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Chapter 6

Audiovisual Feedback Devices for Chest Compression Quality during CPR

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Abstract

During cardiopulmonary resuscitation (CPR), chest compression quality is the key for patient survival. However, several studies have shown that both professionals and laypeople often apply CPR at improper rates and depths. The use of real-time feedback devices increases adherence to CPR quality guidelines. This chapter explores new alternatives to provide feedback on the quality of chest compressions during CPR. First, we describe and evaluate three methods to compute chest compression depth and rate using exclusively the chest acceleration. To evaluate the accuracy of the methods, we used episodes of simulated cardiac arrest acquired in a manikin model. One of the methods, based on the spectral analysis of the acceleration, was particularly accurate in a wide range of conditions. Then, we assessed the feasibility of using the transthoracic impedance (TI) signal acquired through defibrillation pads to provide feedback on chest compression depth and rate. For that purpose, we retrospectively analyzed three databases of out-of-hospital cardiac arrest episodes. When a wide variety of patients and rescuers were included, TI could not be used to reliably estimate the compression depth. However, compression rate could be accurately estimated. Development of simpler methods to provide feedback on CPR quality could contribute to the widespread of these devices.

Keywords: cardiopulmonary resuscitation, chest compression quality, compression depth, compression rate, feedback devices, chest acceleration, thoracic impedance

1. Introduction

The sequence of actions linking a victim of out-of-hospital cardiac arrest with survival is described by the chain of survival, which consists of four independent links: early activation

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of the emergency medical services, early cardiopulmonary resuscitation (CPR), early defibrillation, and early advanced care. The four links of the chain of survival are important, but early CPR and early defibrillation are pivotal for a successful outcome of the patient [1]. CPR consists of cycles of chest compressions and ventilations delivered to the patient to artificially maintain a minimal flow of oxygenated blood to the vital organs, whereas defibrillation consists in the passage of electrical current through the myocardium (cardiac muscle) to terminate certain lethal arrhythmias. In out-of-hospital settings, early defibrillation is normally procured using an automated external defibrillator (AED).

There is a strong evidence that the quality of chest compressions is related to the chance of successful defibrillation [2–4]. Current resuscitation guidelines [1] emphasize the importance of providing chest compressions with an adequate depth (between 5 and 6 cm) and rate (between 100 and 120 compressions per minute [cpm]), completely releasing the chest between compressions and minimizing interruptions. However, several studies have shown that both professionals and laypeople often apply CPR at improper rates and depths [5, 6].

In an effort to alleviate this problem, since 2010, resuscitation guidelines recommend monitoring CPR quality and using metronomes and real-time feedback systems to guide rescuers during resuscitation attempts [7]. Metronomes generate regular audible beats that help rescuers to follow the rhythm, while feedback devices are more sophisticated; they measure CPR performance in real time and provide audiovisual messages to guide the rescuer toward target depth and rate. The clinical studies conducted to date had an insufficient power to demonstrate improved survival with the use of feedback devices [8]. As a consequence, ERC guidelines 2015 recommend the use of CPR feedback devices as part of a broader system of care that should include comprehensive CPR quality improvement initiatives, rather than as an isolated intervention. There is, however, strong evidence that feedback improves chest compression quality, [9–12] which has been linked to survival from cardiac arrest [5, 8].

This chapter explores new alternatives to provide feedback on the quality of chest compressions during CPR. First, we briefly describe the history of feedback devices and the different technologies used. Then, we present three methods to provide feedback on chest compression depth and rate based solely on chest acceleration. One of the methods presented particularly a high accuracy in a wide range of conditions and is further discussed in three challenging scenarios. Finally, we assessed the feasibility of using the transthoracic impedance (TI) signal acquired through defibrillation pads to provide feedback on chest compression depth and rate.

2. History of feedback devices

The first CPR feedback devices were mechanical and used force or pressure sensors to provide feedback on chest compression depth [13]. Devices in this category include CPRplus (Kelly Medical Products, Princeton, USA), CPREzy (Health Affairs, London, England), and the more recent Cardio First Angel (Schiller, Baar, Switzerland). These systems guide the rescuer toward the target depth based on the force applied on the chest for each compression. However, stiffness of the chest is not linear [14] and varies among individuals. Tomlinson et al. [15]

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simultaneously measured compression force and depth in 91 adult out-of-hospital cardiac arrest patients. In the studied population, the force required to achieve 38 mm varied from 10 to 54 kg. Even if some of the devices in this category take into account the approximate size of the patient, the wide variation in chest wall elasticity and its changes with time impede an accurate estimation of compression depth from compression force.

To overcome the limitations of force and pressure sensors, electronic systems based on accelerometers were developed. These devices sense the acceleration of the patient's chest during CPR, and they process it in real time to obtain compression depth. By definition, acceleration is the first derivative of velocity with respect to time, and velocity is the first derivative of displacement. Consequently, chest displacement can be obtained from acceleration by applying double integration. However, integration is an inherently unstable process: small integration errors rapidly accumulate causing a significant drift in displacement that impedes accurate estimation of the compression depth. **Figure 1** illustrates the problem of double integration of the chest acceleration with a record acquired while chest compressions were provided to a resuscitation manikin. The acceleration signal (top panel) and the reference compression depth signal obtained from a displacement sensor placed inside the manikin's chest (bottom panel, solid line) were registered. The second panel shows the reference velocity signal computed differentiating the reference compression depth signal (solid line), and the velocity signal computed by numerically integrating the acceleration signal (dashed line). Integration errors quickly accumulate, and during the last seconds, the computed velocity presents a noticeable offset with respect to the reference signal. When numeric integration is performed again, this offset leads to big errors in the computed displacement (bottom panel, dashed line), of more than 20 cm after only 8 s in this example.

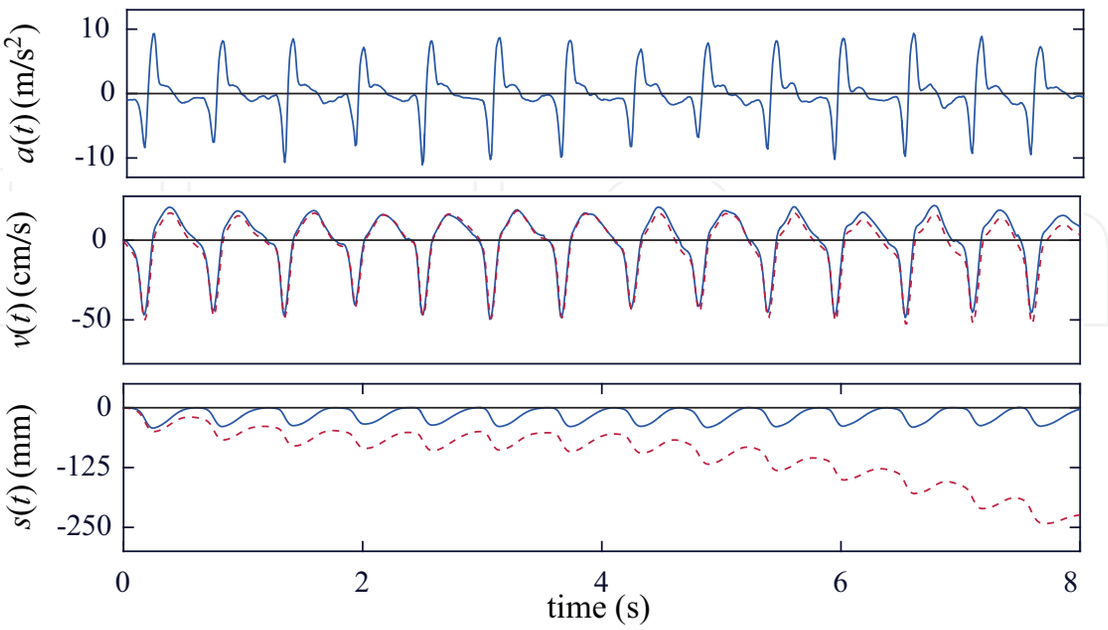


Figure 1. Integration errors in the displacement signal after the application of direct double integration to the acceleration signal.

A possible strategy to reduce the accumulation of integration errors would be to perform the integration for small signal segments, for example, for each compression cycle. For that purpose, the offset of each chest compression should be first identified, and the integration should be reset by applying boundary conditions after each cycle, that is, setting velocity and displacement at those points to zero. Over the last decade, several mechanisms to identify the offset of chest compressions have been conceived, giving rise to complex commercial devices that incorporate additional sensors or use elaborate signal processing techniques. For example, PocketCPR (Zoll Medical, Chelmsford, USA) applies signal processing techniques to set boundary conditions and compensate integrating drift, while CPRmeter (Laerdal Medical, Stavanger, Norway) incorporates an additional force sensor. Both devices are rigid and must be placed between the chest of the patient and the rescuer's hands during CPR to measure chest acceleration.

More recently, Physio-Control (Redmond, USA) presented TrueCPR, a solution to provide feedback on chest compression rate, depth, and chest release based on triaxial magnetic field induction. The device comprises two rigid pads: one of them is positioned between the rescuer's hands and the chest of the patient during CPR, and the other one, longer and flatter, beneath the patient's back. Feedback metrics are estimated from the changes in magnetic field between both pads during CPR. The main disadvantage of this device is that it is bulkier than the others and also rigid.

3. Use of the acceleration signal for chest compression quality

This section briefly describes three methods to compute chest compression rate and depth and to provide CPR feedback to the rescuers using only chest acceleration. For a more detailed description of the methods, see reference [16]. The first method derives from the traditional approach; it consists in applying double integration to compute the compression depth signal. In our proposal, integration is approximated using a stable band-pass filter (BPF) that performs integration while suppressing low frequencies of the signal. The second and third methods do not require computing the compression depth signal: the second method computes velocity to calculate a compression rate and depth value for each compression, while the third one computes rate and depth from the spectral analysis of the acceleration signal (SAA). We used episodes of simulated cardiac arrest acquired using a resuscitation manikin to evaluate the accuracy of the three methods.

3.1. Experimental set-up and data collection

We equipped a Resusci Anne QCPR manikin (Laerdal Medical, Norway) with a photoelectric sensor to register the reference compression depth signal. Chest compressions were delivered in the center of the manikin's chest with a triaxial accelerometer encased in a metal box placed beneath the rescuer's hands. The reference compression depth signal and the three axes of the acceleration were digitized and recorded using a National Instruments (Austin, USA) acquisition card connected to a laptop computer. **Figure 2** shows the experimental set-up used to perform the data collection.

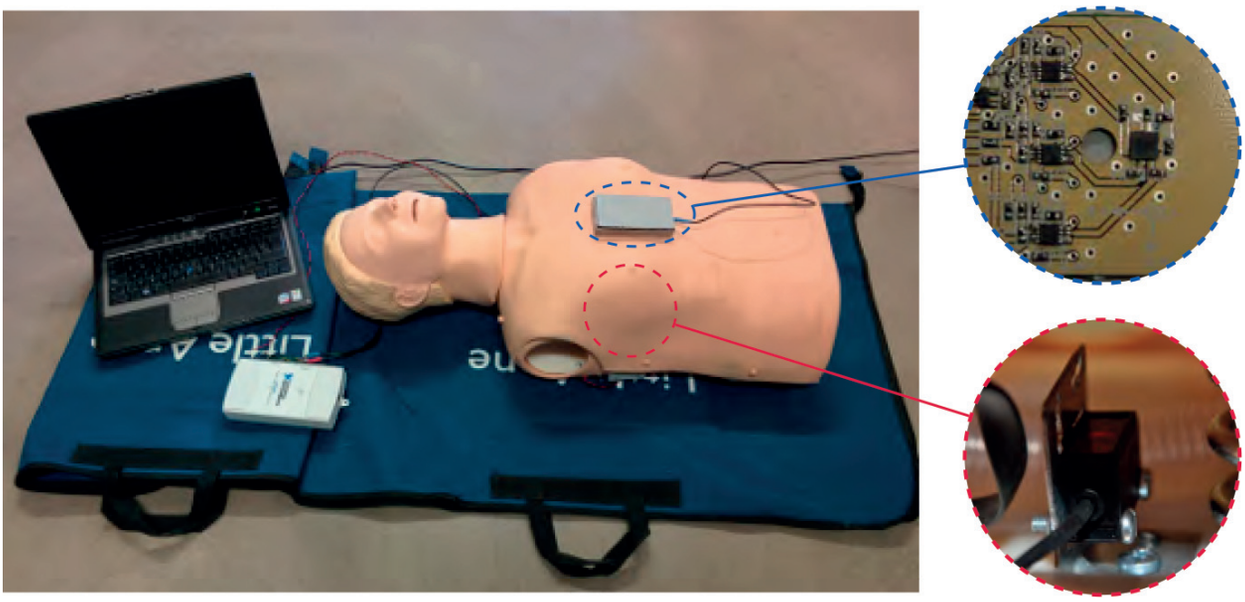


Figure 2. Experimental setup: Resusci Anne QCPR manikin fitted with a displacement sensor, triaxial accelerometer encased in a metallic box, acquisition card, and laptop computer.

Twenty-eight volunteers participated in the recording sessions. They were grouped in couples, and for each couple, four 10-min episodes were recorded. During each episode, volunteers alternated providing 2-min CPR series, each series involving 30 compressions with 5-s pauses in between. A total of 56 episodes were acquired. The experimental protocol was approved by the ethical committee for research involving human subjects of the University of the Basque Country (CEISH UPV/EHU).

3.2. Methods to estimate chest compression rate and depth

3.2.1. Band-pass filter

There are a number of discrete integration algorithms available, the most common one being the trapezoidal rule, because of its trade-off between simplicity and accuracy. Analytically, the implementation of this rule derives in an unstable linear system [16]. In practice, that means that small low-frequency components in the input signal generate low-frequency components in the output with amplitude that increases with time. If no technique is applied to compensate this accumulation of error in the output signal, the system could suffer a numeric overflow.

Our first approach consists in approximating the integration by a stable band-pass filter, designed as the series connection of a high-pass filter and the trapezoidal rule filter, which presents a low-pass response. The high-pass filter is aimed at compensating the instability of the trapezoidal rule filter for low frequencies. **Figure 3** shows the magnitude of the frequency response of the band-pass filter, $H_{\mathrm{BPF}}(f)$, represented by a solid line. Note that for frequencies above 0.6 Hz, the system matches the ideal response of the trapezoidal rule, depicted with a dashed line, whereas for low frequencies, it is stable (it does not tend to infinity, as opposed to the trapezoidal rule response).

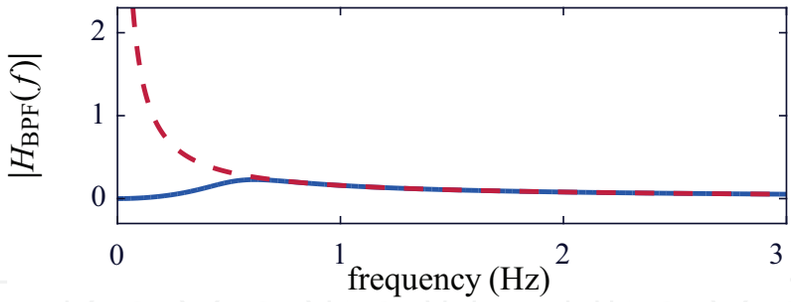


Figure 3. Frequency response of the band-pass filter (solid line) compared to the ideal frequency response of the trapezoidal rule filter (dashed line).

Figure 4 illustrates the process of computing compression depth with this method. First, the acceleration signal $a(t)$ (first panel) is processed with the band-pass filter to obtain velocity, $v(t)$ (second panel). Then, this process is repeated with the velocity to obtain the computed compression depth signal $s_c(t)$ (third panel). Because of the suppression of the low-frequency components and the waveform distortion caused by the filtering process, $s_c(t)$ and the reference compression depth signal $s(t)$ (fourth panel) have different waveforms. However, compression depth and rate can be easily computed by applying a peak detector to $s_c(t)$ and measuring the peak-to-peak amplitude and the distance between the peaks, respectively. Compression rate is computed as the inverse of the distance between two consecutive peaks,

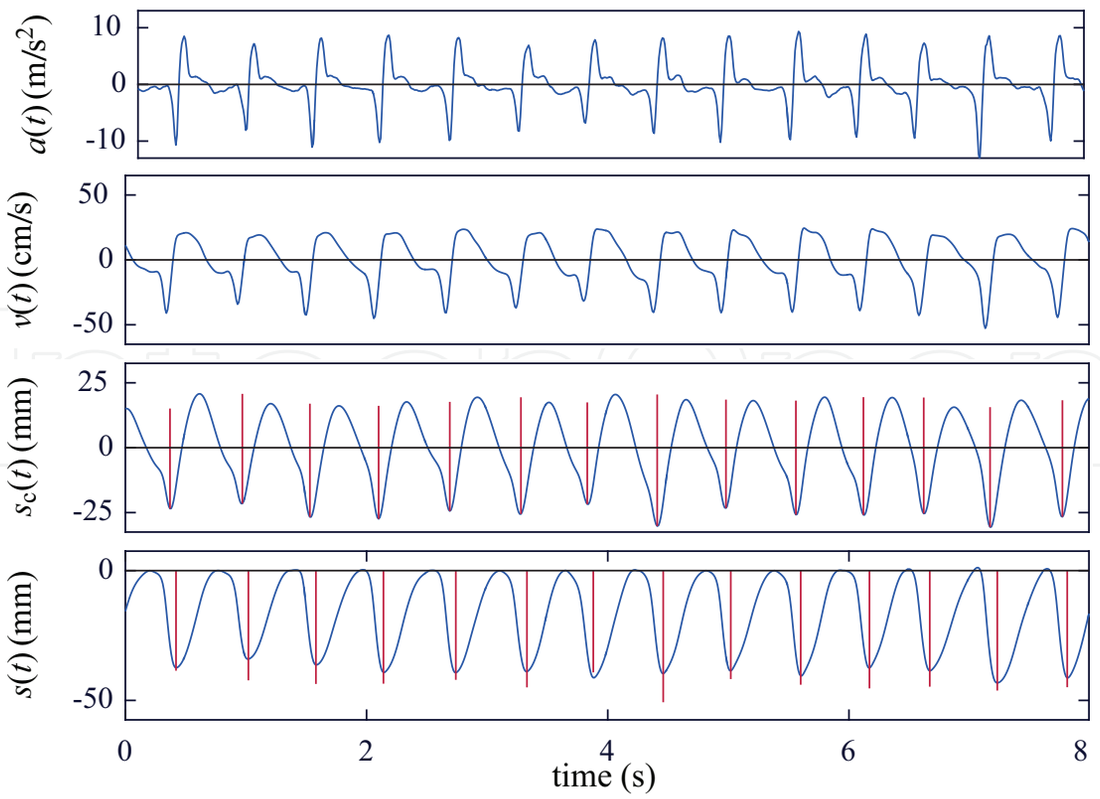


Figure 4. BPF method, based on band-pass filtering.

expressed in compressions per minute (cpm). In **Figure 4**, the detected compressions and their corresponding depths are depicted by vertical lines in the third and fourth panels.

3.2.2. Detection of zero-crossing instants in the velocity signal (ZCV)

In this second method, the compression rate and depth values are directly calculated from the velocity signal, without computing the compression depth signal. For that purpose, the band-pass filter described in the previous section is applied to the acceleration once to obtain the velocity signal. The resulting signal is quite stable and can be processed to identify the zero-crossing instants from positive to negative, which represent the onset of each compression cycle (marked by circles in the second panel of **Figure 5**) and the zero-crossing instants from negative to positive, which correspond to the points of maximum displacement of the chest (marked by crosses in the second panel). For each compression cycle, the compression depth is computed as the area of the velocity signal between the onset and the maximum displacement point (shadowed in the second panel of the figure). Finally, the rate of the chest compressions can be computed as the inverse of the interval between two consecutive zero-crossing instants from positive to negative. In the bottom panel of **Figure 5**, the computed depth values (represented by vertical lines) are drawn over the reference compression depth signal for comparison.

3.2.3. Spectral analysis of the acceleration signal

In this third method, neither the compression depth nor the velocity signal is computed by integration. Instead of that, average compression rate and depth values are computed every 2 s by applying spectral analysis to the acceleration signal [17]. The basis of this method is the assumption that during short intervals with continuous chest compressions, the acceleration

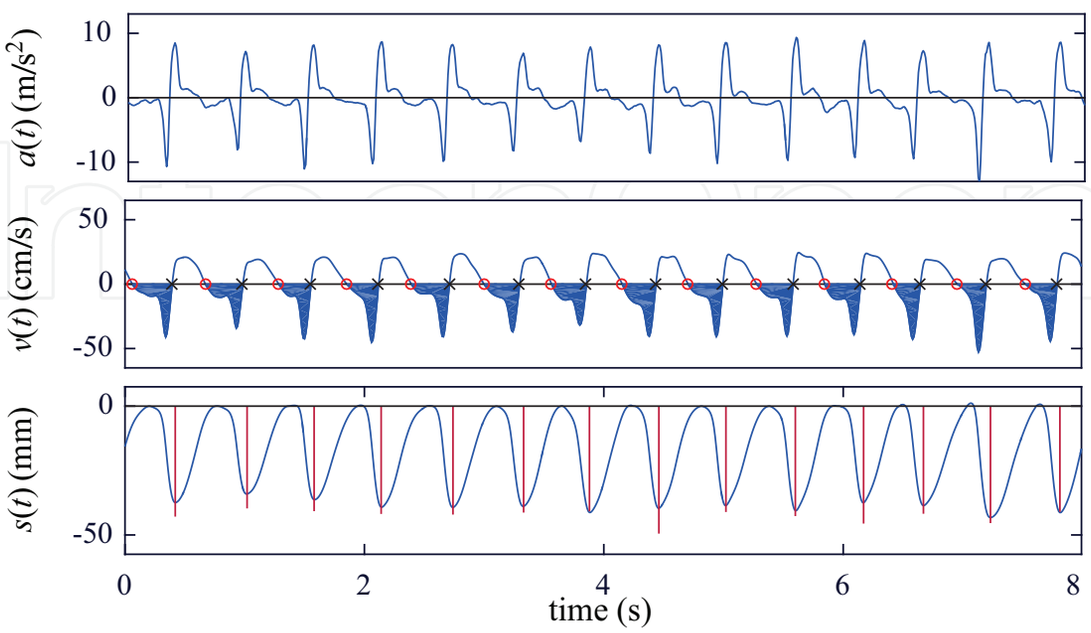


Figure 5. ZCV method, based on the analysis of velocity.

and the displacement signals are quasi-periodic. Consequently, both signals can be modeled as a periodic acceleration and a periodic depth, with a fundamental frequency that represents the average frequency of the chest compressions during the interval. We modeled each 2-s segment of the acceleration and displacement signals using the first three harmonics of their Fourier series representation, without considering the direct current component. **Figure 6** illustrates the procedure followed to apply this method. We first computed the fast Fourier transform (FFT) of the windowed acceleration signal and estimated the module and phase of the three first harmonic components of the acceleration. In the example shown in the figure, the selected window is shaded in the first panel, and its FFT with the identified harmonics is shown in the second panel. Taking into account that acceleration is the second derivative of displacement, when both signals are modeled as periodic, the amplitudes and phases of the spectral components of the compression depth can be derived from the ones of the acceleration. Using these values, a periodic version of the chest displacement during the analysis window can be reconstructed. This last step is represented in the third panel of **Figure 6**. The reference compression depth signal is plotted using a solid line, and the reconstructed signal for the selected window is represented by a dashed line. The reconstructed signal is periodic; i.e., it has the same amplitude for all the compressions, which represent the average compression depth during the analysis window. Average compression rate for each 2-s analysis window is computed from the fundamental frequency of the acceleration, f_{cc}.

3.3. Results

Panel (A) of **Figure 7** shows the boxplots of the error in the estimation of compression depth for each of the methods. On each box, the central mark is the median, and the edges of the box

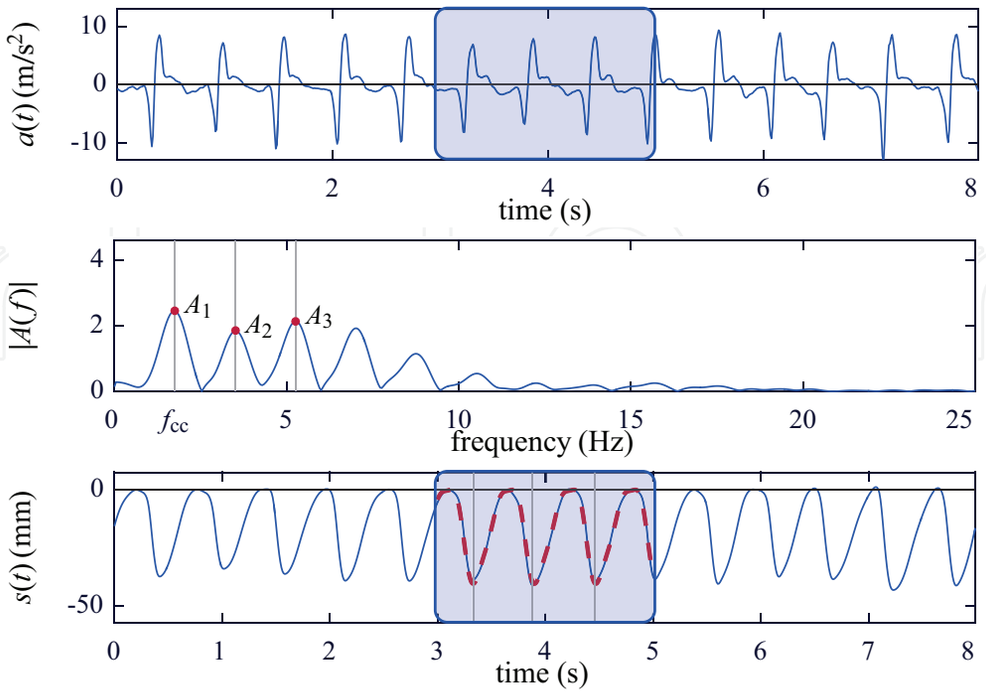


Figure 6. SAA method, based on the spectral analysis of the acceleration.

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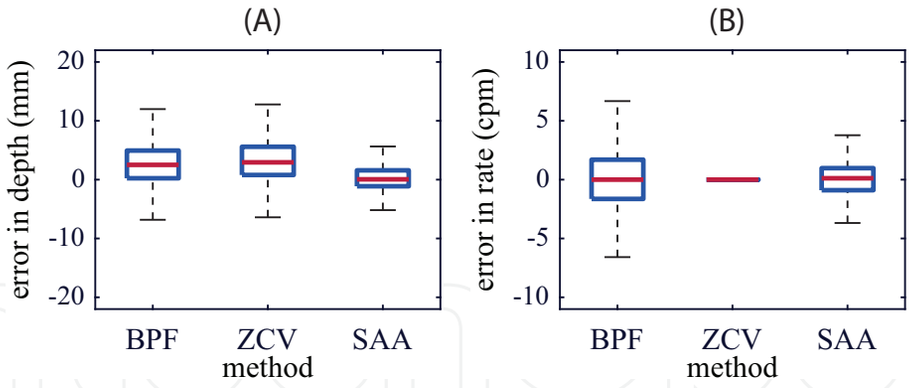


Figure 7. Boxplots of the global error in depth (A) and in rate (B) for the three methods.

are the percentiles 25 and 75, P_{25} and P_{75}, respectively. The whiskers extend to the most extreme data points not considered outliers i.e., within the ±1.5 interquartile range (IQR) interval. Differences in the errors between methods were statistically significant ($p < 0.001$). SAA provided the highest accuracy, while BPF and ZCV displayed a slight tendency to overestimate depth values. Median (P_{25}-P_{75}) unsigned percent error in depth calculation for each method was 5.9 (2.8–10.3), 6.3 (2.9–11.3), and 2.5 (1.2–4.4)%.

Boxplots of the error in rate estimation are represented in panel (B) of **Figure 7**. For the ZCV method, errors were clearly concentrated around zero. Median (P_{25}-P_{75}) unsigned percent error in rate calculation was 1.7 (0.0–2.3), 0.0 (0.0–2.0), and 0.9 (0.4–1.6)% for BPF, ZCV, and SAA, respectively. Differences between methods in error in rate estimation were not statistically significant ($p = 0.49$).

3.4. Discussion

This section presents three strategies for feedback on the rate and depth of chest compressions during CPR by processing exclusively the acceleration signal and assesses their accuracy in a simulated manikin scenario.

The BPF and ZCV tended to overestimate chest compression depth and presented errors above 5 mm in 25% of the compressions. The SAA method, in contrast, was very accurate and not biased, with an error above 5 mm in only about 5% of the cases.

Percent error in rate estimation was very low for the three methods (median of 1.7, 0.0, and 0.9% for BPF, ZCV, and SAA, respectively). Errors of BPF and ZCV methods were mainly caused by the filter transient, particularly at the beginning of each compression series. This influence was higher for the BPF method, in which the filter was applied twice.

Most current CPR feedback devices rely on accelerometry and double integration to estimate chest compression depth. Manufacturers have designed different solutions for the instability problem, often protected by patent rights, based on either using additional pressure or force sensors to detect the onset of each compression cycle, or on advanced filtering techniques requiring reference signals. All these solutions lead to complex devices, limiting their widespread use in the practice, especially for bystanders and first responders to a cardiac arrest.

The methods discussed in this section are based solely on accelerometry and could lead to simpler, flexible, and cheaper devices. For its simplicity and accuracy, the method based on the spectral analysis of the acceleration might be a good candidate for implementation. To further test this method in challenging scenarios, we conducted three additional studies to evaluate the accuracy of the method: (1) when chest compressions were provided to a patient laying on a soft surface, (2) when the feedback device was attached to the rescuer's back of the hand, or to the wrist, or to the forearm, instead of being placed in the usual position between the chest and the rescuer's hands, and (3) when CPR was performed in a moving vehicle, particularly in a moving long-distance train.

When the patient is lying on a mattress or on any soft surface, accelerometer feedback devices overestimate chest compression depth, [18] as the calculated depth corresponds to the total displacement of the chest, that is, the sternal-spinal displacement plus the mattress displacement. This would lead to erroneous feedback, which could contribute to the delivery of shallow chest compressions. We proposed a solution based on two accelerometers incorporating the spectral method. One is placed on the chest to measure the total displacement of the chest, while the other one is placed at the back of the patient and measures the mattress compression distance. The difference between both measurements will correspond to the actual compression depth. This method presented a high accuracy. Detailed results are presented in reference [19].

Current positioning of CPR feedback devices may cause soft-tissue damage to the patient or to the rescuer, along with wrist discomfort. We analyzed the accuracy of the spectral method when the accelerometer was placed in alternative positions that reduce discomfort: the rescuer's back of the hand, the wrist, and the forearm. We compared these results with those obtained in the traditional position and concluded that positioning the device at the back of the hand was the optimal sensor position. Fixed to the wrist or to the forearm, the sensor was subjected to swinging movements or hands separation from the chest, which caused a large overestimation of compression depth. Readers are encouraged to consult reference [20] for further details.

Finally, we studied the performance of the spectral method when tested in a moving long-distance train. Currently, defibrillators are increasingly being installed in public transportation settings, in an effort to provide an early response to sudden cardiac arrest. Early CPR should be also administered in such scenarios, and the CPR feedback devices could increase CPR quality, but to date how the movement of the vehicles affects accelerometer-based devices has not been sufficiently studied. We tested the spectral method in a long distance train with a manikin setup and compared the results with those obtained in static conditions. Errors in depth estimation tended higher in the train, but no statistical differences were found. Rate estimation was very accurate. Our conclusion was that, as the spectral method does not consider frequency components of the acceleration out of the range of chest compressions (1–10 Hz), movement did not affect performance [21].

In conclusion, the spectral method was accurate to compute chest compression depth and rate in a wide set of conditions and could be used to develop a new CPR feedback device. However, the method is not capable of detecting inadequate rescuer's leaning between compressions. Leaning decreases the blood flow throughout the heart and can decrease venous

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return and cardiac output. Guidelines recommend minimizing leaning, but human studies show that a majority of rescuers often lean during CPR and do not allow the chest to recoil fully between compressions. This is the current major drawback of any attempt to derive feedback only from accelerometers. For this reason, some commercial accelerometer-based devices use force sensors to provide feedback on this quality parameter.

4. Transthoracic impedance signal for chest compression quality

Most defibrillators, particularly the simplest devices, acquire only the ECG and the TI signal through the defibrillation pads. A straightforward solution for monitoring and providing feedback on the quality of chest compressions could be using the already available signals in current defibrillators. TI measures the resistance of the thorax to current flow. It is calculated by passing an alternate current (usually 2–3 mA at 20–30 kHz) through the tissue, measuring the voltage drop, and calculating the impedance using the Ohm's law. TI is used to check if defibrillation pads are correctly attached to the patient and to adjust the energy of the defibrillation pulse.

Baseline TI is approximately 70–80 Ω in adults, but changes in tissue composition due to redistribution and movement of fluids cause fluctuations on the TI. For example, blood circulation and respiration (or ventilation) generate oscillations of different amplitudes in the TI. In addition, chest compressions during CPR cause a disturbance in the electrode-skin interface, inducing artifacts on the TI. With each compression, the TI fluctuates around the baseline impedance with amplitude varying from 0.15 Ω to several Ohms. **Figure 8** shows a segment of the compression depth and the TI signals recorded during CPR. In the example, two series of 15 compressions were provided, with pauses for two ventilations in between. The oscillations in the TI signal reflect compressions and ventilations. In general, the waveform of the fluctuations induced by chest compressions is very variable between patients and even along each resuscitation episode.

The aim of this section is to explore the feasibility of using TI signal to provide feedback on the rate and depth of chest compressions.

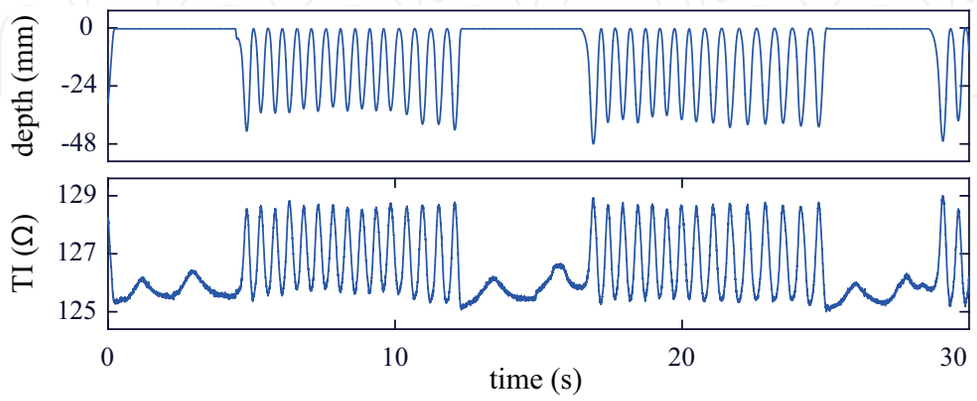


Figure 8. Segment of compression depth and TI signals during CPR. Artifact induced by chest compressions and fluctuation induced by ventilations is clearly visible in the TI signal.

4.1. Use of the TI signal for chest compression quality assessment

Several researchers have investigated the use of TI signal for gathering information on the quality of chest compressions. Some studies focused on detecting the instants of the chest compressions in the TI signals to derive compression rate. Others have studied the relationship between compression depth and the amplitude of the TI fluctuations.

4.1.1. Chest compression rate

The commercial program Codestat (Physio-Control, Redmond, USA) incorporates an automated chest compression and ventilation detector based primarily on the analysis of the TI. The program annotates compression positions and derives the quality parameters compression rate and chest compression fraction (the percentage of time during which chest compressions are provided). Different filtering options allow the user to highlight chest compressions oscillations or ventilation oscillations. Other authors used the TI signal to automatically detect chest compressions in order to estimate the instantaneous compression rate [22]. They found a high correlation between the instantaneous rate computed from the TI and from the compression depth signal. The TI was used also to detect pauses in chest compressions [23] and could be used to measure chest compression fraction.

A comprehensive study that aimed to determine the feasibility of a generic algorithm for feedback on chest compression rate using the TI signal recorded through the defibrillation pads was recently published [24]. Out-of-hospital cardiac arrest episodes were collected equally from three different emergency services and different defibrillator models. The algorithm for computing compression rate was based on the spectral analysis of the TI signal. The gold standard was obtained from reference signals such as the force or the ECG. This approach was accurate under different device front ends and a wide range of conditions, proving the generality of the results. The availability of feedback on the rate of chest compressions could have a significant impact on the quality of CPR, especially in basic life-support emergency systems.

4.1.2. Chest compression depth

Regarding the relationship between chest compression depth and the amplitude of the fluctuations induced in the TI, contradictory results have been found in the literature. An experimental study conducted with swine reported higher amplitudes in the TI oscillations for higher compression depths [25]. Another study using porcine models reported high correlations between TI and systolic blood pressure, end-tidal CO2, cardiac output, and carotid flow [26]. Two clinical studies suggested the potential of TI to identify adequate chest compression depth in patients under cardiac arrest [27, 28]. However, none of those studies included any objective measurement of the actual compression depth; i.e., no gold standard was used to validate the hypothesis. In subsequent studies in which a reference compression depth was included, contradictory results were found, and limited details were provided on the methods and the data analyzed [29, 30]. Finally, a prospective, experimental study with swine by Zhang et al. [31] reported a high correlation between TI and both the compression depth and the coronary perfusion. They found significant differences in the TI fluctuation amplitude between adequate and shallow chest compressions, and a strong linear relationship between TI amplitude and compression depth. Authors concluded that changes in the TI had the potential to

serve as an indicator of the quality of chest compressions. Nevertheless, they acknowledged that further research was required to extrapolate these conclusions to humans.

We present a study aimed to go further into this remaining question regarding TI signal and its application to provide feedback on chest compression quality: Is there a relationship between chest compression depth and TI in humans?

4.2. Estimation of chest compression depth from TI signal

The aim of this study was to analyze the relationship between TI fluctuations and compression depth during out-of-hospital cardiac arrest episodes. First, we analyzed the overall correlation between three morphologic features of the TI and the compression depth. Second, we evaluated the influence of the patient by computing this correlation independently for each patient. Third, we studied the influence of the rescuer, by isolating series of chest compressions corresponding to a unique rescuer-patient pair. Finally, we tried to replicate the experiments by Zhang et al., focusing on the correlation analysis with series of optimal and suboptimal chest compressions, and we assessed the discrimination power of the TI signals to distinguish between shallow and nonshallow chest compressions.

4.2.1. Data collection

The data set used in this study was collected by Tualatin Valley Fire & Rescue (TVF&R), a first response advanced life-support fire agency serving 11 incorporated cities in Oregon, USA. It comprised 623 out-of-hospital cardiac arrest episodes recorded during CPR. The compression depth and TI signals were available for 189 of the 623 episodes. We extracted 60 episodes containing both signals concurrently, with a minimum of 1000 chest compressions per episode. Only chest compressions included in series of at least 10 compressions were considered, yielding a total of 11,667,9 chest compressions. Then, we extracted intervals where the single-rescuer-single-patient pattern was guaranteed. Interruptions in compressions longer than 1.5 s were identified as a possible change of rescuer. We gathered 75 series of this type.

4.2.2. Signal processing and extraction of TI features

Compression depth signal was first processed to compute the maximum depth for each chest compression, $D_{\max}$. The instants when $D_{\max}$ was achieved were computed using a negative peak detector with a static threshold of 15 mm. The cycle of each chest compression was then identified using these instants both in the compression depth and in the TI signals. This procedure is illustrated in **Figure 9**, where each cycle is delimited with vertical dotted lines. TI signal was band-pass filtered to remove baseline and fluctuations caused by ventilations and high-frequency noise. To characterize TI fluctuations, we defined three TI waveform features computed for each chest compression:

- Peak-to-peak amplitude, Z_{ppi}: difference between the maximum and the minimum values of the ith TI cycle.
- Area, A_i: area of the TI during the ith compression cycle.
- Curve length, C_i: length of the curve of the TI signal in the ith compression cycle.

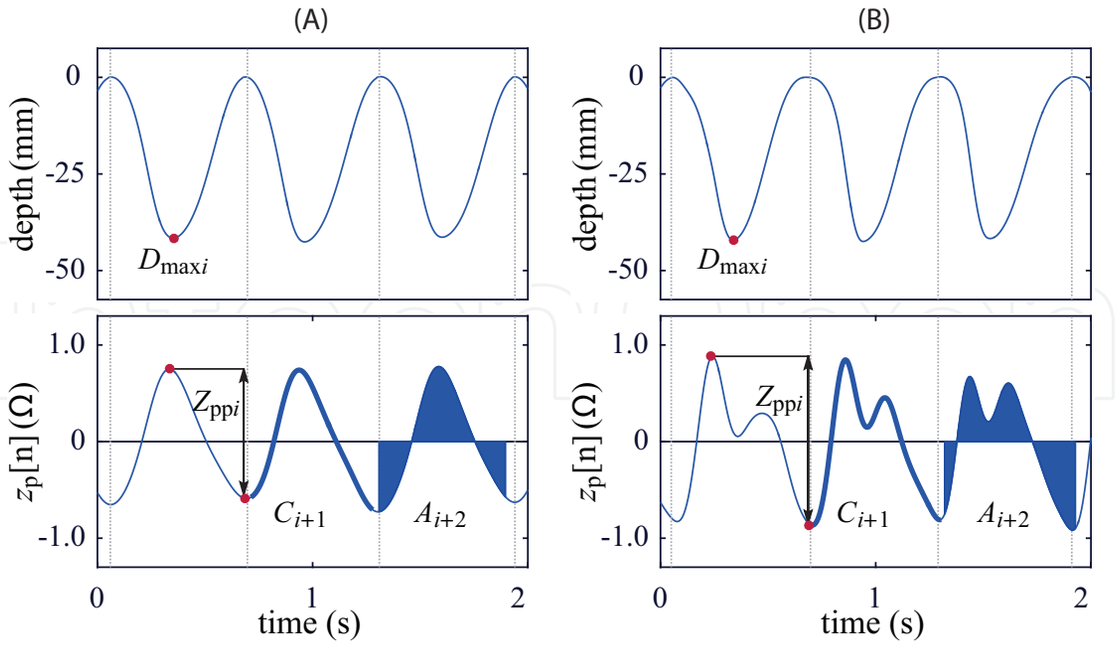


Figure 9. Two examples of the features extracted from the TI signal. The maximum depth is represented in the compression depth signal (top) and the TI features in the TI signal (bottom). Compression cycles are delimited by vertical dotted lines.

Figure 9 illustrates two examples with the extracted features depicted in the compression depth (top) and in the filtered TI signal (bottom). Panel (A) shows quite sinusoidal TI fluctuations, and panel (B) shows a more irregular TI waveform. This is why we computed area and curve length in addition to the peak-to-peak value of TI, as this single feature cannot discriminate between regular and irregular fluctuations. In order to smooth the values of the computed features, the average value of each parameter was computed every 5 s.

4.2.3. Data analysis

The linear relationship between D_{max} and the TI features was tested for the whole population, for each patient independently, and for series of compressions provided by a single rescuer on a single patient. Pearson's correlation coefficient r was computed for each analysis. Univariate linear regression was used to model the relationship between D_{max} and the TI features.

In order to avoid potential variability introduced by the rescuer, we analyzed the relationship between D_{max} and Z_{pp} in a single-rescuer-single-patient pattern. Series with a minimum standard deviation of 7 mm in D_{max} were considered. To avoid bias, a single series per patient was selected, the one with the highest standard deviation. A total of nine series were extracted. Univariate linear regression was used to predict D_{max} using Z_{pp}, and r coefficient was computed for each series and jointly for the whole set.

In order to replicate the procedure by Zhang et al. in their swine model [31], we selected series with optimal and suboptimal series of chest compressions. A series was suboptimal when at least 75% of the compressions were below 38 mm, and optimal when at least 75% of the

compressions were above 50 mm. A total of 12 series (one per patient) were selected. They were jointly analyzed computing *r* and applying univariate linear regression.

Finally, we assessed the discrimination power of the three TI features to classify each 5-s window as shallow (below 38 mm) or nonshallow (above 43 mm) according to the criteria stated by 2005 resuscitation guidelines (valid at the time episodes were collected). We applied a multivariate logistic regression model for the classifier. We split the 60 episodes into a training (40) and a test set (20). The power of the classifier was evaluated in terms of the area under the curve (AUC), and of the sensitivity and specificity in the diagnosis of shallow chest compressions.

4.2.4. Results

Figure 10 shows the scatterplots of D_{max} against each of the TI features for the whole population and the model fitted in each case. In all cases, there was a high dispersion around the regression line. The value of *r* was 0.34, 0.36, and 0.37 for Z_{pp}, *A*, and *C*, respectively. However,

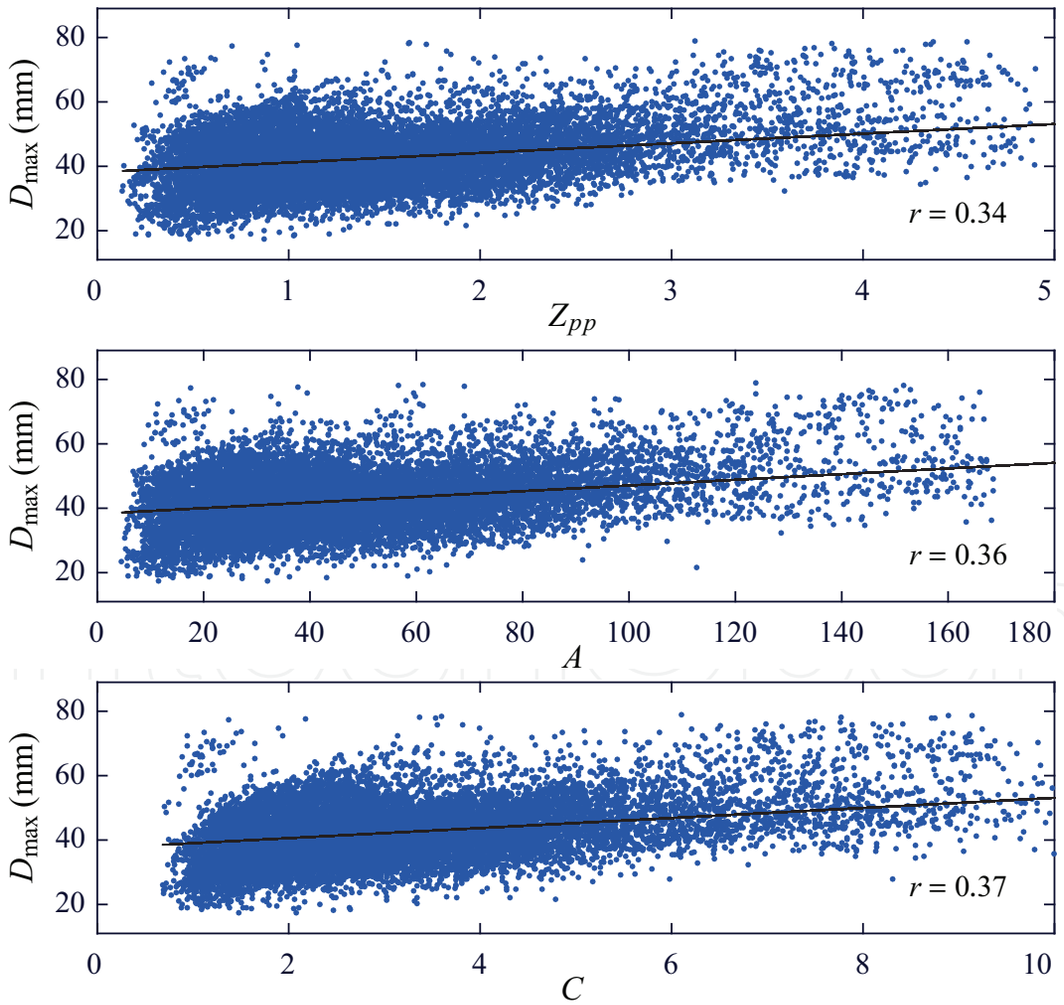


Figure 10. Scatterplots of D_{max} with respect to TI features for the whole population. For each scatterplot, the fitted regression line and the value of *r* are depicted.

the analysis within patients yielded a median (IQR) correlation coefficient r of 0.40 (0.24–0.66) for Z_{pp}, 0.43 (0.26–0.66) for A, and 0.47 (0.25–0.68) for C.

For the nine series in which the single-patient-single-rescuer pattern was maintained, the individual analysis of each series yielded a median r of 0.81 (0.51–0.83). However, when all of them were considered jointly, r decreased to 0.47.

In the analysis parallel to the one conducted by Zhang et al., we considered the set of twelve optimal and suboptimal series. For the optimal group, D_{max} was 57 (54–63) mm and Z_{pp} was 3.0 (2.5–3.7) Ω. For the suboptimal group, D_{max} was 32 (30–34) mm, and Z_{pp} was 0.9 (0.6–1.5) Ω. We obtained a correlation coefficient of 0.87, quite similar to the 0.89 reported by Zhang et al.

Finally, when analyzing the power of each feature to classify 5-s windows as shallow or nonshallow, we found significant differences between groups, but a high overlap between distributions. The logistic regression classifier showed sensitivity, specificity, and AUC of 89%, 49%, and 0.8 for the test set.

4.2.5. Discussion

Our study included a set of out-of-hospital cardiac arrest episodes with a wide variety of patients and rescuers. The results obtained from the analysis of 14,424 values for each feature showed very low correlation with D_{max} ($r < 0.38$ in any case). Prediction of chest compression depth with any of the TI features was highly unreliable. For instance, for any given Z_{pp} value, the probability of error in the prediction of D_{max} is high because of the wide range of corresponding D_{max} values.

The variability of the results between patients was also high. Sex, chest size, body mass, and pads position have been reported to affect TI baseline, and TI fluctuations during ventilations are correlated with the thoracic fat and thoracic circumference. Our results showed also a great dispersion with respect to the regression line between D_{max} and Z_{pp} from one patient to another. Although, for some patients, little dispersion and high correlation values could be observed along the episode, different tendencies were also found within each episode, showing the influence of different rescuers. In these cases, a single regression model will hardly fit all the values.

With a single rescuer, the dispersion of each series decreased, and linearity between D_{max} and Z_{pp} increased notably. Nevertheless, interpatient factors such as chest/electrodes characteristics of the nine patients caused a low correlation when all the series were considered jointly. This emphasizes the inability to define a confident global linear fit.

Finally, we could replicate the high linearity observed between depth and TI amplitude reported by Zhang et al. in the animal model. We also found significant differences between the optimal and the suboptimal groups, but we also found that for a given value of Z_{pp}, D_{max} varied widely. For a proper interpretation of the apparent observed linearity, we should consider the limitations of the analysis. On the one hand, considering only optimal and suboptimal chest compressions shows a biased picture of human out-of-hospital CPR. When

the complete range of compression depths is considered, the correlation coefficient drops to 0.34. On the other hand, the set of patients and rescuers was small (12 patients/12 rescuers in our study, 14 animals/2 rescuers in the study by Zhang et al.). When we included a greater variability (60 patients and 2 to 6 rescuers), higher dispersion was observed and correlation coefficient decreased substantially.

In summary, TI signal can be a feasible indicator for CPR quality parameters such as chest compression rate, chest compression fraction or chest compression pauses. Unfortunately, in this study, we proved that TI is unreliable to predict the key quality parameter of chest compression depth. Nevertheless, we further analyzed, from a practical perspective, the power to discriminate shallow from nonshallow chest compressions, in an effort to achieve a quality feedback method. We tried to discriminate chest compressions <38 mm from those >43 mm. Each TI feature showed different distributions between the two categories, but high overlap between them. The results of the logistic regression classifier allowed us to conclude that it is not possible to safely identify shallow chest compressions using the TI signal.

5. Conclusions

During CPR, the quality of chest compressions is related to patient's survival. Feedback devices guide the rescuers toward target compression depth and rate, and contribute to increase the CPR quality. This chapter explored new alternatives to provide feedback on the quality of chest compressions during CPR. Two strategies were studied: the use of the chest acceleration, which can be acquired using an extra pad placed on the chest of the patient during CPR and the use of the transthoracic impedance (TI) signal, which is acquired by current defibrillators through defibrillation pads. Chest acceleration can be used to accurately compute chest compression rate and depth in a wide range of conditions. TI, in contrast, can be used to accurately compute chest compression rate, but not to identify too shallow chest compressions. The development of simpler feedback devices could contribute to their widespread use and to increase the CPR quality.

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