Heart Rate Detection in Highly Noisy Handgrip Electrocardiogram

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Abstract

This study is to develop the handgrip heart rate detection methodology based on template matching algorithm. A sixth-order Butterworth bandpass filter with a passband of 1 to 30 Hz was used to filter out baseline shift and noise above 30 Hz including power line noise. The resulting QRS waveform will be processed by the matching filter and ready for heart beat detection. The result of detected heart beat will be processed by a weighting function to further minimize the false heartbeat detection. The performance of heart rate detection algorithm was tested under resting and exercising condition. Five Taiwanese male subjects averaged age of 25 were tested. The experimental results showed that the error rates were 0.78% (total of 766 heart beats) at resting condition and 3.83% (total of 3077 heart beats) during exercise.

1. Introduction

Electrocardiogram (ECG) is a noninvasive method to measure the electrical potentials of human heart on the body surface. Using the changes of PQRST waveforms and timing relations, the ECG can offer important diagnostic assistances on many cardiac diseases, for example, atrial and ventricular hypertrophy, myocardial ischemia, infarction, and arrhythmias etc. [1]. However the measurement using conventional leads may be inconvenient in some practices, especially in applications that only require heart rate, for example, the heart rate variability analysis, the real-time heart rate monitoring for sport utility and so on.

The electrocardiogram recorded by handgrip of holding on to a pair of metal electrodes has the advantage of convenient measurement of heart beat at low cost for sport utility. The heart rate detection using the handgrip electrocardiogram has been applied in treadmills to monitor the instantaneous heart rate that adjusting the volume of exercise automatically. However, the major limitation of the handgrip ECG was highly noisy. The noise level that induced by the handgrip measurement during the exercise has degraded the waveform of QRS complex. It is caused by the poor and unstable contact of electrodes from the motion during exercise. This has limited the sensitive of R-peak detection and increasing the difficulty of heart rate detection. The purpose of this study is to develop the heart rate detection methodology of highly noisy handgrip ECG based on template matching algorithm.

2. Methods

The handgrip electrocardiograms were recorded with two sets of handgrip metal leads. The ECG signals were amplified about 700 times by an instrumentation amplifier so that they reached a signal level suitable for the analog to digital converter. A sample of 10 min raw ECG under resting (2 min) and exercising (8 min) with 16-bit resolution at 250 Hz was stored on computer hard disk for subsequent analysis.

Before QRS detection, the ECG signal was passed through a bandpass Butterworth filter to reduce the high-frequency noise level and 60 Hz power line interference. Numerous QRS detection algorithms have been reported such as algorithms based on nonlinear transform [2], amplitude distribution analysis [3], matched filter [4-8], wavelet transform [9], adaptive filter [10], neural network [11] and so on. This study adopted matched filter to detect QRS complex. The basis of matched filter is to calculate a particular correlation coefficient between the QRS template and the input signals to evaluate their similarity. Four matched filters including correlation waveform analysis (CWA) [4,5], area of difference (AD) [6,7], mean area of difference (MAD) [7] and normalized area of difference (NAD) [7,8] are evaluated in this study to select one which is most suitable for QRS detection in handgrip ECG. In this study, we have applied a methodology of including a weight function [12] to further minimize the false detections of QRS complex.

The template matching algorithm for heart rate detection of handgrip ECG proposed in this study included pre-filtering, template selection, matched filter and weighting function were described as follows.

2.1. Pre-filtering

A sixth-order bandpass Butterworth filter with a passband of 1-30 Hz was used to filter out baseline shift and noise above 30 Hz including power line noise. Fig.1 (a) is a typical example of acquired handgrip ECG waveform under exercising. The QRS wave complexes are buried in a large amount of noise. Fig. 1(b) shows the noise level is reduced after filtering.

2.2. Template selection

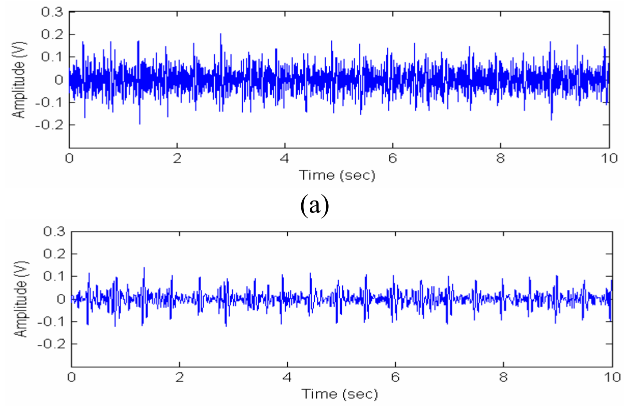
For template matching algorithm, the length of QRS template was 128 ms long. All local maximums within 4 seconds of ECG recording were marked and recorded as possible R-peak candidates. The medium of these local maximums was chosen as the location of a QRS template. Fig. 2 is an example that was showing template selection under resting. The method proposed for template section can prevent that a large noise or an abnormal QRS was selected as a template (Fig. 2(b)). The initial RR interval (RR_{init}) is then defined as the interval between the selected template and next local maximum.

2.3. Matched filter

After the QRS template selected, the matched filter was applied for detecting the remaining QRS complexes. The characteristics of the matching filters were the independence to the changes of the amplitude (IA) and the baseline (IB). The feature of IA may cause false detections because the small noise may be similar to the QRS complex waveforms. The feature of IB is able to prevent the inaccurate correlation coefficients caused by the baseline shift. Four matched filters were evaluated including CWA, AD, MAD and NAD for the selection of template matching algorithm. The correlation coefficients of these four matched filters are defined as follows.

CWA: $$\rho = \frac{\sum_{i=1}^{N}(t_i - \bar{t})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{N}(t_i - \bar{t})^2}\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2}} \quad (1)$$

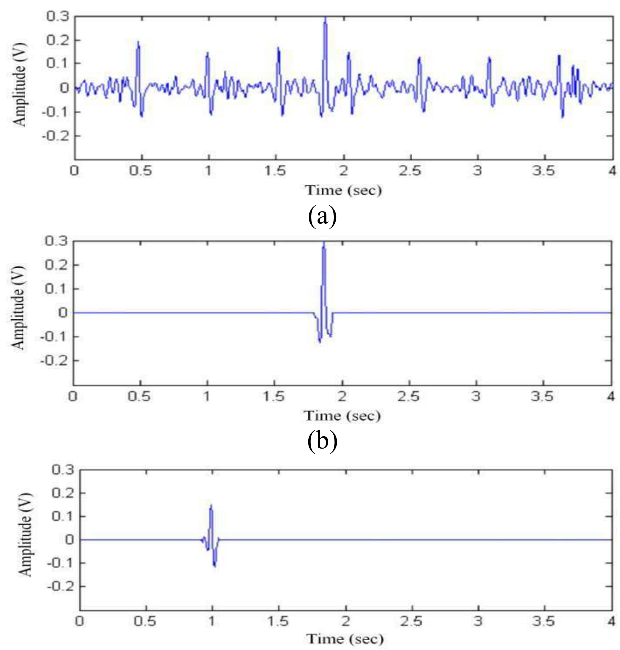
AD: $$\rho = 1 - \frac{\sum_{i=1}^{N}|t_i - s_i|}{\sum_{i=1}^{N}|t_i|} \quad (2)$$



(a)

(b)

Figure 1. A typical example of acquired handgrip ECG waveform under exercising before (a) and after (b) pre-filtering.



(a)

(b)

(c)

Figure 2. An example of QRS template selection: (a) a handgrip ECG under resting, (b) a wrong selection of template, and (c) a correct selection of template.

MAD: $$\rho = 1 - \frac{\sum_{i=1}^{N}|(t_i - \bar{t}) - (s_i - \bar{s})|}{\sum_{i=1}^{N}|t_i - \bar{t}|} \quad (3)$$

NAD: $$\rho = 1 - \sum_{i=1}^{N}\left|\frac{t_i}{\sum_{i=1}^{N}|t_i|} - \frac{s_i}{\sum_{i=1}^{N}|s_i|}\right| \quad (4)$$

where t_i is the QRS template, $\bar{t}$ is the mean value of template, s_i is the input QRS complex, $\bar{s}$ is the mean value of the input QRS, N is the length of template.

The results of correlation coefficients calculated for CWA, AD, MAD and NAD matched filters of the same set of handgrip ECG were shown in Fig. 3. The correlation coefficients of AD and MAD were highlighting the feature of QRS complexes among four matching filters. From the above list matching filters, the preferable matching filter will be the MAD. Because the AD filter has the feature of independent of the baseline drift, in essence, the filter is the IA in nature.

2.4. The weighting function

Fig. 4 (a) is an example of a set of acquired handgrip ECG waveform. If a constant threshold 0.35 was applied to detect the QRS complex, there were several false detections as shown in Fig. 4(b). The correlation coefficient of MAD was set to 0 if it was below 0.35. Therefore, a weighting function was included in process to reduce false detections of the QRS complex [12]. The basis of weighting function is to assume that the variation of RR interval will be small in a short time period. If the predicted QRS time marker has moved further away from the estimated RR_{est}, the probability of existence of a QRS complex is lower. The estimated RR intervals (RR_{est}) was the average of present and 4 previous RR intervals.

$$RR_{est} = \frac{1}{5}\sum_{i=0}^{4} RR(n-i) \tag{5}$$

where RR denotes the RR interval. The initial value of RR_{est} was determined at the stage of template selection.

The search area L_0 and L_1 for the weighting function was shown in Fig. 5. The search range L_0 is defined as $n < RR_{est}$ and L_1 is $n \geq RR_{est}$. The correlation coefficients out of search area were ignored. The search area was defined as following formula.

$$L_0 = L_1 = \beta \times RR_{est} \tag{6}$$

where β is 0.45 that determines the width of search area. Therefore, the weighting function, $u(n)$, was derived as follows.

$$u(n) = \begin{cases} 1 + \dfrac{n - RR_{est}}{\beta \times RR_{est}}, n < RR_{est} \\ \\ 1 - \dfrac{n - RR_{est}}{\beta \times RR_{est}}, n \geq RR_{est} \end{cases} \tag{7}$$

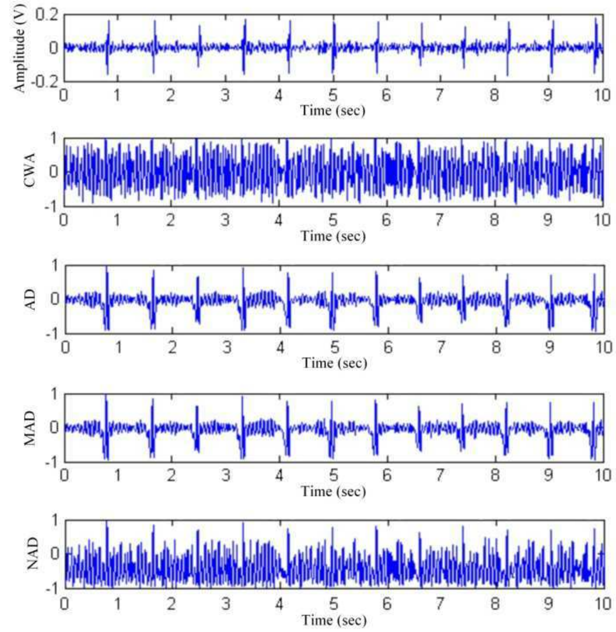
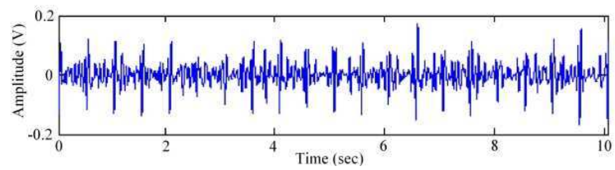
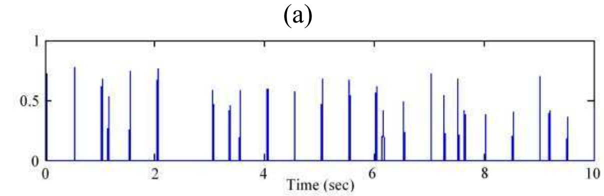


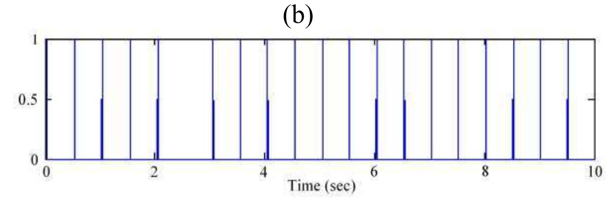
Figure 3. An example of the correlation coefficients using CWA, AD, MAD and NAD matched filters.



(a)



(b)



(c)

Figure 4. An example of the result applying a weighting function.

A weighted correlation coefficient function, $w(n)$, can be calculated by multiplying the correlation coefficients with the weighting function as follows.

$$w(n) = u(n) \times \rho(n) \tag{8}$$

The location of the next QRS complex can be determined by the maximum of $w(n)$. The new RR

interval and the next RR_{est} can be evaluated by last and new QRS locations. The result of QRS detection using the weighting function was illustrated in Fig. 4(c). The location of detected QRS complex is marked as 1. Thus, the use of weighting function can eliminate inaccurate correlation coefficients.

3. Results

The performance of heart rate detection was tested both at resting and at exercising. Five Taiwanese male subjects averaged age of 25 were included in this study. The error rate of QRS detection is defined as follows.

Error rate (%)

$$= \frac{\text{false positive} + \text{false negative}}{\text{total QRS}} \times 100\% , \quad (9)$$

where the QRS detection is said to be false positive if nonQRS wave is detected as a QRS complex and it is said to be false negative if the algorithm fails to detect the QRS complex.

The experimental results showed that the error rates were 0.78% (total of 766 heart beats) at resting condition and 3.83% (total of 3077 heart beats) during exercising.

4. Discussion and conclusions

This study proposed the template matching algorithm for highly noisy handgrip ECG to detect heart rate. The processes are including pre-filtering, a MAD matched filter and a weighting function. As shown, the acquired ECG has a large amount of noise. The result has showed that the template matching algorithm has low error rates for QRS detections. Hence, the heart rate provided by reported method can be applied in treadmills to monitor. The resulting RR interval is perfect for heart rate variability analysis.

Acknowledgements

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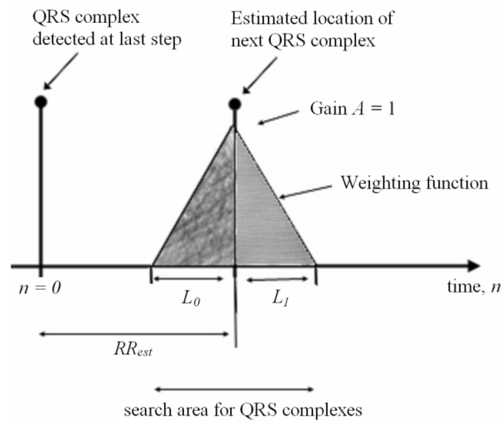

Figure.5 A weighting function diagram

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