Computationally Efficient QRS Detection Analysis based on Dual-Slope Method

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***Abstract*— This paper presents a computationally efficient QRS detection algorithm for wearable electrocardiogram (ECG) applications based on dual-slope analysis. In general, ECG signals of arrhythmias are pseudo-periodic and contaminated with noises like the patient's contraction muscles, respiration, 60 Hz interference and other types which impede correct QRS detection. To resolve this problem, in this paper, a technique is presented which is based on two slopes on both sides of a peak in ECG signal. Based on these slopes, a variable measuring steepness is developed and R peaks are detected. The algorithm was evaluated against MIT/BIH arrhythmia database and achieved 99.38% detection rate. This method was compared with one of the recently developed dual-slope based QRS detection methods. The results showed that the proposed method has 12.48 times faster runtime than the old method.**

I. Introduction

A dramatic growth of interest for wearable technology has been fostered by recent technological advances in sensors, low-power integrated circuits and wireless communications [1]. This interest originates from the need of monitoring a patient over extensive period of time. For cardiac patients, wearable heart monitoring sensors have already become a life-saving intervention ensuring continuous monitoring during daily life. Therefore, it is essential for an accurate diagnosis of heart patients. Patients can be equipped with wireless, miniature and lightweight sensors. The sensors temporarily store physiological data and then periodically upload the data to a database server [2]. These recorded data sets are then analyzed to predict any possibility of worsening patient's situation or explored to assess the effect of clinical intervention. To obtain accurate response with less computational complexity as well as long battery life time, there is a demand of developing fast and accurate algorithm and prototypes for wearable heart monitoring sensors. A computationally efficient QRS detection algorithm is indispensable for low power operation on ECG signal.

In need of detecting QRS complex, most of the early works were proposed based on derivatives of ECG signal [3]. They can be easily implemented with high computational speed. But owing to the inherent variability in ECG, these methods are highly affected by large derivatives of baseline noises [4]. Algorithms based on neural network (NN) [5] showed relatively robust performance against noise but requires exhaustive training and estimation of model parameter. On the other hand, wavelet based methods [6] have the choice problem of mother wavelet. Hence, none of these methods is suitable for giving a long battery performance in wearable devices with high accuracy. Recently, Wang *et al*. proposed a novel dual slope QRS detection algorithm [7] which has less computational complexity as well as high accuracy. Considering that the width of the QRS complex is relatively fixed, in range of 0.06-0.1 sec [8], this algorithm is based on the fact that the largest change of slope usually happens at the peak of QRS complex. The hardware requirement is also low. However, the method has a set of time consuming slope calculations on both sides of each sample. To avoid such time consuming slope calculation, only one sample on each side can be highlighted. By taking advantage of the fact that multiplication of the left and right hand side slope should give us a very high value in QRS complex, in this paper, a new method to detect QRS complex is developed and presented. The proposed method is faster with almost the same accuracy.

This paper is organized as follows. In section II, we discuss the details of Wang *et al*. dual-slope based algorithm for QRS detection. The proposed new approach is discussed in section III. In section IV, evaluation and comparison of both algorithms are given. Concluding remarks are drawn in section V.

II. Dual-Slope QRS Detection Algorithm

Typically, the Q, R and S are three deflections which depict a single event and occur in a rapid succession in ECG signal. Starting from Q wave, a down ward deflection, R wave follows with steepest upward deflection and S wave is any downward deflection after the R wave. The time taken by this event is relatively fixed, in the range of 0.06-0.1 sec. Hence, if we calculate the slope of straight line between two samples in ECG signal which are half of the width of QRS complex away from each other the largest values of slope should be found in QRS complex. To consider a signal section as QRS complex, three criteria are defined to check steepness, shape and height of the signal. If all the criteria are satisfied the local extremes are searched in order to locate R peak. Based on this idea, Wang *et al*. developed their dual-slope QRS detection algorithm.

Considering the fact that the half of the width of QRS complex is in the range of 0.03-0.05 sec, the processing of sample begins by calculating all slopes between the current sample and the samples 0.03-0.05 sec away on both sides. The maximum and minimum slopes from each side are then calculated with signs. The slope difference is obtained

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subtracting the maximum slope of one side and minimum slope of other side. A variable $S_{diff,max}$ is defined by taking the maximum value of slope difference. As the wearable devices are for heart patients, the range is extended to 0.027-0.063 sec to increase the sensitivity for abnormal heart beats.

The equation of calculating the maximum and minimum slopes on both sides and the variable measuring steepness $S_{diff,max}$ are given below:

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

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

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

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

$$S_{diff,max} = max \begin{pmatrix} (S_{R,max} - S_{L,min}) - \\ (S_{L,max} - S_{R,min}) \end{pmatrix}, \quad (5)$$

where f_s is the sampling frequency, a and b are the nearest integers of $0.027 f_s$ and $0.063 f_s$, respectively and z^n is the n^{th} sample in ECG signal.

An adaptive preset threshold is defined as Θ_{diff} which must be updated according to average value of $S_{diff,max}$ of previously detected 8 peaks. $S_{diff,max}$ must be larger than Θ_{diff} to satisfy the first criteria. The rules for updating are given below:

$$\begin{aligned} \Theta_{diff} &= \frac{7680}{f_s} && \text{if } S_{ave} > \frac{20480}{f_s} \\ \Theta_{diff} &= \frac{7680}{f_s} && \text{if } \frac{12800}{f_s} < S_{ave} < \frac{20480}{f_s} \\ \Theta_{diff} &= \frac{7680}{f_s} && \text{if } S_{ave} < \frac{12800}{f_s} \end{aligned} \quad (6)$$

To avoid false high values of $S_{diff,max}$ causing from flat slope on one side and steep slope from other side, another criterion is introduced to check the shape. QRS complex should have a ramp like shape on both sides at an R peak. So the sign of the slope on both sides should be opposite and the value should be grater then a minimum value. The conditions are:

$$\begin{gathered} S_{min} = min(|S_{L,max}|, |S_{R,min}|) > \Theta_{min} \text{ and} \\ sgn(S_{L,max}) = -sgn(S_{R,min}) \\ (if\ S_{L,max} - S_{R,min} > S_{R,max} - S_{L,min}), \end{gathered} \quad (7)$$

$$\begin{gathered} S_{min} = min(|S_{R,max}|, |S_{L,min}|) > \Theta_{min} \text{ and} \\ sgn(S_{R,max}) = -sgn(S_{L,min}) \\ (if\ S_{R,max} - S_{L,min} > S_{L,max} - S_{R,min}), \end{gathered} \quad (8)$$

where the value of Θ_{min} is $1536/f_s$.

The third criterion is based on the height of the slope. For noise and other sharp waves, we have high values of slope but the heights of the slopes are not as high as in QRS complex. So checking the height will eliminate the possibility of detecting such unwanted peaks. Therefore, the third condition is:

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

where H_{cur} is the height of current slope and H_{ave} is the average slope height of previous 8 detected peaks. If all the criteria are satisfied then we look forward to find the local extremes in that signal section followed by adjustment to avoid multiple detections within one section. The one with large value of $S_{diff,max}$ is considered as the R peak.

III. The Proposed Dual-Slope QRS Detection Algorithm

To find the slope difference, a set of slopes needs to be calculated on both sides for each sample which is time consuming. Instead of highlighting all the samples from 0.027 to 0.063 sec, only one sample between these two points can be focused to calculate the slopes on both sides. As R peaks usually have very steep slopes, multiplying both slopes rather taking difference gives us higher values at R peaks in QRS complex. Based on this idea, a new dual-slope QRS detection algorithm is proposed.

In order to get a high value of slope at R peaks, a sample closer to current sample should be highlighted on both sides. Instead of taking a set of points we choose only one sample 0.027 sec away from current sample and calculate the slopes on both sides. The equations to calculate the slopes are:

$$S_{Left} = \left(\frac{z^{-a} - z^{-(a-k)}}{k} \right) \quad (10)$$

$$S_{Right} = \left(\frac{z^{-a} - z^{-(a-k)}}{-k} \right) \quad (11)$$

By multiplying S_{Left} with S_{Right} for each sample, our new steepness measuring variable S_{mult} is evaluated as follows:

$$S_{mult} = S_{left} \times S_{right} \quad (12)$$

To consider a sample as an R peak, the sign of slope on both sides should be opposite, i.e.,

$$sgn(S_{left}) = -sgn(S_{right}) \quad (13)$$

The value of S_{mult} is then compared with a fixed preset threshold value Θ_{mult}, i.e.,

$$S_{mult} > \Theta_{mult} \quad (14)$$

where the value of Θ_{mult} is $18000/f_s$ and f_s is the sampling frequency of ECG signal. The value of Θ_{mult} was selected by trial and error to get optimal result.

If all the conditions are met, local extremes are searched in current signal section to determine the location of R peak. If two detections are too closed to each other, the one with large value of S_{mult} is retained as an R peak.

By taking one sample on each side and multiplying those with each other, the time consuming calculation of a set of slopes followed by searching maximum and minimum slopes is eliminated which makes it even faster and less computable. A flow chart of the proposed dual slope algorithm is given in Fig. 1.

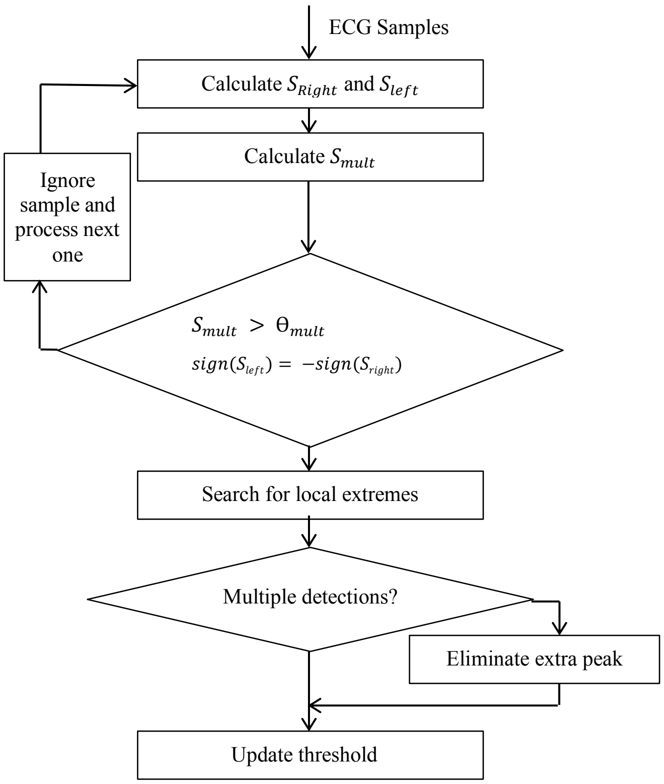

Figure 1. Block diagram of the proposed new dual-slope algorithm.

IV. Result and Discussion

Both the algorithms are evaluated using MIT/BIH arrhythmia database [9] under MATLAB environment on a same computer. It is a standard database with 48 half-hour two channel ECG recordings. These recordings are sampled at 360Hz and have 11 bit resolution over 10 mV.

To analyze the performance, we evaluated false negative (FN) and false positive (FP). A false negative (FN) occurs when algorithm fails to detect an actual QRS complex quoted in the corresponding annotation file of the MIT-BIH database record and a false positive (FP) means a false beat detection. Using FP and FN, we calculated error rate (ER) based on the following equation:

$$ER(\%) = \frac{FP + FN}{Total\ QRS} \quad (15)$$

where Total QRS is total number of QRS complex in the ECG data.

Table I shows the summary of QRS detection for both algorithms. Here, after applying the algorithm of Wang et al. we got slightly different error rate. Figs. 2-4 show the performance of the algorithm. In Fig. 2, the first graph is the ECG signal and detected R peaks are marked as circle "o". The following graphs in Fig. 2 represent $S_{diff,max}$, S_{min} and S_{mult} respectively. It is clear that the variable S_{mult} at R peaks is giving very high values with respect to $S_{diff,max}$ and S_{min} for a same signal section. Figs. 3 and 4 show the robustness of the new approach against baseline drift and signals with large T waves respectively by demonstrating the detected R peaks marked as circle "o". It is clear that regardless of baseline drift or signals with large T waves the QRS complex can be accurately detected.

TABLE I. Performance of the Algorithms using The MIT/BIH Database

Tape	Total	Dual-slope algorithm[7] (based on maximum slope difference)				New Dual-slope algorithm (based on slope multiplication)			
		FN	***FP***	***ER (%)***	***T (sec)***	***FN***	***FP***	***ER (%)***	***T (sec)***
100	2273	2	0	0.09	20.55	2	0	0.09	1.44
101	1865	0	4	0.21	20.50	0	4	0.21	1.6
102	2187	0	0	0.00	20.41	10	0	0.46	1.35
103	2084	0	0	0.00	20.57	0	0	0.00	1.62
104	2229	0	35	1.57	20.47	0	59	2.65	1.38
105	2572	1	72	2.84	20.99	1	82	3.23	1.85
106	2027	4	3	0.35	20.70	0	8	0.39	1.65
107	2137	3	0	0.14	20.68	4	4	0.37	1.42
108	1774	31	23	3.04	20.42	55	53	6.09	1.43
109	2532	4	1	0.20	20.76	5	1	0.24	1.87
111	2124	2	2	0.19	20.89	2	1	0.14	1.44
112	2539	0	0	0.00	20.75	0	2	0.08	1.62
113	1795	1	0	0.06	20.57	1	0	0.06	1.54
114	1879	3	1	0.21	20.71	1	0	0.05	1.68
115	1953	0	0	0.00	20.73	0	0	0.00	1.64
116	2412	5	2	0.29	20.83	3	0	0.12	1.84
117	1535	3	0	0.20	20.62	0	1	0.07	1.44
118	2278	0	0	0.00	20.58	0	2	0.09	1.61
119	1987	0	0	0.00	20.66	0	0	0.00	1.67
121	1863	0	2	0.11	20.62	0	2	0.11	1.57
122	2476	0	1	0.04	20.88	0	0	0.00	1.85
123	1518	0	1	0.07	20.72	0	1	0.07	1.56
124	1619	1	2	0.19	20.73	0	2	0.12	1.61
200	2601	10	30	1.54	20.67	4	47	1.96	1.76
201	1963	51	0	2.60	20.75	38	0	1.94	1.55
202	2136	1	0	0.05	20.78	3	0	0.14	1.71
203	2980	3	79	2.75	20.92	2	67	2.32	1.84
205	2656	0	2	0.08	20.77	1	2	0.11	1.59
207	1860	29	35	3.44	20.53	17	28	2.42	1.72
208	2955	4	18	0.74	20.88	3	16	0.64	1.74
209	3004	0	4	0.13	20.86	0	7	0.23	1.70
210	2650	4	18	0.83	20.98	7	15	0.83	1.76
212	2748	0	10	0.36	20.75	0	13	0.47	1.72
213	3251	1	3	0.12	21.02	3	3	0.18	2.06
214	2265	4	3	0.31	20.86	2	2	0.18	1.78
215	3363	0	2	0.06	20.94	0	0	0.00	1.87
217	2209	8	2	0.45	20.68	3	6	0.41	1.74
219	2154	0	0	0.00	20.85	3	1	0.19	1.78
220	2048	0	0	0.00	20.75	0	0	0.00	1.68
221	2427	6	1	0.29	21.09	8	2	0.41	1.77
222	2483	0	3	0.12	20.58	5	0	0.20	1.40
223	2605	4	1	0.19	20.87	5	1	0.23	1.84
228	2053	18	44	3.02	20.61	2	53	2.68	1.51
230	2256	0	2	0.09	20.88	0	3	0.13	1.59
231	1571	0	0	0.00	20.55	0	0	0.00	1.45
232	1780	0	3	0.17	20.59	2	0	0.11	1.44
233	3079	1	0	0.03	20.13	0	3	0.10	2.01
234	2753	2	0	0.07	20.50	0	0	0.00	1.81
Total	109508	206	409	0.56	20.71	192	491	0.62	1.66

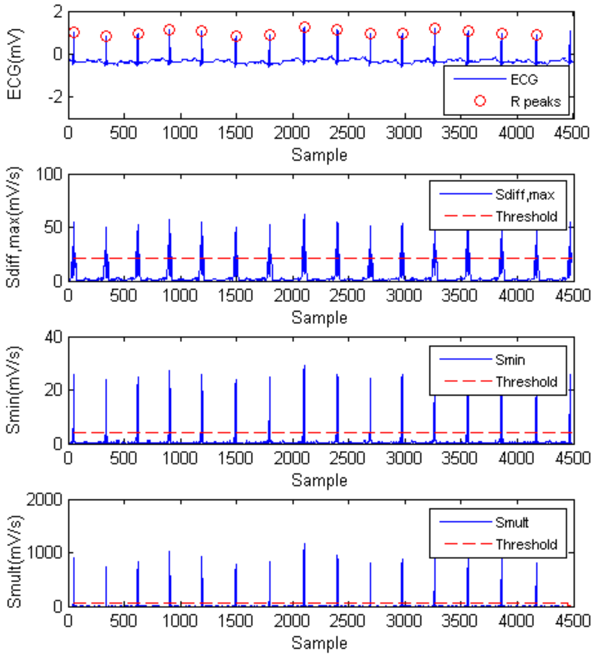

Figure 2. QRS detection over tape 205 of MIT-BIH database shohwing different veriebles for both algorithms.

Furthermore, total time (T) for each recording was calculated using the MATLAB environment based on the same computer for both old and proposed methods. Table II compares the average time taken by these two algorithms. As shown, the proposed method is 12.48 times faster than the previous one with almost the same accuracy. Hence, this algorithm is highly suitable for wearable devices.

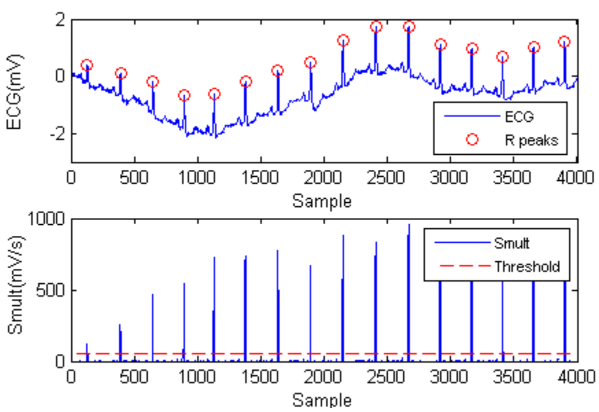

Figure 3. QRS detection over tape 105 of MIT-BIH database with baseline drifts.

TABLE II. COMPARISON OF TWO ALGORITHMS

Method	***Total FN***	***Total FP***	***Error rate***	***Processing Time***
Proposed Dual-Slope	206	409	0.62	1.66
Dual-Slope [7]	192	291	0.56	20.71

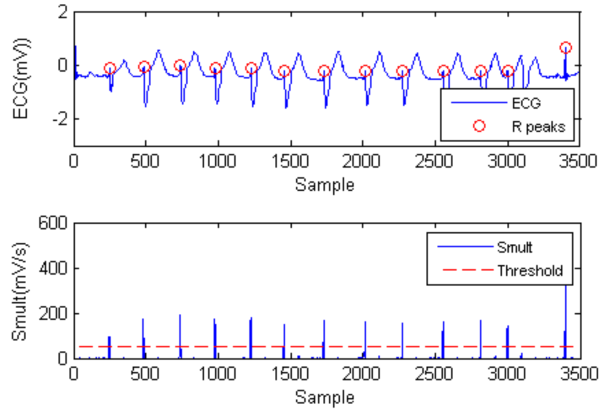

Figure 4. QRS detection over tape 205 of MIT-BIH database with large T waves.

V. Conclusion

In this paper, a new dual slope QRS detection algorithm was presented and its performance was compared with the performance of a recently developed dual-slope based algorithm when applied to MIT-BIH database. The processing time and computational complexity are important factors for successful development of wearable sensors. The proposed algorithm is faster in processing time and lower in computational complexity compared to the previous algorithm.

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