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Unsupervised ECG Classification Using Maximum Likelihood Factor Method

Manpreet Kaur and A. S. Arora

***Abstract*— This paper presents a new approach for classification of ECG Signals. Wavelet coefficients are calculated for QRS complex extracted and these are considered as features. These features have been reduced to feature set by factor analysis procedure using Maximum Likelihood method. The classification has been done by LDA (Linear Discriminant Analysis. The results are compared for different analysis procedure options i.e., Norotation, varimaxrotation, quartimax rotation and equimaxrotation. The signals are taken from MIT-BIH arrhythmia database to classify into Normal, PVC, Paced, LBBB and RBBB. The performance of classification output has been compared by the performance parameters.**

***Index Terms*— ECG, Linear Discriminant Analysis, Maximum Likelihood Method, Holdout Procedures and Orthogonal Rotations**

I. Introduction

THE classification of cardiac arrhythmia is an important tool in ICU and CCU that enables online monitoring of the cardiac activities and require special algorithms for detection and prediction. Sometimes long term (24 hrs) ECG recording is done for identification of abnormal heart beats and their manual editing is time consuming. Hence the use of mathematical tools along with computer base can be a better choice. In the last few decades; many solutions have been given by researchers.

II. Literature Review

Sung-Nien Yu et al., have used combination of independent component analysis and neural networks for ECG beat classification [1]. Jinkon Kim et al., have classified six different beats using extreme learning mach in taking PCA and other statistical features for classification [2]. AtaollahEbrahimZadeh et al., have considered only one morphological feature that is timing to classify three different beats. They have used neural networks, MLP, RBF and SVM Classifiers [3]. BabakMohammadzadeh have used heart rate variability signal as basic signal and extracted linear and nonlinear parameters from it. ANN has been used for arrhythmia classification [4]. I. Jekova et al., have identified five arrhythmias with various classification methods that are kthNN rule, neural networks, discriminant analysis and fuzzy logic [5]. H. Gholam et al. have compared different feed forward neural networks architectures for ECG signal diagnosis [6]. A. Khazaee et al., have used power spectral features. They used support vector machine and genetic algorithm for classification [7]. YunChiYeh et al., have used linear discriminant analysis for classification of ECG signals [8].

The proposed work has considered only the morphological features for the analysis. The frequency sub-band signals components are considered as features and the feature set is reduced with the 'maximum likelihood' type factor method. The next step is the classification, which is done by LDA. The feature reduction method is categorized under no rotation, varimax rotation, quartimax rotation and equamax rotation. The proposed system unsupervised type but still can find its application in Holter analysis.

III. Wavelets for Feature Extraction

Over recent years, wavelets have emerged as one of the most favored tools and are being widely used in the field of science and technology. Wavelets produce time frequency decompositions of signals more effectively than traditional Short Time Fourier Transform (STFT) by employing window of variable width. This is flexible temporal–spectral aspect of the transform allows alocalscale-dependent spectral analysis of individual signal features. In this way both short duration, high frequency and longer duration, lower frequency information can be captured simultaneously.

The signal (t) is decomposed into basis function of time and scale which are dilated and translated version of a basis function ψ(t) which is called mother wavelet. Translation is accomplished by considering all possible integer translation of ψ(t) and dilation is obtained by multiplying t by a scaling factor which is usually 2. The following equation show wavelets are generated from mother wavelet:

$$\Psi_{j,k}(t) = 2^{\frac{j}{2}}\ \Psi(2^{\frac{j}{2}} t - k)$$

where j indicates the resolution level and k is the translation in time. This is called dyadic scaling. Wavelet decomposition is a linear expansion and it is expressed as:

$$F(t) = \sum_{k=-\infty}^{+\infty} c_k \varphi(t-k) + \sum_{k=-\infty}^{+\infty} \sum_{j=0}^{+\infty} d_{j,k}\, \Psi(2^j\, t - k)$$

Manpreet Kaur is with Department of EIE, SantLongowal Institute of Engineering and Technology, Longowal - 148106 (PB) India, aneja_mpk@yahoo.com

A. S. Arora is with Department of EIE, SantLongowal Institute of Engineering and Technology, Longowal - 148106 (PB) India, ajatsliet@yahoo.com

where φ(t) is called the scaling function or father wavelet. c_k and $d_{j,k}$ are the coarse and detail level expansion coefficients, respectively [9]. For current analysis, the detailed coefficients cd4, cd5, cd6, cd7 are taken as features for classifications these sub-band signals have representative components and different distributions to each other [10].

IV. Factor Analysis

Factor analysis is a technique which seeks a simpler structure for a set of variables; variables are linear combinations of factors, accounting usually for correlations (but sometimes for covariance) between variables. Factors are the transformed new (and fewer) variables resulting from factor analysis. Factor analysis often uses the correlation matrix R but can use the covariance matrix S. The correlation matrix R is the m x m matrix of correlations between all pair-wise combinations of the variables. The covariance matrix S is the m x m matrix of covariance values (using the data as a population rather than as a sample i.e., using n rather than n-1 to calculate covariance) between all pair-wise combinations of the variables. Following are the methods used to obtain the factors:

- The principal component method
- The principal factor method
- The maximum likelihood factor method

Maximum likelihood factoring method allows a χ^2 test of the significance of the number of extracted factors.

Rotation of the factor axes is used to improve the factor structure. For this paper orthogonal rotations are used. Three types for these rotations which are considered here:

- *Quartimax rotation* is a method of orthogonal rotation which emphasizes cleaning up the variables in factor analysis, rather than the factors
- *Varimax rotation* is a method of orthogonal rotation which emphasises cleaning up the factors in factor analysis, rather than the variables;
- *Equamax rotation* is a method of orthogonal rotation which combines the criteria for quartimax and varimax, and spreads the variance more equally amongst factors [11].

V. Linear Discriminant Analysis

The objective of discriminant analysis is to classify objects, by a set of independent variables into one of the two or more mutually exclusive and exhaustive categories. For notation let:

X_{ji}: be the i^{th} individual's value of j^{th} independent variable.
b_j: be the discriminant coefficient of the j^{th} variable.
Z_i: be the i^{th} individual's discriminant scores.
Z_{crit}: be the critical value for discriminant score.

Let each individual scores Z be a linear function of the independent variables. That is

$$Z_i=b_0+b_1X_{1i}+b_2X_{2i}+\ldots+b_nX_{ni}$$

If $Z_i>Z_{crit}$, classify individual I as belonging to group 1;
If $Z_i<Z_{crit}$, classify individual I as belonging to group 2;
Classification boundary will then be locus of points. Where

$$b_0+b_1X_{1i}+b_2X_{2i}+\ldots+b_nX_{ni} = Z_{crit}$$

When n (number of independent variables) = 2, the classification boundary is the straight line. Every individual on one side of the line is classified as group 1 and on the other side as group 2. When n=3, the classification boundary is a two dimensional plane in three dimensional space; the classification boundary is generally n-1 dimensional hyper plane in n space [12].

The estimate of error rate can be obtained by Holdout method, where all data but one case is used to calculate the linear classification functions, which hare then used to classify the omitted case either correctly or incorrectly. This holdout procedure is repeated for every individual case (requiring considerable computation effort) and the error rate is determined from the cumulated classifications/ misclassifications of the holdout cases [11].

VI. Performance parameters

There are many approaches in the literature which judge the performance of the classifier. For this paper, Accuracy (Acc), Sensitivity (Se) and Positive predictivity (Pp) metrics are taken as parameters.

1) Accuracy: Overall accuracy of the classifier has been defined as:

$$Acc = \frac{N_T - N_E}{N_T}\ 100$$

Where N_E represents the total number of classification errors and N_T are the total number of beats.

2) Sensitivity: It is the ratio of the number of correctly classified beats (TP) to the total number of beats (TP+FN)

$$Se = \frac{TP}{TP + FN}\ 100$$

Where TP represents the true positive beats and FN represents the false negative beats. True positives are number of correctly detected beats and FN is the number of missed beats.

3) Positive Predictivity: It is the ratio of falsely detected beats (FP) to total number of beats (TP+FP)

$$Pp = \frac{TP}{TP + FP}\ 100$$

Where TP represents the true positive beats and FP represents false positive beats. FP is the number of falsely detected events.

VII. Data for Analysis

The MIT-BIH Arrhythmia database has been used for the analysis. This database contains 25 records of 30minutes duration. The ECG signal is sampled at 360Hz with are solution of 11 bits. Lead II signal has been used for analysis. A total of 15 records are used for analysis the details as shown below.

TABLE
DATA OF BEATS

Type of beats	Normal	PVC	Paced	LBBB	RBBB
Data No	100,101, 103,105	200, 203	107, 217	109,111, 214	118,124, 212,231

VIII. METHODOLOGY

The annotated MIT-BIH raw database has been used for the analysis. The R wave locations of different type of beats are taken from the annotation files. Then total of 144 data samples are taken with R point at the center [10].The extracted beats are categorized as per annotations in the database. Five different types of beats i.e. normal, PVC, Paced beats, LBBB and RBBB are taken for analysis. A total of 1060 beats are extracted with 212 beats of each type making matrix of 1060 ×144.This dataset is designated as labeled dataset. After preparing dataset, the wavelet coefficient are computed using 'db4'.The detailed coefficients cd4,cd5,cd6 and cd7 are taken as features .The sub-band signals have the representative components and different distributions for each type of beat. The total number of 43 features with cd4 having 15, cd5 having 11, cd6 having 9 and cd7 having 8 coefficients. The factor analysis method with maximum likelihood criteria is used for factor reduction .The number of factors to be taken for the analysis is determined from 'variance explained criteria' [11]. Finally a total of 23 features are used for classification. Linear discriminant Analysis is used to classify data and error in classification is checked by holdout procedures. The factor reduction by maximum likelihood method is done by four methods i.e. no rotation, varimax rotation, quartimax rotation and equimax rotation. The classification is done for all four datasets.

For the testing of the method, four unknown dataset with 53 beats of each type are prepared .One test beats set is added to the labeled set for factor calculations. Factors are calculated for 1060+265=1325 beats and then classified with LDA. This procedure is repeated for other test dataset also. The performance is compared in terms of sensitivity, accuracy and positive predictivity.

IX. RESULTS AND DISCUSSIONS

Factor analysis method provides reduction in the dimensionality of the feature set but the factors obtained by any of the technique i.e. with rotation or without rotation is not unique. So this method is not suggested for supervised learning. This unsupervised method finds its application in Holter ECG arrhythmic beats classification. Table I shows the classification results of labeled dataset for factor obtained from no rotation method. The Tables II, III, IV and V show the change in the classification results of labeled set due to recalculation of the factors after adding unknown test data beats. The Tables VII, VIII, IX and X have shown the similar changes in classification of the labeled dataset with classification results shown in Table VI for factors obtained with Varimax rotation. Similarly next tables have shown the output for Quartimax and equamax rotations. From all the above tables it can be concluded that number of factors to be chosen for classification, determined by 'variance explained criteria' [11], remains the same.

In next tables, Table XXI, XXII, XXIII, XXIV classification of unknown beats are shown for the four unknown sets used for testing. The average accuracy of four unknown sets of each type is calculated as 97.925% for no rotation, 97.734% for varimax, 98.206% for quartimax and 98.678 for equimax.

X. CONCLUSIONS

The accuracy of automatic heart beat classification is of great importance for precise cardiac dysfunction diagnosis. Many algorithms for automatic heartbeats classification have been proposed in the literature but because of the fact that ECG datasets with dissimilar beats are used for analysis and therefore the direct comparison is questionable. But the performance of proposed method is found to be competitive to other published result. The proposed method proved to be computationally efficient and hence a potential technique for automatic recognition of arrhythmic beats in ECG monitors or Holter ECG records.

REFERENCES

[1] Sung-Nien Yu, Kuan-To Chou, "Integration of independent component analysis and neural networks for ECG beat classification", *Science Direct, Expert systems with applications* 34 (2008) 2841-2846.

[2] Jinkon Kim, Hang Sik Shin, KwangsooShinandMyoungho Lee, "Robust algorithm for arrhythmia classification in ECG using extreme learning machine", *Medical Engineering* Online 2009,8:31 doi:10.11 Bio86/1475-925X-8-31.

[3] AtaollahEbrahimZadeh, Ali Khazaee, VahidRanaee, "Classification of the electrocardiogram signals using supervised classifiers and efficient features", *Computer methods and programs in Biomedicine*, 99(2010)179-194.

[4] BabakMohammadzadeh –Asl,SeyedKamaledinSetarehdan, "Neural Network based arrhythmia classification using heart rate variability signal", 14th European *Signal Processing Conference* (EUSIPCO 2006),Florence, Italy, September 4-8,2006

[5] I.Jekova, G.Bortolan, I. Christov, "Assessment and comparison of different methods for heart beat classification", *Medical Engineering and Physics,* 30 (2008) 248-257.

[6] H.Gholam, D.Luo, KJ Reynolds, "The comparison of different feed forward neural networks architectures for ECG signal diagnosis", *Medical Engineering and Physics* 28 (2006) 372-378.

[7] A.Khazaee, A. Ebrahimzadeh,"Classification of electrocardiogram signals with support vector machine and genetic algorithm using power spectral features", *Biomedical Signal Processing and Control*, Vol 4, issue 4, October (2010) 252-263.

[8] Yun Chi Yeh, Wen June Wang, CheWunChiou, "Cardiac arrhythmia diagnosis method using linear disciminant analysis on ECG signals", *Measurement* 42 (2009) 778-789.

[9] Mohammad Ali Tinati and BehzadMozaffary, 'A Wavelet Packets Approach to Electrocardiograph Baseline Drift Cancellation', Hindawi Publishing Corporation, International JOURNAL OF Biomedical imaging, Volume 2006, Article ID 97157, 1-9.

[10] MihyeSong,Jeon Lee Sung Pil Cho, KyoungJoung Lee ,Sun Kook Yoo, 'Support Vector Machine based arrhythmia classification using reduced features', International journal of Control Automation and Systems, vol. 3,no.4, pp 571-579, December 2005.

[11] http://www.statistixl.com/

[12] Donald G Morrison, "On Interpretation of Discriminant Analysis", Journal of Marketing Research, Vol VI, May 1969, 156-63.

A. Classification Table for factors calculated with No-Rotation method

TABLE I
CLASSIFICATION RESULTS OF LABELED DATA SETS

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	24	97.2	89.56	206	6	25	97.2	89.18
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	205	7	10	96.7	94.35
5	RBBB	212	191	21	4	90.1	97.95	190	22	4	89.6	97.94
	%Acc					95.9					95.7	

TABLE II
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FIRST TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	25	97.2	89.18	206	6	25	97.2	89.18
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	207	5	5	97.6	97.64
4	LBBB	212	205	7	9	96.7	95.79	205	7	9	96.7	95.79
5	RBBB	212	190	22	4	89.6	97.94	190	22	4	89.6	97.94
	%Acc					95.8					95.8	

TABLE III
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF SECOND TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	25	97.2	89.18	206	6	25	97.2	89.18
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	207	5	5	97.6	97.64
4	LBBB	212	205	7	8	96.7	96.24	206	6	9	96.7	96.24
5	RBBB	212	191	21	4	90.1	97.95	190	22	4	89.6	97.94
	%Acc					95.8					95.8	

TABLE IV
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF THIRD TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	27	98.1	88.51	208	4	29	98.1	87.76
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	206	6	10	97.2	95.37
5	RBBB	212	189	23	1	89.2	99.47	186	26	1	87.7	99.46
	%Acc					95.9					95.6	

TABLE V
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FOURTH TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	28	98.1	88.13	208	4	30	98.1	87.39
2	PVC	212	207	5	2	97.6	99.04	207	5	3	97.6	98.57
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	205	7	9	96.7	95.79
5	RBBB	212	188	24	1	88.7	99.47	185	27	2	87.3	98.93
	%Acc					95.8					95.4	

B. Classification Table for factors calculated with Varimax method

TABLE VI
CLASSIFICATION RESULTS OF LABELED DATA SETS

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	207	5	25	97.6	89.22	207	5	29	97.6	87.71
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	206	6	5	97.2	97.63	206	6	5	97.2	97.63
4	LBBB	212	205	7	9	96.7	95.79	205	7	10	96.7	95.35
5	RBBB	212	191	21	3	90.1	98.45	186	26	3	87.7	98.41
	%Acc					95.8					95.4	

TABLE VII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FIRST TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	24	97.2	89.56	206	6	25	97.2	89.18
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	205	7	9	96.7	95.79	205	7	9	96.7	95.79
5	RBBB	212	191	21	4	90.1	97.95	190	22	4	89.6	97.94
	%Acc					95.8					95.7	

TABLE VIII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF SECOND TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	25	97.2	89.18	206	6	25	97.2	89.18
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	205	7	9	96.7	95.79	205	7	10	96.7	95.35
5	RBBB	212	190	22	4	89.6	97.94	190	22	4	89.6	97.94
	%Acc					95.8					95.7	

TABLE IX
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF THIRD TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	207	5	26	97.6	88.84	206	6	27	97.2	88.84
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	206	6	11	97.2	94.93
5	RBBB	212	189	23	3	89.2	98.44	187	25	3	88.2	98.42
	%Acc					95.8					95.5	

TABLE X
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FOURTH TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	28	98.1	88.13	207	5	27	97.6	88.46
2	PVC	212	207	5	2	97.6	99.04	207	5	3	97.6	98.57
3	Paced	212	207	5	5	97.6	97.64	205	7	5	96.7	97.62
4	LBBB	212	206	6	8	97.2	96.26	206	6	11	97.2	94.93
5	RBBB	212	188	24	1	88.7	99.47	187	25	2	88.2	98.94
	%Acc					95.8					95.5	

C. Classification Table for factors calculated with Quartimax method

TABLE XI
CLASSIFICATION RESULTS OF LABELED DATA SETS

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	207	5	25	97.6	89.22	207	5	28	97.6	88.08
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	205	7	8	96.7	96.24	205	7	10	96.7	95.35
5	RBBB	212	191	21	3	90.1	98.45	187	25	3	88.2	98.42
	%Acc					95.9					95.5	

TABLE XII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FIRST TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
			206	6	24	97.2	89.56	206	6	26	97.2	88.79
1	Normal	212										
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	206	6	5	97.2	97.64	206	6	5	97.2	97.64
4	LBBB	212	205	7	9	96.7	95.79	205	7	10	96.7	95.35
5	RBBB	212	192	20	4	90.6	97.96	189	23	4	89.2	97.93
	%Acc					95.8					95.6	

TABLE XIII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF SECOND TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
			208	4	28	98.1	88.13	208	4	28	98.1	88.13
1	Normal	212										
2	PVC	212	20φφ7	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	206	6	5	97.2	97.63	206	6	5	97.2	97.63
4	LBBB	212	206	6	10	97.2	95.37	206	6	10	97.2	95.37
5	RBBB	212	187	25	1	88.2	99.47	187	25	1	88.2	99.47
	%Acc					95.7					95.7	

TABLE XIV
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF THIRD TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	28	98.1	88.13	208	4	28	98.1	88.13
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	206	6	10	97.2	95.37
5	RBBB	212	188	24	1	88.7	99.47	187	25	1	88.2	99.47
	%Acc					95.8					95.7	

TABLE XV
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FORTH TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	28	98.1	88.13	207	5	27	97.6	88.46
2	PVC	212	207	5	2	97.6	99.04	207	5	3	97.6	98.57
3	Paced	212	207	5	5	97.6	97.64	205	7	5	96.7	97.62
4	LBBB	212	206	6	8	97.2	96.26	206	6	11	97.2	94.93
5	RBBB	212	188	24	1	88.7	99.47	187	25	2	88.2	98.94
	%Acc					95.8					95.5	

D. Classification Table for factors calculated with Equimax method

TABLE XVI
CLASSIFICATION RESULTS OF LABELED DATA SETS

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	206	6	25	97.2	89.18	206	6	26	97.2	88.79
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	207	5	5	97.6	97.64
4	LBBB	212	205	7	8	96.7	96.24	205	7	9	96.7	95.79
5	RBBB	212	191	21	4	90.1	97.95	189	23	4	89.2	97.93
	%Acc					95.8					95.7	

TABLE XVII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FIRST TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	28	98.1	88.13	207	5	28	97.6	88.08
2	PVC	212	207	5	2	97.6	99.04	207	5	3	97.6	98.57
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	206	6	8	97.2	96.26	206	6	10	97.2	95.37
5	RBBB	212	188	24	1	88.7	99.47	187	25	1	88.2	99.47
	%Acc					95.8					95.6	

TABLE XVIII
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF SECOND TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	207	5	25	97.6	89.22	206	6	27	97.2	88.41
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	205	7	8	96.7	96.24	205	7	10	96.7	95.35
5	RBBB	212	191	21	3	90.1	98.45	188	24	4	88.7	97.92
	%Acc					95.9					95.5	

TABLE XIX
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF THIRD TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	207	5	25	97.6	89.22	206	6	27	97.2	88.41
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	205	7	8	96.7	96.24	205	7	10	96.7	95.35
5	RBBB	212	191	21	3	90.1	98.45	188	24	4	88.7	97.92
	%Acc					95.9					95.5	

TABLE XX
CHANGE IN CLASSIFICATION RESULTS OF LABELED DATA SETS WITH ADDITION OF FORTH TEST DATASET

			LDA Classification					Holdout Classification				
S No	Type of Beats	Total No. of beats	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)	No of beats correctly classified	No. of FN beats	No. of FP beats	Se (%)	Pp (%)
1	Normal	212	208	4	29	98.1	87.76	206	6	31	97.2	86.92
2	PVC	212	207	5	2	97.6	99.04	207	5	2	97.6	99.04
3	Paced	212	207	5	5	97.6	97.64	206	6	5	97.2	97.63
4	LBBB	212	207	5	8	97.6	96.24	206	6	11	97.2	94.93
5	RBBB	212	185	27	2	87.3	98.93	183	29	3	86.3	98.39
	%Acc					95.7					95.1	

TABLE XXI
CLASSIFICATION RESULTS OF UNKNOWN BEATS OF SET1

S.No.	Types of beats	NOROTATION		VARIMAX		QUARTIMAX		EQUIMAX	
		Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)
1	Normal	94.33	100	96.22	100	98.11	100	100	100
2	PVC	96.27	100	96.22	100	96.23	100	96.23	98.08
3	Paced	100	98.15	100	98.15	98.11	98.11	100	98.15
4	LBBB	98.11	98.11	98.11	98.11	98.11	96.30	98.11	98.11
5	RBBB	100	92.98	100	94.64	100	96.36	100	100

TABLE XXII
CLASSIFICATION RESULTS OF UNKNOWN BEATS OF SET2

S.No.	Types of beats	NOROTATION		VARIMAX		QUARTIMAX		EQUIMAX	
		Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)
1	Normal	100	100	100	100	100	100	100	100
2	PVC	100	100	100	100	100	100	100	100
3	Paced	100	100	100	100	98.11	100	100	100
4	LBBB	100	100	100	100	100	98.15	100	100
5	RBBB	100	100	100	100	100	100	100	100

TABLE XXIII
CLASSIFICATION RESULTS OF UNKNOWN BEATS OF SET3

S.No.	Types of beats	NOROTATION		VARIMAX		QUARTIMAX		EQUIMAX	
		Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)
1	Normal	92.45	94.23	86.79	92	94.34	96.15	94.34	96.15
2	PVC	100	100	100	100	100	100	100	100
3	Paced	100	100	100	100	100	100	100	100
4	LBBB	100	98.15	100	98.15	100	100	100	98.15
5	RBBB	92.45	92.45	90.56	87.27	96.23	94.444	94.34	94.34

TABLE XXIV
CLASSIFICATION RESULTS OF UNKNOWN BEATS OF SET4

S.No.	Types of beats	NOROTATION		VARIMAX		QUARTIMAX		EQUIMAX	
		Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)	Se(%)	Pp(%)
1	Normal	90.56	97.96	90.56	97.96	90.56	97.95	96.22	96.22
2	PVC	98.11	100	98.11	100	98.11	100	98.11	100
3	Paced	100	98.15	100	98.15	100	98.15	100	98.15
4	LBBB	98.11	98.11	98.11	100	98.11	98.11	98.11	100
5	RBBB	98.11	91.23	100	91.38	98.11	91.22	98.11	96.29