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QRS Detection Based on Discrete Wavelet Transform for ECG Signal with Motion Artifacts

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ABSTRACT

Motion artifacts in ECG signals recorded during physical exercises activities can affect the diagnosis of arrhythmia. To minimize the faults in arrhythmia detection, it was important to choose accurate algorithm for detecting QRS in ECG signal with noises produced during physical movements of the patients. Therefore, choosing the QRS detection algorithm with good competency for the signal affected by noises and motion artifacts is needed for arrhythmia detection analysis. The QRS detection based on Discrete Wavelet Transform was implemented and presented in this paper. The performance of the algorithm was assessed using the MIT-BIH Arrhythmia Database and MIT-BIH Noise Stress Database. For the MIT-BIH Arrhythmia database, the average Sensitivity (Se) and positive Predictivity (+P) of the algorithm were 98.24% and 98.61%, respectively. The algorithms had a lower average false negative rate (FNR) than the pan Tompkins algorithm when applied to the MIT-BIH noise stress test database, which was 0.033% for record 118 and 0.032% for record 119, respectively. The results demonstrated that the algorithms perform well when dealing with arrhythmia data and motion artifact at various levels of signal to noise ratio.

1. Introduction

The electrocardiogram (ECG) signal provides information about the condition of the heart through the representation of the electrical waves of the cardiac cycle [1]. It has been used to detect abnormalities in cardiovascular for long-term monitoring by cardiologists for a variety of diagnosis purposes including the detection of arrhythmia [2,3]. However, the performance of arrhythmia detection can be affected in ECG signals recorded during running and physical exercises activities. This is because of the signal producing contaminated with noises arising from body movements activities [1,4].

The QRS complex is the prominent and peculiar feature of an ECG signal [3]. One of the important steps can provide substantial input to improve arrhythmia detection is accurately identified of the

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QRS complex in heartbeat since it directly influences the final detection process [5,6]. ECG signal variability changes over time and relying on individual activities, exhibit stochastic and nonstationary behaviour that reflect the variations in the amplitude of the heartbeats. However, the signal quality degraded by real-world motion artifacts occurs unpredictably and directly interferes with the nature of the signal that can impair the reliability of the QRS detection and diagnosis process [5]. Even though, numerous QRS detection techniques have previously been proposed and have become even more prevalent recently [6,7-9]. Due to the physical noise variation of the patients, choosing the QRS detection algorithm with good competency with the noisy data is needed in the analysis of arrhythmia detection [10,11].

Among the various QRS detection techniques, the Wavelet transforms a considered be less computational and complex but contributes good efficiency for analysis ECG especially in nonstationary signals [12,13]. Wavelet transform was used on a wide range of applications to solve the problem in ECG signal including the ECG characteristics waves detection [14]. Nonetheless, one of the problems with the many detection techniques is their attention commonly for good quality clinical data and lack of evaluation using noisy data. Hesitate with that, the QRS detection algorithm based on discrete wavelet transform was implemented and presented in this paper using arrhythmia data with motion artifact noises to evaluate the performance of the algorithm. These findings will contribute to our main goal of developing a method for detecting arrhythmia during running and physical exercise activities in the future.

This paper is organized as follows: Section II describes the databases used in this study, the discrete wavelet transform algorithm, the QRS detection implementation, and the evaluation matrices used to measure performance. Finally, Section IV presents the conclusion of this study.

2. Material and Method

2.1 Database

The ECG recordings from two databases provided by the Physionet website are used in this study. Two annotated ECG signals are used which are: 1) MIT-BIH Arrhythmia Database (MIT-BIH) [14,15] and 2) MIT-BIH Noise Stress Test Database (MIT-NST) [14]. The database was selected to identify the limitations of the algorithms towards standard arrhythmia data and noises elements in the signal. MIT-NST data has been selected to understand the effect of motion artifact, since the standard real-life data during physical activities is hard to collect.

MIT-BIH is an open-source arrhythmia database. This database is employed widely by a researcher to test their algorithms for QRS detection [6-9]. The database consists of 48 ECG recordings from 47 subjects; all sampled at 360Hz for half an hour duration using a Holter monitor. In most records, the upper signal obtains from modification of Lead II except for record 102, 104 and 114 that acquire from lead V5 [15]. However, the normal QRS complex is frequently recognized in the upper signal because the normal beats in the lower signal are commonly difficult to identify. In this paper, all the recordings were used for the evaluation from the MIT-BIH database excluded recordings 102, 104 and 114. Record 222 was also omitted because of many Nodal (junctional) escapes in the signal [9].

The MIT-NST is also an open-source database for arrhythmia with 12 half-hour ECG recordings [14,15]. The recordings have noisy sections for each file with 24, 18, 12, 6, 0 or -6 db of signal to noise ratio (SNR). This database provides three half-hours of noise recordings and is generated through the addition of calibrated noise from physically active volunteers to clean recordings (record 118 and 119 from the MIT-BIH database). During two-minute segments following with two-minute clean sections, each file was added with the noise after the first 5 minutes.

The ECG signal in MIT-NST contained the electrode motion artifacts in the arrhythmia beat with the beat annotations to recognize the QRS complex even when the noise conceals the signal visually. Two cardiologists manually annotated all recordings in the databases, and the annotation was also encapsulated in this dataset [15,16]. The heartbeat annotation for the fiducial points such as QRS complex and the abnormal beat is essential to assess the QRS detection and arrhythmia detection performance. It is basic to have the actual QRS location on ECG data for assessment of the detection algorithms to evaluate the performance accuracy.

2.2 Discrete Wavelet Transform

A wavelet is a set of functions in the form of small waves that represent the signal. In the wavelet domain, the signal has focused on energy with time and suited to implement to the nonstationary signal analysis such as an ECG [12]. Wavelets are useful because they are limited in time and frequency also can give better resolution compared with Fourier transform [12,18]. Also, wavelet analysis is based on the signal decomposition by using the family of wavelet functions like Fourier series analysis where the basis function was chosen from sinusoids. When a signal is deconstructed into wavelets, it is called a Wavelet Transform.

In the wavelet transform, a signal convolves with predefined mother wavelet to decompose a signal. The wavelet transforms allowed a sparser representation of the signal to divide the signal into different frequency bands. It decomposes a specified signal into several levels associated with the signal frequency components and analyses each level with a particular resolution. Because signal features are often localized in time and frequency, analysis and estimation are easier when working with reduced sparser representations. Consequently, the wavelet transform can be a beneficial approach intended for analysis of the ECG signal.

The wavelet transform is the operation of the wavelet function $\Psi(t)$ and the signal $f(t)$. The discrete wavelet transform is expressed as Eq. (1).

$$X_{j,k} = \int_{-\infty}^{\infty} \mathrm{f(t)}\, \Psi_{\mathrm{j,k}}(\mathrm{t})\mathrm{dt} \tag{1}$$

The original will reconstruct by selecting an orthonormal wavelet basis $\Psi_{j,k}(t)$. To produce approximation coefficients A, the scaling function can be convolved with the signal. The approximation coefficient of the signal $f(t)$ can be defined as Eq. (2)

$$A_{j,k} = \int_{-\infty}^{\infty} \mathrm{f(t)}\phi_{\mathrm{j,k}}(\mathrm{t})\mathrm{dt} \tag{2}$$

Where $\phi(t)$ is scaling function, j is scale and k are locations respectively. The original signal f(t) below discrete wavelet transform with a range of scale n, can be denoted as Eq. (3).

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t) \tag{3}$$

Where $f_n(t)$ define signal approximation and is specified by Eq. (4).

$$f_n(t) = A_{n,k}\phi_{n,k}(t) \tag{4}$$

and $d_j(t)$ is detail signal approximation in scale j.

In the wavelet transform, a signal convolves with predefined mother wavelet to decompose a signal. The wavelet transforms allowed a sparser representation of the signal to divide the signal into different frequency bands. It decomposes a specified signal into several levels associated with the signal frequency components and analyses each level with a particular resolution. Because signal features are often localized in time and frequency, analysis and estimation are easier when working with reduced sparser representations. Consequently, the wavelet transform can be a beneficial approach intended for analysis of the ECG signal.

2.3 QRS Detection Implementation

The wavelet-based approach for QRS detection is executed using MATLAB software. Figure 1 shows the comparison of implementation Symlets Wavelet Transform.

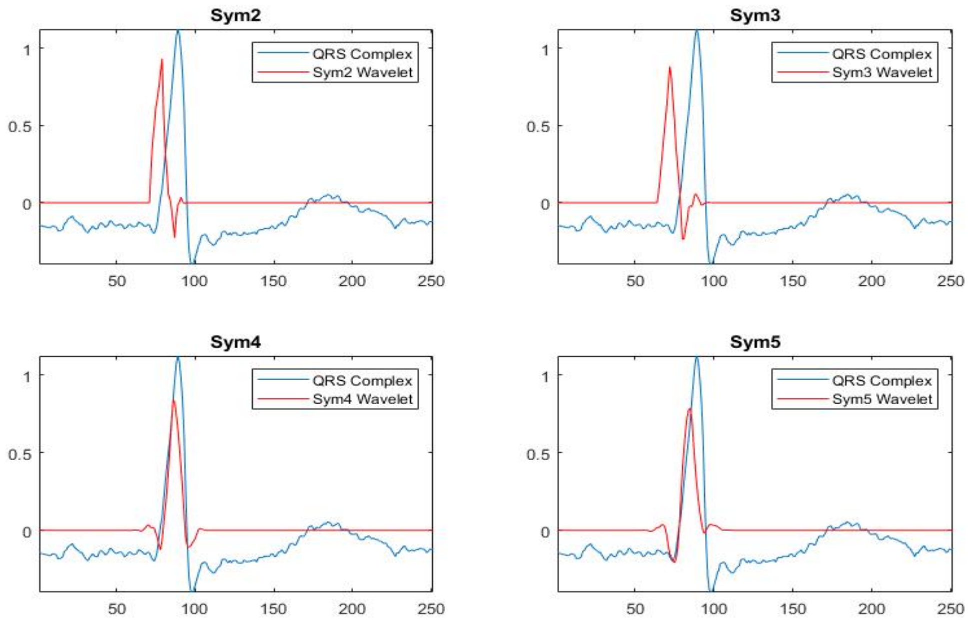


Fig. 1. Comparison of Symlets Wavelet Transform

There is no specific way to choose a wavelet instead of the selection is focused on application-oriented were related to a particular application [17]. The wavelet selection determines when the form of signal to be analysed. It is a common practice to consider more accurate physical properties that resemble the appearance signal to select the wavelet function. There are several wavelets familiar such as Haar, Daubechies, Biorthogonal, Symlets, and Coiflets. However, the Symlets (Sym4) wavelet has been found to provide more similarity features than others [16]. Besides, the energy spectrum that focused on low frequencies shows that wavelet structural resemblance with QRS complexes as shown in Figure 1.

Figure 2 and Figure 3 illustrate the process flow of the QRS detection algorithm and their implementation to finding the QRS peak.

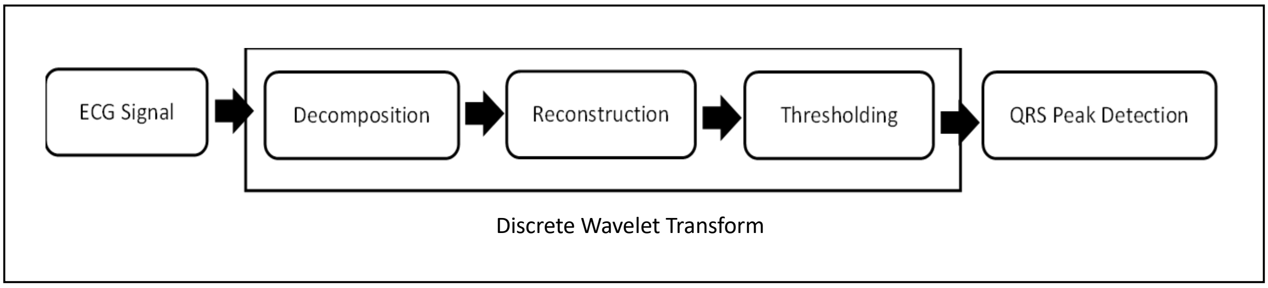
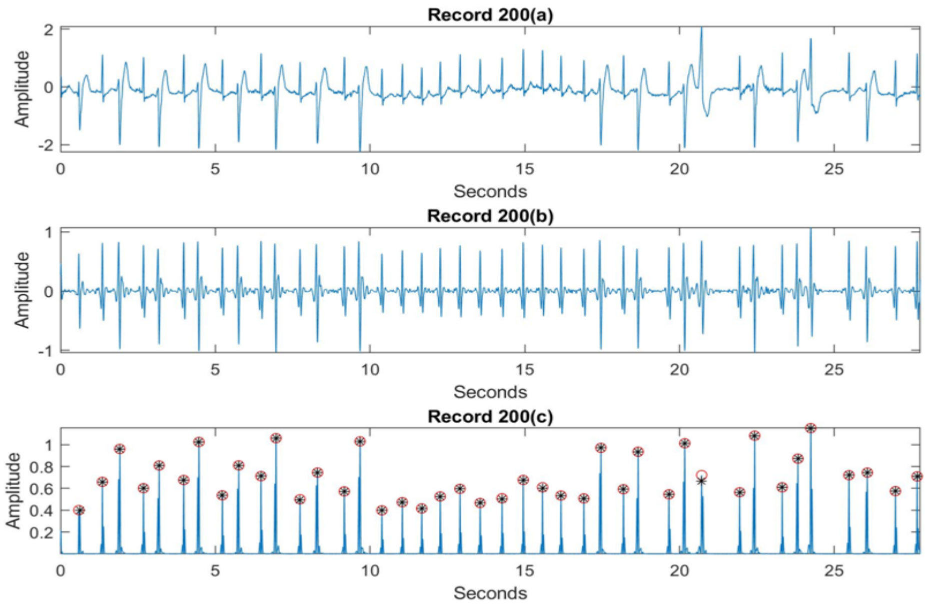
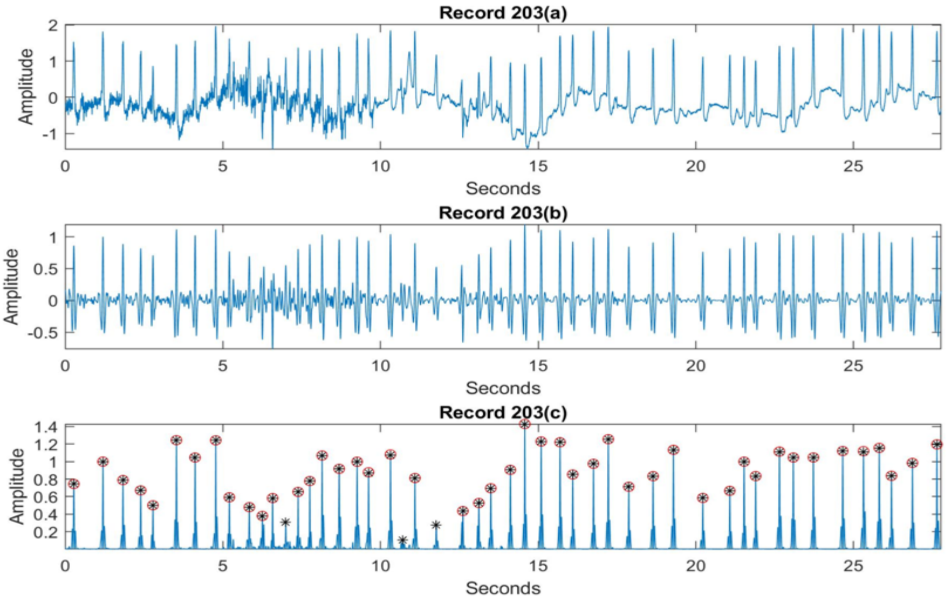


Fig. 2. Process flow of the QRS detection algorithm

In the Figure 3, record 200 and 203 from MIT-BIH database was used to show the implementation process. In this study, the decomposition process used default Sym4 transform to decomposed ECG signal into levels 4 and 5. The QRS complex was retained, and samples are reduced when the original ECG signal down samples by wavelet decomposition by making a maximum value of 80% of the threshold. In this case, the values for invariably QRS peaks are above the threshold. Then, the decomposed signal be reconstructed into an actual signal by first multiplying the down-sampled signal. To reconstruct the ECG waveform to a frequency-localized version, scales 4 that corresponds to the approximate frequency 11.25, 22.5 Hz bands and scale 5 with 5.625, 11.25 Hz wavelet coefficients were used. Then the wavelet coefficients produced the squared absolute values of the signal approximation that employed a QRS algorithm to identify the R peak. The output after the isolation of scales 4 and 5 is shown in Figure 3 (b). Figure 3 (c) shown the final output of R peak in QRS complex from the wavelet transform (red circle) and the annotation.



a) Record 200



b) Record 203

Fig. 3. Raw signal data, Output of isolating QRS wave (Level 4 and 5) and R peak detection for a) Record 200 and b) Record 203

2.4 Performance Evaluation

The performance measures to evaluate the algorithms were described in this section. A MATLAB toolbox called the Physionet Waveform Database (WFDB) toolbox and reference annotation of the heartbeat read from the downloadable MATLAB package, is used for evaluation [19]. Three measurements were used to evaluate the accuracy of the algorithms in this study which is the Sensitivity (Se), Positive predictivity (+P) and False negative rate (FNR).

The measurement of Se, +P, and FNR is computed by the Eq. (5), Eq. (6) and Eq. (7). Sensitivity is also known in the literature as recall and positive predictivity as a precision while the false negative rate is known as misclassification rate [17].

$$Se = TP/(TP + FN) \tag{5}$$

$$+P = TP/(TP + FP) \tag{6}$$

$$FNR = FN/(FN + TP) \tag{7}$$

To assess the performance of the algorithms, each recognized QRS need to be categorized as TP, FP and FN where TP denotes as the number of true positive beats or correct detection of R peak in QRS complexes, FP denotes as the number of false positive beats or misdetection, and FN as the number of false negative beats or undetected QRS peak in the evaluation phase. Sensitivity reflected the proportions of TP to a total number of TP and FN value as shown in Eq. (5). Positive predictivity reflected the proportions of TP towards the total of TP and FP value. The false negative rate is the value of the proportion of FN value to total FN and TP value.

3. Results and Discussion

All the data was processed in MATLAB version R2017B and a 4.00GHz Intel Core i7-7y75 processor. ECG signal from MIT-BIH [14-15] and MIT-NST [16] database is used for the validation. The evaluation was divided into two sections to demonstrate the competency of the discrete wavelet transform for QRS detection:

i. the evaluation of QRS detection on arrhythmia data
ii. the evaluation of QRS detection in a noisy element with a different signal-to-background noise ratio (SNR).

The measurement for the evaluation performance is Se, +P, and FNR as shown in Eq. (5) to Eq. (7).

3.1 Evaluation of QRS Detection on Standard Arrhythmia Data

The discrete wavelet transform was implemented in this study to find reliable QRS detection towards detection of arrhythmia. The evaluation was performed on arrhythmia database to examine the ability of the QRS detection algorithm. The MIT-BIH database collected in clinical settings devote the ECG arrhythmia recordings with practically contribute with artifact. The discrete wavelet transform algorithm was applied to the 44 records from MIT-BIH database as shown in Table 1. Record 105 is also being considered for evaluation as a difficult noisy recording [20].

Table 1 shows the results obtained when the algorithm was applied to standard arrhythmia data. According to this table, the algorithm performs well, with a total average of 98.24% Se, 98.61% +P, and 0.02% FNR. The respective QRS detection performance for each records had high Se (all > 90% except record 105 and 108 with 83.48% and 77.82%) and high +P (all > 97% except record 105 with 46.12%). The algorithm did achieve 100% for both Se and +P from 25% of all the records of the MIT-BIH database. However, the presence of high-grade noise and artifact in an ECG signal with the multiform arrhythmia can occasionally influence the detection accuracy of the algorithm, and thus, increasing the value of false negative as seen in results for records 105 and 108. The result from the above record should be mostly recognized to either the constraint of the algorithm or the constraint of this data records itself.

Table 1
QRS detection algorithm performance with MIT-BIH database

Records	TP	FN	FP	Se (%)	*+P* (%)	FNR (%)	Records	TP	FN	FP	Se (%)	*+P* (%)	FNR (%)
100	2273	0	0	100	100	0.000	202	2125	11	0	99.49	100	0.005
101	1863	2	5	99.84	99.73	0.001	203	2929	51	17	98.29	99.42	0.017
103	2084	0	0	100	100	0.000	205	2650	6	0	99.77	100	0.002
105	2147	425	2508	83.48	46.12	0.142	207	1679	181	2	90.22	99.88	0.089
106	2015	12	1	99.41	99.95	0.006	208	2869	86	62	97.09	97.88	0.028
107	2135	2	1	99.91	99.95	0.001	209	3005	0	2	100	99.93	0.000
108	1372	391	0	77.82	100	0.182	210	2566	84	5	96.83	99.81	0.031
109	2529	3	1	99.88	99.96	0.001	212	2748	0	0	100	100	0.000
111	1930	194	0	90.78	100	0.084	213	3251	0	1	100	99.97	0.000
112	2539	0	0	100	100	0.000	214	2256	6	1	99.73	99.96	0.003
113	1795	0	47	100	97.45	0.000	215	3361	2	0	99.94	100	0.001
115	1953	0	0	100	100	0.000	217	2205	3	2	99.86	99.91	0.001
116	2391	21	4	99.13	99.83	0.009	219	2154	0	0	100	100	0.000
117	1535	0	0	100	100	0.000	220	2048	0	0	100	100	0.000

118	2278	0	2	100	99.91	0.000	221	2419	8	0	99.67	100	0.003
119	1987	0	3	100	99.85	0.000	223	2601	4	0	99.85	100	0.002
121	1859	4	0	99.79	100	0.002	228	2012	41	5	98	99.75	0.020
122	2476	0	0	100	100	0.000	230	2256	0	3	100	99.87	0.000
123	1518	0	1	100	99.93	0.000	231	1571	0	0	100	100	0.000
124	1619	0	0	100	100	0.000	232	1748	32	0	98.2	100	0.018
200	2598	3	4	99.88	99.85	0.001	233	3077	2	0	99.94	100	0.001
201	1882	81	0	95.87	100	0.040	234	2750	3	0	99.89	100	0.001
Average											98.24	98.61	0.02

3.2 Evaluation of QRS Detection on ECG Signal contained with Motion Artifacts Noises

The experiment was carried out in this study to better understand the effects of the noise element with SNR on the performance of the QRS detector. We tested the 12 corrupted signals from the MIT-NST database from records 118 and 119 of the MIT-BIH database at various SNRs to see how different levels of noise affected a detection algorithm. In this study, varying SNRs such as 24db, 18db, 12db, 6db, 0db, and -6db for records 118 and 119 are used, as shown in Tables 2 and 3. The noise influence had an effect on the MIT-NST records for electrode motion artifact (EM). Electrode motion artifact is frequently regarded as one of the most difficult noises to remove because it cannot be easily removed by simple filters and, like other types of noise, can mimic the presence of ectopic beats [21].

According to the tables, the performance of the algorithms degrades as SNR decreases. When compared to other signals, a signal with SNR 24db to 6db achieves high Se >95% for both records, while a signal with SNR 24db and 18db achieves high +P >95%. Furthermore, the signal with SNR 24db to 12db performs well with 0% FNR. For SNR values less than 0db, the algorithm performance of Se and +P degrades significantly in both records, depending on the amount of noise and signal quality. An analysis performance shows that when increasing the noise contribution, FN remains highest, which makes the performance worse.

Table 2
Comparison of Discrete Wavelet Transform with Pan Tompkins algorithm applied to the Record 118

SNR	Discrete Wavelet Transform			Pan Tompkins		
(dB)	Se (%)	*+P (%)*	FNR (%)	Se (%)	*+P (%)*	FNR (%)
24	100	99.91	0.000	100	99.96	0.000
18	100	97.14	0.000	100	99.96	0.000
12	100	85.06	0.000	99.96	95.39	0.000
6	98.16	73.34	0.018	97.76	79.39	0.022
0	92.76	64.4	0.072	91.09	70.87	0.089
-6	89.29	58.2	0.107	71.47	60.50	0.285
Average	96.70	79.68	0.033	93.38	84.3	0.066

Table 3
Comparison of Discrete Wavelet Transform with Pan Tompkins algorithm applied to the Record 119

SNR (dB)	Discrete Wavelet Transform			Pan Tompkins		
	Se (%)	*+P (%)*	FNR(%)	Se (%)	*+P (%)*	FNR (%)
24	100	99.85	0.000	100	100	0.000
18	100	97.55	0.000	100	99.9	0.000
12	100	83.55	0.000	99.95	87.92	0.001
6	98.94	71.1	0.011	98.09	74.28	0.019
0	93.31	61.53	0.067	89.63	64.34	0.104
-6	88.83	53.96	0.112	66.48	54.21	0.335
Average	96.85	77.93	0.032	92.36	80.10	0.076

In this study, the performance of a discrete wavelet transform was compared to the well-known Pan Tompkins algorithm for QRS detection [8,22]. Considering the Pan Tompkins algorithm performs with low computational and complexity and high efficiency in clean ECG signals, how the algorithm behaves in a noisy environment must be considered. Table 2 and Table 3 show the comparison of the result between these two algorithms. In this comparison, both algorithms tested on the same conditions, nor using the same data. According to the results, the discrete wavelet transform has good sensitivity in the noisy artifact signal with a total average of Se is 96.70% compared with Pan Tompkins algorithm 93.38% for record 118.The performance of the algorithms also good in the record 119 with 96.85% sensitivity compared 92.36% of Pan Tompkins algorithm.

For the signal with the low-level SNR -6db, the algorithm performs better than Pan Tompkins algorithm with 89.29% compared 71.47% sensitivity for record 118, 88.83% compared 66.48% for record 119. Although the algorithm has good sensitivity for both records, the performance of +P in the comparison is significantly lower for record. According to the results in Tables 2 and 3, the algorithms outperform the pan Tompkins algorithm by 79.68% for record 118 and 77.93% for record 119. It can be noticed that the performance of the discrete wavelet transform algorithm will score higher detection rate with higher FN that degraded the +P value. Based on the comparison results, we can conclude that the discrete wavelet algorithm outperforms the others in MIT-NST data, with 0.033% FNR versus 0.066% FNR for record 118 and 0.032% FNR versus 0.076% FNR for record 119.

4. Conclusion and Future Works

This paper successfully implemented and evaluated a discrete wavelet transform for QRS detection using the Symlets 4 wavelet. The algorithms were carried out with less computational and complexity. This study found that the choice of mother wavelets was application-oriented, with the choice focusing on the type of data itself. Our results show that the algorithms perform well when dealing with arrhythmia data and motion artifacts at various levels of signal to noise ratio. It was also discovered that artifacts and noises have an impact on algorithm performance. The algorithms' ability to identify QRS in a noisy element, particularly a motion artifact signal, must also be validated. The findings will be used to develop a method for detecting arrhythmia during physical exercise.

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