An automatic system for the comprehensive retrospective analysis of cardiac rhythms in resuscitation episodes

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Abstract

Aim: An automatic resuscitation rhythm annotator (ARA) would facilitate and enhance retrospective analysis of resuscitation data, contributing to a better understanding of the interplay between therapy and patient response. The objective of this study was to define, implement, and demonstrate an ARA architecture for complete resuscitation episodes, including chest compression pauses (CC-pauses) and chest compression intervals (CC-intervals).

Methods: We analyzed 126.5h of ECG and accelerometer-based chest-compression depth data from 281 out-of-hospital cardiac arrest (OHCA) patients. Data were annotated by expert reviewers into asystole (AS), pulseless electrical activity (PEA), pulse-generating rhythm (PR), ventricular fibrillation (VF), and ventricular tachycardia (VT). Clinical pulse annotations were based on patient-charts and impedance measurements. An ARA was developed for CC-pauses, and was used in

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combination with a chest compression artefact removal filter during CC-intervals. The performance of the ARA was assessed in terms of the unweighted mean of sensitivities (UMS).

Results: The UMS of the ARA were 75.0% during CC-pauses and 52.5% during CC-intervals, 55-points and 32.5-points over a random guess (20% for five categories). Filtering increased the UMS during CC-intervals by 5.2-points. Sensitivities for AS, PEA, PR, VF, and VT were 66.8%, 55.8%, 86.5%, 82.1% and 83.8% during CC-pauses; and 51.1%, 34.1%, 58.7%, 86.4%, and 32.1% during CC-intervals.

Conclusions: A general ARA architecture was defined and demonstrated on a comprehensive OHCA dataset. Results showed that semi-automatic resuscitation rhythm annotation, which may involve further revision/correction by clinicians for quality assurance, is feasible. The performance (UMS) dropped significantly during CC-intervals and sensitivity was lowest for PEA.

***Keywords:* —** Cardiac arrest, cardiopulmonary resuscitation, cardiac rhythm classification, automatic resuscitation rhythm annotator

1. INTRODUCTION

The annotation of cardiac rhythms in full-length resuscitation episodes would contribute to a richer retrospective analysis of resuscitation data and to a better understanding of the interplay between therapy and patient response.[1] It could help to determine optimal chest compression strategies, a better understanding of the effects of chest compression pauses and their duration, or to maximize the likelihood of successful defibrillation attempts.[2-7] To date, cardiac rhythm classification and the identification of rhythm transitions with and without chest compression artefacts have been done manually by expert clinicians. However, manual annotation is cumbersome, time-consuming, and error-prone, and these factors may have precluded the annotation of rhythms in large databases of resuscitation episodes.

An automatic or semi-automatic rhythm annotator would open the possibility of annotating the currently available large resuscitation datasets.[8-11] In previous contributions we addressed the design of (semi)-automatic resuscitation rhythm annotators based on ECG analysis.[12,13] When designed and tested on a quality-controlled dataset, the overall performance of our algorithms was 77.7% in the classification of rhythms into the five typical resuscitation rhythm categories: asystole (AS), pulseless electrical activity (PEA), pulse-generating rhythm (PR), ventricular fibrillation (VF), and ventricular tachycardia (VT). In this manuscript, the term *resuscitation rhythm category* refers to a mixture of rhythm class and clinical state. There are four ECG rhythm classes VT, VF, AS and organized (ORG), and two medical states for presence or absence of detectable pulse. The latter results in PR and PEA annotations for ORG rhythms. Furthermore, identification of pulse using only the ECG is a complex biomedical signal processing challenge,[12,13] and this work assesses partially the extent to which one can use ECG data alone for that purpose.

The proposed algorithms in our previous works were conceived to annotate artefact-free 3-second isolated ECG segments; consequently, they worked only during chest compression pauses. Short isolated ECG data segments cannot fully represent the dynamics and transitional state changes between rhythms occurring in complete resuscitation episodes. More importantly, artefact-free segments ignore the presence of cardiopulmonary resuscitation (CPR) artefacts, which are present during 50-80% of the duration of the episodes.[14-16] In this paper, we introduce an improved classification algorithm, but above all, we describe the functional architecture of a resuscitation rhythm category classification system for full episodes, an architecture that addresses intervals with and without CPR artefacts. Furthermore, we demonstrate and evaluate the accuracy of the system on a comprehensive dataset of clinically annotated complete resuscitation episodes. This architecture integrates a body of knowledge developed over the last decade in signal processing applied to resuscitation data annotation, in line with the general annotation framework proposed by Eftestøl et al.[1] for the comprehensive analysis of resuscitation data.

2. MATERIALS AND METHODS

2.1 Resuscitation episode dataset

The dataset comprises 126.5h of ECG and chest compression depth (CCD) signal derived from the acceleration recordings as explained by Aase et al.[17] from 281 patients suffering out-of-hospital cardiac arrest (OHCA). Data collection was conducted between March 2002 and September 2004 to evaluate the quality of CPR in three cities: Akershus (Norway), Stockholm (Sweden), and London (UK).[3,18] Modified Heartstart 4000 (Philips Medical Systems, Andover, MA, USA) defibrillators with enhanced monitoring capabilities were used to record the data. ECG data were sampled at 500 Hz with 16 bits per sample and a resolution of 1.031 μV per least significant bit. The study was approved by ethical boards at each site. The need for informed consent from each patient was waived as decided by these boards in accordance with paragraph 26 of the Helsinki Declaration for human medical research. The study was registered as a clinical trial at http://www.clinicaltrials.gov/, (NCT00138996).

In the original study,[3] the initial rhythm category and all transitions throughout the episodes were annotated into five categories (AS, PEA, PR, VF, VT) under two different conditions: 1) during chest compression pauses (CC-pauses) in which there were no CPR-artefacts, and 2) during chest compression intervals (CC-intervals) in which there were significant CPR-artefacts. The CCD from CPR assist-pads was used to recognize CC-intervals.

Data was annotated concurrently by an anesthesiologist specialized in advance life support and by a biomedical engineer with expertise in resuscitation science, to ensure adherence to rhythm definitions.[3] Differences were adjudicated by consensus between the two reviewers. During CC-intervals rhythm transitions were annotated conservatively, i.e. only when clear signs of the rhythm transition were observable such as QRS complexes appearing during CPR after asystole (AS to PEA). The reviewers followed these definitions for rhythm categories.[3,13] AS for rhythms with peak-to-peak amplitude below 100 μV, and/or rates under 12 bpm. Rhythms with supraventricular activity (QRS complexes) and rates above 12 bpm were labelled as either PR or PEA. Pulse annotations (PR) were based on clinical annotations of return of spontaneous circulation made in patient charts during CPR, and on the observation of fluctuations in the TTI signal aligned with QRS complexes. Irregular ventricular rhythms were annotated as VF. Fast and regular ventricular rhythms without pulse, and rates above 120 bpm were annotated as VT.

Finally, data were reviewed by an independent biomedical engineer, and intervals with severe noise, large artefacts (not due to compressions), or with loss of ECG signal were labelled as uncertain and discarded from further analysis.

2.2 Architecture for rhythm category classification of resuscitation episodes

The proposal for the functional architecture of the automatic resuscitation rhythm annotator (ARA) is shown in Fig 1, and it consists of four subsystems. The first subsystem is a CC-interval detector in which compressions are detected using the CCD signal.[19] During CC-intervals CPR artefacts are removed from the ECG using a CPR-artefact removal filter (CARF),[20] during CC-pauses the ECG remains untouched. The next subsystem, the rhythm classification engine (RCE), is the core algorithm of the ARA and classifies the ECG into the five resuscitation rhythm categories. The final subsystem, the post-processing filter, combines consecutive rhythm labels from the RCE to avoid rapidly changing annotations during transitional states. The CC-interval detector and CARF have been described elsewhere,[19,20] so we describe the RCE and the post-processing filter in the following.

2.3 Rhythm classification engine

The RCE is an improved version of our classification algorithms,[12,13] and it was designed to classify artefact-free 3-s ECG segments. It consists of a neural network committee machine that combines the decisions of 10 artificial neural networks (ANNs). The detailed technical description is provided in Appendix A. The dataset used to train the ANNs had no CPR-artefacts,[13] so the RCE was designed to work during CC-pauses or after CPR-artefact suppression. To classify a complete episode, the RCE was applied to 3-s segments with an overlap of 2-s, this produced a rhythm category annotation every second.

2.4 Post-processing filter

The output of RCE is a sequence of rhythm labels, one label every second. During long sequences of a particular rhythm some isolated annotations from the other classes may appear. For instance, during a long VF interval, we may have some AS labels (short segments of lower amplitude) or some PEA labels (short segments with a more organized pattern). These labels either could be misclassifications of the ARA, or caused by the localness (short analysis intervals) of the ARA. To address these effects and partially benefit from the mutual information of adjacent labels two post-processing blocks were added, a moving average filter to avoid isolated label changes (see Appendix A), and a post-processing filter that replaces rhythm labels sustained during less than 6s with the previous rhythm label.

2.5 Evaluation of the performance

The detailed performance evaluation of the ARA can be summarized in a 5-class confusion matrix, with the correct classifications in the diagonal and the incorrect classifications for each rhythm category class into the rest of the classes outside the diagonal, see Rad et al.[13] for a comprehensive description. In addition, the overall performance of our system was evaluated using a summarizing metric, the unweighted mean of sensitivities (UMS). UMS is the average of the sensitivities for each rhythm type (proportion of correct classifications), and in an application with multiple classes (5 rhythm categories) and imbalanced data (different rhythm prevalence) it is an adequate summary of the performance of the ARA.[13] UMS is computed from the confusion matrix as the average of the values of its diagonal. Confusion matrices and UMS were computed separately for intervals with and without CPR-artefacts, since rhythm analysis during CPR is much less reliable even in simpler shock/no-shock decision scenarios.[21]

3. RESULTS

The aggregate duration of the 281 episodes was distributed in 62.7h during CC-pauses, 54.5h during CC-intervals, and 9.3h in intervals labeled as “uncertain” due to the high level of background noise. The numbers of hours for each rhythm type, as labeled by expert clinicians, during both CC-pauses and CC-intervals are summarized in Table 1.

The performance of the ARA during CC-pauses and CC-intervals are shown in Table 2. Data are presented in the form of confusion matrices. For each rhythm category, misclassification rates into other rhythm categories are read row-wise, and the values of the diagonals show the sensitivities for each rhythm category. In addition, the table shows the numbers of hours of data for each possibility. The overall performance in terms of UMS of our ARA during CC-pauses and CC-intervals were 75.0% and 52.5%, respectively. Filtering CC-artefacts improved the performance of the ARA since without CARF the overall performance dropped 5.2-points to 47.3%, see Table 3.

Fig. 2 and 3 show examples of rhythm annotations by the ARA. Fig. 2 shows two successful examples where the annotations by the ARA match the manual ones, however Fig. 3 shows examples in which there are misclassified segments. Fig. 3 panel (a) shows a 35-second interval that was annotated as PEA by clinicians. The ARA misclassified a 12s CC-pause interval (10-22s) as AS because no evident complexes occurred in the ECG, and during the CC-interval the CARF removes the artefact but leaves a filtering residual that is misclassified as VF, a well-known problem in shock/no-shock decision during CPR.[20,22] The example in Fig. 3 panel (b) shows a VF in which there are intervals of lower amplitude (fine VF) that are misclassified as AS. However, during 15s CC-interval (20-35s) the CARF efficiently removes the artefact revealing the underlying VF.

4. DISCUSSION

This paper presents an automatic system for the comprehensive retrospective analysis of resuscitation episodes that integrates different subsystem which were designed either exclusively for this task (RCE) or for other tasks but adapted to the current system, such as the CARF[20] or the chest compression detector.[19] To the best of our knowledge, this is the first system capable of annotating resuscitation rhythms (5 types) and chest compression events automatically for complete episodes (or datasets of episodes). Furthermore, the rhythm annotation performance of the system was demonstrated using a comprehensive dataset of resuscitation rhythms, as a proof of concept study that allowed the identification of caveats and areas of improvement and future research.

4.1 Performance for rhythm category annotation on complete episodes

The UMS of the ARA during CC-pauses and during CC-intervals were 75% and 52.5%, respectively. These UMS figures are 55-points and 32.5-points above the 20% value a random guess would achieve in this 5-state problem. During CC-pauses, the UMS was 2.7 percentage points below that of our previous experiments with a simpler RCE.[13] However, those experiments were conducted using isolated 3-s ECG segments of quality-controlled data (1.4h of data) suitable for the development of the RCE, i.e. segments with a single rhythm category and no artefacts. When taken to a real scenario, i.e. the annotation of a large repository of resuscitation data, performance drops due to the presence of transitional rhythms, borderline rhythms, and artefacts.

During chest compressions, the use of a CPR-artefact removal filter (CARF) increased the UMS 5.2-points, from 47.3% to 52.5%. CPR artefacts pose a great challenge to rhythm identification, a well-known problem also for shock advice algorithms.[21] For the shock/no-shock decision problem, filtering increases the average performance by 14 to 17 points.[20,23,24] However, resuscitation rhythm annotation is much more complex since there are four misclassification possibilities for each rhythm category. In this study, we used a CARF designed for the shock/no-shock decision problem in combination with an RCE designed to annotate artefact-free ECG segments. Future developments should explore the design of CARFs for resuscitation rhythm annotation and the design of RCEs specifically for rhythm classification during CC-intervals, in line with some recent developments for shock advice algorithms.[25]

4.2 Post-processing of annotations and contextual analysis of ECG data

An ARA system is conceived to retrospectively annotate data, and could therefore use and process all data in the episode before producing the final rhythm labels. In the current study the RCE was designed using isolated ECG segments, and the ARA system used contextual information only to remove isolated mislabeled rhythms (moving average filter) or rhythm annotations sustained during less than 6-s (post-processing filter). Although limited in scope, the use of these two blocks improved the UMS by 4.4 and 3.7 percentage points during CC-pauses and CC-intervals, respectively. These results evidence that future ARA designs will strongly benefit from the use of contextual information and general knowledge of resuscitation rhythm dynamics,[26] such as rhythm prevalence, the prevalence of patterns in rhythm changes,[7] or the probabilities of rhythm transitions.[27]

To highlight the necessity of the contextual analysis of ECG data further, one can scrutinize on the labeling process of the demonstrated examples in Fig 3 panel (a). Even in the labeling process, an expert needs the contextual analysis of the ECG signal to label each segment correctly. In this figure, an expert can only identify PEA in either 10-22s or 22-35s intervals by looking at the previous and probably future segments of the ECG signal. In fact, the reason that our algorithm fails to classify those ECG segments correctly is that it analyses the isolated segments without considering the contextual information.

Higher level (expert-level) contextual information can also be used to improve the accuracy during chest compressions. For instance, if the rhythm labels are the same before and after a series of chest compressions, it would be safe to assume no rhythm transitions occurred during compressions. This simple post-processing increases the UMS for CC-intervals by further 3.6-points (52.5% to 56.1%) in our data. Consequently, more elaborate techniques like identifying the possible and likely rhythm transitions during compressions, or only allowing a single transition during a chest compression interval may increase the accuracy of the ARA, and should be explored in the future.

4.3 Main sources of misclassification

An in-depth look at the confusion matrices reveal the most frequent occurrences of misclassification. During CC-pauses AS and PEA are the rhythms most difficult to identify. AS is frequently mislabeled as PEA (20%) or VF (8%), indicating the frequent presence of bradycardia (borderline AS/PEA) and fine VF (low amplitude VF). PEA is also misclassified as AS (9%) but most frequently as PR (24%), underlining the inherent difficulties of pulse detection based solely on the ECG.[28,12] The use of additional signals and/or data when available, such as the transthoracic impedance or the end-tidal CO_2 levels, should definitely improve PEA/PR discrimination.[29] PEA is the rhythm with largest variability and future developments may focus on specific PEA detectors.

During chest compressions, the sensitivity for most rhythm categories drops considerably, even after filtering. The filter has an overall positive impact, and its efficiency is demonstrated by the increase in AS sensitivity from 18% before filtering to 51% after filtering. Interestingly, filtering increased VF sensitivity from 71% to 86%, which was better than the 82% obtained during CC-pauses. On the other hand, many other rhythms were misclassified as VF after filtering, for instance PEA classified as VF was 13% before filtering and 27% after filtering. This shows that filtering residuals, which frequently resemble VF,[22] were still large and that the CARF subsystem could be further improved or should be tailored to resuscitation rhythm annotation (see Fig. 3a for an example).

4.4 Practical implementation considerations

The current accuracy of the ARA means the system is semi-automatic, since it would still need a final revision/correction by a clinician to ensure the quality of the annotations. However, compared to annotating rhythms anew, the workload will be considerably reduced, and corrections would be limited to instances with rare rhythm transitions and/or rhythms with high misclassification rates such as PEA.

The quality of the ECG signal is very important for rhythm annotation. In our dataset 9.3h of data (7% of time) were discarded because the quality of the recordings was not sufficient for any further processing, these data had been labeled as “undecided” or “uncertain” by human experts. Those 9.3h of data were not considered in our analysis. In the future, intervals with low quality ECG should be automatically detected using a signal quality index subsystem, in line with some recent developments in ECG signal processing.[30]

Another important aspect is the availability of signals, particularly for the chest compression detector and the CARF subsystems. Our dataset contained compression depth data (or compression acceleration) which facilitated the identification of CC-intervals and the design of the CARF. Many other datasets may not have synchronized signals from CPR feedback devices, for instance large datasets acquired using LIFEPAK (Physio-Control, Redmond WA, USA) defibrillators.[31] In those cases, the chest compression detector and the CARF can be adapted to use the transthoracic impedance, which would make the ARA applicable to most of the datasets currently available for research. Some studies on the accuracy of impedance-based chest compression detection,[19] and CPR artefact removal[24] suggest the accuracy of the ARA may not be much affected if based on the impedance, although it remains to be proved.

5. CONCLUSION

We have defined and implemented an architecture for an automatic resuscitation rhythm annotator, and we have demonstrated its performance using a large dataset of resuscitation cases. This system opens the possibility of annotating rhythms in large datasets of resuscitation data, and although its current accuracy requires the manual revision of the automatic annotations, the workload for clinicians would be considerably reduced.

Conflict of interest

The authors have no conflicts of interest except LW who represent NAKOS in Stryker Medical Advisory Board and has been PI for studies sponsored by Zoll and Stryker in addition to patent holder of patents licensed to Stryker and Zoll.

Appendix A.

Rhythm classification engine

The RCE designed for this study is an evolution of our previous RCE, and uses the same ECG features.[13] Our previous RCE was based on a single artificial neural network (ANN); our current evolution improves the robustness of the rhythm classifier by combining 10 ANNs in a committee machine. Each ANN had two hidden layers and 25 hidden neurons per layer. The number of neurons in the output layer was five in order to classify each feature vector into one of the five rhythm categories (AS, PEA, PR, VF, VT). All neurons in both hidden and output layers had the hyperbolic tangent activation function. The Levenberg–Marquardt optimization method[32] with Bayesian regularization backpropagation[33] algorithm was used to train each ANN.

The RCE was developed using the quality-controlled data described in Rad et al.[13] ANNs were trained by using 10-fold cross-validation committee,[34,35] and a wrapper-based feature selection method was used in each training fold to obtain 14 features for classification.[13] The final rhythm label of the 10-ANN committee machine was obtained applying a trimmed mean (10% of the lowest/highest values were discarded) to the 10 outputs. In the final stage, a 9-s moving average filter is used to smooth the fast fluctuations (cancel the isolated rhythm changes) in the output of ANNs.

Fig. 1. The architecture of automatic resuscitation rhythm annotator (ARA). In the first step, chest compressions are detected in Chest Compression Interval Detector subsystem using CCD. CCD is the chest compression depth signal derived from the acceleration recordings. In the next step, if there is no CPR-artefact the ECG directly passes to Rhythm Classification Engine (RCE), but if there is CPR-artefact at first CPR artefacts are removed using a CPR-artefact removal filter (CARF). RCE classifies every second of ECG into the five resuscitation rhythm categories by using overlapping sliding windows. In the final step, rhythm annotations sustained during less than 6-s is replaced by previous rhythm label in Post-processing Filter block.

Fig. 2. Panels (a) and (b) show two successful examples where the annotations by the ARA match the manual annotations by clinicians. In each panel the first plot shows the original ECG annotated by clinicians, the second plot shows the CCD, and the third plot shows the ECG after applying CARF (ECG_f) and annotated by ARA. The gray vertical lines indicate start/end of the CC-intervals. During CC-pauses ECG_f is the same as ECG since CARF is applied only during CC-intervals. “C” before the rhythm name indicates annotations during CC-intervals.

Fig. 3. Panels (a) and (b) show two examples in which there are misclassified segments by ARA. In each panel the first plot shows the original ECG annotated by clinicians, the second plot shows the CCD, and the third plot shows the ECG after applying CARF (ECG_f) and annotated by ARA. The gray vertical lines indicate start/end of the CC-intervals, and the red vertical lines show incorrect rhythm changes in ECG_f. During CC-pauses ECG_f is the same as ECG since CARF is applied only during CC-intervals. “C” before the rhythm name indicates annotations during CC-intervals.

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Table1

The number of hours for each rhythm type in our dataset during both CC-pauses and CC-intervals; the numbers in parentheses show the corresponding proportion of the total time.

Rhythm	**CC-pauses**	**CC-intervals**
AS	15.2(24.2%)	20.1(36.8%)
PEA	16.9(27.0%)	19.4(35.5%)
PR	20.2(32.2%)	2.3(4.2%)
VF	10.0(16.0%)	12.5(22.9%)
VT	0.4(0.6%)	0.3(0.6%)
Total	62.7(100%)	54.6(100%)

Table2

Table 2

The confusion matrices of cardiac rhythm classification of resuscitation episodes during CC-pauses and during CC-intervals by using CARF; the numbers show the classification/misclassification rates and the duration in hours for each possibility in parenthesis.

		ARA label				
		AS	PEA	PR	VF	VT
Clinicians' label during CC-pauses	AS	**66.8% (10.17)**	19.8% (3.02)	3.6% (0.54)	8.3% (1.27)	1.5% (0.23)
	PEA	9.3% (1.57)	**55.8% (9.43)**	24.4% (4.12)	5.8% (0.98)	4.8% (0.81)
	PR	1.2% (0.24)	6.9% (1.40)	**86.5% (17.45)**	0.8% (0.17)	4.6% (0.92)
	VF	9.1% (0.91)	2.9% (0.29)	1.3% (0.13)	**82.1% (8.23)**	4.6% (0.46)
	VT	2.7% (0.01)	0.0% (0.00)	2.7% (0.01)	10.8% (0.04)	**83.8% (0.31)**
Clinicians' label during CC-intervals	AS	**51.1% (10.25)**	10.7% (2.14)	5.9% (1.18)	29.4% (5.91)	3.0% (0.60)
	PEA	10.2% (1.98)	**34.1% (6.60)**	23.2% (4.50)	26.5% (5.13)	6.0% (1.17)
	PR	4.8% (0.11)	13.5% (0.31)	**58.7% (1.35)**	17.8% (0.41)	5.2% (0.12)
	VF	7.2% (0.90)	1.4% (0.17)	1.9% (0.24)	**86.4% (10.76)**	3.1% (0.38)
	VT	3.6% (0.01)	0.0% (0.00)	3.6% (0.01)	60.7% (0.17)	**32.1% (0.09)**

Table3

Table 3

The confusion matrix of cardiac rhythm classification of resuscitation episodes during CC-intervals without using CARF; the numbers show the classification/misclassification rates and the duration in hours for each possibility in parenthesis.

		ARA label				
		AS	PEA	PR	VF	VT
Clinicians' label during CC-intervals	AS	**17.9% (3.46)**	21.6% (4.16)	5.9% (1.14)	34.2% (6.59)	20.4% (3.94)
	PEA	1.7% (0.33)	**42.3% (8.02)**	25.0% (4.75)	13.0% (2.47)	17.9% (3.40)
	PR	0.4% (0.01)	22.9% (0.52)	**53.7% (1.22)**	7.1% (0.16)	15.9% (0.36)
	VF	0.7% (0.09)	2.1% (0.25)	1.3% (0.16)	**70.9% (8.64)**	25.0% (3.04)
	VT	3.7% (0.01)	0.0% (0.00)	3.7% (0.01)	40.7% (0.11)	**51.9% (0.14)**

Figure1
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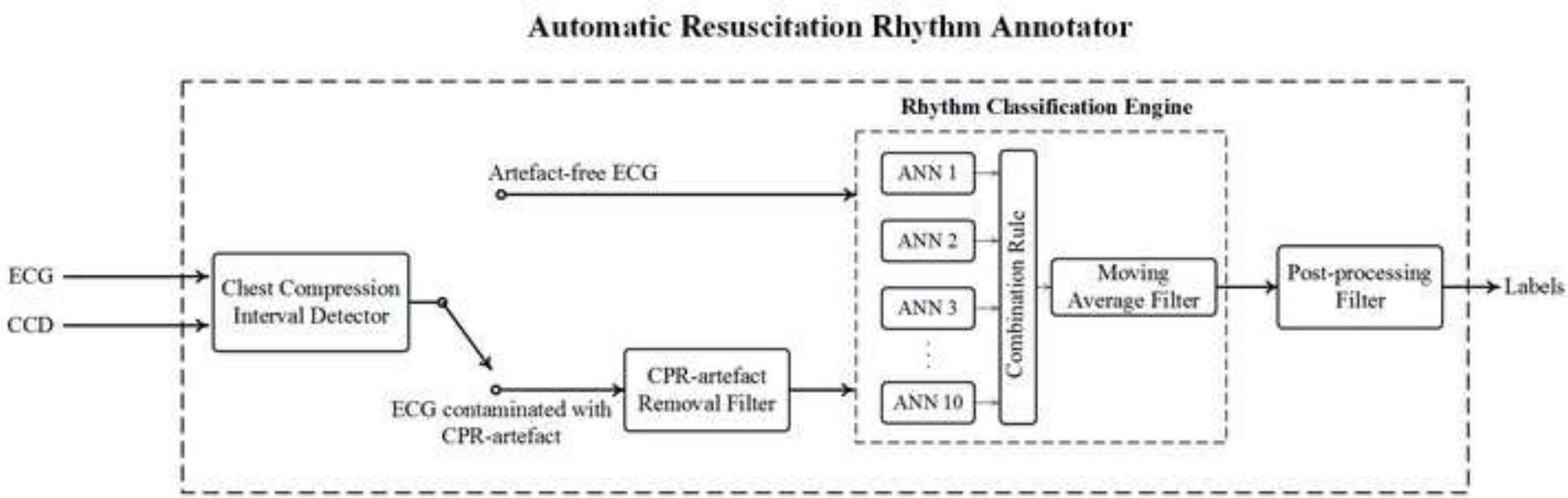

Figure2

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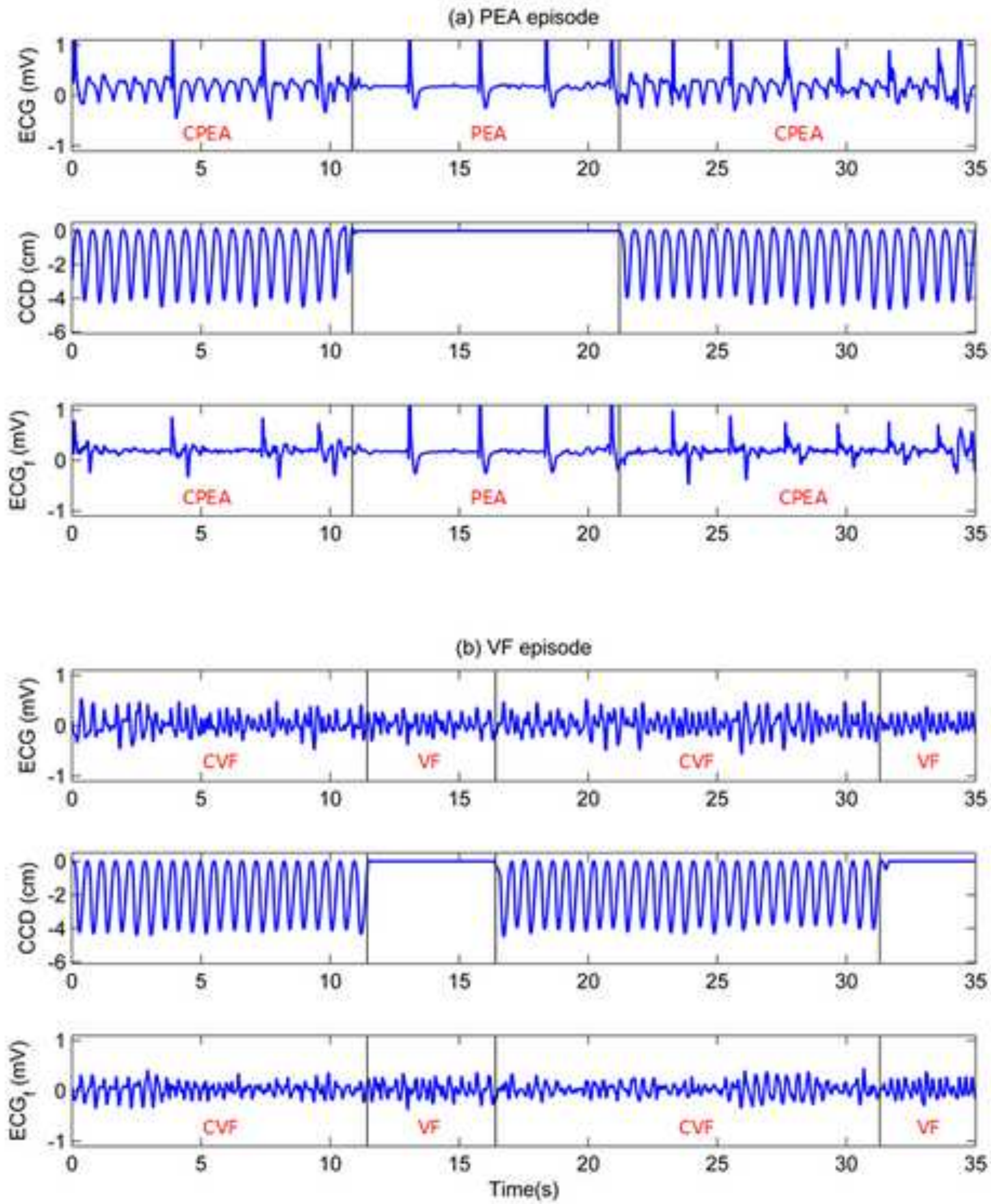

Figure3

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