Phase Space Reconstruction Approach for Ventricular Arrhythmias Characterization

T. Rocha, S. Paredes, P. de Carvalho, J. Henriques, M. Antunes

Abstract - **Ventricular arrhythmias, especially tachycardia and fibrillation are one of the main causes of sudden cardiac death. Therefore, the development of methodologies, enable to detect their occurrence and to characterize their time evolution, is of fundamental importance. This work proposes a non-linear dynamic signal processing approach to address the problem. Based on the phase space reconstruction of the electrocardiogram (ECG), some features are extracted for each ECG time window. Features from current and previous time windows are provided to a dynamic neural network classifier, enabling arrhythmias detection and evolution trends assessment. Sensitivity and specificity values, evaluated from public MIT-BIH databases, show the effectiveness of the proposed strategy.**

I. Introduction

Cardiovascular diseases are the leading cause of death in developed countries. In the context of cardiovascular problems, the ventricular arrhythmias (VA) assume a very important role. In fact, their incidence in population can lead to situations of severe complexity and risk. Particularly, ventricular fibrillation (VF) is potentially fatal, being considered the main cause of sudden cardiac death. Moreover, VA evolve from simple premature ventricular contractions, which are in most situations benign, to ventricular tachycardia (VT) and finally to critical ventricular fibrillation episodes. Therefore, the development of methodologies able to detect not only the occurrence of these arrhythmias but also their evolution trends is of extreme importance for the conception of early prevention systems.

For ventricular arrhythmias detection several algorithms have been developed, enabling to distinguish between normal sinus rhythms (NSR) and VT/VF, as well as to distinguish between VT and VF. Some methods have employed sequential hypothesis testing [1], autoregressive modeling of ECG [2], time domain and frequency domain features [3], and Wavelet analysis [4]. Other works have investigated template matching algorithms to distinguish NSR from VT and NSR from VF [5]. For discrimination between VT and VF, rate and irregularity analysis, correlation waveform analysis, spectral analysis and time-frequency analysis have been employed. Neural networks and fuzzy systems have also been applied to VT and VF detection [6].

In the last years there has been an increasing interest in applying techniques from the domains of non-linear analysis and chaos theory, to the study of ECG signals and, in particular, for arrhythmias detection. As a consequence, new signal classification approaches have emerged. Some of these approaches used features like correlation dimension, Lyapunov exponents, fractal dimension, entropy and complexity measure, to characterize arrhythmias [7], [8]. Other approaches used features extracted from the phase space reconstruction (PSR) [9], [10], and others followed a modeling approach based on PSR [11], [12].

For ventricular arrhythmias prediction, one of the greatest challenges in cardiology, few works have been developed. Actually, some features can be extracted from the ECG which give an indication of VF increased risk, therefore, of the arrhythmia trends evolution [13]. One of these features is the heart rate variability (HRV). M. Baumert *et al*. [14] used HRV measures for short-term forecasting of VT. Wessel *et al.* [15], also used HRV analysis and showed that a loss of short-term variability precedes the onset of a VT. Thong and Goldstein [16] proposed the "*vagal fatigue index*" feature, extracted from HRV, and showed that this feature is an efficient predictor of sustained VA. Following different approaches, other solutions have been proposed. Minija *et al*. [17] used neural networks (NN) for VF prediction and classification, based on ST segment analysis. Jekova *et al*. [18] used modified K-nearest neighbors algorithm for the prediction of VF and VT.

Although the detection problem has been extensively addressed with satisfactory results, few achievements have been made on the trends of arrhythmias evolution. In this work an integrated strategy for VA characterization is proposed, dealing simultaneously with their detection and trends evolution. Based on a PSR methodology, some appropriate features are extracted for each ECG time window. The decision module consists of a dynamic neural network, which uses features from current and previous time windows, enabling the detection of arrhythmias evolution trends. Moreover, the proposed strategy presents a low complexity, thus suitable to be incorporated into personal health (*phealth*) systems.

The paper is organized as follows: in the section 2 the proposed methodology is described. In section 3 some validation results using MIT-BIH databases are presented and, finally, in section 4, some conclusions are drawn.

This work was supported by MyHeart EU project (IST-2002-507816) and CISUC (Center for Informatics and Systems of University of Coimbra).

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II. PROPOSED METHODOLOGY

A. Scheme

Figure 1 depicts the schematic diagram of the strategy followed in the current work. The input consists of the discrete ECG signal, considering usual pre-processing techniques, in particular normalization and baseline removal. The algorithm is evaluated by windowing segments of the ECG under analysis. The followed strategy considers, for each window, a phase space reconstruction procedure. Then, from the obtained two-dimensional trajectory, some relevant features are extracted. Features from current and previous windows are provided to a time delay neural network classifier (TDNN), enabling the characterization of VA. Due to its ability to incorporate time, the neural structure is effective to capture the dynamics of the arrhythmias evolution. For the decision system four features have been considered. The first, spatial filling index, has been successfully employed to distinguish NSR from VT and VF [5], [10]. The other three features have been developed within this work, exploiting the distribution characteristics of the reconstructed phase space trajectory.

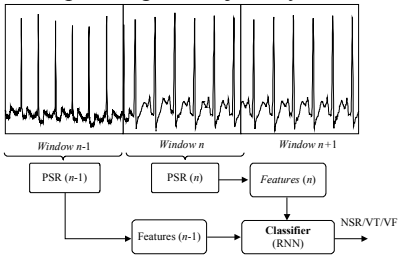

Figure 1. VA arrhythmias characterization scheme.

B. Phase Space Reconstruction

Phase space reconstruction is a technique used to represent the non-linear characteristics of a dynamic system, consisting of a simple plot of signal time-lagged vectors [19]. Considering the signal as a time series $x(1)$, $x(2)$, …, $x(n)$, where n is the number of points, the time lagged vectors of the multidimensional phase space are determined according to (1),

$$Xi = \left[x_i \quad x_{i+\tau} \quad \ldots \quad x_{i+(d-1)\tau} \right] \qquad i = 1 \ \ldots \ n-(d-1)\tau \qquad (1)$$

where τ is the time delay between the points of the time series, and d is the embedding dimension which corresponds to the number of phase space coordinates.

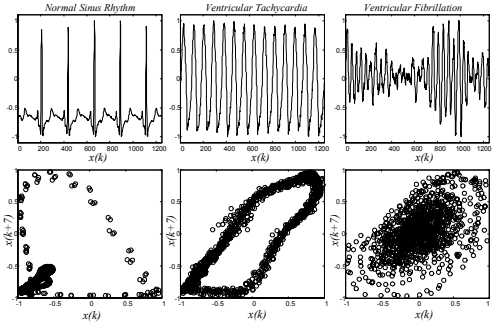

Figure 2. PSR for NSR, VT and VF signals.

The PSR is carried out by plotting the original signal against the delayed versions of itself. The present work uses a two-dimensional PSR (d=2) and a time delay τ equal to 7, which was established as a suitable choice in the case of ECG signals [19]. As it can be seen in Figure 2, the PSR (τ=7) has the capacity to distinguish between the three types of signals: NSR, VT and VF. In fact, the shape of the trajectories is clearly distinct for each case.

C. Features Extraction

1. Spatial filling index

The first step to determine the spatial filling index is to reconstruct a two-dimensional phase space of the ECG signal. Given the ECG signal $x(1)$, $x(2)$, …, $x(n)$, the A matrix is obtained as (2).

$$A = \begin{bmatrix} x(1) & x(1+\tau) \\ x(2) & x(2+\tau) \\ \ldots & \ldots \\ x(n-\tau) & x(n) \end{bmatrix} \qquad (2)$$

Dividing each element (i,j) of matrix A by $q=max|x(k)|$ $(1 \le k \le n)$, a normalized matrix B is obtained. In two dimensions, the phase space plot corresponding to B matrix ranges from -1 to +1 on either axis. This phase space area is divided into small square areas of size $R \times R$, originating $N=2/R$ grids (being $2/R$ an integer number). The phase space matrix C (dimension $R \times R$), is determined with each element $C(i,j)$ equal to the number of phase space points falling into the grid $g(i,j)$. A new matrix P is obtained, dividing each element of C by M, given by (3).

$$P = \frac{1}{M} C, \quad M = \sum_{i,j=1}^{N} C(i,j) \qquad (3)$$

Each element $P(i,j)$ represents the probability that a phase space point falls into the grid $g(i,j)$. Squaring each element of P, the R matrix is determined. Being S the sum of all points of R, the spatial filling index (η) is finally obtained as (4).

$$\eta = \frac{S}{N^2} \qquad (4)$$

2. Standard deviation of the curve of C column averages

Taking the average of each column of C matrix, a curve characterizing the distribution of points in the phase space is obtained, inspired by the idea of Radon transform [20]. Figure 3 depicts examples of these curves, for the NSR, VT and VF signal types, revealing their discrimination capacities. The second feature is the standard deviation of the curve.

3. Area of the curve of C column averages

The third feature is the percentage of area in the extremities of the curve of C column averages. From Figure 3, it is clear that the area under this curve can be used to distinguish between ECG signal types. As seen, for VT signals, the area under the curve near the extremities is higher than in the other cases.

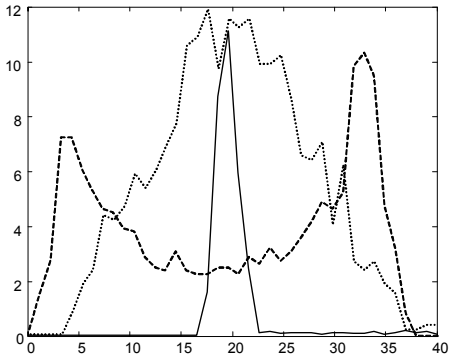

Figure 3. C matrix column averages: NSR (—), VF(…), VT(---).

4. Ellipse based feature

The fourth feature is based on the phase space points distribution. As it is depicted by Figure 2, in the NSR case, the distribution of the points is concentrated on a center; in the VT case, the points are grouped in an elliptic shape; in the VF case, the points are randomly distributed (by the interior, the border and the exterior of the ellipse). The number of points in each one of these regions (center, border and remaining) is used to discriminate the signals. Given a representation of a signal in the phase space the method proposed by [21] is used for fitting ellipses to scattered data.

D. Classifier

The classifier consists of a dynamic neural network (time delay neural network), where the number of hidden neurons has been determined experimentally (10): small enough for fast training and generality, but sufficiently large to give adequate accuracy. The parameters (weights and bias) that characterize the NN, have been trained using the Levenberg Marquardt algorithm [22].

III. VALIDATION RESULTS

All the functionalities related to databases access, signal processing and validation results were implemented in Matlab [23]. The input consists of the discrete ECG signal (250 samples per second), followed by a normalization and a baseline removal process. The algorithm was evaluated by windowing five seconds segments.

A. MIT-BIH Databases and Validation Parameters

To validate the detection algorithms public databases were used: MIT-BIH Malign Arrhythmia Database (MVA) and Creighton University Ventricular Tachyarrhythmia Database (CVT) [24]. To estimate the quality of the detection algorithm, the sensitivity (SE) and the specificity (SP) have been evaluated.

The algorithms effective validation regarding arrhythmias evolution trends, was not possible to assess once there are no available databases to perform this task. To characterize the trends evolution, the variation of the features extracted from PSR over the time was correlated with the transition between arrhythmias of different natures.

B. Training

Regarding validation, a data base of 51 signals was created. It contains the three ECG signal classes (table I) and the extracted features indicated. For MVA and CVT data sets, the number of windows was 420 (35 minutes) and 102 (8.5 minutes), respectively. The data base was randomly divided into training and validation data sets. As mentioned, the TDNN was trained using the Levenberg Marquardt algorithm and the number of hidden neurons was determined experimentally.

TABLE I
ECG DATA SET

Signal	NSR	VT	VF	*Signal*	NSR	VT	VF
MVA				**CVT**			
#418	420	0	0	#009	90	0	12
#419	420	0	0	#010	63	0	39
#420	361	59	0	#011	74	0	28
#421	336	84	0	#012	102	0	0
#422	380	40	0	#013	90	0	12
#423	328	92	0	#014	102	0	0
#424	420	0	0	#015	81	0	21
#425	414	6	0	#016	79	0	23
#426	276	13	131	#017	93	0	9
#427	242	178	0	#018	96	0	6
#428	408	12	0	#019	93	0	9
#429	417	3	0	#020	49	0	53
#430	137	72	211	#022	79	0	23
#602	339	81	0	#023	81	0	21
#605	413	7	0	#024	88	0	14
#607	387	33	0	#025	94	0	8
#609	418	2	0	#026	86	0	16
CVT				#027	97	0	5
#001	43	0	59	#028	99	0	3
#002	102	0	0	#029	75	0	27
#003	93	0	9	#030	26	0	76
#004	47	0	55	#031	99	0	3
#005	84	0	18	#032	92	0	10
#006	80	0	22	#033	84	0	18
#007	36	0	66	#034	89	0	13
#008	85	0	17	#035	96	0	6

C. Results and discussion

The performance of the method, regarding arrhythmias detection is presented in table II. The detection results are superior when considering independently each data base. Applied to all databases the method has a sensitivity of 92.3% and specificity of 98.2%, revealing its capacity to perform detection tasks.

TABLE II
CLASSIFICATION PERFORMANCE

	MVA		CVT		
	VT	VF	VT	VF	**ALL**
Episodes	682	342	0	701	**1725**
Sensitivity	92.6	97.6	n.a.	92.8	**92.3**
Specificity	94.3	99.2	n.a.	96.4	**98.2**

Figure 4 shows the time evolution of the ECG and related features, for CVT data base (record #001). As can be seen, the features clearly show the transition from a NSR to a VF. Figure 5 shows a comparable situation, in the presence of a transition from a NSR to a VT (MVA data set, record #420).

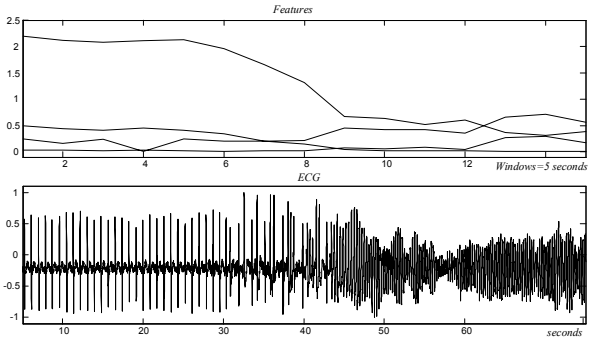

Figure 4. Features and ECG signal; transition from a NSR to a VF.

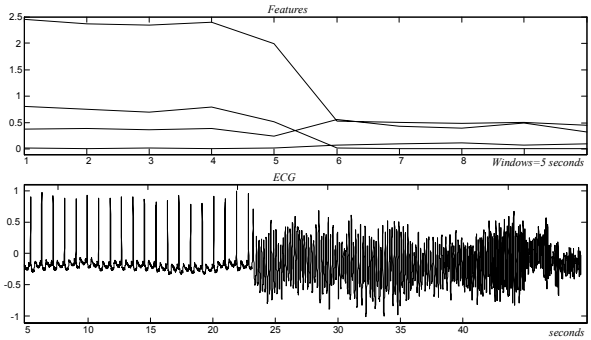

Figure 5. Features and ECG signal; transition from a NSR to a VT.

Although some indicators can be captured from the above simulations, in the future, these evolution trends will be investigated and combined with dynamic modeling tools (state space model, for instance). The final goal will be the arrhythmias trend prediction and the risk stratification assessment, thus a step forward with respect to current models related to arrhythmias characterization.

IV. CONCLUSIONS

In this paper a strategy for VA characterization was proposed, using a phase space reconstruction of the ECG, from where some features were extracted. Features from current and previous time windows were provided to a dynamic neural network classifier, enabling the detection and characterization of arrhythmias trends evolution. The validation of the algorithms was based on public MIT-BIH databases.

The main goal was to introduce a preliminary strategy able to deal with the dynamic characterization of arrhythmias and, consequently, for risk stratification and early diagnosis issues. Currently, this topic is of fundamental research in the context of preventive tools of next generation *phealth* systems. However, there are theoretical and experimental challenges, which are potential to further research. Future work will be mainly directed to the development of a multi-parametric analysis system, incorporating other relevant aspects in the decision system, namely HRV parameters, non-linear and complexity measures.

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