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

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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 comprised 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. Moreover, the energy surface distribution of segmented QRS complex is analyzed 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:

\[
Y_s(i) = \frac{1}{2N+1}(Y(i+N) + Y(i+N-1) + \ldots + Y(i-N))
\]  

(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, \(h_l(n)\) and \(g_l(n)\) 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 \(a_l(n)\) and detailed coefficients \(d_l(n)\) can be obtained with the following equations:

\[
a_l(n) = h_l(n)X(n) = \sum h_l[n-k]X[k]
\]  

(2)

\[
d_l(n) = g_l(n)X(n) = \sum g_l[n-k]X[k]
\]  

(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.

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

\[
Se = 1 - \frac{FN}{TP + FN} = \frac{TP}{TP + FN}
\]  

\[
Sp = 1 - \frac{FP}{TP + FP} = \frac{TP}{TP + FP}
\]

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.

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Fig. 1 Filtering and QRS complex detection for MITDB data # 117 (10 s data for better visualization)
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:
\[ T(f, \tau) = \int_{-\infty}^{\infty} [x(t)w(t-\tau)]e^{-j2\pi ft}dt \] (6)

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

\[ E(f, \tau) = |T(f, \tau)|^2 \] (7)

![Amplitude spectrogram of QRS complex and Power spectrum of QRS complex for MITDB # 117](image)

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:

\[ P(x | C_k) = \frac{P(x | C_k)P(C_k)}{\sum_{k'} P(x | C_{k'})P(C_{k'})} \] (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:

\[
P(x \mid C_k) = \prod_{j=1}^{d} P(x^j \mid C_k)
\]

(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](image)

**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:

\[
d_{i}(x)\ln \left( P(C_i) \right) + x^T C^{-1} m_i + \frac{1}{2} m_i^T C^{-1} m_i
\]

(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%.

**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 “\(x \geq \text{threshold}\)” or “\(x \in \text{set}\)”, 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.
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

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