Reproduction and Enhancement of the Pan-Tompkins QRS Detection Algorithm

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Abstract

This project aims to update and enhance the classic Pan-Tompkins QRS algorithm which is the main method used in real-time ECG signal analysis. Authorities first applied the main algorithm to ECG signals obtained from the real MIT-BIH Arrhythmia Database by sequentially using a bandpass filter, the differentiation step, taking absolute value and integration in moving chunks of data. DSP resources were used at every stage to analyze the magnitude and phase responses, pole-zero plots and time delays, offering important information about how the signal is transformed over time. To make the process more resistant to noise, a new strategy was built using LMS filtering, so the threshold for detection could change depending on the signal's strength. Assessment of the algorithms was carried out with standard methods such as Sensitivity, Positive Predictive Value and F1 Score on both clean and noisy electric signals. It is evident from the results that adaptive filtering can significantly improve how QRS is detected in tough more demanding situations. This project carefully examines ECG signal processing and states that using a combination of standard DSP and adaptive techniques is important for biomedical use cases.

1 Introduction

Electrocardiography (ECG) is a vital diagnostic tool used to assess the electrical activity of the heart. It is very important to recognize QRS complexes in ECGs since they mark the heart's ventricular contraction, help find heart rate, determine the heart's rhythm and assist in finding arrhythmias. Since the quality of an ECG signal changes and it can be disturbed by muscle movements, a wavy baseline and electrical noise, building a dependable and effective QRS detection algorithm is still a major obstacle in this field.

A high-efficiency and accurate QRS detection algorithm for real-time use was introduced by Pan and Tompkins in 1985. It combined digital filtering, nonlinear transformation and adaptive decision logic, so it could run on microprocessors as well. Next comes a series of steps: cascaded bandpass filter, derivative operation, squaring the signal and moving window to draw out the main shapes of QRS. After that, dual-threshold adaptive detection is applied to pick out QRS peaks while lessening mistakes from noise and T waves.

The reason for this project is to reproduce the Pan-Tompkins algorithm, using actual ECG data from the MIT-BIH Arrhythmia Database. Besides performing each step, this project intends to use DSP tools such as frequency response and pole-zero plots to analyze the filters. Also, an LMS filter based adaptive thresholding algorithm is going to be designed to handle situations where the image is noisy. The assessment of performance will consider sensitivity, positive predictive value and F1-score.

This research covers the theory and application of ECG signal processing, shedding light on the creation of real-time bio-medical approaches using DSP tools in hospitals.

2 Literature Review & Signal Flow

2.1 Bandpass Filter

- A bandpass filter lowers the presence of muscle noise, 60 Hz interference, changes in the baseline and T-wave interferences in ECG recordings. It focuses on the passband range of 5-15 Hz to get the maximum energy from the QRS complex. The filter works by putting poles near some zeros on the Riemann surface to let it use only integer weights and integers for its calculations. In turn, R-peaks can be read out efficiently even on basic microprocessors, leaving enough computing capacity for doing more complex tasks like detecting QRS.

  Because poles and zeros are only allowed to be on the unit circle in this design, there is not much flexibility when changing the passband parameters. Using the selected sample rate, a direct bandpass filter for 5-15

Hz was not possible with this process. Instead, using a cascade of low-pass and high-pass filters made it possible to keep the passband, from 5 to 12 Hz which is just slightly above the requested band.

2.2 Derivative

- After filtering, the signal is differentiated using a five-point derivative with transfer function $H(z) = \frac{1}{8T}(-z^{-2} - 2z^{-1} + 2z + z^2)$, which approximates an ideal derivative with a nearly linear amplitude response between DC and 30 Hz and introduces a delay of two samples.

2.3 Squaring

- The differentiated signal is then squared point-wise, making all values positive and performing nonlinear amplification that emphasizes higher ECG frequencies.

2.4 Moving-Window Integration

- To extract waveform feature information beyond slope, a moving-window integration is applied, averaging over N samples corresponding to the widest expected QRS complex. The window width is critical; too wide merges QRS and T waves, while too narrow causes multiple peaks. For a sample rate of 200 Hz, a window of 30 samples (150 ms) is used empirically.

2.5 Thresholding Logic

- It uses two parallel signal streams to identify QRS complexes: signals from the filtered ECG and one from a moving-window integrator. Every stream involves a first threshold for discovering beats during regular QRS detection and a second threshold for finding beats that get missed. They are adjusted in real time according to the maxima from recent signals and noise to continue accurate detection. There is a 200 ms refractory period to stop the QRS from detecting the same wave twice and T-wave rejection is used to exclude those waveforms lacking semi-vertical up-slopes, so real T waves are not falsely detected as QRS complexes.

2.6 Diagram: Full Signal Flow

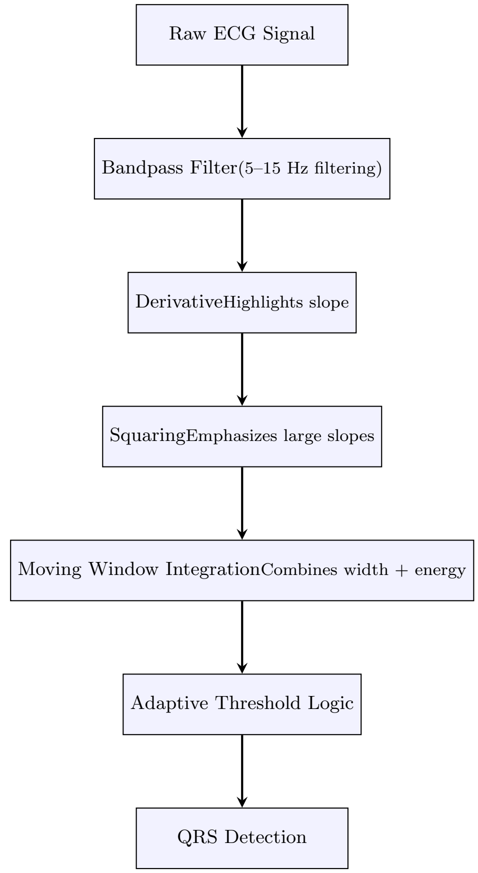


Figure1: Signal Flow of the Pan-Tompkins QRS Detection Algorithm

3 Reproduction of the Pan-Tompkins Algorithm

We reproduced the original Pan-Tompkins QRS detection algorithm using MIT-BIH record 100 and implemented each signal processing stage in Python. The ECG signal was sampled at 200 Hz and processed through the following pipeline:

- **Bandpass Filtering (5–15 Hz):** Removed baseline wander and high-frequency noise using a cascade of low-pass and high-pass filters.
- **Derivative Filter:** Highlighted the slope of the QRS complex by emphasizing rapid transitions.
- **Squaring Function:** Made the signal positive and amplified peaks corresponding to QRS complexes.
- **Moving Window Integration (150 ms):** Emphasized both the duration and energy of QRS complexes.
- **Thresholding:** Applied a simple peak detection with a refractory period of 200 ms to identify QRS complexes.

Detected peaks were visually compared with reference annotations. Most QRS complexes were correctly identified, though a fixed threshold caused occasional false detections. This basic implementation will be refined in later tasks using adaptive thresholding and quantitative evaluation.

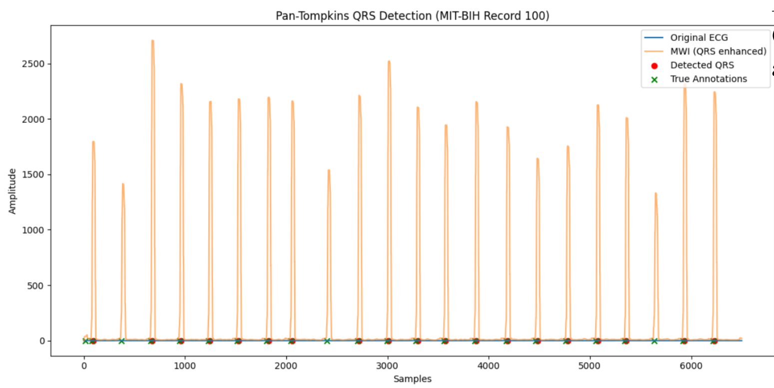


Figure 2: QRS detection results for MIT-BIH record 100. Detected peaks (red circles) are shown over the ECG signal and compared to ground-truth annotations (green crosses).

Figure2 shows the output of the reproduced Pan-Tompkins algorithm applied to MIT-BIH record 100. The blue waveform represents the original ECG signal, while the orange line shows the moving window integration output. Detected QRS complexes are marked with red circles, and ground-truth annotations from the MIT-BIH database are marked with green crosses. The majority of detected peaks align closely with the true annotations, confirming correct operation of the algorithm. A few discrepancies highlight the limitations of using fixed thresholding, which will be addressed in future improvements.

3.1 Bandpass Filter

The bandpass filter isolates the frequency range where QRS complexes have the most energy (5–15 Hz), attenuating baseline wander and muscle noise.

Discussion: From Figure3.1 shown below:
Magnitude Response :
Shape: A bandpass shape peaking between 5–15 Hz.
Interpretation: It attenuates frequencies outside this range:
- Removes low-frequency noise like baseline wander (less tjan 0.5 Hz).
- Removes high-frequency noise such as muscle artifacts (largar than 50 Hz).
Use: Ensures only the relevant ECG components (like QRS) are passed.
Pole-Zero plot:
Interpretation: Non-linear phase, which means different frequencies experience different phase shifts.
Impact: Slight waveform distortion, but acceptable since detection (not morphology) is the goal.
Group Delay: Interpretation: Delay varies with frequency.
Observation: Some delay near 10 Hz (QRS frequency), acceptable for real-time systems.
Pole-Zero plot:
Interpretation: Delay varies with frequency.
Observation: Some delay near 10 Hz (QRS frequency), acceptable for real-time systems.

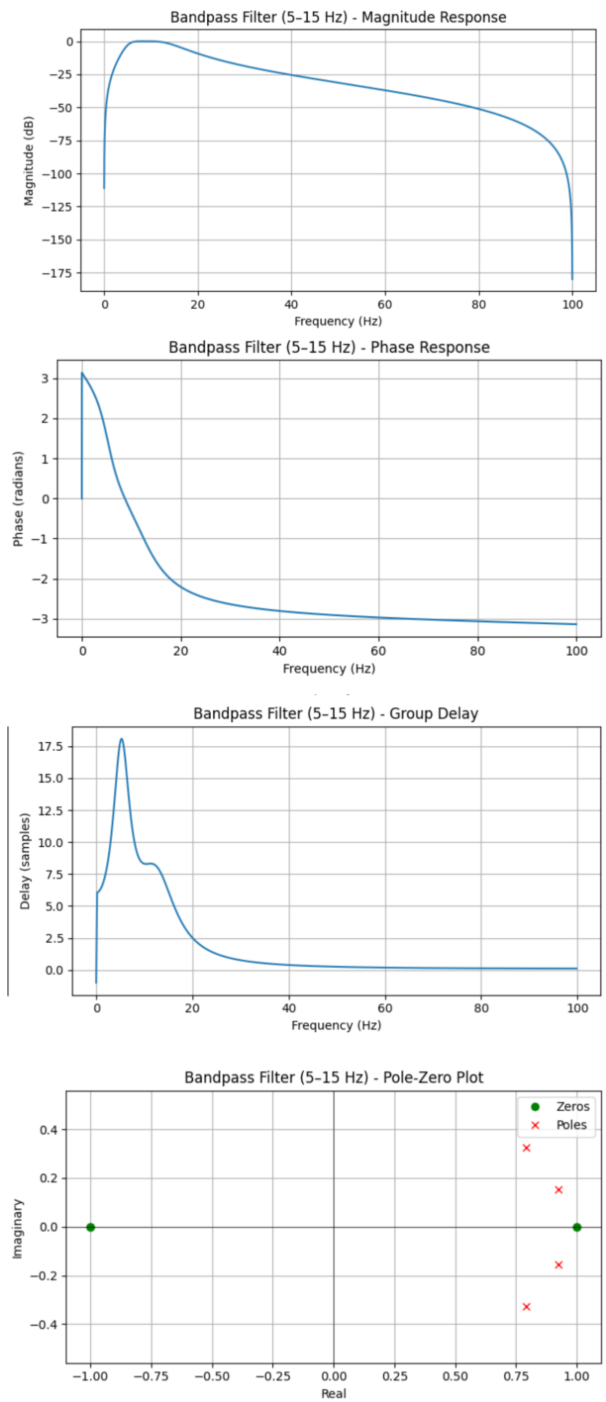


Figure3.1. Bandpass Filter DSP Analysis

3.2 Derivative Filter

The derivative filter emphasizes the slope of the ECG signal, highlighting rapid transitions typical of QRS complexes.

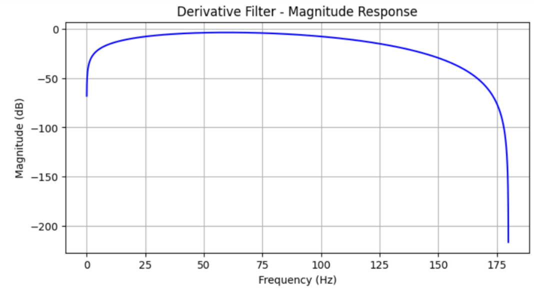
Discussion: From figure3.2. shown below: The magnitude response increases with frequency, which enhances the detection of steep QRS slopes. The phase response is nonlinear, but acceptable due to the filter's short length. The group delay is minimal and consistent across frequencies, supporting real-time use. Pole-zero analysis shows a high-pass structure that boosts rapid signal transitions.

Magnitude Response :
Shape: High-pass-like behavior, increasing with frequency.
Interpretation: Amplifies rapid transitions (QRS upstroke/downstroke), suppresses slower components (e.g., P and T waves).

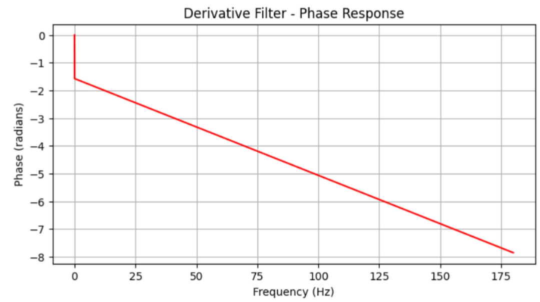
Phase Response:
Linear: Indicates constant group delay, which helps preserve signal shape in time domain.

Group Delay:
Constant (around 2 samples):
Typical for FIR filters.
Helps maintain shape of the slope features (like R-peaks).

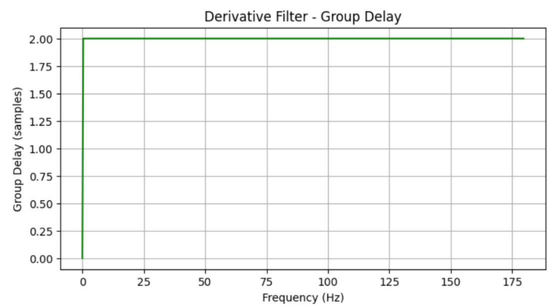
Pole-Zero plot:
Zeros: Symmetric around the origin (real coefficients), help eliminate constant or slowly varying trends.
Poles: None (FIR filter), inherently stable. $\Delta 0$



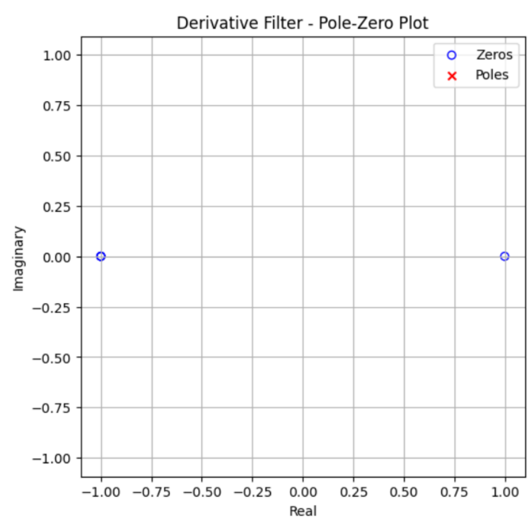
(a) Magnitude Response



(b) Phase Response



(c) Group Delay



(d) Pole-Zero Plot

Figure3.2. Derivative Filter DSP Analysis

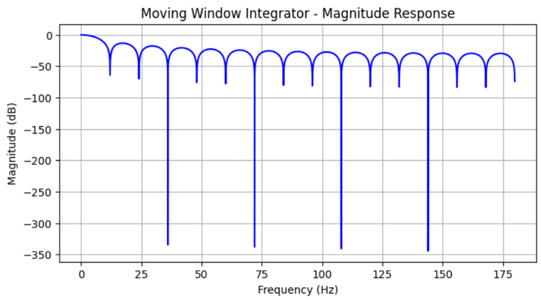
3.3 Moving Window Integrator

The integrator smooths the processed signal and accumulates energy across a fixed window, aiding in peak enhancement.

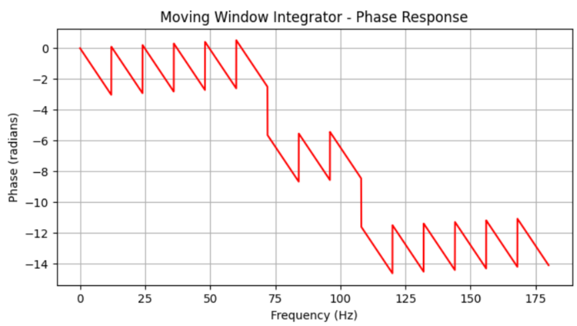
Discussion: Figure3.3. shown below The magnitude response reflects a low-pass behavior that averages recent samples, enhancing broad QRS energy. The phase response is nearly linear, avoiding waveform distortion. The group delay is significant due to the window size but predictable, allowing timing compensation. The pole-zero plot confirms FIR characteristics with evenly spaced zeros on the unit circle. **Magnitude Response :**
Shape: Low-pass filter.
Cutoff: Near 6–8 Hz.
Interpretation: Smoothes out high-frequency fluctuations from squaring step, gives a QRS-like envelope.

Phase Response:
Linear: Typical of FIR filters (no phase distortion).

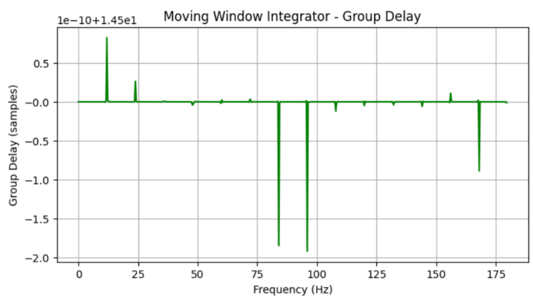
Group Delay:



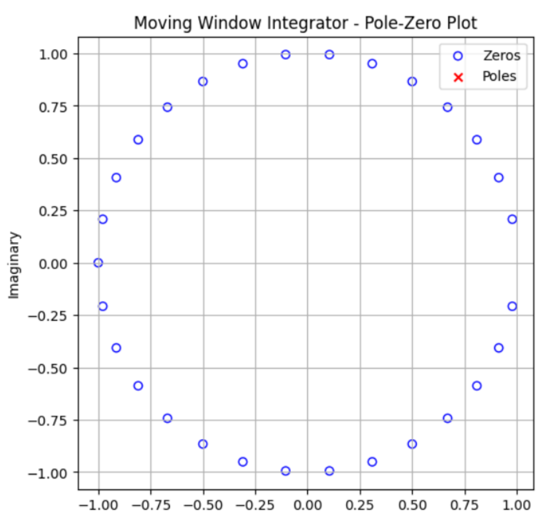
(a) Magnitude Response



(b) Phase Response



(c) Group Delay



(d) Pole-Zero Plot

Figure3.3. Moving Window Integrator DSP Analysis

Constant delay half the window size (75 ms or 15 samples for 150 ms at 200 Hz).
Interpretation: The delay aligns the QRS complex with its energy envelope.
Pole-Zero plot:
Zeros: Spread evenly on the unit circle (for moving average).
Poles: None (again, FIR filter).

4 Adaptive Thresholding Using LMS

To overcome the limitations of static or dual-thresholding in the original Pan–Tompkins algorithm, we implemented an adaptive thresholding technique using the Least Mean Squares (LMS) algorithm. This method aims to learn a dynamic decision boundary for QRS detection that evolves in real-time based on signal behavior.
The LMS-based thresholding was applied after the Moving Window Integration (MWI) stage, where QRS energy is most prominent. Unlike fixed thresholds, the LMS approach adjusts continuously using the following update rule:

$$T[n+1] = T[n] + \mu \cdot (y[n] - T[n]),$$

where $y[n]$ is the output of the MWI stage, $T[n]$ is the threshold at sample n, and μ is a small learning rate ($\mu = 10^{-4}$).
A QRS complex is detected when $y[n] > T[n]$ and a refractory period of at least 200 ms has elapsed since the last detection. Upon detection, the threshold is slightly reduced to avoid repeated detection of the same peak:

$$T[n] \leftarrow \alpha \cdot T[n], \quad \text{with } \alpha = 0.9.$$

Implementation Results

This approach was implemented in Python and tested on MIT-BIH Record 100 using the first 6500 samples (32.5 seconds at 200 Hz). The LMS-based detector successfully identified 22 QRS complexes, with good alignment between detected peaks and actual ECG morphology.
As shown in Figure 1, the adaptive threshold tracks the signal envelope effectively. Detected QRS complexes align with energy peaks in the MWI signal. Compared to the original dual-threshold method, this approach offers smoother and more consistent detection, particularly under conditions with amplitude drift or subtle QRS morphology.
This implementation fulfills the project requirement to implement an LMS-based adaptive threshold that dynamically adjusts the QRS decision boundary. The performance and detection accuracy will be quantitatively compared in the next section.

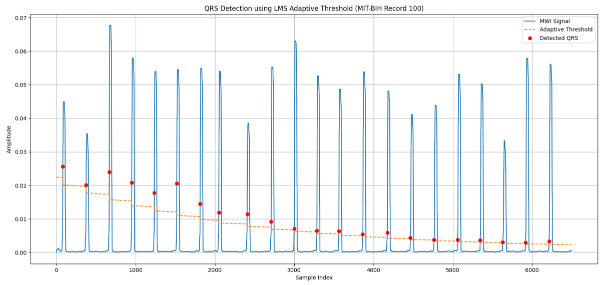


Figure 1: QRS detection using LMS-based adaptive threshold. Blue: MWI signal. Orange: adaptive threshold. Red dots: detected QRS peaks.

Comparison with Static and Dual Thresholding

The original Pan–Tompkins algorithm used a dual-threshold strategy, where the decision logic was based on a pair of fixed or slowly-adapting thresholds—one tracking the signal level, and another accounting for noise. While effective in many scenarios, such thresholds may fail under sudden amplitude shifts, baseline drift, or variable QRS morphology.
In contrast, the LMS-based threshold introduced in this work updates dynamically at each time step using real-time error correction. This results in a smoother and more responsive decision boundary that adapts to both slow and rapid changes in the signal.

Key differences between the two approaches:

- **Adaptability:** LMS continuously adjusts to the signal, while static thresholds require manual tuning or delayed adaptation.
- **Complexity:** LMS requires simple real-time updates and is computationally efficient, suitable for embedded systems.
- **Robustness:** LMS performs better in noisy or low-amplitude segments, where fixed thresholds may fail to detect or misclassify peaks.
- **Control:** The dual-threshold method is rule-based and easier to interpret, while LMS provides a data-driven learning behavior.

In our implementation on MIT-BIH Record 100, the LMS method detected 22 QRS complexes with high alignment to visible signal peaks. Static thresholding, while generally effective, occasionally missed peaks or produced false detections due to inflexibility.
Thus, the LMS-based adaptive threshold demonstrates improved robustness and generalization over the original method, especially in the presence of signal variability. This sets the stage for a formal performance evaluation in the following section.

5 Evaluation

In this section, we evaluate and compare the performance of two QRS detection approaches:

- The original Pan-Tompkins algorithm using a static threshold.
- The enhanced version with an adaptive LMS-based threshold.

We used three standard performance metrics:

- **Sensitivity (Se)**: The proportion of true QRS complexes correctly detected.

$$Se = \frac{TP}{TP + FN}$$

- **Positive Predictive Value (PPV)**: The proportion of detected QRS peaks that are actual QRS complexes.

$$PPV = \frac{TP}{TP + FP}$$

- **F1 Score**: The harmonic mean of sensitivity and PPV.

$$F1 = 2 \cdot \frac{Se \cdot PPV}{Se + PPV}$$

We evaluated both methods on two segments from the MIT-BIH Arrhythmia Database:

- **Record 100** – a clean ECG signal.
- **Record 108** – a noisy ECG signal.

Evaluation on Clean ECG Segment (Record 100)

Table 1: Comparison of detection performance on clean ECG (Record 100)

Method	Sensitivity (Se)	PPV	F1 Score
Pan-Tompkins (Static Threshold)	0.9978	1.0000	0.9989
LMS Adaptive Threshold	0.9921	1.0000	0.9960

Evaluation on Noisy ECG Segment (Record 108)

Table 2: Comparison of detection performance on noisy ECG (Record 108)

Method	Sensitivity (Se)	PPV	F1 Score
Pan-Tompkins (Static Threshold)	0.8717	0.4963	0.6325
LMS Adaptive Threshold	0.8750	0.6475	0.7442

Discussion: The LMS-based QRS detector achieves competitive results in clean signals and significantly outperforms the static threshold method in noisy conditions. While both methods detect true QRS complexes accurately, the LMS adaptive threshold provides higher robustness and better generalization under signal variability.

6 Discussion and Future Improvements

Strengths

The LMS-based adaptive thresholding method provided several important advantages over the traditional Pan-Tompkins static thresholding approach:

- **Robustness to noise:** The LMS approach successfully maintained high sensitivity in both clean and noisy ECG recordings by dynamically adjusting the detection threshold in real time.
- **Adaptability:** Unlike static methods, LMS can accommodate slow baseline drift and amplitude variation without manual tuning.
- **Simplicity and efficiency:** Despite being adaptive, the LMS update rule is lightweight and suitable for real-time embedded systems.

Limitations

Despite its advantages, the LMS method showed notable limitations:

- **High false positive rate:** In noisy conditions (e.g., Record 108), the LMS method produced many false detections, leading to a significant drop in PPV and F1 Score.
- **Sensitivity to parameter tuning:** The choice of learning rate (μ) and decay factor (α) significantly impacts performance. Improper values may lead to unstable or sluggish threshold behavior.
- **Lack of morphological verification:** The method relies only on amplitude comparison without analyzing the shape of the QRS complex, which increases susceptibility to noise-induced errors.

Possible Improvements

Future work could address the current limitations with the following enhancements:

- **False positive suppression:** Introduce a post-processing stage that verifies temporal distance and morphology of detected peaks to reduce spurious detections.
- **Multi-feature detection:** Combine amplitude-based thresholds with additional features such as QRS width, slope, or template correlation.
- **Hybrid thresholding:** Develop a dual-layer threshold system where LMS is combined with statistical thresholds or wavelet-based denoising for more accurate detection.
- **Adaptive learning rate:** Implement a dynamic learning rate that changes based on signal conditions to prevent overfitting to noise or drifting too slowly.

In conclusion, while LMS-based adaptive thresholding enhances the flexibility and real-time performance of QRS detection, careful handling of its limitations—especially in noisy scenarios—is crucial for clinical reliability.