ARRHYTHMIA CLASSIFICATION BASED ON NOVEL DISTANCE SERIES TRANSFORM OF PHASE SPACE TRAJECTORIES

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ABSTRACT

Cardiac arrhythmia is a serious disorder in heart electrical activity that may have fatal consequences especially if not detected early. This motivated the development of automated arrhythmia detection systems that can early detect and accurately recognize arrhythmias thus significantly improving the chances of patient survival. In this paper, we propose an improved arrhythmia detection system particularly designed to identify five different types based on nonlinear dynamical modeling of electrocardiogram (ECG) signals. The new approach introduces a novel distance series (DS) domain derived from the reconstructed phase space (RPS) as a transform space for the signals that is explored using classical features. The performance measures showed that the proposed system outperforms state of the art methods.

Index Terms—Arrhythmia, nonlinear dynamical modeling, automated arrhythmia detection.

1. INTRODUCTION

Electrocardiogram (ECG) is a non-invasive diagnostic tool used for assessment of the heart electrical activity. Through characterization of ECG patterns, physicians can recognize irregularities in the heart rhythm, known as arrhythmias. Such arrhythmias may be life threatening and thus early detection is important for improving chances of patient survival [1].

Researchers have developed many algorithms to provide robust arrhythmia classification. Ge *et al*. [2] introduced a method based on autoregressive (AR) modeling for ECG data. The AR coefficients were fed to generalized linear model for classification. On the other hand, Song *et al*. [3] used SVM with fifteen morphology-based features and two rhythm-based features to classify ECG signals after preprocessing using wavelet transform. Jadhav *et al*. [4] proposed an ensemble that uses a new feature elimination method that is able to reduce huge number of features efficiently.

Many studies followed different approach to classify certain arrhythmias through addressing the nonlinear dynamics of the heart. Owis *et al*. [5] used largest Lypanov exponent and correlation dimension as features to classify five arrhythmias and applied *t*-test to study the significance of the proposed features. Roberts *et al*. [6] utilized artificial neural networks to characterize three ventricular arrhythmias based on histogram features derived from the reconstructed phase space (RPS). Povinelli *et al*. [7] introduced statistical modeling of RPS using Gaussian mixture models with Bayesian maximum likelihood estimation for recognition of four types of arrhythmias. Amann *et al*. [8] detected ventricular fibrillation based on the number of points occupying the reconstructed 2D phase space, which was different from that computed for the normal sinus rhythm. Koulaouzidis *et al*. [9] diagnosed two ventricular arrhythmias by analysis of RPS using the box counting method with a novel statistical index derived from classical statistical analysis of this method.

In this paper, we present an automated arrhythmia detection system exploiting the nonlinear dynamical behavior of the ECG signals through analysis of RPS of five different types of arrhythmias obtained from MIT-BIH Arrhythmia Database. We propose a novel formulation of distance series (DS) transform domain derived from RPS. Several features such as Fourier, wavelet and autoregressive model coefficients are computed for each DS. Classical feature selection and classification techniques are used to experimentally verify the performance of the new features.

2. MATERIALS AND METHODS

Nonlinear dynamical modeling of the ECG signals has been recently used to characterize the underlying dynamics of the heart based on its electrical activity measurements. According to Takens [10], if these measurements were taken from a system that has an attractor, the RPS for these measurements would have the same dynamical properties as the true attractor. Consequently, the characterization of the RPS for the ECG signals will reflect the heart functionality.

2.1. Phase Space Reconstruction

In this work, the time-delay embedding method proposed by [10] and [11] was used for the phase space reconstruction where the optimal delay-time and the optimal embedding dimension are selected based on the mutual information between time-shifted versions of the signal and the Cao's method respectively.

Let $\{x_k : k = 1, 2, \ldots, N\}$ be the observed time series, the reconstructed m-dimensional phase space $Y(m)$ can be constructed as the following matrix:

$$Y_i(m) = \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_M \end{bmatrix} = \begin{bmatrix} x_1 & x_{1+\tau} & \cdots & x_{1+(m-1)\tau} \\ x_2 & x_{2+\tau} & \cdots & x_{2+(m-1)\tau} \\ \cdots & \cdots & \cdots & \cdots \\ x_M & x_{N-m\tau} & \ldots & x_N \end{bmatrix}, \tag{1}$$

where $M = N - (m-1)\tau$, N is the length of the original time series, m is the optimal embedding dimension, and τ is the optimal delay time.

2.1.1. Optimal selection of delay time

The delay-time τ for every ECG signal was selected as the first local minimum of the graph of the mutual information versus the time lags. The mutual information between time series x_k and the delayed version of the same time series $x_{k+\tau}$ is given by the following equation:

$$I(\tau) = \sum_{i=1}^{N_s}\sum_{j=1}^{N_s} P[x_k(i), x_{k+\tau}(j)] log_2 \frac{P[x_k(i), x_{k+\tau}(j)]}{P[x_k(i)]P[x_{k+\tau}(j)]}, \quad k = 1,2,\ldots,N-(m-1)\tau \ . \qquad (2)$$

Here N_s is the total number of the probability bins or states, $P[x_k(i)]$ is the probability of x_k belonging to state i, $P[x_{k+\tau}(j)]$ is the probability of $x_{k+\tau}$ belonging to state j, $P[x_k(i), x_{k+\tau}(j)]$ is the joint probability of x_k belonging to state i, and $x_{k+\tau}$ belonging to state j at the same time. According to [12], $P[x_k(i)]$ can be calculated as follows:

$$P[x_k(i)] = \frac{n(i)}{N-(m-1)\tau}, \qquad (3)$$

where $n(i)$ is the number of data points in x_k belonging to state i and $N-(m-1)\tau$ is the length of x_k. Probabilities $P[x_{k+\tau}(i)]$ and $P[x_k(i), x_{k+\tau}(j)]$ can be calculated in the same way. In this work, the optimal τ is computed as the average of the calculated lags for all signals in the training dataset.

2.1.2. Optimal selection of embedding dimension

We used Cao's method [13] to estimate the minimum embedding dimension for every ECG signal in the training dataset. The method is based on the principal that if m is the true embedding dimension, then two points that are close to each other in m dimensional space will remain close in $m+1$ dimensional space and hence called true neighbors. This method starts to reconstruct the phase space using embedding dimension $m=1$ and then increase it until the number of the false nearest neighbor approaches zero. Cao's function is defined as follows:

$$E(m) = \frac{1}{N-m\tau}\sum_{i=1}^{N-m\tau}\frac{\left\|Y_i(m+1) - Y_{n(i,m)}(m+1)\right\|}{\left\|Y_i(m) - Y_{n(i,m)}(m)\right\|}. \qquad (4)$$

Here $Y_{n(i,m)}(m)$ is the nearest neighbor of $Y_i(m)$ in the m dimensional space and $\|*\|$ denotes the maximum norm function. The minimum embedding dimension is identified as the value of m at which the measure $E_1(m)$ approaches one with $E_1(m)$ defined as:

$$E_1(m) = \frac{E(m+1)}{E(m)}. \qquad (5)$$

In some cases even with random signals $E_1(m)$ may still approach one. Therefore, a more robust function $E_2(m)$ is defined by Cao to distinguish between deterministic and random signals such that:

$$E_2(m) = \frac{E^*(m+1)}{E^*(m)}, \qquad (6)$$

where,

$$E^*(m) = \frac{1}{N-m\tau}\sum_{i=1}^{N-m\tau}\left|x_{i+m\tau} - x_{n(i,m)+m\tau}\right|. \qquad (7)$$

Here, $x_{n(i,m)+m\tau}$ is the nearest neighbor of $x_{i+m\tau}$. The signal is said to be deterministic if the value of $E_2(m)$ is not unity for at least one value of the embedding dimensions. In this work, the optimal m was computed as the average of the calculated embedding dimensions for the training dataset.

2.2. Feature Extraction

We define a novel distance series (DS) domain representing a transformation of the original multi-dimensional phase space into a one-dimensional transform space constructed from the Euclidian distance between every point in the phase space and the origin. In other words, this transform space maps how consecutive points in the original phase space move closer to or farther from a reference point (here, the origin of the phase space). A set of features are extracted from this new DS space including their raw values, autoregressive model parameters, magnitude of discrete Fourier transform, and wavelet transform coefficients.

2.2.1. Distance Series (DS)

Aiming to characterize the complex variations in RPS, DS maps their complex multidimensional trajectory into a one-dimensional space. We present calculation of the distance series D_i defined as the Euclidian distance between every point in the phase space Y_i and the origin, which can be calculated as:

$$D_i = \sqrt{\sum_{j=1}^{m} {Y_{ij}}^2}, \qquad i = 1,2,\ldots,M. \qquad (8)$$

If successive values of D_i show smooth behavior, this indicates a slow trajectory and/or a small region of support in the phase space. On the other hand, large changes of such values indicate a trajectory that is moving with large steps and/or large support in the phase space. It should be noted that this mapping allows capturing more information about the trajectory than the traditional measures of complexity.

2.2.2. Autoregressive (AR) Model

AR modeling is a popular technique used in time series analysis. An AR model of order p can be written as:

$$D_i = \sum_{j=1}^{p}\alpha_j D_{i-j} + \varepsilon_i \ , \qquad (9)$$

where p represents the number of points in the past that will be used to model the current point and ε_i denotes a zero mean white noise with variance δ^2, while α_j represent the model coefficients that will be used as features. To calculate the AR coefficients, we used Burg's algorithm. As for the model order, it was selected to be the order that produces the maximum possible accuracy over the training phase.

2.2.3. Transform-Domain Features

Two sets of transform-domain features for DS were extracted including the magnitude of the discrete Fourier transform and the wavelet decomposition coefficients. To illustrate the utility of this approach, when the trajectory points have the same distance from the origin, the Fourier transform is concentrated near DC with no high-frequency components. Otherwise, it will contain a spectrum that is characteristic to global changes of the distance in the phase space. The wavelet decomposition provides a time-frequency representation of the decomposed series, which allows the detection of local variations in the original phase space trajectory.

The selection of wavelet decomposition parameters (i.e., selection of basic wavelet and number of levels) was not found to be critical for this work. Therefore, we report results based on using Daubechies 6 family with 8 levels to allow repeating the procedure by readers but do not exclude the possibility of getting similar results with other wavelet decomposition parameters.

2.3. Feature selection and classification

Fisher score [14] was used for feature selection purposes. In addition, the proposed system was evaluated using the basic K-nearest neighbor classifier (KNN) to reflect the strength of the proposed features.

2.4. Dataset Description

MIT-BIH Arrhythmia Database [15] contains 48 ECG recordings of half an hour duration. The database include 19 different types with each having of 300 samples. Table 1 shows the 30 records that were used to test our methodology.

Table 1: Records used to test the proposed methodology.

Type	Count	Records
N	1500	100,101,105, 106, 114,116,200,209,233,234
APC	1317	100,118,202,209,220,222,232
PVC	1274	106,116,119,200,203,208,213,221,223,233
LBBB	1131	109,111,207,214
RBBB	1037	118,124,212,231,232

3. RESULTS AND DISCUSSION

To illustrate the validity of the proposed approach, we computed the average of the DS raw values for each type as shown in Fig. 1. The average DS values over the whole training dataset were plotted versus all possible time lag indices which are linear indices corresponding to those of the RPS. Thus, the first point in the reconstructed phase space given by RPS $(0, \tau, 2\tau, 3\tau)$ corresponds to the first time lag index and the last point defined as RPS$(N-3\tau, N-2\tau, N-\tau, N)$ corresponds to the last time lag index.

Based on the information shown in Fig. 1, it is possible to conclude that the different types exhibit different DS patterns. It is

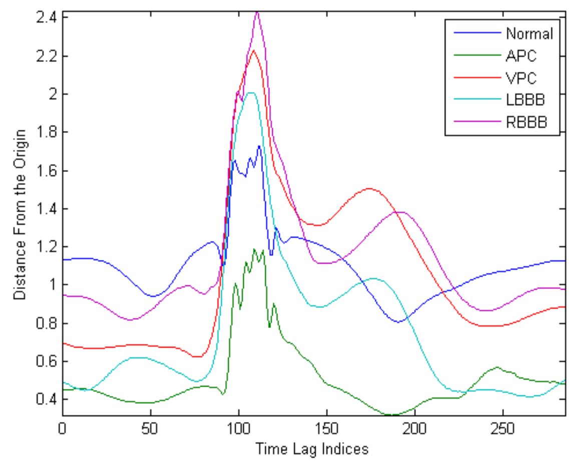

Fig. 1: The average DS calculated for different beat types.

clear that type RBBB possess the largest peak value indicating that its trajectory is moving very fast from a certain point (Departure point) in the space to a far point (Peak value point) and then it returns to a point (Arrival point) that is near to the departure point again. While for VPC, the peak value is lower than that in case of type RBBB with a departure point that is closer to the origin and an arrival point that is more distant from the origin. Comparing DS curves with that for type LBBB, it is obvious that this type has lower peak value. As for the normal beats, the peak value that is greater than the peak value in case of APC and less than that for all other beats. Moreover, the normal beats have the farthest departure point while APC beats have the nearest departure point.

To assess the performance of the proposed algorithm, 30 ECG records from MIT-BIH Arrhythmia database were used to perform 6 different experiments using 10-fold cross validation scheme on a PC with Intel® Core™ i7 2.66 GHz processor and 4 GB RAM. The 6 experiments were meant to try different combinations of features with the aim of finding the best set of features that maximize the system performance.

The six experiments comprise the following features which were fed separately and in combinations to the system: DS values, the coefficients of the 6^{th} order AR model, the magnitude of the

Table 2: Average of the best performance measures obtained.

Features	nf	Accuracy	Sensitivity	Specificity	PPV	NPV
DS Values	120	98.10 %	98.25 %	99.45 %	98.26 %	99.45 %
Magnitude of Fourier Transform	100	94.17 %	95.09 %	98.62 %	95.59 %	98.45 %
Wavelet Coefficients	80	98.56 %	99.11 %	99.45 %	98.29 %	99.71 %
DS Values + Wavelet Coefficients	80	98.18 %	99.13 %	**99.47** %	**98.34** %	99.72 %
AR Coefficients + Wavelet Coefficients	100	**98.70 %**	**99.54** %	99.42 %	98.19 %	**99.85** %
All Features	100	98.58 %	99.28 %	99.44 %	98.26 %	99.77 %

Table 3: Comparison between the proposed methods and other studies.

Method	Features	Classification	Accuracy
[16]	Qualitative Features	Fuzzy C-means	93.57 %
[17]	Qualitative Features	Hidden Markov model	89.74 %
[18]	Qualitative Features	Fuzzy Logic	94.03 %
[19]	S-Transform based features and temporal features	Neural Network	97.95 %
[20]	Wavelet Transform based features + Timing Features	SVM	95.89 %
[21]	Principal Component Analysis Coefficients	SVM	98.11%
Proposed	AR Coefficients + Wavelet Coefficients	KNN	**98.70 %**

Table 4: Testing time for the proposed experiments.

Features	DS Values	Magnitude of FT	Wavelet Coefficients	DS Values + Wavelet Coefficients	AR + Wavelet Coefficients	All Features
Time (s)	0.4278	0.4269	0.4284	0.4289	0.4305	0.4317

Fourier transform (FT), and the wavelet decomposition coefficients. In Table 2, different experiments were evaluated in terms of accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). The experiment that used wavelet and AR coefficients gave the best results. It is worth mentioning that all indicated performance measures are acquired at $k = 1$ that showed the best performance of the KNN classifier.

Different methods in the literature were developed to classify the same beat types. The methods presented in [16-18] use qualitative features with different classification techniques while the method developed by [19] presented S-transform based features combined with wavelet and temporal features. In addition, methods in [20], [21] used the support vector machines (SVM) with different set of features as shown in Table 3. Moreover, all these methods employed sophisticated classifiers. In contrast, the proposed system utilized a very simple classifier and got the highest accuracy compared to the aforementioned methods. This reflects the robustness of the proposed DS approach and validates its value for this application.

Although the proposed algorithm seems to be complicated, the testing time shown in Table 4 indicates that the system meets the relevant AAMI standard [22] for maximum classification time. Therefore, the processing time of the proposed approach is practical and suggests potential for clinical use.

4. CONCLUSION

In this paper, we presented an automated system for arrhythmia classification that can differentiate between five types of ECG signals; namely, normal, APC, VPC, LBBB, and RBBB. We propose a novel formulation of distance series (DS) transform domain derived from RPS that provide more information about the phase space trajectory. The raw DS domain values were used in addition to features derived from them to come up with a feature vector for each sample. Fisher score algorithm and KNN classifier were used for feature selection and classification respectively to measure the performance of the proposed approach. The best accuracy was achieved using the AR coefficients combined with the wavelet decomposition coefficients of DS. Moreover, the computation team on a modest computing platform was shown to meet practical constraints for clinical use.

5. REFERENCES

[1] M. S. Thaler, "The only EKG Book You'll Ever Need," Lippincott Williams & Wilkins, USA, 6th edition, 2012.

[2] D. Ge, N. Srinivasan and S. M. Krishnan," Cardiac arrhythmia classification using autoregressive modeling," BioMedical Engineering OnLine, vol. 1. no. 1, 2002.

[3] M. Song, J. Lee, S. P. Cho, K. J. Lee, and S. K. Yoo," Support Vector Machine Based Arrhythmia Classification Using Reduced Features," International Journal of Control, Automation, and Systems, vol. 3, no. 4, pp. 571-579, 2005.

[4] S. Jadhav, S. Nalbalwar, A. Ghatol," Feature elimination based random subspace ensembles learning for ECG arrhythmia diagnosis," Soft Computing, vol. 18, no. 3, pp. 579–587, 2014.

[5] M. I. Owis, A. H. Abou-Zied, a. B. M. Youssef, and Y. M. Kadah, "Study of features based on nonlinear dynamical modeling in ECG arrhythmia detection and classification," IEEE Trans. Biomed. Eng., vol. 49, no. 7, pp. 733–736, 2002.

[6] F. Roberts, R. Povinelli, and K. Ropella, "Identification of ECG arrhythmias using phase space reconstruction," Princ. Data Min. Knowl. Discov., pp. 411–423, 2001.

[7] R. Povinelli, "Time series classification using Gaussian mixture models of reconstructed phase spaces," *Knowl. Data*, vol. 16, no. 6, pp. 779–783, 2004.

[8] A. Amann, R. Tratnig, and K. Unterkofler, "Detecting ventricular fibrillation by time-delay methods," IEEE Trans. Biomed. Eng., vol. 54, no. 1, pp. 174–177, 2007.

[9] G. Koulaouzidis, S. Das, G. Cappiello, E. B. Mazomenos, K. Maharatna, P. E. Puddu, and J. M. Morgan, "Prompt and accurate diagnosis of ventricular arrhythmias with a novel index based on phase space reconstruction of ECG," Int. J. Cardiol., vol. 182, pp. 38–43, 2015.

[10] F. Takens, "Detecting strange attractors in turbulence," *Dyn. Syst. Turbul. Warwick 1980*, vol. 898, pp. 366–381, 1981.

[11] N. H. Packard, J. P. Crutchfield, Farmer J. D., and S. R. S., "Geometry from a Time Series," *Phys. Rev. Lett.*, vol. 45, no. 9, pp. 712–715, 1980.

[12] G. Williams, *Chaos Theory Tamed*. 1997.

[13] L. Cao, "Practical method for determining the minimum embedding dimension of a scalar time series," *Phys. D Nonlinear Phenom.*, vol. 110, no. 1–2, pp. 43–50, 1997

[14] R. O. Duda, P. E. Hart and D. Stork, "Pattern Classification," Wiley,USA,2nd edition, 2002.

[15] G. B. Moody, R. G. Mark ,"The impact of the MIT BIH Arrhythmia Database,"IEEE Eng. in Med. and Biol. Vol. 20, no.3, pp.45-50, 2001.

[16] Y. C. Yeh, W. J. Wang, and C. W. Chiou, "A novel fuzzy c-means method for classifying heartbeat cases from ECG signals," Meas. J. Int. Meas. Confed., vol. 43, no. 10, pp. 1542–1555, 2010.

[17] H. Chen, T. Hong, and H. Chen, "Automatic Cardiac Arrhythmias Recognition from ECG Signal Based on Hidden Markov Model," vol. 20, no. 8, pp. 2672–2678, 204.

[18] Y. Yeh, "An Analysis of ECG for Determining Heartbeat Case by Using the Princi- pal Component Analysis and Fuzzy Logic," vol. 14, no. 2, pp. 233–241, 2012.

[19] M. K. Das and S. Member, "ECG Arrhythmia Recognition using Artificial Neural Network with S-transform based Effective Features."

[20] A. E. Zadeh and A. Khazaee, "High efficient system for automatic classification of the electrocardiogram beats," Ann. Biomed. Eng., vol. 39, no. 3, pp. 996–1011, 2011.

[21] R. J. Martis, U. R. Acharya, K. M. Mandana, a. K. Ray, and C. Chakraborty, "Application of principal component analysis to ECG signals for automated diagnosis of cardiac health," Expert Syst. Appl., vol. 39, no. 14, pp. 11792–11800, 2012.

[22] Cardiac monitors, heart rate meters, and alarms, Association for the Advancement of Medical Instrumentation,2002.