Ventricular Fibrillation Detection using a Leakage/Complexity Measure Method

JCTB Moraes, M Blechner, FN Vilani, EV Costa

Escola Politécnica da Universidade de São Paulo, São Paulo, Brazil

Abstract

This paper presents a new method for detecting Ventricular Fibrillation (VF) based on a two step processing. The first one, based on the published VF Filter Leakage Method, consists in sampling data from the ECG and filtering it so that the more the signal resembles a sinusoidal wave, the lower the filter's output value will be. This idea comes from the VF wave inspection which shows that it has some sinusoidal characteristics. In order to avoid false positive occurrences due to Ventricular Tachycardia (VT) episodes (which are sinusoidal as well), a second step, based on the Complexity Measure algorithm, was used consisting in generating a binary sequence by comparison between the sampled data and an adjustable threshold, and then, using this sequence to calculate the signal's disorder level. The achieved sensitivity for the VF algorithm was 70.32% and its predictivity was 94.66%.

1. Introduction

The correct diagnosis of life threatening arrhythmias such as Ventricular Fibrillation (VF) is extremely important in analysis systems for real time ECG. The goal of this study was to implement an algorithm for Ventricular Fibrillation detection in a computerized cardiac arrhythmia monitor so an alarm is activated in case of VF. Since this is a fatal arrhythmia it is necessary to achieve a precise detection, with the lowest delay as possible. This article presents an algorithm which combines two methods in cascade for VF detection, one acting as a complement to the results presented by the other.

The first method employed is VF Filter Leakage [1] proposed by Kuo, S. and Dillman, R. Its analysis is done both in the time domain and in the frequency domain. The second is Complexity Measure [2] proposed by Zhang, X. S. et al. Its analysis is done in the time domain only.

2. Materials and methods

The database selected to test the efficacy of the method was the Creighton University Sustained Arrhythmia Database (CUDB), as suggested by the Association for the Advancement of Medical Instrumentation, ANSI/AAMI EC57 [7], for containing episodes of VF in nearly all its records. This database contains 35 records, 8 minutes long each. Our complete database, however, included other records generated by the commercial simulator Dynatech Nevada Medsym 300B, since the CUDB contains few episodes of Ventricular Tachycardia (VT). On the other hand, the MIT BIH does not give any standard software for testing VF episodes and it was needed to develop a software according to ANSI/AAMI EC57 Standard for this purpose. 7 of the 35 records in the CUDB were excluded from the testing because some of them were incomplete; others did not present VF episodes and most had high amplitude noise and movement artifacts which compromised the analysis results. So, in order to be as rigorous as possible our complete test database consisted of 30 records sampled at 250Hz. This database is available on CD_ROM - MIT_BIH Arrhythmia Database (http://ecg.mit.edu).

Using the *xform* software available on the MIT-BIH database CD-ROM, the following changes were made: change in gain from 200 adu/mV to 160 adu/mV (adu = analog to digital unit), the output format from 212 to 16, resolution from 11 bits to 12 bits and baseline from 1024 to 2048.

Figure 1 presents a block diagram of the algorithm.

The first step of processing for the algorithm is made of a band pass filter with upper and lower corner frequencies, respectively, of 0.7Hz and 16Hz. This filter was made according to the paper by Ligtenberg, A. and Kunt, M. [3]. The parameters used were: L = 200 and K = 4. Such procedure is performed to remove possible offset which cause baseline wandering and components with frequencies above the expected in cardiac rhythms.

The frequency-response gain for this filter is plotted in Figure 2.

The second step is made of the VF Filter Leakage as proposed by Kuo, S. and Dillman, R [1]. This method separates nearly sinusoidal waveforms from the rest. Since Ventricular Fibrillation is a signal similar to a sinusoid, the idea is to find its predominant frequency and move such signal by a sample number equivalent to a half period to try minimize the sum of the signal and its shifted copy.

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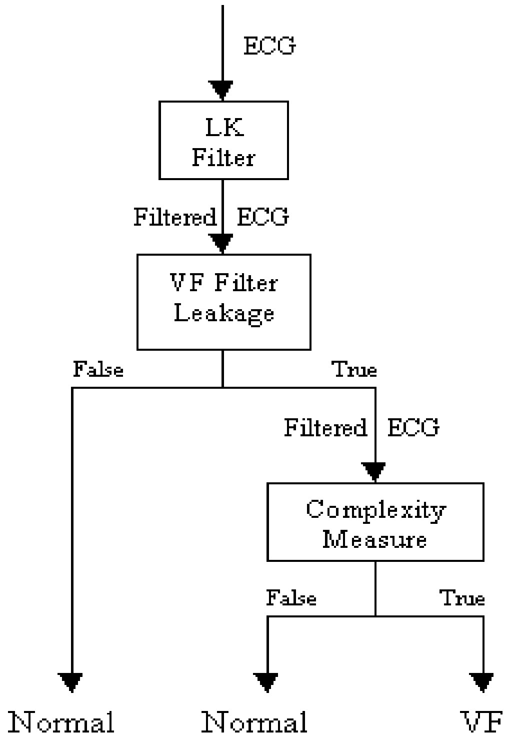

Figure 1. Block diagram of the detection algorithm.

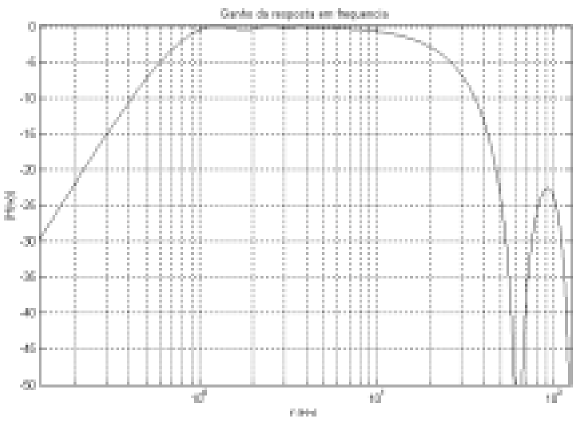

Figure 2. Graphic of the frequency-response gain for the LK Filter with L = 200 and K= 4.

The result is divided by the sum of the modules of all samples in the window in order to prevent the sum from depending on the amount of samples used in each iteration. Inevitably, in cases of Ventricular Tachycardia a low value on the output of the VF filter is observed, since this waveform is also sinusoidal in form for some cases. This could generate false positive occurrences. Tests have shown insufficient performance of the VF Filter used with the method proposed by Kuo, S. and Dillman, R in estimating the frequency of the equivalent sinusoidal signal. The application of FFT (Fast Fourier Transform) [4] for this purpose was shown as more efficient. Using the last 3 seconds of signal (750 samples), the FFT is calculated and the frequency in which the highest amplitude occurs is found. Period is given in samples and calculated with the equation (1):

$$T = \frac{1}{f} \cdot f_{samp} \tag{1}$$

where f is the predominant signal frequency in the truncated ECG and f_{samp} is the sample frequency (250Hz). If the equivalent sinusoidal signal frequency is between 2Hz and 9Hz the next step is taken. If not, the conclusion is it is not Ventricular Fibrillation.

Filtering is calculated with the correlation technique through the equation (2):

$$VF\ filter = \frac{\sum_{i=T/2}^{N-1} | x_i + x_{i-T/2} |}{\sum_{i=T/2}^{N-1} [| x_i | + | x_{i-T/2} |]} \tag{2}$$

where x_i is the i^{th} signal sample; T is the period calculated in equation (1) and N is equal 500 since it corresponds to the last 2 seconds in the truncated ECG. The algorithm continues the detection if the output is lower than the threshold between 0 and 1. If VF Filter is less than 26/64 (the threshold proposed by the authors of the method) it could represent a VF. Test results suggest this threshold yields satisfactory results. This procedure is repeated each second during the ECG by moving the window.

The combination of both methods was conceived so the Complexity Measure would act as a secondary algorithm, correcting results in regions where the VF Filter method would possibly fail: once identified by the VF Filter, the signal (which could mean Ventricular Fibrillation or Ventricular Tachycardia) is submitted to the Complexity Measure calculations so that a final conclusion can be reached regarding the presence or absence of Ventricular Fibrillation.

The third processing step, executed only in case the answer from the last process is positive (i.e. VF Filter < 26/64), is composed of 2 stages: 1^o – generate a binary string by comparing the signal with a threshold in an 8 second window (n=2000 points) as following: subtract from each x_i point the mean value of the samples in window x_m; obtain the positive and negative peaks (V_p and V_n, respectively); count the amount of x_i in the interval $[0<x_i<0.1V_p]$ and the amount of x_i in the interval $[0.1V_n<x_i<0]$ (P_c and N_c respectively). If $(P_c+N_c) <0.4n$, the threshold is $T_d=0$. If the former condition is not satisfied, verify if $P_c<N_c$. If the inequality is valid, then

$T_d = 0.2V_p$, if not, $T_d=0{,}2V_n$; the points are converted to a binary string through a simple comparison method. If $x_i<T_d$, $s_i=0$, if not, $s_i=1$. An alteration in the binary string generation method was made so it would be immune to noise up to 20% of signal amplitude: once T_d is defined, if $s_{i-1} = 0$, in order to make s_i equal to 1, x_i must be higher than $T_d+0.2V_p$, similarly, if $s_{i-1} = 1$, in order to make s_i equal to 0 x_i must be lower than $T_d-0.2V_p$. This adaptation brought significant improvement in results when compared with the results from the original method proposed by Zhang XS. et al. [2]. 2^o – use the string to calculate the degree of signal disorder (c(n)) as following: S and Q represent two strings and SQ a correlation of both; $SQ\pi$ is the SQ string without its last element; at first, c(n)=1, $S=s_1$, $Q=s_2$, $SQ\pi=s_1$. After a certain number of operations, $S=s_1,s_2,...,s_r$ and $Q=s_{r+1}$; if Q is a substring from $SQ\pi$, S does not change and Q becomes s_{r+1},s_{r+2} etc, until Q is no longer a substring from $SQ\pi$; S then becomes the combination of S and Q ($s_1,s_2,...,s_r,s_{r+1},...,s_{r+i}$), $Q=s_{r+i+1}$ and c(n)=c(n)+1. This is done until Q is the last character in the string. Notice that the more different substrings are found during the processing of the signal contained in the window, the more complex this signal is, i.e., the chances this is a Ventricular Fibrillation increase. Kaspar F and Schuster HG [6] describe this algorithm in more detail. The normalized value for c(n) (Complexity Measure) is then calculated with the equation (3):

$$C(n) = c(n) \cdot \frac{\log_2(n)}{n} \quad (3)$$

Therefore, the detection of Ventricular Fibrillation occurs in cases where the signal presents a disorderly behavior, where C(n) is above a threshold between 0 and 1. If C(n) is higher than 0.1, it means VF. It is worth to point out that the threshold proposed by Zhang XS. et al. in [2] is 0.486. Inevitably, not only Ventricular Fibrillation but also very noisy signals can generate a false detection. This procedure is also repeated each second so there is synchronism between the two methods, i.e., the windows used in the calculation of the VF Filter and the Complexity Measure move together.

3. Results

The individual results for each method were compared with the performance of the algorithm proposed in this article. Sensitivity and predictivity were calculated by equations (4) and (5) respectively, as proposed by ANSI/AAMI EC57 [7]:

$$SE = \frac{TP}{TP + FN} \quad (4)$$

$$+P = \frac{TP}{TP + FP} \quad (5)$$

where TP = true positive, FN = false negative, FP = false positive and each one of the parameters represents the total sum of the overlap times, false negative and false positive, respectively, for all records analyzed. Table 1 shows the comparison.

Table 1. Comparison of method results individually and combined.

Method	Se (%)	+P (%)
VF Filter only	71.05	85.62
C. M. only	89.95	46.40
VF Filter + C. M.	70.32	94.66

The high sensitivity value of the Complexity Measure method individually is due to the fact that this method is very sensitive to signals with any kind of irregularity. Its predictivity is, therefore, very low, since the occurrence of false positives is too high. The improvement noted with the use of the complete algorithm is the increase in predictivity when compared to the VF Filter method. This is due to the fact that Ventricular Tachycardia episodes, mainly the ones present in the records generated by the simulator, were identified as VF by the VF Filter, but the complete algorithm did not accuse VF. This slight decrease in sensitivity is due to the higher strictness of the complete algorithm in concluding this is a VF signal.

The obtained results prove the efficacy of the VF Filter Leakage algorithm in separating apparently sinusal rhythms from the rest. Depending on the morphology of these events, Complexity Measure is capable of separating VT episodes from VF episodes. Due to the size of the windows, there can be a delay of up to 8 seconds in detections, compatible with the delay found in other algorithms proposed in the literature [2] and it is appropriate for the use in real time monitoring systems.

Figure 3 presents a segment of the record Cu01 with a VF episode and the notes made by the algorithm. The first signal corresponds to the original signal, the second is the result of its pre-filtration by the LK filter, the third corresponds to the output values of the VF filter calculated each second (250 samples), the fourth, the values of C(n) also calculated each second. In this case, the algorithm took 4 seconds to begin detection from the instant the VF episode started.

4. Discussion and conclusions

This work yielded two valuable conclusions: the first was an improvement in performance of the algorithm proposed by Kuo, S and Dillman R., since the use of a more precise algorithm such as the FFT allows for a better definition of the predominant signal frequency and,

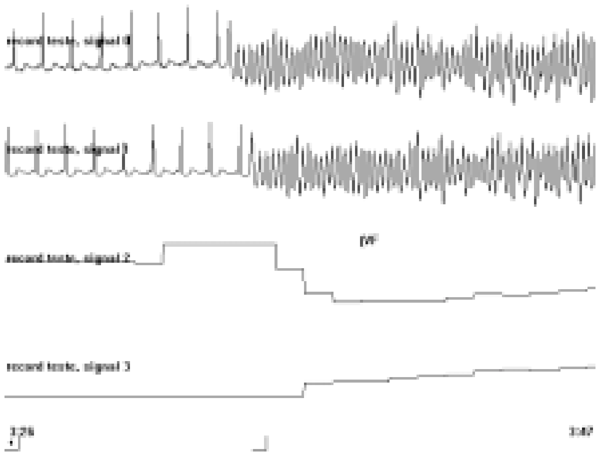

Figure 3. Record Cu01: beginning of detection by the VF Filter and subsequent confirmation by the Complexity Measure.

therefore, a more precise filtering, which increases the efficacy of the algorithm. Note that the use of FFT was suggested by the authors of the VF Filter method, but its high computing cost and resource limitations at the time made the use of such method unfeasible. However, with the availability of ever faster processors with low power consumption, the relative computing cost of this algorithm is being reduced. The use of DSPs may lower such cost even more.

The second conclusion of this work results from the use of a second method which, after the addition of the noise effect reduction step, allowed for a more precise distinction of the Ventricular Fibrillation episodes. Several tested methods have failed in detecting VF at times, but such errors did not occur at the same episodes. The use of two algorithms in series combines the advantages of both methods, making the algorithm more reliable in detecting such episodes.

At last, it is important to point out that currently there are several studies being made with techniques such as the Ventricular Fibrillation detection with Wavelets [5] instead of FFT, which could increase the precision in detecting Ventricular Fibrillation episodes even further.

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Address for correspondence

José Carlos Teixeira de Barros Moraes
Av. Prof. Luciano Gualberto – Travessa 3, n. 158
CEP 05508-900, São Paulo. SP. Brazil
jcmoraes@leb.usp.br