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A New Approach for ICD Rhythm Classification based on Support Vector Machines

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Abstract-- **Inappropriate shocks due to misclassification of supraventricular and ventricular arrhythmias remain a major problem in the care of patients with Implantable Cardioverter Defibrillators (ICDs). The purpose of this study was to investigate the ability of a new covariance-based support vector machine classifier, to distinguish ventricular tachycardia from other rhythms such as supraventricular tachycardia. The proposed algorithm is applicable on both single and dual chamber ICDs and has a low computational demand. The results demonstrate that suggested algorithm has considerable promise and merits further investigation.**

I. INTRODUCTION

Mortality benefits from placement of implantable cardioverter defibrillators (ICDs) - battery operated devices implanted in the chest that constantly monitor the heartbeat and if necessary deliver electrical shocks to restore the normal heart rhythm - have been demonstrated in multiple studies and have led to a significant increase in the number of patients receiving ICDs and the number of lives saved due to ICD therapy. However, inappropriate shocks due to misclassification of supraventricular tachycardia (SVT) - which doesn't need therapy - and ventricular tachycardia (VT) - which needs therapy - occur in up to 40% of patients [1-5]. ICD shocks are physically painful, decrease quality of life, and if recurrent cause an extremely high amount of patient anxiety and trauma. Inappropriate shocks may also be proarrhythmic [6-10].

So far, various discriminating algorithms have been proposed to distinguish between VT and SVT [8, 11-18]. However, current algorithms do not adequately discriminate supraventricular and atrial arrhythmias from ventricular tachycardia, resulting in inappropriate therapy [19-34]. In this study, we have proposed a new algorithm that utilizes support vector machine (SVM) classifiers to differentiate these rhythms from each other.

SVM is an optimization based approach for solving machine learning problems. It classifies points by assigning them to one of two disjoint half spaces [35]. In this study, we have used proximal support vector machine (PSVM) which classifies points depending on their proximity to one of two parallel planes and does not contain the extensive computational implementation of standard SVMs [36].

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II. METHODS

A. Data Description

In this study we examined 70 arrhythmia detection episodes resulted in ICD therapy, obtained from 22 ICD patients in the Multicenter Automatic Defibrillator Implantation Trial (MADIT II) [3]. Each episode consists of three signals: Atrial, Ventricular and Shock electrograms and starts with the baseline rhythm followed by the onset of either ventricular or supraventricular tachycardia.

The binary ICD electrograms were converted into MATLAB compatible text files by using Cygwin to create a Unix-like environment for MS-Windows and running WFDB (WaveForm DataBase) library tools. Both Cygwin and WFDB software packages were obtained from PhysioNet website [37]. The rest of the processing steps are performed by MATLAB.

B. Feature Extraction

Feature extraction is the first important task in developing the SVM classifier. In this work, feature vectors are obtained by the following steps:

1. The covariance matrix of each beat is estimated as defined below:

$$R_{beat(i)} = X_{beat(i)}.X_{beat(i)}^{T} / n_{beat(i)} \quad (1)$$

Where $X_{beat(i)}$ contains the time series of ith beat, $n_{beat(i)}$ represents the length of ith beat and ^{T} denotes the transpose operator. Each episode consists of three electrograms: atrial, ventricular and shock; but in single-chamber ICDs the atrial electrogram is not available. Therefore, to examine the performance of the algorithm for both single and dual chamber ICDs, two implementations have been tested. In the first implementation, all three available electrograms have been used to calculate the covariance matrix whereas in the second implementation, only ventricular and shock electrograms have been included. Thus for dual-chamber ICDs, $X_{beat(i)}$ is a 3-by-$n_{beat(i)}$ matrix consisting of all three electrograms and for single-chamber ICDs, a 2-by-$n_{beat(i)}$ matrix containing ventricular and shock electrograms.

The covariance matrices represent the second-order statistical properties of each beat, which provide more stable quantities for classification purposes compared to the actual time series. The diagonal elements show the signal power of each electrogram, whereas non-diagonal elements explain the cross-correlation between different electrograms for each beat.

2. For each patient a number of normal heartbeats are used as a tuning set and the patient's normal template is obtained by averaging the covariance matrices of the beats in this tuning set:

$$R_{template} = \frac{1}{N}\sum_{j=1}^{N} R_{beat(j)} \tag{2}$$

where N is the total number of normal beats in the tuning set and $R_{beat(j)}$ is the covariance matrix of jth beat. In this study N was 4.

Since different patients have different variability within their normal beats, the tuning set is used to obtain a normalization factor:

$$D_{norm} = \max_{j=1:N}[norm(R_{beat(j)} - R_{template})] \tag{3}$$

Since the tuning set is acquired for each patient individually, normal template and normalization factor are unique for each patient and help the algorithm to adapt to each individual patient's characteristics.

The proposed classification rule is based on the assumption that supraventricular arrhythmias are less different from normal rhythms compared to ventricular arrhythmia and can be classified based on their differences from the normal template. So the difference of each beat's covariance matrix from the normal template is calculated as follows:

$$R_{d(i)} = (R_{beat(i)} - R_{template}) / D_{norm} \tag{4}$$

Normalizing to the normalization factor D_{norm}, compensates the different variability among patients.

3. The last step is constructing the feature vector from R_d. Since R_d is a symmetric matrix, only the upper (or lower) triangle is used. For single chamber implementation, R_d is a 2-by-2 matrix and the upper triangle has 3 entries. For dual chamber implementation, R_d is 3-by-3 and upper triangle has 6 entries:

$$\begin{aligned} V_{d(i)} &= [R_{d(i)}(1,1)^2, R_{d(i)}(1,2)^2, R_{d(i)}(2,2)^2] \\ V_{d(i)} &= [R_{d(i)}(1,1)^2, R_{d(i)}(1,2)^2, R_{d(i)}(1,3)^2, R_{d(i)}(2,2)^2, R_{d(i)}(2,3)^2, R_{d(i)}(3,3)^2] \end{aligned} \tag{5}$$

C. PSVM Classifier

PSVM classifies points by assigning them to the closest of two parallel bounding planes that are pushed apart as far as possible (For details refer to Fung 2001 [36]). The output of PSVM is a vector w and a constant γ that define the separating plane $x^T w=\gamma$ midway between the bounding planes. x and w are column vectors in the n-dimensional real space R^n (n=3 for single chamber and n=6 for dual chamber), x is transposed to a row vector by the transpose operator ^{T}. Each point is then classified by [36]:

$$x^T w - \gamma \begin{cases} > 0, & then \quad x \in class1 \\ < 0, & then \quad x \in class2 \\ = 0 & then \quad x \in either \quad class \end{cases} \tag{6}$$

In this study, each heartbeat's feature vector V_d is assigned to either class1 (VT) or class2 (non-VT) using the above rule (replace x^T by $V_{d(i)}$ for each beat). If 3 or more beats in each episode are assigned to VT class, then that episode is classified as VT.

III. RESULTS

The proposed algorithms were tested on 70 therapy episodes recorded from 22 ICD patients. There were a total of 48 SVT and 22 VT episodes. All the episodes were annotated by cardiologists and compared with the algorithms' results. Figures 1 and 2 graphically depict examples of how VT and SVT episodes are classified. In both figures the top three graphs show atrial, ventricular and shock electrograms. The bottom graph displays the value of $V_{d(i)}w$-γ for each beat. If the value of ($V_{d(i)}w$-γ) is positive the corresponding beat is classified as VT. Figure 1 (VT episode) shows that how the ($V_{d(i)}w$-γ)s turn into positive values at the onset of VT whereas in figure 2 (SVT episode) they remain below zero.

TABLE 1
Dual Chamber Implementation

	Training	Testing
Specificity	95.17%	93.52%
Sensitivity	100%	100%

TABLE 2
Single Chamber Implementation

	Training	Testing
Specificity	93.76%	92.33%
Sensitivity	100%	100%

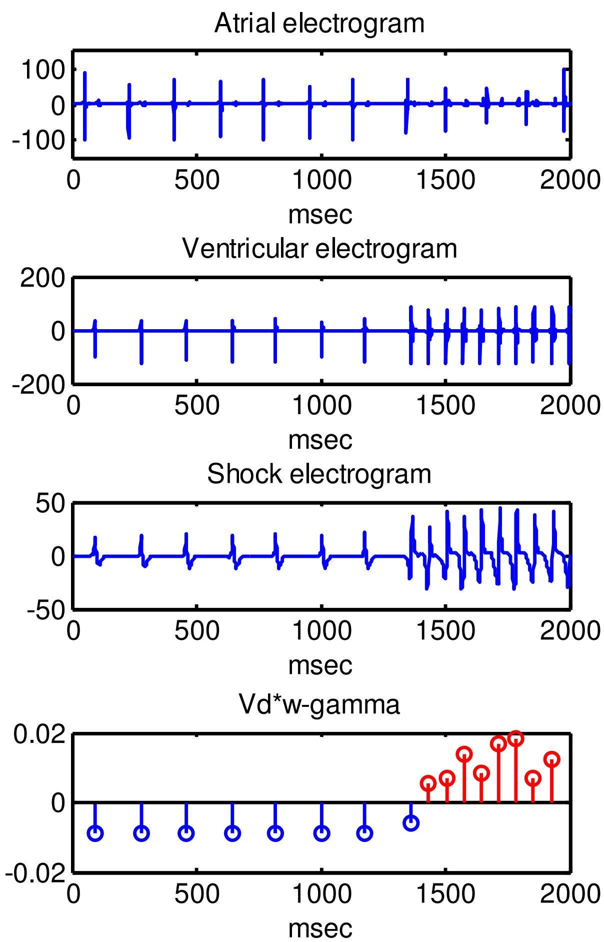

Figure 1- Example of a VT episode. The top three graphs show atrial, ventricular and shock electrograms. The bottom graph displays the value of $V_{d(i)}w\text{-}\gamma$ for each beat. Beats with positive values of $V_{d(i)}w\text{-}\gamma$ (displayed in red) are classified as VT.

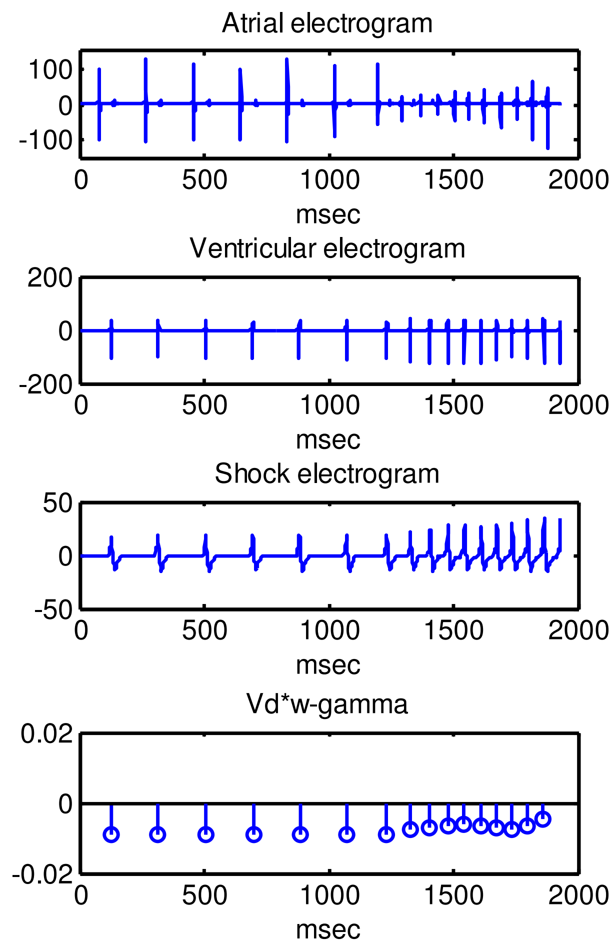

Figure 2- Example of an SVT episode. The top three graphs show atrial, ventricular and shock electrograms. The bottom graph displays the value of $V_{d(i)}w\text{-}\gamma$ for each beat. All the beats have negative values of $V_{d(i)}w\text{-}\gamma$ and therefore are classified as non-VT.

Table 1 summarizes the results of applying the algorithm on all three electrograms - dual chamber implementation- obtained from 7-fold cross validation (with roughly the same proportions of VT and non-VT episodes in training/testing sets). In a K-fold cross validation method the dataset is divided into K equal sized folders and the test is repeated K times each time using one of the folders as testing folder and the others as training set. Then the average classification rate across all K times is computed as the final result. This way we can make sure that the final result is not dependent on the way we choose testing and training folders and each episode gets to be in the test set exactly once. The average sensitivity achieved in both training and testing sets is 100% and the average specificity of training and testing sets is 95.17% and 93.52% respectively.

For single-chamber implementation, where only ventricular and shock electrograms are available, the presented algorithm was again able to achieve 100% sensitivity for both training and testing and the average 0f 93.76% and 92.33% specificity for training and testing sets, respectively. Results are summarized in Table 2.

IV. Discussion

These results suggest that covariance-based SVM classifier may be an effective method for ICD rhythm classification and may decrease inappropriate shocks. The algorithm is applicable in both single and dual chamber ICDs and has a very high speed and low computational load. The ideal 100% sensitivity was achieved for both single and dual chamber implementations. Choosing a unique tuning set for each patient helps the algorithm to adapt to each individual patient's characteristics. Since the square of the difference of covariance coefficients have been used to obtain the feature vectors, the separating plane acquired from the linear PSVM is equivalent to a separating ellipsoid (3-dimentional for single chamber and 6-dimentioanl for dual chamber ICDs) around the normal template. Any point outside this ellipsoid will be classified as VT.

One of the limitations in this study was the small number of normal beats available for each patient. Having a larger tuning set not only helps in obtaining more reliable normal templates and normalization factors, but is also useful in training the SVM classifier. It is worth mentioning that all the episodes evaluated in this study were spontaneous rather than induced.

In conclusion we have investigated the application of SVMs for ICD rhythm classification. The results are very promising and demonstrate the potential effectiveness of this algorithm for ICD rhythm discrimination.

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