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Comprehensive Analysis and Processing of ECG Data Using Advanced Techniques

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Abstract*— Accurately analyzing an electrocardiogram (ECG) signal holds significant importance in this particular application, aiming to extract specific characteristics within the ECG signals crucial for identifying potential cardiovascular irregularities. However, this objective is notably challenging due to the frequent corruption or presence of noise in the desired ECG signals. Wavelet analysis emerges as a comprehensive solution to address these challenges. The paper presents a comprehensive analysis aimed at automatically detecting R-peaks in single-lead digital ECG data. Utilizing wavelet transforms proves highly effective in examining such signals. This study harnesses wavelets as a method to filter and scrutinize noisy ECG signals, employing them specifically for identifying the positions of the QRS complex occurrences within the analysis period. Moreover, inter-beat intervals (IBIs) computation and visualization based on peak detection within an ECG signal have been presented for heart rate variability (HRV) analyses.*

Keywords— ECG Signals; HRV; *IBIs*; Analysis; Wavelet.

1. INTRODUCTION

Cardiovascular diseases demand advanced methodologies to ensure effective assessment and management of cardiac for enduring as a substantial global health concern [1-3]. This paper unfolds a novel MATLAB-based paradigm for the in-depth analysis of ECG signals, placing particular emphasis on the extraction of Inter-Beat Intervals (IBIs). IBIs, derived from successive R-peaks in the ECG waveform, unfold a nuanced panorama of heart rate variability, offering profound insights into cardiovascular health [4]. The introduction encapsulates a comprehensive literature review exploring pivotal studies on peak detection algorithms and delineating MATLAB's pivotal role in the realm of biomedical signal processing. The research objectives are oriented towards the development of a robust methodology for ECG signal analysis, coupled with the extraction of substantive insights into the dynamics of cardiac activity [5, 6].

In-depth investigations have meticulously scrutinized a spectrum of peak detection algorithms, showcasing their prowess in the identification of R-peaks. The precision of peak detection stands as a linchpin for extracting rich information embedded within ECG signals. Pioneering work has underscored MATLAB's adaptability and versatility in implementing sophisticated signal processing algorithms tailored for ECG analysis [7]. The modular architecture of MATLAB serves as a cornerstone, enhancing the platform's attractiveness for diverse biomedical research endeavours [8]. Transcending the realm of peak detection, the research conducted has ventured into the intricate realm of Inter-Beat Intervals (IBIs) and their profound implications on heart rate variability and cardiovascular health [9]. This exploration stands as a critical stride towards the realization of personalized medicine and the refinement of risk assessment in cardiovascular disorders [10-12].

The electrocardiogram (ECG) captures the heart's electrical activity throughout a single cardiac cycle, displaying a recurring sequence of P, QRS, T, and occasionally U waves, as shown in Fig. 1. These waves signify the rhythmic depolarization and repolarization of the myocardium, corresponding to atrial and ventricular contractions in each cardiac cycle [13, 14].

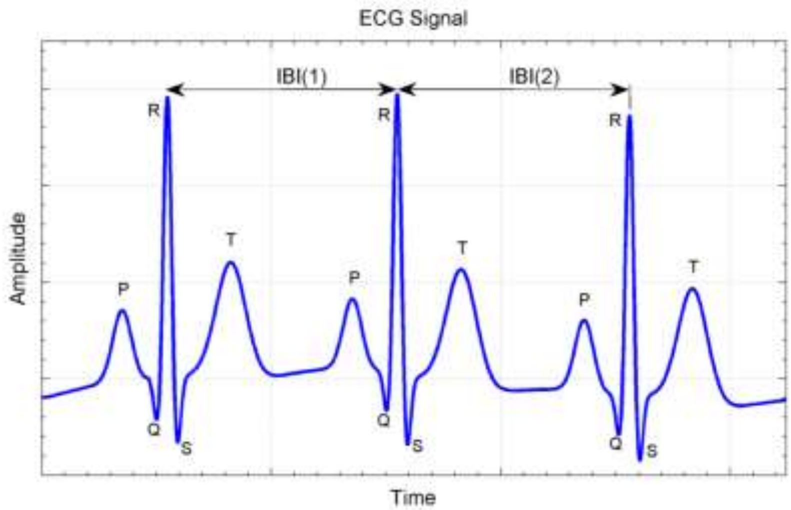

Figure 1. The process of determining IBI. This simulated ECG comprises three beats, each represented with arbitrary units for time and amplitude. The time intervals corresponding to the IBI are marked as IBI(1) and IBI(2). Additionally, the ECG morphology is depicted, showcasing five distinct waves: P, Q, R, S, and T.

ECG recordings involve the placement of electrodes on the body surface, employing a standard 12-lead system to provide a comprehensive view of cardiac activity. ECG serves as a crucial diagnostic tool for various cardiac conditions. Its diverse features, such as the PR interval, QRS interval, QT interval, ST interval, PR segment, and ST segment, are utilized to assess cardiac health. Various computer-assisted analysis techniques aim to extract these temporal features from digitized ECG data. Among these, the detection of QRS complexes and R-peaks forms the foundation for nearly all automated ECG analysis algorithms [15, 16].

The QRS complex represents the heart's electrical activity during ventricular contraction, offering valuable insights into the heart's current state based on its timing and shape. QRS detection serves as the starting point for analyzing other ECG features like P and T waves, as well as the ST segment. Accurate QRS detection holds significance not only for Heart Rate Variability analysis but also for diagnosing different cardiac conditions [12, 17].

The literature presents various QRS detection algorithms, broadly classified into amplitude and derivative-based, digital filter-based, template matching, nonlinear transformation-based, and wavelet-based methods [8, 18-21]. Derivative-based approaches focus on the ECG signal's high-frequency content, which generates prominent derivative magnitudes, making them widely adopted due to their implementation simplicity and low computational complexity. Template matching methods compare standard QRS templates with multiple ECG segments through cross-correlation. Although these methods exhibit lower noise sensitivity, they demand manual segmentation of ECG data and involve higher computational complexities. Nonlinear Hilbert transform techniques enhance the QRS signature to elevate detection probabilities. The utilization of digital filters to isolate the QRS complex based on its frequency content introduces computational complexities. Wavelet-based approaches localize R-peaks via selective decomposition of the ECG signal and comparison across different scales, requiring suitable mother wavelets and scale values [22]. An innovative and efficient strategy was recently developed, utilizing a histogram and an improved genetic algorithm to search and identify QRS regions.

ANN or SVM is also used as a classifier to detect the QRS complex. A statistical-based approach was used for the detection of R-peaks and other time-plane features of the ECG. The detected R-peaks are not always accurate and can have false or missed peaks [4, 23]. Algorithms to increase detection sensitivity by processing the RR intervals were proposed. Difficulties in accurate QRS detections rise because of the physiological variability of the QRS complex and the presence of different noises in the ECG signal. The noise sensitivities of 9 different algorithms were tested to infer that the derivative-based approaches had a higher performance index for low-frequency noises, while algorithms based on digital filtering performed well for high-frequency noise [4, 23].

Moreover, extracting key features from ECG signals is crucial for this application, as they can reveal hidden patterns indicating potential cardiovascular issues. However, noise and signal corruption often make this analysis challenging. Enter wavelet analysis: a powerful tool that tackles these problems head-on. It's like a Swiss Army knife for signal processing, bringing together previously scattered techniques under one roof. Wavelets offer a versatile toolbox for analyzing signals at multiple resolutions, like zooming in on a picture to see more detail. Imagine using this to focus on tiny features within the ECG, like the intricate peaks and valleys that hold valuable clues about heart health. Wavelets also shine at filtering out noise, like sifting through sand to find a hidden treasure. By removing unwanted distortions, they make those hidden patterns in the ECG crystal clear. The power of wavelets is their breadth of applications. They work with continuous and discrete data, meaning they can tackle a wide range of signals beyond ECGs. From processing sounds and images to analyzing scientific data, their versatility shines across diverse fields [24, 25].

In this paper, wavelet analysis is a game-changer for accurate ECG analysis. It provides powerful tools to unlock hidden secrets within the signal, paving the way for improved cardiovascular diagnostic and monitoring capabilities.

2. WAVELET TRANSFORM (WT)

Particularly, the "wavelet" transform (WT) plays a significant role in analyzing non-stationary signals, providing an alternative to conventional methods like the Short-Time Fourier Transform (STFT) or Gabor transform [6, 19, 26]. The key distinction lies in their approach: unlike the STFT, which relies on a single analysis window, the WT employs shorter windows for high frequencies and longer ones for low frequencies. Additionally, the WT is linked to time-frequency analysis based on the Wigner-Ville distribution [3, 16, 27].

In certain scenarios, it proves beneficial to interpret the WT as a signal breakdown into a series of foundational functions called wavelets. These wavelets originate from a singular prototype wavelet via dilations, contractions, and shifts. The continuous wavelet transform (CWT) involves summing the signal multiplied by scaled and shifted versions of the wavelet function across all time instances, as illustrated in the equation below:

$$\mathrm{CWT}(a,\tau) = \frac{1}{\sqrt{a}}\int s(t)\psi\left(\frac{t-\tau}{a}\right)dt \quad (1)$$

Within this equation, the variable "a" signifies the scaling factor responsible for either elongating or compressing the function. The variable τ represents the translation factor, facilitating the displacement of the mother wavelet along the axis. The term s(t) denotes an integrable signal, the cumulative of which is to be multiplied by the translated mother wavelet. Lastly, the mother wavelet, symbolized as $\psi(t)$, is a function dependent on the scaling and translation factors, much like the continuous wavelet's outcome. It's noteworthy that as the basis function transformation CWT expands, so does the width of the resulting function [27].

Working with discretized signals is frequently preferred. Transitioning into the discrete domain not only reduces workload but also enables achieving equally precise outcomes by carefully selecting scales and positions based on powers of two. This approach is known as the discrete wavelet transform (DWT), defined as:

$$\mathrm{DWT}(m,n) = 2^{-\frac{m}{2}}\sum_k s(k)\psi(2^{-m}k-n) \quad (2)$$

The Discrete Wavelet Transform (DWT) is frequently termed as decomposition by wavelet filter banks. This nomenclature arises from the DWT's utilization of two filters: a low pass filter (LPF) and a high pass filter (HPF) to break down the signal into various scales. The LPF's output coefficients are termed as approximations, defining the signal's essence, while the HPF's output coefficients are referred to as details, offering nuanced information [28].

Moreover, the decomposition process within DWT is iterative [29]. The approximation signal can undergo further decomposition, dividing the signal into multiple levels of lower-resolution components. The process of multiple-level decomposition can be visualized in a wavelet decomposition tree. Among all the levels of detail, only the final level of approximation is retained. This level supplies adequate data to reconstruct the original signal entirely through complementary filters. It should noted that the "wavelet toolbox" in MATLAB has been utilized in this paper.

3. FEATURES OF ECG WAVES

Automated detection of ECG waves holds significant importance, especially in prolonged recordings, as it unlocks a wealth of clinical insights derived from intervals and amplitudes outlined by key points. The efficacy of such automated systems hinges on precise and reliable QRS complex detection. This complex determination is crucial for heart rate evaluation and serves as a benchmark for aligning beats. As previously illustrated, the QRS complex stands as the signal's most defining waveform, characterized by heightened amplitudes. It often serves as a reference for detecting other waves, like the P and T complexes, which are intermittently valuable [16, 29].

The papers' feature extraction methods primarily concentrate on QRS complex detection, identifying characteristic points, and endeavouring to locate any associated P and T waves. Wavelet transform emerges as a highly promising technique due to its localization in both frequency and time domains. It aids in distinguishing ECG waves from noise, artifacts, and baseline drift. This transformation encapsulates a signal's temporal aspects at various resolutions, facilitating enhanced analysis of ECG signals characterized by cyclic patterns at diverse frequencies.

While wavelet transformation isn't overly challenging as a mathematical tool for signal decomposition, the complexity arises in selecting a mother wavelet optimized for a given signal and its application. The discrete wavelet transform holds natural advantages in ECG analysis. Traditionally, ECG feature extraction involves employing a bandpass or matched filter to suppress P and T waves and noise before characteristic detection. In contrast, the discrete wavelet transform implicitly conducts frequency domain filtering, imparting robustness to the system and enabling direct application on raw ECG signals. This capability aligns with the discrete wavelet transform's inherent nature, often termed decomposition by wavelet filter banks.

4. METHODOLOGY

The digital ECG data from this single lead is structured as a two-dimensional array, incorporating time instances and corresponding sample points. The process encompasses four distinct stages meticulously designed to ensure precise detection of the R peaks.

4.1 Refining Raw Data through Smoothing and Filtering

The derivative-based approach tends to accentuate high-frequency noises within the data, resulting in amplified difference signals induced by this noise. An initial stage of smoothing and filtering is employed on the ECG data to counter this effect. This process aims to eliminate power frequencies and high-frequency noise components present in the ECG signal.

4.2 Detecting R waves in an ECG

This illustration demonstrates the utilization of wavelets for electrocardiogram (ECG) signal analysis. ECG signals often exhibit non-stationary behaviour, implying that their frequency composition evolves over time, capturing significant events.

Wavelet analysis dissects signals into time-varying frequency components, allowing for the examination of localized signal characteristics in time and frequency domains. This approach facilitates more manageable analysis and estimation by working with sparser representations of the signal. The QRS complex, encompassing three deflections in the ECG waveform, signifies the depolarization of the right and left ventricles and stands out as a prominent feature in human ECGs. For this demonstration, an ECG waveform is loaded and plotted, featuring annotated R peaks within the QRS complex, annotated by multiple cardiologists. The ECG data and annotations are sourced from the MIT-BIH Arrhythmia Database, sampled at 360 Hz.

Utilizing wavelets enables the creation of an automated QRS detector, which is beneficial for applications such as R-R interval estimation. Two fundamental advantages of employing wavelets as feature detectors are:

The wavelet transform segregates signal components into distinct frequency bands, resulting in a more concise representation of the signal.

Often, a wavelet resembling the feature you aim to detect can be identified.

The wavelet closely resembles the QRS complex, rendering it a favourable choice for QRS detection. To provide a clearer demonstration, extract a QRS complex and generate a plot showcasing the comparison between the extracted QRS complex and a dilated, translated 'sym4' wavelet.

4.3 R Peak Detection

The R peaks represent the positive peaks within the QRS segments. Their identification involves a comparison of relative magnitudes within each QRS region. A search for the maximum value is conducted on these relative magnitudes within each window, aimed at eliminating errors caused by baseline fluctuations.

- Within each detected QRS window, the algorithm computes the maximum and minimum amplitude values from the ECG data array.
- The mean value of the maximum and minimum amplitudes is subtracted from all data points within that window to derive the relative magnitudes.
- The position of the maximum relative magnitude corresponds to the R-point location within the respective QRS window. It's important to note that the absolute maximum value within the QRS window isn't chosen as the R-point location to avoid potential misidentification of the S-point.

4.4 Processing RR Intervals

The acquired R peaks might not always be entirely precise, leading to potential missed peaks or false detections. To ensure accuracy in detection, specific criteria are applied in processing the RR intervals.

- A minimum difference of 200 ms between two consecutive R peaks is considered. Any peaks detected within this time frame following the first peak are categorized as noise peaks and subsequently removed.
- Calculating the average RR interval for five consecutive R peaks, comprising two on each side of the R peak corresponding to the peak with the highest difference, serves as a reference for RR interval processing.

- Processing of all consecutive RR intervals involves comparing them with the calculated average RR interval to verify their consistency.

The methodology can be summarized as the following: Utilization of the squared absolute values derived from the signal approximation, generated through wavelet coefficients, and apply a peak detection algorithm to locate the R peaks accurately. The Signal Processing Toolbox™, which can be used through the application of the findpeaks function, can assist in identifying these peaks [7] and plotting the R-peak waveform obtained via the wavelet transform, indicating the automatically detected peak locations.

5. Results and discussion

In this paper, the ECG data and corresponding annotations originate from the MIT-BIH Arrhythmia Database, with a sampling rate of 360 Hz [30].

5.1 Case 1. mit200 ECG signal (noise free)

The results of the analysis of such case of study have been shown in Figs. 2, 3, 4, and 5. Figure 2 shows the ECG waveform displaying the QRS complex R peaks annotated by two or more cardiologists. Moreover, Fig. 3 shows a Comparison between the application of the Sym4 Wavelet and QRS Complex. The figures show that the 'sym4' wavelet exhibits similarities to the QRS complex, rendering it a favourable option for QRS detection. To provide a clearer illustration, extract a QRS complex and generate a plot comparing the result with a dilated and translated 'sym4' wavelet.

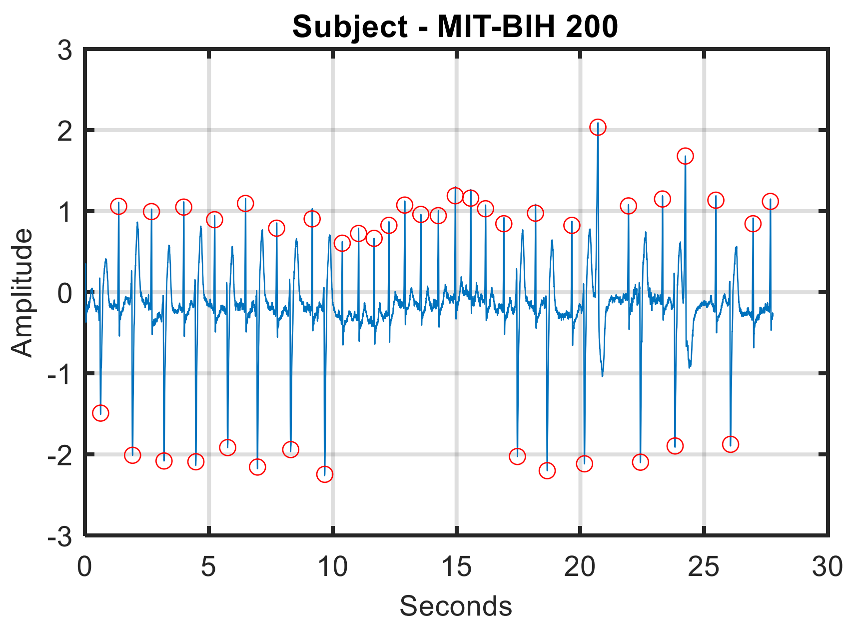

Fig. 2. The ECG waveform displaying the QRS complex R peaks

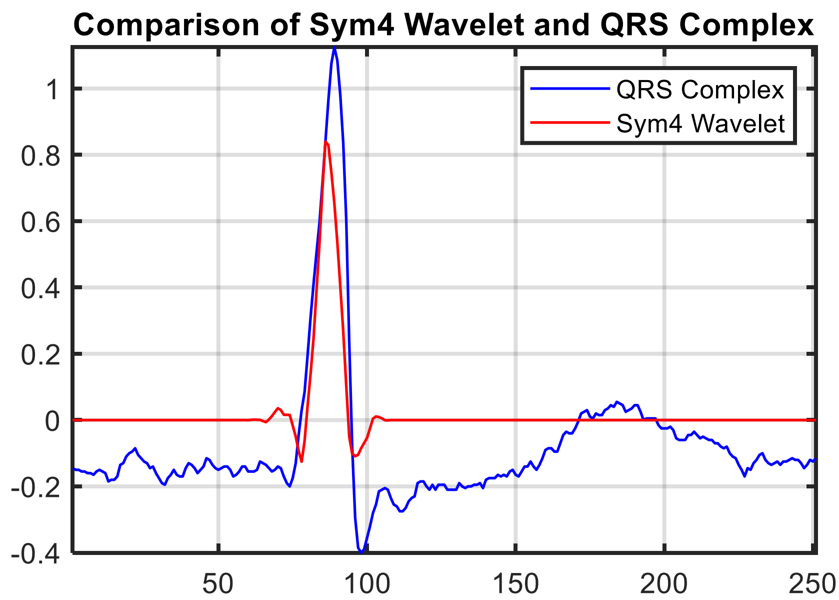

Fig. 3. A Comparison between the application of the Sym4 Wavelet and QRS Complex

Unlike traditional wavelet transforms, MODWT doesn't skip any parts of the signal. It analyzes every single point, making it perfect for capturing even subtle details like the R peaks. By using MODWT, The Amplification of the R peaks makes them more prominent and easier to identify. Moreover, it results in reducing the noise and interference, further clarifying the R peak signal. So, the analysis of the ECG waveform in more detail provides valuable insights into heart rhythm and health. Moreover, in simpler terms, MODWT acts like a filter that sharpens the focus on the R peaks, making them stand out like the lead singers in the symphony of the heart rhythm. The results of the application of the MODWT function can be shown in Fig. 4. So, Utilize the squared absolute values obtained from the signal approximation constructed using wavelet coefficients, then apply a peak detection algorithm to identify the R peaks.

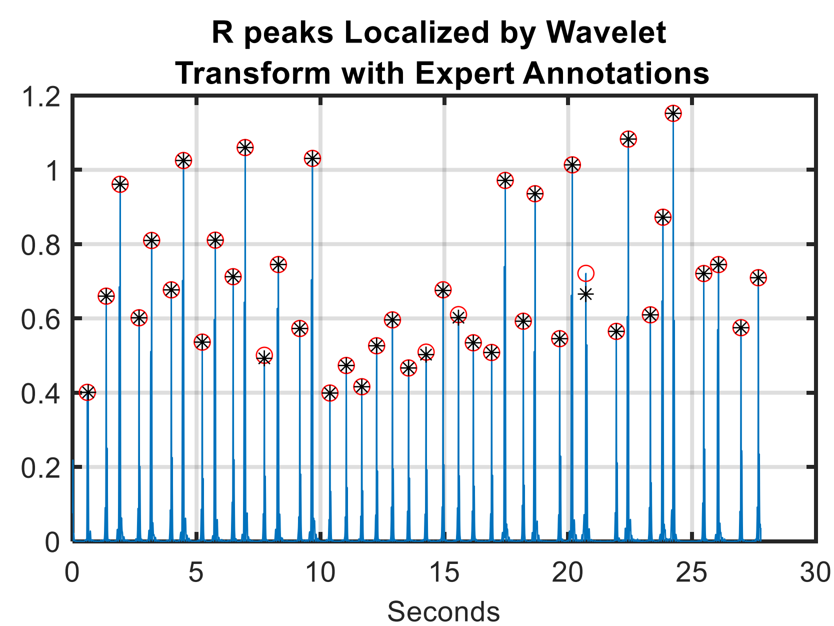

Figure 4. R-Peaks Identified via Wavelet Transform alongside Expert Annotations

A comparison of the values of time interval and peak locations provides expert and automatically detected peak times, which can be considered, respectively. The next step is employing the wavelet transform to enhance R peaks, exhibiting a 100% hit rate and no false positives. The heart rate calculated using the wavelet transform stands at 88.60 beats/minute, closely aligned with 88.72 beats/minute for the annotated waveform.

Working on the squared magnitudes of the original data demonstrates the wavelet transform's proficiency in isolating R peaks, significantly simplifying the detection process with an acceptable as shown from the results section. Attempting analysis of the raw data may lead to misidentifications, such as when the squared S-wave peak surpasses the R-wave peak around 10.4 seconds. Applying findpeaks to the squared magnitudes of the original data yields twelve incorrect positive detections.

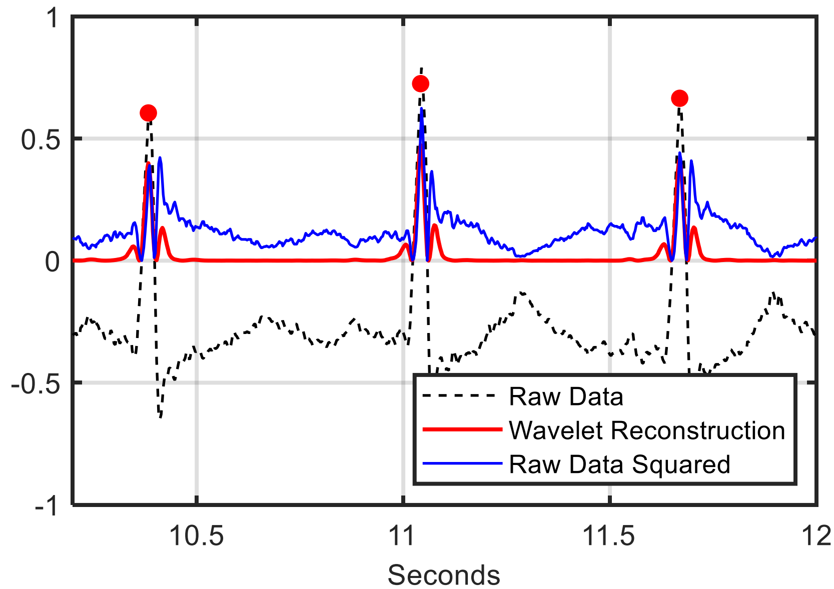

Figure 5. R peaks with the wavelet transform

5.2 Case 2. mit203 ECG (corrupted by noise)

In this case study, the mit203 ECG (corrupted by noise) has been considered. In electrocardiography (ECG), the R peaks represent the electrical activity associated with ventricular depolarization. Polarity switches in R peaks can indicate abnormal conduction or irregularities in the heart's electrical system. When an ECG is distorted by noise apart from polarity switches in the R peaks, several factors could contribute to this distortion:

- Electromagnetic Interference (EMI): External sources such as power lines, electronic devices, or muscle activity can introduce noise into the ECG signal.
- Movement Artifacts: Patient movement during the ECG recording can cause signal distortions due to electrode displacement or motion-related interference.
- Baseline Wander: Slow fluctuations in the baseline caused by respiration or movement can obscure the ECG signal, making it difficult to identify the underlying waveforms.
- Muscle Noise: Electrical activity from nearby muscles, especially in cases of patient restlessness or tremors, might interfere with the ECG signal.

To mitigate noise and obtain a clearer ECG:

- Ensure proper electrode placement and good skin preparation to minimize interference.
- Use appropriate filtering techniques or specialized equipment to reduce noise.
- Encourage the patient to remain still during the ECG recording to minimize motion artifacts.
- Check for potential sources of electromagnetic interference in the environment.

The results of such a case study have been shown in Figures 6 and 7. Figure 6 shows the ECG signal of the MIT-BIH 203 with Expert Annotations. Moreover, Fig. 7 represents the location of the R-Waves with the application of Wavelet Transform.

The results show that the hit rate remains at 100% with no false alarms. Moreover, the earlier instances featured a basic wavelet-based QRS detector relying on a signal approximation formed from modwt Wavelet Transform. In addition, the intention was to showcase the wavelet transform's capability to separate signal components rather than construct the most resilient wavelet-transform-based QRS detector. It's feasible, for instance, to capitalize on the wavelet transform's multiscale analysis of the signal to improve peak detection.

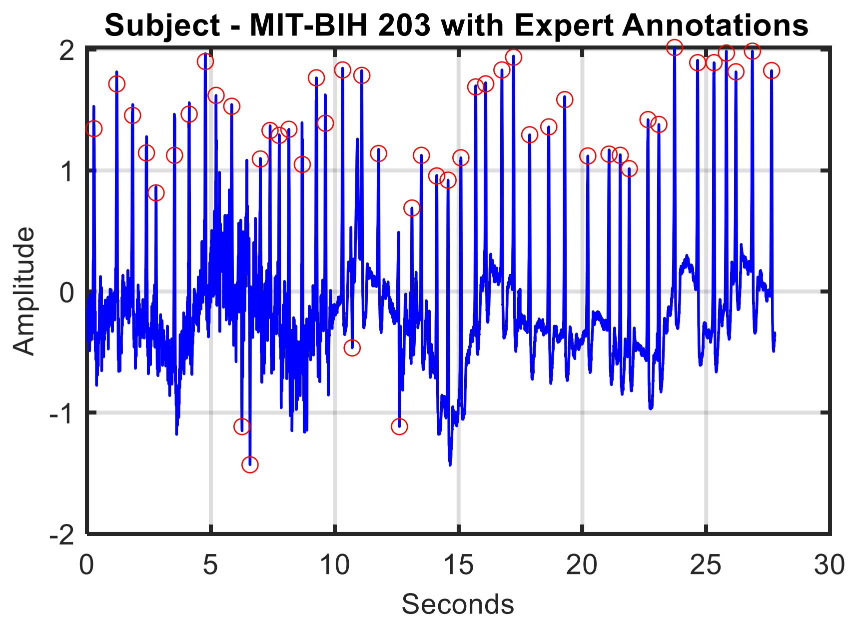

Figure 6. Case 2 ECG signal of the MIT-BIH 203 with Expert Annotations

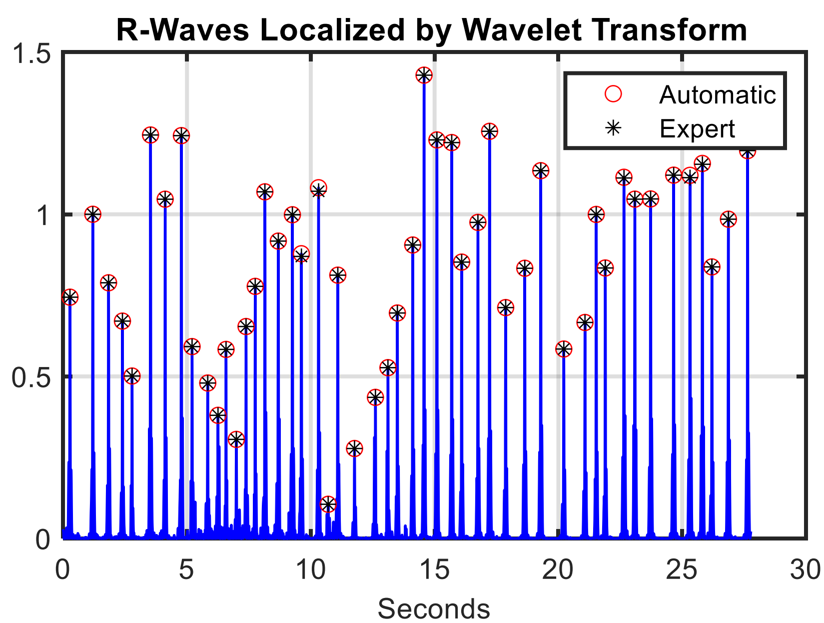

Figure 7. Location of the R-Waves with the application of Wavelet Transform

5.3 Case 3. Calculations of IBIs

This case is related to Inter-Beat Intervals (IBIs) computation and visualization based on peak detection within an ECG signal. This line computes the inter-beat intervals (IBIs) by taking the differences between consecutive peak locations. The variable IBIs stores these differences, representing the time intervals between successive R peaks in the ECG signal.

Converting the detected peak locations (locs) into a time scale can take place after the calculation of the previous difference. It uses the sampling frequency (in this case, 360 Hz) to convert the peak locations from sample indices to time units (e.g., seconds), creating a time-scale variable containing the time-scale representation of the peak locations.

The results are shown in Figure 8. The plotted graph provides a visual representation of the variations in inter-beat intervals over time, offering insights into the heart rate dynamics captured by the ECG signal. The calculation of IBIs is based on peak detections in the ECG signal, conversion to a time scale if necessary, and subsequent visualization of these intervals over time for further analysis and interpretation of heart rate variations.

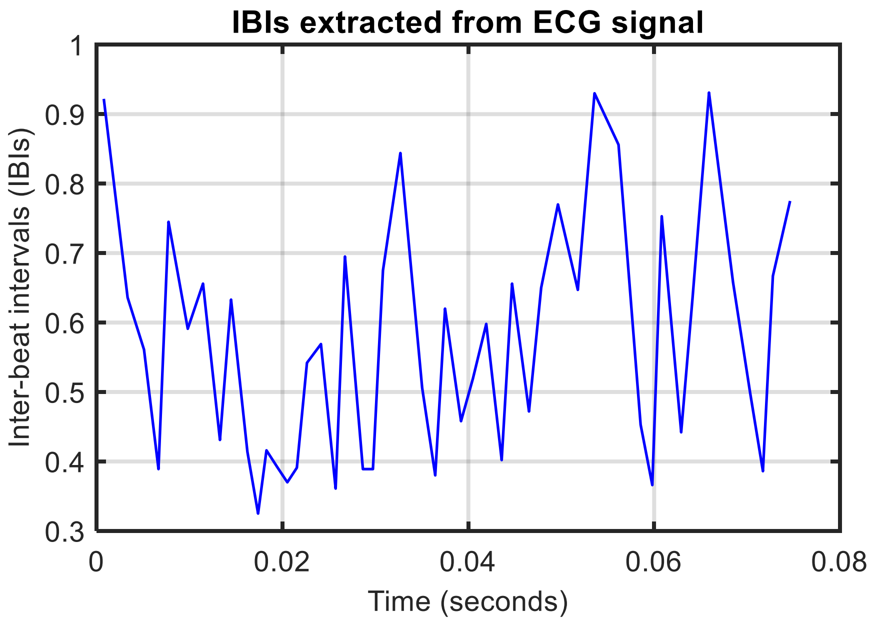

Figure 8. IBIs extracted from ECG signal.

6. Conclusions

In this paper, the authors highlighted the benefit of employing wavelet transform in combination with a noise thresholding technique. Additionally, we explored the potential of identifying the positions of QRS complexes within ECG signals and introduced a straightforward detection algorithm. By utilizing wavelet thresholding, the signal undergoes effective noise removal, enabling the application of uncomplicated detection logic for QRS identification. This method's primary advantage lies in its efficiency, facilitating less time-consuming analyses for prolonged ECG signal assessments. In future work, more advanced analysis methods of heart rate variability and other artificial intelligence algorithms should be applied for deep analysis of the ECG and HRV.

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