SVM Classification of Sparse Set of 1:1 Ventricular and Supraventricular Tachycardia

Mario de-Prado-Cumplido[1], Ángel Arenal-Maíz[2], Mercedes Ortiz-Patón[2] and Antonio Artés-Rodríguez[1]

[1] Department of Signal Theory and Communications, Universidad Carlos III de Madrid, Avda. de la Universidad 30, 28911 Leganés-Madrid, Spain

[2] Laboratory of Cardiac Electrophysiology, Hospital General Universitario Gregorio Marañón, C. Doctor Esquerdo 46, 28007 Madrid, Spain

Abstract. Inappropriate classification of Supraventricular Tachycardias with 1:1 atriovetricular conduction is a mayor issue in dual-chamber implantable cardioverter defribillators. In order to distinguish Supraventricular from Ventricular Tachycardias a new methodology is proposed. The tachyarrhythmia episodes ECGs are characterized into feature vectors, which are then classified using a Support Vector Machine. The best features of the vectors are selected by means of several Feature Selection methods. The performance of the algorithm overcomes existing algorithms for implantable devices.

1 Introduction

Despite automatic implantable cardioverter-defibrillators (AICDs) show a very good performance dealing with heart diseases, inappropriate therapies are still a mayor issue. New generation of dual-chamber AICDs have the ability to take into account atrial-ventricular relationships, and in particular, to detect the chamber which originates the tachycardia. Nevertheless, the reduction of inaccurate detection of this new devices have not been totally proved, specially for tachycardias with a stable 1:1 atrioventricular relationship.

In this paper we tackle the problem of discriminating Supra Ventricular Tachycardias (SVT) from Ventricular Tachycardias (VT) with 1:1 conduction; this property is the main cause of the high complexity of the problem. Although the frequency of occurrence of this arrhythmias is low, inappropriate therapies (i.e., small specificity) cause annoyance in the patient and may initiate a more compromising tachyarrhythmia. (See for example [2], [1]). Usually data bases of pathological episodes are of reduce size, which constitute and additional difficulty to bound the statistical accuracy of the results.

The electrocardiogram (ECG) of the tachyarrhythmia episodes is registered in the AICDs as sequences of intervals between beats times. The difference between adjacent intervals, known as Heart Rate Variability (HRV), has been of great interest for the research community in the last decades, due to HRV signals gather information about the complex processes that controlls the heart behavior [3]. We aim to implement SVT/VT classification based in these HRV signals.

de-Prado-Cumplido M., Arenal-Maíz Á., Ortiz-Patón M. and Artés-Rodríguez A. (2005).
SVM Classification of Sparse Set of 1:1 Ventricular and Supraventricular Tachycardia.
In *Proceedings of the 1st International Workshop on Biosignal Processing and Classification*, pages 95-101
DOI: 10.5220/0001195600950101

The classification step is carried out with a classifier known as Support Vector Machine (SVM), which is the state-of-the-art technique for knowledge discovery and classification tasks, among others applications [5], [6], and is well founded in the Statistical Learning Theory. The SVM classifiers have shown competitive results applied to datasets with low ratio sample-size/number-of-dimensions, property very useful for our problem. The characterization process of the HRV signals we have implemented is over-informative, so Feature Selection (FS) methods must be applied in order to choose the most informative variables. Our overall process for SVT-VT classification can be seen in Figure 1.

This methodology was applied to 1:1 tachycardia episodes obtained from a Spanish hospital, Hospital Gregorio Marañón (Madrid, Spain). We will show that the algorithm we present increases the specificity percentages of present AICDs devices, while maintaining 100% of sensitivity.

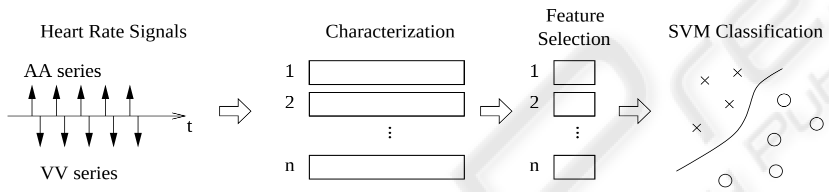


Fig. 1. General summary of the methodology. The heart rate intervals signals are coded into a set of characterization vectors; the best features are fed into a SVM classifier

The paper is structured as follows: Section 2 explains the medical problem, the signals used and its characterization vectors. Section 3 details the methodology implemented, while the results are described in Section 4. Finally, the paper is closed with some final remarks in Section 5.

2 Definition of the medical problem and the data

Ventricular Tachycardias (VT) and supraventricular ones require different therapies; inappropriate shocks for SVTs can induce a ventricular arrhythmia. The main criterion to distinguish them is to identify the chamber responsible of the origin of the tachycardia. This is specially problematic with stable atrioventricular relationship, i.e, when there is a 1:1 conduction.

The episodes are registered in the AICDs (model 7276 Gem III AT; Medtronic Inc.) as the sequence of interval times from beat to beat in each chamber. Assuming that a_i contains the times of the beats in the atria, the atrial HRV is $\{aa_1, \cdots, aa_r, \cdots\} = \{a_2 - a_1, \cdots, a_{r+1} - a_r, \cdots\}$. In the same way, the ventricular HRV is $\{vv_1, \cdots, vv_r \cdots\} = \{v_2 - v_1, \cdots, v_{r+1} - v_r, \cdots\}$, where v_i are the instants for ventricular beats. The series used in our study are based in those sequence of intervals:

$$\begin{aligned} s_1(i) &= \{aa_{r-24+i} - vv_{r-24+i}\} \\ s_2(i) &= \{aa_{r-24+i} - vv_{r-25+i}\} \end{aligned} \quad (1)$$

where $i = \{1, 24\}$ and v_r and a_r are the last beats previous to the tachycardia detection instant according to the AICD criteria. We have focused only in this 24 intervals $\{aa_{r-23}, \cdots, aa_r\}$ and $\{vv_{r-24}, \cdots, vv_r\}$ because it is the minimum time needed by the AICDs to decide SVT or VT for the different episodes. The actual labelling has been set inspecting the episodes stored in the AICDs. Classical algorithms for classifying VTs are related with onset and stability of the variability; take into account that $s_1(i)$ and $s_2(i)$ contains not only this information but indications about the chamber of origin of the tachycardia.

Typical measurements of variability include mean and variance calculation, as well as frequency domain or geometrical calculations or more complex ones as mutual information (see [4] for explanation on these measures). We have chosen the mean and variance of the complete series s_1 and s_2, the mean and variance of groups of 4 intervals, and the mean and variance of these latter values. Consequently, for each tachycardia episode a 32-dimension features vector is set.

3 Design of the classification method

This section describes the algorithms used in our classification scheme. Feature Selection algorithms have been applied to the SVT and VT vectors, characterized as describe previously, in order to improve the error probability (in terms of sensitivity and specificity) and to discover the features that better describes the tachycardias. The episodes are then classified with a SVM, obtaining both linear and nonlinear boundaries for the decision regions.

3.1 Feature Selection

Feature Selection (FS) methods are used as a preprocessing step in classification problems, in which datasets are commonly composed of samples of two variables [7].

Consider a set of l tachyarrhythmias represented by the value of their $n = 32$ characteristics (constructed as explained in the previous section): $(\mathbf{x}_i, y_i)$, where $i = 1, \ldots, l$, $\mathbf{x}_i \in \mathcal{R}^n$, and the set labels $y_i \in \{-1, 1\}$ denotes whether the arrhythmia is a SVT ($y_i = -1$) or a VT ($y_i = 1$). In FS, the objective is to find a subset of components of $\mathbf{x}$ that is optimal following a given criterion. The algorithms used in this article are the well-known fisher score, Kolmogorov-Smirnoff test and Recursive Feature Elimination (RFE).

Fisher score method consists in computing the fraction $F(i) = \dfrac{(\mu^+ - \mu^-)^2}{(\sigma^+)^2 + (\sigma^-)^2}$, where μ^+ and σ^+ are the means and variance of feature or dimension i ($i \in 1, n$) for samples with label $y_j = +1$; μ^- and σ^- are calculated for samples $y_j = -1$. Fisher FS is a linear method which maximizes the separation of the mean of the classes while forcing minimum interclass variance. Kolmogorov-Smirnov test, a nonlinear FS algorithm, ranks more favorably the features with mayor statistical relation with the labels, through this equation: $KS(i) = \sqrt{n} \sup \left\{ \hat{P}(X \leq f_i) - \hat{P}(X \leq f_i, y = 1) \right\}$, where f_i is the i-th feature and $\hat{P}$ the corresponding empirical distribution. Finally, RFE runs for n iterations eliminating in each of them the feature that modifies the least the probability error of the classifier. The two former FS methods are filter algorithms, while the latter belongs to wrapper methods, because RFE takes into account the output of the classifier to estimate the ranking of features.

Fisher criterion, Kolmogorov-Smirnov test and RFE has been applied to our data set, and the more informative features has been used to train the classifier.

3.2 Support Vector Machine Classifiers

The nonlinear SVM classifier maps the input variable $\mathbf{x}_i$ into a high dimensional (often infinite dimensional) feature space, and applies a maximum margin algorithm with regularized complexity in this feature space. All the appearances of the mapping ϕ are within dot products, which can be substituted by a kernel function. The nonlinear SVM with kernel $K(\cdot,\cdot) = \boldsymbol{\phi}(\cdot)\boldsymbol{\phi}(\cdot)$ is equivalent to a regularization problem in the reproducing kernel Hilbert space H_K: minimize the functional,

$$\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i \tag{2}$$

subject to

$$\begin{aligned} y_i(\mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_i) + b) &\geq 1 - \xi_i \ \forall i = 1,\dots,l \\ \xi_i \quad &\geq 0 \quad \forall i = 1,\dots,l \end{aligned}$$

Once found the optimum $\mathbf{w}$, the mappings of the SVMs for unseen samples $\mathbf{x}$ are of the form

$$\hat{y}(\mathbf{x}) = \text{sign}\left(\mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}) + b\right) \tag{3}$$

where bias b can be used to generate a pseudo ROC curve and adjust the balance between errors of type $\hat{y}_i = 1|y_i = -1$ (miss error) and $\hat{y}_i = -1|y_i = 1$ (false alarm error).

In this article we have used two kernels: the linear kernel ($K(\mathbf{x}_i,\mathbf{x}_j) = \mathbf{x}_i^T\mathbf{x}_j$) and the well-known Gaussian Kernel, $K(\mathbf{x}_i,\mathbf{x}_j) = \exp\left(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2\right)$, where γ controls the width of the Gaussian. The former presents a higher probability of error, but has the advantage of being more interpretable, while gausian kernel has a more accurate performance at the expense of simplicity in the solution. Simulations have been run with both kernels.

The tunable parameters C and γ and the error probability (sensibility and specificity) of the SVM are estimated by a cross-validation approach. The SVM is trained with all the episodes except one, and the result is evaluated for that sample. The procedure is repeated for all the episodes, and the final figures are an average of all the steps; this procedure is known as Leave-One-Out, and tends to generate slightly pessimistic error probabilities.

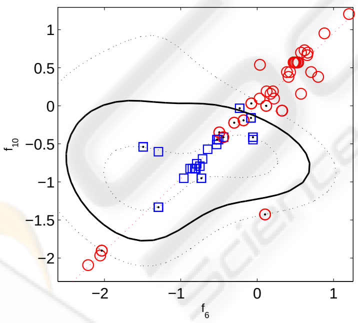
4 SVT vs VT Classification Results

A set of 61 arrhythmias, 40 SVTs and 21 VTs, all of them showing a 1:1 conduction, has been processed as explained in Section 2. In order to obtain confidence margins for the results and assure their statistical validity, we have used a bootstrap resampling (see [8]) of the episodes, with 15 resamples, so the specificity is expressed as the mean of the estimator plus its standard deviation. Bootstrap errors are calculated by evaluating repeatedly the estimator under study, that in our case are the SVM error probabilities.

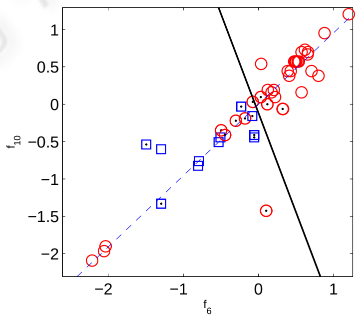
The best performance, in terms of sensibility ($\frac{\#\hat{y}=1|y=1}{\#y=1}$) and specificity ($\frac{\#\hat{y}=-1|y=-1}{\#y=-1}$), were obtained when the SVM was trained with the top 4 ranked variables according to the Kolmogorov-Smirnov test. RFE chose approximately the same features, specially for the top rated ones. Fisher score selected other features, but the error probability of the SVM has been worst, due to the linear behavior of this FS method. The meaning of the selected features are related with means and standard deviations of series in eq. (1), as explained in Table 1.

Table 1. Four best features according to Kolmogorov-Smirnov test and their meaning

No. of feature	Meaning
f_6	mean of the full inter-chamber HRV, s_2
f_{10}	mean of $\{s_2(13), s_2(16)\}$
f_7	mean of $\{s_2(1), s_2(4)\}$
f_{16}	standard deviation of $\{s_2(5), s_2(8)\}$



(a)



(b)

Fig. 2. Example of a) non-linear and b) linear classifiers. Squares and circles represent VTs and SVTs, respectively. The continuous curves is the boundary between the two types of tachycardias

Two types of SVM classifiers has been proved, a nonlinear gaussian and a linear one. In Figure 2 an example of a classification with only 2 variables, f_6 and f_{10}, is shown. Note that the boundary between both classes (squares for SVT and circles for

VT) is clearly a non-linear curve. In this case, 4 SVTs have been considered as VTs. The dashed line represent the direction of maximum variance of the data set when only those variables are taken into account. It would be easy to implement an algorithm that with just 2 thresholds: check if the episode is in the upper right or bottom left areas of the figure, and decide then that it is a SVT case, or, otherwise, decide a VT. For the linear SVM drawn in Figure 2 b) a simple classification rule can be derived: *if* $(f_6 > 200)$ *AND* $(f_{10} > 195)$ *decide VT* (the values in the figure are normalized).

Table 2 shows the performance of the SVMs, depending on the number of variables. Classification with more than 4 variables performs worse in term of sensibility and specificity. As mentioned before, specificity values include their bootstrap standard error. Sensibility, on the contrary, has been forced to be 100%, at the expense of a lower specificity; this has been done adjusting conveniently the bias parameter b of the SVM. For comparison, in [1], a study with data from AICDs showed a 60% of specificty in VT/SVT detection; the set of tachycardies in this case includes both 1:1 conduction SVTs and normal SVTs. In [2], 160 SVTs episodes were used, only 16 of them showing 1:1 conduction. Although the algorithm used in [2] shows an 89% specificity, all 16 1:1 SVTs were misclassified. Consequently, the proposed methodology clearly overcomes existing algorithms for AICDs.

Table 2. Results for both linear and non-linear SVMs, for the most informative features; we also include the parameters of the best classifier

	Non-linear Classifier			Linear Classifier		
#features	Sensibility	Specificity	Params	Sensibility	Specificity	Params
2	100	89.95 ± 3.90	$C : 100, \gamma : 2$	100	80.80 ± 6.97	$C : 100$
3	100	88.60 ± 5.71	$C : 100, \gamma : 3$	100	79.91 ± 6.73	$C : 10$
4	100	85.57 ± 4.88	$C : 100, \gamma : 4$	100	77.28 ± 8.17	$C : 10$

5 Conclusions and Further Work

In this paper we present a methodology for discriminate 1:1 ventricular tachycardias from supraventricular ones, based on real signals from dual-chambers AICDs. This pathology constitute a mayor issue due to existing algorithms do not perform with a satisfactory level of specificity. Additionally, the occurrence frequency of this tachyarrhythmias is low, and the size of our data base is consequently small. The presented methodology has obtained results that improve the specificity of existing AICDs algorithms.

Our methodology could be used to explore other measurements on the HRV, just creating new feature vectors without modifying the rest of the algorithms; new measurements coul be based, for example, in mutual information or morphological criteria. In order to implement SVM classifier into the AICD devices it would be necessary to study and reduce its computational burden.

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