RELIABILITY OF FIBRILLATION DETECTION ALGORITHMS IN AUTOMATIC EXTERNAL DEFIBRILLATORS (AEDs)

A. Amann[1], R. Tratnig[2], K. Unterkofler[2]

[1]Department of Anaesthesia and Intensive Care Medicine, Leopold-Franzens-Universität Innsbruck, Anichstr. 35, A-6020 Innsbruck, Austria
[2]Department of Computer Science, Applied Mathematics Group, FH-Vorarlberg, Achstr. 1, A-6850 Dornbirn, Austria
E-mail: Anton.Amann@uibk.ac.at

SUMMARY: A central component in automatic external defibrillators (AED) is the detection of ventricular fibrillation by means of appropriate detection algorithms. In the scientific literature there exists a wide variety of methods and ideas for handling this task. To test the quality of an algorithm for ECG analysis, it is essential to do this with a large amount of commented data under equal conditions. For our investigation we used the BIH-MIT data bank and the CU data bank.

In this test we analyzed eleven different fibrillation detection algorithms. The results are expressed in the quality parameters sensitivity[1] and specificity[2]. They are obtained by comparing the decision suggested by the algorithm with the annotated decision suggested by cardiologists. The cardiologists' decisions are considered as true. We distinguish only between ventricular fibrillation and no ventricular fibrillation, since the annotations do not include a differentiation between ventricular fibrillation and ventricular tachycardia. The closer the quality parameters are to 1, the better the algorithm works.

INTRODUCTION

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 are already commented by qualified cardiologists. Such data banks are, for example, the BIH-MIT or the AHA data bank.

Additionally, if the ECG data have been changed by artifacts, e.g., various loud noises or artifacts caused by cardiopulmonary reanimation (CPR), it is interesting to find out how well the algorithms still work. In real applications of defibrillators these kinds of artifacts occur frequently, but they should not affect the results of the analysis. The aim of good fibrillation detection algorithms is the possibility of doing an analysis also during CPR with a suppression of artifacts of motion. By the use of such algorithms the reanimation could be applied up to a few seconds in advance of the defibrillation. Moreover, the analysis of the ECG to test for the necessity of defibrillation could be carried out without interrupting the manual reanimation.

The parameters for the reliability of fibrillation detection algorithms are their sensitivity and specificity. These values should be 1 in the ideal case and should not differ much in an AED application. Since the annotation of ECG data may not always be completely correct, experienced cardiologists should inspect the discrepancies between the results of the analysis and the annotations of the data in order to ascertain whether the results of the algorithm are perhaps also justified.

MATERIALS AND METHODS

The fibrillation detection algorithms considered here are partly taken from the scientific literature, two of them are our own. The first five are taken from reference [4].

(1) The threshold crossing intervals algorithm (TCI) [5] operates in the time domain. Decisions are based on the number of signal crossings through a certain threshold.
(2) The autocorrelation algorithm (ACF) [2] analyses the periodicities within the ECG.
(3) The VF filter algorithm (VF) [3] applies a narrow band elimination filter in the region of the mean frequency of the considered ECG signal.
(4) The spectral algorithm (SPEK) [1] works in the frequency domain and studies the energy content in different frequency bands by means of Fourier analysis.
(5) The last algorithm of ref [4] is the complexity measure algorithm (CPLX) [6]. It transforms the ECG signal into a binary sequence and searches for repeating patterns.
(6) The standard exponential (STE) algorithm counts the number of crossing points of the ECG signal with an exponential curve decreasing on both sides. The decision for the defibrillation is made by counting the number of crossings.
(7) An improved version of (6) (SEN, new standard exponential) lifts the decreasing exponential curve at the crossing points onto the following relative maximum. This modification gives rise to better detection results.

[1] Sensitivity = TP/(TP+FN); TP: number of true positive decisions, FN: number of false negative decisions
[2] Specificity = TN/(TN+FP); TN: number of true negative decisions, FP: number of false positive decisions

(8) A further algorithm (RTR) compares the ECG with predefined reference signals (sine rhythm and fibrillation reference signal) and makes its decision by calculation of the residuals in the L^1 norm.
(9) An algorithm similar to (8) that uses the L^2 norm instead of the L^1 norm.
(10) A simple wavelet based algorithm (WVL) operates like (4) in the frequency domain.

All algorithms are implemented in MATLAB using a graphical user interface. For analysis, we selected the data in steps of one second and investigated intervals of 8 seconds length. These 8-second sequences were tested with all algorithms. Finally we recorded the results together with the annotation in an output file.

RESULTS

The quality parameters are presented in the following table 1. A perfect analyzing tool should have sensitivity and specificity 1. In this investigation the analyzed signals were not changed by, for example, adding noise or CPR artifacts. The data sets were taken from the BIH-MIT data bank (48 files, 2 channels per file, each channel 1805 seconds long) and the CU data bank (35 files, 1 channel per file, each channel 508 seconds long).

Table 1: Quality of fibrillation detection algorithms (sensitivity, specificity), rounded on 3 digits

	MIT data bank		CU data bank		overall results	
	Sens.	Spec.	Sens.	Spec.	Sens.	Spec.
TCI (1)	0.650	0.836	0.728	0.716	0.721	0.828
ACF[3](2), P=95%	0.332	0.459	0.439	0.605	0.431	0.470
ACF[4](2), P=99%	0.594	0.301	0.598	0.510	0.598	0.316
VF (3)	0.294	0.999	0.334	0.980	0.331	0.998
SPEK (4)	0.220	1.000	0.302	0.997	0.296	1.000
CPLX (5)	0.063	0.924	0.591	0.878	0.554	0.921
STE (6)	0.545	0.834	0.551	0.674	0.551	0.822
SEN (7)	0.965	0.387	0.861	0.475	0.868	0.394
RTR (8)	0.759	0.973	0.745	0.945	0.746	0.971
RL2 (9)	0.608	0.973	0.656	0.962	0.653	0.972
WVL[5] (10)	0.290	0.999	0.267	0.995	0.269	0.999

DISCUSSION

In real applications of AEDs the value for specificity is more important than the value for sensitivity. Therefore a low number of false positive decisions should tried to be achieved, also if this process makes the number of false negative decisions higher.

Up to now the results were only examined with undisturbed data from the mentioned data banks. Noise or CPR were not added. In the future, we shall use data changed by addition of artifacts like noise or CPR. A CPR filter will be used to preprocess the data. Using a good CPR filter should result in only little change in quality compared to undisturbed data. The significant parameters that will be compared are again sensitivity and specificity. Also we want to refine if necessary the analyzing parameters and modify the algorithms to improve our results. A future aim is also the creation of a SIMULINK application to offer a very concise utilization of the different functions. Furthermore the automatic detection of more subtle rhythm disturbances like ventricular tachycardia or other syndromes is planned.

REFERENCES

[1] S. Barro, D. Cabello, J. Mira, and R. Ruiz, Algorithmic sequential decision making in the Frequency domain for life threatening ventricular Arrhythmias and imitative artifacts: a diagnostic system, J. Biomed. Eng. **11**, 320-328, (1989).

[2] S. Chen, M.M. Mower, and N.V. Thakor, Ventricular fibrillation detection by a regression test on the autocorrelation function, Medical & Biological Engineering & Computing, **25**, 241-249, (1987).

[3] R. Dillman and S. Kuo, Computer Detection of Ventricular Fibrillation, Computers in Cardiology, IEEE Computer Society, 347-349, (1978).

[4] I. Jekova, Comparison of five algorithms for the detection of ventricular fibrillation from the surface ECG, Physiol. Meas. **21**, 429-439, (2000).

[5] K.Y. Pan, N.V. Thakor, and Y.S. Zhu, Ventricular Tachycardia and Fibrillation Detection by a Sequential Hypothesis Testing Algorithm, IEEE Transactions on Biomedical Engineering, **37**, 837-843, (1990).

[6] N.V. Thakor, Z.Z. Wang, X.S.Zhang, and Y.S. Zhu, Detecting Ventricular Tachycardia and Fibrillation by Complexity Measure, IEEE Transactions on biomedical engineering, **46**, 548-555, (1999)

[3] probability of 95% in the Fisher distribution => $\alpha = 0.05$ in $F(\alpha, k_1, k_2)$ with $k_1=1$, $k_2=5$

[4] probability of 99% in the Fisher distribution => $\alpha = 0.01$ in $F(\alpha, k_1, k_2)$ with $k_1=1$, $k_2=5$

[5] wavelet algorithm similar to SPEK (4), but with weighted FT