Are Dual-Channel Methods as Accurate as Multi-Channel Methods to Suppress the CPR artifact?

Unai Ayala[1], Joar Eilevstjønn[2], Unai Irusta[1], Trygve Eftestøl[3], Erik Alonso[1], Digna Gonzalez[1]

[1]University of Basque Country, Bilbao, Spain
[2]Laerdal Medical, Stavanger, Norway
[3]University of Stavanger, Stavanger, Norway

Abstract

A reliable diagnosis by automated external defibrillators (AED) during cardiopulmonary resuscitation (CPR) would reduce hands-off time, thus increasing the resuscitation success. Several filters based on one (dual-channel) or multiple (multi-channel) reference signals have been proposed to remove the artifact induced on the ECG by chest compressions. However these filters were optimized and their performance evaluated using different ECG data and AED algorithms.

In this study, we have re-optimized and evaluated the performance of two dual-channel filters using the same ECG data and AED algorithm used to develop and test a well known multi-channel filter. The accuracy of the tested multi-channel and dual-channel filters was similar. Dual-channel filters need fewer reference channels and a lower computational burden and can be more easily incorporated to current AED.

1. Introduction

The mechanical activity from the chest compressions during cardiopulmonary resuscitation (CPR) introduces artifacts in the ECG. These artifacts modify the waveform of the ECG and rhythm analysis of automated external defibrillators (AED) becomes unreliable. Therefore, CPR must be stopped for a reliable diagnosis by the AED. These hands-off intervals adversely affect the probability of success of the defibrillation shock [1]. Filtering the CPR artifact would allow a reliable diagnosis during CPR, thus reducing the hands-off interval and increasing resuscitation success.

It is not possible to filter the CPR artifact from the human ECG using fixed coefficient filters because they present a large spectral overlap. In the last decade, several adaptive filters have been proposed to suppress the CPR artifact, either by analyzing the ECG rhythm alone or by using additional reference signals correlated with the artifact. The latter provide better results. Filters based on one (dual-channel) [2, 3] or more than one (multi-channel) [4] reference signals have been proposed to suppress the CPR artifact from out-of-hospital cardiac arrest episodes (OHCA). Both filtering schemes reported similar results in terms of the proportion of correctly detected shockable (sensitivity) and nonshockable (specificity) rhythms after filtering. However, the comparison between them have two sources of bias, filters were developed and tested using different OHCA data and different shock advice algorithms (SAA).

The aim of this study is to present an unbiased comparison between multi-channel and dual-channel filters. Both filtering schemes will be optimized and evaluated using the same database of OHCA records and the same SAA.

2. Methods

2.1. ECG database

The database used in this study was originally conceived to evaluate the MC-RAMP multi-channel filter [4]. The dataset is a subset of a large database acquired in a prospective study of OHCA patients [5], annotated by expert reviewers in five rhythm types: ventricular fibrilation (VF) and fast[1] ventricular tachycardia (VT) in the shockable category and asystole (ASY), pulseless electrical activity (PEA) and pulse generating rhythm (PR) in the nonshockable category. The surface ECG and several additional reference channels were acquired using a modified version of Laerdal Medical Heartstart 4000 defibrillator with a sampling rate of 500 Hz and 16 bit resolution. The ECG had a resolution of 1.031 µV and the acquisition bandwidth was 0.9–50 Hz.

The database is composed of 184 shockable (178 VF and 6 VT) and 388 nonshockable (104 ASY, 228 PEA and 16 PR) registers. Each register is 20 s long with the initial

[1]Heart rate above 150 beat per minute (bpm)

10 s corrupted by CPR followed by 10 s of clean ECG, and contains all channels resampled at 200 Hz. The database was randomly distributed into a training set to determine the optimal working point of the filters and a test set to evaluate their performance. Each set has 89 VF, 3 VT, 52 ASY, 114 PEA and 8 PR episodes.

2.2. CPR suppression methods

We have compared the efficacy of the MC-RAMP multi-channel filter [4] to that of two dual-channel filters: the LMS filter [2] and the Kalman filter [3].

2.2.1. MC-RAMP filter

The MC-RAMP filter, which was originally optimized and evaluated for the data used in this study [4], uses four reference signals to model the artifact: ECG common mode voltage, transthoracic impedance, compression acceleration and compression depth (CD). The filter determines what reference channels to use depending on their energy and their cross-correlation to the corrupted ECG. Optimal results were obtained for 5 filter coefficients per reference channel and a coefficient update window length of 400 samples.

2.2.2. LMS and Kalman filters based on the chest compression rate

The LMS and Kalman filters are based on a model of the CPR artifact described in detail in [2]. The artifact is almost periodic during chest compressions and can be modeled through a Fourier series representation using N harmonics of time-varying Fourier coefficients $a_k(n)$ and $b_k(n)$. During pauses in chest compressions, defined as intervals longer than 1 s between consecutive compressions, the artifact is made zero. The compression and pause intervals are combined in a single model using an amplitude envelope $A(n)$ which is 1 during chest compressions and 0 during pauses. The complete model of the artifact is given by the following equation:

$$\hat{s}_{cpr}(n) = A(n) \cdot \sum_{k=1}^{N} a_k(n)\cos(k\phi(n)) + b_k(n)\sin(k\phi(n)) \tag{1}$$

where $\phi(n)$ is the instantaneous phase of the compressions derived from the instantaneous frequency. This frequency, the inverse of the interval between consecutive compressions, is updated every new compression. The instants of the compression were automatically marked on the CD reference channel using a peak detector for compression depths greater than 1.5 cm.

The LMS and Kalman filters are two efficient methods to estimate the values of $a_k(n)$ and $b_k(n)$. The LMS filter is described in detail in [2] and the Kalman filter in [3]. An optimal compromise between an accurate representation of the CPR artifact and the computational burden is obtained for $N = 5$ harmonics [2]. Then each filter depends on a single parameter: μ_0 the LMS step-size of the fundamental component in the LMS filter, and q_0 the variance of the noise process of the fundamental component in the Kalman filter. The step size (μ_k) or the variance (q_k) for k-th harmonic are adjusted in the following way:

$$\mu_k = \frac{1}{k}\mu_0 \quad \text{and} \quad q_k = \frac{1}{k}q_0 \tag{2}$$

2.3. Shock advice algorithm

The performance of the filters was optimized and evaluated in terms of the sensitivity and specificity of an offline PC version of the SAA used in the Laerdal Medical Heartstart 4000 defibrillator. The algorithm analyses two or three 3 s segments of the ECG for a shock/no-shock decision, and diagnoses shock for VF and for VT with rates above 150 bpm. The ECG is fed to the algorithm at 200 Hz with 16 bit resolution.

3. Results

3.1. Optimization of the dual-channel filters

The LMS and Kalman filters have been reoptimized using the training dataset and the SAA of the Heartstart 4000 as done by Eilevstjønn et al. for the MC-RAMP filter.

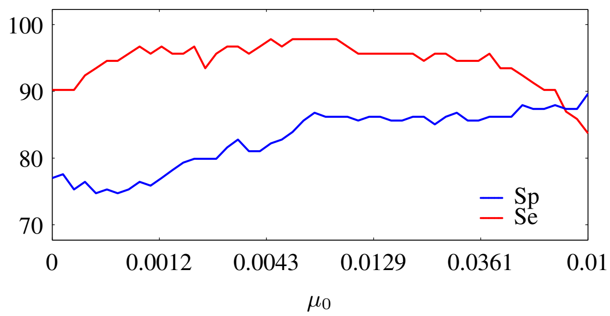
The only adjustable parameter of the LMS filter is μ_0. Fig. 1(a) shows the sensitivity and specificity after filtering of the LMS filter for the different values of μ_0. As shown in Fig. 1(a), the specificity is always below 95 %, the minimum value recommended by the American Heart Association (AHA) for nonshockable rhythms[6]. However, for μ_0 above $2.8 \cdot 10^{-3}$ the specificity is over 80%, close to the values reported for the MC-RAMP filter. So we defined the following working range of the LMS filter:

$$2.8 \cdot 10^{-3} < \mu_0 < 80 \cdot 10^{-3} \tag{3}$$

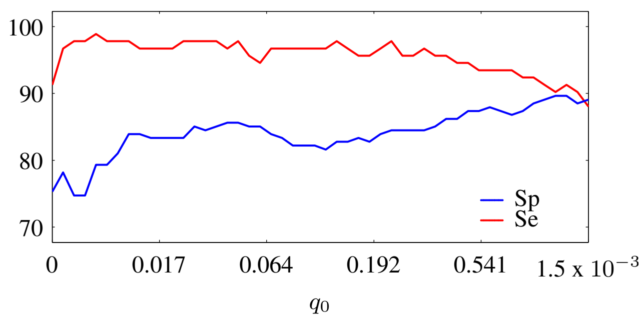
where the sensitivity was above 90 %, the minimum value recommended by the AHA for VF, and the specificity was above 80 %. The optimum working point was defined as the value of μ_0 that yielded the maximum accuracy (proportion of correctly identified registers) in the working range of the filter:

$$\mu_0 = 7.1 \cdot 10^{-3} \tag{4}$$

achieving a sensitivity and specificity of 97.8% and 86.8%.



(a) Optimization of LMS filter



(b) Optimization of Kalman filter

Figure 1. Sensitivity (Se) and specificity (Sp) after filtering for the corrupt interval of the training dataset.

The only adjustable parameter of the Kalman filter is q_0. Fig. 1(b) shows the sensitivity and specificity after filtering of the Kalman filter for the different values of q_0. For q_0 above $8 \cdot 10^{-6}$ the specificity was over 80 %. We defined the following working range of the Kalman filter:

$$8 \cdot 10^{-6} < q_0 < 1.3 \cdot 10^{-3} \qquad (5)$$

adopting the same criteria described for the LMS filter. The best working point for the training dataset was:

$$q_0 = 4.7 \cdot 10^{-5} \qquad (6)$$

for a sensitivity and specificity of 97.8 % and 85.6 %.

3.2. Evaluation of the performance

The performance of the filters was evaluated using the test dataset. We calculated the sensitivity and specificity for the clean interval and for the corrupted interval both before and after filtering. The results are summarized in Table 1 for the three filtering methods. All filters were used in their optimal working point.

The sensitivity and specificity before filtering were 81.5% and 67.2% for the corrupt interval and 97.8% and 98.9% for the clean interval. After filtering, the sensitivity and specificity of the corrupt interval increased to 94.6% and 81.6% respectively for both the LMS and the Kalman filters, for an accuracy of 86.1%. The sensitivity and specificity after filtering reported for the optimal working point of the MC-RAMP filter were 96.7% and 79.9%, for an accuracy of 85.7%. The sensitivity of the MC-RAMP filter is two points better than for LMS and Kalman filter, however, the specificity is two points lower. The overall accuracy is around 86% for all filtering methods.

Table 1. Sensitivity and specificity for the test database before and after filtering.

	During CPR		Without CPR	
	Se(%)	Sp(%)	Se(%)	Sp(%)
Without filter	81.5	67.2	97.8	98.9
MC-RAMP filter	96.7	79.9	97.8	98.3
LMS filter	94.6	81.6	97.8	98.9
Kalman filter	94.6	81.6	97.8	98.9

Fig. 2 shows a filtering example of a register with an underlying VF rhythm. The ECG signal in the corrupt interval is misclassified as a nonshockable rhythm. Filtering reveals the underlying VF and the ECG signal is correctly identified as shockable. All three filters reveal the underlying VF rhythm despite the small differences in the ECG waveform obtained by the different filters.

4. Discussion and conclusions

The sensitivity and specificity values obtained after filtering the corrupted ECG with multi-channel and dual-channel methods are very similar. In fact, the accuracy of all three filters is almost the same, so their performance is similar in terms of the diagnosis of the SAA. However, the MC-RAMP filter is more complex because it requires the acquisition of four additional reference channels and is computationally more demanding. The LMS and the Kalman filters are based on a simple model of the CPR artifact which only requires the acquisition of the instantaneous chest compression rate, and could therefore be easily incorporated in current AED.

Our results suggest that the simple model of the CPR artifact expressed by Equation (1) is as accurate as models based on the information obtained from multiple reference channels. The artifact can be efficiently estimated using only the instantaneous chest compression rate and its harmonic components.

Filtering improved both the sensitivity and the specificity during CPR by around 13 points. The sensitivity after filtering was above the value recommended by the AHA for VF. However, the specificity after filtering is around 80 %, well below the 95 % recommended by the AHA. Using these filters directly may be detrimental for survival because it could either increase the amount of unnecessary shocks or CPR could be

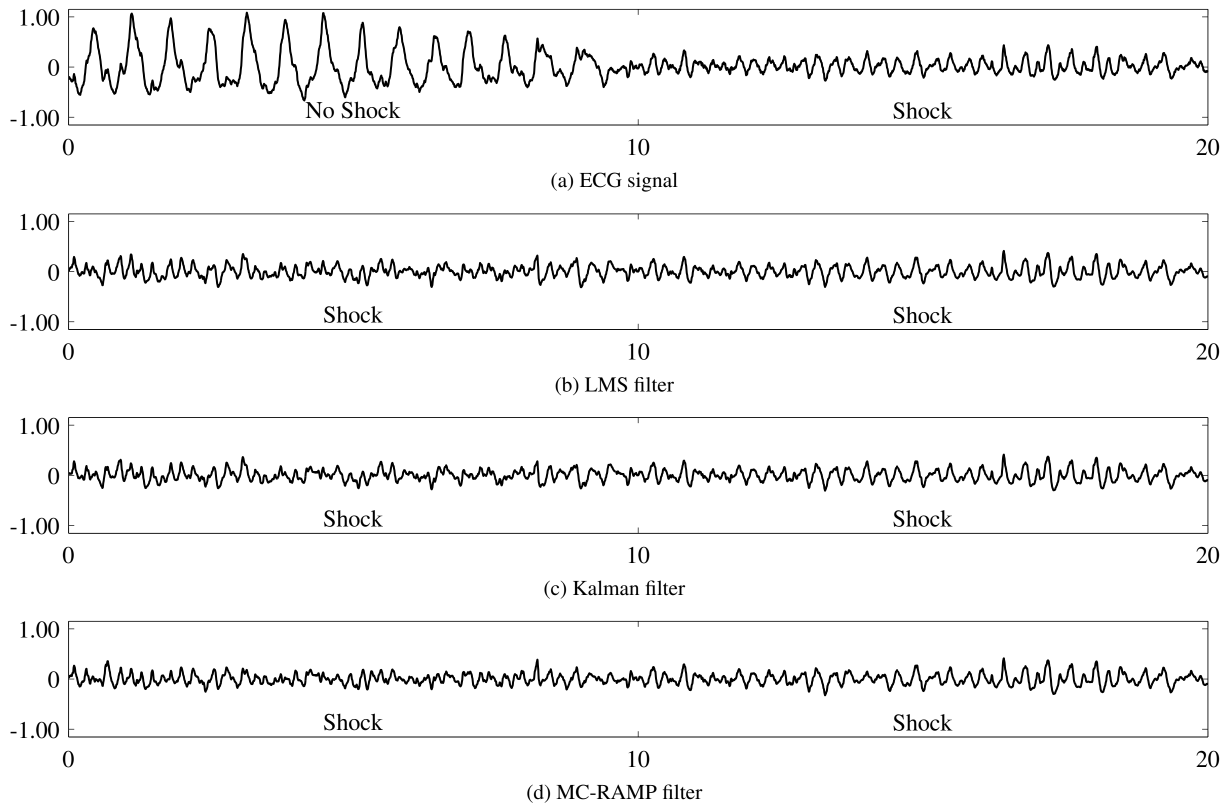


Figure 2. Filtering example of a corrupted VF. The corrupted ECG interval is misclassified as nonshockable before filtering. After filtering the underlying VF is revealed and the rhythm is correctly classified as shockable.

stopped unnecessarily for rhythm analysis in patients with nonshockable rhythms. Further efforts should be focused on improving the specificity, a possible approach is to combine the design of SAA and CPR suppression methods.

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Address for correspondence:

Unai Ayala
School of Engineering
Department of Electronics and Telecomunications
Alameda Urquijo, s/n 48013 Bilbao (Spain)
E-mail address:unai_ayala@ehu.es