A Low-complexity QRS Detection Algorithm Based on Morphological Analysis of the QRS Complex

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Abstract: - QRS detection in the magnetocardiogram (MCG) and electrocardiogram (ECG) signals is very crucial as the first step for evaluating the cardiac function. Unlike most of the published algorithms which are aimed at increasing the detection accuracy by using complex signal-processing techniques, we propose a new, low-complexity QRS detection algorithm based on morphological analysis of the QRS complex. The algorithm does not need to remove the baseline wander, and the R waves can be quickly detected by the wave steepness function. The performance of the proposed algorithm was evaluated on the MIT-BIH arrhythmia database and MCG data recorded by the multi-channel MCG system. The sensitivity (SE) and positive prediction (+P) for MIT-BIH database were 99.69% and 99.87%, respectively. Also, the accuracy of 97.22% is achieved for MCG data. Compared to other published results, the processing time of one hour ECG data was reduced to 0.187s. The lower computational time makes the proposed method can be used in portable devices, for example, a Smartphone.

Key-Words: - Magnetocardiogram; wave steepness function; Morphological analysis; QRS complex.

1 Introduction

QRS detection is very crucial as the first step for evaluating the cardiac function. All the other components, such as P-wave, S-wave, RR interval, QT interval and ST interval et al., can be found with the reference of QRS complex. Thus, accurate detection of QRS complex becomes the foremost and critical objective[1]. Scholars have proposed a variety of algorithms to identify QRS complexes in recent decades. These algorithms have many different forms, but can be broadly classified into the following categories: wavelet transform [2-4], artificial neural network (ANN) [5, 6], Hilbert transform[7, 8], and empirical mode decomposition (EMD)[9, 10]. In wavelet-based algorithms, Merah proposed a new QRS complex detection method based on stationary wavelet transform [2], and Abibullaev made use of four different wavelet basis functions to detect QRS complex [11]. However, wavelet transform is very sensitive to the selection of mother wavelet that affects the detection performance of QRS complex [12]. In ANN, sigmoidal radial basis function, support vector machine, and backward propagation neural network were extensively used because of the advantage of being effective in nonlinear and non-stationary environment [5]. However, ANN is expensive because of the need for a large amount of memory for training, setting and evaluation of the model parameters [1]. Hilbert transform is an odd filter and has the ability to identify QRS complex. However, Hilbert transform may not be able to recognize low-amplitude R-wave. EMD has the drawback of being time-consuming, because the extraction of intrinsic mode functions needs a series of iterations.

In addition to the above drawbacks, the mentioned methods used a lot of complex transforms to increase the accuracy of QRS complex. However, for portable devices, the power consumption and the overall complexity should be low. Hence, the challenge of current QRS complex detection methods lies in increasing the detection accuracy, noise-robustness of the detection, and reducing the computational burden.

To address these challenges, we propose a new, low-complexity QRS detection algorithm based on morphological analysis of QRS complex. Unlike the existing methods, the algorithm does not need to remove the baseline wander. To effectively detect the QRS complex, we define the wave steepness function, which can be used to detect the R-wave.

To increase the detection accuracy of QRS complex, two measures were implemented: a) Identify the direction of the R-wave, and delete the peak points whose direction is inconsistent with the R-wave; b) Define the pseudo R peak point, then remove all the pseudo R peak points.

In order to evaluate the performance of the proposed algorithm, the QRS detection accuracy and computational time were compared with the published algorithms using the MIT-BIH arrhythmia database. The reduction in computational time and high detection accuracy confirms the effectiveness of the proposed algorithm.

2 Proposed Method

This section explains the proposed algorithm in detail. The flow diagram of the algorithm is given in Figure. 1. As can be seen from the Figure 1, the algorithm includes the following four steps:

1) Detect all the peaks of the ECG or MCG data.

Assuming that the ECG or MCG data is y(n) with 'N' sampling points. In order to detect all the peaks of y(n), first, y(n) is differentiated according to the following equation:

$$y'(n) = \frac{d}{dn} y(n) \tag{1}$$

$y'(n)$ is the differential result of y(n). Then, a nonlinear transformation is applied to $y'(n)$, the result of the nonlinear transformation is g(n).

$$g(n) = \begin{cases} -1 & y'(n) < 0 \\ 1 & y'(n) > 0 \end{cases} \tag{2}$$

Finally, the g(n) is differentiated according the equation (3) and the points whose differential result do not equal to 0 are the peaks.

$$g'(n) = \frac{d}{dn} g(n) \tag{3}$$

2) Select the steep peaks from the above peaks.

To select the sharp peaks, we define the wave steepness function according the following formula:

$$sp(k) = \frac{py(k) - py(k-1)}{px(k) - px(k-1)} \tag{4}$$

py(k) is the k-th peak, k is the ordinal number of peaks. px(k) is the time of py(k). sp(k) is the wave sharpness of py(k).

When the absolute value |sp(k)| of sp(k) satisfies the following formula, py(k) is a steep peak.

$$|sp(k)| = \frac{\max(|sp(k)|)}{5} \tag{5}$$

$\max(|sp(k)|)$ is the maximum value of the sequence {|sp(k)|, k=1,2,3…,M}.

3) Select the peaks whose directions are consistent with R-wave direction from the above steep peaks.

To select the peaks in line with the direction of the R-wave, we need to find the direction of the R-wave. Take a section of data {py(j), j=1,2,…L} from the steep peaks {py(j), j=1,2,…,M} (Note that L<M), and find the direction of the R-wave according the following formula:

$$flag = \begin{cases} 1 & \max(|py(j)|) - \min(|py(j)|) > 0 \\ -1 & \max(|py(j)|) - \min(|py(j)|) < 0 \\ 0 & \max(|py(j)|) - \min(|py(j)|) = 0 \end{cases} \tag{6}$$

Here, max(|py(j)|) is the maximum value of the sequence {|py(j)|, j=1,2,…,L}, min(|py(j)|) is the minimum value of the sequence {|py(j)|, j=1,2,…,L}. When flag=1, the direction of R-wave is downward (convex wave), When flag=-1, the direction of R-wave is upward (concave wave), else when flag=0, the result is wrong, then it is need to take another piece of data from the sharp peak points and re-determine the direction of R-wave.

After finding the direction of the R-wave, it is necessary identify the direction of each steep peaks according to the following equation.

$$DP(j) = \begin{cases} 1 & py''(j) < 0 \\ -1 & py''(j) > 0 \end{cases} \tag{7}$$

DP(j) is the direction of the j-th steep peak, $py''(j)$ is the result of quadratic differential of py(j). When the value of DP(n) is equal to the value of flag, the peaks of the n-th steep peak is consistent with R-wave direction.

4) Identify and delete the pseudo R peaks.

The pseudo R peak is defined by the following equation:

$$\begin{cases} py(j) < \overline{py(j)} \times 0.2 \\ py(j) < py(j+1) \,\|\, py(j) < py(j-1) \end{cases} \tag{8}$$

$\overline{py(j)}$ is calculated by the following formula.

$$\overline{py(j)} = \sum_{i=1}^{N} \frac{py(i)}{N} \tag{9}$$

When py(j) satisfies the equation (8), py(j) is a pseudo R peak point.

After removing all of the pseudo R peak points, the remaining peak points are the desired R peak points.

3 Results

3.1 MCG data

The performance of the proposed algorithm was evaluated on the MCG data recorded by a multi-

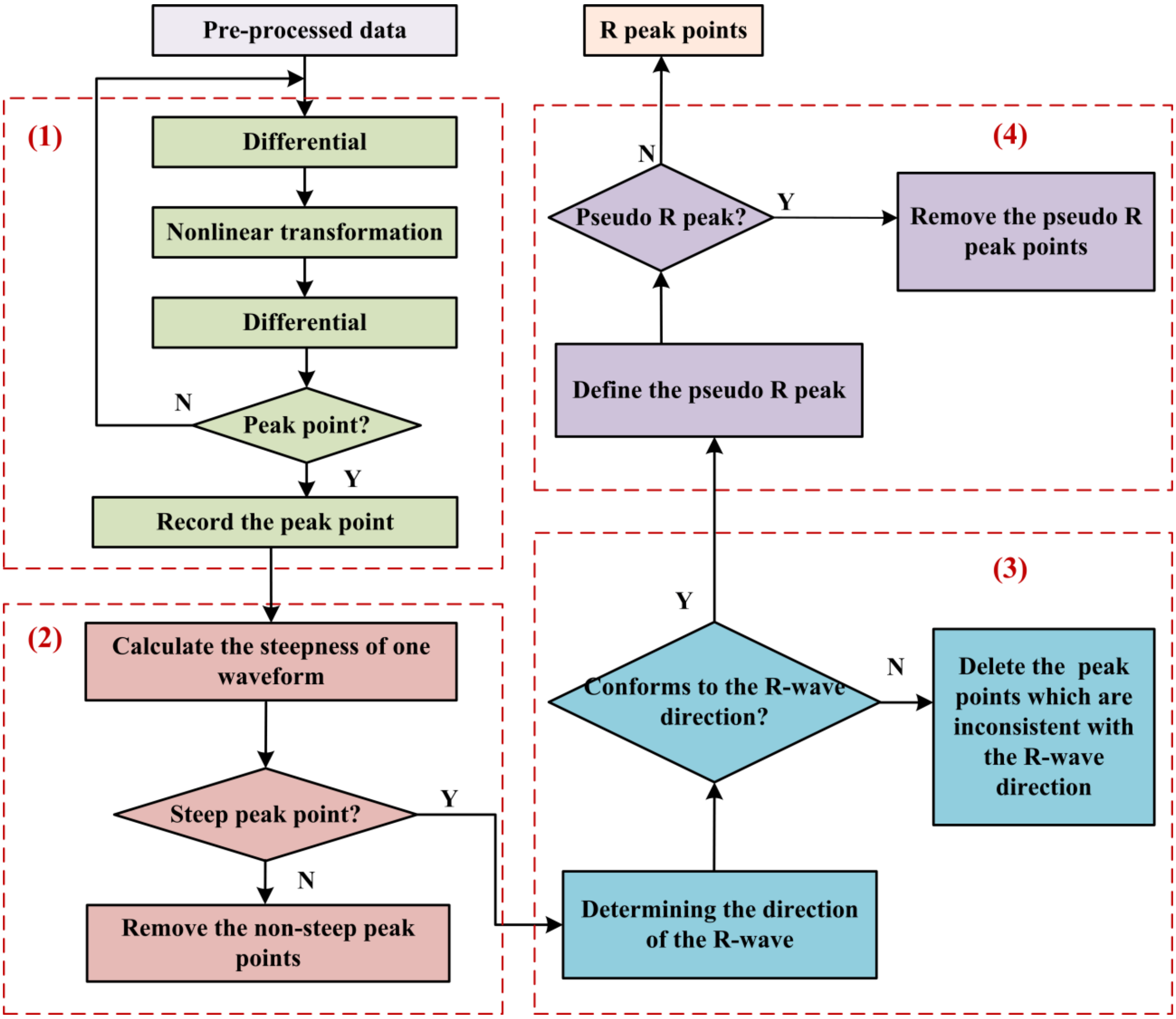

Fig.1 The flow diagram of the proposed algorithm: (1) Identify all the peak points of the pre-processed data; (2) Select the steep peak points from the peak points; (3) Select the peak points whose direction are consistent with R-wave direction from the steep peak points; (4) Identify and delete the pseudo R peak points.

channel MCG system and the MIT-BIH arrhythmia database. The QRS detection results of MCG data are shown in Figure 2. Fig.2(a) shows an instance of the MCG data with baseline wander. In order to accurately detect the peaks of R-wave, the first step of the proposed algorithm is to detect the entire peaks in the MCG data, the detection results are the red dots in Fig.2(b). Then the steep peaks were selected from the above peaks, as shown in Fig.2(c).

To increase the detection accuracy of QRS complex, the steep peaks whose direction are consistent with the R-wave were filtered out, as shown in Fig.2(d). Finally, the pseudo R peaks were deleted and the desired R peaks were selected, as shown in Fig.2(e).

To evaluate the performance of the proposed method, we calculated the QRS detection accuracy (Ac) of MCG data according to the following equation,

$$Ac(\%) = \frac{TP}{TP + FN + FP} \tag{10}$$

Here FP indicates the detection of a QRS peak when there is actually none, FN indicates that the algorithm failed to detect an actual beat, and TP is the number of QRS correctly detected [13]. The QRS detection accuracy for one hour MCG data is 97.22%.

3.2 MIT-BIH Arrhythmia Database

Then the MIT-BIH Arrhythmia Database was used to evaluate the performance of the proposed algorithm. The MIT-BIH Arrhythmia Database contains 48 ECG records which are filtered by a band-bass filter (0.1 to 100Hz) and a digital notch filter (60Hz). To evaluate the performance of the proposed algorithm, the sensitivity (Se) and positive prediction (+P) were calculated by the following equations:

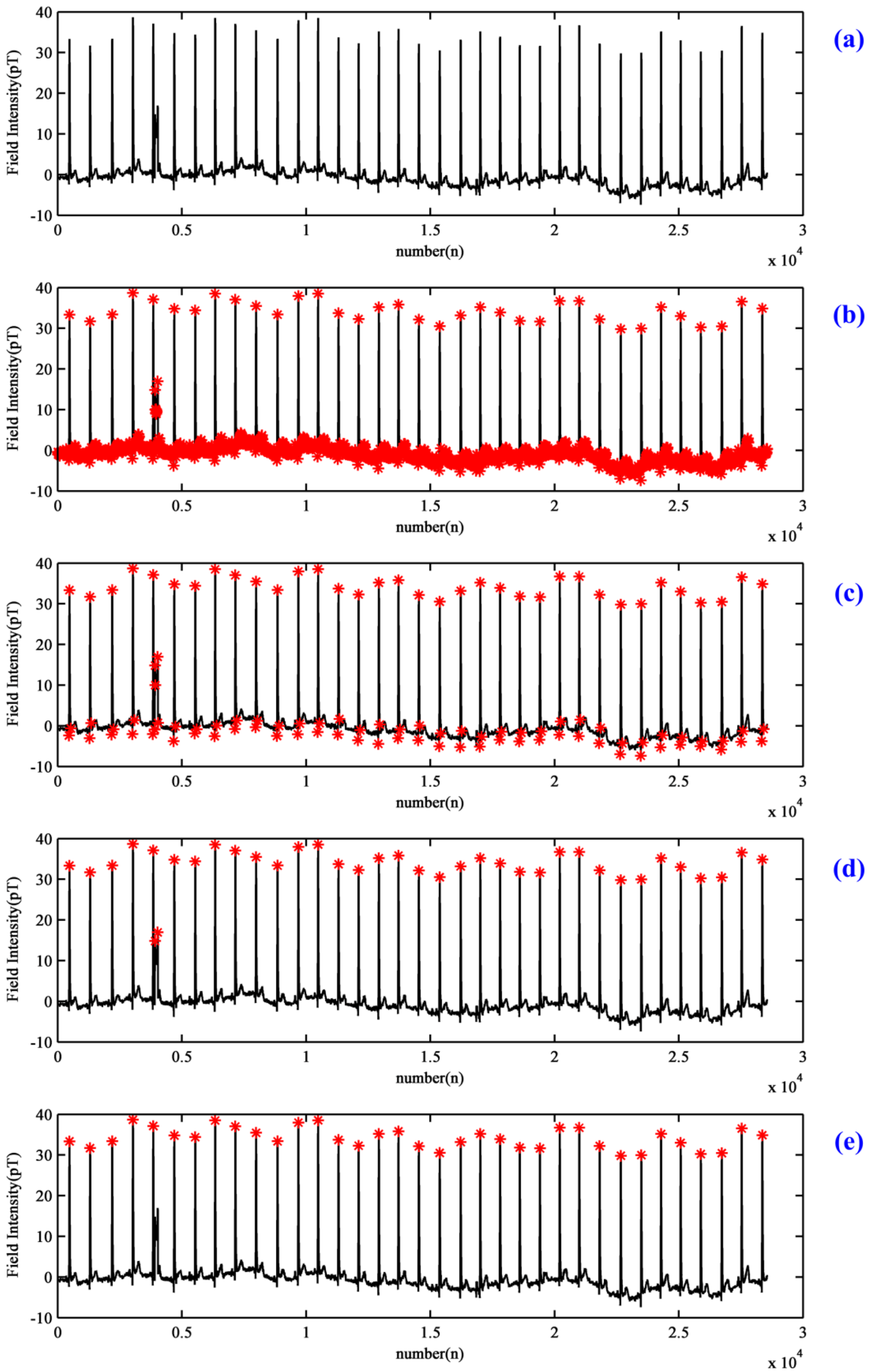

Fig.2 The recognition results of the QRS complex: (a) the pre-processed MCG data; (b) the peak points in the MCG data; (c) the steep peak points selected from the peak points; (d) the peak points which are consistent with R-wave direction screened from the steep peak points; (e) the desired R peak points

Table 1. The performance of the proposed method using the MIT-BIH database

Tape	Total	FP	FN	Se(%)	+P(%)
100	2273	0	2	99.91	100
101	1865	0	1	99.95	100
102	2187	0	0	100	100
103	2084	0	3	99.86	100
104	2229	10	5	99.78	99.55
105	2572	18	12	99.54	99.31
106	2027	0	6	99.70	100
107	2137	0	4	99.81	100
108	1774	20	8	99.55	98.89
109	2532	2	6	99.76	99.92
111	2124	0	2	99.91	100
112	2539	0	1	99.96	100
113	1795	0	0	100	100
114	1879	3	4	99.79	99.84
115	1953	1	0	100	99.95
116	2412	6	18	99.26	99.75
117	1535	0	1	99.93	100
118	2278	0	2	99.91	100
119	1987	0	1	99.95	100
121	1863	0	0	100	100
122	2476	0	1	99.96	100
123	1518	6	4	99.74	99.61
124	1619	4	3	99.82	99.75
200	2601	4	0	100	99.85
201	1963	2	60	97.03	99.90
202	2136	1	12	99.74	99.95
203	2980	16	20	99.33	99.47
205	2656	0	6	99.77	100
207	1860	12	8	99.57	99.36
208	2955	2	24	99.19	99.93
209	3004	0	1	99.97	100
210	2650	6	22	99.18	99.77
212	2748	2	3	99.89	99.93
213	3251	4	27	99.18	99.88
214	2265	4	9	99.60	99.82
215	3363	2	6	99.82	99.94
217	2209	0	2	99.91	100
219	2154	0	4	99.81	100
220	2048	0	0	100	100
221	2427	1	8	99.67	99.96
222	2483	5	2	99.92	99.80
223	2605	0	2	99.92	100
228	2053	15	22	98.94	99.27
230	2256	0	0	100	100
231	1571	0	1	99.94	100
232	1780	0	11	99.39	100
233	3079	0	2	99.94	100
234	2753	0	1	99.96	100
Total	109508	146	337	99.69	99.87

$$Se(\%) = \frac{TP}{TP + FN} \tag{11}$$

$$+P(\%) = \frac{TP}{TP + FP} \tag{12}$$

The QRS detection results for the MIT-BIH Arrhythmia Database are shown in Table 1. The Se and +P for MIT-BIH database are 99.69% and 99.87%, respectively.

3.3 Performance comparison

The QRS detection performance of the proposed algorithm was compared with other published algorithms in Table 2. The proposed method shows improved performance compared to the results of algorithms in [13-17] and comparable results compared to the results in [9, 18].

Table 2. Comparison of the proposed method with other algorithms for QRS detection based on the MIT-BIH Database

Authors	Proposed algorithm		Results		Database
	Pre-processing stage	Detection stage	Se(%)	+P(%)	
Pal et al.[9] **(2012)**	EMD	Morphological analysis	99.88	99.96	21 signals of MIT-BIH
Das et al.[18] **(2011)**	EMD+Wavelet	Dynamic threshold	99.84	99.96	17 signals of MIT-BIH
Proposed	Low-pass Filter+notch filter	Morphological analysis	99.69	99.87	Full MIT-BIH
Zidelmal et al.[19] **(2012)**	Wavelet	Dynamic threshold	99.64	99.82	Full MIT-BIH
Deepu et al.[13] **(2015)**	Low-pass Filter+notch filter	linear predictor	99.64	99.81	Full MIT-BIH
Phyu et al.[20] **(2009)**	Wavelet	Dynamic threshold	99.63	99.89	Full MIT-BIH
Nielsen et al.[21] **(2012)**	Wavelet	Dynamic threshold	99.63	99.63	Full MIT-BIH
Chen et al.[14] **(2006)**	Wavelet	Dynamic threshold	99.55	99.49	45 signals of MIT-BIH
Raquel et al.[17] **(2015)**	Differentiation	Dynamic threshold	99.54	99.74	Full MIT-BIH
Ieong et al.[16] **(2012)**	Wavelet	Dynamic threshold	99.31	99.70	Full MIT-BIH
Laila et al.[15] **(2012)**	Wavelet+Hilbert	Dynamic threshold	96.30	97.83	Full MIT-BIH

Table 3. Comparison of computation time

Authors	Methods	ECG data	Waves studied	Processing time (s)
Li et al.[22] **(1995)**	Wavelet Transform	10 min, 2 leads	P-QRS-T	60
Yochum et al.[23] **(2016)**	Wavelet Transform	10 min, 12 leads	P-QRS-T	48.6
Yeh et al.[24] **(2008)**	Difference Operation Method	10 min, 2 leads	QRS	30
Madeiro et al.[25] **(2012)**	Derivative, Hilbert and Wavelet	15 min, 2 leads	QRS	4.52
Manikandan et al.[8] **(2012)**	Shannon energy envelope estimator	15min, 1 lead	R	2.24
This work	Morphological analysis	60 min, 2 leads	QRS	0.187

Computational time is an important indicator to evaluate the performance of the algorithm, and the less the better. The comparison of the computation time with the other published work is shown in Table 3. The mean computation time of the proposed algorithm is 0.187s for 60 minutes long ECG and on the 2 leads. As shown in Table 3, the computation time of the proposed algorithm is significantly less than the literatures [22-24].

The computation time of the methods depend on the following several factors: the amount of processing data, the operating system, the processing power of the computer, and the memory. The proposed algorithm is implemented with LABVIEW. If C language and a parallelization process were used instead, the computation time could be reduced by 10%, or even more. In this case, the proposed method can be used in portable devices, for example, a Smartphone.

4 Conclusions

QRS detection in the MCG and ECG signals is very crucial as the first step for evaluating the cardiac function, and the challenge of current QRS complex detection method lies in increasing the detection accuracy, noise-robustness of the detection, and reducing the computational burden. Therefore, in this paper, we proposed a new QRS detection algorithm based on the morphological analysis of the QRS complex. The algorithm does not need to remove the baseline wander, and there is no complex signal processing technology, which greatly reduce the complexity of the algorithm.

The MIT-BIH arrhythmia database and MCG data were used to evaluate the performance of the proposed algorithm. The sensitivity and positive prediction for MIT-BIH database were 99.69% and 99.87%, respectively. Also, the accuracy of 97.22% is achieved for MCG data. The observation from the results shows good performance of the QRS detection. The lower computational time makes the proposed algorithm to be applied to real-time detection of QRS complex.

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