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The Accuracy on the Common Pan-Tompkins Based QRS Detection Methods Through Low-Quality Electrocardiogram Database

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QRS complex detection has been extensively studied over the past decades. Pan-Tompkins based methods were the most widely used QRS complex detectors. These methods could obtain high accuracy on high-quality clinical ECG data. However, the accuracy of the Pan-Tompkins based QRS detection methods on a low-quality ECG database should be clarified. In this paper, three Pan-Tompkins based QRS complex detectors were tested on both high and low-quality ECG databases, i.e., the original Pan-Tompkins method and the following improved versions of Pan-Tompkins based method with mean and median peak level estimation respectively. Two hundred 10-minute ECG recordings from the 2014 PhysioNet/CinC Challenge were used (100 from the high-quality database and 100 from the low-quality database). Accuracy was used as the performance criterion for the methods. All three Pan-Tompkins based QRS detection algorithms had high detection accuracies on the high-quality ECG database (>99%), whereas relatively low detection accuracies were reported for the low-quality ECG database (76.03% was the highest result for the Pan-Tompkins based method with median peak level estimation and 74.49% was the lowest result for the original Pan-Tompkins method). We found that it is better to use the median peak level estimation to avoid the sudden amplitude change effects. In addition, the original Pan-Tompkins method had the highest computational efficiency. In this study, the performance of three common Pan-Tompkins based QRS complex detection algorithms were systematically analyzed and their noise responses were also tested. The conclusion generated by this study could potentially offer important reference for the reasonable use of those methods.

Keywords: Electrocardiogram (ECG), Pan-Tompkins Based QRS Complex Detection, ECG Signal Quality.

1. INTRODUCTION

Cardiovascular diseases (CVD's) is the most common cause of death globally. In 2012, CVD's were the cause of death for about 17.5 million people, which equates to about 31% of all global deaths.[1] An electrocardiogram (ECG) signal, the expression of the myocardium electrical activity on the body's surface, provides important information about the status of cardiac activity.[2] The accurate heart beat detection of ECG signal plays a fundamental role in monitoring of CVD's.[3]

The QRS complex is the most striking waveform within the ECG signal; it serves as the basis for the automated determination of the heart rate, as well as the benchmark point for classifying the cardiac cycle and identifying any abnormality. Over the last few decades, the QRS complex detection has been extensively studied. The method introduced by Pan and Tompkins (Pan-Tompkins)[4] in 1985 was the best representative. It was widely used and has been cited extensively in the literature as an unofficial benchmark for QRS detector performance.[1,3,5,6] The features in this method were peak energy and double adaptive thresholds. The Pan-Tompkins algorithm has been found to have a higher accuracy for various beat morphologies than other traditional real-time methods developed before 1990.[7] In 1986, by optimizing parameter selection and threshold estimation, Hamilton and Tompkins[8] improved the original Pan-Tompkins algorithm. In the past two decades, the Hamilton-Tompkins algorithm has been also widely used for HRV (Heart Rate Variability) analysis for a variety of applications such as detection of OSAS (Obstructive Sleep Apnea Syndrome) in children,[9] compression for optimal transmission and storage for ECG analysis,[10] etc. Because their focus on mostly high-quality ECG database and not on the low-quality ECG database, the application of Pan-Tompkins based algorithms can be problematic for the low signal quality ECG waveforms. The quality of signals monitored by portable devices becomes an important concern as mobile healthcare rises. It may also challenge the current signal processing algorithms.

Telehealth systems are experiencing increased adoption, not only due to the convenience of being able to monitor health within the home, but also due to the potential significantly

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reduced costs to users and health care providers alike. However, a decrease in signal quality is a fundamental problem associated with measuring a patient's ECG in a telehealth environment. The ECG signals recorded from the dynamic and mobile equipment are inevitably noise-corrupted, consisting of more uncontrollable aspects, such as physiology, pathology, and artificial effects. The performance of the Pan-Tompkins based algorithms were not systematically evaluated for these signals. Thus, we tested the performance of three Pan-Tompkins based algorithms on both high and low quality ECG signals in this study.

2. METHODS

2.1. Data

Two hundred ECG recordings from the 2014 PhysioNet/CinC Challenge[11,12] were used in this study. These recordings were from two databases: 100 recordings (named 100∼199, sampled at 250 Hz) from the training set, and another 100 recordings (sampled at 360 Hz) from the augmented training set. Each recording was 10 min long. The signal quality of ECG signals in the training set were always good, whereas the quality of the ECG signals in the augmented training set were very poor. Thus, the training set was used as a high-quality ECG database and the augmented training set was used as a low-quality ECG database during this study. All ECG recordings had the manually annotated QRS complex locations and these locations were used as the references for algorithm evaluations.[13] The data has a standard WFDB format and they were read by the Matlab software through 'rddata.m', which is a standard WFDB function provided in the PhysioNet.

2.2. Pan-Tompkins Based QRS Detection Algorithms

The original Pan-Tompkins algorithm[4] is one of the most widely used QRS detectors.[1,6,14] Figure 1 shows its flow diagram. First, the Butterworth band-pass filter was used to filter the ECG signal at a frequency range of 5–15 Hz. After filtering, the signal was differentiated by a five-point derivative and squared point by point. Then, the squared ECG signal was transferred into an integrated energy signal. Two sets of adaptive thresholds were employed to detect the QRS peaks in both filtered ECG signal and integrated energy signal. Then, an optimization step was performed to re-detect the peaks. The RR interval less than 360 ms was first rechecked to see whether it was a T wave. If the RR interval was larger than the RR interval missed limit (RRML), the searching back program was performed to find the missed beats. Then, the thresholds automatically adapt to the characteristics of the signal because they were based upon the running signal and noise peak levels that were detected in the ongoing processed signals. For the purposes of calculating the signal and noise peak levels in this algorithm, the iterative peak level estimator was used. A newly detected peak must first be classified as a noise or signal peak. Equation (1) was used to determine the detection threshold:

$$\mathrm{DT} = \mathrm{NPL} + \mathrm{TC} \times (\mathrm{QRSPL} - \mathrm{NPL}) \tag{1}$$

where DT is the detection threshold, NPL is the noise peak level, TC is the threshold coefficient, and QRSPL is the QRS signal peak level. In this algorithm, TC is 0.25.

Then a 200 ms refractory blanking technology was applied to eliminate the possibility of a false detection. Finally, the peak points through all detections were determined as QRS positions.

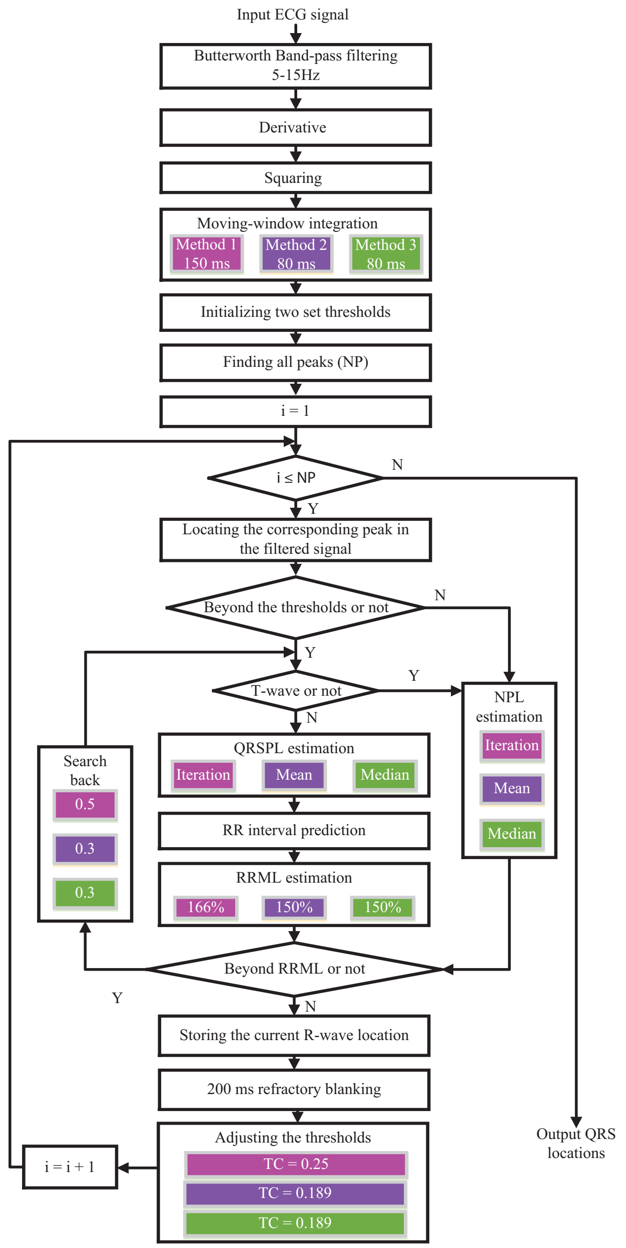

Fig. 1. The flow diagram for the original Pan-Tompkins method (marked pink), the modified Pan-Tompkins method with mean estimation (marked purple) and the modified Pan-Tompkins method with median estimation (marked green).

In 1986, Hamilton and Tompkins improved the Pan-Tompkins method by optimizing parameter selection and threshold estimation.[7] Form this literature, we proposed two improved versions of Pan-Tompkins based method, and named them as modified Pan-Tompkins method with median estimation and modified Pan-Tompkins method with mean estimation, respectively. Figure 1 and Table I both show the differences between these three methods. The differences can be summarized in six aspects:
(1) Integration moving-window width: 150 ms in the original Pan-Tompkins method, whereas 80 ms in the two modified Pan-Tompkins methods.
(2) QRS peak level estimation method: iteration in the original Pan-Tompkins method and using mean and median of the eight

Table I. Summary of the differences among the three methods.

Difference	The original Pan-Tompkins method	The modified Pan-Tompkins method with mean estimation	The modified Pan-Tompkins method with median estimation
Integration window width	150 ms	80 ms	80 ms
Peak level estimation	Iteration	Mean of the eight most-recent beats	Median of the eight most-recent beats
Threshold I	NPL + 0.25 (QRSPL-NPL)	NPL + 0.189 (QRSPL-NPL)	NPL + 0.189 (QRSPL-NPL)
Threshold II	0.5 of Threshold I	0.3 of Threshold I	0.3 of Threshold I
RR interval prediction	Mean of the eight most-recent beats	Mean of the eight most-recent beats	Mean of the eight most-recent beats
RR interval missed limit	166% of RR interval	150% of RR interval	150% of RR interval

most-recent beats in the two modified Pan-Tompkins methods respectively.

(3) Noisy peak level estimation method: iteration in the original Pan-Tompkins method and using mean and median of the eight most-recent beats in the two modified Pan-Tompkins methods respectively.

(4) Threshold coefficient: 0.25 and 0.189 for the original Pan-Tompkins method and the two modified Pan-Tompkins methods respectively.

(5) Search back threshold: 0.5 and 0.3 times of the detection threshold for the original Pan-Tompkins methods and the two modified Pan-Tompkins methods, respectively.

(6) RR interval missed limit: 166% and 150% of the average RR interval for the original Pan-Tompkins methods and the two modified Pan-Tompkins methods, respectively.

2.3. Evaluation Methods

As suggested from the 2014 PhysioNet/CinC Challenge,[12] four statistics were used to measure the performance of the three Pan-Tompkins based QRS detection methods:

$$\text{Se\_ave} = \frac{1}{n}\sum_{i=1}^{n}\frac{\text{TP}_i}{\text{TP}_i+\text{FN}_i}\times 100\% \tag{2}$$

$$\text{PPV\_ave} = \frac{1}{n}\sum\_i = 1^n\frac{\text{TP}_i}{\text{TP}_i+\text{FP}_i}\times 100\% \tag{3}$$

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

$$\text{PPV\_gro} = \frac{\text{TP}}{\text{TP}+\text{FP}}\times 100\% \tag{5}$$

where TP, FP, and FN denote true positives (correctly detected beats), false positives (erroneously detected beats outside of the tolerance window, or additional detected beats within a tolerance window), and false negatives (undetected reference beats), respectively. TP_i, FP_i and FN_i denote the statistics for the i-th recording,[12] Se_ave and PPV_ave represent the average sensitivity and positive predictivity for all recordings in the high and low-quality databases, respectively, and Se_gro and PPV_gro represent the corresponding gross sensitivity and positive predictivity. Accuracy (Acc) was used as the performance criterion for the methods and was defined as:

$$\text{Acc} = \frac{1}{4}(\text{Se\_ave}+\text{PPV\_ave}+\text{Se\_gro}+\text{PPV\_gro}) \tag{6}$$

Figure 2 shows an example of TP (marked as blue 'o'); FN (green '+') and FP (pink 'o') detections form the recording of 41,778 in the low-quality database. A red '+' indicated reference QRS annotations (R_ref). The tolerance time window of 50 ms is denoted by the vertical gray areas to confirm the TP detections. If the detected QRS location is within the current vertical grey area, it is considered to be a TP detection. If the detected QRS location is out the current vertical grey area, it is considered to be an FP detection. If there is no detected QRS location within the current vertical grey area, it is considered to be an FN detection. If more than one detected QRS locations exists within the current vertical grey area, one is considered to be a TP detection and the others are considered to be FP detections.

3. RESULTS

Tables II and III show the detection results of the three QRS detection methods on the high/low-quality ECG databases, respectively. As shown in Table II, all three QRS detection algorithms had high Acc results for the high-quality ECG signals (>99%). However, as shown in Table III, the detection accuracies decrease significantly for the low-quality ECG signals. The modified Pan-Tompkins method with median estimation reported the highest Acc result at 76.03%, and the original Pan-Tompkins method gave the lowest Acc result of 74.49%.

Tables II and III also show the average time costs of the three methods by analyzing 10 s ECG signals. In this study, all of the methods were implemented in MATLAB 2014a (The MathWorks, Inc., Natick, MA, USA) on Intel TM i5 CPU 3.30 GHz. As shown, the original Pan-Tompkins method had the highest computational efficiency.

4. DISCUSSION

As summarized in both Figure 1 and Table I, the parameter and threshold settings were the differences noticeable among each of the three methods. These three algorithms had almost

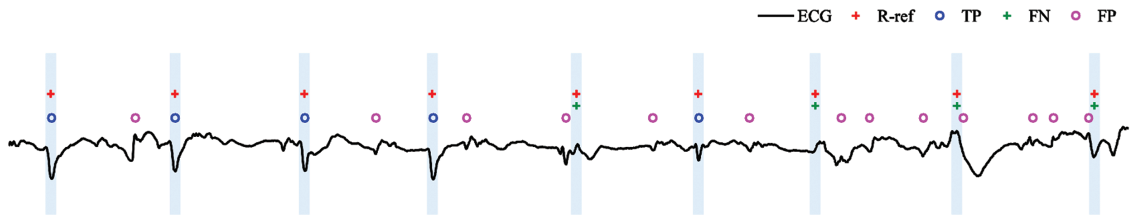

Fig. 2. Example of TP (marked as blue 'o'), FN (green '+') and FP (pink 'o') detections from the recording 41,778 in the low-quality database. Red '+' indicated reference QRS annotations (R_ref). The tolerance time window of 50 ms is denoted by the vertical gray areas.

Table II. Detection results of the three algorithms on the high-quality ECG databases.

Method	No. TP	No. FN	No. FP	Se_ave (%)	PPV_ave (%)	Se_gro (%)	PPV_gro (%)	Acc (%)	Time (ms)
The original Pan-Tompkins method	72,337	76	126	99.91	99.84	99.90	99.83	**99.87**	**5.14**
The modified Pan-Tompkins method with mean estimation	72,350	63	143	99.92	99.81	99.91	99.80	**99.86**	**5.82**
The modified Pan-Tompkins method with median estimation	72,355	58	152	99.93	99.80	99.92	99.79	**99.86**	**5.92**

Table III. Detection results of the three algorithms on the low-quality ECG databases.

Method	No. TP	No. FN	No. FP	Se_ave (%)	PPV_ave (%)	Se_gro (%)	PPV_gro (%)	Acc (%)	Time (ms)
The original Pan-Tompkins method	57,540	21,078	18,989	73.17	76.41	73.19	75.19	**74.49**	**5.67**
The modified Pan-Tompkins method with mean estimation	59,679	18,939	20,491	75.91	75.86	75.91	74.44	**75.53**	**6.58**
The modified Pan-Tompkins method with median estimation	61,289	17,329	23,296	78.63	75.08	77.96	72.46	**76.03**	**6.64**

similar detection accuracies for the high-quality ECG signals (see Table II). However, the detection accuracies varied significantly for the low-quality ECG signals (see Table III). The modified Pan-Tompkins method with median estimation reported the best Acc result at 76.03% and the original Pan-Tompkins method gave the worst Acc results at 74.49%. The modified Pan-Tompkins method with median estimation also gave the largest TP detections at 61,289, and FP detections at 23,296. The original Pan-Tompkins method gave the smallest TP detections at 57,540 and FP detections at 18,989. The detection accuracies could be improved by the improved parameter and threshold settings in the modified Pan-Tompkins methods.

The peak level estimation of the original Pan-Tompkins method was iteration. The sudden amplitude greatly affected this estimator. Due to the adaptation to large amplitude peaks, the thresholds increased and may never decrease again, resulting in no further peaks being detected and no further threshold adaptation. Figure 3 illustrates an example from recording 2,714 in low-quality ECG database. In this episode, there were several QRS complex with sudden amplitude changes of some ectopic ventricle beats, such as the 4th, 5th, 7th, and 15th beats. There were only four detected beats for original Pan-Tompkins method, while there were 12 and 15 detected beats for the two modified Pan-Tompkins methods, respectively.

The sudden amplitude change also affected the modified Pan-Tompkins method with mean estimation. However, it had a 30% search back threshold of detection rather than a 50%, which could improve this situation. Therefore, there were 11 TP detections in the modified Pan-Tompkins method with mean estimation, while there were four TP detections in the original Pan-Tompkins method. However, the modified Pan-Tompkins method with mean estimation was also influenced if there is a strong sudden change in amplitude. Figure 4 shows an example from recording 1,683 in the low-quality ECG database. In this episode, there were four TP and eight FP detections in the original Pan-Tompkins method and modified Pan-Tompkins method with mean estimation, while there were 11 TP and 10 FP detections in the modified Pan-Tompkins method with median

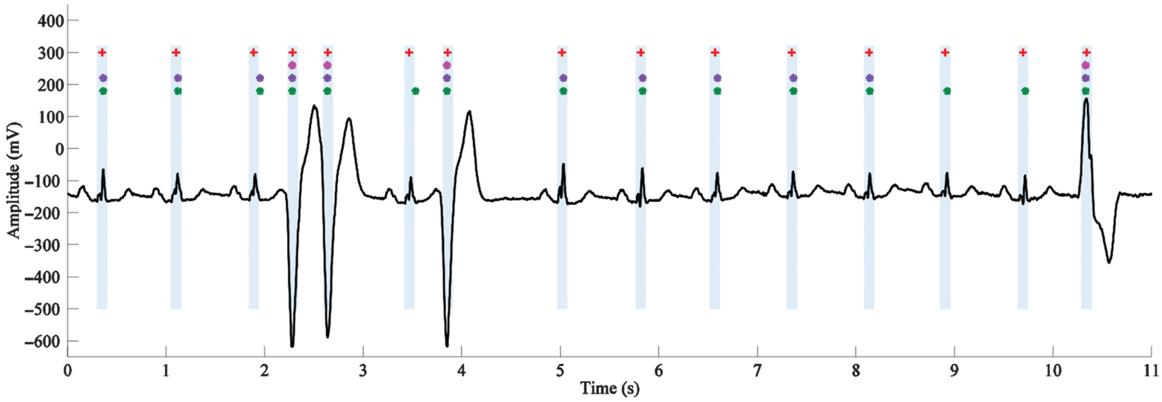

Fig. 3. Example from recording 2,714 in the low-quality ECG database: The original Pan-Tompkins method (4 TP and 0 FP, marked as pink asterisks); the modified Pan-Tompkins method with mean estimation (11 TP and 1 FP, marked as purple asterisks); the modified Pan-Tompkins method with median estimation (13 TP and 2 FP, marked as green asterisks). The annotations points of reference were marked as red crosses.

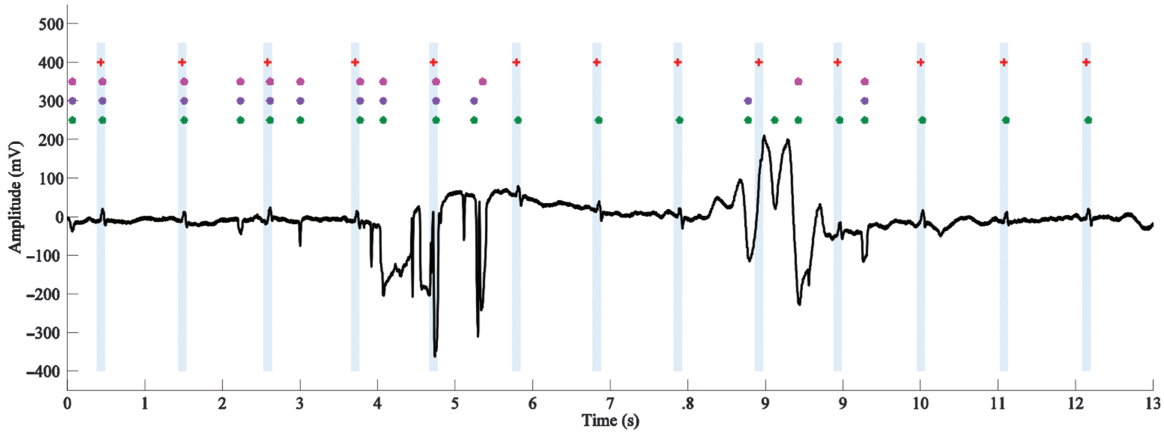

Fig. 4. Example from recording 1,683 in the Low-quality ECG database: The original Pan-Tompkins method (4 TP and 8 FP, marked as pink asterisks); the modified Pan-Tompkins method with mean estimation (4 TP and 8 FP, marked as purple asterisks); the modified Pan-Tompkins method with median estimation (11 TP and 10 FP, marked as green asterisks). The annotations points of reference were marked as red crosses.

estimation. In this episode, the sudden amplitude change also influenced the modified Pan-Tompkins method with mean estimation. The modified Pan-Tompkins method with median estimation employed the median value of the eight most-recent beats as peak level, which could reject the influence of the sudden amplitude change.

5. CONCLUSION

In this study, the performance of the three Pan-Tompkins based QRS complex detection algorithms were systematically compared on both high and low-quality ECG databases from the 2014 PhysioNet/CinC Challenge.

These three QRS detection algorithms primarily had the same high detection accuracies for the high-quality ECG signals, whereas the output was relatively different and the low-quality ECG signals had low accuracy. The Pan-Tompkins based method with median peak level estimation reported the best Acc results at 76.03% and the method with iteration peak level estimation gave the worst Acc results at 74.49%. It was discovered that the median peak level estimation was better to avoid the effect of the sudden amplitude changes. In addition, the original Pan-Tompkins based method had the higher computational efficiency.

In conclusion, we have systematically studied the performance of three Pan-Tompkins based QRS complex detection algorithms and tested their noise response. The conclusions derived by this work could potentially provide integral reference for the reasonable use of those methods.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest to this work.

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