Feasibility of Wavelet-Kernel Novelty Detectors for Identifying Ventricular Tachycardia

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Abstract

Hybrid wavelet-support vector classifiers have recently been suggested as efficient rate independent recognition scheme for endocardial electrograms (EEs) usable in implantable cardioverter defibrillators (ICDs). However, these schemes involve waveforms of the normal sinus rhythm (NSR) as well as the pathological rhythm.

In this study, we assess the feasibility of hybrid wavelet-kernel novelty detectors to discriminate between NSR and ventricular tachycardia (VT). These schemes only involve waveforms of NSR for the learning task.

Consecutive beats were selected as morphological patterns of NSR and VT. These patters were represented by their multilevel concentrations using a lattice structure based wavelet decomposition. The lattice angles were optimized for kernel based novelty detectors. In a blind analysis of the independent test set, our scheme outperformed the correlation waveform analysis with best fit alignment which is a well accepted method for arrhythmia recognition. However, the performance of wavelet-support vector classifiers was not achievable.

We conclude that wavelet-kernel novelty detectors are feasible for the rate independent identification of VTs. Our scheme is of a low complexity and suitable for efficient real-time implementations. However, further studies are needed to evaluate their performance in the clinical practice.

1. Introduction

Sudden cardiac death is a major public health concern worldwide. The implantable cardioverter–defibrillator (ICD) is an automated antitachycardia device and accepted to be the most effective therapy for preventing sudden cardiac death due to tachyarrhythmias [1]. Usually, the information of the endocardial electrogram (EE) utilized by an ICD is the heart rate. However, the rate is of limited reliability in some clinical situations. Although additional detection enhancements are used in third generation ICD–systems, inappropriate ICD therapy occurs in up to 13% of the patients who received such a device [2].

A major challenge for rate–algorithms used in these devices is the discrimination of ventricular tachycardia (VT) with 1:1 retrograde conduction from sinus tachycardia. Here time–domain methods based on template matching [3] or neural networks [4] can be used. A drawback of these methods is that the classification takes place in the original signal space where the dimensionality is often high and features being irrelevant for classification are under consideration. The superiority of wavelet decompositions before the classification over the direct application of the classifier on the original signal space has been shown, e.g., see [5]. Especially, the multilevel concentrations of adapted wavelet decompositions have recently proven to be suitable for arrhythmia detection [6, 7].

Recently, hybrid wavelet-support vector classifiers have been suggested as efficient rate independent recognition scheme for EEs usable in ICDs [8, 9]. However, these schemes rely on an optimal hyperplane classification in kernel feature spaces and involve waveforms of the normal rhythm as well as the pathological rhythm.

In this study, we introduce hybrid wavelet-kernel novelty detectors and assess their feasibility for the discrimination of normal sinus rhythm (NSR) from VT. These schemes only involve waveforms of the normal rhythm for the learning task. Therefore, they are especially advantageous for patients suffering from VT with multiple morphologies.

2. Methods

2.1. Data Segments

Bipolar EEs were obtained from the apex of the right ventricle using the distal pair of a 6-F quadripolar electrode catheter in 10 patients with inducible monomorphic VT. The EEs were amplified (HBV 20, Biotronik, Berlin, Germany), filtered (10–500 Hz), and digitized with 2kHz, 12 bit resolution (DT 2824–PGH, Data Translation, Marlboro, MA, USA). Data segments (DS) of 10 s duration

0276–6547/03 $17.00 © 2003 IEEE

Computers in Cardiology 2003;30:529–532.

were recorded during normal sinus rhythm (NSR) and VT. Consecutive beats were selected as morphological patterns of NSR and VT within a time–frame of 256ms.

2.2. Feature Extraction by the Lattice Structure

All two channel normalized paraunitary (NP) filter banks with at least one vanishing moment of the high pass filter can be parameterized by the lattice structure [10], where the polyphase matrix of the analysis bank $\mathbf{H}_{\mathrm{pol}}(z)$ has a decomposition of the form

$$\mathbf{H}_{\mathrm{pol}}(\mathbf{z}) = \left(\prod_{\mathbf{k}=\mathbf{0}}^{\mathbf{K-1}} \mathbf{G}(\vartheta_{\mathbf{k}})\mathbf{T} \right) \mathbf{G}(\vartheta_{\mathbf{K}}), \qquad (1)$$

where $\mathbf{G}(\vartheta_k) = \begin{pmatrix} \cos\vartheta_k & \sin\vartheta_k \\ -\sin\vartheta_k & \cos\vartheta_k \end{pmatrix}$, $\mathbf{T} = \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix}$, and finally the space $\mathcal{P}^K := \{\vartheta = (\vartheta_0, \ldots, \vartheta_{K-1}) : \vartheta_k \in [0, \pi)\}$ can serve to parameterize all two–channel paraunitary filter banks with at least one vanishing moment of the highpass filter, see [10, 11, 9] for detailed discussions. To emphasize this parameterization we will use the superscript ϑ later. The corresponding lattice structure implementation of the filter bank is shown in Fig. 1.

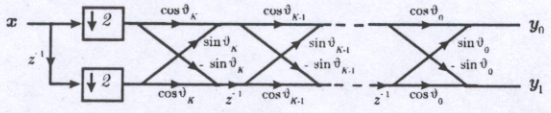

Figure 1. Lattice implementation of a two-channel NP analysis bank with input signal $\mathbf{x}$ and output signals $\mathbf{y}_0$ and $\mathbf{y}_1$.

For a fixed EE waveform $\mathbf{x}$ we define the function $\boldsymbol{\xi}_{\mathbf{x}} : \mathcal{P} \to \mathbb{R}^J$

$$\boldsymbol{\xi}_{\mathbf{x}}(\vartheta) = (\xi_1(\vartheta), \ldots, \xi_J(\vartheta)) = \left(\|\mathbf{d}_1^{\vartheta}\|_{\ell^p}^p, \ldots, \|\mathbf{d}_J^{\vartheta}\|_{\ell^p}^p \right)$$

and set $\boldsymbol{\xi}_i(\vartheta) = \boldsymbol{\xi}_{\mathbf{x}_i}(\vartheta)$ $(i = 1, \ldots, M)$. One may leave out some levels here if the carry noise or no substantial information.

This function carries the multilevel concentration of an EE waveform $\mathbf{x}$. Multilevel concentrations belong to a very low dimensional pattern space and are robust against local instabilities in time [9].

2.3. Novelty Detection

Suppose we are given set of M samples and a description is required. We try to find sphere with a minimum volume, containing all data in the hard case (no outliers in training set) and most of the data in the soft case (the training set may contain outliers). Instead of constructing this sphere in the original space, we construct it in a high dimensional feature space which is induced by a kernel of a reproducing kernel Hilbert space. All patters which lay outside the sphere are detected as novel instances which do not correspond to the learned class [12, 13]. The minimal sphere can be obtained by the following optimization problem:

$$\min_{\mathbf{a}\in\mathcal{F}_K, R\in\mathbb{R}, \mathbf{u}\in\mathbb{R}^M} R^2 + \lambda \sum_{i=1}^{M} u_j \qquad (2)$$

subject to

$$\begin{aligned} \|\Phi(\boldsymbol{\xi}_i(\vartheta)) - \mathbf{a}\|^2 &\leq R^2 + u_i \quad (i = 1, \ldots, M), \\ u_i &\geq 0 \quad (i = 1, \ldots, M). \end{aligned} \qquad (3)$$

where the $\Phi : \mathcal{X} \subset \mathbb{R}^J \longrightarrow \mathcal{F} \subset \ell^2$ denotes the feature map from the pattern space to kernel feature space, $\mathbf{a}$ is the center of sphere.

For the adaptation of multilevel concentration features, we apply genetic algorithms to optimize the lattice angels such that a training set of M NSR beats $\mathcal{A}(\vartheta) = \{\boldsymbol{\xi}_i(\vartheta)) \in \mathcal{X} : i = 1, \ldots, M\}$ is as compact as possible in the feature space.

3. Results

In Fig. 2 we have shown the specificity as well as the sensitivity distributed in the lattice parameter space for one patient as example (for filters of order 5 which we have used exclusively in this study). It is noticeable that a couple of angles corresponds to 100 % accuracy in this a posteriori analysis. Unfortunately, this result is hard to obtain in a blind analysis where we have to determine the unknown parameters a priori as we will see.

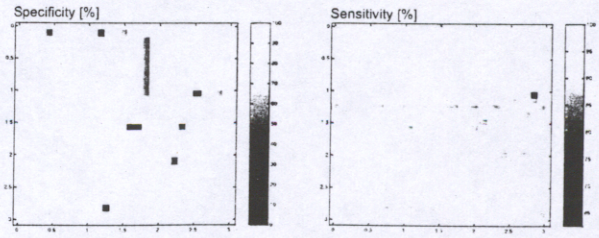

Figure 2. The specificity and sensitivity in the lattice parameter space.

For the blind analysis on the whole data set, we separate the total data set in a training set of 8 NSR beats and an independent test set of 32 beats (NSR: 16, VT: 16) for the individual patient of our group of 10 patients.

In Fig. 3 the specificity for the presented hybrid novelty detector (decompositions level 2 to 8 and a Gaussian kernel with standard deviation 1.0) as well as for the correlation waveform analysis with best fit alignment (CWABF) [3, 14] and the hybrid wavelet support vector classifier [8, 9] are shown. The sensitivity was 100% for the hybrid approaches and was used as constraint for the CWABF. This is of course a physiologically sensible choice.

It is noticeable that the hybrid novelty detector performs better than the CWABF but is inferior to the hybrid classifier. Nevertheless, it only involves the NSR signals. Therefore, it is more appropriate for patients suffering from VT with multiple morphologies as the binary support vector classifier.

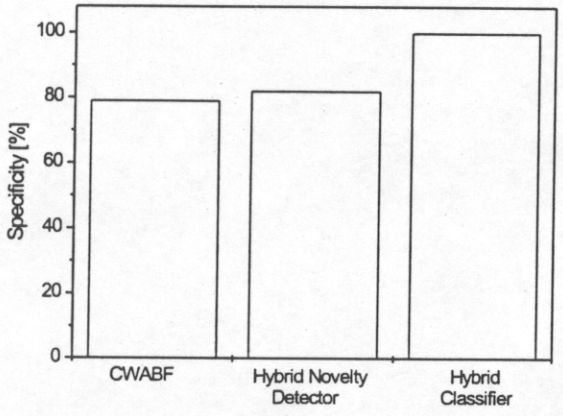

Figure 3. Performance of the CWABF, the hybrid novelty detector, and the hybrid wavelet–support vector classifier.

4. Conclusion

We have assessed the feasibility of hybrid wavelet–kernel novelty detectors in arrhythmias identification. Our scheme allows for an inclusion of prior knowledge about EE waveforms, namely local instabilities in time.

The presented scheme outperformed the CWABF but was inferior to hybrid wavelet–support vector classifiers.

We conclude that wavelet-kernel novelty detectors are feasible for the rate independent identification of VTs. Our scheme is of a low complexity and suitable for efficient real-time implementations in ICDs. However, further studies are needed to evaluate their performance in clinical practice. An increase in the performance seems to be achievable by better a priori adaptation criteria. Especially, the inclusion of more data in the learning processes seems to be promising and is easy to realize as only beats from the physiological rhythm are needed.

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