NOISE SENSITIVITY OF THREE SURFACE ECG FIBRILLATION DETECTION ALGORITHMS

Irena Zhekova*, Albert Cansell#, Ivan Dotsinsky*
Centre of Biomedical Engineering, Sofia, Bulgaria
Bruker Medical, Wissembourg, France

***Abstract**. The widening application of automatic external defibrillators (AED) presents very strong requirements toward external electrocardiogram (ECG) signal analysis. In a previous study the performance of five well-known detection algorithms was assessed by test signals from the ECG-signal databases of the American Heart Association (AHA) and the Massachusetts Institute of Technology (MIT). The results obtained were used as a basis for testing the noise sensitivity of three of these algorithms. Realistic noises were obtained by simulation and recording of signal disturbance by various motions during resuscitation and defibrillation episodes (body shudder, convulsions and gasps, cable movement, car transportation). The sensitivity and specificity of the detection algorithms were evaluated using electrocardiogram signals mixed with these noises.*

1 Introduction

A number of studies have demonstrated that early defibrillation is the major solution to increase survival rate from cardiac arrest (Charbonnier, 1994). Often a shock must be applied in conditions of absence of a qualified person. The accuracy of the automatic diagnosis should match the diagnosis of experienced medical personnel.

Reliable and accurate detection of ventricular fibrillation (VF) from the surface electrocardiogram is a rather difficult task (Clayton *et al* 1993). It can be further complicated in the presence of noise in the analyzed signal.

The sensitivity and specificity of five favoured detection algorithms were assessed in a previous work (Jekova, 2000), with signals other than the ones used for their evaluation by the respective authors. Three of these algorithms yielded relatively good results and were selected for further consideration in conditions of noise. In order to achieve an adequate comparison, it was decided to use the same data segments as in the former study, by adding several types of noise.

2 Electrocardiogram signals and noise

ECG signal files containing SR and VF intervals were selected from the AHA and MIT databases. Representative intervals of 8s with non-shockable ECG signals, labeled for convenience 'sinus rhythm' (SR), which they usually are, and 8s with VF were taken out of each file. A total of 71 SR and 90 VF episodes were thus collected. The SR epochs were selected in exclusion of very low amplitude signals (below 0.25 mV), paced beats, gross artifacts, frequency above 150 bpm, and transitions from normal to abnormal rhythms.

Representative records of the two types of signals SR and VF are given in figures 1a and 2a respectively.

The detection of SR and VF was only examined in this study. The separate recognition of ventricular tachycardia (VT) required a modified approach, which involved additional investigation, therefore it was not considered here.

Six types of noise recordings were reported by Dotsinsky et al.,1999. It was decided that two of them – cardiopulmonary resuscitation (CPR) and arms movement disturbances – should be not taken into account, as the accepted rules require stopping CPR before automatic defibrillation.

Representative epochs of the other four types of disturbance were then chosen, with an example shown in figure 1b (2b). This is a patient cable movement artifact. The spectra of the artefactual signals were rather similar, containing well expressed low frequency components (even after having applied 1 Hz high-pass filter), as seen in the spectrum of the above disturbance (figure 3). The ECG records selected from the respective databases were mixed with the disturbances. Preprocessing was applied on all signals using: i) a notch filter to virtually eliminate powerline interference, ii) a high-pass filter with cutoff frequency at 1 Hz to suppress residual baseline drift, and iii) a second-order low-pass Butterworth filter with a cutoff frequency at 30 Hz to reduce muscle noise, following the approach of Thakor *et al.* (1990).

The signal to noise ratio (measured using peak-to-peak amplitudes) varied from 20 for high amplitude ECGs combined with low amplitude noises, down to 2 in the opposite case, and strongly depending on the specific time-interval of ECG and noise (figure 1c and 2c).

3 Algorithms

A former study of five SR/VF detection algorithms (Jekova, 2000) was used as a basis for the present investigation. The three algorithms showing best results were selected for detailed evaluation. One was the time-domain procedure called 'threshold crossing intervals' (TCI), proposed by Thakor *et al* (1990). The two other were frequency domain methods - the VF-filter (Kuo and Dillman 1978) and the spectrum analysis (Barro *et al* 1989).

Each of the three methods was implemented as a computer algorithm by means of the software package MATLAB. The selected ECG segments, combined with each of the types of noise, were subjected to identification as SR or VF. The corresponding sensitivities and specificities were computed.

Short descriptions of the three methods and their software implementation are given below.

3.1 *Threshold crossing intervals (TCI)*. (Thakor *et al* 1990)

The signals are converted to binary impulses by comparison with a threshold. For each one-second segment *S*, a threshold at 20% of the maximum value is set. The

$$TCI = \frac{1000}{(N-1) + \frac{t_2}{t_1+t_2} + \frac{t_3}{t_3+t_4}} [ms]$$

threshold is allowed to adapt every second to the signal amplitude changes. The time-intervals between two consecutive crossings of the threshold are measured. Then the mean TCI is calculated. N is the number of impulses in *S*; t_1 is the time-interval from the beginning of S back to the falling edge of the preceding impulse; t_2 is measured from the beginning of S to the start of the next pulse; t_3 is the interval between the end of the last pulse to the end of S; t_4 is taken from the end of S to the start of the next pulse.

If TCI≥ 400ms, the segment is classified as SR, otherwise it is VF, as we are not considering VT in this study.

3.2 *VF-filter* (Kuo and Dillman 1978)

The VF-filter technique corresponds to a narrow band-stop filter applied to the signal, assumed to be quazi-sinusoidal, with central frequency equivalent to the mean signal frequency. The output is the VF-filter leakage. The mean period of a fixed length of data is obtained from the equation:

$$T = 2\pi \frac{\sum_{i=1}^{m} |V_i|}{\sum_{i=1}^{m} |V_i - V_{i-1}|}$$

where *Vi* are the signal samples and *m* - the number of data points in one mean period.

The narrow bandstop filter is implemented by combining the ECG data with a copy of the data shifted by half a period. The VF-filter leakage is computed as:

$$leakage = \frac{\sum_{i=1}^{m} \left| V_i + V_{i-\frac{T}{2}} \right|}{\sum_{i=1}^{m} \left(|V_i| + \left| V_{i-\frac{T}{2}} \right| \right)}$$

This algorithm was originally applied (by its authors) in segments of signals obtained by a monitoring system, where no QRS complexes or paced beats could be detected. The signal amplitude was measured and two thresholds for VF-filter leakage were set. If the signal was higher than the amplitude of the last detected QRS (in a previous segment) divided by three and the leakage was <0.406, VF was identified. Otherwise the leakage must be less than 0.625 in order to identify VF. We did not apply QRS detection, therefore only the higher threshold was used for this test.

3.3 Spectral analysis (Barro *et al* 1989)

Spectral analysis is applicable to VF detection because of the narrow band of frequencies, reported to be between 4 and 7 Hz (Murray *et* al 1985, Clayton *et al* 1991), compared to the wider frequency band SR signals, having components even above 20 Hz.

Each data segment is multiplied by a Hamming window and transformed in the frequency domain by Fast Fourier Transform (FFT). Four spectrum parameters are obtained: the normalized first spectral moment (FSMN) and A_1, A_2, A_3:

$$FSMN = \frac{1}{F}\frac{\sum Amp_i f_i}{\sum Amp_i}$$

Here F is the frequency of the component with the highest amplitude (called peak frequency) in the range 0.5-9 Hz;
f_i is the i-th frequency in the FFT between 0 and 100 Hz;
Amp_i is the corresponding amplitude;
A_1 is the sum of amplitudes between 0.5 Hz and F/2, divided by the sum of amplitudes between 0.5 Hz and 20F;
A_2 is the sum of amplitudes between 0.7F and 1.4F divided by the sum of amplitudes between 0.5 Hz and 20F;
A_3 is the sum of amplitudes in 0.6 Hz bands around the 2-nd to 8-th harmonics (2F-8F), divided by the sum of amplitudes in the span of 0.5 Hz to 20F.
VF is detected if $FSMN \leq 1.55$, $A_1 > 0.19$, $A_2 \geq 0.45$, $A_3 \leq 0.09$.

4. Results and discussion

After having mixed signals and noise as described above, 8-second segments of SR and VF were subjected to evaluation by the three algorithms and classified as shockable or nonshockable rhythms. The sensitivity and specificity of the three algorithms were computed. The results are presented in Table 1 for each type of disturbance and, for comparison, with 'pure' signals.

Table 1. Sensitivities and specificities of the assessed algorithms

Algorithm	Specificity [%]					Sensitivity [%]				
	conv.	car	cab.	gasp	'pure' signal	conv.	car	cab.	gasp	'pure' signal
TCI	69	72	66	70	**75**	94	94	90	93	**98**
VF-filter	91	91	91	91	**91**	94	92	89	93	**94**
Spectrum	93	94	96	93	**93**	74	74	70	78	**79**

4.1 TCI

In a previous study, using ECG signals from the databases mentioned above, the method had shown a high sensitivity of 98%, but a specificity of only 75%. As expected, adding noise to the same signals lowered both parameters by about 5% (mean). The worst result was obtained for the 'cable movement' type of disturbance.

4.2 VF-filter algorithm

As explained above, no QRS detection was applied in this study. Therefore, only the higher threshold was used. Nevertheless, this algorithm allowed to reach the best results both with noise-free and with disturbed ECG. The specificity remained unchanged and the sensitivity was affected by an average of only 2%. However, the cable movement artifact was again the most disturbing, reducing the sensitivity by 5%.

4.3 Signal spectrum algorithm

In our former work (Jekova, 2000) it was found that using the original descriptors, 100% specificity and only 3% sensitivity were obtained. The reason was the lower

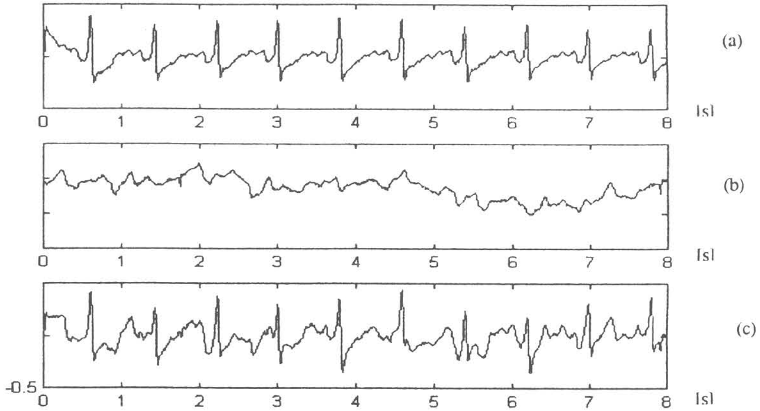

Figure 1. (a) Eight-second segment of a sinus rhythm signal from the MIT vfdb – 427, signal 0; (b) Segment of the patient cable movement disturbance; (c) combination of (a) and (b).

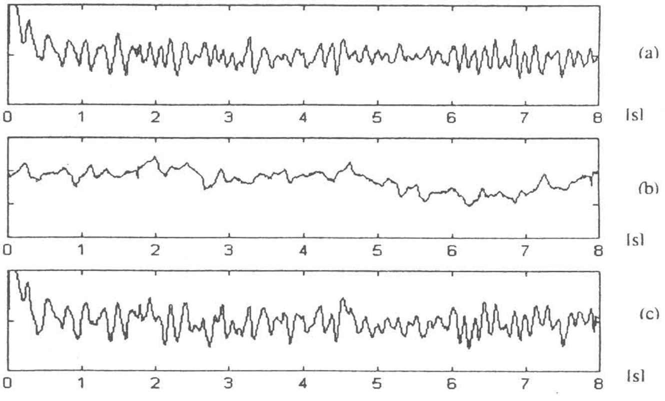

Figure 2. (a) Eight-second segment of a fibrillation episode from the MIT vfdb – 427, signal 0; (b) Segment of patient cable movement disturbance; (c) combination of (a) and (b).

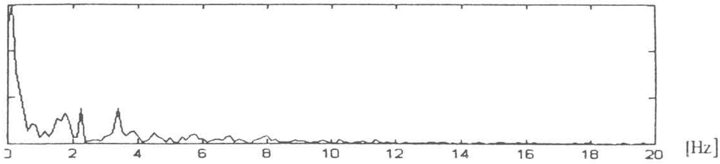

Figure 3. The spectrum of the patient cable movement disturbance.

peak frequency (F) of the evaluated VF segments from the databases used (F=3.4 Hz), compared to the frequency band reported by the authors (4 to 7 Hz). The following changes were then made: the rhythm was identified as VF if FSMN≤2.5, A2≥0.35, A3≤0.25. A1 was not used, as it worsened the detection results. A3 might be used, but it did not contribute to improvement. These changes were done in an attempt to achieve the best results with noise-free signals, namely 79% sensitivity and 93% specificity.

The addition of noise decreased the sensitivity by 5% (mean), but the cable movement caused a reduction of 9%.

There was a slight unexpected increase of the specificity for two of the artifacts. This could be explained with the growth of the sum of amplitudes between 0.5 Hz and 20F caused by these noises, thus reducing the value of A2 and increasing that of FSMN.

5. Conclusion

It was rather difficult to define the most disturbing types of artifact that could cover by their particularities all significant real cases. Nevertheless, at least a first attempt at a comparison is presented here. It seems to be useful for the assessment of these well-known fibrillation detection algorithms.

The simulated artifacts and the results of this study might be used in the development of newer algorithms with improved disturbance immunity. Excessive noise will inevitably degrade the performance of any type of signal analysis scheme. Therefore, the development of artifact recognition procedures with convenient warning and/or analysis-blocking procedures, adaptable to the corresponding algorithms, seems necessary.

References

Barro S, Ruiz R, Cabello D and Mira J 1989 Algorithmic sequential decision-making in a frequency domain for life threatening ventricular arrhythmias and imitative artifacts: a diagnostic system *Journal of Biomed. Eng.* **11** 320-328

Charbonnier F M 1994 Algorithms for arrhythmia analysis in AEDs *Defibrillation of the heart. ICDs, AEDs and manual* ed W A Tacker (St. Louis: Mosby) pp 196-222

Clayton R H, Murray A and Campbell R W F 1993 Comparison of four techniques for recognition of ventricular fibrillation from the surface ECG *Med. & Biol. Eng. & Comput.* **31** 111-117

Dotsinsky I., Jekova I. and Christov I. Simulator for movements accompanying the emergency electrocardiogram recordings, *Proc. 8-th Internat Nat*. Conf. *"Electronics '99"*, book 2, Sozopol, Sept.23-25, 1999, pp 28-31.

Jekova I. 2000 Comparison of five algorithms for the detection of ventricular fibrillation from the surface ecg. Physiol. Meas. **21** (in press).

Kuo S and Dillman R 1978 Computer detection of ventricular fibrillation Proc. Computers in Cardiology 1978, IEEE Computer Society Press, Long Beach, California 347-349

Murray A, Campbel R W F and Julian D G 1985 Characteristics of the ventricular fibrillation waveform *Proc. Computers in Cardiology 1985, IEEE Computer Society Press, Washington DC* 275-278

Thakor N V, Zhu Y S and Pan K Y 1990 Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm *IEEE Trans. Biomed. Eng.* **37** 837-843