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Feed Forward Neural Network Optimized Using PSO and GSA for the Automatic Classification of Heartbeat

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Abstract: In this paper, an automatic classifier has been developed using Feed Forward Neural Network (FFNN) to classify the ECG signals between different heartbeats. Here, the classifier is trained independently bymorphological, heartbeat interval features and temporal features using Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The trained classifier then classifies the beats into Normal beat (N), Premature Ventricular Contraction (PVC), Right Bundle Branch Block Beat (R), Fusion of Paced and Normal Beat (f), Fusion of Ventricular and Normal Beat (F) and the Atrial Premature Beat (A). The classifier performance is validated using the benchmark database such as MIT-BIH and the performance of the classifier trained independently using PSO and GSA is compared. It is observed that FFNN trained with GSA performs better than the one trained with PSO.

Key words: Feed Forward Neural Network (FFNN) · Particle Swarm Optimization (PSO) · Gravitational Search Algorithm (GSA) · Heart beats · Normal beat (N) · Premature Ventricular Contraction (PVC) · Right Bundle Branch Block Beat (R) · Fusion of Paced and Normal Beat (f). Fusion of Ventricular and Normal Beat (F) and Atrial Premature Beat (A)

INTRODUCTION

Heartbeat classification is a significant step in the diagnosis of arrhythmia [1, 2]. An arrhythmia is the sign of irregular heartbeat, which may be too fast or too slow or inconsistent. A normal person's heart rate lies in the range of 60-100 beats per minute (BPM). If the rate is less than the normal rate then it is the indication of bradycardia and tachycardia if the rate is larger than the normal rate [3]. Various techniques such as electrocardiogram (ECG), Holter Monitoring, Event Recorder, Chest X-ray and so on are utilized to analyze arrhythmias, among theseutilizing ECG is the general approach.Traditionally, physicians analyze the cardiac activity via ECG signal manually and determine the presence of arrhythmia, which is a time consuming process.

In recent years, computerized technique has been used for the automatic classification of ECG signals. Several machine learning techniques such as expert systems, heuristic approaches, self-organizing map, Markov models, linear regression, support vector machine and neural networks and so on have been employed for the classification of heart beats. Among these techniques classifications using neural network provides promising results.

Thus, in this paper a Feed Forward Neural Network (FFNN) has been employed to classify the ECG signals into six beats: Normal beat (N), Premature Ventricular Contraction (PVC), Right Bundle Branch Block Beat (R), Fusion of Paced and Normal Beat (f). Fusion of Ventricular and Normal Beat (F) and Atrial Premature Beat (A). Here the FFNN is trained independently using PSO and GSA techniques with temporal, heartbeat intervals and morphological features of the heart beat in the signal. The extracted features are fed into FNN to classify the different types of beats.

The rest of the paper is organized as follows: section II presents the research work that has been carried out in order to classify the heartbeats, section III describes the proposed approach, results are discussed in section IV and finally section V concludes the paper.

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Related Work: In [4] support vector machine has been used for classifying the ECG signals into one of sixteen classes. Independent Component Analysis (ICA) and wavelet transform has been utilized to extract morphological features from the heartbeat and dynamic feature is extracted by computing the RR interval. The dynamic and morphological features are combined into a single feature vector and provided as input to the classifier. In [5] the heart beat is classified into supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F),unknown beat (Q) and normal beat (N). Substantial features are extracted using wavelet transform (WT) and S-transform (ST) approaches. The extracted features are then given as input to the Multilayer Perceptron Neural Network (MLPNN) for the purpose of classification and the MIT-BIH arrhythmia database has been used for analyzing the performance of the classifier.

In [6] discrete wavelet transform has been applied to extract features of ECG signals acquired from the MIT-BIH database. These features are fed into Support Vector Machine (SVM) and Extreme Learning Machine (ELM) to classify between four types of beats such as LBBB, PVC, Normal and RBBB. In [7] heartbeat classification has been done by improving morphological feature vector with ST-segment information. Here support vector machine classifier has been utilized for classification. In [8] boosting algorithm has been utilized to classify the ECG beats. The input to the classifier is RR data that were obtained using Symlet approach. The accuracy of the classifier was analyzed using MIT-BIH database.

[9] Proposed a system to classify three types of electrocardiogram beats. The system consists of three modules a feature extraction module, a classifier module and an optimization module. The shape features and timing features are extracted and combined to efficiently categorize the patterns. The multi class support vector machine has been used as a classifier. The optimized feature selection is performed using particle swarm optimization to feed the classifier.

[10] Introduced a local ECG beat classifier to profile the patient's cardiac behavior. The repetition-based packet processing techniques has been used to classify the detected features for any individuals. The approach has been tested against the MIT-BIH arrhythmia database. The result shows that the technique attains high accuracy of the database.

A waveform similarity and RR interval based classification method is proposed in [11] for classifying electrocardiogram (ECG) beat. The signal of ECG is denoised using the wavelet-transform-based techniques. The Heartbeats, sampled at 128 points are extracted on the R-peak by centering on it in the ECG signals. The sample numbers per heart beat is then reduced to 16 to set up a feature. The RR intervals surrounding the beat are also included as a feature[12].

The research of this paper [13] to develop the Disease prediction scheme in order to provide perfect treatments for the heart disease patient's.This scheme is implemented by using the Naïve Bayes- a data mining modeling technique to discover and extract the hidden patterns and relationships associated with the heart disease.

MATERIALS AND METHODS

Figure 1 shows the block diagram of the proposed classifier system.Initially the noise present in the ECG signals is removed by applying median filters. Feature extraction is performed on the denoised ECG signal to extract RR interval features, heartbeat interval features and morphological features. The extracted features are then fed into FFNN classifier that is trained independently using PSO and GSA to classify heartbeats into N, A, F, f, R and PVC respectively.

Materials: The MIT-BIH database [12] has been utilized to assess the performance of the classifier. The database comprises of 48 records of two 30 minute lead signals indicated as lead A and B. Out of the 48 records, 23 records enumerated from 100 to 124 indicate NSR (Normal Sinus Rhythm) and remaining 25 records enumerated from 200 to 234 represent the cardiac abnormalities. Initially, all the signals are filtered utilizing a BPF (band pass filter) with a pass band of 0.1 t0 100 Hz and sampling of the signals is done at 360Hz.

Preprocessing: Acquired ECG signals comprises several kinds of noises such as frequency interference, electrode contact noise, baseline drift, motor artifacts, internal amplifier noise, polarization and muscle noise. Among these, baseline wandering significantly impacts the ECG signals, which is generally below 0.5 Hz. These noises are eliminated using two median filters with 200ms and 600 ms width. Initially a median filter with a width of 200 ms is used to filter P waves and QRS complex and then the median filter of 600 ms width is used to remove T waves. The resulting signal comprises the baseline, which is removed by subtracting it from the original signal.

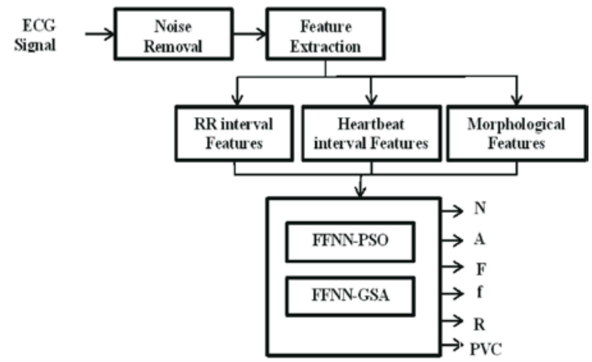

Fig. 1: Block Diagram of the Proposed Classifier

Though baseline drift has been removed, there exists some kind of noise that impacts the feature extraction process of the ECG signals. These noises are removed by applying wavelet transform based approach. Initially the signals are decomposed into five sub bands by applying Daubechies wavelet. Then for each sub band a threshold value is obtained to acquire the detailed co-efficient of the original and noisy signals. The expression for computing the threshold is

$$T = \sigma.(2.\log n)^{\frac{1}{2}} \quad (1)$$

Here, σ is the standard deviation of the noise, n is the number of samples. An optimal threshold is then obtained which is the minimum error between the detailed co-efficient of the original and noisy signals respectively. Here soft thresholding approach is used to obtain the detailed wavelet coefficients ($w_{i,j}$) which is given as:

$$d(w_{i,j}) = \begin{cases} 1 & w_{i,j} \geq T \\ 0 & otherwise \end{cases} \quad (2)$$

Finally the denoised signal is reconstructed to obtain the original signal by applying InverseDiscrete Wavelet Transform IDWR.

Feature Extraction: The intent of the feature extraction process is to extract a set of features that finely describes the signal. The extracted features should hold maximum information regarding the signal. In this study three types of features such as fourheartbeat interval features, four RR intervals and morphological features (five QRS complex features and four T wave features) areextracted.

RR Interval Features: RR interval is the interim between two consecutive heartbeat FP (fiducial point), which is the R peak. The pre-RR interval is the interim between the current heartbeat and the previous heartbeat and the post-RR is the interim between the current beat and the next beat. The average and the local average RR interval are the average of all the RR intervals identify an average of the 10 recent RR intervals.

Heartbeat Interval Features: In this study, five interval features such as QRS duration, the time interval between QRS offset and onset, ST duration, the time interval between the offset of S wave and the onset of the T wave, PR duration, the duration between the P and R wave onset and QT duration, the time interval between the onset of the Q wave and the offset of T wave are extracted.In order to extract these features, each interval's starting and ending point are identified and then subtracting the ending point from the starting point. Figure 2 shows the ECG waveform intervals.

Morphological Features: Here, twokinds of morphological features such as QRS complex and T wave features are extracted by employing a linear interpolation approach. Here two sampling windows w1 (-80 to +100ms) that coversQRS morphological features and w2 (+150 to +420 ms) that covers the T- wave are considered. A sampling rate of 60Hz is applied to w1 to extract five QRS morphological features and rate of 20 Hz is applied w2 to extract four T wave features.

Classification: The extracted features are fed into FFNN to classify the ECG signals between different heartbeats: Normal beat (N), Premature Ventricular Contraction (PVC), Right Bundle Branch Block Beat (R), Fusion of Paced and Normal Beat (f). Fusion of Ventricular and Normal Beat (F) and Atrial Premature Beat (A). The FFNN comprises of an input layer, one or more hidden layers and an output layer. Figure 3 represents the general structure of the FFNN. Training an FFNN is identifying set of weights that provides desired output. The weights are improved until the difference between the actual output corresponding to the training set and the desired output reaches produces minimum error. In this study, the optimization of the error value by applying PSO and GSA algorithm.

Particle Swarm Optimization: Particle Swam Optimization (PSO) is an optimization technique based on the socio-psychological principle. It employs a population of individuals to concurrently search favorable regions of the search space. Each particle represents a candidate solution and each particle has its own memory p_i, where

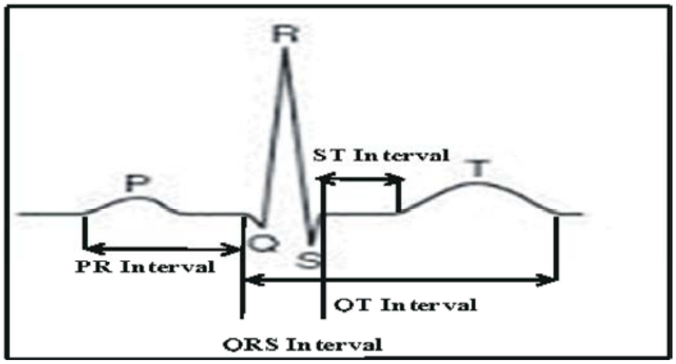

Fig. 2: ECG Waveform Intervals

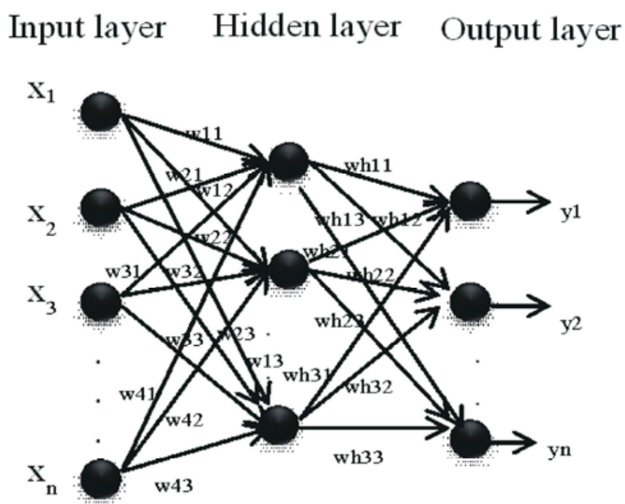

Fig. 3: FFNN Structure

i=1,2,..,n (n is the number of particles) that maintains the best location that has detected by the particle during its search. The velocity and the location of the particle are updated and the global best location experienced by a particle and the local best solutions of the neighboring particles is exchanged among the entire population. A fitness function is employed to evaluate the performance of each particle.

Here, the particles correspond to the weights of the FFNN and the dimension is the total number of weights. Here, weight matrix between the input and hidden layer and hidden layer and the output layer are represented as $W^{[ih]}$ and $W^{[ho]}$ respectively. The position of the particle is represented as $p_i = \left\{p_i^{[ih]}, p_i^{[ho]}\right\}$ and the velocity of the ith particle is expressed as $v_i = \left\{v_i^{[ih]}, v_i^{[ho]}\right\}$ respectively. The particles are manipulated using the following expression:

$$v_k^{'[ih][ho]} = v_k^{[ih][ho]}(m,n) + \left\{\alpha\beta\left(p_k^{[ih][ho]} - w_k^{[ih][ho]}\right) + ba\left(p_b^{[ih][ho]} - w_k^{[ih][ho]}\right)\right\}/t \tag{3}$$

$$w_k^{'[ih][ho]} = w_k^{[ih][ho]} + v_k^{[ih][ho]} \tag{4}$$

Here, m,n represents the matrix row and column, a and b are positive constants, t is the time step, α and β are the random numbers between 0 and 1 and $v_k^{'[ih][ho]}$ and $w_k^{'[ih][ho]}$ are the new values for the velocity and weight. The fitness value of the kth particle is expressed using:

$$f = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{j=1}^{o}(t_{ij} - p_{ij})^2\right] \quad (5)$$

Here, t_{ij} is the target output p_{ij} is the predicted output and N is the number of training samples.

Gravitational Search Algorithm: Gravitational Search Algorithm (GSA) is a population based heuristic algorithm in which the individuals of the population are denoted as an agent (weights) and it is described by the mass and the position. Each agent changes its position based on the force of attraction. The GSA algorithm searches for the position value having the best fitness. Figure 4 illustrates the GSA algorithm for weight update.

Step 1: Initialize the number of agents

$\{W = W^{[ih]}W^{[ho]}\}$,

Step 2: Compute gravitational Constant G(t)

$G(t) = G_0 \exp(\beta T/N)$

Here G_0 is set to 180, β to 10 and N is the number of iterations and these value decreases in order to control the searching process accuracy.

Step 3: Perform fitness evolution

$$f(t) = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{j=1}^{o}(t_{ij} - p_{ij})^2\right]$$
$$bst - fit(t) = \min f(t)$$
$$worst - fit(t) = \max f(t)$$

Step 4: Compute the gravitational and inertia mass.

$$M_i(t) = \frac{m_i(t)}{\sum_{k=1}^{N} m_k(t)}$$
$$m_i(t) = \frac{f(t) - worst - fit(t)}{brt - fit(t) - worst - fit(t)}$$

Step 5: Compute total force and acceleration of the agent $F_j^n = \sum_{j=1,k\neq j}^{N} rn_k F_{jk}^n$, rn is the random number.

$$F_{jk}^n = G(t)\frac{M_i(t).M_k(t)}{d_{ij}(t)+\varepsilon}\times\left(W_k^{[ih][ho]}(t) - W_j^{[ih][ho]}(t)\right)$$

$$a_i^n = \frac{F_j^n}{M_i(t)}$$

Step 6: Perform Velocity and position update using

$$v_i^{[ih][ho]}(t+1) = rn_i v_i^{[ih][ho]}(t) + a_i^n$$
$$W_i^{[ih][ho]}(t+1) = W_i^{[ih][ho]}(t) + v_i^{[ih][ho]}(t)$$

Step 5: Perform step 2 to step 5 until stopping criterion is met

Fig. 4: GSA Weight Update Algorithm

RESULTS AND DISCUSSION

MIT-BIH database was utilized as a data source for analyzing the performance of the proposed heartbeat classifier. In this study, the training data set is built with 8 records randomly taken from the MIT-BIH dataset and testing data set is built with 8 records that are randomly chosen. Table 1 shows the training and the testing data set employed in this study. The performance of the classifier is measured using sensitivity and accuracy.

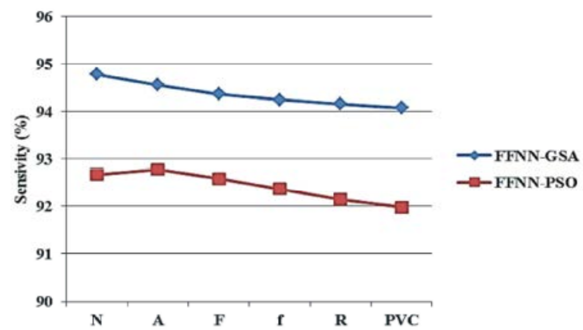

Fig. 5: Sensitivity of the Proposed Classifier

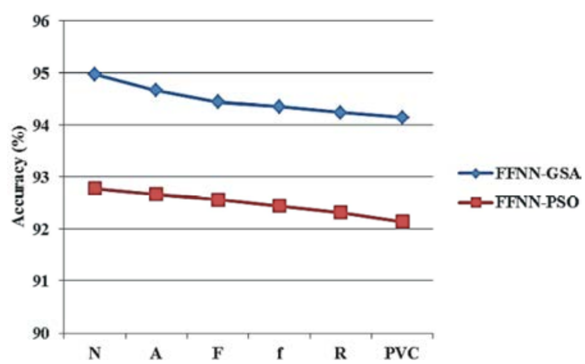

Fig. 6: Accuracy of the Proposed Classifier

Table 1: Training and Testing Data Set

Data Set	MIT Code							
Training set	100	119	202	205	209	212	213	217
Testing Set	103	105	106	200	210	214	219	222

Table 2: Overall Sensitivity and Accuracy

Classifier	Sensitivity (%)	Accuracy(%)
FFNN-PSO	92.42	92.49
FFNN-GSA	94.37	94.47

Accuracy and sensitivity are given as:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Figure 5 and 6 shows the sensitivity and accuracy of the FFNN classifier trained using PSO and GSA. From Figure 5 it is obvious that the sensitivity of the six types of beats that are classified by FFNN trained using GSA are 94.78%, 94.56%, 94.37 %, 94.25 %, 94.16 % and 94.08 % respectively, which is more compared to the one that is trained using PSO.

From Figure 6 it is clear that the accuracy of the six types of beats that are classified by FFNN trained using GSA are 94.98%, 94.67%, 94.45 %, 94.36 %, 94.25 % and 94.15 % respectively, which is more compared to the one that is trained using PSO. Table 2 shows the overall accuracy and sensitivity of the proposed classifier.

CONCLUSION

Heartbeat classification is a significant step in the diagnosis of arrhythmia. Thus in this paper, an automatic classifier has been developed using Feed Forward Neural Network (FFNN) to classify the ECG signals between different heartbeats. Here, the classifier is trained independently using Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) with morphological, heartbeat interval features and temporal features. The trained classifier then classifies the beats into N, A, F, f, R and PVC. The performance of the classifier is analyzed in terms of sensitivity and accuracy and it is shown that FFNN-GSA classifier provides an overall sensitivity and accuracy of about 94.37 % and 94.47 % respectively.

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