

# Distinction of Ventricular Fibrillation and Ventricular Tachycardia Using Cross Correlation

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## Abstract

The accurate discrimination of ventricular tachycardia (VT) from ventricular fibrillation (VF) is an important issue in Automated External Defibrillator (AED) and other cardiac monitoring systems. The correlation function of the ECG signal is an adequate tool for detecting irregularities or noise in signals. Therefore, methods for VF/VT discrimination based on the autocorrelation of the ECG signal and on the cross correlation of the ECG signal with different templates have been proposed. Our work is focused on the use of the cross correlation of the ECG signal with a segment of the same ECG signal, instead of using a given template.

The developed algorithm has been tested on a database consisting of 179 human VF and 74 human VT records. The new algorithm classifies accurately 313 VF windows (90.2% sensitivity) and 179 VT windows (96.75% sensitivity). These results improve those obtained from other techniques, considered as a reference, for the same records database.

## 1. Introduction

Ventricular fibrillation and ventricular tachycardia are both life-threatening cardiac arrhythmias. Regarding to the functionality of AEDs or other similar devices, it is dramatically important to quickly discriminate between both rhythms, as VT can be terminated by cardioversion, delivering low energy shocks in synchronization with the heart beat, whereas VF requires high-energy defibrillation shocks.

In the last ten years, many algorithms based on time or frequency domain, or on combined techniques have been proposed to automatically discriminate VF from VT, both for external and for implantable devices.

In the first case, Thakor *et al.* developed a sequential detection algorithm based on the average threshold crossing intervals [1]. Another technique also based on sequential algorithm was proposed by Chen *et al.* [2, 3]. It tries to measure the time irregularity of the cardiac rhythm through the characteristic referenced as “blanking variability” independently from the cardiac frequency. Zhang *et al.* have designed a method for detecting VF

and VT by complex measure [4].

Chen *et al.* have already proposed the analysis of the ECG signal autocorrelation function and the application of a regression test to the resultant positive peaks to discriminate VF/VT rhythms [5].

Our work presents a VF/VT discrimination method based on the analysis of the cross correlation function between two segments of the same ECG signal.

## 2. Materials and methods

### 2.1. VF/VT records database

The designed algorithm has been developed and tested on a VF and VT rhythms database. It consists of 179 records belonging to cardiac rhythms classified as VF and of 74 records belonging to VT rhythms, all of them recorded from surface ECG signals. The records source has been the MIT (Massachusetts Institute of Technology) and the AHA (American Heart Association) databases, the Electrophysiology Department of the Basurto Hospital in Bilbao (Spain) and also several rhythms registered by the Emergency Services using Life-Pack 12 and Life-Pack 500.

The algorithm applies a signal window of 4.8 seconds. Therefore, the 179 VF records contain 347 windows of 4.8s, considered VF, and the 74 VT records contain 185 VT windows.

All the signals have been preprocessed by a bandpass filter (0.7 – 35Hz) in order to suppress DC components, baseline drifts and possible electrical network interference.

### 2.2. Cross correlation method

A VF rhythm has more irregular frequency and amplitude patterns than a VT rhythm. In general, all the VF/VT discrimination methods try to evaluate the ECG signal regularity in order to classify it as VF or VT.

In this work, we propose the use of the cross correlation of two parts of ECG signal to evaluate its regularity. The starting point is an ECG preprocessed signal with a duration of 4.8s (N samples),  $s[n]$ ; the first 0.6 seconds (L samples) of  $s[n]$  is taken as the reference signal,  $y[n]$ ; the second part of 4.2s (M samples of  $s[n]$ ) constitutes the base signal to measure the regularity of

$s[n]$ . By this way:

$$\begin{aligned} y[n] \quad n=0 \dots L-1 &= s[n] \quad n=0 \dots L-1 \\ x[n] \quad n=0 \dots M-1 &= s[n] \quad n=L \dots N-1 \end{aligned}$$

The regularity of the signal is evaluated by the cross correlation of  $x[n]$  with regard to the signal reference  $y[n]$ , and is calculated through the next expression:

$$r_{xy}[n] = \sum_{m=n}^{n+L} x[m] \cdot y[m-n] \quad n=0 \dots M-L \quad (1)$$

In order to make the value of the cross correlation independent from the energy level of the starting ECG signal, the expression (1) is normalized in relation to the reference signal energy. Therefore, the cross correlation which has been used to evaluate the regularity of the ECG signal is given by the next expression:

$$r_{xy}[n] = \frac{\sum_{m=n}^{n+L} x[m] \cdot y[m-n]}{\sum_{m=0}^{L-1} y^2[m]} \quad n=0 \dots M-L \quad (2)$$

If the ECG signal  $s[n]$  were perfectly periodic,  $r_{xy}[n]$  would present positive, equally spaced and with the same amplitude peaks.

Two examples corresponding to a window of a VF signal and a VT signal are presented in Fig. 1 and 2, respectively. It is observed that the distribution and the amplitudes of the cross correlation peaks are more uniform in a VT than in a VF signal.

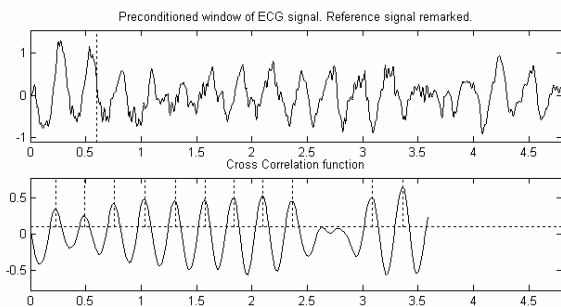


Figure 1. Example of a VF signal window (the reference segment is remarked) and the cross correlation function.

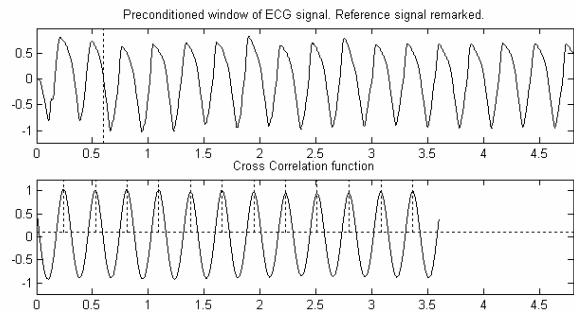


Figure 2. Example of a VT signal window (the reference segment is remarked) and the cross correlation function.

### 2.3. Significant parameters

To quantify the irregularity of the analyzed signal window, three significant parameters are considered from the function  $r_{xy}[n]$ .

The first parameter is the number of positive peaks of the cross correlation function. They will only be considered those that exceed a threshold, established in the 10% of the reference signal energy.

On the other hand, the distance between two consecutive peaks gives a measure of the cardiac frequency in that interval. The standard deviation of the cardiac frequencies, measured in beats per minute (bpm), of each window of 4.8s, is the second parameter,  $stdf$ . For a signal window corresponding to a VF record, it is expected a higher  $stdf$  value, compared to the calculated for a VT window.

Finally, it has been obtained the standard deviation of the peak amplitudes for each window,  $stda$ . Again, for a VF window, the expected  $stda$  value is higher than for a VT window.

### 2.4. Discrimination algorithm

With the purpose of discriminate quickly those signal windows too much irregular, it has been decided that if the number of peaks is less than 8, the window is classified as VF.

For the rest of the signals, it has been studied the probability distribution of the standard deviations of the cardiac frequencies and the peak amplitudes,  $stdf$  and  $stda$ , respectively. Analysing these distributions and focusing on the different results obtained for the VF and the VT windows, discrimination criteria can be based just on these differences.

Fig. 3 presents the Probability Distribution Function (PDF) of the  $stdf$  parameter for the VF and VT windows.

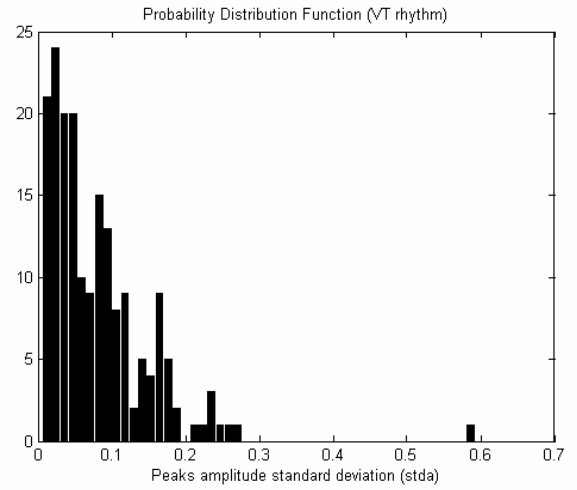
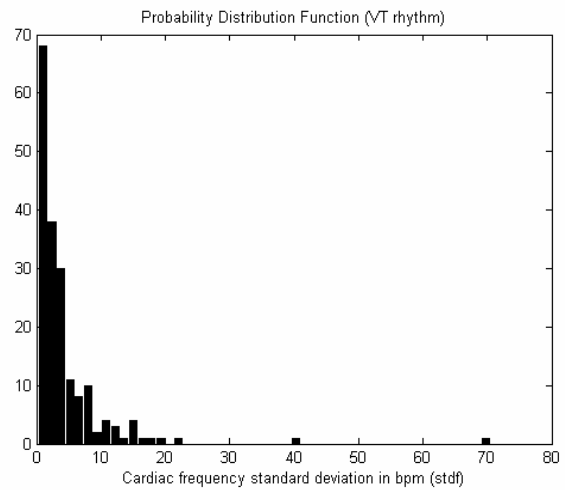
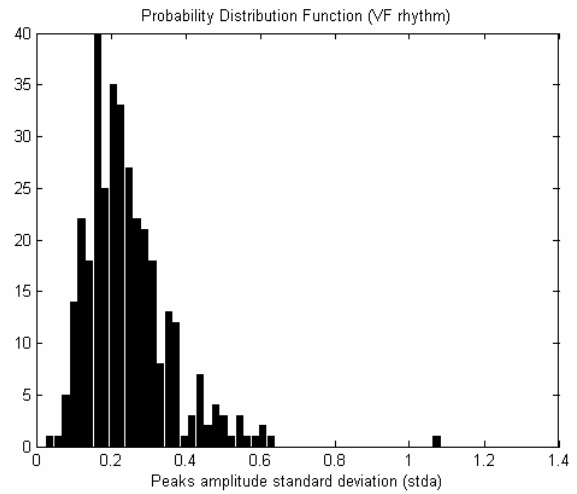
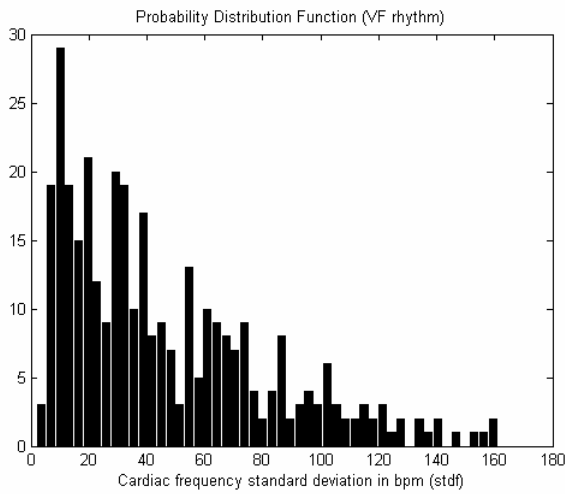


Figure 3. Probability Distribution Function of the standard deviation of the cardiac frequencies.

In the PDF corresponding to VT rhythms, it can be seen that the *stdf* parameter only exceeds the value 10 in few cases, whereas for VF rhythms, only few cases appear under the value 10.

Fig. 4 presents the PDF of the *stda* parameter for all the VF and VT windows. Again it is observed the relevance of this parameter for discriminating VF/VT rhythms.

Figure 4. Probability Distribution Function of the standard deviation of the peak amplitudes.

Finally, a scatter diagram of *stdf* and *stda* is shown in Fig. 5. From this distribution, we have defined the significant thresholds for the design of the VF/VT windows classification algorithm.

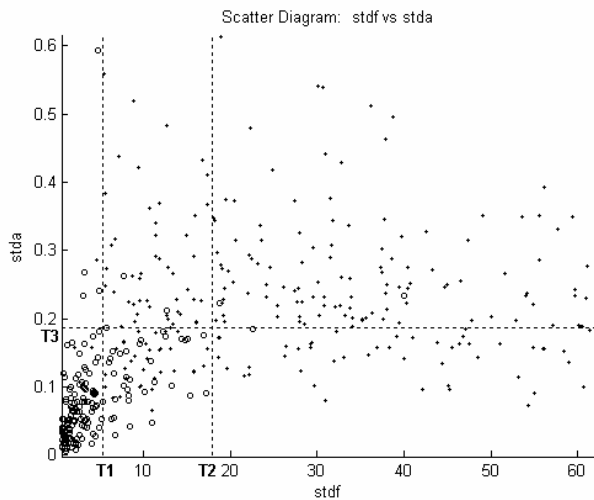


Figure 5. Scatter diagram of *stdf* and *stda*. VF occurrences are marked “+” and VT occurrences are marked “o”.

The next chart represents the developed decision algorithm:

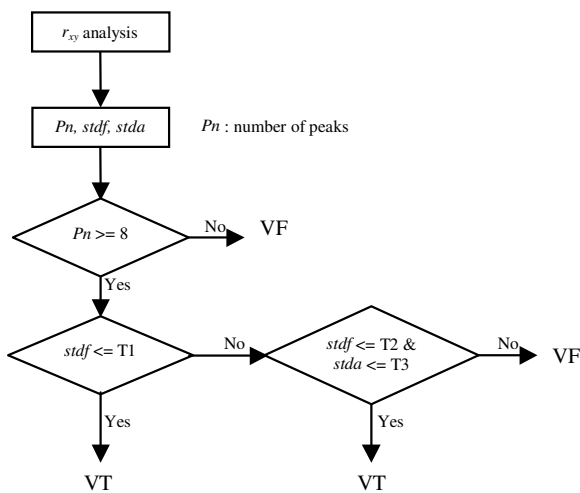


Figure 6. VF/VT discrimination algorithm.

### 3. Results

Once the algorithm is applied to the VF/VT database, 313 VF windows and 179 VT windows have been correctly classified, thus obtaining a sensitivity of 90.20% for VF rhythms and a sensitivity of 96.75% for VT rhythms.

As a reference method, we have applied a variation of the regression test on the autocorrelation function proposed in [5] by Chen *et al.*

Testing this algorithm on the same VF/VT database, worse discrimination results have been obtained: 303 windows classified as VF from the total of 347 (87.31% sensitivity) and 167 windows classified as VT from the total of 185 (90.27% sensitivity).

### 4. Conclusions

A VF/VT discrimination algorithm has been designed, based on the analysis of the cross correlation function between segments of the same ECG signal. The algorithm testing on the VF/VT rhythms database has resulted in better VF and VT sensibilities, improving those obtained from other reference methods. Despite of these satisfactory results, it is necessary to remark that the algorithm has been adjusted on the same test database.

As an important achievement, this method provides two parameters to face the VF/VT discrimination: one of them is linked to the cardiac frequency uniformity along the analysis window, and the other is related to the signal amplitude uniformity along the signal window.

### Acknowledgements

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