A Simple Impedance-Based Method for Ventilation Detection During Cardiopulmonary Resuscitation

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Abstract

During cardiopulmonary resuscitation, excessive ventilation rates decrease cardiac output, thus reducing the chance of survival. We have developed a simple method to automatically detect ventilations based on the analysis of the thoracic impedance signal recorded through defibrillation pads. We used 18 out-of hospital cardiac arrest episodes that contained both ventilations provided during chest compressions (CCs) and during pauses in CCs. The detection algorithm first identified fluctuations on the preprocessed impedance signal. Then, it characterized the fluctuations by features for amplitude, duration and slope. Finally, a decision system based on static and dynamic thresholds was applied in order to determine whether each fluctuation corresponded to a ventilation. Sensitivity (Se) and positive predictive value (PPV) for the test set (2831 ventilations) were 97% and 94%, respectively. Before intubation (343 ventilations), Se and PPV were 92% and 79%, and 97% and 97% after intubation. The performance was very similar for intervals with and without CCs. The proposed method could be implemented in automatic external defibrillators for ventilation rate monitoring.

1. Introduction

Cardiac arrest is the sudden cessation of the heart's effective pumping function. Medical treatment of cardiac arrest involves early cardiopulmonary resuscitation (CPR) and early defibrillation. During CPR, ventilations and chest compressions (CCs) provide oxygen to the lungs and help oxygenated blood circulate to the vital organs. High-quality CPR is an important factor for the successful resuscitation of cardiac arrest patients. Resuscitation guidelines recommend providing chest compressions and ventilations with a 30:2 ratio before intubation and continuous CCs with a ventilation rate of 8-10 per minute afterwards [1].

Unfortunately, hyperventilation is often reported for both in-hospital and out-of-hospital cardiac arrests (OHCAs) [2, 3]. In animal studies, these excessive ventilation rates resulted in decreased coronary perfusion pressures and poor outcomes [4].

Early defibrillation, i.e., the application of an electrical shock to the heart, is another key intervention during cardiac arrest. Automated external defibrillators (AEDs) have reduced the time to such treatment for OHCAs. It has been suggested that incorporating feedback systems into these devices could help rescuers to improve CPR quality [5]. Most AEDs acquire not only the ECG, but also the thoracic impedance (TI) through defibrillation pads. This signal fluctuates during ventilation because of lung volume changes. The TI increases during inspiration (the air inside the lungs is a poor conductor) and decreases during expiration. Consequently, the analysis of the TI could be useful for ventilation monitoring during CPR. However, the amplitude and durations of the TI fluctuations vary widely along the resuscitation episode and among different patients [6]. Moreover, patient movement and CCs induce artifacts in the TI, which makes the identification of the fluctuations induced by ventilations difficult.

In this study, we present a simple adaptive method for automatically detecting ventilations during CPR, based on the analysis of the TI signal acquired by the defibrillator. We evaluated the method with OHCA records.

2. Materials and methods

2.1. Database description and annotation

The dataset used in this study was a subset of a large database of OHCA episodes recorded between 2002 and 2004 in three European cities during a prospective study on CPR quality [5, 7]. The surface ECG and several reference channels were recorded using modified versions of Hearstart 4000 defibrillators (Philips Medical Systems, Andover, MA, USA). The impedance was

acquired through the defibrillation pads with a sampling rate of 500 Hz and a resolution of 0.74 mΩ per least significant bit. Using an external compression sensor, the force and acceleration of the CCs were also recorded. For this study we extracted the force and TI signals.

From the full database (361 episodes) we excluded those that had been classified as not usable for ventilation studies due to low quality of the impedance signal (100). We visually reviewed the remaining 261 episodes to select those which contained both intervals in which chest compressions and ventilations were applied alternatively (before intubation) and intervals in which they were applied simultaneously. We found 36 episodes that met this criterion and randomly selected half of them.

The mean duration of the selected episodes was 45 ± 18 min, and they contained 6057 ventilations, 2235 of them during CCs.

Five signal processing engineers independently annotated the position of the ventilations in each episode using a custom-developed graphical user interface. There was consensus for 95% of the annotations. A majority criterion was applied to the rest to obtain the annotations for reference. Episodes were randomly split into a training set to optimize the parameters of the ventilation detection method and a test set to evaluate its performance.

2.2. Impedance-based ventilation detection

Ventilations and CCs produce identifiable variations in the TI, slow and fast fluctuations, respectively. Fig. 1 shows a segment of a record that contains intervals with and without CCs. During compressions, force was applied in the chest of the patient (first panel), and fast fluctuations were induced in the TI (second panel). In this case, during the pauses in CCs (intervals in which the force was zero), the patient was ventilated, and slow fluctuations appeared in the TI. Each fluctuation is characterized by its maximum and its two adjacent minima (circled in red in the figure). The interval between the first minimum and the maximum and between the maximum and the second minimum represent the inspiration and the expiration time, respectively.

The ventilation detection method we proposed preprocessed the TI, identified fluctuations, characterized them by features of amplitude, duration and slope and classified them as ventilation or non-ventilation following a decision system based on thresholds. The next subsections describe each of these steps in depth.

2.2.1. Preprocessing of the TI signal

First, the TI was filtered using a 3rd-order Chebyshev low-pass filter with a cutoff frequency of 0.6 Hz, in order to minimize the effects of the CCs. Fig. 2 shows a segment
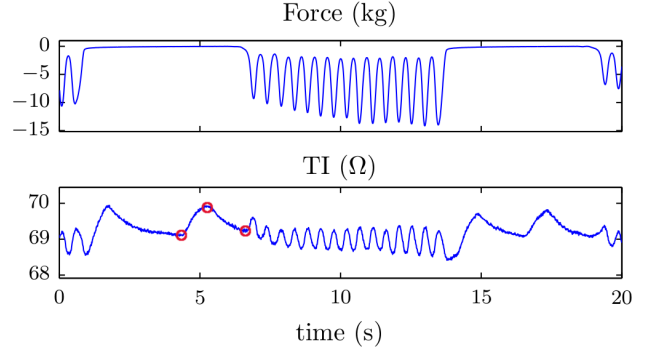

Figure 1. Fluctuations induced by CCs and ventilations in the TI.

of a record in which ventilations and CCs were applied simultaneously. In the original impedance (second panel), the fluctuations induced by ventilations and by CCs were overlapped. Preprocessing reduced the fluctuations caused by the CCs (third panel).

2.2.2. Fluctuation identification

Each ventilation interval was detected identifying the maximum and the two minima of each fluctuation as shown in Fig. 1.
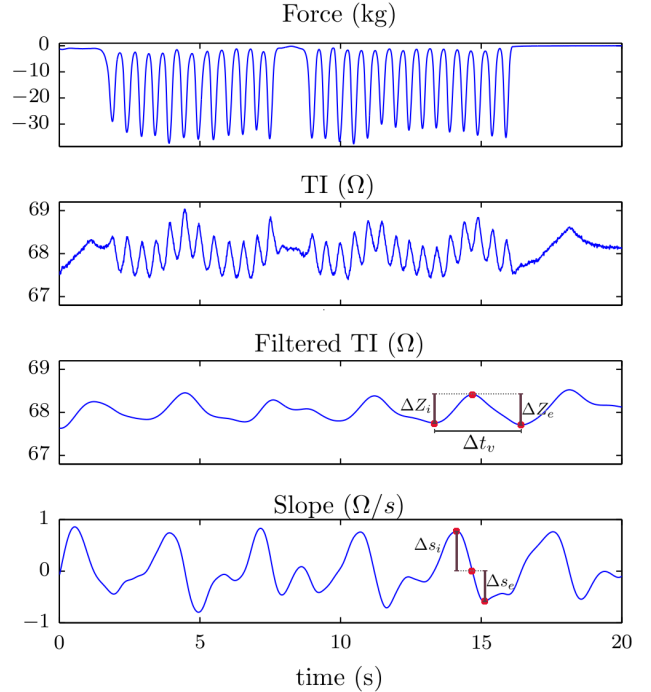

Figure 2. Effect of preprocessing in a segment where ventilations and CCs are overlapped. Features for the filtered TI and the slope signals are depicted.

2.2.3. Feature extraction

In this stage, every fluctuation was characterized by five features extracted from the TI and the slope signal, computed as its first difference. The features are depicted in Figure 2 and defined as follows:

- For the preprocessed TI signal:
  - ΔZ_i: Amplitude variation during inspiration time.
  - ΔZ_e: Amplitude variation during expiration time.
  - Δt_v: Ventilation duration, i.e., the addition of the inspiration and the expiration time.
- For the slope signal:
  - Δs_i: Amplitude variation during inspiration, i.e., the rising rate of the impedance.
  - Δs_e: Amplitude variation during expiration, i.e., the falling rate of the impedance.

2.2.4. Fluctuation classification

Finally, each fluctuation was classified as ventilation if the computed parameters were above certain thresholds. We applied a static threshold for the duration ($Th_{dur} = 1s$) and two dynamic thresholds for the TI amplitude (Th_{amp}), and for the slope parameters (Th_{slp}):

$$Th_{amp} = \min(\frac{a}{N} \sum_{k=1}^{N} \min(\Delta Z_{i,k}, \Delta Z_{e,k}), Th_{amp,max})$$

$$Th_{slp} = \min(\frac{s}{N} \sum_{k=1}^{N} \min(\Delta s_{i,k}, \Delta s_{e,k}), Th_{slp,max})$$

The dynamic thresholds started with the initial values Th_{amp0} and Th_{slp0}. For each detected ventilation, the thresholds were updated as a weighted average of the parameters of the N last ventilations, being a and s the weighting coefficients for the amplitude and the slope, respectively. $Th_{amp,max}$ and $Th_{slp,max}$ were the upper boundaries for the thresholds. We optimized the parameters with the training set to balance the percentage of annotated ventilations that were detected (sensitivity, Se) and the percentage of detected ventilations that were correct (positive predictive value, PPV), while maintaining a Se above 90%. The values we obtained were: $Th_{amp0} = 0.1$, $Th_{slp0} = 0.25$, $N = 5$, $a = 0.3$, $s = 0.4$, $Th_{amp,max} = 0.5$, and $Th_{slp,max} = 0.9$.

2.3. Performance evaluation

We evaluated the performance of the method in terms of Se and PPV. The maximum admissible tolerance for the position of the ventilations was 150 ms. We provide separate results for intervals before and after intubation, and for intervals with and without CCs.

3. Results

For the training set, the Se and PPV were 96% (95% confidence interval, CI, 95-97) and 96% (95-96), respectively. Table 1 summarizes the results for the whole test set and for intervals before and after intubation and with and without CCs. Results per episode varied between 95-100% (Se) and 88-100% (PPV).

Table 1. Se and PPV for the test set.

	Se (95% CI)	PPV (95% CI)
Whole test set	97% (96-97)	94% (94-95)
Before intubation	92% (89-95)	79% (75-83)
After intubation	97% (96-98)	97% (96-98)
Intervals with CCs	97% (95-97)	95% (94-96)
Intervals without CCs	97% (95-97)	94% (93-95)

Figure 3 shows a segment in which four ventilations, the first two provided during CCs, were correctly identified. The reference annotations are depicted with solid red lines in the first panel, and the detected ventilations with dotted lines in the second panel.
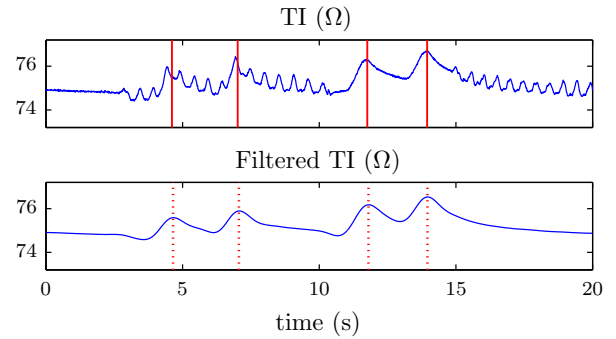

Figure 3. Four ventilations correctly identified.

In the segment shown in Fig. 4, one of the ventilations was not identified. In the filtered TI, the onset of the second CC interval masked the fluctuation induced by the ventilation, so the parameter ΔZ_e was too low to permit detection.

Fig. 5 shows an interval with two false detections. The onset and the offset of the CC interval altered the filtered TI and ventilations were wrongly identified.

4. Discussion and conclusions

We developed a simple but effective impedance-based automatic detection system that identified 97% of the annotated ventilations with a PPV of 94%. Our focus in this work was simplicity, so we preprocessed the
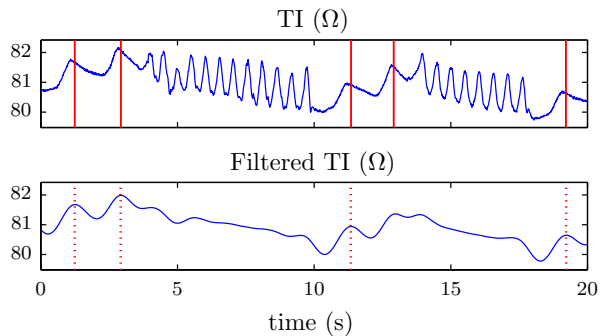
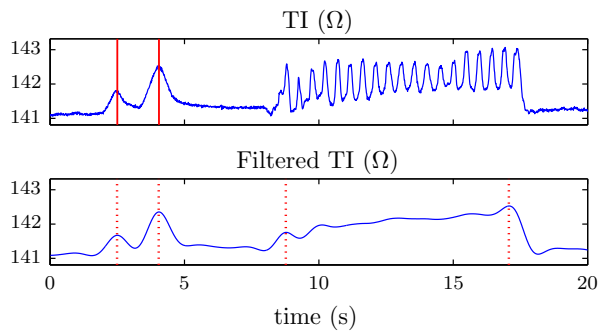Figure 4. Example of a missed ventilation.

Figure 5. Example of false detections.

impedance with a single fixed-coefficients filter and identified the ventilation instants. This information is sufficient to calculate the number of ventilations delivered per minute, which is the ventilation-related parameter that Kramer-Johansen et al. recommend to report CPR quality [8]. The method we propose could be implemented in current AED for ventilation rate feedback without requiring additional devices, although a good quality TI signal is required.

Due to adaptive thresholding, our method performed similarly for intervals with and without CCs. However, we obtained worse scores before than after intubation. The ventilation/CC alternation complicated the detection, because the onset/offset of the CC intervals altered the filtered TI signal, as shown in Fig. 4 and Fig. 5.

Other more complex methods have been proposed to detect not only the instants of ventilations, but also the onsets and offsets. Risdal et al. [6] proposed a pattern-recognition based system with an adaptive filtering scheme using several reference signals. They reported 90% Se and 96% PPV with a larger set of episodes extracted from the same original database.

To validate the results of this work, the method should be tested with more episodes, ideally containing independent data for ventilation annotation such as spirometry-capnography measurements.

Acknowledgements

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