



## Clinical paper

# Reliable extraction of the circulation component in the thoracic impedance measured by defibrillation pads<sup>☆</sup>



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## ARTICLE INFO

## Article history:

Received 22 February 2013

Received in revised form 3 May 2013

Accepted 23 May 2013

## Keywords:

Thoracic impedance

Automated external defibrillator (AED)

Pulse-generating rhythm (PR)

Pulseless electrical activity (PEA)

Circulation detection

## ABSTRACT

**Aim:** To analyze the feasibility of extracting the circulation component from the thoracic impedance acquired by defibrillation pads. The impedance circulation component (ICC) would permit detection of pulse-generating rhythms (PRs) during the analysis intervals of an automated external defibrillator when a non-shockable rhythm with QRS complexes is detected.

**Methods:** A dataset of 399 segments, 165 associated with PR and 234 with pulseless electrical activity (PEA) rhythms, was extracted from out-of-hospital cardiac arrest episodes by applying a conservative criterion. Records consisted of the electrocardiogram and the thoracic impedance signals free of artifacts due to thoracic compressions and ventilations. The impedance was processed using an adaptive scheme based on a least mean square algorithm to extract the ICC. Waveform features of the ICC signal and its first derivative were used to discriminate PR from PEA rhythms.

**Results:** The segments were split into development (83 PR and 117 PEA rhythms) and testing (82 PR and 117 PEA rhythms) subsets with a mean duration of 10.6 s. Three waveform features, peak-to-peak amplitude, mean power, and mean area were defined for the ICC signal and its first derivative. The discriminative power in terms of area under the curve with the testing dataset was 0.968, 0.971, and 0.969, respectively, when applied to the ICC signal, and 0.974, 0.988 and 0.988, respectively, with its first derivative.

**Conclusion:** A reliable method to extract the ICC of the thoracic impedance is feasible. Waveform features of the ICC or its first derivative show a high discriminative power to differentiate PR from PEA rhythms (area under the curve higher than 0.96 for any feature).

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## 1. Introduction

Detecting signs of circulation is essential in interventions for cardiopulmonary resuscitation (CPR), especially when either lay people or professionals use defibrillators. Up until 1998, the European Resuscitation Council guidelines required pulse checking to determine cardiac arrest in basic life support [1]. Since 2000, the carotid pulse has not been included in the protocol [2] as it was proved to be both time-consuming and inaccurate [3,4]. The 2010 guidelines established recognition of cardiopulmonary arrest based on unresponsiveness and abnormal breathing [5]. When using an automated external defibrillator (AED), they recommend

resuming immediate CPR after the shock is provided or after no-shock is indicated. The rescuer should watch continuously for the responsiveness of the patient looking for movement and normal breathing.

In that context, an automated circulation detection method integrated with the shock advice algorithm (SAA) of the AED would help the rescuer to recognize signs of circulation. The SAA analyzes the cardiac rhythm in artifact-free intervals, with no chest compressions or ventilations. When the SAA detects a non-shockable rhythm with the presence of QRS complexes, an automated circulation detector would discriminate pulseless electrical activity (PEA) rhythms, with no circulation, from pulse-generating rhythms (PR).

Transthoracic-impedance plethysmography measured with four electrodes has been used for decades as a non-invasive technique for estimating stroke volume and cardiac output [6]. The thoracic impedance (TI) provides information regarding the blood circulation; pulse-generating heartbeats produce small temporary changes in impedance [7] and a close relationship between changes

<sup>☆</sup> A Spanish translated version of the summary of this article appears as Appendix in the final online version at doi:10.1016/j.resuscitation.2013.05.020.

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in TI and variable aortic pressures has been shown [8]. Current AEDs measure the TI continuously through self-adhesive defibrillation pads. Therefore, it has been suggested that the AEDs should be expanded to include the TI as a potential hemodynamic sensor [9–13].

The TI signal recorded through defibrillation pads may show different components: (1) a baseline impedance of 50–120  $\Omega$  depending on the patient size and body composition; (2) fluctuations due to thoracic compressions and ventilations between 0.2 and several ohms; (3) an impedance circulation component (ICC) with fluctuations less than 100 m $\Omega$  in pulse-generating rhythms; and (4) other noise and artifacts due to movement, electrode-skin contact, and so on. The intervals for rhythm analysis in the AED are free of compressions and ventilations. In these intervals, the ICC, if present, could be detected provided there is an effective noise removal. Reliable extraction of the ICC is key to detecting the presence of the pulse automatically. The magnitude of the ICC is smaller in PEA rhythms than in PR due to the lack of circulation in PEA rhythms. The hypothesis of this study is that a reliable method can be developed to extract the circulation component from the impedance recorded through defibrillation pads. The method could be integrated into the pulse detection system of an AED and launched during analysis intervals. The technical issues involved in that integration would be beyond the scope of this paper. The pulse detector would require further studies that guarantee the system is not extra time-consuming, does not increase the no flow time, and helps the rescuers to improve resuscitation rates.

## 2. Materials and methods

### 2.1. Data materials

The data were obtained from a prospective study of out-of-hospital cardiac arrest (OHCA) episodes, recorded between March 2002 and September 2004 in Akershus, Stockholm, and London [14,15]. The study was designed to measure the quality of out-of-hospital CPR performed by ambulance personnel in adherence to the resuscitation guidelines of 2000. A modified version of the HeartStart 4000 defibrillators (Philips Medical Systems, Andover, MA, USA) was used to record the following signals with a sampling rate of 500 Hz: the surface ECG (resolution 1.03  $\mu$ V per least significant bit with bandwidth 0–50 Hz), the TI (resolution 0.74 m $\Omega$  per least significant bit with bandwidth 0–80 Hz) by applying a sinusoidal excitation current (32 kHz, 3 mA peak to peak) between the defibrillation pads, and additional reference channels. Expert reviewers annotated the episodes using five rhythm types: ventricular fibrillation (VF) and ventricular tachycardia (VT) in the shockable category, and asystole (AS), PEA, and PR in the non-shockable category. PR intervals were annotated either when a pulse was detected clinically or when TI changes simultaneous with cardiac contractions were detected [14].

Retrospectively, we extracted segments from those episodes with 4–15 s duration, according to the typical length for the analysis pauses in an AED, and with the TI signal free of artifacts due to chest compressions or ventilations. To avoid uncertainty in the PR/PEA classification of the extracted segments, a restrictive criterion was applied in the extraction: the PEA segments were extracted from episodes with a complete absence of PR annotations along the episode, and the PR segments were selected from the final interval of the episodes annotated with return of spontaneous circulation and with the patient admitted alive to hospital. Several segments from the same patient were considered if they corresponded to

separate stages of the intervention. Each record consisted of two signals, the ECG and the TI, both downsampled to  $f_s=250$  Hz.

The database was split randomly into two datasets for development and testing, each with a similar number of patients and segments. When a patient contributed with more than one segment they were separated into the two datasets. Table 1 presents a summary of the composition of the database which comprised 399 segments from 127 patients.

### 2.2. Adaptive extraction of the ICC signal from the TI signal

The ECG signal,  $ecg[n]$ , and the TI signal,  $z[n]$ , where  $n$  is the time sample number, were digitally processed. The former was processed to compute the instantaneous frequency of the QRS complexes,  $f[n]$ . From the latter the ICC signal,  $icc[n]$ , was extracted.

#### 2.2.1. ECG signal processing

As shown in Fig. 1, the ECG signal was band-pass filtered at 0.5–30 Hz to suppress the baseline drift and the high-frequency artifacts. QRS complexes were annotated automatically using an offline Matlab version of the QRS detector running in the commercial monitor-defibrillator Reanibex 800 (BexenCardio, Ermua, Spain). The detector is compliant with the standard IEC [16] and reported sensitivity and positive predictive values above 99.5% when tested on the MIT-BIH database. Instants of the QRS complexes,  $n_i$   $i = 1, \dots, M$ , were computed for the  $M$  complexes of the segment. The frequency  $f[n]$  is constant between  $n_i$  and  $n_{i+1}$ , the instants in samples of two consecutive QRS complexes. It was computed as:

$$f[n] = \frac{1}{(n_{i+1} - n_i)} \quad n_i \leq n < n_{i+1} \quad \text{for } i = 1, \dots, M - 1, \quad (1)$$

Fig. 2 shows the ECG signal,  $ecg[n]$ , for a PR segment (panel a) and for a PEA segment (panel b). Red dashed lines depict the instants of the QRS complexes.

#### 2.2.2. TI signal processing

The TI signal,  $z[n]$ , was preprocessed as shown in Fig. 1. First, the direct component (DC) due to the baseline impedance was removed by subtracting the mean value. Then, the high-frequency noise was suppressed using a low-pass filter with a  $f_{c1}$  cut-off frequency. Finally, the signal was high-pass filtered with a  $f_{c2}$  cut-off frequency to suppress low-frequency components below the fundamental frequency of the circulation component. Fig. 2 shows the raw impedance signal,  $z[n]$ , and the preprocessed signal,  $z_p[n]$ , for a PR segment (panel a) and a PEA segment (panel b).

The  $z_p[n]$  signal consisted of the ICC and additional noisy components that were removed using an adaptive scheme that incorporates a least mean square (LMS) algorithm [17]. Previous knowledge on spectral analysis of the TI circulation component in hemodynamically stable volunteers [18] showed that the circulation component could be modeled adequately with the first three harmonics. A model based on Fourier coefficients with time-varying amplitude and phase was applied as follows:

$$\begin{aligned} i\hat{c}c[n] &= \sum_{k=1}^3 A_k[n] \cos(2\pi knf[n] + \varphi_k[n]) \\ &= \sum_{k=1}^3 \hat{a}_k[n] \cos(2\pi knf[n]) + \hat{b}_k[n] \sin(2\pi knf[n]). \end{aligned} \quad (2)$$

Fig. 1 shows the three stages of the adaptive scheme used to compute the ICC. Each stage extracts the component of the TI correlating with one of the first three harmonics of the  $f[n]$ . The LMS

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