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A PD Control-based QRS Detection Algorithm for Wearable ECG Applications

Changmok Choi, Younho Kim, Kunsoo Shin

Abstract—**We present a QRS detection algorithm for wearable ECG applications using a proportional–derivative (PD) control. ECG data of arrhythmia have irregular intervals and magnitudes of QRS waves that impede correct QRS detection. To resolve the problem, PD control is applied to avoid missing a small QRS wave followed from a large QRS wave and to avoid falsely detecting noise as QRS waves when an interval between two adjacent QRS waves is large (e.g. bradycardia, pause, and arioventricular block). ECG data was obtained from 78 patients with various cardiovascular diseases and tested for the performance evaluation of the proposed algorithm. The overall sensitivity and positive predictive value were 99.28% and 99.26%, respectively. The proposed algorithm has low computational complexity, so that it can be suitable to apply mobile ECG monitoring system in real time.**

I. Introduction

Electrocardiogram (ECG) records the temporal profiles of the electrical excitation processes in the myocardium in the form of waves, peaks, and lines. ECG provides the image of the electrical generation and reflects the excitation processes in the heart by non-invasive electrodes attached to the body surface. The ECG of the patients with cardiovascular disease should be monitored over days and weeks for vital function analysis and emergency help.

The advances of current wireless technologies will enhance quality of a cardiovascular management service. These advances would make a user wear just a lightweight ECG sensor including a microprocessor that judges whether arrhythmia appears. When arrhythmia appears, the microprocessor can be programmed to transmit the ECG data via telephone lines to medical experts to interpret it. For the successful real-time diagnosis, a highly accurate QRS detection algorithm is indispensible.

The QRS wave determination has been accomplished by comparing the magnitude of QRS waves or obtained feature values against a threshold. In 1970s, a fixed threshold was used [1], and this threshold value should be set according to individuals. However, magnitude of the feature in QRS waves varies even in individuals (called intra-individual variability [2]) due to respiration, motion artifacts, and beat types (e.g. normal a beat or a premature ventricular contraction beat). In 1980s, a variable threshold was introduced base on magnitude of a few previous QRS waves [3]. When a new QRS wave was determined, the threshold was updated as a percentage of the QRS wave magnitude. The threshold value did not change before a new QRS wave appeared. Recently, Iliev et al. suggested a constantly decreasing threshold at a fixed rate irrespective of QRS wave occurrence [4]. The threshold was automatically set high just after a QRS wave appeared, and the threshold became low over time. This method indirectly reflected a psychological refractory period of the cardiovascular system because time duration (approximately 0.4s~1.2s [5]) exists between two QRS waves.

We present a new variable threshold method using a proportional–derivative (PD) controller [6] that has been widely applied in industrial control systems. The proposed method was motivated because we found challenging issues with developing a QRS detection algorithm for ECG data from 78 patients with various cardiovascular diseases. When a large premature ventricular contraction beat was detected, a high threshold was set due to the large QRS magnitude. When a small normal beat followed the large beat, the small one could be missed because its magnitude could be less than the threshold. A decreasing rate of threshold could be set high to detect a small beat following a large beat. The high decreasing rate of a threshold could not miss the small beat following a large beat, but it could detect small noise peaks as QRS waves in a case that a QRS wave did not appear for a long time (> 2s: some types of arrhythmia such as atrioventricular block and sinus pause). The PD controller helped to resolve the aforementioned challenging issues. The controller aimed to continuously decrease a threshold over time not at a constant rate but at a variable rate proportional to a difference between a current threshold value and a target threshold value (a predefined value to be converged). In addition, when a QRS wave was detected and its magnitude was much larger than the current threshold value, the controller avoided an abrupt threshold change for a possible case when the following beat was small.

II. Materials and Methods

A. Data Acquisition

We requested a clinical experiment to Samsung Medical Center (Seoul, the Republic of Korea) to acquire ECG data from 78 patients with various cardiovascular diseases. All

C. Choi is with the Future IT Research Center, Samsung Advanced Institute of Technology (SAIT), Samsung Electronics Co., Ltd., Yongin, the Republic of Korea (phone: +82-31-280-9528; fax: +82-31-280-9560; e-mail: cm7.choi@samsung.com).

Y. Kim and K. Shin are with the Future IT Research Center, Samsung Advanced Institute of Technology (SAIT), Samsung Electronics Co., Ltd., Yongin, the Republic of Korea (e-mail: yh92.kim@samsung.com and bosco.shin@samsung.com).

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patients have signed the informed consent form under an Institutional Review Board (IRB) protocol for this study. A self-developed wearable ECG sensor with a built-in amplifier (x100) was attached to each patient, and the sensor consisted of three electrode nodes for biopotential measurement and a Bluetooth module for wirelessly sending ECG data. The patient also wore a data logger including a Bluetooth module to save 24hrs ECG data from the sensor. All patients were not hospitalized, but did daily activities without any restrictions. The sampling frequency of ECG data was 250 Hz. Medical experts picked some 7-8s samples including various types of arrhythmia among the 24hrs ECG data for each subjects, and they annotated QRS waves and a type of arrhythmia.

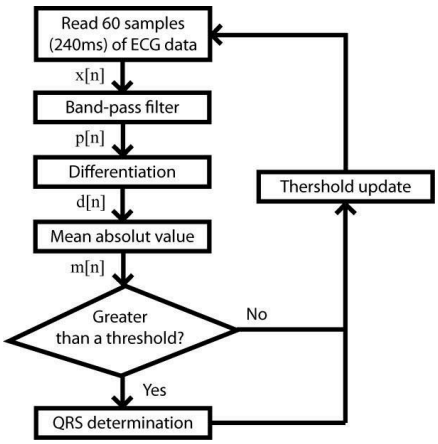

Fig. 1. Algorithm structures.

B. Preprocessing

Fig. 1 shows a flowchart of the proposed algorithm. We first applied a finite impulse response (FIR) band-pass filter using Hamming window to reduce high-frequency noise. The filter order was the 41th, and the high and low cut-off frequencies was 10 and 25Hz taking into account the frequency bandwidth of QRS waves [7]. The QRS wave is a steep spike indicating the signal has reached the atrioventricular node and the ventricles are about to contract. To catch the steep spike, a differentiation formula is implemented as follows:

$$d[n] = p[n+1] - p[n]. \quad (1)$$

p[n] is a low-pass filtered data at the time n, and d[n] is the differential value at the time n. Then, a mean absolute value is obtained to get average effects of differentiation values surrounding R-peaks as follows:

$$m[n] = \sum_{i=-5}^{+5} |d[n+i]|. \quad (2)$$

C. QRS Candidate Selection

An analysis window is used to efficiently select QRS candidates considering a psychological refractory period of the cardiovascular system. It has been well known that it is difficult to appear a QRS wave in 240 ms after a QRS wave appears. The length of the analysis window is set as 240 ms (60 samples in our sampling frequency 250 Hz).

Among the 60 samples of low-pass filtered data, our algorithm searches local minimum/maximum peaks that could be QRS candidates using following criteria:

$$\left(p[j] - p[j-i]\right) \times \left(p[j] + p[j+i]\right) > 0, \quad i = 1, 2, ..., 5. \quad (3)$$

j is a local index of the detected QRS wave location in an analysis window. Since the length of the analysis window is 60, j = 1, 2, ..., 60. Among the peaks satisfied with the criteria (3), the algorithm selects the QRS candidate wave that has the maximum mean absolute value.

D. Threshold Adjustment

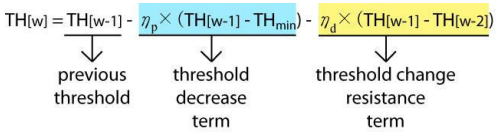

Fig. 2. The threshold adjustment rule by PD control. TH[w] was a threshold magnitude in the w-th analysis window. η_p and η_d were a proportional gain and a derivative gain, respectively. TH_{min} was the predefined minimum value of threshold.

Mean absolute value of the selected QRS candidate wave is compared to a threshold, and the threshold is not fixed but variable. Fig. 2 shows the threshold adjustment by PD control; w is an index of an analysis window, and TH[w] is a threshold at the w-th window. The PD control is performed at every 60 samples (240 ms = the length of the analysis window used in this method). The minimum value of threshold is defined, and the threshold tries to converge to the defined minimum value. This update rule consists of three terms: a previous threshold term, a threshold decrease term, and a threshold change resistance term.

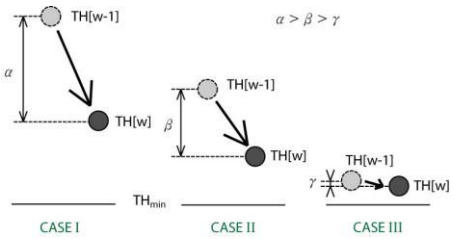

Fig. 3. The effects of a threshold decrease term.

The role of the threshold decrease term in Fig. 2 is described in Fig. 3. CASE I described a moment when a previous threshold is located far from the minimum threshold. In this case, a threshold decrease term can be large because the large difference between a previous threshold and the minimum threshold. This large decrease of the threshold helps

to detect a QRS wave following a large QRS wave. CASE III describes when a previous threshold is located close to the minimum threshold. In this case, a threshold decrease term can be small because of the large difference between a previous threshold and the minimum threshold. This small decrease of the threshold helps to avoid small noise peaks although a QRS wave does not appear for a long time.

The role of the threshold change resistance term in Fig. 2 is to avoid an abrupt threshold change for a possible case when the following QRS wave is small. Some examples are described in Fig. 4. CASE I and II described a moment when any QRS waves are not detected. The threshold is decreased by the threshold decrease term. In CASE I, when the difference of the thresholds at between w-1 and w-2 is large, the threshold change resistance term ($\eta_d > 0$) reduces the decreasing amount of the threshold that is originally supposed to be done without it ($\eta_d = 0$). In CASE II, when the difference of the thresholds at between w-1 and w-2 is small, effects of the threshold change resistance term becomes also small. CASE III and IV describe a moment when a QRS wave is detected. When a QRS wave appears at w-1, the threshold at w-1 is changed to the magnitude of the features at the location of the detected QRS wave. CASE III describes that a large QRS wave is detected at w-1 and the high threshold at w-1 is set. However, the large threshold may miss the next small QRS wave. Therefore, the threshold change resistance term ($\eta_d > 0$) reduces abruptly increasing amount of the threshold that is originally supposed to be done without it ($\eta_d = 0$). When a small QRS wave appears in CASE IV, since the difference of the thresholds at between w-1 and w-2 is small, effects of the threshold change resistance term becomes also small. We defined η_p, η_d, and TH_{min} as 0.5, 0.1, 0.02 by trial and error.

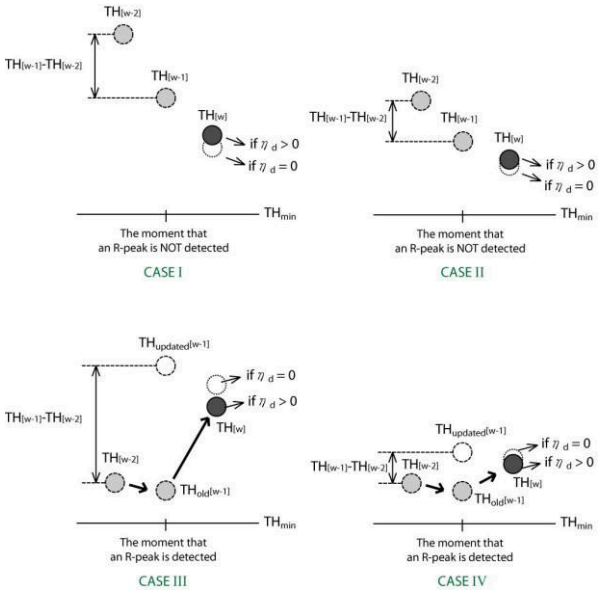

Fig. 4. The effects of a threshold change resistance term.

The PD control is performed not every sample but every 60 samples considering computational complexity as an important factor for a wearable application. The PD control has two multiplicative operations, and if we apply the PD control at every single samples, 500 multiplicative operations would be performed per second (f_s = 250 Hz). The computational load is reduced when the PD control is performed at every 60 samples such that only 8.33 multiplicative operations per second are required.

In the analysis window, the threshold is decreased by a linear interpolation using the current threshold and the estimated next threshold as shown in Fig. 5. The next threshold is estimated as follows:

$$TH_{est}[w+1] = TH[w] - \eta_p \times (TH[w] - TH_{\min}) - \eta_d \times (TH[w] - TH[w-1]). \quad (4)$$

The interpolation was performed as follows:

(5)

K is the number of samples in an analysis window, and k is a representative QRS candidate selected in *C. QRS Candidate Selection*. k is a local index of the detected QRS wave location in the w-th analysis window. In our method, $K = 60$, so that $k = 1, 2, ..., 60$.

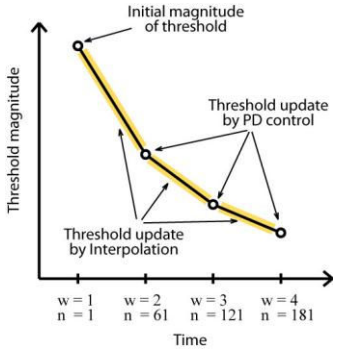

Fig. 5. Illustration of the threshold update. n is a integer representing a sample number, and w is a integer representing an index of an analysis window. n increases at every 4 ms, and w increases at every 60 ms.

E. QRS Determination

When a mean absolute value of the selected QRS candidate wave is greater than the threshold calculated from (5), the selected QRS candidate wave is finally determined as a QRS wave. Otherwise, it is regarded as noise. The determined QRS wave is solely selected in a 240ms analysis window, but an interval between adjacent two determined QRS waves could be less than 240ms if another QRS wave is selected in the next analysis window. When the interval is less than 240ms, the mean absolute values of the corresponding QRS waves are compared. The bigger one is determined as a QRS wave, and the smaller one is regarded as noise.

III. Results and Discussion

Fig. 6 shows ECG data from a patient with pause arrhythmia (3.8s between two QRS waves). The PD controller makes a threshold converge to the predefined minimum threshold value, so that the threshold cannot reach to the mean absolute value of noise peaks. This is effective to avoid falsely detected QRS waves when an interval between adjacent two determined QRS waves is large (e.g. bradycardia, pause, and arioventricular block).

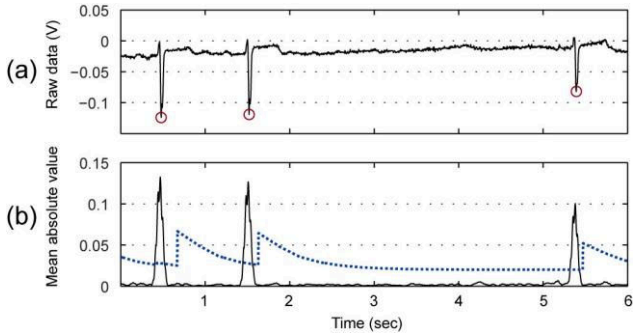

Fig. 6. (a) Raw ECG data from a patient with pause arrhythmia and (b) mean absolute value data. Red circles in (a) represents detected R-peaks and a blue dot line in (b) represents a threshold.

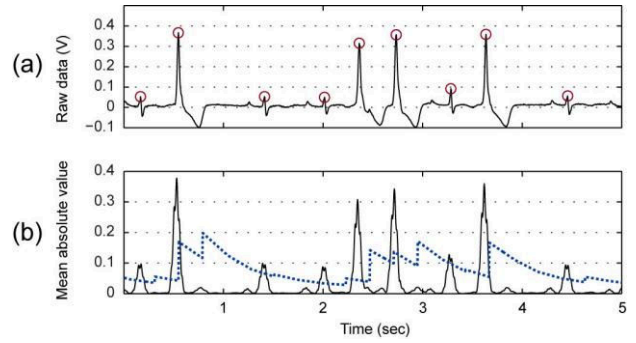

Fig. 7. (a) Raw ECG data from a patient with premature ventricular contraction beats and (b) mean absolute value data. Red circles in (a) represents detected R-peaks and a blue dot line in (b) represents a threshold.

Fig. 7 shows ECG data from a patient with several premature ventricular contraction beats. The magnitude of premature ventricular contraction beats is much larger than those of normal beats. Although the PD controller impedes abruptly big increasing change of a threshold when a large feature value appears, it rapidly decreases when a threshold is large relative to the predefined minimum threshold value. This is effective not to miss detecting a small QRS wave following a large QRS wave.

We evaluated the performance of the developed algorithm using TP (true positive), FP (false positive), FN (false negative), SE (sensitivity), PPV (positive predictive value), and FPH (positive per hour) [8]. The overall number of beat annotation is 13033 where the global obtained results are as follows: the TP is 12939, the FP is 96, and the FN is 94. Therefore, our algorithm reports a sensitivity of 99.28% and a positive predictive value of 99.26%. The FPH is 3.22, so that our algorithm may falsely detect approximately three beats per hour.

IV. Concluding Remarks

We developed a QRS detection algorithm using PD control, and evaluated its performance using clinical ECG data from 78 patients who suffered from with cardiovascular diseases. Our algorithm was aimed to correctly detect QRS waves in arrhythmia regardless of intervals and magnitudes of QRS waves. We should notice that computational complexity of our algorithm is not heavy compared to literatures using wavelet transform [9] and Hilbert transform [10]. The low computational complexity is an important factor for successful development of a wearable sensor. Our algorithm can be extended to other applications such as obstructive sleep apnea syndrome [11].

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