ECG Beat Classification using the Integration of S-transform, PCA and Artificial Neural Network

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Abstract

Electrocardiography is an important tool in diagnosing the condition of the heart. In this paper, we propose a scheme to integrate the Stockwell Transform (ST), Principal Component Analysis (PCA) and Neural Networks (NN) for ECG beat classification. The ST is employed to extract the morphological features. In addition, PCA is among considerable techniques for data reduction. A Back Propagation Neural Network (BPNN) is employed as classifier. ECG samples attributing to six different beat types are sampled from the MIT-BIH arrhythmias database for experiments. In this paper comparative study of performance of six structures such as FCM-NN, PCA-NN, FCM-ICA-NN, FCM-PCA-NN, ST-NN and ST-PCA-NN are investigated. The test results suggest that ST-PCA-NN structure can perform better and faster than other techniques.

Keywords: Artificial Neural Network, ECG, Principal Component Analysis, S-transform

1. Introduction

Automatic Electrocardiogram (ECG) signal classification is essential to detect the cardiac arrhythmias which is one of the reason for increasing mortality rate1–2. An effective Computer Aided Diagnosis (CAD) system is required to diagnosis the changes of heart activity. Now a days heart disease is very difficult to diagnosis due to the large variation in the morphological of ECG waveforms of different patients as well as same patients. Therefore, the ECG pattern classification technique is considered as a typical problem of classification with extracted features.

In recent years, a number of researchers have reported various methods for ECG beat classification using neural network classifier[3–4]. The very popular classifier is conventional Back Propagation Neural Networks (BPNN) which is able to recognize ECG arrhythmia more accurately, but it has slow convergence to local and global

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minima. In order to overcome this convergence problem, many classifiers techniques are proposed by researchers[5–8]. In[6] has extracted the ECG signal represented features using Independent Component Analysis (ICA) in frequency domain[6]. In[7], have designed a classifier model which is the integration of Independent Component Analysis and Neural Network Classifiers (ICA-NN) along with R-R intervals to discriminate eight types of ECG beats. In[8], have compared the classification performance of Principal Component Analysis (PCA)-Neural Network (NN) with wavelet transform. In[9], have combined FCM, ICA, NN and compared with the structure ICA-NN for the same.

In this paper, we have designed the integration of ST-PCA-NN to classify the six types of ECG beats. The proposed structure is composed of three stages: S-Transform (ST), Principal Component Analysis (PCA), and Neural Networks (NN). The ST layer is used for feature extraction of morphological of ECG signals, where as the second stage, principal component analysis is reduced the extracted features and final stage works as a classifier. In this study, the features are extracted using S-Transform due to its time-frequency localization properties[10]. The S-transform has the following advantages that distinguishes it from Wavelet Transform (WT) and other transforms: 1. Frequency invariant amplitude response, 2. Progressive resolution and 3. Absolutely referenced phase information. Besides, the S-transform represents the signal in time-frequency domain rather than the time-scale axis used in the wavelet[11]. Therefore, the interpretation of the frequency information in the S-transform is more straightforward than in the Wavelet Transform (WT) which will be beneficial to extract the important features from ECG signal. The name of the optimal linear transformation is PCA which seeks a projection of the input vectors onto a lower dimensional feature vector that exists the maximum amount of energy among all possible transformations. In the case, the PCA is used to reduce the dimensionality of morphological features by a factor of 30. The Multilayer Perceptron (MLP) neural network classifier is used to classify the ECG arrhythmias to the appropriate class using the resultant features. The performance of the proposed model ST-PCA-NN is found to be more generalized, accurate and faster than the existing techniques presented in[7–9].

This paper is oriented as follows: Section 2 is discussed the background theory of this proposed technique. The proposed framework is analyzed in Section 3. Results and discussion are described in details in Section 4. Finally, some conclusions are drawn in Section 5.

2. Background Theory

2.1 S-Transform

The S-transform, introduced by[10,11] is a time-frequency distribution which is similar to Short Time Fourier transform (STFT) except that this width and height of the analyzing window are permitted to scale with changes in the frequency, which is similar to continuous wavelet transform. The flowchart of the S-transform is shown in Figure 1. The continuous S-transform $S(\tau, f)$ is defined as[12],

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(\tau-t)^2 t^2}{2}} e^{-i2\pi ft} dt \tag{1}$$

where $h(t)$ is a input signal. A voice $S(\tau, f_0)$ is defined as a one dimensional function of time for a constant frequency f_0, which shows how the amplitude and phase for this exact frequency changes over time. If the time series $h(t)$ is windowed (or multiplied point by point) with a window function (Gaussian function) $g(t)$ then the resulting spectrum is

$$H(f) = \int_{-\infty}^{\infty} h(t) g(t) e^{-i2\pi ft} dt \tag{2}$$

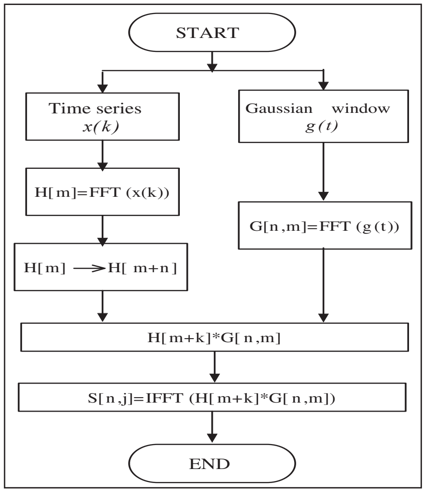

Figure 1. Flowchart of the discrete S-transform.

where generalized Gaussian function is

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}} \tag{3}$$

and then allowing the Gaussian to be a function of translation τ and dilation (or window width) σ. The following equation is a special case of the multi resolution Fourier transform because there are three independent variables in it, it is also impractical as a tool for analysis.

$$S(\tau, f, \sigma) = \int_{-\infty}^{\infty} h(t) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\tau)^2}{2\sigma^2}} e^{-i2\pi ft} dt \tag{4}$$

Simplification can be achieved by adding the constraint restricting the width of the window to σ to be proportional to the period (or inverse of the frequency).

$$\sigma(f) = \frac{1}{|f|}$$

The reasons[11] for taking Gaussian window are as follows: 1. It is symmetric in time and frequency-the Fourier transform of a Gaussian is Gaussian, 2. There are no side lobes in a Gaussian function, 3. It uniquely minimizes the quadratic time frequency moment about a time frequency point. The Discrete S-transform[13] of the ECG signal $h[kT]$ is given by

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{N}} \tag{5}$$

where, $H\left[\frac{n}{NT}\right]$ is the Fourier Transform of h[kT] and j, m, n = 0, 1, ..., (N–1).

2.2 Principal Component Analysis (PCA)

PCA is a well-established statistical technique which is used for data analysis, data compression and dimensionality reduction[8]. It is based on the assumption that most information about classes is contained in the directions along which the variations are the largest. The purpose of the PCA is to condense the information of a large set of correlated variables into a few variables ("principal components"), while not throwing overboard the variability present in the data set. PCA is a standardized linear projection which maximizes the variance in the projected space. The algorithm of the PCA is described in algorithm 1.

Algorithm 1: Feature reduction technique using PCA

1: Initialize the input data.
2: Calculate the mean from the given input.
3: Subtract the mean from the original data.

4: Covariance is calculated from the following equation:

$$\operatorname{cov}(x,y)=\frac{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)\left(X_i-\bar{X}\right)}{(n-1)}$$

where, $\bar{X}$ is the mean of input data.

5: Calculate the eigen vectors and eigen value of the covariance matrix.

6: Form a feature vector using eigen vector and value.

7: Derive the new data set by the following formula Final data = Row feature vector * Row data adjust.

where, Row Feature Vector is the matrix with eigenvectors in the columns transpose and Row data adjust is the mean adjusted transpose.

2.3 Multi Layer Perceptron

The brain has the ability to perform tasks such as pattern recognition, perception and motor control much faster than any computer - even though events occur in the nanosecond range for silicon gates and milliseconds for neural systems. An artificial Neural Network (NN) is a model of biological neural systems that contains similar characteristics. In this work, a three-layered feed-forward NN is used as the classifier which is trained with the error back propagation. The input signals of NN are formed by feature length that is obtained by ST and PCA. The back propagation training with generalized delta learning rule is an iterative gradient algorithm designed to minimize the root mean square error between the actual output of a multi-layered feed-forward NN[14] and a desired output. Each layer is fully connected to the previous layer, and has no other connection. The back propagation algorithm is explained in algorithm 2.

Algorithm 2: Back-propagation algorithm

1: Initialize the all weights and biases which will be small real random values.

2: Give the input vector x(1), x(2)....,x(N) and corresponding desired response d(1), d(2).....d(N), one pair at a time, where N is the training of training patterns.

3: Calculation of actual outputs using Eq. (3) to calculate the output signals $y1$, $y2$...., $y(NM)$

$$y_i=\varphi\left(\sum_{j=1}^{NM-1} w_{ij}^{(M-1)}\ x_{ij}^{(M-1)}+b_i^{(M-1)}\right), i=1,\dots\dots\dots, N_{M-1}$$

4: Updation of weights ($w(ij)$) and biases (b_i) using the following formulas:

$$\Delta w_{ij}^{(l-1)}(n)=\mu.\,x_j(n).\,\delta_i^{(l-1)}(n)$$

$$\Delta b_i^{(l-1)}(n)=\mu.\,\delta_i^{(l-1)}(n)$$

where,

$$\delta_i^{(l-1)}(n)=\begin{cases}\varphi'\left(net_i^{(l-1)}(n)\right)\left[d_i-y_i(n)\right] l=M\\ \varphi'\left(net_i^{(l-1)}(n)\right)\sum_k w_{ki}\,.\delta_k^{l}(n)\, 1\le 1\le M\end{cases}$$

In which $x_j(n)$ = output of node j at iteration n, l is layer, k is the number of output nodes of neural network. K is output layer, ϕ is the activation function. The learning rate is denoted as μ

It is seen from the above equation that a large value of the learning rate may lead to faster convergence but may also suffers in oscillation. To minimize the oscillation a momentum term may be added to the basic weight updating equation to achieve faster convergence. After completing the training procedure of the neural network, the weights of MLP are kept for fixed level and are used in the testing purpose.

3. Proposed Frame Work

The block diagram of the proposed technique is shown in Figure 2. This method is divided into four steps: 1. Preprocessing 2. Feature extraction 3. Feature reduction 4. Classification by neural networks which are described as follows.

3.1 Preprocessing

ECG signal are taken from MIT-BIH arrhythmia database for classification evaluation. The most important information lies before and after R peak of the ECG signal. This database contains 48 ECG recordings, each containing 30-min segment selected from 24hrs recordings of 48 individuals. Each ECG signal is passed through a band pass filter at 0.1-100Hz and sampled at 360Hz. ECG signals are sampled at 360 Hz. A segment is defined as R-R intervals of all ECG arrhythmias. 50 sample segments are chosen to attribute the six ECG beat types from MIT-BIH arrhythmia database. The selected six beat types are Normal beat (NORM), Left Bundle Branch Block Beat (LBBB), Right Bundle Branch Block Beat (RBBB), Artial Premature Beat (APB), Premature Ventricular Contraction (PVC), Paced Beat (PB) which is mentioned in Table 1. In each case, 50 percent of the ECG beats are selected for training and remaining 50 percent used at the testing stage. The preprocessing of the samples is normalized with zero mean and unity standard deviation in order to reduce the effect of bias due to signal amplitude.

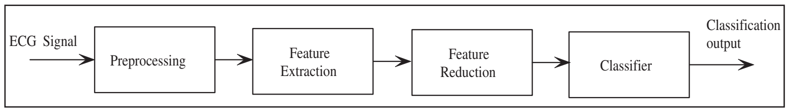

Figure 2. Block diagram of proposed method.

Table 1. Description of the selected ECG arrhythmias and # tape numbers

Arrhythmia	NORM	LBBB	RBBB	PVC	APB	PB
Tape No.	100,101	109,214	118,124	106,119	209,222	102,104 [t]
	108,105	111,207	212,231	200,213	220,223	107,217 [b]
Training segment	8	8	8	8	9	9
Testing segment	8	8	8	8	9	9

3.2 Feature extraction

A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a pattern. Features are used to represent patterns with the goal of minimizing the loss of important information. A feature extraction is the determination of a feature or a feature vector from a pattern vector. The procedure of the morphological feature extraction is shown in algorithm 3.

Algorithm 3: Morphological feature extraction

1: 200 samples are selected around the R-peak.
2: Apply S-transform on selected samples of the ECG signals.
3: Choose a band frequency of (3-20Hz) from the S-transform of ECG signal. The QRS complex energy and least amount of high and low frequency noises are laid in the band of frequency (3-20Hz) [16].
4:Obtain the morphological feature from each sample by averaging its frequency. The extracted morphological features are shown in figure 3.

The S-transform of the morphological feature is shown in Figure 3.

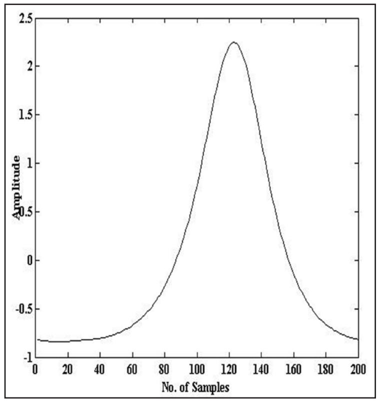

Figure 3. Feature extraction using S-transform.

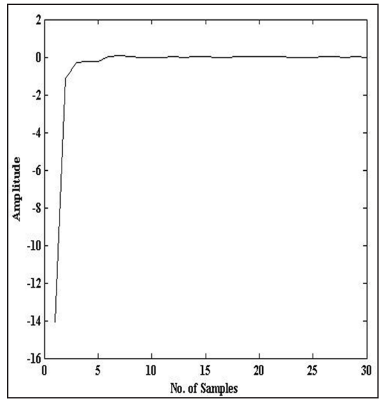

Figure 4. Feature extraction using ST-PCA.

3.3 Feature Reduction by PCA

In our proposed framework, training input patterns at the classifier stage are reduced by PCA. By this process, number of segments in each type of arrhythmia are reduced. Segments reduction are made separately for each type of ECG arrhythmias. In the case, the PCA is used to reduce the dimensionality of morphological features by a factor of 30. The number of input nodes of neural network is same to the optimum number of principal components. The physical interpretation of the reduced features are shown in Figure 4.

3.4 Classifier

In this context, the Back-Propagation Neural Network (BPNN) is used as a classifier which contains three-layer. The first layer is the input layer that has the PCA reduced features. The second layer, also called the hidden layer, has 25 neurons and the output layer has six neurons, which is equal to the number of ECG beat types to be classified. There are three commonly activation functions such as logistic function, hyperbolic tangent function, and identity function. In this study, the hyperbolic tangent functions are used. The weight and bias values in the BPNN are updated with a learning rate of 0.2 which is same for all techniques.

4. Results and Discussion

In Table 3 is depicted the Misclassification Number (MCN) and Rate of Misclassification Number (RMC) using NN. We have selected randomly two samples from each of the records in the database. The selected samples constitute a 50*200 data matrix. In our proposed ST-PCA-NN technique, the number of samples of input training pattern is 30 segments which are obtained after reduction by PCA. The performance of ST-PCA-NN is shown in Table 2. It is seen from the table that % error in case of proposed ST-PCA-NN techinque is least in comparison to other existing methods. It also shows that % of accuracy is higher in our proposed technique ST-PCA-NN which is

Table 2. Comparison of different ECG signal classification methods

Sl. No	Architechture	Size of training	Average Training error	Average test error	No. of iteration	Training time in sec
1	FCM-ICA-NN	200*38	3.99*	0.45	12728	2765.69
2	FCM-PCA-NN	37*38	3.99*	0.13	3028	656.42
3	FCM-NN	200*38	3.99*	0.25	7087	1624.75
4	PCA-NN	37*50	3.99*	0.21	6883	1525.57
5	ST-NN	200*50	3.99*	0.31	8015	1723.12
6	ST-PCA-NN	30*50	3.99*	0.07	2358	494.38

Table 3. Misclassification results of each arrhythmias

Arrhythmias type of test pattern	Number of segments	NN	
		MCN	RMC(%)
NORM	8	0	0
LBBB	8	0	0
RBBB	8	1	12.5
PVC	8	0	0
APB	9	0	0
PB	9	0	0
Total	50	1	2

comparable with other techniques. It is indicated from the table that the training time in case of ST-PCA-NN 494.38 sec where as ST-NN, FCM-ICA-NN, PCA-NN, FCM-NN and FCM-PCA-NN techniques[7–9] have the training time 1723.12 sec, 2765.69 sec, 1525.57 sec, 1624.75 sec and 656.42 sec respectively, which is much more than the our technique keeping the constant training error at $3.99*10^{-4}$. Above all the number of iterations the ST-PCA-NN is only 2358 which is less than other methods. These above results are a significant improvement over other existing methods compared for ECG signal classification using same number of ECG records which is being used in other reported techinque.

5. Conclusion

In this work, a novel technique is developed for ECG beat classification. In this context, we have considered ST for feature extraction PCA for feature reduction and a neural network for classifier. In order to overcome the difficulty of intensive computational time taken using NN classifier, attempt has been made to reduce the number of input data points using PCA which is beneficial for automatic ECG beat classification in real time mode. The features are extracted using ST which is used for accurate classification of ECG signal. The advantages of ST and PCA incorporated with NN classifier which could able to outperform some of the existing classifiers. The proposed ST-PCA-NN technique enhances the performance to recognize and classify ECG beats in terms of faster rate and better accuracy.

6. References

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