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ECG Rhythm Analysis during Manual Chest Compressions Using an Artefact Removal Filter and Random Forest Classifiers

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Abstract

Interruptions in cardiopulmonary resuscitation (CPR) decrease the chances of survival. However, CPR must be interrupted for a reliable rhythm analysis because chest compressions (CCs) induce artifacts in the ECG. This paper introduces a double-stage shock advice algorithm (SAA) for a reliable rhythm analysis during manual CCs. The method used two configurations of the recursive least-squares (RLS) filter to remove CC artifacts from the ECG. For each filtered ECG segment over 200 shock/no-shock decision features were computed and fed into a random forest (RF) classifier to select the most discriminative 25 features. The proposed SAA is an ensemble of two RF classifiers which were trained using the 25 features derived from different filter configurations. Then, the average value of class posterior probabilities was used to make a final shock/no-shock decision. The dataset was comprised of 506 shockable and 1697 non-shockable rhythms which were labelled by expert rhythm resuscitation reviewers in artifact-free intervals. Shock/no-shock diagnoses obtained through the proposed double-stage SAA were compared with the rhythm annotations to obtain the Sensitivity (Se), Specificity (Sp) and balanced accuracy (BAC) of the method. The results were 93.5%, 96.5% and 95.0%, respectively.

1. Introduction

Minimum "hands-of" intervals during cardiopulmonary resuscitation (CPR) are required to improve the chances of a successful defibrillation [1]. In current practice CPR is interrupted every 2 minutes for a reliable analysis of the heart rhythm. In fact, chest compressions (CCs) provided during CPR induce artifacts in the ECG that impede a reliable rhythm analysis of shock advice algorithms.

Over the last 15 years, many efforts have been made to achieve a continuous rhythm analysis without interruptions to CPR therapy. Different approaches have been proposed, such as rhythm analysis during ventilation pauses [2, 3], however the main approach has been designing adaptive filters to suppress the artifact and then diagnose using a SAA for artifact-free ECG [4]. Nevertheless, the accuracy of this approach is still poor. Adaptive filters substantially reduce CC artifacts with high SNR improvements, however filtering residuals frequently resemble a disorganized rhythm. In these cases, SAAs may produce a wrong shock diagnosis as the majority of the SAAs used are designed for artifact-free ECGs. This is the reason why current methods have a high capacity to detect shockable rhythms, Sensitivity (Se), but a low capacity to detect non-shockable rhythms, Specificity (Sp).

Recently, a multistage algorithm was introduced to increase the Sp [5] (supp materials). In brief, this algorithm uses two recursive least squares (RLS) filters and a SAA of a commercial defibrillator in three decision stages. Although this solution considerably improves the Sp of previous approaches, it still does not meet American Heart Association's criteria for a reliable rhythm diagnosis (Sp>95%, Se>90%) during manual CCs. Another approach to increase the Sp was the use of machine learning techniques to classify the ECG after using an adaptive CPR artifact suppression filter [6].

In this paper, we propose a method for a reliable shock advise during manual CCs, which combines the both aforementioned approaches: a double stage RLS filtering [5] and a SAA algorithm based on random forest (RF) classifiers [6] which benefits from both filtering configurations to reach a reliable shock/no-shock decision.

2. Materials and methods

2.1. Dataset

The data were obtained from a prospective study of out-of-hospital cardiac arrest (OHCA) patients gathered between March 2002 and September 2004 by the emergency services of London, Stockholm and Akershus and coordinated by the Oslo University Hospital. The ECG and the compression depth (CD) signals were acquired using a modified version of Laerdal's Heartstart 4000 defibrillator (4000SP) and were resampled to 250 Hz. A notch and a Hample filter were used to remove 50 Hz noise and spiky artifacts from the ECG, respectively. Finally, the ECG was band limited to 0.5-40 Hz. CC instants (t_k) were automatically marked in the CD signal using a negative peak detector for depths above 1 cm, see figure 1.

The dataset used in this study contained 2203 records obtained from 273 OHCA patients. Each record (see figure 1) consisted of two consecutive intervals: a 15-sec interval which includes continuous CCs, and a 5-sec interval free of artifact. The latter interval was reviewed by expert resuscitation rhythm reviewers to annotate the patient's underlying rhythm as shock/no-shock and use it as ground truth. In total there were 506 shockable and 1697 non-shockable rhythms.

2.2. Filtering the CC Artifact

In this work, the used CC artefact suppression method is based on a recursive least squares (RLS) filter adapted to estimate periodic interferences [5]. The RLS filter estimates the time-varying coefficients ($a_k(n)$ and $b_k(n)$) of a multiharmonic model of the artifact whose fundamental frequency ($f_0(n)$) is derived from the chest compression instants (t_k):

$$s_{cc}(n) = \sum_{k=1}^{N} a_k(n) \cos(k2\pi f_0(n)nT_s) + \qquad (1)$$
$$b_k(n) \sin(k2\pi f_0(n)nT_s)$$

$$f_0(n) = \frac{1}{t_k - t_{k-1}} \quad t_{k-1} < nT_s \leq t_k \qquad (2)$$

The CC artifact is iteratively estimated ($\hat{s}_{cc}$) and subtracted from the corrupted ECG (s_{cor}), to obtain the clean ECG ($\hat{s}_{ecg}$), as shown in figure 1.

In the RLS filter there are two degrees of freedom, the number of harmonics needed to model the artifact (N) and the forgetting factor (λ) which controls the coarseness of the filter. In this paper, the corrupted ECG was filtered for two configurations of the RLS filter (N/λ) following the optimal configuration of the multistage algorithm described in [5] for manual CCs. In the first stage, the corrupted ECG was coarsely filtered ($\hat{s}_{ecg\lambda_1}$) using a λ of 0.987 whereas in the second stage the ECG was finely filtered ($\hat{s}_{ecg\lambda_2}$) with a λ fixed to 0.998. In both stages N was set to 4.

2.3. Feature engineering

For each filtered ECG ($\hat{s}_{ecg\lambda_1}$, $\hat{s}_{ecg\lambda_2}$), a multi-resolution analysis is employed to extract 244 features. Only the interval from 4 s to 12 s was used to compute features. First 4 s were left out to avoid RLS filtering transients. The 8-second ECG segments were decomposed by discrete wavelet transform (DWT) into its subbands with the Daubechies 4 wavelet and 7 levels of decomposition generating a set of approximation coefficients a_7 and seven sets of detail coefficients d_1 to d_7. The ECG was then reconstructed, $s(n)$, by using detail coefficients $d_3 - d_7$. Reconstructed signals corresponding to each set of detail coefficients (d_3 to d_7) were also generated: $s_3(n)$ to $s_7(n)$.
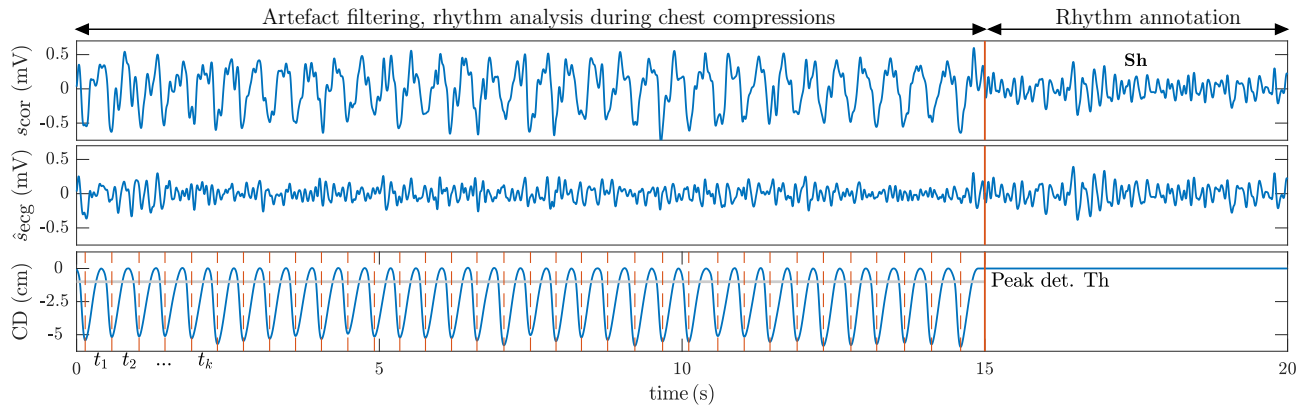

Figure 1. Example of a 20 s episode of the database. The top panel shows the ECG of a patient with a shockable rhythm (Sh): the first 15 s are corrupted by the CC artifact and the last 5 s are free of artifact showing the patient's underlying rhythm. The second pannel shows the filtered ECG and the bottom panel the CD signal with the CC instants (t_k).

For each filtered signal 244 features were computed [7–9] based on the multi-resolution analysis. The features were ranked by importance in each random forest (RF) classifier using the out-of-bag error [10]. For each set the top ranked 25 features were selected for classification.

2.4. Classification

The last step in the proposed SAA is classification. An ensemble of two RF classifiers were combined to reach a shock/no-shock decision, as can be shown in the last block of figure 2. The first classifier was trained using the selected 25 features from $\hat{s}_{\text{ecg}\lambda_1}$ whereas the second one was trained using the selected 25 features from $\hat{s}_{\text{ecg}\lambda_2}$. The final shock/no-shock decision was made based on the average value of the class posterior probabilities of two RF classifiers. The class with the higher average value of class posterior probabilities was chosen for shock/no-shock decision.

Both RF classifiers had 300 decision trees. Each tree was trained using bootstrapped replicas of the training data and the prior probabilities of each class (shock/no-shock) were balanced for each tree by using resampling. The cost function was defined to penalize the wrong diagnosis of nonshockable rhythms by a factor of 95/90 based on the AHA recommendation.

2.5. Model assessment

A 10-fold cross-validation (CV) scheme was used to train and test the SAA. Folds were partitioned patient-wise ensuring that the rhythm prevalences matched to at least 85% the prevalences for shockable and nonshockable rhythms of the whole dataset (quasi-stratified).

Test segments were diagnosed as shock/no-shock based on the average value of class posterior probabilities (see section 2.4). These diagnoses were compared with the rhythm annotations to obtain the following performance metrics: Se, Sp and Balanced Accuracy (BAC), that is, the mean value of Se and Sp. In order to obtain the statistical distributions of these metrics the process was repeated 100 times. The results were compared to those obtained using the classical approach, filtering followed by a SAA designed for artifact-free ECG [11], in a single stage and

multistage configurations.

3. Results

The mean (95% confidence interval) Se, Sp and BAC of the proposed double-stage SAA were 93.5% (92.9-94.0), 96.5% (96.2-96.6) and 95.0% (94.7-95.3), respectively. The classical approach in an optimal multistage configuration, as described in [5], yielded a Se, Sp and BAC of: 91.7%, 93.7% and 92.7%, far below the obtained results using our proposed double-stage SAA.

A classical single stage solution produced an Se, Sp and BAC of 96.3%, 81.3% and 88.8%, respectively. The results for the best single RF-classifier (λ_2) were 92.8% (92.3-93.5), 96.5% (96.2-96.7) and 94.7% (94.4-95.0), respectively. These results meet the minimum 90% Se and 95% Sp performance goals recommended by the American Heart Association (AHA).

Table 1 shows the selected features for $\hat{s}_{\text{ecg}\lambda_1}$ and for $\hat{s}_{\text{ecg}\lambda_2}$, with the following notation: feature name (signal/wavelet coefficient). The first nine features of both columns are described by Figuera *et al* [7]. Features from 10 to 15 in the left column and from 10 to 12 in the right column were introduced by Rad *et al* [8]. Fuzzy Entropy (FuzzEn), the Signal Integral parameter (SignInt), the Peak Power Frequency (PPF), the Smoothed Nonlinear Energy Operator (SNEO) and the Hjorth Mobility parameter are described in [9,12], [13], [14], [15] and [16], respectively. The remaining features were designed for this work: the number of QRS-like peaks (Npeak) and the Euclidean distance between the Hjorth Mobility and the Hjorth Mobility of the second degree (Mx2).

4. Discussion

This work introduces a double-stage SAA for a reliable rhythm analysis during CPR inspired by two solutions proposed in the literature to increase the Sp for rhythm analysis during CCs [5, 6]. Our proposed SAA algorithm consists of a double-stage RLS filtering, multiresolution analysis for feature extraction, and two RF classifiers.

A single filtering stage followed by a commercial SAA yielded a Se and a Sp of 96.3% and 81.3% respectively. Using an ad-hoc SAA designed to diagnose filtered ECGs
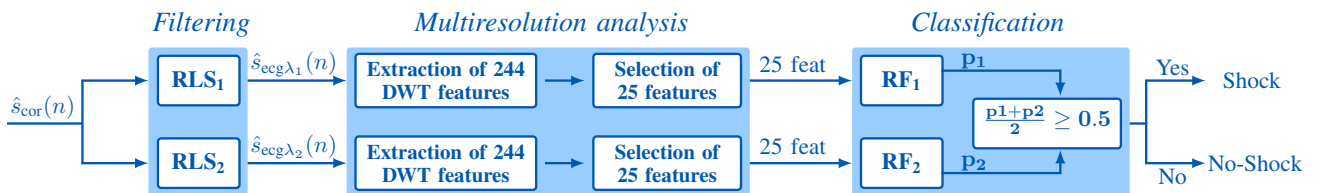

Figure 2. Arquitecture of the proposed double-stage SAA.

Feature	$\hat{s}_{\text{ecg}\lambda_1}$	Feature	$\hat{s}_{\text{ecg}\lambda_2}$
1	x1 $(s(n))$	1	x1 $(s(n))$
2	x4 $(s(n))$	2	x4 $(s(n))$
3	SamEn (d_3)	3	SamEn (d_3)
4	SamEn $(s_3(n))$	4	SamEn $(s_3(n))$
5	SamEn $(s_4(n))$	5	SamEn $(s_4(n))$
6	vfleak$(s(n))$	6	vfleak$(s(n))$
7	count2 $(s(n))$	7	count2 $(s(n))$
8	count3 $(s(n))$	8	x3 $(s(n))$
9	bCP $(s(n))$	9	bCP $(s(n))$
10	IQR $(\dot{d}(5))$	10	First Quartile(d_5)
11	IQR (d_7)	11	Positive Area$(s(n))$
12	IQR $(\dot{d}_7)$	12	Negative Area$(s(n)$
13	IQR $(\ddot{d}_5)$	13	Mean(d_4)
14	Var (d_5)	14	Mx(d_6)
15	$\mu_2(d_7)$	15	PPF$(s(n))$
16	FuzzEn$(s(n))$	16	FuzzEn$(s(n))$
17	FuzzEn$(s_3(n))$	17	FuzzEn$(s_3(n))$
18	Mx2$(\hat{s}_{\text{ecg}\lambda_1})$	18	FuzzEn$(s_4(n))$
19	SNEO$(s(n))$	19	SNEO$(s(n))$
20	SignInt(d_7)	20	SignInt(d_7)
21	SignInt(d_5)	21	Mean$(s(n))$
22	Std$(\dot{d}_3)$	22	Std$(\dot{d}_3)$
23	Mean(d_3)	23	Mean(d_3)
24	Mean$(\dot{d}_3)$	24	Mean$(\dot{d}_3)$
25	Npeak$(s(n))$	25	Npeak$(s(n))$

Table 1. The 25 features selected by the two RF classifiers.

the Sp was increased in 15.2 points although the Se was reduced in 3.5 points. This significant increase in Sp allowed the AHA requirements to be met with an overall BAC of 94.7%. The results were further increased with the addition of the double stage filtering, obtaining a BAC of 95.0%.

In conclusion, this study confirms that ad-hoc decision algorithms for the filtered ECGs provide a reliable rhythm analysis during CPR and that the results would be further improved if the SAA combined the information derived from differently filtered ECG signals.

Acknowledgements

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