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Clinical paper

Automatic cardiac rhythm interpretation during resuscitation☆

Ali Bahrami Rad[a,b,*], Kjersti Engan[a], Aggelos K. Katsaggelos[b], Jan Terje Kvaløy[c], Lars Wik[d], Jo Kramer-Johansen[d], Unai Irusta[e], Trygve Eftestøl[a]

[a] Department of Electrical Engineering and Computer Science, University of Stavanger, 4036 Stavanger, Norway
[b] Department of Electrical Engineering and Computer Science, Northwestern University, Evanston, IL 60208, USA
[c] Department of Mathematics and Natural Sciences, University of Stavanger, 4036 Stavanger, Norway
[d] Norwegian National Advisory Unit on Prehospital Emergency Medicine (NAKOS) and Department of Anaesthesiology, Oslo University Hospital and University of Oslo, Pb 4956 Nydalen, 0424 Oslo, Norway
[e] Communications Engineering Department, University of the Basque Country UPV/EHU, Alameda Urquijo S/N, 48013 Bilbao, Spain

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ABSTRACT

Aim: Resuscitation guidelines recommend different treatments depending on the patient's cardiac rhythm. Rhythm interpretation is a key tool to retrospectively evaluate and improve the quality of treatment. Manual rhythm annotation is time consuming and an obstacle for handling large resuscitation datasets efficiently. The objective of this study was to develop a system for automatic rhythm interpretation by using signal processing and machine learning algorithms.
Methods: Data from 302 out of hospital cardiac arrest patients were used. In total 1669 3-second artifact free ECG segments with clinical rhythm annotations were extracted. The proposed algorithms combine 32 features obtained from both wavelet- and time-domain representations of the ECG, followed by a feature selection procedure based on the wrapper method in a nested cross-validation architecture. Linear and quadratic discriminant analyses (LDA and QDA) were used to automatically classify the segments into one of five rhythm types: ventricular tachycardia (VT), ventricular fibrillation (VF), pulseless electrical activity (PEA), asystole (AS), and pulse generating rhythms (PR).
Results: The overall accuracy for the best algorithm was 68%. VT, VF, and AS are recognized with sensitivities of 71%, 75%, and 79%, respectively. Sensitivities for PEA and PR were 55% and 56%, respectively, which reflects the difficulty of identifying pulse using only the ECG.
Conclusions: An ECG based automatic rhythm interpreter for resuscitation has been demonstrated. The interpreter handles VT, VF and AS well, while PEA and PR discrimination poses a more difficult problem.

Introduction

Systematic review in order to identify specific factors during resuscitation episodes is a key to identify different quality aspects of therapy. Identifying such factors enables comparison of different therapeutic approaches, e.g., chest compression strategies, effect of interruptions, shock success, etc.[1–6] The process seeks to determine the relationship between therapy and the patient's response captured from the time series data (TSD) recorded by external defibrillators. Thoracic impedance and accelerometer signals are examples of TSD from which information about chest compressions and ventilation can be extracted to compute quality indicators while the electrocardiogram (ECG) and end tidal CO_2 ($ETCO_2$) provide information about the patient's response.[1–7] Manual rhythm annotation is a time consuming task and an obstacle for handling large datasets efficiently. Eftestøl et al.[8] demonstrated recently how rhythm state and chest compression sequence annotations could be used as a basis from which higher-level review parameters can be derived automatically. In addition, Ayala et al.[9] demonstrated automatic techniques to determine chest compressions, and Irusta et al.[10] proposed an algorithms for cardiopulmonary resuscitation (CPR) artifact removal. In this work, we propose an algorithm for automatic rhythm interpretation. In a final stage, all these subsystems will be linked together to produce a fully automatic system for resuscitation episode review.

For a detailed account of the patient's state/response, rhythm interpretation requires a more detailed rhythm classification than that provided by shock advice algorithms.[11,12] It generally involves rhythm classification into five categories: ventricular tachycardia

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* Corresponding author at: Department of Electrical Engineering and Computer Science, University of Stavanger, 4036 Stavanger, Norway.
E-mail address: ali.bahrami.rad@uis.no (A.B. Rad).

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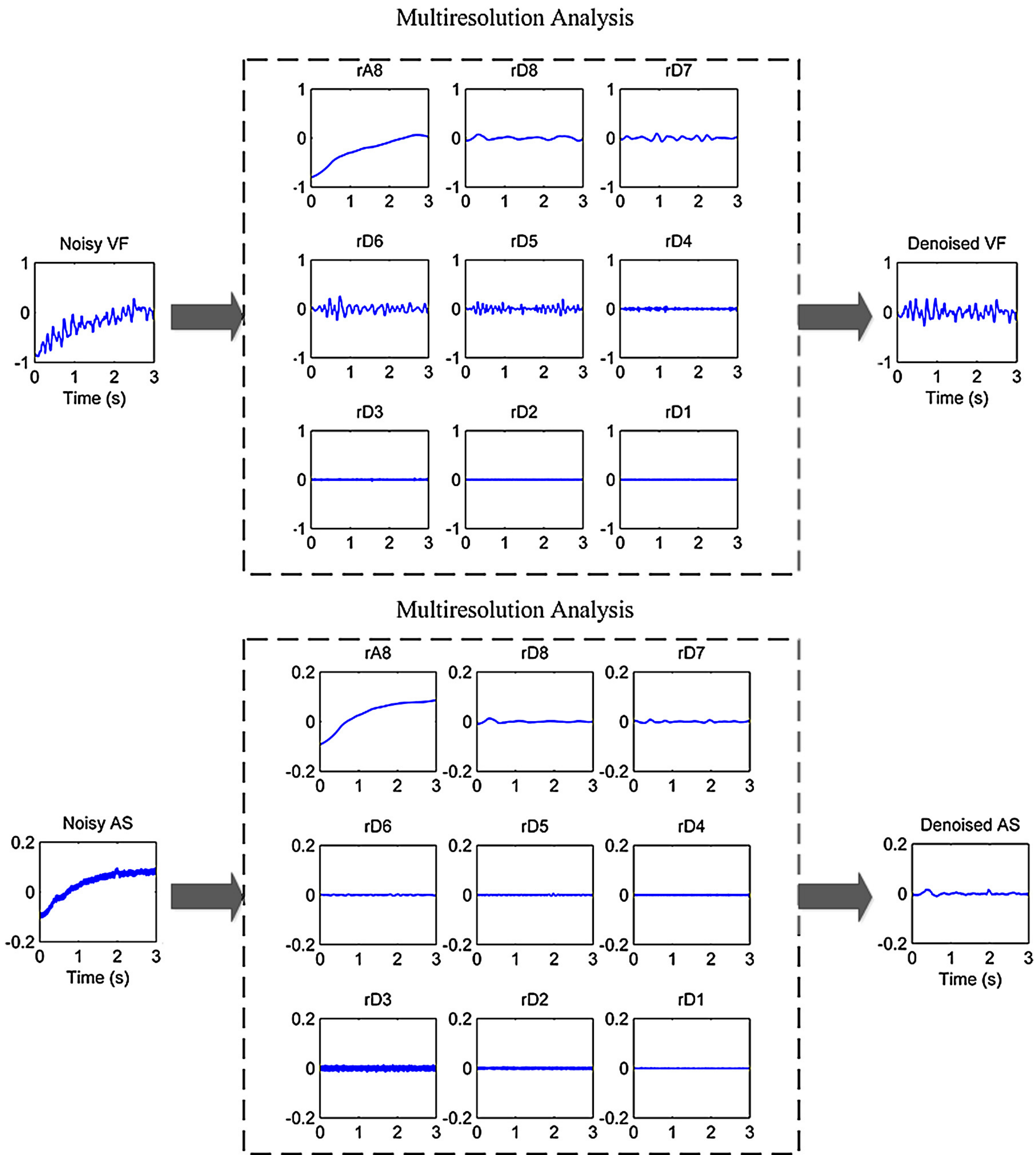

Fig. 1. Denoising process of two noisy cardiac rhythms VF and AS. In all plots the *y* axes are the amplitudes of the ECG in mV which are shown in the different ranges for better representation. In the top figure a noisy VF rhythm (baseline wander or low-frequency noise) is denoised using multiresolution analysis. rA8 is the reconstructed signal from approximation coefficients of level 8. rD1 to rD8 are the reconstructed signal from detail coefficients of levels 1–8. Low-frequency noise is represented in rA8. In the bottom figure a noisy AS rhythm (with both low-frequency and high-frequency noise) is denoised. High-frequency noise is represented in rD3, rD2 and rD1. Again, low-frequency noise is represented in rA8.

(VT), ventricular fibrillation (VF), pulseless electrical activity (PEA), pulse generating rhythms (PR) and asystole (AS). In the present study, we build on earlier attempts,[13,14] developing a generalizable algorithm with a specific focus on feature extraction, feature selection, and model assessment.

Materials and methods

ECG dataset

We extracted ECG data from 302 out-of-hospital cardiac arrest (OHCA) patient records. The original study was done to measure CPR quality in three geographic locations Akershus (Norway), Stockholm (Sweden), and London (UK) between March 2002 and September 2004.[2,15] The surface ECG was recorded by modified Heartstart 4000 defibrillators with enhanced monitoring capabilities. The sampling rate was 500 Hz with a resolution of 1.031 μV per least significant bit, which is equivalent or superior to that of current state of the art defibrillators. For the original studies, recordings were annotated by expert reviewers using the five rhythm types (VT, VF, PEA, PR, AS), and chest compression intervals were annotated using the compression depth available from a CPR assist-pad. ECG segments were automatically extracted based on these annotations with the following criteria: 3-second duration, a single rhythm, and no chest compression artifacts.