VENTRICULAR FIBRILLATION DETECTION AND OPTIMAL PARAMETER SET SELECTION BY MEANS OF DISCRIMINANT ANALYSIS

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Reliable and correct external electrocardiogram (ECG) signal analysis is of crucial importance for further development of automatic external defibrillators (AED) and their use by non-specialists. We proposed and evaluate a set of ECG parameters, derived from the output signal of a band-pass digital filter and from an in-house developed wave detection method. The extracted parameters were evaluated by means of discriminant analysis. It attained specificity between 92.1% and 95.4% and sensitivity between 96.8% and 93.4% respectively for different combinations of the proposed parameters. The parameter evaluation and the detection ability assessment were performed on ECG recordings from the widely recognized databases of the American Heart Association (AHA) and Massachusetts Institute of Technology (MIT).

1. INTRODUCTION

Reliable and correct external electrocardiogram (ECG) signal analysis is of crucial importance for further development of automatic external defibrillators (AED) and their use by non-specialists. They should provide accuracy for shockable and non-shockable rhythms classification, comparable to this of trained medical personnel.

Many software methods for ventricular fibrillation (VF) detection have been proposed. In the time-domain, the most well-known are the threshold crossing intervals [1] and auto-correlation function methods [2]. In the frequency-domain two methods are favoured – the spectrum analysis [3] and the VF-filter [4]. Some authors apply neural networks [5,6] and wavelet transform [7,8,9]. Despite the variety of available methods, reliable and accurate VF detection has still not been achieved.

By means of dicriminant and factor analysis we aimed at assessment the classification ability of some parameters extracted from the external ECG. 2. Simulator prototype development

2. MATERIAL AND METHOD

2.1 ECG signals

We used 99 full-length ECG signal recording files from the standard Massachusetts Institute of Technology (MIT) and American Heart Association (AHA) long-term VF databases, all sampled at 250 Hz, 12-bit resolution. These databases contain difficult for classification signals. The non-shockable dataset included normal sinus rhythms, branch blocks, ECGs with ectopic beats, bigeminy, trigeminy, supraventricular tachycardia, non-shockable VTs below 180 bpm, bradycardia, low amplitude ECGs, noise contaminated signals. The shockable dataset included coarse and fine fibrillation, and VT signals of rates above 180 bpm. Each 10 s epoch of all above described records were annotated by an experienced cardiologist and a biomedical engineer and labeled as "non-shockable", "shockable", "asystoly" and "noise". Thus we analyzed a total of 10968 non-shockable and 2919 shockable ten-second episodes.

2.2 Signal preprocessing and parameter calculation

The signals were preprocessed with 1-30 Hz 'monitor-type' ECG bandwidth filter. We passed all ECG recordings through a designed band-pass digital filter with integer coefficients (central frequency at 14.6 Hz, bandwidth from 13 Hz to 16.5 Hz) [10] in order to suppress the main fibrillation frequency components (below 7 Hz) and to pass the normal heart rhythm signals with frequency in the range of 16 Hz. We processed the absolute value of the filter output signal (AbsF) (see fig.1) and derived nine parameters, numbered from 'C1' to 'C9', for each 10 s epoch:

- C1 - number of AbsF samples with amplitude above 0.5*Max AbsF value;
- C2 - number of AbsF samples with amplitude above the Mean AbsF value;
- C3 - number of AbsF samples with amplitude in the range (Mean value±Mean deviation);
- C4 - number of AbsF samples with amplitude above 2*(Mean AbsF value);
- C5 - number of AbsF samples with amplitude above 0.75*Max AbsF value;
- C6 - number of AbsF samples with amplitude above 0.25*Max AbsF value;
- C7 - sum of all AbsF samples divided by the Max AbsF value;
- C8 - sum of all AbsF samples divided by the Max signal value of the non-filtered ECG;
- C9 - sum of all AbsF samples multiplied by the Max AbsF value and divided by the Max signal value of the non-filtered ECG.

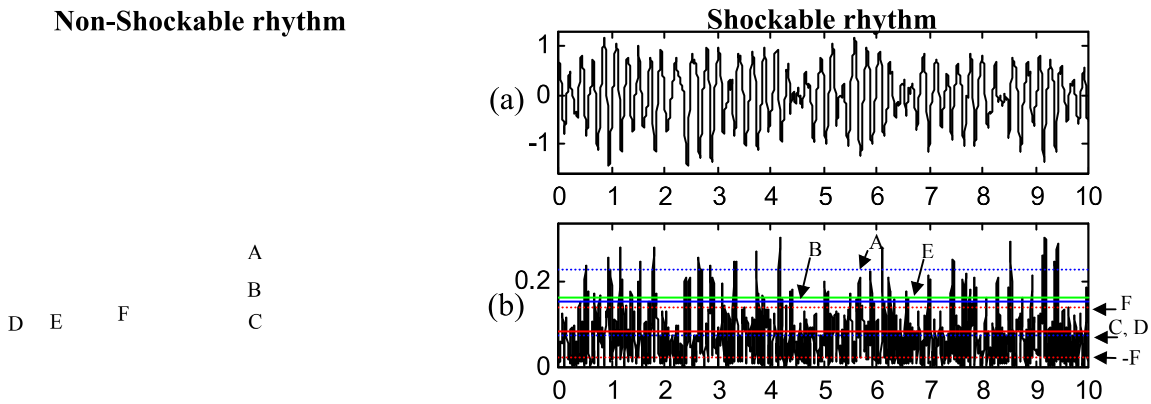

Fig.1:Examples of non-shockable (N) and shockable (S) rhythms:(a) – The original N and S signals;(b) - band-pass filtering of N and S signals;
*(Thresholds) – A=0.75*Max;B=0.5*Max;C=0.25*Max;D=Mean;E=2*Mean;F=Mean+/-standard deviation*

Additionally, we applied an in-house developed algorithm [10] for detection of ventricular fibrillation (VF) and tachycardia waves in the original ECG signal. The algorithm detects all successive positive and negative peaks and identifies the significant waves in each 10 s time-interval, using amplitude and time criteria (see fig.2). We measured the following nine wave parameters, averaged for the entire 10 s epoch:

- Tp and Tn - rising edge and falling edge durations;
- |Tp-Tn| - absolute value of the difference between the falling and rising edge durations;
- Sp and Sn - upslope and downslope values, calculated as the difference between the positive and the negative peak of each half-wave divided by its duration. The slope is scaled with respect to the mean peak-to-peak value to assure a relative amplitude independence;
- |Sp-Sn| - absolute value of the difference between the upslope and downslope values;
- WB - number of detected waves;
- WD - number of positive or negative peaks with amplitude out of the range (positive or negative mean peak value ± 25%). This parameter counts only the positive peaks when the positive mean peak value is higher than the negative one. In the opposite case, it counts only the negative peaks;
- WF – in case of (WD<0.125*WB), this parameter presents the signal frequency in beats-per-minute as the number of detected waves in 10s interval multiplied by six. Otherwise it is calculated as the reciprocal value of the parameter Period, proposed by Kuo and Dillman [4].

All calculation procedures were performed with the software package Matlab.

(a)

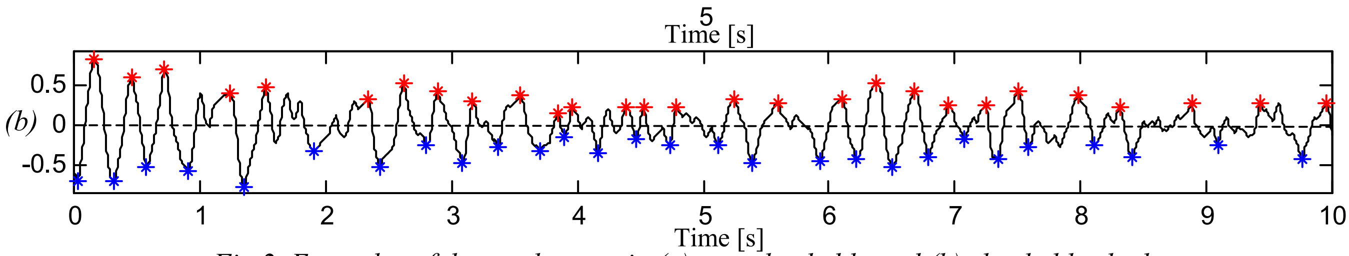

Fig.2. Examples of detected waves in (a) non-shockable and (b) shockable rhythms.

2.3 Standard and stepwise discriminant analysis

Using discriminant analysis to differentiate between shockable and non-shockable rhythms (ShR and NShR), two linear discriminant functions of the *n*-dimensional vector *x* are calculated – equations 1 and 2. In our case *n=18*.

$$F'(x) = \sum_{i=1}^{n} w'_i x_i + a' \qquad (1)$$

$$F''(x) = \sum_{i=1}^{n} w_i'' x_i + a'' \qquad (2)$$

Here w_i', w_i'' and a', a'' are the corresponding discriminant coefficients and constants. Equation 1 relates to the possibility the signal described by vector x to be non-shockable, and the opposite possibility is given by equation 2. These two discriminant functions are computed for the assessed ECG signal and it is labeled as non-shockable rhythm or shockable rhythm, depending on which of the values of *F'* or *F''* is higher.

When using standard discriminant analysis all selected parameters are included in the discriminant functions. In case of stepwise discriminant analysis, the weight of each parameter is estimated (the ability of each of them to separate the two classes), by comparing with a predefined value *F*. For $F>4$ the corresponding parameter is included in the two discriminant functions (1) and (2). For $F\leq 3.96$ the parameter is not included. The best discriminating parameter is first included. After that its combinations with the remaining parameters are analyzed. The best combination, which satisfies the *F* criteria, is included at final version of the discriminant functions. Iteratively, the best combination is combined with each of the remaining *(n-1)* parameters, etc., until the inclusion of a new parameter does not improve the classification.

The specificity and sensitivity, and the discriminant coefficients and constants were computed using the program package Statistica.

3. RESULTS

Table 1 shows the sensitivities (ability to recognize correctly NShR), specificities (ability to recognize correctly ShR) and discriminant functions obtained by standard discriminant analysis for each parameter, extracted from the ECG.

Parameter	Sp[%]	Se[%]	F' (for NShR)	F'' (for ShR)	Graph
C1	91.5	90.3	0.0178*C1-2.3866	0.0441*C1-11.1024	
C2	86.9	97.7	0.0360*C2-12.7045	0.0563*C2-30.0761	
C3	82.6	99.2	0.0433*C3-42.0742	0.0319*C3-23.1915	
C4	73.4	80.4	0.1635*C4-27.0292	0.1338*C4-18.3263	
C5	88.4	80.6	0.0550*C5-2.8559	0.1005*C5-7.9123	
C6	91.5	95.2	0.0086*C6-2.6494	0.0231*C6-14.9094	
C7	90.2	96.3	0.0221*C7-4.7709	0.0454*C7-17.9396	
C8	69.1	58.6	0.1023*C8-6.6917	0.1235*C8-9.4252	
C9	53.1	78.8	0.0002*C9-1.7839	0.0001*C9-1.0418	
Tp	56.0	92.5	0.0159*Tp-1.7342	0.0066*Tp-0.8735	
Tn	45.3	81.1	0.0146*Tn-1.3042	0.0095*Tn-0.9514	
|Tp-Tn|	75.3	94.9	0.0289*|Tp-Tn|-2.9613	0.0070*|Tp-Tn|-0.8257	
Sp	36.4	53.9	0.0485*Sp-1.3444	0.0480*Sp-1.3305	
Sn	51.9	88.4	0.0376*Sn-1.6480	0.0215*Sn-1.0087	
|Sp-Sn|	72.2	97.0	0.0677*|Sp-Sn|-2.7747	0.0180*|Sp-Sn|-0.8447	
WB	90.6	76.8	0.0585*WB-3.0795	0.1180*WB-10.3650	
WD	85.5	75.1	0.1449*WD-0.9436	0.5340*WD-4.0951	
WF	73.1	76.9	0.0121*WF-1.5968	0.0203*WF-3.2080	

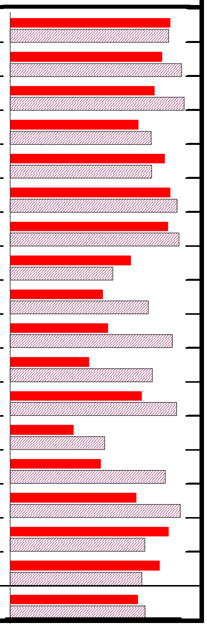

Table 1. Standard discriminant analysis – specificity (Sp■), sensitivity(Se▨) and discriminant functions F'(non-shockable rhythms) and F''(shockable rhythms) for each parameter.

Table 2 illustrates the sensitivities, specificities and discriminant functions calculated by means of stepwise procedure at each discriminant analysis step.

Step	Parameters	Sp[%]	Se[%]	F' (for NShR)	F'' (for ShR)
1	**C6**	91.5	95.2	0.0086*C6-2.6494	0.0231*C6-4.9094
2	**C6, WD**	92.1	96.8	0.0083*C6+0.0754*WD-0.7152	0.0218*C6+0.3515*WD-16.337
3	**C6, WD, C7**	93.8	94.6	-0.0633*C6-0.0322*WD +0.1319*C7-10.5898	-0. 0278*C6+0.2770*WD +0.0913*C7-20.1095
4	**C6, WD, C7, C4**	94.4	93.7	-0.06*C6-0.056*WD +0.1301*C7+0.1667*C4-10.5898	-0.0249*C6+0.2567*WD +0.0898*C7+0.142*C4-39.8801
5	**C6, WD, C7, C4, WB**	95.4	93.4	-0.059*C6+0.1772*WDif +0.1332*C7+0.1871*C4-0.0666*WB-39.5945	-0.0246*C6+0.3181*WD +0.0906*C7+0.1474*C4-0.0176*WB-40.0013

Table 2. Stepwise discriminant analysis – specificity (Sp), sensitivity(Se) and discriminant functions F'(non-shockable rhythms) and F''(shockable rhythms) on each step.

Additionally we applied factor analysis, using the method of the principal components. Thus we grouped the 18 parameters in 4 factors, which contain relatively correlated parameters:

- *Factor 1* – C1, C2, C3, C5, C6, C7, |Tp-Tn|, |Sp-Sn|, WB;
- *Factor 2* – C8, WF, WD;
- *Factor 3* – Tp, Tn, Sp, Sn;
- *Factor 4* – C4, C9.

We assessed the classification ability of three more parameter combinations, based on the results of the factor analysis. We combined:

1. The best parameters from Factor1 (C6), Factor2 (WD) and Factor4 (C4), without including the best parameter from Factor3 (Tp), because it shows very low specificity;
2. We added WB to the first combination, because it was estimated that this parameter has relatively low correlation with the other parameters in Factor1;
3. We exclude WD from the second combination.

The sensitivities, specificities and discriminant functions for each of the parameter combination obtained by standard discriminant analysis are shown in Table 3.

Parameter combination	Sp[%]	Se[%]	F' (for NShR)	F'' (for ShR)
C6, WD, C4	93.3	95.1	0.1674*C4+0.0107*C6+0.05* WD -30.1897	0.1425*C4+0.0238*C6+0.3299* WD-36.2357
C6, WD, C4, WB	94.4	95.0	0.1856*C4+0.0131*C6-0.0597*WB+0.2608*WD-30.1897	0.1463*C4+0.0243*C6-0.0127*WB+0.375*WD-36.3
C6, C4, WB	94.7	94.9	0.18*C4+0.013*C6-0.0399*WB-31.0158	0.1382*C4+0.0243*C6+0.0157* WB-35.1107

Table 3. Standard discriminant analysis – specificity (Sp), sensitivity(Se) and discriminant functions F'and F'' for three parameter combinations extracted by means of Factor analysis.

4. DISCUSSION AND CONCLUSION

We applied standard discriminant analysis to assess the classification ability of each parameter extracted from the processed ECG signal. Considering the results in Table 1, the first top 5-ranked parameters for NShR clustering are: C1, C6, WB, C7 and C5, which provide specificity from 91.5% down to 88.4%. Respectively, the first top 5-ranked parameters for ShR clustering are: C3, C2, |Sp-Sn|, C7 and C6, which determine sensitivity between 99.2% and 95.2%. Unfortunately the parameters, which assure high specificity do not perform high sensitivity and vice versa. It is evident that only the parameter C6 is common for the two groups, combining 91.5% specificity and 95.2% sensitivity.

Since there is no parameter providing 100% separation between the two rhythms, we applied a stepwise discriminant analysis to search for parameter set, which combines higher specificity and higher sensitivity. The results in Table 2 show that the parameter combination C6 and WD (Step 2) has the highest sensitivity (96.8%) and acceptable specificity (92.1%), whereas the set C6, WD, C7, C4, WB (Step 5) provides highest specificity (95.4%) but the lowest sensitivity (93.4%).

The factor analysis shows that there is considerable correlation between some of the parameters (see Factor1-4) and therefore their grouping is useless. It was found that combining uncorrelated parameters, even they individually feature with relatively low specificity and sensitivity is more efficient. The combination of parameters that belong to different factors lead to balanced results for specificity (from 93.3% to 94.7%) and sensitivity (from 94.9% to 95.1%) – see Table 3.

Since there are different parameter combinations, which provide relatively similar specificity and sensitivity (about 94% and 95% respectively), and the computation time depends on the number of parameters included in the discriminant functions, the choice of the parameter set should consider the available computation resources.

6. REFERENCES

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