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A Computationally Efficient QRS Detection Algorithm for Wearable ECG Sensors

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Abstract: **In this paper we present a novel Dual-Slope QRS detection algorithm with low computational complexity, suitable for wearable ECG devices. The Dual-Slope algorithm calculates the slopes on both sides of a peak in the ECG signal; And based on these slopes, three criterions are developed for simultaneously checking 1)Steepness 2)Shape and 3)Height of the signal, to locate the QRS complex. The algorithm, evaluated against MIT/BIH Arrhythmia Database, achieves a very high detection rate of 99.45%, a sensitivity of 99.82% and a positive prediction of 99.63%.**

Index Terms **- Electrocardiogram, QRS detection, wearable sensors, low complexity.**

I. Introduction

With a fast aging society, there is an emerging trend for personalized healthcare adoption in many countries. Personalized healthcare advocates a prevention-oriented healthcare, in which each person is equipped with wearable or implantable sensors to monitor the vital signs continuously. These vital signs are transmitted to a remote health monitoring centre, where computers and doctors are keeping an eye on the health condition of each individual. If any abnormal condition is detected, the person will be informed with either text messages or voice calls from remote doctor for a clinic appointment. In the prevention-oriented healthcare system, continuous cardiac ECG monitor plays an important role. Such ECG recording devices are expected to generate significant amount of data needed to be transmitted to remote monitoring centre. Meanwhile, the limited battery life of wearable devices greatly affects the recording time. To lengthen the recording time, it is desirable to adopt low power QRS detection algorithms in wearable ECG sensors.

In published literature for QRS detection, various derivative-based algorithms have been proposed[1]. However, the detection rates of these algorithms are not very satisfactory[1]. The traditional derivative-based algorithms periodically compare the differentiated waveform with an empirical threshold to locate the QRS complex. The performance of this algorithm is highly affected by baseline noises, whose derivatives can be quite high as well. Considering that the width of QRS complex is relatively fixed, in the range of 0.06-0.1s[2], and in QRS complex there are usually two large slopes, the widths of these two slopes in QRS complex are approximately 0.03-0.05s. Hence, instead of directly taking derivatives of the ECG signal, we can focus only on the slope of straight line connecting two samples that are separated by this width. If the values of the slope are calculated for any two samples that are separated by this width, then the largest values should be found in the QRS complex. To enhance the detection performance, the slope difference between left hand side and right hand side can be compared with an adaptive threshold, making use of the fact that the largest change of slope usually happens at the peak of QRS complex. Based on this idea, the proposed Dual-Slope QRS detection algorithm is developed.

This paper is organized as follows. In Section II, we discuss the details of the algorithm proposed. In Section III, the evaluation results of the algorithm against the MIT/BIH arrhythmia database is given. Concluding remarks are drawn in Section IV.

II. Proposed Algorithm

If a signal section is to be detected as QRS complex, it must have steep slopes with width close to the slope width in QRS section. Besides, it somewhat should have a ramp like shape and the height (amplitude) of the peak should be high enough. Based on this, we developed three criterions for checking the signal section's steepness, shape and height respectively. If a signal section can satisfy all three criterions, a peak should exist in the current section. Then local extremes are searched to locate the peak position, followed by adjustment which aims to avoid multiple detections within the same QRS complex.

The details of each step are given in the following subsections. And a flowchart of the proposed Dual-Slope algorithm is given in Fig. 1.

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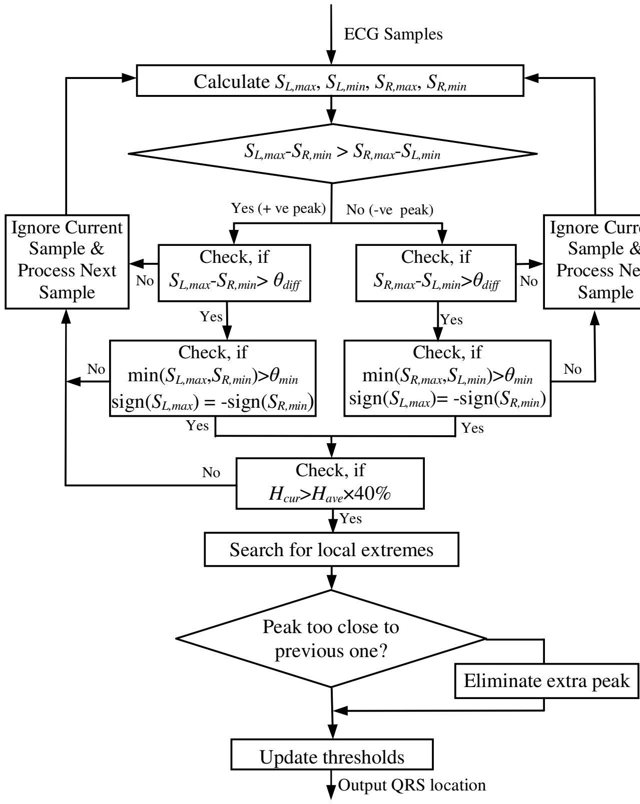

Fig. 1. Block diagram of the proposed Dual-Slope algorithm

A. Criterion 1

Since the width of QRS complex from the peak to baseline is usually in the range of 0.03-0.05s, when a sample is processed, only the samples located between 0.03-0.05s away from the current sample are highlighted. Then the slopes of the straight lines connecting the highlighted samples to the current sample are calculated with signs. After that, the maximum and minimum slope on each side are taken and stored. By taking the difference of the two steeper slopes on each side, we can get a variable measuring the steepness of the current processed section. And the first criterion is that this value measuring steepness should be larger than an adaptive threshold.

Note that 0.03-0.05s is the width for normal ECG. Heart patients are the major users for wearable ECG devices, and in-order to make the algorithm sensitive to abnormal heartbeats, the width of the slope assumed is extended to 0.027-0.063s.

The equations calculating the maximum and minimum slopes on each side are given as follows:

$$S_{L,max} = \max_{a\le k\le b}\left(\frac{z^{-b} - z^{-(b-k)}}{k}\right), \quad (1)$$

$$S_{L,min} = \min_{a\le k\le b}\left(\frac{z^{-b} - z^{-(b-k)}}{k}\right), \quad (2)$$

$$S_{R,max} = \max_{a\le k\le b}\left(\frac{z^{-b} - z^{-(b+k)}}{k}\right), \quad (3)$$

$$S_{R,min} = \min_{a\le k\le b}\left(\frac{z^{-b} - z^{-(b+k)}}{k}\right), \quad (4)$$

where a is equal to the nearest integer of $0.027f_s$, b is equal to the nearest integer of $0.063\,f_s$, z^n is the ECG sample at nth location, and f_s is the sampling frequency of the ECG signal.

Subtracting the maximum slope of one side by the minimum slope on the other side, "slope differences" are obtained. The higher value between these two "slope differences" is taken as the variable measuring steepness, $S_{diff,max}$, i.e.

$$S_{diff,max} = \max\Big(\big(S_{R,max} - S_{L,min}\big), \big(S_{L,max} - S_{R,min}\big)\Big). \quad (5)$$

Note that Equation (5) also applies to negative peak cases. This leads to the following detection criterion.

Criterion 1: For a signal section to be considered as a QRS complex, the $S_{diff,max}$ must be larger than a preset threshold θ_{diff}, i.e.

$$S_{diff,max} > \theta_{diff} \quad (6)$$

θ_{diff} is calculated and updated according to the average value of $S_{diff,max}$ from the previous 8 peaks, denoted by S_{ave}. The rules for updating are given as follows:

$$\begin{cases} \theta_{diff} = \frac{7680}{f_s} & \text{if } S_{ave} > \frac{20480}{f_s}, \\ \theta_{diff} = \frac{4352}{f_s} & \text{if } \frac{12800}{f_s} < S_{ave} < \frac{20480}{f_s}, \\ \theta_{diff} = \frac{3840}{f_s} & \text{if } S_{ave} < \frac{12800}{f_s}. \end{cases} \quad (7)$$

Note that the recordings in MIT/BIH Arrhythmia Database have 11bit resolution over a 10 mV range. Hence the full scale of one sample is 2048. All the numerical values appearing in this section are based on this scale. And all the thresholds are obtained by tuning the performance on the MIT/BIH Arrhythmia Database.

B. Criterion 2

R peaks usually have steep slopes on both sides. If the "max slope difference" in Criterion 1 is the difference between a flat slope on one side and a very steep slope on the other side, the value of $S_{diff,max}$ can be quite high as well. But in this case it should not be considered as a peak. To eliminate this false condition, Criterion 2 is introduced to ensure that the slopes are steep on both sides.

Criterion 2: A signal section is considered as a QRS complex if the following conditions are satisfied.

$$\begin{cases} S_{min} = min\big(|S_{L,max}|, |S_{R,min}|\big) > \theta_{min} \\ \quad and\ sgn\big(S_{L,max}\big) = -sgn\big(S_{R,min}\big) \\ \big(if\ S_{L,max} - S_{R,min} > S_{R,max} - S_{L,min}\big), \\ \\ S_{min} = min\big(|S_{R,max}|, |S_{L,min}|\big) > \theta_{min} \\ \quad and\ sgn\big(S_{R,max}\big) = -sgn\big(S_{L,min}\big) \\ \big(if\ S_{L,max} - S_{R,min} < S_{R,max} - S_{L,min}\big), \end{cases} \quad (8)$$

where θ_{min} is a fixed preset threshold with the value of $1536/f_s$, and f_s is the sampling frequency of the ECG signal. The two cases in Equation (8) are for positive peaks and negative peaks respectively.

C. Criterion 3

Sometimes T wave or P wave or noise sections can produce large slopes as well. However, the heights of these slopes are usually much smaller than those of QRS complex. Hence, by comparing the height of current slope H_{cur} with the average slope height of the previous 8 detected peaks H_{ave}, wrong detections can be avoided by only accepting H_{cur} larger than certain factor of H_{ave}.

Criterion 3: A signal section is considered as a QRS complex if the slope height satisfies the following condition:

$$H_{cur} > H_{ave} \times 0.4 \quad (9)$$

D. Search for Local Extremes and Adjustments

If all the above three conditions are met, the local maximum or minimum (depending on positive or negative peak) is searched in the current signal section to determine the location of the peak.

To avoid multiple detections within one QRS complex as illustrated in Fig. 2, self-correction is performed whenever two detections are too close to each other. The one with larger value of $S_{diff,max}$ is retained as an R peak, while the other one is discarded.

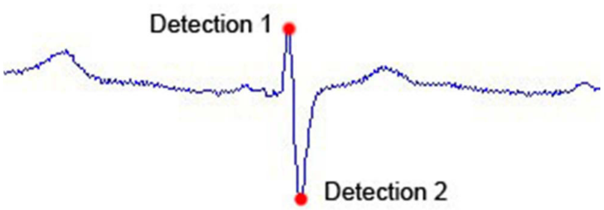

Fig. 2. Multiple detections within one QRS complex

E. Computational Complexity

The proposed algorithm has been implemented in hardware for testing. Serial structures were used in order to reduce the amount of hardware resources. Based on the implementation, we found that the total hardware required is very low and therefore is suitable for low power operation in ECG sensors. An estimated hardware summary is given in Table I.

TABLE I
HARDWARE SUMMARY OF PROPOSED ALGORITHM

Adder	Multiplier	Comparator
14	5	15

III. EXPERIMENTAL RESULTS

The proposed algorithm is evaluated using the MIT/BIH Arrhythmia Database according to American Nation Standard EC38. MIT/BIH database is a benchmark database with 48 half-hour two-channel ambulatory ECG recordings. These recordings have 11-bit resolution over 10mV and are sampled at 360Hz.

To evaluate the detection performance, false positive (FP) and false negative (FN) are used. False positive represents a false beat detection and false negative means that the algorithm fails to detect a true beat. Furthermore, by using FP and FN, the sensitivity (Se), positive prediction (+P) and detection error (DER) are also calculated using the following equations:

$$Se\ (\%) = \frac{TP}{TP + FN} \quad (10)$$

$$+P\ (\%) = \frac{TP}{TP + FP} \quad (11)$$

$$DER = \frac{FP + FN}{Total\ QRS} \quad (12)$$

where TP stands for true positive, meaning the number of QRS correctly detected. Table II shows the summary of QRS detection for all recordings. Figs. 3-6 show the performance of the algorithm. The first graph in each figure shows the original signal and the marked R peak by the proposed algorithm. The second graph shows the values of $S_{diff,max}$ and $\theta_{diff,}$ in Criterion 1. The third graph shows the values of S_{min} and θ_{min} in Criterion 2. Fig. 3 shows the detection performance against signals with large T waves. Fig. 4 shows that baseline drift does not affect the performance much. The detection performance on ECG signals with sharp changing peak amplitudes is demonstrated in Fig. 5.

TABLE II
PERFORMANCE OF THE PROPOSED ALGORITHM USING THE MIT/BIH DATABASE

Tape	Total	FP	FN	Se (%)	+P (%)	DER
100	2273	0	1	99.96%	100.00%	0.0004
101	1865	1	0	100.00%	99.95%	0.0005
102	2187	0	0	100.00%	100.00%	0
103	2084	0	1	99.95%	100.00%	0.0005
104	2229	58	0	100.00%	97.46%	0.0260
105	2572	72	1	99.96%	97.28%	0.0284
106	2027	3	3	99.85%	99.85%	0.0030
107	2137	0	2	99.91%	100.00%	0.0009
108	1774	21	23	98.72%	98.83%	0.0248
109	2532	0	0	100.00%	100.00%	0
111	2124	2	1	99.95%	99.91%	0.0014
112	2539	0	0	100.00%	100.00%	0
113	1795	0	1	99.94%	100.00%	0.0006
114	1879	5	1	99.95%	99.73%	0.0032
115	1953	0	0	100.00%	100.00%	0
116	2412	2	24	99.01%	99.92%	0.0108
117	1535	1	0	100.00%	99.93%	0.0007
118	2278	6	0	100.00%	99.74%	0.0026
119	1987	0	0	100.00%	100.00%	0
121	1863	0	2	99.89%	100.00%	0.0011
122	2476	0	0	100.00%	100.00%	0
123	1518	1	0	100.00%	99.93%	0.0007
124	1619	1	2	99.88%	99.94%	0.0019
200	2601	30	0	100.00%	98.86%	0.0115
201	1963	0	51	97.47%	100.00%	0.0260
202	2136	1	4	99.81%	99.95%	0.0023
203	2980	79	3	99.90%	97.42%	0.0275
205	2656	0	0	100.00%	100.00%	0
207	1860	15	15	99.20%	99.20%	0.0161
208	2955	5	39	98.69%	99.83%	0.0149
209	3004	4	0	100.00%	99.87%	0.0013
210	2650	18	4	99.85%	99.33%	0.0083
212	2748	4	0	100.00%	99.85%	0.0015
213	3251	0	3	99.91%	100.00%	0.0009
214	2265	3	5	99.78%	99.87%	0.0035
215	3363	0	0	100.00%	100.00%	0
217	2209	17	1	99.95%	99.24%	0.0081
219	2154	0	0	100.00%	100.00%	0
220	2048	0	0	100.00%	100.00%	0
221	2427	2	4	99.84%	99.92%	0.0025
222	2483	5	0	100.00%	99.80%	0.0020
223	2605	1	1	99.96%	99.96%	0.0008

228	2053	44	3	99.85%	97.90%	0.0229
230	2256	2	0	100.00%	99.91%	0.0009
231	1571	0	0	100.00%	100.00%	0
232	1780	2	0	100.00%	99.89%	0.0011
233	3079	0	2	99.94%	100.00%	0.0007
234	2753	0	2	99.93%	100.00%	0.0007
Total	109508	405	199	99.82%	99.63%	0.005516

Table III compares the existing algorithms with the proposed one. As shown, the proposed method achieves third lowest detection error rate. The BPF with search-back method & Multiscale morphology method offer slightly better performance. However the computational complexities of these algorithms are relatively high. Hence, compared with other published algorithms the proposed algorithm gives reasonable detection accuracy with low computational complexity and therefore is suitable for low power wearable sensor applications.

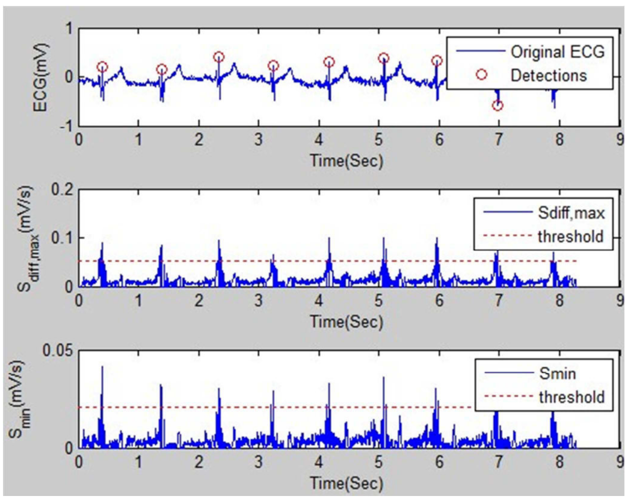

Fig. 3. QRS detection over tape 114 of the MIT/BIH database with large T waves.

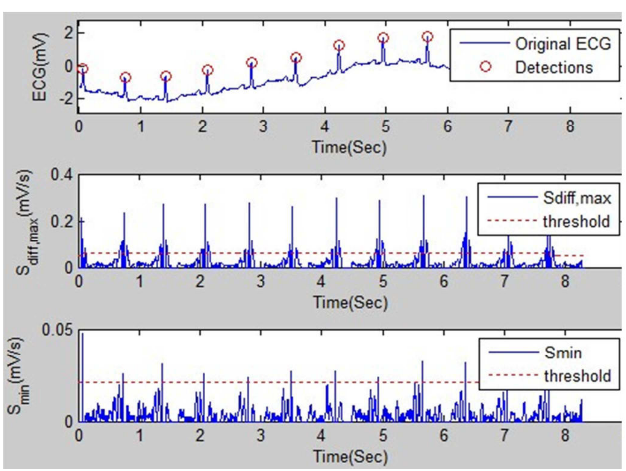

Fig. 4. QRS detection over tape 105 of the MIT/BIH database with baseline drifts.

TABLE III
PERFORMANCE COMPARISON WITH OTHER PUBLISHED ALGORITHM

Method	Total FP	Total FN	DER (%)	Ref
Wavelet De-noising	459	529	0.960%	[3]
Filter Banks	406	374	0.712%	[4]
BPF/Search-back	248	340	0.537%	[5]
Multiscale Morphology	213	204	0.390%	[6]
Proposed method	405	199	0.552%	-

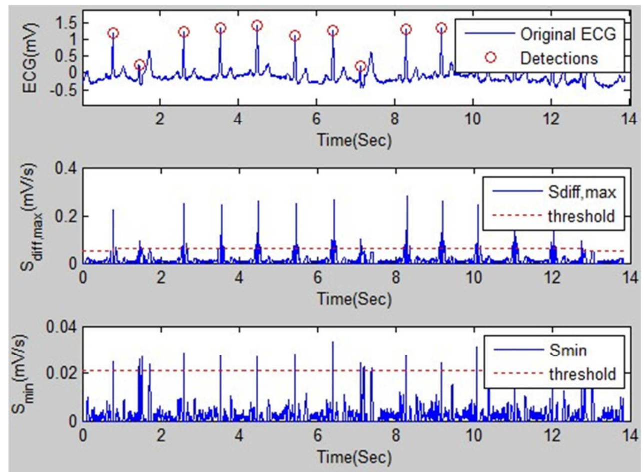

Fig. 5. QRS detection over tape 202 of the MIT/BIH database with sharp changing peak amplitudes.

IV. CONCLUSION

An accurate and computationally efficient Dual-Slope QRS detection algorithm has been presented. The Dual-Slope QRS detection algorithm calculates slopes on both sides of the peaks in ECG. Three criteria on steepness, shape and height respectively are developed to locate the QRS complex. The computational complexity of the proposed algorithm is very low and hence a low power implementation for wearable ECG sensors is achievable. The algorithm was evaluated against MIT/BIH database and achieved a detection rate of 99.45%, a sensitivity of 99.82% and a positive prediction of 99.63%.

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