Filtering the Cardiopulmonary Resuscitation Artifact: Influence of the Signal-to-Noise-Ratio on the Accuracy of the Shock Advice Algorithm

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Abstract

A reliable diagnosis by automated external defibrillators (AED) during cardiopulmonary resuscitation (CPR) would reduce hands-off time, thus increasing the resuscitation success. Several filtering techniques have been proposed to remove the artifact induced on the ECG by chest compressions. The improvement in the signal-to-noise ratio (SNR) has been widely used to test the performance of the filter, using artificial mixtures of ECG signals and CPR artifacts.

In this work, we analyzed the influence of the SNR, estimated from corrupted out-of-hospital cardiac arrest episodes, on the AED diagnostic accuracy before and after artifact removal. Filtering improved the sensitivity for records with low SNR, however the specificity was largely independent of the SNR. Moreover, the total specificity decreased after filtering due to misclassified asystole records.

1. Introduction

Cardiopulmonary resuscitation (CPR) and early defibrillation are essential in the treatment of out-of-hospital cardiac arrest (OHCA). Chest compressions during CPR may induce an artifact on the ECG compromising the reliability of the shock advice algorithm (SAA) of automated external defibrillators (AED). Consequently, the interruption of CPR is mandatory during the rhythm analysis interval. Unfortunately, these "hands-off" intervals considerably reduce the probability of a successful resuscitation outcome. The removal of the CPR artifact would allow a reliable rhythm analysis during CPR, therefore minimizing the "hands-off" intervals and increasing the resuscitation success.

In the last decade, several CPR artifact suppression methods have been designed based on adaptive filtering approaches. Traditionally, these filters have been tested with artificially corrupted signals, obtained as the sum of a clean ECG and a CPR artifact with a known signal-to-noise ratio (SNR). The goodness of the filtering method was then tested by varying the SNR, i.e., under different levels of corruption, and analyzing the improvement in the SNR after filtering the corrupted ECG [1].

However, in a clinical scenario, it is necessary to assess how much the suppression of the artifact improves the diagnosis of the SAA. For this aim, the accuracy of the SAA to detect shockable (sensitivity) and non-shockable (specificity) rhythms are evaluated before and after the removal of the artefact [1, 2].

In this work, we estimated the SNR of corrupted OHCA records. Then we analyzed the diagnostic accuracy of a SAA before and after the suppression of the artifact in terms of the estimated SNR. Shockable and non-shockable records were separately studied because the influence of the SNR on each rhythm group is different.

2. Methods

2.1. ECG database

Our data is a subset of a large database of OHCA episodes [3], annotated by expert reviewers in five rhythms 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 non-shockable category.

We extracted 381 records from 299 patients arranged in three groups: shockable (89 samples, 84 VF and 5 VT), non-shockable asystole (88 samples) and non-asystolic (nASY) non-shockable (204 samples, 166 PEA and 38 PR). The records are 31 s long with a common annotated underlying rhythm. CPR was administered in the initial 15.5 s interval, corrupting the ECG. CPR was stopped in the last 15.5 s and the ECG is free of artifact. For each record, we also extracted the compression depth signal to track the activity due to the chest compressions.

The ECG and the compression depth signals were downsampled from 500 to 250 Hz and preprocessed with an order-four Butterworth bandpass filter (0.7–30 Hz). The resolution was 1.031 μV per least significant bit.

[1] rate above 150 bpm

2.2. Estimating the SNR

Assuming that the underlying ECG and the CPR artifact are uncorrelated, the corrupted ECG registered through the defibrillation pads can be expressed as:

$$c_{\text{ecg}} = s_{\text{ecg}} + s_{\text{cpr}}, \tag{1}$$

and, in terms of signal power:

$$P_{\text{c}} = P_{\text{ecg}} + P_{\text{cpr}}. \tag{2}$$

Consequently, the SNR (measured in dB) is defined as:

$$\text{SNR} = 10 \log_{10}\left(\frac{P_{\text{ecg}}}{P_{\text{cpr}}}\right) = 10 \log_{10}\left(\frac{P_{\text{ecg}}}{P_{\text{c}} - P_{\text{ecg}}}\right). \tag{3}$$

Therefore, high SNR values mean low CPR artifact power and viceversa.

The underlying ECG in the corrupted interval is unknown, but it appears in the interval without artifact. Assuming that the power of the underlying ECG is the same in both intervals we can obtain an estimation of the SNR of the record using eq. (3).

In some cases, the artifact was negligible and its estimated power (P_{cpr}, calculated from eq. (2)) was negative. These absurd values correspond to very high SNR values, we adopted a SNR value of 25 dB for these cases.

For the ASY records the power of the underlying ECG is negligible and the first 15.5 s interval is a pure CPR artifact, consequently the SNR tends to -∞ dB. We did not estimate the SNR for this group.

2.3. Filtering the corrupted ECG

The CPR suppression method used in this work is based on a Kalman filter that uses the instantaneous frequency of the chest compressions as the reference signal, see [4] for a full description. The instantaneous frequency is estimated by locating the instants when the chest is fully compressed in the compression depth signal, as described in [5]. We applied the Kalman filter (using its optimum operating point [4]) to the OHCA records. The filter estimated the artifact, $\hat{s}_{\text{cpr}}$, to obtain the estimated underlying ECG as:

$$\hat{s}_{\text{ecg}} = c_{\text{ecg}} - \hat{s}_{\text{cpr}}. \tag{4}$$

2.4. Measuring the SAA performance

We used an off-line version of the SAA running in a commercial AED, the Reanibex 200 (Osatu S. Coop., Ermua, Spain). The algorithm processes three consecutive non-overlapping 4.8 s signal intervals and advises a shock if at least two are classified as shockable. The 15.5 s intervals defined for the ECG records were sufficient for a shock/no-shock decision.

We calculated the sensitivity and the specificity of the SAA in the clean interval, and before and after filtering in the corrupted interval. By comparing the SAA decision in the two intervals (same underlying rhythm), we could evaluate how the CPR artifact affected the performance of the SAA.

3. Results

The distribution of the estimated SNR is shown in Fig. 1(a) for the shockable records and in Fig. 1(b) for the nASY records. 12.4 % of the shockable records (11/89) and 13.7 % of the nASY records (28/204) presented a negligible artifact power (SNR=25 dB). For the rest, the mean SNR value was -1.7 ± 6.8 dB for the shockable records and -0.6 ± 7.8 dB for the nASY group.

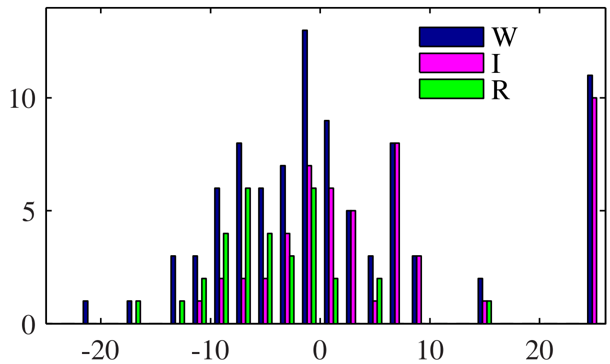
Table 1 is a summary of the results for the SAA. The sensitivity increased from 58.4 % to 94.4 % after filtering. The 52 records correctly classified before and after filtering (group I in Fig. 1(a)) presented a mean SNR of 1.3 ± 5.6 dB. The 32 records recovered (group R in Fig. 1(a)), i.e. an initial wrong diagnosis turned correct after filtering, had a mean SNR of -4.3 ± 6.0 dB. Finally, only 5 records were misclassified before and after filtering, the corruption level was high (SNR < -12.5 dB) in 3 records, and low (SNR > -1.3 dB) in 2 records. The sensitivity was 97.8 % (87/89) for the artifact-free intervals.

The specificity for the nASY group was the same before and after filtering, 92.6 %. The 178 records correctly classified before and after filtering (group I in Fig. 1(b)) presented a mean SNR of 0.0 ± 7.6 dB. The 11 records recovered after removing the artifact (group I in Fig. 1(b)), had a mean SNR of -3.2 ± 5.6 dB. Fig. 1(b) shows, however, how another 11 records correctly classified as non-shockable before filtering were misclassified after filtering (group M), with a mean SNR of -8.0 ± 8.0 dB. Finally, the specificity was 98.5 % (201/204) for the artifact-free intervals.

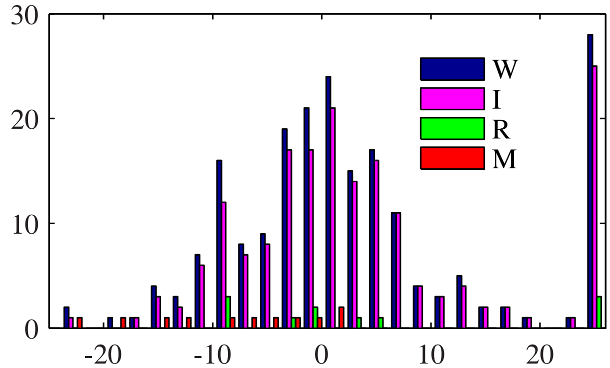
The specificity for the ASY group decreased from 86.4 % to 81.0 % after filtering. Fifteen corrupted records correctly diagnosed before filtering were misclassified after filtering, whereas only 11 records were recovered after

Table 1. Performance of the SAA before and after the suppression of the CPR artifact.

		After					
		Shockable		**nASY**		**ASY**	
		NS	S	NS	S	NS	S
Before	NS	5	32	178	11	61	15
	S	0	52	11	4	11	1



(a) SNR distribution for the shockable records.



(b) SNR distribution for the nASY records.

Figure 1. Distribution of the estimated SNR for the corrupted intervals of the shockable and the nASY groups. In the legends, W refers to the whole set; I to the records correctly classified before and after filtering; R to the records whose diagnosis turned correct after filtering; M to the records whose diagnosis turned wrong after filtering.

filtering. The specificity was 100 % for the artifact-free intervals.

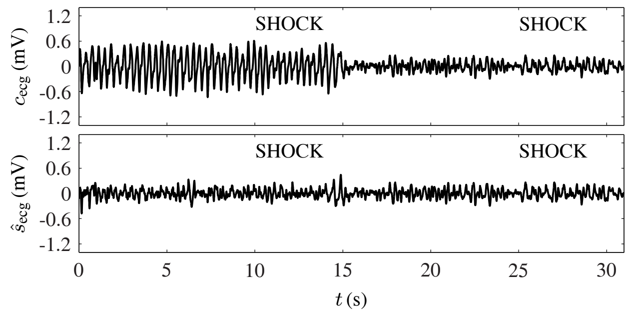
4. Discussion and conclusions

4.1. Regarding shockable OHCA records

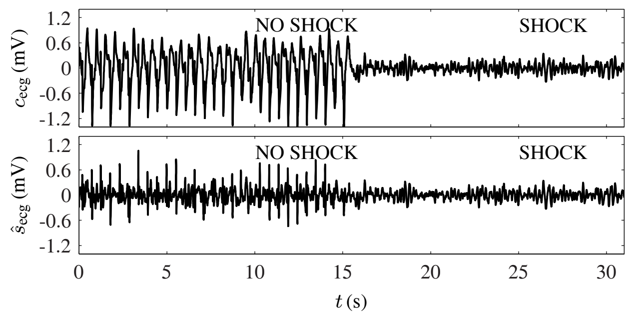
Our study shows that, when the artifact power was low (high SNR), the corrupted records were prone to be correctly classified before and after filtering (see Fig. 1(a)). However, some strongly corrupted records were correctly classified before filtering, because the artifact appears like a fast ventricular tachycardia (Fig. 2(a)) or a disorganized and fast VF-like artifact.

Filtering improved the SNR, causing an increase in sensitivity. The SAA diagnosis turned correct after filtering for 32 shockable records, which in general showed a high corruption level.

The 5 shockable records misclassified before and after filtering showed very different levels of corruption.



(a) Example from the **I** group, SNR $= -8.9$ dB.



(b) Example of non recovered record, SNR $= -12.9$ dB.

Figure 2. Examples from the shockable subset, showing the corrupted and filtered ECG and the SAA decision.

Fig. 2(b) presents a record with a very high corruption level (SNR $= -12.9$ dB). After filtering, spiky residuals appeared due to the waveform of the artifact, these spikes were misinterpreted as QRS complexes by the SAA. Fine VF was the underlying rhythm for the 2 records with high SNR, after filtering the estimated ECG resembled an asystole.

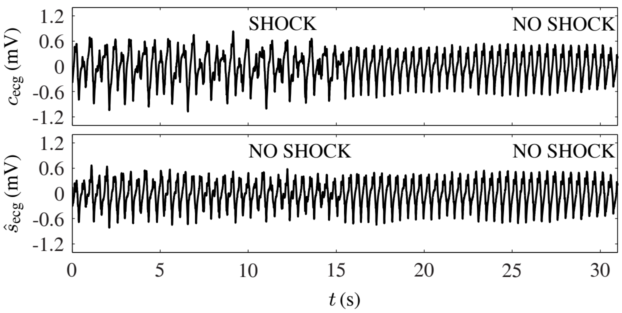
4.2. Regarding non-shockable records

In the nASY group, 87.3 % of the records were correctly classified before and after filtering. In the corrupted intervals, the artifact appeared as an organized rhythm with rates below the threshold for shockable VT, causing a no-shock decision.

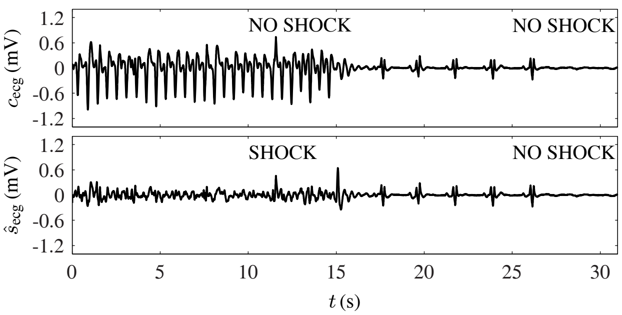
Only 11 records were recovered after filtering. In general, they presented high SNR, but again we observed a VF-like artifact that caused a wrong diagnosis before filtering. As shown in Fig. 3(a), a regular underlying rhythm appeared after the suppression of the artifact.

In contrast, 11 records presenting low SNR were missed due to VF-like filtering residuals, Fig. 3(b) shows an example. The SNR improvement after filtering did not caused a correct SAA diagnosis.

A high percentage (86.4 %) of the records in the ASY group were correctly diagnosed before filtering. In those cases, the artifact was interpreted as a non-shockable orga-

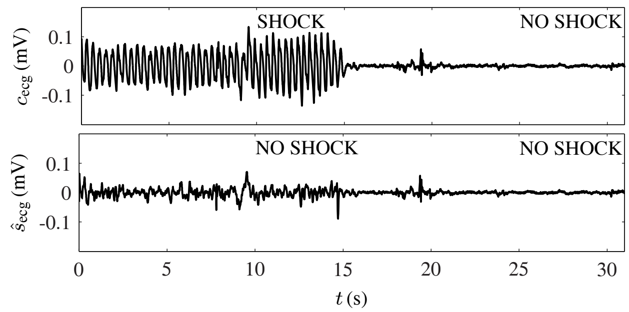


(a) Example for the **R** group, SNR $= -4.7$ dB.

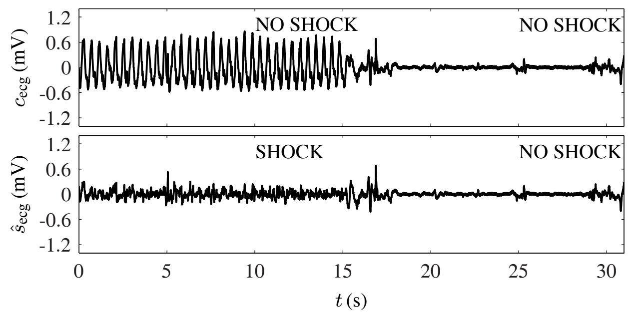


(b) Example for the **M** group, SNR $= -14.9$ dB.

Figure 3. Examples from the nASY subset, showing the corrupted and filtered ECG and the SAA decision.



(a) Example of successful filtering for an ASY record.



(b) Example of an ASY record missed after filtering.

Figure 4. Examples from the ASY subset, showing the corrupted and filtered ECG and the SAA decision.

nized rhythm.

After filtering 11 ASY records were recovered and 15 were missed. The recovered records presented an organized low amplitude artifact with rate above the threshold for shockable VT. As shown in Fig. 4(a), the filter efficiently removed the artifact and the underlying rhythm was correctly identified as asystole. For the missed records, although the filter substantially removes the artifact, the filtering residuals resemble fine VF producing a wrong diagnosis as shown in the example in Fig. 4(b).

4.3. Conclusions

In the last decade, many efforts have focused on the design of sophisticated filters to efficiently suppress the CPR artifact. Our experiment shows that although filtering improves the SNR in all cases, the sensitivity increases but the specificity decreases after filtering. The accurate diagnosis of non-shockable rhythms during CPR is still not possible, and a preliminary analysis based on the SNR is not conclusive when the goodness of the filter is evaluated in terms of the diagnostic accuracy of an AED.

Acknowledgements

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