Shock Advisory Neural Network for Continuous Detection of Ventricular Fibrillation, Organized Rhythm and Asystole during Cardiopulmonary Resuscitation

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Abstract

This study presents a shock-advisory system (SAS) for continuous rhythm analysis during cardiopulmonary resuscitation (CPR) aiming to align with different resuscitation actions in out-of-hospital cardiac arrest (OHCA) for ventricular fibrillation VF (shock), organized rhythm OR (pulse check) and asystole ASYS (continue chest compressions). Two stages of convolutional neural network with raw ECG input (10s, 125Hz) were combined to generate a ternary rhythm decision (VF, OR, ASYS).

In a total of 2838 OHCA interventions from automated external defibrillators (AED), we extracted episodes with VF (training/test: 409/393), OR (2151/2025), ASYS (4613/3979), around the standard AED analysis, following 2-minutes of CPR. The algorithm was applied in 1-second sliding mode, giving 21 decisions during CPR (CPR-ECG) and 10 decisions in presence of artifact-free ECG (Clean-ECG). The true positive rate of SAS on the test-set (CPR-ECG, Clean-ECG) is: VF (93.1%, 98.1%), OR (72.1%, 87.5%), ASYS (82.1%, 91.1%). Major OR false negatives (24.5%, 11.5%) are detected as ASYS, and inversely, major ASYS false negatives (4.5%, 12.6%) are detected as OR. These errors do not affect SAS specificity. With VF sensitivity (93.1%, 98.1%), OR specificity (96.6%, 99%) and ASYS specificity (92.9%, 99.2%), the presented SAS algorithm provides competitive performance during CPR.

1. Introduction

Out-of-hospital cardiac arrest (OHCA) is a critical medical emergency that requires immediate intervention through cardiopulmonary resuscitation (CPR). Concomitant use of automated external defibrillators (AEDs) requires a shock delivery with minimal hands-off pauses [1–4]. Advanced shock-advisory systems (SAS) that analyse the electrocardiogram (ECG) during CPR have been extensively studied over the past decade using machine learning and deep neural networks (DNNs) [5–10]. Nevertheless, confirmatory stage in hands-off pauses is still mandatory in 30–100% of cases, according to a comparative study of four AED SAS analyzing the heart rhythm during chest compressions (CC) [11].

This study aims to develop SAS algorithm for continuous rhythm analysis during CPR, expanding beyond the conventional binary decision (shock: Sh, no-shock: NSh) to a ternary decision model (ventricular fibrillation: VF, organized rhythm: OR, asystole: ASYS). This approach aligns with different resuscitation actions for each rhythm: VF (shock), ASYS (continue CC), OR (pulse check) [7].

2. ECG database

The ECG database was collected from 2838 OHCA interventions with commercial AEDs (DEFIGARD TOUCH 7, Schiller Medical SA, France) used by the Paris Fire Brigade in 2017. The reanimation protocol applied CPR with 30:2 compression to ventilation ratio and CC rate of 100–120 min^{-1}, paused every 2 min for a standard AED rhythm analysis.

The period of interest in OHCA interventions was defined as 30 s before to 10 s after the start of the standard AED analysis, following 2-minutes of CPR (Figure 1). ECG episodes during CPR (CPR-ECG) were considered up to 30 s before AED analysis; ECG episodes in presence of artifact-free ECG (Clean-ECG) last 10 s after the start of the AED analysis. Start and stop CPR times can occur randomly during CPR-ECG. The heart rhythm was annotated by consensus of three cardiologist based on the observation of the Clean-ECG signal, into three major classes: VF (peak-to-peak amplitude >200 μV); OR (normal sinus rhythm, agonic rhythms, atrial fibrillation and flutter, AV blocks, supraventricular and ventricular escape rhythms, rushes more than 3 triplets); ASYS (peak-to-peak amplitude $\leq$ 100 μV for more than 4 s). The rhythm homogeneity in the period of interest was verified by automatic and manual revisions.

A total of 13,570 periods of interest were identified and split patient-wise to training/test subsets: VF (409/393), OR (2151/2025), ASYS (4613/3979).

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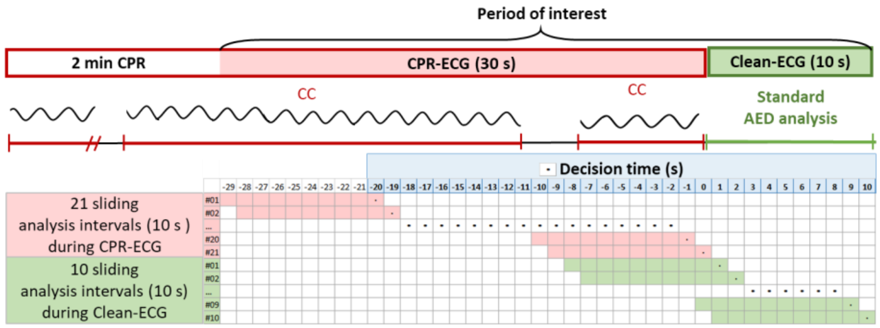

Figure 1. Strategy for continuous rhythm analysis during CPR with 31 decision times [−20 s; 10 s] in the period of interest, including 21 analyses with decisions during CPR-ECG and 10 analyses with decisions during Clean-ECG. Clean-ECG analyses include both CC and artifact-free samples in different proportions. CC: chest compressions.

3. Methods

A SAS algorithm with raw ECG input (10s, 125Hz) was designed with a ternary rhythm decision (VF, OR, ASYS) and applied for continuous rhythm analysis during CPR in 1-second sliding mode, without preconditions based on the presence of CC. SAS feature extraction and classification functionalities are based on a 2-stage DNN processing according to the scheme in Figure 2:

1. DNN (Stage1) provides a shock advisory decision with an output probability for a shockable rhythm $p_{SH}\in[0;1]$, using a pretrained 3-layer convolutional model for a binary Sh/NSh decision during CPR [6]. The training process used the total training dataset.
2. DNN (Stage2) provides a NSh rhythm decision with an output probability of OR or ASYS $p_{ORvsASYS} \in [0;1]$. It uses the same convolutional architecture as Stage1, but is trained in this study with the objective for minimizing the binary cross-entropy within the NSh rhythms (OR and ASYS) in the training dataset.
3. Two scaling modules normalize the outputs of Stage1 and Stage2 to a common threshold of 0.5, given that each stage may have different thresholds by design.
4. The arithmetic module generates the global set of ternary output probabilities $\{p_{VF}, p_{OR}, p_{ASYS}\}$:
   - $p_{VF} = p_{SH}$
   - $p_{OR} = p_{ORvsASYS}(1 - p_{SH})$
   - $p_{ASYS} = (1 - p_{Sh})(1 - p_{ORvsASYS})$
5. $Rhythm\ decision = \begin{cases} VF, p_{VF} \geq 0.5 \\ OR, p_{OR} \geq p_{ASYS} \\ ASYS, otherwise \end{cases}$

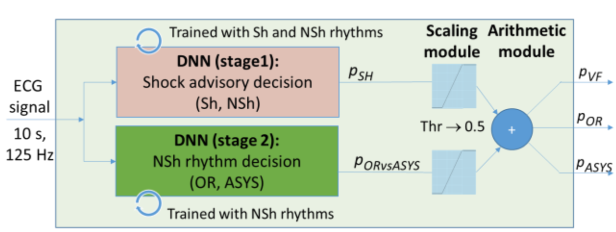

Figure 2. SAS with two-stage DNN with probabilistic output decision for three rhythms $\{p_{VF}, p_{OR}, p_{ASYS}\}$.

The performance of the SAS algorithm with ternary output is estimated with True Positive Rate (TPR: proportion of cases correctly classified in its rhythm class) and False Negative Rate (FNR: proportion of cases not classified in its rhythm class). Additionally, the shock advisory performance is estimated in terms of Sensitivity for Sh rhythms (Se: proportion of VF cases detected in VF-class) and Specificity for NSh rhythms (Sp: proportion of OR+ASYS cases not detected in VF-class).

4. Results and discussion

The SAS is run in 1-second sliding mode, giving 21 decisions during CPR-ECG and 10 decisions during Clean-ECG within the period of interest (Figure 1). The sliding analysis intervals of 10 s include random proportions of chest compression and ventilation periods as recorded in OHCA. Using an intervention of a patient in VF (Figure 3), we illustrate the sliding outputs $\{p_{VF}, p_{OR}, p_{ASYS}\}$ with p_{VF} dominant during overall Clean-ECG and great part of CPR-ECG, and p_{ASYS} dominant elsewhere. The latter is a wrong decision, which can be explained with the low signal-to-noise ratio and relatively low VF amplitude.

Figure 4 illustrates test statistics of TPR and FNR over time. It shows a relatively stable TPR for sliding decision times during CPR and a gradual increase in TPR for sliding decision times after the end of CPR. This increase corresponds to the observed effect of hands-off time on the performance improvement [5]. Table 1 summarizes the results for all decisions during CPR-ECG and Clean-ECG, showing that the mean TPR (CPR-ECG, Clean-ECG) is: VF (93.1±0.6%, 98.1±1%), OR (72.1±1.1%, 87.5±4.9%), ASYS (82.1±1%, 91.1±3.6%). Figure 4 and Table 1 show that during CPR, the major errors in FNR for VF (6.2±0.8%) and OR (24.5±0.9%) are primarily due to mis-classification as ASYS. Conversely, FNR for ASYS is due to detection either as OR (10.8±1.1%) or VF (7.1±0.6%).

Using the data in Table 1, we compute the SAS shock advisory performance (CPR-ECG, clean-ECG): Se for VF (93.1±0.6%, 98.1±1%), Sp for OR (96.6±1%, 99±4.8%), and Sp for ASYS (92.9±1%, 99.2±3.3%).

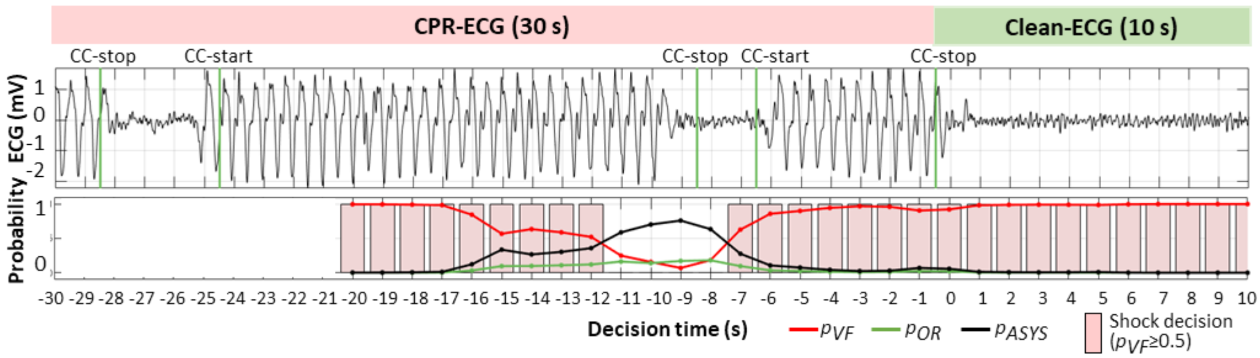

Figure 3. Continuous rhythm analysis during CPR in VF example: Input ECG and trends of the DNN output probabilities.

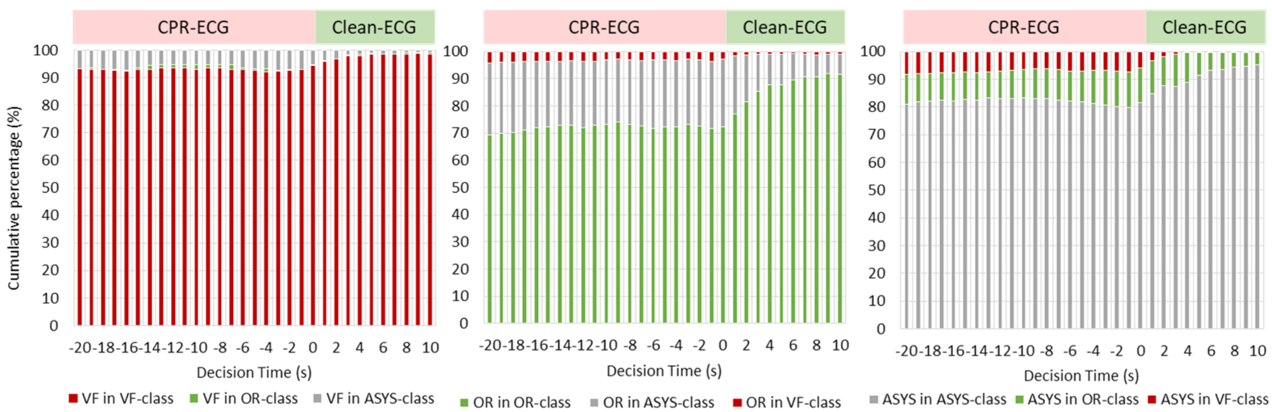

Figure 4. Test performance of the continuous rhythm analysis during CPR run at 1 s sliding mode, presented as cumulative TPR+FNR for rhythms VF (left), OR (middle), ASYS (right). 100% corresponds to all cases per rhythm.

Table 1. Test performance of the continuous rhythm analysis during CPR run at 1 s sliding mode, presented as TPR (gray cells) or FNR. Data present mean value ± standard deviation of 21 decisions during CPR-ECG and 10 decisions during Clean-ECG (bars in Figure 4). Clean-ECG results are derived on signals that can present both CC and artifact-free samples.

Rhythms	Cases	CPR-ECG, decision time [-20 s; 0 s]			Clean-ECG, decision time [1 s; 10 s]		
		VF, %	OR, %	ASYS, %	VF, %	OR, %	ASYS, %
VF	393	93.1±0.6	0.7±0.6	6.2±0.8	98.1±1.0	0.3±0.2	1.6±1.0
OR	2025	3.4±0.4	72.1±1.1	24.5±0.9	1.1±0.3	87.5±4.9	11.5±4.7
ASYS	3979	7.1±0.6	10.8±1.1	82.1±1.0	0.8±1.0	8.1±2.9	91.1±3.6

Table 2. Test performance of the continuous rhythm analysis during CPR with focus on OR sub-rhythms. Data are reported as % (number of cases) for specific decision times in CPR-ECG [0 s] and Clean-ECG [10 s]. Highlighted cells denote TPR.

OR sub-rhythms	Total Cases	CPR-ECG, decision time [0 s]			Clean-ECG, decision time [10 s]		
		VF, %(n)	OR, %(n)	ASYS, %(n)	VF, %(n)	OR, %(n)	ASYS, %(n)
Agonic	218	6.4 (14)	26.2 (57)	67.4 (147)	3.7 (8)	65.6 (143)	30.7 (67)
Normal sinus rhythm	527	1.9 (10)	87.5 (461)	10.6 (56)	1.1 (6)	96.6 (509)	2.3 (12)
Atrial fibrillation	395	1.8 (7)	82 (324)	16.2 (64)	0.8 (3)	96 (379)	3.3 (13)
Atrial flutter	14	14.3 (2)	57.1 (8)	28.6 (4)	14.3 (2)	50 (7)	35.7 (5)
AV block, 2nd degree	47	0 (0)	83 (39)	17 (8)	0 (0)	97.9 (46)	2.1 (1)
AV block, 3rd degree	157	3.2 (5)	71.3 (112)	25.5 (40)	0 (0)	90.5 (142)	10 (15)
Supraventricular escape	159	1.9 (3)	76.1 (121)	22 (35)	0 (0)	96.9 (154)	3.1 (5)
Ventricular escape	504	3.2 (16)	67.5 (340)	29.4 (148)	0.2 (1)	93.8 (473)	6 (30)
Ventricular rushes >3 triplets	4	0 (0)	100 (4)	0 (0)	0 (0)	100 (4)	0 (0)
Total	2025	2.8 (57)	72.4 (1466)	24.8 (502)	1 (20)	91.7 (1857)	7.3 (148)

The only study we found to report continuous rhythm analysis during CPR with ternary output [7] is used for comparison. Considering the disclosed TPR (CPR-ECG, Clean-ECG) for VF (90%, 94%), OR (89%, 96%), ASYS (81%, 88%), our SAS algorithm demonstrates superior performance for VF by (3.1%, 4.1%) and ASYS by (1.1%, 3.1%) but is inferior for OR by (-16.9%, -8.5%). The latter is mainly due to detection of OR as ASYS that does not decrease the SAS Sp for OR (CPR-ECG: 96.6% vs. 97%, Clean-ECG: 99% vs. 100%), considering this study vs. [7]. Instead, the presented algorithm works at higher Se for VF.

The additional analysis of the test performance with focus on OR sub-rhythms in Table 2 is provided with the purpose to identify the major sources of errors in this study. Part of the errors are due to the “gray area” in our annotation policy, giving a priority for the annotation of an OR rhythm in conditions similar to ASYS (2 complexes 4s apart). The agonic rhythm, which is slow and consisting of regular or irregular complexes with wider than high morphology, different than the typical QRS-T pattern, is most commonly detected as ASYS (CPR-ECG: 67.4%, Clean-ECG: 30.7%) but rarely misled as VF (6.4%, 3.7%). The ventricular escape rhythm with slow and irregular atypical complexes ≤ 35 min^{-1} is prevalent in OR (25%), but misdiagnosed as ASYS (29.4%, 6%), and rarely as VF (3.2%, 0.2%). The supraventricular escape rhythm and AV block 3rd degree, representing about 16% of all ORs, are also slow rhythms that are often mistaken as ASYS (22–25.5%, 3.1–10%) but almost never as VF (1.9–3.2%, 0%). Although the atrial flutter is very rare in our OHCA database (0.7%) and actually does not influence the total OR performance, we note a potential problem with misclassification as ASYS (28.6%, 35.7%) and VF (14.3%, 14.3%) due to the slow heartrate in combination with regular saw-tooth flutter waves. The remaining three OR sub-classes (normal sinus rhythm, atrial fibrillation and AV block 2nd degree) are representative to the common OR population (48%) for which the misclassification rate is limited for ASYS (<17%, <3%) and VF (<1.9%, <1.1%), leading to TPR increase up to 87.5% during CPR, and up to 97.9% during clean ECG. In the context of the observed disparity in performances for different OR sub-rhythms, it is truthful to report details about the included rhythms.

In conclusion, the presented two-stage DNN SAS provides accurate and stable classification of the primary resuscitation rhythms during CPR with mean TPR of 93% VF, 72% OR, 82% ASYS and standard deviation of 1%. Performance improves when artifact-free parts during hands-off time are included in analysis, reaching mean TPR of 98% VF, 88% OR, 91% ASYS. With Se of 93–98% VF, the resulting Sp is 97–99% OR, 93–99% ASYS.

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