Chest Compression Metrics During Manual Cardiopulmonary Resuscitation: a Manikin Study

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Abstract

Chest compression quality during cardiopulmonary resuscitation (CPR) is defined by adequate rate and depth, with complete chest recoil. Other metrics are duty cycle, or the recently introduced release velocity. However, the relationship between metrics is not sufficiently understood.

Our aim was to design and validate tools for the automated annotation and analysis of compression metrics during manual CPR in a simulated manikin setting.

Eleven volunteers delivered chest compressions on a manikin equipped with a distance sensor to measure chest displacement. Compression depth signal was acquired during 2-min sessions, with different chest stiffness and target compression rates. The annotated metrics for each compression were: compression and decompression duration (T_c, T_d), compression depth (d_p), duty cycle (DC), compression velocity (CV), and release velocity (RV).

We annotated 31451 compressions in 132 recordings, and analyzed the distributions of the annotated metrics: d_p decreased with increasing rate and stiffness. DC, CV and RV increased with rate, and differed with stiffness. CV and RV showed a strong linear correlation with the ratio d_p/T_c and d_p/T_d, respectively.

The study provided a reliable framework for the characterization of chest compressions during manual CPR, and could be extended to human data.

1. Introduction

Quality of chest compressions during cardiopulmonary resuscitation (CPR) plays a critical role in the treatment of out-of-hospital (OOH) cardiac arrest. Delivering early and high-quality chest compressions to the patient generates a minimal but critical amount of blood flow to the heart and the brain, and contributes to enhance survival.

Current recommendations for adult high-quality chest compressions are: depth of at least 50 mm, without exceeding 60 mm; rate between 100 and 120 compressions per minute (cpm); allowing complete chest recoil between compressions, and minimizing interruptions [1]. In addition, a duty cycle of 50% is recommended, that is, half of the compression cycle should be spent compressing the chest. Target values for compression quality metrics have been determined by clinical findings from animal and human studies, and have evolved through the years in parallel to clinical evidence [2,3].

However, resuscitation committees state the need of additional studies on the relationship between compression parameters (especially depth and rate), and how optimal values vary in relation to different patient stiffness. In addition, release velocity (RV) has been recently proposed as a novel quality metric [4], although its relation with current quality metrics is not sufficiently understood.

The aim of this study was to design tools for automated annotation and analysis of chest compression metrics and to test them in a simulated and controlled manikin setting. We also wanted to study the relationship between the current and newly proposed chest compression metrics.

2. Materials and methods

2.1. Experimental setup

A resuscitation manikin (Resusci-Anne QCPR, Laerdal Medical, Norway) was equipped with a resistive distance sensor (SP1-4, Celesco, USA) for continuous recording of the chest displacement. The manikin included three different springs to model human chest stiffness: soft, standard, and hard, accounting for the significant variability of chest stiffness between patients suffering from cardiac arrest [5].

Compression depth signal obtained from the distance sensor was digitized using a data acquisition card (USB NI-6211, National Instruments, USA) connected to a laptop computer. Signals were stored in Matlab® (Mathworks, USA) format, with a sampling frequency of 500 Hz and a 16-bit resolution. Figure 1 shows the experimental setup used in the study: the acquisition card connected to the laptop, and the manikin torso with the three springs: from left to right, yellow (soft stiffness), steel grey (standard), and blue (hard).

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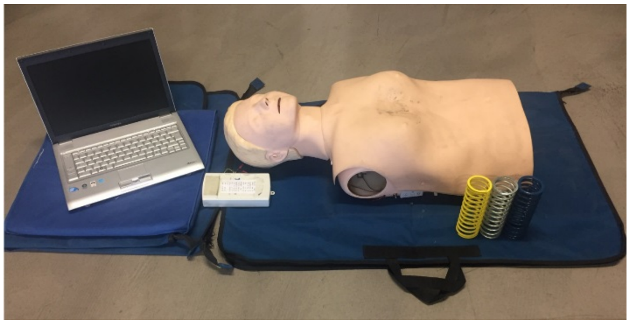

Figure 1. Experimental setup. From left to right: laptop computer, acquisition card, manikin torso, and springs for simulating different chest stiffness.

Eleven volunteers received a basic CPR course and signed an informed consent form before initiating the experimental sessions. They were instructed to deliver continuous chest compressions to the manikin during 2 minutes without pauses. The degree of stiffness and the target compression rate were randomly selected for each experiment. Target compression rate was 80, 100, 120, or 140 cpm, and was guided with a metronome. Volunteers were coached to avoid leaning, i.e., to allow complete recoil of the chest between chest compressions.

2.3. Data annotation

We developed Matlab® tools for the automated annotation of different metrics associated to each chest compression instance in the recorded compression depth signal. These tools also allowed visual inspection of the records and of the annotated metrics. Figure 2 shows an example of the resulting annotations for a single chest compression.

First, we obtained the continuous chest velocity signal (Figure 2, top) as the first derivative of the compression depth signal (bottom). We used these two signals to identify some *fiducial* points and metrics for each compression.

Second, we applied a simple peak detector to the compression depth signal to identify compressions with a depth of at least 10 mm.

For each compression instance, the following *fiducial* points were annotated (Figure 2, bottom panel):

- Instant of the maximum negative depletion of the compression depth signal, t_{dp}. This instant corresponded to a negative to positive zero crossing instant in the chest velocity.
- Start and end of the compression cycle, t_{s} and t_{e}, respectively, which corresponded to null chest velocity.
- Effective start of the compression cycle, $t_{\mathrm{s\_ef}}$, defined as the point where a certain depth, d_{th}, is achieved.
- Effective end of the compression cycle, $t_{\mathrm{e\_ef}}$, defined as the point where the manikin chest was released up to d_{th}.

The annotated metrics were:

- Compression depth, d_{p}: value of the compression depth signal at the time t_{dp}.
- Compression time, T_{c}: time required to achieve d_{p}, from the effective start of the compression:
$$T_{\mathrm{c}} = t_{\mathrm{dp}} - t_{\mathrm{s\_ef}}$$
- Decompression time, T_{d}: time required to release the chest:
$$T_d = t_{e\_ef} - t_{dp}$$
- Compression velocity, CV: maximum chest velocity during the compression time.
- Release velocity, RV: maximum chest velocity during the decompression time.
- Duty cycle, DC: percentage of time spent in compression relative to the duration of the compression cycle:
$$DC = 100 \cdot T_c/(T_c + T_d)$$

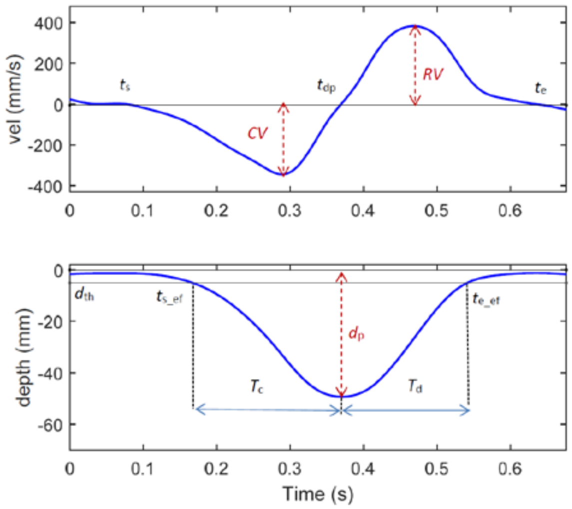

Figure 2. Example of annotated *fiducial* points and metrics for one chest compression cycle.

2.4. Data analysis

As the annotated metrics did not pass the Lilliefors normality test, their distributions were characterized by their median and 25th and 75th percentiles (P_{25}-P_{75}). Distribution of computed metrics was analyzed in relation to stiffness and compression rate. We applied Kruskal-Wallis test for comparison between groups, and a p-value < 0.05 was considered significant.

We also assessed the relationship between compression depth, release velocity and decompression time using univariate linear regression and Pearson's correlation coefficient, r. Our hypothesis was that there would be a strong linear relationship between RV and the ratio d_p/T_d,. A similar analysis was conducted with compression velocity, CV and the ratio d_p/T_c.

We also classified chest compressions individually as high-quality or low-quality chest compressions to analyze the power of RV as a reliable quality parameter. For this analysis, we classified as high-quality chest compressions those with depth between 50 and 60 mm and compression rate between 100 and 120 cpm.

3. Results

We visually inspected all the episodes after the automated annotation. We discarded 315 compressions that did not exceeded the 10 mm threshold. A total of 31451 chest compressions were annotated in 132 episodes, with a mean 238 (47) compressions per episode.

The threshold d_{th} for determining the effective start and end of the compression cycle was fixed at 5 mm.

Figure 3 shows the distributions of some of the analyzed metrics. For the whole population, median (P_{25}-P_{75}) d_p was 48.7 (43.1-53.7) mm; DC was 50.9 (48.7-52.8) %; RV was 485.0 (423.4-541.4) mm/s and CV was 470.0 (406.5-542.5) mm/s.

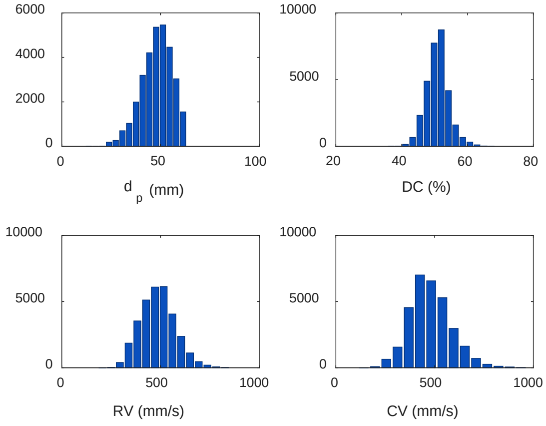

Figure 3. Histograms of some of the computed compression metrics.

3.1. Compression metrics in relation to stiffness and compression rate

Table 1 shows the variation of the computed compression metrics with increasing stiffness. Results were statistically different for all the metrics.

Figure 4 shows the variation of metrics as a function of compression rate. Continuous line represents the median value, while dashed lines represents P_{25} and P_{75}. There were significant differences depending on target compression rate for all the metrics.

Table 1. Compression metrics for different grades of stiffness. d_p in mm; DC in %; RV and CV in mm/s. Values are expressed as integers for clarity

Metric[1]	**Stiffness**		
	Soft	**Standard**	**Hard**
d_p	54 (48-57)	49 (44-53)	45 (40-49)
DC	51 (49-52)	52 (50-53)	50 (48-53)
RV	502 (455-550)	466 (406-527)	478 (414-549)
CV	448 (417-540)	447 (392-524)	489 (413-578)

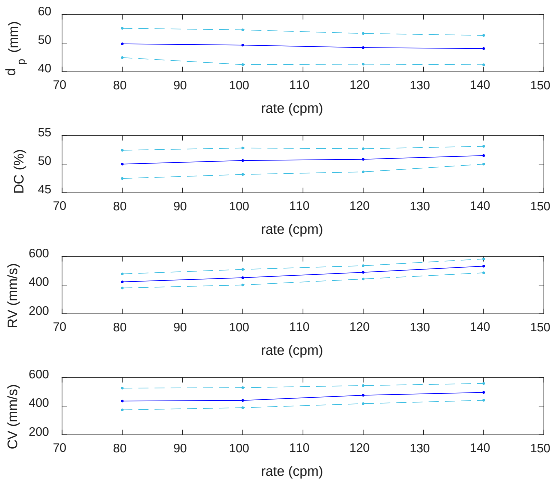

Figure 4. Variation of compression metrics as a function of compression rate.

3.2. Relationship between compression depth and chest velocity

Release velocity RV showed a high linear relationship with the ratio d_p/T_d when all chest compressions were considered. The correlation coefficient was 0.97. Compression velocity CV showed also a high linear relationship with the ratio d_p/T_c, with a correlation coefficient of 0.94.

Figure 5 shows the scatter plot and the models fitted to all values jointly. According to this, a good approximation to the actual release velocity as a function of the ratio depth-decompression time would be:

$$RV = 1.32 \cdot \frac{d_p}{T_d}$$

A similar approximation could explain the relation between CV and the ratio d_p/T_c:

$$CV = 1.33 \cdot \frac{d_p}{T_c}$$

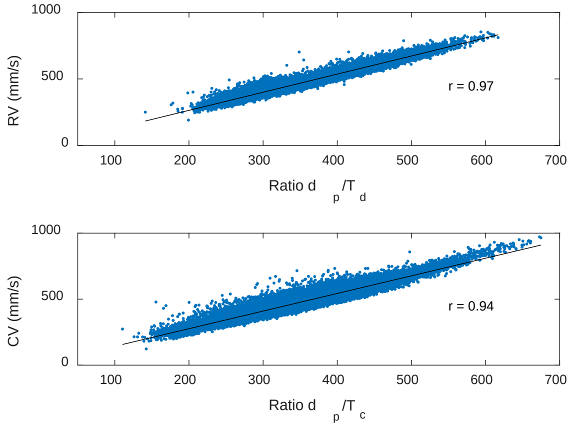

Figure 5. Linear relationship between RV and d_p/T_d (top) and between CV and d_p/T_c (bottom).

Finally, Figure 6 shows the distribution of RV for high-quality and low quality chest compressions.

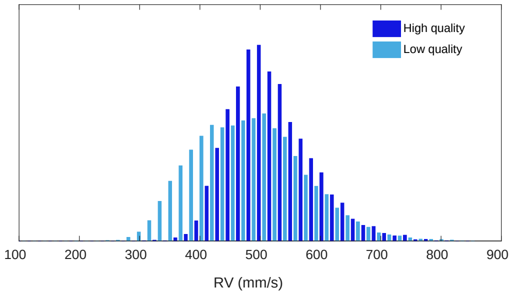

Figure 6. Histograms of RV for high-quality (dark) and low-quality (light) chest compressions.

4. Discussion and conclusions

Extensive analysis of chest compression parameters could contribute to a better understanding of CPR dynamics and the relationship between current and novel quality metrics. Our study provided automated tools for this characterization that could be useful for the analysis of human CPR data.

Our results confirmed that the minimum recommended 50 mm compression depth is difficult to achieve, at least in a manikin model, and that depth decreases with rate and with stiffness. Chest velocities during compression and decompression also depended on stiffness and rate. We also found a linear correlation between velocity and depth, but results did not confirm the potential value of RV as a reliable metric to differentiate between good and poor quality chest compressions. In any case, it should be considered an additional compression metric, complementary to rate and depth.

Availability of compression depth signal in human OHCA data requires the use of commercial CPR feedback devices, mostly based on accelerometers [6]. Deriving depth from acceleration is not straightforward and requires measuring chest force to account for chest release [6]. Nevertheless, the experimental setup presented here allows the reliable assessment of the relationship among different compression metrics, avoiding the uncertainty associated to the estimate of compression depth signal.

6. Conclusions

This study provided a reliable framework for the characterization of chest compressions during manual CPR. Assessing the relationship among chest compression metrics could lead to a better understanding of the optimal chest compression procedure.

Acknowledgements

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