Adaptive Filtering Methods for ECG Waveform Restoration during Cardiopulmonary Resuscitation

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Abstract

An artifact-free ECG is essential during cardiopulmonary resuscitation (CPR) to decide adequate therapy. Chest compressions (CCs) cause artifacts that alter the ECG waveform. This study analyzes the effectiveness of CPR artifact suppression filters to restore the ECG. For that purpose, artificial mixtures of artifact-free ECGs and CPR artifacts mixed at different signal-to-noise ratios (SNR_{in}) were used. Several configurations of three state-of-the-art filters were compared: Least Mean Squares (LMS), Recursive Least Squares (RLS) and Kalman. Performance was evaluated by comparing the artifact-free ECGs and the filtered ECGs in terms of the restored SNR (SNR_{res}) and the Pearson's Correlation coefficient (PCC). RLS was the best option with a mean SNR_{res} of 3.3 dB at the optimal working point, slightly above the LMS algorithm in terms of SNR_{res}. The similarity of the restored and the clean ECG increased with SNR_{in}, obtaining PCC values above 0.6 for SNR_{in} > -5 dB. In conclusion, suitable filtering methods to restore ECG waveforms during CPR were proposed, that would enhance the reliability of the ECG analysis during CCs.

1. Introduction

High quality cardiopulmonary resuscitation (CPR) and early defibrillation are key for the survival of out-of-hospital cardiac arrest (OHCA) patients [1]. In particular, uninterrupted chest compressions (CCs) provided during CPR are of critical importance [2]. Whereas basic life support responders rely on the shock advice algorithm (SAA) of a commercial defibrillator for a shock/no-shock decision, advanced life support (ALS) clinicians visually evaluate the ECG to decide suitable therapeutic interventions. Unfortunately, in both scenarios, CCs must be interrupted to avoid the confounding effects of CPR artifacts on the ECG. These interruptions, which compromise coronary perfusion pressure, worsen CC fraction and may result in decreased survival [2].

Several adaptive filters have been designed to remove CPR artifacts, ranging from filters that use addtional reference signals correlated with the artifact to simpler but less effective filters that analyze the ECG alone [3]. Taking advantage of the quasi-periodic nature of CPR artifacts, adaptive filters based on the multiharmonic-model of the artifact have also been explored [4]. The latter are the ones that offer, to date, the best compromise between simplicity and performance. The underlying ECG waveform is unknown during CCs which complicates the measuring of filter perfomance as the real and the filtered ECG waveforms can not be directly compared. Therefore, most of the state-of-the-art adaptive filters have been indirectly evaluated in terms of the sensitivity and specificity of a commercial SAA applied to the filtered ECG [3].

This study addresses the above-mentioned knowledge gap by using artificial mixtures of artifact-free ECGs recorded during OHCA and CPR artifacts obtained in the absence of electrical activity of the heart (asystole) to evaluate the performance of several state-of-the-art filters. The mixture model allows to know the underlying rhythm of the patient and the performance of the filter can therefore be evaluated in terms of ECG waveform restoration. In this way, suitable filter configurations to restore ECG waveforms during CPR could be determined, allowing reliable clinical decisions without interrupting CPR therapy.

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2. Materials

CPR artifacts were obtained from a large prospective clinical trial designed to measure CPR quality during OHCA. Details on the study can be found at [5]. The raw data for this trial consisted of the ECG and the compression depth (CD) signals derived from accelerometer data. From this study, a subset of 1192 10-s segments corresponding to 177 patients was extracted with concurrent ECG and CD signals. These segments were acquired in the presence of asystole and during CCs. Asystole is the complete absence of electrical activity in the heart. Therefore, in these intervals the only activity in the ECG is the one induced by the CCs. These segments are therefore a suitable alternative to simulate CPR artifacts in the artifical mixtures.

Artifact-free ECGs, which simulate the real underlying rhythm of the patient in the artificial mixture, were extracted from three OHCA public databases: CUDB, VFDB and AHADB [6]. From these public databases, a subset of 5724 10-s ECG segments was extracted from 67 OHCA patients during the absence of CCs. These segments include both shockable (ventricular tachycardia and ventricular fibrillation) and non-shockable rhythms (organized rhythms).

3. Methods

3.1. Mixture model

The artificial corrupted ECG signal, $x(n)$, is the mixture of an artifact-free ECG, $s_{\text{ecg}}(n)$, and a CPR artifact segment, $s_{\text{cpr}}(n)$, recorded during asystole:

$$x(n) = s_{\text{ecg}}(n) + \alpha s_{\text{cpr}}(n) \tag{1}$$

The signal-to-noise-ratio (SNR) of $x(n)$ is controlled by the positive-valued weight α:

$$\text{SNR}_{\text{in}} = 10 \cdot \log_{10}\left(\frac{P_{\text{ecg}}}{\alpha^2 P_{\text{cpr}}}\right) \tag{2}$$

where P_{ecg} and P_{cpr} denote the power of $s_{\text{ecg}}(n)$ and $s_{\text{cpr}}(n)$, respectively.

The subscript 'in' indicates that the SNR applies to the filter input signal $x(n)$. In terms of signal power and SNR_{in}, α is given by:

$$\alpha = \sqrt{\frac{P_{\text{ecg}}}{P_{\text{cpr}}} \cdot 10^{-\frac{\text{SNR}_{\text{in}}}{10}}} \tag{3}$$

First, for each patient, 4 artifact-free ECGs were randomly selected, half of which were shockable and the other half were non-shockable rhythms, obtaining $67 \cdot 4 = 268$ signals, $s_{\text{ecg}}(n)$. Then, each of these resulting signals was mixed with 15 randomly selected CPR artifacts, $s_{\text{cpr}}(n)$, for 7 different SNR_{in} values, ranging from -15 dB to 15 dB in steps of 5 dB. So, the final artificial database consisted of $268 \cdot 15 \cdot 7 = 28140$ corrupted ECG segments, $x(n)$.

3.2. Adaptive filtering

During CCs, the CPR artifact was modeled as a quasi-periodic interference composed of N harmonics and vary-

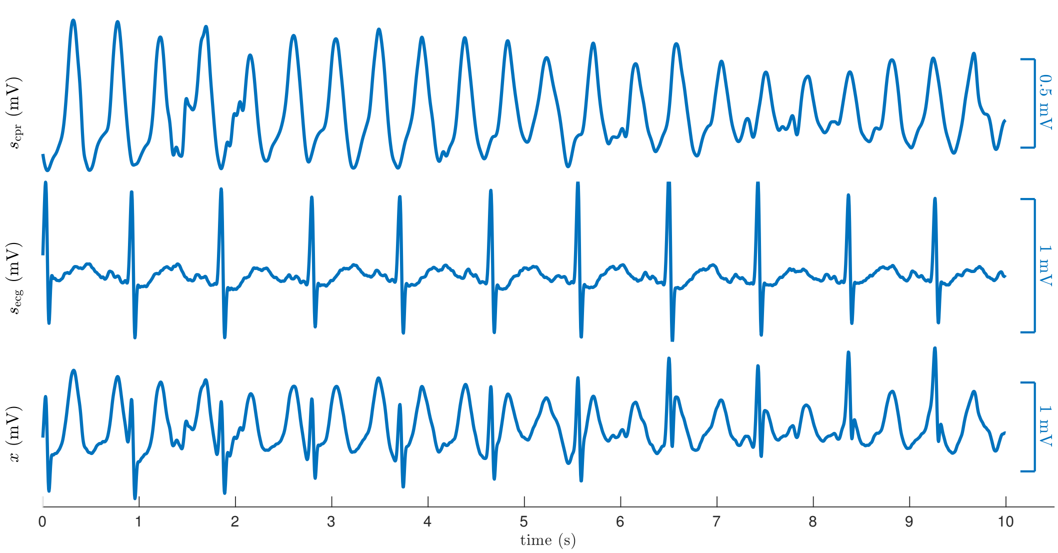

Figure 1. Mixture model. From top to bottom: a CPR artifact segment recorded during CCs, an artifact-free ECG acquired during the absence of CCs and an artificially corrupted ECG segment derived from the mixture of the previous signals for a SNR_{in} of -5 dB.

ing fundamental frequency, $f_0(n)$:

$$s_{\text{cpr}}(n) = \sum_{k=1}^{N} a_k(n)\cos(k\omega_0(n)n) + b_k(n)\sin(k\omega_0(n)n)$$

$$f_0(n) = \frac{1}{t_k - t_{k-1}} \quad t_{k-1} < nT_s \leq t_k$$

where $\omega_0(n)$ is the discrete angular frequency, T_s is the sampling period and t_k are the time instants of the CCs that were automatically marked on the compression depth signal using a negative peak detector with a -1.5 cm threshold.

The Fourier coefficients, $a_k(n)$ and $b_k(n)$, define the adaptive filter that adjusts to the time-varying characteristics of the artifact. The restored ECG, $\hat{s}_{\text{ecg}}(n)$, was obtained by subtracting the model estimate, $\hat{s}_{\text{cpr}}(n)$, from the artificially corrupted ECG signal, $x(n)$.

In this study, Recursive Least Squares (RLS) [7], Least Mean Squares (LMS) [4] and Kalman filters [8] were explored for estimating $a_k(n)$ and $b_k(n)$. All filter types employ criteria to minimize the error between $x(n)$ and $\hat{s}_{\text{cpr}}(n)$ at the harmonics of $f_0(n)$. Different number of harmonics (N) and many adaptability coefficients were tested for each filter within the following working ranges: $1 \leq N \leq 5$, $0.0001 \leq \mu \leq 0.01$ for the LMS, $0.985 \leq \lambda \leq 0.9999$ for the RLS and $1 \cdot 10^{-7} \leq \mu \leq 1 \cdot 10^{-4}$ for the Kalman filter.

3.3. Performance metrics

Two measures were computed to evaluate filter performance in terms of ECG waveform restoration: the SNR of the restored signal (SNR_{res}) and the Pearson's Correlation Coefficient (PCC) to measure the similarity between the restored, $\hat{s}_{\text{ecg}}(n)$, and the artifact-free ECG, $s_{\text{ecg}}(n)$:

$$\text{SNR}_{\text{res}} = 10 \cdot \log_{10}\left(\frac{P_{\text{ecg}}}{P_{\text{e}}}\right) \tag{4}$$

$$\text{PCC} = \frac{\sum_{n=1}^{L} s_{\text{ecg}}(n) \cdot \hat{s}_{\text{ecg}}(n)}{\sqrt{\sum_{n=1}^{L} s_{\text{ecg}}^2(n)}\sqrt{\sum_{n=1}^{L} \hat{s}_{\text{ecg}}^2(n)}} \tag{5}$$

where P_{ecg} and P_{e} are the power of $s_{\text{ecg}}(n)$ and $e(n) = s_{\text{ecg}}(n) - \hat{s}_{\text{ecg}}(n)$, respectively.

Performance metrics were computed over the 2-10 s interval of the restored ECG, $\hat{s}_{\text{ecg}}(n)$, the first 2 s were left out to avoid adaptive filtering transients.

4. Results

Table I shows the best configuration for each filter in terms of the mean SNR_{res} obtained for all tested SNR_{in} values, as well as the mean SNR_{res} and PCC values reached with that configuration.The RLS filter was the best option with a mean SNR_{res} and PCC of 3.3 dB and 0.74, slightly above the LMS algorithm in terms of SNR_{res}.

	Best Configuration	$\textbf{SNR}_{\textbf{res}}$	**PCC**
RLS	$N = 2$, $\lambda = 0.9994$	3.3	0.74
LMS	$N = 4$, $\mu = 0.0013$	3.2	0.74
Kalman	$N = 2$, $q = 6.1 \cdot 10^{-6}$	3.1	0.73

Table 1. The optimal working point for each adaptive filter in terms of the mean SNR_{res} obtained for all tested SNR_{in} values. The mean PCC and SNR_{res} values reached using those configurations are also shown.

The left plot of Figure 1 shows the mean SNR_{res} obtained using the best performing filter, RLS, in terms of the configuration parameters, λ and N. The optimal working range for the RLS filter in terms of λ was around values close to 1, i.e narrower bandwidth filters were overall more effective at artifact removal. Regarding the number of harmonics, intermediate values were preferred, $N \in \{2, 3, 4\}$.

The right plot of Figure 1 shows the mean improvement obtained in SNR ($\text{SNR}_{\text{res}} - \text{SNR}_{\text{in}}$) and the mean PCC values reached after applying the optimal configuration of the filters as a function of SNR_{in}. At high corruption levels (up to -5 dB) the SNR increase was above 5 dB. As SNR_{in} increases, the improvement in SNR becomes smaller. Even so, for $\text{SNR}_{\text{in}} = 10\,\text{dB}$, where the power of the clean ECG is 10 times higher than the CPR artifact, the noise was reduced by approximately 1.5 dB at the output of the filters. The similarity of the restored and the clean ECG increased with SNR_{in}, obtaining PCC values above 0.6 for $\text{SNR}_{\text{in}} > -5\,\text{dB}$.

As in real CPR scenarios the SNR_{in} is unknown, the optimal configuration of the RLS filter was also analyzed for strong and low CPR artifact corruption levels. For $\text{SNR}_{\text{in}} > 0\,\text{dB}$, the optimal working point of the RLS was $N = 5$ and $\lambda = 0.9999$, whereas for $\text{SNR}_{\text{in}} < 0$ the best performance was obtained for $N = 1$ and $\lambda = 0.9860$. Therefore, less harmonics and coarser filtering is required as the artifact power increases at the input of the filter.

5. Discussion

The present study provides an evaluation of ECG waveform restoration following adaptive CPR artifact cancellation filtering. With this approach, signal quality indices can be determined providing insight into how accurately the underlying ECG rhythms can be restored with filtering during the administration of CCs.

Three of the best state-of-the-art adaptive filters were compared using the restored SNR and the PCC as signal quality indices: RLS, LMS and Kalman. The best per-

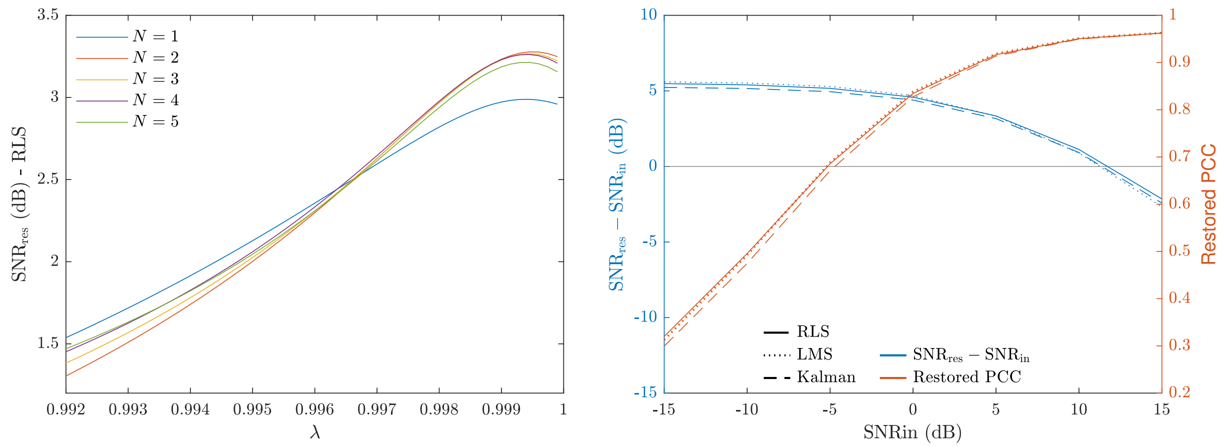

Figure 2. The left plot shows the performance of the RLS filter in terms of mean SNR_{res} as a function of the configuration parameters, λ and N. The right plot shows the mean improvement obtained in SNR ($\text{SNR}_{\text{res}} - \text{SNR}_{\text{in}}$) and the mean PCC values reached using the optimal working point of the filters in terms of SNR_{in}.

forming configuration setting was determined for each filter and, although the 3 filters performed similarly, the RLS filter resulted to be the best alternative for the removal of CPR artifacts. In addition, optimal filtering configurations were proposed depending on the power of the CPR artifact at the input of the filter.

In conclusion, suitable filter configurations to restore ECG waveforms during CPR were determined, allowing reliable clinical decisions without interrupting CPR therapy.

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