Adaptive Electrocardiogram Enhancement in Strong Noise Environment

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Abstract

The electrocardiogram (ECG) is a common and important indicator for diagnosing cardiovascular diseases. The wearable ECG monitoring equipment provides patients with long-term ECG monitoring. But the acquisition signals are susceptible to motion artifact (MA). Reducing MA while ECG processing will help accurately analyse the ECG and make a correct judgment on patients. This paper mainly analyses how to enhance the ECG collected under long-term monitoring and tries to propose an adaptive ECG enhancement method which is composed of adaptive division of human motion state and a modified adaptive Wiener filter based on Bayesian estimation. The method is evaluated on MITDB and CPSC2019 database, as well synchronous ECG, and three-axis acceleration data in the real world. The heart rate performance index is designed, and it is found that the heart rate calculation accuracy can be improved by 24.5% after the ECG is enhanced. It is proved that the method can achieve a good performance of ECG enhancement under different body motion states.

1. Introduction

Electrocardiogram (ECG) contains many morphological features, which consist of a series of characteristic waveforms (P, Q, R, S, T, and U), and is a diagnosing indicator for cardiovascular disease [1, 2].

The importance of ECG in disease prevention and treatment causes the development of ECG monitoring and processing. Wearable ECG acquisition devices, which are comfortable to wear and have no time limitation, can achieve long-term monitoring. For instance, both GTWN from Georgia Institute of Sensorws [3] and T-shirt with 12-lead fabric electrodes from Zhang [4] are typical wearable devices. However, motion artifact (MA) is overlapped with ECG in the frequency domain and results in ECG misdiagnosis.

To reduce misdiagnosis, researchers preliminarily used traditional band-pass filter to pre-process ECG and eliminate noise outside ECG frequency band. But it was difficult to suppress MA. Hence, other methods were considered. Wiener filter can be used in continuous and discrete stationary stochastic processes. Using Wiener filter and other methods, Sharma denoised ECG and compared the results according to signal-to-noise ratio (SNR) and power spectral density (PSD) which proved that Wiener filter has great performance [5]. Woolfson firstly proposed a time-varying Wiener filter of fetal ECG with wavelet transform [6], and after that, Wiener filter was improved to denoise high resolution ECG (HRECG). Lander introduced a posterior Wiener filter which was conducted on time-frequency plane and was the basis of new time-frequency plane Wiener filter [7, 8]. Combination of discrete wavelet transform and Wiener filter had the best performance on HRECG denoising in aspect of Least squares [9]. A two-step ECG denoising algorithm from Nikolaev [10] and adaptive Wiener filter from Wang [11] and Gunarathne [12] were used to denoise ECG. However, most methods are based on the stability of ECG. If ECG is collected in strong noise environment, the accuracy of Wiener filter will decline.

Therefore, many methods analysed ECG with reference signals. Using acceleration sensors to acquire reference data, which is highly relevant to ECG, Zhang created a new normalized LMS algorithm [13]. Tanweer observed reference signals by using nine-axis acceleration and then denoised ECG with Savitzky-Golay filter. In addition, using reference signals, ECG can also be divided into different windows. Researchers can consider which windows can be used. For example, by using Inertial Measurement Unit (IMU) and electromyogram signals, Wei chose and saved proper windows to improve accuracy of ECG processing [14]. The above methods achieved better performance of ECG denoising.

This work combines the RR interval of ECG and IMU data to achieve window division for which ECG can be chosen to save or discard. A modified adaptive Wiener filter is designed meanwhile to denoise ECG. Eventually, an adaptive ECG enhancement method is introduced.

2. Methods

2.1. Motion state division

The acceptability of ECG is determined by the ECG quality assessment, which contains two types, namely the basic quality assessment and the diagnostic quality assessment [15]. Basic quality assessment means that the R wave is still clearly visible under noise, and the information on heart rate can be extracted. As shown in Figure 1, for motion state division, this paper selects IMU data and RR interval of ECG as reference data to evaluate ECG quality with 2-group basic quality assessment method. ECG can be classified into different windows by the results. The signal windows with less interference will be chosen for further analysis, and those with more interference will be discarded directly.

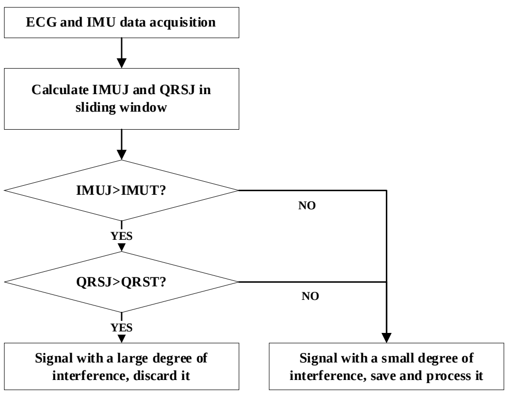


Figure 1. Flow chart of motion state division using IMU data and RR interval.

While acquiring ECG, IMU is used to obtain synchronized reference data. In this paper, the amount of data that exceeds a threshold (IMUT) is selected as the basis for judgment.

For the R wave detection results, the judgement is based on whether the RR interval is evenly distributed. A threshold (QRST) is set in advance to determine whether the difference (QRSJ) between an RR interval and the average of all RR intervals is greater than QRST.

The IMU judgement basis IMUJ is defined as:

$$\mathrm{IMUJ} = \sum_{i=m}^{n} (\mathrm{sign}(\, x(i)^2 + y(i)^2 + z(i)^2), \mathrm{Thr}) \qquad (1)$$

where n and m are the last and first point coordinate of the sliding window. Thr is a threshold set for IMU data sum of squares and IMUJ indicates the total number of points that exceed IMUThr. The value of Thr is 1.

The RR interval judgement basis QRSJ is defined as:

$$\mathrm{QRSJ} = \mathrm{sign}(\, \mathrm{RRt} - \mathrm{RRm}, \mathrm{QRST}\,) \qquad (2)$$

where RRt is each RR interval and RRm is the average of all RR intervals.

The function sign is defined as:

$$\mathrm{sign}(\, X, \mathrm{Thres}\,) = \begin{cases} 1, & X \geq \mathrm{Thres} \\ 0, & X < \mathrm{Thres} \end{cases} \qquad (3)$$

The IMU-based and RR interval-based flag bits are evaluated jointly. ECG segment where both flag bits are 1 at the same time are finally marked as 1.

2.2. Modified adaptive Wiener filter

For ECG, local ECG S(n) is assumed to be disturbed by noise N(n) at discrete time point n. S(n) and N(n) are uncorrelated. The observed ECG Y(n) is defined as:

$$Y(n) = S(n) + N(n), \; n = 0,1,\ldots,N\text{-}1 \qquad (4)$$

The prior $\Phi_s(n)$ of S(n) is estimated using the average of PSD of the QRS:

$$\widehat{\Phi_s}(n) = \frac{\sum \Phi_{QRS}(\,n\,)}{m} \qquad (5)$$

The prior $\Phi_n(n)$ of N(n) is estimated using the average of the PSD between RR interval:

$$\widehat{\Phi_n}(n) = \frac{\sum \Phi_{SQ}(\,n\,)}{m - 1} \qquad (6)$$

where m is the total number of R waves, $\widehat{\Phi_s}(n)$ and $\widehat{\Phi_n}(n)$ is the estimated value.

The location of each wave is initially estimated based on the length of each wave of the standard ECG, the location of the R wave, and the sampling frequency. The estimated prior SNR γ is defined as:

$$\gamma = \frac{\widehat{\Phi_s}(n)}{\widehat{\Phi_n}(n)} \qquad (7)$$

After Y(n) is made to be zero-mean by preprocessing, the error estimate between the desired output $\mathbf{S(n)}$ and the actual output $\hat{S}(n)$ is defined as:

$$\mathbf{e_x}(n) = \mathbf{S}(n) - \hat{\mathbf{S}}(n) = \mathbf{S}(n) - \mathbf{h}^{\mathbf{T}}\mathbf{Y}(n) \qquad (8)$$

where $\mathbf{h} = [h_0, h_1, \ldots, h_{L-1}]^T$ is the transpose of a finite impulse response (FIR) filter of length L, $\mathbf{Y(n)} = [Y_{L-1}, Y_{L-2}, \ldots, Y_0]^T$ is a window vector containing L samples of observed signals.

Assuming that the best estimate of the pure ECG $\mathbf{S_o}(n)$ is $\hat{\mathbf{S}}_\mathbf{o}(n)$, the optimal Wiener filter coefficient $\mathbf{h_o}$ can be obtained:

$$\mathbf{h_o} = \underset{h}{\mathrm{argmin}} \{\, \mathbf{e_x^2}(n) \,\} \qquad (9)$$

According to the Wiener-Hoff equation,

$$\mathbf{R_y}\ \mathbf{h_o} = E\{\, \mathbf{Y}(n)\mathbf{S}(n) \,\} = \mathbf{r_y} - \mathbf{r_v} \qquad (10)$$

where $\mathbf{R_y}$ is the correlation matrix of $\mathbf{Y(n)}$, $\mathbf{r_v}$ and $\mathbf{r_y}$ are correlation vectors, which are the first column of the correlation matrix $\mathbf{R_v}$ of $\mathbf{N(n)}$ and $\mathbf{R_y}$ respectively. Therefore, $\mathbf{h_o}$ can be defined as:

$$\mathbf{h_o} = \mathbf{u_1} - \mathbf{R_y^{-1}}\ \mathbf{r_v} \qquad (11)$$

where $\mathbf{u_1} = [1, 0, \ldots, 0]^T$. Compared to ECG, the additional noise value is assumed to be equivalent to short-time white noise. $\mathbf{r_v}$ and $\mathbf{h_o}$ can be defined as:

$$\mathbf{r_v} = \Phi_n \mathbf{u_1} \qquad (12)$$

$$\mathbf{h_o} = \mathbf{u_1} - \Phi_n \mathbf{R_y^{-1}} \mathbf{u_1} = \left[\, 1 - \frac{\Phi_n}{\mathbf{R_y}[0]},\ 1 - \frac{\Phi_n}{\mathbf{R_y}[1]}, \ldots,\ 1 - \frac{\Phi_n}{\mathbf{R_y}[L-1]} \,\right] \qquad (13)$$

So, the Wiener filter calculation parameters can be changed simultaneously according to the state. The final output of modified adaptive Weiner filter is calculated as:

$$\hat{\mathbf{S}}(n) = \mathbf{h_0}(n)^T \mathbf{Y}(n) = \left(1 - \frac{\Phi_n}{\mathbf{R_y}[n]}\right) \mathbf{Y}(n), \; n = 0, 1, \ldots, L \qquad (14)$$

2.3. Heart rate performance index

Heart rate refers to the number of heart beats per minute and is calculated from n adjacent R wave detection points as shown in:

$$\mathrm{HeartRate}[i] = \left[\frac{n * \mathrm{SampleFrequence}}{\mathrm{Rpoints}[i] - \mathrm{Rpoints}[i-n]} * 60 \right] \quad (15)$$

where Rpoints[i] denotes the ith occurrence of the R wave, HeartRate[i] is the instantaneous heart rate corresponding to that moment, and the units of heart rate are converted to counts per minute in the calculation process. Heart rate performance index is calculated as:

$$HR_{score} = \frac{hr_{score}}{L} \quad (16)$$

$$hr_{score} \mathrel{+}= \begin{cases} 1, & hr_{der}[i] \le 0.05 * hr_{Ref} \\ 0.75, & hr_{der}[i] \le 0.1 * hr_{Ref} \\ 0.5, & hr_{der}[i] \le 0.15 * hr_{Ref} \\ 0.25, & hr_{der}[i] \le 0.2 * hr_{Ref} \end{cases} \quad (17)$$

$$hr_{der}[i] = hr[i] - hr_{ref} \quad (18)$$

Where $hr[i]$ is the instantaneous heart rate at the ith R wave and hr_{ref} is the reference value (or threshold), hr_{ref} setting varies with each ECG. L is the number of R waves.

3. Results

3.1. Database

This paper uses the MITDB and CPSC2019 databases to simulate the enhancement algorithm and collect eight different samples for practical validation. Two sets of experiments are performed for each sample in each type of motion state for 20s. ECG and IMU data are collected simultaneously at 1024Hz. The specific experimental content is designed as shown in Table 1.

Table 1. The experimental content.

No.	Type	Content
1	Relax	Stand Stationary(20s)
2	Jog	Relax(5s)→Jog(10s)→Relax(5s)
3	Walk	Relax(5s)→Walk(10s)→Relax(5s)
4	Chest Expansion	Relax(2s)→CE(16s)→Relax(2s)
5	Jump	Relax(2s)→Jump(16s)→Relax(2s)

3.2. Results of motion state division

We choose ECG in the jogging state for verification, as shown in Figure 2. For the IMU signal, the IMUT is set to 100 per segment, segment duration is 0.5s, and the data overlap between sliding windows is 0.25s. for R wave, the value of QRST is 40.

There are some distorted signals will be missed. This may be because some of the noise amplitude is larger than the R wave, or IMU data in windows is smaller than adjacent window. We set a threshold (LThres). The data segment whose length is less than LThres is discarded directly. The value of LThres is 1000.

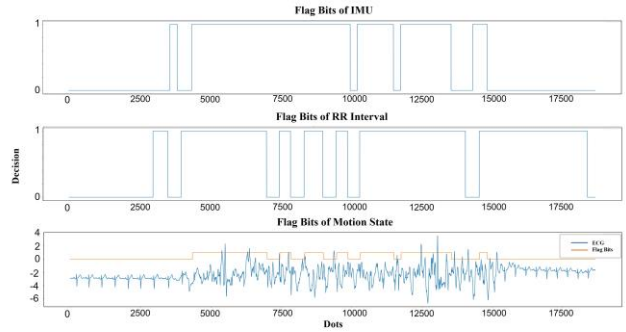


Figure 2. Flag bits determined by IMU and RR interval.

3.3 Results of enhancement method

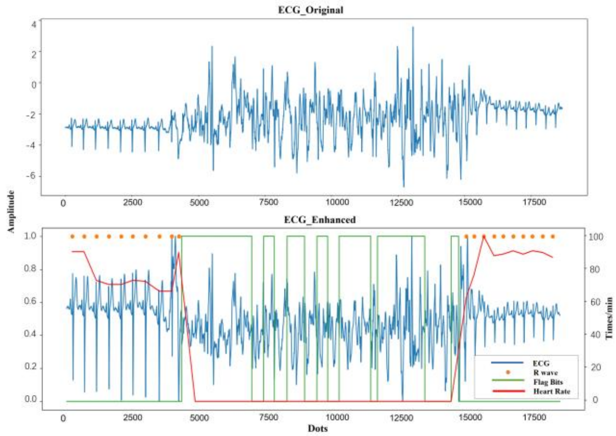
We implement an adaptive ECG enhancement method based on the above methods. The real-time synchronous IMU and ECG data in different motion states are used as input signals, and the noise interference outside the signal frequency band range is removed through pre-processing, then the motion intensity is judged using the motion state division method, and the retained data segment is used as the input signal for adaptive Wiener filter to suppress the noise in the signal frequency band. The result is shown in Figure 3.

The method can distinguish the different motion state of ECG accurately, and automatically turning off the R-wave detection algorithm and heart rate calculation method when the exercise intensity is too high and mark the heart rate value as -1 to indicate that this ECG segment is of no use. The results of ECG enhancement method using heart rate index are shown in Table 2.

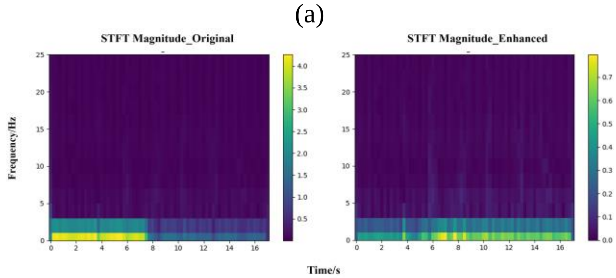
Table 2. HR_{score} before and after enhancement.

State	HR_{score} before	HR_{score} After	State	HR_{score} before	HR_{score} After
Jog	0.2309	0.2875	Walk	0.0143	0.0147
Jog	0.2500	0.2571	Jump	0.3495	0.3804
Relax	0.0596	0.0601	Jump	0.2396	0.2401
Relax	0.0760	0.0769	CE	0.0621	0.0626
Walk	0.0289	0.0294	CE	0.2695	0.2700

ECG in jogging state has a significant increase in heart rate index as it contains data segment of higher motion intensity. The index in relaxing sate is almost unchanged, reflecting minimal MA interference. Due to the adaptive Wiener filter resulting in improved R wave localization accuracy, there are small improvement in other index for less intense exercise.



(a)



(b)

Figure 3. Result of ECG enhancement. (a) Comparison of ECG before and after enhancement. (b) Comparison of STFT result before and after enhancement.

4. Discussion

In this work, an adaptive Enhancement method was proposed for ECG analysis. It contains a motion state division method, a modified adaptive Wiener filter based on Bayesian estimation. Based on the needs of clinical diagnosis, ECG was assessed for quality in 2 groups, and the retained ECG was filtered using adaptive Wiener filter to remove MA. The accuracy of heart rate calculation was effectively improved by up to 24.5% according to the heart rate index, which provides for the analysis of wearable ECG monitoring algorithms. The index is only applicable to the comparison in same motion state, which is due to the different thresholds selected between the different states. This is also a shortcoming of this method.

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