ECG Arrhythmia Recognition using Artificial Neural Network with S-transform based Effective Features

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***Abstract*—In this paper, a potential application of Stockewell transforms (S-transform) is proposed to classify the ECG beats of the MIT-BIH database arrhythmias. Feature extraction is the important component of designing the system based on pattern recognition since even the best classifier will not perform better if the good features are not chosen properly. In this study, S-transform is used to extract the eight features which are appended with four temporal features. In this work, the performances of two approaches are compared to classify the five classes of ECG beats which is recommended by AAMI EC57 1998 standard (Association for the Advancement of Medical Instrumentation). The first approach uses temporal and S-transform based feature set, whereas the second approach uses the wavelet transform based features. These features from two approaches are independently classified using feed forward neural network (NN). Performance is evaluated on several normal and abnormal ECG signals of the MIT-BIH arrhythmia database using two techniques such as temporal and S-transform with NN classifier (TST-NN) and other wavelet transform with NN classifier (WT-NN). The experimental results demonstrate that the TST-NN technique shows better performance compared to the WT-NN technique.**

Keywords*—*Artificial neural network (NN), Electrocardiogram (ECG), S-transform (ST), Wavelet transform (WT).

I. Introduction

Electrocardiograms (ECG) is a noninvasive test of measuring the electrical activity of the heart. Due to the high mortality rate of heart disease, it is crucial to accurately detect and discriminate of different ECG arrhythmias in the early stage of disease so as to allow effective treatment. So, an effective computer aided diagnostic (CAD) system is needed to design a powerful pattern classifier as well as feature extractor that is capable of extracting important information from the raw data. The most difficult problem faced by todays automatic ECG analysis is the large variation in the ECG morphologies; not only among different patients but also in a single patient. The ECG waveforms may vary for the same patient at different time and may be alike for different patient having different types of beats. This causes the beat classifiers performing well on the training data and performs poorly with different patients ECG waveforms.

A large number of researchers have proposed the classification of ECG signals [1] - [9]. In [1], the authors classified four types of ECG beats using the discrete wavelet transform based feature set with combined neural network. The wavelet transform and particle swarm optimization technique are used to classify the six types of ECG beats(normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), artial premature contraction (APC), premature ventricular contraction (PVC) and paced beats (PB) with 88.84% accuracy in this literature [2]. In [3], the authors classified six types of ECG beats (N, LBBB, RBBB, APC, VPC, and PB. A comparative study of the heart beat classification performances of two methods presented in this paper [4]. They also classified five classes of ECG beats. In Dipti *et al.* [5] have used fuzzy c-means clustering, PCA and neural network for ECG arrhythmia classification using a limited number of ECG files of MIT-BIH database. In [6], authors presented the experimental pilot study to investigate the effects of pulsed electromagnetic field (PEMF) at extremely low frequency (ELF) in response to photoplethysmographic (PPG), electrocardiographic (ECG), electroencephalographic (EEG) activity using discrete wavelet transform based features. In [7], the authors have shown at an accuracy of 62 % over 20 files of MIT-BIH arrhythmia database using self organizing maps and learning vector quantization. In [8], the authors classified ECG beats into five standard classes using morphological and temporal features set with linear discriminants classifier. A comparative study of discrete wavelet transform (DWT), continuos wavelet transform (CWT) and discrete cosine transform (DCT) on ECG arrhythmia classification are presented and classified five ECG beats using limited number of ECG beats of MIT-BIH database in this literature [9]. However all aforementioned techniques have following drawbacks. (i) In general, all these methods have not performed well due to their inconsistent performance when classifying a new patients ECG waveform. (ii) Most of these techniques are tested only on limited data sets (iii) Despite many ECG classification methods offered in the earlier literature, only few have employed a standard classification scheme of arrhythmia beats such as ANSI/AAMI EC57:1998 [10]. (iv) Most of them use either time or frequency domain representation of the ECG signals as features.

In this paper, a novel approach is proposed to patient adaptation while avoiding the aforementioned limitations. ECG classification strongly depends on extraction of features from ECG waveforms. In this work, the features are extracted using S-transform (ST) due to its time-frequency localization properties [11]. The S-transform has the following advantages that distinguishes it from wavelet transform (WT) and other transforms: (i) frequency invariant amplitude response (ii) progressive resolution and (iii) absolutely referenced phase information. Besides, the ST uses time-frequency axis rather than the time-scale axis used in the wavelet [12]. Therefore, the interpretation of the frequency information in the ST is more straightforward than in the WT which will be beneficial to extract the important features from the ECG signal. The extracted S-transform based eight features with four temporal features (taken from RR intervals of ECG signal) are applied to the input of artificial neural network (NN). The aim of this paper is to design a simple methodology for arrhythmia beat classification, with highest diagnostic sensitivity even when used for large database.

The rest of the paper is designed as follows: Section II presents the database used in this context. Section III reviews the basic concepts and properties of S-transform. The proposed scheme is described in Section IV. Performance results and discussion are explained in details in Section V. Finally, the conclusions of the paper are reported in Section VI.

II. ECG DATA

In this study, ECG data of MIT-BIH arrhythmia data base [13] are used for performance evaluation of the proposed ECG beat classification technique. This database contains 48 ECG recordings, each containing 30-min segments 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. The 44 records from MIT-BIH arrhythmia database are used for performance assessment, where 4 paced beats [7] are not included for this evaluation. This database contains different types arrhythmias. In this paper, the normal and arrhythmia beats are combined based on AAMI standard. The AAMI convention is used to combine the beats into five classes of interest which is described below in Table I [10].

III. BACK GROUND THEORY

A. S-transform

The S-transform, introduced by Stockwell *et al.* [11] is a variable window of short time Fourier transform (STFT) or an extension of wavelet transform which is based on a scalable localizing Gaussian window and supplies the frequency dependent resolution. The continuous wavelet transform (CWT) of $x(t)$ is defined as

$$W(\tau, d) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau, d)dt \quad (1)$$

where, t is the time, τ denotes the time of spectral localization and d is the width of the wavelet w(t,d) which controls the resolution. Then the S-transform (ST) is defined as a CWT with a specific mother wavelet multiplied by phase factor

$$S(\tau, f) = e^{-j2\pi f\tau} W(\tau, d) \quad (2)$$

where the mother wavelet is defined as

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-j2\pi ft} \quad (3)$$

It is noted that scale parameter is the inverse of the frequency f. The wavelet in (3) does not satisfy the property of zero mean for an admissible wavelet. Therefore, (2) is not absolutely a CWT. In other words, the S-transform is not equal to CWT, the S-transform is given by

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-i2\pi ft} dt \quad (4)$$

If the time series *x*(t) is windowed (or multiplied point by point) with a window function (Gaussian function) *g*(t) then the resulting spectrum is

$$X(f) = \int_{-\infty}^{\infty} x(t)g(t) e^{-i2\pi ft} dt \quad (5)$$

where generalized Gaussian function is

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}} \quad (6)$$

and then allowing the Gaussian to be a function of translation τ and dilation (or window width) σ.
The reasons [12] for taking Gaussian window are as follows: (i) It is symmetric in time and frequency-the Fourier transform of a Gaussian is Gaussian, (ii) There are no side lobes in a Gaussian function, (iii) It uniquely minimizes the quadratic time frequency moment about a time frequency point.
The relation between the S-transform(ST) and Fourier transform can be written as

$$S(\tau, f) = \int_{-\infty}^{\infty} X(\alpha+f) e^{-\frac{2\pi^2\alpha^2}{f^2}} e^{j2\pi\alpha\tau} d\alpha, \qquad f \neq 0. \quad (7)$$

The Discrete S-transform [12] of the ECG signal *x*[kT] is given by

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} X\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{N}} \quad (8)$$

where, $X\left[\frac{n}{NT}\right]$ is the Fourier transform of $x\left[kT\right]$ and j, m, n = 0,1,...,$(N-1)$. The output of ST is a complex valued matrix whose rows indicate the frequency and column indicates the time. The ST-amplitude, which is used to analyze the ECG signal is defined as

$$A(kt, f) = \left| S\left[kT, \frac{n}{NT}\right] \right|$$

IV. PROPOSED SCHEME

The block diagram of the proposed classification technique is shown in Fig. 1. In this context, the proposed classification technique consists of three main stages such as (i) preprocessing and QRS detection, (ii) feature extraction and (iii) classifier. The pre-processing stage involves following two sub-stages: (i) normalizes the amplitude of ECG signals to a mean zero. This reduces the DC offset and eliminated the amplitude variance file to file. (ii) The bandpass filter (3-20Hz) is used to reduce the influence of noise such as power line interference, baseline wander and motion artifacts which are generally embedded with acquired signal. In this paper, we have discussed on classification only. Many researchers have proposed QRS detection algorithm with detection accuracy greater than 99%. So, we did not integrate the beat detection. In this study, Pan Tomkins' algorithm is taken for detection the QRS complexes of ECG signals [14].

TABLE I. AAMI CLASS

N = any beat that does not fall into the S, V, F, or Q categories described below (a normal beat or a bundle branch block beat)
S = a supraventricular ectopic beat, an atrial or nodal (junctional) premature or escape beat, or an aberrated atrial premature beat
V = a ventricular ectopic beat, a ventricular premature beat, an R-on-T ventricular premature beat, or a ventricular escape beat
F = a fusion of a ventricular and a normal beat
Q = a paced beat, a fusion of a paced and a normal beat, or a unclassified beat

Fig. 1. Block diagram of proposed classification method

A. Feature Extraction

Feature extraction is the important component of designing the system based on pattern recognition since even the best classifier will not perform better if the features used as inputs are not chosen well. A feature extractor should reduce the pattern vector (i.e., the original waveform) to a lower dimension, which contains most of the important information from the original vector [15]. Two types of features are extracted from one ECG cardiac cycle: a) Wavelet based features b) S-transform based feature set along with temporal features.

1) Wavelet based features: The choice of appropriate wavelet and the number of decomposition levels are very important section on analysis of ECG signals using wavelet transform (WT) [6]. The decomposition levels are selected based on the maximum frequency components of the ECG signals. The levels are taken such that those parts of the signal correlate well with the wavelet coefficients. In this paper, the number of decomposition levels is taken to be 4 i.e. ECG signals are decomposed into the details D1-D4 and one approximation coefficient A4. The Daubechies wavelet of order 2 (db2) is chosen due to its similar morphological structure with the ECG signals. The computed discrete wavelet coefficients of the ECG signals of each record are used as the feature vectors representing the signals. Therefore, the feature set of the wavelet coefficients is used to reduce the dimensionality of the extracted feature vectors. The following features are extracted using WT to represent the time-frequency distribution of the ECG signals:

WF1. Maximum of the wavelet coefficients in each subband.

WF2. Mean of the wavelet coefficients in each subband.

WF3. Minimum of the wavelet coefficients in each subband.

WF4. Standard deviation of the wavelet coefficients in each subband.

Total 20 features are extracted using WT which are the desired input to the classifier.

2) S-transform based features along with temporal: In this context, temporal features are extracted directly from one ECG cardiac cycle whereas morphological features are extracted using S-transform.

a) Temporal features: RR-intervals are calculated as the interval between successive heartbeats. The temporal features are extracted as follows: (i) Pre-RR interval: RR-interval between a given heartbeat and the previous heartbeat, (ii) Post RR-intervals: The RR-interval between a given heartbeat and the following heartbeat, (iii) Average RR-intervals: The mean of the RR-intervals for a recording and is considered as the same value for all heartbeats in a recording, (iv) Local average RR-interval: Averaging the RR-intervals of ten RR-intervals surrounding a heartbeat [8].

b) S-transform based features: We have selected a window of -250ms to +250ms around the R-peak as found in the QRS detection algorithm, i.e. 180 samples are selected around the R-peak. The S-transform is applied to selected ECG samples to obtain ST-matrix. Features are taken from the plots of ST-matrix as well as the ST-matrix contour. These features are very useful for detection, classification and quantification of relevant parameters of ECG signals. Eight features are extracted from the S-transform output, of which, four from the time-frequency contour (TF-contour) and remaining four from the time maximum amplitude plot (TmA-plot) [16]. Total eight features are described below in two cases.

Case 1. Feature extraction from TF-contour

SF1: Standard deviation of the contour having the largest frequency amplitude of TF-contour

SF2: Mean of contour having largest frequency amplitude of TF-contour

SF3: The energy of contour having largest frequency amplitude of TF-contour

Case 2. Extraction of features from TmA-plot.

SF4: Maximum value of TmA-plot.

SF5: Minimum value of TmA-plot.

SF6: Mean value of the TmA-plot.

SF7: Standard deviation of TmA-plot.

SF8: Maximum energy of TmA-plot.
The eight S-transform based feature set along with four

temporal features are used to classify the ECG arrhythmias of MIT-BIH database.

B. *Classifier*

A three-layered feed-forward neural network (NN) [17] is used and trained with the error back propagation which is shown in Fig. 2. The input signals of NN are formed separately by S-transform based feature set along with four temporal features and wavelet based features. The output layer has five neurons, which is equal to the number of ECG beat types to be classified. The back propagation training

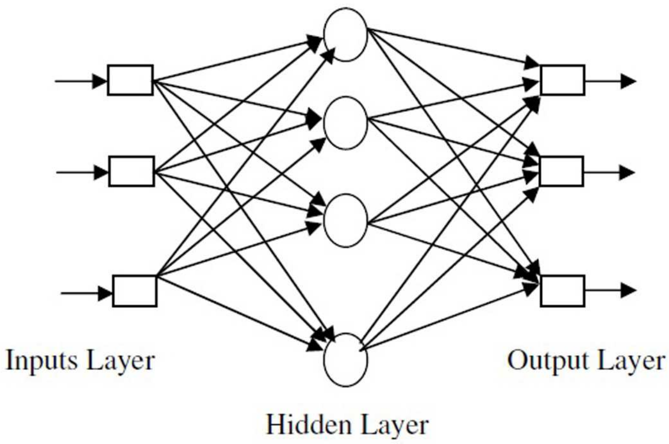

Fig. 2. Block diagram of artificial neural network

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 and a desired output. Each layer is fully connected to the previous layer, and has no other connection. Many activation functions such as logistic function, hyperbolic tangent function, and identity function are used in NN classifier. The hyperbolic tangent function is chosen in this application. The performance of the NN mostly depends on the selection of hidden nodes. However, there are no such techniques to select the number of hidden nodes for better performance of the classifier. The number of hidden nodes are chosen empirically in this application which is shown in Fig 3. The weight and bias values in the BPNN are updated with a learning rate of 0.5.

V. Results and Discussion

In this paper, 44 records of MIT-BIH arrhythmia database are taken for evaluation of the proposed technique. A common training data set is developed for this work, which contains a total of 245 representative beats, including 75 from each type- N, S and V beat, and all (13) type F and all (7) type Q beats. These beats are randomly selected from the first 20 records (picked from the range 100-124) excluding paced beats of the MIT-BIH data base [7]. The NN classifier is trained with a total of 245 common training beats and first 5-min of each patient specific record (200-234). The remaining 25-min of each record is used as testing data for evaluation of the two techniques. In this work, classification performances are evaluated using two techniques such as TST-NN and WT-NN. Beat by beat classification performance of WT-NN and proposed TST-NN are depicted in Table II for 24 ECG records. The summary tables show how groups are being misclassified. It

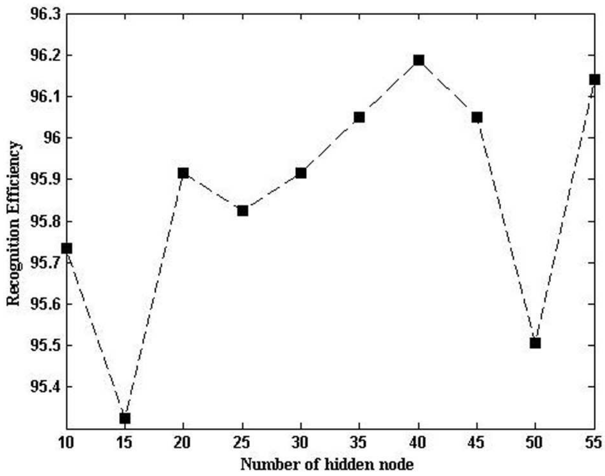

Fig. 3. Selection of the hidden nodes

is seen from the Table II that 235 supra-ventricular (S) beats are misclassified as normal (N) beats for proposed method whereas for WT-NN method, 1001 supra-ventricular beats are misclassified as normal beat. Similarly, 119 normal (N) beats are misclassified as fusion (F) beats and 120 fusion beats are misclassified as normal beats in proposed technique. In WT-NN method, 139 normal beats are misclassified as fusion beats where as 158 fusion beats are misclassified as normal beats. Fusion beats are difficult to distinguish from normal beats because fusion beats are the union of ventricular and normal beats and their morphology and timing information can also closely resembles with normal beats. Also, the detection sensitivity of normal beats and fusion beats are comparably more than WT-NN method. It is also explained that the detection sensitivity of all classes using proposed TST-NN is better compared to WT-NN technique. Classification performance is evaluated using two common metrics found in the literature [7]. (i) Accuracy (Acc): It measures the overall system performance over all classes of ECG arrhythmias ($Acc = \frac{TP+TN}{TN+FN+TP+FP}$), (ii) Sensitivity ($Sen$): It is the rate of correctly classified events among all events ($Sen = \frac{TP}{TP+FN}$), where, TP, TN, FP and FN are true positive, true negative, false positive and false negative respectively. Classification performance of all techniques is shown in Table III. It is explained from the table that for 24 common testing records, the accuracy of the N, V, S, F and Q classes are 96.3%, 97.1%, 97.9%, 99.2% and 99.6% respectively using the proposed TST-NN technique where as the WT-NN based method provides the accuracy 93.8% of N, 98.0% of V, 96.3% of S, 99.1% of F and 99.9% of Q class. On the other hand the sensitivity of the N, V, S, F, and Q are 97.0%, 84.8%, 50.8%, 54.7% and 0.0% respectively whereas the proposed TST-NN method gives best sensitivity than other method. It is also observed that no Q class beat is detected from the WT-NN based and other technique where as the proposed method detects the 37.5% Q beats. The summary table IV shows the automatic ECG classification using different methods. Chazal *et al.* used the morphology and heartbeat interval features for five beat class and reported 85.9% accuracy [8]. Hu *et al.* classified the Four types of ECG beats using a mixture of experts approach and achieved 94% of accuracy [7]. The Jiang *et al.* classified five types of ECG beats using Hermite transform coefficients and time intervals between

TABLE II. BEAT-BY-BEAT CLASSIFICATION RESULTS FOR 24 RECORDS OF MIT-BIH ARRHYTHMIA DATABASE

AAMI CLASS	Confusion Matrix [TST-NN]					AAMI CLASS	Confusion Matrix [WT-NN]				
	N	V	S	F	Q		N	V	S	F	Q
N	40641	563	381	119	138	N	40574	521	600	139	8
V	293	4316	114	65	20	V	652	4075	72	9	0
S	235	413	1677	1	12	S	1001	115	1187	7	28
F	120	38	2	419	33	F	158	115	4	335	0
Q	3	2	0	0	3	Q	5	3	0	0	0

TABLE III. CLASSIFICATION PERFORMANCE OF THE PROPOSED METHOD TST-NN AND COMPARISON WITH WT-NN.

Method	N		V		S		F		Q	
	Acc	**Sen**	**Acc**	**Sen**	**Acc**	**Sen**	**Acc**	**Sen**	**Acc**	**Sen**
WT-ANN	93.8	97.0	98.0	84.8	96.3	50.8	99.1	54.7	99.9	0.0
ST-NN	96.3	97.1	97.0	89.8	97.7	71.7	99.2	68.5	99.6	37.5

TABLE IV. SUMMARY TABLE OF THE ECG CLASSIFICATION ACCURACY USING DIFFERENT TECHNIQUES

Literature	Features	Classifier	Classes	Accuracy
de Chazal *et al.*, [8]	Morphology and heartbeat interval	Linear discriminant	5	85.9
Hu *et al.*, [7]	Time domain features	Mixture of experts	2	94
Jiang *et al.*, [18]	Hermite function parameters and RR interval	Block based NN	5	96.6
Inan *et al.*, [19]	WT and timing interval	Neural network	3	95.2
Proposed Method	ST and temporal features	Neural Network	5	97.95

two neighboring R-peaks of ECG signals as features and block based neural network as a classifier with 96.6% accuracy [18].

The multi scale wavelet and timing information features are used as a feature for three classes of ECG beats(Normal, VPC and other classes of betas) with accuracy of 95.16% [19]. In this work, we have compared the performance of two approaches: (i) S-transform based features with temporal features (ii) Wavelet transform based features The first method performance gives highest average classification accuracy of 97.95% respectively compared to the other two methods. Overall classification performance of the proposed method (TST-NN) is better compared to WT-NN based method and other existing technique even with less number of training data set.

VI. CONCLUSION

In this piece of work, a novel method is designed to classify the ECG arrhythmia for each patient individually. In this proposed technique, the S-Transform is effectively employed to extract the eight features which are combined with four temporal features (pre RR, post RR, local RR and avg RR). In this study, we have compared the performances of two methods. The first method uses S-transform based features along with four temporal feature set and NN classifier whereas, second method uses WT based feature set with same classifier separately. The overall results show a significant improvement and better recognition accuracy compared to the WT-NN and other earlier reported technique. The proposed methodology (TST-NN) can be used in tele-medicine applications, arrhythmia monitoring systems, cardiac pacemakers, remote patient monitoring and in intensive care units.

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