Adaptive Filtering in ECG Denoising: A Comparative Study

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Abstract

The performance of several adaptive filter (AdF) algorithm implementations was investigated in the context of cleaning noisy ambulatory ECGs. Together with a noisy ECG signal, both body movement measured with accelerometers and skin-electrode impedance (SEI) were considered as reference signals to the AdF.

ECG with artificial motion artifacts were generated by combining clean ECGs with noise signals. Several implementations and combinations of AdFs, and two reference signals (accelerometers and SEI) were investigated. Performance was measured by evaluating the output (sensitivity (Se) and positive predictivity (+P)) of a beat detection (BD) algorithm.

Using AdF algorithm improved the performance of a BD algorithm as compared to non-filtering. SEI used as reference signal outperformed accelerometers. A variant of LMS, LMS sign-error, gave the best performance from all implementations considered. However, distortion observed in the filtered signal is high and therefore, these results cannot be extended to other features within the ECG.

1. Introduction

In recent years, new ambulatory cardiac monitors have been developed for continuous ECG monitoring. These devices are portable and have an autonomy that is increasing with the advance of low-power micro-electronics. Integration of microprocessors allows performing some embedded signal processing and automatic interpretation. However, in ambulatory conditions, noise increases with higher levels of activity. Motion artifacts could reduce signal quality significantly, making ECG interpretation very difficult.

Several methods for noise reduction and motion artifact removal have been proposed in the literature. Traditional denoising techniques were based on time averaging [1] and frequency analysis such as filter banks [1] or the wavelet transform [2]. In addition, blind source separation (BSS) techniques have been also proposed for separating ECG and noise, as these signals are uncorrelated. In previous work, the performance of PCA [3] and ICA [4] has been investigated by our group.

In adaptive filtering (AdF), a filter is applied after adjusting its parameters in time to a time varying noise. This is particularly useful when the noise is non-stationary as it is the case with ambulatory motion artifacts. However, a reference signal has to be recorded in addition to the ECG. Several adaptive filtering approaches have been proposed to obtain an adequate reference signal such as measurement of skin-electrode impedance (SEI) [5, 6], skin stretching measured with optical sensors [6, 7] or accelerometers [8, 9]. However, more research is required to understand the outcome and limitations of these methods.

In this work, the performance of different implementations of AdF algorithms is investigated in the context of motion artifact reduction in ECG signals.

2. Methods

2.1. Adaptive filtering

AdF is a nonlinear filter whose coefficients are continually changing in order to meet pre-defined conditions. This is a data-driven approximation that requires an additional reference signal as input in order to calculate the filter coefficients. It performs a continuous update of its coefficients using only the information available in the environment [10]. This technique has been used in several applications, such as signal denoising.

It has also been used for cleaning ECG signals corrupted with several sources of noise [5-9]. In the case of motion artifacts, a reference signal that is highly correlated with the noise is required. The block diagram of AdF is shown in Figure 1.

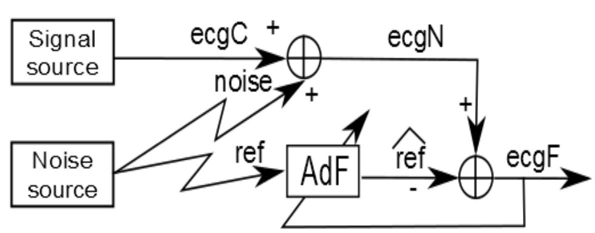

Figure 1. Block diagram of an AdF system.

In this application, the heart (*signal source*) generates the clean ECG (*ecgC*). A *noise source* produces a *noise* signal which is recorded simultaneously with *ecgC* and reference signal (*ref*). The noisy ECG (*ecgN*) is the summation of *ecgC* and *noise*. The filtered ECG (*ecgF*) is obtained by subtraction of *ecgN* minus the estimated reference signal ($\widehat{\text{ref}}$). In an ideal case, the coefficients of AdF would be properly tuned. Then, the estimated reference would be equal to the noise, resulting in a filtered ECG that would be equal to the clean signal.

The Wiener solution is the foundation of AdF algorithms [10]. By using mean-square error (MSE) it minimizes the difference between the input and the estimated reference signals. Theoretically, it is the optimal solution. However, it requires a matrix inversion, which cannot always be calculated. This prevents this solution to be practical in a real system.

Alternative solutions are the algorithms based on least-mean-square (LMS) and recursive least-squares (RLS) techniques [10]. The LMS algorithm is a steepest-descent-based algorithm which uses the gradient of MSE surface to update the coefficients. The RLS algorithm uses the inversion lemma to update the coefficients recursively. In comparison to LMS, RLS has a higher convergence speed. However, it also has higher computational complexity and can have stability problems.

In this work, five AdF algorithms existing in the literature were selected for study. These methods were based on both LMS and RLS techniques.

Three algorithms based on LMS were selected for evaluation: LMS [10]; LMS sign-error [10], which uses the sign function to reduce the computational complexity of LMS; and constrained LMS sign-error [10], which introduces constrains so that the coefficients must satisfy certain initial conditions. Only one RLS algorithm was selected for evaluation.

In addition, convex AdF [11-13] was also selected for evaluation. This algorithm combines two independent AdFs: one with a fast convergence speed and a second one with high accuracy. The combination of two LMS sign-error algorithms was used in this implementation.

Two reference signals were investigated: SEI and motion measured with accelerometers.

2.2. Data collection

Clean ECG signals were obtained by recording 3-unipolar lead ECGs from 10 healthy subjects. For each subject a recording of 1 hour was obtained while the subject was at rest. 3-channel noise recordings were obtained by placing electrodes on the back of the subjects at the height of the lumbar curve where ECG signals were negligible. In addition, SEI was obtained at one of the channels, and the sensor movement was recorded with a 3D accelerometer. Then, the subjects were asked to move randomly. For each subject, 1-hour recording was obtained. Signals were recorded with a sampling frequency of 512 Hz. All recordings were filtered by a high pass filter with cut-off frequency of 0.05 Hz and a 50 Hz notch filter. Each 3-channel noise signal was then added to each 3-channel clean ECG. SNR was calculated. Values ranging from 10 to -18 dB were available with significant sample size. Figure 2 shows one example of SEI, acceleration, pure noise, clean ECG, and a combination of both noise and clean ECG.

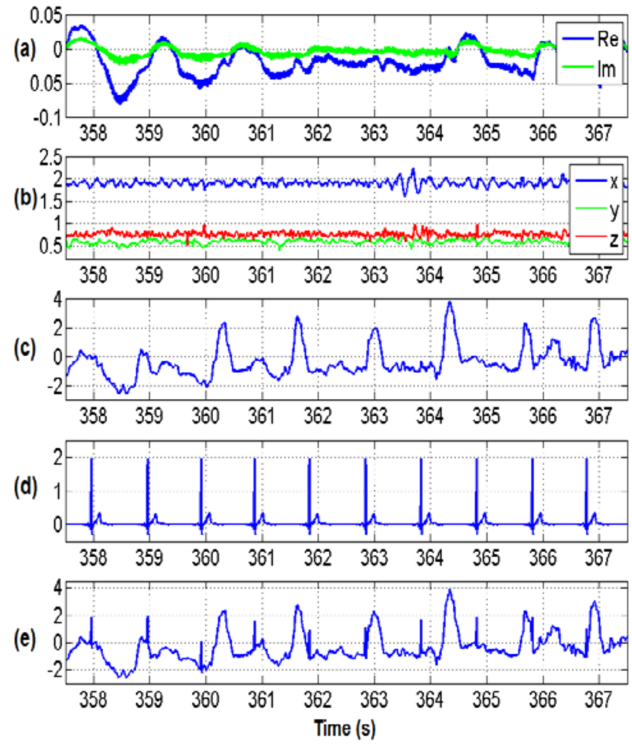

Figure 2. Extract of: (a) SEI signal, (b) 3D acceleration, (c) noise from motion artifacts, (d) clean ECG and (e) sum of both noise and clean ECG signals. The SNR of the combined signal is of -16.6 dB.

2.3. Evaluation criteria

In order to evaluate the performance of the different AdF algorithms, the output of a beat detection algorithm [15] was used. The beat detector was applied to both the output signal after filtering and to the signal before filtering. The detections were compared with the annotations obtained before adding the noise in order to calculate the Sensitivity (Se) and Positive Predictivity (+P). From these two parameters, +P is more sensitive to noise due to the fact that high voltage peaks in the ECG caused by motion artifacts, might be mistaken with QRS complexes and wrongly detected as such (false positive).

Median values were calculated as a representative value for each SNR.

3. Results

An example of an unfiltered ECG signal together with four filtered ECGs (using LMS algorithm with the accelerometer as reference, RLS, convex AdF and LMS sign-error with the SEI as reference) is shown in Figure 3. The performance of LMS algorithm with the accelerometers as reference is poor. The RLS does not enhance the BD performance. Both convex AdF and LMS sign-error get some enhancement of the QRS complexes leading to a better performance of BD. However, the morphology of the original clean ECG (that is before adding the noise) is not preserved after AdF, introducing distortion in the QRS and filtering out the P and T waves.

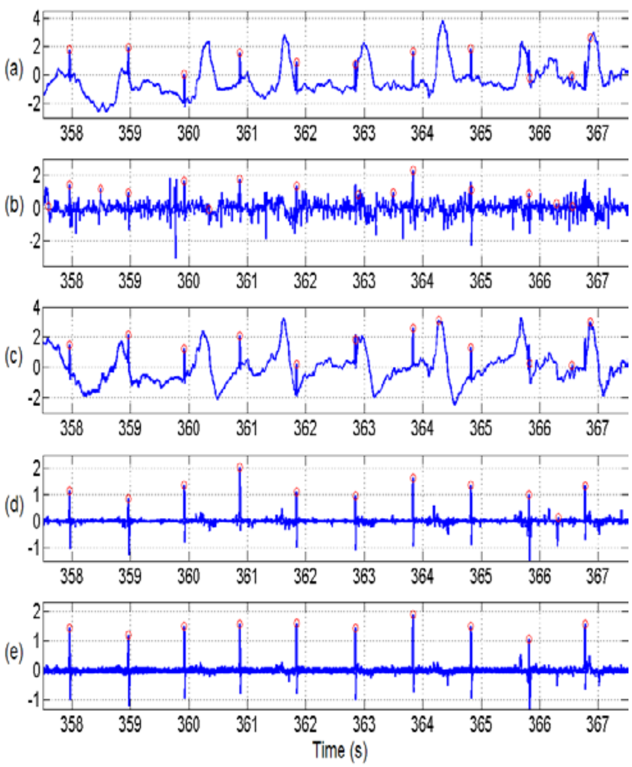

Figure 3. (a) Noisy ECG, (b) filtered ECG using LMS algorithm with the accelerometer as reference, (c) filtered ECG using RLS algorithm (d) filtered ECG using convex AdF and (e) filtered ECG using LMS sign-error with the SEI as reference. Output from BD is plotted with red marks.

Figure 4 shows the Se and +P of studied algorithms together with non-filtered signals. A summary of these results are also in Table 1. The minimal SNR value that gives a 100% of accuracy in terms of Se and +P is given for each evaluated AdF algorithm.

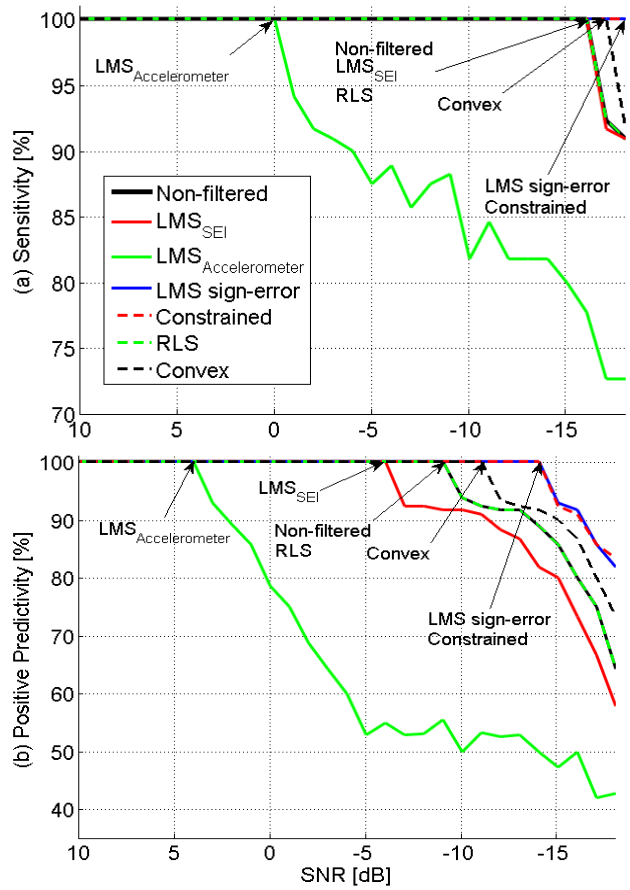

Figure 4. Evaluation results of LMS and RLS-based AdF algorithms. (a) Se and (b) +P of the BD algorithm.

Table 1. Minimal SNR values when Se and +P start to drop from 100%

Algorithm	Se=100% (min SNR)	+P=100% (min SNR)
Unfiltered	-16 dB	-9 dB
LMS_{SEI}	-16 dB	-6 dB
$LMS_{Accelerometer}$	0 dB	+4 dB
LMS sign-error	-18 dB	-14 dB
Convex	-17 dB	-11 dB
Constrained	-18 dB	-14 dB
RLS	-16 dB	-9 dB

Accelerometers vs. Skin-electrode Impedance

The performance of LMS using accelerometers and SEI as reference was initially compared. The performance was better when SEI was used as reference (minimal SNR value that gave a Se=100% was -16dB and +P=100% was -6 dB) as compared to accelerometers (minimal SNR value that gave a Se=100% was 0dB and +P=100% was +4 dB). Therefore, SEI was used as reference signal for further evaluation of AdF algorithms in this study.

Least-Mean-Square vs. Recursive Least-Square

The performance of RLS was better (minimal SNR value that gave a Se=100% was -16dB and +P=100% was -9 dB) than with the LMS algorithm (minimal SNR value that gave a Se=100% was -16dB and +P=100% was -6 dB). However, it was not better than the performance obtained with non-filtered signals (minimal SNR value that gave a Se=100% was -16dB and +P=100% was -9 dB), which makes these algorithms not good methods for ECG denoising.

Other implementations

The convex AdF improved the BD as compared to using non-filtered signal with Se and +P equal to 100% down to SNR=-17dB and -11dB respectively.

From all algorithms evaluated in this study, the best performance was achieved with the implementations: LMS sign-error and constrained LMS sign-error with Se=100%: min SNR=-18dB and +P=100%: min SNR=-14dB.

Computational complexity

Although computational time was not measured, in terms of computational complexity, LMS sign-error is the simplest algorithm. As constrained LMS sign-error add an additional matrix multiplication, the complexity increases. RLS has probably the highest computational complexity due to matrix division required on each iteration.

4. Conclusions

This work investigated the performance of different implementations of AdF algorithms in denoising ECG signals recorded in ambulatory conditions.

Results showed that using AdF (LMS sign-error algorithm) improved the performance of a BD algorithm as compared to non-filtering the signals. After filtering with this method, the BD obtained a Se of 100% for SNR down to -18 dB and a +P of 100% for SNR down to -14 dB as compared to Se and +P of 100% for SNR down to -16 dB and -9 dB respectively obtained with non-filtered signals. Other implementations of AdF did not give satisfactory results. In addition, it was found that using skin-electrode impedance as a reference signal was superior to accelerometers. However, a significant amount of distortion on the filtered ECG signals was observed.

As a limitation of this study, a beat detection algorithm was used in order to evaluate the signal quality. Therefore, the effect of these methods on other characteristics of the signal (such as P and T waves or QRS morphology) was not studied.

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