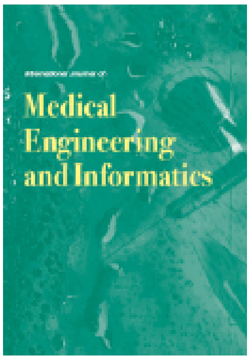

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Classification of ECG arrhythmia using significant wavelet-based input features

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Abstract: This paper proposes an automated approach to classify ECG arrhythmia using wavelet transform and neural network. Wavelet-based optimal ECG feature sets are prepared followed by regression plots in curve fitting. These feature sets are further used for pattern recognition to distinguish in between normal or abnormal arrhythmia classes using multi-layer perceptron neural network (MLP NN). To evaluate performances of the designed classifier accuracy, selectivity and sensitivity parameters are measured. The average accuracy of the classifier is 99.05% which is comparatively higher than the existing methods with dependence on less input features.

Keywords: ECG arrhythmia; MLP NN; performance indices; regression plot; wavelet transform.

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1 Introduction

Cardiac arrhythmia a life threatening abnormality of heart if not detect early and/or interpreted improperly. The electrocardiogram (ECG) plays an imperative role in the primary diagnosis of arrhythmia, a measure of cardiac activity of heart. It is an important bio-electrical signal, recorded by placing ECG electrodes on various locations on body surface. ECG signal consists of P, QRS complex, T wave, various segments and intervals which is used to represent cardiac activity.

However, interpretation of real-time ECG signal is a major challenge before medical professionals. Because ECG signal waveform consists of different features for clinically significance, including:

1 temporal/time-domain features (RR interval, PQ, PR, QT segments and duration)

2 morphological/spatial features (amplitude of signal waveform)

3 statistical features (mean, median and standard deviation)

4 frequency domain features (energy and entropy).

These features may vary from person to person for same arrhythmia and even for same patient in different recorded time. Thus extraction of useful features from a non-stationary and time varying ECG and their classification in a particular class of arrhythmia, as recommended by Association for the Advancement of Medical Instrumentation (AAMI) is a tedious job. In addition, complexity and difficulty of implementation with high accuracy to automatically detect and analyse cardiac arrhythmia is also a challenge in real life applications, as reported by Acharya et al. (2007).

ECG signal processing consists of noise removal pre-processing stage, extraction of useful features is feature extraction stage and pattern recognition stage, used to classify extracted ECG features in various classes of arrhythmia. For last few decades, wavelet transform has emerged as a popular technique used in noise removal and feature extraction. It has capability to localise time and frequency domain features, simultaneously. It preserve real ECG features as compared to classical methods, i.e., high pass, low pass, adaptive or finite impulse response digital filters which distort the time-varying ECG signal as discussed by EI Hanine et al. (2014), and Feher (2017). Selection criteria of wavelet transform includes choice of wavelet function, level of decomposition and set of threshold rules.

For automatic detection and classification of ECG arrhythmia, neural network-based classifier is a promising technique, as it is inspired by real biological neurons structure of human body. Back propagation neural network (Dewangan and Shukla, 2016), radial basis function neural network (Rai et al., 2014), feed-forward neural network (Luz et al., 2016), genetic algorithm with back propagation (Li et al., 2017), 1D and 2D convolution neural network (Yıldırım et al., 2018; Labati, 2019) are some good approaches reported in literature, that used DWT-based features extraction method followed by neural network classifier. Savalia et al. (2017) used convolution layer stacking with max pooling for feature extraction. To classify large number of feature sets, deep learning is a good approach, as proposed by Acharya et al. (2017). Method of processing and classification of 2D ECG signals are reported by Ji et al. (2019). The method uses empirical mode decomposition for noise removal and faster R-CNN architecture for classification.

In the light of the above factors, the work focuses to optimise the extracted ECG using wavelet-transform method. The sets obtained are fed to a neural network-based classifier to automatically detect and categorise into various classes of ECG arrhythmia. The ECG signals used to train, test and validate the classifier are downloaded from The MIT BIH Arrhythmia Database in MATLAB v2013.

2 Methodology

The proposed methodology consists of four major stages:

1 wavelet transform-based pre-processing

2 feature extraction stages

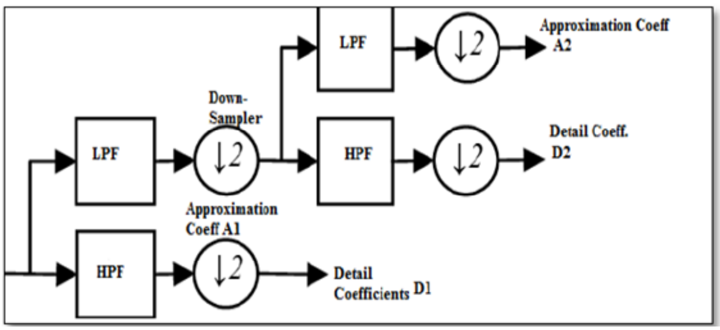
3 optimal selection of ECG features

4 classification of arrhythmia’s using neural network-based architecture.

2.1 Discrete wavelet transforms method

It is a promising mathematical tool which provides spatial and spectral localisation of nonlinear and non-stationary signal in various resolution bands; called multi-resolution analysis (MRA). DWT breaks the signal into approximation and detailed coefficients, resulting from low pass and high pass filtering respectively as shown in Figure 1.

Figure 1 DWT at decomposition level 2



But representation of ECG signal using wavelet transform produces large number of wavelet coefficients at each decomposition level. These large datasets become problematic in clinical diagnosis to interpret cardiac activities.

2.2 Neural network-based classifier

2.2.1 Multi-layer perceptron neural network (MLP NN)

It is one of the supervised learning method to create and train data in a defined network using back propagation (Levenberg-Marquarlt) with feed forward technique. Generally, MLP consists of minimum of three layers of nodes:

1 input layer that represents input features set

2 hidden layer

3 output layer, equivalent to classes to be classified.

This type of feed forward network uses nonlinear activation sigmoid transfer function in the hidden layer for function fitting and a linear transfer function in the output layer (Savalia et al., 2018). The network is adjusted according to:

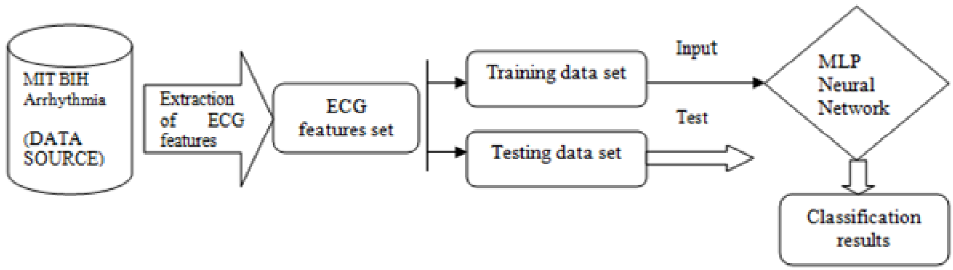
1 its error called training phase

2 its independent performance measurement called testing phase

3 its generalised measurement for network performance called validation phase.

Here, we used 70% ECG samples for training purpose and 15% for testing and 15% for validation in a feed forward neural network. Wavelet transform-based extracted ECG feature sets are used as inputs and normal/abnormal are two outputs of NN classifier, as shown in following architectural model.

Figure 2 Neural network classifier



2.2.2 Regression plots

The proposed classifier applies a function fitting process (NN start in MATLAB Toolbox in Mathsworks, 2013) on extracted wavelet-based input feature vectors. It produces a set of target outputs, called regression plots (R), which measures the correlation between outputs and target. If R is 1, it shows best data fit, used to optimise input feature sets.

3 Experimental results and discussion

3.1 ECG signal datasets

Six types of arrhythmic signal waves are used to represent mal-functioning of heart. These are:

1 normal sinus rhythm (N)

2 atrial fibrillation (AF)-unsynchronised electrical activity

3 premature ventricular contraction (PVC)-bypasses ventricles

4 atrial flutter (AFu)-rapid contraction of cardio muscles

5 left bundle branch block (LBBB)

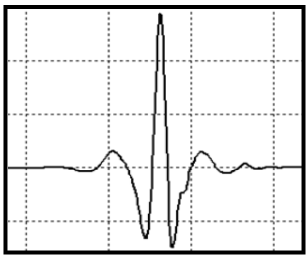
6 right bundle branch block (RBBB)-blockage in conduction path at left and right side of heart chambers, respectively.

Their single ECG waveforms are illustrated in Figure 3.

One such ECG signal sampled at frequency 360 Hz of 30 minutes recording, downloaded in MATLAB wavelet GUI tool box is shown in Figure 4.

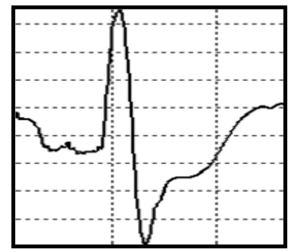
The above signal has low frequency baseline wander (BLW) noise and high frequency power line interference (PLI) noise. This BLW makes signal offset of 0.4 mV from baseline and PLI corrupts lower scale detail coefficients. By applying DWT at decomposition level 9, using Daubechies wavelet function (db6), noisy wavelet coefficients are obtained at each level. Approximation coefficient a_9 and detail coefficient d_2 are used to represent BLW noise and PLI noise, respectively, as shown in Figure 5.

Figure 3 ECG signal waveform of different types of arrhythmia, (a) normal (b) left bundle branch block (c) atrial fibrillation (d) right bundle branch block (e) atrial flutter, (f) premature ventricular contraction

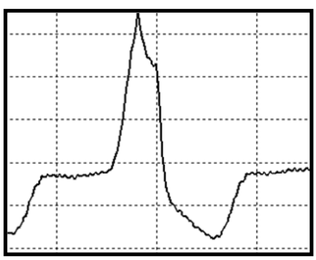


(a)

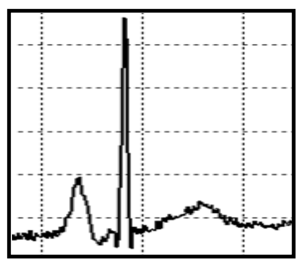
(b)



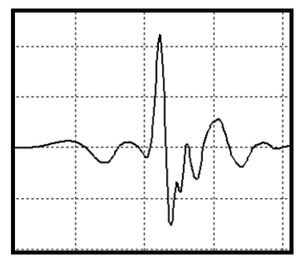
(c)



(d)

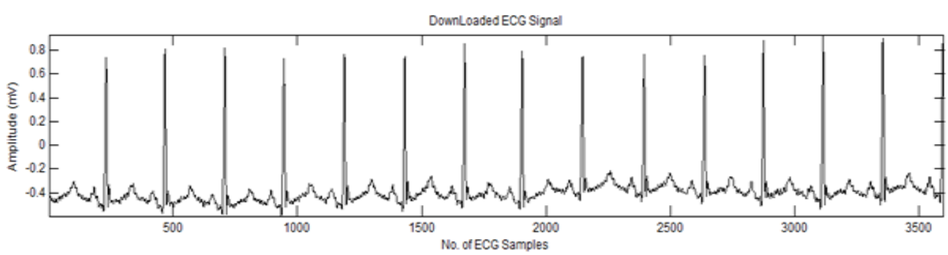


(e)



(f)

Figure 4 Downloaded original noisy ECG signal (record 100.dat), with offset of 0.4 mV



Truncation and zeroing of these noisy wavelet coefficients are used to remove above said noises. Rest of wavelet coefficients are shrunk using soft thresholding with fixed threshold rule. All modified detail coefficients are shown Figure 6.

After applying inverse discrete wavelet transform (IDWT) all these coefficients are reconstructed to obtain de-noised ECG signal, which will be processed further in feature extraction. All extracted features are arranged in various groups [Figures 7(a) to 7(e)] for data fitting, to measure value R.

As lower scale coefficients d_1–d_3 is usually affected by noise. Therefore, their elimination will certainly improve classification accuracy. Now, extracted wavelet based features are fitted in MATLAB neural network input-output and curve fitting tool (Using MATLAB Neural Network Toolbox, 2013), to optimised input features sets with associated target outputs. As number of wavelet coefficients increase as shown in Figure 7(d) data fitting approaches y = x. Thus, the trained network achieves reasonably good response for associated targets, if input feature vectors are details coefficients from d_1–d_9 after making d_1–d_3 zero, and adding them to approximation coefficient a_9, as shown in Figure 7(e).

Figure 5 Noisy wavelet coefficients at decomposition level 9

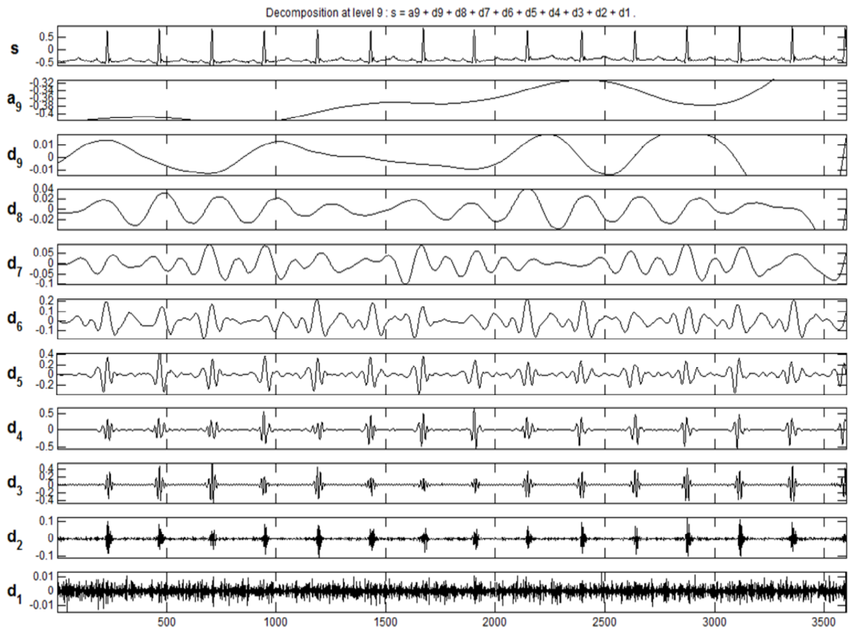


Figure 6 Modified wavelet coefficients (see online version for colours)

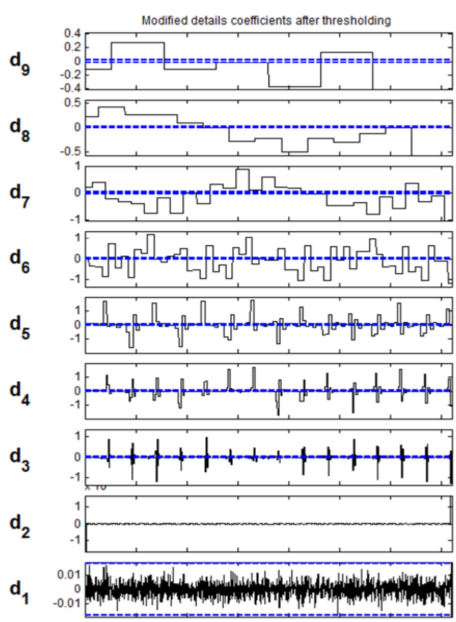
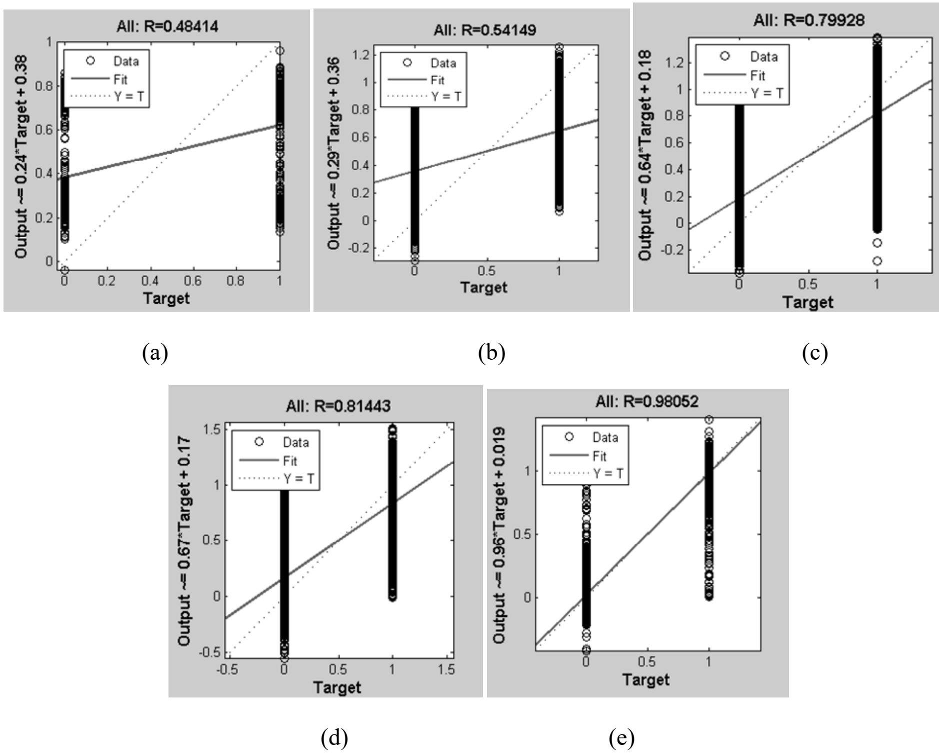


Figure 7 Extracted ECG features fitting and diversions with target (a) d_1–d_3, R = 0.48 (b) d_4–d_6, R = 0.54 (c) d_7–d_9, R = 0.79 (d) d_1–d_9, R = 0.81 (e) (d_1–d_9) + a_9+ (d_1–d_3 = 0), R = 0.98



3.2 *Performance indices for recognising pattern in neural network classifier*

The proposed work uses MATLAB Neural Network Pattern Recognition tool (Using MATLAB Neural Network Pattern Recognition Tool, 2013), to classify extracted ECG features. To evaluate performance of the proposed classifier, following parameters are measured:

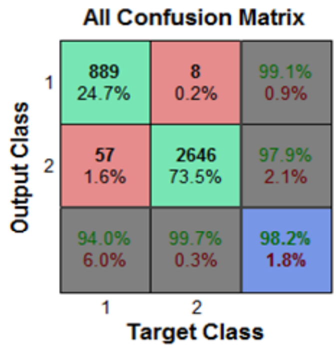
$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (1)$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (3)$$

Here, TP (true positive, correctly identified events), TN (true negative, correctly rejected events), FP (False positive, incorrectly detected events) and FN (false negative, incorrectly rejected events). Thus, sensitivity and specificity define the effectiveness of trained network in correctly identifying abnormal and normal ECG, respectively. All these parameters are tabulated in confusion matrix. One such confusion matrix plot, obtained through simulation of proposed classifier is shown in Figure 8.

Figure 8 Confusion matrix of normal ECG beat type (see online version for colours)



Similarly, all six types of ECG signals are plotted through confusion matrix. Summary of the proposed method in terms of performance parameters are shown in Table 1.

Table 1 Performance indices of proposed classifier

S. no.	*ECG beat types*	*Sensitivity*	*Selectivity*	*% accuracy*
1.	Normal	94	99.7	98.2
2.	Left bundle branch block	92	96.5	98.8
3.	Right bundle branch block	96.3	99.9	99.5
4.	Premature ventricular contraction	97.7	99.1	98.6
5.	Premature atrial contraction	97.9	99.2	99.9
6.	Atrial fibrillation	93.5	97.9	99.2
Average accuracy				*99.05*

Thus, the proposed method offers average accuracy of 99.05%. Comparison of proposed work with other existing methods, to classify ECG arrhythmia signals, is summarised in Table 2.

Table 2 Comparison of different feature extraction techniques from an ECG signal

Author	*Method feature extraction/classification*	*Features*	*Accuracy*
Das and Ari (2014)	Transform method/MLP NN	Mixed features	96%
Li and Zhou (2016)	Wavelet transform/radial forest	Energy and entropy-based	94%
Dewangan and Shukla (2016)	Wavelet transform/Neural Network	Mixed features	87
Savalia et al. (2017)	Convolution and max pool neural network	Temporal and spectral features	88.7
Proposed method	*Wavelet transform/MLP neural network*	*Wavelet-based*	*99.05*

Thus, the proposed work improves the classifier accuracy by using less input features.

4 Conclusions

This work focuses on feature extraction and classification stages of ECG signal analysis. In feature extraction, wavelet-based ECG features are extracted and optimised, using regression plots in neural network tool box. The combination of selective features and MLP neural network significantly improves the classification accuracy. From the experimental results, it can be concluded that the average accuracy of classifier for abnormal but regular ECG arrhythmia is: N, LBBB, RBBB, PVC, AF and AFu are 98.2%, 98.8%, 99.5%, 98.6%, 99.9% and 99.2%, respectively. The limitation is proposed method will not identify randomly occurring irregular abnormal beats even if the person is monitored for long. It works well for persons having a fairly constant abnormality.

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