Detecting Ventricular Fibrillation by Time-Delay Methods

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***Abstract*—A pivotal component in automated external defibrillators (AEDs) is the detection of ventricular fibrillation (VF) by means of appropriate detection algorithms. In scientific literature there exists a wide variety of methods and ideas for handling this task. These algorithms should have a high detection quality, be easily implementable, and work in realtime in an AED. Testing of these algorithms should be done by using a large amount of annotated data under equal conditions. For our investigation we simulated a continuous analysis by selecting the data in steps of 1 s without any preselection. We used the complete BIH-MIT arrhythmia database, the CU database, and files 7001–8210 of the AHA database. For a new VF detection algorithm we calculated the sensitivity, specificity, and the area under its receiver operating characteristic curve and compared these values with the results from an earlier investigation of several VF detection algorithms. This new algorithm is based on time-delay methods and outperforms all other investigated algorithms.**

***Index Terms*—Automated external defibrillator (AED), ECG analysis, sinus rhythm (SR), ventricular fibrillation (VF), ventricular fibrillation detection.**

I. Introduction

Sudden cardiac arrest is a major public health problem and one of the leading causes of mortality in the western world. In most cases, the mechanism of onset is a ventricular tachycardia that rapidly progresses to ventricular fibrillation (VF) [1]. Approximately one-third of these patients could survive with the timely employment of a defibrillator.

Besides manual defibrillation by an emergency paramedic, bystander defibrillation with automatic external defibrillators has also been recommended for resuscitation [2]. These devices analyze the electrocardiogram (ECG) of the patient and recognize whether a shock should be delivered or not. The quality of the mathematical algorithms for detection of VF used by these devices is of vital importance.

To gain insight into the quality of an algorithm for ECG analysis, it is essential to test the algorithms under equal conditions with a large amount of data, which has already been annotated by qualified cardiologists. Commonly used annotated databases are Boston's Beth Israel Hospital and MIT arrhythmia database (BIH-MIT), the Creighton University ventricular tachyarrhythmia database (CU), and the American Heart Association database (AHA)[1].

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[1]ANSI/AAMI EC38:1998 Ambulatory electrocardiographs: "The incidence and variety of VF in the AHA and MIT databases are not sufficient to allow those databases to serve as substitutes for the CU database (DB) for the purposes of 5.2.14.5. An evaluation of VF detection using the 80 records of the AHA DB and the 48 records of the MIT DB should supplement the required CU DB evaluation, however, as the CU DB does not contain a sufficient sample of signals likely to provoke false VF detections."

We used the complete BIH-MIT and CU database, and the files 7001–8210 of the AHA database [3]–[5]. For each algorithm approximately 330 000 decisions had been calculated. No preselection of certain ECG episodes was made to simulate the situation of a bystander more accurately.

In this paper we present a new VF detection algorithm. Besides the quality parameters *Sensitivity* and *Specificity*, we calculated the *Positive Predictivity* and *Accuracy* of the new algorithm.

The quality parameters were obtained by comparing the VF/no VF decisions suggested by the algorithm with the annotated decisions suggested by cardiologists. The cardiologists' decisions are considered to be correct. We distinguished only between VF and no VF, since the annotations do not include a differentiation between VF and ventricular tachycardia. The closer the quality parameters are to 100%, the better the algorithm works.

To represent the quality of an algorithm by its sensitivity and specificity bears some problems. A special algorithm can have a high sensitivity, but a low specificity, or conversely. Which one is better? To come to a common and single quality parameter, we use the receiver operating characteristic (ROC) curve. The sensitivity is plotted in dependence of (1–specificity), where different points in the plot are obtained by varying the critical threshold parameter in the decision stage of the algorithm. By calculating the area under the ROC curve (we call this value "integrated receiver operating characteristic" (IROC), it is possible to compare different algorithms by one single value. We compare the ROC curve of our new algorithm with the ROC curves of the best four standard algorithms investigated in [6].

II. Time-Delay Algorithm

The time-delay algorithm [phase space reconstruction (PSR)] is based on a method which is used to reconstruct the so-called phase space. It analyzes signals in order to identify a dynamic law or random behavior. The signal $x(t)$ is plotted in a diagram in the following way: on the x-axis we plot $x(t)$, on the y-axis $x(t + \tau)$, τ being a proper time constant. Such a plot is called a two dimensional phase space diagram.

We observe that a typical VF signal[2] produces a curve in the diagram, that fills the area in an irregular way. The curve is almost uniformly distributed over the entire diagram. However, for a normal sinus rhythm (SR) the curve in the phase space diagram shows a regular structure, only small parts of the area are filled, and the curve is concentrated to a restricted region of the plot. In the special case of a periodic signal for example, where τ is a multiple of the period all points lie on a line of 45 degrees.

Based on phase space plots $(x(t), x(t+\tau))$ we differentiate SR from VF. We determine the area of the plot filled by the curve. To achieve this, we produce a 40×40 grid and count the boxes visited by the ECG signal. The 40×40 grid stretches from the minimum to the maximum of the investigated raw ECG signal. We then calculate a measure d defined by

$$d = \frac{\text{number of visited boxes}}{\text{number of all boxes}}. \tag{1}$$

If d is higher than a certain threshold d_0, we classify the corresponding ECG episode as VF. We chose $\tau = 0.5$ s and for the threshold $d_0 = 0.15$.[3] The number of boxes is 1600. The critical threshold parameter which is varied to obtain the ROC curve is d_0.

[2]VF signals are supposed to be of irregular nature.

[3]The number of boxes, i.e., 40×40, the value for $\boldsymbol{\tau}$, and $\boldsymbol{d}_0$ were selected and fixed after some tests. Note: the size of the boxes varies with the chosen ECG episode.

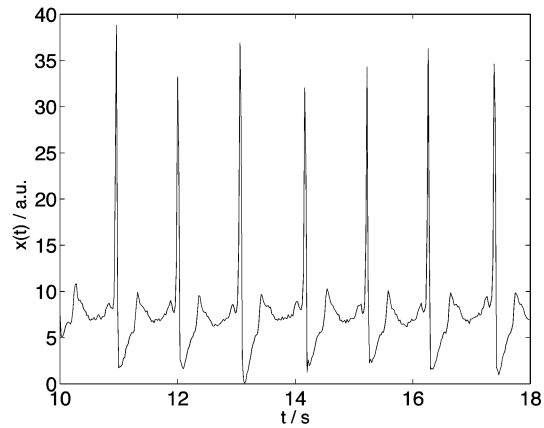

Fig. 1. SR episodes in the ECG signal cu01 from the CU database. a.u.: arbitrary units.

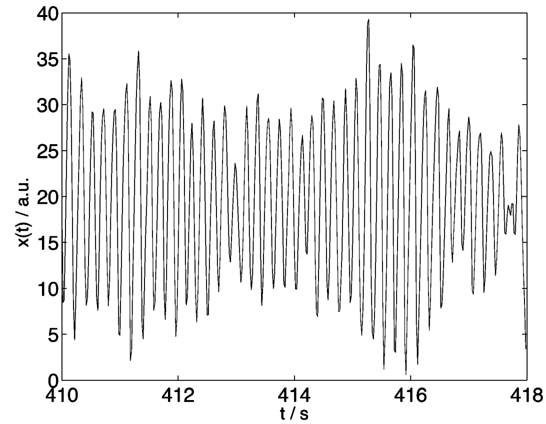

Fig. 3. VF episode in the ECG signal cu01 from the CU database.

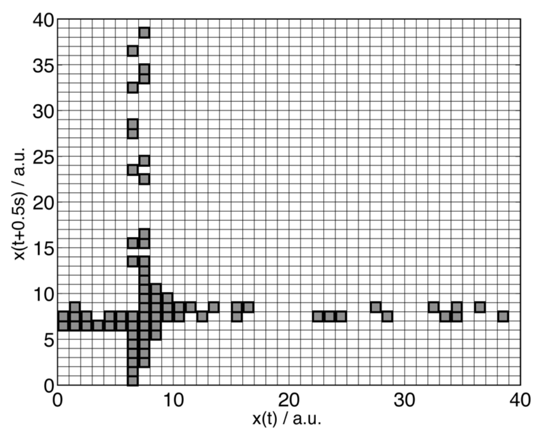

Fig. 2. Data points of SR episodes in the ECG signal cu01 from the CU database; visited boxes visualized in a phase space diagram, $\boldsymbol{d = 74/1600 = 0.05}$.

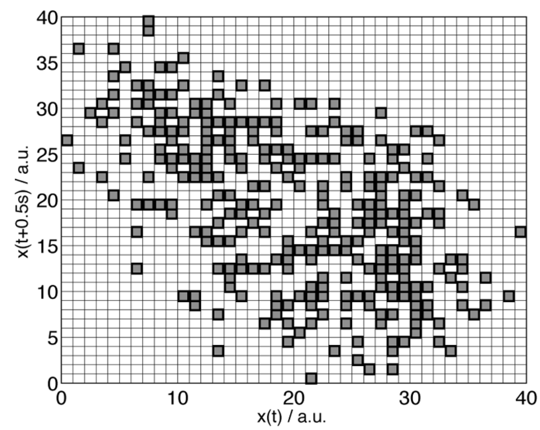

Fig. 4. Data points of a VF episode in the ECG signal cu01 from the CU database; visited boxes visualized in a phase space diagram, $\boldsymbol{d = 295/1600 = 0.18}$.

For the implementation of our algorithm, we first down-sample the ECG data to a frequency of 50 Hz, since we do not expect much information in the frequency region above this value. In addition a reduced data set speeds up the calculation. Furthermore, in the phase space plot, we only consider the positions of the discrete ECG data points to calculate the measure d and do not connect the data points by straight lines or any other curves, which would indicate the underlying dynamics. The reason is, that connected data in the phase space plot do not improve the quality of the algorithm, but rather decrease it.

Fig. 1 shows a typical SR signal from the CU database and the corresponding phase space plot is illustrated in Fig. 2.

Fig. 3 shows a VF signal from the CU database and the corresponding phase space plot is illustrated in Fig. 4.

III. Evaluation and Results

For the new algorithm tested in this paper we used the same prefiltering process as in [6]. The filtering process is carried out in a MATLAB routine, called *filtering.m*.[4]

The filtering algorithm works in four successive steps. First, the mean value of the signal is subtracted from the signal. Second, a moving averaging filter is applied in order to remove high-frequency noise. Then, a drift suppression is carried out. This removes slow signal changes, which originate from external sources and are not produced by the heart. In a last step a Butterworth filter with a cutoff frequency of 30 Hz eliminates frequencies higher than 30 Hz, which seem to be of no relevance in our simulations. By applying this filtering process also the behavior of the signal acquisition by a defibrillator is simulated in a reasonable way.

In this paper we chose ECG episodes of window length of 8 s. 8-s intervals have shown to give the best performance for every algorithm investigated in [6]. For the investigation we tried to simulate a continuous analysis by selecting the data in steps of 1 s without any preselection. The decision of an algorithm analyzing an episode of 8-s window length is assigned to the endpoint of that interval. This is the point of view when one proceeds in realtime. However, when recorded ECG sequences are annotated the annotator always can look ahead.

The quality parameters are presented in the following tables and figure. The perfect algorithm would have values for sensitivity, specificity, positive predictivity, accuracy, and IROC of 100%, assuming that the annotations are 100% correct.

The data sets were taken from the BIH-MIT database (48 files, 2 channels per file, each channel 1805 s long), the CU database (35 files, 1 channel per file, each channel 508 s long), and the AHA database (files 7001–8210, 40 files, 2 channels per file, each channel 1800 s long). Thus, the total number of decisions per algorithm (window length $=$ 8 s) is $2 \cdot 48 \cdot (1805 - 7) + 35 \cdot (508 - 7) + 2 \cdot 40 \cdot (1800 - 7) = 333\,583$.

[4]The function *filtering.m* for preprocessing can be found on the website http://www2.staff.fh-vorarlberg.ac.at/~ku/VF/.

TABLE I
QUALITY OF VF DETECTION ALGORITHMS: SENSITIVITY (SE), SPECIFICITY (SP), AND INTEGRATED RECEIVER OPERATING CHARACTERISTIC CURVE (IROC) IN PERCENT, DATABASE (DB), THRESHOLD $d_0 = 0.15$

DB	*MIT DB*		*CU DB*		*AHA DB*		*overall results*		
	Se	Sp	Se	Sp	Se	Sp	Se	Sp	IROC
TCI	74.5	83.9	71.0	70.5	75.7	86.9	75.1	84.4	82
VF	29.4	100	30.8	99.5	16.9	100	18.8	100	87
SPEC	23.1	100	29.0	99.3	29.2	99.8	29.1	99.9	89
CPLX	6.3	92.4	56.4	86.6	60.2	91.9	59.2	92.0	87
PSR	74.8	99.2	70.2	89.3	80.4	96.8	79.0	97.8	94

TABLE II
POSITIVE PREDICTIVITY (PP), ACCURACY (AC), AND CALCULATION TIME (CT) IN PER CENT, CALCULATION TIME IN PERCENT OF THE REALTIME OF THE DATA, DATABASE (DB), THRESHOLD $d_0 = 0.15$

DB	*MIT DB*		*CU DB*		*AHA DB*		*overall results*		
	PP	Ac	PP	Ac	PP	Ac	PP	Ac	ct
TCI	0.8	83.9	38.9	70.6	54.4	84.9	31.1	83.6	2.1
VF	82.4	99.9	94.5	85.2	98.9	85.7	97.7	93.0	1.9
SPEC	60.6	99.8	92.0	84.6	97.3	87.7	96.1	93.8	1.9
CPLX	0.1	92.3	52.7	80.3	60.7	86.5	40.8	89.2	2.5
PSR	13.4	99.2	65.0	85.1	83.8	94.0	77.3	96.2	1.7

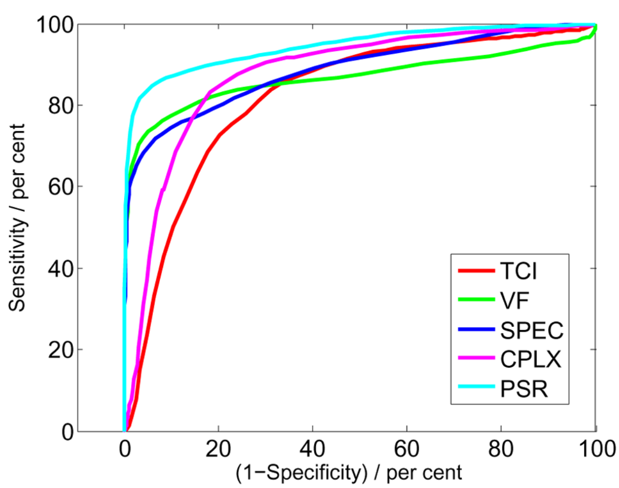

Fig. 5. ROC curves for investigated algorithms.

TABLE III
SENSITIVITY OF VF DETECTION ALGORITHMS IN PERCENT FOR A WINDOW LENGTH OF 8 S

Parameter	Se if Sp = 95	Se if Sp = 99
TCI	25.3	1.3
VF	73.4	59.7
SPEC	69.8	58.9
CPLX	38.8	5.8
PSR	83.8	70.4

Table I shows the values for the sensitivity, the specificity, and the IROC of the new algorithm and the corresponding values for other algorithms investigated in [6].[5] A short description of all these algorithms can be found there, too. The overall results are directly calculated from all 333 583 decisions.

Table II shows the values for the positive predictivity, the accuracy, and the calculation time of the new algorithm and the corresponding values for the other algorithms.

[5]Threshold crossing intervals algorithm (TCI) [7], VF filter algorithm (VF) [8], spectral algorithm (SPEC) [9], and complexity measure algorithm (CPLX) [10].

Fig. 5 compares the ROC curve of the new algorithm with the corresponding ROC curves of some other algorithms investigated in [6].

Table III finally shows the values for the sensitivity of the investigated algorithms, if, due to an appropriate adaption of the threshold parameters, the specificity is 95% or 99%, respectively.

IV. DISCUSSION AND CONCLUSION

In real applications of AEDs, the specificity is more important than the sensitivity, since no patient should be defibrillated due to an error of analysis which might cause cardiac arrest. Therefore, a low number of false positive decisions should be achieved, even if this increases the number of false negative decisions.

The different performances of an algorithm on the different databases reflect the different nature of these databases as described earlier.[1]

Fig. 5 lets us compare different algorithms at a fixed specificity. In practice one fixes a minimal value s_0 for the specificity which should be above, e.g., 80%. An even more appropriate quality measure for VF detection algorithms would be a "partial area index", i.e., the area under the ROC curve for specificity greater than a minimal value s_0.

From that point of view the two algorithms SPEC and VF are clearly better than the newer algorithms CPLX and TCI, though VF and CPLX have the same IROC value. In the region where the specificity is greater than 90% the older algorithm VF performs even better than the algorithm SPEC. These two algorithms operate in the frequency domain, which makes them more likely sensible for electronic interferences.

The algorithm CPLX utilizes methods from chaos theory. Our approach was inspired by phase space reconstruction methods. We decided to define our own measure, which is simple, can be computed fast, and is justified by excellent results.

Our new algorithm PSR clearly yields the best values for the integrated receiver operating characteristic. In addition, at any given specified specificity the algorithm PSR yields far the best sensitivity. It is even the fastest of all algorithms.

A different new algorithm based on the Hilbert transform which uses the same new simple measure is presented in [11].

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