Filtering Chest Compression Artifacts Improves the Performance of VF-detection Parameters

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Abstract

Cardiopulmonary resuscitation (CPR) artifact filtering techniques have not been successfully combined with commercial shock advice algorithms (SAA) to diagnose the rhythm during CPR. Recently, a promising new approach based on using SAAs especially designed to diagnose the filtered ECG has been introduced. This study evaluates the impact of filtering CPR artifacts on the shock/noshock decision for several well-known VF-detection parameters.

The detection accuracy of 22 VF-detection parameters was calculated for artifact-free ECG segments and for ECG segments corrupted by chest compressions before and after filtering. Performance was measured in terms of: area under the curve of the receiver operating characteristic curve, and sensitivity/specificity for the shock/noshock decision.

Filtering the CPR artifact improved the detection capacity of most parameters, and showed that combining features after filtering may be a successful strategy.

1. Introduction

Chest compression artifacts (CC-artifacts) during cardiopulmonary resuscitation (CPR) impede a reliable rhythm analysis by the shock advice algorithms (SAA) of current automated external defibrillators (AED). However, interrupting CPR for a reliable analysis adversely affects the probability of survival. A reliable SAA during CPR would avoid CPR interruptions and increase the probability of survival.

Several methods have been proposed to diagnose the rhythm during CPR including filtering the artifact and designing SAAs to diagnose the corrupted ECG. These methods are generally evaluated in terms of their sensitivity and specificity, i.e. their capacity to detect shockable and nonshockable rhythms, respectively. In most studies sensitivity was above 90%, the performance goal recommended by the American Heart Association (AHA) when AEDs analyze artifact-free ECGs [1]. However, specificity rarely exceeded 85%, far from the 95% recommended by the AHA. Recently, a promising new approach based on using a SAA specially designed to diagnose the filtered ECG has been introduced. This method successfully met the AHA recommendations [2].

The aim of this study was to evaluate the impact of filtering CPR artifacts on the shock/noshock decision for several well-known VF-detection features.

2. Methods

2.1. ECG database

Two databases were used for this study: an artifact-free database and a database of ECG corrupted by CPR artifacts. The artifact-free database was extracted from 370 out-of hospital cardiac arrest (OHCA) episodes acquired by the Oslo University Hospital (Norway) in 2012. The database of corrupted ECG was extracted from a large two-phase OHCA study conducted between 2003 and 2005. This database included CPR/no-CPR annotations derived from the compression depth (CD) signal acquired by a CPR feedback device. The initial ECG rhythm types and all subsequent rhythm transitions were already annotated in both databases by consensus between an experienced clinician and a biomedical engineer.

Following previous studies on VF detection, the features were evaluated using 8-s ECG segments [3, 4]. Consequently, 8-s ECG-segments were extracted from both databases. In addition, the CD signal was also extracted in the corrupted database to enable the adaptive filtering of the CPR artifact. The final composition of the ECG databases is shown in Table 1.

Rhythm Type	Artifact-free	Corrupt
Shockable	318 (72)	1185 (69)
Nonshockable	1572 (165)	4000 (142)

Table 1. Number of 8-s segments (patients in parenthesis) for the shockable and nonshockable rhythms.

2.2. CPR suppression filter

CPR artifacts were suppressed using a state of the art method based on an LMS filter [5]. The LMS filter adaptively estimates the harmonic content of the CPR artifact by fitting a quasi-periodic additive artifact model. In this model the time-varying fundamental frequency of the artifact is derived from the CC marks obtained from the CD signal. The filter estimates the artifact, $\hat{s}_{\text{cpr}}$, and subtracts it from the corrupt ECG, s_{cor}, to obtain the filtered signal, s_{filt}:

$$s_{\text{filt}}(n) = s_{\text{cor}}(n) - \hat{s}_{\text{cpr}}(n).$$

Fig. 1 shows a filtering example in which the CPR artifact is visible during chest compressions, and the underlying rhythm is revealed after filtering. The t_k instants indicate the CC marks. For this study the optimal values of the filter parameters were used, as described in [5].

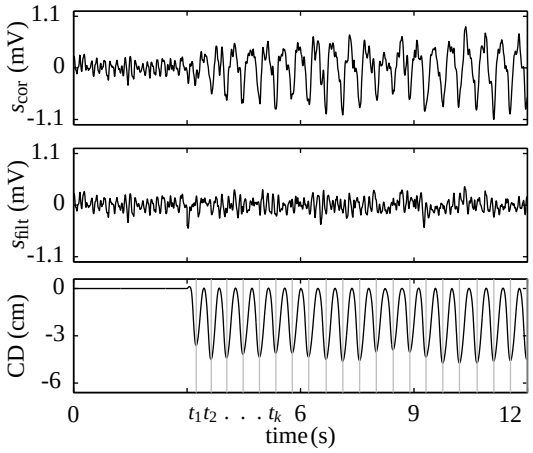

Figure 1. Filtering example for a 12 s segment. Removing the CC-artifact from s_{cor} reveals the underlying VF. To estimate the artifact the CC marks obtained from the CD were used.

2.3. VF detection features

For each 8-s segment a set of 22 VF detection parameters from four representative ECG analysis domains were computed. The detailed description of the methods can be found in [2–4, 6, 7], with references to the original papers. The following features were computed:

- **Time Domain.** It includes the analysis of the amplitude, slope, sample distribution and heart rate estimators. The evaluated features were: nP, bS, Count1, Count2, Count3, Threshold Crossing Interval (TCI), Threshold Crossing Sample Count (TCSC), Kurtosis, FreqBin and Mean Absolute Voltage (MAV).
- **Time-Frequency Domain.** Based on the wavelet analysis of the segments described in [6]. A single feature was evaluated: Morphological Consistency Residual (MCR).
- **Spectral Domain.** It includes the analysis of the spectral concentration, normalized spectral moments or the relative power content in different frequency bands. The evaluated features were: A1, A2, A3, FSMN, VFleak, Pm and Ph.
- **Complexity Domain.** A sample of the most representative methods that evaluate the complexity of the ECG including: Sample Entropy (SpEn), Complexity Measure (CM), Phase Space Reconstruction (PSR) and a phase plot of the Hilbert transform (HILB).

2.4. Data analysis

The performance of the VF detection features was evaluated in terms of the receiver operating characteristic curve (ROC) analysis. All features were calculated for the artifact-free, the corrupted and the filtered segments. Performance was measured in terms of: area under the curve (AUC), and sensitivity/specificity for the shock/noshock decision. Two cut-off points were computed in the ROC curve: sensitivity for a 95% specificity (AHA goal), and specificity for a 90% sensitivity (AHA goal).

3. Results

A summary of the ROC curve analysis for the 22 VF features is shown in Table 2 for the artifact-free, the corrupt and the filtered segments.

For the artifact-free segments four features met AHA sensitivity and specificity goals: bS, count2, count3 and nP. These are all time domain features designed to detect the presence of QRS complexes (nonshockable rhythms) by either analyzing the amplitudes of the high frequency components of the ECG or the slope of the ECG. Their ROC curves for the clean segments are shown in Fig. 2. All four features were very robust with AUC values above 0.965.

For the corrupt segments the performance of the features degraded, and all features were far from meeting AHA goals. The AUC substantially decreased for the spectral features, in some cases by over 0.2, while the AUC of other features (CM, count1 or count2) was only marginally affected by the artifact. The spectral distribution of

	Artifact-free			Corrupt			Filtered		
Feature	AUC	Se	Sp	AUC	Se	Sp	AUC	Se	Sp
nP	0.969	90.6	95.1	0.952	82.4	89.5	0.953	82.9	91.4
bS	0.986	93.4	97.1	0.948	78.6	89.6	0.964	88.6	94.2
Count1	0.961	78.6	91.0	0.927	66.8	80.3	0.929	63.4	81.3
Count2	0.992	95.6	98.2	0.966	84.1	90.6	0.966	84.6	93.0
Count3	0.983	91.8	96.1	0.950	75.3	86.6	0.951	75.6	88.0
TCI	0.901	55.3	72.1	0.780	28.3	42.4	0.847	36.9	61.1
TCSC	0.858	7.9	76.1	0.756	4.1	59.9	0.873	11.4	77.9
Kurt	0.852	33.0	57.4	0.759	7.1	59.3	0.856	15.4	72.5
FrqBin	0.826	21.4	57.4	0.814	32.4	48.5	0.889	45.9	70.9
MAV	0.849	8.8	73.5	0.753	6.7	57.6	0.864	10.5	76.3
MCR	0.951	77.4	87.2	0.931	62.9	81.4	0.922	58.6	79.5
A1	0.668	17.3	21.8	0.531	3.5	11.9	0.643	9.3	31.9
A2	0.883	62.9	61.8	0.666	7.3	26.4	0.792	36.3	29.8
A3	0.870	59.7	51.8	0.665	15.9	22.5	0.786	27.8	36.8
FSMN	0.872	58.5	61.3	0.675	11.9	30.7	0.777	26.1	33.1
Vfleak	0.781	44.7	24.4	0.716	8.1	29.9	0.875	53.2	61.1
Pm	0.752	40.6	24.9	0.635	27.9	11.5	0.816	42.4	45.1
Ph	0.756	7.2	53.6	0.616	5.9	29.6	0.627	1.9	36.1
SpEn	0.969	88.7	94.0	0.914	68.6	69.2	0.954	75.2	88.9
CM	0.848	32.4	61.1	0.812	32.5	41.5	0.893	46.5	70.5
PSR	0.915	67.0	71.9	0.843	23.9	66.6	0.884	41.4	73.5
HILB	0.929	72.6	79.5	0.842	22.1	66.7	0.873	30.0	73.0

Table 2. ROC curve analysis of the VF detection features in terms of AUC, sensitivity (Se) and specificity (Sp). The sensitivity corresponds to a 95% specificity in the ROC curve, and the specificity to a 90% sensitivity.

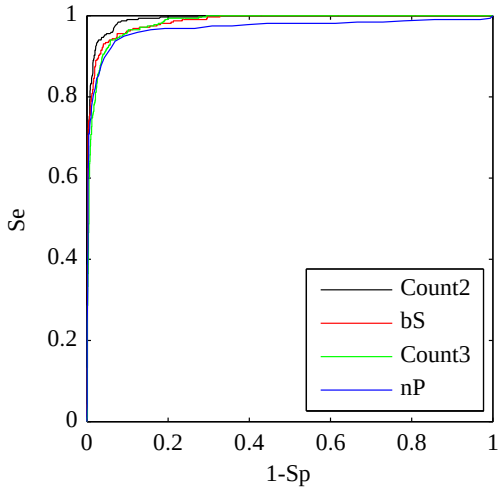

Figure 2. ROC curves for the artifact-free segments of the four features that meet AHA goals.

the ECG power is very affected by the presence of CPR artifacts. However, features that analyze only the high-frequency bands (above 10 Hz) of the ECG, such as Count{1,2,3} or MCR, are less affected by CPR artifacts which normally concentrate most their power below 10 Hz.

Filtering improved the performance of the features. The increase in AUC was largest for the spectral features, showing that the adaptive filter successfully removed the artifact despite the spectral overlap between the artifact and the underlying rhythm. In fact, for the features marginally affected by the artifact, filtering had no impact on the AUC. Five features (bS, Count2, Count3, nP and SpEn) had AUCs above 0.95 after filtering, and the best performance was obtained for bS with values close the AHA recommendations. For the cut-off points of the ROC curve, filtering improved the sensitivity for bS by 10 points and the specificity by 5 points. Fig. 3 shows the ROC curves for the bS feature for all types of segments.

4. Discussion and conclusions

Recent studies have renewed the interest on the detection of VF in artifact-free ECG using classical features [4, 7]. This study is a comprehensive evaluation of the performance of VF detection features in the scope of resuscitation, and thus evaluates those features on OHCA data, both free of artifact and during CPR. Our results for artifact free data are marginally worse than those reported for public databases [4, 7]. Nonshockable OHCA rhythms

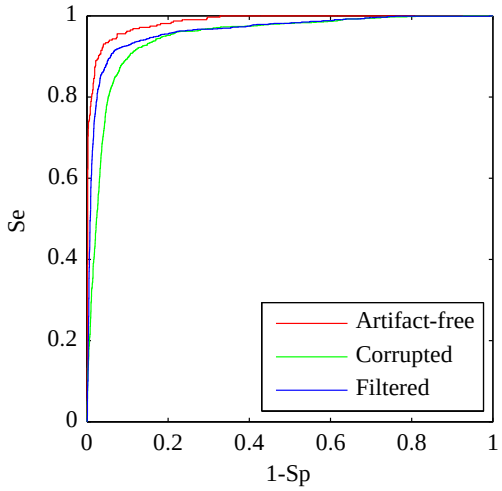

Figure 3. ROC curves of bS, the best overall feature, for all the segments. Filtering improved the performance, although AHA goals were not met.

are more irregular than those found in public databases, and VF in OHCA records is first recorded minutes after its onset at a time at which its frequency and amplitude characteristics may have degraded.

Our results confirm that the accurate detection of VF during CPR is much more challenging. The spectral overlap of the CPR artifact with OHCA rhythms largely affects the performance of many VF detection features. Filtering successfully removes the artifact, as evidenced by the increase in performance of the features. However, for an AHA compliant algorithm features evaluating different and non complimentary ECG characteristics should be combined in a machine learning framework. Our results suggest that analyzing the slope of the ECG (bS and nP) in combination with the amplitudes of the higher frequency bands (count2 and count3) and the complexity of the ECG (SpEn) may be a promising approach.

Filtering the artifact may be a technically challenging problem. In this study the filter used the CC-marks obtained from the CD signal acquired from an external CPR aid pad. These devices may not always be available in a resuscitation scenario. The performance of the features should be analyzed when the CC-marks are obtained from the transthoracic impedance, which is always acquired through the defibrillation pads. The results should not vary substantially [8]. Alternatively, the feasibility of an algorithm that uses exclusively the ECG should be explored, using a combination of features marginally affected by the CPR artifact.

Finally, in this study the analysis was conducted for 8-s ECG segments. Algorithms that diagnose an artifact-free ECG using shorter segments (around 3-5 s) should be explored. These algorithms could be used to shorten pre-shock pauses and to analyze the rhythm during ventilation pauses in CPR, thus minimizing or eliminating interruptions in CPR.

Acknowledgements

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