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RESEARCH ARTICLE

CARDIAC ABNORMALITIES CLASSIFICATION USING PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Cardiac patients require long term monitoring of Electrocardiogram signals. However, it is a very tedious and time-consuming task to analyze the ECG recording beat by beat in a long-term monitoring. This is because the abnormal heart beats can occur randomly and a long-term ECG record, say 24 hours, may contain hundreds of thousands of beats. Hence, it is highly desirable to automate the entire process of ECG classification. The present work proposes a technique for ECG classification. First, the ECG signals belonging to each category were extracted from the MIT-BIH arrhythmia database features are extracted from the ECG signal using Principal Component Analysis (PCA) .This process drastically reduces the dimensionality of the vectors to be classified. The feature vectors thus obtained are used to train a neural network (NN) classifier. After the network is trained, its performance in terms of its generalizing ability is tested on a separate test dataset which was not used during training. The outcome showed that the FF neural network performance is better.

INTRODUCTION

Electrocardiogram (ECG) is the record of the electrical potentials produced by the heart. The electrical wave is generated by depolarization and repolarization of certain cells due to movement of Na+ and k+ ions in the blood. The ECG signal is typically in the range of 2 mV and requires a recording bandwidth of 0.1 to 120 Hz (Acharya, 2007). The ECG is acquired by a non-invasive technique, i.e. placing electrodes at standardized locations on the skin of the patient (Moss, 1996). The ECG signal and heart rate reflects the cardiac health of human heart. Any disorder in heart rate or rhythm or change in the morphological pattern of ECG signal is an indication of cardiac aabnormalities. It is detected and diagnosed by analysis of the recorded ECG waveform. The amplitude and duration of the P-QRS-T-U wave contains useful information about the nature of disease related to heart.

An Electrocardiogram or ECG is an electrical recording of the heart and is used in the investigation of heart disease. This ECG can be classified as normal and abnormal signals. One of the most important problems in ECG analysis is automatic beat delineation. This is needed in many cases ranging from simple heart rate computations to serving as the first stage of complex automatic diagnosis. Beat delineation techniques have to start by identifying features in the ECG signal that can constantly be detected in each heartbeat. Simply by looking at an ECG plot, it can be noticed that the QRS complex is the predominant feature in every beat. The other features of the ECG signal, like the P wave and T wave, are sometimes too small to be detected (Yang Xiao, 2010).

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This makes the QRS complex the feature that can yield the best detection accuracy. The generalization performance of the traditional classifiers are not sufficient for the correct classification of ECG signals. To overcome this problem Neural Network (NN) classifier is used which work by searching for the best value of the parameters that tune its discriminant function, and upstream by looking for the best subset of features that feed the classifier. The main problem in automatic ECG signal recognition and classification is that related features are very susceptible to variations of ECG morphology and temporal characteristics of ECG. This problem is resolved by applying dimensionality reduction using PCA to reduce the training overhead and thus we get higher accuracy. The extracted features may comprise morphological features, such as the width and height of the QRS complex, QRS complex area, positions of *P, Q, S* and *T* waves etc. (O'Dwyer, 2000 and Pietka, 1988), heart beat temporal intervals such as R-R interval, P-R interval (Karlik,, 1996 and Chazal, 2004), etc. Several techniques have been used for classification of ECG beats, such as linear regression (Young, 1964,) support vector machines (SVMs) (Zellmer, 2009 and Zhang, 2005), neural networks (Hu, 1994), mixture-of experts approach (Hu, 1997) etc. The main objective of this paper is to propose a computer based automated system for classification of the ECG signal. Normal Sinus Rhythm (NSR), Atrial Premature Contraction (APC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB) and Premature Ventricular Contraction (PVC) signals of the MIT-BIH Database are used as reference. Principal Component Analysis (PCA) technique is used to reduce the dimensionality of test signal. Classification is done using Neural Network classifier namely Feedforward and Radial Basis Function.

Proposed Work

Our work is related to ECG pattern recognition and classification. The ECG consists of three basic waves: the P, QRS, and T. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, namely, the atrial depolarization (P wave), the ventricular depolarization (QRS complex), and the ventricular repolarization (T wave). ECG signal does not look the same in all the leads of the standard 12-lead system used in clinical practice. They usually change over different leads. Most cardiovascular diseases are caused by some kind of physical malfunction of one or several parts of the heart. This can certainly have a reflection on the shape of the ECG signal. So we conduct our research on a single-beat basis, attempting to discriminate different diseases from ECG data. The following block diagram in the Figure 1 shows the workflow of the proposed work.

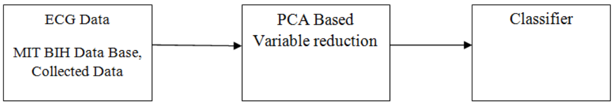

Figure 1. Proposed Block Diagram

We obtain our data set from MIT-BIH Arrhythmia Database (MIT/BIH, 1979). The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database (www.physionet.org/physiobank/database/mitdb/).

A new database from the original database for our experiment, where each signal represents a single heart beat as detailed in Table 1. To test the integrated method, a set of signals is extracted from MIT-BIH. Since there are a few categories of abnormal QRS complexes in one record, we select different abnormal signals from several records so that the classification ability of the method can be studied conveniently. Five types of signals appeared frequently in the database are selected. The extracted data of ECG complexes is centered around R peak. Considered that some PVC duration is great and sometimes R peak detection may be not the centre of the complex, we have selected segment of 75ms before the fiducial point and 75ms after it. Signals are arranged in order to form a matrix where each column represents a signals. The data set has five types of signals: Normal Sinus Rhythm(NSR), Atrial Premature Contraction (APC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC). These reference signals were taken from the following records from MIT BIH Arrhythmia database.

Table 1. ECG Data Set

S.No	Nature of ECG Data	No. of ECG data for analysis
1.	Normal Sinus Rhythm	100
2.	Atrial Premature Contraction	78
3.	Left Bundle Branch Block	80
4.	Right Bundle Branch Block	80
5.	Premature Ventricular Contraction	72

Feed Forward ANN: A typical feed forward ANN consists of many processing units or nodes which are distributed in multiple layers, viz, an input layer, one or more hidden layers and an output layer, each layer comprising of a set of highly interconnected processing elements (neurons) as shown in Fig. 2. The neurons in each layer are connected to those in the immediate next layer through acyclic feed forward connections. A single layer of hidden neurons are enough to provide the desired accuracy in most of the forecasting situations. The input vector representing the pattern to be recognized is presented to the input layer and distributed to the subsequent hidden layers and finally to the output layer via the weighted connections. Each neuron in the network operates by taking the sum of weighted inputs and passing the result through a nonlinear activation function, which is usually a sigmoid or hyperbolic tangent function. In a fully connected feed forward ANN of Fig. 2 with *ni* input and *nhn* hidden neurons, the relationship between the *K-th* output and input neurons is mathematically represented by,

$$O_k = F\left(w_{bias\_h}^{k} + \sum_{j=1}^{nhn} \left\{ w_{ho}^{jk} \times G\left(w_{bias\_o}^{j} + \sum_{m=1}^{p} w_{ih}^{mj}\, x_m \right) \right\} \right) \quad (1)$$

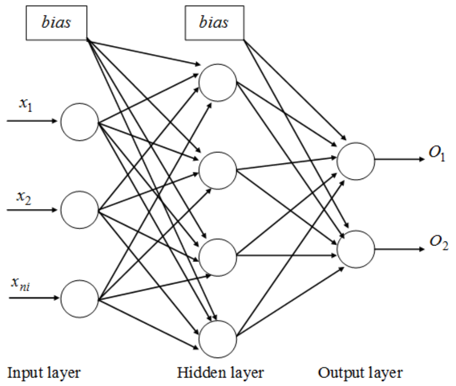

Fig. 2. Architecture of feed forward neural network

The knowledge required to map the input patterns and output is embodied in the form of weights. Initially the weights appropriate to a given problem domain are unknown. The network does not inherit the ability to deal with the problem to be solved until a set of appropriate weights is found. The process of finding useful set of weights and bias is called training. The process of training begins with tutoring a set consisting of specimen inputs with associated outputs. Training the network involves adjusting the connection weights to correctly map the training set vectors at least to within some defined error limit such as mean squared error (MSE). If the training set is good, then the network shall be able to correctly estimate the output even for the inputs not belonging to the training set. The application of neural network to a recognition problem involves two distinct phases: training phase and operational phase. The network weights are adopted to reflect the problem domain during the training phase. The weights are frozen and the network when presented with test data, predicts the correct output in the operational phase. The ANN training is an unconstrained nonlinear minimization problem which iteratively updates the weight and bias parameters with the goal of minimizing the MSE between the desired and actual output values. The best known training algorithm is the standard back-propagation (BP). It modifies the weights and biases towards the fastest decrease of the error function, i.e. towards the negative of the gradient. Let y^k be the target value of k^{th} output neuron for a given training pattern O^k be the actual output produced by k^{th} output neuron for a given training pattern and can be evaluated for l^{th} layer neurons through treating the outputs of previous $(l - 1)^{th}$ layer as inputs by

$$O_k(l) = F_k\left(\sum_j \left\{w^{jk}\ O_j(l-1)\right\}\right) \quad (2)$$

$Err = \frac{1}{2}\sum_{k=1}^{no}(O_k - T_k)^2$ be the measure of net error for each training pattern (3)

w^{jk} is the weight from j^{th} neuron of $(l - 1)^{th}$ layer to k^{th} neuron of l^{th} layer

Where O_k (l) is the output of k^{th} neuron at l^{th} layer F^k is a differentiable and non-decreasing function at k^{th} neuron and w^{jk} is the weight to be adjusted.

The error can be reduced by adjusting the weights in the negative direction of the gradient of *Err*. The gradient of *Err* with respect to w^{jk} is represented as

$$-\frac{\partial Err}{\partial w^{jk}} = \delta^k\ O_j \quad (4)$$

Where δ^k is defined as

$$\delta^k = F_k'(y_k - O_k) \text{ if } k \text{ is an output neuron} \quad (5)$$

$= F_k' \sum_j \delta^j\ w^{jk}$ if k is an arbitrary neuron in hidden layer (6)

F_k' is the derivative of F_k

The rule of adjusting weights can be derived using Eq. (4) and given as

$$\Delta w^{jk}(t+1) = \Re\,\delta^k\ O_j + \Im\,\Delta w^{jk}(t) \quad (7)$$

Where $\Re$ is the learning rate parameter and $\Im$ is the momentum constant to determine the effect of past weight changes. The flowchart of the backpropagation learning algorithm involving Eqs. 2-7 is shown in Fig. 3.

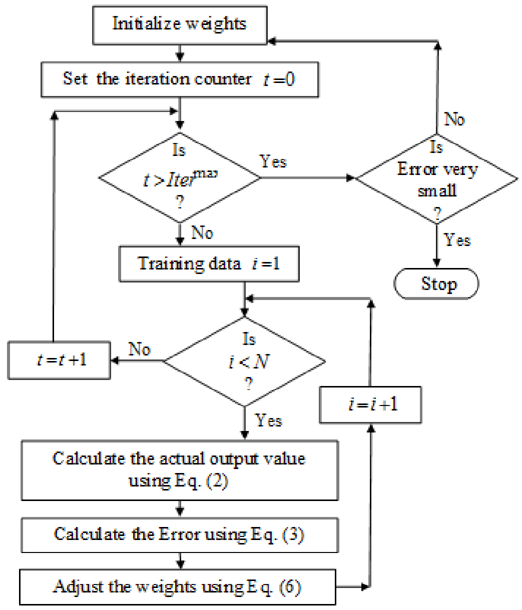

Fig. 3 Flowchart of the backpropagation learning algorithm

Radial Basis Function Network

Radial basis function (RBF) networks have been studied since the mid-1980s, and they were first introduced in the solution of real multivariable interpolation and approximation problems. Unlike the well known multilayer-perceptron approach, which is based on a unit computing a nonlinear function of the scalar product of the input and weight vectors, the design of RBF network is viewed as a curve-fitting problem in a high-dimensional space. Consequently, training becomes searching for a surface in a multidimensional space that provides a best fit to the training data. Such a surface may be represented by a complex function consisting of a network of radial basis functions; the form and the number are determined such that the data points of an input vector can be mapped to that of the output vector with a satisfactory level of accuracy. The general RBF network consists of two fully connected layers namely, hidden and output layers as shown in Fig. 4 The input nodes are directly connected to the hidden layer neurons. The output of the *j - th* hidden neuron can be written in the form of a non-linear Gaussian distribution function as The neurons of the output layer have a linear transfer function. It is simply the weighted summation of outputs of all hidden neurons connected to that output neuron.

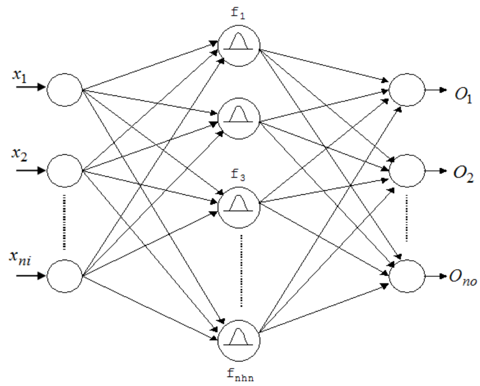

Fig. 4. Structure of Radial Basis Function Network

The output O_k (o) of k - th neuron is

$$O_k(o) = \sum_{j=1}^{nh} W_{kj}\ O_j(h) \quad (9)$$

With this structure, the transformation from the input space to the hidden layer is non-linear, due to the use of Gaussian distribution functions. The hidden layer linked to the output layer, however, is linear. The main advantages of this configuration are that it allows the mathematics to be simple and the computational effort to be relatively low.

RESULTS AND DISCUSSION

Applying PCA to ECG leads that are statistically independent gives n new signals or principal components. The first signal corresponds to the principal component with highest variance while the *n-th* signal corresponds to the principal component with the lowest variance. We apply PCA to our dataset containing all ECG signals. These signals are of 5 different arrhythmias namely, Atrial Premature Contraction, Left Bundle Branch Block, Normal Sinus Rhythm, Right Bundle Branch Block beat and Premature Ventricular Contraction. Samples in the form of text are saved in excel file and then called in MATLAB. Then in MATLAB we apply PCA on the data. We get 450x20 matrix of Eigen vectors or Principal Components. And we get New Data by multiplying this Eigen Vectors Matrix with Original data Matrix. This new data is nothing but the old data organised in a new way. When classification is done, results could have an error rate,

Table 2. Confusion Matrix

		Predicted Class					
		Class-1	Class-2	Class-3	Class-4	...	Class-n
Actual Class	Class-1	Accurate					
	Class-2		Accurate				
	Class-3			Accurate			
	Class-4				Accurate		
	...					Accurate	
	Class-n						Accurate

either fail to identify an abnormality, or identify an abnormality that is not present. The result for each input fundus image can be divided into true positive (TP), a sample correctly classified as positive; true negative (TN), a sample correctly classified as negative; false positive (FP), a sample wrongly classified as positive; and false negative (FN), a sample wrongly classified as negative. A confusion matrix, containing information about actual and predicted classifications, is usually formed to visualize the performance of the algorithm as shown in Table 2. Each column of the matrix represents a predicted class, while each row represents the actual class.

Table 3. Confusion Matrix for RBF

		Predicted Class				
		NSR	APC	LBBB	RBBB	PVC
Actual Class	NSR	15	2	1	1	1
	APC	1	12	2	1	0
	LBBB	0	1	13	1	1
	RBBB	2	1	1	12	0
	PVC	1	0	1	2	8

Table 4. Confusion Matrix for FF

		Predicted Class				
		NSR	APC	LBBB	RBBB	PVC
Actual Class	NSR	17	1	0	1	1
	APC	2	12	0	1	1
	LBBB	1	0	13	1	1
	RBBB	2	2	0	11	1
	PVC	2	1	1	0	8

The diagonal cells in the matrix with matching actual and predicted classes are the correct predictions and these points should be maximised for greater accuracy. The blue cells in that table are the cells for the correctly classified points. In an ideal scenario, all other yellow coloured cells should have zero points. That is, a good classification system should reduce the FP and FN values to as close as zero. The other common quantitative performance measures, such as, accuracy, sensitivity and specificity, are also used in this thesis. The accuracy represents the percentage of correctly classified samples; sensitivity indicates the percentage of correctly classified positive samples, and specificity signifies the percentage of correctly classified negative samples.

They are computed by $Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}$ (10)

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (11)$$

$$Specificity = \frac{TN}{(TN+FP)} \quad (12)$$

The outcome of our classification algorithm is tabulated in Table 3 and 4.

Conclusion

Automatic detection of cardiac abnormalities could be very important in clinical usage and lead to early detection of a fairly common malady and could help contribute to reduced mortality. In this research work, the use of Neural Networks for classification of the ECG beats is presented. The PCA has been used in this work for feature reduction. It was found that the accuracy of proposed algorithms are nearly around 96.5 % and 93.2% for Feedforward and RBF classifier respectively for proposed scheme with dimension reduction using PCA. It is concluded that Feedforward algorithm is better than RBF.

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