Multimodal Biosignal Analysis Algorithm for the Classification of Cardiac Rhythms during Resuscitation

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Abstract

Monitoring the heart rhythm during out-of-hospital cardiac arrest (OHCA) is important to improve treatment quality. OHCA rhythms fall into five categories: asystole (AS), pulseless electrical activity (PEA), pulse-generating rhythms (PR), ventricular fibrillation (VF) and ventricular tachycardia (VT). This paper introduces an algorithm to classify these OHCA rhythms using the ECG and the thorax impedance (TI) signals recorded by the defibrillation pads. The dataset consisted of 100 OHCA patient files from which 2833 4-s signal segments were extracted: 423 AS, 912 PE, 689 PR, 643 VF, and 166 VT. The Stationary Wavelet Transform (SWT) was used to obtain 95 features from the ECG and the TI. Random Forest classifiers were used, features were ranked during training using random forest importance, and models with increasing number of features were evaluated. The optimal classifier was obtained combining 50 ECG and TI features, with a median (80% confidence interval) average recall of 86.5% (80.6-89.4). The recall for AS/PEA/PR/VF/VT were 96.3% (93.0-98.5), 77.8% (68.1-89.2), 88.7% (79.5-93.6), 94.4% (90.2-97.4) and 77.3% (52.9-91.3), respectively.

1. Introduction

Out-of-hospital cardiac arrest (OHCA) is one of the main causes of death in developed countries, and a major public health problem. The number of OHCA cases treated annually by Emergency Medical Systems exceeds 250,000 in Europe [1] and 180,000 in the United States [2]. OHCA has an average incidence of 55 cases per 100,000 person-years [3] and a survival rate of 7.1%.

To increase OHCA survival, it is necessary to provide the patient with adequate treatment during the arrest, but also to identify the factors that influence the patient's response to treatment [4], [5]. The patient's state is at large linked to its cardiac rhythm, which in OHCA is categorized into five groups, namely: asystole (AS), pulseless electrical activity (PEA), pulse-generating rhythms (PR), ventricular fibrillation (VF) and tachycardia (VT).

Rad et al. [6] introduced 5-class OHCA rhythm classification using the ECG. Since then, other ECG-based 5-class classifiers have been developed [7]. However, using only the ECG may limit classification accuracy, particularly the distinction of rhythms that albeit having visible QRS complexes may or may not have a palpable associated mechanical activity. That is, the distinction between PEA (no pulse) and PR (pulse). PEA/PR classification improves when other signals such as the thoracic impedance (TI) or the capnogram are also used [8], [9]. Defibrillators currently record the TI to adjust defibrillation energy levels and to monitor the quality of cardiopulmonary resuscitation (CPR) [10]. The TI signal shows a correlated fluctuation with each beat when the patient regains circulation, as can be seen in Figure *1*. Therefore, the TI can be a good indicator of pulse.

The objective of this study was to improve the accuracy of ECG-only methods for 5-class OHCA rhythm classification by using for the classification the ECG and the TI signals recorded by the defibrillation pads.

2. Materials and methods

2.2. Dataset

The dataset was a subset of OHCA episodes obtained from a study conducted between March 2002 and September 2004 to measure the quality of CPR in three European cities: Akershus (Norway), Stockholm (Sweden), and London (UK) [11]. Defibrillators based on the Heartstart 4000 (Philips Medical Systems, Andover, Mass) were used to record the data. The raw data consisted of the ECG, TI, and CPR pad signals, sampled at 500 Hz with 16 bit resolution. All recordings were annotated by experts for the original study into the five OHCA rhythm types.

For this study, all the original signals were down sampled to 250 Hz and 4-s ECG and TI segments were extracted from 100 OHCA patients: 42 Akershus, 30 Stockholm, 28 London. The segments corresponded to a single rhythm type and showed no artefact due to CPR compressions or noise. All the labels of the segments were reviewed by authors (HL, UI, TE) to remove noise in annotations, and a consensus decision was used as ground truth. The final audited dataset contained 2833 segments: 423 AS, 912 PE, 689 PR, 643 VF, and 166 VT.

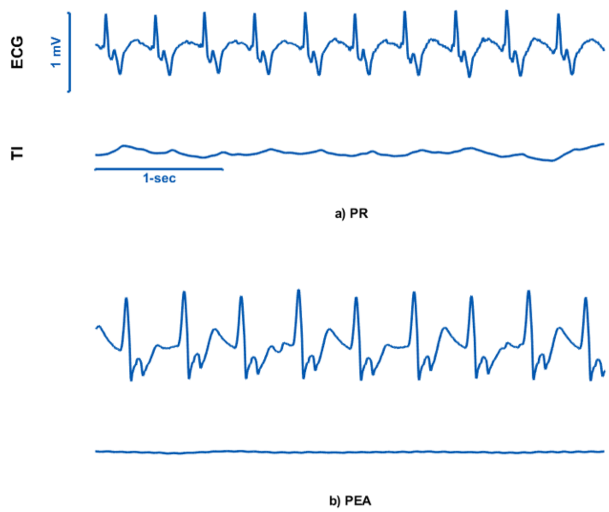

Figure 1. ECG and TI signals of PEA and PR rhythms. When the patient has spontaneous pulse (PR in panel a), activity associated with each heartbeat can be observed in the impedance waveform; this activity is absent when there is no pulse (PEA, panel b).

2.2. Feature Extraction

Multi-resolution analysis based on the Stationary Wavelet Transform (SWT) was conducted to decompose ECG and TI segments into their sub-bands and obtain the denoised ECG and TI. Features were extracted from the denoised ECG and TI and their sub-band components [12].

At each decomposition level the approximation (low-pass), a_i, and detail (high-pass), d_i, coefficients were generated. Eight decomposition levels were used to obtain a_8 and $d_8, \ldots\, d_1$, and the denoised $d_3 - d_8$ coefficients were used to reconstruct the denoised ECG and TI signals. A total of 95 features were extracted as follows:

- *ECG features* (65 from the ECG and its $d_3 - d_8$ coefficients): SampEn, x1, x2, bCP, count1, count2, count3, bWT, Npeak, vfleak, expmod, hilb, IQR, FQR, tcsc, mav, frqbin, cm, kurt, A1, A2, A3, AR_c, AR_n ,m2_s, m3_s, m4_s, v1, v2, v3, v4, v5, v6, v7, v8, v9, Pf0, LAC, Pnh, mSl. A detailed description of the features can be found in [7], [13], [14] and [15].
- *TI features* (30 from the TI and its $d_3 - d_6$ coefficients and its combination with the ECG): the mean power of the TI and the mean cross-power between ECG and TI [16], the first-order derivative of the TI and the peak amplitude of the Fast Fourier Transform (FFT) of the first-order derivative of the TI [17], and the magnitude-squared coherence and the cross power spectral density of ECG and TI.

2.2. Classification

To design the classifier 100 training-test partitions of the database were constructed. For each partition, 70% of the data were used to train the classifier and 30% for validation. Data was partitioned patient-wise and in a quasi-stratified way, so that the rhythm prevalence on each set (train/test) for each class was at least 75% of the prevalence for the full dataset.

Random Forest algorithms were used to build the classifiers. For each partition, features were ranked during a first training process based on the random forest importance. The models were then trained again and tested using the N most important features. Models with increasing number of features were evaluated.

2.3. Evaluation

Confusion matrices and the associated metrics were used to evaluate the performance of the classifiers. For each class i, Recall (R_i), Precision (P_i) and F1-score ($F_{1,i}$) were computed and the Average Recall (AR) was used as a global metric:

$$R_i = \frac{TP_i}{TP_i + FN_i} \qquad P_i = \frac{TP_i}{TP_i + FP_i}$$

$$F_{1,i} = \frac{2 \cdot (R_i \cdot P_i)}{R_i + P_i} \qquad AR = \frac{1}{5}\sum_{i=1}^{5} R_i$$

where TP_i, FN_i, and FP_i are the true positives, false negatives and false positives for each class. The stacked matrices for the 100 partitions were obtained and the associated metrics were computed.

3. Results

The best classifier was obtained combining 50 ECG and TI features, with a median (80% confidence interval, CI) AR of 86.5% (80.6 – 89.4), 0.6 points above of the best model using only ECG features (30 features). The stacked confusion matrix and the R_i, P_i and $F_{1,i}$ of the best classifier are shown in Figure *2* and Table 1. The AR (median, 80% CI) for the 100 train/test repetitions are shown in Figure *3*, as a function of the number of features N included in the classifier.

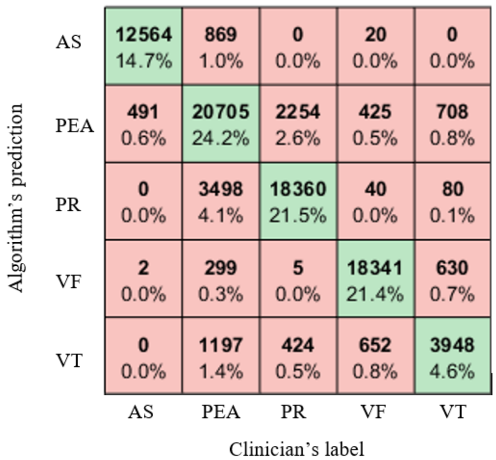

Figure 2. Stacked confusion matrix for the best model for the 100 partitions.

	Performance metrics (%)		
Class	R_i	P_i	$F_{1,i}$
AS	96.3 (93.0-98.5)	94.5 (88.2-97.7)	95.0 (91.7-97.0)
PEA	77.8 (68.1-89.2)	85.4 (75.5-90.9)	80.6 (73.2-87.2)
PR	88.7 (79.5-93.6)	84.4 (71.8-95.5)	86.2 (76.9-91.5)
VF	94.4 (90.2-97.4)	95.6 (91.0-98.1)	94.9 (92.1-96.7)
VT	77.3 (52.9-91.3)	66.1 (50.0-77.7)	69.9 (53.5-79.1)

Table 2. Median (80% CI) values of recall, precision and F_1-score for the best classifier model.

3. Discussion

This work introduces a robust and accurate approach for multiclass OHCA rhythm classification, improving the accuracy by using a multimodal approach based on the ECG and the TI signals.

The developed classifier has improved the accuracy of algorithms published in the literature, correctly identifying, in average, the rhythm in 86.5% of the cases. This result presents an 8.8-point improvement over the one obtained by *Rad et al.* [6]. Several reasons explain the improvement. First, a thoroughly quality controlled dataset with few noisy annotations [6]. Second, the addition of the TI signal [8], [15]. And finally, an improved ECG feature extraction based on the SWT [7], [12].

Although the use of TI features was aimed to improve PEA/PR discrimination, the confusion matrix in *Figure 2* shows that PEA/PR distinction is still the major source of classification errors. Although the TI provides additional information, an accurate distinction is not possible with F_1-scores of 80.6% and 86.2%, for PEA and PR respectively.

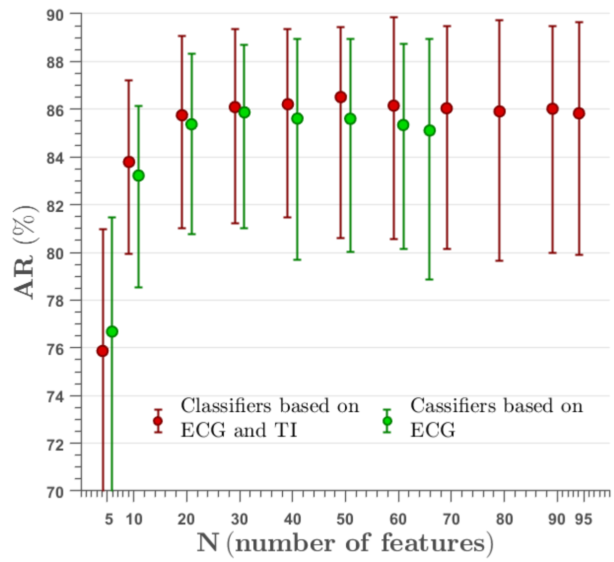

Figure 3. Median (80% CI) *AR* of the classifiers. For each *N* 100 models were evaluated using random train/test partitions.

A further increase may be expected adding information from other OHCA sources, such as the capnogram [9], although this information may not always be available in the defibrillator. Figure *4* shows a PR rhythm segment misclassified as PEA. There are TI fluctuations but weakly correlated with the heartbeats in the ECG, which presents wide QRS complexes, typically found during PEA. However, our results show that adding information from the TI improves PEA/PR distinction in a 5-class classifier.

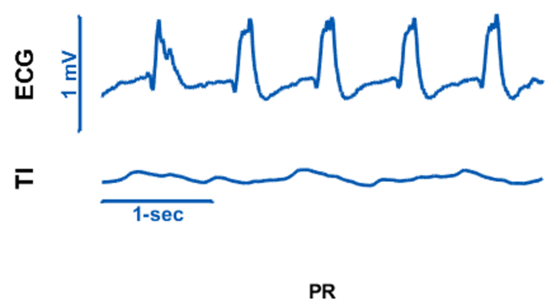

Figure 4. PR rhythm segment misclassified as PEA.

The second large source of errors was the identification of VT, in line with the results presented in *Rad et al* [6]. The cause here is the low prevalence of VT in OHCA, which makes it difficult for the models to accurately characterize VT segments. In the future data augmentation may be used to artificially grow the VT class during training.

In conclusion, a robust 5-class OHCA heart rhythm classifier has been developed. The results confirm that combining ECG and TI signal characteristics produces a more precise classifier than using only the ECG characteristics.

Acknowledgements

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