A Pediatric Shock Advice Algorithm Based on the Regularity of the Detected Beats

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Abstract

Automated External Defibrillators (AED) detect fatal ventricular arrhythmias: ventricular fibrillation (VF) and ventricular tachycardia (VT). We have developed an algorithm based on the regularity of the detected beats to accurately discriminate VF from nonshockable rhythms in pediatric patients.

The beat detection method is based on a preprocessing band pass filter (5-35 Hz) followed by a nonlinear energy operator (NEO). The discrimination algorithm uses three parameters: the number of detected beats, the coefficient of variation of the interval between beats and the content around the zero line of the output of NEO. The values of these parameters were used in a decision tree that identified irregular shockable rhythms (VF), and slow and fast regular rhythms, classified as nonshockable. VT was excluded in the design of the algorithm because it is often a regular but shockable rhythm.

The algorithm was tested on a database of 1091 records (959 nonshockable, 62 VF and 70 VT) from 650 pediatric patients. The specificity was 99.7% and the VF sensitivity was 96.6%. 33% of the VT windows were identified as shockable, 65.2% as fast nonshockable and 1.8% as slow nonshockable. The regularity of the detected beats can accurately discriminate VF from nonshockable rhythms. However, an additional stage to discriminate fast nonshockable rhythms from fast and regular VT is needed for a shock advice algorithm.

1. Introduction

The use of Automated External Defibrillators (AED) in children under 8 years of age was approved in the year 2003 [1]. The rhythm analysis algorithm of an AED for pediatric use must safely detect fatal ventricular arrhythmias, ventricular fibrillation (VF) and ventricular tachycardia (VT), in children.

AED arrhythmia detection algorithms are difficult to test in children because fatal ventricular arrhythmias are rare in pediatric patients. Several studies [2–4] have reported the sensitivity and specificity of AED algorithms on proprietary databases of pediatric arrhythmias, however the amount of ventricular arrhythmias was well below AHA requirements [5].

VF is an irregular rhythm as compared to the regular normal rhythms. Different approaches have been described to detect VF, for instance: the frequency domain, the autocorrelation function or the Lempel-Ziv complexity measure [6, 7]. We propose a new method based on the regularity of the detected beats. The method is simple and computationally cheap it can therefore easily be implemented in an AED. Furthermore the VF detection method was developed and tested on a pediatric database.

The algorithm was conceived as a VF detection algorithm, VT was excluded from the design because fast monomorphic VT is a shockable regular rhythm. The performance of the algorithm on VT records was nevertheless assessed to show what modifications are needed for a full AED shock advice algorithm.

2. Materials and methods

We used a database of pediatric rhythms to develop and test the VF detection method. The database which was created to test pediatric AED shock advice algorithms, is an extension of a previously reported database [8]. More rhyhtms were added in the 2006-2008 period and three new hospitals contributed to extend the database: Donostia Hospital in San Sebastian, Hospital Gregorio Marañón in Madrid and San Joan de Deu Hospital in Barcelona.

Table 1. Collected pediatric records grouped by age.

		Shock		**No Shock**		
Age group [a]		VF	VT	NSR	SVA	Other
<1y	(40)	3	10	14	40	2
1y-8y	(375)	17	41	313	150	39
>8y	(235)	42	19	213	152	36
Total	(650)	62	70	540	342	77

[a] Number of patients shown in parenthesis.

Following the AHA guidelines for the design of AED shock advice algorithms [5] the ECG records in the database contain a single rhythm and have no artifact. The sampling frequency is $f_s = 250\ Hz$.

The database contains 1091 records from 650 patients (mean age: 7.4 ± 4.6 years), classified by three independent cardiologists in the rhythm categories specified by the AHA. Table 1 shows a summary of the number of ECG records, the final classification reflects the consensus decision of the cardiologists. The database was split in age groups because the use of AEDs in children was approved for the 1 to 8 years of age group. The nonshockable rhythms were grouped in three broad categories: normal sinus rhythm (NSR), supraventricular arrhythmias (SVA), and other. The SVA category included supraventricular tachycardia and atrial flutter/fibrilation while the other category included the rest of the nonshockable rhythms specified by the AHA.

2.1. The shock advice algorithm

A quick decision is important for survival in a cardiac arrest scenario, consequently we designed the AED shock advice algorithm to give a diagnosis in less than $10\ s$. Our approach consists in the analysis of three consecutive $3.2\ s$ windows, the diagnosis of the record is the predominant diagnosis of the windows. This means that an episode is diagnosed in either $6.4\ s$ or $9.6\ s$. The algorithm is based on the beat detection process, ECG beats are detected in windows of $3.2\ s$ with no previous information.

2.1.1. ECG beat detection: the Nonlinear Energy Operator

The beat detection algorithm consists of an order four butterworth passband filter ($5 - 35\ Hz$) followed by a nonlinear energy operator (NEO). The beats were detected using thresholds adapted to the signal amplitude. The low frequency cutoff of the filter was selected to maximize the energy of the QRS complex, in particular to suppress the influence of large T waves.

NEO has been shown to be an estimate of the instantaneous energy of a signal, and can be therefore be used to detect spikes [9]. In pulsed rhythms those spikes correspond to the QRS complex, during VF no such spikes should be detected. For a discrete signal NEO is defined as follows:

$$\psi[x(n)] = x^2(n) - x(n-1)x(n+1)$$

Beats were marked as the local maximums of $\psi[x(n)]$ that exceeded an heuristically determined threshold (Th):

$$Th = 0.025 \cdot \max[x^2(n)]$$

a refractory period of $150\ ms$ was left between consecutive beats.

2.1.2. Parameters for VF detection

We used three parameters derived from the beat detection processed to discriminate VF. The first parameter was the number of beats detected (N_p), which serves to identify fast and slow rhythms. The regularity of the detected beats was measured using the coefficient of variation (the ratio of standard deviation to the mean) of the intervals between consecutive beats (ΔT_i), that is:

$$CV_T = \frac{\sigma_{\Delta T_i}}{\mu_{\Delta T_i}}$$

The third parameter was the content around the zero line of the output of the NEO (BC_ψ). This parameter was calculated as the P_{35} percentile of the output of NEO. BC_ψ was made independent of the values of NEO by normalizing it to the median value of NEO in the detected peaks, and expressed as a percent value. Figure 1 shows the set of parameters for an NSR and a VF window, NEO emphasizes the differences between pulsed (spiky) and irregular rhythms.

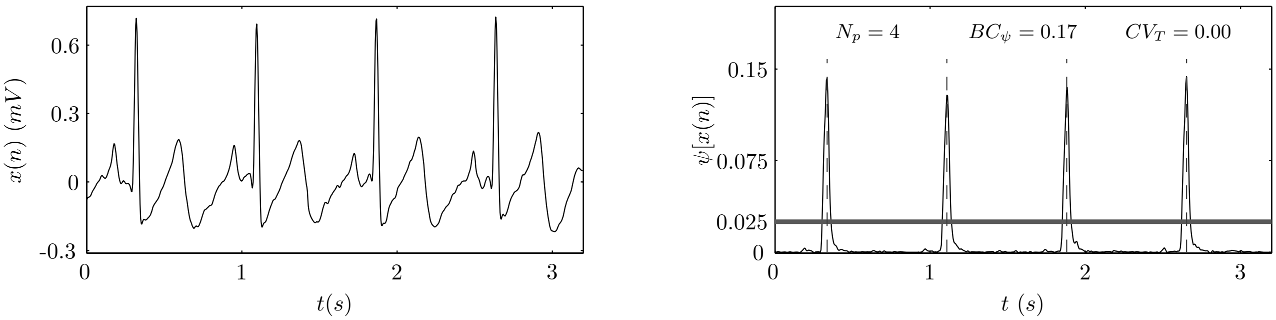
2.1.3. The decision tree

We analyzed 3746 windows of nonshockable rhythms and 156 windows of VF. There was therefore a strong bias toward the detection of nonshockable rhythms. Furthermore the duration of the records was not uniform, the longest record was 51 windows long and the shortest had one window. To prevent these two sources of bias the windows were weighted so each record had the same importance within its class, we gave 66% of the total weight to the nonshock class and 33% to the shock class because AHA performance goals are more exigent for nonshockable rhythms [5].

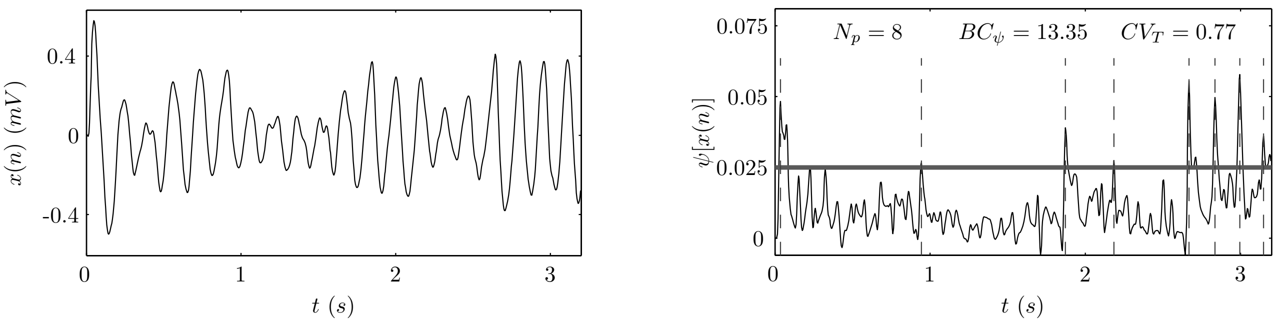
The windows were classified using a decision tree, induced using the C4.5 decision tree algorithm on the whole set of available windows. Figure 2 shows the decision tree. In the tree the nonshockable rhythms are further split into fast and slow rhythms using the number of detected beats. Nonshockable rhythms having more than 7 beats in the window are classified as fast because the mean heart rate would be above 120 bpm.

3. Results

Table 2 shows the per window and per record results, when the decision tree was applied to the database. A record was diagnosed using the predominant diagnosis of the windows of that record. Fast and slow nonshockable windows were considered nonshockable. There was an



(a) NSR window in the time domain and at the output of NEO



(b) VF window in the time domain and at the output of NEO

Figure 1. NSR and VF in the time domain and at the output of NEO, NEO has been normalized to have a fixed threshold: $Th = 0.025$. The content of NEO around the zero line is high for pulsed rhythms and low for VF, as measured by BC_ψ. The detected beats are regularly spaced in pulsed rhythms and are very irregular for VF where the beats have no physical meaning.

important distinction between slow and fast rhythms, most NSR and other windows were slow (2304/2357, 97.8%) while most SVA windows were fast (1174/1389, 84.5%). The results for fast VT, which was not considered in the design of the algorithm, show that it was either correctly diagnosed as shockable (33/221, 33.0%) or confused as a fast nonshockable rhythm (144/221, 65.1%).

However, except for fast VT, the results of table 2 were computed on the database used to develop the algorithm. In order to obtain a better estimate of the sensitivity and specificity of the algorithm we performed a ten fold cross validation procedure on the weighted windows. The specificity for the nonshockable rhythms was then 99.7% and the sensitifity for VF was 96.6%. These results are representative of the per record results because the weighting procedure assigns an equal weight to each record in a class regardless of the number of windows.

4. Discussion

We have developed a new method to detect VF based on a decision tree induced from three parameters related to the regularity of the heart beats. The beats were detected using a nonlinear transformation: NEO. The method was successfully tested using a 10 fold croos validation procedure on a pediatric database. We obtained a specificity of 99.7% for nonshockable rhythms and a sensitivity of 96.6% for VF.

The method fails to diagnose fast VT as shockable, 33.0% of the VT windows were detected as shockable and

$BC_\psi \leq 1.86$
| $N_p \leq 7$: $\mathbf{NS_s}$
| $N_p > 7$: $\mathbf{NS_f}$
$BC_\psi > 1.86$
| $CV_T \leq 0.17$
| | $N_p \leq 7$: $\mathbf{S}$
| | $N_p > 7$: $\mathbf{NS_f}$
| $CV_T > 0.17$: $\mathbf{S}$

Figure 2. Decision tree. The possible diagnosis are $\mathbf{S}$ for shockable (VF), $\mathbf{NS_s}$ for slow nonshockable and $\mathbf{NS_f}$ for fast nonshockable.

Table 2. Sensitivity and Specificity per window and per record, the results in parenthesis correspond to the 1-8 years of age subset of patients. The nonshockable windows are classified into fast and slow as shown in figure 2. The 95% confidence interval was calculated using the adjusted Wald interval.

	Results per window				Results per record			
	$\mathbf{NS_s}$	$\mathbf{NS_f}$	S	sens/spec	n_R	sens/spec	95% CI	AHA goal
NSR	2021 (1243)	47 (31)	6 (2)	99.7% (99.8%)	540 (313)	99.6% (99.7%)	98.6% (98.0%)	$> 99\%$
SVA	214 (59)	1174 (568)	1 (1)	99.9% (99.8%)	342 (150)	100% (100%)	98.7% (97.0%)	$> 95\%$
Other	283 (164)	0 (0)	0 (0)	100% (100%)	77 (39)	100% (100%)	94.3% (89.3%)	$> 95\%$
VF	1 (0)	0 (0)	155 (45)	99.4% (100%)	62 (17)	98.4% (100%)	90.6% (78.4%)	$> 90\%$
VT	4 (0)	144 (82)	73 (58)	33.0% (41.4%)	70 (41)	31.4% (41.5%)	- -	$> 75\%$

67.0% as nonshockable. However, 97.3% (144/148) of the windows diagnosed as nonshockable were diagnosed as fast nonshockable windows, and were therefore mistaken as SVA. A complete algorithm, capable of identifing VT as shockable, requieres the addition of a SVA/VT discrimination algorithm. The AHA performance goals (95% specificity for SVA and 75% sensistivity for VT) indicate that the algorithm must be designed to accurately detect SVA. Adult AED algorithms based on rate might missdiagnose fast SVA as shockable [1,4], our approach is robust beacuse it is based on regularity.

Previous studies of AED algorithms on pediatric databases reported comparable results. Cecchin et al. [2] obtained 96% sensitivity for VF and a 100% specificity. The VT sensitivity was 71%, below the AHA performance goal. Atkinson et al. [3] obtained a 98.6% sensitivity for VF and a specificity of 99.5%. The sensitivity for VT was 100% but it was tested on three samples so the results were not conclusive. Atkins et al. [4] recently reported a sensitivity of 100% for VF and 94.9% for VT and an overall specificity of 99.5%.

Our VF detection method compares well with previously reported results for AED performance on pediatric databases. The classification of nonshockable rhythms as fast or slow groups fast VT with SVA. An additional SVA/VT discrimination stage is therefore needed for a full pediatric shock advice algorithm, however this VF detection method is a good framework for a full AED algorithm.

References

[1] Samson R, Berg R, Bingham R, Pediatric Advanced Life Support Task Force ILCOR. Use of automated external defibrillators for children: an update. an advisory statement from the pediatric advanced life support task force, international liaison committee on resuscitation. Resuscitation Jun 2003;57(3):237–243.

[2] Cecchin F, Jorgenson DB, Berul CI et al. Is arrhythmia detection by automatic external defibrillator accurate for children?: sensitivity and specificity of an automatic external defibrillator algorithm in 696 pediatric arrhythmias. Circulation May 2001; 103(20):2483–2488.

[3] Atkinson E, Mikysa B, Conway JA et al. Specificity and sensitivity of automated external defibrillator rhythm analysis in infants and children. Ann Emerg Med Aug 2003;42(2):185–196.

[4] Atkins DL, Scott WA, Blaufox AD et al. Sensitivity and specificity of an automated external defibrillator algorithm designed for pediatric patients. Resuscitation Feb 2008;76(2):168–174.

[5] Kerber RE, Becker LB, Bourland JD et al. Automatic external defibrillators for public access defibrillation: recommendations for specifying and reporting arrhythmia analysis algorithm performance, incorporating new waveforms, and enhancing safety. a statement for health professionals from the american heart association task force on automatic external defibrillation, subcommittee on aed safety and efficacy. Circulation Mar 1997; 95(6):1677–1682.

[6] Jekova I. Comparison of five algorithms for the detection of ventricular fibrillation from the surface ECG. Physiol Meas Nov 2000;21(4):429–439.

[7] Amann A, Tratnig R, Unterkofler K. Reliability of old and new ventricular fibrillation detection algorithms for automated external defibrillators. Biomed Eng Online 2005;4:60.

[8] Irusta U, Aramendi E, Ruiz de Gauna S, Ruiz J, Gutierrez J, Bodegas A, Pastor E, Benito F. Development of a pediatric ecg rhythm database for the assessment of the rhythm analysis algorithms of automated external defibrillators. In Proc. Computers in Cardiology. 2006; 609–612.

[9] Mukhopadhyay S, Ray G. A new interpretation of nonlinear energy operator and its efficacy in spike detection IEEE Trans Biomed Eng Feb. 1998;45(2):180–187.

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