Are Nonlinear Ventricular Arrhythmia Characteristics Lost, as Signal Duration Decreases?

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Abstract

A novel, nonlinear, phase space based method to quickly and accurately identify life-threatening arrhythmias is proposed. The accuracy of the proposed method in identifying sinus rhythm (SR), monomorphic ventricular tachycardia (MVT), polymorphic VT (PVT), and ventricular fibrillation (VF) for signals of at least 0.5s duration was determined for six different ECG signal lengths. The ECG recordings were transformed into a phase space, and statistical features of the resulting attractors were learned using artificial neural networks. Classification accuracies for SR, MVT, PVT and VF were 93-96, 95-100, 79-91, and 81-88%, respectively. As expected, classification accuracy for the proposed method was essentially equivalent for ECG signals longer than 1s. Surprisingly, classification accuracy for this new method did not degrade for 0.5s ECG signals, indicating that even such short duration signals contain structures predictive of rhythm type. The phase space method's classification accuracy was higher for all segment durations compared to two other methods.

1. Introduction

In the US, hundreds of deaths occur daily due to ventricular fibrillation (VF) [1]. Automatic cardioverter defibrillators (ACD), both internal and external to the body, have proven to be effective therapy for terminating such ventricular arrhythmias. There is evidence [2] to suggest that the sooner electronic therapy is delivered following the onset of VF, the greater the success of terminating the arrhythmia, and thus, the greater the chance of survival. Before delivering shock therapy, an ACD must automatically and accurately identify a cardiac rhythm as life threatening.

We attack the problem of rapid, accurate, and automatic cardiac rhythm identification with a novel combination of dynamical systems methods, stochastic models, and machine learning techniques. We form phase spaces from ECG signals and construct statistical features based on the natural measure of the trajectories in these phases spaces. The resulting features serve as input to a set of artificial neural networks (ANNs), which are trained to recognize the four cardiac rhythms studied here. This is based on our previous work in heart arrhythmia classification [3], motor fault identification [4], and speech recognition [5].

We compare the new approach to two popular methods [6] for heart rhythm classification used in implantable devices – a heart rate estimate and a gradient probability density function (PDF). Other approaches [6] to cardiac rhythm classification include frequency based signal processing techniques such as autocorrelation, spectral analysis, time-frequency distributions, coherence analysis, and heart rate variability. To insure sufficient frequency resolution, these algorithms typically require five or more seconds of data to classify the rhythms. Our interest is in developing a method that can classify heart rhythms in less than five seconds. Such short duration classification may be important to predicting onset and termination of arrhythmias.

Although there is little work in the application of phase space techniques to cardiac rhythm identification, Kaplan [7, 8] modeled heart arrhythmias with phase space attractors in an attempt to show that heart rhythms are chaotic. Bettermann and VanLeeuwen [9] have demonstrated that the physiological changes in heart beat complexity between sleeping and waking states are not a simple function of the heart beat intervals. Rather, the changes are related to the existence of phases in the heart period dynamics.

In the remainder of this paper, we discuss the data set used; explain the new method and the comparative methods; and present comparative classification accuracy results for six different ECG signal durations. We then discuss the implication of these results and point to further research directions.

2. Data

Simultaneous recordings of surface leads II and V1 of a normal 12 lead ECG were obtained from six patients during EP testing and/or automatic implantable cardioverter/defibrillator (AICD) implementation. Each of these patients exhibited sustained episodes of MVT, PVT, VF, and/or SR rhythms. Two independent cardiac electrophysiologists classified the ECG recordings in 4s epochs. Their initial classifications were in agreement for 80% of the epochs. After consultation, they concurred on the remaining 20%. Samples of the four different rhythm morphologies are illustrated in Figure 1.

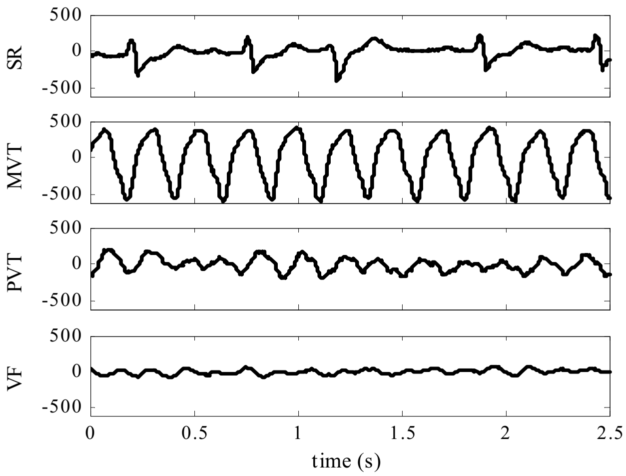

Figure 1. Example recordings rhythm morphologies: SR, MVT, PVT, and VF.

The recordings were antialias filtered with a cutoff frequency of 200Hz and subsequently digitized at 1,200Hz. In this study, the 4s classified data is subsequently segmented into 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0s contiguous intervals of SR, MVT, PVT, or VF rhythms. Each data segment is zero-meaned.

3. Method

The proposed method is a time domain approach that uses features based on the natural measure of the phase space trajectory. Both linear and nonlinear characteristics of the signal are maintained through the construction of such a phase space. Examples of the resulting phase spaces are illustrated in Figure 2. We will refer to the pattern traced out in the phase space as the attractor, although the term attractor has a mathematical foundation [10], it is common in the literature to refer to the trajectories formed from data as attractors when their behavior exhibits steady state characteristics.

3.1. Phase space feature generation

A two-dimensional phase space is constructed by plotting the II and V1 ECG recordings against each other as illustrated in Figure 2. Visually, the resulting patterns in the phase space can be differentiated. The goal is to learn and then automatically identify these patterns. We define statistical features of the attractor, which is normalized using patient dependent out-of sample SRs, based on the natural measure and the standard deviation distance of the phase space points from the origin.

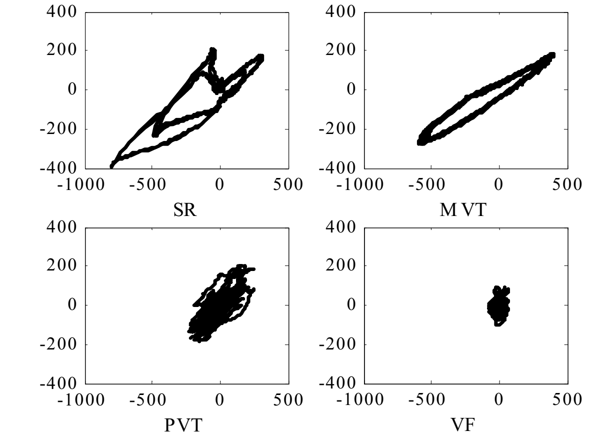

Figure 2. Generated two-dimensional phase space for examples of SR, MVT, PVT, and VF. Note the different rhythms occupy a different region of the phase space.

The phase space is partitioned into 100 feature regions, 10 on each axis. Each axis of the phase space is partitioned into 10 equally filled histogram strips. The strip boundaries of each lead are then used to define the boundaries of the 100 bins. Figure 3 shows this partitioning for an SR rhythm.

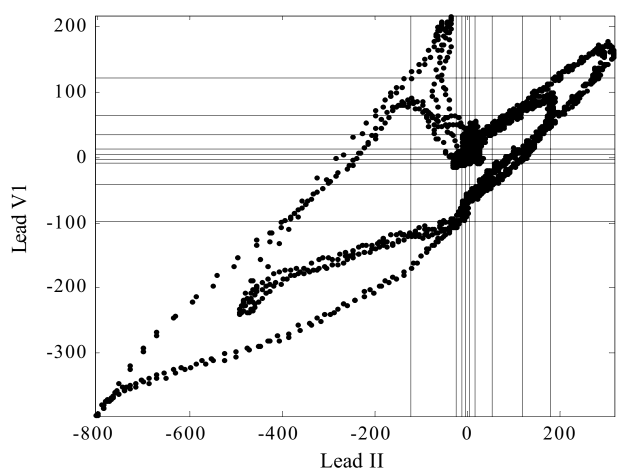

Figure 3. Example of feature bin boundaries for a 2.5s recording of sinus rhythm

3.2. Attractor learning

The attractors are learned using ANNs with 101 inputs, one output, and two hidden layers. Four (one for each rhythm type) ANNs were trained using the Levenberg-Marquardt algorithm in MATLAB. The inputs to the ANNs were the frequency of data points in each feature bin and the standard deviation distance of the phase space

Table 1 – Confusion Matrices a) phase space classification 0.5s, b) phase space classification 3.0s, c) heart rate classification 0.5s, d) heart rate classification 3.0s, e) gradient PDF classification 0.5s, and f) gradient PDF classification 3.0s.

a)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	572	2	14	12	95.3%
MVT	2	252	8	1	95.8%
PVT	18	9	198	27	78.6%
VF	9	1	19	213	88.0%

b)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	92	2	1	2	94.9%
MVT	0	40	1	0	97.6%
PVT	0	4	31	2	83.8%
VF	1	0	5	30	83.3%

c)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	415	68	50	67	69.2%
MVT	4	11	202	46	4.2%
PVT	25	19	60	148	23.8%
VF	39	22	73	108	44.6%

d)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	55	31	11	0	56.7%
MVT	0	5	32	4	12.2%
PVT	4	12	18	3	48.7%
VF	1	16	16	3	8.3%

e)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	473	80	33	14	78.8%
MVT	66	125	44	28	47.5%
PVT	0	29	106	117	42.1%
VF	1	13	73	155	65.0%

f)	Classified As				
	SR	MVT	PVT	VF	Accuracy
SR	88	9	0	0	90.7%
MVT	6	23	3	9	56.1%
PVT	0	6	13	18	35.1%
VF	0	5	5	26	72.2%

points from the origin. Leave-one-out cross-validation [11] was used in the training and testing of the ANNs. Classification was determined by the *argmax* (maximum output) of the individual ANNs.

3.3. Comparative analysis classification

The new method is compared to a heart rate based approach and a gradient PDF technique [6]. All methods are applied on a segment-by-segment basis.

The heart rate approach is used in most AICDs to discriminate rhythms [12]. First, each 0.5 to 3.0s segment is lowpass filtered at 50Hz to remove any 60Hz noise. Next, an amplitude detection threshold of 60% of the maximum amplitude is set. The time between threshold crossings, including a 120ms blanking period, is determined. The heart rate is calculated as the average time between crossings. If only one crossing is detected, the segment is classified as SR. Otherwise, the rhythms are classified as VF for heart rates $<$ 200ms, PVT $<$ 400ms, MVT $<$ 600ms, and SR $\geq$ 600ms [12, 13].

For the gradient PDF method, each data segment is downsampled to 120Hz. The absolute magnitude of the segment is normalized to 1000 units. Using the central difference estimator, the slope is determined for each data point. The percentage of slopes between ±25 units is determined for each segment and the PDF (mean and variance) of such slopes for each rhythm type is calculated. A maximum likelihood classification for each test rhythm is made.

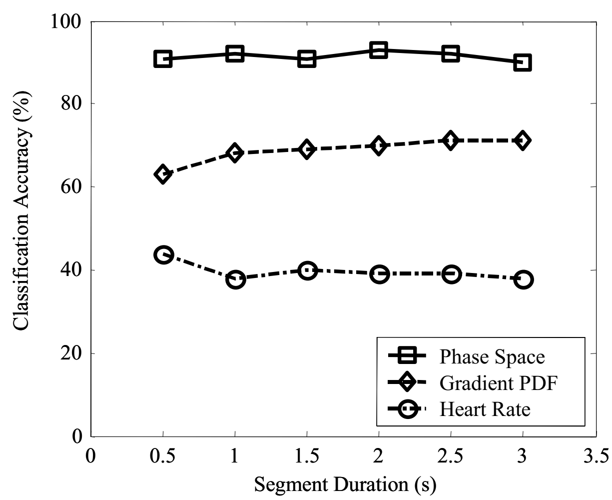

Figure 4. Comparative accuracy results

4. Results

For the phase space method, the overall classification accuracies were 91, 92, 91, 93, 92, and 90% for 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0s ECG segments, respectively. Classification accuracies for SR, MVT, PVT and VF were 93-96, 95-100, 79-91, and 81-88%, respectively. As expected, the largest misclassification occurred between the PVT and VF signals.

The comparative overall accuracy for all three methods is shown in Figure 4. Table 1 contains the confusion matrices for 0.5 and 3.0s durations. For the heart rate method, the largest misclassifications occurred with MVT and VF being classified as PVT. For the gradient PDF method, the largest misclassifications were PVT rhythms being classified as VF.

5. Discussion

The goal was to determine the shortest time interval for which ventricular arrhythmias could be accurately classified using the phase space method. With average SR heart rates of 87 beats per minute, many of the 0.5s SR segments did not span a full heartbeat. Thus, it was expected that the classification accuracy for segments of less than 1.0s would degrade. However, we found that the accuracy for 0.5s segments to be comparable to the accuracy for all other segment durations. This suggests that nonlinear ventricular arrhythmia characteristics are not lost as signal duration decreases – at least for the proposed method and for signals of 0.5 to 3.0s in duration. Additionally, the phase space method's classification accuracy was higher for all durations as compared to the heart rate and gradient PDF approaches.

While identifying characteristics unique to various arrhythmias is interesting from a signal processing point of view, our ultimate goal is to improve therapy as well as better understand mechanisms leading to the onset and termination of arrhythmias.

Currently, high-energy shock therapy is a proven method for terminating VF. However, these high-energy shocks have been found to be harmful to the myocardium [14]. Due to the hemodynamic consequences that accompany the onset of VF, a preventive approach for treating ventricular arrhythmia is preferable, such as low-energy shock, pacing regimens and/or drug administration to prevent the fatal arrhythmia from occurring in the first place. The sooner therapy can be delivered following the onset of VF, the greater the probability of terminating VF [2]. However, we do not propose to use the classification scheme described in this paper to shock an arrhythmia after 0.5s. Instead, we suggest that the proposed algorithm may be used to increase the confidence of automatic classification schemes by accumulating short continuous classifications. These phase space methods might also be useful in predicting the onset and/or termination of arrhythmias.

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