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Research article

Metrics of impulsiveness of manual chest compressions for out-of-hospital cardiopulmonary resuscitation

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ABSTRACT

Aim: Propose new metrics of impulsiveness of manual chest compressions (CCs) that account for shape and duration, separate the characteristics of the compressive part of the CC cycle from those of the recoil part, and are uncorrelated to CC depth and rate.
Methods: We conducted a retrospective analysis of adult out-of-hospital cardiac arrest monitor-defibrillator recordings having CPR data. Specifically, episodes of adult patients with $\geq$ 1000 compressions free of leaning were examined. CCs were obtained from the depth signal of the valid episodes, and we calculated the novel metrics: compression area index (CAI), recoil area index (RAI), compression impulsiveness index (CII) and recoil impulsiveness index (RII). Generalized linear mixed-effects models and Jonckheere-Terpstra trend analyses were employed to measure differences between populations and trends, and the absolute value of Pearson's correlation coefficient $|r|$ was used to report dependence between variables. Statistics are reported as median and interquartile range.
Results: We analyzed 982,340 CCs corresponding to 453 episodes, for which we calculated their CAI, RAI and duty cycle (DC). We analyzed the metrics for various populations: age, sex, any ROSC achieved and disposition, and found that CAI was significantly different according to patient disposition and RAI relative to age and sex ($p < 0.05$). None of the metrics was correlated strongly to depth or rate ($|r|$ values of 0.22 or smaller), and all of them varied for CC series corresponding to the same rescuer over the course of resuscitation ($p_{\text{trend}} < 0.05$). However, we observed that the metrics are not balanced, in that for any value of DC, CAI and RAI span almost their entire ranges.
Conclusion: The proposed metrics correctly and completely describe manual CC waveforms, improve upon the DC, since they depend on the signal waveform, and provide additional information to current indicators of quality CPR, depth and rate. Furthermore, they allow to differentiate the compressive and recoil parts of the CC cycle, reflecting influence of the rescuer (via CAI or CII) and of the biomechanics of the patient's chest (via RAI or RII). Thus, they have

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the potential to contribute to better understanding CPR dynamics and, eventually, to enhanced quality of CPR practice as additional indicators of proper manual CC technique.

1. Introduction

In sudden cardiac arrest, a key link in the chain of survival is early cardiopulmonary resuscitation (CPR). Chest compressions and ventilations are essential elements of modern CPR, and quality indicators for these maneuvers have been established both by the American Heart Association (AHA) and the European Resuscitation Council (ERC) guidelines [1,2], as well as by other Committees on Resuscitation worldwide.

Guidelines include recommendations for compression depth, rate, complete release and hands-on time, based on consensus examination of available evidence, which constitute current references for CPR quality. However, the precise relationships among these parameters and their effects on patients' haemodynamics, and ultimately to survival, are still not well understood [3], warranting further research. One potential advance stems from the use of high-impulse chest compression (HI-CC) techniques, defined as those characterized by a "brief" duration and applied with "moderate force" [4,5]. HI-CC methods have been associated with improved haemodynamics in animals and, as a consequence, to better cardiac outcomes, since the early 80s [4–9] but research in this area has had little continuity over the years and a small impact on current resuscitation guidelines. Traditionally, works in the literature have mainly characterized HI-CC through reduced duty cycles[1] (DC), i.e. such that the duration of the compressive part of the CC waveform is smaller than half its total duration [2,8,10,11]. This has been reflected in the latest AHA guidelines [2], which mention two studies [12,13] reporting DC in clinical practice below 50%. Even so, they do not provide enough evidence of improved haemodynamics or survival, which is why the current recommendation of 50% for DC remains.

Our hypothesis is that impulsiveness might be better characterized through a morphological analysis of the depth waveform, combined with its duration, especially for manual CCs. The purpose of this study was to better examine the impulsiveness of the CC signal, for the compressive and recoil parts of the cycle, derived from an existing out-of-hospital cardiac arrest (OHCA) dataset. Improved quantification of impulsiveness might facilitate replication of the success of animal studies in human studies, providing evidence of their usefulness as an additional quality indicator. To that end, we introduce four new metrics of impulsiveness, and examine the DC as well as depth and rate to assess the independent value of our approaches. We propose that these new metrics may contribute to a better understanding of CPR dynamics, reflecting characteristics of the rescuer and of the biomechanics of the chest, leading to a renewed interest in this field and, eventually, to enhanced quality of CPR practice.

2. Materials and methods

2.1. Data collection

Data used in the analysis were extracted from a collection of adult ($\geq$ 18 years old) OHCA resuscitation episodes, collected by Tualatin Valley Fire & Rescue (Tigard, OR, USA) from 2013 through 2017. Further details of this database can be found in our previous studies [14,15]. No patient sensitive information was required for this study.

Episodes were collected using HeartStart MRx monitor-defibrillators equipped with Q-CPR monitors (Koninklijke Philips N.V, Amsterdam, The Netherlands), which incorporate force and acceleration sensors. Rescuers received real time feedback on chest compression (CC) depth, rate and presence of leaning from the monitors. Acceleration and force signals were extracted from the monitor-defibrillators and analyzed with Matlab® (Natick, MA, USA). Depth and velocity signals were computed from chest acceleration during compressions, as previously described in other publications [16].

2.2. Data inclusion and annotation

Each compression was automatically detected in the velocity signal by using a 25 mm/s threshold, and corroborated by a peak force of at least 5 kg-F. Leaning was annotated for the intervals of time in which the force exceeded a 2.5 kg-F at the end of the compression, representative of the rescuer not releasing adequately [16]. All episodes included in the study contained at least 1000 compressions free of leaning.

Several annotations were performed for each CC in the depth signal, and the following parameters were calculated (see Fig. 1 (b)):

- **Peak depth (d_p)**: maximum value of the depth signal (measured in mm).
- **Compression time (T_c)**: duration of the compression part of the cycle (in s).
- **Recoil time (T_r)**: duration of the recoil part of the cycle (s).
- **Compression area (CA)**: area under the depth curve corresponding to the compression part of the cycle.
- **Recoil area (RA)**: area under the depth curve corresponding to the decompression part of the cycle.

[1] The duty cycle of the CC corresponds to the proportion of the duration of the compression phase with respect to the total duration of the CC cycle.

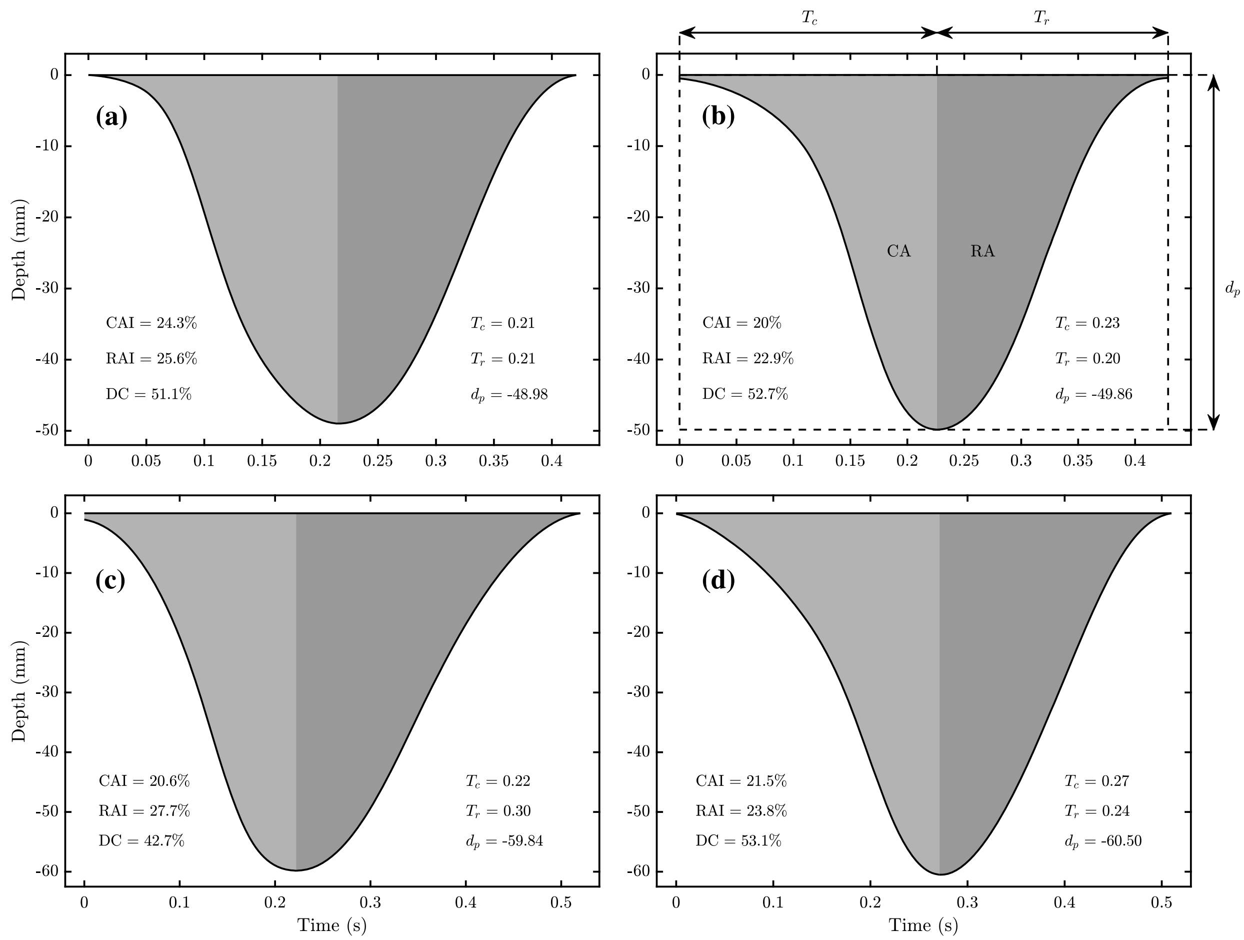

Fig. 1. Graphical examples of the comparison between the metrics DC and CAI, with signals extracted from our database. (a-b) Comparison of waveforms presenting very similar values of DC, for fixed depth and duration, but large variation of CAI. (c-d) Comparison of waveforms presenting very similar values of CAI, for fixed depth and duration, but large variation of DC.

In addition, we identified CC pauses as intervals of time lasting longer than 5 seconds in which no CC had been detected; and CC series as sets of successive CCs between 2 consecutive pauses.

2.3. Metrics of impulsiveness

We developed the following metrics of impulsiveness to characterize the resuscitation maneuvers:

- **Compression area index (CAI)**: proportion of the area under the depth curve corresponding to the compression part of the cycle, CA, with respect to the area of the rectangle depicted in Fig. 1 (b).
- **Recoil area index (RAI)**: proportion of the area under the depth curve corresponding to the recoil part of the cycle, RA, with respect to the area of the rectangle of Fig. 1 (b).

These metrics are smaller for more impulsive signals, and therefore provide inverse measurements of impulsiveness of CCs. For comparison with CAI and RAI, we also computed the **duty cycle** of each compression. The idea behind the definition of the inverse metrics was to compare them to the DC of the CCs.

In addition, we calculated the **impulse factor** of each CC, defined as the relation between its maximum absolute value and its mean absolute value [17–20] (see Supplementary Material). In particular, we obtained the impulse factor of the compression ($\mathrm{IF_c}$) and of the decompression ($\mathrm{IF_r}$) parts of the cycle.

We also defined and calculated the following metrics of impulsiveness:

- **Compression impulsiveness index (CII)**: direct measurement of the impulsiveness of the compressive part of the cycle of a CC. It is computed as the inverse of CAI, resulting directly proportional to $\mathrm{IF_c}$ and inversely proportional to DC (see Supplementary material).

Table 1
Patient characteristics and disposition of cases with extended CPR (≥1000 compressions, leaning absent). ROSC refers to any event of return of spontaneous circulation.

Characteristic	Observed Value
Age (y), median (IQR)	66 (53–75)
Sex, n (%)	
Female	153 (33.8)
Male	300 (66.2)
Initial EGC rythm, n (%)	
Shockable (VF/VT)	116 (25.6)
Pulseless electrical activity	119 (26.3)
Asystole	210 (46.3)
Not recorded	8 (1.8)
Return of Spontaneous Circulation (ROSC), n (%)	145 (32)
Disposition, n (%)	
Died in field	170 (37.5)
Died in emergency department	166 (36.6)
Died after hospital admission	89 (19.7)
Discharged alive	20 (4.4)
Unknown	8 (1.8)

- **Recoil impulsiveness index (RII)**: direct measurement of the impulsiveness of the decompression part of the cycle. It is computed as the inverse of RAI, resulting directly proportional to IF_r and inversely proportional to $1 - DC$ (see Supplementary material).

Therefore, CII (or CAI) is composed of a duration dependent factor (DC) and a shape dependent factor (IF_c). This is like saying that the metric decomposes the waveform into a characteristic used for mechanical CPR, the DC, associated to rectangular force signals; and a characteristic relevant to the shape of manual CPR, the IF_c. In effect, the higher the IF of the compression or the lower its DC, the greater its impulsiveness according to CII. A similar reasoning applies to RII (or RAI).

2.4. Statistical analysis

Distributions of the metrics and annotations are reported in the form of tables and box plots, which include median and interquartile ranges, IQR, (25% and 75% percentiles). Comparisons among population groups were analyzed with generalized linear mixed-effects (GLME) models, for which the patient was used as a random factor [21]. Trends of the metrics with respect to the number of CCs were assessed with Jonckheere-Terpstra tests [15,22] for series between pauses. For both types of analyses, p-values smaller than 0.05 were considered significant. Statistical dependence of the metrics in relation to compression depth and rate were assessed using Pearson's linear correlation coefficient per patient in absolute value, $|r|$.

3. Results

3.1. Description of the database

Of all the CCs from the 616 original cases corresponding to adults, we discarded those with evidence of leaning (7.4% of all available CCs). Subsequently, we imposed the episode inclusion criteria of at least 1000 CCs with leaning removed, which left us with 453 patients for analyses. As a result, we analyzed a total of 982,340 CCs, with median 1957 (1408–2762) CCs per episode. The general characteristics of the database are reported in Table 1.

For this cohort of patients, the median age was 66 (53–75) years old, and 34% were female. Initial ECG rhythm was asystole in 46.3% of the episodes, shockable in 25.6%, and pulseless electrical activity in 26.3%. Return of spontaneous circulation (ROSC) was achieved in the field, at some point during the extended CPR procedures, in 32% of the patients. Among those with recorded disposition, death occurred in the field in 37.5% of the episodes, in the emergency department in 36.6% and after hospital admission in 19.7%; and 4.4% of the patients survived to hospital discharge. These are representative of patients with extended CPR, who are known to have less favorable outcomes [14].

Median compression depth was 51.8 (44.2–59.2) mm, and median compression rate was 112.6 (104.5–120.8) compressions per minute (cpm).

3.2. Characteristics of the metrics

In Table 2 we present overall statistics of CAI, RAI, DC, CII and RII. For reference, we also include information of IF_c and IF_r. Values of CAI, characterized by a median of 18.1%, are smaller than those of RAI, of median 26.0%, indicating greater impulsiveness

Table 2
Metrics characteristics given as median (25%–75% percentiles) for the CCs of patients categorized according to the percentage of CCs complying with guidelines (50–60 mm & 100–120 cpm) and for all CCs (global). The values of IF_c and IF_r are also given for reference and completeness.

Metric	<25% (n = 254)	25-50% (n = 146)	>50% (n = 34)	Global (n = 453)
CAI (%)	18.0 (15.8–20.0)	18.2 (16.2–20.0)	17.8 (16.0–19.4)	18.1 (16.0–20.0)
RAI (%)	25.9 (23.7–28.1)	26.2 (24.1–28.3)	26.1 (24.1–28.1)	26.0 (23.9–28.2)
DC (%)	39.9 (35.3–43.6)	40.6 (36.8–43.6)	40.5 (37.0–43.3)	40.2 (36.0–43.6)
CII	5.6 (5.0–6.3)	5.5 (5.0–6.2)	5.6 (5.1–6.2)	5.5 (5.0–6.3)
RII	3.9 (3.6–4.2)	3.8 (3.5–4.2)	3.78 (3.6–4.2)	3.8 (3.5–4.2)
IF_c	2.2 (2.0–2.4)	2.2 (2.0–2.4)	2.2 (2.1–2.4)	2.2 (2.0–2.4)
IF_r	2.3 (2.1–2.6)	2.2 (2.1–2.5)	2.3 (2.0–2.5)	2.3 (2.1–2.5)

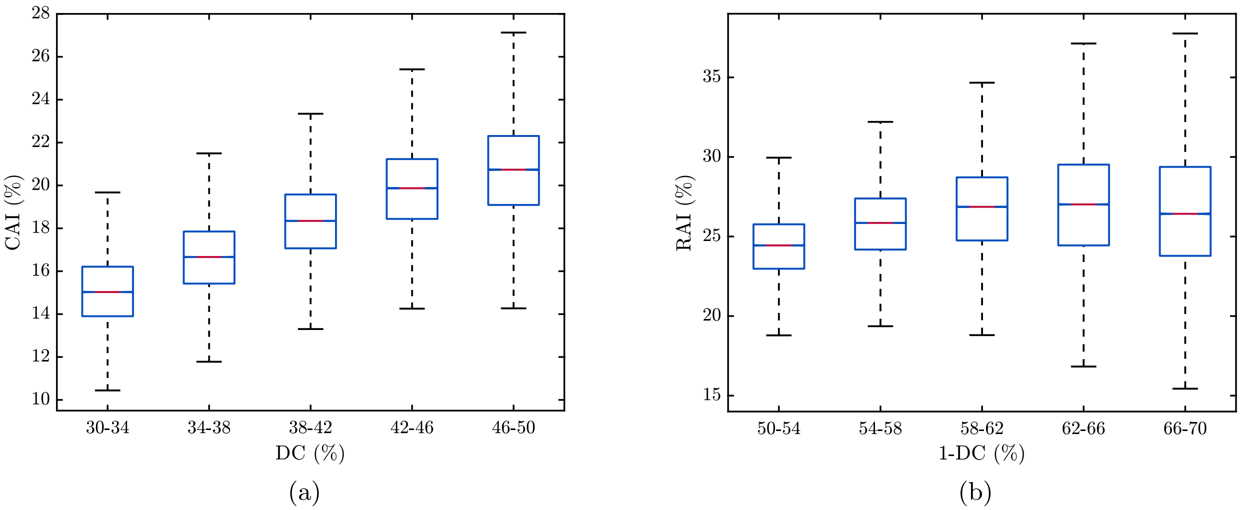

Fig. 2. Boxplots of the variations of CAI and RAI with respect to DC and 1 − DC, quintilized within their full observed range (more specifically, from 30% to 50%, and from 50% to 70%, respectively).

of the compression phase. This is representative of our database, since it happens in 98% of all analyzed CCs. The same behavior is reflected by values of CII, with median 5.5, which are larger than those of RII, with median 3.8.

Fig. 2 shows boxplots of the variations of CAI and RAI with respect to DC and $1 - \mathrm{DC}$, quintilized from 30% to 50%, and from 50% to 70%, respectively. Due to the linear case-wise relation with DC, the median values of CAI tend to increase with respect to DC (Fig. 2 (a)). A similar initial trend is seen in between RAI and $1 - \mathrm{DC}$, which ends ups plateauing (Fig. 2 (b)). Moreover, we observe that the variations of the metrics are not balanced; indeed, no matter the value of DC or $1 - \mathrm{DC}$, both CAI and RAI span almost their entire ranges of possible values. For instance, for DC constrained from 38% to 42%, CAI can take values from 13.30% to 23.42%, well beyond its 25% and 75% percentiles (see Table 2).

Table 2 further shows statistics of the metrics for the CCs of patients categorized according to the percentage of CCs complying with guidelines [2,23] (depth between 50 and 60 mm and rate between 100 and 120 cpm). Differences among categories were found to not be statistically significant for CAI ($p = 0.35$) or RAI ($p = 0.27$) but significant for DC ($p = 0.01$).

We also analyzed CAI, RAI and DC for different populations: patients grouped by age, sex, ROSC achieved or not and disposition. The results of such analysis are presented in Table 3, where median and IQRs for each metric and population are given, as well as the p-value of the grouping. Significant differences were found for CAI according to disposition ($p = 0.01$), for RAI regarding age ($p \ll 0.05$) and sex ($p \ll 0.05$), and for DC relative to age ($p \ll 0.05$).

3.3. Relation with depth and rate

We present the distributions of $|r|$ for all episodes in Table 4. Note that, before computing values of $|r|$, we normalized all metrics to their median over the first 100 compressions, in order to properly combine patients with differing statistics [14,15]. Specifically, CAI presents a median $|r|$ value with respect to depth of 0.16, RAI of 0.16 and DC of 0.22. Then, CAI presents a median $|r|$ value with respect to rate of 0.13, RAI of 0.10 and DC of 0.10. It is noteworthy that all correlations are very small, and that CAI and RAI were characterized by a median correlation comparable to that of DC for all considered scenarios.

Table 3
Median (25%–75% percentiles) for each metric and population, and significance *p*-value of the grouping. The *p*-values are obtained from the fit of GLME models to each of the populations, with the group as fixed variable and the patient as random variable.

Characteristic	CAI (%)	RAI (%)	DC (%)
Age, (y)			
≤ 55	18.1 (16.0–19.9)	25.1 (23.2–27.1)	41.0 (36.8–44.2)
56–65	18.2 (16.1–20.3)	25.9 (23.7–28.1)	40.5 (36.5–43.9)
66–75	18.2 (16.1–20.1)	26.5 (24.4–28.5)	40.4 (36.3–43.7)
≥ 76	(15.6–19.8)	26.9 (24.6–29.1)	38.8 (34.4–42.2)
p-value	0.35	$\ll 0.05$	$\ll 0.05$
Sex,			
Female	18.2 (16.1–20.1)	26.7 (24.7–28.9)	40.3 (36.3–43.5)
Male	18.0 (15.9–20.0)	25.7 (23.5–27.8)	40.2 (35.9–43.6)
p-value	0.74	$\ll 0.05$	0.92
Any ROSC,			
No	18.0 (15.9–20.0)	25.9 (23.7–28.1)	40.2 (35.9–43.7)
Yes	18.2 (16.2–20.1)	26.3 (24.2–28.4)	40.3 (36.4–43.4)
p-value	0.18	0.13	0.77
Disposition,			
Died in field	17.8 (15.7–19.7)	26.5 (24.4–28.7)	39.8 (35.6–43.3)
Died in emergency department	18.0 (15.9–20.0)	25.7 (23.5–27.9)	40.2 (35.9–43.7)
Died after hospital admission	18.4 (16.4–20.3)	26.2 (24.0–28.3)	40.5 (36.6–43.7)
Discharged alive	18.9 (17.1–20.6)	25.5 (23.6–27.2)	41.2 (38.0–43.7)
p-value	0.01	0.24	0.32

Table 4
Median (IQR) values of Pearson's correlation coefficient in absolute value, $|r|$, for each metric with respect to depth and rate.

Metric	$\|r\|$ vs depth	$\|r\|$ vs rate
CAI	0.16 (0.08–0.31)	0.13 (0.06–0.20)
RAI	0.16 (0.08–0.28)	0.10 (0.05–0.18)
DC	0.22 (0.11–0.35)	0.10 (0.05–0.18)

Table 5
Variations of CAI, RAI and DC in % after 20 sets of 10 CCs for populations according to age and sex, as well as overall.

Characteristic	ΔCAI (%)	ΔRAI (%)	ΔDC (%)
Global	+2.16	+3.66	-1.34
Age, (y)			
≤ 55	+2.19	+3.70	-1.38
56–65	+2.10	+3.19	-1.12
66–75	+2.30	+3.35	-1.37
≥ 76	+2.03	+4.33	-1.43
Sex,			
Female	+2.22	+4.24	-1.94
Male	+2.13	+3.36	-1.03

3.4. Evolution of the metrics

In order to analyze the time evolution of the different metrics, we obtained their variations within series for sets of 10 successive CCs, after normalizing each set to the first set of the series. A total of 5,440 series of median (IQR) length 190 (119–222) CCs were used. Fig. 3 shows how median (solid line) and 25% and 75% percentiles (dashed line) of CAI and RAI increased within series, and of DC decreased when every patient was considered. We found statistical significance with regard to tendency of variation for all metrics (p_{trend} values $\ll 0.05$).

In Table 5 we also present the total variation of each metric after 20 sets of 10 CCs for populations according to age and sex, as well as overall. The tendencies are the same globally as the are for each population, i.e. increasing for CAI and RAI and decreasing for DC. Variations are also very similar in absolute value, except for RAI for patients over 76 years of age and for females, which are substantially higher, and for DC for females, which is lower.

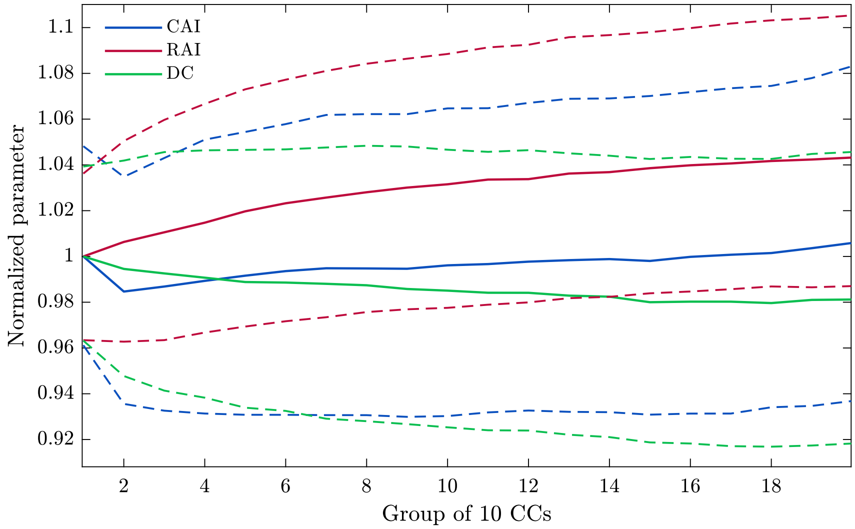

Fig. 3. Time evolution of CAI, RAI and DC within series, grouping CCs in sets of 10 successive CCs and normalizing each set to the first set of the series. Solid lines indicate median values of the metrics every 10 CCs for series lasting around 200 CCs.

4. Discussion

In modern CPR, simple application of the maneuver is just not enough, and resuscitation guidelines [1,2] include optimal ranges for rate, depth and complete release and hands-on time, among others, based on careful analysis of available evidence. Nevertheless, non-conclusive associations between individual CC quality parameters and favorable neurological outcomes have been reported [3], which opens up opportunities for improving the maneuver of CC.

One area that warrants attention [24] is relative to HI-CC techniques. These were first studied by Maier et al. in a classical study [4] in which researchers considered the effects of varying manual compression rate, force and duration in intact chronically instrumented dogs. This practice resulted in augmented cardiac blood flow and better cardiac outcomes when CCs of "brief" duration were applied with "moderate force". Swart et al. [5] then proposed a controlled porcine model, based on a mechanical CPR method, where compression rate, duration and ventilation rate were fixed, while the duty cycle was allowed to vary. They found significantly better haemodynamic measurements when shorter compression durations were used. More recently [25,26], release velocity (RV) has also been proposed as a potential CPR quality parameter, but the association between RV and survival remains unclear [27].

Despite compressive waveform types having been considered in the literature [8,10,28,29], over the last 20 years studies have mainly focused on the duty cycle of the CC, associating shorter DCs (less than 50%, and as low as 20% [5]) to greater impulsiveness [6–8,12,24,30]. However, DC is a metric inherited from machinery applications, and only makes straightforward sense in scenarios with mechanical CC devices, employing rectangular force waveforms. Therefore, it is not a sufficient descriptor of manual CC methods, since it fails to take the compression signal shape into consideration and, furthermore, completely omits quantification of the dynamics of chest recoil.

In order to properly describe the impulsiveness of CCs, in this paper we present new metrics of impulsiveness capable of accounting for the duration and the shape of CCs, as well as of differentiating the compression and decompression phases of the CC cycle. These are CAI, RAI, CII and RII). Table 2 shows that both DC and IF vary substantially across the patients from our database. This information can only be captured by metrics such as CAI and RAI, or their inverses, because they are formed as linear combinations of DC and IF. In the same table we observe that CAI and RAI are very different from each other, confirmed by CAI being smaller than RAI for 98% of the CCs of our database. This is a consequence of a greater impulsiveness of the compression phase, which may reflect that CAI is more related to characteristics of the rescuer and RAI to the biomechanical characteristics of the of the patient's chest. Table 3 further shows that CAI was significantly different for groups according to disposition ($p = 0.01$), whereas RAI was significantly different with regards to age ($p \ll 0.05$) and sex ($p \ll 0.05$). This is not surprising, since it is well known that the characteristics of the chest differ according to patient type and over the course of resuscitation [21]. These findings are relevant, but they should be contrasted with further retrospective or prospective studies in order to establish the precise relationships to such populations.

The variations of the metrics of impulsiveness are not aligned, since no matter the value of DC (or $1 - \mathrm{DC}$), both CAI and RAI span almost their entire possible ranges (see Fig. 2). For instance, for DC constrained from 38% to 42%, CAI can take values as distant as 13.30% and 23.42%, due to the shapes of the manual waveforms, well beyond its global 25% and 75% IQR (see Table 2). This can be better understood with a series of examples comparing specific CCs extracted from our database. The first example corresponds to the comparison between Fig. 1 (a) and (b). While the two waveforms have very similar maximum depths, total durations and DC (less than 5% difference, from 51.1% to 52.7%), they vary much more significantly in CAI (more than 20%, from 24.3% to 20%). Our metric correctly captures their difference in impulsiveness, by a change in $\mathrm{IF_c}$ of 25% from 2.1% to 2.6%. The second example corresponds to the comparison between Fig. 1 (c) and (d). In this case, the two waveforms have comparable maximum depths, total durations and values of CAI (less than 5% variation, from 20.6% to 21.5%) but present very different DC (more than 20% variation, from 42.7% to 53.1% DC). Due to a 19% variation of IF_c from 2.07% to 2.47%, our metric correctly characterizes the CCs with similar impulsiveness.

Nowadays, impulsiveness is not an indicator of CPR quality, and performing chest compressions in an impulsive way is not encouraged, taught or monitored. This is clearly reflected by Tables 2 and 4. In the former, metrics were calculated for the CCs of patients categorized according to the percentage of CCs adhering to guidelines. Differences among categories were found to not be statistically significant for CAI ($p = 0.35$) or RAI ($p = 0.27$). In the latter, the same idea is reinforced, and supports the independence of all considered metrics with respect to depth and rate. These make them possible candidates to be incorporated as additional indicators of CPR quality, that could be adapted into training and real time feedback.

Our metrics also show significant variations within series of CCs in between pauses, with median CAI and RAI increasing by 2.16% and 3.66% respectively for 200 consecutive CCs, which translates into reduced impulsiveness of both phases of the CC cycle. We believe that the decrease of impulsiveness in the compression phase might be more directly related to rescuer fatigue, and that of the recoil phase to alterations in chest stiffness, or other physiological and biomechanical characteristics of patients. Furthermore, variations are more pronounced for patients over 76 years of age and females, which once again may be reflective of the properties of their chests [21].

Last of all, even if we have derived and applied our metrics to depth signals, nothing prevents their use with force signals. However, one should keep in mind that force is much less often available and, not only that, it does not correctly capture the chest response to the force applied by the rescuer. In fact, within decompression, the force follows how rescuers release when lifting their hands, whereas the depth shows the combined effects of release and chest dynamics (recoil) [15].

4.1. Limitations

We analyzed recordings from a single EMS agency database. Compression depth and rate showed little dispersion among episodes and during resuscitation efforts, likely due to real-time feedback. Consequently, our results may not be generalizable to other agencies or settings where feedback is not present, even though we found no statistical differences when guidelines were not fully complied with. In addition, our episode inclusion criteria may be a form of selection bias that needs to be acknowledged.

5. Conclusions

A thorough review of the literature on modern CPR has evidenced a lack of continuity and applicability of HI-CC techniques and, in general, the absence of a proper definition of CC impulsiveness. Even though a metric, DC, has recently resurfaced as a candidate for such analysis, we have concluded that it cannot accurately characterize the wide disparity of signal shapes derived from manual CPR compressions. Motivated by this fact, we propose new metrics of impulsiveness, CAI and RAI, capable of including the concept of duration as DC, that also account for the essential contribution of the CC shape via the impulse factor, IF. We derive the metrics and apply them to the depth waveform, since it is often available and because it shows the joint effect of force and chest response in a single signal. Moreover, their inverses, CII and RII, properly account for direct measure of impulsiveness.

Our metrics correctly and completely describe CC waveforms, are uncorrelated to depth and rate and allow to differentiate the compressive and recoil parts of the CC cycle, reflecting influences of the rescuer and of the patient's biomechanical properties of the chest. In consequence, we believe they could contribute to conducting studies aimed at better understanding CPR dynamics and, eventually, to enhanced quality of CPR practice as additional indicators of proper manual CC technique.

Ethics statement

The database is part of the Portland Resuscitation Outcomes Consortium Epidemiological Cardiac Arrest Registry, approved by the Institutional Review Board (IRB00001736) of the Oregon Health & Science University (OHSU). No patient sensitive information was required for this secondary observational study. Data were de-identified before any analysis was conducted, and the data needed for the research could not be connected in any way to the identity of the subjects.

CRediT authorship contribution statement

Jose Antonio Urigüen: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sofía Ruiz de Gauna:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Jose Julio Gutiérrez:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Izaskun Azcárate:** Writing – review & editing, Visualization, Validation. **Mikel Leturiondo:** Writing – review & editing, Visualization, Validation, Software, Data curation. **Koldo Redondo:** Writing – review & editing, Visualization, Validation. **James Knox Russell:** Writing – review & editing, Validation, Resources, Methodology, Formal analysis, Data curation. **Mohamud Ramzan Daya:** Writing – review & editing, Supervision, Resources.

Declaration of competing interest

The database is part of the Portland Resuscitation Outcomes Consortium Epidemiological Cardiac Arrest Registry, approved by the Institutional Review Board (IRB00001736) of the Oregon Health & Science University (OHSU).

All authors declare no conflict of interest.

Data availability

The data used for this article are not directly available due to the authors not having permission to share them. However, a subset of the database, containing values of CAI, RAI and DC for each CC, may be requested to the corresponding author and authorized if considered reasonable.

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Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e28739.

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