Low-Distortion Baseline Removal Algorithm for Electrocardiogram Signals

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Abstract

A new ECG baseline removal method is presented in this paper. This method is based on the Savitzky-Golay polynomial smoothing filter. Since this filter is defined in the time domain, it has the advantage of following the trend of the baseline wander. The results from this method are compared to the cubic spline method and a heart rate adaptive high-pass filter. The comparison shows that the SG baseline filter has comparable performance to these two other established methods. This new method is simple, and does not require extra knowledge about the ECG, such as isoelectric points required by the cubic spline method or the heart rate required by the high-pass filter. Thus it is more suitable for implementation in ECG monitoring systems

1. Introduction

Baseline variation, as shown in Fig. 1, is a major type of noise in electrocardiogram (ECG) signals. Baseline variation is related to impedance variation between the recording electrode and the skin and it is often due to respiration or other body movement.

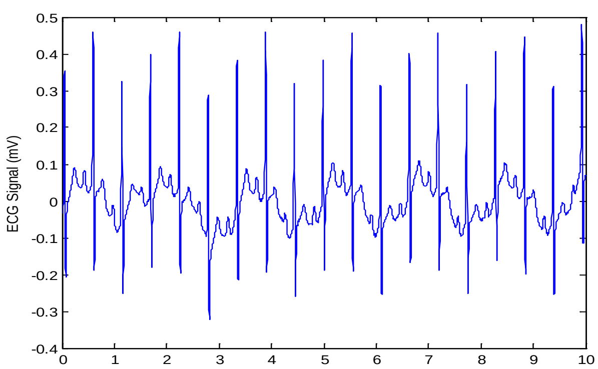

Fig 1. ECG signal with baseline variation caused by respiration.

Baseline interference within the ECG is a low frequency signal below 0.8Hz [1], while the frequency of the heart rhythm signal is usually above 0.05Hz [1]. Thus, the frequency band of the baseline noise overlaps with the interested ECG signal and therefore a simple high-pass filter is not sufficient for removing baseline interference. There are a variety of methods for baseline removal from ECG, including high-pass filtering, adaptive filtering, wavelets, time-frequency analysis, curve fitting, etc. The most commonly used approach is the cubic spline method [2]. A cubic spline is fitted on the isoelectric reference points to estimate the baseline, which is then subtracted from the original ECG to produce the baseline removed signal. The cubic spline method is prone to error in the calculation of the isoelectric reference points, especially in the presence of noise [1].

The simplest baseline removal approach is to use a high-pass filter. However, since the baseline is a type of in-band noise, it is hard to set a cut-off frequency that completely separates the ECG signal from the baseline. Using a low cutoff frequency will result in a filter that is unable to completely remove the baseline interference, while using a high cutoff frequency will result in a filter that distorts the ST segment. Adapting the cutoff frequency using the patient's current heart rate improves the performance of a high pass filter baseline removal technique [3]. According to Fourier theory, the frequency spectrum of a periodic signal is non-zero only on the base frequency and harmonics. This means that if the period is T, the lowest frequency is 1/T. An ideal ECG, which has constant heart rate and identical morphology for each heart beat, can be treated as a periodic signal, so the lowest frequency is HeartRate/60 (Hz). If one sets the cutoff frequency to this value, the low frequency noise can be removed without affecting the ECG. This approach works very well on high heart rate ECG, but when the heart rate is low, in which case the cutoff frequency is low, it may not completely remove the baseline or distort the ST segment. This method also adds system complexity and margin for error that may not be ideal for some real-time patient monitoring systems.

A new approach for baseline removal from the ECG is proposed in this paper. It is derived based on the Savitzky-Golay (SG) filter, a least squares smoothing filter [4]. It is used in this paper to estimate the baseline, which is then subtracted from the original ECG to produce the baseline removed signal.

2. Method

In this section we introduce the SG filter and provide details of the baseline removal technique using this filter. The SG filter is a polynomial smoothing filter [4]. Unlike conventional filter design techniques, which define properties in the frequency domain, and then translate to the time domain, the SG filters are defined directly in the time domain.

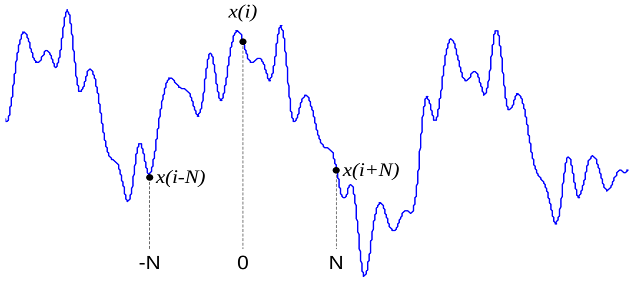

Fig. 2. Local polynomial fit of the SG filter. The central point is always indexed as *0* with the window sliding through the signal.

The SG filter determines the smoothed value for each data point by performing a local polynomial fit in a window. The polynomial function is defined as

$$p(n) = a_0 n^0 + a_1 n^1 + a_2 n^2 + \cdots + a_M n^M , \qquad (1)$$

where M is the polynomial order, n is the independent variable, a_0, a_1, …, a_M are polynomial coefficients. As shown in Figure 2, if the input signal is $x(i)$, the window length is $2*N+1$, then a least squares polynomial fit centered at the ith sample can be expressed as a matrix equation BA=X, namely,

$$\begin{bmatrix} (-N)^0 & (-N)^1 & \cdots & (-N)^M \\ \vdots & \vdots & \vdots & \vdots \\ (-1)^0 & (-1)^1 & \cdots & (-1)^M \\ (0)^0 & 0 & 0 & 0 \\ (1)^0 & 1 & \cdots & 1^M \\ \vdots & \vdots & \vdots & \vdots \\ (N)^0 & N^1 & \cdots & N^M \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_M \end{bmatrix} = \begin{bmatrix} x(i-N) \\ \vdots \\ x(i-1) \\ x(i) \\ x(i+1) \\ \vdots \\ x(i+N) \end{bmatrix} . \qquad (2)$$

Its lease-squares solution is

$$A = \left(B^T B\right)^{-1} B^T X . \qquad (3)$$

The smoothed value of the *ith* sample, denoted as $y(i)$, can then be calculated as

$$y(i) = a_0 n^0 + a_1 n^1 + a_2 n^2 + \cdots + a_M n^M \Big|_{n=0} = a_0 . \qquad (4)$$

Eq. (4) indicates that the smoothed value is determined by a_0 only. According to Eq. (3), a_0 is the inner product between the first row in $\left(B^T B\right)^{-1} B^T$ and X. Eq. (2) indicates that the matrix B is completely determined by the window size, $2*N+1$, and the polynomial order M, so $\left(B^T B\right)^{-1} B^T$ is known once these two parameters are known. Let the first row in $\left(B^T B\right)^{-1} B^T$ be $\left[h(-N) \;\cdots\; h(-1) \;\; h(0) \;\; h(1) \;\cdots\; h(N)\right]$, then $y(i)$ can be written as

$$y(i) = \sum_{n=-N}^{n=N} h(n) x(i+n) . \qquad (5)$$

The first row in $\left(B^T B\right)^{-1} B^T$ is symmetric with respect to the central point, $n=0$, so Eq. (5) can be rewritten as

$$y(i) = \sum_{n=-N}^{n=N} h(n) x(i-n) . \qquad (6)$$

The right hand side of Eq. (6) is the convolution between $h(n)$ and $x(n)$. Therefore, the output of the SG filter is the input filtered by an FIR filter that is determined by the window size and the polynomial order. Since the FIR filter is symmetric, the SG filter has a linear phase response and a delay of half the window size.

One of the key features of the SG filter is that it can be designed to handle edge effects gracefully; however, this is beyond the scope of this paper.

Figure 3 shows the flowchart of the baseline removal method based on the SG filter. The ECG signal is first low-pass filtered to remove most of the interested ECG frequency components. A symmetric FIR filter with 100 taps is used to avoid distortion. The cutoff frequency is 0.8Hz so all baseline frequency components are preserved in the output. A SG filter is then applied to extract the baseline and the baseline is subtracted from the delayed original signal. The output is the baseline removed ECG.

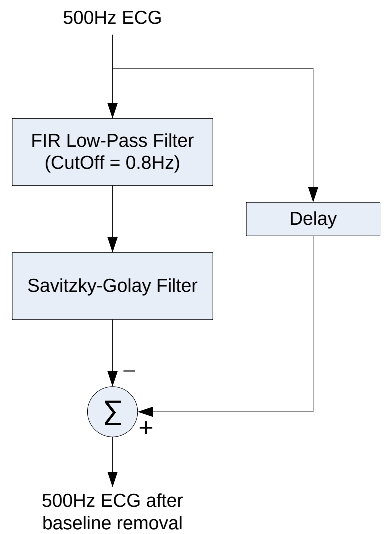

Fig. 3. Flowchart of the SG baseline filter.

The low-pass FIR filter is designed to remove sharp QRS spikes so the SG filter polynomial fit may provide proper estimation of the baseline. The SG filter is a special smoothing filter with the cutoff frequency determined by the window length and the polynomial order. Long window length and low polynomial order results in a low cutoff frequency. With a 500Hz sampling rate, a window size of 2*250+1 and polynomial order of 2 this SG filter introduces a 500ms delay.

Based on Eq. (6), the computation complexity of a SG filter with window size 2*N+1 is the same as a FIR filter with 2*N taps, so the computation complexity of the filter in Fig. 3 is equal to a FIR filter with 500 taps. Such a large number of taps is not realistic for a real time system.

Fig. 4 shows another approach that focuses on reducing the computation load. The ECG signal is low-pass filtered by an anti-aliasing filter, then down-sampled to 12.5Hz. The SG filter is then applied to extract the baseline and the baseline is up-sampled to 500Hz by linear interpolation. It is finally subtracted from the delayed original signal. The output is the baseline removed ECG. With this approach, the SG filter is applied to 12.5Hz, so the window size can be reduced to 2*6+1 and cover the same window as Fig. 3. The computation load is reduced to a FIR filter with 12 taps, the polynomial order is still set to 2 and the delay is 480ms delay. All of which make it suitable for a real time monitoring system.

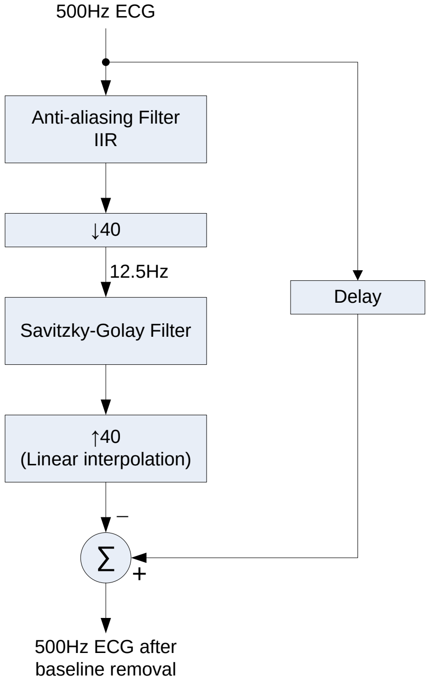

Fig. 4. Flowchart of the SG baseline filter with down-sampling and up-sampling stages.

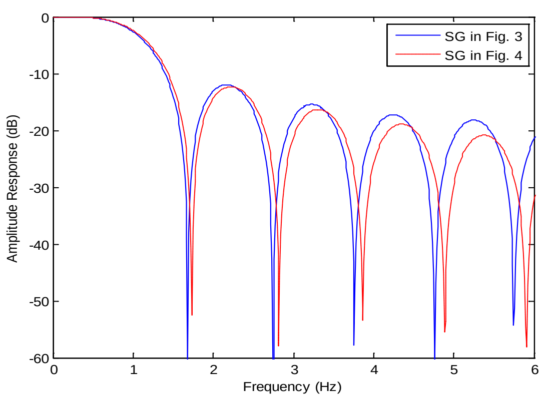

Fig. 5. Frequency responses of SG filters used in Fig. 3 and 4.

Fig. 5 compares the SG filters used in Fig. 3 and Fig. 4. The frequency responses are very similar; therefore, Fig. 3 is used to generate the results in this paper

3. Results

Fig. 6 illustrates the performance of the SG baseline filter. The original ECG contains baseline wander caused by respiration. The low-pass filtered signal shows that the QRS spikes are mostly removed but there are still P and T waves. The SG filtered signal shows the estimated baseline. The output signal shows the ECG after baseline removal with no noticeable baseline wander.

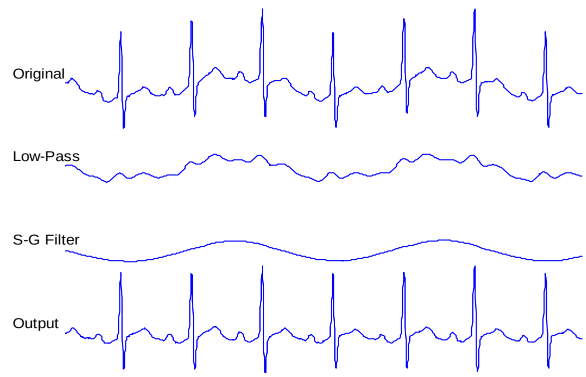

Fig. 6. Performance of SG baseline filter on ECG with baseline. Duration is 4s and average R-wave peak amplitude is 0.9mV.

Another way to evaluate the baseline removal quality is to cut the ECG waveform into one-heart-beat segments, and average the R-wave aligned segments [2]. Since the baseline noise is usually not synchronized to the heart rate, the averaged segment is the baseline-free ECG. Fig 7 shows the average performance of Fig. 6 using forty nine beats. Note that the averaged waveforms are very similar, the difference is close to a straight line.

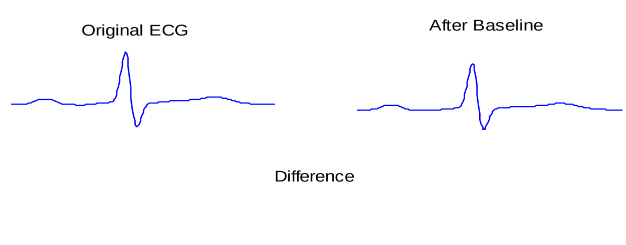

Fig. 7. Average performance of the SG baseline filter on ECG with baseline.

Figure 8 illustrates the performance of the SG baseline filter on an ECG without baseline. The averaged performance is given in Fig. 9. Note that the baseline estimation from the SG filter is close to a straight line, and the output waveform is identical to the original input.

Fig. 8. Performance of SG baseline filter on an ECG without baseline. Duration is 4s and R-wave peak amplitude is 0.2mV.

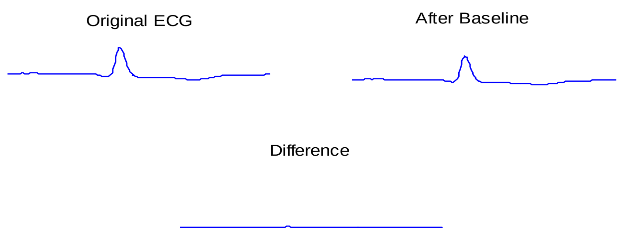

Fig. 9. Performance of SG baseline filter on ECG without baseline.

The results from the SG baseline filter are compared to the cubic spline method and the high-pass filter with the cutoff frequency adapted to heart rate. Figure 10 and Fig. 11 show the comparison of these three methods, with Fig. 10 for respiration artifact, and Fig. 11 for motion artifact. Note that the performances of these methods are comparable. Similar results have been observed on the ECG data collected from 20 patients.

Fig. 10. Performance comparison of baseline removal techniques. The original 16 second ECG has baseline variation caused by respiration. The average R-wave amplitude is 0.9mV.

Fig. 11. Performance comparison of baseline removal techniques. The original 16 second ECG has baseline variation caused by motion. The average R-wave amplitude is 0.5mV.

4. Conclusions

The Savitzky-Golay time-domain smoothing filter described in this paper provides a low distortion baseline removal algorithm for ECG signals. The SG filter estimates baseline noise from the ECG signal by performing a local polynomial fit in a data window and this baseline noise is removed by simply subtracting the estimated baseline from the raw ECG signal. This SG baseline removal method provides a simple approach that preserves the ST segment and does not need extra knowledge about the ECG, such as the isoelectric points required by the cubic spline method or the heart rate required by the high-pass filter, thus making it more suitable for implementation in real-time ECG monitoring systems. More tests are still needed to verify the effectiveness of this approach, especially in cases of low heart rate and tall T-wave

References

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