

Spatial Projection of Tachycardia Electrograms for Morphology Discrimination in Implantable Cardioverter Defibrillators

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Abstract

Discrimination of Ventricular Tachycardia (VT) from Supra-Ventricular Tachycardia (SVT) remains a major challenge for appropriate therapy delivery in Implantable Cardioverter Defibrillators (ICDs), especially in single chamber devices. We propose here a new discrimination algorithm that analyzes, with a machine learning approach, the morphology of a two-dimensional representation of both a far-field and a near-field ventricular sensing channel. Features extracted from this representation allow comparisons between curves. Thus, arrhythmia discrimination is performed by comparing an arrhythmia curve to a reference curve.

A statistical classifier was trained on a private database and tested on the standard Ann Arbor Electrogram Libraries. Our discrimination algorithm demonstrated high sensitivity and specificity for VT/SVT discrimination. The requirements of this algorithm make it appropriate for implementation in the simplest ICD system.

1. Introduction

Discrimination of Ventricular Tachycardia (VT) from Supra-Ventricular Tachycardia (SVT) remains a major challenge for appropriate therapy delivery in Implantable Cardioverter Defibrillators (ICDs), especially in single chamber devices where the atrial signal is not available. Unlike SVT, VT is a life-threatening arrhythmia that may lead to sudden death unless an appropriate shock is delivered. Conversely, inappropriate shocks are very painful and stressful for patients and can also trigger a life-threatening tachyarrhythmia. The Madit II study [1] shows that inappropriate shocks occurred in 11.5% of the prophylactic ICD (single and double chamber devices) patients and accounted for 31.2% of the total shock episodes. There is clearly a need for further improvements in arrhythmia discrimination.

The discrimination in ICDs is performed from endocar-

dial measurements of the electrical activity of the heart, named electrograms (EGMs). Historically, only time intervals extracted from EGMs were used for diagnosis. In the last decade, an additional analysis of the shape of a single EGM channel resulted in improved performances [2–4]. We propose in this paper a morphology discrimination algorithm based on a new two-dimensional representation of both a far-field and a near-field right ventricular sensing channel, available in standard ventricular leads (Figure 1).

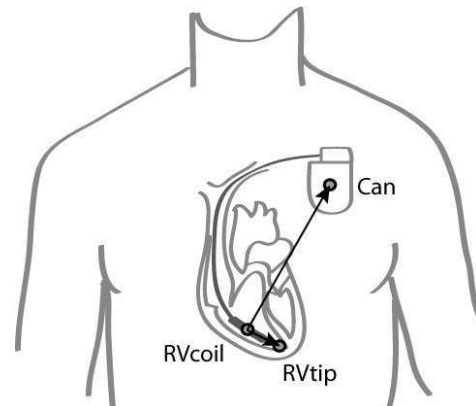


Figure 1. The simplest ICD system: a single-chamber ICD with a single-coil lead. The distal (RVtip) and the proximal (RVcoil) electrode are positioned in the right ventricle, the can is implanted in the left sub-clavicular position. The two EGM configurations used in this study are RVcoil-RVtip and RVcoil-Can.

2. Methods

2.1. Overview of the algorithm

The algorithm is based on the comparison between a Normal Sinus Rhythm (NSR) template beat and an arrhythmia beat (Figure 2). The NSR beat is commonly obtained by averaging m consecutive slow beats. A morpho-

logical description of this reference beat is subsequently computed based on a new two-dimensional representation.

When an arrhythmia is detected, the cardiac cycles are described in the same way as the reference beat. Morphological features are computed in order to compare each arrhythmia beat to the reference. The decision is based on a statistical classification of these features together with rhythmological features.

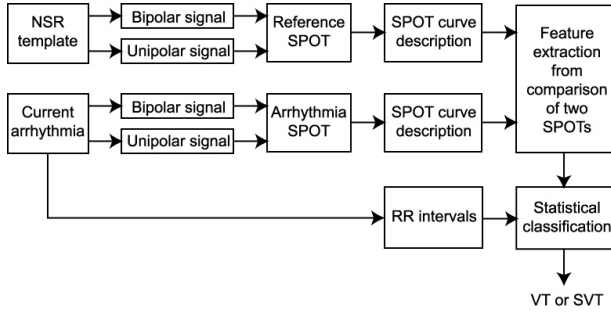


Figure 2. Overview of the morphology algorithm

2.2. SPOT curve representation

The two-dimensional representation of EGMs is called “Spatial Projection Of Tachycardia”(SPOT). The SPOT curve of a cardiac cycle is the plot of the amplitude of the far-field sensing signal versus the amplitude of the near-field sensing signal, with time as a parameter. However, a SPOT curve does not correspond to the entire cardiac cycle, but to a significant portion of a heartbeat centered on the R wave (typically 80 ms).

Figure 3 shows three SPOT curves for the same patient, one during an NSR, one during a VT and one during an SVT. Our discrimination algorithm consists of comparing each arrhythmia SPOT curve with a reference one. The underlying assumption is that, for a given patient, the morphology of an SVT SPOT curve is similar to that of the reference curve constructed from normal EGMs, while the SPOT curve for a VT is significantly different: this is justified by the fact that the electrical signals pertaining to normal heartbeats and to SVT heartbeats originate from the atria and follow the same electrical conduction pathway to the ventricles, while VT electrical signals, originating from the ventricles, have different activation patterns, leading to a change in the morphology of the signals measured by the electrodes. Figure 3 illustrates this phenomenon: the SVT SPOT curve is similar to the reference SPOT curve up to a scale factor, while the VT SPOT curve is very different in direction and shape.

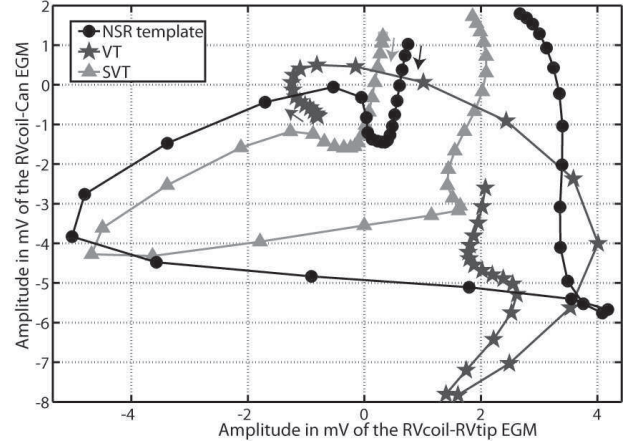


Figure 3. Three SPOT curves for a single patient. EGMs were sampled at 500 Hz.

2.3. Description of a single SPOT

For implementation in an ICD, a simple and inexpensive method is required to describe a SPOT curve. As can be seen in Figure 3, a difference in direction or shape is a discriminant factor. Therefore, two geometrical descriptors are extracted from each curve in this new representation: the velocity vector and the curvature at each point. Let $b(t)$ be the amplitude of the bipolar near-field signal at time t and $u(t)$ the amplitude of the unipolar far-field signal at time t . Velocity vectors are obtained by using a discrete approximation of the derivatives at each point for each EGM channel. We denote by u' and b' the time derivatives of u and b respectively. Let $\mathbf{V}(t) = (b'(t), u'(t))$ be the velocity vector of a SPOT curve at time t .

The Euclidean norm of each velocity vector $\mathbf{V}(t)$ is computed as:

$$N(t) = \sqrt{b'^2(t) + u'^2(t)}$$

Second derivatives are computed similarly to first derivatives. The curvature, which is the inverse of the radius of curvature, is then computed as follows:

$$C(t) = \frac{(b'(t)^2 + u'(t)^2)^{\frac{3}{2}}}{u''(t)b'(t) - b''(t)u'(t)}$$

The curvature can increase dramatically, especially at points where the velocity is small. For that reason, a weighted curvature \hat{C} is used. The weight at time t corresponds to a power of the norm of the velocity $N(t)$.

Figure 4 illustrates this description based on the SPOT curves of Figure 3: each SPOT curve is described at each point by the direction of the velocity vector (Figure 4a), its norm (Figure 4b) and the weighted curvature (Figure 4c).

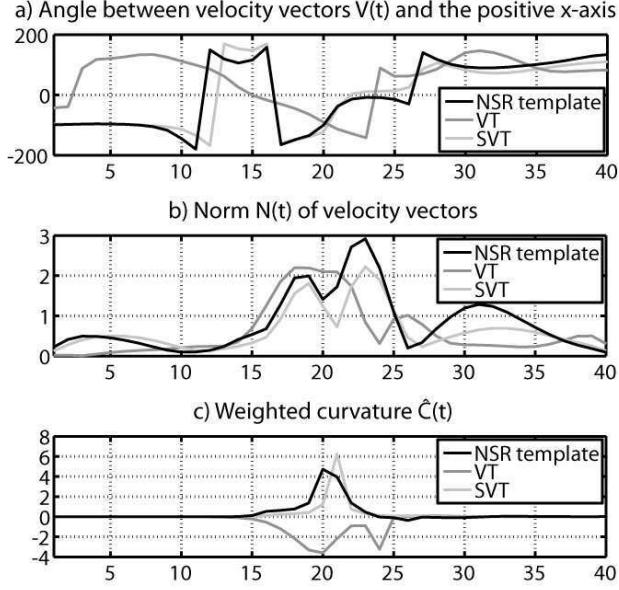


Figure 4. Description of SPOT curves

2.4. Comparison between arrhythmia and NSR SPOT curves

In order to discriminate between VT and SVT, a comparison between each current arrhythmia SPOT curve and the reference SPOT curve must be performed. Therefore, three candidate features are computed from the previous descriptors.

The first feature is the average angle of the relative velocity vectors $AngV$. The angle $\alpha(t)$ of the relative velocity vectors at time t is given by:

$$\begin{aligned}\alpha(t) &= \arccos\left(\frac{\langle \mathbf{V}_{ref}(t), \mathbf{V}_{test}(t) \rangle}{N_{ref}(t)N_{test}(t)}\right) \\ &= \arccos\left(\frac{b'_{ref}(t)b'_{test}(t) + u'_{ref}(t)u'_{test}(t)}{N_{ref}(t)N_{test}(t)}\right)\end{aligned}$$

where $0 < \alpha(t) < \pi$.

Let n be the number of points of each SPOT. Then, $AngV$ is defined as:

$$AngV = \frac{1}{n} \sum_{t=1}^n \alpha(t)$$

It is known that electrodes inside the heart are essentially motionless, so that a rotation between two SPOT curves is a discriminant factor. Such a rotation would be reflected by $AngV$.

The correlation coefficient CN between the norms of the velocity is the second descriptor:

$$CN = \frac{\sum_{t=1}^n N_{ref}(t)N_{test}(t)}{\|N_{ref}\| \|N_{test}\|}$$

Finally, the correlation coefficient CC between the curvatures can be computed as:

$$CC = \frac{\sum_{t=1}^n \hat{C}_{ref}(t)\hat{C}_{test}(t)}{\|\hat{C}_{ref}\| \|\hat{C}_{test}\|}$$

The amplitude of the signal may vary, so that the representation must be size-invariant. The correlation coefficient complies with this requirement.

2.5. Arrhythmia discrimination with a machine learning approach

As illustrated by previous clinical trials, morphology algorithms combined with rhythm discriminators perform better than morphology algorithms alone. For that reason, two additional timing descriptors are added to the set of features: the cardiac frequency BPM and the standard deviation $StdRR$ of the RR intervals during the arrhythmia, estimated from a few cycles preceding the current beat.

A statistical classifier is subsequently trained on a set of arrhythmias. In order to reduce the complexity of the classifier (critical when the training set is small), feature selection is performed to discard non-informative features. First, features are ranked by Gram-Schmidt orthogonalization [5, 6]. Then, the random probe method [7] provides an estimate of the probability for a feature to be irrelevant, and allows keeping the probability of false positive (i.e. the probability of retaining a feature although it is not informative) below a predetermined limit. This results in the selection of p features.

The classifier is intended to divide the feature space into two regions, providing the equation $E(\mathbf{x}) = 0$ of the boundary surface, where \mathbf{x} is the feature vector whose components are the values of the selected features. The value of $sgn(E(\mathbf{x}))$ indicates whether the beat described by vector \mathbf{x} belongs to one class or the other. This procedure is an offline procedure and is done only once on a fixed training data set. Then, the sole equation of the boundary surface is downloaded into the ICD; the latter computes $sgn(E(\mathbf{x}))$ for each beat when an arrhythmia is detected.

A robust type of statistical classifier is used: a Support Vector Machine (SVM) classifier [8] with a gaussian radial basis kernel. In this case, the equation of the boundary surface is given by:

$$E(\mathbf{x}) = \sum_{i=1}^l \alpha_i \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}\|^2}{2\sigma}\right) + b = 0$$

where l is the number of support vectors; \mathbf{x}_i are the p -dimensional support vectors; α_i and b are parameters estimated by the statistical learning, and σ is a fixed parameter chosen by cross-validation during model selection. The arrhythmia is classified as SVT if $E(\mathbf{x}) < 0$, as VT otherwise.

3. Results

Electrograms from two different databases were used in this study. All arrhythmias were induced during electrophysiological studies. The sampling rate used for evaluation was 500 Hz.

Feature selection, model training and model selection were performed from a private database including 29 induced VT and 19 induced SVT from 32 patients (57 ± 15.5 years, 87.5% men, 50% Ischemic Heart Disease). With a risk of keeping a feature although it is irrelevant of 10%, *AngV*, *BPM*, *CN* and *StdRR* are selected among the five candidates. The procedure provided a classifier with 96.6% sensitivity (1 FN) and 94.7% specificity (1 FP) on that database. It was tested on the standard Ann Arbor Electrogram Libraries (AAEL): 64 VT and 7 SVT from 41 patients (61.9 ± 13.2 years, 82.9% men, 73.1% Coronary Artery Disease). On those fresh data, the classifier had 96.9% sensitivity (2 FN) and 85.7% specificity (1 FP). Results are shown in table 1.

It is important to notice that the entire arrhythmia databases could not be used because a spontaneous sinus rhythm was not available for every patient.

Table 1. Performances of the SVM classifier

	Sensitivity % (FN)	Specificity % (FP)
Training Set	96.6 (1)	94.7 (1)
Test Set	96.9 (2)	85.7 (1)

4. Discussion

4.1. Limitations

The problem of template updating was not addressed yet but we did check the posture-invariance of our representation. Recordings of NSR were performed for 9 patients in different postures (sitting, standing, supine, prone, left/right lateral decubitus). For one patient, the same recordings were performed 4 months later. These preliminary results show that our features are independent of posture and that template updating must be performed periodically. However, more recordings must be analyzed for substantiating those claims.

Another limitation is the fact that all arrhythmias used for validation were induced. Therefore, the criterion of sudden onset could not be evaluated.

Finally, there is, unfortunately, no available results on standard databases for comparing our algorithm to other morphology algorithms. However, the simultaneous use of two different types of EGM guarantees a gain of information compared to other algorithms.

4.2. Conclusion

The SPOT-based discrimination algorithm, applied to standard databases of tachyarrhythmias, demonstrated high sensitivity and specificity for VT/SVT discrimination. According to this study, velocity vectors seem to be sufficient for morphological characterization of SPOT curves.

The computational requirements of this algorithm make it appropriate for implementation in every ICD system within the framework of a prospective clinical evaluation.

Acknowledgements

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