Empirical Mode Decomposition for Chest Compression and Ventilation Detection in Cardiac Arrest

Erik Alonso[1], Elisabete Aramendi[1], Digna González-Otero[1], Unai Ayala[1], Mohamud Daya[2], James K. Russell[3]

[1] University of the Basque Country UPV/EHU, Bilbao, Spain
[2] Oregon Health & Science University, Portland, United States
[3] Philips Healthcare, Seattle, United States

Abstract

The thoracic impedance (TI) signal, which reflects fluctuations due to CCs and ventilations, has been suggested as a surrogate to compute CC–rate and ventilation–rate during cardiopulmonary resuscitation. This study developed a method based on empirical mode decomposition (EMD) to compute CC–rate and ventilation–rate using exclusively the TI. Twenty out-of-hospital cardiac arrest episodes containing the TI, compression depth (gold standard for CC–rate), and capnography (gold standard for ventilation–rate) signals were used. The EMD decomposed the TI signal into intrinsic mode functions (IMFs). IMFs were combined based on their median instantaneous frequency to reconstruct separately the CC–signal and the ventilation–signal. Independent CC and ventilation detectors were used based on fixed thresholds for durations and dynamic thresholds for the amplitudes of the fluctuations. Sensitivity and positive predictive value (PPV) for each detector were 99.35%/98.75% and 93.21%/82.40%. CC–rate and ventilation–rate were computed based on instants of CCs and ventilations respectively. When comparing detected rates with rates obtained from the gold standards, the mean (SD) errors were 0.57 (0.55) min^{-1} and 1.10 (1.19) min^{-1} for CC–rate and ventilation–rate respectively. We concluded that CC–rate and ventilation–rate can be accurately estimated applying EMD to the TI.

1. Introduction

The 2010 resuscitation guidelines strongly recommend providing high quality cardiopulmonary resuscitation (CPR) which includes chest compressions (CCs) provided at a rate of at least 100 compressions per min (cpm) and ventilations delivered one every 6–8 s, or at a rate of about 8–10 breaths per minute [1].

It has been reported that the number of patients achieving return of spontaneous circulation decreases as CC–rate decreases, and that too high compression rates may reduce coronary blood flow [2, 3] and decrease the number of compressions with adequate depth [4, 5]. Excessive ventilation, either by rate or tidal volume, is common during resuscitation and it is associated with poorer outcomes of cardiac arrest [6]. Consequently, review software tools have been created to measure the quality of the performed CPR and thus, help improve CPR metrics. These software tools usually require the automated external defibrillators (AEDs) to be equipped with additional hardware such as accelerometers or force sensors, which are relatively expensive accessories for widespread use. Therefore, current commercial AEDs only record the electrocardiogram (ECG) and thoracic impedance (TI) signals through the defibrillation pads. The TI signal is acquired by injecting a sinusoidal current between pads and measuring the resulting voltage. The TI shows fluctuations due to CCs and ventilations (see Fig. 1), and noise components. These fluctuations can be identified and used to compute CC–rates and ventilation–rates. The objective of the current study is, therefore, to develop a method based on the empirical mode decomposition (EMD) of the TI signal to extract both the CC–signal and ventilation–signal, and to compute CC–rates and ventilation–rates in out-of-hospital cardiac arrest (OHCA) episodes.

2. Materials

A convenience sample of 20 OHCA episodes with complete CPR process files were extracted from a large cardiac arrest registry maintained by Tualatin Valley Fire & Rescue (Tigard, Oregon). The files were collected using the Philips HeartStart MRx monitor/defibrillator between 2006 and 2009. Each episode contained concurrent TI, compression depth (CD) and capnography signals. The TI signal (resolution 0.74 $m\Omega$ per least significant bit with 0–80 Hz bandwidth and a sampling rate of 200 Hz) recorded through defibrillation pads by apply-

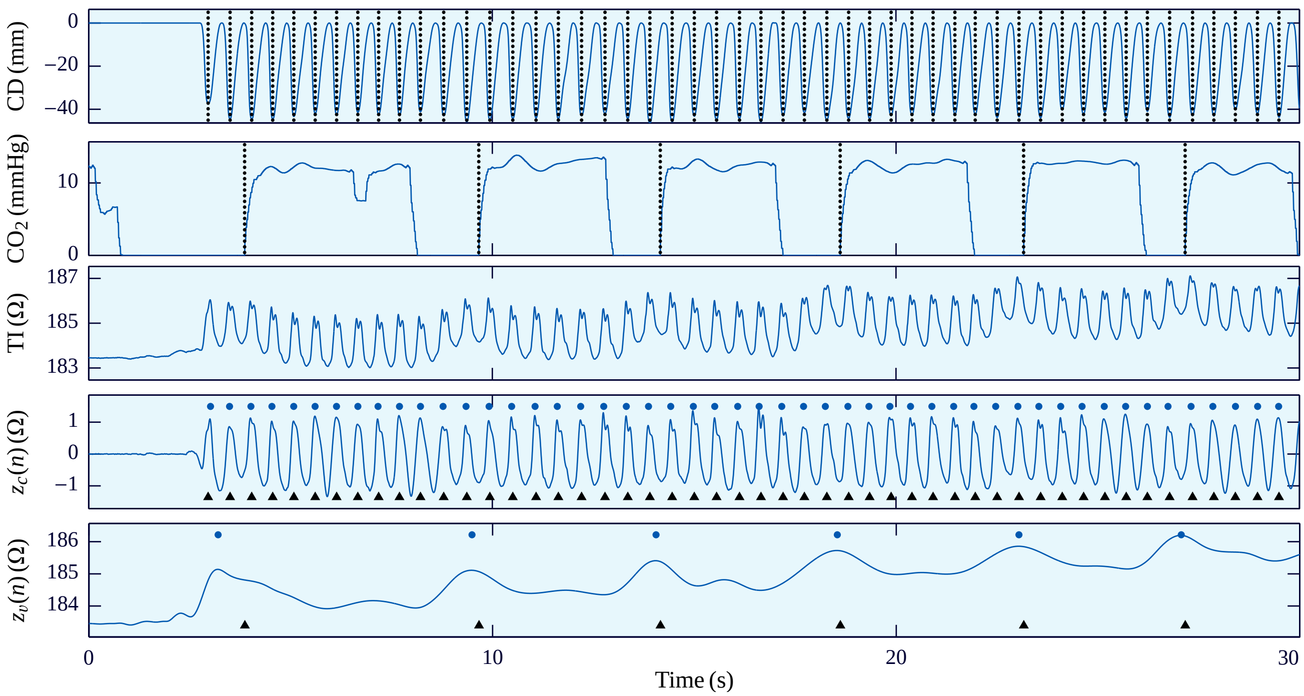

Figure 1. A 30 s segment extracted from an OHCA episode of the dataset analyzed in the study. From top to bottom, the CD, capnography, TI, $z_c(n)$ and $z_v(n)$ signals can be observed. The TI shows rapid fluctuations correlating with the CCs in the CD signal, and slow fluctuations due to ventilations correlating with the upstrokes of the capnography. The black dotted lines represent instants of the compressions and ventilations in the gold standards (CD and capnography respectively). Blue dots in $z_c(n)$ and $z_v(n)$ depict the instants of the detected instants of CCs and ventilations respectively, while black triangles represent the instants of CCs in $z_c(n)$ and instants of ventilations in $z_v(n)$ extracted from the gold standards.

ing a sinusoidal excitation current (32 kHz, 3 mA peak to peak), the CD signal computed from the force and acceleration signals recorded through the CPR assist pad (sampling rate 250 Hz), and the capnography signal acquired using Microstream (sidestream acquisition with a sampling rate of 40 Hz and a resolution of 0.004 mmHg per bit). Fig. 1 shows an example of the signals of interest. The mean (standard deviation, SD) duration of the episode was 88.85 (46.59) s with a mean of 139 (75) compressions and 11 (5) ventilations per episode. A total duration of 1777 s, including 2781 CCs and 221 ventilations, were analyzed.

3. Methods

3.1. Empirical mode decomposition

The EMD was first proposed by Huang et al. [7] as a signal decomposition algorithm based on a consecutive removal of the elemental signals called intrinsic mode functions (IMFs). Basically, an IMF represents the oscillation mode embedded in the signal, and it meets two requirements: (1) the number of extrema and zero crossings must be either equal or differ by one, and (2) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. For any signal, $x(t)$ the IMFs are found by the sifting algorithm which consists of an iterative procedure with the following steps:

1. Find all local maxima and minima.
2. All the local maxima are connected by a cubic spline as the upper envelope, $M(t)$, and the same procedure is followed with the local minima to compute lower envelope, $m(t)$.
3. The mean of the envelopes is calculated as $e(t) = (M(t) - m(t))/2$
4. $e(t)$ is subtracted from the signal: $x(t) = x(t) - e(t)$
5. Return to step 1, or stop if $x(t)$ remains nearly unchanged, i.e. if the standard deviation between $x(t)$ and $x(t) - e(t)$ is below 0.3 [7].
6. An IMF is obtained, $\varphi(t)$, then remove it from the signal, $x(t) = x(t) - \varphi(t)$, and return to 1 if $x(t)$ has more than one extremum (neither a constant nor a trend).
7. If $x(t)$ does not have more than one extremum, then the residue, $r(t)$, is left.

For each episode, the median instantaneous frequency of each IMF was calculated as the median value of in-

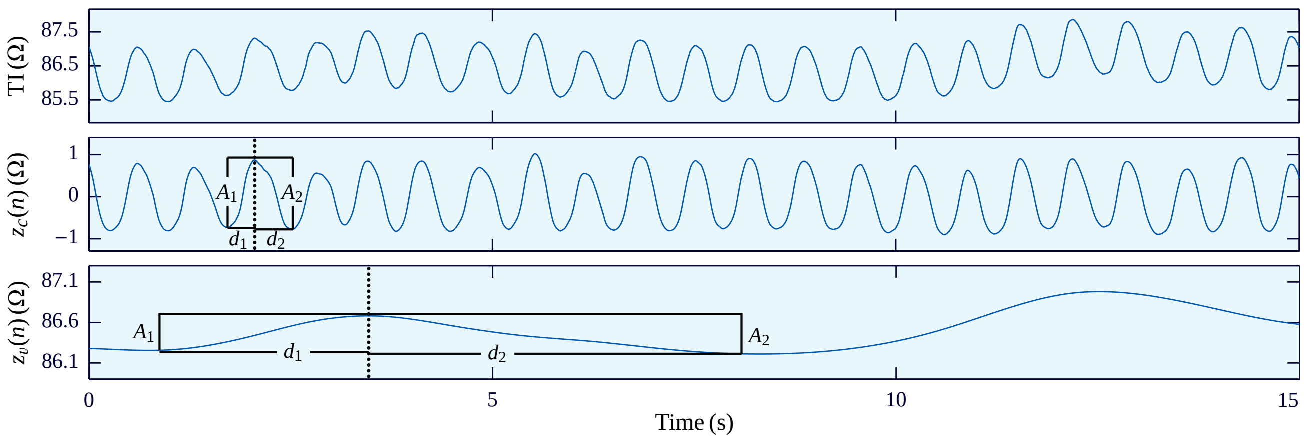

Figure 2. A 15 s segment extracted from an OHCA episode of the dataset analyzed in the study. From top to bottom, the TI, $z_c(n)$ and $z_v(n)$ signals can be observed. The four features extracted for each local maxima detected in $z_c(n)$ and $z_v(n)$ are depicted.

verse of the time interval between fluctuations. Those IMFs with a median instantaneous frequency below 0.6 Hz were combined and added to $r(t)$ in order to compose the ventilation–signal, $z_v(n)$. Those IMFs with a median frequency between 0.6–15 Hz were combined to obtain the compression–signal, $z_c(n)$. IMFs with a median instantaneous frequency above 15 Hz were not considered as they had little information to provide, mostly, related to high frequency noise.

3.2. Feature extraction

The $z_c(n)$ and $z_v(n)$ signals were independently analyzed to identify the instants of the local maxima which might be potential CCs or ventilations respectively. For each local maximum, the next features were extracted:

- A_1: The trough-to-peak amplitude of the fluctuation.
- A_2: The peak-to-trough amplitude of the fluctuation.
- d_1: Duration of the trough-to-peak rise.
- d_2: Duration of the peak-to-trough fall.

Fig. 2 shows an example of the features extracted from both $z_c(n)$ and $z_v(n)$.

3.3. Compression detector

The CC–detector identified local maxima in $z_c(n)$ corresponding to chest compressions. The detector assessed the duration of the fluctuation ($d_1 + d_2$) against a static threshold and the mean amplitude, mean value of A_1 and A_2, against a dynamic threshold. The weighted average of the mean amplitude of the last detected CCs (a maximum of 6) was used as the dynamic threshold. If the duration and amplitude of the fluctuation were above the static and dynamic thresholds respectively, the fluctuation was considered as CC. A refractory time was established to avoid false positive detections due to second and third harmonics of the fluctuations. More details of the CC–detector are given in [8].

3.4. Ventilation detector

The ventilation detector identified the local maxima in $z_v(n)$ corresponding to ventilations. The detector evaluated the inflation time (d_1) against a static threshold and the inflation amplitude, A_1, against a dynamic threshold. The weighted average of the minimum amplitude of the last detected ventilations (a maximum of 5) was used as the dynamic threshold. If the inflation time and amplitude were above the static and dynamic thresholds respectively, the fluctuation was considered as ventilation. A refractory time was established to avoid false positive detections. More details of the ventilation detector are given in [8].

3.5. Evaluation

The accuracy of the methods to detect CCs and ventilations were evaluated in terms of sensitivity and positive predictive value (PPV). Sensitivity was defined as the percentage of CCs/ventilations correctly detected, and PPV as the percentage of detected CCs/ventilations corresponding to real CCs/ventilations. The instants of CCs and ventilations were used to compute the mean CC–rate and mean ventilation–rate for each episode as the inverse of the median interval between instants of CCs and ventilations respectively. The mean rates were compared with those computed from the gold standards in order to compute the errors. The CD and capnography signals were accepted as gold standards for CCs and ventilations respectively. The instants of CCs/ventilations were manually annotated in the gold standards.

4. Results

Fig. 1 illustrates a 30 s segment of an episode of the database. The original TI signal, and the reconstructed compression–signal, $z_c(n)$, and ventilation–signal, $z_v(n)$, can be observed. The performance of the ventilation and compression detector is also shown. Blue dots depict the instants of compressions/ventilations detected by the compression/ventilation detector in $z_c(n)$/$z_c(n)$. Whereas the black triangles represent the gold standard for compressions/ventilations in $z_c(n)$/$z_c(n)$. In this case, all ventilations and compressions are correctly detected.

Compression and ventilation detectors showed a sensitivity/PPV of 99.35%/98.75% and 93.21%/82.40%, respectively. Mean (SD) errors of $0.57\,(0.55)\,\mathrm{min}^{-1}$ and $1.10\,(1.19)\,\mathrm{min}^{-1}$ were reported for CC–rate and ventilation–rate respectively when they were compared with those computed from the gold standard.

5. Discussion and conclusions

In this study we proposed a new methodology based on EMD to separate the compression–signal and ventilation–signal extracted from the TI signal. A chest compression detector and a ventilation detector were independently applied to the compression signal, $z_c(n)$, and the ventilation signal, $z_v(n)$, to later compute CC and ventilation rates based on the instants of the detected compressions and ventilations. The compression detector showed a great performance, while the sensitivity/PPV and mean error values obtained for the ventilation detector were quite good and similar to those reported by other authors [8, 9]. The capnography used as gold standard for ventilation detection sometimes presents artifacts due to chest compressions and other factors that make the identification of ventilations difficult. Other gold standards, as the volume or flow signals obtained through mainstream capnography, would permit a more rigorous evaluation of the ventilation detector.

We conclude that the EMD can be used to accurately decompose the TI signal into compression and ventilation signals that permit to compute CPR metrics in debriefing of cardiac arrest episodes.

Acknowledgements

This work received financial support from the Spanish Government (projects TEC2012-31928 and TEC2012-31144), from the Basque Government (grants BFI-2010-174, BFI-2010-235 and BFI-2011-166) and from the UPV/EHU (unit UFI11/16).

References

[1] Berg RA, Hemphill R, Abella BS, Aufderheide TP, Cave DM, Hazinski MF, Lerner EB, Rea TD, Sayre MR, Swor RA. Part 5: adult basic life support: 2010 american heart association guidelines for cardiopulmonary resuscitation and emergency cardiovascular care. Circulation November 2010; 122(18 Suppl 3):S685–705.

[2] Abella BS, Sandbo N, Vassilatos P, Alvarado JP, O'Hearn N, Wigder HN, Hoffman P, Tynus K, Vanden Hoek TL, Becker LB. Chest compression rates during cardiopulmonary resuscitation are suboptimal: a prospective study during in-hospital cardiac arrest. Circulation February 2005; 111(4):428–434.

[3] Wolfe JA, Maier GW, Newton JR, Glower DD, Tyson GS, Spratt JA, Rankin JS, Olsen CO. Physiologic determinants of coronary blood flow during external cardiac massage. The Journal of Thoracic and Cardiovascular Surgery March 1988; 95(3):523–532.

[4] Stiell IG, Brown SP, Christenson J, Cheskes S, Nichol G, Powell J, Bigham B, Morrison LJ, Larsen J, Hess E, Vaillancourt C, Davis DP, Callaway CW, Resuscitation Outcomes Consortium (ROC) Investigators. What is the role of chest compression depth during out-of-hospital cardiac arrest resuscitation? Critical Care Medicine April 2012;40(4):1192–1198.

[5] Monsieurs KG, De Regge M, Vansteelandt K, De Smet J, Annaert E, Lemoyne S, Kalmar AF, Calle PA. Excessive chest compression rate is associated with insufficient compression depth in prehospital cardiac arrest. Resuscitation November 2012;83(11):1319–1323. ISSN 1873-1570.

[6] O'Neill JF, Deakin CD. Do we hyperventilate cardiac arrest patients? Resuscitation April 2007;73(1):82–85.

[7] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH. The empirical mode decomposition and the hilbert spectrum for nonlinear and nonstationary time series analysis. Proceedings of the Royal Society of London Series A Mathematical Physical and Engineering Sciences August 1998;454(1971):903–995.

[8] Alonso E, Ruiz J, Aramendi E, González-Otero D, Ruiz de Gauna S, Ayala U, Russell JK, Daya M. Reliability and accuracy of the thoracic impedance signal for measuring cardiopulmonary resuscitation quality metrics. Resuscitation August 2014;Under review.

[9] Edelson DP, Eilevstjønn J, Weidman EK, Retzer E, Hoek TLV, Abella BS. Capnography and chest-wall impedance algorithms for ventilation detection during cardiopulmonary resuscitation. Resuscitation March 2010;81(3):317–322.

Address for correspondence:

Erik Alonso
Department of Communications Engineering
Alameda Urquijo, s/n 48013 Bilbao Spain
E-mail address: erik_alonso@ehu.es