Automated Algorithm for QRS Detection in Cardiac Arrest Patients with PEA

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Abstract

Pulseless electrical activity (PEA) is one of the most common rhythms during a cardiac arrest (CA), and it consists in lack of palpable pulse in presence of electrical activity in the heart. The main treatment for a CA is the cardiopulmonary resuscitation (CPR), including chest compressions and ventilations, together with defibrillation shocks and drugs when necessary. The therapy of PEA depends on its characteristics, mainly the morphology of the QRS complex. Well known algorithms for QRS complex detection and delineation were designed for hemodynamically stable patients with pulsed rhythm (PR). The aim of this study was to develop an automatic method for QRS complex detection in patients with PEA during CA. The database for this study consists of 5128 PEA segments from 264 in-hospital CA patients. The ECG signal was decomposed using the stationary wavelet transform, a peak detector was applied on the third detail component and a multicomponent verification was set to detect the peaks. Finally, a time alignment of the detected QRS complexes was performed using the original ECG signal. The proposed method presents median (IQR) Se/PPV/F1 values of 92.4(15.2)/88.5(15.4)/88.8(15.6) for PEA segments.

1. Introduction

Cardiac arrest (CA) is a main cause of death in the industrialized world, with an average incidence of 55 per 100.000 persons-year and a survival rate below 8.4% [1,2]. An early recognition and a rapid treatment of the CA are essential to enhance survival chance, and the treatment depends on the heart rhythm of the patient [3]. The pulseless electrical activity (PEA) is one of the most frequent rhythms by the time the emergency services arrive, with an incidence between 20-30% and 40-60% in out- and in-hospital CA, respectively [4–6].

PEA is a clinical condition with a electromechanical dissociation, characterized by organized cardiac electrical activity without palpable pulse [7]. The cardiopulmonary resuscitation (CPR) and pharmacological treatment of a PEA during a CA depends on the characteristics of the PEA. Recent studies have shown that PEAs with narrow QRS duration and high slopes have better prognosis and deserve different treatment in contrast to those with wider QRS complex in which immediate pharmacological treatment is advised [8–10].

ECG waves delineation is essential for rhythm characterization. Once ECG is delineated information such as hear rate, and wave segment duration and amplitude features can be computed. The QRS complex is the most characteristic waveform in the ECG and its detection is the most critical step in ECG delineation [11, 12].

Several automatic methods have been proposed in the literature for QRS detection and delineation in patients with pulsed rhythm (PR) [11–15]. Wavelet transform is considered a encouraging technique for QRS detection and delineation. Decomposing ECG in different frequency band details allows discriminating different waves in the ECG avoiding the baseline and high frequency noise [11]. The QRS is usually identified detecting the maximum slope point of the R wave, which is considered the reference point of the QRS complex and it has high amplitude that makes easier to detect [11, 13].

Well known automated QRS detectors have not been evaluated in patients during PEA. In this study an automated algorithm was designed for QRS complex detection in PEA rhythms.

2. Materials

The database used in this study is a subset of a larger in hospital CA episodes database. It consists of 264 episodes, recorded by emergency services and include

ECG, transthoracic impedance (TI) and ventilations signals. 89 of those episodes were from St. Olav University Hospital (Norway), 136 from Hospital of the University of Pennsylvania (USA) and 39 from Penn Presbyterian Medical Center (USA). The 89 episodes from Norway were recorded using LIFEPAK-20 (Stryker, Redmond, USA) defibrillators between 2018 and 2021, while the 175 episodes form USA hospital were recorded using HeartStart MRx-defibrillators (Philips Medical Systems, Andover, Massachusetts, USA) between 2008 and 2010.

All episodes were manually assessed and annotated by expert clinicians. Rhythm type and QRS complexes were annotated in the ECG signal, and the intervals with chest compressions identified in the TI signal. Intervals with duration between 3-6 s were selected in chest compression pauses, and separated in 3 s segments. A total of 5128 segments with a mean duration of $3.47\,\mathrm{s}$ per segment were extracted. The total duration of the database was $335\,\mathrm{min}$, with 19085 heart beats, 3.7 per segment.

3. Methods

Figure 1 shows the overall scheme of the proposed algorithm. First, the ECG signal was decomposed using a 8-level stationary wavelet transform (SWT). Then, possible peaks were searched in the 3rd detail component and a multicomponent evaluation was applied to validate those peaks. Finally, the peak positions were searched in the maximums of the ECG signal.

3.1. SWT decomposition

For the SWT decomposition Daubechies-3 mother wavelet was applied and 8-level decomposition used, following procedures proposed in [2, 15].

3.2. QRS reference point detection

As the energy of the QRS complex is concentrated in 3-40 Hz frequency band [16, 17] the detailed components d3-d5 were analysed to detect the QRS reference points. An example of a PEA segment decomposition in d3, d4 and d5 details is shown in Figure 2.

The QRS reference points were computed in the d3 detail component applying the amplitude threshold given in 1. A minimum peak to peak distance of $100\,\mathrm{ms}$ was established between consecutive peaks.

$$Th_3 = 0.5 * \max(-d3) \tag{1}$$

A multicomponent evaluation was applied in d4 and d5 detail components. Peaks predected in d3 were considered as QRS reference points only if its value in d4 and d5 detail coefficients were above th4 and th5 thresholds:

$$Th_4 = 0.4 * \max(-d4) \tag{2}$$

$$Th_5 = 0.2 * \max(-d5) \tag{3}$$

3.3. Align QRS reference points

Finally, the QRS reference points computed in the previous steps were time aligned with the maximum of the ECG signal in a tolerance interval of $150\,\mathrm{ms}$ before and after the detected peak.

3.4. Statistical evaluation

QRS instants manually annotated by clinicians were considered as ground truth for evaluation purposes. A QRS was considered correct if detected in a range of $100\,\mathrm{ms}$ around the ground truth. Algorithms were evaluated in terms of sensitivity (Se), percentage of correctly detected QRS complexes; positive predictive value (PPV), percentage of detected QRS complexes that are actually QRS; and

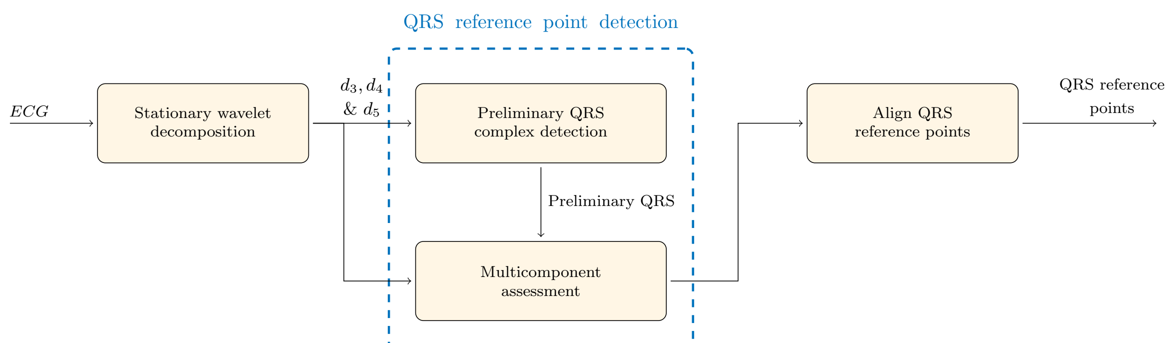

Figure 1. Overall scheme of the automatic algorithm to detect QRS complexes during PEA.

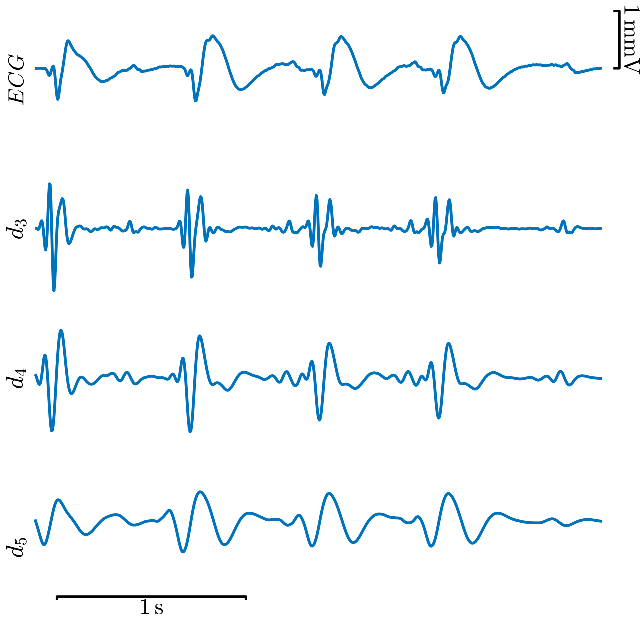

Figure 2. Examples of the ECG signal and its detail components d_3, d_4 and d_5.

F-score (F1), the harmonic mean of Se and PPV. The performance metrics were calculated per patient, and the final results were presented as the median (interquartile range, IQR) for all patients.

The QRS detector proposed in the study was compared with two QRS detection/delineation algorithms proposed in the literature: Martinez et al. [12] and Elola et al. [18].

4. Results

The performance metrics are shown in the Table 1 in terms of Se, PPV and F1. It can be observed that the proposed algorithm outperformed the best literature algorithm in more than 6 points of F1. Its higher Se means that it correctly detects many QRS complexes missed by the other algorithms.

Table 1. Performance metrics for the proposed algorithm and two other methods. The table shows the median (IQR) values for Se, PPV and F1.

	Se (%)	PPV (%)	F1 (%)
This study	92.4 (15.2)	88.5 (15.4)	88.8 (15.6)
Martinez et al. [12]	75.6 (16.4)	89.1 (18.9)	80.0 (16.6)
Elola et al. [18]	82.7 (28.5)	84.5 (28.7)	82.7 (28.3)

5. Discussion and conclusions

The detection and delineation of QRS complexes is widely used in rhythm characterization during CA. However, automated methods proposed in the literature have not been tested with organized PEA rhythms. This study is the fist proposing an automatic algorithm for QRS complex detection in patients in CA presenting PEA.

Comparing to proposals by Martinez et al. [12] and Elola et al. [18], our algorithm outperforms in 10 points of Se with similar PPV values. Two are the main reasons for this improvement. Firstly, the proposed technique is better adapted to the chaotic and variable characteristics of QRS complex during CA. Secondly, CPR therapy implies that the ECG analysis intervals are limited to pauses between compressions, with a duration of 3-10 s. Unlike other published methods, the proposed algorithm was optimized for short-duration segments.

This work is subject to a number of limitations. On the one hand, the database has a limited number of patients, and only in-hospital CA were included in this study. On the other hand, the algorithm assumes that all segments are organized rhythms with PEA, and it would required an adaptation for other organized rhythms or non-organized rhythms.

This study is the first step for the development of automatic algorithms that characterize the QRS complex of PEA patients during a CA. This characterization could assist and guide clinicians in determining the most appropriate resuscitation treatment.

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