG traces for direct visual comparison:
  Black – Clean ECG (ground truth).
  Blue – IRM Denoised ECG.
  Magenta – Wavelet Denoised ECG
  Cyan – Adaptive LMS Filtered ECG.
  Thick Red – Hybrid IRM + Wavelet ECG.
- The comparison clearly shows that:
  IRM preserves morphology well.
  Wavelets reduce noise but can be over smooth.
  LMS filtering adapts but may distort morphology.
  Hybrid IRM + Wavelet gives the closest match to the clean ECG.
- This validates the hybrid method as the best approach for practical ECG denoising.

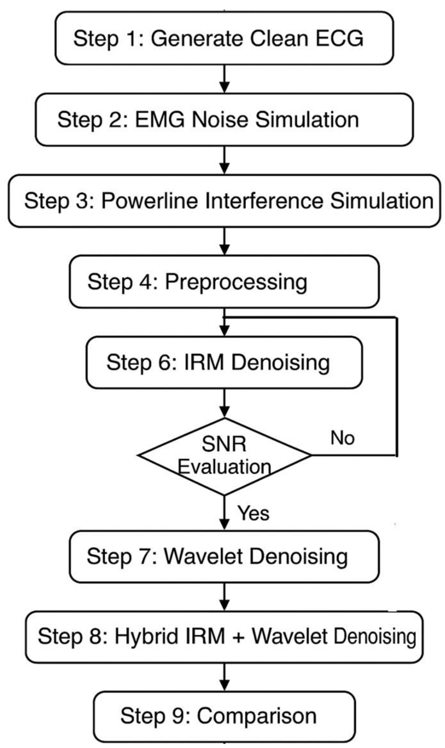

Fig. 9 Flow Chart

IV. CONCLUSION

A hybrid denoising approach combining the Iterative Regeneration Method (IRM) and Wavelet Transform was successfully developed and implemented for the effective removal of EMG noise, power line interference, and other artifacts from ECG signals. The proposed method preserves important morphological features of the ECG while enhancing signal quality, which is critical for accurate clinical interpretation. The iterative nature of IRM enables beat-wise adaptive denoising while the wavelet stage further suppresses residual noise without distorting the diagnostic features. The performance evaluation using SNR maps and visual comparisons confirms the robustness and efficiency of the hybrid approach over individual denoising techniques such as pure wavelet or LMS filtering.

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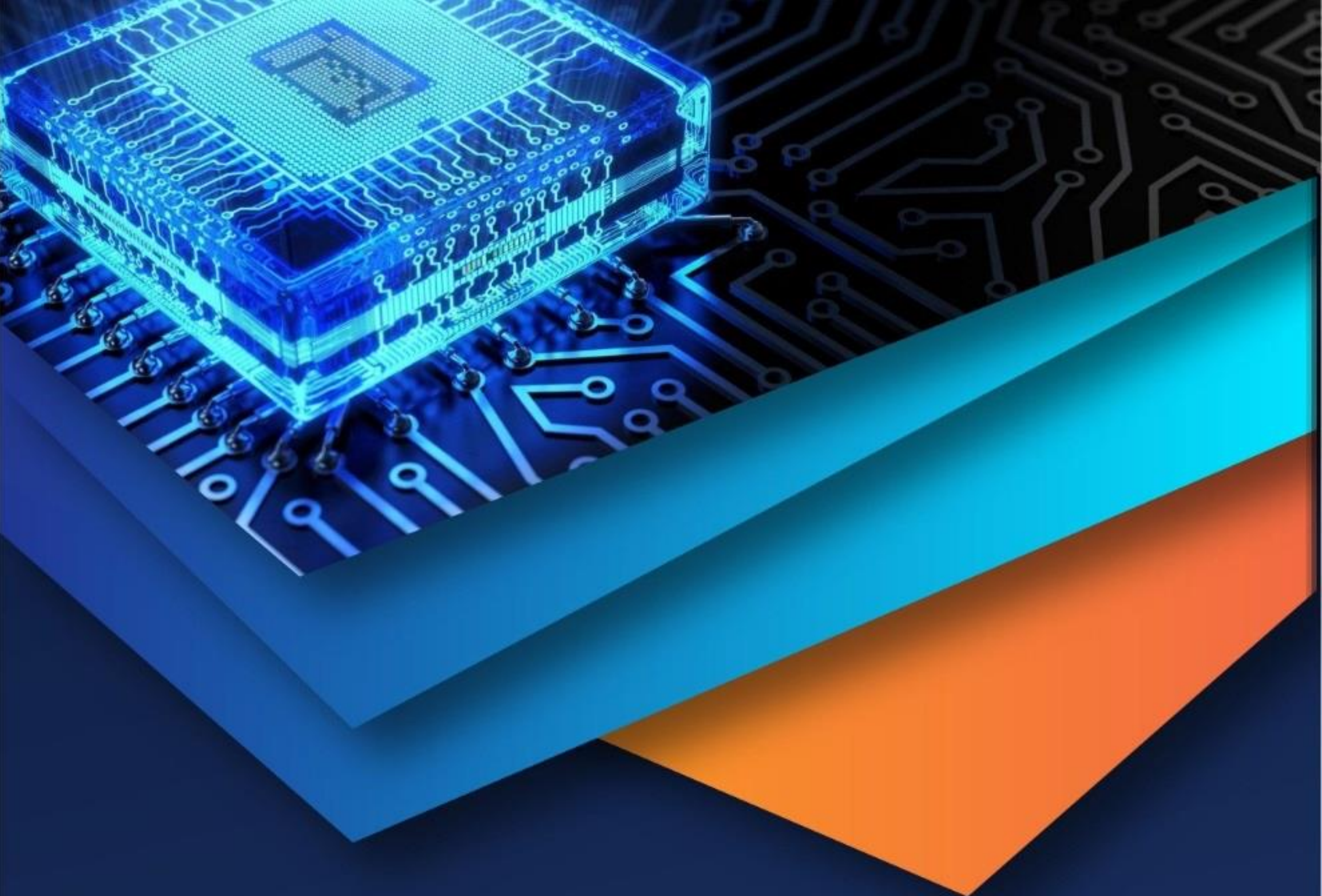

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