Analysis of Pan-Tompkins Algorithm Performance with Noisy ECG Signals

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Abstract. The Pan-Tompkins Algorithm is the most widely used QRS complex detector for the monitoring of many cardiac diseases including in arrhythmia detection. This method could provide good detection performance with high-quality clinical ECG signal data. However, the numerous types of noise and artefacts that exist in an ECG signal will produce low-quality ECG signal data. Because of this, the performance of Pan-Tompkins-based QRS detection methods using low-quality ECG signals should be further investigated. In this paper, the performance of the Pan-Tompkins algorithm was analysed in extracting the QRS complex from standard ECG data that includes noise-stressed ECG signals. The algorithm's QRS detection reliability was tested using MIT-BIH Noise Stress Test data and MIT-BIH Arrhythmia data. The performance of the algorithm was then analysed and presented. This paper shows the capability of the Pan-Tompkins algorithms in handling noisy ECG signals.

1.Introduction

An electrocardiogram (ECG) is a graphical representation of the electric waves generated during a cardiac cycle. It provides information about heart rate morphology and rhythm [1, 2]. Cardiologists use ECG to diagnose and monitor cardiac diseases including the detection of arrhythmia [3, 4, 5]. A normal-rhythm ECG signal, as shown in Figure 1, consists of a P-wave and a QRS complex along with T-waves. The QRS complex and R-peaks play an essential role in many algorithms used for automated ECG analyses [6, 7]. Based on the identified QRS complex and R-wave, the rest of the waves and ECG features can be detected [2].

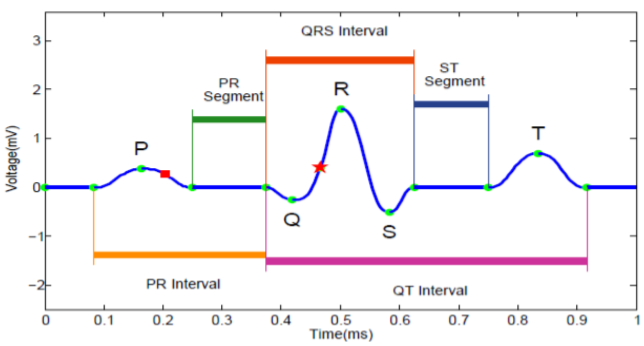

Figure 1: ECG Features

During the recording process, numerous types of noise can exist in the ECG signal [8, 9]. Furthermore, the ECG signal is composed of different subjects and devices commonly manifested by the variations in the amplitude of the heartbeat. This situation produces a low-quality signal that can impact the QRS detection performance [10]. Many approaches to improve QRS and R-wave detection have been proposed in previous work [6, 11]. One of the most commonly used methods is the QRS detection algorithm introduced by Pan and Tompkins [12]. This algorithm is the most widely used and most frequently cited approach for the extraction of QRS complexes from an ECG signal.

Based on a past literature review, this algorithm could provide good QRS detection performance using high-quality clinical ECG signal data [8, 11, 13]. However, the capability of the Pan-Tompkins algorithm in detecting the QRS complexes in low-quality and noisy signals, especially ambulatory ECG signals, still needs to be clarified. Thus, in this paper, the Pan-Tompkins algorithm was tested and analysed using a noisy ECG signal with different signal-to-noise ratios (SNRs). The experiment was applied to investigate the performance of the algorithm in different noise environments. The performance of the algorithm in QRS complex detection using noisy data was evaluated and discussed to further the main research objective of this study in the future, which is to develop an arrhythmia detection method in a noisy environment. Hence, this study also tested the QRS algorithm with standard arrhythmia data to assess the performance of the QRS detection algorithm using the proposed arrhythmia detection approach in a noisy environment. The results of all these evaluations are reported in Section 5.

The remainder of this paper is organised as follows: Section 2 explains the noise and artefacts present in an ECG signal; Section 3 outlines the databases used in this study. Then, the implementation of the algorithm and the evaluation performance of the algorithms are given in Sections 4 and 5. The final section summarises this work.

2.Methodology

2.1 Noises and Artefacts in ECG Signals

The recognition of ECG signal characteristics might be influenced or contained by the presence of noise and artefacts. In this study, the QRS complex was used as a characteristic of the ECG signal. These artefacts could emerge due to physiological and non-physiological factors, such as muscle activity, skin movements, electrical devices or improper use of the equipment [13]. There are four common types of noise in ECG signals: 1) Motion Artefact (MA); 2) Baseline Wander (BW); 3) Muscle Noise (EMG); and 4) Power Line Interference. The MA is usually the most difficult to handle and is a result of the subject movement that is more closely related to random limb movement. Meanwhile, BW is a common low-frequency signal that usually stems from the subject motion or leads. Finally, EMG is a signal contaminated with muscular contraction artefacts whereas Power Line Interference occurs at multiples of the main frequency (50 Hz or 60 Hz) [10, 12].

2.2 Databases

Two annotated ECG databases were used in this study: 1) The MIT-BIH Noise Stress Test Database (NST) [14] and 2) The MIT-BIH Arrhythmia Database (MIT) [15]. The databases are summarised in Table 1 and are further described in the following sections.

2.2.1 The MIT-BIH Noise Stress Test Database (NST)

The NST database [14] contains 12 half-hour ECGs and three half-hour noise recordings. The ECG signal in NST was produced based on two clean records from the MIT-BIH Arrhythmia Database (Records 118 and 119) with (24, 18, 12, 6, 0 and −6) dB signal-to-noise ratio (SNR). During two-minute segments alternating with clean sections, the noise was added at the beginning after 5 minutes of each file. The three noise recordings were collected from physically active volunteers with standard ECG recorders and equipment. The noise recording contained typical artefacts in an ambulatory signal such as the Baseline Wander, the EMG, and the Motion Artefact.

Table 1: A Comparison between the NST and MIT databases

Characteristics	**Databases**	
	NST	**MIT**
Device Type	Hospital Holter	Hospital Holter
Signal Type	Ambulatory ECG	Ambulatory ECG
Record	12	48
Duration	30 minutes	30 minutes
Activity Type	N/A	N/A
SNR	(24, 18,12,6,0, -6) dB	N/A
Noise	Artefacts in ambulatory ECG and motion artefact (from the physically active subject)	Artefacts in ambulatory ECG

2.2.2 MIT-BIH Arrhythmia Database (MIT)

The MIT database [15] has reportedly been used in many publications. This database includes 48 heartbeat recordings at 360 Hz. Each record of 47 different patients is 30 minutes in duration and contains two leads: 1) Lead A, modification of Lead II and; 2) Lead B, regular lead V1, V2, V5 or V4. The database has been employed by researchers to test algorithms for QRS detection and arrhythmia detection and classification [1]. As per Mood and Mark [16], Lead A is commonly used to identify the characteristics of heartbeats while Lead B is normally used to identify arrhythmic types Supraventricular ectopic beats and Ventricular ectopic beat.

2.3 Pan-Tompkins Algorithm

The Pan-Tompkins algorithm is generally used as a QRS detection algorithm in real-time approaches [12]. This algorithm utilises the amplitude, slope, and width of an integrated window to identify the R-peaks in QRS complexes [12]. The algorithm consists of two stages, which are pre-processing and decision. In pre-processing, the raw ECG signal is prepared as input to the detection process. Pre-processing includes noise removal, signal smoothing, and width and QRS slope increasing. Then, the thresholds are used to only consider the signal peaks and eliminate the noise peaks in the decision stage.

The algorithm consists of a band-pass filter (Low Pass and High Pass Filters), derivatives, a squaring function, a moving window integration (WMI), threshold, and decision, as shown in the diagram in Figure 2. The sampling rate of this method is 200 Hz. In this algorithm, the false detection produced by the noise and artefact present in the ECG signal was reduced using a digital band-pass filter. To adapt to the changes in QRS morphology and heart rate, the thresholds were automatically adjusted with the parameter in the decision stages. The detailed algorithm process flow is presented in the flowchart of Figure 3.

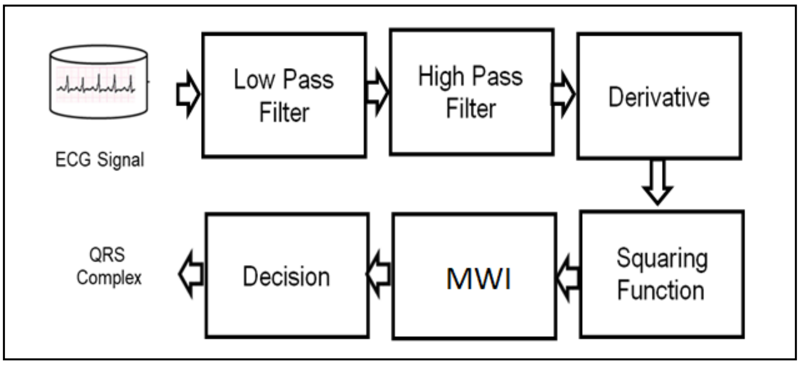

Figure 2: A block diagram of The Pan-Tompkins algorithm

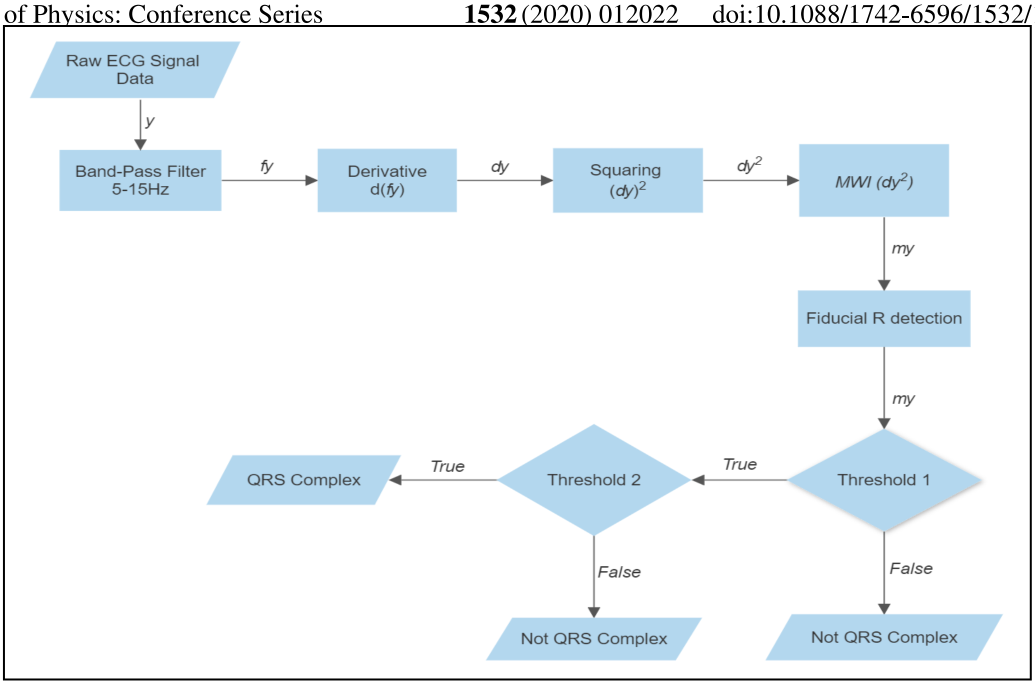

Figure 3: The Process Flow of the Pan-Tompkins algorithm

The explanations of each process are given with the output. These show the implementation of the algorithms using the NST database (Record 118e12) and the MIT database (Record 118). In Figure 2, the output of each process in the algorithm is presented. Since Record 118e12 (NST) with 12 dB SNR was produced from Record 118 (MIT), a comparison between both records of noisy and clean data can also be observed. A more detailed explanation of each process is given below [12].

2.3.1 Band-Pass Filter

The band-pass filter reduces the influence of noise. The desirable passband maximises the QRS energy up to a suitable frequency. The Low Pass Filter (LPF) and High Pass Filter (HPF) were cascaded to achieve an approximately 5–15 Hz passband. LPF was used to remove the high-frequency noise such as EMG, Power Line Interference, and T-wave interference while allowing the low-frequency signals to be recorded. HPF was used to remove the low-frequency noise such as the Baseline Wander.

Figures 4.1 and 4.2 show the raw ECG signal (a) and the output of the Band-Pass Filter process (b). Since NST data was added with the Motion Artefact noise, this data produced a lower quality ECG signal compared to the MIT data. The noise is illustrated in Figure 4.1(a) where the signal displays unstable amplitudes, which influenced the R-peak identification in the signal. However, this digital band-pass filter output shows that the Motion Artefact signal was improved and a better quality signal was produced after filtering, as shown in Figures 4.1(b) and 4.2 (b).

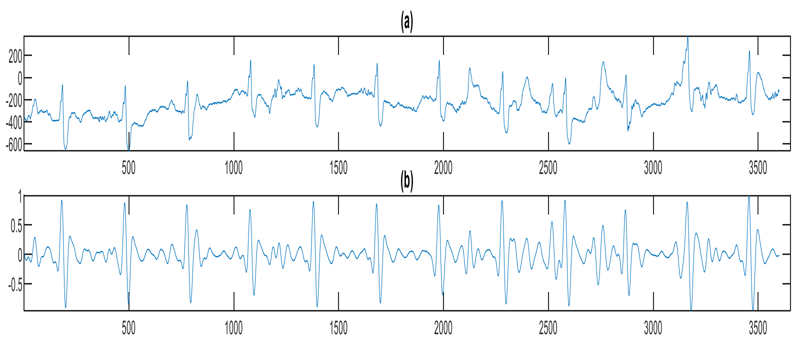

Figure 4.1: NST Database (a) Raw Signal Data and (b) Filtered Data

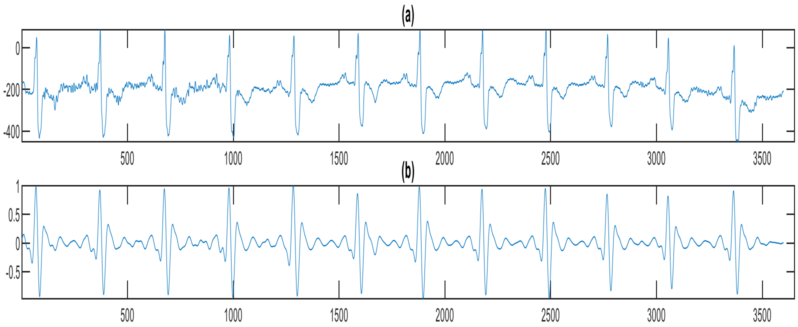

Figure 4.2: MIT Database (a) Raw Signal Data and (b) Filtered Data

2.3.2 Derivative

After the filtering process, the ECG signal was differentiated i.e. the slope information was determined using the ideal QRS complex from other waves. The low-frequency P- and T-waves were suppressed in the derivative process to gain high-frequency signals existing in the higher slopes of the QRS complex. Figures 5.1 and 5.2 show the output of the Derivative process, which enhanced the slope of the QRS complex in both signals.

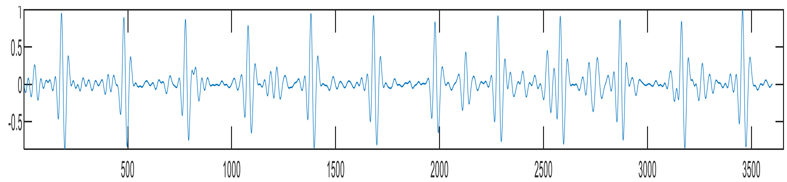

Figure 5.1: NST Database (Derivative Output)

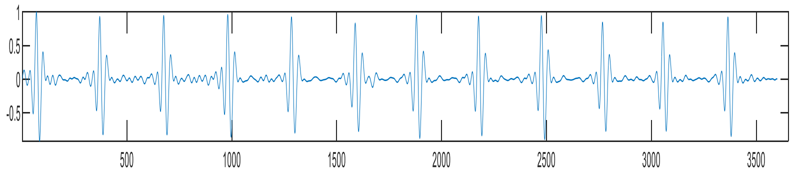

Figure 5.2: MIT Database (Derivative Output)

2.3.3 Squaring Function

From the derivative process, the signal was squared so that all components of the signal displayed a positive value, as shown in Figures 6.1 and 6.2. The higher amplitudes in the signal related to the QRS complex were further enhanced. The squaring function helps reduce the usual higher amplitudes from T-waves that cause false detection. This process emphasises large differences from the QRS complexes. However, in a noisy environment, as seen in Figure 6.1, there are still false positives in the signal since the Motion Artefact interferes with the detection process.

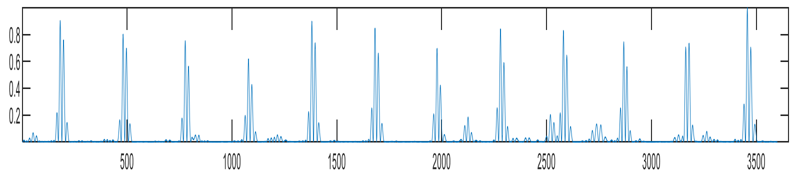

Figure 6.1: NST Database (Squaring Output)

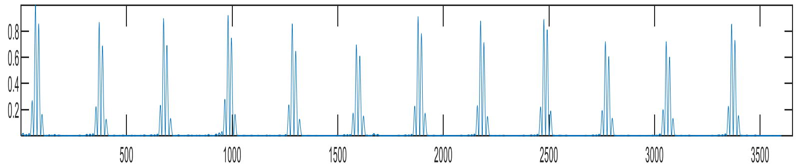

Figure 6.2: MIT Database (Squaring Output)

2.3.4 Moving Window Integration (MWI)

The MWI is performed to acquire information from the waveform feature with the addition of the R-wave slope. The integrated window is important in this process. The widest integrated window must be used to match with a possible QRS complex. A window with a width of 30 samples (150 ms) was used in this algorithm since the sample rate was 200 samples/s [12]. Figures 7.1 and 7.2 show the slope of the R-wave found in the signal. The output in Figure 7.1 shows that the algorithm is still capable of detecting the high amplitudes of the R-wave slope in the signal although the false detection of the R-wave slopes was still observed in a noisy environment.

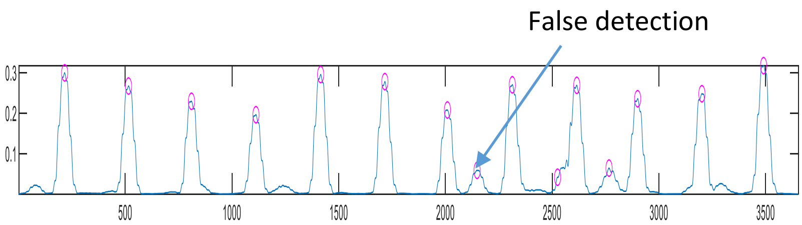

Figure 7.1: NST Database (MWI Output)

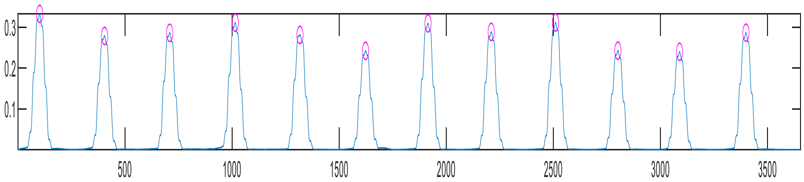

Figure 7.2: MIT Database (MWI Output)

2.3.5 Decision

Once the signal is pre-processed, the next step is the decision stage. This step is performed to decide whether or not the result of the MWI is a QRS complex by using the thresholds. Two thresholds were used to ensure the right peak was chosen. The threshold can be automatically adjusted to improve the QRS complex detection. Figures 8.1 and 8.2 show the QRS complex detected in the NST and MIT data.

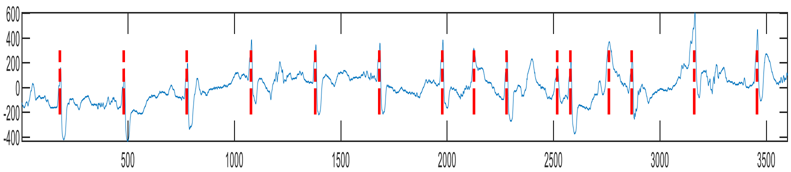

Figure 8.1: NST Database (QRS complex detected)

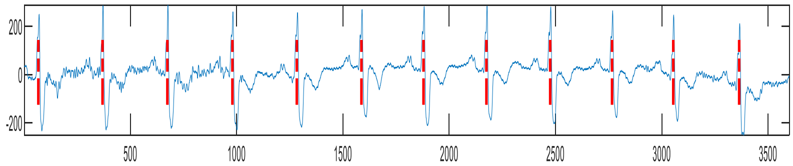

Figure 8.2: MIT Database (QRS complex detected)

3.Result and Discussion

The experiments were conducted using a standard database and noise test data. The performance evaluation of the algorithm utilised 12 records of NST (with different SNRs) [14] and 48 records from MIT [15]. The data was processed in MATLAB R2017B software. The reference annotation and WFDB toolbox provided by pyhsionet website were used for this evaluation [16]. According to ANSI/AAMI [17], the evaluation of the QRS algorithm should use Sensitivity (Se) and Positive predictivity (+P) as a measurement parameter. Furthermore, many previous works related to QRS detection also used these two parameters to evaluate algorithm performance [6][13]. Based on the above rationale, this study also used the same parameters for the evaluation process. Sensitivity is defined as the probability of correctly identified QRS while Positive predictivity represents the probability of QRS identified among the true QRS. Sensitivity and Positive predictivity are computed using Equations (1) and (2), respectively:

$$Se = \frac{TP}{TP+FN} \tag{1}$$

$$+P = \frac{TP}{TP+FP} \tag{2}$$

where True Positive (TP) is the number of QRS correctly identified, False Negative (FN) is the number of QRS incorrectly identified, and False Positive (FP) is the number of peaks that do not correspond to the QRS.

This study is related to an extended future research to develop an arrhythmia detection approach in a noisy environment. However, this study only focused on the QRS detection phase. Hence, the evaluation process must consider the performance of the system in the presence of noise and arrhythmia signals. Two experiments were carried out in this study to evaluate the performance of the Pan-Tompkins algorithm. These experiments were run to achieve the following goals: 1) to validate the capabilities of the algorithm in detecting low-quality and noisy signal environments with different levels of SNR; and 2) to test and observe the QRS detection performance on standard arrhythmia data using the same procedure used for noisy data.

To achieve the first objective, the noise test database (NST) with different levels of SNR was used in the experiments. The SNR was used to compare the signal level with the noise level. The signal with SNR was used in these experiments to discover the competency of the algorithm in handling different levels of noise environments. The record created by data 118 and 119 was used in this test. Both are affected by the Motion Artefact noise, which is the most difficult to handle because this type of noise can imitate the presence of ectopic heartbeats [8]. Different SNR levels for the same ECG record was analysed and the results shown in Table 2. In particular, the SNR values ranging from 24 dB to −6 dB were tested.

Table 3 below shows the performance of the algorithms using NST data. Based on the results, the algorithms could achieve higher sensitivity and predictivity with the noisy signal when the SNR ranged from 24 dB to 18 dB, equal to 100% and 99.96%, respectively, for record 118 and 100% and 100%, respectively, for record 119. However, the detection performance decreased with a higher SNR in the signal i.e. −6 dB for both records. This result shows that the algorithm was still capable of detecting QRS in a noisy signal. However, the detection performance could be affected by corrupting signals when the level of the noise is increased.

Figure 9 shows the effect of algorithm behaviour under different signal-to-noise ratios. An analysis of the performance results indicates that increasing the noise contributed to the worst detection performance. The performance results confirm that the algorithm can manage a signal with noise up to 12 dB SNR. In fact, for SNR higher than 12 dB, results with a minimum level of noise were increasingly attained. For SNR values lower than 6 dB, the Se and +P decreased depending on the amount of noise in the signal.

Table 2: Levels of SNR in NST database

	SNR (dB)	Records 118	Records 119
Low Noise	24	118e24	119e24
	18	118e18	119e18
	12	118e12	119e12
	6	118e06	119e06
	0	118e00	119e00
High Noise	−6	118e_6	119e_6

Table 3: Performance analysis using the NST database

Records	*Se* (%)	*+P* (%)
118e24	100	99.96
118e18	100	99.96
118e12	99.96	95.39
118e06	97.76	79.39
118e00	91.09	70.87
118e_6	71.47	60.50
119e24	100	100
119e18	100	99.9
119e12	99.95	87.92
119e06	98.09	74.28
119e00	89.63	64.34
119e_6	66.48	54.21

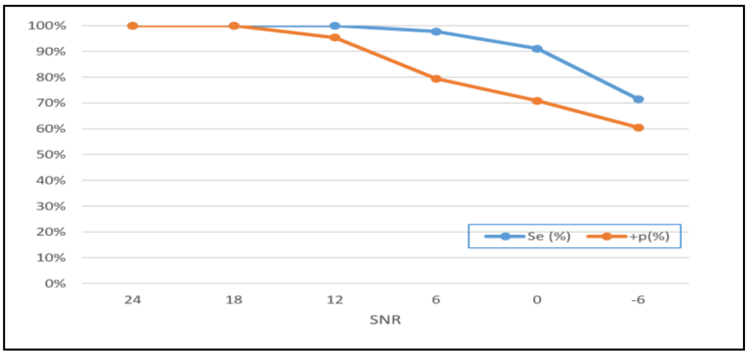

Figure 9: Analysis of algorithms behavior with different SNR

To achieve the second research objective, an experiment was run to assess the performance of the algorithm in detecting QRS in MIT data. The MIT data is the most widely used standard database recommended by ANSI/AAMI for arrhythmia detection [1]. This experiment was done to ensure that the same procedure using the algorithm for noisy data is used for the arrhythmia data. Also, the performance of the algorithm could provide input in the decision to choose the best QRS method for arrhythmia detection. Table 4 shows the evaluation of the results of the algorithm using MIT data. From Table 4, the performance of the algorithm with all records (rec) using the MIT data yielded higher sensitivity and positive predictivity including record 118 (100% of Se and 99.96% of +P) and 119 (100% of Se and 100% of +P), which was the same record used for the NST data. The QRS detection result for arrhythmia data shows that the algorithm is a good detection technique for arrhythmia ECG signal data. Based on this output, it is confirmed that the Pan-Tompkins algorithm, based on the same procedure as the noisy data, can be used as a QRS detection technique for arrhythmia detection.

Table 4: Performance analysis using MIT database

Records	*Se*	+*P* (%)	Records	*Se*	+*P* (%)
100	100	100	201	96.64	100
101	99.89	99.73	202	99.53	100
102	100	100	203	97.11	99.25
103	99.95	100	205	99.74	100
104	98.70	98.57	207	98.98	99.68
105	99.46	98.27	208	98.65	99.83
106	99.85	100	209	100	99.97
107	99.25	100	210	98.45	99.85
108	99.77	83.27	212	100	100
109	99.80	100	213	99.94	100
111	99.48	100	214	99.82	99.96
112	100	100	215	99.91	100
113	100	100	217	99.82	99.91
114	99.95	100	219	100	100
115	100	100	220	100	100
116	99.05	99.87	221	99.84	100
117	100	100	222	99.07	99.07
118	100	99.96	223	99.54	100
119	100	100	228	99.66	99.56
121	99.89	100	230	100	100
122	100	100	231	100	100
123	99.80	100	232	100	99.94
124	99.32	100	233	99.90	100
200	99.85	99.85	234	99.89	100

4.Conclusion

This study presented the performance results of the Pan-Tompkins algorithm in the detection of QRS complexes in noisy ambulatory ECG data with varying signal-to-noise ratios and standard arrhythmia data. The algorithm presented in this paper was formed via a band-pass filter (LPF and HPF), derivatives, square, integral, and threshold process. Two experiments were run to evaluate algorithm performance. In conclusion, the Pan-Tompkins algorithm was capable of performing the QRS detection process for noisy signal data. The output of the NST data with different Motion Artefact noise levels (SNR) showed that the algorithms produced good detection sensitivity (> 90%) at an SNR level of 24 dB to 6 dB. However, the existence of the noise and artefact signals, especially strong noises from the motion artefact such as at SNR −6 dB, were the factors that affected the performance of the algorithm in detecting the QRS complexes. Also, improvement is still needed to achieve good detection performance for noisy signals, especially with high-intensity noises. Besides, the result also showed that the algorithm's competence in detecting the QRS complex in arrhythmia data yielded high sensitivity (> 96%). This result confirms that the Pan-Tompkins algorithm is also suitable to use as a QRS detection method to detect arrhythmia.

Acknowledgments
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