Discrimination between Ventricular Tachycardia and Ventricular Fibrillation Using the Continuous Wavelet Transform

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Abstract

An efficient and precise discrimination algorithm for the two malign cardiac rhythms, namely VT and VF rhythms, is of great importance in the design of AEDs. The method put forward in the present work exploits the regularity observed in the coefficients of the Continuous Wavelet Transform (CWT) of a VT segment.

In a preliminary stage the wavelet analyzing function yielding the best results is selected. The ECG records are then divided in segments of 4.8 seconds where the CWT coefficients are calculated for those scales considered significant. The separation of the peaks in the time evolution of the coefficients is proportional to the cardiac frequency and the amplitude of the peaks is more uniform as the rhythm becomes more regular. The discrimination parameters selected for the algorithm are based on the dispersion of the position and the amplitude of those peaks.

The accuracy achieved, 94.74%, improves the results obtained by previously reported methods.

1. Introduction

Cardiac defibrillators, both the automated external defibrillators (AED) and the implantable devices, must discriminate in a quick and exact way the two malign cardiac rhythms, namely ventricular fibrillation (VF) and ventricular tachycardia (VT). Despite an electrical shock treatment being suitable for both rhythms, in the case of a VF episode a high energy shock is recommended (typically 200J applied on the chest and 20J in the case of implantable devices). On the other hand VT rhythms must be treated through low-energy cardioversion (the shock is applied in synchronism with the heart beat).

In recent years many efforts have been aimed at characterizing both arrhythmias by means of diverse techniques such as the sequential hypothesis algorithm proposed by Thakor et al. [1], based on the probability distribution of the Threshold Crossing Intervals (TCI). Following a different line Zhang et al. [2] developed a method using a complexity measure for VF/VT detection. Other techniques based on the peak analysis of the cross-correlation function [3] or on a regression test applied to the peak values of the autocorrelation function [4] have also been proposed.

The approach introduced in this article is based on the application of wavelet techniques to biomedical signals and in particular to the analysis of ECG records. Compared to the conventional time-frequency approach Addison et al. have suggested an energy based method using the CWT [5] in order to make visible the underlying structures within the VF waveform. The discrimination method described in the current paper relies on the regularity of the CWT decomposition of the ECG signal.

2. Methods

2.1. Wavelet Transform for discrimination

Wavelet Transforms allow signals to be decomposed highlighting both frequency characteristics and the location of particular features in a time series. The approach is substantially different from the classical Fourier analysis where the spectrum only contains globally averaged information. The new method proposed consists on using the CWT as an innovative tool to analyze unexplored structures of ECG records and in particular of VF and VT episodes.

Initially several wavelet techniques were considered and the CWT was chosen. Despite providing much redundant information the CWT offers more clarity and resolution in the transform domain and allows for greater temporal resolution.

The CWT of a time signal $x(t)$ is defined as:

$$C_{a,b} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \Psi\left(\frac{t-b}{a}\right) \cdot x(t)\, dt$$

where a and b are continuous valued scale and translation parameters and Ψ is the analyzing wavelet function.

Following the ECG signal observation method suggested in the lines above, focus is put on the selection of the appropriate parameters to use in the discrimination.

The a-priori discrimination criterion is based on earlier contributions [3], i.e. a VT rhythm exhibits a higher degree of regularity in time and frequency than a VF rhythm.

The application of the CWT to VF and VT signals makes visible the most suitable regularity structures for discrimination. Fig. 1 and 2 show the CWT scalogram obtained by the application of a 64-scale WT, using *dmey* wavelet, on a VT and a VF signal respectively. The scalogram corresponding to the VT signal exhibits a high degree of regularity in the vertical components (highlighted in Fig. 1) that is not present in the scalogram of the VF rhythm.

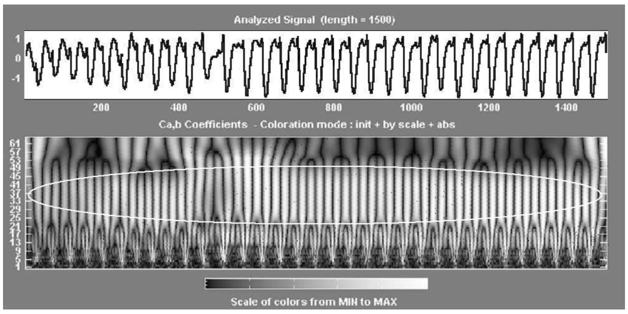

Figure 1. ECG signal in samples and CWT scalogram of a VT rhythm.

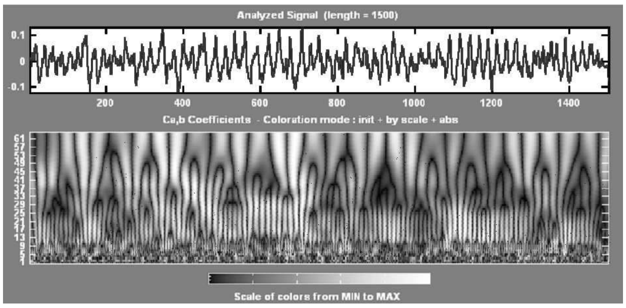

Figure 2. ECG signal in samples and CWT scalogram of a VF rhythm.

2.2. Selection of the analyzing wavelet function

Numerous wavelet functions have been discussed in the literature, the most adequate one for our purposes being the function showing the most uniform behavior of the regularity observed for VT signals. As shown in Fig. 1 the scalogram is particularly regular on the vertical components. Based on 16 VT records, a numerical value of the dispersion, reflecting such regularity, was obtained.

Initially the cardiac frequency of each signal was calculated and the corresponding scale in the CWT scalogram, named $scale\_frq$, was taken as the reference scale. Three additional scales, corresponding to 10% jumps in the scale axis were then selected, two above and one below the reference scale: $0.9\,scale\_frq$, $1.1\,scale\_frq$ and $1.2\,scale\_frq$. The positions of the peaks of the signals corresponding to those scales were calculated and the mean value of the standard deviation (in samples) of the interval between consecutive peaks was adopted as the selection parameter.

The averaged results for a wide selection of different wavelet functions are summarized in Table 1. The *dmey* analyzing wavelet function was selected as it shows the most uniform behavior in regularity.

Table 1. Sorted averaged values of the dispersion of regularity (minor best).

Analyzing wavelet function	**Dispersion of the Regularity**
dmey	5.37344
bior1.3	5.75299
meyr	5.87797
db1	6.28105
coif2	6.91936
coif4	6.92519
sym8	7.01613
db5	8.36212
bior3.7	8.65912
rbio1.3	9.06956
bior2.6	9.74062
rbio3.7	9.77485
rbio2.6	9.98663
sym2	11.3429
db10	11.3591
sym5	14.4596
gaus8	14.4747
morl	24.6136
gaus4	31.4603
gaus1	45.3606
mexh	50.375

2.3. VT/VF record databases

For the development of the discrimination method proposed in the present paper a 60 VF and 25 VT record database was used. The results were then verified on a different database composed of 119 VF and 49 VT records. All records are surface ECG signals with an average duration of 15 seconds. Following the AHA recommendations each record corresponds to a unique type of rhythm and to a single patient.

The origin of the databases used is diverse. Records have been chosen from the following sources:

1. The Cardiac Electrophysiology unit of the Basurto hospital. These records were obtained through the Cardiolab system or by a digitalization of paper records.
2. The MIT-AHA database.
3. Interventions, using either manual or automated external defibrillators, of the medical Emergency Services.

Table 2 details the source and number of the records, both in the development and validation stages.

Table 2. ECG database description.

Development DB			Validation DB		
Origin	No.		Origin	No.	
	VF	VT		VF	VT
Basurto H	19	15	Basurto H	40	25
MIT-AHA	17	6	MIT-AHA	27	12
Emerg. Serv.	24	4	Emerg. Serv.	52	12
Total	60	25	Total	119	49

Prior to their CWT decomposition all signals were resampled at a 250 samples per second rate and preprocessed to eliminate DC interferences, baseline drifts and possible interferences from the power supply network.

2.4. The discrimination method

As discussed in the preceding section, the fundamental discrimination criterion proposed in the present article is based on the higher regularity, both in frequency and amplitude patterns, of the VT rhythms when compared to the VF rhythms. The aim is thus to obtain significant parameters which reflect the regularity and periodicity in VT signals by means of their wavelet decomposition.

A 4.8 second analysis window was selected for the algorithm. The CWT decomposition was then applied to each segment of the records in the VF/VT development database. Considering the average duration of the records two to three analysis windows were required per record.

In order to select the most accurate discrimination parameters four new scales from the CWT scalogram were used, starting with the one showing the maximum energy values of the wavelet coefficients, $scale\_Emax$. An analysis of the peaks in $scale\_Emax$ was then used to estimate the frequency of the signal. This frequency corresponds to a new scale called $scale\_frq$. Two additional scales, obtained using 10% jumps above and below $scale\_frq$, complete the four scales.

In the four selected signals, the position and amplitude of the peaks were calculated as the basis for the definition of the following three discrimination parameters:
1. The normalized standard deviation of the amplitude of the peaks in the four scales: std_amp.
2. For each of the four scales the mean value in bpm-s of the interval between consecutive peaks is calculated, the standard deviation of those four values being the second parameter: std_pos.
3. The standard deviation (in bpm) of the interval between consecutive peaks in $scale\_frq$: std_pos_frq.

A thorough analysis of the mentioned parameters for VT and VF rhythms is required for the definition of the discrimination thresholds. Figs. 3 and 4 show the distribution of the *std_amp* parameter for all the VF and VT windows as well as the selected thresholds.

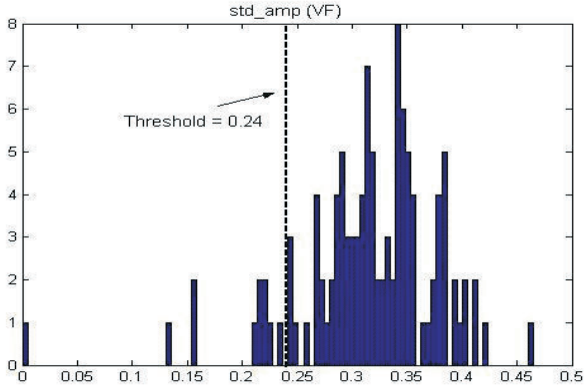

Figure 3. Histogram of the *std_amp* parameter for all the VF windows in the development database.

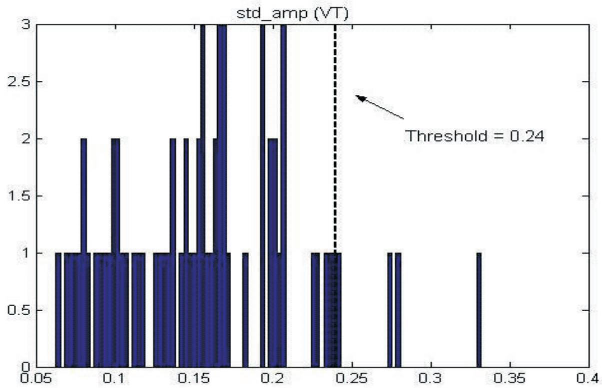

Figure 4. Histogram of the *std_amp* parameter for all the VT windows in the development database.

The two frequency related parameters, *std_pos* and *std_pos_frq*, are then compared by means of a dispersion diagram. This allows the definition of a straight line as a discrimination boundary, as pointed out in Fig. 5.

3. Results

After properly fixing the thresholds using the windows in the VF/VT development database, the algorithm was

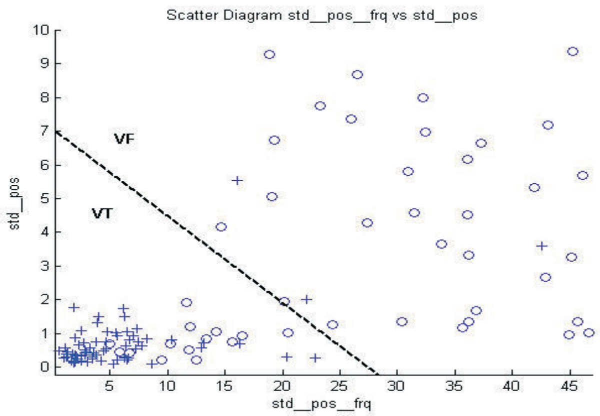

Figure 5. Comparison of the frequency discrimination parameters (zoomed) for VF(o) and VT(+).

verified on the validation VF/VT database. Out of the 234 VF windows 224 were correctly classified while out of the 116 VT windows 111 were properly discriminated, yielding a sensitivity of 95.73% for VF rhythms and 95.69% for VT rhythms.

In order to compare the obtained sensitivities with previously reported results [3, 4] the databases used must match. This requires the addition of the results from the development database. The new sensitivities are then 95.10% (330/347) for VF rhythms and 94.05% (174/185) for VT rhythms.

Table 3 compares the sensitivities obtained with the ones resulting from the aforementioned algorithms and shows an improvement on the accuracy by the proposed algorithm.

Table 3. Comparison of results: proposed algorithm and previously reported algorithms.

Algorithm	Sensitivity VF	Sensitivity VT	Accuracy
CWT	95.10%	94.05%	94.74%
Cross-correlation	90.20%	96.75%	92.48%
Autocorrelation	87.31%	90.27%	88.35%

4. Discussion and conclusions

The present paper discusses a new algorithm for the discrimination by an AED of VT and VF rhythms based on the CWT. The accuracy obtained, 94.74%, improves previously reported results which were computed on the same ECG record database. If emphasis is put on the episodes, rather than on the observation windows, out of the 119 VF episodes only one is not detected in any of its windows, while 1 out of the 49 VT episodes shows this same result.

A limitation of the algorithm is a consequence of the generic a-priori discrimination criterion, i.e. the regularity in frequency and amplitude of the VT rhythms. VT rhythms often exhibit momentary irregularity while VF rhythms can exhibit momentary regularity. In our opinion an accuracy near 100% is not attainable by strictly following the regularity criterion.

A possible way to improve the accuracy is to define a dubious state in the discrimination stage for those segments close to the decision thresholds. The dubious segments could then possibly be classified using time related parameters as suggested by [1, 2].

Acknowledgements

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