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Original paper

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 126.5 h 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 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.

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

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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-s 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 and Sherman [1] for the comprehensive analysis of resuscitation data.

Materials and methods

Resuscitation episode dataset

The dataset comprises 126.5 h of ECG and chest compression depth (CCD) signal derived from the acceleration recordings as explained by Aase and Myklebust [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 were annotated concurrently by an anesthesiologist specialized in advanced 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 labeled 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 transthoracic impedance 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 labeled as uncertain and discarded from further analysis.

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.

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.

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 6 s with the previous rhythm label.