Classification Probability Analysis for Arrhythmia and Ischemia Using Frequency Domain Features of QRS Complex

Akash Kumar Bhoi[1*], Karma Sonam Sherpa[2], Bidita Khandelwal[3]

[1]*Department of Applied Electronics & Instrumentation Engineering*
Sikkim Manipal Institute of Technology, SMU, India
E-mail: akash730@gmail.com

[2]*Department of Electrical & Electronics Engineering*
Sikkim Manipal Institute of Technology, SMU, India
E-mail: karmasherpa23@gmail.com

[3]*Department of General Medicine*
Central Referral Hospital and SMIMS, SMU, India
E-mail: drbidita@gmail.com

[*]*Corresponding author*

Received: June 23, 2015 **Accepted: November 09, 2015**

Published: December 22, 2015

Abstract: *Two of the most common cardiovascular diseases are myocardial ischemia and cardiac arrhythmias. Using the frequency domain features of QRS complex (i.e., frequency of the maximum peak in power spectrum and total average power) the proposed approach analyzes classification probability for these diseases by implementing Linear Discriminant Analysis (LDA) and Decision Tree. Moreover the classification probability is visualized using Naive Bayes classification algorithm. The methodology includes the QRS complex detection technique which is mainly comprises of three stages: Stage-1 – baseline drifts and noise cancellation using Moving Average Filter (MAF) and Stationary Wavelet Transform (SWT); Stage-2 – R-peaks localization using threshold based windowed filter: Stage-3 – Q and S inflection points detection using search interval method. To perform uniform classification probability analysis, the proposed methodology is evaluated with 108 selected episodes which show 100% accuracy in QRS complex detection. The 108 episodes includes 36 lengthy ECG recordings from FANTASIA database (healthy subjects), MIT-BIH Arrhythmia database (arrhythmic subjects) and Long-Term ST database (ischemic subjects) respectively. Moreover, the energy surface distribution of segmented QRS complex is analysed with Short-Term Fourier Transform (STFT) which transforms time domain information of the complex into time-frequency domain.*

Keywords: *Ischemia, Arrhythmia, LDA, Decision tree, Naive Bayes classification.*

Introduction

Ischemia and Arrhythmias are not imminently life-threatening conditions and the further critical problems can be prevented with therapeutic methods. Most of the Holter ECG machines do not classify abnormalities and they require offline or post processing techniques. Signal processing and pattern recognition tasks can be embedded on the real-time machine to compute the diagnostic requirement [6, 9, 31]. For frequency-based features, frequency spectrum of individual QRS complex is found in the range of 0-20 Hz. The spectrum has maximum amplitude at 4 Hz in Ventricular Tachycardia (VT) and its amplitude decreases as the frequency increases [26]. The frequencies of Ventricular Fibrillation (VF) are concentrated between 4-7 Hz [23]. In the time-frequency technique, Wavelet Transform (WT) has applied to extract the features of cardiac arrhythmias [9, 31]. Applying these symptomatic

features, linear discriminates and Artificial Intelligent (AI) approaches have been proposed to improve the classification of cardiac abnormalities including wavelet neural networks [9], Artificial Neural Network (ANN) [1, 4, 26, 32], and fuzzy hybrid neural networks [27, 34]. Yazdani et al. [35] implemented fixed structure Mathematical Morphology (MM) operators to detect QRS complexes in the ECG. Karimipour et al. [21] introduced a simple, low-latency, and accurate algorithm for real-time detection of P-QRS-T waves in the electrocardiogram (ECG) signal. Christov et al. [7] have reviewed the algorithms for detection and classification of the QRS complexes. Combined criteria have been introduced dealing with the QRS areas and amplitudes, the wave shapes evaluated by steep slopes and sharp peaks, vectorcardiographic (VCG) loop descriptors, RR intervals irregularities [7]. We have also reviewed several existing algorithms and methods for QRS complex detection as well as the effect of QRS complex on various critical cardiovascular conditions [3]. Jekova et al. [20] presented an ECG database, named "PacedECGdb" which contains different arrhythmias generated by HKP (Heidelberger Praxisklinik) simulator, combined with artificially superimposed pacing pulses that cover the wide ranges of rising edge (from < 10 μs to 100 μs) and total pulse durations (from 100 μs to 2 ms) and correspond to various pacemaker modes. It could be used for development and testing of methods for pace detection in the ECG. Christov et al. [8] described the automatic detection of QRS-onset and T-end based on the minimum value of the angle between two segments having a common midpoint and equal lengths of 10 ms. Minimum angle is searched in defined time intervals delineated separately for the Q and T.

Lin [24] converts each QRS complexes to a Fourier spectrum from ECG signals; the spectrum varies with the rhythm origin and conduction path. The variations of power spectrum are observed in the range of 0-20 Hz in the frequency domain. To quantify the frequency components among the various ECG beats, grey relational analysis (GRA) is performed to classify the cardiac arrhythmias. Exarchos et al. [11] proposed a methodology for the automated creation of fuzzy expert systems, applied in ischaemic and arrhythmic beat classification. A few other articles suggesting the ischemic effect can be analyzed using QRS complex are; morphological changes of QRS slopes upon ischemia [28], changes in QRS morphology due to slowing of intra myocardial conduction during ischemia [14, 15, 17], the QRS complex is a better marker of ischemia than the traditional ST index [5, 21]. Tanev [33] describes very fast procedure for accurate QRS detection in long term ECG Holter recordings, followed by classification of the complexes in normal and ectopic. The proposed methodology involves the frequency domain features of QRS complex and classifies three conditions (i.e., healthy, arrhythmic and ischemic) evaluating standard databases (e.g., FANTASIA, MIT-BIH arrhythmia database (MITDB) and Long-Term ST database (LTSTDB)). The classification probability estimated with Naive Bayes classification algorithm whereas LDA and decision tree are implemented for disease classification.

ECG databases

The three different classes of ECG signals (i.e., healthy, arrhythmic and ischemic) are selected from FANTASIA database, MITDB and LTSTDB respectively. The proposed methodologies have been tested over all ECG recording of healthy subjects from FANTASIA database [18], arrhythmic patients from MITDB [13] and ischemic patients from LTSTDB [19] having 1st row (signal) with the duration of 1 hour. The ECG recording of FANTASIA and LTSTDB databases are having 250 Hz sampling frequency with 0.004 s sampling interval and MITDB database are having 360 Hz sampling frequency with 0.0027 s sampling interval. But out of them only 108 (i.e., 36 data from each database) selected ECG data are tabulated (Table 1),

which, satisfy the QRS detection performance (i.e., sensitivity and the specificity) to be 100%.

Baseline drift and noise cancellation

The ECG signals are passed through pre-processing stages where the baseline drifts and noise (i.e., low frequency and high frequency components) is eliminated. The baseline drift of ECG signal is removed by applying Moving Average Filtering (MAF) [22] and the process is equivalent to low pass filtering with the response of the smoothing given by the difference equation by the difference equation:

$$Y_S(i) = \frac{1}{2N+1}\left(Y(i+N) + Y(i+N-1) + \ldots + Y(i-N)\right) \quad (1)$$

where $Y_S(i)$ is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of $Y_S(i)$, and $2N + 1$ is the span. The moving average smoothing method used by Curve Fitting Toolbox follows these rules [22]:

- The span must be odd.
- The data point to be smoothed must be at the center of the span.
- The span is adjusted for data points that cannot accommodate the specified number of neighbours on either side.
- The end points are not smoothed because a span cannot be defined.

The Stationary Wavelet Transform [25] is similar to the Discrete Wavelet Transform but the SWT [2], output signal is never sub sampled. Considering a given signal $X[n]$ of length $N = 2^J$ for few integer J, where, $h_1(n)$ and $g_1(n)$ are the impulse responses of the low pass filter and the high pass filter. The impulse responses are chosen such that the outputs of the filters are orthogonal to each other. The approximation coefficients $a_1(n)$ and detailed coefficients $d_1(n)$ can be obtained with the following equations:

$$a_1(n) = h_1(n) X(n) = \sum h_1[n-k] X[k] \quad (2)$$

$$d_1(n) = g_1(n) X(n) = \sum g_1[n-k] X[k] \quad (3)$$

The filtering result can also be observed from Fig. 1 for MITDB data # 117 having baseline drift and noise. The low frequencies components are removed after Fast Fourier Transform (FFT) and the signal is restored applying Inverse Fourier Transform (IFT).

QRS complex detection

The default size windowed filter is applied to the noise free input ECG signal to detect the maximum peaks. The small peaks or values are eliminated using a threshold filter and significant ones are preserved. The filtering performance is improvised by adjusting size of the windowed filter and finally, the *R*-peaks are detected and localized. After that search interval implemented to detect the two inflection points before and after the *R*-peaks (i.e., *Q* and *S* point). The normal QRS complex duration is 0.04-0.11 s [30], so the search interval-1 is defined which locates 0.027 s before and after the *R* point. The minimum value before *R* point is marked as point Q_1 and after *R* point is denoted as point S_1 [36]. Search interval-2 is defined such that 0.055 s before and after *R* point. The minimum value point

behind R is Q_2 and after R is S_2 [36]. Check the position and amplitude of Q_1 and Q_2 to conform the position of Q. If their position is different and amplitude of Q_1 is greater than Q_2, then the position of Q_1 is the position of Q or vice versa. If the position of S_1 and S_2 are same, their position is the position of S. Otherwise, if $V_{S_2} > V_{S_1}$ the position of point S locates the position of point S_1; else, the position of point S locates on the position of point S_2, where V_{S_i} is the amplitude of point S_i, i = 1, 2 (Fig. 1) [36]. To evaluate the classification probability of healthy, arrhythmia and ischemia using LDA and decision tree, 100% accurately detected QRS complexes (without QT complex inversion) of 108 episodes are selected.

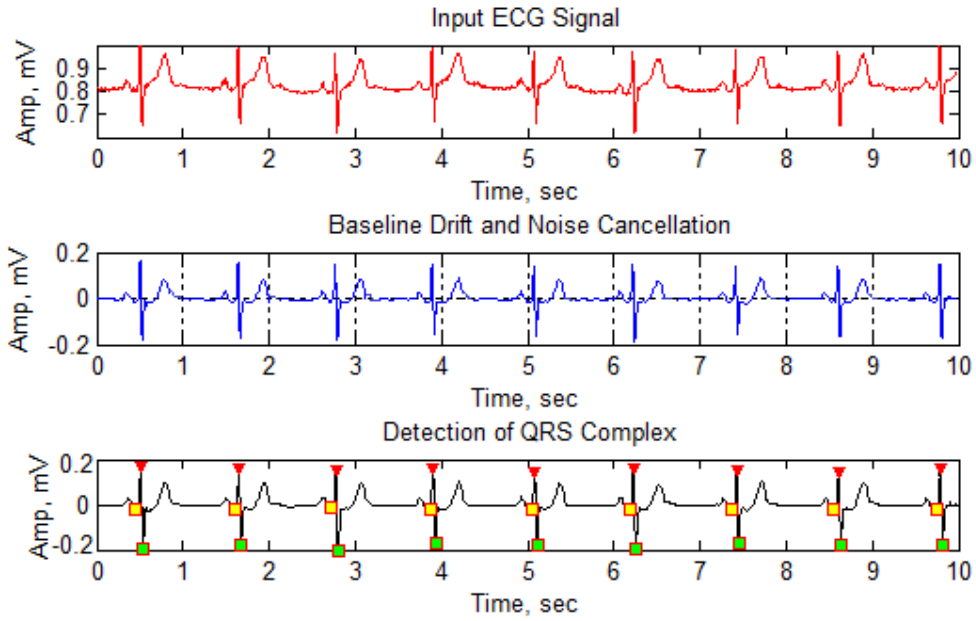


Fig. 1 Filtering and QRS complex detection for MITDB data # 117
(10 s data for better visualization)

The performance of the methodologies is evaluated by the sensitivity (*Se*) and the specificity (*Sp*). The *Se* and *Sp* are normally computed by [36]:

$$Se = 1 - \frac{FN}{TP + FN} = \frac{TP}{TP + FN} \tag{4}$$

$$Sp = 1 - \frac{FP}{TP + FP} = \frac{TP}{TP + FP} \tag{5}$$

False Positive (FP) and False Negative (FN) beats are zero for the selected sets of signals (i.e., three databases) whereas; the True Positive (TP) beats are 100%. Here *Se* and *Sp* found to be 100% for the selected 36 signals (i.e., 108 data) from each databases. Further the frequency domain features are extracted from the segmented *mean QRS complexes* of 1 hour duration based ECG signals and are tabulated in Table 1.

Table 1. Frequency domain features of *mean QRS complexes*

Fantasia	Peak_Freq	Pwr	MITDB	Peak_Freq	Pwr	LTSTDB	Peak_Freq	Pwr
f1o01	8.6207	0.1774	100	21.1765	0.2951	s20011	7.8125	0.1866
f1o02	11.3636	0.1720	101	15.2432	0.1349	s20051	14.7059	0.3942
f1o04	12.5000	0.2843	105	5.6250	0.1630	s20061	11.3636	0.2361
f1o05	16.6667	0.2960	106	18.9474	0.3275	s20071	13.8889	0.2468
f1o06	11	0.1350	109	5.7143	0.2517	s20081	11.3636	0.2148
f1o07	9.6154	0.1918	111	6.5455	0.1626	s20091	6.4103	0.1445
f1o09	10	0.1009	112	9.4737	0.1756	s20101	10.2154	0.0841
f1o10	12.5000	0.2976	113	18.9474	0.2995	s20111	10.4167	0.3104
f1y01	13.8889	0.2211	114	17.4217	0.2600	s20121	7.2133	0.0939
f1y02	13.1579	0.2053	115	12	0.1975	s20131	11.2156	0.1529
f1y03	15.6250	0.2742	117	11.2500	0.2531	s20141	10	0.1841
f1y04	12	0.1555	119	14.9571	0.1309	s20151	6.5789	0.1569
f1y05	14.1241	0.1391	121	7.3469	0.2433	s20161	13.1579	0.2958
f1y06	16.6667	0.2713	122	9.2308	0.2670	s20171	11.9048	0.2651
f1y07	10.4167	0.1611	123	8.5714	0.1629	s20181	12	0.1284
f1y08	15.6250	0.2607	124	6.6667	0.2058	s20191	7.1429	0.2144
f1y09	14	0.1196	200	8.1818	0.1904	s20201	12.5000	0.2656
f1y10	15.6250	0.2945	202	6	0.1416	s20211	20.8333	0.2987
f2o01	14.7059	0.2339	203	5.2174	0.2091	s20221	4.7170	0.1481
f2o02	13.2561	0.1523	205	7	0.1351	s20231	15.6250	0.3028
f2o03	9.2593	0.1733	208	8.1742	0.1367	s20241	7.5758	0.1441
f2o04	13.8889	0.2662	210	5.9016	0.1592	s20251	4.3860	0.1928
f2o06	14	0.1173	212	8.3721	0.2067	s20261	7	0.1040
f2o07	9.6154	0.1864	213	10.1246	0.1490	s20271	12	0.1146
f2o09	13.1579	0.2826	214	5.9016	0.1431	s20272	14.7059	0.2671
f2o10	10.4167	0.1778	215	15	0.3308	s20273	13.8889	0.2674
f2y01	15.6250	0.2618	220	22.5000	0.3220	s20274	11.9048	0.2085
f2y02	10.4167	0.2563	221	12.2512	0.0988	s20281	10.4167	0.1938
f2y03	15.6250	0.2616	222	11.6129	0.1586	s20291	13	0.1146
f2y04	10.4167	0.1821	223	7.5000	0.1831	s20301	15.6250	0.3274
f2y05	12	0.1081	228	9.7297	0.1585	s20331	17.8571	0.2847
f2y06	13.3151	0.1492	230	13.1572	0.1776	s20341	11.3636	0.2434
f2y07	11.3636	0.1970	231	13.3333	0.2474	s20351	6.7568	0.1597
f2y08	9.6154	0.1812	232	14.3721	0.1500	s20361	10	0.1212
f2y09	9.2593	0.1635	233	11.2500	0.3527	s20371	12.1562	0.1146
f2y10	15.8333	0.2944	234	8.3721	0.1552	s20381	16.6667	0.2789

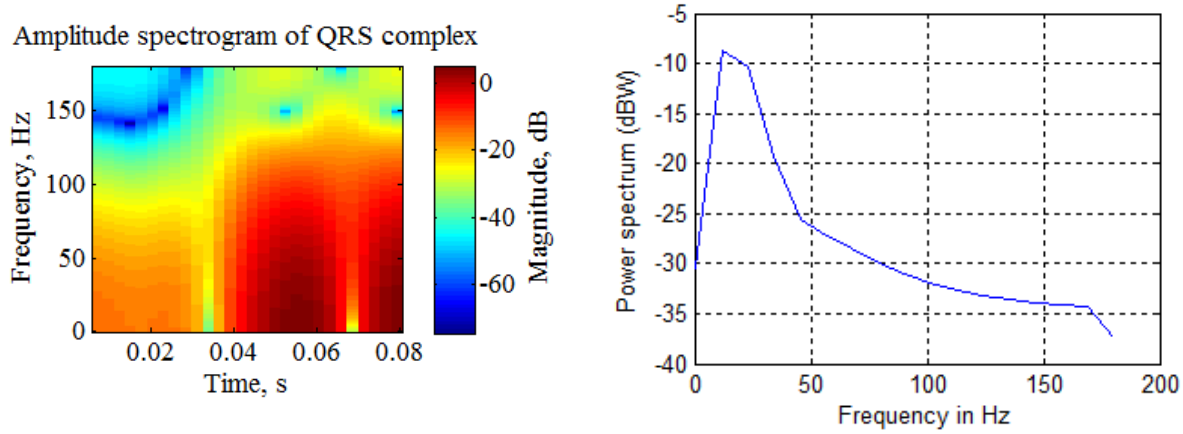
Short time Fourier transform

The Short Time Fourier Transform (STFT) is applied on the segmented *mean QRS complex* accumulated from all the detected QRS complexes of ECG signal and that being further used for frequency domain feature extraction. The STFT is the technique for non-stationary signal analysis that transforms signal information from time domain into time-frequency domain. The main concept of the STFT is to consider a non-stationary signal as a stationary signal over short periods of time within a window function [12, 30]. The computation of STFT can be defined as follows:

$$T(f,\tau)=\int_{-\infty}^{\infty}\left[x(t)w(t-\tau)\right]e^{-j2\pi ft}dt \tag{6}$$

where $w(t-\tau)$ is the window function. From Eq. (6) the STFT maps signal $x(t)$ into two-dimensional function in time, τ and frequency, f. The energy surface distribution of STFT called spectrogram (Fig. 2a) can be computed from the following equation:

$$E(f,\tau)=|T(f,\tau)|^2 \tag{7}$$



a) b)

Fig. 2 The spectrogram and power spectrum of QRS complex for MITDB # 117: a) result of STFT; b) Peak frequency of 11.25 Hz at maximum power.

The frequency of the maximum peak in power spectrum is calculated from the periodogram power spectral density estimate and the total average power and power over a frequency band also computed. In the frequency-domain, the total average power is computed as the sum of the power of all the frequency components of the *mean QRS complexes*. The value of power (pwr in Table 1) calculated as the sum of all the frequency components available in the power spectrum of the signal. The peak frequency and power of *mean QRS complexes* are tabulated (Peak_Freq in Table 1) for all three standard databases.

Naive Bayes' classifiers

In probability theory, Bayes' theorem relates the conditional and marginal probabilities of two random events. It is often used to compute posterior probabilities given observations. Let $x=(x^1, x^2,..., x^d)$ be a d-dimensional instance which has no class label and our goal is to build a classifier to predict its unknown class label based on Bayes theorem. Let $C=\{C_1, C_2, ..., C_k\}$ be the set of the class labels. $P(C_k)$ is the prior probability of C_k, (k = 1, 2, ..., K) that are inferred before new evidence; $P(x|C_k)$ be the conditional probability of seeing the evidence x if the hypothesis C_k is true. A technique for constructing such classifiers to employ Bayes' theorem to obtain:

$$P(x|C_k)=\frac{P(x|C_k)P(C_k)}{\sum_{k'}P(x|C_{k'})P(C_{k'})} \tag{8}$$

A Naive Bayes' classifier assumes that the value of a particular feature of a class is unrelated to the value of any other feature, so that:

$$P(x \mid C_k) = \prod_{j=1}^{d} P(x^j \mid C_k) \tag{9}$$

Naive Bayes' probability classifier is often useful to analyse the probability of data classification instead of relying on labels to reveal the class that a particular observation falls into. The proposed approach visualizes the classification probability of healthy, ischemic and arrhythmic classes using frequency domain features before subjected to LDA and decision tree classifier (Fig. 3).

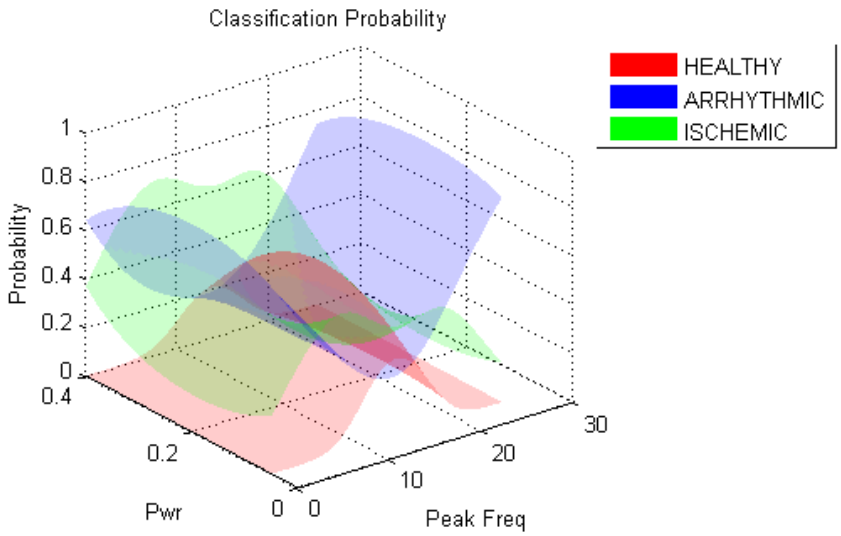


Fig. 3 Naive Bayes' probability classifiers

Linear discriminant analysis

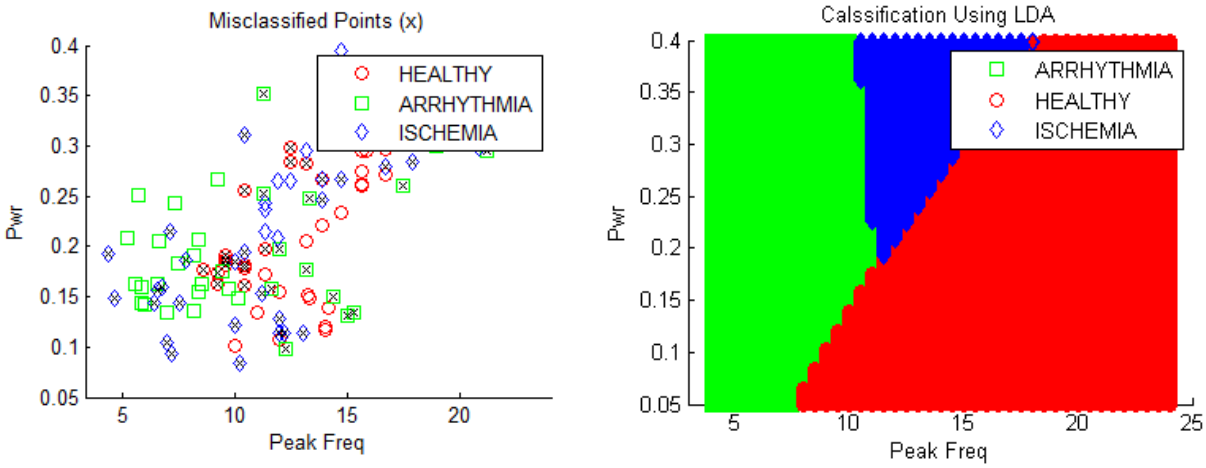
In this case, multi-class Linear Discriminant Analysis (LDA) to classify three unknown group of ECG signals (i.e., healthy, arrhythmic and ischemic) based on the frequency domain features (e.g., peak frequency and power) of QRS complex by calculating of mean, global mean, mean subtraction, transpose, covariance, probability, frequencies and at the end defining thresholds for each class on the distributed space area [16]. Duda et al. [10] described in the mathematical derivation of the LDA as:

$$d_i(x)\ln\left(P(C_i)\right) + x^T C^{-1} m_i + \frac{1}{2} m_i^T C^{-1} m_i \tag{10}$$

where m_i is the N length of mean vector for i^{th} class C_i is the $N \times N$ covariance matrix for the i^{th} class, $P(C_i)$ is the prior probability of class C_i. The selected class is the one that has the highest value of $d_i(x)$.

Without any further assumptions, the resulting classifier is referred to as Quadratic Discriminant Analysis (QDA). The resubstitution error of LDA, which is the misclassification error (Fig. 4(a), adding cross marks) on the training set (observations with known class labels), is found to be 52.78%. Moreover the misclassification error for QDA is 50.93%.

Taking frequency domain QRS features of arrhythmic and healthy signals for classification, where, resubstitution error of LDA is found to be 37.50% and misclassification error of QDA is found to be 25.00%.



a) b)

Fig. 4 Classification of three classes using LDA:
(a) misclassification result; (b) classification using LDA.

Decision tree

When considering classification tasks, a decision tree (T) is a tree shaped classifier which consists of nodes (t) and edges. Any tree originates from a node without any incoming edge, called *root node*. The *terminal nodes*, *i.e.* nodes which do not possess any out coming edges, are called *leaves*. The remaining nodes are called internal nodes. To each leaf, a class or even a class probability is assigned. Each of the non-leave nodes represents a split regarding the input space. Such split is represented by a decision $\Phi(.)$. Most often, univariate decision, i.e., $\Phi(.) = \Phi(x)$ of the from "$x \geq threshold$" or "$x \in set$", where x represents a single attribute, are considered.

The decision tree can be linearized into decision rules and used for operation search and decision analysis. The proposed work visualizes the classification (Fig. 5) of healthy (i.e., FANTASIA), arrhythmia (i.e., MITDB) and ischemia (i.e., LTSTDB) subjects and prune tree with best level (Fig. 6) also formulated at SL: 8.59. The misclassification error is 24.07% for decision tree. The misclassification error for healthy and arrhythmia QRS features (frequency domain) during classification found to be 8.33%. The misclassification result of decision tree is relatively lower than that of the LDA and QDA.

Conclusion

The time domain information of detected QRS complex is transform into time-frequency domain with STFT. The frequency domain information, i.e., peak frequency of power spectrum and average power of the QRS complex are computed for each sets of data. The classification probability is estimated with the tabulated features for the three different classes, i.e., healthy, arrhythmic and ischemic. The classification performance is visualized and analyzed with the misclassification results for Naive Bayes' classification, LDA, QDA and decision tree.

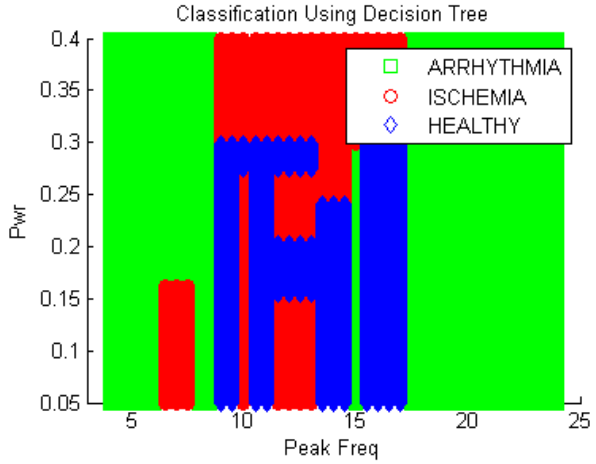


Fig. 5 Result of decision tree classifier

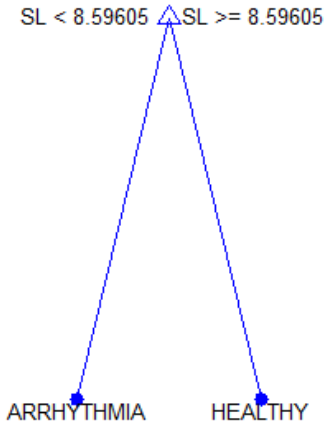


Fig. 6 Best level prune tree

The classification result of decision tree is found to be promising and the prune tree with best level shows the major classification between data sets of arrhythmia and healthy subjects. The misclassification error of both LDA and QDA is much lower when arrhythmic and healthy signals are considered for classification. The better classification results can be expected with large number of data sets where the future scope lies and certainly this will formulate new research objective with exploring new possibility in the cardiovascular disease, decision making and pattern recognition.

References

1. Acharya R., A. Kumar, P. S. Bhat, C. M. Lim, S. S. Lyengar (2004). Classification of Cardiac Abnormalities Using Heart Rate Signals, Medical & Biological Engineering & Computing, 42(3), 288-293.
2. Barsanti R. J., J. Gilmore (2011). Comparing Noise Removal in the Wavelet and Fourier Domains, IEEE 43rd Southern Symposium on System Theory, 163-167.
3. Bhoi A. K., K. S. Sherpa (2014). QRS Complex Detection and Analysis of Cardiovascular Abnormalities: A Review, International Journal Bioautomation, 18(3), 181-194.
4. Bortolan G., C. Brohet, S. Fusaro (1996). Possibilities of Using Neural Networks for ECG Classification, Journal of Electrocardiology, 29(Suppl 1), 10-16.
5. Carsten M., J. F. Gavela, M. Harris (2006). Combining Algorithms in Automatic Detection of QRS complexes in ECG Signals, IEEE Transactions on Information Technology in Biomedicine, 10(3), 468-475.
6. Chazal D. P., M. O' Dwyer, R. B. Reilly (2004). Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features, IEEE Transactions on Biomedical Engineering, 51(7), 1196-1206.
7. Christov I., I. Jekova, V. Krasteva, I. Dotsinsky, T. Stoyanov (2009). Rhythm Analysis by Heartbeat Classification in the Electrocardiogram, International Journal Bioautomation, 13(2), 84-96.
8. Christov I., I. Simova (2006). Fully Automated Method for QT Interval Measurement in ECG, Computers in Cardiology, 33, 321-324.
9. Dickhaus H., H. Heinrich (1996). Classifying Biosignals with Wavelet Networks – A Method for Noninvasive Diagnosis, IEEE Engineering in Medicine and Biology, 103-111.
10. Duda R., P. Hartand, D. Stork (2000). Pattern Classification, 2nd Ed., New York, Wiley Interscience.

11. Exarchos T. P., M. G. Tsipouras, C. P. Exarchos, C. Papaloukas, D. I. Fotiadis, L. K. Michalis (2007). A Methodology for the Automated Creation of Fuzzy Expert Systems for Ischaemic and Arrhythmic Beat Classification Based on a Set of Rules Obtained by a Decision Tree, Artificial Intelligence in Medicine, 40, 187-200.
12. Gade S., K. G. Hansen (1997). The Analysis of Nonstationary Signals, Sound and Vibration, 31, 40-46.
13. Goldberger A. L., A. L. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, H. E. Stanley (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals, Circulation, 101(23), e215-e220.
14. Hamlin R. L., F. S. Pipers, H. K. Hellerstein, C. R. Smith (1969). Alterations in the QRS during Ischemia of the Left Ventricular Free-wall in Goats, Journal of Electrocardiology, 2, 223-228.
15. Hamlin R. L., F. S. Pipers, H. K. Hellerstein, C. R. Smith (1968). QRS Alterations Immediately Following Production of Left Ventricular Free-wall Ischemia in Dogs, American Journal of Physiology, 215, 1032-1040.
16. Hargrove L. J., E. J. Scheme, K. B. Englehart, B. S. Hudgins (2010). Multiple Binary Classifications via Linear Discriminant Analysis for Improved Controllability of a Powered Prosthesis, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18(1), 49-57.
17. Holland R. P., H. Brooks (1976). The QRS Complex during Myocardial Ischemia: An Experimental Analysis in the Porcine Heart, Journal of Clinical Investigation, 57, 541-550.
18. Iyengar N., C. K. Peng, R. Morin, A. L. Goldberger, L. A. Lipsitz (1996). Age-related Alterations in the Fractal Scaling of Cardiac Inter Beat Interval Dynamics, American Journal of Physiology, 271, 1078-1084.
19. Jager F., A. Taddei, G. B. Moody, M. Emdin, G. Antolic, R. Dorn, A. Smrdel, C. Marchesi, R. G. Mark (2003). Long-term ST Database: A Reference for the Development and Evaluation of Automated Ischaemia Detectors and for the Study of the Dynamics of Myocardial Ischaemia, Medical & Biological Engineering & Computing, 41(2), 172-183.
20. Jekova I., V. Tsibulko, I. Iliev (2014). ECG Database Applicable for Development and Testing of Pace Detection Algorithms, International Journal Bioautomation, 18(4), 377-388.
21. Karimipour A., M. R. Homaeinezhad (2014). Real-time Electrocardiogram P-QRS-T Detection-delineation Algorithm Based on Quality-supported Analysis of Characteristic Templates, Computers in Biology and Medicine, 52, 153-165.
22. Kaur M., B. Singh, Seema (2011). Comparison of Different Approaches for Removal of Baseline Wander from ECG Signal, Proceedings of the 2nd International Conference and Workshop on Emerging Trends in Technology, 1290-1294.
23. Khadra L., A. A. Fahoum, S. Binajjaj (2004). A New Quantitative Analysis Technique for Cardiac Arrhythmia Classification Using Bispectrum and Bicoherency, Proceedings of the 26th Annual International Conference of the IEEE EMBS, 13-16.
24. Lin C. H. (2008). Frequency-domain Features for ECG Beat Discrimination Using Grey Relational Analysis-based Classifier, Computers and Mathematics with Applications, 55, 680-690.
25. Mallat S. (1998). A Wavelet Tour of Signal Processing, Academic Press, San Diego, USA.

26. Minami K., H. Nakajima, T. Toyoshima (1999). Real-time Discrimination of Ventricular Tachyarrhythmia with Fourier-transform Neural Network, IEEE Transactions on Biomedical Engineering, 46(2), 179-185.
27. Osowski S., L. H. Tran (2001). ECG Beat Recognition Using Fuzzy Hybrid Neural Network, IEEE Transactions on Biomedical Engineering, 48(11), 1265-1271.
28. Pueyo E., L. Sornmo, P. Laguna (2008). QRS Slopes for Detection and Characterization of Myocardial Ischemia, IEEE Transactions on Biomedical Engineering, 55(2), 468-747.
29. Rangayyan R. M. (2001). Biomedical Signal Analysis: A Case-study Approach, Wiley Interscience, New York, pp. 18-28.
30. Rioul O., M. Vetterli (1991). Wavelets and Signal Processing, IEEE Signal Processing Magazine, 8, 14-38.
31. Shuren Q., J. Zhong, Z. Hongjun (2003). The ECG Recording Analysis Instrumentation Based on Virtual Instrument Technology and Continuous Wavelet Transform, Proceedings of the 25th Annual International Conference of the IEEE EMBS, 3176-3179.
32. Silipo R., C. Marchesi (1998). Artificial Neural Networks for Automatic ECG Analysis, IEEE Transactions on Signal Processing, 46(5), 1417-1425.
33. Tanev S. (2012). Ventricular Beat Detection and Classification in Long Term ECG Recordings, International Journal Bioautomation, 16(4), 273-290.
34. Yang W., Z. Y. Sheng, N. V. Thakor, X. Y. Hong (2001). A Short-time Multifractal Approach for Arrhythmias Detection Based on Fuzzy Neural Network, IEEE Transactions on Biomedical Engineering, 48(9), 989-995.
35. Yazdani S., J. M. Vesin (2014). Adaptive Mathematical Morphology for QRS Fiducial Points Detection in the ECG, Computing in Cardiology, 41, 725-728.
36. Yeh Y. C., W. J. Wang (2008). QRS Complexes Detection for ECG Signal: The Difference Operation Method, Computer Methods and Programs in Biomedicine, 91, 245-254.

Assist. Prof. Akash Kumar Bhoi, M.Tech., Ph.D.
E-mail: akash730@gmail.com

Akash Kumar Bhoi has completed his B.Tech. (Biomedical Engineering) from the TAT, Bhubaneswar and M.Tech. (Biomedical Instrumentation) from Karunya University, Coimbatore in the year 2009 and 2011 respectively. He is pursuing Ph.D. from Sikkim Manipal University, India. He is working as an Assistant Professor in the Department of Applied Electronics and Instrumentation at Sikkim Manipal Institute of Technology (SMIT), India since 2012. He is a member of ISEIS and IAENG, an Associate member of UACEE and Editorial Board member of IJAEEE, IJAEEE, ITSI-TEEE, IJECCE and IJCTT and a reviewer of IJET, IJCT, IJBSE, IJMI, AJBLS. His areas of research are biomedical signal processing, medical image processing, sensor and transducer and medical instrumentation. He has published papers in national and international journals and conferences. He has also published 3 book chapters. He has participated in workshops, seminars and conferences.

Karma Sonam Sherpa, Ph.D.
E-mail: karmasherpa23@gmail.com

Karma Sonam Sherpa has completed his B.E. (Electrical Engineering) from the MREC, Jaipur, and M.Tech. (Power Electronics and Machine Drives) from IIT, Kharagpur in the year 1996 and 2003 respectively. He has a Ph.D. from Sikkim Manipal University. He has been serving SMIT, Sikkim for the last sixteen years. Presently, he is a Professor in the Department of Electrical and Electronics Engineering and officiating head of the Department of Electrical and Electronics Engineering and Department of Applied Electronics and Instrumentation Engineering. He is a life member of ISTE, IEI and System Society of India. His areas of interests are electric power distribution system, power electronics and electrical drives. He has published papers in national and international journals and conferences. He has organized workshops, seminars and conferences.

Dr. Bidita Khandelwal, MD.
E-mail: drbidita@gmail.com

Dr. Bidita Khandelwal did her MD Medicine in 1998 from Assam University. She joined Sikkim Manipal Institute of Medical Sciences in 2000 as an Assistant Professor in Department of Medicine and since 2009 heads the Department. Since 2015 Dr. Bidita Khandelwal is a Professor. She is a life member of API, IMA, IACM and RSSDI. Other posts held are Chairperson of complaint committee on Sexual Harassment at work place, Chairperson of IEC, Ayurveda Regional Research Institute, Vice chairman API East Zone, Editorial Board member of IJEM, a Member of Academic Senate of SMU, a Member of Sikkim Medical Council, Coordinator post graduate studies and an External expert for Board of Study. She is a Member of Research Protocol Evaluation Committee, Publication Evaluation committee, Institutional Ethics Committee, Hospital Management Committee, Infection Control Committee, Promotion Committee, State Task Force, Pharmacovigilance Committee. She has special interest in diabetes mellitus and has several publications related to it.