Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 7s (2025)

Wavelet Packet Transform Based Adaptive R-Peak Detection in ECG Signals Using CSE Database

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Article History:

Received: 19-10 - 2025

Revised: 05-12 - 2025

Accepted: 13-12 - 2025

Abstract:

Accurate detection of P, QRS, and T waves is essential for automatic electrocardiogram (ECG) analysis and cardiac diagnosis. This paper presents a robust ECG delineation method based on Wavelet Packet Transform (WPT) combined with adaptive peak detection. The ECG signal from the CSE database sampled at 500 Hz is first preprocessed using a Kaiser window-based FIR bandpass filter (0.5–40 Hz). A level 4 WPT decomposition is applied to enhance the QRS complex. R peaks are detected using energy-based thresholding, and P and T waves are identified using physiological search windows around each R peak. The proposed method demonstrates reliable detection performance and accurate counting of P, R, and T waves, making it suitable for clinical ECG analysis. For this methos the result is for detection of QRS complexes with a accuracy of 98.57.

Introduction: Cardiovascular diseases remain a major global health concern, making accurate ECG analysis essential for early diagnosis. The electrocardiogram contains clinically significant components such as P, QRS, and T waves. Among these, reliable detection of the QRS complex is fundamental for heart rate estimation and rhythm analysis. Conventional wavelet methods provide limited frequency resolution for ECG processing. Wavelet Packet Transform (WPT) offers improved time–frequency decomposition, making it suitable for accurate ECG feature extraction.

Objective: The objective of this study is to develop a robust and adaptive R-peak detection algorithm using Wavelet Packet Transform. The method aims to enhance QRS complexes while suppressing noise and baseline disturbances. It also seeks to improve detection accuracy using adaptive thresholding and physiological constraints. The proposed approach is evaluated using the CSE ECG database sampled at 500 Hz.

Methods: The ECG signals are preprocessed using a Kaiser window-based FIR bandpass filter (0.5–40 Hz) to remove noise and baseline drift. A level-4 Wavelet Packet Transform with db6 wavelet is applied for detailed frequency decomposition. Selected nodes corresponding to the QRS frequency band are reconstructed to enhance QRS energy. First derivative, squaring, and moving average integration are performed for energy enhancement. Adaptive thresholding with a refractory period is used for accurate R-peak detection.

Results: The proposed algorithm was tested on the complete CSE ECG dataset containing 17,988 QRS complexes. The method achieved 17,625 true positives, 363 false negatives, and 106 false positives. The sensitivity obtained is 97.8%, and positive predictivity is 98.57%. The detection error rate is limited to 2.60%. These results demonstrate reliable and consistent R-peak detection performance.

Conclusion: A Wavelet Packet Transform-based adaptive R-peak detection method has been successfully implemented and validated. The level 4 db6 decomposition effectively enhances QRS components while suppressing noise. Adaptive thresholding combined with physiological constraints improves detection reliability. The method achieves high sensitivity and positive predictivity on the CSE database. The proposed approach is suitable for automated ECG analysis applications.

Keywords: ECG, Wavelet Packet Transform, P wave detection, T wave detection, QRS detection, Biomedical signal processing.

1. Introduction

Nowadays, heart diseases are a major issue worldwide for human life. However, many heart problems can be controlled or treated effectively if they are diagnosed early using clinically important ECG features. The electrocardiogram (ECG) signal consists of several peaks known as P, Q, R, S, T, and U, in Fig. 1, which represents an ideal ECG waveform. An ECG signal contains important information such as P-wave, PR-interval, PR-segment, QRS complex, ST-segment, ST-interval, and T-wave. The P-wave gives information about atrial depolarization, the QRS complex gives information of ventricular depolarization, T-wave represents ventricular repolarization. The human ECG signal has a frequency range from 0.05 Hz to 150 Hz, but most of the useful clinical information lies between 0.05 Hz and 45 Hz [3].

QRS detection is an important part of ECG analysis. Incorrect detection can increase memory usage and cause wrong QRS interpretation. Faster and reliable QRS detection allows physicians and automated ECG systems to respond to patients in a timely manner [1, 2, 3]. Many QRS detection methods have been reported in previous studies, including methods based on the wavelet transform [2]. However, the conventional wavelet transform gives a limited number of frequency bands for filtering ECG signals before QRS detection. To solve this limitation, researchers have introduced Wavelet Packet Transform (WPT), which offers a larger number of frequency sub-bands and improves QRS detection performance.

Wavelet analysis is a rapidly growing signal processing method that uses wavelets and related functions to efficiently analyze non-stationary signals, such as ECG signals. It provides good resolution in both time and frequency domains; therefore, it is well suited for ECG signal processing. Due to these advantages, wavelet analysis is widely used for ECG signal processing, analysis, compression, and synthesis [4]. Wavelet packet decomposition, performed using the

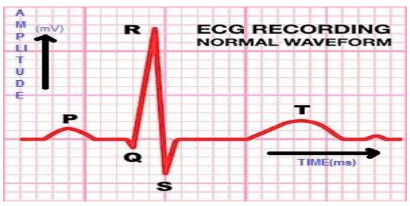

Fig. 1 Normal ECG waveform

Wavelet Packet Transform (WPT), is based on the concept by Wickerhauser [4], which extends the traditional multiresolution analysis of wavelet theory. In this approach, not only the low-frequency components (approximations) but also the high-frequency components (details) are further decomposed in a similar manner, resulting in improved frequency resolution [5].

1.1 Pre-processing

Initially, unwanted noise is removed from the ECG signal through an appropriate filtering technique while preserving the true morphology of the waveform. Accurate identification of the R-peak is a crucial and primary stage in ECG signal analysis. After locating the R-peaks, the remaining components of the ECG waveform and their corresponding characteristics can be extracted and examined. The heart rate is determined by measuring the time interval between consecutive R-peaks. A heart rate less than 60 beats per minute is classified as bradycardia, whereas a rate exceeding 100 beats per minute is considered tachycardia.
In this, the wavelet packet transform (WPT) is used to identify R peaks from the filtered ECG signal. For this signal is examined in two stages: preprocessing and feature extraction, is shown in Fig. 2.

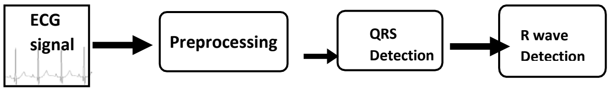

Fig 2: Block Diagram of Analysis Method

1.2 Baseline Drift Removal

To eliminate baseline wander and motion-related disturbances while preserving the integrity of the R-waves, the first derivative of the filtered ECG signal is computed. This differentiation step emphasizes regions with steep slopes in the waveform. In particular, the transition from the Q wave to the R wave represents the steepest upward slope, while the transition from the R wave to the S wave corresponds to the steepest downward slope. As a result, the R-peak can be located at the zero-crossing point between the positive and negative extrema in the differentiated signal. [03,06]

1.3 Moving Average Integrator

The moving average integrator is used to combine information about the slope and duration of the QRS complex. It smooths the signal and highlights the energy of the QRS complex over time. In this stage is to extract important features of the ECG waveform, especially the R-wave slope. The window length is usually chosen to match the widest QRS complex. If the window is too wide, it may also include T-wave information. If the window is too narrow, a single QRS complex may produce multiple peaks, which can make detection difficult [3].

1.4 Wavelet Packet Based Feature Extraction

Feature extraction is carried out through wavelet-based analysis using the Wavelet Toolbox in MATLAB. The Wavelet Packet Transform (WPT) offers strong time–frequency representation by examining high-frequency components within short time spans and low-frequency components across longer durations. This multiresolution approach decomposes the signal into various frequency bands and scales by employing filter banks with different cutoff frequencies. The scaling process is achieved through systematic up-sampling and down-sampling operations. In the Discrete Wavelet Transform (DWT), where only approximation coefficients are further decomposed, WPT breaks down both approximation and detail coefficients at every level, resulting in a full binary tree structure [7]. This decomposition results in uniform frequency resolution across all sub-bands, which is not achieved by conventional DWT. In this work, the Daubechies-6 (db6) wavelet is preferred due to its morphological similarity to the QRS complex. The ECG signal is decomposed up to the third level, producing eight uniform frequency sub-bands. The ECG is a non-stationary signal containing clinically significant features, particularly the QRS complex, which exhibits dominant energy in the 5–25 Hz frequency range. Classical Fourier methods are not enough to analyze such transient events due to their insufficiency of time localization. Although DWT improves time–frequency representation, it decomposes only the approximation coefficients at each level, leading to non-uniform frequency resolution.

To address this limitation, Wavelet Packet Transform is employed. WPT provides finer and uniform frequency decomposition, making it more effective for isolating QRS complexes and enhancing feature extraction performance [12].

1.5 QRS Reconstruction and Detection

The wavelet packet nodes corresponding to the QRS frequency band are reconstructed to obtain a QRS-enhanced signal. This reconstruction emphasizes the high-energy components of the QRS complex while suppressing noise and other ECG components. An adaptive thresholding technique is then applied to the reconstructed signal to identify candidate R-peaks. To reduce false detections, a physiological refractory period is incorporated, ensuring that multiple peaks within a single cardiac cycle are not detected as separate R-peaks.

2. Methods

2.1 ECG Dataset

The ECG signals are obtained from the CSE (Common Standards for Electrocardiography) database. Each record: Duration: 10 seconds, Sampling frequency: $f_s = 500$ Hz, each record contains 5000 samples.

2.2 Preprocessing

2.2.1Baseline Removal

The ECG signal is detrended to remove linear baseline drift: $x_d(n) = x(n) - \text{trend}(x(n))$

2.2.2 Bandpass Filtering

A Kaiser window-based FIR bandpass filter is designed with: Passband: 0.5–40 Hz

Filter order: 100

Kaiser parameter: $\beta = 3.5$

The filtered signal is: $y(n) = x_d(n) * h(n)$

Zero-phase filtering (filtfilt) is used to prevent phase distortion.

2.3 Wavelet Packet Transform

The Wavelet Packet Transform is an advanced form of Discrete Wavelet Transform in which both the approximation and detail components are recursively decomposed at each level of the analysis.

At decomposition level j, the WPT coefficients are defined as:

$$W_{j,k}(n) = \sum_{m} W_{j-1,m}(m)\, h_k(n-2m)$$

where:

- $h_k$are quadrature mirror filters
- $j = 4$in this study
- $k$represents node index

The Daubechies-6 (db6) wavelet is selected due to its morphological similarity to the QRS complex.

At level 4, selected nodes corresponding to dominant QRS frequency components are reconstructed:

$$x_{WPT}(n) = \sum_{k\in\{1,2\}} W_{4,k}(n)$$

This reconstruction enhances QRS energy while suppressing noise.

2.4 QRS Energy Enhancement

To emphasize the sharp slope of QRS:

First Derivative $\quad d(n) = x_{WPT}(n) - x_{WPT}(n-1)$

Squaring Operation $\quad s(n) = d^2(n)$

Moving Average Integration $\quad E(n) = \frac{1}{M}\sum_{k=0}^{M-1} s(n-k)$

where $M = 20$.

The energy signal is normalized before thresholding.

2.5 Adaptive R-Peak Detection

An adaptive threshold is defined as: $T = 0.2 \times \max(E(n))$

Candidate peaks are detected when: $E(n) > T$

To avoid multiple detections within a single cardiac cycle, a physiological refractory period of 0.4sec. is enforced. The exact R-peak location is refined by searching for the maximum amplitude within ±50 ms around each detected candidate in the filtered ECG signal.

2.6 R-Peak Localization

To avoid multiple detections due to closely spaced peaks, a refractory period of 300 ms is enforced. Within each refractory window, only the first detected peak is retained and labeled as the final R-peak. This strategy ensures accurate localization of R-peaks corresponding to individual cardiac cycles and improves the reliability of the detection process [9,10].

2.7 Algorithm for detection

1. Load CSE-ECG database files case by case.
2. A Finite Impulse Response (FIR) bandpass filter designed using the Kaiser window method is first implemented to suppress noise present in the ECG signal. The bandpass filter is configured with cutoff frequency range from 0.5 Hz to 40 Hz to preserve the essential ECG components while eliminating unwanted disturbances.
3. After filtering, the baseline-corrected signal is passed through a differentiator function, diff(x), which calculates the difference between consecutive samples. This operation approximates the first derivative of the signal and emphasizes rapid changes in the waveform.
4. The differentiated signal typically exhibits low amplitude and large variations. To enhance the significant components and stabilize the baseline, the output of the differentiator is squared. This squaring operation magnifies prominent features, particularly those related to the QRS complex.
5. Although baseline drift and noise are largely minimized, minor interference may remain. To further refine the signal and improve feature visibility, the ECG is processed using the orthogonal Daubechies wavelet (db6). The signal is decomposed in to four levels, where each level contains both approximation and detail coefficients. For QRS complex detection, the approximation and detail coefficients up to the fourth level are retained, while higher-level components are discarded. The fourth level decomposition provides optimal results for accurate QRS identification.
6. Following QRS detection, variations in QRS amplitudes are observed across different recordings. Therefore, a threshold-based approach is applied to identify and mark the R-peaks. First, the maximum peak value of the processed signal is determined. A threshold is then set at 20% of this maximum amplitude. An envelope is positioned based on this threshold, and the average value within the envelope is calculated to accurately locate the R-peaks, as demonstrated in the results.

3. Results

In this work, a QRS detection and R-wave identification method based on the Daubechies wavelet transform is applied to a standard ECG database. The db6 wavelet is selected because its shape closely resembles the morphology of the ECG waveform, leading to improved detection accuracy. The performance results are presented in a table that lists the total number of actual QRS complexes (R-peaks), along with true positives (TP), false negatives (FN), and false positives (FP) for the complete CSE-ECG library dataset-3. Each ECG recording in this dataset has a duration of 10 seconds and is sampled at 500 Hz, producing 5000 samples per record. The table further includes evaluation metrics such as detection rate (DR), positive predictivity (+P), and sensitivity (Se). FN (false negative): Indicates that the proposed method failed to detect a real beat.

False Positive (FP): Refers to instances where the algorithm identifies a heartbeat even though no actual beat exists.

True Positive (TP): Represents heartbeats that are correctly recognized by the detection method.

Sensitivity (Se%): Measures the proportion of actual heartbeats that are accurately detected by the algorithm, expressed as a percentage.

$$Se\,\% = \frac{TP}{TP+FN} * 100 \qquad \text{... (3.1)}$$

Positive Predictivity (+P%): Represents the proportion of detected heartbeats that are truly valid beats, expressed as a percentage.

$$+\mathrm{P}\,\% = \frac{\mathrm{TP}}{\mathrm{TP+FP}} * 100 \qquad \text{... (3.2)}$$

Detection Error Rate (DR%): Represents the percentage of incorrectly identified beats, indicating the overall rate of detection errors.

$$\mathrm{DR}\,\% = \frac{\mathrm{FP+FN}}{\mathrm{TP+FN}} * 100 \qquad \text{... 3.3)}$$

3.1 R Peak Analysis

The proposed algorithm was tested on the complete CSE database.

Parameter	Value
Total QRS	17988
TP	17625
FN	363
FP	106
Sensitivity	97.8%
Positive Predictivity	98.57%
Detection Error Rate	2.60%

The high sensitivity and positive predictivity demonstrate that the proposed WPT-based approach accurately detects R-peaks with minimal false detections.

3.2 Graphical Analysis

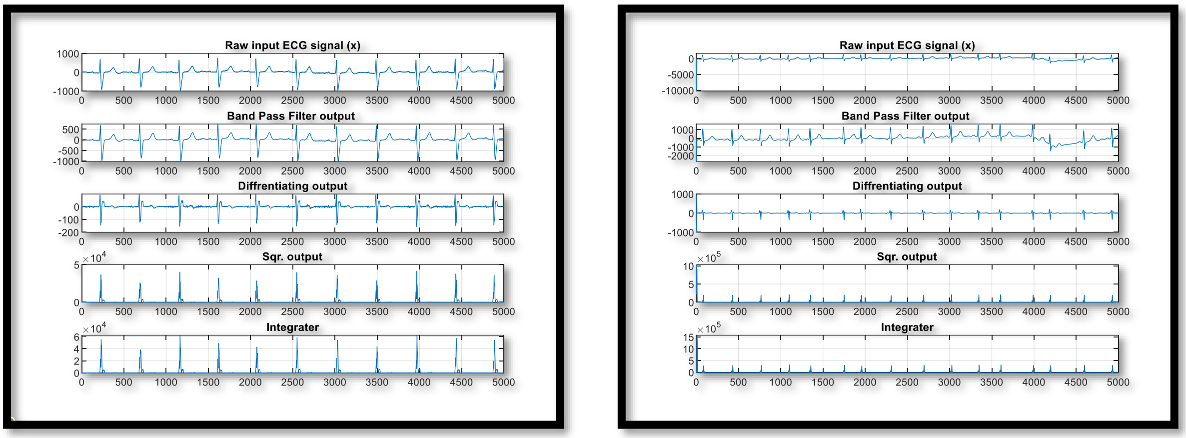

Fig.3 Filtered - CSE ECG Data Set MO1_001_V1V6

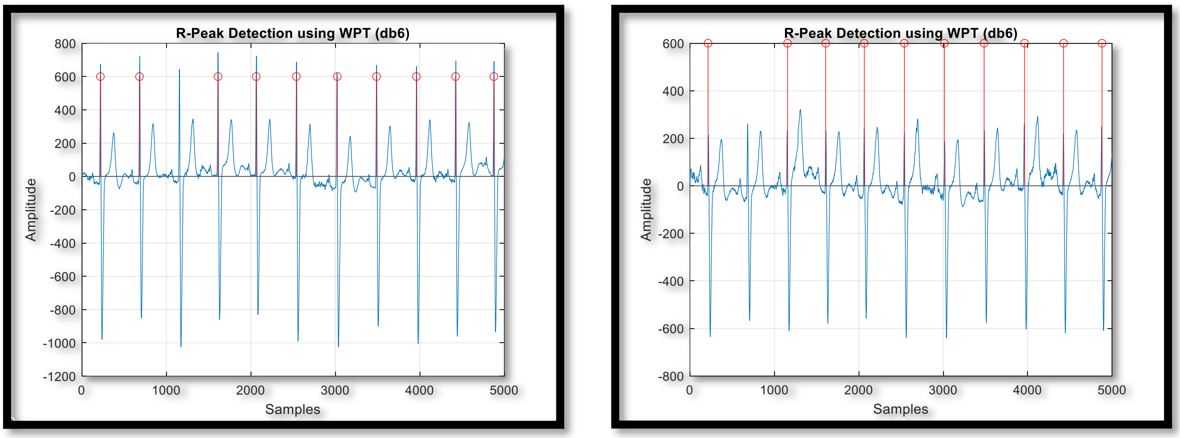

Fig.4-WPT- CSE ECG Dataset case MO1_001_V1,V6

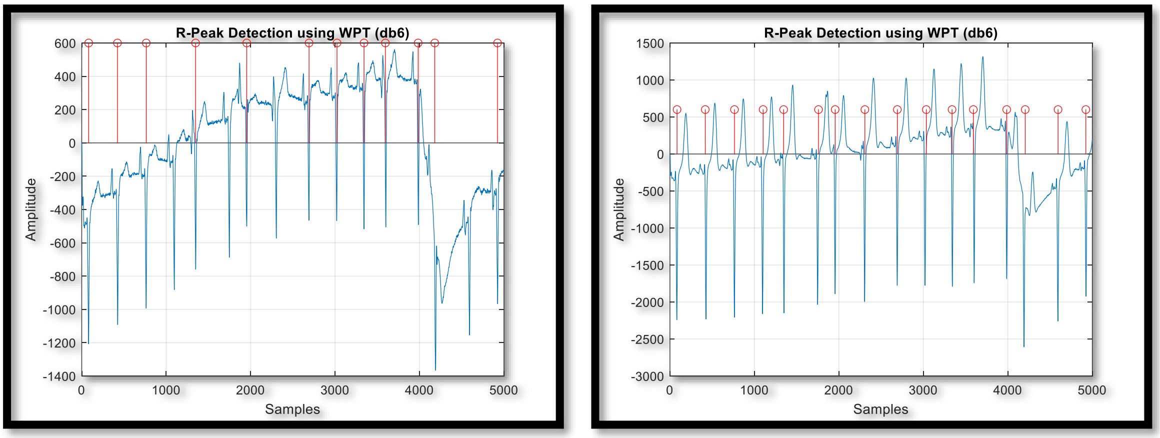

Fig. 5-WPT-CSE ECG Dataset case MO1_006_V2, AVR

4. Discussion

The experimental results confirm that the Wavelet Packet Transform provides improved frequency resolution compared to conventional DWT-based methods. By decomposing both approximation and detail coefficients, WPT enables more precise isolation of QRS frequency components. The use of db6 wavelet enhances morphological similarity with the QRS complex, contributing to improved detection accuracy.

The achieved sensitivity (97.8%) and positive predictivity (98.57%) indicate strong detection capability with minimal false alarms. The incorporation of adaptive thresholding and a physiological refractory period significantly reduces multiple detections within a single cardiac cycle. Compared to classical derivative-based approaches, the proposed method demonstrates greater robustness against noise and baseline variations.

Although the performance is satisfactory, minor false negatives occur in low-amplitude or noisy ECG segments. Future improvements may include dynamic threshold adaptation and testing on more diverse pathological datasets to further validate robustness.

5. Conclusion

A robust R-peak detection method based on Wavelet Packet Transform has been proposed and evaluated using the CSE ECG database. The algorithm employs level 4 db6 wavelet decomposition, energy - based enhancement, and adaptive thresholding with physiological constraints. Experimental results demonstrate high sensitivity and positive predictivity, confirming the effectiveness of the proposed approach for automatic ECG analysis.
Future work will focus on testing the algorithm on noisy datasets and extending the approach to complete ECG delineation.

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