

Development of a Real-time QRS Beat Classifier Using a Nonlinear Trimmed Moving Averaging-based System

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Abstract

In this paper, a real-time QRS beat classification system devised based on a nonlinear trimmed moving averaging filter is presented. Such a nonlinear system aims to identify the abnormal beat of ventricular origin from the normal one. The proposed beat classifier can function in parallel with a real-time QRS detector, permitting the tasks of beat detection and diagnosis to alternate with each other. Algorithm performance was evaluated against the ECG recordings selected from the MIT-BIH arrhythmia database. Numerical results demonstrated that over 99.8% beat identification rate can be achieved by the algorithm.

1. Introduction

It has been widely acknowledged that QRS detection provides an important basis for *heart rate* (HR) computation [1]. In fact, to obtain instantaneous HR estimates with its applications to physiological monitoring or to *heart rate variability* (HRV) assessments, an automated beat diagnosis immediately after the beat detection might facilitate these applications further. Although numerous techniques for QRS detection have been developed previously, most of them cannot automatically identify the beat types of the detected QRS complexes. In this study, an automated beat diagnostic algorithm devised based on a nonlinear system is therefore developed. In conjunction with a real-time QRS detector, the proposed beat classifier can be applied to further identifying the abnormal beat of ventricular origin from the normal one once a QRS complex is detected, thus involving minimal human efforts for review of the detected heart beats.

2. Methods

2.1. Trimmed moving average

A “generalized” moving averaging process can be defined as

$$y[n] = \mathbf{f}^t T\{\mathbf{x}_n\}, \quad (1)$$

where $\mathbf{x}_n = [x[n] \ x[n-1] \ \cdots \ x[n-M+1]]^t$ is an $M \times 1$ vector of input data at time n (where M defines the

averaging interval), $y[n]$ is the filter output, T denotes the algebraic ordering transformation, and $\mathbf{f} = [f_1 \ f_2 \ \cdots \ f_M]^t$ is an $M \times 1$ vector of weighting or filter coefficients. The ordering transformation T is such that $T\{\mathbf{x}_n\}$ is an algebraically ordered version of

$$[x[n] \ x[n-1] \ \cdots \ x[n-M+1]]^t$$

ranked from the smallest to the largest. Also, in all cases of averaging process considered \mathbf{f} is constrained by

$$[1 \ 1 \ \cdots \ 1]\mathbf{f} = 1. \quad (2)$$

Considering Eq. (1), it is important to realize that while the linearity of the filtering operation is retained, an averaging operation is applied to the nonlinearly transformed input data. For convenience, suppose the averaging interval M is restricted to odd values. Then, a number of special cases can be respectively defined as follows.

1. *The Moving Averaging Process*: defined by setting

$$f_k = \frac{1}{M}, \quad \text{for } k = 1, 2, \dots, M. \quad (3)$$

Note that this is the only case where the linearly smoothing operation holds.

2. *The Moving Median Process*: defined by setting

$$\begin{aligned} f_k &= 1, \quad \text{for } k = \frac{M+1}{2}; \\ &= 0, \quad \text{otherwise.} \end{aligned} \quad (4)$$

3. *The Trimmed Moving Averaging Process*: defined by setting

$$\begin{aligned} f_k &= 0, \quad \text{for } k = 1, \dots, N \\ &\quad \text{and } M - N + 1, \dots, M; \\ &= \frac{1}{M - 2N}, \quad \text{otherwise.} \end{aligned} \quad (5)$$

These filter coefficients f_k 's represent the application of a moving averaging operation to the input data, but with the N largest and N smallest values from the input sequence removed. It should be noted that while for $N = 0$ the trimmed moving averaging filter functions like a moving averaging operation to the input data, for $N = \frac{M-1}{2}$, it is simply reduced to a median filter. That is, the trimmed moving averaging filter can be viewed as a compromise between the moving averaging and the median filters [2].

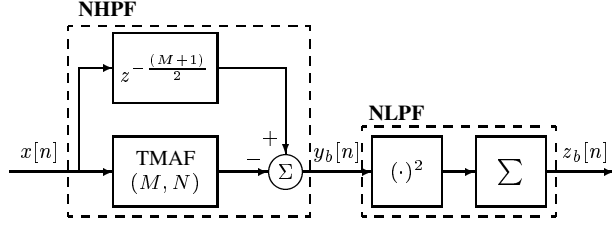


Figure 1. The feature extraction part of the proposed QRS beat diagnostic system.

2.2. Architecture of the beat classifier

We approach this beat classification problem via a pattern recognition technique, including the tasks of feature extraction and pattern classification. Details are respectively described as follows.

2.2.1 Feature extraction

The feature extraction system is formed by a cascade of a *nonlinear highpass filter* (NHPF) and a *nonlinear lowpass filter* (NLPF), as depicted in Fig. 1. First, the NHPF is constructed by a parallel combination of an ideal delayed system and a *trimmed moving average filter* (TMAF). The NHPF output $y_b[n]$ is then determined by subtracting the TMAF output from the delayed version of the input signal $x[n]$, expressed as

$$y_b[n] = x[n - \frac{M+1}{2}] - \mathbf{f}^t T\{\mathbf{x}_n\}, \quad (6)$$

where $T\{\mathbf{x}_n\}$ and \mathbf{f} have the same definitions as those addressed in Eqs. (1) and (5), respectively. According to the descriptions in previous section, the TMAF indicated in the figure performs a moving averaging operation on the sorted M windowed ECG samples (from the smallest to the largest) but with the N largest and smallest values removed, permitting a nonlinearly lowpass filtering and thus allowing the overall sub-system between the input signal $x[n]$ and $y_b[n]$ to function like an NHPF.

Generally speaking, the frequencies associated with a *premature ventricular contraction* (PVC) should distribute in a lower band than those associated with a normal QRS waveform. Therefore, we may speculate that with appropriate selections of TMAF parameters (M, N) significant suppression of the P, T waves as well as the abnormal beats, such as PVC's, can be achieved while the impulse-like waveforms, such as the normal QRS beats, are further elevated.

As for the NLPF part, it is composed of a squaring function followed by a moving window summation. From

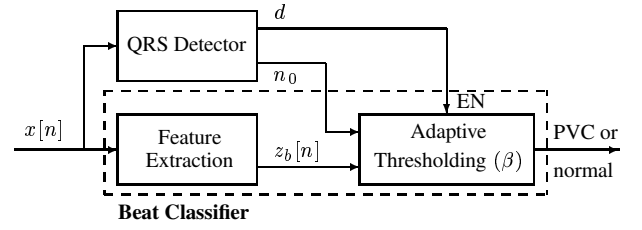


Figure 2. A schematic block diagram of the proposed beat classifier and its connection to an existing QRS detector.

Fig. 1, the NLPF output is calculated from

$$z_b[n] = \sum_{k=0}^{K-1} y_b^2[n-k], \quad (7)$$

where K represents the summation interval and $z_b[n]$ is referred to as the feature or characteristic waveform. In general, determination of the value of K is dependent upon the sampling rate of the original ECG signal. Empirically, $K = 30$ is a typical choice when the ECG sampling rate is 200 Hz [3], [4].

2.2.2 Pattern classification

To perform the task of pattern classification, a thresholding scheme employing an adaptive threshold is applied to the characteristic waveform, $z_b[n]$, resulting from a moving window summation of the squared NHPF output. The threshold, denoted as Th_b , is automatically adjusted by

$$Th_b = \beta \times 0.4 \text{ PEAK}_b + (1 - \beta) \times Th_b, \quad (8)$$

where PEAK_b is the local maximum, which exceeds the current value of Th_b , newly detected in $z_b[n]$ and β represents the “forgetting factor,” restricted to the positive fraction numbers (*i.e.*, $0 \leq \beta \leq 1$). From Eq. (8), we may see that each new value of Th_b is determined from the running estimate of the characteristic signal peak as well as the prior and current values of the threshold itself.

Fig. 2 gives a schematic block diagram illustrating how the beat classifier works. It should be noted that the beat classifier is devised to work in parallel with an existing real-time QRS detector. That is, an ECG signal $x[n]$ is simultaneously inputted into both the QRS detector and the beat classifier, as indicated in Fig. 2. The steps of beat classification are itemized as follows.

1. In Fig. 2, d represents the binary indication of QRS detection result. Initially, $d=0$. d is set to 1 once a QRS complex is detected.
2. Since d directly connects to the enable (EN) of the thresholding unit of the beat classifier, each time when a QRS complex is detected the thresholding mechanism will be enabled.

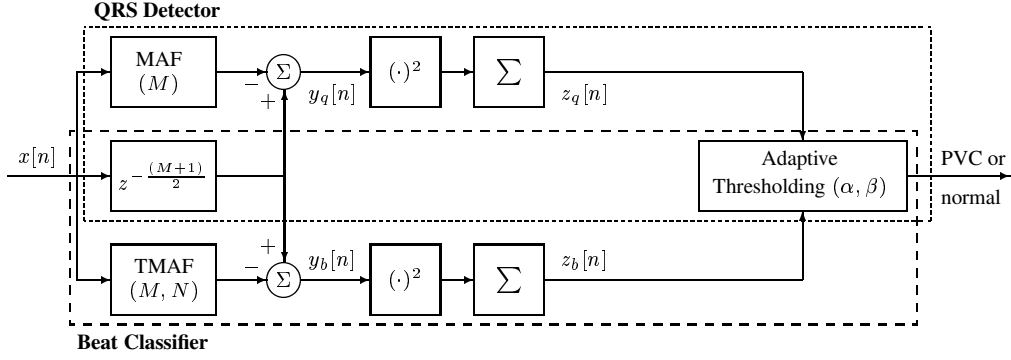


Figure 3. A functional block diagram of the QRS detection with beat diagnosis system.

3. When the thresholding mechanism is initiated, it first accepts the temporal location of the detected QRS complex, denoted as n_0 . Note that here n_0 is selected as the peak location of the original R wave. Suppose the processing delay between the original ECG and its corresponding characteristic wave $z_b[n]$ is zero, thus $z_b[n_0]$ will be a local maximum of $z_b[n]$. Beat classification is then achieved simply by applying the decision rule as

$$\begin{aligned} \text{if } z_b[n_0] \geq Th_b &\Rightarrow \text{Normal;} \\ \text{if } z_b[n_0] < Th_b &\Rightarrow \text{PVC.} \end{aligned} \quad (9)$$

4. The threshold value Th_b is updated by Eq. (8) only if $z_b[n_0] \geq Th_b$.
5. d is reset to 0, until a new QRS detection occurs.

2.3. Combining the QRS detection with beat diagnosis

Notice that since the beat classifier is designed to jointly work with a QRS detector, the performance of beat classification is thus unavoidably *dependent* upon the QRS detection results. Therefore, it is essential that a reliable QRS detector with a minimal error detection rate be employed for the performance evaluation of the proposed beat classifier. In this study, a moving average-based real-time QRS detector [5], also developed in our laboratory, was thus adopted for this purpose. Such an overall functional block diagram is as shown in Fig. 3.

The adopted QRS detector (encompassed by the dot box) is combined with the proposed beat classifier (encompassed by the dash box) in the manner as manifested in Fig. 3. It can be seen that both algorithms share with the same delay element. Moreover, their individual thresholding systems have been integrated into one, thus allowing a two-step pattern classification. That is, each time the occurrence of a QRS complex detection will be immediately followed by a QRS diagnosis. A demonstrative example of such a two-step classification is given in Fig. 4. In this

figure, the top panel shows a 25-s ECG data segment, the middle and the bottom panels give its corresponding characteristic waveforms $z_q[n]$ and $z_b[n]$ resulting from the feature extraction parts of the QRS detector and the beat classifier, respectively, as indicated in Fig. 3. The two-step classification is then performed as follows:

• **Step 1.** An adaptive threshold is applied to $z_q[n]$ for detecting QRS complexes by the decision rule as [5]

$$\begin{aligned} \text{if } z_q[n] \geq Th_q &\Rightarrow \text{QRS complex;} \\ \text{if } z_q[n] < Th_q &\Rightarrow \text{None,} \end{aligned} \quad (10)$$

where Th_q denotes the adaptive threshold and is updated by

$$Th_q = \alpha \times 0.15 \text{ PEAK}_q + (1 - \alpha) \times Th_q, \quad (11)$$

where PEAK_q is defined exactly in the same way as PEAK_b , except that it is derived from $z_q[n]$. Similarly, α represents the “forgetting factor” for the QRS detection algorithm [5], where $0 \leq \alpha \leq 1$.

• **Step 2.** Once a QRS complex is detected and its temporal location n_0 is found, a secondary adaptive threshold, adjusted by Eq. (8), will be applied to $z_b[n_0]$ to perform the beat classification simply using the decision rule as formulated in Eq. (9).

As a result, setting $(M, N) = (7, 2)$ and $(\alpha, \beta) = (0.05, 0.05)$ it is revealed from Fig. 4 that while the 27 QRS complexes in the ECG segment were all detected, the 22 normal and 5 PVC beats were also correctly diagnosed.

3. Performance evaluation

We adopted the MIT-BIH arrhythmia database to evaluate the algorithm. Each ECG recording in the database is thirty minutes in length with the sampling rate $f_s = 360$ Hz. To reduce the number of computations, we here resampled the original ECG data to an adequately lower rate of 200 Hz.

Tests conducted using the ECG recordings consisting of PVC and normal QRS beats drawn from the MIT-BIH arrhythmia database produced overall classification

Table 1. Performance of the nonlinear trimmed moving averaging-based QRS beat classifier in identifying the normal from the PVC beats. Note that here the results remained the same as the values of both thresholding parameters (α, β) were selected as positive fraction numbers over a wide range, say from 0.01 to 0.5 or so.

Recording no.	no. of total beats	no. of normal QRS beats	no. of PVC beats	classification accuracy
100	2273/2273	2272/2272	1/1	100%
119	1987/1987	1543/1543	444/444	100%
123	1515/1518	1515/1515	0/3	99.8%

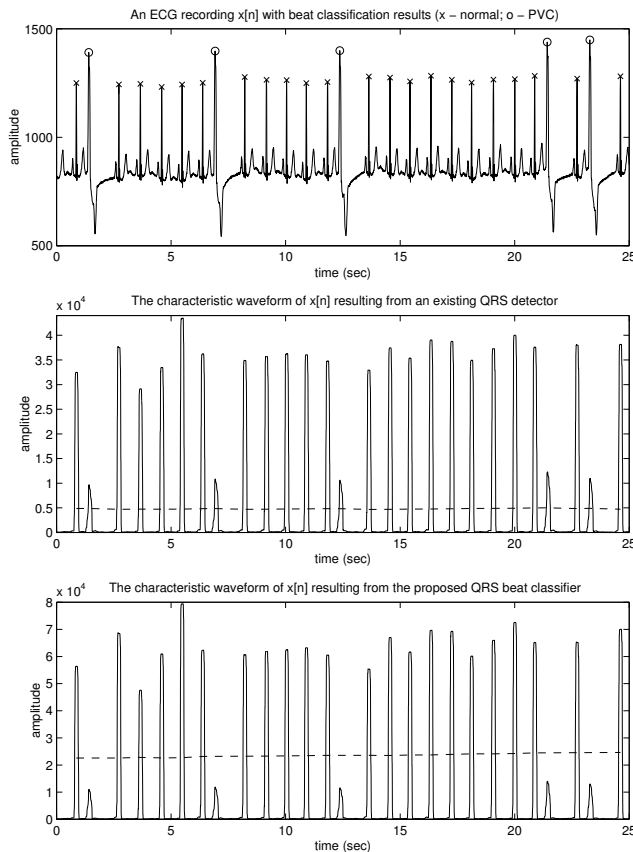


Figure 4. Top: a 25-s raw ECG data segment; middle: $z_q[n]$ corresponding to the raw ECG; bottom: $z_b[n]$ corresponding to the raw ECG. The QRS beat classification results are also labeled on the ECG plot in top panel (x: normal, o: PVC).

accuracy above 99.8% with $(M, N)=(7, 2)$, as listed in Table 1. It should be noted that in the MIT-BIH arrhythmia database there are only three ECG recordings (no.100, no.119 and no.123) containing PVC beats. The numerical results showed the proposed algorithm was very promising. On the other hand, it should be pointed out the reason that the algorithm could not identify all the three PVC's in recording no.123 was because the QRS detector adopted here, unfortunately, had failed to detect each one of them at the QRS detection stage first, thus there was no way for the

QRS classifier to perform the subsequent beat diagnosis.

4. Conclusion

In this paper, a nonlinear trimmed moving averaging-based QRS beat diagnostic algorithm is introduced. The novel algorithm can reliably function in parallel with a real-time QRS detector, permitting the tasks of QRS detection and beat diagnosis to alternate with each other. In addition, no data preprocessing is required for the algorithm thus allowing a simple realization of it. Moreover, numerical results showed the algorithm performance was not critically dependent upon the choices of (α, β) , implying a degree of robustness over a wide range of noise contamination.

Acknowledgements

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