Classification of Cardiac Rhythms during Load-Distributing Band Cardiopulmonary Resuscitation

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Abstract

Rhythm analysis is crucial during cardiopulmonary resuscitation (CPR) in order to make decisions about therapy. Nowadays, chest compressions (basic treatment for cardiac arrest) must be stopped for reliable rhythm analysis, because of the artefact they induce in the ECG signal, jeopardizing the favorable outcome of the patient. In this work, a method to discriminate between asystole (AS), organized (OR) and shockable (Sh) rhythms is proposed during ongoing mechanical chest compressions using Load Distributed Band (LDB, Autopulse) device during out-of-hospital cardiac arrest. The artefact was reduced using an adaptive filter, 83 features were extracted based on stationary wavelet transform and a random forest classifier was applied. The unweighted mean of sensitivities in the 10-fold cross-validation was 84.3% *and mean F1-score was* 83.4%*. Besides, the algorithm met American Heart Association requirements, with a sensitivity of* 91.0% *and a specificity of* 97.2% *for Sh class.*

1. Introduction

Current cardiopulmonary resuscitation (CPR) guidelines identify early defibrillation and high quality CPR as key therapies for a successful outcome after out-of-hospital cardiac arrest (OHCA) [1]. In particular, uninterrupted and high-quality chest compressions (CCs) are of critical importance. The use of automatic mechanical chest compression devices may provide this and consequently is increasingly used in the prehospital setting. Although their use has not shown benefits in survival [2], mechanical devices guarantee high quality CCs and their use is specially recommended in scenarios where manual CCs are impractical such as during transport or invasive procedures [3].

Awareness of the patient's cardiac rhythm provides the rescuer insight into the hemodynamic status of the patient, allowing the rescuer to adjust the resuscitation therapy to the patient's needs. International guidelines describe treatment pathways based on cardiac rhythm, i.e., defibrillation attempts for shockable rhythms (ventricular fibrillation (VF) and tachycardia (VT)), resuming CCs for asystolic rhythms (AS) and suspicion of the return of spontaneous circulation (ROSC) with the therapies that this entails for organized rhythms (OR). So there is clearly a need for OHCA rhythm classification algorithms to guide the rescuer during resuscitation therapy.

Although many multiclass OHCA rhythm classification algorithms have been developed during the last decade, most of them are designed to classify the rhythm during CC pauses [4, 5]. Unfortunately, interruptions in CCs to classify the rhythm lead to interrupted perfusion of vital organs and lower chances of survival [1]. Efforts have been made to develop accurate OHCA rhythm analysis methods during CCs, but all of them are focused on manually given CCs and not in those administered by mechanical devices. In addition, the majority of these studies only perform binary classification to discern shockable (VF, VT) and non-shockable rhythms (AS, OR), and they do not comprise a multiclass classification for all types of rhythms that may be present during an OHCA episode. The only study which comprises a multiclass rhythm analysis during manual CCs was performed by Isasi et al. [6]. This algorithm is composed of an adaptive filter that removes the artifacts induced by the CCs in the ECG, followed by a machine learning algorithm which uses several discriminative parameters extracted from the filtered ECG to perform the classification.

The aim of this study is to develop the first multiclass OHCA rhythm analysis algorithm during CCs provided by a mechanical device. This algorithm comprises an adaptive filter to remove the artifact caused by mechanical CCs from the ECG and a classification stage based on a Random Forest (RF) classifier to perform the multiclass rhythm classification between shockable (VF, VT), AS and OR rhythms.

2. Materials and methods

2.1. Dataset

The database used in the present study was extracted from the randomized controlled Circulation Improving Re-

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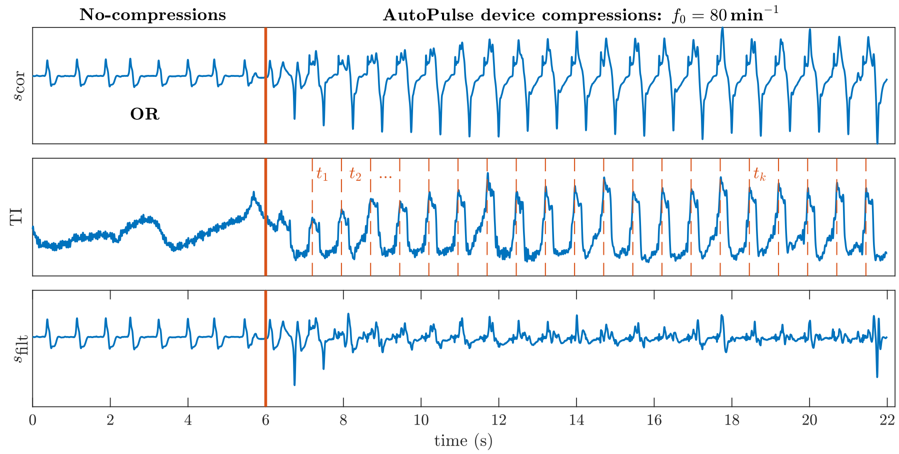

Figure 1. An example of a dataset segment corresponding to a patient with an organized rhythm. From top to bottom: the corrupted ECG, $s_{\mathrm{cor}}(n)$, the thoracic impedance (TI), and the filtered ECG, $s_{\mathrm{filt}}(n)$, after the removal of the estimated CPR artefact. In the first 6 s there is no artefact and the underlying OR is visible. Filtering, $s_{\mathrm{filt}}(n)$, reveals the underlying rhythm of the patient in the artefacted interval, last 16 s. The TI shows a fluctuation correlated with each CC applied by the AutoPulse device and was therefore used to identify mechanical CC intervals. Both in the fluctuations of the TI and in the interference induced by the CCs in $s_{\mathrm{cor}}(n)$, can be observed that mechanical CCs have a fixed rate of 80 min^{-1}.

suscitation Care (CIRC) trial conducted between March 2009 and January 2011 by three emergency services in the United States and two services in Europe [7]. The aim of this study was to compare the effectiveness of the automated load distributing band (LDB, AutoPulse mechanical device) CPR with high quality manual CPR in terms of survival. The AutoPulse device provides CCs in a fixed position and a constant rate of 80 min^{-1} ($\mathrm{f}_0 = 1.33\,\mathrm{Hz}$). Anonymized waveform data from the Lifepak 12 and 15 monitor-defibrillators (Physio-Control, Redmond, WA, USA) was exported to Matlab (MathWorks Inc., Natick, MA) with a sampling period of $\mathrm{T_s} = 4\,\mathrm{ms}$. The data included the ECG and thoracic impedance (TI) signals together with the compression instants (see $\mathrm{t_i}$ in Figure 1) detected by the Code Stat data review software.

The use of the AutoPulse device was identified when the compression rate stabilized at the device's fixed rate of 80 min^{-1} for at least 16 s (see last 16 s in Figure 1). Then, 22 s signal segments were automatically extracted following these criteria: unique rhythm type in the entire segment, and an interval of 16 s with AutoPulse CCs followed or preceded by a 6 s without CCs (see Figure 1). The intervals during CCs were used to develop the OHCA rhythm classification algorithm, whereas the artifact-free intervals were used to annotate the underlying rhythm. Final database consits of 5813 segments extracted from 880 OHCA patients which include 1616 AS, 3043 OR and 1116 shockable (Sh) rhythms.

2.2. Filtering the CPR artefact

The CPR artefact was modeled as a quasi-periodic interference using a Fourier series truncated to N harmonics and locked to the fundamental frequency of the AutoPulse device, f_0:

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

The time-varying in-phase, $a_k(n)$, and quadrature, $b_k(n)$, coefficients were adaptively estimated using the Recursive Least Squares (RLS) algorithm to minimize the error between the corrupt ECG and the estimated artefact at the harmonics of f_0 [6]. The underlying/filtered ECG, $\mathrm{s_{filt}}(n)$, was then obtained by substracting the estimated artifact from the corrupted ECG, $\mathrm{s_{cor}}(n)$. The RLS solution has only one hyperparameter, the forgetting factor (λ).

2.3. ECG preprocessing

The ECG signal was denoised using a method based on stationary wavelet transform. First, the ECG was decomposed in 8 levels of detail coefficients ($d_{1,\mathrm{ecg}}$-$d_{8,\mathrm{ecg}}$) using a Daubechies 2 mother wavelet. Then, the universal threshold was calculated as follows:

$$\gamma = \sigma\sqrt{2\mathrm{ln}(\mathrm{N})} \qquad (2)$$

where N is the length of the signal and σ is calculated as:

$$\sigma = \frac{\mathrm{Median}\{|\mathrm{d}_{1,\mathrm{ecg}}|\}}{0.6745} \quad (3)$$

Soft thresholding was applied to the detail coefficients and the denoised ECG signal (s_{ecg}) was reconstructed using $d_{3,\mathrm{ecg}}$-$d_{8,\mathrm{ecg}}$ coefficients, which corresponds to 0.49–31.5 Hz band approximately.

2.4. Feature engineering

A total of 83 features were extracted from different domains, details can be found in [5, 8, 9]:

- **Time domain:** x1, x2, bCP, count1, count2, count3, the number of QRS-like peaks (Npeak), vFleak, Expmod, TCSC and MAV for s_{ecg}.
- **Spectral domain:** bWT, A1, A2, A3, x3, x4 and x5 for s_{ecg}.
- **Complexity analysis:** Sample Entropy for s_{ecg} and $d_{3,\mathrm{ecg}}$-$d_{8,\mathrm{ecg}}$; HILB, Frqbin, CM and Kurtosis (Kurt) of a binary signal extracted from the ECG for s_{ecg}.
- **Statistical analysis:** interquartile range and first quartile for $d_{3,\mathrm{ecg}}$-$d_{8,\mathrm{ecg}}$; skewness and kurtosis for s_{ecg} and $d_{3,\mathrm{ecg}}$-$d_{8,\mathrm{ecg}}$; mean and standard deviation for $|d_{3,\mathrm{ecg}}|$-$|d_{8,\mathrm{ecg}}|$, $|s_{\mathrm{ecg}}|$ and their first difference signals.

2.5. Rhythm classification algorithm

All the features were used to train and evaluate a Random Forest (RF) classifier with 300 trees. In order to address class imabalance, each tree was trained using the same number of observations per class by oversampling the minority classes. Besides, the splitting of each tree was stopped when the number of observation was lower than 15 in the node.

2.6. Evaluation

The RF model was trained and evaluated using patient-wise 10-fold cross-validation. The algorithm was evaluated in terms of sensitivity (Se) per class, arithmetic mean between all sensitivities (unweighted mean of sensitivities, UMS), F1-score per class and mean of F1-scores. Besides, specificity (Sp) for Sh rhythms was computed by joining AS and OR classes as non-shockable rhythms. This metric was computed because the AHA requires a minimum Se of 90% and a Sp of 95% for shock advice algorithms.

3. Results

Figure 2 shows the cumulative confusion matrix using 10-fold cross-validation, $\lambda = 0.9902$ and $N = 50$. The UMS was 84.3% and mean F1-score was 83.4%. The Se and F1 scores per class were 81.9%/80.1%/91.0% and 76.6%/83.4%/90.0% for AS/OR/Sh, respectively. It can be observed that most of the errors come from the discrimination between AS and OR classes, both non-shockable rhythms. However, AHA requirements are still met, since for Sh class, Se was 91.0% ($> 90\%$) and Sp 97.2% ($> 95\%$).

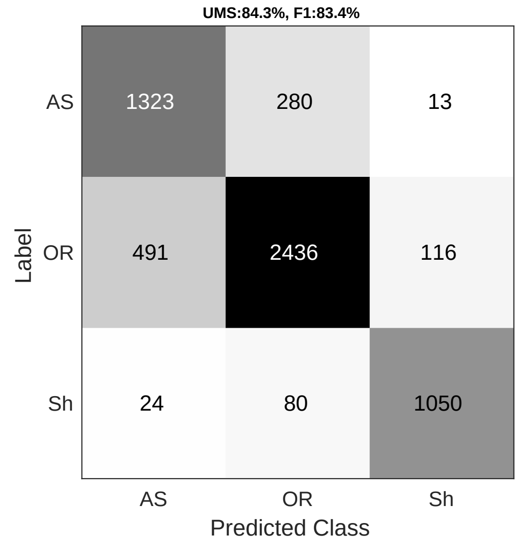

Figure 2. Cumulative confusion matrix using 10-fold cross-validation.

Figure 3 shows the performance metrics in terms of λ for different values of N. A maximum for UMS and mean F1 can be observed for $\lambda = 0.9902$ and $N = 50$. Besides, for $\lambda < 0.988$ Se for Sh class began to decrease, and keeping this value around the maximum was important to ensure a Se above 90% for Sh class.

4. Conclusion

An algorithm to discriminate between three different ECG rhythms during ongoing mechanical chest compressions using AutoPulse device was proposed. The algorithm could be implemented and may help to improve survival rates during OHCA, allowing continuous rhythm analysis and avoiding pauses to provide CCs.

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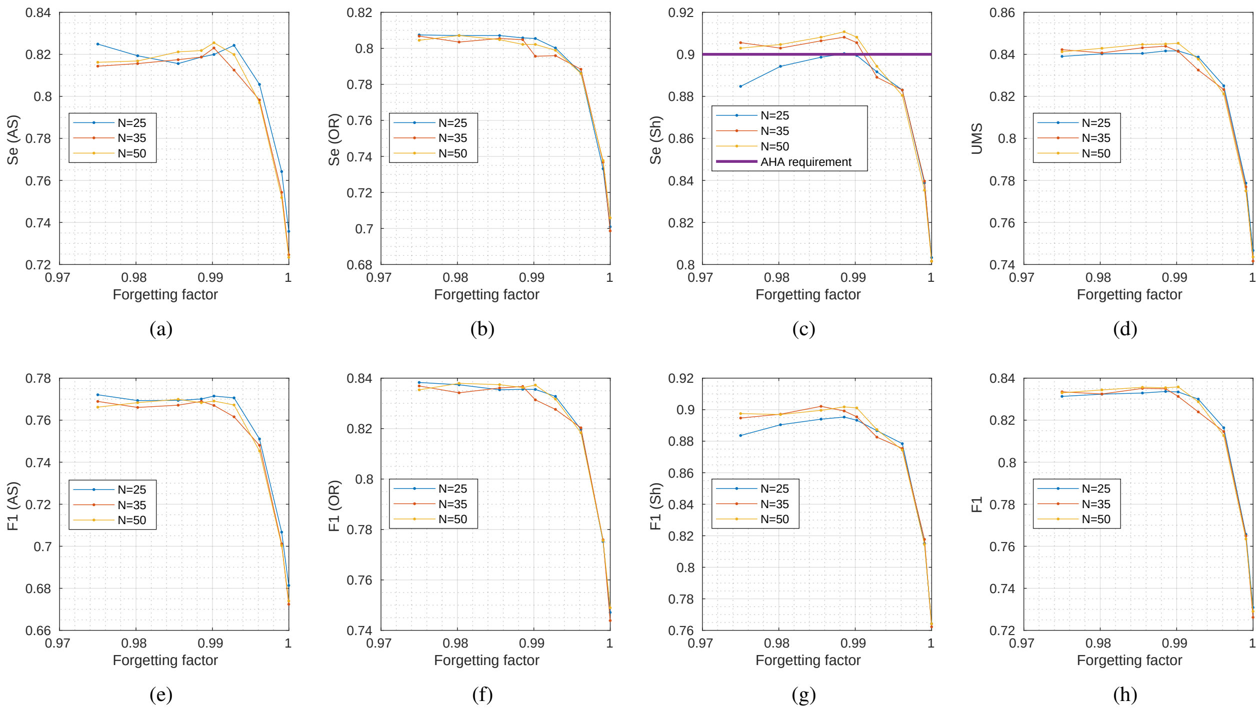

Figure 3. Sensitivities (Se) and F1-scores per class, unweighted mean of Se (UMS) and mean F1 in terms of the forgetting factor (λ) for different values of N.

References

[1] J. Soar, B. W. Böttiger, P. Carli, K. Couper, C. D. Deakin, T. Djärv, C. Lott, T. Olasveengen, P. Paal, T. Pellis *et al.*, "European resuscitation council guidelines 2021: adult advanced life support," *Resuscitation*, vol. 161, pp. 115–151, 2021.

[2] S. Rubertsson, E. Lindgren, D. Smekal, O. Östlund, J. Silfverstolpe, R. A. Lichtveld, R. Boomars, B. Ahlstedt, G. Skoog, R. Kastberg *et al.*, "Mechanical chest compressions and simultaneous defibrillation vs conventional cardiopulmonary resuscitation in out-of-hospital cardiac arrest: the linc randomized trial," *Jama*, vol. 311, no. 1, pp. 53–61, 2014.

[3] M. E. H. Ong, K. E. Mackey, Z. C. Zhang, H. Tanaka, M. H.-M. Ma, R. Swor, and S. D. Shin, "Mechanical cpr devices compared to manual cpr during out-of-hospital cardiac arrest and ambulance transport: a systematic review," *Scandinavian journal of trauma, resuscitation and emergency medicine*, vol. 20, no. 1, pp. 1–10, 2012.

[4] A. B. Rad, K. Engan, A. K. Katsaggelos, J. T. Kvaløy, L. Wik, J. Kramer-Johansen, U. Irusta, and T. Eftestøl, "Automatic cardiac rhythm interpretation during resuscitation," *Resuscitation*, vol. 102, pp. 44–50, 2016.

[5] A. B. Rad, T. Eftestøl, K. Engan, U. Irusta, J. T. Kvaløy, J. Kramer-Johansen, L. Wik, and A. K. Katsaggelos, "Ecg-based classification of resuscitation cardiac rhythms for retrospective data analysis," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 10, pp. 2411–2418, 2017.

[6] I. Isasi, U. Irusta, A. B. Rad, E. Aramendi, M. Zabihi, T. Eftestøl, J. Kramer-Johansen, and L. Wik, "Automatic cardiac rhythm classification with concurrent manual chest compressions," *IEEE Access*, vol. 7, pp. 115 147–115 159, 2019.

[7] L. Wik, J.-A. Olsen, D. Persse, F. Sterz, M. Lozano Jr, M. A. Brouwer, M. Westfall, C. M. Souders, R. Malzer, P. M. van Grunsven *et al.*, "Manual vs. integrated automatic load-distributing band cpr with equal survival after out of hospital cardiac arrest. the randomized circ trial," *Resuscitation*, vol. 85, no. 6, pp. 741–748, 2014.

[8] I. Isasi, A. B. Rad, U. Irusta, M. Zabihi, E. Aramendi, T. Eftestøl, J. Kramer-Johansen, and L. Wik, "Ecg rhythm analysis during manual chest compressions using an artefact removal filter and random forest classifiers," in *2018 Computing in Cardiology Conference (CinC)*, vol. 45. IEEE, 2018, pp. 1–4.

[9] C. Figuera, U. Irusta, E. Morgado, E. Aramendi, U. Ayala, L. Wik, J. Kramer-Johansen, T. Eftestøl, and F. Alonso-Atienza, "Machine learning techniques for the detection of shockable rhythms in automated external defibrillators," *PloS one*, vol. 11, no. 7, p. e0159654, 2016.

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