J Electr Eng Technol.2018; 13(5): 2080-2085
http://doi.org/10.5370/JEET.2018.13.5.2080

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

A Simple and Robustness Algorithm for ECG R- peak Detection

Md Saifur Rahman*, ChulhyungChoi*, Young-pil Kim* and Sikyung Kim†

Abstract – There have been numerous studies that extract the R-peak from electrocardiogram (ECG) signals. All of these studies can extract R-peak from ECG. However, these methods are complicated and difficult to implement in a real-time portable ECG device. After filtration choosing a threshold value for R-peak detection is a big challenge. Fixed threshold scheme is sometimes unable to detect low R-peak value and adaptive threshold sometime detect wrong R-peak for more adaptation. In this paper, a simple and robustness algorithm is proposed to detect R-peak with less complexity. This method also solves the problem of threshold value selection. Using the adaptive filter, the baseline drift can be removed from ECG signal. After filtration, an appropriate threshold value is automatically chosen by using the minimum and maximum value of an ECG signals. Then the neighborhood searching scheme is applied under threshold value to detect R-peak from ECG signals. Proposed method improves the detection and accuracy rate of R-peak detection. After R-peak detection, we calculate heart rate to know the heart condition.

Keywords: ECG, NLMS, Adaptive filter, Baseline wander, R-peak, BPM, HRV.

1. Introduction

Cardiovascular information latent into electrocardiogram (ECG) signals. As a result, ECG plays a vital role to detect and assess the cardiovascular diseases accurately. ECG signal is a representation of a heart activity during depolarization and repolarization of the heart. Heartbeats detection help to analyze heart rate variability (HRV) and cardiovascular diseases. ECG waveform characteristics are shown in Fig.1. There are six waves like P, Q, R, S, T and U. Heartbeats are calculated by R-R interval. However, R peak detection from ECG is not a simple task by dint of noise such as power line interference and baseline drift. There are several studies about R-peak detection from ECG signals. Sasan Yazdani [1] proposed a method to detect R-peak using sliding window technique. However, this technique is bounded by minimum distance 250ms and the normalized amplitude greater than 0.02mV. Another disadvantage of this technique is a high-pass filter. Sometimes high-pass filter failed to remove non-linear baseline drift. Ravanshad [2] used the level-crossing method to detect R-peak. However, this technique can give an accurate result for some fixed number of resolution and quantization.

During Low amplitude of R-peak, this method missed R-peak. Martínez [3] and Bahoura [4] proposed method based on wavelet transformation for R-peak detection. The disadvantage of this method disadvantage is computational complexity which is a big problem for portable ECG device. Pan j. [5] analyzed slope, amplitude and width of a QRS complex for R-peak detection. They used back-forth threshold method to detect R-peak accurately which increased the method complexity for a portable device with low power processor. Others researcher used mathematical morphology to detect R wave [6, 7]. In this paper, we proposed an efficient, robustness and low complexity algorithm to detect R-peak from ECG signals. The proposed technique works based on min-max and neighbour searching method. This method also works for any kind of peak detection.

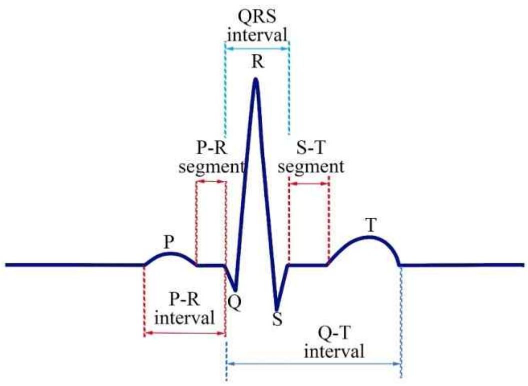


Fig. 1. Representation of P, Q, R, S and T wave in ECG signal

2. The Proposed Algorithm

2.1 Block diagram

Fig. 2. illustrates the block diagram of the proposed

† Corresponding Author: Dept. of Electrical and Electronic Engineering, Kongju National University, Korea. (skim@kongju.ac.kr)
* Dept. of Electrical and Electronic Engineering, Kongju National University, Korea. (r.rabbe@yahoo.com, {cch019, dudvlf456}@naver.com)
Received: August 23, 2017; Accepted: April 25, 2018

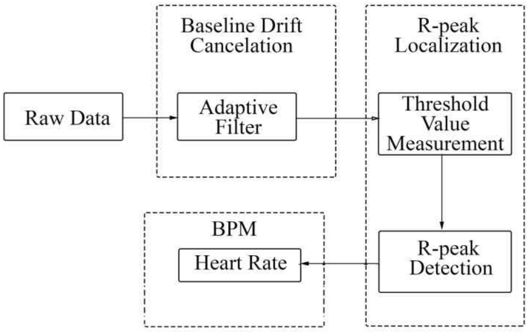


Fig. 2. Block diagram for proposed algorithm

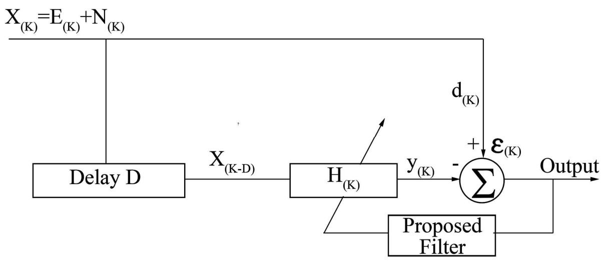


Fig. 3. Block diagram for NLMS filter

algorithm for R-peak detection and heart rate measurement. This algorithm works based on five steps.

- Raw ECG data measurement
- Baseline drift filtrations
- Threshold value measurement
- Local maxima detection
- Heart rate calculation

2.1.1 Baseline drifts filtrations

The baseline drift and power line signal are common noise with the high-frequency component. These noises hampered to detect R peak from ECG signal. For this reason, signal filtration is required to remove baseline drift and power line noise. We used normalized least mean square (NLMS) filter. Fig. 3. shows the block diagram for NLMS filter. Eq. (1) presents the coefficient of the filter.

$$H_{(k+1)} = H_{(k)} + \frac{\mu\varepsilon_{(k)}X_{(k)}}{X^H_{(k)}X_{(k)}} \tag{1}$$

Where, k is the number of sample. $X_{(k)}$, is the measured ECG signal corrupted by noises. $H_{(K)}$ is the filter coefficient. $X^H_{(k)}$ is the hermitian transpose. The adaptive filter output $y_{(K)}$ can be expressed as

$$y_{(K)} = \sum_{i=0}^{K-1} H_{(K)} \times X_{(K-i)} \quad = H^T_{(K)} \times X_{(K)} \tag{2}$$

$y_{(K)}$ is the adaptive filter output.

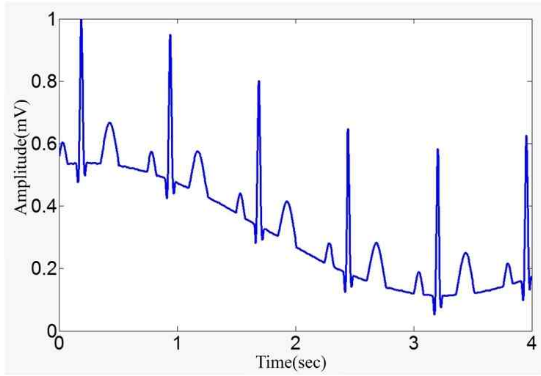


Fig. 4. Measured raw ECG data with baseline noise

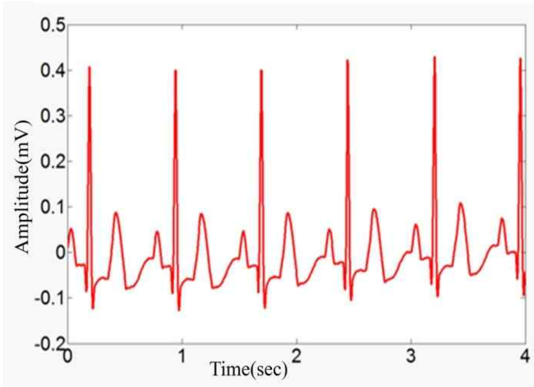


Fig. 5. Baseline wanders reduction from ECG signal

$$\varepsilon_{(K)} = d_{(K)} - y_{(K)} \tag{3}$$

Error signal $\varepsilon_{(K)}$ is calculated by getting the difference between desired signal $d_{(K)}$ and filter output, $y_{(K)}$. μ is the step size and L is the filter order.

Fig. 4. shows the measured raw ECG data corrupted by baseline drift. Baseline drift is removed after applying NLMS filter which present in Fig. 5. The adaptive filter is very effective for linear and non-linear baseline drift.

2.1.2 Threshold value measurement

For the R-peak detection, the maximum and minimum value of the filtered ECG signals are calculated to setup the threshold value of the R-peak detection. Let's say that the filtered ECG data can be represented as:

$$\text{Filtered ECG} = \{a_1, a_2, a_3, \ldots, a_n\} \tag{4}$$

Here, n is the number of ECG data.

The maximum ECG amplitude of ECG data can be written as

$$Amp_{max} = max\{a_1, a_2, a_3, \ldots, \; a_n\} \tag{5}$$

The minimum ECG amplitude of ECG data can be

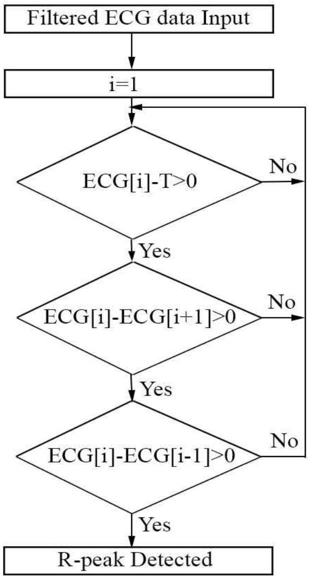


Fig. 6. R-peak detection flowchart

written as

$$Amp_{min} = min\{a_1, a_2, a_3, \dots, a_n\} \tag{6}$$

The threshold value of the R-peak detection can be expressed as

$$Threshold, T = \frac{\frac{Amp_{max} + Amp_{\min}}{2} + Amp_{max}}{2} \tag{7}$$

2.1.3 R-peak Identification

The R-peak detection can be obtained from the flowchart as shown in Fig. 6. The filter ECG data is input and assigned with the index number i as the sequential data ECG[i] of the filtered ECG data. The index number of the sequential ECG data is assigned with 1.For the next step, the sequential EWCG data ECG[i] is compared with the threshold value T given in Eq. (7). If the ECG[i] is greater than T, the ECG[i] is compared with ECG[i+1].Otherwise the ECG index i is automatically increased one. If ECG[i] is greater than ECG [i+1], then ECG[i] is compared with ECG [i-1].Otherwise the ECG index i is automatically increased one. Finally ECG[i] is higher than ECG [i-1] then R-peak could be detected. Otherwise, the ECG index i is automatically increased one

2.1.4 Heart rate calculation

With the R-peak result, the heart rate is calculated from R-R interval. The sample rate is the number sample per minute. The heart rate can be expressed as

$$\text{Heart rate (BPM)} = \frac{Sample\ rate \times 60\ second}{R - R\ interval} \tag{8}$$

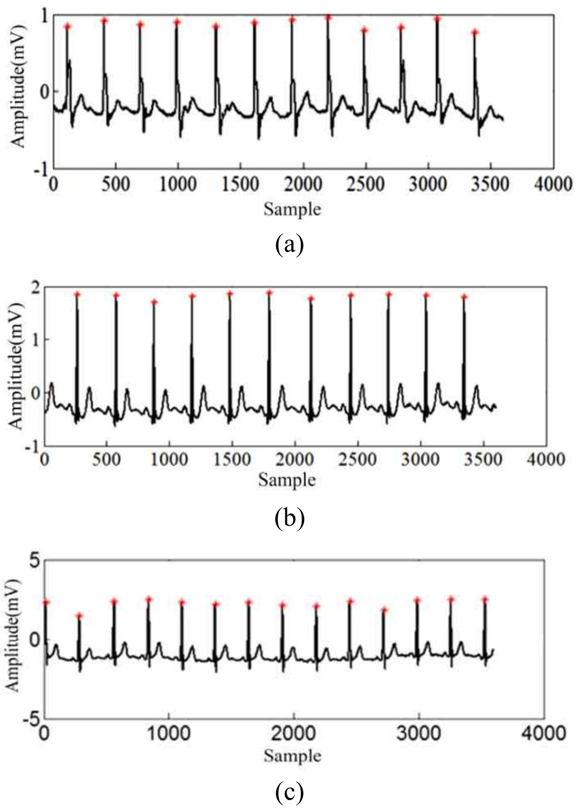


Fig. 7. R Peak detection result using (a) 102, (b) 103 and (c) 116 MIT/BIH arrhythmia data

3. Experimental Result and Discussion

The proposed algorithm has been evaluated based on MIT/BIH arrhythmia ECG database and MS400 ECG simulator. Firstly Raw ECG data pass through the adaptive filter to eliminate baseline drift. After eliminating baseline drift detected R-peak is shown in Fig. 7. In the figure, RED star shape indicates the location of the R peak. Table 1 shows the R-peak detection results for several ECG dataset. The performance of our algorithm evaluated by Eq. (9) and 10.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{9}$$

$$Accuracy = \frac{TP}{TP + FP} \times 100\% \tag{10}$$

Where TP is the number of R-peak detect correctly and FN is the number of R-peak undetected. FP shows the number of R-peak detected incorrectly.MIT/BIH database records 104,105,111,116,205,210,228 generally corrupted by severe baseline drift and abrupt. Several methods are unsuccessful in detecting properly these ECG records. However, our developed method detection rate is 100% for 104,105,111,116,205,210,228 records which is represent in Fig. 7.

Table 1. R-peak detection from MIT/BIH arrhythmia database using proposed method

MIT/BIH ECG Data	Num. of Sample	TP	*FN*	*FP*	*Sen. (%)*	*Acc (%)*
100	2272	2272	0	0	100	100
101	1869	1869	0	0	100	100
102	2186	2186	0	0	100	100
103	2083	2083	0	0	100	100
104	2228	2228	0	0	100	100
105	2602	2602	0	0	100	100
106	2027	2027	0	0	100	100
111	2124	2124	0	0	100	100
116	2411	2411	0	0	100	100
202	2137	2137	0	0	100	100
205	2656	2656	0	0	100	100
208	2962	2962	0	0	100	100
210	2650	2650	0	0	100	100
214	2266	2266	0	0	100	100
215	3362	3362	0	0	100	100
221	2427	2427	0	0	100	100
228	2077	2077	0	0	100	100
Total	40339	40339	0	0	100	100

Table 2. Performance comparison with existing algorithm

Method	Total MIT/ BIH ECG Data	Average Sen.(%)	Average Acc(%)	Ref. no.	Computation time
Proposed method	40339	100	100	-	Low
Sasan and jean	40339	99.65	99.76	[1]	High
Ravanshad et al.	40339	88.192	99.32	[2]	High
Martinez et al.	40339	99.8	99.86	[3]	High
Bahoura et al.	40339	99.83	99.88	[4]	Moderate
Pan and Tompkins	40339	99.75	99.54	[5]	Moderate
Zhang and Lian	40339	93.86	99.784	[6]	High
Yazdani and Vesin	40339	99.826	99.593	[7]	High
Moody and Mark	40339	99.77	99.34	[8]	High
Lee et al.	40339	92.88	98.2	[9]	Moderate
Li et al	40339	99.97	99.99	[10]	Moderate

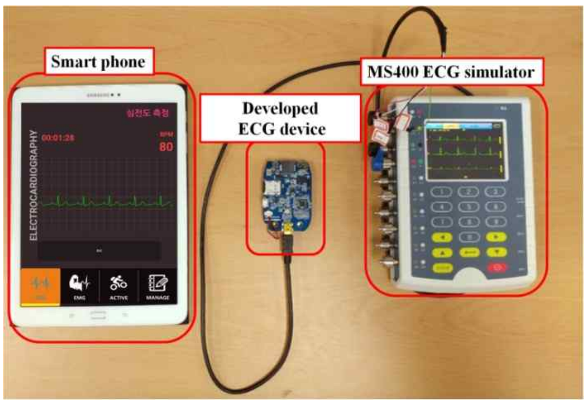


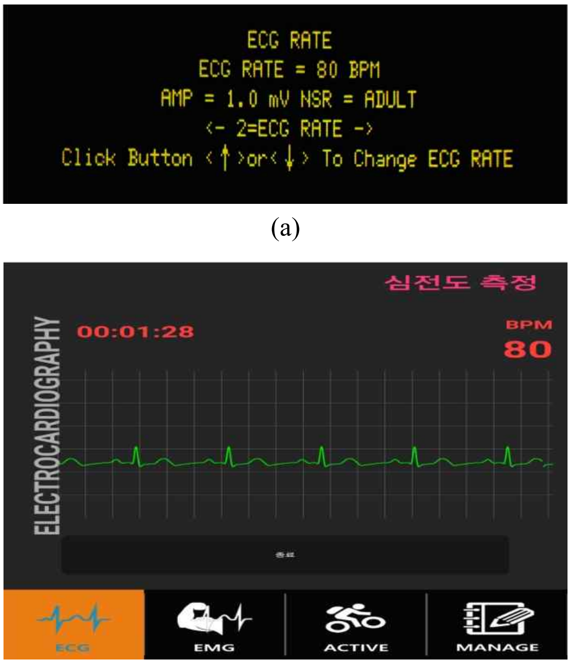
Fig. 8. Developed mobile ECG module

The comparison results with other existing algorithm based on accuracy and senility shown in Table 2. Our algorithm has accuracy and sensitivity on average 100% whereas other methods have less than 100%.The proposed algorithm computational complexity is also relatively low. As a result, this algorithm is very useful for the portable ECG device with limited resource.

Fig. 8. show that our own developed ECG measurement system to check the real-time performance of our proposed technique. Our developed module includes nRF51822 BLE system with Arm-cortex processor and ads1298 ADC (Analog to Digital Converter) which ensures the high computational ability. This BLE chip transfer data module to Android apps to display the heart rate and ECG waveform.

The developed device also include Secure Digital (SD) card to save 24 hours ECG data. We developed a windows application for offline ECG data analysis from SD card. Fig. 10. shows the ECG measurement (a) from the patient body using developed ECG device and (b) ECG feature extraction using windows application using saving ECG data from SD card.

To evaluate the accuracy of our real-time ECG application, we used MS400 ECG simulator and our own developed Android application. Heart rate depends on R-R interval. AS a result, if any R-peak missed heart rate also changed. This comparison also proved that our R-peak detection rate is high which is shown in Fig. 9. To check more efficiency, proposed algorithm pass into different heart rate using ECG simulator. Table 3 illustrates different heart rate and detection rate of proposed method.



(a)

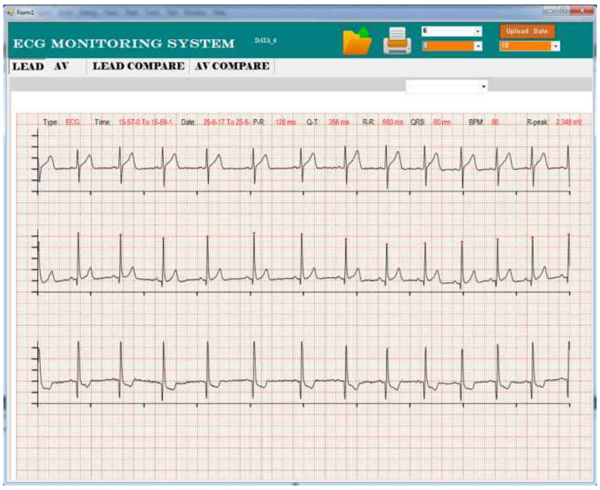
(b)

Fig. 9. Heart rate comparison between (a) ECG simulator MS400 and (b) developed Android application

Table 3. Heart Rate accuracy comparison

Sample Number	Simulator (HR)	Proposed method (HR)	*Accuracy (%)*	*Simulator (HR)*
1	15	15	100	15
2	20	20	100	20
3	30	30	100	30
4	40	*40*	100	40
5	*50*	50	100	50
6	*80*	*80*	100	80
7	*100*	100	100	100
8	*140*	140	100	140
9	*200*	*200*	100	200
10	*320*	*320*	100	320

(a)



(b)

Fig. 10. Offline ECG Features extraction

4. Conclusion

In this paper, a simple algorithm is developed to detect R-peak from an ECG signals. R peak has a great impact on heart diseases analysis. This method not only detects R peak but also heart rate to know the heart activity. Proposed method is robustness and simple to implement for real-time ECG measurement. To prove the capability of our proposed method, we used MIT/BIH arrhythmia database and our own developed portable module. This entire scenario, proposed method gives 100% accuracy compared to existing methods. Accurate heart rate also proved that R peak detection has no error and this method is very effective to detect real-time heart diseases.

References

[1] S. Yazdani and J. M. Vesin, “A Novel Preprocessing Tool to Enhance ECG R-wave Extraction,” in *Computing in Cardiology Conference (CinC), 2016, 11-14 Sept. 2016*.

[2] N. Ravanshad, H. Rezaee-Dehsorkh, R. Lotfi, and Y. Lian, “A level-crossing based QRS-detection algorithm for wearable ECG sensors,” *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 1, pp. 183-192, 2014.

[3] J. P. Martinez, R. Almeida, S. Olmos, A. P. Rocha, and P. Laguna, “A Wavelet-Based ECG Delineator Evaluation on Standard Databases,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 570-581, 2004.

[4] M. Bahoura, M. Hassani, and M. Hubin, “DSP implementation of wavelet transform for real time ECG wave forms detection and heart rate analysis,” *Comput. Methods Programs Biomed.*, vol. 52, no. 1, pp. 35-44, 1997.

[5] 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.

[6] F. Zhang and Y. Lian, “QRS detection based on multiscale mathematical morphology for wearable ECG devices in body area networks,” in *IEEE Transactions on Biomedical Circuits and Systems*, 2009, vol. 3, no. 4, pp. 220-228.

[7] S. Yazdani and J. M. Vesin, “Extraction of QRS fiducial points from the ECG using adaptive mathematical morphology,” *Digit. Signal Process. A Rev. J.*, vol. 56, pp. 100-109, 2016.

[8] G. B. Moody and R. G. Mark, “Development and evaluation of a 2-lead ECG analysis program,” in *Computers in cardiology*, 1982, pp. 39-44.

[9] J. Lee, K. Jeong, J. Yoon, and M. Lee, “A simple real time QRS detection algorithm,” in *18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam 1996*,

[10] C. Li, C. Zheng, and C. Tai, “Detection of ECG characteristic points using wavelet transforms,” *IEEE Trans Biomed Eng*, vol. 42, no. Bmei, pp. 21-28, 1995.

Md Saifur Rahman He received B.Sc degree in computer science and engineering from Ahsanullah University of science and technology, Bangladesh, in 2016. He is currently a master research assistant in the electrical, electronics and control engineering at Kongju National University, Republic of Korea. His research interests are robust control, filtering and signal processing.

ChulhyungChoi He received M.Sc degree in Electrical and Electronic Control Engineering from Kongju National University, Republic of Korea, in 2014. He also received Ph.D in Electrical and Electronic Control Engineering from Kongju National University, Republic of Korea, in 2018. His research interests are Electric/electronic, Medical Engineering.

Young-pil Kim He received M.Sc degree in Electrical and Electronic Control Engineering from Kongju National University, Republic of Korea, in 2016. Presently pursuing Ph.D. in Electrical and Electronic Control Engineering from Kongju National University, Republic of Korea. His research interests are Electric/electronic, power electronics

Sikyung Kim He received M.Sc degree from Korea University, Republic of Korea, in 1988. He also received Ph.D from Texas A&M University, USA, in 1994. His research interests are Electric/electronic, Power electronics, information communication. Currently, he is a professor with the Dept. of Electrical and Electronic Control Engineering at Kongju National University, Republic of Korea.