Study on the Linear Relation Between Chest Compression Depth and the Fluctuation Caused in the Thoracic Impedance Acquired by Defibrillation Pads

Erik Alonso[1], Digna González-Otero[1], Elisabete Aramendi[1], Sofía Ruiz de Gauna[1], Jesús Ruiz[1], Unai Ayala[1], James K Russell[2]

[1] University of the Basque Country UPV/EHU, Bilbao, Spain
[2] Philips Healthcare, Seattle, United States

Abstract

The thoracic impedance (TI) signal, available in current automated external defibrillators, has been proposed as an indicator of the compression depth (CD) in animal models of cardiac arrest. This study analysed the linear relationship between the maximum CD and the fluctuation caused in the TI in 19 out-of-hospital cardiac arrest episodes. The mean of the CD maxima, D_{max}, and the mean peak-to-peak fluctuation, Z_{pp}, were computed for every 5 s from the CD and TI signals, respectively. Three analyses were performed: distributions of D_{max} and Z_{pp} in all episodes, linear relation between D_{max} and Z_{pp} (correlation coefficient for every episode, R_e, and for the complete dataset, R_c) and time evolution of the correlation coefficient, R_i, for three consecutive intervals along every episode. Median ($25^{th} - 75^{th}$ percentiles) for Z_{pp} were 1.12 (0.78 - 1.48), 1.35 (0.94 - 1.89) and 1.67 (1.09 - 2.33) Ω for D_{max} <38, 38≤ D_{max} ≤51 (optimal compressions), and D_{max} >51 mm respectively. High overlap between the three distributions was observed. R_e varied between 0.04-0.83 (median=0.34), and R_c was 0.27. Time evolution of R_i did not show any tendency. R_i varied between 0.06-0.94 (median=0.52). Linearity between D_{max} and Z_{pp} showed high variability between episodes in humans. The correlation coefficient for the complete dataset was low.

1. Introduction

Quality of chest compressions (CC) during cardiopulmonary resuscitation (CPR) is a major determinant of cardiac arrest outcome. High quality CC are associated with better outcomes in both animals and humans [1]. The quality of CC is evaluated using CPR quality parameters such as compression rate, depth and full chest recoil [2].

Resuscitation guidelines recommend that CC should be applied with an adequate depth [3]. Nevertheless, several studies show that shallow CC are common during cardiac arrest [4]. Consequently, mechanisms for real-time CPR feedback have been incorporated into automated external defibrillators (AEDs). Accelerometers and force sensors have been used in order to measure CPR quality parameters such as rate and depth of the compressions. These mechanisms require important hardware modification in existing AEDs. By contrast, thoracic impedance (TI) signal is available in current commercial AEDs together with ECG signal. The TI signal is acquired through standard defibrillation pads by passing an alternating current between electrodes and measuring the resulting voltage. As the TI shows fluctuations due to CC, it has been used to compute instants of compressions [5], instantaneous compression rate [6] and interruptions in compressions [7]. However, no relationship between the TI and the compression depth (CD) has been established so far.

In a recent clinical study with animals in cardiac arrest, Zhang et al. reported a strong correlation between CD and the fluctuations caused by CC in the TI [8]. Therefore, the aim of this study was to analyse to which extent linear relationship between CD and TI fluctuations could be applicable to a human model with out-of-hospital cardiac arrest (OHCA) episodes. The study also pretended to analyse the viability of identifying compressions with adequate depth in an OHCA scenario using exclusively the TI signal.

2. Materials

A convenience sample of 19 OHCA 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. In every episode between two and six rescuers performed the CPR. Each episode was extracted containing two signals: the TI signal (resolution 0.74 $\mathrm{m\Omega}$ per least significant bit with 0-80 Hz bandwidth) recorded through defibrillation pads by applying a sinusoidal excitation current (32 kHz, 3 mA peak to peak), and the CD signal computed from the force and acceleration signals recorded through the CPR assist pad. Fig. 1 shows an example. Mean du-

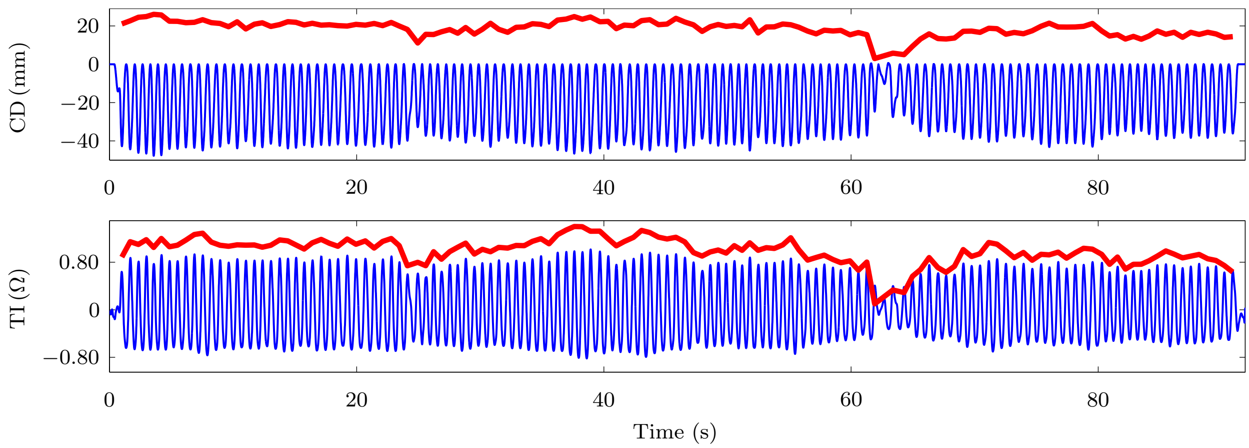

Figure 1. CD and TI signals for an interval of an episode of the dataset. The evolution of parameters D_{max} and Z_{pp} are traced on the plots. This example shows a good correlation between two parameters.

ration of the episodes was 2215±556 s, with 2162±831 compressions per episode with 42.77±1.36 mm depth. The complete dataset contained a total of 41078 compressions.

3. Methods

3.1. Processing of CD and TI signals

A negative peak detector with a static threshold of 15 mm was used to automatically detect the instant, t_i, of maximum depth in each compression. The compression interval signal, $x_i[n]$, corresponding to the i^{th} compression was marked in the TI signal between $t_i - D$ and $t_i + D$, where D is half of the time-difference between i^{th} and $(i+1)^{th}$ compressions. Every t_i was matched with its corresponding $x_i[n]$ in the TI signal. The matching process was visually inspected and if needed, manually corrected in order to avoid errors due to delays between the CD and the TI signals.

The TI signal was preprocessed to obtain $z_{\text{p}}[n]$. It was downsampled to 100 Hz and, band-pass filtered between 0.6-7 Hz (order 6 Chebyshev filter with 0.1 dB of peak-to-peak ripple in the passband) in order to remove the baseline drift, the fluctuations caused by ventilations and high frequency noise. To characterize the fluctuations caused by CC, the peak-to-peak amplitude, Z_{pp}, was computed for every $z_{\text{pi}}[n]$ which represents the corresponding $x_i[n]$ in the $z_{\text{p}}[n]$ as shown in Fig. 2. Z_{ppi} corresponds to the peak-to-peak amplitude of the fluctuation for the i^{th} compression and was defined as follows:

$$Z_{\text{ppi}} = \max_i - \min_i \tag{1}$$

where $\max_i$ denotes the maximum positive peak and $\min_i$ the minimum negative peak after the $\max_i$ within $z_{\text{pi}}[n]$ (see Fig. 2).

Taking into consideration the procedure followed by Zhang et al. [8], every 5 s both the mean values of the CD maxima, D_{max}, and the mean values of the peak-to-peak fluctuation, Z_{pp}, were computed from the CD signal and $z_{\text{p}}[n]$, respectively. Evolution of D_{max} and Z_{pp} values for an interval of episode are traced in Fig. 1.

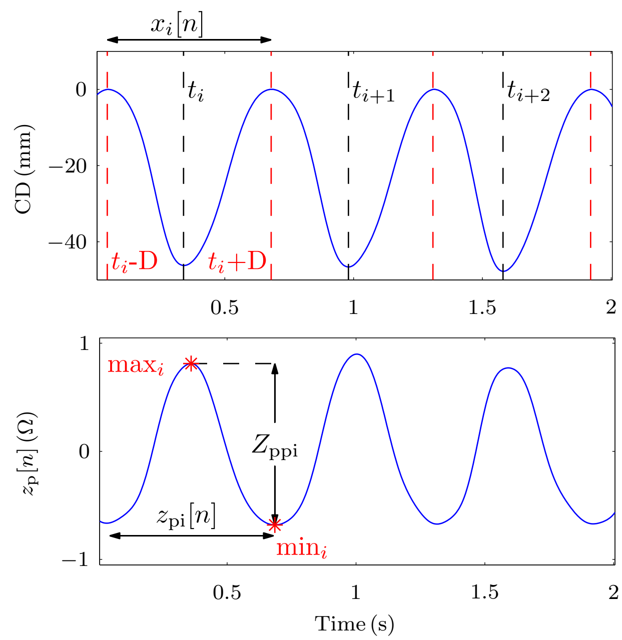

Figure 2. CD and $z_{\text{p}}[n]$ signals for an interval of an episode of the dataset. $x_i[n]$, $z_{\text{pi}}[n]$ and Z_{ppi} are depicted in the plot.

3.2. Analysis of distributions

D_{max} and Z_{pp} were individually tested using the one sample Kolmogorov-Smirnov test to analyse if they come

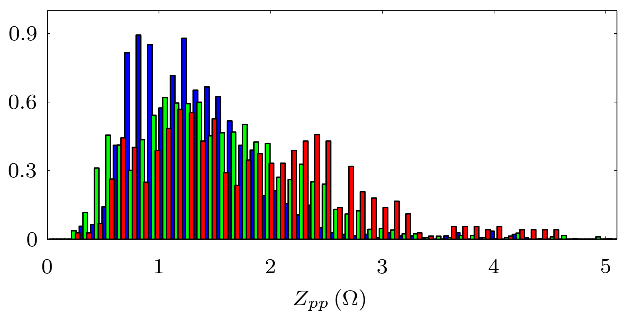

Figure 3. Distributions of Z_{pp} for the three different groups of CC: shallow (blue), optimal (red) and too deep (green).

from a normal distribution. D_{max} values and their corresponding Z_{pp} values were split into three groups corresponding to shallow ($D_{max} < 38\,\mathrm{mm}$), optimal ($38 \leq D_{max} \leq 51\,\mathrm{mm}$) and too deep ($D_{max} > 51\,\mathrm{mm}$) CC according to 2005 resuscitation guidelines [3], which were in effect when the dataset was collected. These groups were tested using Barlett's test to see if they came from normal distributions with the same variance. Finally, the groups were tested using Kruskal-Wallis test to see if there were significant differences between medians.

3.3. Linear analysis

Linear analysis was carried out between D_{max} and Z_{pp}. The linearity was tested with Pearson correlation coefficients and univariate linear regression used to fit a model to the data which tried to predict D_{max} using Z_{pp}. Correlation coefficients for every episode (R_e) and for the whole database (R_c) were calculated. For each episode the time evolution of the correlation coefficient in three consecutive intervals of equal duration, R_i, was computed along every episode.

4. Results

Kolmogorov-Smirnov tests for D_{max} and Z_{pp} were rejected as they did not follow a normal distribution (p<0.01). Barlett's test showed that shallow, optimal and too deep groups did not come from normal distributions with the same variance (p<0.01). Kruskal-Wallis test concluded that there were significant differences between medians of each group (p<0.01). Thus, median ($25^{th} - 75^{th}$ percentiles) for shallow, optimal and too deep groups were 1.12 (0.78 - 1.48), 1.35 (0.94 - 1.89) and 1.67 (1.09 - 2.33) Ω, respectively. Fig 3 shows the distribution for the shallow (blue), optimal (red) and too deep (green) compressions. Although medians of the three groups are significantly different, the high overlap between them is high, which makes the discrimination difficult.

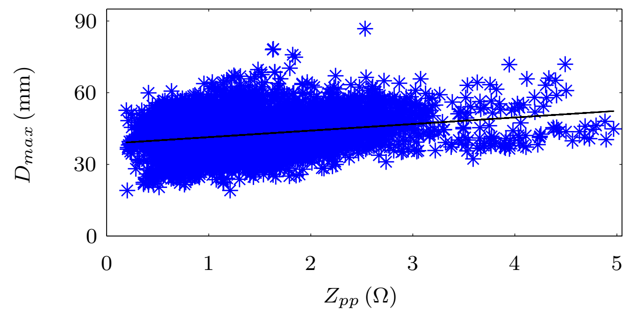

Figure 4. Model fitted using univariate linear regression for the whole database.

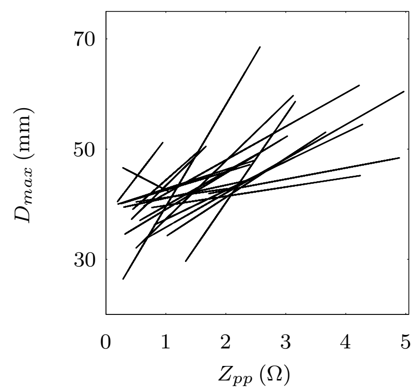

Figure 5. Models fitted using univariate linear regression for each of the 19 episodes of the database.

Fig 4 shows the model fitted (black line) using univariate linear regression for the whole database. Visual inspection permits identifying an underfitting problem. Predictions made using this model would incur large errors. Low correlation was found between D_{max} and Z_{pp} for the whole database, $R_c = 0.27$.

Fig 5 represents the model fitted using univariate linear regression for each of the 19 episodes. There is a large variability between models fitted for each episode, R_e ranging from 0.04 to 0.83. Median ($25^{th} - 75^{th}$ percentiles) values for R_e were 0.34 (0.20 - 0.61).

Fig 6 depicts the results obtained for each episode when the time evolution of the correlation coefficient was analysed. Median ($25^{th} - 75^{th}$ percentiles) duration of the intervals was 589.73 (474.60 - 728.71) s. For each episode, the blue circle, red diamond and black circle represent the correlation coefficients, R_i, for the first, second and third intervals, respectively. R_i varies from 0.06 to 0.94. Median ($25^{th} - 75^{th}$ percentiles) values for R_i were 0.52 (0.32 - 0.70), 0.49 (0.32 - 0.79), 0.52 (0.26 - 0.64) and 0.52 (0.39 - 0.70) for all, first interval, second interval and third interval values, respectively. The time evolution of R_i does not show any clear tendency and median values of R_i for the three intervals are very similar.

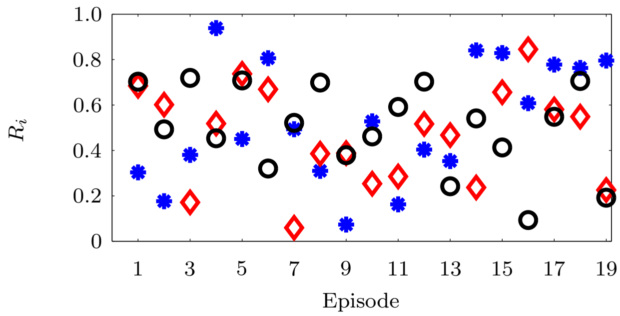

Figure 6. Time evolution of the correlation coefficient per episode. Blue circles, red diamonds and black circles depict the correlation coefficients for first, second and third intervals respectively in each episode.

5. Discussion and conclusions

In this study the linear relationship between D_{max} using Z_{pp} has been analysed in a OHCA scenario. Univariate linear regression has been used to fit a model to the data and to try to predict D_{max} using Z_{pp}. Pearson correlation coefficients have been calculated for the whole database (R_c) and for every episode (R_e). Furthermore, the time evolution of the correlation coefficient, R_i, has been computed along each episode dividing it into three consecutive intervals with the same duration.

In a recent study by Zhang et al. [8], the relationship between TI changes with the CD in a porcine model of cardiac arrest was investigated. They used 2 min segments in which two emergency medical doctors provided CCs with optimal ($> 50\,\text{mm}$) and suboptimal ($< 35\,\text{mm}$) depth. The peak-through amplitude change of the TI during each compression was averaged for every 5 s, obtaining a feature similar to our Z_{pp}. They found high correlation given by a Pearson correlation coefficient equal to 0.89, between that feature and the D_{max}. They also found a great difference in the TI amplitude between two groups (1.45$\pm$0.37 vs 0.47$\pm$0.12, p$<$0.001) for optimal and suboptimal depths.

Unlike those promising results in animals, in our study with humans using OHCA records, the Pearson correlation coefficient was 0.27 for the whole dataset and a median ($25^{th} - 75^{th}$ percentiles) values of 0.34 (0.20 - 0.61) when the analysis was performed per episode. When the time evolution of the correlation coefficient was analysed along each episode, no clear tendency was found. Finally, when we tried to distinguish three groups of CC (shallow, optimal and too deep), although the medians were significantly different, the high overlap between them makes the discrimination very difficult. Nevertheless, further studies are necessary in order to test if any non-linear relationship could fit the data well enough to predict D_{max} using Z_{pp} when several rescuers and different patients are involved. Other features of the TI waveform might be useful to discriminate optimal from suboptimal CC.

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] 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 2005;111(4):428–434.

[2] Kramer-Johansen J, Edelson DP, Losert H, Khler K, Abella BS. Uniform reporting of measured quality of cardiopulmonary resuscitation (CPR). Resuscitation 2007;74(3):406–417.

[3] Nolan J, European Resuscitation Council. European resuscitation council guidelines for resuscitation 2005. section 1. introduction. Resuscitation 2005;67 Suppl 1:S3–6.

[4] Wik L, Kramer-Johansen J, Myklebust H, Sreb H, Svensson L, Fellows B, Steen PA. Quality of cardiopulmonary resuscitation during out-of-hospital cardiac arrest. JAMA the journal of the American Medical Association 2005;293(3):299–304.

[5] Stecher FS, Olsen JA, Stickney RE, Wik L. Transthoracic impedance used to evaluate performance of cardiopulmonary resuscitation during out of hospital cardiac arrest. Resuscitation 2008;79(3):432–437.

[6] Aramendi E, Ayala U, Irusta U, Alonso E, Eftestøl T, Kramer-Johansen J. Suppression of the cardiopulmonary resuscitation artefacts using the instantaneous chest compression rate extracted from the thoracic impedance. Resuscitation 2012;83(6):692–698.

[7] Gonzalez-Otero D, de Gauna S, Ruiz J, Ayala U, Alonso E. Automatic detection of chest compression pauses using the transthoracic impedance signal. In Computing in Cardiology (CinC), 2012. 2012; 21–24.

[8] Zhang H, Yang Z, Huang Z, Chen B, Zhang L, Li H, Wu B, Yu T, Li Y. Transthoracic impedance for the monitoring of quality of manual chest compression during cardiopulmonary resuscitation. Resuscitation 2012;83(10):1281–1286.

Address for correspondence:

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