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Wavelet-based Features for Characterizing Ventricular Arrhythmias in Optimizing Treatment Options

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***Abstract*— Ventricular arrhythmias arise from abnormal electrical activity of the lower chambers (ventricles) of the heart. Ventricular tachycardia (VT) and ventricular fibrillation (VF) are the two major subclasses of ventricular arrhythmias. While VT has treatment options that can be performed in catheterization labs, VF is a lethal cardiac arrhythmia, often when detected the patient receives an implantable defibrillator which restores the normal heart rhythm by the application of electric shocks whenever VF is detected. The classification of these two subclasses are important in making a decision on the therapy performed. As in the case of all real world process the boundary between VT and VF is ill defined which might lead to many of the patients experiencing arrhythmias in the overlap zone (that might be predominately VT) to receive shocks by the an implantable defibrillator. There may also be a small population of patients who could be treated with anti-arrhythmic drugs or catheterization procedure if they can be diagnosed to suffer from predominately VT after objectively analyzing their intracardiac electrogram data obtained from implantable defibrillator. The proposed work attempts to arrive at a quantifiable way to scale the ventricular arrhythmias into VT, VF, and the overlap zone arrhythmias as VT-VF candidates using features extracted from the wavelet analysis of surface electrograms. This might eventually lead to an objective way of analyzing arrhythmias in the overlap zone and computing their degree of affinity towards VT or VF. A database of 24 human ventricular arrhythmia tracings obtained from the MIT-BIH arrhythmia database was analyzed and wavelet-based features that demonstrated discrimination between the VT, VF, and VT-VF groups were extracted. An overall accuracy of 75% in classifying the ventricular arrhythmias into 3 groups was achieved.**

***Index Terms*— Human Ventricular Fibrillation, Ventricular Tachycardia, Wavelet Analysis, Pattern Classification**

I. INTRODUCTION

A vast majority of patients suffering ventricular arrhythmias could be grouped into two major categories of ventricular tachycardia (VT) and ventricular fibrillation (VF). VT is an abnormally fast rhythm with organized electrical activity whereas VF is disorganized and lethal of the arrhythmias. Often the arrhythmia starts as an organized VT and degenerates into disorganized and lethal VF. The treatment options for these two types of arrhythmias are different. When a patient is diagnosed with VT, usually a catheterization procedure is performed to ablate the source re-entrant circuit while an implantable cardioverter-defibrillator (ICD) is administered for patients who are more prone to VF. Existing ICD devices analyze short periods of electrograms and apply VF/VT detection algorithms to chooses between pacing or shock in treating the arrhythmias [1]. ICDs have protected patients from VF for the last 30 years, however, they do suffer from problems associated with battery life-time (requiring periodic invasive procedures), lead wire issues, and external interferences [2]. In diagnosing patients for VT or VF treatment, there exist a small population of patients who might be experiencing arrhythmias in the overlap zones in between VT and VF. These patients might be suffering from arrhythmias that originate from predominately VT sources. If by analyzing their intracardiac electrogram data obtained from the ICD shock records an objective assessment can be made on the degree of affinity of the arrhythmias towards VT or VF, it might be of assistance for the clinician to decide on the treatment options (i.e., anti-arrhythmic drugs or undergo VT ablation procedure which is a long term better solution). As a first step in attempting to arrive at such an objective assessment the proposed work presents a methodology to classify or scale the range of ventricular arrhythmias into VT, VF, and the VT-VF overlap zones using surface electrograms.

Owing to the complex signal morphology that changes with time (especially the non-stationary nature of VF signals) it is a challenging issue to identify these overlap zones between VT and VF using simple time-domain or frequency domain signal processing tools. Hence, the proposed work uses wavelet analysis (a time-scale technique) to segregate the surface electrograms into VT, VF, and VT-VF signals. While there are many existing techniques that can detect VT and VF onsets, as discussed in [1], detecting the VT-VF overlap zone is challenging and is a novel approach in optimizing the choice of treatment. Wavelet analysis is attractive for this study as they are better suited for studying morphological (time-scale) patterns and are computationally less expensive and hence could provide near real-time feedbacks in assessing the ventricular arrhythmias [3]. There have been many studies performed where the Dominant Frequency, Frequency Bandwidth and peak height [4] as well as harmonic analysis [5] have been used to analyze VT/VF. Most of these works however use this information in predicting the shock outcome during resuscitation then for the above stated motivation of this paper. The block diagram of the proposed method is shown Figure 1. The paper is organized as follows, Section II

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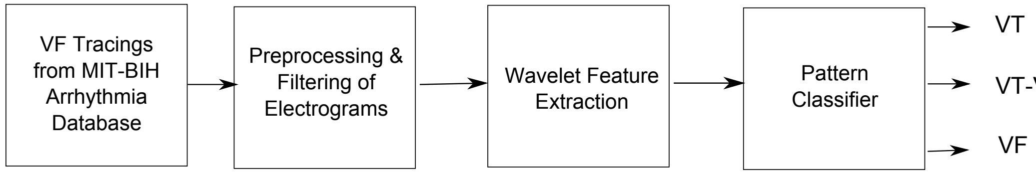

Fig. 1. Block diagram outlining the study

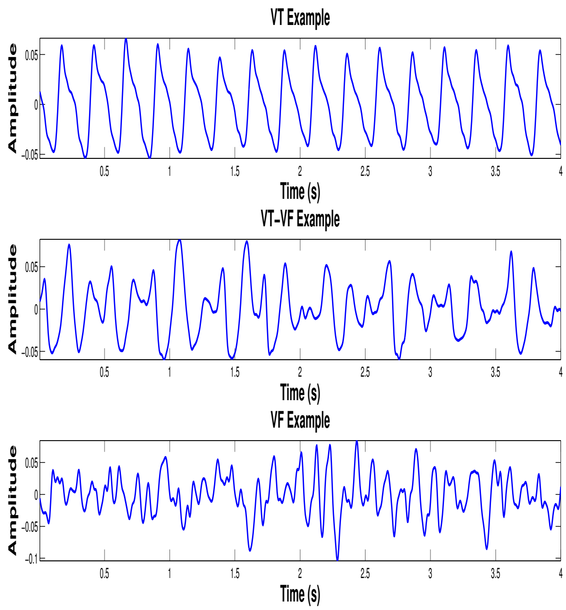

Fig. 2. Sample signals from VT, VT-VF, and VF groups

presents the details on the database and the methodology, Section III presents the results and discussions and the conclusions are provided in Section IV.

II. METHODS

A. Database

A database of 24 surface electrogram segments (4 seconds each) were extracted from the physiobank archive [6] found from the MIT-BIH Database. In particular 12 patients were used from the Creighton University Ventricular Tachyarrhythmia Database as well as the MIT-BIH Malignant Ventricular Arrhythmia Database. All signals were downsampled uniformly at 250 Hz and bandpass filtered between 0.3Hz to 30Hz [7]. The signals were normalized, which reduced the variance between the average signal levels while preserving the relative signal variation. Of these 24 signals, 8 VT, 8 VF, and 8 VT-VF (overlap zone) candidates were chosen by experienced electrophysiologists at the Toronto General Hospital, Toronto, Canada. This segregation served as the ground truth against which the proposed methodology was evaluated. Figure 2 shows a sample signal from each of the 3 group.

B. Frequency Analysis

Existing works have used frequency analysis to study VF electrograms and have extracted features such as dominant frequency, bandwidth, harmonicity for various applications [4]. Most of these works were motivated in predicting shock outcomes during cardiac resuscitation [8]. We performed our initial analysis using the 24 four second segments. Based on the observed differences in the signal morphologies between VT and VF (i.e. VT is predominately mono component, VF is multicomponent), features that highlight the spread of signal energy over frequency were considered. We extracted and studied the bandwidth and the harmonicity as an indicator for the organization levels of VT, VF, and VT-VF signals. While there was a good separation between the VT and VF signals as expected, the features performed poorly in discriminating the VT-VF signals from VF signals. This logically lead us to the joint time-frequency and time-scale techniques where the information is spread simultaneously over time and frequency/scale providing more flexibility in characterizing subtle time-varying signal characteristics.

C. Wavelet Analysis

Wavelet analysis have been applied to VF electrogram analysis by many existing methods including our previous works [9], [3] however in a different problem domain. In continuous wavelet transform (CWT), a signal $x(t)$ is expressed as a combination a scaled (dilated) and translated version of a mother wavelet (a small waveform satisfying certain properties) and is given by the following equation.

$$C_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a}\right) dt \qquad (1)$$

The coefficients associated with the scale a and translation b parameters then provide the signal information spread over specific range of scales and times. All the 24 signals from the database were filtered (0.3Hz to 30Hz) and energy normalized and decomposed into continuous wavelet coefficients using the complex Morlet wavelet. A complex wavelet was used as in order to analyze the temopral evolution of frequency [10]. The wavelet coefficients were normalized as a percentage of the total signal energy given by the following.

$$\hat{C}_x(a,b) = \frac{100 \times (|C_x(a,b)| \times |C_x(a,b)|)}{\sum(|C_x(a,b)| \times |C_x(a,b)|)} \qquad (2)$$

Scalograms using the normalized wavelet coefficients were constructed for each of the signals. Scalograms are 3D plots representing the energy distribution (z axis) of the signal over different scales (y axis) and time (x axis).

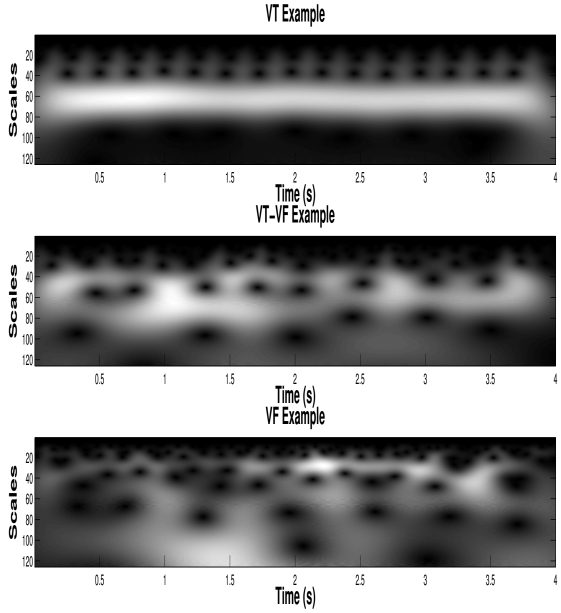

Fig. 3. Scalogram for a sample signals from VT, VT-VF, and VF groups

D. Wavelet Features

We analyzed the scalograms for the three groups of signals (VT, VF, and VT-VF) and observed that the energy distribution between VF and VT-VF having distinct patterns in terms of their energy spread over time and scale. VT was obviously different with energy concentrated on few scales over the entire time. Figure 3 shows the scalograms for a sample signal from each of the groups. The scalograms found in Figure 3 correspond to the arrhythmia signals found in Figure 2. In order to quantify the differences observed in the scalograms we extracted the following features.

Number of islands: Depending upon the organization levels of the electrograms, the signal energy is distributed over multiple components spread over time and scale. Hence a threshold was applied to retain the most significant coefficients i.e., only those islands (confined areas of energy distributed over time and scale) that accounted for the top 25% of the signal energy.

$$\frac{|\tilde{C}_x(a,b)|}{\sum\sum|\hat{C}_x(a,b)|} = 25\% \tag{3}$$

$\tilde{C}_x$ represents the peak coefficients that represent 25% of the signal energy. The threshold (δ) was then computed by obtaining the coefficient that will retain 25% of the signal energy.

$$D_{x,I_i}(a,b) = |C_x(a,b)| > \delta \tag{4}$$

D_{x,I_i} provided us with multiple components or islands of interest for which we extracted the time width of each component. The peaks of interest or islands of components (components that were found to be above the threshold) were obtained by using the Moore-Neighbor tracing algorithm proposed by [11].

Average time-width: This feature represents the width of a particular D_{x,I_i} with respect to time. The width signifies the duration of a particular component found from the signal. It would be expected that VT signals would have a much larger time width signal, due to the monotonic nature of the signal, VT-VF would have multi-component, yet relatively larger time width when compared to a VF signal.

Once the feature was extracted, a weighted mean was taken across all the components to arrive at an average time width which best represents the signal at hand. The time width was then obtained for all four second sample signal in the database.

III. RESULTS AND DISCUSSION

All the 24 signals were decomposed into wavelet coefficients and the features as explained in the previous section were extracted. These two features indirectly represented the number of components and average time width of the signal energy which in turn is related to the organization levels of the three group of signals. The box-plot of the features are shown in Figures 4-5. It is evident from the average time-width box-plot (Figure 5) that there are 3 distinct groups. VF occupied the compact and lowest of the average time-width range due to the fact that the signal energy is well spread in the time-scale plane resulting in islands of smaller area. VT-VF and VT had increasing average time-widths with VT being well separated from the other two. The discrimination demonstrated between the VT, VT-VF and VF that expresses the power of the proposed approach, even though there is some overlap between the three groups. The number of islands feature did not perform well, since a significant overlap could be observed between the VF and VT-VF group. So we used only the average time-width feature and performed an automated pattern classification.

A linear discriminant analysis (LDA) based classifier was used to perform the classification [12]. Since the database was small, we performed cross validation of the results using the leave-one-out method where the classifier is trained with all samples but one and the left out sample was used as a testing set. This is repeated by leaving out each of the sample as the testing set and training with the remaining samples. The results of all the iterations were then averaged to obtain the classifier accuracy. Table I shows the results obtained for the 3 group classification using the LDA based classifier and the leave-one-out method with the average time-width feature. An overall classification accuracy of 75% was achieved. The statistical analysis of the group mean indicated a significant difference ($p \leq 0.0007$).

From the Table I we could observe that 2 out of the 8 VF signals were misclassified into the VT-VF group and 2 out of 8 VT-VF signals were classified into the VF group. This is explained by the fact that medians of VF and VT-VF are

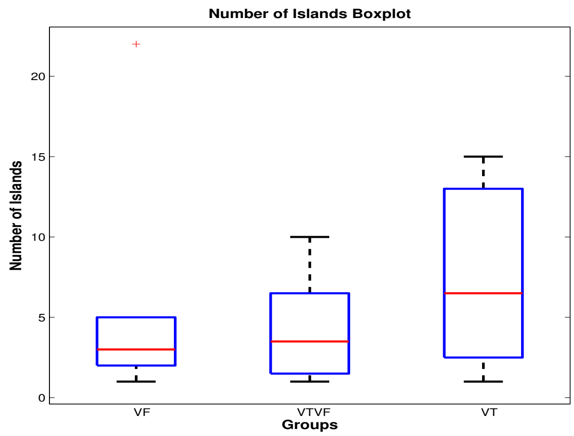

Fig. 4. Boxplot of the number of islands feature showing distribution for the 3 groups

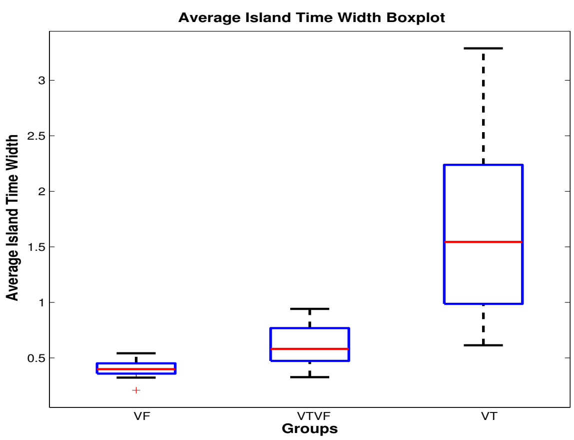

Fig. 5. Boxplot of the average time-deviation feature showing distribution for the 3 groups

closer resulting in a overlap which is naturally expected. Similarly 2 out of the 8 VT signals were classified into VT-VF group which is the closest neighboring group. We analyzed the misclassified signals of VF and VT-VF and observed them to contain portions of the the other group characteristics present in them (i.e., the misclassified VF signal contained organized structures and the vice versa for the misclassified VT-VF signals). Similarly the misclassified VT signals demonstrated temporal signal modulations which resulted in increased islands, explaining the migration of VT towards the VT-VF groups. The interesting information we gather from this analysis is that there is a natural transition from VT to VF, which could be defined as VT-VF.

TABLE I

CROSS-VALIDATED: LINEAR DISCRIMINANT ANALYSIS WITH LEAVE-ONE-OUT METHOD, % - PERCENTAGE OF CLASSIFICATION.

Method	Groups	VF	VT-VF	VT	Total
Cross-validated	VF	**6**	2	0	8
	VT-VF	2	**6**	0	8
	VT	0	2	**6**	8
%	VF	**75**	25	0	100
	VT-VF	25	**75**	0	100
	VT	0	25	**75**	100

IV. CONCLUSIONS AND FUTURE WORKS

We have presented a wavelet based methodology to discriminate the ventricular arrhythmias especially the VT-VF type signals which are in the overlap zone of VT and VF. Our analysis revealed that we can capture the subtle morphological changes between the three groups of signals using wavelet analysis. This will lead us to objectively asses the VT-VF type arrhythmias and compute their affinity towards VT or VF. The future work will investigate the proposed features on a larger database that also includes normal sinus rhythm episodes and explore other time-frequency/time-scale features in categorizing VF arrhythmias, that might lead to better focal therapies.

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