Adaptive Baseline Wander Removal in the ECG: Comparative Analysis With Cubic Spline Technique *

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Abstract

Baseline wandering is a classical problem in ECG records, that generally produces artifactual data when measuring ECG parameters. In this work we present and analyse a cascade adaptive filter for removing the baseline wander preserving the low frequency components of the ECG. This cascade adaptive filter works in two stages. The first stage is an adaptive notch filter at zero frequency. The second stage is an adaptive impulse correlated filter that, using a QRS detector, estimates the ECG signal correlated with the QRS occurrence. In this way, we preserve all the signal components correlated with the QRS complex. We analyse the frequency response of the filter, showing that the filter can be seen as a comb filter without the dc lobe. Finally, we have applied the method on ECG signals from the MIT-BIH database and we have compared its performance with the cubic spline approach. The method may remove baseline wander in real time without needing to calculate the isoelectric levels, and preserving the low frequency ECG clinical information, that are the major limitations of other methods.

1 Introduction

Baseline wander in the ECG records produces artifactual data when measuring ECG parameters. Particularly, ST segment measures are strongly affected by this wandering. These baseline interferences can be induced by electrode changes due to perspiration, movement and respiration, and are specially relevant in ECG records obtained during exercise testing. The frequency components of the baseline wander are usually below 0.5 Hz but, in case of stress test, this limit can be higher. Thus, these components can be in the same range than the low frequency ECG components like those of ST segment. Then, removal of the baseline can adversely alter the ECG clinical information.

Several methods have been used in the literature to eliminate the baseline wander. The first is ensemble averaging. This approach is adequated when the ECG signal remains constant in each beat, but this is not the situation in many real ECG records. Other method is polynomial interpolation. Linear interpolation introduces significant distortions. A third order approximation called cubic spline [1] achieves better results. Interpolation makes use of a previous knowledge of the ECG isoelectric levels estimated from the PR intervals (knots). This is a nonlinear approach which performance depends on the knots determination accuracy, and it is degraded as the knots become more separated (low heart rate). Other method that overcomes this problem is digital narrow-band linear-phase filtering [2]. This method can be implemented in real time, but has two major problems: first, the filter requires to be a FIR filter with a long impulse response and then a large number of coefficients; second, given that ECG and baseline wander spectra usually overlap, it is not possible to remove the baseline wander with a linear filter without distorting the ECG components. Sörnmo [3] has proposed a time-varying filtering technique that selects different cut-off frequencies of the linear filter as a function of the heart rate or the baseline level. This filter improves the time invariant FIR filter performance, but can yet distort the ST components and has high computational requirements. Adaptive filtering has been recently proposed [4] to cancel the baseline drift. This filter is an adaptive transversal filter [5] with one weight, where the reference input is a constant and the primary input is the ECG signal. This filter, when using the LMS algorithm in the adaptation process is equivalent to a linear notch filter, that takes the advantage of the adaptive implementation but still modifies the ST components [4].

The AHA recommends that the cut-off frequency of a high-pass filter for removing the dc component of the ECG should not exceed 0.05 Hz [6]. It is also stated [2] that, if linear phase is preserved, the cut-off frequency can be chosen taking the fundamental frequency of the heart rate or lower (< 0.8 Hz). If these conditions are satisfied, the baseline wander of higher frequencies will still remain at the filtered ECG. To solve this problem we propose a cascade adaptive filter. First a high-pass notch filter [4] is applied at a cut-off frequency lower than 0.8 Hz, removing the dc component and frequencies lower than those where ST components appears. After that, taking advantage of the recurrent behaviour of the ECG signal, we apply an adaptive impulse correlated filter (AICF) [7]. This filter removes remaining baseline wandering (not correlated with the QRS) preserving the QRS correlated ECG components (in particular the ST segment), except the dc component removed in the first stage. We ilustrate applications of this filter on ECG records from MIT-BIH database affected by baseline drift.

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2 The cascade adaptive filter

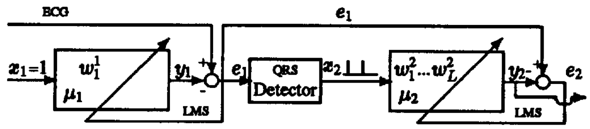

Figure 1: The cascade adaptive filter

The cascade adaptive filter that we propose is plotted in fig. 1. It consists of a first stage adaptive notch filter at zero frequency, and a second stage AICF. The AICF filter becomes a linear filter when using the LMS algorithm [7]. In this work we present a detailed study of the frequency behaviour of the cascade adaptive filter as function of the LMS gain parameters. Considerations on those parameter values more appropriated for baseline removal is also presented.

2.1 The adaptive zero-frequency notch filter

The first stage is an adaptive transversal high-pass filter (notch at zero frequency) [5] with one weight. The primary input is the ECG signal contaminated by baseline wander. The reference input is a constant ($x_1 = 1$) and the output signal is the error signal e_1 (Fig. 1). The filter uses the LMS algorithm

$$w_1^1(k+1) = w_1^1(k) + 2\mu_1\, e_1(k)\, x_1(k)\,. \qquad (1)$$

The cut-off frequency at -3 dB is $f_c = \frac{\mu_1}{\pi} f_s$, where f_s is the sampling rate [5]. The convergence time is $1/(4\mu_1)$ samples. Selecting $\mu_1 = 0.001$ and for a $f_s = 1000$ Hz, we get a convergence time of 0.25 seconds and a cut-off frequency of 0.3 Hz. This frequency satisfies the limit stated in [2] (0.8 Hz) for high-pass filtering, but in the output signal e_1 still remain baseline contaminations of frequencies higher than 0.3 Hz. This transfer function is plotted in fig. 2.

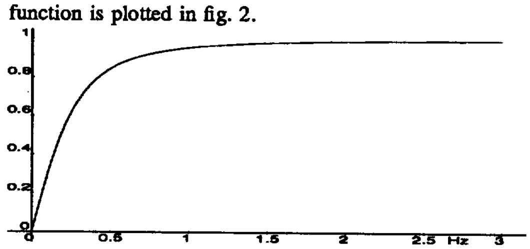

Figure 2: Transfer function of the adaptive notch filter.

2.2 The adaptive impulse correlated filter

To remove the remaining contamination at frequencies higher than 0.3 Hz, we filter again the signal e_1 (Fig. 1) with an AICF [7]. This second stage adaptive filter is an adaptive transversal filter with L weights, that uses as primary input the signal we want to filter e_1, and as reference input a unit impulse sequence (x_2) correlated with each QRS complex. This procedure needs a QRS detector to generate the impulse sequence x_2 (Fig. 1). The filter requires a number L of weights as large as the number of samples that the P-QRS-T complex spans. The output signal is taken at y_2. The LMS gain constant in this second stage filter is μ_2, and the convergence time is $L/(4\mu_2)$ samples,

$$w_i^2(k+1) = w_i^2(k) + 2\mu_2\, e_2(k)\, x_2(k-i+1)\,. \qquad (2)$$

2.2.1 Frequency analysis

To study the behaviour of the AICF (Fig. 3) we can suppose the primary input ($d(k) = s(k) + n(k)$), composed by the consecutive linking of the L-sample noisy recurrences of each P-QRS-T complex. $s(k)$ is the repetitive stimulus-generated response, and $n(k)$ is the disturbing signal. The reference input, $x(k)$, is composed by a periodic unit impulse repeated each L samples.

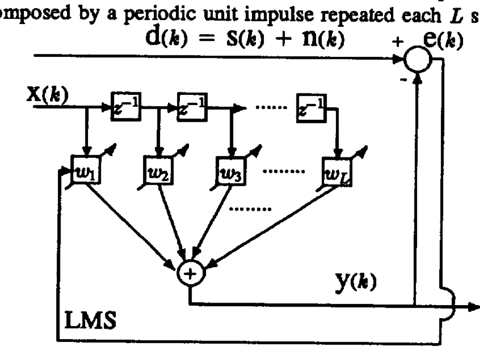

Figure 3: Adaptive impulse correlated filter (AICF)

In [7] it is shown that this filter, when using the LMS algorithm, is equivalent to a linear exponentially-weighted averager which output, after processing N recurrences, is expressed as:

$$y(k) = \sum_{m=1}^{N} 2\mu_2\, (1-2\mu_2)^{N-m}\, d(k-(N-m+1)L)\,. \qquad (3)$$

Because of the $\delta[k]$ function properties (3) can be expresed as:

$$y(k) = \sum_{m=1}^{N} 2\mu_2(1-2\mu_2)^{N-m} \sum_{k'=-\infty}^{k'=\infty} d(k')\delta[k'-(k-(N-m+1)L)] \qquad (4)$$

$$y(k) = d(k) * \left[\sum_{m=1}^{N} 2\mu_2(1-2\mu_2)^{N-m}\delta[k-(N-m+1)L]\right] \qquad (5)$$

where $*$ denotes the convolution operation. Then the output signal $y(k)$ is the primary input signal $d(k)$ convolved with an exponentially weighted finite impulse serie. This can be considered as a filter operation whose impulse response $h[k]$ is:

$$h[k] = \sum_{m=1}^{N} 2\mu_2(1-2\mu_2)^{N-m}\delta[k-(N-m+1)L]\,. \qquad (6)$$

Denoting $(1-2\mu_2) = e^{-1/\tau}$ we can write

$$h[k] = 2\mu_2 e^{-N/\tau} \sum_{m=1}^{N} e^{m/\tau}\delta[k-(N-m+1)L]\,. \qquad (7)$$

$$h[k] = 2\mu_2 e^{-N/\tau} e^{k/\tau L}\, (u[k] - u[k-NL]) \sum_{m=-\infty}^{\infty} \delta[k-mL]\,. \qquad (8)$$

and calling

$$b[k] = e^{-N/\tau} e^{k/\tau L} \left(u[k] - u[k - NL]\right) \tag{9}$$

$$c[k] = \sum_{m=-\infty}^{\infty} \delta[k - mL] \; , \tag{10}$$

we get $h[k] = 2\mu_2 \; b[k] \; c[k]$. The discrete Fourier transform $H(\Omega)$ of $h[n]$ is $H(\Omega) = 2\mu_2 B(\Omega) * C(\Omega)$, where Ω is the normalized frequency. Computing $B(\Omega)$ and $C(\Omega)$ [8]:

$$B(\Omega) = e^{-N/\tau} \sum_{k=0}^{NL} e^{k/\tau L} e^{-j\Omega k} = \frac{e^{-N/\tau} - e^{-j\Omega NL}}{1 - e^{(1/\tau L - j\Omega)}} \tag{11}$$

$$C(\Omega) = \frac{2\pi}{L} \sum_{n=-\infty}^{\infty} \delta\left(\Omega - \frac{2\pi n}{L}\right) \tag{12}$$

Taking these results in $H(\Omega)$ and considering the recurrence number $N \to \infty$ (steady state), we have

$$\begin{aligned} H(\Omega) &= 2\mu_2 \frac{2\pi}{L} \frac{1}{2\pi} \int_{2\pi} B(\Theta) \; C(\Omega - \Theta) \; d\Theta \\ &= -\frac{2\mu_2}{L} e^{-j\Omega NL} \sum_{n=0}^{L-1} \frac{1}{1 - e^{\left[\frac{1}{\tau L} - j\left(\Omega - \frac{2\pi n}{L}\right)\right]}} \end{aligned} \tag{13}$$

This filter is a comb filter with lobes repeated at frequencies multiples of the fundamental frequency (f_0) of the P-QRS-T complex ($f_0 = f_s/L$), that includes a time delay factor of the N processed recurrences. The -3 dB cut-off of each lobe is $\frac{\mu_2}{\pi} f_0$ far from the central frequency of the lobe. In fig. 4 we present the

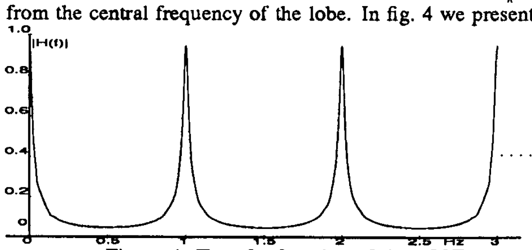

Figure 4: Transfer function of the AICF.

transfer function module for $f_s = 1000Hz$, $L = 1000$ samples ($f_0 = 1$ Hz) and $\mu_2 = 0.05$. This implies a cut-off frequency of each lobe respect to the central frequency of $f_c = 0.016$ Hz. The lobe width is proportional to the μ_2 value. Thus, lower μ_2 value gives narrower lobes but also higher convergence time ($L/4\mu_2$). Then, a compromise must be taken to select μ_2 value.

2.3 The two stages cascade filter

The AICF filter extracts the deterministic signal that repeats at each QRS recurrence including the dc component (n=0 in (13)). This dc component is not desirable since it includes baseline variations, but if μ_2 is selected to give $\frac{\mu_2}{\pi} f_0 < \frac{\mu_1}{\pi} f_s$ the first lobe of the comb filter will be attenuated by the high-pass filter of the first stage. This condition implies that $\mu_2 < \mu_1 L$. The resultant cascade filter removes the dc component and those components not correlated with the QRS complex, preserving the

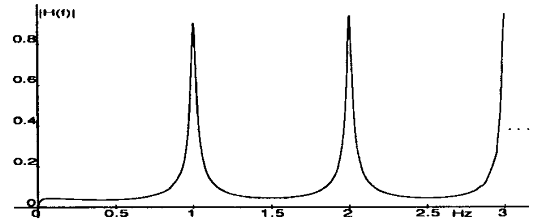

Figure 5: Transfer function of the cascade filter

QRS correlated components (ST segment). In fig. 5 we plot the resultant transfer function module $|H(f)|$ of the cascade filter for L=1000 samples, $f_s = 1000$ Hz ($f_0 = 1$ Hz), $\mu_1 = 0.001$ and $\mu_2 = 0.05$ ($\mu_2 < \mu_1 L$). This graphic must be interpreted carefully because the comb filter does not apply to the output of the high-pass filter e_1. The first stage high-pass filter applies to the ECG signal and the AICF applies to the output of the previous stage (e_1) but the performance study has been done assuming periodic inputs (removing the inter P-QRS-T complex interval). Thus, remaining baseline variations at frequencies multiples of f_0 in the e_1 signals, that in accordance with fig. 5 would remain at the output y_2, really would be removed because they are not correlated with the QRS occurrence. The ST components at frequencies different of f_0 multiples, in the original ECG and in the e_1 signal, that in accordance with fig. 5 would be removed, are preserved because are correlated with the QRS complex and then translated to multiples of f_0 when considering the comb filter.

3 Application to real ECG records

In fig. 6 we present an real ECG affected by baseline wander and sampled at 1000 Hz; the output of the adaptive high-pass filter, e_1, using μ_1=0.001; the cascade filter output y_2 using μ_2=0.05; the real ECG corrected with cubic splines technique (Spli) [1] and the real ECG high-pass filtered with a second order Lynn filter at a cutt-off frequency of 0.8 Hz. We can corroborate how the adaptive high-pass filter, with a cut-off frequency of 0.3 Hz, does not remove the whole baseline wander in e_1 and then the AICF, at the filter output y_2, removes the remaining variations and all signal interferences not correlated with the QRS complex [7]. In this case (low frequency baseline wander and adequated knot determination at the PR interval) splines and high-pass filter achieves also good baseline wander reduction. Fig 7 shows other ECG record results using $L = 600$ samples, and same μ_1, μ_2 and sampling rate. In this case we present a signal that has higher frequency baseline wander and motion artifact. Our cascade filter made a good correction whereas the splines do not work as well due to the limitation of knots determination. In fig 8 are the results on the record 103 of the MIT-BIH database (18':08" to 18':18") seconds. Sampling rate is 360 Hz, $\mu_1 = 0.003$, $\mu_2 = 0.05$ and $L = 320$ samples. We can corroborate that, in case of sudden baseline drift, the cascade filter works much better than the spline technique.

4 Conclusions

The proposed cascade adaptive filter allows to remove the base-

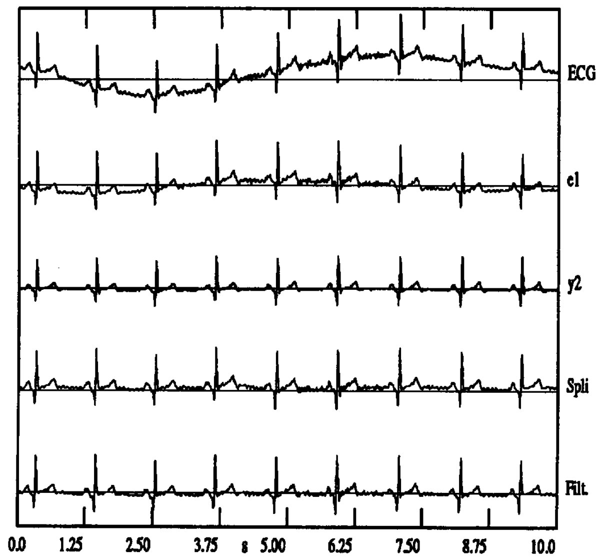

Figure 6: *ECG, adaptive high-pass filtered, cascade filtered, spline corrected and high-pass filtered signals*

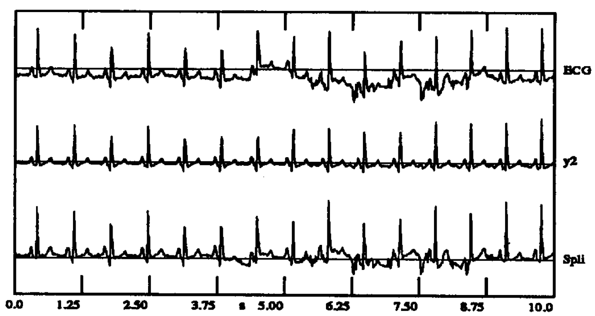

Figure 7: *ECG, cascade filtered, and spline corrected signals*

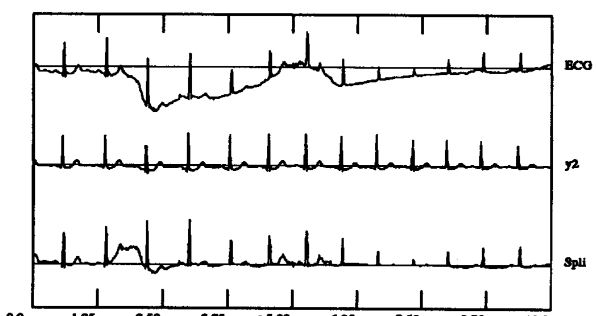

Figure 8: *ECG, cascade filtered, and spline corrected signals*

line wander present in the ECG, preserving the components of clinical information. It removes frequencies below 0.3 Hz and those higher than 0.3 Hz not correlated with the QRS occurrence. Then, as the ST segment repeats with each QRS it has frequency components that fall into the fundamental lobe and its harmonics of fig. 5, and then are preserved at the output filter. This filter can efficiently be implemented in the adaptive form with the only requirement of a real-time QRS detector and does not need to compute the knots as in the cubic splines technique. In addition the filter removes all interferences not correlated with the QRS as 50/60 Hz, motion artifact and EMG. The filter removes the dc component of the ECG, thus, it is recomended to measure ST level with respect to the PR or TP isoelectric segments determined at the baseline corrected signal.

The frequency response becomes a function of the LMS gain parameters (μ_1 and μ_2) of the two adaptive filter stages. It is shown that its behaviour can be interpreted as a comb filter without the dc lobe.

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