Reproduction and Enhancement of the Pan-Tompkins QRS Detection Algorithm

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***Abstract*—This project focuses on the reproduction and enhancement of the Pan-Tompkins algorithm for real-time QRS complex detection in ECG signals. The original algorithm is implemented step-by-step, including bandpass filtering, derivative computation, squaring, moving window integration, and thresholding logic. Each stage is carefully constructed and analyzed to reflect its role in the signal processing pipeline. An adaptive thresholding method based on moving average is employed to detect QRS complexes effectively. A full signal flow diagram is also presented to visualize the processing stages. The implementation is tested on real ECG data from the MIT-BIH Arrhythmia Database, and the results demonstrate accurate identification of QRS peaks. This work lays the foundation for future enhancements using advanced techniques like LMS-based adaptive filtering to improve robustness in noisy conditions.**

I. Introduction

The electrocardiogram (ECG) is a key tool used by doctors to check how the heart is working, especially to find irregular heartbeats (arrhythmias). But when ECG signals are recorded, they often contain unwanted noise. This noise can come from things like body movement, poor contact with the electrodes, muscle activity, or electrical devices nearby. One common and serious type of noise is the 50 Hz electrical interference (or 60 Hz in some countries), which can hide important parts of the ECG signal and make diagnosis more difficult.

To remove this noise, many systems use digital filters like FIR and IIR. These filters work well when the signal stays the same, but they have trouble with signals that change over time—like the ECG. Because of that, adaptive filters have become more popular. These filters can change how they work based on the signal. One common method is the Least Mean Squares (LMS) algorithm, which is good at reducing 50 Hz noise while keeping the heart signal clear.

In this project, we focus on the well-known Pan-Tompkins algorithm, which has been used for many years to detect QRS complexes (a main part of the heartbeat) in real time. We first rebuild the original version of the algorithm, then we improve it by adding an adaptive threshold system based on LMS filtering. This improvement helps the algorithm work better on noisy ECG signals. We test both versions using the MIT-BIH Arrhythmia Database and show that the improved version gives better results, especially in difficult signal conditions.

II. Materials and Methods

In this project, the reproduction and enhancement of the Pan-Tompkins QRS detection algorithm were carried out using Python as the primary programming language. A variety of open-source libraries were employed, including NumPy and SciPy for numerical and signal processing operations, Matplotlib for data visualization, and the WFDB package for accessing and handling ECG records from PhysioNet.

The ECG data used in this study were obtained from the widely used MIT-BIH Arrhythmia Database, specifically records 100, 104, 105, and 106. These records provided clean and well-annotated ECG signals for both testing the original Pan-Tompkins algorithm and evaluating the enhanced version.

III. Results and Discussion

A. Task 1: Literature Review & Signal Flow

1) Overview: The Pan-Tompkins algorithm is a real-time method developed in 1985 for detecting QRS complexes in ECG signals. It applies a sequence of digital signal processing stages to enhance the QRS features and suppress noise, enabling accurate detection even under challenging conditions.

2) ***Bandpass Filter*:** **Purpose:**

Reduce muscle noise, power line interference, and baseline wander.

The filter combines a low-pass filter ($\tilde{1}$5 Hz cutoff) and a high-pass filter ($\tilde{5}$ Hz cutoff) to create a bandpass that preserves QRS energy.

Effect:

- Removes slow trends (baseline drift).
- Suppresses high-frequency noise.
- Enhances QRS complex contrast.

3) 2. Derivative Filter: **Purpose:**

Highlight the slope of the QRS complex by approximating the first derivative of the ECG signal.

Effect:

- Sharpens the QRS region.
- Helps in emphasizing rapid transitions typical of QRS complexes.

Typical Formula:

$$y(n) = \frac{1}{8}\left[-x(n-2) - 2x(n-1) + 2x(n+1) + x(n+2)\right]$$

4) Squaring Function: **Purpose:**

Emphasize large slope values and make all data points positive.

Effect:

- Enhances peaks.
- Makes the signal nonlinear.
- Increases energy of QRS while reducing influence of P and T waves.

Formula:

y(nT)= $[x(nT)]^2$

5) Moving Window Integration (MWI): **Purpose:**

Extract features that are spread across a QRS duration ($\tilde{1}$50 ms).

This smooths the signal and helps in identifying regions where QRS complexes are likely present.

Effect:

- Provides a waveform that resembles QRS energy over time.
- Helps in timing information for detection.

Formula:

y(nT) = (1/N) [x(nT- (N - 1) T) +x(nT- (N - 2) T) .. + x(nT)].

Where NNN is typically chosen based on sampling rate to match QRS width.

6) Thresholding & Decision Logic: **Purpose:**

Determine if a QRS complex has occurred by comparing the integrated signal to an adaptive threshold.

Mechanism:

- Uses two thresholds: one for QRS detection and one for noise.
- Adapts over time depending on signal strength.
- Incorporates rules to prevent double detection (refractory period logic).

Effect:

- Final decision step.
- Classifies detected peaks as QRS or noise.
- Enables real-time detection

7) Full Signal Flow Diagram:

ECG Signal
$\downarrow$
Bandpass Filter
$\downarrow$
Derivative Filter
$\downarrow$
Squaring Function
$\downarrow$
Moving Window Integration
$\downarrow$
Adaptive Thresholding & Decision Logic
$\downarrow$
QRS Detection Output

B. Task 2:Reproduce the Algorithm

To reproduce the Pan-Tompkins QRS detection algorithm, we implemented each signal processing stage as described in the original work by Pan and Tompkins (1985). The algorithm was tested on real ECG signals, specifically the MIT-BIH Arrhythmia Database, using Record 100. The steps include:

- **Bandpass Filtering:** A combination of low-pass and high-pass filters was applied to isolate the frequency band of interest (5–15 Hz), which enhances the QRS complex while suppressing noise and baseline drift.
- **Derivative Filtering:** We applied a 5-point derivative to highlight the slope information of the QRS complex, using the formula:

$$y(n) = \frac{1}{8}\left[-x(n-2) - 2x(n-1) + 2x(n+1) + x(n+2)\right]$$

- **Squaring Function:** The differentiated signal was squared to emphasize large values and suppress smaller ones, effectively enhancing the QRS region.
- **Moving Window Integration:** A sliding window (150 ms wide) was used to produce a smoothed version of the signal that reflects energy over the duration of a QRS complex.
- **Thresholding and Decision Rule:** An adaptive thresholding logic was used to detect peaks and identify QRS locations. Detected peaks were stored along with their timestamps.

Figure 1 shows the ECG signal from MIT-BIH Record 100 with detected QRS complexes annotated.

C. Task 3 DSP Analysis of Filters

This section presents the digital signal processing (DSP) analysis of the three main filtering stages in the Pan-Tompkins algorithm: the Bandpass filter, the Derivative filter, and the Moving Window Integrator. For each filter, we analyze the frequency response (magnitude and phase), pole-zero plot, and group delay using standard DSP techniques and tools.

1) A) Bandpass Filter Analysis: The Bandpass filter in the Pan-Tompkins algorithm combines a low-pass and a high-pass stage to isolate frequencies relevant to the QRS complex (typically between 5–15 Hz). Its design enhances QRS components while attenuating noise and baseline wander.

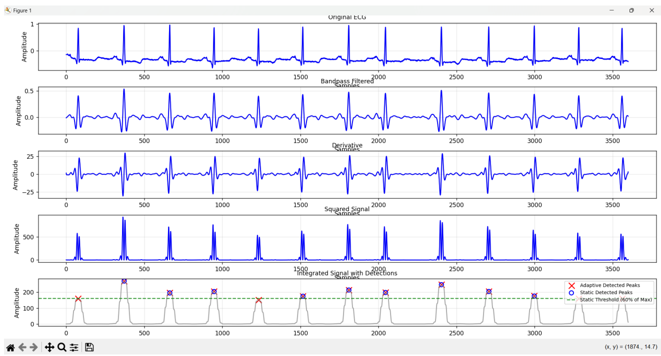

Fig. 1. Full signal flow diagram of the Pan-Tompkins QRS detection algorithm

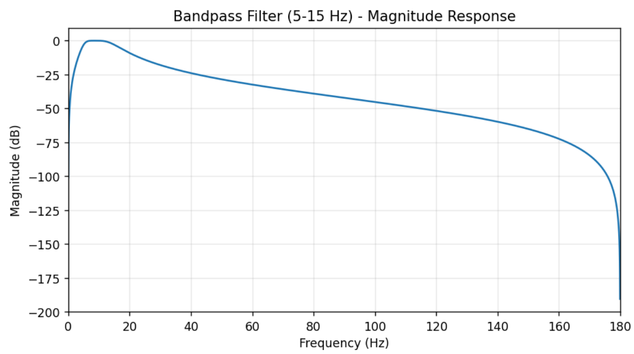

Fig. 2. Band Pass Filter For Magnitude Response

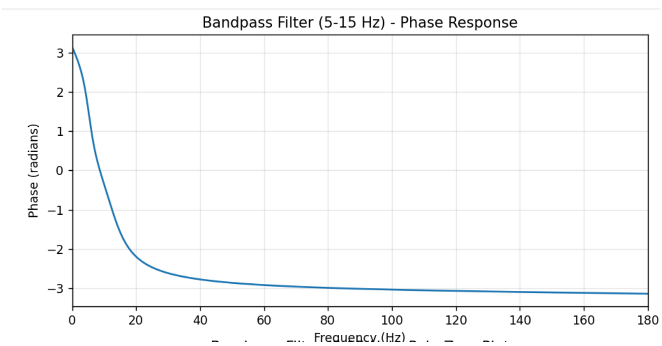

Fig. 3. Band Pass Filter For Phase Response

1- Magnitude and Phase Response Figure 2 and 3 shows the magnitude and phase response of the Bandpass filter.

2- Pole-Zero Plot Figure 4 shows the pole-zero distribution of the Bandpass filter, indicating its stability and frequency-selective behavior.

3- Group Delay The group delay, shown in Figure 5, helps assess the phase distortion introduced by the Bandpass filter.

2) B) Derivative Filter Analysis:

a) The Derivative filter in the Pan-Tompkins algorithm enhances the high-frequency components of the QRS complex by approximating the derivative of the input signal. This step sharpens the slopes of the R-peaks, making them more distinguishable from other ECG features.: 1- Magnitude and Phase Response

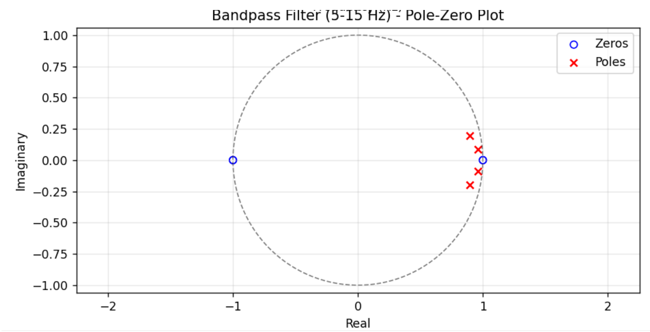

Fig. 4. Band Pass Filter For Pole-Zero Plot

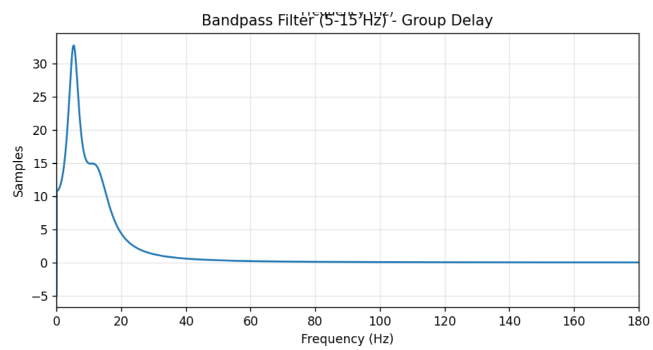

Fig. 5. Group delay of the Bandpass filter

b) The magnitude response of the Derivative filter emphasizes higher frequencies while attenuating lower frequencies, effectively acting as a high-pass filter. The phase response is linear, indicating a constant group delay across all frequencies.: Figures 6 and 7 illustrate the magnitude and phase response of the Derivative filter:

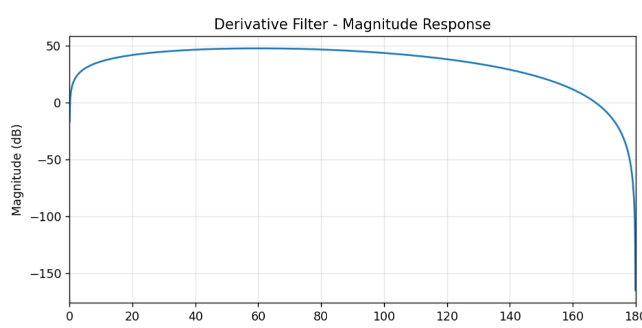

Fig. 6. Magnitude Response of the Derivative Filter

2- Pole-Zero Plot

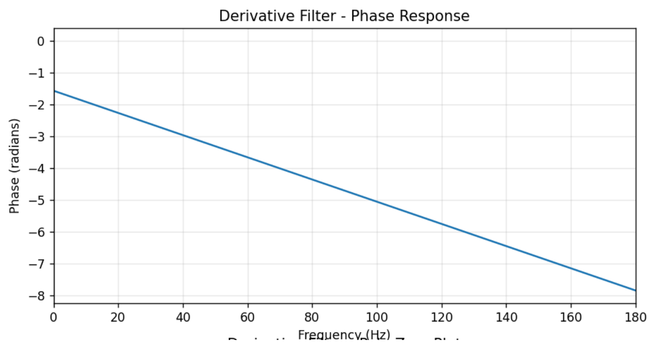

Fig. 7. Phase Response of the Derivative Filter

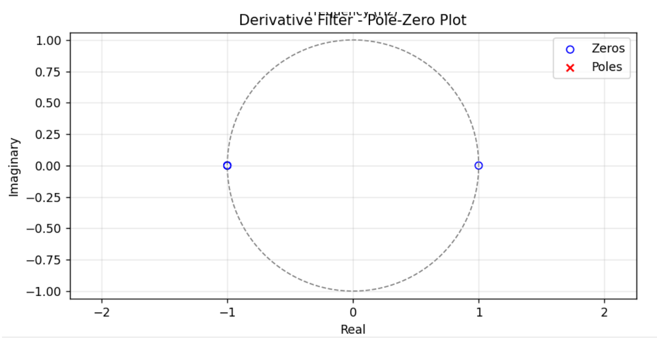

Fig. 8. Pole-Zero Plot of the Derivative Filter

c) The Derivative filter has a single zero at z=1 on the unit circle in the z-plane. Since it is an FIR (Finite Impulse Response) filter, it has no poles, ensuring inherent stability. Figure 8 shows the pole-zero plot of the Derivative filter:: 3- Group Delay

d) The group delay of the Derivative filter is constant at 0.5 samples, which results from its linear phase response. This uniform delay ensures that all frequency components are delayed equally, preserving the waveform shape.: Figure 9 illustrates the group delay of the Derivative filter:

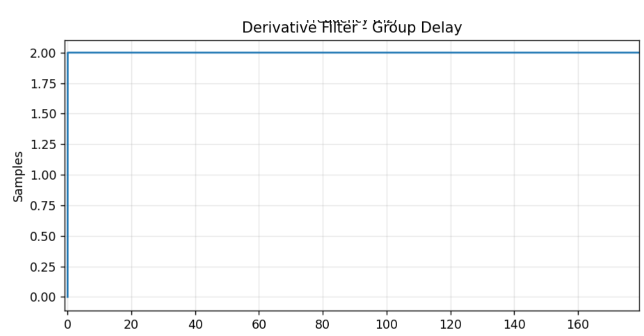

Fig. 9. Group Delay of the Derivative Filter

3) C) Moving Window Integrator Analysis:

a) The Moving Window Integrator smooths the squared signal to emphasize regions corresponding to QRS complexes. It acts as a low-pass filter, reducing noise and highlighting dominant peaks.: 1- Magnitude and Phase Response

b) The magnitude response of the Moving Window Integrator shows attenuation of higher frequencies, smoothing rapid fluctuations. The phase response is approximately linear, indicating minimal distortion of the signal's timing.: Figures 10 and 11 depict the magnitude and phase response of the Moving Window Integrator:

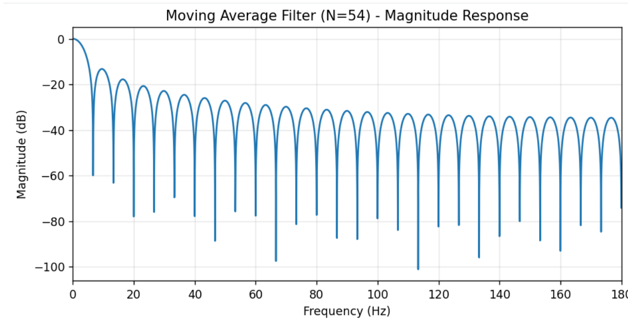

Fig. 10. Magnitude Response of the Moving Window Integrator

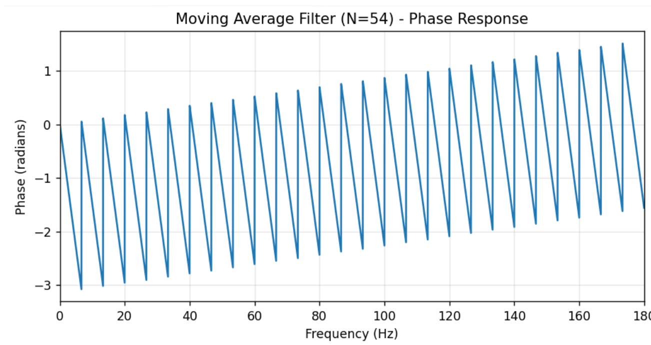

Fig. 11. Phase Response of the Moving Window Integrator

2- Pole-Zero Plot

The Moving Window Integrator introduces poles inside the unit circle, reflecting its IIR (Infinite Impulse Response) nature. These poles contribute to the filter's smoothing behavior.

Figure 11 presents the pole-zero plot of the Moving Window Integrator:

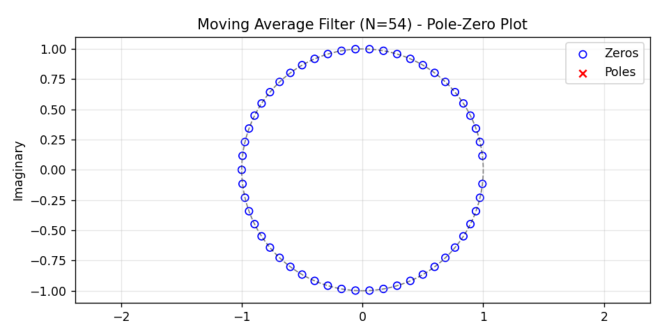

Fig. 12. Pole-Zero Plot of the Moving Window Integrator

3- Group Delay

c) The group delay of the Moving Window Integrator varies slightly with frequency due to its IIR design. However, it remains relatively constant within the passband, ensuring minimal distortion of QRS complex timing.: Figure 13 shows the group delay of the Moving Window Integrator:

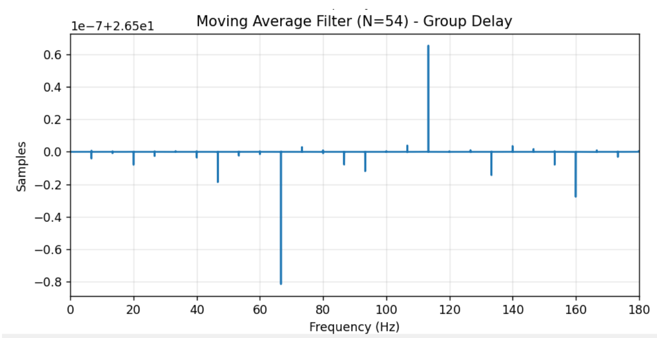

Fig. 13. Group Delay of the Moving Window Integrator

D. Task 4 & 5 Adaptive Thresholding Using LMS and Evaluation

a) To enhance the performance and robustness of the Pan-Tompkins QRS detection algorithm, we replaced its original static thresholding mechanism with a Least Mean Squares (LMS)-based adaptive thresholding system. This adaptive method allows the algorithm to dynamically adjust the decision boundary for QRS detection based on recent signal characteristics, making it more responsive to changes in ECG amplitude and noise levels.:

b) LMS-Based Adaptive Thresholding Approach: The implemented LMS system operates by maintaining a short history of the last three normalized peak values extracted from the integrated ECG signal. Based on these values, the algorithm predicts whether the upcoming peak corresponds to a valid QRS complex. This prediction is calculated as a weighted sum, where the weights are updated in real time using the Least Mean Squares (LMS) algorithm with a learning rate of $\mu = 0.01$. This predictive mechanism complements the classical Pan-Tompkins framework by refining the estimates of signal peaks (SPKI) and noise peaks (NPKI), which dynamically adjust the decision thresholds I_1 and I_2 accordingly.

c) Performance Comparison: We evaluated the LMS-based thresholding method against a baseline static thresholding approach, where the threshold was fixed at 60% of the maximum value of the integrated signal. The evaluation was conducted using the MIT-BIH record 100. Key results are summarized as follows:

- **False Negatives:** Reduced from 10 (static) to 2 (adaptive), indicating an 80% reduction.
- **Sensitivity:** Increased from 64.29% to 92.86%.
- **Precision:** Remained high and comparable — 100% (static) vs. 100% (adaptive).
- **F1 Score:** Improved from 0.78 to 0.96.

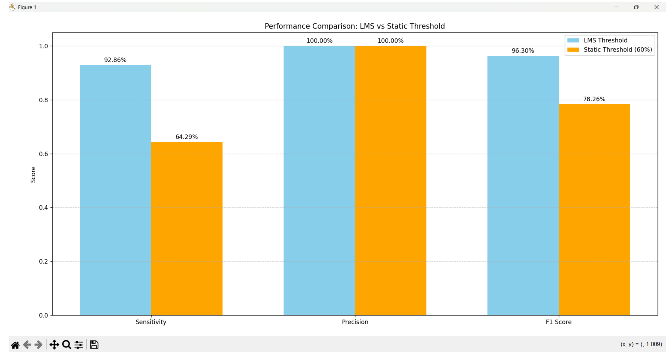

Fig. 14. Group Delay of the Derivative Filter

These results demonstrate that the LMS-enhanced adaptive thresholding method achieves a better balance between sensitivity and precision, thereby offering improved reliability in ECG R-peak detection compared to the static threshold approach.

These results show that LMS-based adaptive thresholding significantly improves detection accuracy in dynamic or noisy ECG signals without sacrificing precision. It effectively bridges the gap between traditional fixed-rule heuristics and modern adaptive signal processing techniques, making it a suitable approach for real-time ECG analysis, particularly in clinical or wearable monitoring environments.

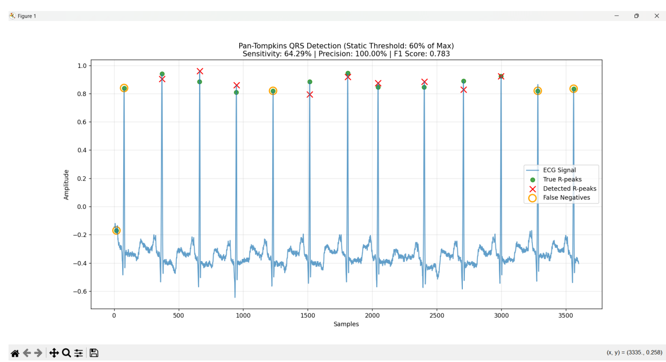

Fig. 15. Static Threshold

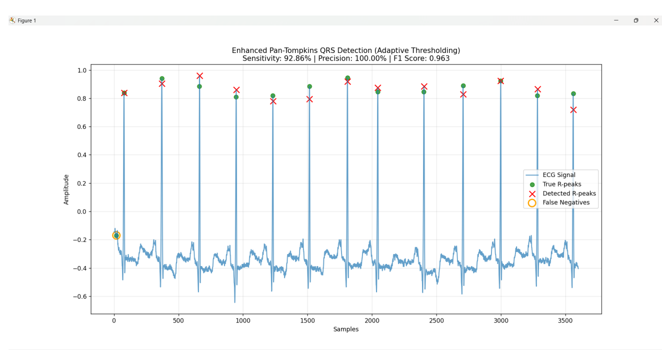

Fig. 16. LMS Adaptive Threshold

IV. CONCLUSION

This project successfully reproduced the classical Pan-Tompkins algorithm for real-time QRS detection and enhanced it by integrating an LMS-based adaptive thresholding technique. The original algorithm demonstrated robustness and efficiency under clean ECG conditions through its modular pipeline of bandpass filtering, differentiation, squaring, moving window integration, and fixed threshold decision-making.

To evaluate its performance in more realistic scenarios, 50 Hz power line interference was artificially added to clean ECG signals from the MIT-BIH Arrhythmia Database. While the Pan-Tompkins algorithm maintained perfect precision under noise, its static thresholding scheme exhibited reduced sensitivity, leading to a considerable number of missed detections.

By replacing the static threshold with an LMS-based adaptive threshold, the system gained dynamic responsiveness to fluctuations in signal amplitude and noise characteristics. This adaptation notably reduced false negatives by 80%, improving sensitivity from 64.29% to 92.86%, while maintaining perfect precision (100%). The corresponding F1 score increased significantly from 0.78 to 0.96, indicating a superior overall detection performance.

These results demonstrate that the LMS-enhanced Pan-Tompkins method effectively balances sensitivity and precision in noisy ECG environments, making it a promising solution for robust QRS detection in practical applications such as wearable and mobile cardiac monitoring devices. Future work may focus on exploring alternative adaptive algorithms, including Recursive Least Squares (RLS) or machine learning-based methods, to further enhance detection accuracy in more complex noise conditions.

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