# Sequential VT/VF Discrimination Algorithm Based on Wave Mode Sample Entropy for Adult and Pediatric Patients

U Irusta, J Ruiz, S Ruiz de Gauna, E Aramendi

University of the Basque Country, Bilbao, Spain

## Abstract

*The two fatal ventricular arrhythmias, Ventricular Fibrillation (VF) and Ventricular Tachycardia (VT), are better treated using different electrical therapies: a lower energy cardioversion for VT and a defibrillation shock for VF. Automated External Defibrillators (AED), whose use for children is recommended since 2003, should discriminate between VT and VF in adult and pediatric patients.*

*We propose a new method to discriminate VT from VF that applies sequential hypothesis testing to the wave mode sample entropy values of the ECG. Wave mode sample entropy values are calculated every second using overlapping 4 second signal windows. The algorithm was designed using a development database of 154 adult cases, 53VT/101VF, and then tested on two independent databases: an adult database of 92 cases, 64VT/28VF, and a pediatric database of 78 cases, 49VT/29VF.*

*We obtained an overall accuracy of 96.8%, 94.3% for VT and 98.0% for VF, for the development database. The accuracies obtained for the test databases were: 94.6% for the adult patients, 93.8% for VT and 96.4% for VF; and 94.9% for the pediatric patients, 93.9% for VT and 96.6% for VF. The algorithm accurately discriminates VT from VF in adult and pediatric patients.*

## 1. Introduction

The electrical shock treatment is different for the two fatal ventricular arrhythmias; Ventricular Fibrillation (VF) is better treated applying a high energy shock while Ventricular Tachycardia (VT) is reverted using low-energy cardioversion, a synchronized shock. It is therefore convenient that electrical defibrillators, both implantable or Automated External Defibrillators (AED), accurately discriminate the two types of shockable arrhythmias.

Based on two independent studies, the International Liaison Committee on Resuscitation (ILCOR) approved the use of AED in children under 8 years of age in the year 2003 [1]. Consequently, VT/VF discrimination methods should be applicable to pediatric and adult patients, that is independent of age specific characteristics such as the higher heart rate of pediatric patients.

Most VT/VF discrimination methods exploit that VT is a more regular and less complex rhythm than VF. Several parameters have been applied to measure complexity and regularity in ventricular arrhythmias: the distribution of Threshold Crossing Intervals (TCI) [2], Blanking Variability (BV) [3] or Complexity Measure (CM) [4, 5].

We propose an alternative measure of the regularity of the ECG based on the sample entropy introduced by Richman et al [6]. We have modified the vector comparisons which are now based on the similarity of the shape of the vectors rather than on the value of the samples; such vector similarity is termed Wave Mode approximate [7].

The Wave Mode Sample Entropy (WMSE) values are calculated every second using overlapping signal windows of 4 seconds. We discriminate VT from VF by applying the Sequential Hypothesis Testing (SHT) algorithm [2, 5] to the sequence of WMSE values. The method was developed using an adult VT/VF database and tested on two independent databases: an adult database and a pediatric database. This is, to our knowledge, the first time in which a VT/VF discrimination method is tested on pediatric and adult rhythms.

## 2. Materials and methods

### 2.1. Wave mode sample entropy

Different methods that estimate entropy, the rate of information production, have been devised to analyze the regularity and complexity of physiological time series. Approximate Entropy (ApEn) was introduced by Pincus [8] in 1991. In the year 2000, Richman et al. [6] proposed a new family of statistics, Sample Entropy (SampEn), that reduce the bias due to self-matches in ApEn.

SampEn is the negative logarithm of the conditional probability that two sequences similar for $m$ points remain similar for $m + 1$ points, excluding self-matches. For a

time series of $N$ points, $\{u_i,\ i = 1,..,N\}$ we form the $k = 1,..,N-m+1$ vectors of length $m$ as follows: $\mathbf{x}_m(k) = \{u_{i+k},\ i = 0,..,m-1\}$. Then the distance between two such vectors is calculated using the maximum norm as:

$$d(\mathbf{x}_m(k), \mathbf{x}_m(l)) = \max_{i=0,..,m-1}(|u_{i+k} - u_{i+l}|)$$

If the distance between two different vectors is below a threshold $r$, the vectors are considered similar and 1 is added to the similarity count, $B^m(r,N)$. Repeating the process for vectors of length $m+1$ we obtain a second similarity count $A^m(r,N)$ and the sample entropy is defined as:

$$\text{SampEn}(m,r) = \lim_{N\to\infty} -\ln \frac{A^m(r,N)}{B^m(r,N)}$$

which is estimated using the statistic:

$$\text{SampEn}(m,r,N) = -\ln \frac{A^m(r,N)}{B^m(r,N)} \qquad (1)$$

Following Ning et al. [7] we use shape rather than coordinates to measure similarity. Wave Mode similarity is based on the principle that vectors which only differ in base line content should be added to the similarity count, so the mean value is subtracted from each vector to obtain a new family of vectors:

$$\boldsymbol{\varphi}_m(k) = \mathbf{x}_m(k) - \frac{1}{m}\sum_{i=0}^{m-1} u_{i+k}$$

then the similarity counts are calculated for the vectors $\{\boldsymbol{\varphi}_m(k)\}$ and $\{\boldsymbol{\varphi}_{m+1}(k)\}$, and the WMSE is calculated applying equation (1).

There are no guidelines to choose the optimum values for the critical parameters: $m$ and $r$. In order to make the SampEn scale-invariant, the tolerance $r$ is chosen as a fraction of the standard deviation ($\sigma$) of the time series, although Ning et al. [7] propose the use of a Basic Measure ($BM$) which for white noise is proportional to $\sigma$:

$$BM = \sqrt{\frac{\sum_{i=1}^{N}(u_{i+1}-u_i)^2}{N}} = \sqrt{E[(u_{i+1}-u_i)^2]}$$
$$= \sqrt{E[u_{i+1}^2 + u_i^2 - 2u_{i+1}u_i]} \underset{\text{White Noise}}{\equiv} \sqrt{2}\sigma$$

$m = 4$ and $r = 0.2 \cdot BM$ were used to compute WMSE values in this study.

For an ECG record of $N$ samples a set of WMSE values will be calculated using a sliding observation window of fixed length $N_w$ and starting sample $t_{sk}$. The window will be shifted by $L < N_w$ samples, that is the observation windows partially overlap. The vector of observed WMSE values $\mathbf{S}_k = \{S_j\}_{j=0,..,k}$ reflects the time evolution of the WMSE values from $t_{so} = 0$ to $t_{sk} = kL$.

### 2.1.1. Sequential hypothesis testing

Given $\mathbf{S}_k = \{S_j\}_{j=0,..,k}$, a vector of observed WMSE values, we want to discriminate between the two hypothesis (VF or VT): $H_{VF}$ and $H_{VT}$. The log-likelihood ratio for $\mathbf{S}_k$ is:

$$\ln \Lambda_k = \ln\left(\frac{L(\mathbf{S}_k|H_{VF})}{L(\mathbf{S}_k|H_{VT})}\right)$$

where $L(\mathbf{S}_k|H_r)$ is the likelihood of observing $\mathbf{S}_k$ given the hypothesis $H_r$ is true. Two threshold values determine the decision rule:

$$A = \frac{1-\beta}{\alpha}, \qquad B = \frac{\beta}{1-\alpha}, \qquad (A > B > 0)$$

where $\alpha$ and $\beta$ are, respectively, the probabilities of rejecting $H_{VT}$ or $H_{VF}$ when these are true. If $\ln\Lambda_k > \ln A$ (or $\ln\Lambda_k < \ln B$) the algorithm selects $H_{VF}$ (or $H_{VT}$). If the log-likelihood ratio falls between the two threshold values the test is undecided, the observation window is shifted $L$ samples and a new WMSE value ($S_{k+1}$) is added to the vector of observations to repeat the test.

Assuming that the observed values are independent and normally distributed ($S_{VF} \sim N(\mu_{VF}, \sigma^2_{VF})$; $S_{VT} \sim N(\mu_{VT}, \sigma^2_{VT})$), the likelihood function is:

$$L(\mathbf{S}_k|H_r) = \frac{1}{\sigma_r\sqrt{2\pi}}\prod_{j=0}^{k} e^{-\frac{1}{2}\left(\frac{S_j-\mu_r}{\sigma_r}\right)^2}$$

and the log-likelihood ratio assumes the simple form:

$$\ln\Lambda_k = k\ln\left(\frac{\sigma_{VT}}{\sigma_{VF}}\right) + \frac{1}{2\sigma^2_{VT}}\sum_{j=0}^{k}(S_j-\mu_{VT})^2$$
$$- \frac{1}{2\sigma^2_{VF}}\sum_{j=0}^{k}(S_j-\mu_{VF})^2 \qquad (2)$$

## 2.2. The VT/VF discrimination method

Figure 1 shows the flow chart describing the VT/VF discrimination method. Every second ($L = f_s$) a new value of the WMSE is calculated using an observation window of 4 seconds ($N_w = 4f_s$), where $f_s$ stands for the sampling frequency. The set of WMSE values obtained after $k$ seconds are arranged in a vector of observations $\mathbf{S}_k$, used to compute the log-likelihood ratio, equation (2). The mean and standard deviations in equation (2) are calculated using the development database described in section 2.3:

$$\text{VF}: \quad \mu_{VF} = 1.663 \qquad \sigma_{VF} = 0.276$$
$$\text{VT}: \quad \mu_{VT} = 0.814 \qquad \sigma_{VT} = 0.316$$

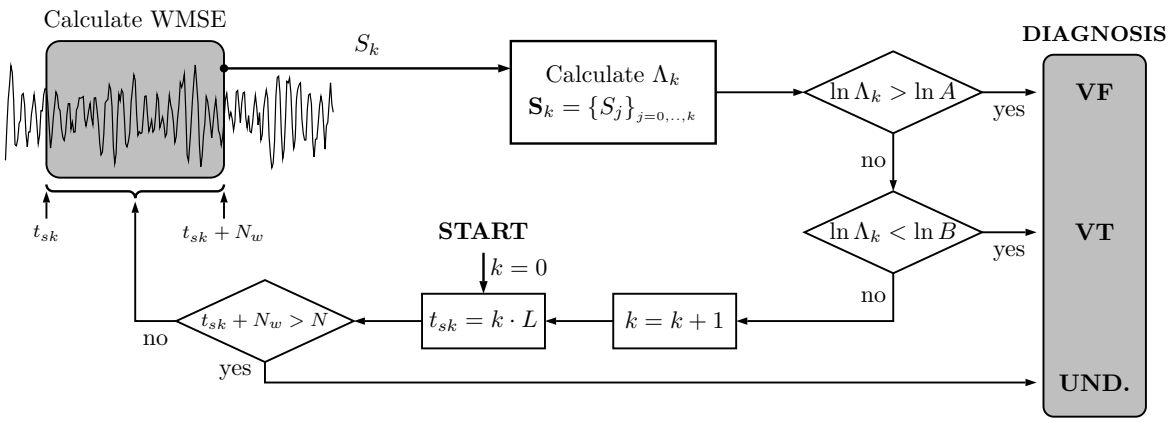


Figure 1. A sliding window of $N_w$ samples is used to construct a sequence of observed WMSE values $\mathbf{S}_k$. If the vector of observations is not sufficient to decide the type of rhythm (log-likelihood ratio test) the observation window is shifted $L$ samples and a new observation is added. The process ends when either a diagnosis or the end of the ECG record are reached.

The log-likelihood ratio is compared to the two thresholds that determine the type of rhythm. We set the probability of rejecting VT when it is true to $\alpha = 0.1$ and VF to $\beta = 0.2$. If at time $k$ the log-likelihood ratio test is within the threshold limits the diagnosis cannot be decided. Then the observation window is shifted 1 second and the process repeated until either a diagnosis or the end of the ECG record are reached.

## 2.3. Databases of VT and VF records

Three ventricular arrhythmia databases, obtained from independent sources, were used: one to develop the algorithm and two to validate the algorithm for adult and pediatric patients. All the database samples had a minimum duration of 9 seconds to guarantee the SHT algorithm results in a diagnosis.

The development database is a subset of the ventricular arrhythmias found in the Reanibex 200 AED testing library, it contains 154 adult cases, 53VT/101VF. The test adult database consists of 92 cases, 64VT/28VF obtained from electrophysiology studies conducted at the Donostia Hospital in Spain. The pediatric database is a subset of the ventricular rhythms of the database described in [9].

We have decreased the number of samples of the 4 second observation windows by lowering the sampling frequency of the original VF/VT records. Figure 2 represents the normalized averaged power spectral density of all the VF and VT episodes (development + testing), the contribution of the frequencies above $15\ Hz$ to total power is negligible, so all the records were downsampled to $f_s = 50\ Hz$ ($N_w = 200$). The samples were then preprocessed using a band-pass filter with passband $1.5 - 20\ Hz$.

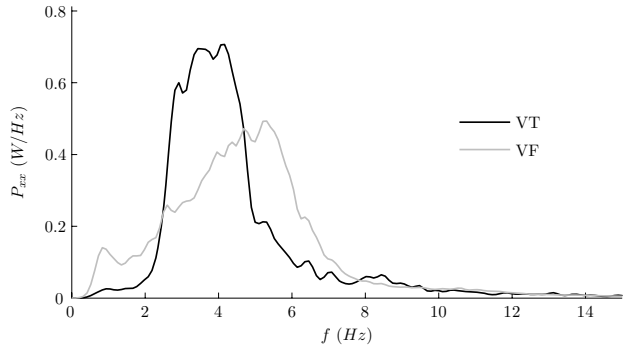


Figure 2. Averaged normalized power spectral density of the VF and VT episodes, calculated using Welch's method with 4.8s hamming window and 50% overlap.

## 3. Results

We calculated the WMSE values for all the overlapping 4 second windows in the three databases, these values were then sequentially tested to reach a VT/VF diagnosis. Table 1 summarizes the results obtained for the development and the two testing databases. Despite the different origin and nature of the databases the WMSE values for all the VF databases are similar. There are small differences in the WMSE values for the VT databases because of the different heart rates and morphologies of the VTs.

The overall detection accuracy is 95.7%, 96.8% for the development database and 94.7% for the testing databases. The algorithm detects VF more accurately (97.5%) than VT (94.0%). Accuracy and VF/VT sensitivities are similar in both (pediatric and adult) testing databases. These

Table 1. Summary of the results for the development and testing databases.

| Database [a] | | Results | | |
|---|---|---|---|---|
| | | WMSE [b] | sensitivity | accuracy |
| **Develop.** | | | | |
| VF | (101) | $1.66 \pm 0.28$ | 98.0% | **96.8%** |
| VT | (53) | $0.81 \pm 0.31$ | 94.3% | |
| **Test: adult** | | | | |
| VF | (28) | $1.67 \pm 0.31$ | 96.4% | **94.6%** |
| VT | (64) | $0.71 \pm 0.25$ | 93.8% | |
| **Test: ped.** | | | | |
| VF | (29) | $1.70 \pm 0.30$ | 96.6% | **94.9%** |
| VT | (49) | $0.89 \pm 0.24$ | 93.9% | |
| **Total** | | | | |
| VF | (158) | $1.67 \pm 0.29$ | 97.5% | **95.7%** |
| VT | (166) | $0.80 \pm 0.28$ | 94.0% | |

[a] Number of samples in parenthesis.
[b] Mean value $\pm$ standard deviation.

results show that WMSE (or SampEn) values serve to discriminate VT from VF, regardless of the patient age group.

On average a diagnosis was reached in $4.34 \pm 0.87$ $s$, in fact 80.24% of the episodes were diagnosed on the first observation window ($4s$). All cases but one (a VT from the test adult database) reached a VT or VF diagnosis.

## 4. Discussion

We present a method to discriminate VT from VF based on the regularity of the ECG, quantified using a new entropy, WMSE, derived from the well known SampEn. Successive WMSE values are sequentially tested to avoid misclassification due to local regularities/irregularities in the rhythm.

The algorithm has a higher sensitivity for VF than for VT. The development database contains more VF than VT (approx 2:1), which is not reflected in the testing databases (approx 1:2). The results are therefore biased toward VF detection, but this better represents the AED scenario where VF is more frequent than VT.

The accuracy is higher than that reported in previous papers where SHT was used in combination with a regularity measure, TCI [2] or BV [3]. Each work is based on different VT/VF databases, consequently the results are not fully comparable. In fact Chen et al [3] tested TCI on their database and the accuracy fell from the 100% reported in [2] to 84%. Recently an SHT algorithm based on CM [5] was shown to have a 97% accuracy but the algorithm was developed and tested on the same database which only contained 30 samples.

We have for the first time reported the performance of an algorithm on a pediatric database. Since 2003, when the ILCOR updated its recommendation to allow the use of AEDs in children between 1-8 years of age, all rhythm detection algorithms to be implemented in an AED should be tested for pediatric use.

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Address for correspondence:

Unai Irusta
School of Engineering
Department of Electronics and Telecomunications
Alameda Urquijo, s/n 48013 Bilbao (Spain)
E-mail: unai.irusta@ehu.es