An Accurate Shock Advise Algorithm for use during Piston-Driven Chest Compressions

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Abstract

Mechanically delivered chest compressions induce artifacts in the ECG that can lead to an incorrect diagnosis of the shock advice algorithms implemented in the defibrillators. This forces the rescuer to stop cardiopulmonary resuscitation (CPR) compromising circulation and thus reducing the probability of survival. This paper introduces a new approach for a reliable rhythm analysis during mechanical compressions which consists of an artifact supression filter based on the recursive least squares algorithm, and a shock/no-shock decision algorithm based on machine learning techniques that uses features obtained from the filtered ECG. Data were collected from 230 out-of-hospital cardiac arrest patients treated with the LUCAS CPR device. The underlying rhythms were annotated in artifact-free intervals by consesus of expert resuscitation rhythm reviewers. Shock/no-shock diagnoses obtained through the decision algorithm were compared with the rhythm annotations to obtain the sensitivity (Se), specificity (Sp) and balanced accuracy (BAC) of the method. The results obtained were: 94.7% (Se), 97.1% (Sp) and 95.9% (BAC).

1. Introduction

High quality cardiopulmonary resuscitation (CPR) and early defibrillation are the most influential factors explaining survival from out of hospital cardiac arrest (OHCA) [1]. Current advanced life support guidelines state that minimum interruptions in chest compressions (CCs) are required during CPR to improve the chances of a successful defibrillation [1]. Unfortunately, current defibrillators require interrupting CPR during rhythm analysis because CCs produce artifacts in the ECG that can lead to an incorrect shock/no-shock diagnosis.

Adaptive filtering of the CC artifact has been the major approach to allow rhythm analysis during CCs, ranging from filters that use additional reference signals correlated with the artifact to simpler but less effective filters that analyze the ECG alone [2]. Taking advantage of the quasi-periodic nature of CC artifacts, adaptive filters based on the multiharmonic modelling of the artifact have also been explored [3]. Diagnosing the filtered ECG by a commercial shock advice algorithm (SAA) has become general practice to evaluate the performance of these algorithms [2]. This allows the estimation of the Sensitivity (Se) and Specificity (Sp), that is the proportion of correctly identified shockable and nonshockable rhythms, respectively. However, the SAAs used were originally designed to analyze artifact-free ECG and not to diagnose the filtered ECG.

Most rhythm analysis methods have been devoted to manual CPR [2]. However recently methods to analyze the rhythm during mechanical CCs delivered by piston driven devices have been developed [4–6]. These methods were based on the SAA of commercial AEDs [7, 8] for the shock advise decision, and either showed poor performance [4, 5] or involved several filtering stages and excessive computational demands [6].

This study proposes a method for a reliable shock advise during mechanical CCs provided by the LUCAS-2 (Physio Control/Jolife AN, Lund, Sweeden) piston driven device. The method combines an adaptive filter based on the recursive least-squares (RLS) algorithm to remove the artifact and a shock/no-shock decision algorithm based on a support vector machine (SVM) classifier to diagnose the rhythm after filtering.

2. Materials and methods

2.1. Materials

The data used for this study were gathered by the emergency services of Oslo and Akershus (Norway) using LifePak 15 defibrillators (Physio-Control Inc., Redmond, WA, USA). ECG and thoracic impedance (TI) signals were recorded and resampled to 250 Hz (see [4] for a detailed description of the data). The ECG was band limited to 0.5-40 Hz using an order 8 Butterworth filter.

The dataset extracted from this data consisted of 1045 segments of 20 s from 230 patients, whereof 201 were shockable rhythms and 844 nonshockable (270 asystole, 574 organized). The first 15 s of the segment included continuous CCs and were used to develop our solution. The last 5 s, free of artifact, were used by the expert reviewers to annotate the patient's underlying rhythm as shockable/nonshockable and used as ground truth. Figure 1 shows an example of a 20 s ECG segment corresponding to an underlying nonshockable rhythm.

2.2. Methods

Filtering the CC Artifact

CC artifacts were removed from the ECG using a RLS filter based on the multiharmonic Fourier modelling of the artifact, the filter is described in detail in [5, 6]. In brief, during CCs the artifact is modelled as an N-term Fourier series with time varying coefficients ($a_k(n)$ and $b_k(n)$) and a constant fundamental frequency, $f_0 = 1.694\,\mathrm{Hz}$ (about 101 compressions min^{-1}), which is fixed by the LUCAS-2:

$$s_{\mathrm{cc}}(n) = \sum_{k=1}^{N} a_k(n)\cos(k2\pi f_0 n T_s) + \quad (1)$$

$$b_k(n)\sin(k2\pi f_0 n T_s) \quad (2)$$

where T_s is the sampling period. The RLS filter estimates the time-varying coefficients ($a_k(n)$ and $b_k(n)$) and subtracts the estimated artifact from the corrupted ECG (s_{cor}) to give the filtered ECG ($\hat{s}_{\mathrm{ecg}}$), see Figure 1.

In this paper we used the optimal configuration of the filter as described in [6], which has two degrees of freedom. First, a parameter to decide the number of harmonics to be used in the method, $\gamma = 0.0023$ which roughly corresponds to an average number of $N = 23$ harmonics. Second, the RLS solution's forgetting factor, $\lambda = 0.9899$.

Feature extraction

A set of 59 shock/no-shock decision features were extracted from the filtered ECG. Only the interval from 4 s to 12 s (see the highlighted interval in figure 1) was used for feature extraction. First 4 s were left out to avoid RLS filtering transients. These features have been comprehensively studied and described [9–11] to classify OHCA rhythms. The features are:

- **Time domain features**. TCI, TCSC, Exp, Expmod, MAV, count1, count2, count3, x1, x2 and bCP [9].
- **Spectral domain features**. vFleak, M, A1, A2, A3, x3, x4, x5, bWT and bW [9]; FuzzEn [11, 12].
- **Wavelet domain features**. IQR ($d_{3\text{-}7}$), Var ($d_{3\text{-}7}$), first quartile of $d_{3\text{-}7}$ (FQ ($d_{3\text{-}7}$)), IQR ($s(n)$), IQR ($\dot{s}(n)$), IQR ($\ddot{s}(n)$), $\mu_{2\text{-}4,s}$, $\mu_{3\text{-}4,\dot{s}}$, $a_{1\text{-}4}$ and σ_v^2 [10]; Li feature [9].
- **Complexity features**. CM, CVbin, abin, Frqbin, Kurt, PSR, HILB and SamEn [11, 12].

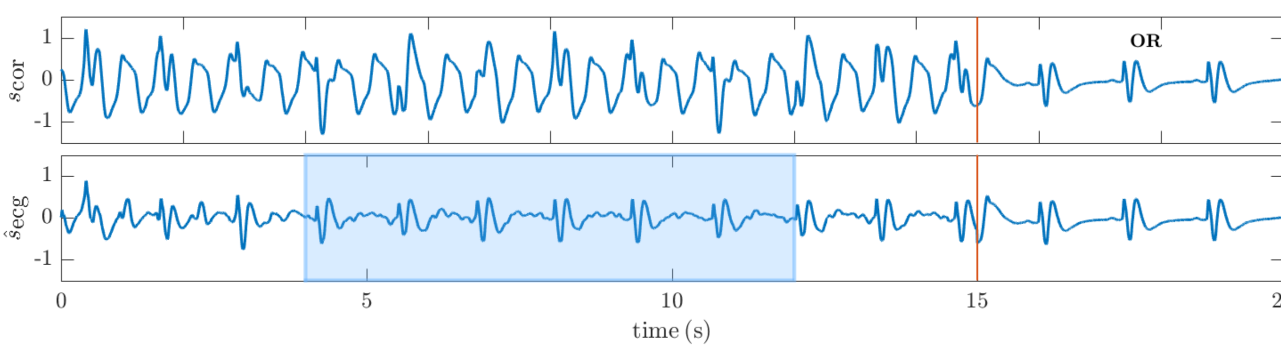

Figure 1. Example of a 20 s episode of the database. The top panel shows the ECG of a patient with a nonshockable organized rhythm (OR): the first 15 s are corrupted by the CC artifact, and the last 5 s are free of artifact showing the patient's underlying rhythm. The bottom panel shows the filtered ECG which reveals the patient's rhythm during CCs.

Architecture of the model and evaluation

A 10-fold cross-validation (CV) architecture was used for feature selection and model optimization and assessment. Folds were partitioned patient-wise and ensuring that the rhythm prevalences matched (to at least 90%) the prevalences for shockable and nonshockable rhythms seen in the whole dataset (quasi-stratified). The main classifier used for the shock/no-shock decision was optimized using the most relevant subset of k features selected in the training data and used to classify the test segments. These diagnoses were compared with the ground truth to obtain the performance of the solution in terms of Se, Sp and BAC (the mean value of Se and Sp).

Feature selection

We used the ReliefF [13] feature selection method to choose the k features used in the main classifier. This supervised filter-based method is an extension of the well-known Relief [14] for multiclass and regression problems. The key idea of Relief is to estimate the relevance of features according to how well their values distinguish between the instances of the same and different classes that are near to each other (neighbours). Whereas Relief only relies in a single neighbour to calculate the importance of the features, ReflíefF considers the contribution of several neighbours, making the algorithm more robust dealing with noisy data. In this study the number of neighbours was fixed to 50. Feature selection was performed for $k = 1, ...59$ so as to find which value of k offered the best compromise between dimensionality and performance.

Shock/no-shock classification algorithm

Support Vector Machine (SVM) classifier with a gaussian kernel was used for the shock/no-shock decision. Selecting an optimal SVM model involves selecting two parameters: γ and C, the width of the Gaussian Kernel and the flexibility of the decision boundary, respectively [15]. The values of C and γ that maximized the BAC were determined in the 10-fold CV loop doing a 25x25 logaritmic grid search in the ranges $10^{-1} < C < 10^{1.5}$ and $10^{-3} < \gamma < 10$. The procedure was repeated 50 times to estimate the statistical distributions of the performance metrics and the optimal parameters of the SVM model. These distributions will be reported as mean (95% CI, confidence interval).

3. Results

Figure 2 shows the mean values of Se, Sp and BAC obtained in the 50 random repetitions as a function of the number of features (k) selected in the training data. The best compromise between model simplicity and performance was obtained for $k = 24$ as the mean BAC slightly increases for a greater value of k. In this working point ($k = 24$), the mean value of the optimal configuration (C/γ) of the SVM classifier was 10.62/0.02 obtaining a Se, Sp and BAC of 94.7% (93.5-95.6), 97.1% (95.5-97.8) and 95.9% (95.4-96.5), respectively. This is a considerable improvement over using the RLS filter followed by a commercial SAA [7, 8], which resulted in a Se, Sp and BAC of 98.1%, 87.0%, 92.5% respectively.

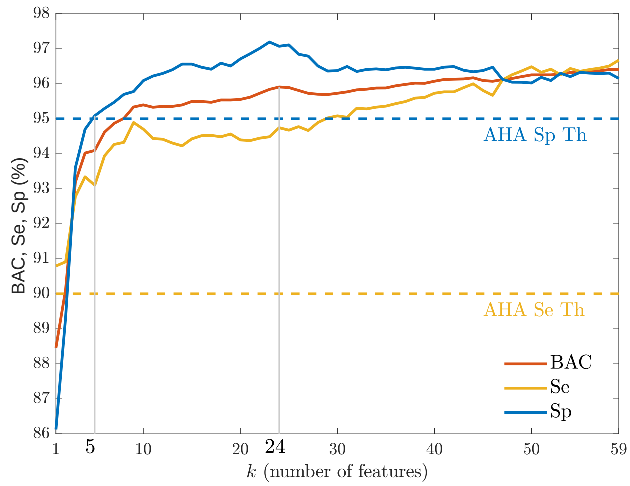

Figure 2. Mean values of the performance metrics as a function of the number of features (k) used in the classifier.

However, as shown in Figure 2, American Heart's Association's (AHA) requirements for a reliable rhythm diagnosis (Se>90% and Sp>95%) are met with as few as 5 features. In fact, the distributions of Se, Sp and BAC for $k = 5$ were: 93.1% (90.5-95.5), 95.1% (94.1-95.9) and 94.1% (92.7-95.4). Table 1 shows the 10 features selected in the 50 random repetitions of the 10-fold CV for $k = 5$:

Feature	N	Feature	N_f
x1	500	A1	169
vfleak	494	IQR (d_3)	86
x2	491	count3	75
x4	414	IQR (d_2)	24
FQ (d_3)	246	IQR (d_1)	1

Table 1. The features selected in 50 random repetitions ranked by the number of times (N_f) they were selected for $k = 5$.

4. Discussion

This work introduces a new method for a reliable rhythm analysis during mechanical CCs. It consists of an adaptive

RLS filter designed to remove the CC artifact and a shock/no-shock decision algorithm using multiple ECG features and a state of the art machine learning classifiers. The results show that the best trade-off between model dimensionality and performance was obtained using 24 features, obtaining a BAC of 95.9%. However, AHA compliant performance was obtained with only 5 features.

In our previous work [6] a single filtering stage followed by a commercial SAA yielded Se, Sp and BACs of 98.1%, 87.0% and 92.5% in this same dataset. By using a machine learning approach we were able to boost the BAC by 3.4 points with an increase in Se and Sp of -3.4 and 10.1 points respectively. This shows that it is possible to accurately decide whether to shock the patient during mechanical CCs using a single filtering stage. In the past we obtained AHA compliant results using 2 filtering stages and 3 decision stages [6], with lower BAC and higher computational demands.

In conclusion, the method presented in this paper is, to the best of our knowledge, the computationally cheapest method for a reliable rhythm analysis during mechanical CCs, according to AHA recommendations.

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