Binary Classification for Linear Approximated ECG Signal in IoT Embedded Edge Device

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***Abstract*—Abnormal beat detection in electrocardiogram (ECG) signal is an important research subject. Abnormal beat detection can be used effectively for adaptive signal compression according to normal/abnormal beat, and it enable to save time and cost of arrhythmia diagnosis by providing the detected abnormal beats to cardiologist. However, the fiducial point detection for feature value extraction has low reliability and is difficult to implement in embedded edge devices due to the auxiliary signal acquisition and complex algorithm for detection. In this study, we propose a method that expresses a signal as a small number of vertices using linear approximation and detects an abnormal beat quickly and reliably using the feature value of vertices. The proposed method is based on the similar distribution of feature values of the approximate vertices for the same type of beat. As a result of an experiment on a record containing premature ventricular contraction (PVC) whose shape was deformed from a normal beat, we confirmed that the proposed algorithm enable to detect whole abnormal beat correctly.**

***Keywords*—electrocardiogram; binary classifier; linear approximation, embedded device**

I. Introduction

ECG signal indicates the electrical activity of the heart. ECG signal is widely used biological signal for early diagnosis and prevention of heart disease. Recent developments in software and hardware technologies increase interest in ECG signal by making it possible to measure signals in real-time using wearable embedded device even during daily life [1]. Arrhythmia diagnosis analyzes the ECG signal based on the detection of an abnormal beat, but the abnormal beat occurs aperiodically. Therefore, the burden of cost and time required for cardiologists to analyze ECG signal is increasing, and studies on automatic analysis of ECG signal are being actively conducted in order to improve this.

This study proposes a method to detect abnormal beat. We can reduce the time and cost required for analysis by detecting an abnormal beat and providing only abnormal beat to a cardiologist. In addition, it enables to save costs for data transmission and storage by compressing unnecessary normal beat information to reduce the amount of data. This reduces power consumption and memory usage of embedded devices, enabling long-time operation and cost reduction.

The conventional abnormal beat detection method detects a fiducial point, which is the boundary between the waveform region and the baseline region, and classifies the abnormal beat based on the feature values such as the time interval and the amplitude difference between the fiducial points [2]. However, for this purpose, various auxiliary signals, such as derivatives, average filters, and Hilbert transforms [3]–[5] are required. Also this auxiliary signal increases the execution time and memory usage, which gives a large burden on the operation of the embedded device. In addition, it is also difficult to determine the threshold of the feature values for classifying beats because the shapes of normal and abnormal beats appear in various ways depending on the individual.

In the proposed method, a template cluster is generated which including various types of normal and abnormal beat templates. The template with the highest counter from the template cluster represents the normal beat because the incidence of normal beat is higher than that of abnormal heartbeat. And the template with the lowest similarity to the representative normal beat (RNB) becomes the representative abnormal beat (RAB). Then, each of the RNB and RAB is linear approximated. The linear approximation proposed by Ref. [6], [7] not only has a high ECG signal compression rate, but also allows independent signal compression for each beat, thus minimizing the approximation error for various types of abnormal beat.

The approximation error is the smallest when the same type of template's linear approximation result is applied, and the approximation error increases when the different type of template is applied. Based on this, we classify the input beat by using the type of the template with the smallest error. Fig. 1 shows a proposed abnormal beat detection algorithm flow.

II. Proposed Algorithm and Experimentation

A. Preprocessing

In this paper, we used datum 119 from MIT-BIH ADB [8] provided by Physionet which is suitable for applying the proposed algorithm. This record is widely used in the study of abnormal beat detection because it contains a large number of PVCs.

First, a Butterworth band-pass filter of 1-25 Hz is applied to suppress high-frequency and low-frequency noise such as

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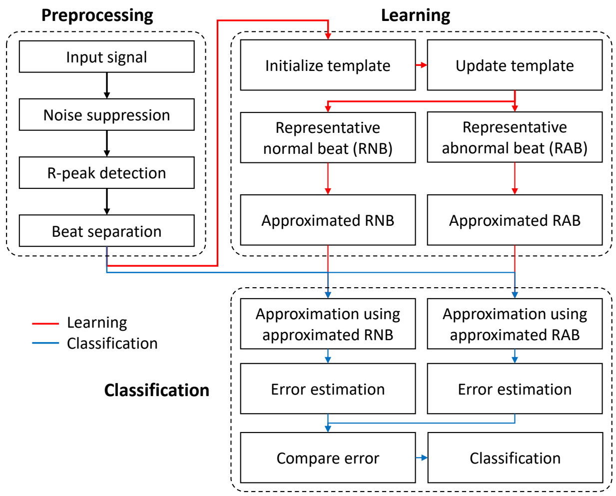

Fig. 1. The proposed algorithm flow.

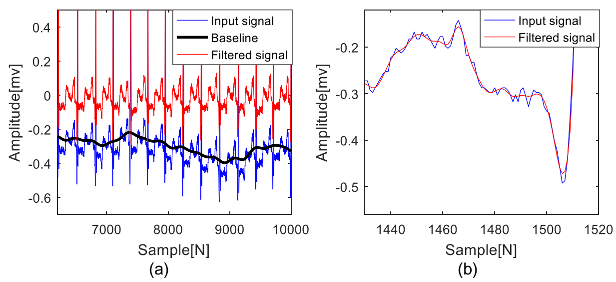

Fig. 2. Filtered signal, (a) high-pass filter, (b) low-pass filter.

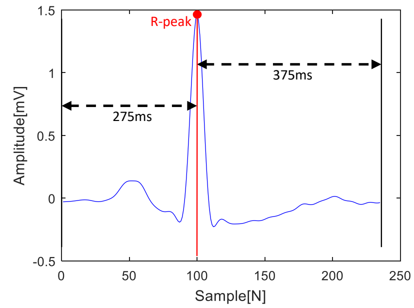

Fig. 3. Beat separation centering on R-peak.

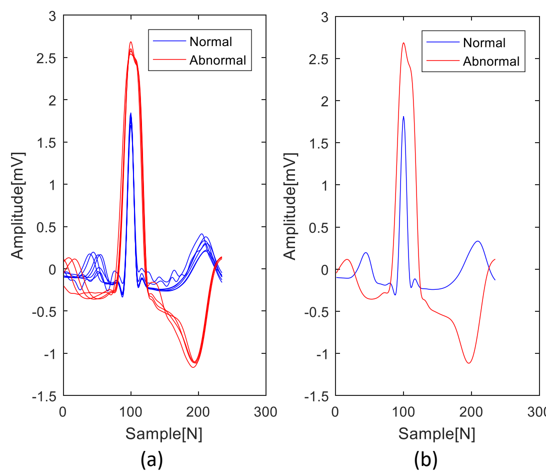

Fig. 4. Determination of RNB and RAB from template cluster, (a) template cluster, (b) RNB and RAB from (a).

baseline fluctuation and power noise. Fig. 2 shows the result of noise suppression filter

The filtered signal separates the beat based on the R-peak, and the Pan's method [9] is a representative method of detecting the R-peak. Each beat are divided into the region of 275 ms before and 375 ms after the R-peak [10]. This section is widely used as a beat interval including the P-wave, QRS complex, and T-wave. Fig. 3 shows the heart rate acquired around the R-peak.

B. Template Cluster Generation

Depending on the individual, the shape and frequency of the normal beat vary. Most beats are normal and have a similar shape that repeats periodically. On the other hand, abnormal beat occurs aperiodically, and variations appear in various ways depending on the individual's heart disease. Therefore, it is necessary to learn a normal beat and an abnormal beat according to an individual through signal measurement for a long time.

The template cluster can reliably generate various types of templates based on the Pearson similarity, by repeatedly updating template through a weighted mean between similar beats and adding unsimilar beat as a new template [11]. In particular, the counter of template, which means the number of updates and used for the weighted mean, can be used to determine the RNB. Fig. 4 is the templates of the normal beat and abnormal beats.

C. Linear Approximation

The linear approximation proposed by Lee optimizes the dynamic programming based on the characteristics of the ECG signal, and effectively expresses the signal with a small number of vertices in real-time [12], [13]. Fig. 5 is the result of applying a linear approximation to the representative normal and abnormal beat in the Fig. 4(b).

D. Feature Extraction

For the same type of beat, the linear approximation results are similar. Fig. 6 shows the distribution of the amplitude difference of 20 vertices between the 1985 input beats (1541 normal beats and 444 abnormal beats) and RNB.

In the case of a normal beat, the distribution of the amplitude difference is close to 0, and in the case of an abnormal beat, it has a high error distribution, which can be emphasized by squared it. Therefore, the error between the two beats can be measured through the sum of squares of the amplitude difference. Fig. 7 shows the result of measuring the error from RNB and RAB for the entire input beats, respectively.

For the input beat, the errors for the RNB and RAB are measured, respectively, and the beat is classified by the type

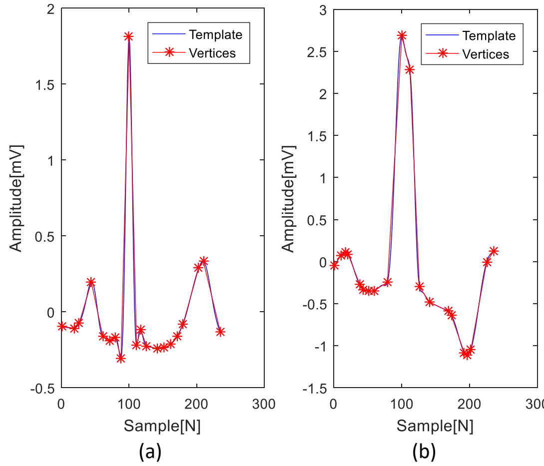

Fig. 5. Linear approximation results with 20 vertices, (a) approximated RNB, (b) approximated RAB.

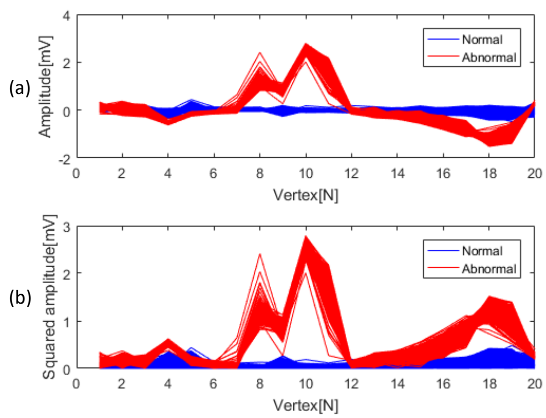

Fig. 6. The distribution of amplitude difference. (a) amplitude difference with RNB, (b) squared distribution of (a).

of representative beat with small error. We can confirm that whole 444 abnormal beats were detected, and there was no false detection of the normal beat as shown in Fig. 7.

III. Conclusion

In the proposed method, after obtaining RNB and RAB using template cluster, we can detect abnormal beats by comparing errors by applying the result of linear approximation of the RNB and RAB. The experimental results confirmed the possibility of the proposed algorithm by stably performing the detection of PVCs.

The template cluster generation was able to determine a reliable RNB and RAB while minimizing the memory usage based on the weighted mean. Also, the linear approximation greatly reduced the amount of computation by acquiring only a small number of vertex that well represents the beat. In addition, the amplitude difference could be effectively expressed by acquiring the amplitude feature values only for samples with a large curvature including the fiducial point.

In further works, we aim to detect various types of abnormal beat using reliable feature values other than the amplitude of

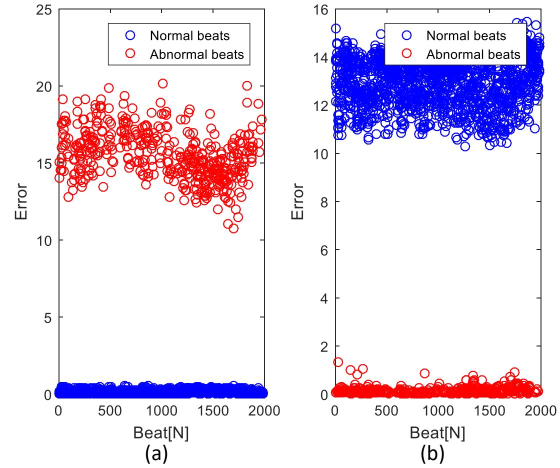

Fig. 7. Error distribution, (a) error with RNB, (b) error with RAB.

the vertex, such as an angle with neighboring vertex, time or amplitude difference from R-peak.

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