Suppression of the Respiration Artefact and Extraction of the Cardiac Component in the Thoracic Impedance Recorded Through Defibrillation Pads

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Abstract

Circulation detection by checking the carotid pulse in cardiac arrest patients during cardiopulmonary resuscitation (CPR) has been reported inaccurate. Thoracic impedance (TI) measured via the defibrillator pads has been recently proposed for the assessment of circulation during CPR. However, ventilation artefacts severely corrupt and spectrally overlap the cardiac component of the TI. This study proposes an adaptive scheme to suppress respiration artefacts and extract the circulation component from the TI recorded through the defibrillation pads.

The database consisted of 12 records from hemodynamically stable volunteers including the TI and the ECG. Each record contained intervals without respiration and intervals with 5 respiration rates.

R-R intervals detected in the ECG were used to estimate the instantaneous frequency of the cardiac component of the TI. An adaptive scheme was applied to estimate the amplitude and phase of the three-harmonic model of the cardiac component.

The method was evaluated in terms of signal-to-noise ratio (SNR) improvement, and in terms of the normalized cross correlation coefficient of the circulation components obtained during respiration and in artefact-free intervals.

1. Introduction

Recognition of cardiac arrest is essential in resuscitation scenarios. Manual carotid pulse checking is the most extended method to detect presence of pulse, but it has been proved to be both inaccurate and time-consuming [1]. Eberle et al. [1] reported a sensitivity and specificity of 90% and 55% respectively, defining sensitivity as the capacity to correctly identify absence of pulse and specificity as the capacity to correctly identify presence of pulse. More accurate methods are highly required to be integrated in the basic life assistance of patients in cardiac arrest.

Transthoracic-impedance plethysmography has been used as a non-invasive measure of stroke volume and cardiac output [2, 3]. Thoracic impedance (TI) measured through automated external defibrillator (AED) pads have been recently proposed as a potential hemodynamical sensor during cardiopulmonary resuscitation (CPR) [4, 5]. Variations of the TI reflect information about the blood circulation, which may be used to provide the rescuer with feedback to improve CPR quality. Nevertheless, the small cardiac component of the TI is highly corrupted by the artefacts due to ventilations during CPR. There is severe spectral overlap between both components which makes the decomposition of the signal and therefore, the extraction of circulatory component difficult.

In this study we propose an adaptive scheme to suppress respiration artefacts and extract the circulation component from the TI recorded through the defibrillation pads. It was adjusted and tested with hemodynamically stable volunteers. A very preliminar evaluation was also performed with real cardiac arrest episodes corrupted by ventilation artefacts.

2. Materials

The dataset used in this study was acquired from 8 hemodynamically stable volunteers. It consisted of 12 records composed by ECG and TI signals with a duration of 360 s. Both were recorded through standard defibrillator pads (DP Electrode Pads, Philips Medical Systems, Seattle, WA, USA) using a sampling rate of 250 Hz. An ECG amplifier (ECG100C, Biopac Systems Inc., Santa Barbara, CA, USA) and an electrobioimpedance amplifier (EBI100C, Biopac Systems Inc., Santa Barbara, CA, USA) were used.

Each record was composed by 5 intervals and each interval was divided into 2 subintervals: the first 60 s corrupted with respirations at a specific respiration rate, followed by a 12 s artefact-free subinterval without respirations. Respiration rates recommended by current resuscitation guidelines were considered in successive intervals [6]: 9, 12, 15, 18 and 21 respirations/min. Fig. 1 shows an example of the ECG and TI recorded through AED defibrillation pads corresponding to the rate of 15 respirations/min.

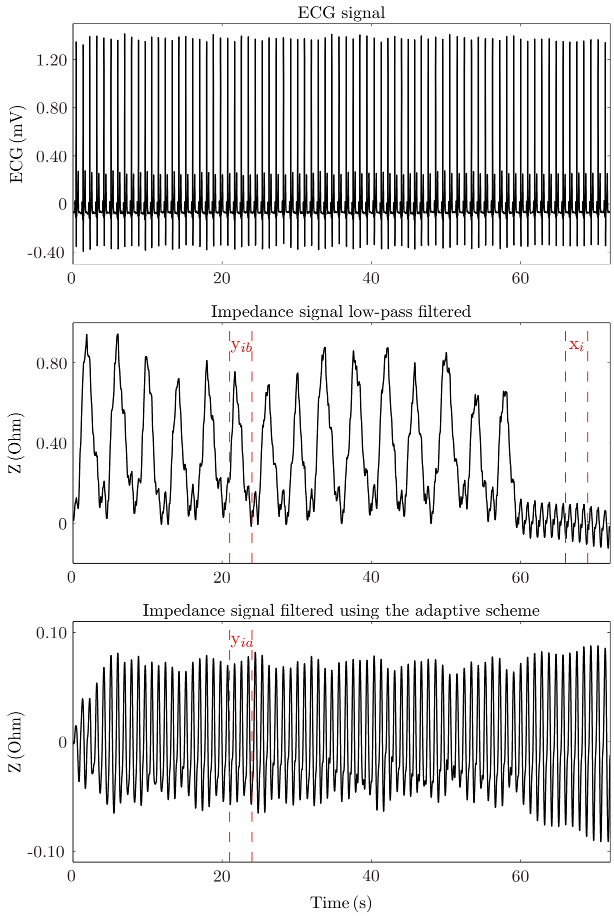

Figure 1. First plot shows the preprocessed ECG signal. The second and third plots show the TI signal low-pass and adaptively filtered respectively.

3. Methods

3.1. Extraction of the circulation component

The ECG signal was preprocessed using an eight-order Butterworth band-pass filter (0.5-30 Hz) and a RR detector applied to detect the instants of the R waves and compute the mean cardiac frequency (f_c). The TI was first low-pass filtered to 7 Hz with a five-order Chebyshev filter to remove high frequency noise. Then, it was high-pass filtered with a five-order Chebyshev filter with a cutoff frequency adjusted to $f_c - 0.1$ Hz in order to reduce respiration artefacts. Furthermore, the TI was adaptively filtered using an adaptive scheme [7] which uses the R instants as reference signal aiming to extract the circulation component. Basically, the circulation component was modelled as a nearly periodic signal using three harmonics of slowly changing amplitude and phase. The amplitude and phase of each harmonic were estimated by the adaptive scheme, which is based on the LMS algorithm [8] and tracks the evolution of the spectral composition of the circulation component. The fundamental frequency of the model of the circulation component was the instantaneous cardiac frequency computed from the R instants.

3.2. Evaluation

The respiration artefact suppression method was evaluated in terms of cardiac component signal to respiration noise ratio (SNR) improvement, and in terms of the normalized cross correlation coefficient. This assessment was carried out for each interval of the record.

The SNR improvement was computed as the difference between the SNR of the TI after, SNR$_a$, and before the adaptive filtering, SNR$_b$, as shown in 1, for each respiration rate of the record.

$$SNR = SNR_a - SNR_b \tag{1}$$

The cross correlation coefficients (ρ) between 3 s template of the clean interval, x$_i$, and the corresponding corrupted intervals, y$_i$, (see Fig. 1) were computed before (y$_{ib}$) and after (y$_{ia}$) adaptive filtering along the complete record applying: (2).

$$\rho = max(abs(\frac{\hat{R}_{xy}}{\sqrt{P_x \cdot P_y}})) \tag{2}$$

where P_x and P_y were the estimated mean power of N samples of x$_i$ and y$_i$ respectively. $\hat{R}_{xy}$ represents all the positive samples ($m \geq 0$) of the cross correlation calculated as follows:

$$\hat{R}_{xy}[m] = \frac{1}{N} \sum_{n=0}^{N-m-1} x[n+m] \cdot y^*[n] \qquad m \geq 0 \tag{3}$$

Fig. 2 shows the normalized cross correlation coefficient for the set of five respiration rates of a record.

As a very preliminary try, the method was also tested with the TI recorded in real cardiac arrest episodes during ventilations. Samples of pulsed and pulseless rhythms were considered to visually inspect the cardiac component extracted from the TI.

4. Results

Fig. 3 shows the mean SNR improvement per interval for the whole database. The central mark of each box represents the median value, and the edges depict 25th and 75th percentiles.

Table 1 summarizes the SNR improvement per ventilation rate as median and 25th-75th percentiles. The

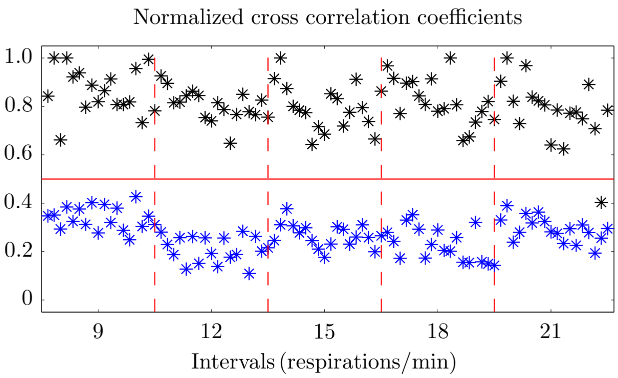

Figure 2. Example of the normalized cross correlation coefficients extracted from a record before (blue) and after the adaptive filter (black).

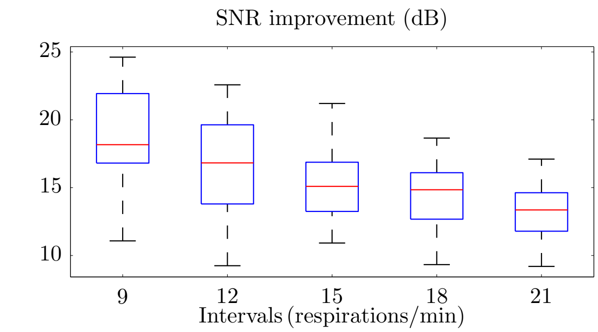

Figure 3. Box plots for SNR improvement per ventilation rate. On each box the median, and the 25^{th} and 75^{th} percentiles are depicted.

mean±std of the normalized cross correlation coefficients before (ρ_b) and after adaptive filtering (ρ_a) are also shown.

On the one hand, panel a of Fig. 4 shows an example of a real out-of-hospital record in which the underlying rhythm is a PR (Pulse given Rhythm). The method described above was applied in order to suppress the ventilation artefacts. The extracted cardiac component of the TI can be observed in the third plot of the figure. Amplitude variations linked to the pulse-generating heartbeats are evident.

On the other hand, panel b of Fig. 4 shows an example of PEA (Pulseless Electrical Activity) where the extracted circulation component denotes lower amplitude changes with each heartbeat than in the PR case.

Table 1. Summary of the results obtained in the evaluation of the method. The SNR is expressed as median (25-75 percentiles) and the normalized cross correlation coefficients as mean±std.

Ventilation rate (respiration/min)	SNR (dB)	ρ	
		ρ_b	ρ_a
9	18(17-22)	0.41±0.13	0.81±0.14
12	17(14-20)	0.35±0.14	0.79±0.18
15	15(13-17)	0.43±0.12	0.81±0.12
18	15(13-16)	0.40±0.14	0.80±0.13
21	13(12-15)	0.35±0.14	0.79±0.15

5. Discussion and conclusions

In this study we assessed the feasibility of suppressing the respiration artefacts and extracting the circulation component of the TI recorded through standard defibrillation pads. We used an adaptive filtering scheme based on modelling the cardiac component as a signal with three harmonics of the instantaneous frequency extracted from the ECG with the instantaneous time-varying amplitude and phase adaptively estimated using an LMS algorithm.

The method was adjusted and tested with records from hemodynamically stable volunteers. It was evaluated in terms of SNR improvement and normalized cross correlation coefficient before and after the adaptive removal of respiration artefacts. Up to five respiration rates were considered and a mean improvement of 16 dB was obtained.

The artefact suppressing scheme was applied to real cardiac arrest episodes with ventilation artefacts. The cardiac component extracted from the TI permitted to visually discriminate pulsed from pulseless rhythms.

In this study an effective method was proposed to extract the circulation component of the TI recorded through the defibrillation pads. Satisfactory results were reported with hemodynamically stable volunteers and evidence for pulse detection purposes in real cardiac arrest episodes. Current AEDs record the TI signal as well as the ECG signal. This method could be integrated in an AED to detect presence of pulse in basic life support.

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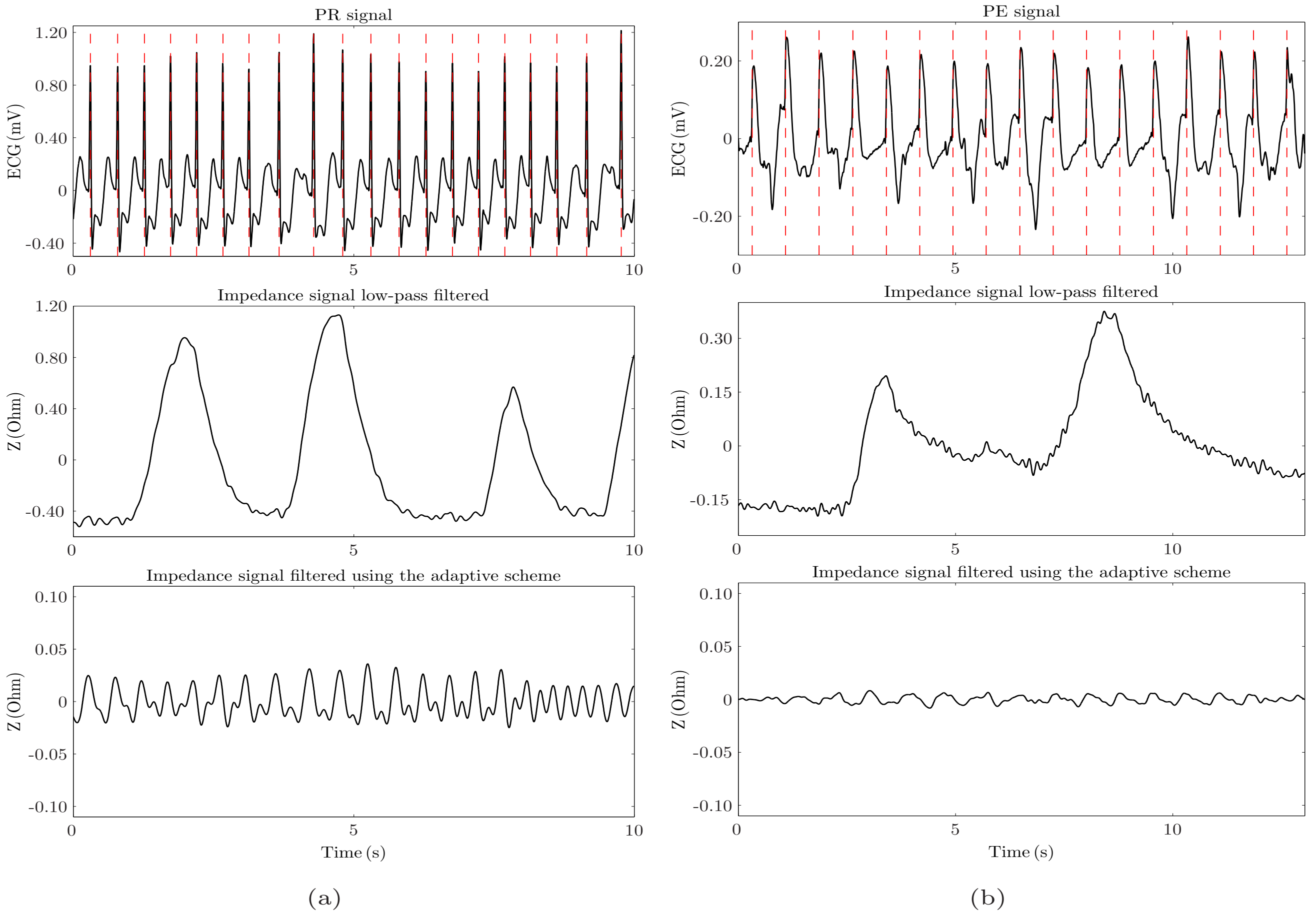

Figure 4. Example of PR (a) and PEA (b) signals where the first plot represents the preprocessed ECG signal. The second and third plots show the TI signal low-pass and adaptively filtered respectively.

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