

LOW-COST ADAPTIVE METHOD FOR REAL-TIME ECG BASELINE WANDER REMOVAL WITH REDUCED P AND T WAVE DISTORTION

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Abstract: An adaptive algorithm for the removal of baseline wander in ECG is presented. The scheme is based on a single-tap LMS filter that estimates the baseline signal. The baseline is further processed by a moving average filter. This way, reduced distortion of P-Q and S-T segments is achieved with a low computational cost. Moreover, the proposed system has a short impulse response that makes it appropriate for real-time applications.

1 INTRODUCTION

The performance of signal processing tasks on electrocardiograms (ECG's) is greatly affected by the presence of noise artefacts. Among these artefacts, baseline wander is a component of measured ECG's typically due to patient motion whose frequency components are usually considered to be below 0.1 Hz (Sörnmo, 1991). However, its energy may occasionally span over a wider range of frequencies, thus distorting the lowest frequency components of the P-QRS-T complex, that is, P-Q and S-T segments (Barati and Ayatollahi, 2006), which are useful for the diagnosis of certain pathologies. Classical high-pass filtering of the ECG for the removal of baseline wander has the drawback of requiring filters with very narrow transition bands, therefore resulting in FIR filters having long responses (Sörnmo, 1991). For this reasons alternative approaches have been proposed in literature up to now. As referred next, these approaches can be roughly classified in two groups: adaptive schemes on the one hand and methods based on ECG signal decomposition on the other.

Adaptive schemes were firstly proposed in (Thakor and Zhu, 1991), where a single-tap adaptive filter based on the least mean squares (LMS) rule is described. This filter behaves as a simple low-pass filter and introduces significant P-QRS-T complex distortion due to the width of its transition band. An im-

provement for this system which consists in an additional stage that estimates the P-QRS-T complex is described in (Laguna et al., 1992). This procedure intends to avoid the above-mentioned distortion at the risk of masking beat-to-beat variations of the P-QRS-T complex. A different approach consisting of a filter bank from which one output is adaptively selected was introduced in (Sörnmo, 1991). This scheme intends to avoid distortion and does not blur beat-to-beat variations, but it has a significantly higher computational cost.

More recently, other algorithms have been published that are based on different ECG signal decompositions, namely wavelet (Zhang, 2005), empirical mode decomposition (Weng et al., 2006) and independent component analysis (Barati and Ayatollahi, 2006). These algorithms tend to provide better performance than adaptive methods, but at the cost of much higher processing delays and computational costs, hence the difficulty to apply them to real-time systems.

Within this paper, an adaptive filtering scheme based on (Thakor and Zhu, 1991) is presented. This system inherits from adaptive systems the advantage of a low computational cost while it avoids P-QRS-T distortion by low-pass filtering of the estimated baseline. This has the effect of achieving a narrower transition band in frequency domain at the cost of only a few computations more while maintaining the pro-

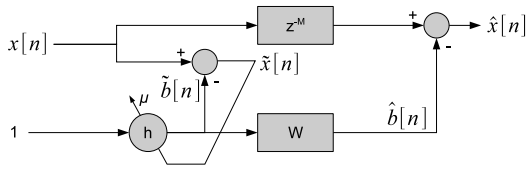


Figure 1: Block diagram of the proposed system: $x[n]$ is the original ECG with baseline wander, (h, μ) is a single-tap LMS filter, $\tilde{b}[n]$ is a baseline estimate, such estimate is smoothed to produce $\hat{b}[n]$, z^{-M} is a delay of M samples and $\hat{x}[n]$ is the ECG without baseline wander.

cessing delay well below the duration of one heart beat.

2 SYSTEM DESCRIPTION

The overall proposed system set-up is depicted in figure 1. The ECG signal is assumed to arrive into the system sampled at a certain sampling frequency f_s and superimposed to the baseline wander. This input signal is named $x[n]$ in the figure. It acts as the target signal of an adaptive LMS filter with a single tap h and a constant input equal to 1. The learning rate of the LMS algorithm is μ and its output ($\tilde{b}[n]$) is an estimate of the ECG baseline. Thus, $\tilde{x}[n] = x[n] - \tilde{b}[n]$ is an ECG with reduced baseline wander (Thakor and Zhu, 1991). From the same figure, the transfer function between signals $x[n]$ and $\tilde{x}[n]$ in z-domain can be derived:

$$H(z) = \frac{\tilde{X}(z)}{X(z)} = 1 - \frac{2\mu}{1 - z^{-1} \cdot (1 - 2\mu)} \quad (1)$$

and, from it, the frequency response (dashed line in figure 2). This system behaves as a filter with a notch at zero frequency and a bandwidth that depends on the choice of μ . The graph in figure 2 indicates that acceptable attenuation levels below 0.5 Hz can only be achieved at the cost of unacceptable distortions around 1 Hz.

Figure 3 (up) illustrates the relevance of the above-mentioned distortion. An ECG is a quasi-periodic signal whose spectrum, specially at low frequencies, is formed by peaks placed at the fundamental frequency (1.12 Hz in this case) and its harmonics. Frequency components below 5 Hz in a clean ECG, that is, the first four or five harmonics, correspond to the P and T waves (Sörnmo and Laguna, 2005). Consequently, if when removing baseline wander (the peak below 0.5 Hz in this case) significant distortion is allowed nearby the ECG's fundamental frequency and its first multiples, this should have an effect on the form of P and T waves.

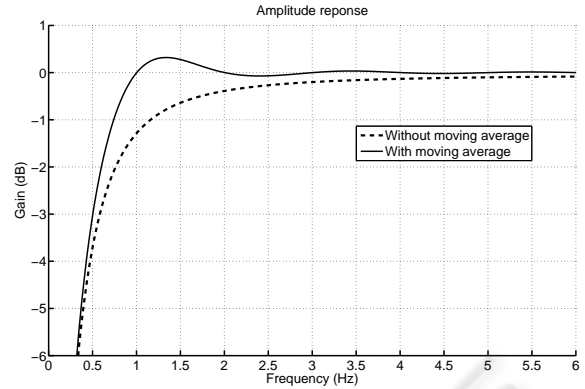


Figure 2: Frequency response of the adaptive scheme in (Thakor and Zhu, 1991) for $\mu = 0.005$ and $f_s = 360$ Hz (dashed line) and the herein proposed system (continuous line) for the same conditions, being W a rectangular window with 361 coefficients and $M = 180$.

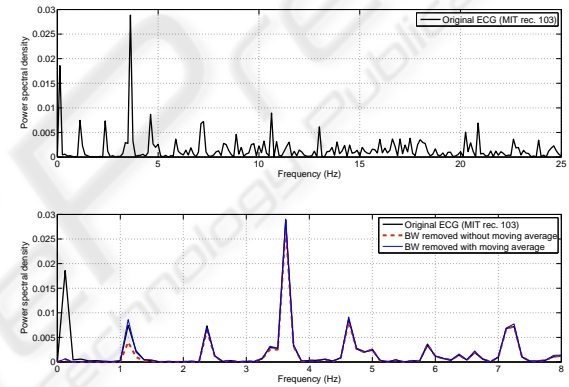


Figure 3: Periodogram-based spectrum estimation of ECG MIT record no. 103 (Physionet, 2007) (up) and comparison with processed ECG's for baseline wander removal (down).

The previously described system, which exactly corresponds to (Thakor and Zhu, 1991), can be easily improved if the baseline estimate $\tilde{b}[n]$ is smoothed by a moving average filter with transfer function equal to $W(z)$, thus producing a smoother estimate of the baseline $\hat{b}[n]$ (figure 1). The group delay of filter $W(z)$ can be compensated by means of a delay of M samples introduced in $x[n]$ before subtracting $\hat{b}[n]$ so as to produce a less distorted ECG $\hat{x}[n]$. This way, the system function becomes:

$$\hat{H}(z) = \frac{\hat{X}(z)}{X(z)} = z^{-M} - W(z) \cdot \frac{2\mu}{1 - z^{-1} \cdot (1 - 2\mu)} \quad (2)$$

If $W(z)$ is chosen such that its value is zero for $z = e^{j\omega_k}$, where $\omega_k/2\pi$ are frequencies in which the ECG has significant components, then the whole filter $\hat{H}(z)$ can be ensured to have unit amplitude response for those frequencies, thus achieving a reduction in

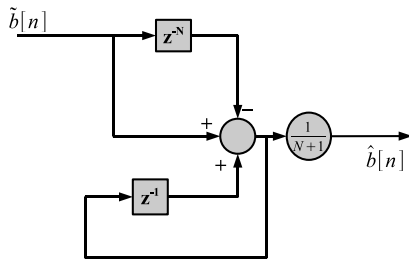


Figure 4: Implementation proposal for the moving average.

the distortion within those bands:

$$\hat{H}(e^{j\omega_k}) = e^{-jM\omega_k} - W(e^{j\omega_k}) \cdot \frac{2\mu}{1 - e^{-j\omega_k} \cdot (1 - 2\mu)} = e^{-jM\omega_k} \quad (3)$$

Figure 2 shows the frequency response of this modified system compared to that of the original one. It can be seen that while similar attenuations are achieved for frequencies below 0.5 Hz, null distortions are achieved for frequencies $\omega_k/2\pi$ equal to 1 Hz and its harmonics. In other words, the exact frequency response depends on both μ and $W(z)$; however, the zeroes of $W(e^{j\omega})$ correspond to unit amplitudes of $\hat{H}(e^{j\omega})$ which ensure little distortion at the frequencies of interest and, in addition, make the whole system response less sensitive to the choice of μ .

3 IMPLEMENTATION ISSUES

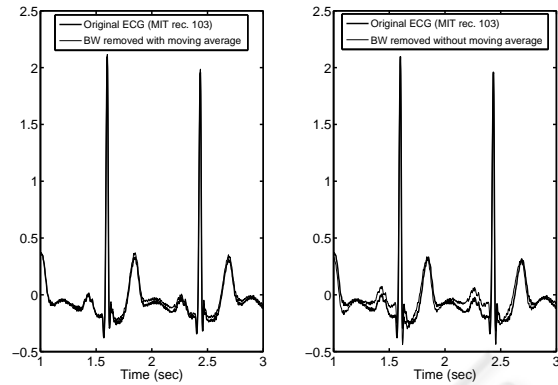
Recalling equation (1) and transforming it into time domain:

$$\tilde{x}[n] = (\tilde{x}[n-1] + x[n] - x[n-1]) \cdot (1 - 2\mu) \quad (4)$$

Therefore, the original system requires two additions plus one product per ECG sample. The number of necessary operations per sample of the modified system depends on the specific implementation chosen for W . In figure 4, an implementation proposal based on a $2M$ -order rectangular moving average filter is drawn. Such implementation only requires two additions and one product per sample:

$$\hat{b}[n] = (\hat{b}[n-1] + \tilde{b}[n] - \tilde{b}[n-2M-1]) \cdot \left(\frac{1}{2M+1} \right) \quad (5)$$

This, together with the original scheme and the additional subtraction illustrated at the right of figure 1, results in a total of five additions and two products per sample. This makes the scheme especially appropriate for real-time implementation. Specifically,


 Figure 5: Original (*thick line*) and processed (*thin line*) ECG's for the herein proposed system (*left*) and the system in (Thakor and Zhu, 1991) (*right*).

for $f_s = 360$ Hz only 1800 additions and 720 products per second are required. This results in a total of 2520 floating point operations (FLOP) that, considering that the performance of current digital signal processors easily reaches 150 million FLOP per second (Texas Instruments, 2008), means that less than $17 \mu\text{s}$ of computation are required per second.

4 RESULTS

Figure 5 shows the results of applying both schemes to the same ECG record reported in (Weng et al., 2006), namely record 103 of the MIT database (Physionet, 2007), and with the same conditions. The plots show that the new system including the moving average $W(z)$ produces a noticeably better match between reference and processed signals than the adaptive system without the moving average. Quantitatively, a signal-to-error ratio (see (Weng et al., 2006) for its definition) equal to 22.9 dB can be achieved with the herein introduced scheme for the first 2,000 samples of this record, whereas the system in (Thakor and Zhu, 1991) reaches 17.2 dB. Note that the results reported in (Weng et al., 2006) are also around 17.2 dB for the same part of the record and the herein reported improvement up to 22.9 dB has been achieved with a computationally simpler algorithm.

Figure 6 provides a deeper insight in the origin of the performance improvement. The upper part of the figure shows the root mean square (RMS) difference between the processed ECG and the original signal for both evaluated methods. It can be noticed how the filter with the moving average equalises the distortion along the whole P-QRS-T complex, while the absence of the moving average has the consequence of some parts of the complex being more distorted than others. A quantification of such distortion is plotted in

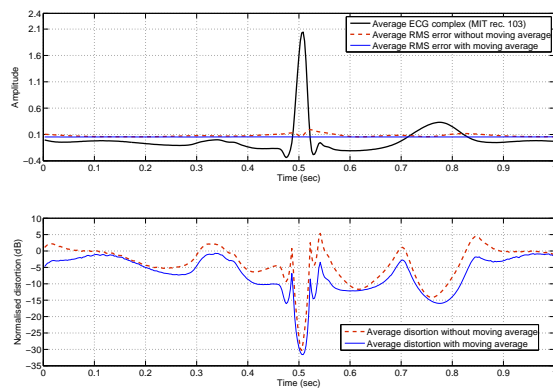


Figure 6: RMS error with respect to the original ECG averaged per P-QRS-T complex for the full MIT record no. 103 (up) and averaged distortion along the P-QRS-T complex in dB, calculated as the inverse of the signal-to-error ratio (down).

the bottom graph. Namely, the inverse of the instantaneous signal-to-error ratio averaged for all P-QRS-T complexes has been chosen as a measure of distortion. It can be seen that improvements of up to 5 dB are achieved for the P-Q segment, the S wave and the end of the T wave.

This effect can also be assessed in spectral domain by analysing the spectra of original and processed ECG's. These spectra are depicted in the bottom graph of figure 3. While both baseline wander removal algorithms remove the spectral peak below 0.5 Hz, the herein proposed system achieves so without affecting the first harmonic of the ECG, while a significant distortion is produced if the moving average is not used.

5 CONCLUSIONS

Within this paper an evolved adaptive system for the removal of ECG baseline wander has been introduced. Both the low computational complexity and the short delay (about half a beat period) of the scheme make it useful for real-time implementation. At the same time, preliminary tests indicate that this system may outperform other more complex systems in terms of signal distortion without any averaging that lasts for more than one heart beat, and without any P-QRS-T averaging at all, thus avoiding the masking of beat-to-beat variations.

A supplementary improvement on the proposed baseline removing system could be achieved by adapting the lengths of the filter W and the shift register M to the beat-to-beat period. If, within the ECG processing posterior to baseline wander removal, QRS detection is to be performed, then the

reduced distortion in frequency domain should be achieved exactly at the harmonics of the ECG fundamental frequency without specifically increasing the computational complexity of the baseline filter.

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REFERENCES

- Barati, Z. and Ayatollahi, A. (2006). Baseline wandering removal by using independent component analysis to single-channel ECG data. In *Proc. of the International Conference on Biomedical and Pharmaceutical Engineering ICBPE 2006*, pages 152–156. ID: 1.
- Laguna, P., Jane, R., and Caminal, P. (1992). Adaptive filtering of ECG baseline wander. In *Proc. of the 14th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, volume 14, pages 508–509.
- Physionet (2007). The MIT-BIH arrhythmia database. URL: <http://www.physionet.org/physiobank/database/mitdb/>.
- Sörnmo, L. (1991). Time-varying filtering for removal of baseline wander in exercise ECGs. In *Proc. of Computers in Cardiology*, pages 145–148.
- Sörnmo, L. and Laguna, P. (2005). *Bioelectrical Signal Processing in Cardiac and Neurological Applications*. Elsevier Academic Press.
- Texas Instruments (2008). Digital signal processing (DSP) development tools. URL: http://www.ti.com/home_p_dsp.
- Thakor, N. V. and Zhu, Y. (1991). Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. *IEEE Transactions on Biomedical Engineering*, 38(8):785–794.
- Weng, B., Blanco-Velasco, M., and Barner, K. E. (2006). Baseline wander correction in ECG by the empirical mode decomposition. In *Proc. of the 32nd IEEE Annual Northeast Bioengineering Conference*, pages 135–136.
- Zhang, D. (2005). Wavelet approach for ECG baseline wander correction and noise reduction. In *Proc. of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEMBS 05*, pages 1212–1215.