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A Comparative Study on QRS Complex Detection Algorithms for ECG Signal Analysis: A Review

Ashwini Kundanagar[1], Shankar.B.B[2]
Department of [1,2]Department of Electronics and Communication Engineering,
College Nitte Mahalinga Adyanthaya Memorial Institute of*
Technology, Karnataka, India

ABSTRACT
In this article, various QRS complex detection methods for electrocardiogram (ECG) data processing are compared. A dataset of at least 50 ECG signals is used to develop and analyze four well-known methods, including Pan-Tompkins, Wavelet Transform, Hilbert Transform, and Convolutional Neural Networks (CNN). The sensitivity, positive predictive value, and efficiency of each algorithm are assessed. All algorithms, with Pan-Tompkins having the maximum efficiency, attain high sensitivity and positive prediction values, according to the results. While Hilbert Transform exhibits better accuracy in detecting QRS complexes with low amplitude and noise and is used in the case of noisy or diseased signals, Wavelet Transform is used to identify the peaks, onsets, and endings of P and T waves, and CNN exhibits the potential for further development with more training data.

With a less power-intensive detection system that was designed with good accuracy and a detection time of 2.53sec, the PESS technique of detecting the r-peak with high accuracy and processing time of 1.77sec. Compared to WT, PT, energy derivative, etc., a time-dependent entropy calculation-based technique provides more accurate results. A quadratic filter circuit produces more precise results than a quadratic filter circuit and increases the QRS signal-to-noise ratio in low-amplitude QRS waves. A sparse prediction's goal is to detect interior patterns from random input signals with greater sensitivity than CNN. Researchers and practitioners may learn from the comparison study to select the best QRS complex detection algorithm for their unique application and dataset.

Keywords:* *ECG, Deep Learning, Machine Learning, QRS, Quadratic Filter, ECS Signals, Detection Algorithm.

I. INTRODUCTION
With roughly 17.8 million fatalities per year, cardiovascular illnesses are the leading cause of death globally. The electrocardiogram (ECG) is the most common method used to diagnose cardiovascular illness. Every day, over 3 million ECGs are produced worldwide. As wearable technology develops, more and more ECGs are being produced for analysis. In order to interpret ECGs generated by wearable technology and to reduce the effort for clinicians, automated diagnostic approaches are required. The electrical impulses generated throughout a cardiac cycle are represented visually by an electrocardiogram (ECG). It provides information on the morphology and rhythm of heart rate. ECG is a tool used by cardiologists to monitor heart health and identify cardiac problems such arrhythmias, hyperkalemia, and myocardial infarction. The lengths and amplitudes of the ECG signals may be used to gather a wealth of medical data. R-peak identifiability in the ECG signal is essential for calculating heart rate and spotting arrhythmias.

There are several different waves that make up the ECG signal, including P-waves, QRS complexes, and T-waves. A short-duration pulse with a large R-peak is known as a QRS complex. Automatic computer-based techniques are mostly focused on locating QRS complexes [1]. Clinically, it's critical to correctly identify the QRS complex. The morphology of the QRS changes whenever the atria and ventricles depolarize or repolarize prematurely or slowly, deviating from the usual ECG sinus rhythm [2]. This variation in QRS morphology is further associated with one or more cardiac diseases.

The P wave, QRS complex, and T wave are some of the many components that make up an ECG signal [2]. A computer-based ECG analyzer is necessary since it is difficult to visually examine a non-stationary signal. A common technique for determining heart rhythm abnormalities and heart rate variability (HRV) is R-peak identification in the electrocardiogram (ECG) [4]. To find the R-peak in the ECG, several signal processing methods have been created. Pan-Tompkin's method [3], artificial neural network (ANN) [5], heuristic methods [7], wavelet transform (WT) [9], Hilbert transform [5], empirical mode of decomposition [55], Shannon energy with Hilbert transform method [56], and Shannon energy envelope [7] are some of the other techniques for identifying R-peaks in ECG. The Pan-Tompkins technique (PT) [3] is a low complexity algorithm that produces lesser accuracy and is based on moving average fifilter and peak detection. Furthermore, accuracy is reduced since peak detection relies on an amplitude threshold.

Complex rules are necessary for ANN [7] to identify R-peak. The effectiveness of heuristic approaches [7] depends on the selection of the band pass filter's (BPF) appropriate bandwidth as well as the length of the moving window utilized for integration. To get QRS event, wavelet-based approaches [8] require the selection of an appropriate mother wavelet and scales. Although there are few entries in the MIT database, the Hilbert transform, and empirical mode of decomposition provide great accuracy. The SEHT (Shannon energy with Hilbert transform approach) [6] has high R-peak detection accuracy. The SEHT's Hilbert transform is not suited for real-time implementation since it consumes a lot of memory and causes delays. SEHT finds several noise peaks in ECG data with a prolonged pause. For storing ECG data samples throughout the computation of the Hilbert transform in the frequency domain, a very large memory buffer is needed. By utilizing simply, the Shannon energy envelope, Zhu and Dong [7] have created an R-peak detection technique known as PSEE. Again, the usage of an amplitude threshold for valid pair peak identification has an impact on the algorithm's performance. By contrasting the HRV estimation derived from concurrently captured ECG and PPG signals from forty participants, ***Esgalhado et al.***'s research [5] was conducted. Here, the Hilbert Double Envelope Method (HDEM), a peak detection technique based on the Hilbert transform, is presented.

II. LITERATURE SURVEY

In 1985, ***PAN et al. [3]*** suggested a technique for the real-time detection of QRS complex. It reliably detects QRS complexes based on digital examinations of the slope, amplitude, and breadth. Using a particular digital bandpass filter, the interference in ECG signals is minimized in its many forms. The use of low thresholds, made feasible by this filtering, has boosted detection sensitivity. The system dynamically modifies thresholds and settings on a periodic basis in response to ECG changes including variations in QRS shape and heart rate. The standard 24H MIT/BIH arrhythmia database's QRS complexes are accurately recognized by this method 99.3% of the time. An analog filter is used to bandlimit the ECG signal at 50 Hz. An ADC samples at a rate of 200 samples per second the ECG

On "Open source ecg analysis," in Computers in Cardiology, ***Hamilton et al. [8]*** woke. To try to reduce this duplication of work, we are developing and making open-source ECG analysis tools available. Our open source QRS detectors exhibit sensitivity and positive predictivities that are close to 99.8% on the MIT/BIH and AHA arrhythmia datasets. Our beat classifier has a sensitivity of 93.91% and a positive predictivity of 96.48% on the MIT/BIH arrhythmia database, and a sensitivity of 93.2% and a positive predictivity of 97.83% on the AHA arrhythmia database.

W.Fu, F.Du, and colleagues [9] used SEE and HT to find QRS complexes. Using Shannon's theory, one may compute Shannon's energy and use it to efficiently reduce undesirable low-energy disturbances and enhance high-energy detection. In order to assess the signal, envelop and determine the position of the R peak, HT transforms the original signal into an analytical signal. MIT-BIH Arrhythmia Database is used, and the average detection accuracy, sensitivity, and positive predictivity are 99.69%, 99.81%, and 99.88% respectively.

The study of ***Elgendi et al.*** [11] is concentrated on the ECG signal's QRS frequency ranges. The QRS complex has certain frequency ranges and geometries for various noise and abnormalities in ECG data. The three primary steps of the technique shown here are bandpass filtering, creating potential blocks, and thresholding. A one beat ECG signal that has undergone Butterworth bandpass filtering is used to generate blocks of interest using two moving averages. With SE and PPR, the 8-20Hz bandpass frequency range provides the best signal-to-noise ratio for locating QRS complexes. 98.31%.

By contrasting the HRV estimate derived from concurrently collected ECG and PPG signals from 40 participants, ***Salado and Arnaldo et al.*** [12] add work. Here, the Hilbert Double Envelope Method (HDEM), a peak detection technique based on the Hilbert transform, is presented. The effectiveness of Pan-Tompkins and Wavelet-based peak detection techniques was also examined. For each method, the time, frequency, and nonlinear HRV parameters were determined, and the Pearson correlation, T-test, and RMSE were assessed. The HDEM algorithm produced the best overall results, with sensitivity values for the ECG and PPG signals of 99.07% and 99.45%, respectively.

Shannon energy envelop was the method of choice by ***RAKSHIT et al.*** [13] to identify QRS complexes in ecg data. The procedure is divided into four stages: the first stage involves extracting the Shannon energy envelop; the second stage involves noise suppression and QRS complex enhancement through band pass filtering; the third stage involves peak estimation without considering any threshold amplitude; and the fourth stage involves the detection of true R-peaks.

III. QRS COMPLEX DETECTION METHODS USED IN OUR COMBINATION ALGORITHM

The PT and wavelet QRS detection methods, which are among the top performing algorithms for this job, are subject to our combination technique [17]. We briefly discuss both approaches in this section; the reader is directed to the related publications for further information.

3.1: PT Method

The most well-known illustration of a filter threshold technique for QRS complex detection is the PT algorithm [1]. It consists of a moving window integrator, a differentiator, a squaring operation, and a bandpass filter. The bandpass filter eliminates extraneous sounds. The integrator performs a smoothing operation, whose window length may be changed so that features of a given width are accented, while the differentiator and squaring operation emphasize steep significant features.

The threshold is the main variable in the PT technique. In areas where the filtered signal increases beyond the threshold, QRS complexes may be seen. A QRS complex is searched for if the filtered signal climbs beyond a second, lower threshold 2 (a set percentage of), but no peak is found during a time interval. Additionally, QRS complexes cannot be placed next to one another within 0.3 s (refractory time2). The R-peak maxima in the filtered signal's amplitudes determine how dynamically the thresholds and 2 are changed. See [1] for a more thorough explanation of the algorithm.

The threshold parameter is intriguing in relation to our combination strategy. This parameter allows us to adjust the algorithm's sensitivity and, therefore, the quantity of QRS complexes that are identified. If is raised, only highly obvious maxima in the filtered signal are discovered (and are thus almost certainly QRS complexes), but if is decreased, more maxima are anticipated, some of which may be noise.

3.2: Wavelet Method

We employed the wavelet QRS detector reported by Mallat and Hwang [11] and Li et al. [10] in our tests.

Like a Fourier decomposition, the wavelet transform breaks down a signal into a collection of basic functions. The sine function's dilatations and translations serve as the foundation functions in the Fourier decomposition. Comparatively, the mother wavelet is a prototype function (x) with limited support, and the wavelet basis functions are dilations (described by a parameter a) and translations (characterized by a parameter b). Thus, the definition of the function x(t)'s transformation W (a, b) is:

$$W(a,b)(x) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt. \qquad (1)$$

The lower frequency components of the signal as a function of time (b in the converted space) may be determined by looking at the constituents of the broader (more dilated) basis functions (big a). Similar to large a, tiny a's components provide high-frequency details about the signal as a function of time. The wavelet transformation may be easily done by selecting a = 2j and b = 2j l (referred to as the "dyadic" wavelet transform) [12]. As a result, we receive a series of functions (indexed by j), which are referred to as "scales." High scales carry low-frequency signal information, whereas low scales include high-frequency signal information.

The first four scales of the wavelet transformation are considered in the wavelet QRS detection technique from Li et al. [10]. The QRS complex and high-frequency noise are present in the first scale. All four scales can plainly see the QRS complex since it is so prominent, but the second and third scales are where it is most noticeable. The fourth scale comprises data with a lower frequency, such as baseline drift and T-wave information. Clear peaks in each scale must be identified, and they must be accurately matched across the various scales, to use the wavelet approach to detect QRS complexes. See [10] for further information.

IV. COMBINATION APPROACH

4.1: Motivation

The PT algorithm does well at picking up on distinct QRS complexes but struggles to pick up on larger QRS complexes, such as premature ventricular contractions. Although the wavelet approach is occasionally prone to overlook certain complexes with conventional shapes, it is better able to detect broader and strangely shaped QRS complexes. We want to create a better QRS complex identification method by merging the predictions of the two classifiers and correcting for the inadequacies of the separate algorithms. A good example of an ensemble classifier is our combination technique (see, for instance, [13]). An ensemble classifier can be more accurate than any of its individual members, as was mentioned in [13], if the individual classifiers outperform random guessing and make distinct (uncorrelated) mistakes on fresh data points [19]. This serves as a theoretical driving force for our strategy.

The second rationale is based on empirical validation, and it examines the maximum improvement that can be made by merging the base algorithms, assuming the ideal decision-making process if the predictions of the two classifiers differ. Section III-B will provide more details on this.

4.2: Oracle Experiments

By assuming the ideal choice strategy (the "oracle experiment"), we calculate the maximum performance improvement that our combination technique can accomplish over the separate algorithms in this section.

First, it is plausible to assume that this conclusion is approved ("majority vote") if the two algorithms agree to forecast the location of a QRS complex or not.

Sometimes when both algorithms arrive at the incorrect conclusion, the combination will also be inaccurate. As a result, the accuracy of the two independent algorithms sets an intrinsic lower constraint on the error rate that may be attained by the ideal combination. The goal of the Oracle experiment is to make the right choice utilizing the cardiologist annotation if the two algorithms dispute on whether a QRS complex is present at a certain moment. Formally, this may be understood as adding a third classifier to the ensemble that makes a perfect classification (equivalent to the manual annotation) and adopting the decision of the three classifiers that received the majority of the votes. This experiment is being conducted in order to give the best potential outcome by combining the two distinct algorithms. The oracle experiment's findings (described in Section IV) show that by combining the two distinct detection techniques in the best possible way, the QRS detection performance may be significantly enhanced. This shows that complimentary information regarding the position of the QRS complexes is included in both the PT and wavelet approaches. This is a powerful motivator for a combo strategy.

4.3 : Combination Algorithm

In our combination technique, the wavelet and PT algorithms are initially conducted concurrently. This choice is acceptable if both classifiers concur on whether to forecast a QRS complex location at time t. The main concept is to execute the PT algorithm3 locally (i.e., in an appropriate time frame around time t), but with altered threshold, if the two individual classifiers disagree at time t. To be more precise, we introduce two parameters, [0; 1] and [1;], that describe, respectively, how much the local PT rerun's PT threshold will be reduced and increased. When the wavelet technique detects a QRS complex site at time t but the PT method does not, the parameter is utilized to lower the PT threshold. When PT identifies a QRS complex site at time t but wavelet does not, the factor is employed to raise the PT threshold. In an effort to mimic the wavelet choice, the parameters and assess the "confidence" of the PT decision with regard to a threshold modification. Acceptance of the QRS complex in the output depends on the outcome of the local PT rerun with the modified threshold. Table I shows the decision-making process for our data-driven combination method.

PT	WVT	local decision strategy	output of combin. algor.
0	0	accept	0
0	1	local rerun PT, $\theta' = \alpha \cdot \theta, \quad \alpha \in [0,1]$	output PT rerun
1	0	local rerun PT, $\theta' = \beta \cdot \theta, \quad \beta \in [1,\infty)$	output PT rerun
1	1	accept	1

Table No.1 : Combination Algorithm

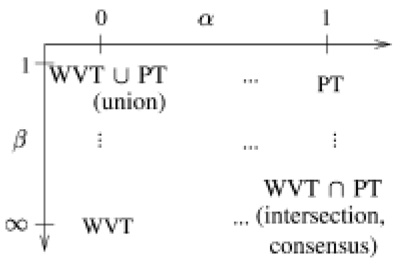

Figure No. 1 : Theoretical "limiting cases" of the combination algorithm in the two dimensional array of (α, β)-values. WVT: wavelet, PT: Pan–Tompkin's method.

Two parameters, and are introduced for a number of reasons. First, by choosing the correct parameter values, a parameterization of the decision strategy enables the combination method to be adjusted to various data sets. Second, by using two different threshold adjustment values, it is possible to individually treat QRS complexes that PT and wavelet missed. Additionally, our combination technique may achieve various straightforward combinations of the two classifiers with the right parameter values, as illustrated in Fig. 1: The combination approach is equal to the wavelet method when both parameters are set to zero; when both parameters are set to one, the PT method is recovered. Choosing = 0 and = 1 results in the logical "OR" of the two binary predictions, which is identical to the Boolean union of the two sets of QRS complex locations, for local PT and wavelet predictions on the presence of a QRS complex at time t. The next step is to set = 1 and locally to actualize the logical "AND" or "consensus" decision, in which a QRS complex is only recognized if and only if it is predicted by both the wavelet and the PT algorithm (corresponding to the Boolean intersection of the QRS complex locations). It is clear from Fig. 1 that as is raised, the QRS complexes predicted only by the wavelet technique are gradually eliminated. However, as is increased, the contribution of QRS complexes predicted only by the PT algorithm is eliminated.

V. METHODOLOGY

5.1: Database

Our QRS complex detection technique was created and evaluated using the MIT-BIH Arrhythmia Database. This collection comprises 48 half-hour extracts of two-channel ambulatory ECG recordings sampled at 360 Hz, comprising 25 recordings from individuals with clinically severe but uncommon arrhythmias and 23 recordings taken at random from a mixed group. 110 million beats total—or, on average, 2280 to 450 per patient—are stored in the MIT-BIH database. [20] and the Internet both include further details on the database.5 As the underlying algorithms were created for a single channel input, the algorithms in this work were only tested using the first of the two channels from each clip.

We partitioned the data into training and test sets by extracting every third snippet. The ideal values for the parameters and were determined using the training set (30 excerpts, 66 103 QRS complexes), and the test set (17 excerpts, 41 529 QRS complexes) was utilized to assess the algorithms using the parameter values derived from the training set.

5.2: Error Rate

We will cover a variety of topics while talking about the algorithms' accuracy. False positives (FP) refer to improperly identified QRS complexes, and false negatives (FN) refer to missing QRS complexes. We'll refer to the overall error (# error) as the sum of FP and FN. We will provide the overall error as a percentage of all annotated QRS complexes (% error) as well as its absolute value. If a QRS complex is found within 100 ms of the annotation time, it is considered to have been appropriately identified. If this tolerance is decreased, the paper's overall results remain unaffected.

CONCLUSION

The comprehensive analysis of various QRS complex detection methods for ECG data processing provides valuable insights for researchers and practitioners in the field. The study examined four prominent techniques, namely Pan-Tompkins, Wavelet Transform, Hilbert Transform, and Convolutional Neural Networks (CNN), utilizing a dataset of over 50 ECG signals.

The results highlight the strengths and efficiencies of each method, with Pan-Tompkins demonstrating the highest efficiency. Additionally, all algorithms exhibited commendable sensitivity and positive predictive values. Specifically, Hilbert Transform demonstrated superior accuracy in detecting QRS complexes with low amplitude and noise, making it a crucial tool for noisy or diseased signals. Wavelet Transform proved invaluable in identifying the peaks, onsets, and endings of P and T waves. Meanwhile, CNN showcased promising potential for further development, particularly with increased training data**.**

The study introduced two novel techniques, the PESS method with a detection time of 1.77 seconds and the time-dependent entropy calculation-based technique, both offering enhanced accuracy compared to existing approaches. The implementation of a quadratic filter circuit also emerged as an effective strategy to improve signal-to-noise ratios in low-amplitude QRS waves. Moreover, the sparse prediction method exhibited heightened sensitivity in detecting interior patterns from random input signals, surpassing the capabilities of CNN. These findings empower researchers and practitioners with a comprehensive understanding of the strengths and limitations of each algorithm, enabling them to make informed decisions in selecting the most suitable QRS complex detection technique for their specific application and dataset.

In essence, this comparative study advances the field of ECG data processing by providing a nuanced evaluation of diverse detection methods, ultimately contributing to the refinement of diagnostic and monitoring systems for cardiovascular health.

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