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Short paper

Pilot study on VF-waveform based algorithms for early detection of acute myocardial infarction during out-of-hospital cardiac arrest

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Abstract

Introduction: On-scene detection of acute coronary occlusion (ACO) during ongoing ventricular fibrillation (VF) may facilitate patient-tailored triage and treatment during cardiac arrest. Experimental studies have demonstrated the diagnostic potential of the amplitude spectrum area (AMSA) of the VF-waveform to detect myocardial infarction (MI). In follow-up, we performed this clinical pilot study on VF-waveform based discriminative models to diagnose acute MI due to ACO in real-world VF-patients.

Methods: In our registry of VF-patients transported to a tertiary hospital (Nijmegen, The Netherlands), we studied patients with high-quality VF-registrations. We calculated VF-characteristics prior to the first shock, and first-to-second shock changes (Δ-characteristics). Primary aim was to assess the discriminative ability of the AMSA to detect patients with ACO. Secondarily, we investigated the discriminative value of adding ΔAMSA-measures using machine learning algorithms. Model performances were assessed using C-statistics.

Results: In total, there were 67 VF-patients with and 34 without an ACO, and baseline characteristics did not differ significantly. Based on the AMSA prior to the first defibrillation attempt, discrimination between ACO and non-ACO was possible, with a C-statistic of 0.66 (0.56–0.75). The discriminative model using AMSA + ΔAMSA yielded a C-statistic of 0.80 (0.69–0.88).

Conclusion: These clinical pilot data confirm previous experimental findings that early detection of MI using VF-waveform analysis seems feasible, and add insights on the diagnostic impact of accounting for first-to-second shock changes in VF-characteristics. Confirmative studies in larger cohorts and with a variety of VF-algorithms are warranted to further investigate the potential of this innovative approach.

Keywords: Cardiac arrest, Ventricular fibrillation, Waveform analysis, Acute myocardial infarction, Acute coronary syndrome, Machine learning

Introduction

Ventricular fibrillation (VF) out-of-hospital cardiac arrest (OHCA) occurs frequently and carries a poor prognosis.[1] In many cases, the cause of VF is acute coronary occlusion (ACO), for which early coronary angiography (CAG) and intervention might be beneficial.[2] At present, identification of ACO is restricted to the subset of patients regaining organised rhythm,[3] which hampers timely and aetiology-directed treatment for the VF-population as a whole. A potential tool for earlier detection of an ACO may be analysis of the VF-waveform of the defibrillator-derived electrocardiogram (ECG).

VF-waveform characteristics, particularly the amplitude spectrum area (AMSA), are increasingly recognised as predictors of defibrillation success and survival.[4,5] In terms of potential new treatment options, real-time AMSA-quantification has been incorporated in "smart" defibrillators to guide shock delivery, an innovative technique under active investigation in a randomised trial to try and improve defibrillation success (NCT03237910).

From the perspective of diagnostic options using VF-waveform analysis, the first in-human experimental data have recently been published demonstrating the feasibility to detect myocardial infarction (MI). These findings gave rise to the innovative concept of a diagnos-

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https://doi.org/10.1016/j.resuscitation.2022.03.025
Received 1 February 2022; Received in Revised form 14 March 2022; Accepted 20 March 2022

tic defibrillator.[6] Several clinical studies have shown associations between MI, VF-signal characteristics and changes in VF-morphology during the course of the arrest.[7–10]

However, a clinical study on the diagnostic performance of VF-waveform analysis has not yet been performed. To provide first insights, we present a pilot study in which we studied VF-waveform based discriminative models to detect acute MI due to ACO in a real-world VF-cohort.

Methods

Study population

From our OHCA-registry,[11] we studied adult VF-patients transported to the Radboudumc (Nijmegen, The Netherlands). We excluded patients without (analysable) defibrillator ECG-recordings or with insufficient information to determine the presence/absence of ACO. According to local ethical legislation, written informed consent was not necessary to obtain for this non-interventional observational study (Dutch Act on Medical Research involving Human Subjects).[11]

Data acquisition

Collection of baseline characteristics (EMS and hospital records) followed Utstein recommendations.[12] ECG-signals (sampling frequency 125 Hz) were obtained with defibrillator pads (Lifepak12, PhysioControl). Signal analyses (Matlab 2020a, Mathworks) were performed on three-second, artefact-free VF-segments prior to the first shock for calculation of AMSA (frequency interval 2–48 Hz) and a series of other commonly studied VF-characteristics (i.e. mean absolute amplitude, dominant frequency, organisation index).[4,6] Moreover, in patients with > 1 shock, we calculated relative changes between the first and second shock (Δ-characteristics).[9,13]

Study aim

Primary aim was to assess the performance of a single-variable approach to distinguish ACO from non-ACO patients, using AMSA prior to the first defibrillation attempt. Secondarily, we studied the discriminative ability of machine learning based models combining AMSA and ΔAMSA-measures. Finally, we explored models combining various VF-characteristics.

Group definition

Categorisation into either ACO or non-ACO was based on previously reported methodology using information from patient charts, CAG/autopsy findings, and 12-lead ECGs.[3,10,14] In short, we firstly assessed whether or not patients fulfilled the criteria of the universal definition of myocardial infarction.[3] If so, a patient was classified as ACO (i) in case an acute occlusion was found during CAG/autopsy and/or (ii) in case of ST-segment elevation corresponding with acute localised MI. All other patients were categorised as non-ACO.[3,14]

Discriminative approaches

For the primary aim (single-variable approach), AMSA was used as continuous test variable (Table 1). For multiple-variable approaches, machine learning techniques were used, with the construction of support vector machine (SVM) models, adhering to previously reported methodology (Supplement 1).[6] For internal validation, five-fold cross-validation was used (*crossval* function in Matlab), according to a cross-validation partition (*cvpartition* function) in which each of the five training sets and corresponding validation sets had a fixed 60/40 ratio of ACO and non-ACO cases.

Statistics

Continuous variables were assessed for normal distribution. In case of non-normality, data were described as medians (interquartile ranges) and compared using Mann Whitney U-tests. Categorical variables were presented as numbers (percentages) and compared using χ^2-tests (SPSS 25, IBM). Receiver operating characteristic (ROC) analysis was performed (MedCalc 19.1.3, MedCalc Software) for assessment of discriminative ability. C-statistics (95% CI) were considered the main outcome measure for model performances, and compared using DeLong's method. $P < 0.05$ was considered statistically significant.

Results

Baseline characteristics and VF-characteristics

Of the 253 OHCA VF-patients transported to the Radboudumc, 102 were excluded due to the lack of (analysable) ECG-tracings and 40 due to insufficient clinical information to determine ACO-status (Supplement 2). Of the 111 analysed patients, median age was 62 years, 71% were men and ACO was present in 60%. No differences in baseline characteristics were observed, except for a trend towards higher response times in the ACO vs. the non-ACO group (8 vs. 7 minutes, p = 0.05). Seventy-five patients (68%) received > 1 shock (Table 2). There was a significant difference in AMSA between ACO and non-ACO patients (14.4 mVHz [7.3–16.4] vs. 8.8 [6.1–11.9]), p = 0.005, as well as in MAA (0.14 mV [0.10–0.18] vs. 0.11 [0.07–0.14]), p = 0.01.

Table 1 – VF-waveform analysis in the detection of acute coronary occlusion: approaches used in this study.

Approach	Method	VF-waveform information	Input features
Primary aim: AMSA-only			
#1	Single variable	AMSA-only	AMSA
Secondary aim: AMSA + ΔAMSA			
#2	SVM model	AMSA-only and AMSA-course	AMSA, ΔAMSA
Exploratory analyses: Additional VF-characteristics			
#3	SVM model	Entire set of VF-characteristics	AMSA, MAA, DF and OI
#4	SVM model	Entire set of VF-characteristics and their course	AMSA, MAA, DF, OI, ΔAMSA, ΔMAA, ΔDF and ΔOI

Table showing the four different approaches for constructing discriminative models. Approaches #2 and #4 only apply to patients receiving > 1 shock. ACO = acute coronary occlusion; AMSA = Amplitude spectrum area;, DF = Dominant frequency; MAA = Mean absolute amplitude; OI = Organisation index; SVM = Support vector machine; VF = Ventricular fibrillation; Δ = Relative changes in VF-characteristics between shock 1 and 2.

Table 2 – Characteristics of the study population.

	All patients N = 111	ACO N = 67	Non-ACO N = 44	p-value
Demographics				
Age (years)	62 (51–71)	60 (49–71)	62 (54–62)	0.45
Male sex	79 (71)	49 (73)	30 (68)	0.57
Arrest characteristics				
Public arrest	49 (44)	30 (45)	19 (43)	0.87
Witnessed arrest (n = 108)	93 (86)	57 (88)	36 (84)	0.56
Bystander CPR (n = 108)	72 (77)	44 (68)	28 (65)	0.78
AED shock (n = 108)	9 (8)	5 (8)	4 (9)	0.49
Response time (min) (n = 101)	8 (6–10)	8 (6–11)	7 (5–9)	0.05
Number of EMS shocks	3 (1–6)	4 (1–6)	3 (1–5)	0.27
$\geq$ 2 EMS shocks	75 (68)	47 (70)	28 (64)	0.47
Clinical outcome				
Survival to discharge	52 (47)	31 (46)	21 (48)	0.88
VF-waveform				
AMSA (mVHz)	9.9 (6.5–14.7)	8.8 (6.1–11.9)	14.4 (7.3–16.4)	0.005
Δ AMSA	1.13 (0.90–1.54)	1.17 (0.96–1.56)	1.11 (0.92–1.54)	0.63
MAA (mV)	0.12 (0.08–0.16)	0.11 (0.07–0.14)	0.14 (0.10–0.18)	0.01
Δ MAA	1.12 (0.85–1.40)	1.14 (0.88–1.43)	1.20 (0.88–1.45)	0.59
DF (Hz)	4.00 (2.66–5.65)	3.66 (2.66–5.32)	4.65 (2.66–6.82)	0.17
Δ DF	1.10 (0.86–1.50)	1.10 (0.89–1.60)	1.13 (0.88–1.41)	0.65
OI	0.47 (0.34–0.62)	0.49 (0.35–0.64)	0.45 (0.33–0.58)	0.16
Δ OI	0.87 (0.58–1.25)	0.82 (0.58–1.25)	0.97 (0.63–1.49)	0.19

Table showing baseline characteristics in all patients (first column), patients with an underlying ACO (second column) and patients without an underlying ACO (third column). P-values represent comparisons between ACO and non-ACO patients. ACO = Acute coronary occlusion, CPR = Cardiopulmonary resuscitation, AED = Automated external defibrillator, EMS = Emergency medical services, AMSA = Amplitude spectrum area, MAA = Mean absolute amplitude, DF = Dominant frequency, OI = Organisation index, Δ = Relative change in VF-characteristics between shock 1 and 2 (eg, ΔAMSA = AMSA2/AMSA1).

Representative examples of used VF-signals can be found in Fig. 1.

Identification of ACO

Discrimination between ACO and non-ACO patients with the single-variable approach (using only the AMSA prior to the first shock) resulted in a C-statistic of 0.66 (0.56–0.75), Fig. 2, left panel. The SVM-model using AMSA and ΔAMSA resulted in a C-statistic of 0.80 (0.69–0.88), Fig. 2, right panel. Models that combined AMSA-based measures with the other studied VF-characteristics did not improve diagnostic performance (Supplement 3).

Discussion

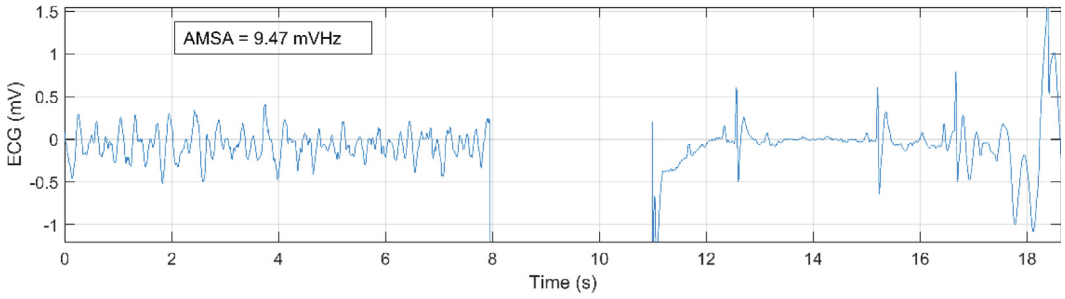
In the setting of cardiac arrest, we present the first clinical study on the diagnostic performance of VF-waveform analysis of defibrillator-derived ECG-measures. We found that AMSA was moderately able to detect patients with an ACO, while incorporation of ΔAMSA-measures tended to improve diagnostic performance. These pilot-data require further confirmation, as this innovative technology may eventually contribute to earlier diagnosis and timely triage of OHCA-victims with a treatable underlying cause.

Animal and human studies demonstrated that VF due to MI has distinct ECG-characteristics, i.e. low voltages and lower frequency content, with a more marked effect in acute MI than in prior MI.[7–10,15] In an animal study, acute MI could be diagnosed with a single-variable approach, using AMSA-only (C-statistic 0.85).[15] Recently, the first in-human proof of concept study was published, demonstrating the feasibility of detection of prior MI in an experimental setting (C-statistic 0.61).[6] The present real-world OHCA-study builds on these findings, and provides data on detection of acute MI, with a C-statistic of 0.66 for the single-variable approach (AMSA-only).

Applying machine learning techniques combining AMSA with ΔAMSA, discriminative ability tended to improve (C-statistic 0.80 vs. 0.66, p = 0.07) in the subgroup with > 1 shock. Changes in AMSA may reflect changes in myocardial perfusion and myocardial metabolic state, with improvement after chest compressions.[9,13,16–22] Although on a group level, univariate comparisons showed no difference in Δ-characteristics between groups (Table 2), it was with machine learning algorithms that we identified the potential distinctive ability of ΔAMSA (Supplement 4 for a graphical illustration). In line with our previous study, machine learning algorithms that combined various VF-characteristics did not improve model performances.[6]

Appreciating the clinical potential of the concept of a diagnostic defibrillator, the main implication of our findings is that larger studies are warranted. Current diagnostics for MI are limited to the subset of patients regaining organized rhythm, using a 12-lead ECG, often in a later phase of the arrest.[3] VF-analysis is possible in all patients, using a single-lead 3-second VF-recording, and in a very early phase of the arrest, potentially shortening the delay-to-diagnosis, and facilitating early hospital transportation and prompt angiography. Importantly, ACO constitutes a major cause of difficult-to-defibrillate VF.[23,24] Especially this group with a treatable underlying cause may constitute a target population for early hospital transportation in case of refractory VF, with support of a mechanical resuscitation devices or ECMO.[25]

1a: VF-signal of a patient with an acute coronary occlusion



1b: VF-signal of a patient without an acute coronary occlusion

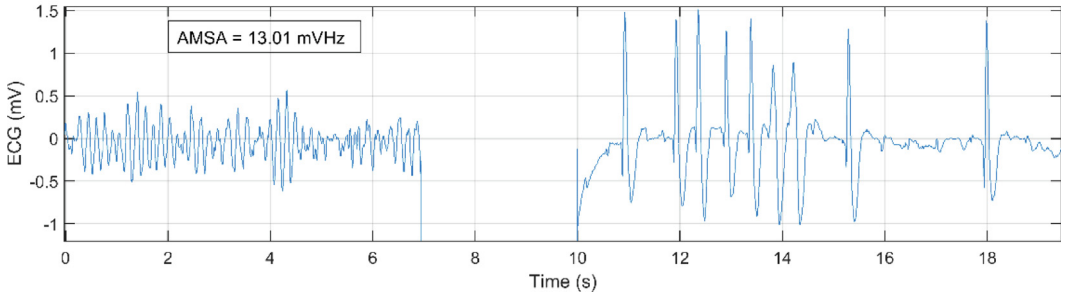


Fig. 1 – Representative examples of in-field VF-signals used for analysis. 1a: VF-signal of a patient with an acute coronary occlusion. 1b: VF-signal of a patient without an acute coronary occlusion. Figure showing two representative out-of-hospital VF-signals that were used for analysis in the present study, acquired from defibrillator read-outs. Fig. 1a shows a VF-signal of a patient with an acute coronary occlusion, with a calculated AMSA of 9.47 mVHz, and Fig. 1b shows a VF-signal of a patient without acute coronary occlusion, with a calculated AMSA of 13.01 mVHz. VF = Ventricular fibrillation, AMSA = Amplitude spectrum area.

In case of confirmative data, additional optimisation of the diagnostic algorithms is needed, which requires multiple datasets on larger populations. Another issue that may contribute to improved diagnostic accuracy is the possible interplay between infarct localisation and the direction of the recording ECG-lead.[6,7,10]

In this pilot study we focussed on the overall diagnostic ability of the developed algorithms. Future studies may develop an optimal cut-off point for in-field use. We propose initially focussing on a high positive predictive value to identify patients with a high chance of underlying ACO that most likely benefit from earlier transportation. Importantly, a careful risk/benefit analysis must be made, where the potential benefits of early transportation (earlier targeted therapy) must be weighed against its downsides (costs and risks of transport to a high-care hospital with ongoing CPR).

In terms of feasibility, currently studied "smart" defibrillators already possess the technology for real-time AMSA-assessment. Thus, with sufficient additional proof that early MI-diagnosis is possible, future studies with diagnostic algorithms could pave the way towards new, more individualized, aetiology targeted strategies to improve outcome after cardiac arrest.

Limitations

Our findings should be interpreted in the context of a pilot study, and considered hypothesis generating. In the current study, we used only established VF-characteristics in a cohort of limited sample size, and did not perform external validation on a separate sample. In order to provide the most robust results possible, we performed internal 5-fold cross-validation as is common in machine learning studies.[26] Corroborative studies are warranted with larger cohorts to improve feature acquisition and selection, develop more accurate machine learning models, and to externally validate the developed algorithms. Moreover, exclusions due to absence of analysable ECG-segments limit generalisability. Our findings can not be extrapolated to paediatric patients, in whom the association between VF-characteristics and underlying disease or outcome is unclear.[27] These limitations should be put in the context of the study's strength, which is that this is the first clinical study on this potentially important topic.

Conclusion

This pilot study on OHCA-patients provides the first evidence that detection of MI due to an acute coronary occlusion seems feasible with use of VF-waveform analysis, particularly with input on VF-changes from the first to second shock. These findings support the concept of smart diagnostic defibrillators and call for further investigation in larger studies.

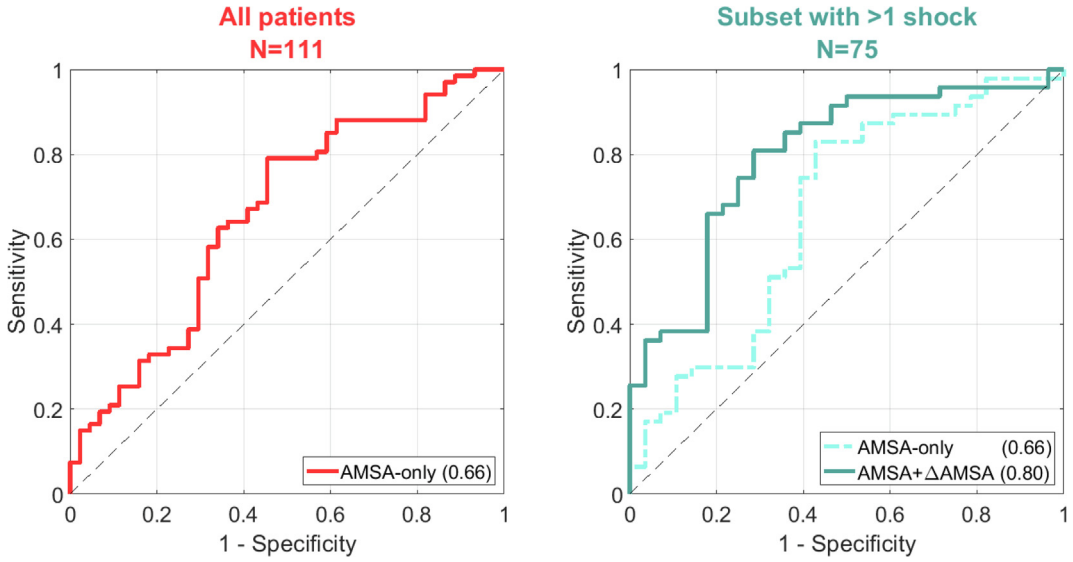


Fig. 2 – ROC-curves for detection of acute coronary occlusion with use of the VF-waveform. Figure showing ROC-curves of different approaches to discriminate ACO from non-ACO patients. a): AMSA-only, prior to the first shock attempt, based on the total study population (n = 111); b): light blue represents AMSA-only, prior to the first shock attempt, based on the subset with > 1 shock (n = 75); dark blue represents a support vector machine (SVM) model with the AMSA prior to the first shock and the relative AMSA-change with the second shock (DAMSA), based on the subset with > 1 shocks (n = 75). ACO = Acute coronary occlusion, VF = Ventricular fibrillation, AMSA = Amplitude spectrum area, ROC = Receiver operating characteristic.

Conflicts of Interest

Prof N. van Royen received research grants from Abbott, Biotronik, AstraZeneca and Philips, and professional fees from Abbott, Microport, Amgen and Medtronic. At the time of the registry, Prof M.J. de Boer was a member of the European advisory board on interventional cardiology of Medtronic. All other authors have no conflicts of interest to declare.

Funding.

None.

CRediT authorship contribution statement

Jos Thannhauser: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing - original draft. **Joris Nas:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing - original draft. **Koen van der Sluijs:** Conceptualization, Formal analysis, Investigation, Methodology, Writing - original draft. **Hans Zwart:** Formal analysis, Investigation, Methodology, Writing - review & editing. **Menko-Jan de Boer:** Data curation, Supervision, Writing - review & editing. **Niels van Royen:** Data curation, Supervision, Writing - review & editing. **Judith Bonnes:** Data curation, Writing - review & editing. **Marc Brouwer:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Writing - original draft.

Acknowledgements

None.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resuscitation.2022.03.025.

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REFERENCES

1. Kiguchi T, Okubo M, Nishiyama C, et al. Out-of-hospital cardiac arrest across the World: First report from the International Liaison Committee on Resuscitation (ILCOR). Resuscitation 2020;152:39–49.
2. O'Connor RE, Ali ASA, Brady WJ, et al. Part 9: acute coronary syndromes. Circulation 2015;132:S483–500.
3. Thygesen K, Alpert JS, Jaffe AS, et al. Fourth universal definition of myocardial infarction (2018). Eur Heart J 2018;40:237–69.
4. Ristagno G, Mauri T, Cesana G, et al. Amplitude spectrum area to guide defibrillation: a validation on 1617 patients with ventricular fibrillation. Circulation 2015;131:478–87.

5. Indik JH, Conover Z, McGovern M, et al. Association of amplitude spectral area of the ventricular fibrillation waveform with survival of out-of-hospital ventricular fibrillation cardiac arrest. J Am Coll Cardiol 2014;64:1362–9.
6. Thannhauser J, Nas J, Rebergen DJ, et al. Computerized analysis of the ventricular fibrillation waveform allows identification of myocardial infarction: A proof-of-concept study for smart defibrillator applications in cardiac arrest. J Am Heart Assoc 2020;9:e016727.
7. Bonnes JL, Thannhauser J, Hermans MC, et al. Ventricular fibrillation waveform characteristics differ according to the presence of a previous myocardial infarction: A surface ECG study in ICD-patients. Resuscitation 2015;96:239–45.
8. Hulleman M, Salcido DD, Menegazzi JJ, et al. Predictive value of amplitude spectrum area of ventricular fibrillation waveform in patients with acute or previous myocardial infarction in out-of-hospital cardiac arrest. Resuscitation 2017;120:125–31.
9. Ristagno G, Tang W, Xu TY, Sun S, Weil MH. Outcomes of CPR in the presence of partial occlusion of left anterior descending coronary artery. Resuscitation 2007;75:357–65.
10. Nas J, van Dongen LH, Thannhauser J, et al. The effect of the localisation of an underlying ST-elevation myocardial infarction on the VF-waveform: A multi-centre cardiac arrest study. Resuscitation 2021;168:11–8.
11. Verhaert DV, Bonnes JL, Nas J, et al. Termination of resuscitation in the prehospital setting: A comparison of decisions in clinical practice vs. recommendations of a termination rule. Resuscitation 2016;100:60–5.
12. Perkins GD, Jacobs IG, Nadkarni VM, et al. Cardiac Arrest and Cardiopulmonary Resuscitation Outcome Reports: Update of the Utstein Resuscitation Registry Templates for Out-of-Hospital Cardiac Arrest: A Statement for Healthcare Professionals From a Task Force of the International Liaison Committee on Resuscitation (American Heart Association, European Resuscitation Council, Australian and New Zealand Council on Resuscitation, Heart and Stroke Foundation of Canada, InterAmerican Heart Foundation, Resuscitation Council of Southern Africa, Resuscitation Council of Asia); and the American Heart Association Emergency Cardiovascular Care Committee and the Council on Cardiopulmonary, Critical Care, Perioperative and Resuscitation. Resuscitation 2015;96:328–40.
13. Thannhauser J, Nas J, van Grunsven PM, et al. The ventricular fibrillation waveform in relation to shock success in early vs. late phases of out-of-hospital resuscitation. Resuscitation 2019;139:99–105.
14. Chen N, Callaway CW, Guyette FX, et al. Arrest etiology among patients resuscitated from cardiac arrest. Resuscitation 2018;130:33–40.
15. Indik JH, Allen D, Gura M, Dameff C, Hilwig RW, Kern KB. Utility of the ventricular fibrillation waveform to predict a return of spontaneous circulation and distinguish acute from post myocardial infarction or normal Swine in ventricular fibrillation cardiac arrest. Circ Arrhythm Electrophysiol 2011;4:337–43.
16. Eftestol T, Wik L, Sunde K, Steen PA. Effects of cardiopulmonary resuscitation on predictors of ventricular fibrillation defibrillation success during out-of-hospital cardiac arrest. Circulation 2004;110:10–5.
17. Ohlenburg H, Lakomek F, Bohn A, Quan W. Initial AMSA and increased AMSA after CPR predict ROSC in out-of-hospital cardiac arrest. Resuscitation 2016;106:e7.
18. Li Y, Gong Y, Quan W, Wei L, Ristagno G. The increase in AMSA value (delta) during CPR highly predicts first shock success in out-of-hospital cardiac arrest. Resuscitation 2017;118:e59.
19. Schoene P, Coult J, Murphy L, et al. Course of quantitative ventricular fibrillation waveform measure and outcome following out-of-hospital cardiac arrest. Heart Rhythm 2014;11:230–6.
20. Gazmuri RJ, Kaufman CL, Baetiong A, Radhakrishnan J. Ventricular Fibrillation Waveform Changes during Controlled Coronary Perfusion Using Extracorporeal Circulation in a Swine Model. PLoS ONE 2016;11:e0161166.
21. Nakagawa Y, Amino M, Inokuchi S, Hayashi S, Wakabayashi T, Noda T. Novel CPR system that predicts return of spontaneous circulation from amplitude spectral area before electric shock in ventricular fibrillation. Resuscitation 2017;113:8–12.
22. Reynolds JC, Salcido DD, Menegazzi JJ. Correlation between coronary perfusion pressure and quantitative ECG waveform measures during resuscitation of prolonged ventricular fibrillation. Resuscitation 2012;83:1497–502.
23. Yannopoulos D, Bartos JA, Raveendran G, et al. Coronary artery disease in patients with out-of-hospital refractory ventricular fibrillation cardiac arrest. J Am Coll Cardiol 2017;70:1109–17.
24. Nas J, Thannhauser J, van Dijk E, et al. Coronary angiography findings in patients with shock-resistant ventricular fibrillation cardiac arrest. Resuscitation 2021;164:54–61.
25. Yannopoulos D, Bartos J, Raveendran G, et al. Advanced reperfusion strategies for patients with out-of-hospital cardiac arrest and refractory ventricular fibrillation (ARREST): a phase 2, single centre, open-label, randomised controlled trial. Lancet 2020;396:1807–16.
26. Liu Y, Chen PC, Krause J, Peng L. How to read articles that use machine learning: users' guides to the medical literature. JAMA 2019;322:1806–16.
27. Raymond TT, Pandit SV, Griffis H, et al. Effect of amplitude spectral area on termination of fibrillation and outcomes in pediatric cardiac arrest. J Am Heart Assoc 2021;10. e020353.