Performance of VF Detection Parameters in an Algorithm Design Scenario and in a Real Resuscitation Scenario

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Abstract

Detection of Ventricular fibrillation (VF) in automated external defibrillators (AED) is tested following the recommendations of the American Heart Association (AHA). However, nonshockable out-of-hospital cardiac arrest (OHCA) rhythms may be very different from those covered in the AHA recommendations. In this study we compare the performance of four VF detection parameters for a testing database of rhythms covered by the AHA recommendations and a database of OHCA rhythms.

Spectral parameters performed better than parameters related to the heart rate or the complexity for the testing database but worse for the OHCA database. The performance of the parameters was very different in an algorithm design scenario compliant with the AHA statement and in a real resuscitation scenario.

1. Introduction

Ventricular Fibrillation (VF) is the first observed rhythm in 40 % of out-of-hospital cardiac arrest (OHCA). The most important determinant of survival from VF cardiac arrest is early defibrillation, which out of hospital is normally provided by an automated external defibrillator (AED). The AED automatically analyzes the patient's ECG rhythm and if VF is detected it instructs the rescuer to deliver a defibrillation shock.

The framework to test AED rhythm analysis algorithms was established in a set of recommendations of the American Heart Association (AHA) [1]. Several classical VF detection methods have been extensively tested within the AHA framework using public ECG databases from adult patients [2, 3], and proprietary rhythm databases from adult and pediatric patients [4]. The AHA puts emphasis on security to avoid unnecessary shocks, that may damage the heart, in patients with nonshockable rhythms and a palpable pulse. However, the most frequent nonshockable rhythms in OHCA, asystole and pulseless electrical activity (PEA), occur in patients with no palpable pulse. Fig. 1 shows three examples of OHCA PEA, with different rates and morphology, but without narrow QRS complexes found in pulsed rhythms.

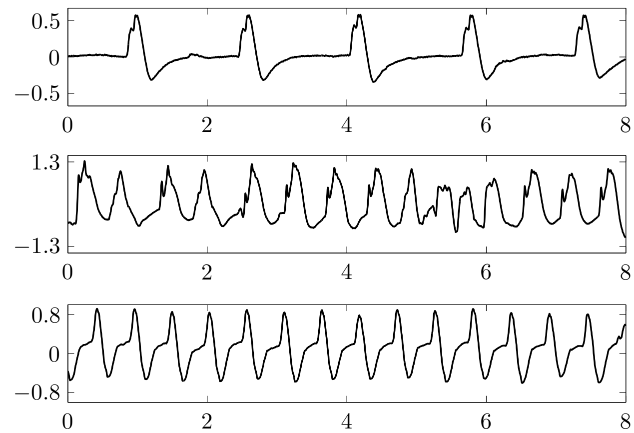


Figure 1. Three examples of PEA from OHCA episodes

The aim of this study is to assess how the performance of four well-known VF detection parameters changes when a database of AHA compliant rhythms or a database of real OHCA rhythms are used.

2. Materials and methods

2.1. ECG databases

We used two databases of surface ECG rhythms: a testing database of rhythms covered in the AHA recommendations, and a database of OHCA rhythms. Asystole was excluded from the study because we only considered ECG rhythms that displayed cardiac electrical activity.

Testing database

We extracted ECG data from public databases containing at least 10 s of a pure rhythm. We used the CU ventricular tachyarrhythmia, the AHA series 1, and the MIT-BIH databases[1]. The extracted ECG were visually selected and the rhythms were classified in the AHA rhythm types according to the annotations in the databases and the visual inspection of the rhythms. Nonshockable rhythms included normal sinus rhythm (NSR), atrial fibrillation (AF), supraventricular tachycardia (SVT), premature ventricular contractions (PVC), sinus bradycardia (SB), heart blocks and other nonshockable arrhythmias.

We selected a total of 575 rhythms from 242 records for this study. All channels were included totaling 1057 ECG samples, Table 1 presents a summary of the composition of the database. The ECG were resampled to 250 Hz and filtered with an order 10 high-pass filter with a 0.8 Hz cutoff to remove baseline wander and an order 14 chebyschev bandstop filter centered at 60 Hz to remove power line interference.

Table 1. Composition of the testing database. Several rhythms were extracted from the same record and all ECG channels of the rhythm were included in the database.

Rhythm type	ECG	Rhythms	Record
Shockable			
VF	135	89	50
Nonshockable	922	486	232
NSR	400	206	159
AF	129	65	30
SVT	138	77	59
PVC	149	76	55
SB	37	23	22
Blocks	36	20	15
Other	33	19	16
Total	1057	575	242

OHCA rhythms

The database of OHCA rhythms is a subset of a large database acquired in a prospective study of OHCA patients [5]. Nonshockable rhythms were classified into asystole, PEA and pulse-giving rhythms (PR) by expert reviewers. Both PEA and PR were rhythms with QRS complexes but with (PR) or without (PEA) blood flow. Blood flow was indicated by a clinically detected pulse or by changes induced in the thoracic impedance [5]. Our subset contains 83 VF and 204 nonshockable (166 PEA and 38 PR) rhythms, with a duration of 10 s.

The surface ECG was acquired using the Laerdal HeartStart 4000 defibrillator, at a sampling rate of 500 Hz and 16 bits for a resolution of 1.031 µV per least significant bit. The ECG acquisition bandwith was 0.9–50 Hz. The rhythms in our subset were resampled to 250 Hz and power line interference was removed using a 14 order chebyschev bandstop filter centered at 50 Hz.

2.2. VF detection parameters

We analyzed four VF detection parameters. Two are related to the spectral concentration of the ECG, A_2 [6] and the VF leakage (VFleak) [7], another is a measure of the complexity of the ECG (CM) [8] and finally the Threshold Crossing Interval (TCI) [9], a time-domain estimate of the heart rate. The parameters were computed for 8 s ECG segments as done in [2,3], we used the 1–9 s interval of the ECG in our databases.

VFleak. First the mean period of the ECG is estimated and then the ECG is combined with a copy shifted half a period. VFleak is a measure of the residue after this process. For a purely sinusoidal signal the combination of the signal and its shifted version cancels out. The waveform of VF rhythms is more sinus-like than that of nonshockable rhythms with narrow QRS complexes, VFleak is therefore smaller for VF than for nonshockable rhythms.

$\boldsymbol{A_2}$. First the FFT of the Hamming-windowed ECG segment is computed and components with amplitudes smaller than 5 % of the maximum amplitude are set to zero. Then, the frequency (F) corresponding to the maximum amplitude in the 0.5–9 Hz band is identified. A_2 is the ratio of the area of the amplitudes in the 0.7F–1.4F band to the total area. VF concentrates its spectrum in a narrow band around F while nonshockable rhythms distribute their energy in the harmonics of the cardiac frequency due to fast changing QRS complexes. A_2 is therefore larger for VF than for nonshockable rhythms.

CM. First the ECG is binarized as described in [8]. CM is the normalized value of the Lempel-Ziv complexity measure of the binary sequence and measures the rate of occurrence of new patterns within the binary sequence. VF is inherently more complex than nonshockable rhythms, CM is therefore larger for VF than for nonshockable rhythms.

TCI. First, a heart beat is detected every time the ECG crosses the detection threshold, which adjusts dynamically every second to 20 % of the peak value of the signal during that second. TCI is calculated every second as the mean interval between consecutive beats. For an 8 s segment there are 8 TCI values, we assigned the average value to the 8 s segment. During VF the ventricular activity is fast and the ECG presents lower interbeat intervals than for

[1]The MIT-BIH arrhythmia, malignant ventricular arrhythmia, supraventricular arrhythmia, atrial fibrillation and normal sinus rhythm databases

nonshockable rhythms. TCI is therefore smaller for VF than for nonshockable rhythms.

3. Results

We computed each parameter for the 8 s ECG segments in the two databases. Table 2 shows the mean value of the parameters per rhythm type. The values obtained for VF in both databases are similar for all parameters except A_2. A_2 is smaller and the spectral spread larger in VF from the OHCA database. However, the most important differences occur among nonshockable rhythms. VFleak decreases and A_2 increases for nonshockable rhythms from OHCA. This shows that PEA, particularly wide complex PEA, has a much smaller spectral spread than the nonshockable rhythms from public databases which normally have larger bandwidths due to narrow QRS complexes. The mean value of TCI for nonshockable rhythms is larger in the OHCA database (410 ms) than in the testing database (390 ms). In particular, the TCI value for SVT is comparable to that of VF. Fast supraventricular rhythms covered in the AHA statement may present rates comparable to the ventricular rate of VF, something that rarely occurs with OHCA PEA. Nonshockable rhythms present a smaller complexity when obtained in an OHCA setting. The process to compute CM involves a binarization phase linked to the rate of the rhythm, faster rhythms present larger CM values, as evidenced by the values obtained for SVT, RSN and SB.

The detection performance of the parameters was evaluated by comparing the decision of the VF detection algorithm to the annotated rhythm types. In this manner we computed the proportions of correctly identified VF (sensitivity) and nonshockable rhythms (specificity). Then we evaluated the sensitivity and specificity for each decision threshold to calculate the receiver operating characteristics (ROC) curve. The global performance of the VF detection parameters were assessed in terms of the area under the ROC curve (AUC). Fig. 2(a) and Fig. 2(b) show the ROC curves for the four parameters for the testing and the OHCA databases respectively. Table 3 is a summary of the ROC curve analysis including the AUC value, the sensitivity for a 95 % specificity (the minimum value recommended by the AHA for OHCA nonshockable rhythms) and the specificity for a 90 % sensitivity (the minimum value recommended by the AHA for VF). VFleak and A_2 are more accurate than CM and TCI for the testing database. However when applied to OHCA rhythms the performance of A_2 and VFleak degrades substantially and the performance of CM and TCI improves. The latter present a better detection performance for OHCA rhythms.

Table 2. Value of the parameters (mean and std) per rhythm type for the testing and the OHCA databases.

	Rhythm	VFleak	A_2	CM	TCI (ms)
Testing	VF	0.55 (0.15)	0.52 (0.15)	0.25 (0.08)	226 (90)
	RSN	0.80 (0.06)	0.14 (0.07)	0.18 (0.09)	433 (231)
	AF	0.78 (0.06)	0.15 (0.07)	0.21 (0.09)	407 (201)
	SVT	0.76 (0.06)	0.17 (0.10)	0.23 (0.08)	282 (124)
	PVC	0.77 (0.06)	0.21 (0.07)	0.20 (0.08)	324 (120)
	SB	0.81 (0.06)	0.16 (0.08)	0.14 (0.07)	514 (200)
	Blocks	0.75 (0.08)	0.20 (0.09)	0.16 (0.04)	413 (161)
	Other	0.77 (0.06)	0.18 (0.08)	0.15 (0.05)	413 (163)
OHCA	VF	0.56 (0.11)	0.42 (0.13)	0.26 (0.06)	216 (54)
	PEA	0.69 (0.09)	0.29 (0.11)	0.15 (0.05)	424 (160)
	PR	0.70 (0.10)	0.26 (0.12)	0.18 (0.05)	345 (155)

Table 3. ROC analysis for the VF detection parameters for the testing and the OHCA databases.

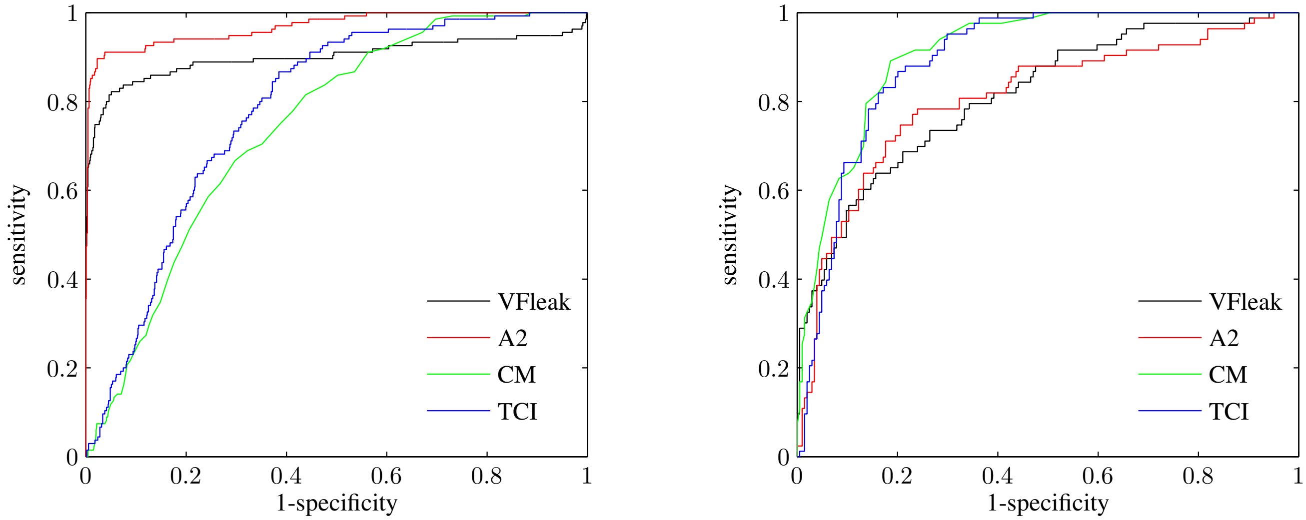
	Testing			OHCA		
Param	AUC	Se [a]	Sp [b]	AUC	Se [a]	Sp [b]
VFleak	0.90	81%	51%	0.81	40%	48%
A_2	0.97	91%	96%	0.81	45%	39%
CM	0.74	12%	44%	0.91	49%	76%
TCI	0.78	16%	55%	0.89	37%	73%

[a] Sensitivity for a 95 % specificity.
[b] Specificity for a 90 % sensitivity.

4. Discussion and conclusions

Parameters that measure the spectral concentration, VFleak and A_2, have been reported to be more accurate than CM and TCI in studies using adult rhythms extracted from public databases[2, 3] and AHA compliant databases of adult and pediatric rhythms[4]. Our results confirm those previous findings. However, in an OHCA scenario the performance of A_2 and VFleak degrades substantially and the performance of CM and TCI improves above that of A_2 and VFleak.

The degradation of the performance of VFleak and A_2 for OHCA rhythms has two reasons. VF gathered out-of-hospital is normally prolonged VF and the rhythm may have deteriorated. VF obtained from public databases is normally closer to the onset of the arrhythmia and shows a larger spectral concentration. More importantly nonshockable rhythms in OHCA, particularly PEA, are frequently associated to slow ventricular rhythms with wide QRS complexes, which result in a larger spectral concentration than rhythms with narrow QRS complexes.



(a) Testing database (b) OHCA database

Figure 2. ROC curves for the VF detection parameters for the testing database and the OHCA database.

The performance of TCI and CM improves for OHCA rhythms because nonshockable rhythms in an out-of-hospital setting have lower rates. The AHA puts emphasis on security and therefore covers fast nonshockable rhythms, in fact high rate pediatric SVT has been identified as a problematic arrhythmia when AED algorithms are adapted for pediatric use. However, fast supraventricular rhythms that compromise the performance of TCI or CM are not frequently observed in an OHCA scenario.

This study shows that parameters applicable to AED rhythm recognition may perform very differently in an algorithm design/test scenario compliant with the AHA statement and in a real application/resuscitation scenario.

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