

ECG Baseline Extraction by Gradient Varying Weighting Functions

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Abstract— The electrocardiogram (ECG) signal is important for diagnosing cardiovascular diseases. However, in realistic scenario, the measured ECG signal is prone to be interfered by the artifacts caused from the respiration and the movement of patients. This artifact is called baseline wandering or baseline drifting and will lead to misdiagnosis if it is severe. Thus, pre-processing the measured ECG signal is necessary to make correct diagnosis. In this paper, we proposed a robust pre-processing method for extracting the baseline of ECG signals by the gradient varying weighting function. Our approach is adaptive to the input signal and is able to preserve the features of the ECG signal precisely. Simulation results show that our method outperforms other frequently used baseline extraction methods and has a good performance even if the input ECG signal is severely interfered by baseline drifting.

I. INTRODUCTION

The electrocardiogram (ECG) signal is a recording of the heart activity over a period of time using the electrodes attached to the surface of the skin. In clinical practice, an ECG is a critical tool to diagnose heart abnormalities by several features such as the QRS complex, the RR interval, the PT interval, and the amplitudes of R-wave peaks, etc.

However, several types of interferences will be involved in the data collecting process. Baseline wandering is one of the common artifacts in ECG signal collected from real world, which is mainly caused by the respiration and the movement of the patients, equipment, and the unskilled operator of medical staffs. Baseline wandering will ruin the important features of ECG signals and lead to severe misjudgement for cardiac diseases due to incorrectly detecting R peaks, see Fig. 1. Therefore, extracting the baseline precisely is a critical pre-processing step before cardiovascular diseases diagnosis.

Many approaches have been proposed and widely used in ECG baseline extraction. The techniques can be categorized into two classes. One is to process in the frequency domain such as IIR filtering and FIR filtering [1]. The other class is to process in the time domain such as the mean-median filter [2], moving average [3], polynomial fitting [4] and the Savitzky-Golay (S-G) smoothing filter [5]. In general, frequency domain processing is by designing a high pass filter. However, it is hard to select the pass band frequency properly and is uneasy to be adaptive to the real-time ECG signal. For time domain processing methods, the median filter and the moving average approach is to calculate the average of signal values in a window with a specific size and the result is treated as the

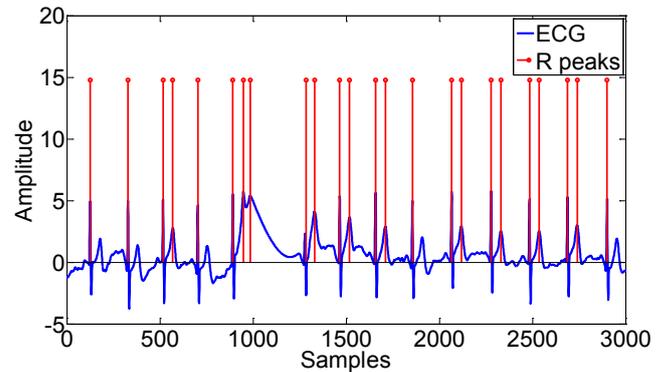


Fig. 1 R-wave peak detection without baseline removal. Some T wave peaks are large and may be misidentified as R-wave peaks.

estimated baseline. This kind of methods may attenuate crucial R-wave peaks while suppressing the baseline noise. The polynomial fitting method uses an appropriate order of the polynomial to approximate the ECG signal without baseline drifting. The S-G filter method performs a local polynomial regression to smooth a signal by determining a proper polynomial degree and filter coefficients. However, if the baseline drifts very seriously or the magnitudes of P waves and T waves are too large, the performances of these methods will be affected.

In this paper, we proposed a robust baseline extraction method based on the gradient weighting function.

The contribution of this work lies on two aspects. First, we proposed a method without the prior knowledge of the baseline frequency. We also avoid the complicated mathematical calculation. Therefore, the proposed method can be performed in real time. Second, our proposed approach can efficiently extract the baseline drifting and preserve the R-wave peaks of ECG signals simultaneously. Simulations for the MIH/BIH arrhythmia database and the data provided by National Taiwan University Hospital (NTUH) show that the proposed method works well even when ECG signals seriously drift.

The paper is organized as follows. In Section II, the proposed method is introduced in detail. In Section III, the simulation results and the comparisons with other baseline extraction approaches are presented. The discussion and conclusion are given in Section IV.

II. PROPOSED METHOD

The QRS complex is a crucial feature in an ECG signal to specify other feature. Perfect detection of the QRS complex is essential for diagnosing cardiovascular diseases. Thus, we try to develop a method that can preserve QRS complexes and extract the baseline accurately at the same time. We think that the proposed gradient varying weighting function is able to achieve the two goals simultaneously. We introduce it in the next subsection.

A. Gradient Varying Weighting Function

Extracting the baseline by moving average directly may attenuate the QRS complexes, since the output of moving average around R-wave peaks is usually high. In order to preserve QRS complexes precisely, we design a weighting function based on the gradient in the neighborhood area of the current position. The weighting function is named the *gradient varying weighting function* and is defined as follows:

$$w[n] = \frac{1}{d + |x[n+k] - x[n-k]|} \quad (1)$$

where n is the current position of the ECG signal, $x[n]$ is the current value of the ECG signal, k the window size we specified for computing the gradient in the neighborhood, and d is a constant to balance the influence of the gradient $|x[n+k] - x[n-k]|$. All of the parameters can be designed for specific requirements. In (1), we can distinguish QRS complexes from other parts of the ECG signal by choosing the proper window size k . The suggested value for k would depend on number of samples for QRS complexes. For an ECG signal with sampling frequency 360 Hz, k is suggested to be about 2.

In this way, we can obtain a smaller weighting value in the location with a larger gradient, such as the QRS complex, and obtain a larger weight in the location with a smaller gradient. In Fig. 2, the behavior of the gradient varying weighting function in (1) is presented. It can be observed that the values of $w[n]$ are smaller when encountering QRS complexes.

B. Baseline Calculation

After defining the gradient varying weighting function, the baseline is formulated as

$$b[n] = \frac{\sum_{m=n-\Omega/2}^{n+\Omega/2} x[m]w[m]\cos[\pi(n-m)/\Omega]}{\sum_{m=n-\Omega/2}^{n+\Omega/2} w[m]\cos[\pi(n-m)/\Omega]} \quad (2)$$

where $b[n]$ is the estimated baseline, Ω is the window size, $w[n]$ is defined in (1), and $x[m]$ is the value of input ECG signal. The baseline is estimated by multiplying the input ECG signal with the gradient varying weighting function, correlating with a cosine function, and further dividing by the sum of $w[m]\cos[\pi(n-m)/\Omega]$ for normalization.

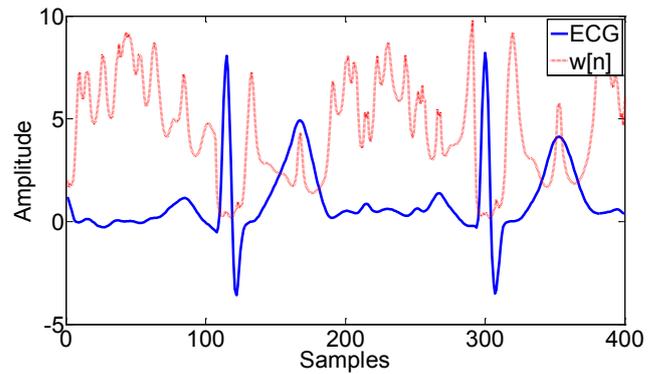


Fig. 2 The relation between gradient varying weighting function $w[n]$ (defined in (1)) and an ECG signal. Note that the weighting function $w[n]$ has a small value when the gradient is large.

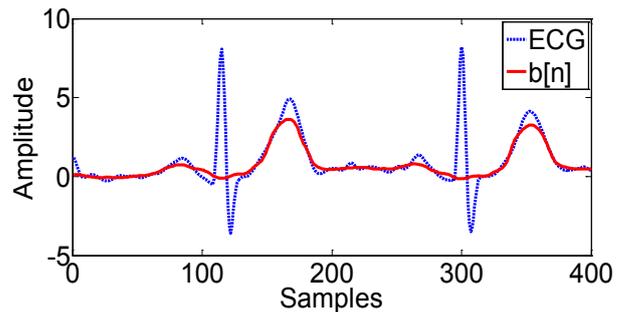


Fig. 3 The characteristic of $b[n]$ and an ECG signal.

Note that, two weighting functions, $w[m]$ and the cosine function, are used to determine the baseline in (2). The first weighting function $w[m]$ (defined in (1)) has a small value when the gradient is large. It makes the estimated baseline less interfered by the high gradient portion and hence can preserve the QRS complex. The second weighting function $\cos[\pi(n-m)/\Omega]$ decreases with $|n-m|$. It makes $x[m]w[m]$ has a smaller effect on determining $b[n]$ if $|n-m|$ is large.

III. SIMULATION RESULTS AND DISCUSSIONS

In this section, the proposed approach is firstly applied to MIT/BIH arrhythmia database [6][7] and further to the ECGs provided by NTUH with the time duration of 15 seconds. The ECGs from NTUH are all first-hand data without any pre-processing step and most of them are severely interfered by baseline drifting because of the respiration and the movement of patients and the unskilled operation of the medical staffs. The parameters we used for the proposed method are $d = 0.1$ and $k = 2$.

We also compare our method with four other frequently adopted baseline line extraction approaches, including the IIR filtering method (IIR), the moving average method (MA), the polynomial fitting method (PF) (the 4th order polynomial is used here), and the Savitzky-Golay filtering method (S-G).

Two evaluation indexes are utilized in the following simulations.

1. Ratio index:

$$\text{ratio index} = \frac{\text{average magnitude of R-wave peaks}}{\text{average magnitude of non-R-wave parts}} \quad (3)$$

(after extracting the baseline).

A larger ratio index means that the R-wave peak can be well distinguished from the non-R wave part, which is helpful for improving the accuracy of R-wave peak detection.

2. Detection error rate (DER) (%): The DER of R-wave peak detection results is defined as

$$\text{DER}(\%) = \frac{FP + FN}{TP + FN} \quad (4)$$

where TP, FP, FN means true positive, false negative, and false positive, respectively. Whether a baseline extraction method has a good performance can also be measured by the DER of the R-wave peak detection algorithm after adopting the baseline extraction method.

Table I shows the DER of R-wave peak detection for the MIT/BIT Arrhythmia Database [6][7] when using a variety of baseline extraction methods. Except for the baseline extraction procedure, other procedures (template matching, finding the extremes in a 0.25 sec time slot, noise removing, adaptive thresholding, etc) for R-wave peak detection are the same. Table I shows that the DER when adopting the proposed baseline extracting approach is only 0.28%, which outperforms all of the other methods.

We also present the ratio indexes (defined in (3)) of the five baseline extraction methods on eight ECG signals provided by NTUH in Table II. These ECG signals suffer from serious baseline drifting problems and two of them are shown at the tops of Figs. 5(a) and 5(b).

From Table II, it can be seen that the ratio index of the proposed method is higher than those of all the other methods. From Fig. 4, when using the proposed method, the non-R wave parts have very small magnitudes after extracting the baseline, which leads to a larger ratio index.

The results of the detected R peaks on two ECGs provided by NTUH are shown on Fig. 5. Both the two ECG signals have a serious baseline drifting problem. For Fig. 5(a), abnormal movements appear in the ECG waveform. The proposed method can correctly locate R peaks while the other methods cannot. The ECG in Fig. 5(b) has a high T-wave peak around the 2100th sample and has an abnormal movement from the 2450th to the 2750th samples. However, when using the proposed method, the R-wave peaks of this ECG signal can still be detected accurately.

In R-wave peak detection, the abnormal movement of the baseline and the high magnitude of the T-wave peak always lead to the misidentification of R-wave peaks. From the simulations in Fig. 5, when using the proposed baseline extracting algorithm, the two problems can be avoided. Because the proposed method has a higher ratio index than all of the other methods, it will not misidentify a large baseline movement or a large T-wave peak as an R-wave peak.

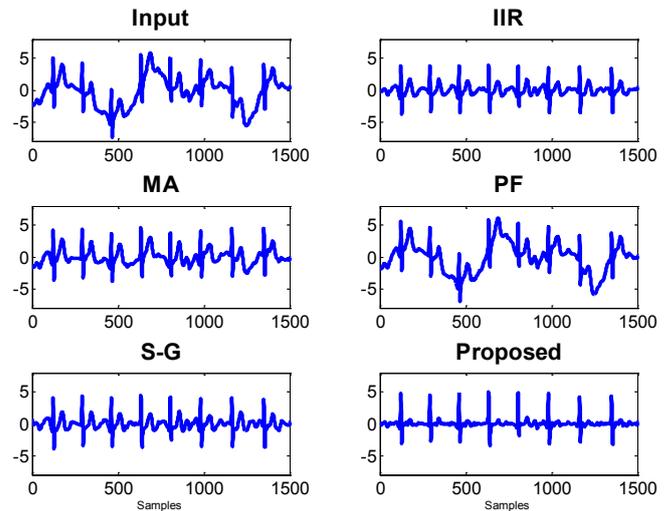


Fig. 4 The results after baseline extraction by different methods.

IV. CONCLUSION

In this paper, we proposed a robust and reliable baseline extraction algorithm by the gradient varying weighting function. In our method, the prior knowledge of baseline frequency is not required. Furthermore, the proposed approach can well distinguish the R-wave peaks from non-R-wave parts. Simulation results show that our method is superior to IIR, MA, PF and S-G baseline extraction approaches in the sense of DER on MIT/BIH arrhythmia database and has a higher ratio index.

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TABLE I

DETECTION ERROR RATE (DER) OF R-WAVE PEAK DETECTION ON THE MIT/BIH ARRHYTHMIA DATABASE [6][7] WHEN USING DIFFERENT BASELINE EXTRACTION APPROACHES (OTHER PROCEDURES ARE THE SAME)

Approach	DER(%)
IIR	0.69
MA	0.46
PF	0.62
S-G	0.41
Proposed	0.28

TABLE II

RATIO INDEXES (DEFINED IN (3)) OF THE PROPOSED METHOD AND OTHER BASELINE EXTRACTION APPROACHES

	IIR	MA	PF	S-G	Proposed
ECG1	7.64	5.38	4.28	7.17	25.83
ECG2	10.36	6.33	5.01	9.36	25.16
ECG3	12.27	9.60	7.73	9.96	63.70
ECG4	13.45	8.76	6.93	12.36	40.87
ECG5	8.06	5.58	2.62	7.54	26.18
ECG6	16.13	10.81	6.78	14.97	41.61
ECG7	12.64	6.41	3.70	11.45	50.43
ECG8	12.90	7.76	3.14	12.27	50.43
average	11.68	7.58	5.02	10.64	40.53

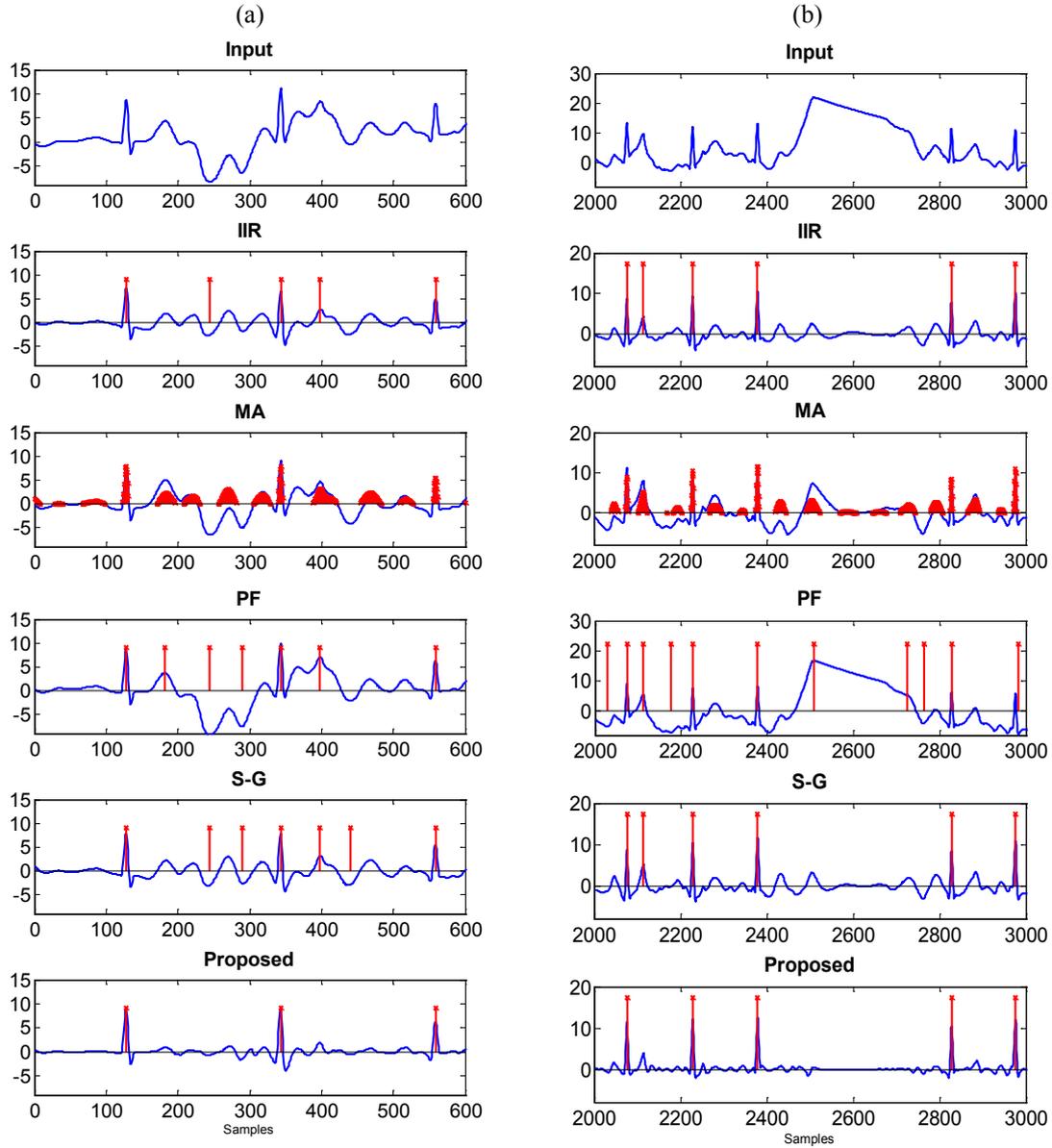


Fig. 5 R-peak detection results for two of the ECG signals provided by NTUH after baseline extraction by different methods. The red spikes indicate the positions of detected R peaks.