Rhythm Classification Using Reconstructed Phase Space of Signal Frequency Sub-bands

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Abstract

A preliminary study in the use of frequency sub-bands with reconstructed phase spaces (RPS) to distinguish between normal and abnormal atrial activity in an attempt to separate the atrial activation components from the ventricular activation components is presented.

Two-second ECG Holter recordings of sinus rhythm (SR), atrial flutter (AFL), atrial fibrillation (AF), supraventricular tachycardia (SVT) and ventricular tachycardia (VT) were filtered into four sub-bands (0.5-5, 5-10, 10-20, and 20-32Hz) and embedded into a 3-dimensional RPS. Gaussian mixture models of the sub-banded RPS were learned

The models learned over the 5-10 and 10-20Hz bands had the best overall classification accuracy. SR was best classified in the 5-10Hz band with no false positives in the 10-20Hz band. AFL's highest classification was in the 10-20 and 20-32 Hz bands, AF in the 0.5-5Hz band, SVT in the 5-10 Hz band, and VT in 10-20 Hz band. When the atrial arrhythmias were folded together into one class, the highest overall classification accuracy increased from 79% in the 10-20 Hz band to 92% in the 5-10 Hz band.

These results are promising for the use of sub-banded RPS in the classification of atrial arrhythmias from surface ECGs.

1. Introduction

It is estimated that over 3.9 million Americans experience some sort of cardiac arrhythmia. Although not all are life threatening, the American Heart Association estimated that 5% of US annual deaths are attributed to arrhythmias. Atrial fibrillation (AF) and atrial flutter (AFL) are the most common arrhythmias, effecting more than 2 million people and causing more than 50,000 deaths annually in the US. Many of these deaths are attributed to strokes caused by the development of systemic arterial emboli [1]. An important clinical application for atrial arrhythmia detection is following cardiac surgery, when patients are monitored for episodes of AF to minimize the risk factor of stroke [2]. In this critical care monitoring, robust and accurate arrhythmia identification is important in order to treat the arrhythmia promptly and correctly.

Many of the current techniques for classification are morphological based discrimination schemes that require accurate detection of the presence and temporal placement of atrial and/or ventricular activations. In unipolar intracardiac electrograms, such detections are fairly simple, as there is little far-field effect from the adjacent chamber. Much research has been done to discriminate supraventricular tachycardias (SVT) from ventricular tachycardias (VT) in implantable devices [3-5]. However, not many patients have intracardiac leads or implantable devices, therefore surface ECGs are used to diagnosis arrhythmias.

Surface ECGs and/or Holter recordings help a physician diagnose cardiovascular disorders in a patient. Holter recordings are prescribed when a patient is experiencing intermittent arrhythmias, and the physician would like to capture the events. Two of the problems with ECG and Holter recordings are that the atrial component of the heartbeat may be small amplitude in surface leads, and AF may be missed in a noisy signal [6].

This is a preliminary study investigating the discrimination of atrial arrhythmias, such as, AF, AFL and SVT from sinus rhythm (SR) and VT using Holter ECG recordings. A novel approach using frequency sub-bands and reconstructive phase space (RPS) [7-10] is used to detect different rhythms. The goal is to separate out the atrial components of an ECG signal to be able to automatically differentiate rhythms that are of atrial origin from ventricular origin.

2. Data and methods

Data collected from lead 1 of Holter recordings of 14 patients experiencing continuous episodes of SR, AF, AFL, SVT, and VT were used in this study. The sampling rate of the data was 128 Hz. Cardiac Evaluation Center (Milwaukee, WI) annotated the Holter recordings. The data was split into 256-point (2-second) segments for classification. There were 20 examples of each rhythm type.

Classification of the data was done using two methods sub-banded RPS and the gradient probability density function [11]. The results from both methods were compared.

2.1. Sub-bands

Research has shown that the majority of energy of atrial activation occupies different frequency bands than ventricular activation [4, 12]. Thus the separation of the data into different frequency bands may allow for better discrimination of rhythms that activated in the atria or ventricles.

The data was forward and backward filtered using 100-point FIR filters to divide the signal into four frequency sub-bands, 0.5-5, 5-10, 10-20 and 20-32Hz. These frequency sub-bands were selected based on studies by Thakor, *et al.* [12] in which they determined the relative power spectra of the ECG, QRS complexes, P and T waves. The minimal frequency cut-off, 0.5 Hz, was chosen to remove baseline wandering without removing diagnostic cardiac information.

2.2. Reconstructed phase space

A reconstructed phase space is a multidimensional embedding of lagged points of a signal. It is topologically equivalent to the original dynamical system provided that the embedding dimension is greater than twice the number of states in the original system [7-9]. A time delay RPS of dimension d and time lag τ is defined by the trajectory matrix:

$$X = \begin{bmatrix} x_{1+(d-1)\tau} & \cdots & x_{1+\tau} & x_1 \\ x_{2+(d-1)\tau} & \cdots & x_{2+\tau} & x_2 \\ \vdots & & \ddots & \\ x_{N+(d-1)\tau} & \cdots & x_{N+\tau} & x_N \end{bmatrix}$$

In this study, the sub-banded signals are segmented into two-second intervals. Each of these filtered segments is zero-meaned, radially normalized, and embedded into a 3-dimensional RPS with a lag of 20 points. The 20-point lag was determined from the average auto-mutual information of SR signals. The embedding dimension was chosen empirically.

A Gaussian mixture model (GMM) models the probability distribution of a statistical variable. In this study, GMMs were used to model the RPS density for different rhythm classes. The probability distribution of the i^{th} rhythm class with M mixtures is defined as

$$\hat{p}_i = \sum_{m=1}^{M} w_{im} \mathcal{N}(x; \mu_{im}, \Sigma_{im}),$$

where μ_{im} is the mean and Σ_{im} is the covariance matrix of the mixture m. An example of a GMM is shown in Figure 1, illustrating a 10-mixture model learned over a two-dimensional sinus rhythm RPS. The mixtures are represented by elliptical contours of equal probability.

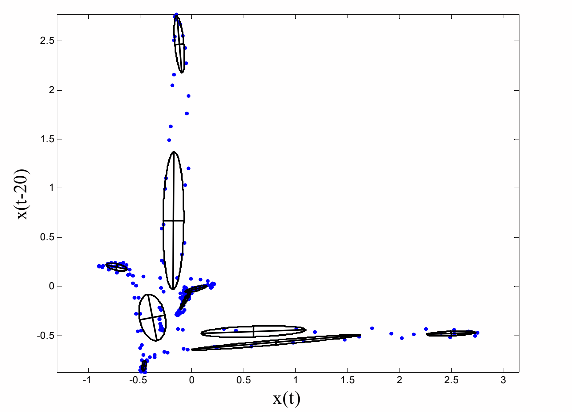

Figure 1 - Gaussian mixture model of a two-dimensional reconstructed phase space of normalized sinus rhythm.

In this study, twenty mixture GMMs were learned over the RPS density for each rhythm class and sub-band using a maximization expectation algorithm. Each GMM model assigned a maximum likelihood that the exemplar under test belonged to a specific rhythm using *argmax(p_i)*. A leave-one-out cross validation was used learn and test GMM models for each exemplar. The classifier for a single frequency sub-band is shown in Figure 2.

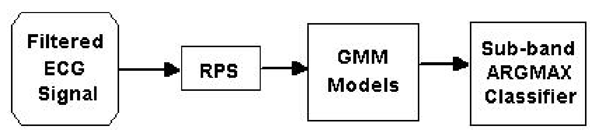

Figure 2 – Reconstructed phase space a single sub-band classifier.

The investigation was extended by combining the sub-band rhythm classifiers into a naive Bayes maximum likelihood classification system. The sub-banded classifier probabilities were fused together using a naïve Bayes maximum likelihood classifier to produce one classification for each segment of data. The fusion Figure 3 illustrates the combination.

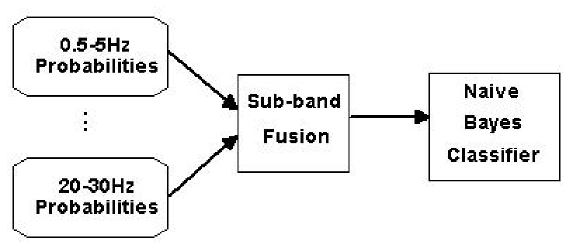

Figure 3 – Naïve Bayes fusion of sub-banded probabilities.

2.3. Gradient PDF

In the gradient probability density function (PDF) method, each data segment is normalized to have an absolute magnitude of 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 exemplar determines the rhythm classification.

3. Results

Leave-one-out cross-validation was used in the building of the GMM models. Each left out exemplar was then classified on the learned models.

3.1. Sub-banded RPS

The sub-banded RPS had different levels of sensitivities for the different rhythms. Across the sub-bands, the highest sensitivity of the different rhythms ranged from 65 to 100%, with SR at 100% and SVT at 65%, which were both found in the 5-10 Hz sub-band. Table 1 lists the highest sensitivity for each individual rhythm and in which sub-band this classification was found. There were no false positives for SR in the 10-20 Hz sub-band. The overall rhythm is the classification accuracy of all the rhythms combined for each sub-band.

Table 1. Highest sensitivity for each rhythm type and in which sub-band it was found.

Rhythm	Sensitivity of Rhythm Classification	Sub-Band (Hz)
SR	100%	5-10
AF	80%	0.5-5
AFL	85%	10-20, 20-32
SVT	65%	5-10
VT	85%	10-20
OVERALL	79%	10-20

Ventricular tachycardia was misclassified as AF, AFL and SVT in all the sub-bands, however only once in all the sub-bands was it misclassified as SR. This occurred in the 5-10 Hz sub-band.

Most misclassifications of the SVT exemplars resulted in being classified incorrectly as AF or AFL. When the classification for all the atrial arrhythmias were combined as one class, the combined atrial class had a classification accuracy of 93.3% and the overall classification increased to 92%, as shown in Table 2.

Table 2. Highest sensitivity of rhythm classes after atrial arrhythmias were folded together.

Rhythm	Sensitivity of Rhythm Classification	Sub-Band (Hz)
SR	100%	5-10
AF/AFL/SVT	93.3%	5-10
VT	85%	10-20
OVERALL	92%	5-10

By combining the sub-bands, the highest sensitivity of AF increased to 95%, AFL to 90%, and VT to 90%. For SR and SVT, their highest sensitivity decreased to 95% and 60%, respectively. The overall classification accuracy increased to 86%. Table 3 shows the results of combining the sub-bands with a Bayesian maximum likelihood classifier for SR, folded atrial arrhythmias, and VT. The overall classification accuracy increased to 94%.

Table 3. Sensitivity of combined sub-bands and atrial arrhythmias folded together.

Rhythm	Sensitivity of Rhythm Classification
SR	95%
AF/AFL/SVT	95%
VT	90%
OVERALL	94%

3.2. Gradient PDF

The classification of the arrhythmias using gradient PDF had lower sensitivity than the sub-banded RPS method. SR had 100% classification accuracy. The classification accuracy for AF and SVT was 0%. Half of the misclassifications of AF were as SR. Table 4 lists the sensitivity for the different rhythms using the gradient PDF method. Table 5 lists the sensitivities after the atrial arrhythmias are folded into one class.

Table 4. Sensitivity for each rhythm type using the gradient PDF method.

Rhythm	Sensitivity of Rhythm Classification
SR	100%
AF	0%
AFL	60%
SVT	0%
VT	65%
OVERALL	45%

Table 5. Sensitivity after atrial arrhythmias are folded together using the gradient PDF method.

Rhythm	Sensitivity of Rhythm Classification
SR	100%
AF/AFL/SVT	41.7%
VT	65%
OVERALL	58%

4. Conclusion

The results of this preliminary study in the use of sub-banded RPS to differentiate atrial arrhythmias from sinus rhythm and ventricular arrhythmias from ECG recordings are promising. The individual sub-bands separated atrial arrhythmias from SR and VT.

Most of the misclassifications of the atrial arrhythmias were when one atrial arrhythmia, such as SVT, was classified as another atrial arrhythmia, AF or AFL. Future studies will need to address a better way to detect the individual atrial arrhythmias, possibly with using sub-banded RPSs as a preprocessor step to separate these arrhythmias from SR and ventricular arrhythmias. Previous studies have shown that the combination of reconstructed phase space with gradient PDF [13] has increased the sensitivity of ventricular rhythm classification. This may be an additional research path to study possibly combining RPS with some of the classical methods such as heart rate and heart rate variability.

When the sub-band RPS probabilities were combined in a Bayesian maximum likelihood classifier the overall classification accuracy increased. Future studies will address weighting the different sub-bands in order not to lose accuracy for the individual rhythms, such as SR decreasing from 100 to 95%.

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References

[1] 2002 Heart and Stroke Statistical Update. Dallas, TX: American Heart Association; 2001.

[2] Lauer MS, Eagle KA. Atrial Fibrillation Following Cardiac Surgery. In: Falk RH, Podrid PJ, editors. Atrial Fibrillation Mechanisms and Management. New York: Raven Press, Ltd.; 1992. p. 127-143.

[3] Jenkins J, Noh KH, Gezennec A, Bump T, Arzbaecher R. Diagnosis of Atrial Fibrillation Using Electrograms from Chronic Leads: Evaluation of Computer Algorithms. PACE 1988;11:622-31.

[4] Slocum J, Sahakian AV, Swiryn S. Computer Discrimination of Atrial Fibrillation and Regular Atrial Rhythms from Intra-Atrial Electrograms. PACE 1988;11:610-21.

[5] Rojo-Alvarez JL, Arenal-Maiz A, Artes-Rodríguez A. Discriminating between supraventricular and ventricular tachycardias from EGM onset analysis: Support vector preprocessing and incremental learning approaches for increased sensitivity and specificity of ICDs. IEEE Engineering in Medicine and Biology Magazine 2002;21(1):16-26.

[6] Chen S-A, Tai C-T, Chiang C-E, Chang M-S. Role of the Surface Electrocardiogram in the Diagnosis of Patients with Supraventricular Tachycardia. Cardiology Clinics 1997;15(4):539-65.

[7] Whitney H. Differentiable Manifolds. The Annals of Mathematics, 2nd Series 1936;37(3):645-680.

[8] Takens F. Detecting strange attractors in turbulence. In: Dold A, Eckman B, editors. Dynamical Systems and Turbulence; 1980; Warwick: Springer-Verlag; 1980. p. 366-381.

[9] Sauer T, Yorke JA, Casdagli M. Embedology. Journal of Statistical Physics 1991;65(3/4):579-616.

[10] Roberts FM, Povinelli RJ, Ropella KM. Identification of ECG Arrhythmias using Phase Space Reconstruction. In: DeRaedt L, Siebes A, editors. Principles and Practice of Knowledge Discovery in Databases (PKDD'01); 2001; Freiburg, Germany: Springer Verlag; 2001. p. 411-423.

[11] Ropella KM, Saad ZS. Quantitative Descriptions of Cardiac Arrhythmias. In: Cabo C, Rosenbaum DS, editors. Quantitative Cardiac Electrophysiology. New York, NY: Marcel Dekker, Inc.; 2002. p. 429-506.

[12] Thakor NV, Webster JG, Tompkins WJ. Optimal QRS detector. Medical and Biological Engineering and Computing 1983:343-50.

[13] Povinelli RJ, Roberts FM, Ropella KM, Johnson MT. Are Nonlinear Ventricular Arrhythmia Characteristics Lost, As Signal Duration Decreases? In: Computers in Cardiology; 2002; Memphis, Tennessee: IEEE; 2002. p. 221-224.

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