R Peak Detection Algorithm based on Continuous Wavelet Transform and Shannon Energy

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ABSTRACT

The R peak detection algorithm is a necessary tool for monitoring and diagnosing the cardiovascular disease. This paper presents the R peak detection algorithm based on continuous wavelet transform (CWT) and Shannon energy. We evaluate the proposed algorithm with the 48 record of ECG data from MIT-BIH arrhythmia database. Results show that the proposed algorithm gives very good DER (0.48%-0.50%) compared to those from previous publications (0.168%-0.87%). We demonstrated that the use of the CWT with a single scaling parameter is capable of removing noises. In addition, we found that Shannon energy cannot improve the DER value but it can highlight the R peak from the low QRS complex in ECG beat leading to the improvement in the robustness of the R peak detection algorithm.

Keywords: R Peak Detection Algorithm; Wavelet Transform; Shannon Energy; Electrocardiography (ECG)

1. INTRODUCTION

In order to be alive, the heart is an important organ to pump the blood containing with the oxygen and the nutrient to cells in our body. Currently, the human behaviors, such as unhealthy diet, physical inactivity, smoking and alcohol, lead to the risk of cardiovascular disease (CVD). These behaviors make the raised blood pressure, the raised blood glucose, and the raised blood lipids resulting in heart attack, stroke, or heart failure. According to the World Health Organization (WHO) report, CVDs are the first cause of death worldwide [1]. In 2012, about 17.5 million people died from CVDs. It is 31% of all global deaths. Moreover, CVDs were the second cause of death in the United Kingdom [2]. It is 27% of all deaths in 2014.

The electrocardiography (ECG) is a standard tool for monitoring and diagnosing diseases related to the CVDs for prevention and treatment. Normally, the ECG signal consists of P wave, QRS complex and T wave. The R peak is important for the heart rate calculation and is used as a preliminary step in beat segmentation algorithm. In practice, the ECG signal recording was often contaminated with a variety of noises such as baseline wandering noise, power line interference noise, muscles noise (electromyography noise), motion artefact noise, and electrode pop or contact noise. These noises cause the difficulty in detecting R peak. Then, the R peak detection algorithm that is capable of eliminating noise is very important.

For over last decades, various R peak detection algorithms were developed [3-11]. The principle of these algorithms consists of 4 main parts: signal pre-processing or noise removal, envelope detection, peak detection, and post-processing. For signal preprocessing, many techniques were applied to suppress noise. One of the well-known techniques is wavelet transform (WT). Many researches developed the R peak detection algorithm based on WT [3-4]. Several wavelet functions were studied including Harr, Gaussian, Mexican hat and Morlet wavelet functions [3]. Results show that the Mexican hat wavelet function provided the highest performance. The output from signal pre-processing part was used for calculating the envelope signal, which is used to define QRS complex duration.

Shannon energy is a successful method in detecting the envelope signal in heart sound [12]. Recently, it was applied in R peak detection algorithm [5, 6]. Results show that the good detection error rate at 0.17% [6] and 0.25% [5] tested with all ECG records from MIT-BIH arrhythmias database can be obtained.

In the peak detection processing part, the thresholding techniques are widely used [5, 7]. Normally, the thresholding techniques are divided into 2 types: the fixed thresholding and the adaptive thresholding. For fixed thresholding, the threshold value will be set to a constant value over time by experts. Although the method has a low computational complexity, it is very sensitive to noises. To improve the performance, the adaptive thresholding method was applied. The threshold value will adjust itself based on the defined mathematical model.

To increase the efficiency of the R peak detection algorithm, some researches included the postprocessing part such as search back method [5-6, 9]. It is the method used for reducing the number of false

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negative. When the algorithm cannot find the R peak within 150% of recent R-R interval, the threshold will be decreased to the half [5].

This paper presents the R peak detection algorithm based on continuous wavelet transform and Shannon energy. We point out the effect on using Shannon energy in our R peak detection algorithm. The rest of this paper is organized as follows. Section 2 describes the details of the proposed R peak detection algorithm and performance evaluation method. The results and discussion are presented in section 3. Finally, conclusions of this paper are given in section 4.

2. THEORY

2.1 Continuous wavelet transform

The continuous wavelet transform (CWT) was used for noise removal process. It is a method for converting a signal into another form that can be represented in time-frequency relationship. The wavelet coefficient of signal, CWT(a, b), can be expressed as

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt, \quad (1)$$

where x(t) is the ECG signal in this paper, $\psi(t)$ is the wavelet function, a is a scaling parameter, and bis a location parameter.

As shown in (1), the output from CWT value indicates the similarity level between the ECG signal x(t) and the wavelet function. In the context of R peak detection algorithm, we need the wavelet function that has a similar shape to the pattern of QRS waveform in the ECG signal so that the QRS signal to noise ratio is maximized. Therefore, the suitable wavelet function is very important. In this work, we use the Mexican hat wavelet function, which is given by

$$\psi(t) = (1 - t^2)e^{-\frac{t^2}{2}}.$$
(2)

We can see from (2) that the Mexican hat wavelet function is the second derivative of a Gaussian function.

2.2 Shannon energy

Shannon energy is one of methods used to generate an envelope of the heart sound for estimating systole and diastole periods [12]. Recently, this method was applied in the field of R peak detection. The Shannon energy, S[n], is formulated by

$$S[n] = -N[n]^2 \log_2 N[n]^2$$
(3)

where N[n] is the normalized ECG signal after noise removal in this paper. The Shannon energy has the

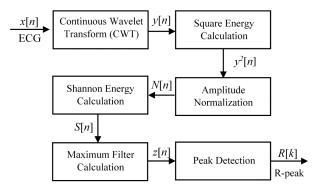


Fig.1: The block diagram of proposed R peak detection algorithm.

better capability in emphasizing the low and medium R peak amplitudes compared to the conventional square energy operation. As a result, the R-peak signal after processing with the Shannon energy does not have significant differences in terms of amplitude. This makes the use of a single thresholding technique in R peak detection algorithm possible.

3. MATERIALS AND METHODS

3.1 Proposed algorithm

Fig. 1 shows a block diagram of the proposed algorithm. The original ECG signal, x[n], was processed with CTW for noise removal. Then, the output from CWT, y[n], was calculated using a square energy operation as given by

$$y^2[n] = y[n] \times y[n]. \tag{4}$$

Subsequently, the output from the square energy operation was normalized with the maximum amplitude of $y^2[n]$, which can be expressed as

$$N[n] = \frac{y^2[n]}{\max(y^2[n])}$$
(5)

Subsequently, we computed the Shannon energy of signal N[n] using (3). Next step, we determine the envelope signal z[n] for defining the QRS time duration used for R peak detection by the maximum filter, which is given by

$$z[n] = \max_{k \in [n-L+1,n]} S[k],$$
 (6)

where L is the length of maximum filter. It was varied from 50 ms to 400 ms in this paper.

In order to detect R peak, we use a single fixed thresholding method, which is given by

$$Thv = \lambda \times \max(z[n]),\tag{7}$$

where λ is a constant. The threshold value Thv determined using λ will separate the R peak from noise. Too low threshold value results in detecting noise as the R peak. On the other hand, too high threshold value lead to missing R peak detection. In this paper, λ was empirically varied to achieve minimum error detection rate. The QRS durations where the R peak signals locate are defined when the output signal from the maximum filter z[n] is greater than the *Thv* value. Then, we compute the R peak location at the maximum value in $y^2[n]$.

3.2 ECG data and performance evaluation

For evaluating the performance of the proposed algorithm, the ECG signal from MIT-BIH arrhythmia databases [10] was analyzed. It consisted of 2 channels of ECG signals acquired at a sampling frequency of 360 Hz for 30 minutes. Moreover, the annotation from an expert was given. To demonstrate the performance of the proposed algorithm, we used three statistical values: the sensitivity (SEN), the positive predictive rate (PPR), and the detection error rate (DER). These values can be computed as follows:

$$SEN = \frac{TP}{TP + FN} \times 100\%, \qquad (8)$$

$$PPR = \frac{TP}{TP + FP} \times 100\%, \qquad (9)$$

$$DER = \frac{FN + FP}{TP + FN} \times 100\%, \qquad (10)$$

where true-positive (TP) is the number of correct R peaks detected by the algorithm, false-negative (FN) is the number of missing R peaks detected, and false-positive (FP) is the number of incorrect R peaks detected by the algorithm.

4. RESULTS AND DISCUSSION

4.1 Parameter optimization

To analyze the capability of noise suppression using CWT and Shannon energy, we vary a scaling parameter a between 2 and 4 with a step size of 0.1. In addition, the maximum filter length (L) was varied between 50 and 400 ms with a step size of 25 ms. We found that the scaling parameter a 2.5 and the maximum filter length L = 275 ms provide the best DER value.

To investigate the effect of Shannon energy on the proposed R peak algorithm, the results from the proposed algorithm with and without Shannon energy operation are shown. Fig. 2 shows the detection error rate from proposed algorithm without Shannon energy calculation at the length L = 275 ms as a function of Thv between 1% and 7% of maximum signal amplitude. The minimum DER value 0.48% is obtained when the Thv is 3% of maximum signal amplitude

Fig. 3 shows the detection error rate from proposed algorithm with Shannon energy calculation at the length L = 275 ms as a function of Thv between

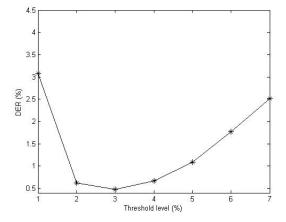


Fig.2: The detection error rate from proposed algorithm without Shannon energy calculation at the length L = 275 ms as a function of Thv.

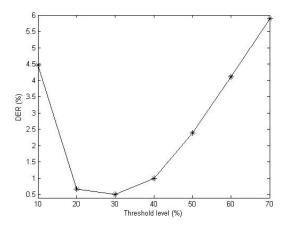


Fig.3: The detection error rate from proposed algorithm with Shannon energy calculation at the length L = 275 ms as a function of Thv.

10% and 70% of maximum signal amplitude. Results show that the minimum DER value 0.50% is obtained when the Thv is 30%.

Although the proposed algorithm without Shannon energy can provide lower DER value than the proposed algorithm with Shannon energy calculation, the range of its threshold value is narrower. In other words, while the range of the Thv that provides the DER value lower than 1.5% is between 2% and 5% for the proposed algorithm without Shannon energy, the wider range of those from the proposed algorithm with Shannon energy is obtained between 20% and 40%. This is very important because it allows for more flexibility when the single fixed thresholding technique in the R peak detection algorithm is used.

4.2 Signal characteristics

To compare the advantage of Shannon energy operation, example results from ECG data record num-

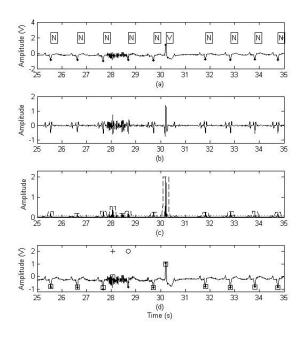


Fig.4: The result of proposed algorithm without Shannon energy calculation applied on ECG signal record 108.

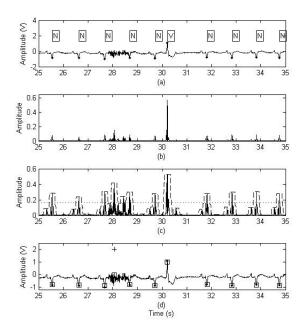


Fig.5: The result of proposed algorithm with Shannon energy calculation applied on ECG signal record 108.

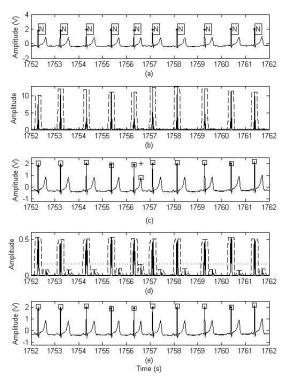


Fig.6: The result of proposed algorithm without and with Shannon energy calculation applied on ECG signal record 113.

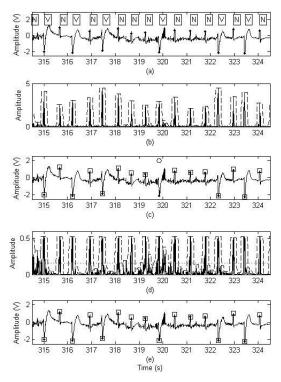


Fig.7: The result of proposed algorithm without and with Shannon energy calculation applied on ECG signal record 200.

ber 108, 113 and 200 are demonstrated. Fig. 4 shows the signal characteristics from the proposed algorithm without Shannon energy calculation on ECG signal record 108. Fig. 4(a) shows the original ECG signal before noise filtering overlaid by the dot markers from the expert from time 25 s to 35 s (x[n]). "N" stands for a normal heart beat and "V" for a premature ventricular contraction beat. The ECG signal in this record consists of noise interference, normal beats and a premature ventricular contraction (PVC) beat. Fig. 4(b) shows the ECG signal after noise removal by CWT (y[n]). As the result, the R peaks on signal y[n]is smoother and clearer. Fig. 4(c) shows the signal from square energy calculation $y^2[n]$ in solid line, the envelope signal z[n] in dashed line, and the threshold level $Thv \ 3\%$ in dotted line. Results show a significant difference in amplitudes of the PVC beat compared to the normal beats. Fig. 4(d) shows the original ECG signal x[n] overlaid by the dot markers from the expert and square markers from the proposed algorithm. The original ECG signal x[n] overlaid by the dot markers from the expert and square markers from the proposed algorithm. The positive marker ("+") and the circle marker ("o") between time 28 s to 29 s present an incorrect R peak detected and a missing R peak detected by the proposed algorithm due to the noise, respectively.

Fig. 5 shows the signal characteristics from the proposed algorithm with Shannon energy calculation on record 108. Fig. 5(a) shows the ECG signal (x[n]). Fig. 5(b) shows the signal from the normalized square energy calculation N[n]. Fig. 5(c) shows the signal from the Shannon energy calculation S[n] in solid line, the envelope signal z[n] in dashed line, and the threshold level 30% in dotted line. Results show that a significant difference in amplitudes of the PVC beat compared to the normal beats form the normalized square energy signal as shown in Fig. 5(b) is reduced. Fig. 5(d) shows R peaks detected by the proposed algorithm with Shannon energy. Results show that the false negative shown in Fig. 4(d) is removed.

Fig. 6 shows the signal characteristics from the proposed algorithm without and with Shannon energy calculation on ECG signal record 113. Fig. 6(a) shows the original ECG signal from time 1752 s to 1762 s (x[n]). The ECG signal in this record consists of high T wave amplitude in the normal heart beats resulting in the difficulty to correctly detect R peak. Fig. 6(b) shows the signal from square energy calculation $y^2[n]$ from the proposed algorithm without Shannon energy calculation in solid line, the envelope signal z[n] in dashed line, and the threshold level 3% in dotted line. As the result, the R peaks on signal $y^2[n]$ is highlighted. Fig. 6(c) shows R peaks detected by the proposed algorithm without Shannon energy. Results show a false positive between time 1756 ms and 1757 ms because the threshold value is lower than the amplitude of T wave. Fig. 6(d) shows

the signal from the Shannon energy calculation S[n]in solid line, the envelope signal z[n] in dashed line, and the threshold level 30% in dotted line. Fig. 6(e) shows all R peaks that are correctly detected by the proposed algorithm with Shannon energy. Results show that Shannon energy calculation allows for the high threshold value resulting in the removal of the false positive due to the high T wave amplitude.

Fig. 7 shows the example result of proposed algorithm without and with Shannon energy calculation applied on ECG signal record 200. Fig. 7(a) shows the original ECG signal from time 314.5 s to 324.5 s, which is contaminated with powerline interference noise. Fig. 7(b) shows the unstable R peak amplitude that was highlighted with the square energy calculation and the threshold value 3% of maximum amplitude in dotted line. Fig. 7(c) shows R peaks detected by the proposed algorithm without Shannon energy. It consists of a false negative beat detection from a PVC beat at around 320 ms due to the use of very low threshold value resulting in the merging of two connected R peak. Fig. 7(d) shows result from Shannon energy calculation. Results show that Shannon energy operation can enhance R peak very well resulting in equal R peak amplitude. Fig. 7(e) shows all R peaks that are correctly detected by the proposed algorithm with Shannon energy. Results show that Shannon energy calculation allows for the high threshold value resulting in the removal of the false positive due to the powerline interference noise.

4.3 Performance evaluation

Table 1 shows the performance of the proposed algorithm without Shannon energy operation on 48 ECG data from MIT-BIH arrhythmia databases. Results show that the proposed algorithm can achieve detection error rate 0.48%, sensitivity 99.69% and positive predictive rate 99.83%. From the total 541 false detections, while the false negative occurs 356 times, the false positive occurs 185 times. Record 203 provide the maximum DER value of 2.89% from the 14 FP values and the 72 FN values because the ECG data from record 203 consists of various noises such as muscle artefact and baseline shift. Moreover, the ECG beat in this record contains a variety of patterns such as suddenly heart rate changing, variant R peak amplitude, and multiform of PVC beats, leading to the difficulty in detecting R peaks.

Table 2 shows the performance of the proposed algorithm with Shannon energy operation. Results show that the proposed algorithm can achieve DER value of 0.50%, sensitivity 99.66% and positive predictive rate 99.83%. From the total 562 false detections, while the false negative occurs 382 times, the false positive occurs 180 times. ECG data record 203 provides the worst DER value of 2.89%, which is the same as the proposed algorithm without Shannon energy. The DER significantly increases in the ECG

Record No.	Total (beat)	TP (beat)	FN (beat)	FP (beat)	SEN (%)	PPR (%)	DER (%)
100	2273	2273	0	0	100.00	100.00	0.00
101	1865	1865	0	4	100.00	99.79	0.21
102	2187	2187	0	0	100.00	100.00	0.00
103	2084	2084	0	0	100.00	100.00	0.00
104	2228	2215	13	15	99.42	99.33	1.26
105	2572	2558	14	22	99.46	99.15	1.40
106	2027	1993	34	2	98.32	99.90	1.78
107	2136	2136	0	0	100.00	100.00	0.00
108	1763	1744	19	12	98.92	99.32	1.76
109	2532	2528	4	0	99.84	100.00	0.16
111	2124	2123	1	1	99.95	99.95	0.09
112	2539	2537	2	10	99.92	99.61	0.47
113	1795	1795	0	8	100.00	99.56	0.45
114	1879	1856	23	1	98.78	99.95	1.28
115	1953	1953	0	0	100.00	100.00	0.00
116	2412	2391	21	2	99.13	99.92	0.95
117	1535	1535	0	$2 \\ 2 \\ 3$	100.00	99.87	0.13
118	2278	2277	1	3	99.96	99.87	0.18
119	1987	1987	0	1	100.00	99.95	0.05
121	1863	1862	1	2	99.95	99.89	0.16
122	2476	2476	0	$\begin{array}{c} 2\\ 0\\ 2\end{array}$	100.00	100.00	0.00
123	1518	1518	0	2	100.00	99.87	0.13
120	1619	1619	0	1	100.00	99.94	0.06
200	2601	2593	8	16	99.69	99.39	0.92
200	1963	1952	11	0	99.44	100.00	0.56
201	2136	2133	3	0	99.86	100.00	0.14
203	2980	2908	72	14	97.58	99.52	2.89
205	2656	2637	19	0	99.28	100.00	0.72
200	1860	1843	17	16	99.09	99.14	1.77
208	2955	2930	25	4	99.15	99.86	0.98
208	3005	3004	1	2	99.97	99.93	0.10
209 210	2650	2623	27	$\frac{2}{3}$	98.98	99.89	1.13
210 212	2748	2023 2748	0	1	100.00	99.96	0.04
212	3251	3242	9	8	99.72	99.75	0.54 0.52
213 214	2262	2258	3 4	3	99.82	99.87	0.32 0.31
$214 \\ 215$	3363	3355	8	0	99.82 99.76	100.00	0.31
$213 \\ 217$	2208	2207	8 1	$\frac{0}{2}$	99.70 99.95	99.91	$0.24 \\ 0.14$
217 219	2208 2154	2154	0	1			$0.14 \\ 0.05$
219 220	$2154 \\ 2047$	$2154 \\ 2047$	0	$1 \\ 0$	$100.00 \\ 100.00$	$99.95 \\ 100.00$	$0.05 \\ 0.00$
$220 \\ 221$	2047 2427	2047 2425	$0 \\ 2$				
$\frac{221}{222}$	2427 2483	$2425 \\ 2481$	$\frac{2}{2}$	0	99.92 00.02	$100.00 \\ 99.96$	$\begin{array}{c} 0.08 \\ 0.12 \end{array}$
	2483 2605			1	99.92		0.12 0.08
223 228	2605 2053	$2604 \\ 2044$	1	$\begin{array}{c} 1 \\ 19 \end{array}$	$99.96 \\ 99.56$	$99.96 \\ 99.08$	$0.08 \\ 1.36$
			9	19			
230	2256	2256	0	2	100.00	99.91	0.09
231	1571	1571	0	0	100.00	100.00	0.00
232	1780	1780	0	4	100.00	99.78	0.22
233	3079	3075	4	0	99.87	100.00	0.13
234	2753	2753	0	0	100.00	100.00	0.00
Total	109491	109135	356	185	99.69	99.83	0.48

Table 1: Performance Evaluation of the Proposed Algorithm without Shannon Energy Operation.

data record 114 because ECG data in this record consist of many R peak amplitude variations. Although, Shannon energy operation can enhance the R peak amplitude, the threshold value 30% of maximum amplitude is too high for this record resulting in many FNs

4.4 Performance comparisons

Table 3 shows the performance comparison of the proposed algorithm with those from other papers using the ECG signal from MIT-BIH arrhythmia databases. The first six articles is sorted from the minimum DER value (0.168%, linear filtering) to the maximum DER value (0.87%, Median filter). The DER from the proposed algorithm without and with

Shannon energy is 0.48% and 0.50%, respectively. We can see that the DER from the proposed algorithm without additional post processing is better than that from the algorithm given in [9], which also uses CWT for noise removal. Most errors in the proposed algorithm are caused by false negative detections. It can solved by introducing some post processing methods such as searchback method using R-R interval information and R-R interval check-up as presented in [5] and [9], respectively. We found that the false positive from the proposed algorithm is very good compared to other publications except for the algorithm given in [6] and [5].

In order to confirm the performance of our proposed algorithm, the five ECG signal records that frequently gives high DER values in other papers,

	Performance 1	*	-	•		••	-
Record No.	Total (beat)	TP (beat)	FN (beat)	FP (beat)	SEN(%)	PPR (%)	DER (%
100	2273	2273	0	0	100.00	100.00	0.00
101	1865	1865	0	4	100.00	99.79	0.21
102	2187	2187	0	0	100.00	100.00	0.00
103	2084	2084	0	0	100.00	100.00	0.00
104	2228	2215	13	13	99.42	99.42	1.17
105	2572	2558	14	23	99.46	99.11	1.44
106	2027	1991	36	2	98.22	99.90	1.87
107	2136	2136	0	0	100.00	100.00	0.00
108	1763	1741	22	10	98.75	99.43	1.82
109	2532	2524	8	0	99.68	100.00	0.32
111	2124	2123	1	2	99.95	99.91	0.14
112	2539	2538	1	11	99.96	99.57	0.47
113	1795	1795	0	4	100.00	99.78	0.22
114	1879	1841	38	1	97.98	99.95	2.08
115	1953	1953	0	0	100.00	100.00	0.00
116	2412	2391	21	$\frac{1}{2}$	99.13	99.92	0.95
117	1535	1535	0	1	100.00	99.93	0.07
118	2278	2277	1	3	99.96	99.87	0.18
119	1987	1987	0	1	100.00	99.95	0.18
119	1863	1862	1	2	99.95	99.89	0.05 0.16
$121 \\ 122$	2476	2476	0	0	100.00	100.00	0.10
$122 \\ 123$	1518	1518	0	$\frac{0}{2}$	100.00	99.87	$0.00 \\ 0.13$
$123 \\ 124$	1619	1619	0			99.87 99.94	0.13
$124 \\ 200$	2601	2595	6	$\frac{1}{17}$	$100.00 \\ 99.77$	$99.94 \\ 99.35$	$0.00 \\ 0.88$
201	1963	1948	15	0	99.24	100.00	0.76
202	2136	2133	3	0	99.86	100.00	0.14
203	2980	2908	72	14	97.58	99.52	2.89
205	2656	2638	18	0	99.32	100.00	0.68
207	1860	1845	15	16	99.19	99.14	1.67
208	2955	2930	25	4	99.15	99.86	0.98
209	3005	3004	1	4	99.97	99.87	0.17
210	2650	2621	29	3	98.91	99.89	1.21
212	2748	2748	0	1	100.00	99.96	0.04
213	3251	3242	9	8	99.72	99.75	0.52
214	2262	2257	5	3	99.78	99.87	0.35
215	3363	3356	7	0	99.79	100.00	0.21
217	2208	2206	2	1	99.91	99.95	0.14
219	2154	2154	0	1	100.00	99.95	0.05
220	2047	2047	0	0	100.00	100.00	0.00
221	2427	2424	3	0	99.88	100.00	0.12
222	2483	2482	1	1	99.96	99.96	0.08
223	2605	2604	1	1	99.96	99.96	0.08
228	2053	2044	9	19	99.56	99.08	1.36
230	2256	2256	0	2	100.00	99.91	0.09
231	1571	1571	0	0	100.00	100.00	0.00
232	1780	1780	Õ	3	100.00	99.83	0.17
233	3079	3074	5	0	99.84	100.00	0.16
234	2753	2753	Ő	Ő	100.00	100.00	0.00
Total	109491	109109	382	180	99.66	99.83	0.50

Table 2: Performance Evaluation of the Proposed Algorithm with Shannon Energy Operation.

i.e., 108, 203, 105, 223 and 207, are compared with the proposed algorithm as shown in Table 4. Results show that the proposed algorithm provides a good DER for record 108 that is one of the most difficult records to be correctly detected. The algorithm in [4] uses S-Transform (ST) for noise filtering and has the post processing operation in its R peak detection algorithm. ST is a time-frequency distribution and the output of ST is a matrix where rows represent the time and columns represent the frequency. Compared with the CWT with a single scaling parameter a used in this paper, ST requires higher computational complexity but provides worse DER value. This shows the capability of using CWT with a single scaling parameter in removing noise.

5. CONCLUSIONS

The R peak detection algorithm based on CWT and Shannon energy is presented. The proposed algorithm was evaluated with the ECG data from MIT-BIH arrhythmia database. Results show that the proposed algorithm give very good DER (0.48%-0.50%) compared to those from previous publications (0.168%-0.87%). We demonstrate that the use of the CWT with a single scaling parameter is capable of removing noises. In addition, we found that Shannon energy cannot improve the DER value but it can highlight the R peak from the low QRS complex in ECG beat after noise removal and square operation such as a PVC beat. This main advantage results in achieving the robust R peak detection algorithm. For

Method of noise		Dest pressing					
removal	TP (beat)	FN (beat)	FP (beat)	SEN (%)	PPR (%)	DER $(\%)$	Post processing
Linear filtering [6]	109401	93	91	99.92	99.92	0.168	Yes
S-Transform [5]	108323	97	171	99.84	99.91	0.25	Yes
Whitening filter [11]	109374	109	210	99.82	99.91	0.29	No
Quadratic filter [7]	109281	202	210	99.82	99.81	0.38	No
CWT [9]	109118	376	218	99.66	99.8	0.54	Yes
Median filter [10]	108099	495	462	99.58	99.55	0.87	Yes
CWT without Shannon energy	109135	356	185	99.69	99.83	0.48	No
CWT with Shannon energy	109158	382	180	99.66	99.83	0.50	No

Table 3: Performance Comparisons of the Proposed Algorithm with other Papers.

Table 4: Performance Comparisons of the Proposed Algorithm with other Papers for First 5 Records that Often Give High DER.

Method of noise removal			$\overline{\text{DER}}$ (%)		
Method of holse removal	108	203	105	228	207
Linear filtering [6]	0.57	1.19	1.25	0.63	0.32
S-Transform [5]	2.44	0.67	1.24	0.54	1.13
Whitening filter [11]	0.51	1.93	0.23	1.03	0.65
Quadratic filter [7]	4.08	1.91	1.52	1.27	2.20
CWT [9]	4.71	2.05	2.02	3.56	1.18
Median filter [10]	2.78	4.33	4.67	1.12	0.81
CWT without Shannon energy	1.76	2.89	1.40	1.36	1.77
CWT with Shannon energy	1.82	2.89	1.44	1.36	1.67

future work, we will improve the proposed algorithm by adding the post processing operation to reduce the false negative and false positive to achieve higher performance.

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