Hybrid EMD and RPF for Robust ECG Denoising and State Estimation

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ABSTRACT:

Electrocardiogram (ECG) signals are often corrupted by different noise sources such as baseline wander, power-line interference, and motion artifacts, which reduce the reliability of cardiac analysis and feature extraction. To overcome these issues, an enhanced ECG denoising approach based on Empirical Mode Decomposition (EMD) combined with a Regularized Particle Filter (RPF) is employed.

First, the ECG data from the MIT-BIH database undergoes signal conditioning, including high pass, notch, and bandpass filtering to suppress drift, interference, and unwanted noise while preserving the useful physiological components. The conditioned signal is then decomposed using EMD, where noise-dominant IMFs are removed and selected components are reconstructed to obtain a cleaner input for further estimation. To improve estimation stability, a Regularized Particle Filter with residual resampling is applied, which reduces particle degeneracy and maintains particle diversity during sequential processing.

Finally, Savitzky Golay smoothing is used to retain ECG morphology while minimizing remaining fluctuations. The performance is evaluated using MSE, SNR, and PRD along with time and frequency domain analyses, effective noise reduction, improved signal reconstruction, and reliable preservation of key cardiac features such as R-peaks and RR intervals.

KEY WORDS:

ECG Denoising, Empirical Mode Decomposition, Regularized Particle Filter, State Estimation, R-Peak Detection, RR Interval Analysis, Biomedical Signal Processing, Noise Removal.

I.INTRODUCTION:

A. MOTIVATION AND BACKGROUND:

Electrocardiography (ECG) is an essential tool for monitoring heart activity and identifying cardiac abnormalities. Accurate interpretation of ECG signals depends on preserving key waveform features such as the QRS complex and R-peaks. However, ECG recordings are often corrupted by baseline drift, power-line interference, and motion artifacts, making reliable analysis difficult.

Existing approaches based only on Particle Filters (PF) provide state estimation under noisy conditions but are limited in handling complex, non-stationary noise and also suffer from particle degeneracy during estimation. To overcome this limitation, this work proposes a hybrid method that integrates Empirical Mode Decomposition (EMD) with a Regularized Particle Filter (RPF). EMD is used to separate noise components before applying RPF for improved and stable ECG state estimation.

The proposed method enhances signal quality while preserving important cardiac features. Performance is validated using MSE, SNR, PRD, and R-peak analysis, showing its suitability for real-time ECG monitoring applications.

B. LITERATURE REVIEW:

ECG signal denoising remains an important research area in biomedical signal processing, as noise significantly affects accurate cardiac analysis. Baseline drift, power-line interference, and motion artifacts degrade signal quality and make reliable feature extraction difficult. Conventional filters such as high-pass, low-pass, and bandpass filters are commonly used,

but their performance is limited when handling the nonlinear and non stationary characteristics of ECG signals. Particle Filter (PF)–based methods have been applied for ECG state estimation because of their ability to operate in nonlinear and noisy environments. PF techniques provide better tracking of ECG waveforms and preservation of important cardiac features compared to conventional filters [1].

However, standard PF implementations are directly applied to noisy ECG signals, which can lead to particle degeneracy and weight collapse, reducing estimation accuracy under non-stationary noise conditions. In the base work, ECG denoising was performed using only the Particle Filter approach without any prior signal decomposition. This limits the performance of PF when the input signal is highly corrupted by noise. Studies suggest that separating noise components before filtering can significantly improve estimation performance. Empirical Mode Decomposition (EMD), being a data-driven decomposition method, has been explored for ECG denoising to isolate useful cardiac information from noise. Combining decomposition techniques with advanced filtering strategies has shown improved noise suppression while preserving ECG morphology.

Motivated by these observations, the present work integrates EMD with a Regularized Particle Filter (RPF) to overcome the limitations of standalone PF-based ECG denoising and achieve more stable and reliable ECG state estimation.

C. LIMITATIONS OF EXISTING METHODS

Existing ECG denoising techniques such as conventional filtering, wavelet transforms, and adaptive filtering methods are effective in reducing certain types of noise but often fail to preserve important waveform characteristics when the signal is affected by nonlinear and non-stationary disturbances. These methods mainly focus on frequency-based noise removal and may introduce distortion in clinically significant features like the QRS complex.

Particle Filter (PF)–based approaches improve ECG state estimation under noisy conditions; however, standard PF methods are directly applied to corrupted ECG signals. This leads to issues such as particle degeneracy and weight collapse, reducing estimation

stability and accuracy when the input signal contains severe noise.

Moreover, many existing methods do not separate noise components before applying estimation algorithms, which limits their ability to perform robust denoising while maintaining waveform morphology. These limitations highlight the need for a preprocessing stage that isolates noise from useful signal information before applying advanced filtering techniques.

D. CONTRIBUTION OF PROPOSED WORK:

This work presents a hybrid ECG signal denoising framework by combining Empirical Mode Decomposition (EMD) with a Regularized Particle Filter (RPF) for improved state estimation. Unlike existing methods that apply Particle Filters directly on noisy ECG signals, the proposed approach introduces EMD as a preprocessing stage to separate noise components from useful cardiac information before filtering.

The Regularized Particle Filter further enhances estimation stability by addressing particle degeneracy through resampling and regularization. This combination improves noise suppression while preserving important ECG waveform characteristics such as the QRS complex and R-peaks.

The effectiveness of the proposed method is validated using performance metrics including MSE, SNR, and PRD, along with R-peak detection and RR interval analysis, demonstrating its suitability for reliable and real-time ECG signal analysis.

E. MANUSCRIPT ORGANIZATION:

This paper is organized as follows. Section II explains the basic principles and background theory of the proposed algorithm. Section III

presents the methodology for ECG state estimation and denoising. Section IV discusses the results and performance evaluation. Finally, the paper concludes with key observations and future scope.

II. BASIC PRINCIPLES AND BACKGROUND THEORY OF THE PROPOSED ALGORITHM

A. THEORETICAL FOUNDATION OF EMPIRICAL MODE DECOMPOSITION (EMD)

Empirical Mode Decomposition (EMD) is an adaptive and data-driven technique used to analyze nonlinear and non-stationary signals such as ECG. It decomposes the signal x(t) into several Intrinsic Mode Functions (IMFs) and a final residual component.

Let the ECG signal be represented as x(t). The decomposition begins by identifying all local maxima and minima present in the signal. These extrema are used to construct the upper and lower envelopes using cubic spline interpolation:

$$e_{max} = spline\ interpolation\ of\ localmaxima\ x(t)$$

$$e_{min}(t) = spline\ interpolation\ of\ localminima\ x(t)$$

The local mean of these envelopes is computed a

$$m(t) = \frac{e_{max}(t) + e_{min}(t)}{2}$$

This mean represents the local trend embedded within the signal. Subtracting this mean from the original signal isolates the oscillatory component:

$$h(t) = x(t) - m(t)$$

For h(t) to qualify as an IMF, it must satisfy two conditions: the number of zero crossings and extrema should be nearly equal, and the mean of the envelopes should be approximately zero. If these conditions are not satisfied, the sifting process is repeated on h(t) until the IMF conditions are satisfied. Once satisfied, the first IMF is obtained as:

$$IMF_i(t) = h(t)$$

The residual signal is then computed as:

$$r_1(t) = x(t) - IMF_1(t)$$

The same procedure is applied to the residual to extract subsequent IMFs. This iterative process continues until the residual becomes a monotonic trend. Finally, the signal can be represented as:

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r(t)$$

In this work, high-frequency IMFs (noise) and the last IMF (baseline drift) are removed, and the denoised ECG signal is reconstructed as

$$ECG_{EMD}(t) = \sum_{i=2}^{n-1} IMF_i(t)$$

B. THEORETICAL FOUNDATIONS OF REGULARIZED PARTICLE FILTER (RPF)

The Regularized Particle Filter (RPF) is a Sequential Monte Carlo–based method used for estimating the hidden state of nonlinear and noisy systems such as ECG signals. Unlike Kalman filters, which assume Gaussian behavior, RPF represents the posterior distribution using multiple weighted samples called particles.

The goal is to estimate the ECG state from x_k noisy measurements z_k using Bayesian filtering:

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})}$$

Here, $p(x_k|z_{1:k})$ is the posterior, $p(z_k|x_k)$ is the likelihood, and $p(x_k|z_{1:k-1})$ is the prior estimate.

Since this expression is difficult to compute directly, it is approximated using N particles x_k^i

with weights w_k^i :

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i)$$

where δ(·) denotes the Dirac delta function.

At the beginning, particles are initialized around the first ECG sample:

$$x_0^i \sim N(x_0, Q), \ \ w_0 = \frac{1}{N}$$

Each particle then evolves using simple randoma walk model:

$$x_k^i = x_{k-1}^i + v_k^i, \ \ v_k^i \sim N(0, Q)$$

The weights are updated based on how close each particle is to the measurement:

$$w_k^i = w_{k-1}^i \cdot \exp\left(-\frac{\left(z_k - x_k^i\right)^2}{2R}\right)$$

The weights are then normalized:

$$w_k^i = \frac{w_k^i}{\sum_{j=1}^N w_k^j}$$

The estimated ECG value at time k is calculated as a weighted average:

$$\hat{x}_k = \sum_{i=1}^N w_k^i x_k^i$$

To check whether most particles have very small weights, the effective sample size is computed:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (w_k^i)^{\wedge}2}$$

If $N_{eff} < \frac{N}{2}$, resampling is carried out to remove low-weight particles. After resampling, a regularization step is applied to maintain particle diversity. In this work, the regularization factor is defined as

$$\sigma_{reg} = 0.05 \times std(x_k^i)$$

and particles are slightly perturbed as

$$x_k^i = x_k^i + \sigma_{reg} N(0,1)$$

This cycle of prediction, update, resampling, and regularization continues for all ECG samples, providing stable and accurate state estimation.

C. JUSTIFICATION FOR EMD AND RPF IN ECG STATE ESTIMATION AND DENOISING

ECG signals are affected by baseline wander, power-line interference, and motion artifacts that often overlap with the actual signal components. Conventional filters can suppress some noise but may distort important features such as the QRS complex and R-peaks, which are essential for cardiac analysis.

Empirical Mode Decomposition (EMD) is suitable for ECG preprocessing because it adaptively separates the signal into intrinsic mode functions without assuming linearity or stationarity. High-frequency IMFs mainly contain noise, while useful cardiac information remains in the middle IMFs. By reconstructing the signal from selected IMFs, noise can be reduced while preserving waveform morphology. This makes EMD effective in isolating noise components before further processing.

After preprocessing, accurate state estimation is still required to track the true ECG waveform. Particle Filter methods work well in nonlinear and noisy conditions, but standard PF suffers from particle degeneracy when applied directly to noisy signals. The Regularized Particle Filter (RPF)

overcomes this issue by maintaining particle diversity after resampling, which improves estimation stability and accuracy.

When RPF is applied to the EMD-processed signal, the estimation becomes more reliable because the input signal already has reduced noise. Thus, EMD acts as a noise separation stage, and RPF performs robust state estimation on the refined signal. This combination enhances ECG denoising while preserving important cardiac features, making it suitable for reliable cardiac monitoring applications.

III. METHODOLOGY FOR ECG STATE ESTIMATION AND DENOISING

The proposed approach performs ECG denoising and state estimation through a sequential pipeline that includes signal conditioning, Empirical Mode Decomposition (EMD), and Regularized Particle Filtering (RPF) as shown in **Figure 1**. The process begins with raw ECG acquisition and ends with reconstruction of a morphologically preserved, denoised ECG signal suitable for cardiac feature extraction.

A. ECG DATA ACQUISITION AND PREPROCESSING:

The ECG signal is acquired from the **MIT-BIH Arrhythmia Database** with a sampling frequency fs =360 Hz. The raw ECG is first normalized to stabilize amplitude:
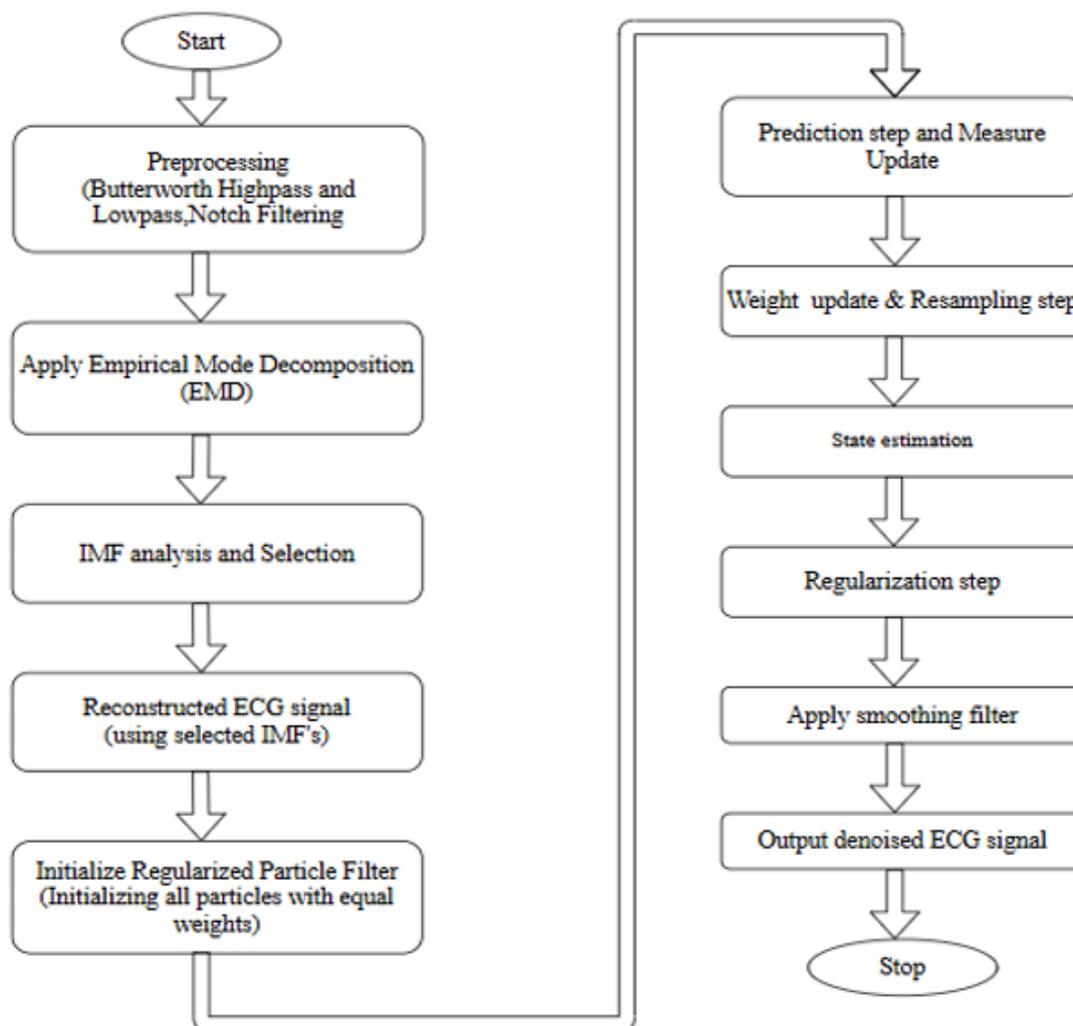
Figure 1. Flowchart of the Proposed Hybrid EMD–RPF Based ECG Denoising System

Power-line interference at 50 Hz is suppressed using a notch filter:

$$ECG_{notch}(n) = filtfilt(N_{notch}(z), ECG_{hp}(n))$$

Finally, a 0.5–100 Hz Butterworth band-pass filter retains the useful ECG spectrum:

$$ECG_{cond}(n) = filtfilt(B_{BP}(z), ECG_{notch}(n))$$

$$ECG_{raw}(n) = \frac{val(1,n)}{\max(|val(1,n)|)}$$

$$where, \quad t = \frac{n}{fs}$$

B. EMPIRICAL MODE DECOMPOSITION (EMD) FOR ADAPTIVE NOISE SEPARATION

To remove common ECG artifacts such as baseline wander, power-line interference, and high-frequency noise, a sequence of Butterworth filters is applied.

Baseline drift is removed using a 0.5 Hz Butterworth high-pass filter:

$$ECG_{hp}(n) = filtfilt(B_{HP}(z), ECG_{raw}(n))$$

After preprocessing, the conditioned ECG signal ECGcond(n) still contains mixed frequency components due to non-stationary noise. To separate useful cardiac information from noise without distorting waveform morphology, Empirical Mode Decomposition (EMD) is

applied. EMD is an adaptive, data-driven technique specifically suitable for nonlinear and non-stationary signals such as ECG.

The conditioned ECG is treated as the initial residual:

$$r^0(n) = ECG_{cond}(n)$$

1) Detection of Local Extrema

All local maxima and minima of $r^0(n)$ are identified. These extrema represent the oscillatory nature of the ECG waveform and are required for envelope formation.

2) Envelope Construction Using Spline Interpolation

The upper and lower envelopes are formed by interpolating the maxima and minima using cubic spline interpolation:

$$E_{upper}(n) = spline(pIdx, h[pIdx])$$

$$E_{Lower}(n) = spline(bIdx, h[bIdx])$$

These envelopes bound the signal from above and below.

3) Local Mean Computation

The local mean of the envelopes is computed as:

$$m(n) = \frac{E_{upper}(n) + E_{lower}(n)}{2}$$

4) Sifting Process (Removal of Local Mean)

The local mean is removed to retain only oscillatory components:

$$h(n) = h(n) - m(n)$$

5) IMF Stopping Criteria

The sifting process continues until the function satisfies the conditions of an Intrinsic Mode Function (IMF):

$$\left(\frac{||h_{prev} - h||}{||h_{prev}||} \right)^2 < 0.2$$

$$|Extrema - zerocrossings| \leq 1$$

6) Extraction of IMF

Once the conditions are satisfied, the function is treated as an IMF:

$$IMF_i(n) = h(n)$$

The residual is updated as:

$$r^i(n) = r^{i-1}(n) - IMF_i(n)$$

7) Iterative Decomposition

The same procedure is repeated on the residual signal until only a monotonic trend remains:

$$r^n(n) \rightarrow trend\ component$$

8) ECG Reconstruction from Selected IMFs

The first two IMFs usually contain high-frequency noise, and the last IMF represents baseline drift. These components are removed. The ECG signal is reconstructed using the intermediate IMFs:

$$ECG_{EMD}(n) = \sum_{i=2}^{n-1} IMF_i(n)$$

C.   STATE–SPACE MODELING AND REGULARIZED PARTICLE FILTERING

After EMD-based preprocessing, the signal $ECG_{EMD}(n)$ is provided as the observation input to the Regularized Particle Filter (RPF) for ECG state estimation. The filtering process follows a sequential Monte Carlo approach with residual resampling and kernel regularization.

1. State–Space Representation

The ECG estimation problem is modeled using a random walk process:

$$x_n = x_{n-1} + v_n, \quad v_n \sim N(0, Q)$$

$$z_n = x_n + w_n, \quad w_n \sim N(0, R)$$

$$where\ z_n = ECG_{EMD}(n)$$

2. Particle Initialization

A set of N=1000 particles is initialized around the first EMD output sample:

$$x_0^i = z_0 + \sqrt{Q}N(0,1)$$

$$w_0^i = \frac{1}{N}$$

3. Prediction (Random Walk Propagation)

At each iteration, particles evolve as:

$$x_n^i = x_{n-1}^i + \sqrt{Q}N(0,1)$$

4. Likelihood-Based Weight Update

The likelihood of each particle with respect to observation is computed as:

$$L^i = \exp\left(-\frac{(z_n - x_n^i)^2}{2R}\right)$$

$$w_n^i = \frac{w_{n-1}^i L^i}{\sum_{j=1}^{N} w_{n-1}^j L^j}$$

5. ECG State Estimation

The ECG estimate is computed as the weighted sum of particles:

$$\hat{x}_n = \sum_{i=1}^{N} w_n^i x_n^i$$

6. Degeneracy Check

Effective particle size is calculated as:

$$N_{eff} = \frac{1}{\sum_{i=1}^{N}(w_n^i)^2}$$

7. Residual Resampling

Residual resampling is performed in two stages:

1. 1.Deterministic replication:

$$N_8^1 = \left[N \cdot w_n^i\right]$$

2.Stochastic selection using residual weights.

This corresponds exactly to the residualResample() function in the code.

8. Regularization (Kernel Jittering)

After resampling, particles are jittered to maintain diversity:

$$\sigma_{reg} = 0.05 \times std(x_k^i)$$

$$x_k^i = x_k^i + \sigma_{reg}N(0,1)$$

C. ECG RECONSTRUCTION AND POST-PROCESSING

After completing the Regularized Particle Filtering process, the clean ECG state at each sample is estimated from the set of weighted particles. The denoised ECG signal is obtained as the weighted mean of all particles.

$$\hat{x}(n) = \sum_{i=1}^{N} w_n^i x_n^i$$

Where

$\hat{x}_n$ is the estimated clean ECG signal,
x_n^i are the particles, and
w_n^i are the corresponding normalized weights.

This estimation provides a noise-reduced ECG waveform while preserving important morphological features such as P, QRS, and T waves.

POST-PROCESSING:

Although RPF significantly reduces noise, minor fluctuations may still remain. To preserve ECG morphology and remove these small variations, a Savitzky–Golay smoothing filter is applied:

$$ECG_{final}(n) = sgolayfilt(\hat{x}(n))$$

This smoothing step enhances waveform clarity without distorting the clinical features of the ECG signal.
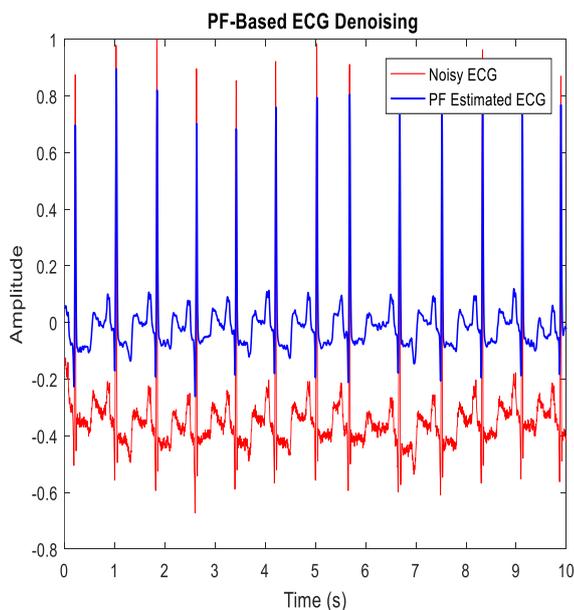
IV. RESULTS AND DISCUSSION

The proposed EMD–RPF framework shows effective ECG denoising by reducing noise while preserving important cardiac features such as the QRS complex. Time-domain plots indicate a smoother reconstructed signal compared to the noisy ECG. Quantitative results achieved an MSE of 0.002052, SNR of 9.78 dB, and PRD of 32.42%, confirming improved signal quality. Frequency domain analysis also shows attenuation of
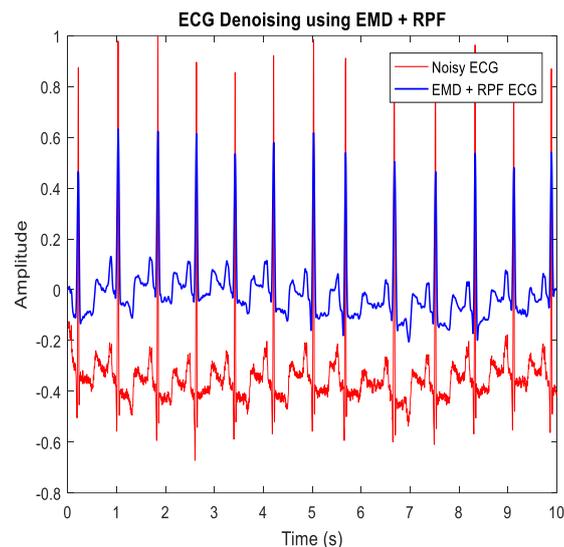
high frequency noise within the ECG band. Overall, the hybrid EMD with Regularized Particle Filter provides more stable and robust state estimation than conventional filtering methods.

A.　ECG SIGNAL NOISE REDUCTION

Fig 2(a) shows the comparison of input noisy ECG signal and the denoised ECG using only particle filter method. **Fig 2(b)** presents the comparison between the noisy ECG and the denoised ECG obtained using the EMD–RPF method. The proposed approach effectively suppresses noise while preserving important ECG features such as QRS complexes and waveform morphology.

Fig 2.b: ECG denoising using EMD and RPF methods

B. FREQUENCY SPECTRUM (FFT) ANALYSIS

The FFT results **Fig 3(b)** indicate that the proposed EMD–RPF method effectively reduces high-frequency noise components beyond the useful

ECG band. Most of the signal energy is concentrated in the low-frequency region (0–20 Hz), confirming improved noise suppression and preservation of essential cardiac information.

Fig 2.a.: ECG denoising using PF method
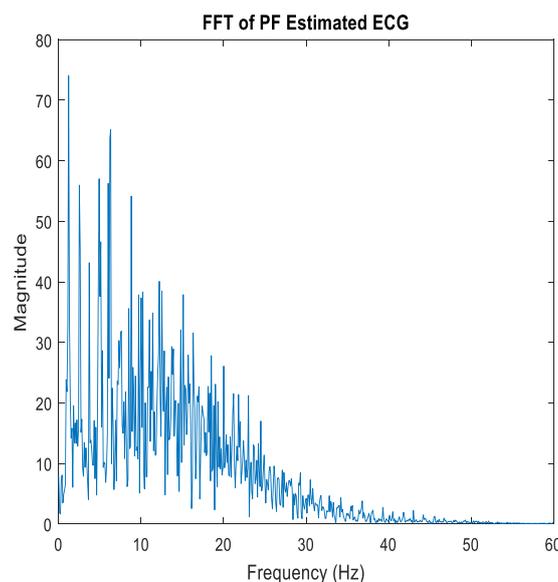
Fig 3.a: PF estimated ECG using frequency Spectrum
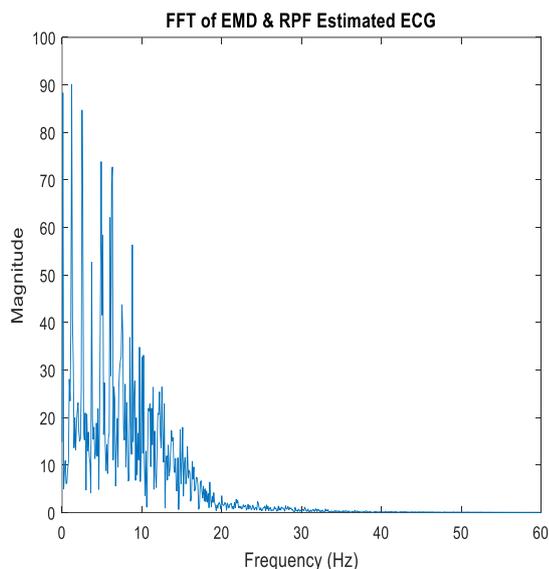
**Fig 3.b:** EMD and RPF estimated ECG using frequency spectrum
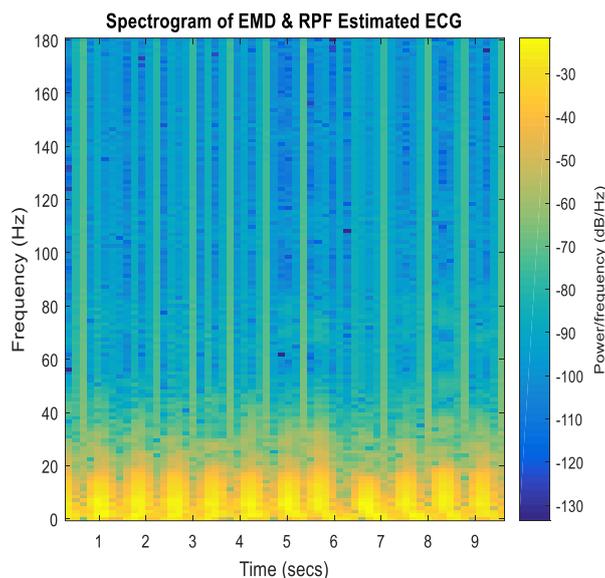
Fig 4.b: Spectrogram of EMD and RPF estimated ECG

C. SPECTROGRAM ANALYSIS

The spectrogram of the noisy ECG shows energy spread across a wide frequency range due to noise and artifacts. After applying EMD and RPF, the spectral energy becomes more concentrated in the lower frequency band indicating effective suppression of high-frequency noise while preserving the essential ECG components.

D. POWER SPECTRAL DENSITY (PSD) ANALYSIS

The PSD plots show that the noisy ECG contains higher power across a wide frequency range due to noise components. After applying the proposed EMD–RPF method, the power at higher frequencies significantly decreases, indicating effective noise suppression.
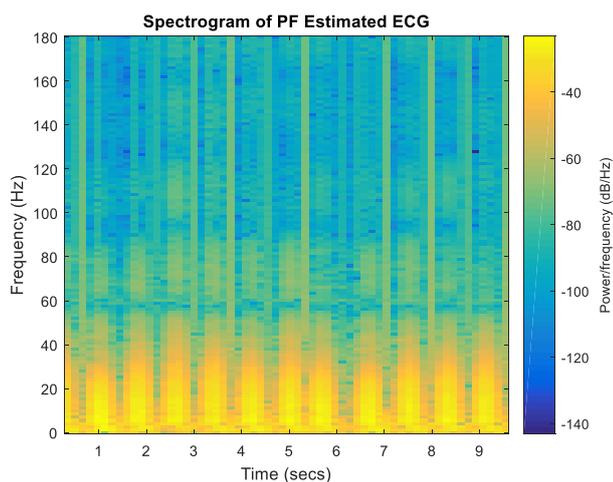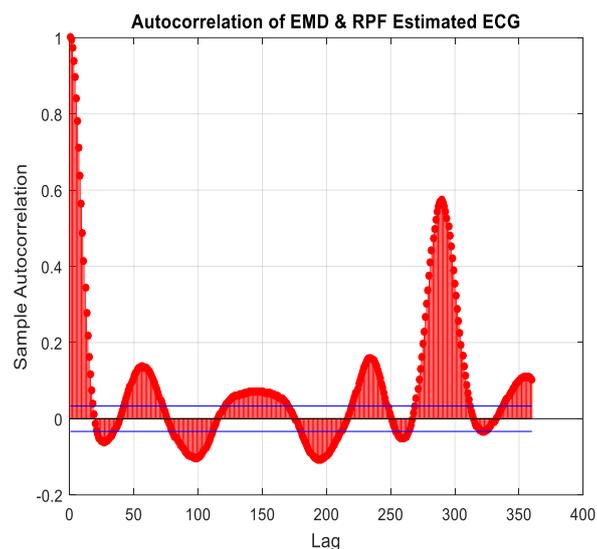

Fig 4.a: Spectrogram of PF estimated ECG
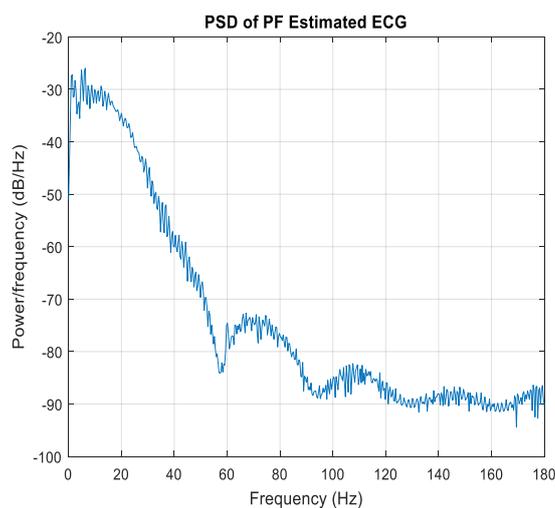
Fig 5.a: PSD of PF Estimated ECG
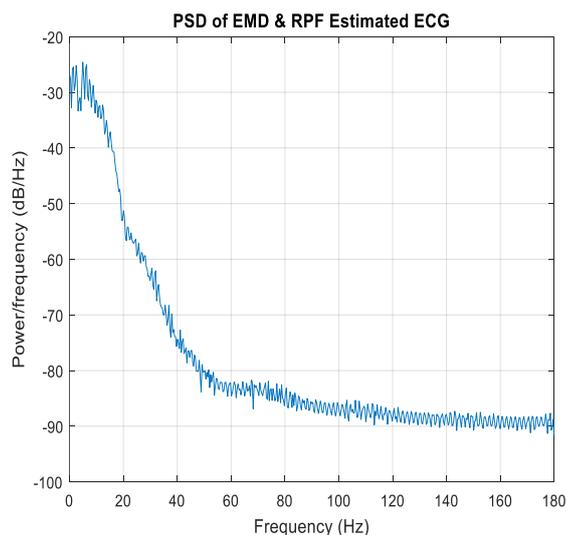
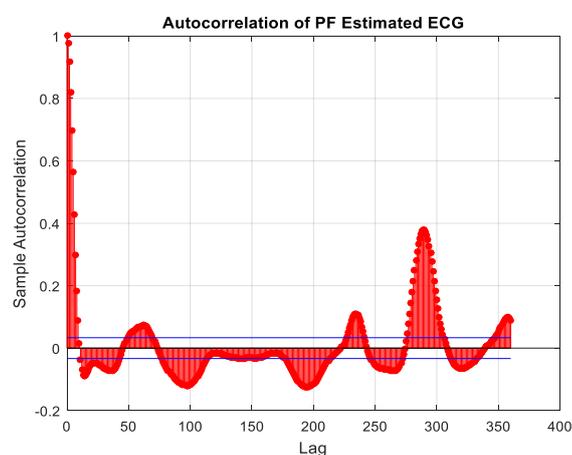**Fig 5.b:** PSD of EMD and RPF Estimated ECG

E. AUTO-CORRELATION ANALYSIS

The autocorrelation plot of the noisy ECG shows peaks and fluctuations due to noise irregular interference and baseline variations. After applying the proposed EMD–RPF method, the autocorrelation becomes more periodic and stable, indicating better preservation of the intrinsic ECG rhythm and improved signal consistency.

Fig 6.a: Auto-correlation of PF estimated ECG

Fig 6.b: Auto-correlation of EMD and RPF estimated ECG
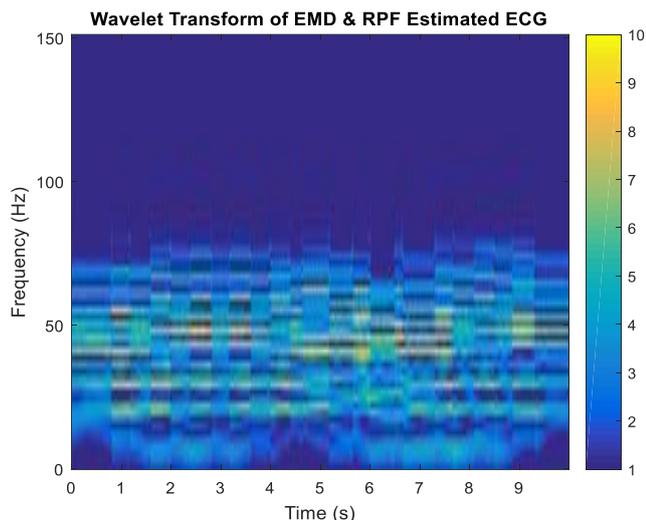
F. WAVELET TRANSFORM ANALYSIS

The wavelet transform shows the time–frequency characteristics of the ECG signal. After EMD and RPF denoising, the coefficients appear more concentrated and less noisy. This indicates effective suppression of noise while preserving the main cardiac features.
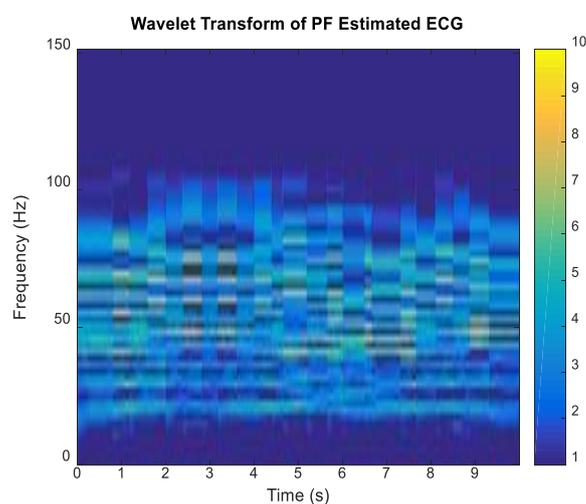

Fig 7.a: Wavelet transform of PF estimated ECG.

Fig 7.b: Wavelet transform of EMD and RPF estimated ECG.

G. R PEAK DETECTION

The detected R-peaks in the denoised ECG signal are consistent with those observed in the base signal, showing that the proposed method maintains the original cardiac information. This confirms that EMD–RPF effectively suppresses noise while preserving QRS complexes and peak positions.
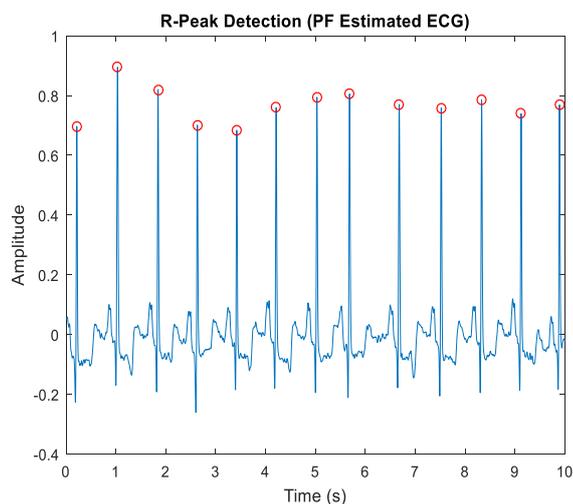

**Fig 8.a:** R peaks detection based on PF estimated ECG
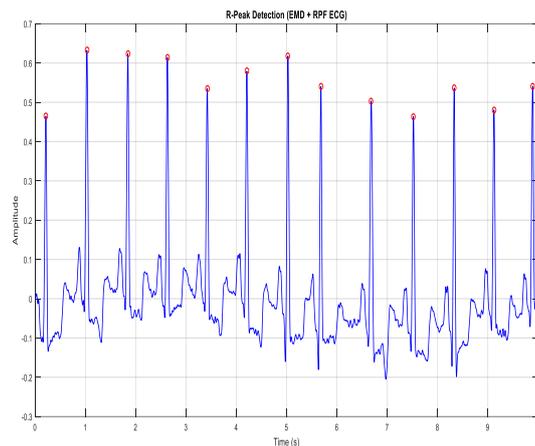
Fig 8.a: R peaks detection based on EMD and RPF estimated ECG.

H. R-R INTERVAL ANALYSIS

The RR intervals of the denoised ECG are consistent with those of the base ECG signal, showing that the proposed method does not distort the heart rate information. This confirms that the EMD–RPF approach preserves the original cardiac timing while effectively reducing noise.
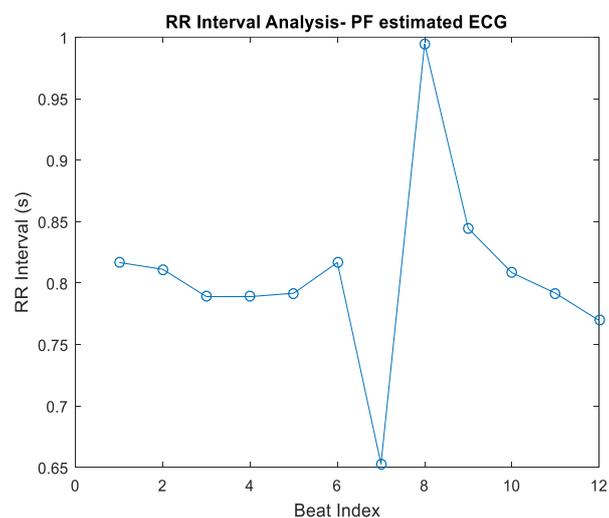

**Fig 9.a:** R-R interval based on PF estimated ECG
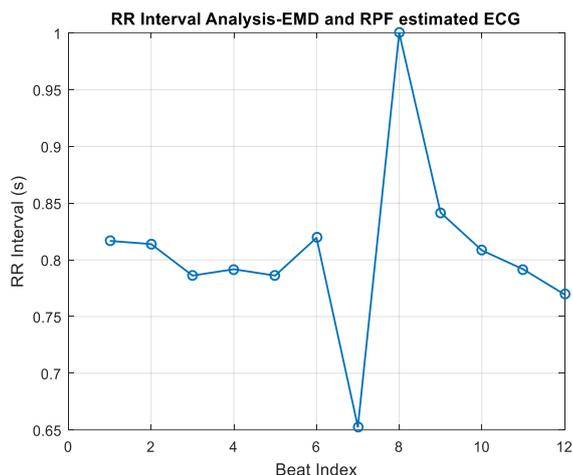
Fig 9.b: R-R interval based on EMD and RPF estimated ECG

I. ECG ENVELOPE EXTRACTION

Envelope extraction highlights the upper and lower bounds of the ECG waveform, capturing its overall amplitude variations. The extracted envelopes remain smooth and consistent after denoising, indicating effective noise suppression without altering the signal morphology.
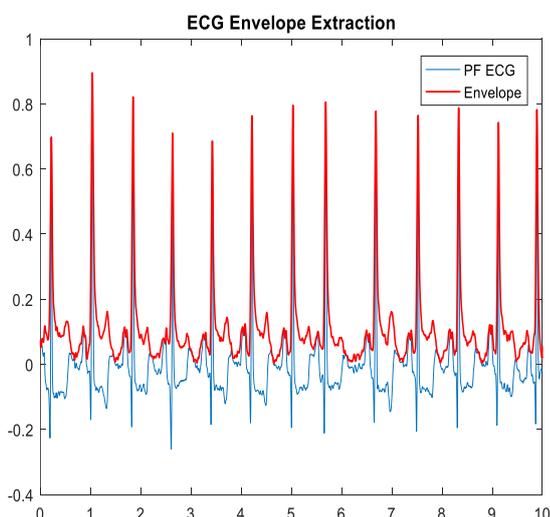
Fig 10.a: Envelope extraction for PF estimated ECG
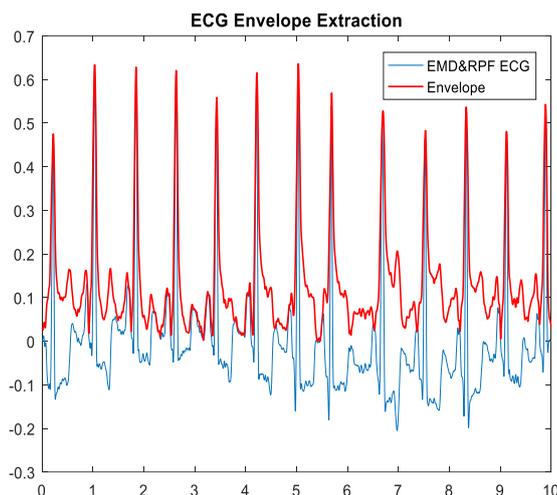
Fig 10.b: Envelope extraction of EMD and RPF estimated ECG

J. COMPARISON BAESD ON PERFORMANCE METRICS

The basic Particle Filter shows performance degradation due to particle degeneracy when handling highly noisy ECG signals. The integration of EMD helps in separating noise-dominant components before state estimation. Further, the use of Regularized Particle Filter improves stability and estimation accuracy, leading to reduced MSE and PRD and increased SNR compared to the conventional PF method is shown in **Table 1**.

METHOD	MSE	SNR	PRD
PARTICLE FILTER BASED ESTIMATED ECG	0.008775	5.46 dB	53.36%
PROPOSED EMD AND RPF BASED ESTIMATED ECG	0.002056	9.78dB	32.42%

Table 1. Comparison between particle filter and EMD-RPF based estimated ECG

From the Table 1., by MSE, SNR, PRD we can say there is better performance of filter when decomposition method is used before it.

V. CONCLUSION

In this work, a hybrid ECG denoising and state estimation framework based on Empirical Mode Decomposition (EMD) and Regularized Particle Filter (RPF) was presented. Initially, the ECG signal was preprocessed and decomposed using EMD to remove high-frequency noise and baseline drift while preserving important cardiac morphology. The reconstructed signal was then processed using RPF to achieve accurate and stable state estimation under nonlinear and non-stationary noise conditions.

The experimental results demonstrate that the proposed EMD–RPF method provides better denoising performance compared to the conventional Particle Filter approach. The reduction in MSE and PRD along with the improvement in SNR confirms effective noise suppression and enhanced signal reconstruction. Time-domain, frequency-domain, and time–frequency analyses such as FFT, PSD, spectrogram, and wavelet transform further validate that the denoised ECG retains essential cardiac features including R-peaks and RR intervals.

Overall, the proposed method successfully overcomes particle degeneracy and instability issues associated with basic PF by incorporating signal decomposition and regularization. Hence, the EMD–RPF framework is suitable for robust ECG signal denoising, accurate state estimation, and reliable cardiac feature extraction, making it applicable for real-time biomedical monitoring and wearable healthcare systems.

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