Fast Non-invasive Ventricular Fibrillation Detection Method using Pseudo Wigner-Ville Distribution

A Rosado, J Guerrero, M Bataller, J Chorro*

Universidad de Valencia, Valencia, Spain, *Hospital Clínico Universitario, Valencia, Spain

Abstract

Detection of Ventricular fibrillation (VF) at an early stage is a crucial point in order to lower the risk of sudden death and allow the specialist to have greater reaction time to give the patient a good recovering therapy and avoid unrecoverable damages to the cardiac tissue. We present an algorithm oriented to real-time detection of Ventricular Fibrillation in order to be used as a part of monitorization systems in Intensive Care Units or ambulatory centres. The study has been done using the AHA (American Heart Association) Database, focusing mainly in the 8200 series, and MIT (Massachussetts Institute of Technology) Database. The detection algorithm combines both time domain and time-frequency domain parameters. Using the appropriate parameters, the detection algorithm discerns between VF and non-VF rhythms, including those VF-like rhythms like some types of ventricular tachycardia (VT) in some cases. A VF-Flutter sensibility of 86%, and an average specificity of 94,3% including VT separation is obtained.

1. Introduction

The main aim consists on the development of a good detection algorithm for ventricular fibrillation based on surface ECG signals using one single lead. Detection of VF through external methods is not as reliable as desired due to different noise sources alterating the ECG signal.

If accurate detection is achieved, the algorithm could be used in ECG monitoring machines located in Intensive Care Units or ambulatory centres.

The algorithm must show a good false detection rejection ratio (specificity) as well as high sensibility, furthermore, it must provide a fast diagnostic in order to allow medical assistants to give the appropriate therapy to the patient as soon as possible.

The main characteristics defining ventricular fibrillation [1,2] are those consisting on the loose of QRS periodicity, actually, QRS disappears, and the ECG signal shows a chaotic appearance, following some kind of oscillations, similar to sinusoids, but very unlike.

Moreover, an important objective consist on the reduction of false detections when similar pathologies arise (e.g. Ventricular Tachycardia). These kind of pathologies receive a different therapy, thus, it is important to have an accurate distinction from VF, for example, if defibrillation is applied during VT instead of VF, serious damages can be produced to the cardiac tissue

Regarding time-frequency distributions, they provide a tridimensional signal representation showing the evolution of spectral components along time (spectral transients), they give idea about the changes taking place in both time and frequency simultaneously. It is very helpful when dealing with ECG signals due to the possibility to extract more information from the signal evolution [3,4].

2. Methods

Using a combined algorithm, computational calculations can be highly reduced due to the usage of simple time domain parameters to separate VF-like from non-VF cases. When VF-like signals are detected, a more elaborated algorithm based on Pseudo Wigner-Ville distribution is obtained, several discriminating parameters are calculated based on the time-frequency domain and a decision on VF presence is taken.

A number of 25 registers have been used (15 for development and 10 for testing). For each patient, the register contains about 30 minutes of monitoring signal. A total of 12.5 hours have been deeply analysed, around 100 minutes contained VF (including Flutter episodes). MIT and AHA registers have been used. In the verification stage, other MIT registers with no VF but containing different pathologies similar to VF are also employed. Special attention needs to be paid to VT, this pathology usually appears as a previous rhythm to VF, although sometimes it can be reverted before arriving to VF. During VT episodes, the ECG signal can be similar to VF signal (specially for polimorphic VT or 'torsade des points'). Matlab® CNRS t-f toolbox is used [5].

A segment length of 128 samples and 125 Hz sampling frequency is used, it gives 1.024 second for the

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analysis segments, which is considered enough to contain at least one QRS complex (if existing in the analysed signal). A general signal pre-processing is done, first, low pass 40 Hz filtering is performed, giving us a free noise signal from the 50 Hz or 60 Hz mains interference, and providing enough wideband to represent VF spectral terms. Moreover, a 'detrend' operation is performed to remove the deviation along the base-line and a zero mean series is obtained.

Four different groups have been defined, corresponding to pathologies 'VF' (including Flutter), 'VT', 'Other' (for other rhythms) and a group containing normal sinus rhythms called 'Normal'. For a parameter to be useful, differences must be appreciated among defined classes.

As stated before, time-domain parameters are used as an initial stage of the VF detection algorithm due to its good behaviour in non-VF rhythms rejection, allowing to discard those segments clearly different from VF, increasing specificity and avoiding the calculation of time-frequency distribution in such cases.

Time domain parameters are obtained through a simple approach. As in VF episodes prominent peaks (QRS) are inexistent, if the time series x(t) is squared (obtaining x'(t)), peaks are increased, dividing x'(t) by its mean we get unit mean. The variance value for x'(t) is closely related to peak (QRS) presence, a high value is considered as non-VF due to prominent peaks presence in the analysed segment. This parameter is called VR.

$$VR = \frac{1}{N}\sum_i \left[\frac{x'(t)_i}{mean(x'(t))} - 1\right]^2 = \mathrm{var}\left(\frac{x'(t)}{mean(x'(t))}\right)$$

The second time domain parameter is called RatioSTD and is obtained as the quotient between the standard deviation of the derivative and the standard deviation of the absolute value of such derivative for the time-series. RatioSTD gives idea about the symmetry between positive and negative values. As we are dealing with zero-mean series (except for the last parameter) such symmetry does not exist in case of normal sinus, however, due to the oscillating nature of VF signals, differences can be appreciated and higher values are obtained.

In order to obtain a complete characterisation of ECG signals concerning ventricular rhythms, a set of time-frequency parameters has been obtained.

Once obtained the time-frequency representation (TFR), as PWV distribution gives negative values, the first step consist on converting every value to its absolute value, that is TFR(t,f)=abs(TFR(t,f)). Following to this, every component less than 10% of the maximum TFR value is eliminated, this fact allows to remove components which may be mainly composed of noise or even small interference terms, obtaining a TFR representation where the main parameters are kept, but noise or minor components are cleared, retaining only the main terms to be analysed.

Regarding time-frequency parameters, we define two spectral bands of interest. BALO (2-14 Hz) and BAHI (14-28 Hz). For VF episodes, BAHI does not contain any energy components, opposite to non-VF rhythms.

A careful selection of time-frequency parameters using statistical discrimination procedures (Wilk's lambda, correlation, $p<0.01$,...) has been done. Different parameter selection approaches have been used, some of them are related to time, some of them to frequency and some others to both domains [6]. After selection of the most discriminant parameters, the following are used in the algorithm:

QTH: Percentage of the total number of non-zero terms existing in BAHI band.

VDL8: Standard deviation of the first-order derivative non-zero terms vector obtained by splitting the temporal segment into eight sub-segments. It is clear that it will take a higher value in case of normal sinus because the existence of bigger oscillations.

LTMP: indicates the maximum temporal length of the area enclosing higher energy than 50% of the maximum. This value is higher in VF episodes than in 'normal' sinus rhythms.

CURVE: Analysing the number of non-zero terms at every frequency bin of spectral resolution in the BALO band, and performing a parabolic approximation for the obtained points, we can see that the curvature of the regression parabola is less during VF than Normal Sinus.

TMY: Number of points in a TFR having an energy between 50% and 100% of the maximum energy value existing in the TFR.

CT8: The temporal segment of the time-frequency distribution is divided into 8 segments, and its energy in BAHI band is measured for every segment.

TE: Total energy of the distribution in BAHI band.

Selected parameters take into account energy content of the analysed signal in different bands, but also, useful information is obtained from non-zero terms, they are simple and easy to calculate.

3. Results

3.1. Parameters

Selected parameters can discern different signal types, results provide a good class separation. In case of temporal parameter RatioSTD, figure 1 shows a box-plot with percentile information about the VF-like and non-VF signals separation made.

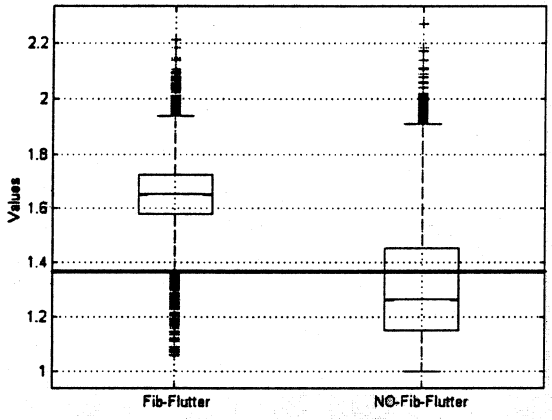

Figure 1. Box-plot results for RatioSTD parameter.

3.2. Detection algorithm

It is proposed a detection algorithm based on a detection tree: first, thresholds are obtained for selected parameters, and a discard/accept algorithm is proposed based on the parameter values existing for the defined classes. If imposed conditions are met, VF detection is acknowledged.

Threshold values selection depends on the parameter and its position in the detection tree, some of them are very restrictive so that a good VF detection is achieved.

As a detection tree, different steps are evaluated. When a step gives a negative result (VF not found), the algorithm evaluation is aborted and a new TFR starts to be analysed when available.

Parameter	Normal	Other	VT	VF-Flutter
TE	6.51E+08 ± 1.04E+09	1.99E+09 ± 5.14E+10	1.21E+10 ± 2.01E+11	9.95E+08 ± 1.77E+09
CT8	3.6 ± 1.6	3.8 ± 1.5	6.3 ± 1.3	6.0 ± 1.3
TMY (50%)	158.6 ± 72.2	158.3 ± 62.6	292 ± 124	251 ± 113
QTH	15.02 ± 10.04	12.30 ± 8.69	6.43 ± 7.61	5.35 ± 7.02
VDL8	99.2 ± 43.8	87.9 ± 38.6	50.3 ± 29.9	46.7 ± 21.2
LTMP (50%)	13.83 ± 11.65	15.43 ± 12.65	24.54 ± 19.03	24.24 ± 18.31
CURVE	0.112 ± 0.123	0.134 ± 0.117	0.038 ± 0.202	-0.008 ± 0.208

Table I. Parameter results (mean ± standard deviation) using PWV for the defined classes.

Time-frequency parameters such as VDL8 showing class separation in figure 2 indicate that VF (FV-Flutter and TV) and non-VF classes (Normal and Other) have a different parameter values and most of the cases can be separated, however, in case of VF and VT, separation is not possible using a single parameter.

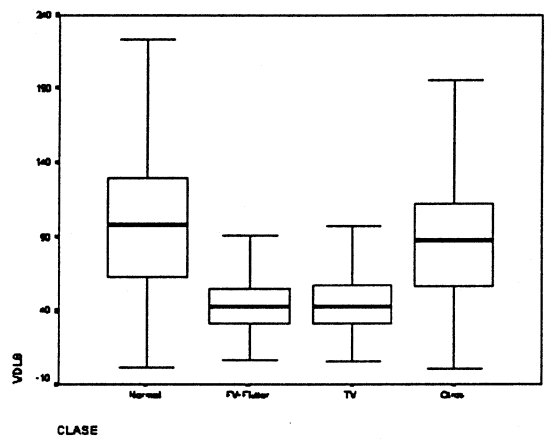

Figure 2. Box-plot results for VDL8 parameter.

Table 1 shows the complete list of results for the analyzed parameters corresponding to the different defined classes.

As it can be seen, certain differences are appreciated, although a refined class separation needs to be made by a detection algorithm.

The algorithm layout starts with the temporal parameters evaluation to eliminate non-VF-like rhythms, if passed, TFR is calculated and as a first stage, a noisy TFR detection is done. Afterwards, parameter thresholds are evaluated and two different approaches are used in order to provide VF indication (figure 3). Two additional parameters are used: **nareas**, giving the number of areas at a 50% energy level in a single TFR, and **dispersion**, indicating how different are the areas present in the same TFR.

In table II it can be seen that good results are obtained for sensibility and specificity to 'Normal' and 'Other' distributions, maintaining a high specificity value for 'VT' pathologies considering inherent difficulties in VT discrimination from VF rhythms.

Sensibility 'VF-Flutter' (%)	85,3
Specificity 'Normal' (%)	98,3
Specificity 'Other' (%)	93,8
Specificity 'VT' (%)	73,9
Global Specificity (%)	94,3

Table II. Classification results for VF detection algorithm.

In general terms, sensibility keeps higher values than specificity, moreover, sensibility maintains a good ratio depending on the analysed file or the time-frequency

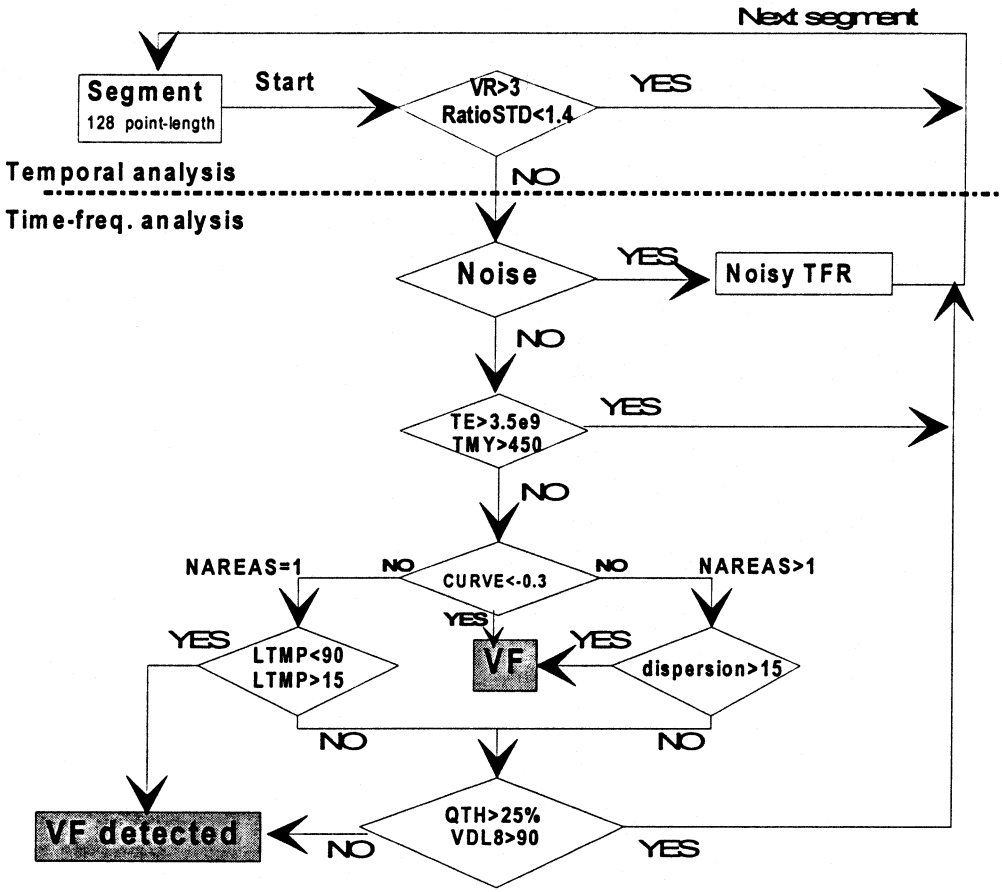

Figure 3. Detection algorithm based on decision tree used to acknowledge VF detection.

representation, but specificity has a high variation. In general terms, we can say that PWV provides quite good results, maintaining high levels of sensibility and specificity. The main reason for this rely on the fact that the chosen parameters allow a better characterisation of VF pathology because of the low frequency content of the signal during VF, thus, a good distinction between high and low frequencies must be made, keeping a good time resolution as well.

The main reason for the false detections to appear arises when the signal is quite poor in quality, which means that noise presence is high, or some artefacts have occurred, producing an VF-like signal; we shall say that an VF-like signal can be produced easily because of its unstructured shape.

4. Conclusion

An algorithm to detect VF through external leads is proposed. It is based on fast time domain parameters and refined using time-frequency parameters to allow VT separation. Furthermore, the algorithm allows fast detection due to low computational parameter selection, obtaining a satisfactory detection ratio.

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Address for correspondence.
Alfredo Rosado Muñoz.
Dpto. Ingenieria Electronica. Universidad de Valencia.
C/ Dr. Moliner, 50. 46100 Burjassot. Valencia. Spain.
e-mail: alfredo.rosado@uv.es