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NEURAL NETWORK BASED ARRHYTHMIA CLASSIFICATION USING HEART RATE VARIABILITY SIGNAL

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ABSTRACT

Heart Rate Variability (HRV) analysis is a non-invasive tool for assessing the autonomic nervous system and specifically it is a measurement of the interaction between sympathetic and parasympathetic activity in autonomic functioning. In recent years, HRV signal is mostly noted for automated arrhythmia detection and classification. In this paper, we have used a neural network classifier to automatic classification of cardiac arrhythmias into five classes. HRV signal is used as the basic signal and linear and nonlinear parameters extracted from it are used to train a neural network classifier. The proposed approach is tested using the MIT-BIH arrhythmia database and satisfactory results were obtained with an accuracy level of 99.38%.

1. INTRODUCTION

One of the methods which is mostly noted by specialists, for assessing the heart activity and discrimination of cardiac abnormalities, is called Heart Rate Variability (HRV). HRV is a nonlinear and nonstationary signal that represents the autonomic activity and its influence on the cardiovascular system. Hence, measurement of heart rate variations and computerized analysis of it is a non-invasive tool for assessing the autonomic nervous system and cardiovascular autonomic regulation . Furthermore, it could give us information about heart deficiency at the present or in the future.

An automated method for the classification of cardiac arrhythmias is proposed based on linear and non-linear analysis of HRV. Time and frequency domain measures in heart rate variability analysis are less successful in the classification of multiple rhythm changes. With the help of measures from non-linear dynamics we can quantify some of the complex structures in heart rate time series [1]. Therefore, we have used a combination of linear and non-linear parameters. These features are used as input in an artificial neural network (ANN), which classifies each segment into one of the arrhythmia classes.

2. MATERIALS AND METHODS

In this paper, we explore the HRV signal as the basic signal to classify cardiac arrhythmias into five classes : normal sinus rhythm (NSR), premature ventricular contraction (PVC), atrial fibrillation (AF), ventricular fibrillation (VF) and and 2° heart block (BII).

The HRV arrhythmia data, obtained using the ECG data from the MIT-BIH Arrhythmia Database which was digitized at a sampling rate of 360Hz. Moreover, due to the lack of the VF data in the MIT-BIH arrhythmia database, the Creighton University Ventricular Tachyarrhythmia Database was resampled at 360 Hz and then used for the VF arrhythmia class.

Our analysis is carried out in three stages. First a preprocessing procedure is used to extract tachograms from the ECGs. In this stage we have used Tompkins algorithm [2] for detection of R peaks. The tachograms are segmented into small segments. Each segment contains 32 RR-intervals and is characterized using the MIT-BIH arrhythmia database annotation. In the second stage, time and frequency domain and nonlinear methods are applied to extract corresponding features. In the third stage the extracted features are used to train a neural network classifier.

Next materials and methods are described. Then the different steps of the proposed algorithm are explained. Finally results obtained on the MIT-BIH arrhythmia database are presented.

3. FEATURE EXTRACTION

The methods for HRV analysis can be divided into linear (time and frequency domain) and nonlinear methods.
In this work, we explored a combination of linear and nonlinear features.

3.1 Time domain analysis

The time domain methods are the simplest to perform and various parameters can be extracted by time domain analysis of the segments [3]. We utilized five time domain parameters as follows:

Mean: Mean of all RR intervals in each segment

Rmssd: Root mean square successive difference of intervals in each segment

SDNN: Standard deviation of the RR intervals in each segment

SDSD: Standard deviation of differences between adjacent RR intervals in each segment

pNN50: Number of successive difference of intervals which differ by more than 50 ms divided by the total number of all RR intervals in each segment

3.2 Frequency domain analysis

Time domain methods are computationally simple but lack the ability to discriminate between sympathetic and para-sympathetic contributions of HRV [4]. Spectral analysis is the most popular linear technique used in the analysis of HRV signals [5]. Spectral power in the high frequency (HF) (0.15-0.4 Hz) band reflects respiratory sinus arrhythmia (RSA) and thus cardiac vagal activity. Low frequency (LF) (0.04-0.15 Hz) power is related to baroreceptor control and is mediated by both vagal and sympathetic systems [3,5]. We used one frequency domain parameter which is

LF/HF: Ratio between LF and HF band powers

3.3 Nonlinear analysis

A complex system like cardiovascular system can not be linear in nature and by considering it as a nonlinear system can lead to better understanding of the system dynamics. We utilized five nonlinear parameters in this work as follows:

3.3.1. SD1/SD2

A relatively recent tool for HRV analysis is the Poincaré plot, which does not require the HRV signal to be stationary [6]. Poincaré plot is a graphical representation of the correlation between successive RR intervals, i.e. plot of $RR(n+1)$ as a function of $RR(n)$ as described in Figure 1. The Poincaré plot may be analyzed quantitatively by calculating the standard deviations of the distances of the $RR(i)$ to the lines $y = x$ and $y = -x + 2 * RR_m$, where RR_m is the mean of all $RR(i)$. The standard deviations are referred to as SD_1 and SD_2, respectively. SD_1 related to the fast beat-to-beat variability in the data, and SD_2 described the longer-term variability of $RR(i)$. The ratio SD_1 / SD_2 may also be computed to describe the relation between these components [7].

3.3.2. ApEn

Approximate entropy (ApEn) is a regularity statistic that quantifies the unpredictability of fluctuations in a time series. ApEn reflects the likelihood that similar patterns of observations will not be followed by additional similar observations. A time series containing many repetitive patterns has a relatively small ApEn and a less predictable (i.e., more complex) process has a higher ApEn [8]. We have used the method proposed in [9] for calculating the ApEn where *m* (pattern length) set to 2 and *r* (criterion of similarity) set to 20% of the standard deviation of the segment, as proposed in [10].

3.3.3. SpEn

Spectral entropy (SpEn) quantifies the spectral complexity of the time series [11]. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by

$$H = \sum_f p_f \log\left(\frac{1}{p_f}\right) \qquad (1)$$

where p_f is the PDF (probability density function) value at frequency f [5].

Heuristically, the entropy is enterpreted as a measure of uncertainty about the event at f. Thus entropy can be used as a measure of system complexity. The spectral entropy H describes the complexity of the HRV [5].

3.3.4. LLE

Lyapunov exponent is simply a measure of how fast two initially nearby points on a trajectory will diverge from each other as the system evolves, thus giving information about the system's dependence on initial conditions [12]. A positive Lyapunov exponent is a strong indicator of chaos [13,14]. Even though an m dimensional system has m Lyapunov exponents, in most applications it is sufficient to compose only largest Lyapunov exponent (LLE).

The average largest Lyapunov exponent is calculated as follows. First, a starting point is selected in the reconstructed phase space and all the points which are closer to this point than a predetermined distance, ε,are found. Then the average value of the distances between the trajectory of the initial point and the trajectories of the neighboring points are calculated as the system evolves. The slope of the line obtained by plotting the logarithms of these average values versus time gives the LLE. To remove the dependence of calculated values on the starting point, the procedure is repeated for different starting points and the average is taken as the average LLE [15].

3.3.5. DFA

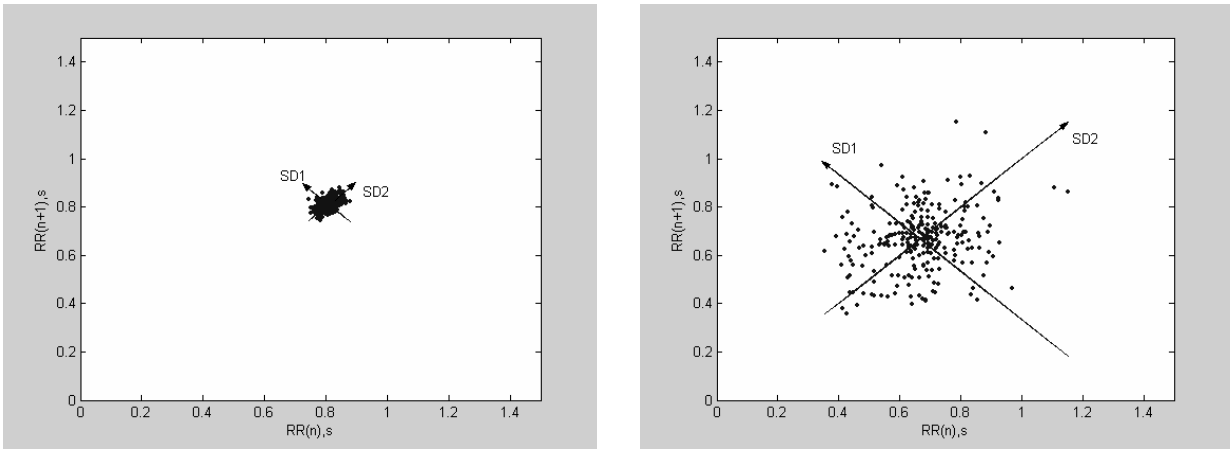
The detrended fluctuation analysis (DFA) is used to quantify the fractal scaling properties of short interval R-R interval signals. This technique is a modification of the root-mean-square analysis of random walks applied to nonstationary signals [16].

The root-mean-square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log-log scale [4].

First, the R-R time series (of total length *N*) is integrated using the equation:

$$y(k) = \sum_{i=1}^{k} (RR(i) - RR_{avg}) \qquad (2)$$

where $y(k)$ is the *k*th value of the integrated series, $RR(i)$ is the *i*th inter beat interval and RR_{avg} is the average inter beat interval over the entire series.



(a) (b)

Figure 1. Poincaré plot of (a) normal subject (b) heart rate with AF

Then, the integrated time series is devided into windows of equal length, *n.* In each window of length *n*, a least-squares line is fitted to the R-R interval data (representing the trend in that window). The *y* coordinate of the straight line segments are denoted by $y_n(k)$. Next, we detrend the integrated time series, $y_n(k)$, in each window. The root-mean-square fluctuation of this integrated and detrended series is calculated using the equation:

$$F(n)=\sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k)-y_n(k)]^2} \quad . \tag{3}$$

This computation is repeated over all time scales (window sizes) to obtain the relationship between $F(n)$ and window size *n* (i.e., the number of beats in a window that is the size of the window of the observation). Typically, $F(n)$ will increase with window size. The fluctuation in small windows related to the fluctuations can be characterized by a scaling exponent (selfsimilarity factor), α, representing the slope of the line relating log $F(n)$ to log *n* [4].

4. NEURAL NETWORK CLASSIFIER

Artificial neural networks (ANNs) are biologically inspired networks that are useful in application areas such as pattern recognition, classification etc.. The decision making process of the ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data. Typically, multilayer feed forward neural networks can be trained as non-linear classifiers using the generalized back propagation algorithm [5,17].

The features extracted from linear and nonlinear analysis are used to train a back propagation neural network. The chosen architecture of the neural network contains: 11 inputs, one hidden layer with 20 neurons and 5 outputs, being a real number in the interval [0,1]. The position of the maximum of the outputs of neural network indicates the membership with the appropriate class. The training of the neural network ends if the sum of the square errors for all segments is less than 0.01 or the maximum number of training epochs is reached (2000 epochs). The number of data set used for training and testing of the neural network classifier and the results for each class are listed in Table2.

5. RESULTS AND DISCUSSION

To evaluate the performance of the proposed classifier, three measures are used and defined as follows:

$$Sensitivity(\%)=\frac{TP}{TP+FN}\times 100 \tag{4}$$

$$Specificity(\%)=\frac{TN}{TN+FP}\times 100 \tag{5}$$

$$Accuracy=\frac{(TP+TN)}{(TP+FN+TN+FP)}\times 100 \tag{6}$$

where TP, TN, FP, and FN stand for true positive, true negative, false positive and false negative, respectively. If for example a segment of HRV with the VF arrhythmia is classified as the VF, then it is said that the segment is classified TP. On the other hand if a non-VF segment is classified as non-VF, then it is said that the segment is classified TN. Any non-VF segment which is classified a VF segment by mistake will produce a FP, while any VF segment which is classified a non-VF segment by mistake will produce a FN result.

For the evaluation of proposed classifier, a total of 1317 segments, which are obtained on the MIT-BIH arrhythmia database, were used and it consisted of 835 NSR segments, 57 PVC segments, 322 AF segments, 78 VF segments and 25 BII segments. Table1 shows the results of classification of test data for each class. The implementation was experimented on a variety of datasets and results presented in Table1 and Table2 represent the average performances.

Table 1. Results from the classification algorithm

	NSR	*PVC*	*AF*	*VF*	*BII*
NSR	*280*	*0*	*0*	*0*	*0*
PVC	*0*	*17.1*	*1.7*	*0*	*0.2*
AF	*0.1*	*3.6*	*104.2*	*0*	*0.1*
VF	*0*	*0*	*1*	*24.8*	*0.2*
BII	*0*	*0*	*0*	*0*	*10*

Table 2. Sensitivity, specificity, and accuracy for each class (units,%)

Arrhythmia Classes	*# of Train & Test segments*	*Sensitivity*	*Specificity*	*Accuracy*
NSR	555,280	100	99.94	99.98
PVC	38,19	90	99.15	98.76
AF	214,108	96.48	99.19	98.53
VF	52,26	95.38	100	99.73
BII	15,10	100	99.88	99.89
Average		*96.37*	*99.63*	*99.38*

6. DISCUSSION AND CONCLUSIONS

In this paper, the neural network classifier is presented as diagnostic tool to aid the physician in the analysis of heart diseases. The neural network classifier was fed by the combination of linear and non-linear parameters derived from the HRV signal.

The proposed NN classifier showed satisfactory performances in discriminating five types of arrhythmia. The accuracy of discrimination of NSR, PVC, AF, VF and BII were 99.98%, 98.76%, 98.53%, 99.73%, and 99.89%, respectively. It is noted that the percentage of NSR segments in the dataset is high, but this is close to reality as ECG recordings have high percentages of normal beats.

The results show that the proposed method is effective for classification of cardiac arrhythmias, with an acceptable high accuracy. It is evident that the combination of the linear and nonlinear features together with the employed classifier is very effective.

The main advantage of the method, compared to other approaches in the literature is that it is completely based on RR-interval signal which can be extracted with high accuracy even for noisy or complicated ECG recordings, while the extraction of all other ECG features or any other type of ECG analysis is seriously affected by noise.

As a salient result, we can conclude that the HRV signal can be used as a reliable indicator of different kinds of heart diseases.

REFERENCES

[1] N. Wessel, A. Voss, J. Kurths, A. Witt, and KJ Osterziel, "24 Hour Heart Rate Variability Analysis Based on New Methods of Non-Linear Dynamics," *IEEE, Comp.Cardio.*, pp. 693-696, 1995.

[2] J. Pan,and WJ. Tompkins, "A Real Time QRS Detection Algorithm," *IEEE.Trans.Biom.Eng.*, vol.32, pp. 230-236, 1985.

[3] Task force of the European society of cardiology and the North American society of pacing and electrophysiology. "Heart rate variability – standards of measurements ,physiological interpretation,and clinical use," *Eur.Hear J.*, vol.17, pp.354-381, 1996.

[4] R.U. Acharya, N. Kannathal,and S.M. Krishnan "Comprehensive analysis of cardiac health using heart rate signals," *Physiol.Meas.*vol. 25, pp. 1139-1151, 2004.

[5] R.U. Acharya, A. Kumar, P.S. Bhat, C.M.Lim, S.S. Iyengar , N. Kannathal,and S.M. Krishnan, "Classification of cardiac abnormalities using heart rate signals," *Med.Biol.Eng.Comp.*, vol.42, pp.288-293, 2004.

[6] J.L.A. Carvalho et.al, "Development of a Matlab Software for Analysis of Heart Rate Variability," *Proc.ICSP02*, pp. 1488-1491, 2002.

[7] M. Tulppo, T.H. Makikallio, T.E.S. Takala, and K.H. Seppanen, "Quantiative Beat-to-Beat Analysis of Heart Rate Dynamics During Exercise," *Am.J.Physiol.*,vol.71, pp.H244-52, 1996.

[8] KLL Ho, GB Moody, CK Peng, JE Mietus, MG Larson, D Levy,and AL. Goldberger, "Predicting Survival in Heart Failure Case and Control Subjects by Use of Fully Automated Methods for Deriving Nonlinear and Conventional Indices of Heart Rate Dynamics," *Circulation* 1997(August),96(3),pp.842-48, 1997.

[9] S.M. Pincus, "Approximate Entropy as a Measure of System Complexity," *Proc. Natl Acad Sci. USA*,vol. 88, pp. 2297–2301,1991.

[10] S.M. Pincus,and A.L. Goldberger, "Physiological Time Series Analysis: What Does Regularity Quantify?," *Am.J.Physiol.*,vol. 266,pp.H1643-1656, 1994.

[11] I.A. Rezek, and S.J. Roberts, "Stochastic Complexity Measures for Physiological Signal Analysis," *IEEE Trans.Biomed.Eng.*, pp. 1186-1190,1993.

[12] JP. Eckman, SO. Kamphorst, D. Ruelle,and S. Ciliberto, "Lyapunov Exponents From Time Series," *Physical Review A*, vol.34(6), pp. 4971-4979, 1986.

[13] H. Kantz,and T. Schreiber, "Nonlinear Time Series Analysis," Cambridge University Press, p.304, 1997.

[14] A. Wolf, JB. Swift, HL. Swinney, and JA. Vastano, "Determining Lyapunov Exponents from a Time Series," *Physica D*, vol.16, pp.285-317, 1985.

[15] I.S. Uzun, M.H. Asyali, G. Selebi,and M. Pehlivan, "Nonlinear Analysis of Heart Rate Variability,"*IEEE, 23rd EMBS conf.*, pp.1581-1584, 2001.

[16] H.V. Huikuri, T.H. Makikallio, C.K. Peng, A.L. Goldberger, U. Hintze, and M. Moller, "Fractal Correlation Properties of R-R Interval Dynamics and Mortality in Patients with Depressed Left Ventricular Function after an Acute Myocardial Infraction," *Circulation 101*, pp.47-53, 2000.

[17] S. Haykin, "Neural Networks a Comprehensive Foundation," MacMillan College Publishing Company, New York, 1995.