A New Shock Advice Algorithm Designed to Classify ECG Signals During Cardiopulmonary Resuscitation

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Abstract

A shock advice algorithm (SAA) that reliably diagnoses the rhythm during cardiopulmonary resuscitation (CPR) would avoid unnecessary CPR interruptions and increase the probability of a successful resuscitation. Current approaches based on filtering the CPR artifact from the ECG or analyzing the corrupted ECG do not meet the American Heart Association's (AHA) requirements for SAA.

This study presents a preliminary design of a SAA to classify the rhythm during CPR. It is based on the analysis of five non-overlapping 3 s *segments of the corrupt and the filtered ECG. A total of 290 non-shockable and 89 shockable records were analyzed and a specificity above the 95% AHA goal was obtained for a 89.5% sensitivity, only half a point below the AHA goal.*

1. Introduction

Chest compressions cause cardiopulmonary resuscitation (CPR) artifacts that change the ECG waveform and render unreliable the rhythm analysis of automated external defibrillators (AED). Interrupting chest compressions for a reliable diagnosis by the AED shock advice algorithms (SAA) adversely affects the probability of survival of patients in cardiac arrest [1]. A reliable method to analyze the ECG during CPR would reduce these interruptions and increase resuscitation success.

In the last decade, several methods have been proposed to analyze the ECG during CPR. Some are algorithms based on features obtained from the corrupt ECG [2, 3]. Others, first adaptively filter the ECG to remove the CPR artifact and then classify the filtered ECG using SAAs found in commercial AEDs [4, 5]. The performance of these methods is evaluated in terms of the proportion of correctly detected shockable (sensitivity) and non-shockable (specificity) rhythms. Methods based on adaptive filters presented better results than methods based only on the analysis of the corrupt ECG. Most methods report sensitivities above 90%, the performance goal recommended by American Heart Association (AHA) [6]. However, the specificities rarely exceed 85%, far from the 95% recommended by the AHA.

The aim of this study was to do a preliminary design of a SAA to be used specifically during CPR that met AHA performance goals. The algorithm uses both the corrupt ECG and the filtered ECG to diagnose the rhythm. The filtered ECG was obtained using a well-known CPR suppression method based on an LMS filter [4].

2. Methods

2.1. ECG database

The database for the design of the SAA was originally extracted to develop the LMS filter from a large collection of out-of-hospital cardiac arrest (OHCA) episodes. These episodes had been annotated by expert reviewers using five rhythm types: ventricular fibrillation (VF) and fast[1] ventricular tachycardia (VT) in the shockable category and asystole (AS), pulseless electrical activity (PEA) and pulse generating rhythm (PR) in the non-shockable category. The episodes contained the ECG and several additional reference channels including the compression depth (CD) used to implement the LMS filter.

The database was composed of 81 VF, 5 VT, 91 AS, 161 PEA and 38 PR records. Given the small amount of VT, VF and VT were combined to form the shockable category with 86 records. All records had a duration of 31 s in which the initial 15.5 s interval was corrupted by CPR artifacts and followed by 15.5 s interval of clean ECG. The SAA was developed using the corrupt interval, the clean interval served to verify the annotated rhythm. The algorithm was designed for a $f_s = 250\,\mathrm{Hz}$, so all the records were resampled to this frequency.

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

2.2. CPR suppression method

The LMS filter estimates the CPR artifact fitting an almost-periodic model of the artifact with a fundamental frequency given by the chest compression frequency [4]. This frequency is obtained from the CD signal. The estimated CPR artifact, $\hat{s}_{\text{cpr}}$, is then subtracted from the corrupt ECG, s_{ecg}, to obtain the filtered ECG, s_{filt}:

$$s_{\text{filt}}(n) = s_{\text{ecg}}(n) - \hat{s}_{\text{cpr}}(n) \qquad (1)$$

The LMS algorithm was used with $N = 5$ harmonics and a step size of $\mu_0 = 0.0178$.

2.3. Description of the SAA

The algorithm was optimized using the complete database. It analyses the ECG in non-overlapping $3\,\text{s}$ segments and gives a shock/no-shock decision per segment. In the corrupt interval, five decisions were obtained per record and the majority decision was adopted for the record.

The algorithm applies three sub-algorithms sequentially, as shown in Fig. 1. First, non-shockable rhythms with very low electrical activity (LEA) such as AS or slow PEA are detected by the LEA algorithm. Then, the conducting algorithm identifies non-shockable rhythms with distinct QRS complexes, i.e. PR rhythms and narrow complex regular PEA. Finally, the PEA algorithm discriminates irregular wide complex PEA from shockable rhythms.

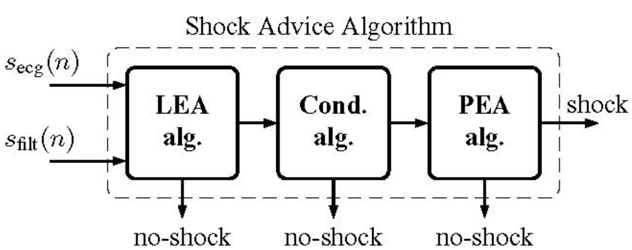

Figure 1. Block diagram of the SAA. The algorithm uses three sub-algorithms for a shock/no-shock decision.

LEA algorithm

Non-shockable LEA rhythms, particularly asystole, is often diagnosed as shockable during CPR because after filtering only a disorganized residue is left. The LEA algorithm was specifically designed to address this limitation.

The LEA algorithm is a simple decision tree that combines four parameters obtained from s_{filt} and s_{ecg}. First the signals are band-pass filtered using an order 10 Butterworth filter that eliminates baseline drift and high frequency noise, and selects the frequency band of interest. The decision rules are applied sequentially in the order in which the parameters are described:

$\mathbf{P_{fmin}}$: The preprocessed (2.5–30 Hz) s_{filt} segment is divided in two non-overlapping windows of $1.5\,\text{s}$. The minimum value of the power of these windows is P_{fmin}, which is small for non-shockable LEA rhythms. LEA rhythms were detected when $\text{P}_{\text{fmin}} < 7 \cdot 10^{-4}$.

$\mathbf{P_c/P_f}$: First s_{ecg} and s_{filt} segments are preprocessed (0.5–30 Hz). $\text{P}_\text{c}/\text{P}_\text{f}$ is defined as the ratio of their powers (s_{ecg} to s_{filt}) which is an estimate of the signal-to-noise ratio (SNR). For non-shockable LEA rhythms s_{ecg} is mainly the CPR artifact (no underlying ECG) so $\text{P}_\text{c}/\text{P}_\text{f}$ is large. LEA rhythms were detected when $\text{P}_\text{c}/\text{P}_\text{f} > 12.5$.

$\mathbf{P_{fL}}$: First the power spectral density with Hamming window is obtained for the preprocessed (0.5–30 Hz) s_{filt} segment. Then P_{fL} is obtained as the percentage of the segment's power below 2.5 Hz. Non-shockable LEA rhythms show slow fluctuations and concentrate most their power in the low frequency band so P_{fL} is large. LEA rhythms were detected when $\text{P}_{\text{fL}} > 58$.

sS: First s_{filt} is preprocessed (2.5–30 Hz) and divided in six non-overlapping windows of $0.5\,\text{s}$. Then the sum of the absolute values of the first-difference (slope) are computed for each window, and the minimum value is sS. Since the ECG varies little and slowly in non-shockable LEA rhythms these rhythms have small values of sS. LEA rhythms were detected when sS $< 2.18 \cdot 10^{-3}$.

Conducting algorithm

Shockable rhythms are characterized by the absence of normally conducted or narrow QRS complexes in the ECG. On the contrary many non-shockable rhythms with electrical activity present clear QRS complexes, this includes most of the PR and many PEA rhythms. The conducting algorithm combines two parameters, bWT and bCP, obtained by processing in the time and frequency domains respectively. The parameters, which are fully described in [7], are combined in a logistic regression classifier to identify non-shockable rhythms when:

$$11.45 \cdot \text{bCP} - 18.02 \cdot \text{bWT} - 3.44 > 0 \qquad (2)$$

PEA algorithm

The last sub-algorithm discriminates shockable rhythms from PEA with low rates or wide complexes, which are not correctly identified as non-shockable by the conducting algorithm. The PEA algorithm is based on a single parameter (ensbCP) obtained in the slope domain. First, s_{filt} is low-pass filtered (cutoff at 25 Hz) and then the square of its first difference is computed, time-averaged with a window of $100\,\text{ms}$ and normalized to unity. The parameter ensbCP is defined as the proportion of time this normalized time-average is below 0.024. The time distribution of the slope is more even in shockable than in PEA rhythms, ensbCP is therefore larger in PEA, which labels the rhythm as shockable when ensbCP < 0.12 and as non-shockable otherwise.

3. Results

Table 1 shows the classification results for the $3\,\mathrm{s}$ segments, both for the complete SAA and its sub-algorithms. A large proportion of asystole was detected by the LEA algorithm by combining features from the corrupt and filtered ECG. The conducting algorithm identified most of the PR segments, which normally present narrow QRS complexes that can be identified after the suppression of the CPR artifact. PEA was detected by the three sub-algorithms, because the PEA group includes rhythms with little electrical activity, with normally conducted QRS complexes, and with low rates and wide complexes. Almost 6% of the shockable segments were detected as non-shockable by the LEA algorithm, normally VF with low amplitudes or low dominant frequencies. Post-filtering spikes, that locally affect the slope of the ECG, caused most of the 4.4% of the shockable segments missed by the PEA algorithm.

The results for the 3 s segments were below the 95% specificity and 90% sensitivity recommended by the AHA. When the record was diagnosed applying a simple majority criterion to the diagnoses of its segments the AHA criteria were met for specificity and almost met for sensitivity, as shown in Table 2. Combining the diagnoses improved sensitivity and specificity by only two points, however there was a larger four point improvement in specificity for asystole.

Fig. 2 shows two examples of correctly classified records. In panel A (asystole) the SNR is large and s_{filt} has low amplitude, the LEA sub-algorithm classifies the rhythm correctly. In panel B (VF) the artefact is large but s_{filt} has sufficient irregular activity with no QRS complexes, and it is detected as shockable.

Table 1. Percentage of 3 s segments identified by each sub-algorithm and by the complete SAA.

	No-shock				
Rhythm	LEA	Cond	PEA	Total	Shock
Non-shockable	40.7	40.1	12.3	93.1	6.9
AS	76.3	6.6	7.9	90.8	9.2
PEA	28.1	48.9	16.0	93.0	7.0
PR	8.9	83.2	6.9	99.0	1.0
Shockable	5.6	2.1	4.4	12.1	87.9

Table 2. Sensitivity and specificity per record, low one-sided 90% confidence intervals in parenthesis.

	Diagnosis		
Rhythm	No-shock	Shock	Se/Sp (%)
Non-shockable	276	14	95.2 (93.3)
AS	86	5	94.5 (90.5)
PEA	152	9	94.4 (91.6)
PR	38	0	100 (95.0)
Shockable	9	77	89.5 (84.5)

4. Discussion and conclusions

This is a preliminary design of a SAA to diagnose rhythms during CPR. The design is based on three important principles: an AHA compliant SAA with emphasis on a high specificity, the use of the corrupt and filtered ECG to improve specificity for asystole, and the combination of several diagnoses to improve the reliability of the algorithm.

This is the first study that reports an overall specificity during CPR above the 95% AHA goal. The sensitivity is only half a point below the AHA goal. A high specificity during CPR is beneficial because it avoids unnecessary CPR interruptions, which are detrimental for the survival of the patient. The sensitivity is lower than the values reported in other studies. However, a lower sensitivity implies prolonging CPR for shockable rhythms, which is not known to be detrimental for survival.

By using the corrupt and filtered ECG the specificity for asystole was above 94%, well over the values reported by other methods which are below 85%. This is important because the prevalence of asystole in OHCA is around 40%, in fact the accurate detection of asystole is one of the limitations of rhythm analysis during CPR.

Combining several diagnoses improves sensitivity and specificity, particularly for asystole. However the simplistic majority approach adopted in this study reports only a 2 point increase in sensitivity and specificity. A more elaborate combination based on the values of the features should be explored to improve the results.

This study is preliminary and has several limitations. The algorithm was developed and tested on the same data, so on a testing database accuracies should be lower. Additionally, an adequate database to develop and test the SAA must be formed by longer registers during CPR that reflect a realistic resuscitation scenario. Furthermore, in longer registers more segment diagnoses are available and more elaborate classification strategies can be explored. Those startegies should focus on minimizing unnecessary CPR interruptions.

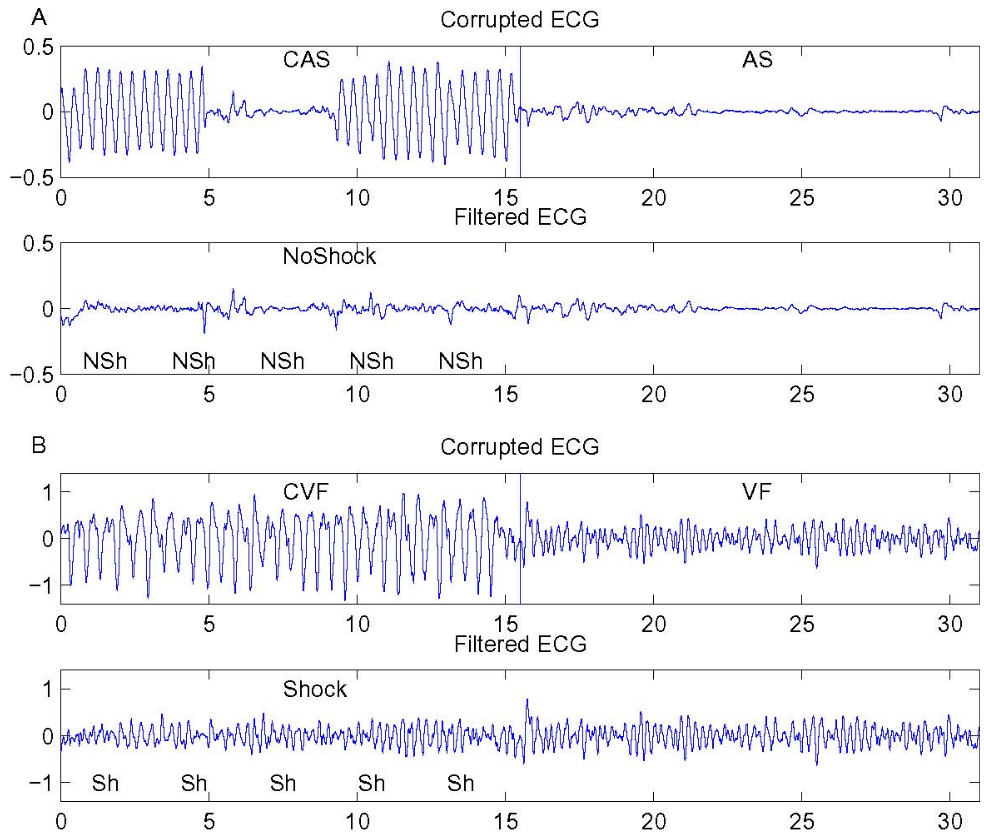

Figure 2. Examples of correctly detected asystole (panel A) and VF (panel B). In the filtered ECG the diagnoses per segment (shock≡Sh, No-shock≡NSh) and for the record are given below and above respectively.

Acknowledgements

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