Application of Prototype Base Fuzzy Classifiers for ECG based Cardiac Arrhythmia Recognition

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Abstract: "As many as 1.4 million children are suffering from heart related diseases in Pakistan" The NEWS (Sunday 18th December, 2006). All over the world major causes of death are heart diseases. Thus, there is need of computer aided reliable system, which can share load of cardiac experts, in monitoring and detecting arrhythmias. The project is aimed at the exploration of the various approaches involved in the Fuzzy learning of a Classification Systems. The objective is to study different techniques involved in effective learning of Fuzzy Classifier from data, and applying the built system on ECG based arrhythmia recognition

Our methodology is based on learning rules from data using prototype based Fuzzy System. DWT was used for feature extraction from segmented QRS complex. The Pruned Weighted Fuzzy K-NN (using fast search) system was used for Beat Classification. The system was also tested after adding different levels of noise in data and for data reduction, giving accuracy of about ~ 97.6% for 6 classes and ~97.0% for 9 classes. Data pruning was used to reduce training samples thus, increasing computational efficiency.

Keywords: Pruning, Nearest Neighbor Classification, Fuzzy Logic, Wavelet Transform, Arrhythmia Recognition

Introduction

Heart diseases are leading cause of deaths in Pakistan and all over the world. In Pakistan, on average 1 out of 4 persons is suffering from cardio vascular diseases.

Early detection of such diseases is necessary, where symptoms can be seen when observed for long period of time, at initial stages. As the chip size is getting smaller, computers and algorithms getting faster, techniques for biomedical signal processing and analysis are getting more reliable. Computer Aided System for automatic Cardiac Disease Diagnosis using ECG is becoming essential for helping experts and reducing their load.

Fuzzy classification system for detection of cardiac diseases using ECG was built. ECG analysis was done to extract useful features from annotated ECG signals of normal persons and patients of various cardiac disorders. Most of the techniques used for beat classification are too rigid and crisp to deal with automated ECG analysis. So, Lotfi A. Zadeh (University of California, Berkeley) purposed Fuzzy Sets, they were able to represent and work on natural language variable, natural language vagueness and noise robust.

The purposed methodology uses Fuzzy k- Nearest Neighbor for the classification purpose, which gives robust and reliable results. The feature extraction was done by wavelet domain analysis of ECG data. 11 features from wavelet domain analysis and RR interval were used for classification giving accuracy of about ~ 97.6% for 6 classes and ~97.0% for 9 classes.

Work presented was aimed at development of an initially offline ECG analysis and Arrhythmia Classification System using ECG. ECG is used because it is most widely used technique for cardiac disease detection and diagnosis. The reason for widespread use of ECG is because; it is noninvasive and reliable technique for getting information about activity of heart. It is an effective way to analyze heart's electrical and mechanical activities. Any abnormality in hearts activity can be seen in ECG.

This paper presents a simple and efficient but effective data pruning algorithm incorporated into fuzzy k-nearest neighbor classifier to minimize space and time complexity during classification. Due to its fuzzy nature, this approach has the added advantage of providing the degree of membership of a query beat among different classes. To reduce time complexity further, an efficient nearest neighbor search implementation called ATRIA [28] has been used in the proposed approach. All these features make the classifier presented in this work, an excellent candidate in the design of a practical classification system such as ECG based cardiac disease diagnosis.

Theory

Electrocardiography deals with the electrical activity of the heart. The condition of cardiac health is given by ECG and heart rate. A study of the nonlinear dynamics of electrocardiogram (ECG) signals for arrhythmia characterization is considered. The statistical analysis of the calculated features indicates that they differ significantly between normal heart rhythm and the different arrhythmia types.

Many researchers have used effective signal analysis techniques for the classification of cardiac rhythms. In this section we present a review of existing approaches for beat classification. Minami [12] have used Fourier Transform (FT) based Frequency Domain techniques for beat classification. This method achieves a Sensitivity/PPV of ~98%.

A technique using filter banks was given by Alfonso [8]. Frequency based techniques for rhythm classification offer more reliable prospects as they are more robust to noise in contrast to time domain methods and present a more effective representation of the QRS complex. Dokur [9] carried out a comparative study Fourier Transform and Wavelet Transform (WT) demonstrating the efficiency of the WT as it provides a higher classification accuracy for ten types of beats from the MIT-BIH Arrhythmia database [10] in contrast to Fourier Transform.

Classifying arrhythmias involves the recognition of characteristic patterns of the electrocardiogram (ECG). Beat classification is an important step in designing an arrhythmia classifier as many arrhythmias simply consist of a single aberrant beat as opposed to a sustained rhythm disturbance. Previous studies have employed different features in most beat classifiers.

Senhadji [25] investigated features extracted from the wavelet coefficients using linear discriminates. Hu [26] used the amplitude of points surrounding the QRS complex as features and a neural network model as the classifier.

Yeap [3] also employed neural networks as the classifier model and used the QRS width and amplitude along with three other measurements made on the ECG as features. It is difficult to compare the results as these studies employed different data sets.

A method extracting 11 features from wavelet decomposition sub-bands of an input ECG signal and applies a probabilistic neural network for classification of 6 types of beats from MIT-BIH Arrhythmia database achieving accuracy greater than 99% was presented by Yu [13].

Method using features such as heart beat intervals, RR-intervals and spectral entropy of the ECG signal along with a NN classifier to achieve an accuracy of 99.02% over the MIT-BIH Arrhythmia database was used by Niwas [13].

ECG analysis by extracting 30 principal components from the ECG signal for classifying 4 types of heart beats from the MIT-BIH arrhythmia database with an accuracy of 99.17% was performed by Hao [15].

Purposed Methodology

The proposed method uses features extracted from ECG through the Dyadic Wavelet Transform as in [19] for ECG delineation. The application of the same wavelet transform for ECG delineation along beat classification reduces overall system complexity. Furthermore, the Dyadic Wavelet Transform makes the feature extraction process more robust to noise. The 11 features used are also very simple to compute from the sub-band decompositions generated from DWT and there is no significant computational load. Moreover we have used PCA for further feature reduction from 11 to 6, making the process more suitable for real-time application.

To develop an efficient beat classifier, features are to be established to distinguish between different beats. The first set of features is extracted from ECG after the beat detection process. This set consists of features based on the R-R interval, the amplitude of points in the beat template and amplitudes of points in QRS template. After the QRS (onset or offset) of each beat detected is determined, features based on the QRS width are extracted. The remaining set of features is extracted after the P wave onset of each detected P wave is determined. This set consists of features based on the P-R interval [27].

As QRS complex is the most important feature of ECG, as it is associated with ventricular activation. QRS complexes are extracted on basis of R-peak identification.

Window size of 64 point is used for QRS extraction centered at R-peaks.

Only two-level DWT is used because of short length of QRS segment. This gives three sets of wavelet coefficients. These are shown in Figure 1.

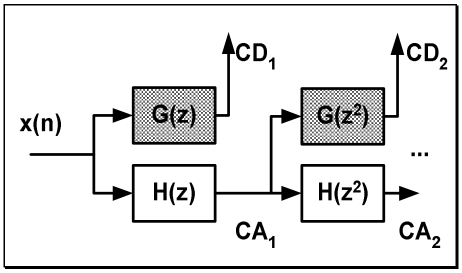

Figure 1Two-level DWT Algorithm a'trous [6]

Primarily QRS complex are used which has zero crossing associated in the Wavelet Transform at scales 21 and 22 [6] therefore we utilize only these two levels.

Features are extracted from wavelet coefficients computed earlier. Details of features are:

- AC power of original signal σ_S^2. This feature measures the power in the original QRS complex signal.
- AC power of wavelet coefficients σ_{A2}^2, σ_{D2}^2 and σ_{D1}^2. This feature measures the power in each of the sub-bands.
- AC power of autocorrelation function of wavelet coefficients $\sigma_{R(A2)}^2$, $\sigma_{R(D2)}^2$ and $\sigma_{R(D1)}^2$. This is a measure of coherence in wavelet sub-bands.
- Ratio of minimum to maximum wavelet r_{A2}, r_{D2} and r_{D1}. These features represent the morphological characteristics of sub-band coefficients and the amount of change in frequency distribution of the ECG signal.

These features are combined with RR interval to get feature set given by $\{\sigma_S^2, \sigma_{D1}^2, \sigma_{R(D1)}^2, r_{D1}, \sigma_{D2}^2, \sigma_{R(D2)}^2, r_{D2}, \sigma_{A2}^2, \sigma_{R(A2)}^2, r_{A2}, RR\}$ for a single beat.

As the features can be on different scales, normalization is necessary to homogenize all features to a same level. The relation used for normalization is given by:

$$x_{ij}^{'} = \text{tansig}\left(\frac{x_{ij} - \overline{x}_j}{\sigma_{x_j}}\right)$$

Where

- x_{ij} is the jth component of the ith feature vector, with
- $\overline{x}_j$ the mean of the jth component of feature vector
- σ_{x_j} variance of the jth component of feature vectors

The normalization function ranges features to [-1, 1].

Classification

Pruned Weighted Fuzzy k - Nearest Neighbor, reduces number of prototype sample to reduce the classification time. This is a proposed methodology for a systematic reduction in prototypes while maintaining the classification accuracy.

Classification:

- For any unknown point X
- Find k-NN (Xj) using ATRIA
- Evaluate membership values using

$$\mu_i(x) = \frac{\sum_{j=1}^{K} \mu_{ij}\left(d_j^{\frac{-2}{m-1}}\right)}{\sum_{j=1}^{K}\left(d_j^{\frac{-2}{m-1}}\right)}$$

$$dj = \left\| x - x_i \right\|$$

- Evaluate weighted firing strengths

$$c(x) = \arg\left(\max_{i=1}^{M} \left(w_i \mu_i(x)\right)\right)$$

Training:

- Selection of border points
- For every point in T,
- Find k- nearest neighbors of other class
- Add these points to prototype set P
- Calculate Class Weights

$$w_{c_i} = \left[\frac{1}{|c_i| / \min\{|c_l| \mid l = 1...M\}} \right]^{1/Exp}$$

$$Exp > 1$$

$$\mu_i(v_i) = \begin{cases} 0.517 + 0.49\, k_i/k & \text{if } class(v_i) = w_i \\ 0.49\, k_i/k & else \end{cases}$$

- For every point in training set
- classify using prototype set P
- if any misclassified
- Add misclassified point to P (IB2)
- Update class weights again on any addition in P

This data has been previously been used for evaluation in [6].In order to provide stable analysis, mean and standard deviation of results of five runs of each experiment by randomly varying training and testing samples, i.e. training and testing datasets are not fixed as in [6]. Following parameters are used for evaluation purpose:

a. Positive Predictive Values (PPV) of each class. PPV is defined by,

$$PPV_c = \frac{TP_c}{TP_c + FP_c}$$

b. Sensitivity Values (Se) of each class. Sensitivity is defined by,

$$Se_c = \frac{TP_c}{TP_c + FN_c}$$

c. Total Accuracy (A) of each class. Total Accuracy is define by,

$$A = \frac{\sum_{k=1}^{M} TP_{c_k}}{N_{test}}$$

d. Geometric Mean of Sensitivity values (G), given by,

$$G = \left(\prod_{k=1}^{M} Se_{c_k} \right)^{1/M}$$

Where, TPc is True Positives of class c, FPc is False Positives in class c, FNc is False Negatives in class c, M is number of classes and Se is sensitivity of kth class.

Noise in ECG comes from a multitude of sources, like electrical interferences, muscular movement etc. Noise in ECG spans across the signal range (0 to ~40Hz) and beyond which is electrical interference (~50 to ~60Hz)[1 (34)]. The test of robustness of our system to noise, we tested the system at different levels of Gaussian white noise which effectively models majority of noise types in the ECG. We analyzed accuracy of the system at different Signal to Noise Ratios, defined by:

$$SNR = 10 * \log\left(\frac{\sigma_s^2}{\sigma_e^2}\right)$$

Where σ_s^2 and σ_e^2 are the power of the signal and noise respectively. The table below shows the effect of noise against positive productivity value, sensitivity and overall classification accuracy. Such robustness removes need of sophisticated signal processing techniques for noise removal thus lowering system complexity.

These results show comparable accuracy to crisp k-NN. However Fuzzy k-NN classifier gives us the membership values of the unknown sample for all possible classes, using these membership values we can calculate a confidence metric showing the distance between winning and runner-up classes. Confidence Metric of i[th] sample is given by:

$$Conf_i = \left(\frac{\mu_{ic_{winning}} - \mu_{ic_{runner-up}}}{\sum_{k=1}^{M} \mu_{i_{c_k}}}\right) 100\%$$

Where, $\mu_{i_{c_{winning}}}$ is the membership of i[th] sample in winning class and $\mu_{i_{c_{runner-up}}}$ is membership in runner-up class.

Results

The results below present positive Geometric means for Sensitivity values and classification accuracy with their mean and standard deviations over 5 runs. For purpose of training N/2 samples were selected each time at random from the dataset and the remaining samples were used as test set. The parameters for Fuzzy and crisp k-NN were optimized using Leave 10% Out Cross Validation. The optimized parameters k = 5 & m = 1.5 were used for obtaining results. The sensitivity for all beats is approximately equal or greater than ~99, with total accuracy ~99.4%.

Using crisp k-NN [6] obtained total accuracy 99.49% with k = 1 without any noise, which seems to be better than Fuzzy k-NN with

99.43% accuracy. Comparison for noise robustness is given in Table 1.

Table 1 Confusion Matrix for FKNN SET6

Data Dist.	N	LBBB	RBBB	PVC	PAC	PB	Total	
N_{train}	3604.6	2428	2387.2	1132.2	848.6	1199.4	11600	
N_{test}	3595.4	2372	2412.8	1167.8	851.4	1200.6	11600	
Class Labels	Confusion Matrix						SEN Mean	SEN Std
N	3546	0	4	0	1	0	99.82	0.09
LBBB	2	2388	9	14	1	0	98.94	0.15
RBBB	2	7	2412	1	3	1	99.50	0.14
PVC	0	10	1	1170	1	0	98.59	0.27
PAC	0	3	0	0	853	0	99.34	0.47
PB	0	1	1	0	0	1169	99.93	0.07
PPV Mean	99.82	99.00	99.24	99.16	99.11	99.95	99.35	
PPV Std	0.11	0.08	0.09	0.24	0.21	0.08	Total Acc.	99.43

For purpose of classification prototype based techniques were used, which are Crisp k-NN, Fuzzy k-NN, Pruned Weighted Fuzzy k-NN. Following **Error! Reference source not found.** shows a comparison of different techniques used during ECG based Arrhythmia recognition.

Table 2 Comparison of techniques

Data Set	Total Accuracy	G. Mean	Method
Set6	99.50%	99.40%	k-NN
Set6	99.43%	99.35%	F k-NN
Set6 ALL	97.60%	94.81%	K-NN
Set6 ALL	97.12%	93.77%	Drop3 k-NN
Set 6 ALL	97.50%	95.24%	W k-NN
Set6 ALL	97.52%	95.05%	P k-NN
Set6 ALL	97.33%	94.98%	PW k-NN
Set6 ALL	97.63%	94.73%	F k-NN
Set6 ALL	97.31%	94.74%	PF k-NN
Set6 ALL	97.30%	95.07%	WF k-NN
Set6 ALL	97.52%	95.05%	P LMNN
Set6 ALL	97.51%	95.03%	WLMNN
Set6 ALL	96.86%	92.81%	LFDA
Set 9	97.30%	86.40%	P k-NN
Set 9	97. 04%	87.90%	F k-NN
Set9	96.83%	86.20%	WF k-NN
Set9	96.74%	89.59%	PWF k-NN
Set6 G (LOPO)	89.24%	80.95%	PWF k-NN

Conclusion

In this work an efficient approach for classification of 9 types of cardiac arrhythmias through ECG using wavelet domain features. The proposed classification methodology utilizes data pruning and efficient nearest neighbor search in order to reduce classification time.

Future Proposals

For future work an online or real-time system can be designed for ECG analysis of single or multiple patients at hospital or even can be used for telemedicine services. It can be interfaced with portable ECG devices (such as Holter meter) with laptops for purpose of portability. It can be modified into an adaptive system if needed by adding or removing prototypes from Prototype Set.

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