World Applied Sciences Journal 6 (11): 1547-1554, 2009
ISSN 1818-4952

Classification of Cardiac Abnormalities Using Reduced Features of Heart Rate Variability Signal

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Abstract: This paper presents an effective arrhythmia classification algorithm using the heart rate variability (HRV) signal. The proposed method is based on the Generalized Discriminant Analysis (GDA) feature reduction technique and the Multilayer Perceptron (MLP) neural network classifier. At first, nine linear and nonlinear features are extracted from the HRV signals and then these features are reduced to only three by GDA. Finally, the MLP neural network is used to classify the HRV signals. The proposed arrhythmia classification method is applied to input HRV signals, obtained from the MIT-BIH databases. Here, four types of the most life threatening cardiac arrhythmias including left bundle branch block, fist degree heart block, Supraventricular tachyarrhythmia and ventricular trigeminy can be discriminated by MLP and reduced features with the accuracy of 100%.

Key words: Heart rate variability . arrhythmia classification . generalized discriminant analysis . multilayer perceptron neural network

INTRODUCTION

Nowadays the cardiac arrhythmias are the most famous causes of mortality. Hence, several techniques have been proposed to identify and detect the different types of arrhythmia. These techniques usually extract desired features from Electrocardiogram (ECG) or Heart Rate Variability (HRV) arrhythmic signals to classify them. Since ECG signal processing is time consuming and too sensitive to the amount of the noise, nowadays, analysis of HRV signal to assess the heart activity and to discriminate different cardiac abnormalities is an alternative approach. HRV signal, which is generated from ECG by calculating the inter-beat intervals, is a non-stationary signal that represents the autonomic activity of the nervous system and the way it influences the cardiovascular system. Hence, HRV analysis can be considered as an important diagnostic tool in cardiology. Some examples of automatic arrhythmia detection and classification methods which have been analyzed ECG signal in the literature are neural networks [1-4], wavelet transforms [5], support vector machines [6, 7], fuzzy logic [8] and the rule-based algorithms [9].

On the other hand, since the RR time intervals are less affected by the noise, analysis of HRV signal is a more robust method. Different HRV signal analysis methods for arrhythmia classification were introduced in the past. Tsipouras and Fotiadis [10] proposed an algorithm based on both time and time-frequency analysis of the HRV signal using neural networks. Acharya *et al*. [11] could classify the input HRV segments into one of the four different arrhythmia classes using multilayer perceptron (MLP) together with a fuzzy classifier. A knowledge-based method for arrhythmia classification into four different categories was proposed by Tsipouras *et al*. [9].

The proposed algorithm in this paper presents an HRV-based arrhythmia classification method which is able to effectively identify four different and more frequently occurring types of cardiac arrhythmia. These arrhythmias are namely the left bundle branch block (LBBB), the first degree heart block (BI), the Supraventricular tachyarrhythmia (SVTA) and the ventricular trigeminy (T). In Fig. 1, the five second segments of ECG signals relating to the mentioned arrhythmias are shown. This algorithm is based on the generalized discriminant analysis (GDA) and MLP classifier. GDA which was first introduced by Baudat and Anouar [12] is a data transformation technique that is considered as a kind of generalization to the linear discriminant analysis (LDA) algorithm. It has become a helpful feature extraction algorithm in recent years [13, 14]. Therefore dimensionality of the input feature space is reduced by GDA. Selection of the useful discriminating features can be achieved simultaneously.

One of the principal applications of Artificial Neural Network (ANN) is pattern recognition. ANNs

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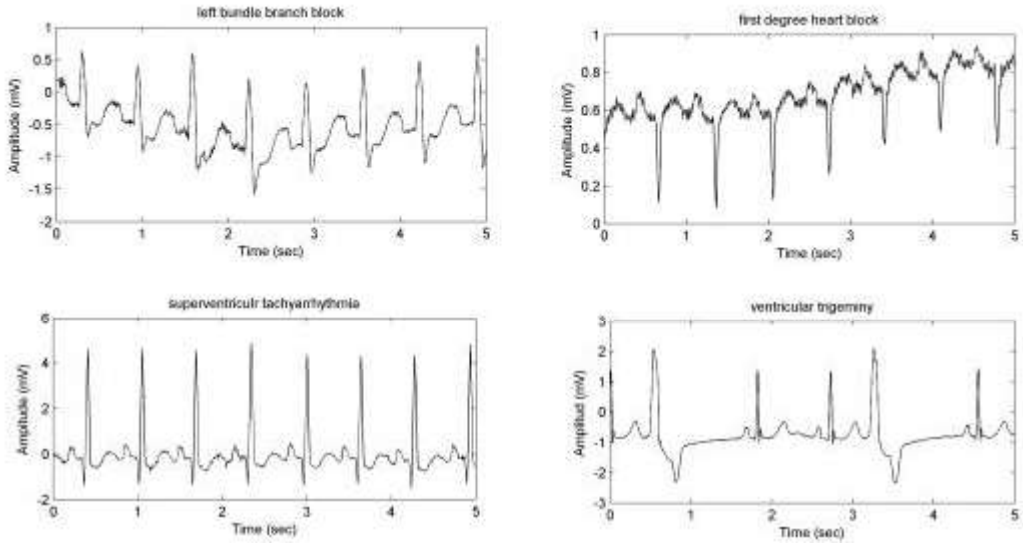

Fig. 1: ECG segments of four types of arrhythmia

have been applied to the biomedical fields of signal compression, enhancement and interpretation. This study has conducted in the third category to classify ECGs. According to the literature, there are different methods of cardiac arrhythmia classification in order to achieve better accuracy. In the present study, logarithmic sigmoid neurons are used to build up the Levenberg–Marquart backpropagation neural networks for the detection of four types of cardiac arrhythmia.

The details of the proposed algorithm for arrhythmia classification from the HRV signal is presented in continue. Section 2 presents the overall block diagram of the proposed method with the details of each block. The results of the application of the proposed algorithm to two databases of MIT-BIH are presented in Section 3. Finally, Section 4 concludes the paper.

MATERIALS AND METHODS

Extracting and preprocessing the signal: The HRV data used in this paper is generated from the ECG signals provided by the MIT-BIH database [15]. The MIT-BIH arrhythmia database is a standard reference for ECG signal processing which includes 48 ECG recordings each with a length of 30 min with a total of about 109,000 RR intervals. All signals in this database were filtered in the frequency range of 0.1-100Hz and were sampled with a sampling rate of 360Hz. Each of the about 109,000 beats was manually annotated by two cardiologists and their annotations were compared. Finally, the reference annotation files were prepared [16]. Here, the ECG signals relating to LBBB and T arrhythmias are extracted from this database. In addition to this database, the MIT-BIH Malignant Ventricular Arrhythmia Database was used to obtain the BI and SVTA signals after resampling them at a rate of 360 Hz. This database includes 22 ECG recordings of subjects who experienced episodes of sustained ventricular arrhythmias. The block diagram of the proposed algorithm is illustrated in Fig. 2. As seen, it comprises 3 steps of preprocessing, feature extraction and reduction and arrhythmia classification.

At first, it is necessary to extract the HRV signals from the ECG signals. Generally, many interfering signals such as the mains 50 Hz, the electromyogram (EMG) signals and also the baseline wandering can affect the extraction process. Hence, these interfering signals are removed from the input ECG signal using a 5-15 Hz bandpass filter [17]. Then the QRS complex in the filtered signals is detected using Hamilton and Tompkins algorithm [18] and the maximum absolute value of the signal within the time window [QRS-280 ms, QRS + 120 ms] is identified as R wave. Then the HRV signal is constructed by measuring the time intervals between the successive R waves in each ECG signal and at last plot these intervals against the time indices. The obtained HRV signals are divided into the same length segments each containing 64 RR intervals and characterized using the database rhythm annotation. Finally, a total number of 270 HRV segments each with 64 RR intervals which contain all four different arrhythmia classes are selected from the above-mentioned database and used in this work.

Feature extraction: The next step in the block diagram is the feature extraction. Generally, the cardiovascular system demonstrates both linear and nonlinear

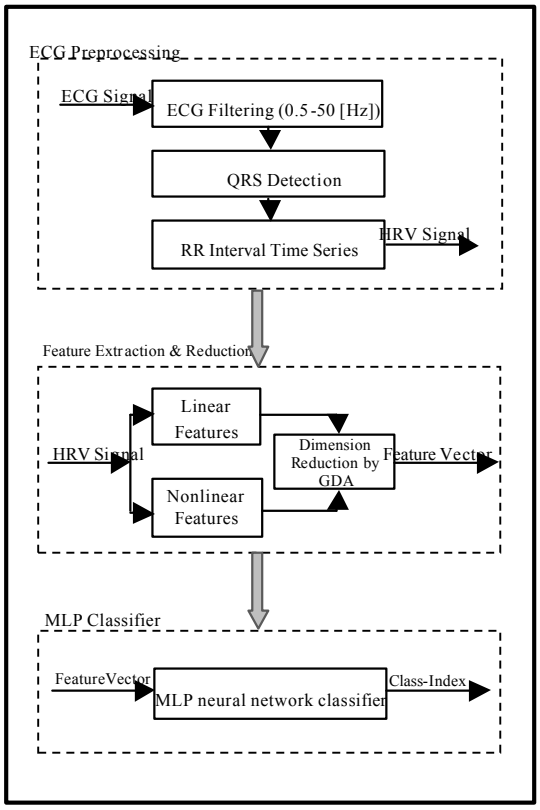

Fig. 2: General structure of arrhythmia classification algorithm

behavior. Therefore, in this work we consider a combination of linear and nonlinear features. The linear features which are obtained from time and frequency domains are calculated based on the proposed standard in [19].

Linear analysis

Time domain features: Four commonly used time domain parameters of the HRV signal which are directly extracted from the RR interval time series are:

Mean HR: The mean value of the heart rate within one minute in each segment. Instantaneous heart rate (beat per minute) is equal to 60 divided by each R-R interval (second).

STD HR: The standard deviation of Instantaneous heart rate in each segment.

pNN50: The number of successive difference of 64 R-R intervals that differs more than 50 ms, respectively, divided by 64.

HRV triangular index: This refers to the integral of the histogram (i.e. total number of RR intervals) divided by the height of the histogram. A bin width of 1/128 is selected according to [19].

Linear analysis

Frequency domain features: Although the time domain parameters are effective, they do not have the ability of discrimination between the sympathetic and parasympathetic contents of the HRV signal [20]. High-frequency (HF) band (0.15-0.4 Hz) of HRV signal shows the cardiac vagal activities such as Respiratory Sinus Arrhythmia (RSA). In fact, HF components are considered as the origin of parasympathetic activities of the cardiovascular system. On the other hand, the low-frequency (LF) band (0.04-0.15 Hz) is related to the baroreceptor control and is mediated by sympathetic systems.

In this work, the power spectral density (PSD) for the HF and LF bands are calculated and the ratio of the LF and HF bands power (LF/HF) is considered as the Frequency domain feature of the HRV signal.

Nonlinear analysis: The HRV signal analysis by use of methods on nonlinear dynamics leads to very valuable information for physiological interpretation of the heart. Hence, four different nonlinear parameters of the HRV signal are used in this work.

SD_1/SD_2: Poincare plot is a graphical representation of the correlation between successive RR intervals. This is obtained plotting each RR interval (RR (n+1)) as a function of the previous interval (RR (n)) in RR interval time series [21]. This plot is quantitively analyzed calculating the standard deviation of the distances of the time series points from the lines $y = x$ and $y = x + 2RR_m$, in which RR_m is the mean of all values of RR interval time series. These values are named SD_1 and SD_2 respectively. In fact, SD_1 represents the fast beat-to-beat variability, while SD_2 describes the relatively long-term variability in the HRV signal [22]. In this work, SD_1/SD_2 is used as the first nonlinear feature which is extracted from HRV segments.

LLE: The Largest Lyapunov Exponent provides useful information about the dependency of system on initial conditions and a positive lyapunov exponent confirms the existence of chaos in the system [23]. For calculating LLE, a point is selected in the reconstructed phase space of the system and all neighbor points residing within a predefined radius ε are determined. As the system evolves, the mean distances between the trajectory of the initial point and the trajectories of the neighbor points are calculated. Then the logarithm of these mean values plots against the time and the slope of the resulting line are considered as *LLE*. The

embedding dimension and the lag are selected to be m = 10 and $\tau = 1$, respectively. The threshold distance ε is selected to be $\sqrt{m}SD$, where SD is the standard deviation of the RR time series [24].

SpEn: The Spectral Entropy shows the complexity of the input time series (HRV segment) in the frequency domain [25]. Large values of *SpEn* show high irregularity and smaller values of it indicate more regular time series. The Shannon's channel entropy is used to estimate the spectral entropy of the process as:

$$SpEn = -\sum_f p_f \log(p_f) \quad (1)$$

In which p_f is the value of the probability density function (PDF) of the process at frequency *f*. Hence, the entropy can be considered as a measure of uncertainty about the event at frequency *f*.

D2: The Correlation Dimension is a measure of complexity of the time series and determines the minimum number of dynamic variables which can model the system. The algorithm which has been proposed in [26] is used to estimate this feature (a value of m = 10 is selected for the embedding dimension).

Feature dimension reduction: Having above-defined features, due to the large variations in the HRV patterns of various arrhythmias, there is usually a considerable overlap between some of these classes of arrhythmia in the feature space. For instance, the SVTA and BI classes demonstrate a large overlap with each other making it difficult to discriminate between them. GDA [12] is a feature transformation mechanism that can minimize the within-class scatter and maximize the between-class scatter. GDA is a nonlinear extension to the ordinary LDA [27]. Considering the input training vectors as:

$$\tau_{XY} = \{(x_1, y_1), \ldots, (x_l, y_l)\}, x \in R^n, y \in Y = \{1,2,...,c\} \quad (2)$$

The within-class and between-class scatter matrices (S_W and S_B) are defined:

$$S_W = \sum_{y \in Y} S_y, S_y = \sum_{i \in I_y} (x_i - \mu_i)(x_i - \mu_i)^T,$$
$$S_y = \sum_{y \in Y} |I_y| (\mu_y - \mu)(\mu_y - \mu)^T \quad (3)$$

The goal of the LDA is to train the linear data projection $z = W^T x$ such that maximizes the ratio of the between-class scatter to the within-class scatter:

$$F(W) = \frac{\det(S_B)}{\det(S_W)} \quad (4)$$

Generally, having a number of independent features which describe the data, LDA creates a linear combination of the features that yields the largest mean differences of the desired classes [28].

In GDA the input vectors are mapped by $\Phi: x \rightarrow F$ to a high dimensional feature space. Then the ordinary LDA is applied on the following mapped data.

$$\tau_{XY} = \{\Phi(x_1, y_1), ..., \Phi(x_l, y_l)\} \quad (5)$$

By employing the kernel functions $K: x \times x \rightarrow R$ the projection vectors are computed. The resulting kernel data projection is:

$$Z = A^T K(x) + b \quad (6)$$

The purpose of GDA is to train the parameters A and b in (6) to increase the between-class scatter and decrease the within-class scatter of the extracted data:

$$\tau_{ZY} = \{(z_1, y_1), \ldots, (z_l, y_l)\}, z_i \in R^m \quad (7)$$

It is worth to notice that the optimal number of eigenvectors for the data transformation is generally equal to N-1, where N is the number of classes [7]. In this work, assuming the number of classes (different arrhythmia to be identified) is four, the number of the original nine features is reduced to three by GDA with a guarantee that the performance is comparable to that of the non-reduced feature set.

Figure 3 and 4 present the box-plots and the feature space plots of the new three features for arrhythmia classes respectively, which are generated by GDA. As seen, the samples relating to the different arrhythmia classes are located adjacent to each other and relatively well separated from the other classes within the feature space. Therefore, the new feature set not only reduces the number of the input features but also increases the classification accuracy by selecting most discriminating features for a better discrimination of the different arrhythmia classes.

Classification: In this study, the MLP neural network is used to classify the HRV segments. The advantage of using this classifier is the rapid execution of the trained network, which is particularly beneficial in signal processing applications [29]. MLP classifier has been widely used in the literature for ECG pattern classification [1-4]. A three-layer feed-forward network, with sigmoid hidden and output neurons was

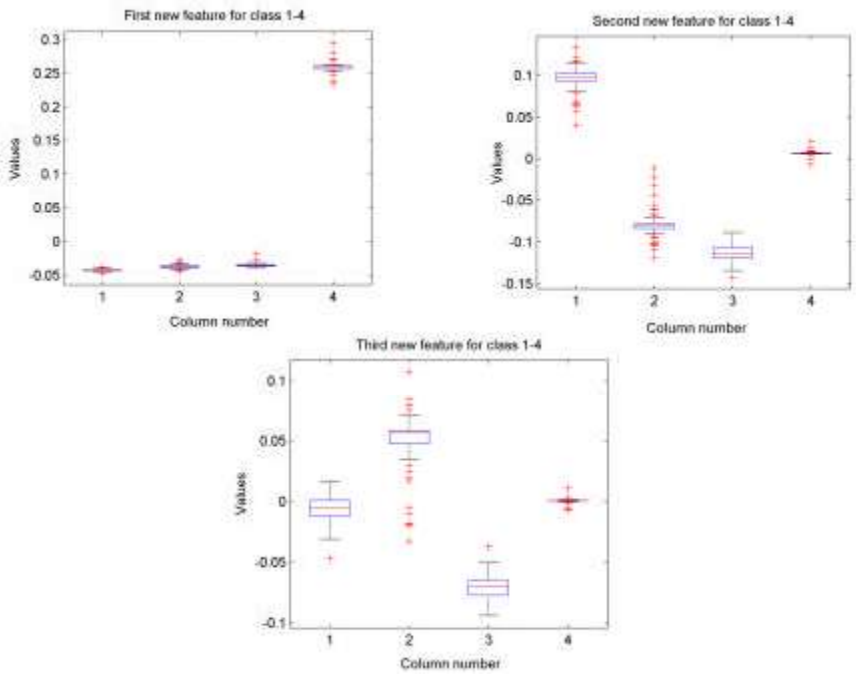

Fig. 3: Box-plots of the new three features for different arrhythmia classes (1 = LBBB, 2 = BI, 3 = SVTA, 4 = T)

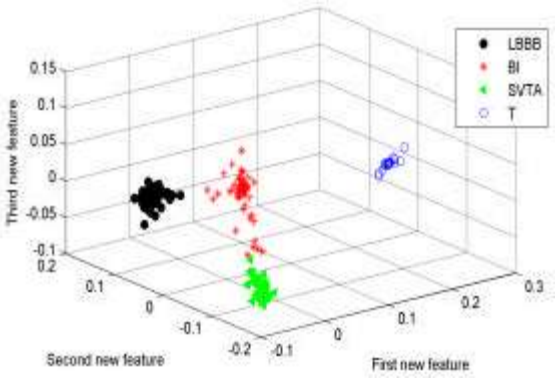

Fig. 4: Feature space plots of first, second and third new features for different arrhythmia classes

developed to classify input vectors. Several MLP network models with different settings for the hidden layers, hidden nodes, learning rate, epochs were trained to reach the optimal configurations with desired precision. This optimal network has 15 inputs (5 inputs for the case of the reduced feature vectors), one hidden layer with 20 neurons and 4 outputs for the four arrhythmia classes each with a real value in the interval [0, 1]. The MLP is trained using the training data set and employing the Levenberg–Marquardt learning rule backpropagation strategy. For each input feature vector, the output with the largest value demonstrates the appropriate class that the input vector belongs to.

The chosen MLP, a pattern recognition network, is implemented in the Neural Network Toolbox™ in MATLAB software package (Licensed MATLAB® version 7.6.0 with Neural Network toolbox).

RESULTS

To evaluate the performance of the proposed algorithm, a total number of 270 HRV segments including 113 LBBB segments, 76 BI segments, 45 SVTA segments and 36 T segments are used. These HRV segments at each class are randomly divided into the train and test sets in an approximate ratio of 70% and 30% respectively. The exact number of the train and test segments for each class is shown in Table 1.

Then the nine linear and nonlinear features are calculated for each HRV segment in the train and test sets. Afterwards, these original features are reduced to only three new features using the GDA algorithm. A radial basis function (RBF) with a kernel width of 1 is chosen as the kernel. Finally, the MLP classifier is trained using the reduced feature vectors of the training set. The procedure including randomly dividing the data set into the train and test sets, training the MLP classifier and testing it by the test data set was repeated 100 times. The average results are demonstrated in Table 1. As seen, when classification process is performed by reduced feature vectors (MLP+GDA) there is no misclassification to any other classes and the proposed classifier is thoroughly accurate. For

Table 1: Comparison of the Confusion Matrix on the test set for two classification methods. The values are average of 100 train and test procedures

Number of train/test segments			Classification (MLP+ORG/MLP+GDA) LBBB		BI		SVTA		T	
79/34	Database annotation	LBBB	33.2	34	0.8	0	0	0	0	0
53/23		BI	1.2	0	21	23	0.5	0	0.3	0
31/14		SVTA	0	0	2.3	0	11.7	14	0	0
25/11		T	0	0	0	0	0	0	11	11

Table 2: Performance analysis of the MLP classifier on the original features and the reduced features in terms of the average values of the four commonly used measures in %

	MLP+ORG				MLP+GDA			
Arrhythmia classes	Sensitivity (%)	Specificity (%)	Positive predictivity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive predictivity (%)	Accuracy (%)
LBBB	97.64	97.32	96.51	97.46	100	100	100	100
BI	91.30	94.74	87.14	93.78	100	100	100	100
SVT	83.57	99.23	95.90	96.49	100	100	100	100
T	100.00	99.54	97.35	99.61	100	100	100	100
Average	93.13	97.71	94.22	96.83	100	100	100	100

comparison, the results of classification with original input features (MLP+ORG) are also shown in Table 1.

In continue, the four famous measures sensitivity, specificity, positive predictivity and accuracy are derived from the proposed algorithm. Furthermore, to compare the efficiency of the proposed method, these parameters are calculated for the MLP classifier which is trained using the nine original features.

$$\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100 \quad (8)$$

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100 \quad (9)$$

$$\text{Positive predictivity}(\%) = \frac{TP}{TP + FP} \times 100 \quad (10)$$

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \quad (11)$$

In equations (8-11), TP, TN, FP and FN stand for true positive, true negative, false positive and false negative, respectively. Table 2 shows the average values of these parameters for both mentioned algorithms (MLP+ORG, MLP+GDA). As it can be seen, the presented method can discriminate all of four arrhythmias with the accuracy of 100%. These results demonstrate the effectiveness of this method in the classification of the four types of cardiac arrhythmia. As a comparative study we can also see the results of the classification using original features. Table 2 shows that the classification using the reduced features has better results than the classification using the original ones. The average values of the performance parameters shows that using the reduced features instead of the original features for classification leads to an increment about 6.9% in the sensitivity, 2.3% in the specificity, 5.8% in positive predictivity and 3.2% in the accuracy. The use of reduced feature vectors on the other hand decreases the MLP training time significantly. Hence, the proposed classification algorithm based on GDA and MLP classifier, not only decreases the processing time but also makes a noticeable increase in the accuracy of classification.

CONCLUSIONS

In this paper, an effective HRV-based arrhythmia classification method is presented. Initially, nine features are extracted from HRV segments. In order to reduce the learning time and also to improve the efficiency of the classifier, three reduced feature vectors are subsequently extracted from nine original ones using the GDA technique. Thereafter, the MLP-based classifier method is used to classify the four types of arrhythmia. The results of the comparative study indicate that the MLP technique outperforms the same classifier which is applied to the original features. The

proposed model has yielded the classification accuracy of 100% for the arrhythmia classes of LBBB, BI, SVTA and T, respectively.

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