Automatic QRS Onset Detection of ECG Signal using Secant Line Slope Formula

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***Abstract*—In automatic electrocardiogram (ECG) signal analysis, the QRS onset must be identified prior to QT interval or QRS duration measurements. These measurements are decisive ECG parameters for diagnosing cardiac abnormalities among cardiologists. Hence, the efficiency of the developed automatic algorithm to detect the QRS onset is essential to obtain an accurate result of the ECG parameters. In this report, an algorithm to detect the QRS onset based on secant line slope formula is proposed. The preprocessing and wave delineation process were implemented in MATLAB using modified Pan-Tompkins algorithm (an established adaptive threshold method). The window of the preceding Q-wave was determined before calculating the slope of secant line along the descending slope for QRS onset detection. The performance of the proposed algorithm was evaluated using 25 subjects from Pusat Perubatan Universiti Kebangsaan Malaysia (PPUKM) and volunteered participants under the approval of Research and Ethics Committee, PPUKM (Code of ethics approval: FF-2013-313). All data were acquired using biosignal amplifier (g.USBamp by g.tec, Austria) with 2 minutes duration of recording and sampled at 512 Hz. The efficiency of the proposed algorithm has obtained a sensitivity of 99.67%, positive predictivity of 99.39%, and accuracy of 99.07%. The result shows stable performance and insensitivity of the proposed algorithm towards ECG wave morphology changes.**

Keywords—automatic ECG detection, Pan-Tompkins algorithm, QRS onset, secant line slope

I. Introduction

The Q-wave is an initial negative deflection of the QRS complex on ECG signal. The beginning of Q-wave or typically termed as QRS onset is also defined as the beginning of R-wave if Q-wave is absent [1]. Fig. 1 represents a typical cycle of ECG trace with delineation of QRS onset and other characteristic points. In ECG signal analysis, QRS onset must be identified earlier before measuring the QT interval or QRS duration. These measurements are decisive ECG parameters for diagnosing cardiac abnormalities among cardiologists, and they require more reliable and accurate methods to avoid misdiagnosis.

The QRS onset can be detected using manual or automatic methods. However, manual detection of QRS onset or any point of waves on the ECG signal is time consuming and prone to produce inaccurate result due to observer's lapse of attention. Automatic detection on the other hand, offers many advantages over the manual method in terms of absolute repeatability of measurement, fast result, immunity from errors related to observer's fatigue, and cost effective [2].

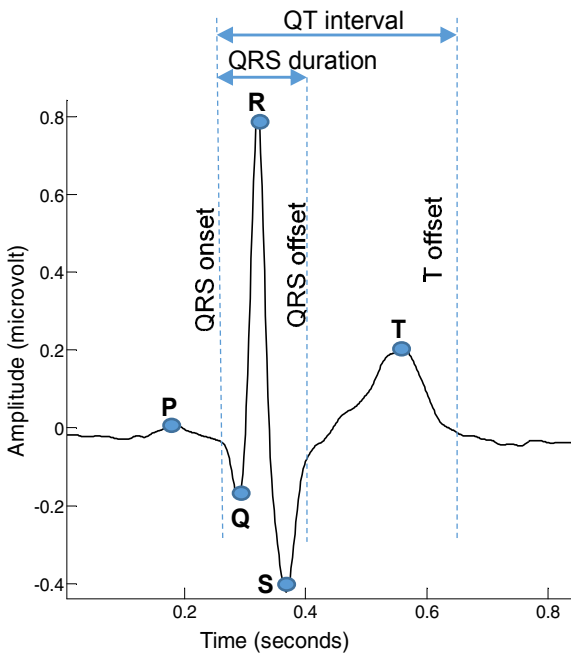

Fig. 1. A cycle of ECG trace with the characteristic point of waves and intervals.

A variety of methods have been used in the literature to detect the QRS onset in specific with modification and extention of the existing QRS complex detection methods [4], [5], [12]. In 1997, a maximum slope method was proposed by [13] to identify the QRS complex with the QRS onset was detected when two successive values of slope exceed the threshold. The method was derived and improved from the first derivative method [5]. However, no statistical analysis was shown to approve the effectiveness of their method in detecting the QRS onset. Subsequently, work in [14] was compared [13] with Pan-Tompkins algorithm [4] and extended the work of [13] with P-wave and T-wave detection. They introduced ECG classification using autocorrelation approach but in certain circumstances, the detected T-wave in the previous beat was found overlapped with the P-wave in the current beat.

Other work by [15] presented an open source algorithm that employed and extended the basics of the simplified curve length transform [16] after filtering. This method applied the adaptive threshold to the length signal to determine the onset and duration of the QRS complexes.

Most recent, [17] proposed a simple algorithm for QRS onset detection based on first differential and adaptive baseline estimation in single channel ECG signals. Prior to QRS onset detection, the R-peaks were obtained using Hilbert transformation. However this method only works reliably with well-defined ECG signal.

In this work, an algorithm to detect the QRS onset based on secant line slope formula is proposed. The preprocessing and wave delineation process are implemented in MATLAB using modified Pan-Tompkins algorithm [4]. After the R-peak is detected, the window of the preceding Q-wave will be determined before calculating the slope of secant line along the descending slope for QRS onset detection.

II. Methodology

A. Data acquisition

The raw ECG signals were acquired using biosignal amplifier (g.USBamp by g.tec, Austria) with 24-bit resolution, as shown in Fig. 2. Four electrodes (RA- right arm, RL-right leg, LA- left arm, and LL- left leg) plus a single unipolar lead (V6), were connected to the biosignal amplifier to obtain clear T-wave from the ECG signal [18].

During the procedure, the Simulink from Mathwork, Inc. was using as the interfacing software. The biosignal amplifier block provides the data in float32 format which then scaled to microvolts. Each data contains of 2 minutes recording and was sampled at 512 Hz. Initially, from four channels of data obtained from a subject, only one channel (lead) was selected as the raw data for the signal processing. The selection was based on non-inverted signal (cause by the polarity of biopotential lead placement) and clear visibility of the QRS complexes and the T-waves.

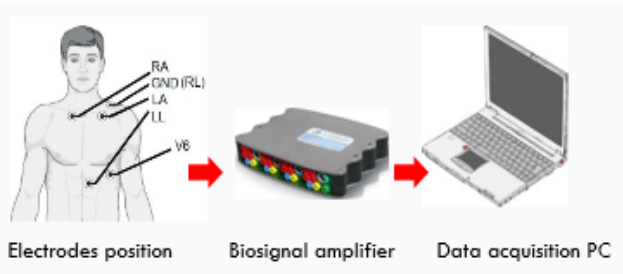

Fig. 2. Graphic representation of data acquisition method.

B. Algorithm Implementation

The algorithm was modified and extended the Pan-Tompkins algorithm, a widely cited study to obtain QRS complexes using the adaptive threshold method. Pan-Tompkins algorithm was developed in assembly language using integer arithmetic [4], which quickly adapt to the ECG signal changes with exemplary detection even in noisy signals. Many studies have proven that this algorithm is more computationally efficient compared to other QRS complex detection methods and possibly implemented into embedded system due to light memory [19], [20]. The block diagram of the proposed algorithm is shown in Fig. 3.

1) Preprocessing Signal: At the preprocessing stage, the first 500 points of a signal data were truncated to eliminate the transient effect. For better visualization and comparison purpose, the DC baseline was removed and the signal was normalized. The DC baseline removal was done by removing the mean of the signal. Meanwhile the normalization was done by rescaling the signal into amplitude of -1 to 1. Originally, at this stage, Pan-Tompkins algorithm applied the digital band-pass filter of 5-15 Hz to the raw signal to attenuate the artefacts. In this work, a few modifications were made at the preprocessing stage to improve the performance of the algorithm. The cut-off frequencies of 0.5 (for baseline drift removal), and 45 Hz (for powerline or network interference) were selected in Butterworth Bandpass digital filter function due to its linear phase characteristic in preserving the original signal with minimized of distortion [21].

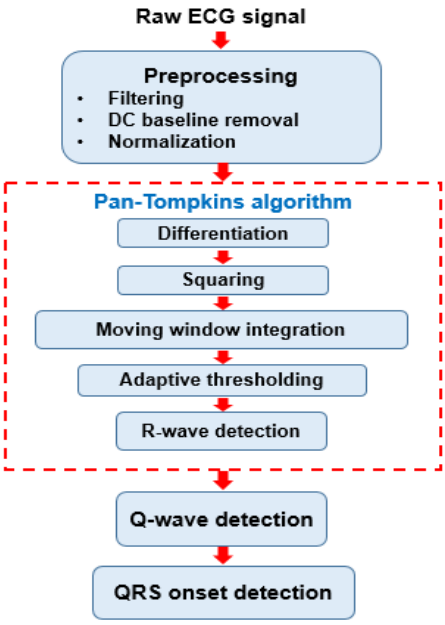

Fig. 3. Block diagram of the proposed algorithm.

2) QRS-complex detection: After the preprocessing stage, the algorithm followed the procedure of Pan-Tompkins algorithm to identify the R-wave in QRS-complex. This stage highlighted the QRS-complex by using the derivative function (1) to provide the QRS-complex slope information. Then the signal was intensified by using the squaring function (2), which also helped in restricting false positive that caused by T-wave [4]. Next, the moving window integration was performed to obtain the width of integrator window, as written in (3). This is a supplementary information of slope in QRS-complex feature, where it produces a roughly pulse-shaped waveform. In (1)-(3), $y(n)$ is the signal output, T is the sampling period, $x(n)$ is the signal input, and N is the number of samples in the width of the integration window [4].

$$y(nT) = (1/8T)\,[-x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T)] \quad (1)$$

$$y(nT) = [x(nT)]^2 \quad (2)$$

$$y(nT) = (1/N)\,[x(nT-(N-1)\,T) + x(nT-(N-2)\,T) + \ldots + x(nT)] \quad (3)$$

3) Adaptive thresholding: In adaptive thresholding procedure, a decision on the pulse whether it corresponds to QRS complex or not (as opposed to a high-sloped T-wave or a noise) will be made. The dual-threshold technique was used to find missed beats, where two separate threshold levels were set up for two sets of threshold. For each set, the level was half of the other. To limit the number of false negatives, this procedure also has searchback algorithm for missed qrs complexes [4], [22].

4) QRS onset detection: Once the peak of R-wave (R-point) is detected, the detection of QRS onset begins with finding the Q-point, a minimum point of Q-wave that falls in the 150 ms range (window size) preceding the R-point. In Fig. 4, along the descending slope preceding the Q-point, another window frame of 42 ms (21 points) is selected to initiate the secant line slope calculation, written in (4) for detecting the QRS onset, where Δx is the stepping of three points in time axis within seven intervals, and $\Delta y(x)$ is the amplitude difference.

$$Slope = \Delta y(x) \,/\, \Delta x \quad (4)$$

From seven intervals of secant line slope calculation, the first point where the slope yields maximum result is chosen as the QRS onset. The window frame of preceding Q-wave must be chosen carefully. If the value is too wide, the algorithm will falsely detect QRS onset point which most probably the P-wave because the similar descending slope feature. Meanwhile, the stepping point is selected as minimum as possible to obtain a precise point of QRS onset.

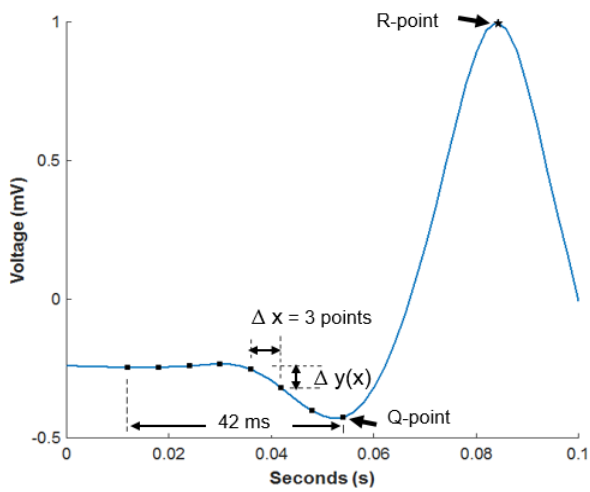

Fig. 4. Secant line slope method for QRS onset detection.

III. Results

Fig. 5 and Fig. 6 represent the MATLAB output for automatic detection of R-wave, Q-wave, and QRS-onset for control subject and MI patient, respectively using the secant line slope method. The efficiency of this algorithm had been evaluated using 25 subjects from Pusat Perubatan Universiti Kebangsaan Malaysia (PPUKM) and volunteered participants under the approval of Research and Ethics Committee, PPUKM (Code of ethics approval: FF-2013-313).

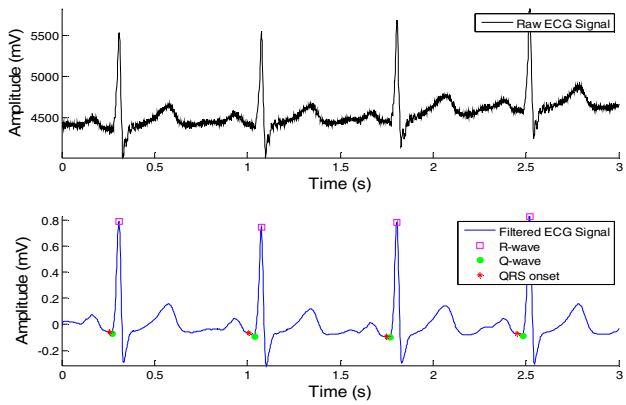

Fig. 5. MATLAB result for control subject with raw signal (top) and automatic detection of R-wave, Q-wave, and QRS-onset (below).

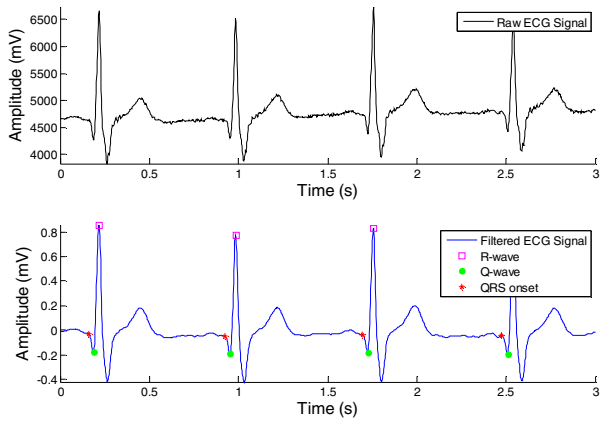

Fig. 6. MATLAB result for MI patient with raw signal (top) and automatic detection of R-wave, Q-wave, and QRS-onset (below).

As shown in Table I, 3648 of actual beats are counted from manual annotation. The algorithm's efficiency was measured using the following statistical formula in (5)-(7) [12], [23]. The QRS onset detection is counted as true positive (*TP*) if the algorithm detects the correct point, false positive (*FP*) if detect the incorrect point, and true negative (*TN*) for missing point.

$$Sensitivity = TP / (TP + FN) \quad (5)$$

$$Positive\ predictivity = TP / (TP + FP) \quad (6)$$

$$Accuracy = TP / (TP + FN + FP) \quad (7)$$

IV. Conclusion

The efficiency of proposed algorithm has obtained a sensitivity of 99.67%, positive predictive of 99.39%, and accuracy of 99.07% even in the presence of significant noise contamination. The result also shows stable performance and insensitivity of the proposed algorithm towards ECG wave morphology changes. This algorithm is an initial part of determining the other parameters in automated ECG analysis, such as QT interval or QRS duration measurement. The completion of the algorithm for automatic measurement of ECG parameters will depend on combining the QRS onset algorithm with the upcoming detection algorithm (QRS offset or T-wave offset). The complete algorithm can be used as the basis of software development in the future.

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TABLE I. Performance evaluation of the proposed method using 25 data from PPUKM and volunteered participants from UKM staff and students

File name	Control subject	MI patient	Actual beats	TP	FP	FN	Sensitivity (%)	Positive Predictivity (%)	Accuracy (%)
sc003	x		158	158	0	0	100.00	100.00	100.00
sc004	x		124	122	2	0	100.00	98.39	98.39
sc006	x		129	129	0	0	100.00	100.00	100.00
sc008	x		139	139	0	0	100.00	100.00	100.00
sc009	x		126	126	0	0	100.00	100.00	100.00
sc010	x		94	94	0	0	100.00	100.00	100.00
sc012	x		157	157	0	0	100.00	100.00	100.00
sc013	x		144	143	0	1	99.31	100.00	99.31
sc015	x		170	169	1	0	100.00	99.41	99.41
sc016	x		130	126	3	1	99.21	97.67	96.92
sc018	x		134	133	1	0	100.00	99.25	99.25
sc019	x		136	136	0	0	100.00	100.00	100.00
sc020	x		151	151	0	0	100.00	100.00	100.00
sc021	x		180	178	1	1	99.44	99.44	98.89
sc022	x		128	127	0	1	99.22	100.00	99.22
sc025	x		119	119	0	0	100.00	100.00	100.00
sc026	x		157	157	0	0	100.00	100.00	100.00
sc027	x		138	138	0	0	100.00	100.00	100.00
sc028	x		147	147	0	0	100.00	100.00	100.00
s002		x	200	192	7	1	99.48	96.48	96.00
s004		x	144	144	0	0	100.00	100.00	100.00
s007		x	164	163	0	1	99.39	100.00	99.39
s008		x	189	189	0	0	100.00	100.00	100.00
sc009		x	156	147	3	6	96.08	98.00	94.23
s011		x	134	130	4	0	100.00	97.01	97.01
Total	**19**	**6**	**3648**	**3614**	**22**	**12**	**99.67**	**99.39**	**99.07**

REFERENCES

[1] P. Laguna, N. V. Thakor, P. Caminal, R. Jane, and H.-R. Yoon, "New algorithm for QT interval analysis in 24-hour Holter ECG: performance and applications," *Med. Biol. Eng. Comput.*, vol. 28, no. 1, pp. 67–73, 1990.

[2] I. I. Christov, I. I. Simova, and C. Cardiology, "Fully Automated Method for QT Interval Measurement in ECG Centre of Biomedical Engineering , Bulgarian Academy of Sciences , Sofia , Bulgaria Automatic selection of a representa- Signal preprocessing," pp. 321–324, 2006.

[3] F. W. Stallmann and H. V Pipberger, "Automatic Recognition of Electrocardiographic Waves by Digital Computer," *Circ. Res.*, no. 9, pp. 1138–1143, 1961.

[4] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, 1985.

[5] G. M. Friesen, T. C. Jannett, M. A. Jadallah, S. L. Yates, S. R. Quint, and H. T. Nagle, "A Comparison of the Noise Sensitivity of Nine QRS Detection Algorithms," vol. 37, no. 1, pp. 85–98, 1990.

[6] H. A. N. Dinh *et al.*, "A Wavelet-Based ECG Delineator: Evaluation on Standard Databases," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 570–581, 2004.

[7] H. A. N. Dinh, D. K. Kumar, and N. D. Pah, "Wavelets for QRS Detection," vol. 24, no. 4, pp. 207–211, 2001.

[8] E. H. El Mimouni and M. Karim, "Novel real-time FPGA-based QRS detector using adaptive threshold with the previous smallest peak of ECG signal," *J. Theor. Appl. Inf. Technol.*, vol. 50, no. 1, pp. 33–43, 2013.

[9] R. Gutierrez, J. J. Garcia, W. P. Marnane, and A. Hernandez, "Novel Real-Time Low-Complexity QRS Complex Detector Based on Adaptive Thresholding," *IEEE Sens. J.*, vol. 15, no. 10, pp. 6036–6043, 2015.

[10] G. V. Van and K. V. Podmasteryev, "Algorithm for detection the QRS complexes based on support vector machine," 2017.

[11] Y. Xiang, Z. Lin, and J. Meng, "Automatic QRS complex detection using two-level convolutional neural network," *Biomed. Eng. Online*, vol. 17, no. 1, pp. 1–17, 2018.

[12] B. U. Köhler, C. Hennig, and R. Orglmeister, "The principles of software QRS detection," *IEEE Eng. Med. Biol. Mag.*, vol. 21, no. 1, pp. 42–57, 2002.

[13] H. H. So and K. L. Chan, "Development of QRS Detection Method for Real-time Ambulatory Cardiac Monitor," in *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1997, pp. 289–292.

[14] K. F. Tan, K. L. Chan, and K. Choi, "Detection of the QRS complex, P wave and T wave in electrocardiogram," in *2000 First International Conference Advances in Medical Signal and Information Processing (IEE Conf. Publ. No. 476)*, 2000, pp. 41–47.

[15] W. Zong, G. B. Moody, and D. Jiang, "A robust open-source algorithm to detect onset and duration of QRS complexes," *Comput. Cardiol.*, vol. 30, pp. 737–740, 2003.

[16] F. Gritzali, "Towards a generalization scheme for QRS detection in ECG waveforms," *Signal Processing*, vol. 15, no. 2, pp. 183–192, 1988.

[17] D. S. Benitez, "A Simple Algorithm for Detection of QRS Onset in Single Channel ECG Signals," in *2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON)*, 2017.

[18] N. Mahri, K. B. Gan, and M. A. M. Ali, "Extracting features similar to QT interval from second derivatives of photoplethysmography: A feasibility study," *IECBES 2014, Conf. Proc. - 2014 IEEE Conf. Biomed. Eng. Sci.*, no. December, pp. 470–473, 2015.

[19] R. A. Álvarez, A. J. M. Penín, and X. A. V. Sobrino, "A Comparison of Three QRS Detection Algorithms Over a Public Database," *Procedia Technol.*, vol. 9, pp. 1159–1165, 2013.

[20] C. Pavlatos, A. Dimopoulos, G. Manis, and G. Papakonstantinou, "Hardware implementation of Pan {&} Tompkins QRS detection algorithm," *Proc. EMBEC'05 Conf.*, p. 5, 2005.

[21] G. Lenis, N. Pilia, A. Loewe, W. H. W. Schulze, and O. Dössel, "Comparison of Baseline Wander Removal Techniques considering the Preservation of ST Changes in the Ischemic ECG: A Simulation Study," *Comput. Math. Methods Med.*, vol. 2017, 2017.

[22] H. Sedghamiz, "Matlab Implementation of Pan Tompkins ECG QRS detector," pp. 1–3, 2014.

[23] AAMI, "American National Standard for Ambulatory Electrocardiographs, Publication ANSI/AAMI EC38-1994, Association for the Advancement of Medical Instrumentation.," 1994.