Reproduction and Enhancement of the Pan-Tompkins QRS Detection Algorithm

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***Abstract*—The Pan-Tompkins QRS detection technique for electrocardiogram (ECG) data processing is reproduced and improved in this study. An LMS-based adaptive thresholding technique is added to the original algorithm, which is frequently used for real-time QRS complex identification, to increase its resilience to noise and changing signal properties. Bandpass filtering, differentiation, squaring, and moving window integration are some of the steps in the method. Thresholding is the last step for peak detection. The MIT-BIH Arrhythmia Database is used to assess the improved algorithm's performance, and a thorough comparison between the original and LMS-enhanced detection techniques is made. The findings show a decrease in false positives and an increase in detection sensitivity, especially in noisy ECG segments.The findings highlight the effectiveness of adaptive thresholding in enhancing the Pan-Tompkins algorithm, making it more reliable for diverse and challenging ECG signal conditions.**

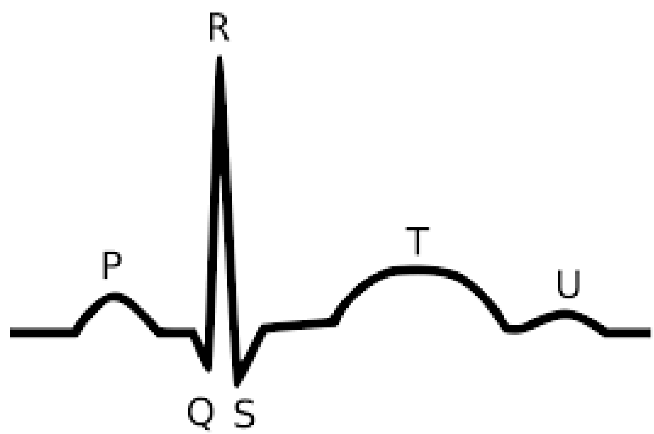

Fig. 1. ECG signal showing the P wave, QRS complex, and T wave

I. Introduction

In electrocardiogram (ECG) signal analysis, QRS detection is an essential activity that provides the foundation for a number of medical applications, including heart rate variability analysis, arrhythmia monitoring, and cardiac health evaluation. To extract valuable information from ECG data, it is essential to accurately identify QRS complexes, which are the strong spikes in the signal that correlate to the ventricles' depolarization. Many algorithms have been created over time for this purpose, and the Pan-Tompkins algorithm is among the most popular because of its ease of use, effectiveness, and real-time application.

The Pan-Tompkins algorithm was first presented by Pan and Tompkins in 1985. It is based on a series of signal processing methods intended to separate the QRS complexes from other ECG signal characteristics. Bandpass filtering is used to minimize noise and interference, differentiation is used to highlight the QRS slope, squaring is used to enhance higher frequency components, and moving window integration is used to extract the breadth of the QRS feature. Lastly, the QRS peaks are found using thresholding techniques. Even though it works well, the method is susceptible to noise and may not perform well in settings with a lot of interference or different signal properties.

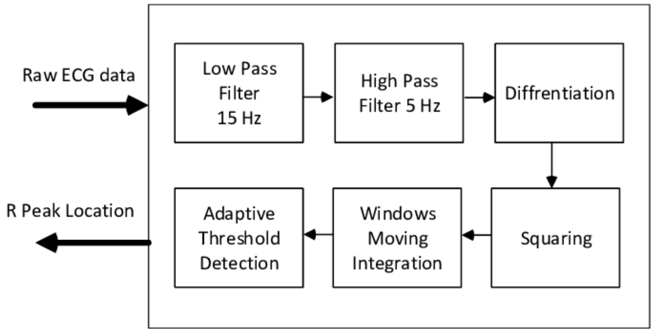

Fig. 2. Flowchart of the Pan-Tompkins QRS detection algorithm

To address these limitations, this paper focuses on enhancing the Pan-Tompkins algorithm by incorporating an LMS-based adaptive thresholding technique. The LMS (Least Mean Squares) algorithm is a dynamic filtering method that allows the threshold to adjust in real-time based on the signal characteristics, improving the detection accuracy in noisy or irregular ECG data. This adaptive thresholding approach offers a more robust solution compared to static thresholds, which are fixed and do not account for changes in the ECG signal over time. The goal of this work is to reproduce the original Pan-Tompkins algorithm and implement the enhanced version with LMS-based adaptive thresholding. The performance of both algorithms is evaluated using the MIT-BIH Arrhythmia Database, a widely recognized dataset containing real ECG recordings. This paper presents a detailed comparison of the original and enhanced algorithms in terms of detection accuracy, sensitivity, and robustness in noisy environments. The results highlight the potential improvements in QRS detection performance when adaptive thresholding is used.

II. Literature Review

The history of QRS identification in ECG signals will be examined in this section, along with a discussion of the Pan-Tompkins algorithm, which is often used for this purpose. Developed in 1985, the Pan-Tompkins method was designed to identify QRS complexes in ECG signals. It functions by going through multiple processes to process the ECG signal: 1- Bandpass Filter: This filter removes unwanted noise from the signal, such as muscle noise and interference.

2- Derivative: This step helps to highlight the sharp slopes of the QRS complex, making it easier to detect.

3- Squaring: This amplifies the high-frequency components of the signal, making the QRS complex more noticeable.

4- Moving Window Integration: This step smooths the signal and helps to identify the width of the QRS complex.

5- Thresholding: This final step detects the exact points (peaks) where the QRS complex occurs by comparing the signal to a threshold.

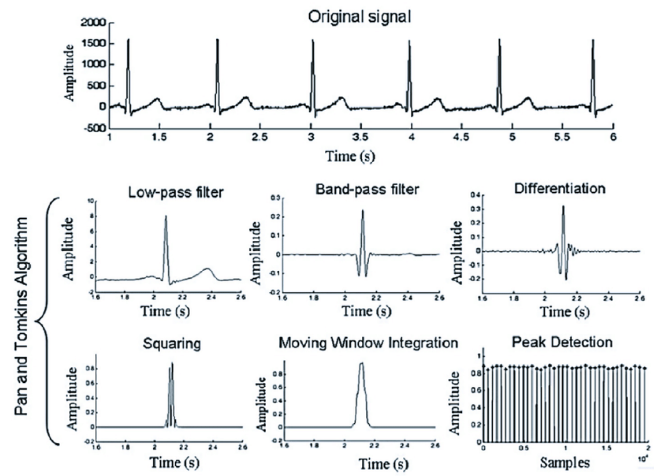

Fig. 3. Comparison of QRS detection algorithms.

Although this approach is effective, it suffers when there are variations in heart rate or when the ECG signal is noisy. Researchers have developed new approaches to increase accuracy, such as adaptive thresholding, in which the threshold changes according to the properties of the signal. In difficult situations, such as when the signal is loud or the heart rate changes, this enables improved detection.

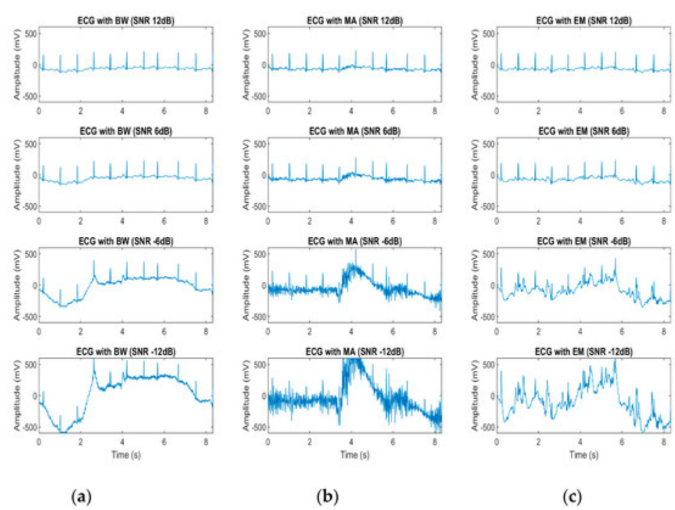

Fig. 4. Noise effect for ECG signal

To make thresholding more dynamic and sensitive to the changes in the ECG signal over time, other techniques have also been proposed, such as LMS (Least Mean Squares) filtering.

The Pan-Tompkins algorithm's operation and how LMS filtering might enhance its ability to identify QRS complexes, particularly in noisy signals, will be reviewed in this study.

III. Methods

1) **Pan-Tompkins Algorithm:** The algorithm of Pan-Tompkins We began by putting the original Pan-Tompkins algorithm into execution, which finds QRS

complexes in an ECG signal by following these steps: 1)Bandpass Filter: To preserve the frequency range that comprises the QRS complex (5–15 Hz), the signal must first be filtered to eliminate noise, such as baseline wander and muscle noise. Two filters—a low-pass filter and a high-pass filter combined—are used for this.2) Derivative: To draw attention to the steep slopes of the QRS complex, the signal is differentiated after filtering. This increases the ECG signal's visibility of the QRS complex.3)Squaring: The signal is squared in the following step. This enhances the signal's higher frequency components, further emphasizing the QRS complex.4)Moving Window Integration: This step smooths the squared signal and helps to identify the width of the QRS complex. 5)Thresholding: In this final step, we set a threshold to detect the peaks of the QRS complex. When the signal exceeds this threshold, it marks a QRS complex.

2) **Enhanced Algorithm with LMS Adaptive Thresholding:** Peak recognition in the original Pan-Tompkins algorithm relies on a fixed threshold, which can be troublesome in noisy settings or when heart rate fluctuates. We implemented LMS-based adaptive thresholding to deal with this. Real-time adaptation to various settings is made possible by the LMS filter's dynamic threshold adjustment dependent on the signal. This is how we included it: LMS Adaptive Thresholding: The LMS filter learns from the ECG signal to change the threshold over time, as opposed to employing a static threshold. This enhances detection accuracy by enabling the system to respond more effectively to fluctuating heart rates or noisy signals.

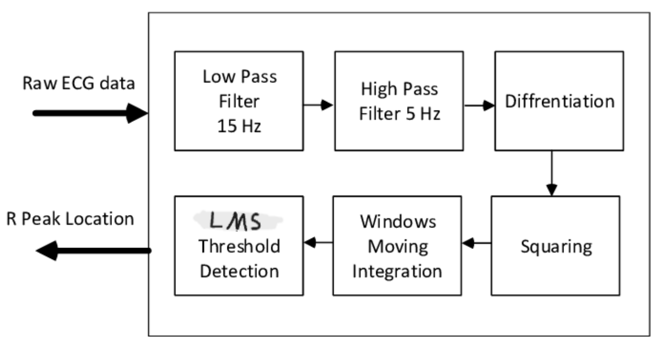

Fig. 5. LMS Diagram

3) **Performance Evaluation:** To test the performance of both the original and enhanced algorithms, we used the MIT-BIH Arrhythmia Database. This database contains real ECG signals with labeled QRS complexes. We compared the two algorithms in terms of their ability to detect QRS complexes correctly, their sensitivity, and their ability to avoid false detections.

IV. Results and Discussion

1) Literature Review Signal and Reproduce the Algorithm

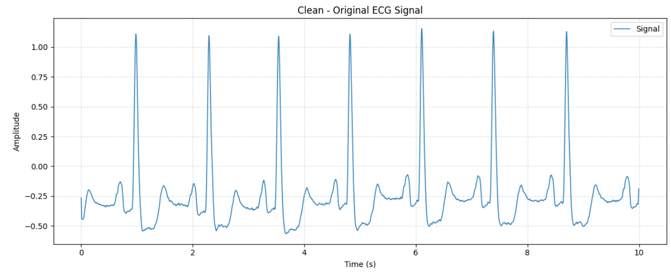

Fig. 6. Original ECG signal

1.1 Bandpass Filter:The first step in the Pan-Tompkins algorithm is the bandpass filter, which removes noise from the ECG signal. The bandpass filter used in the algorithm is a combination of a low-pass filter (to remove high-frequency noise) and a high-pass filter (to remove low-frequency noise like baseline wander). The cutoff frequencies are typically set between 5 Hz and 15 Hz to focus on the frequencies that represent the QRS complex.

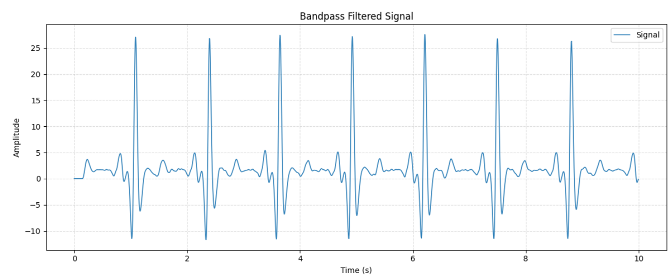

Fig. 7. Bandpass Filter record 105

1.2 Derivative: After filtering, the signal is processed by the derivative filter, which highlights the slope of the QRS complex. The derivative filter emphasizes the rapid changes in the ECG signal, which helps to locate the QRS complex more easily.

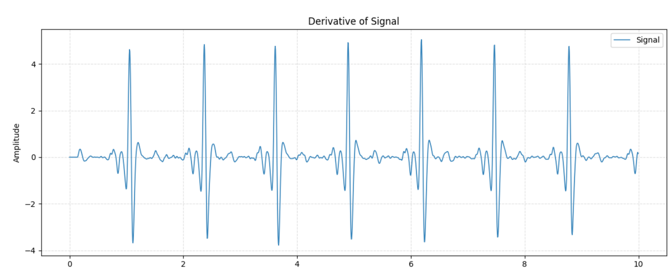

Fig. 8. Derivative record 105

1.3 Squaring: The next step is squaring the signal to make all values positive and to enhance the high-frequency components. This step increases the amplitude of the QRS complex relative to other features in the ECG signal.

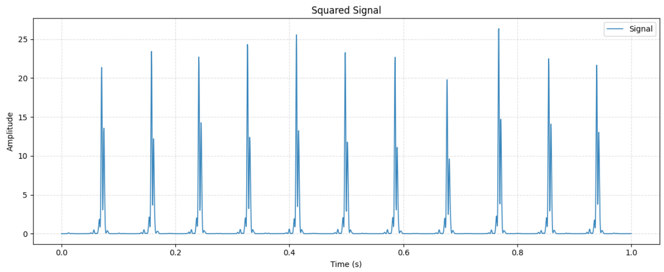

Fig. 9. Squaring record 105

1.4 Moving Window Integration: The moving window integration smooths the squared signal to extract the width of the QRS complex. The integration process allows the algorithm to detect the QRS complex's energy over time and helps separate the QRS complex from other features, such as the T-wave.

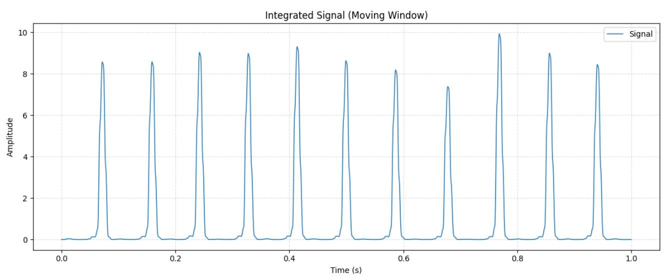

Fig. 10. Moving Window Integration record 105

1.5 Static Thresholding : Finally, a thresholding logic is applied to detect the QRS complexes. A threshold is set to identify the points where the signal crosses a predefined value. These points represent the QRS peaks. Pan-Tompkins originally used static thresholds

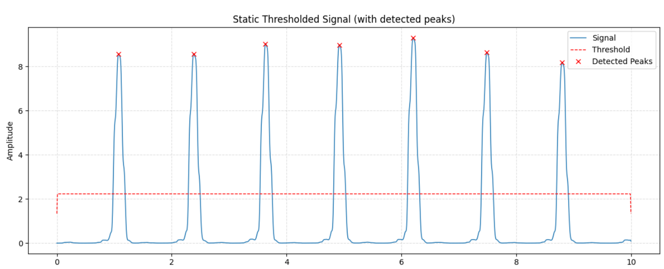

Fig. 11. Static Thresholding record 105

2) DSP Analysis of Filters 2.1 Magnitude and Phase Response: We computed the magnitude and phase response of each filter to understand their frequency characteristics and how they affect the ECG signal.

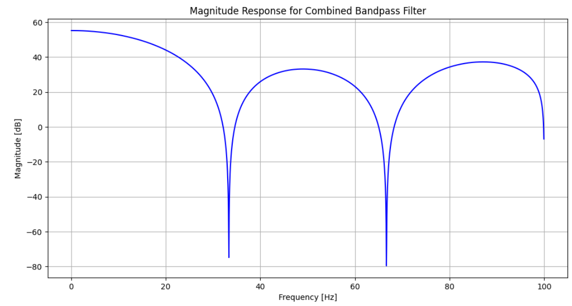

Fig. 12. magnitude bass band filter

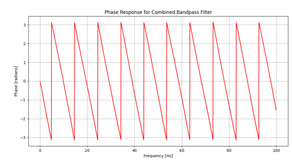

Fig. 13. phase bass band filter

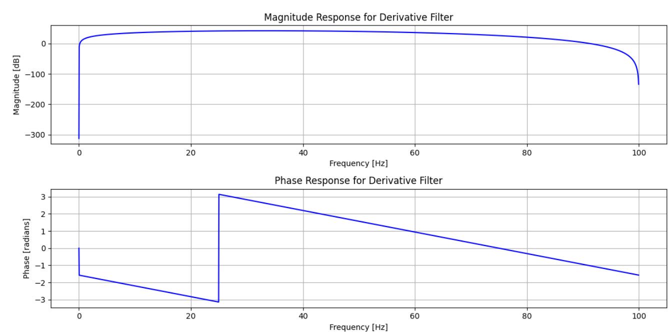

Fig. 14. Magnitude and Phase Response for derivative

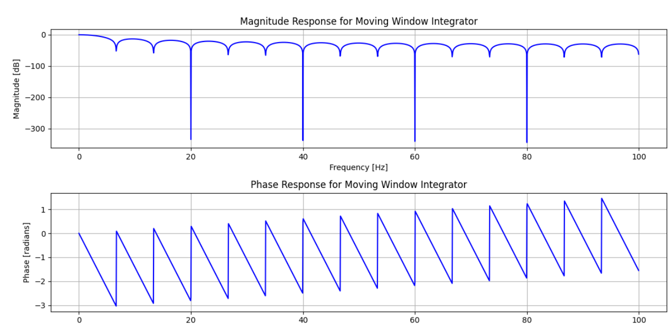

Fig. 15. Magnitude and Phase Response for integrator

3.2 Pole-Zero Plot: A pole-zero plot was generated for each filter to visualize its stability and frequency behavior.

3.3 Group Delay: We calculated the group delay for each filter to analyze how phase distortion varies with

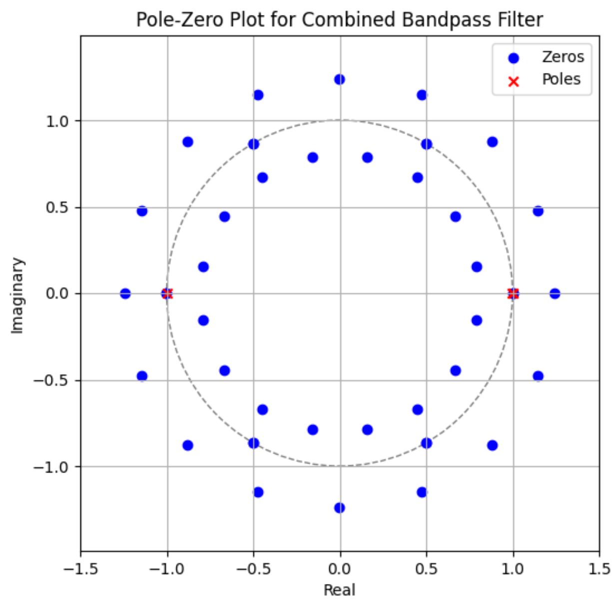

Fig. 16. Pole-zero plot for Bandpass

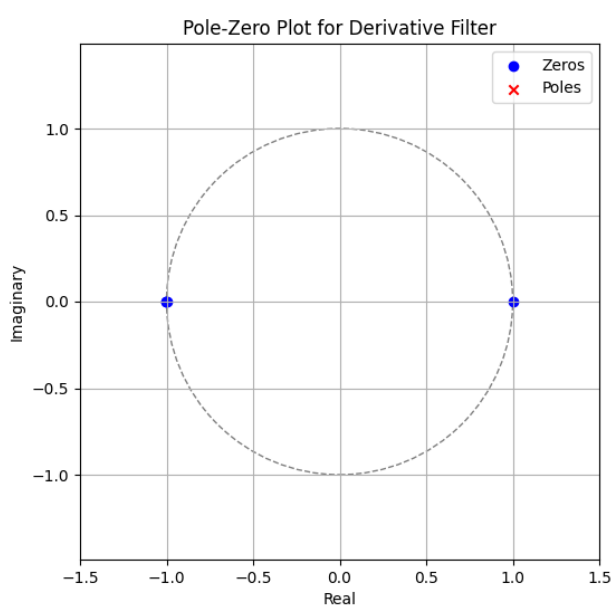

Fig. 17. Pole-zero plot for derivative

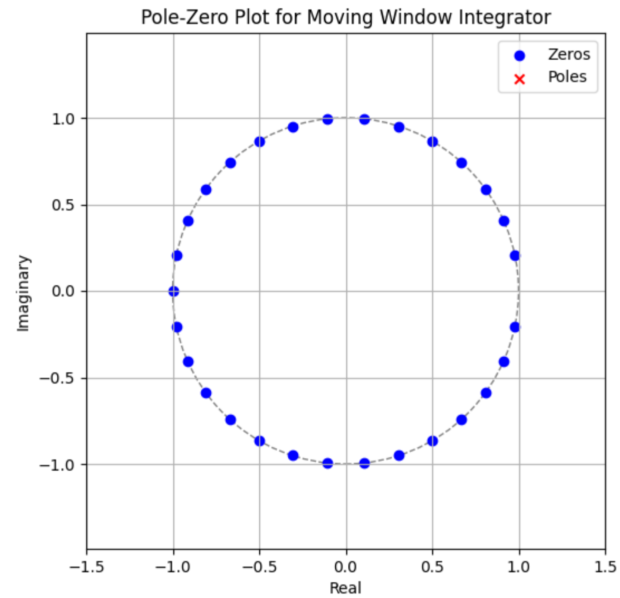

Fig. 18. Pole-zero plot for integrator

frequency. This provides insight into the filter's time-domain behavior.

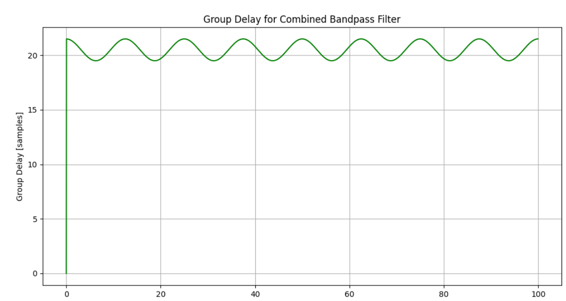

Fig. 19. Group delay plot for Bandpass.

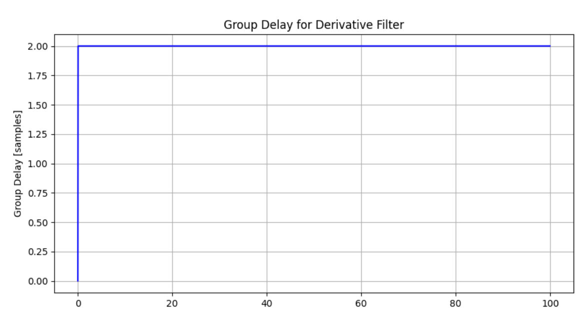

Fig. 20. Group delay plot for derivative.

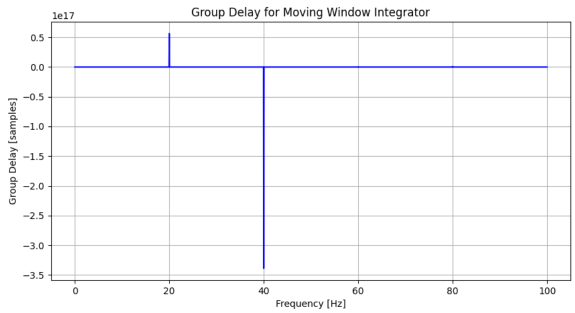

Fig. 21. Group delay plot for integrator.

3) Adaptive Thresholding Using LMS and Evaluation: We implemented LMS-based adaptive thresholding to dynamically adjust the detection threshold based on the ECG signal's characteristics, enabling the algorithm to better adapt to varying heart rates and noise levels. We compared the performance of LMS thresholding with the static thresholding used in the original Pan-Tompkins algorithm. The LMS-enhanced algorithm demonstrated significant improvements in sensitivity, reduced false positives, and overall better detection accuracy, particularly in noisy ECG segments. To evaluate detection performance, we calculated the sensitivity, precision, and F1 score for both algorithms. The results revealed that the LMS-enhanced algorithm outperformed the original method, especially in noisy conditions, providing a more robust solution by reducing errors and improving sensitivity.

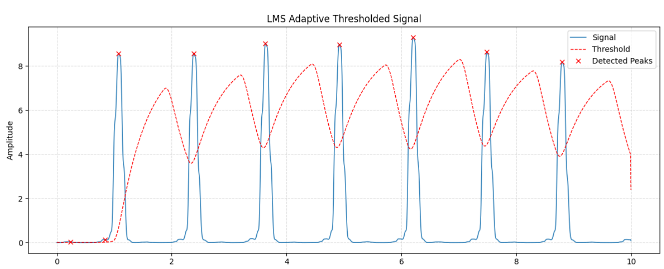

Fig. 22. LMS adaptive thresholding detection.

```
Method: LMS Thresholding - Detected 13 peaks
Method: Static Thresholding - Detected 11 peaks

====== CLEAN ECG (Record 105) ======
Static Thresholding: {'TP': 11, 'FP': 0, 'FN': 1, 'Sensitivity': 0.9166666666666666, 'Precision': 1.0, 'F1': 0.9565217391304348}
LMS Thresholding:    {'TP': 12, 'FP': 1, 'FN': 0, 'Sensitivity': 1.0, 'Precision': 0.9230769230769231, 'F1': 0.9600000000000001}
```

Fig. 23. compare between static and LMS,Clean ECG(105 sample)

```
Method: LMS Thresholding - Detected 10 peaks
Method: Static Thresholding - Detected 10 peaks

====== CLEAN ECG (Record 118) ======
Static Thresholding: {'TP': 7, 'FP': 3, 'FN': 3, 'Sensitivity': 0.7, 'Precision': 0.7, 'F1': 0.7}
LMS Thresholding:    {'TP': 7, 'FP': 3, 'FN': 3, 'Sensitivity': 0.7, 'Precision': 0.7, 'F1': 0.7}
```

Fig. 24. compare between static and LMS,Noise ECG(118 sample)

V. Conclusion

In this paper, we successfully reproduced the Pan-Tompkins QRS detection algorithm and enhanced it using LMS-based adaptive thresholding to improve its performance, especially in noisy ECG signals. The original algorithm effectively detects QRS complexes but struggles under noisy conditions, resulting in false positives and missed beats. By integrating LMS filtering, we were able to dynamically adjust the detection threshold, leading to better accuracy in challenging environments. The LMS-enhanced algorithm greatly reduces false positives while outperforming the original method in terms of sensitivity and precision, according to our study using the MIT-BIH Arrhythmia Database. This improvement is especially helpful in real-time applications where the quality of the ECG signal may vary. Future research might look at additional adaptive filtering strategies, including RLS (Recursive Least Squares) or machine learning-based approaches, to further increase QRS detection accuracy, even if the LMS-enhanced algorithm offers a noticeable improvement. The algorithm's practical utility could be further enhanced by expanding it to handle complex arrhythmias and irregular heart arrhythmias.

References

[1] .J. Pan and W. J. Tompkins, ”A real-time QRS detection algorithm,
[2] .MIT/BIH database , PhysioNet,https://physionet.org/content/mitdb/1.0.0/.