An Efficient Technique for Classification of Electrocardiogram Signals

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***Abstract*—This work describes a Radial Basis Function (RBF) neural network method used to analyze ECG signals for diagnosing cardiac arrhythmias effectively. The proposed method can accurately classify and differentiate normal (Normal) and abnormal heartbeats. Abnormal heartbeats include left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature contractions (APC) and premature ventricular contractions (PVC). This paper proposes a three stage, preprocessing, feature extraction and classification method for the detection of ECG beat types. In the first stage, ECG beats is normalized to a mean of zero and standard deviation of unity. Feature extraction module extracts wavelet approximate coefficients of ECG signals in conjunction with three timing interval features. Then a number of radial basis function (RBF) neural networks with different value of spread parameter are designed. We compared the classification ability of five different classes of ECG signals that were achieved over eight files from the MIT/BIH arrhythmia database.**

***Index Terms*—ECG Beat Classification, Wavelet, Radial Basis Function Neural Network**

I. Introduction

The analysis of ECG has been widely used for diagnosing many cardiac diseases. The development of accurate and quick methods for automatic ECG classification is vital for clinical diagnosis of heart diseases.

In the literature, several methods have been proposed for the automatic classification of ECG signals. In [1], the authors designed a local and global classifier and combined it with a mixture of experts (MOE) approach. In [2] the authors used a feed forward neural network as classifier. They derived five features included the QRS width and offset, amplitude of R segment, the T segment slope and the R-R interval duration. In [3], the authors used morphological information as features and a neural-network classifier for differentiating the ECG beats. In [4], the author used Independent Components Analysis (ICA) for ECG detection. In [5], different classification systems based on linear discriminant classifiers are explored, together with different morphological and timing features obtained from single and multiple ECG leads.

In this paper, we have proposed an automated method for ECG heartbeats classification into five different classes. For feature extraction module, we have used a suitable set of features that consists in both morphological and temporal features, to include both of the shaping and timing information of signal. Then, we investigated the different Radial Basis Function (RBF) neural networks and varied the spread parameter value for functions of those neural networks. Then we have prepared some experiments to measure their performances and compare them.

The paper is organized as follows. Section II explains the feature extraction. Section III presents the classifier. Section IV, describes the database and performance metrics. Section V shows some simulation results. Section VI discusses the results and finally Section VII concludes the paper.

II. Feature Extraction

A. Wavelet Transform

The continuous wavelet transform (CWT) is a generalization of the STFT (Short Time Fourier Transform) that allows for analysis at multiple scales. Similar to the STFT, the CWT makes use of a windowing function to extract signal segments; in this case the window is called a wavelet. Unlike the STFT, the analysis window or wavelet is not only translated, but dilated and contracted depending on the scale of activity under study. Wavelet dilation increases the CWT sensitivity to long time-scale events, and wavelet contraction increases its sensitivity to short time-scale events. The continuous wavelet transform is given by

$$C(a,\tau) = \int \frac{1}{\sqrt{a}} \psi^{*}\left(\frac{t-\tau}{a}\right) x(t)dt \tag{1}$$

Where ψ^* is the complex conjugate of the mother wavelet $\psi^{(t)}$, which is shifted by a time τ and dilated or contracted by a factor prior to computing its correlation with the signal x(t). The correlation between the signal and the wavelet is defined as the integral of their product. The CWT maps x(t) into a bivariate function C(a, τ) that it can be used to determine the similarity between x(t) and a wavelet scaled by a at a given time τ . The correlation is localized in time and is computed over an interval beginning at $t = \tau$ and ending at t = τ + L, where L represents the duration of the wavelet.

Under contraction (a < 1), the wavelet offers high temporal resolution and is well suited for determining the onset of short-time events, such as a spikes and transients. Under dilation, (a > 1), the wavelet offers high spectral resolution and is well suited for determining the frequency of sustained, long-term events, such as baseline wander. This time-frequency trade-off provides a practical tool for ECG analysis.

A tree-structured filter bank can be used to compute the wavelet coefficients C(a, τ) of the continuous wavelet

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transform, but only over a dyadic (power of 2) scale of dilations and contractions. A tree-structured filter bank splits an incoming signal into a lowpass channel using the filter H0(z) and a highpass channel using the filter H1(z). The lowpass channel can be recursively split N times using the same two filters. Signals extracted from the filter bank at higher iteration levels contain increasingly longer time-scale activity, while those extracted from lower levels contain shorter time-scale activity. Using only a dyadic scale of wavelet coefficients one can perfectly reconstruct the input signal; this possibility highlights the redundancy of continuously varying the scale parameter a in the CWT. The reconstruction or synthesis filter bank is a mirror image of the analysis filter bank. The analysis filters H0(z) and H1(z) and the reconstruction filters F0(z) and F1(z) must be carefully chosen such that the decomposed signal can be perfectly reconstructed. The analysis and reconstruction filters have to satisfy antialias and zero-distortion conditions.

Performing wavelet decomposition, involves the following steps:

1. Select a wavelet appropriate for analyzing the signal of interest. The wavelet should have morphological features that match those to be extracted, highlighted, or detected in the input signal.

2. Derive the filters H0(z) and H1(z) so that an efficient filter bank implementation can be used to compute the wavelet coefficients.

3. Derive the filters F0(z) and F1(z) so that an efficient inverse filter bank can be used to reconstruct a new version of the signal from the modified wavelet coefficients.

Fortunately, the filters H0(z), H1(z), F0(z), and F1(z) have already been computed for a large number of wavelet functions, and these filters can be immediately used to study signals of interest. If all the wavelet coefficients produced by the analysis filter bank are preserved and the signal is reconstructed, the synthesized signal will equal the input signal. If some coefficients are selectively preserved, then we are effectively filtering in the time or scale domain as opposed to the conventional frequency domain.

We have used the discrete wavelet transform (DWT). The DWT operates on wavelets that are discretely sampled and is calculated by passing a signal through a collection of filters (a filter bank) in order to decompose a signal into a set of frequency bands. This decomposition allows one to selectively examine or modify the content of a signal within the chosen bands for the purpose of compression, filtering, or signal classification.

The LP filters produce a set of components, called approximations, and the HP filters produce a set of components called details. In general, the overall waveform of a signal will be primarily contained in the approximation coefficients, and short-term transients or high-frequency activity (such as spikes) will be contained in the detail coefficients. If we reconstruct the signal only using the approximation coefficients, we will recover the major morphological component. If we reconstruct the signal only using the detail coefficients, we will recover the spike components [6].

B. Feature Extraction

We constructed ten feature sets based on the ECG data wavelet transform by Daubechies mother wavelet at orders from one to ten, in conjunction with timing information. We tested the various RBF neural network classifiers using each of these feature sets and compared the results. Then we used the best feature set to evaluate the performance of classifier on the all of dataset for the classification of ECG beats into five different classes.

ECG waveform and wavelet transform features were extracted by selecting a window of -300 ms to +400 ms around the R wave as found in the database annotation. The 252-sample vectors were normalized to a mean of zero and standard deviation of unity. This reduced the DC offset and eliminated the amplitude variance from file to file.

In addition to the morphological features, we extracted three local timing features that contributed to the discriminating power of morphology-based features, especially in discriminating morphologically similar heartbeat patterns. They are an R-R time interval ratio (IR) and two R-R time intervals. The IR ratio feature reflects the deviation from a constant beat rate and was defined as:

$$IR_i = \frac{T_i - T_{i-1}}{T_{i+1} - T_i} \tag{2}$$

where T_i represents the time at which the R-wave for beat i occurs. The local RR-interval ratio provides a convenient differentiator between normal beats $(IR_i > 1)$ and PVC beats $(IR_i < 1)$, and is normalized by definition $(IR_i = 1)$ at constant rate). Two other timing features are the next and previous R-R time intervals for each heartbeat. Neural Network Classifier

We have used RBF neural networks as the classifier. RBF neural networks with their structural simplicity and training efficiency are good candidate to perform a nonlinear mapping between the input and output vector spaces. RBF NN is a fully connected feed forward structure and consists of three layers, namely, an input layer, a single layer of nonlinear processing units and an output layer.

The network structure is shown in Figure 1. Input layer is composed of input nodes that are equal to the dimension of the input vector x. The output of the jth hidden neuron with Gaussian transfer function can be calculated as

$$h_j = e^{\frac{-\left\|x-c_j\right\|^2}{\sigma^2}} \tag{3}$$

Where h_j is the output of the jth neuron, $x \in \Re^{n\times 1}$ is an input vector, $c_j \in \Re^{n\times 1}$ is the jth RBF center, σ is the center spread parameter which controls the width of the RBF, and $\|.\|^2$ represents the Euclidean norm. The output of any neuron at the output layer of RBF network is calculated as

$$y_i = \sum_{j=1}^{k} w_{ij} h_j \tag{4}$$

where w_{ij} is the weight connecting hidden neuron j to output neuron i and k is the number of hidden layer neurons.

The mapping properties of the RBF NN can be modified through the weights in the output layer, the centers of the RBFs, and spread parameter of the Gaussian function. The simplest form of RBF network training can be obtained with fixed number of centers. If the number of centers is made equal to the number of input vectors, namely exact RBF, then the error between the desired and actual network outputs for the training data set will be equal to zero. In this work, exact RBF NN was used. The number of RBF centers was made equal to the number of input vectors.

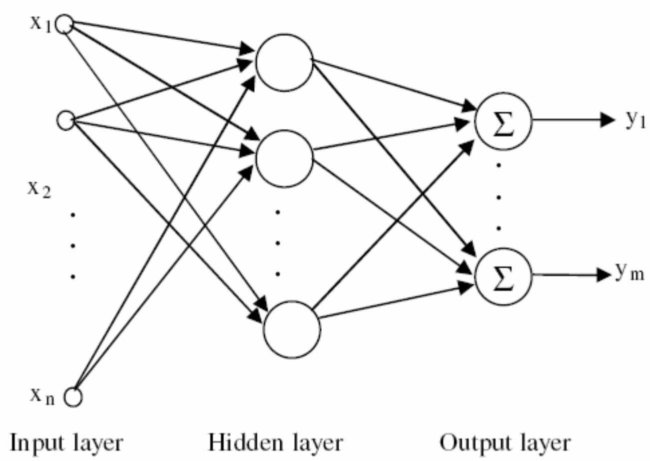

Figure 1. Structure of RBF Neural Network..

III. DATABASE AND PERFORMANCE METRICS

The MIT-BIH arrhythmia database [7] was used as the data source in this study. The database contains 48 recordings, each has a duration of 30 minutes and includes two leads—the modified limb lead II and one of the modified leads V1, V2, V4 or V5. There are over 109,000 labeled ventricular beats from 15 different heartbeat types. The database is annotated both in timing information and beat Classification. For more details about MIT-BIH Arrhythmia database see [8]. The considered beats in this paper refer to the following classes: normal sinus rhythm (Normal), left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature contraction beat (APC) and ventricular premature contraction beat (PVC). We used a total of eight records with numbers: 118, 124, 207, 208, 209, 214, 222, and 223 from the database. We have extracted from them 18,284 beats, 8,291 normal beats, 3,458 LBBB beats, 3,778 RBBB beats, 867 APC beats and 1,890 beats from the PVC type. Also for locating beats in ECG signals we used the annotation files from database.

Various approaches were adopted to evaluate the classifier configurations. In this study, the heartbeat classification abilities are compared by using the following four statistical indices: Accuracy (Acc), Sensitivity (Se), Positive Predictivity (Pp) and Specificity (Sp), which are defined in the following Equations (5-8), respectively.

The most crucial metric for determining overall system performance is, usually, accuracy. We defined the overall accuracy of the classifier for each file as follows:

$$A_{cc} = \frac{N_T - N_E}{N_T} \times 100 \tag{5}$$

In this equation, Acc is the accuracy, and the variables,N_E and N_T, represent the total number of classification errors and beats in the file, respectively. Sensitivity, Se, the ratio of the number of correctly detected events, TP (true positives), to the total number of events is given by:

$$Se = \frac{TP}{TP + FN} \times 100 \tag{6}$$

where FN (false negatives) is the number of missed events. Positive predictivity, Pp, is the ratio of the number of correctly detected events, TP, and the total number of events detected by the analyzer, and it is given by:

$$Pp = \frac{TP}{TP + FP} \times 100 \tag{7}$$

where FP (false positives) is the number of falsely detected events. The specificity, Sp, the ratio of the number of correctly rejected nonevents, TN (true negatives) and the total number of nonevents is given by:

$$Sp = \frac{TN}{TN + FP} \times 100 \tag{8}$$

IV. RESULTS

We have conducted four various experiments. For the first two experiments, random 4,000 beats, 800 from each beat type, were selected from the all 18,284 beats. 75 beats from each class were used for train and the others were used to test the classifiers. In the third experiment, the trained network classified each beats of the records, respectively. For the forth experiment, all of 18,284 beats were used to obtain the overall performance of classifier. However, the size of training samples for each class did not changed. The last experiment shows the good generalization ability of our proposed method, because the all training set was 375 samples, namely around 2% of all beats in experiment. In experiment 1, wavelet coefficients were computed by using the daubechies mother wavelet at level 1. Ten different RBF neural networks with varying number of spread parameter were constructed. They trained by approximate coefficients of daubechies wavelets at various orders. Table I presents the results obtained from this experiment.

To obtain more accurate value of spread and to compare obtained results more in depth over all performance metrics for all classes, experiment 2 was performed. Results are displayed in Table II. Spread parameter was explored in a smaller range and smaller steps.

Table III shows the file-by-file comprehensive results (experiment 3) for a sample feature set and RBF neural network (used db4 wavelet at level 1 and the network with the value of spread parameter of 63.9). Also this sample RBF

Neural network and feature subset were used to evaluate the overall performance of our proposed method over all dataset. The last row of table III shows the performance metrics and Table IV proposes the confusion matrix of the experiment 4.

TABLE I. RESULTS OF EXPERIMENT 1. COMPARING THE PERFORMANCE OF THE CLASSIFIER WITH VARIOUS WAVELET AND SPREAD PARAMETERS. NUMBER OF TRAIN SAMPLES ARE 375 BEATS FROM ALL 4000 BEATS.

Spread	**Daubechies Wavelet**									
	db1	***db2***	***db3***	***db4***	***db5***	***db6***	***db7***	***db8***	***db9***	***db10***
0.1	20.01	20.01	20.01	20.01	20.01	20.01	20.01	20.01	20.01	20.01
1	20.04	20.04	20.04	20.04	20.04	20.04	20.04	20.04	20.04	20.01
10	69.33	69.14	69.06	69.03	68.81	68.70	68.53	68.37	68.23	68.18
20	87.47	87.58	87.52	87.52	87.47	87.44	87.47	87.44	87.44	87.44
30	92.35	92.22	92.41	92.49	92.63	92.74	92.69	92.63	92.63	92.63
40	93.35	93.35	93.32	92.19	92.27	92.23	92.38	92.52	92.60	92.74
50	94.42	94.53	94.51	94.51	93.57	93.65	93.65	93.68	93.76	93.79
60	94.42	94.95	95.00	**95.06**	95.03	95.03	95.03	93.71	93.79	93.82
70	93.49	93.76	93.76	93.90	93.90	94.01	94.09	94.15	94.15	94.26
80	92.27	92.46	92.38	92.63	92.58	93.79	93.84	93.96	94.12	94.29

TABLE II. RESULTS OF EXPERIMENT 2. IN DEPTH COMPARING OF THE PERFORMANCE OF THE CLASSIFIER WITH VARIOUS WAVELET AND SPREAD PARAMETERS. NUMBER OF TRAIN SAMPLES ARE 375 BEATS FROM ALL 4000 BEATS

Spread	**Acc**	**Normal**	**LBBB**	**RBBB**	**APC**	**PVC**										
		Se	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***
63.5	95.23	92.82	98.21	92.82	97.52	99.10	96.45	98.07	99.76	99.03	94.48	97.93	91.94	93.24	99.03	96.02
63.7	95.23	92.82	98.21	92.82	97.52	99.10	96.45	98.07	99.76	99.03	94.48	97.93	91.94	93.24	99.03	96.02
63.9	**95.25**	**92.96**	**98.21**	**92.83**	**97.52**	**99.14**	**96.58**	**98.07**	**99.76**	**99.03**	**94.48**	**97.93**	**91.94**	**93.24**	**99.03**	**96.02**
64.1	95.25	92.96	98.21	92.83	97.52	99.14	96.58	98.07	99.76	99.03	94.48	97.90	91.81	93.10	99.03	96.01
64.3	95.22	92.96	98.21	92.83	97.52	99.14	96.58	98.07	99.76	99.03	94.48	97.90	91.81	93.10	99.03	96.01
64.5	95.22	92.96	98.21	92.83	97.52	99.14	96.58	98.07	99.76	99.03	94.48	97.90	91.81	93.10	99.03	96.01

TABLE III. FILE-BY-FILE DETAILED CLASSIFICATION RESULTS (EXPERIMENT 3 AND 4)

Record	**Acc**	**Normal**			**LBBB**			**RBBB**			**APC**			**PVC**		
		Se	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***	***Se***	***Sp***	***Pp***
118	96.62	NaN	97.45	0	NaN	99.96	0	97.00	100.00	100.00	98.96	99.45	88.79	31.25	99.73	45.45
124	96.96	NaN	98.54	0	NaN	99.24	0	98.36	87.76	99.60	0	99.62	0	55.32	99.93	96.30
207	97.49	NaN	98.52	0	98.49	97.64	99.51	82.35	99.76	94.59	99.06	99.82	97.22	94.28	99.76	96.12
208	98.33	97.60	99.60	99.74	NaN	99.61	0	NaN	100.00	NaN	NaN	99.34	0	99.50	99.24	98.80
209	97.84	97.94	97.14	99.57	NaN	99.73	0	NaN	100.00	NaN	97.13	98.32	89.42	100.00	99.93	33.33
214	97.65	NaN	99.29	0	98.10	100.00	100.00	NaN	99.87	0	NaN	99.56	0	94.14	98.80	90.94
222	75	73.64	92.31	98.96	NaN	93.69	0	NaN	98.99	0	88.46	83.69	35.38	NaN	97.84	0
223	96.77	99.11	97.98	99.46	NaN	99.03	0	NaN	99.84	0	91.67	98.44	62.86	87.53	99.81	99.04
All	**94.64**	**92.12**	**98.35**	**97.89**	**98.26**	**98.61**	**94.28**	**97.22**	**99.72**	**98.92**	**94.81**	**97.32**	**63.77**	**93.81**	**99.38**	**94.56**

V. DISCUSSION

The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal and Reverse Biorthogonal, etc. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application. Selecting a wavelet function which closely matches the signal to be processed is of utmost importance in wavelet applications [9]. Daubechies wavelet families are similar in shape to QRS complex and their energy spectrum is concentrated around low frequencies. For finding the best order of db wavelet we performed the experiment I.

In table I, it can be seen that the best performance for RBF neural network, is achieved by the spread parameter with value 60 that is 95.06% (Best performance is bolded in Table I). The best daubechies wavelet was db4 with level 1. Since the steps of spread increasing are large and Accuracy was the only performance metric that was used, we performed another test (experiment 2).

In the new experiment, steps of spread were 0.2 and the other performance metrics also, computed. RBF Neural Networks with both spread values of 63.9 and 64.1 have best accuracies. But spread of 63.9 has slightly better performance in term of other metrics. Since APC and PVC have most importance in clinical applications, we used the first spread value in the next experiments. The best results are bolded in table II. We attain a high overall accuracy of 95.25% and a good sensitivity of 94.48% for APC arrhythmia, and a sensitivity of 93.24% for PVC heartbeat. Then we investigated various parameter values and structures, and from these we obtained networks and features used for next experiments. In table III the classification results of beats for each record can be seen. Table IV is the confusion matrix of all data classification results. As it can be seen most wrongly classified normal beats are those classified as APC (402 beats). If you see APC beats in table IV, you find that most misclassified APC beats, 30 samples, are classified as normal. The mainspring is that, Normal and APC patterns are morphologically similar to each other. This highlights the importance of three temporal features that we have used in feature set. These features improve the discriminating ability of the classifier, especially in discriminating morphologically similar heartbeat patterns (i.e. Normal and APC beats). About PVC beats this is inversely. Number of PVC beats that classified as normal beats and number of normal beats that classified as PVC beats are 58 and 24, respectively. Small value of misclassified beats between normal and PVC beats focuses on the morphological dissimilarities between Normal and PVC beats. The overall accuracy achieved in this experiment was 94.64% over 18,284 beats (last row of table III). This is lower than the 95.25% accuracy that we achieved over 4000 beats of database. This is consistent with the Inan et al [3] claim, that the same method will, generally, produce lower results when applied to a greater number of files.

VI. CONCLUSION

We have proposed a number of efficient methods for accurate classification of ECG beat for a relatively large set of data. These methods include three modules: an efficient preprocessing module, feature extraction module and classifier. For preprocessing module, we have normalized ECG beats to a mean of zero and standard deviation of unity. In the feature extraction module we have extracted morphological and pre-/post RR-interval based features as the effective features for differentiating various types of ECG beats. Then we prepared some experiments for feature selection. Then a number of radial basis function (RBF) neural networks with different values of spread parameter are designed and compared their ability for classification of five different classes of ECG signals. The mother wavelet was empirically selected to be daubechies with level one. In the first two experiments, the value of spread used in the RBF classifier and the order of mother wavelet, was empirically determined to be 63.9 and four, respectively. Also A classification accuracy of 95.25% for the first dataset (4000 beats) and an overall accuracy of detection of 94.64% were achieved over eight files from the MIT/BIH arrhythmia database.

TABLE IV. CONFUSION MATRIX OF EXPERIMENT 4.

Confusion Matrix	**Normal**	**LBBB**	**RBBB**	**APC**	**PVC**
Normal	7638	167	26	402	58
LBBB	27	3398	7	0	26
RBBB	84	13	3673	2	6
APC	30	2	1	822	12
PVC	24	24	6	63	1773

REFERENCES

[1] Hu, G. M., S. Palreddy, and W, Tompkins, "Patient Adaptable ECG Beat Classifier Using a Mixture of Experts Approach", IEEE Trans. Biomed. Eng., Vol. 44, 1997, pp. 891–900.

[2] TH Yeap, F Johnson, M Rachniowski, "ECG Beat Classification by a Neural Network", Proceedings Annual International Conference of the IEEE EMBS Society pg 1457-58, 1990.

[3] O. T. Inan, L. Giovangrandi, and G. T. A. Kovacs., "Robust Neural-Network-Based Classification of Premature Ventricular Contractions Using Wavelet Transform and Timing Interval Features", IEEE Trans. Biomed. Eng., vol. 53, no. 12, pp. 2507–2515, Dec. 2006.

[4] S. N. Yu, and K. T. Chou., "Selection of significant for ECG beat classification", Expert Systems with Applications, Vol. 36, pp. 2088-2096, 2009.

[5] Chazal P, O'Dwyer M, Reilly RB., "Automatic classification of heartbeats using ECG morphology and heartbeat interval features", IEEE Trans Biomed Eng 2004;51:1196–206.

[6] G. D. Clifford, F. Azuaje, P. E. McSharry, "Advanced Methods and Tools for ECG Data Analysis", Artech House: Norwood, MA 02062, 2006.

[7] R. Mark and G. Moody, "MIT-BIH Arrhythmia Database 1997", [Online]. Available: http://ecg.mit.edu/dbinfo.html

[8] G. B. Moody and R. G. Mark, "The impact of the mit/bih arrhythmia database", IEEE Eng. Med. Biol. Mag., vol. 20, no. 3, pp. 45–50, May- Jun. 2001.

[9] Amara Grap, "An Introduction to Wavelets", IEEE Comp. Sc. And Eng., Vol. 2, No. 2, 1995.