QVAT: QRS Complex Detection based on Variance Analysis and Adaptive Threshold for Electrocardiogram Signal

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***Abstract*—Heart disease is a disease that has a high level of danger. Somebody who has a history of heart disease must be careful in doing daily activities. Paramedics analyze Electrocardiogram(ECG) signals to detect heart abnormalities. Some researchers propose automated methods to analyze the heart condition based on ECG signals. One parameter for assessing heart condition is the distance from R peak to R peak, R is the peak of the QRS complex wave. In this research, we proposed QVAT algorithm that automatically detects QRS complexes, then finds R peaks from an ECG signal. The algorithm that we use consists of several steps, namely: band-pass filter, analysis of variance, adaptive threshold and local maxima. Band-pass filters are used to reduce noise that can cause errors in detection QRS waves. Possible noise due to: interference due to electromagnetic wave voltage, noise of muscle movement. The average of variance is used to strengthen the QRS Complex feature at positive x-coordinates, the adaptive threshold is used to localize the QRS complex. The result of adaptive threshold is a region of interest (ROI) of QRS Complex that is used to find the position of R peak. We use the adaptive threshold since the magnitude and slope features of each subject's ECG signal are different. Evaluating the performance of our proposed algorithm, we tested it to detect the QRS complex in the MIT BIH Arrhythmia database. The proposed algorithm QVAT has a sensitivity Se = 99.79 % and a positive predictive $+P$ = 99.90 %. These results indicate sensitivity of QVAT is better than Pantompkins, Garca Rivas and Xiang. The positive predictive parameter is comparable to Xiang method however it is better than Pantompkins, Garca Rivas.**

***Index Terms*—ECG, QRS Complex detection, Arrhythmia, Variance, Adaptive Threshold.**

I. Introduction

The quality of life of somebody is influenced by the health condition of his body organs, if the body organs are disrupted then the quality of life will drop. One of the body organs that often has problems with age or because of an unhealthy lifestyle is the heart. The heart has a function to pump blood throughout the body. One of the abnormalities that often occurs is the narrowing of arteries that flow through the blood to the heart muscle, resulting in reduced supply of oxygen and nutrients to move the heart optimally. This disorder causes interference with the heart rhythm which can cause health conditions that worsen even cause death. Disorders of the heart rhythm are often called arrhythmia. The definition of cardiac arrhythmia is an abnormality in speed, rhythm and interruption of conduct that causes changes in normal activity in the atria and ventricles. Paramedics detect arrhythmia by analyzing the Electrocardiogram (ECG) signal.

ECG is an electrical signal caused by the heart working to pump blood from the heart throughout the body and back to the heart. The signal is obtained because of the potential difference due to the flow of electrons carried by the blood. Identification of ECG signal features is a search process to find important information on ECG signals. Analysis and recording of ECG signals using electrode sensors mounted on the body, these electrodes are placed in two or more places on the body. The tapping in time units forms a wave that represents the work

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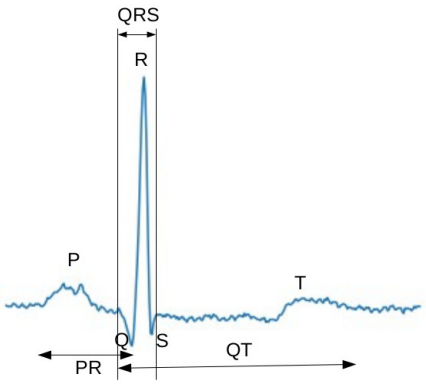


Fig. 1: Electrocardiogram signal

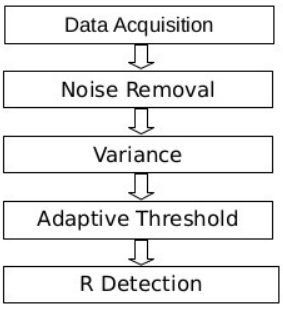


Fig. 2: QVAT methodology

of the heart, as illustrated in the Fig 1. This figure represents 1 period of ECG signal, which consists of 3 important waves: P wave, QRS Complex wave and T wave. The condition of someone's heart health can be analyzed from the magnitude and height of P wave, QRS Complex wave and T wave.

Difficulties and challenges in detecting these waves are: the number of QRS complex in ECG recorded is a huge, and some of them have small magnitude. As illustrated in Fig.1, several previous methods incorrectly detect QRS complexes because: (1) some of T waves are as large as QRS complexes, (2) this is due to the condition of someone's heart condition that is disturbed or there are abnormalities since a somebody is born, (3) the characteristic of ECG signals that have small amplitude (mV) and short duration also cause of error detection, (4) the characteristic of electricity is used power supply, and (5) muscle movement is caused noise of ECG.

There are many studies that have been developed to detect complex QRS waves, including: [1], [2], and [3]. Research [1] implements a micro controller-based QRS complex wave search system with several steps, namely: Differentiation, Integration, Squaring, and History RR values. Whereas Rivas et. al. [2] uses a simpler method than Pantompkins so that the computational cost becomes smaller but has a better level of acuracy. The Rivas method combines the difference between preprocessing and threshold dynamics to detect R. The Pantompkins method is also a reference method of Khamis et al. [3], they add adaptive threshold, and backtracking to re-examine QRS complex that increases robustness of detecting QRS complex. Khamis confirmed the superiority of the method compared to the pantomkins and rivas. The Khamis method has robust ability to detect ECG signals that have a lot of noise. Khamis claims the method used is good for detecting QRS Complex waves from ECG signals generated from telehealth sensors that have many artifacts.

In recent years artificial intelligence and machine learning have been widely applied in biomedical engineering. Some researchers have tried to use machine learning and artificial intelligence to detect and classify QRS Complex signals: [4], [5], [6], [7], [8], [9], and [10]. Mei et al. in the research [5] classified someone suffering from arrhythmia based on heart rate variability and spectral features with single lead ECG data. The author explained his success in classifying between 92 % to 96 %. Research [10] using deep CNN-BLSTM by learning a number of data with RR input intervals and PQRST signals can improve performance accuracy predictive positive $+P$ and sensitivity Se. Classification of ECG signals into 16 classes was carried out by yildirim using CNN [6], in contrast to previous studies yildirim used long duration ECG signals as input to determine this classification.

In this work, we proposed an algorithm based on a heuristic method called QVAT that has stages: band-pass filter, variance analysis, adaptive threshold and local maxima. The study has the advantage of detecting QRS Complex in terms of sensitivity Se and a positive predictive $+P$ from the heuristic method Pantomkins (PTK), Garca Rivas(GR) and deep learning method (Xiang). The paper is organized as follows: Section 2 describes our proposed method QVAT; some experimental results are shown in Section 3; and, finally, some conclusions are discussed in Section 4.

II. Methods

The QRS complex wave detection of QVAT algorithm is illustrated in the Fig. 2, each block of the algorithm will be explained in the subsection.

A. Data

The 20 from 48 records ECG signals in the MIT-BIH arrhythmia database are used in this study. The ECG database recording is sampled at 360 Hz over -5 mV to +5 mV. Each recording comprises two ECG leads, one channel is modified-lead II (MLII) and the other channel are lead V1, V2, V4 or V5. However, we used only MLII channel. All beats of the database are assigned corresponding labels set by cardiologists. Then we check the position of R for confirmation of performance detection. 20 records of MIT-BIH that are selected: 100, 101, 103, 105, 106, 107, 108, 109, 112, 113, 114, 115,116,117, 118, 119, 121, 122, 123 and 124.

B. Noise Removal

We use low-pass filter and high-pass filter as noise removal in the QVAT method to reduce the influence of muscle noise

and interference of electricity. Low-pass filter is a signal filter that is used to pass low frequency signals and eliminate high frequency. Then, we use high-pass filter to pass the signal on a certain frequency band or pass a signal between the specified frequency limits. The ranges of frequencies that are between the upper limit frequency and the lower limit frequency are usually known as a bandwidth filter. This filter reduces the influence of muscle noise and 60 Hz interference of electricity.

C. Variance

Variance is the expectation of the data scattered from the average value. The zero variance value indicates that all values in a set of numbers are the same. A set of numbers are the close to the average produces a variance almost zero. Otherwise, a large variance value is indicated that a set of data are spread around the average. The variance is always non-negative since the value is squared deviation of samples from its average.

The maximum width of the QRS complex on a normal ECG is 0.12 seconds or close to 40 samples if the sample frequency of ECG signal is 360 Hz. The variance equation of the filtered ECG signal is implemented by the QVAT method according to the equation 1. Variance i is represented by var_i, y_{f_i} is the filtered ECG signal i and $\bar{y_f}$ is the mean value from $i-20$ to $i+19$.

$$var_i = \sum_{i-20}^{i+19} \frac{(y_{f_i} - \bar{y_f})^2}{40} \tag{1}$$

D. Adaptive Threshold

An adaptive threshold is used to find ROI of QRS complex where the ROI has an R peak value. Unlike the global threshold technique, the local adaptive threshold selects a different threshold value for each sample of ECG based on the analysis of adjacent signals according to the equation 2. Parameters min, max, and k of the equation are obtained by analyzing the first variance as depicted Fig. 3. First, we find min that is the minimum value between $i-0.05s$ and $i+0.05s$. Since the frequency sample of MIT-BIH arrhythmia database is 360 Hz that the lower and upper limits are $i-180$ and $i+179$. max is the maximum value between $i-180$ and $i+179$ The value of k is the proportion of magnitude R-peak and magnitude 0.6 second before a peak of R. When (x_r,y_r) is the coordinate of the R-peak on a function $f(x)$, then the coordinates 0.5 second before R-peak is the inverse of $f(x_r-20)$.

$$th_i = min + k \times (max - min) \tag{2}$$

The equation 3 is the output of the adaptive threshold that is determined if the signal is greater than the threshold th_i.

$$y_{th_i} = \begin{cases} 1 & \text{if } y_{th_i} > th_i \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

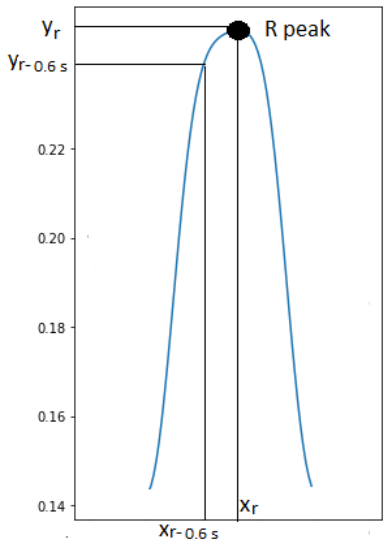


Fig. 3: Variance analysis of filtered ECG signal

E. R peak detection

In this stage, each QRS complex is determined by a region of interest (ROI). Algorithm 1 is used to find the limits of QRS complex ROI. Input algorithm is filtered ECG signal (x_{f_i},y_{f_i}) and result of adaptive threshold (x_{th_i},y_{th_i}). The algorithm has n output R peak as the signal selected as a QRS complex wave. The coordinate of ROI are (x_{roi_n},y_{roi_n}), then we called it the ROI of QRS complex. The R peak detection on every ROI of the QRS complex is performed using a local maxima (greedy algorithm). In an ROI of QRS, the peak value of R is detected starting from the first sample from output algorithm 1 to the final limit of ROI. The biggest value of the ROI is the peak value of R (x_{r_n},y_{r_n}).

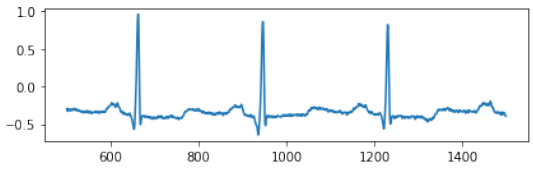
Algorithm 1: Algorithm of QRS complex ROI

```
Data: (x_{f_i},y_{f_i}),(x_{th_i},y_{th_i})
Result: (x_{roi_n},y_{roi_n})
n=0;
while x_{f_i} do
    y_{roi_n} = 0;
    if y_{th_i} == 1 then
        if y_{th_{i-1}} == 0 then
            n++;
        end
        y_{r_n} = x_{f_i} ;
    end
end
```

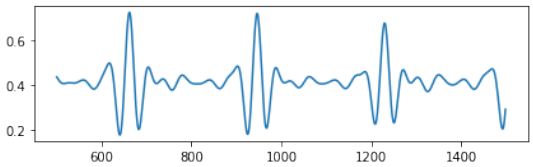
III. Experiment Results

A. The results of the QVAT method

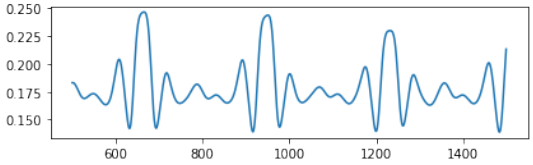
In this subsection, we present the results of the proposed method QVAT in every step as shown in Fig. 4. Fig. 4a shows the results of ECG record on the MIT-BIH arrhythmia database



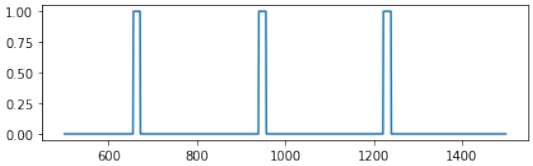
(a) Original ECG



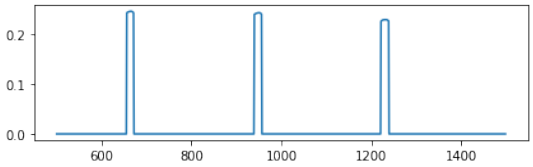
(b) Filtered ECG



(c) Variance of ECG



(d) Adaptive threshold



(e) ROI of variance

Fig. 4: The results of the QVAT method

record number 100 that is recording ECG on the subject of female aged 69 years. Fig. 4b shows the output of the band pass filter, this result is used input of the variance process which has the output shown in Fig. 4c. The process continues the adaptive threshold that has the output as depicted Fig. 4d. Fig. 4e shows the ROI of the variance of filtered ECG selected based on the output of the adaptive threshold.

B. Performance metrics

We investigate performance of our proposed protocol algorithm QVAT using metrics: a sensitivity Se and a predictive positive $+P$. The proposed algorithm is tested by analyzing and comparing $+P$ and Se with other protocols namely PTK [1], GR [2], and Xiang [4]. We use equation 4 and equation 5 to find the sensitivity and the predictive positive. Where TP stands for True Positive is the total number of QVAT Algorithm detecting QRS complex. FP is an abbreviation of the total number of artefacts, noise, P wave or T wave are identified as QRS complexes. Meanwhile, FN (False Negative) is the total number of non detected QRS complexes.

$$Se = \frac{TP}{TP + FN} \times 100\% \tag{4}$$

$$+P = \frac{TP}{TP + FP} \times 100\% \tag{5}$$

Table I is the result of detection of QRS waves on public ECG signals contained in the MIT-BIH arrhythmia Database [11]. The values of TP, FP, and FN in the table are the values of 20 data records at MIT-BIH database on the MLII channel. The worst performance is obtained on record 108, which has 6 in FN. This is because our algorithm has poor ability in detecting ECG signals on signal types that have low magnitude and large distance of RR. The point of table I is the proposed algorithm has a sensitivity is 99.79% and positive predictive is 99.90%.

TABLE I: Performance evaluation of the proposed method

No.	Record	Beats	TP	FN	FP
1	100	370	370	0	0
2	101	340	340	0	1
3	103	354	354	0	0
4	105	416	416	0	1
5	106	331	331	0	0
6	107	352	352	0	0
7	108	283	277	6	0
8	109	431	431	0	0
9	111	348	348	0	2
10	112	426	426	0	0
11	114	275	275	0	0
12	115	314	314	0	0
13	116	394	388	6	0
14	117	250	250	0	2
15	118	363	363	0	1
16	119	326	325	1	0
17	121	302	302	0	0
18	122	420	420	0	0
19	123	247	247	0	0
20	124	251	251	0	0
	Total		6780	13	7

C. Benchmarking the QVAT with other methods

We evaluate our proposed algorithm by comparing our performance and others. Table II shows the accuracy of the proposed algorithm has a value of Sensitivity Se better than PTK, GR and Xiang. The predictive positive $+P$ of QVAT outperforms to PTK, GR and is proportional to the Xiang algorithm.

TABLE II: Comparison result of QRS detection methods

No.	Methods	Se	$+P$	Data
1.	QVAT	99.79	99.90	20 records MIT BIH
2.	Xiang	99.70	99.91	48 records MIT BIH
3.	GR	99.56	99.76	48 records MIT BIH
4.	PTK	99.54	99.74	48 records MIT BIH

IV. Conclusions and Discussion

In this paper, we proposed QVAT that is an algorithm to detect QRS complex in ECG signals. QVAT has several steps in detection QRS complexes, namely: filtering ECG signal, variance analysis, adaptive threshold to find the ROI of QRS complex and then local maxima to predict of R peak. We tested the robustness of the proposed method using 20 records channel MLII of MIT-BIH Arrhythmia Database. The experiment results of the QRS complex detection experiment, the proposed method has a sensitivity $Se = 99.79\%$, this sensitivity is better than the Pantompkins, Garca Rivas and Xiang methods. While the positive prediction $+P$ performance of the proposed method is comparable to the Xiang method and better than the PTK and GR methods, which is 98.90%.

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