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Automatic Classification of ECG signal for Identifying Arrhythmia

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Abstract— An Electrocardiogram (ECG) is a test that records the electrical activity of the heart to locate the abnormalities. Automatic ECG classification is very useful for the cardiologists in medical diagnosis for effective treatments. In this paper, we propose efficient techniques to automatically classify the ECG signals into normal and arrhythmia affected (abnormal) category. For these categories features such as Linear Predictive coefficients (LPC), Linear predictive cepstral coefficients (LPCC) and Mel-Frequency Cepstral Co-efficients(MFCC) are extracted to exemplify the ECG signal. SVM is the model engaged to capture the distribution of the feature vectors for classification and the performance is calculated. ECG records used in this study are collected from MIT-BIH database. The experimental results demonstrate the efficiency of the proposed method. The proposed method can accurately classify and discriminate the difference between normal ECG signal and arrhythmia affected signal with 94% accuracy.

Keywords— Electrocardiogram (ECG), Cardiac Arrhythmia, Linear Prediction Coefficients (LPC), Linear Prediction Cepstral Coefficients (LPCC), Mel-Frequency Cepstral Co-efficients (MFCC), Support Vector Machine (SVM).

I. INTRODUCTION

Heart is the most imperative organ of human body. According to World Health Organisation (WHO) cardiovascular disease (CVD) is the number one cause of death globally. More people die annually from CVD than from any other disease. Each year 9.4 million deaths occur, in this 45% deaths occur due to coronary heart disease. Traditional techniques of Visual analysis of ECG for doctors are complex and time consuming task. Visual analysis needs experience to identify the problems in ECG [1]. This paves a way for Computerised ECG. In computerised ECG the automatic classification of heart disease into normal and abnormal is done in an automated manner. Electrocardiogram is a test that records the electrical activities of the heart. It is an effective and low cost method to discover the abnormalities of the heart. ECG pattern and heart rate variability may have to be observed over several hours. Thus the volume of the data being vast, the study is tedious and time consuming. Therefore, computer-based investigation and classification of diseases can be very helpful in diagnostics [2]. Since visual analysis of long-term recordings of the heart activity, with more than 100,000 ECG beats in a single recording, is difficult to diagnose and can be highly error prone, automated computer analysis is of major significance [6]. It is a challenge to extract the most common and most important theme from amorphous raw ECG data. In this work an automatic classification of ECG signal is done for identifying Arrhythmia. There are various contributions have been made and implemented in literature for ECG beat classification and pattern recognition**.**

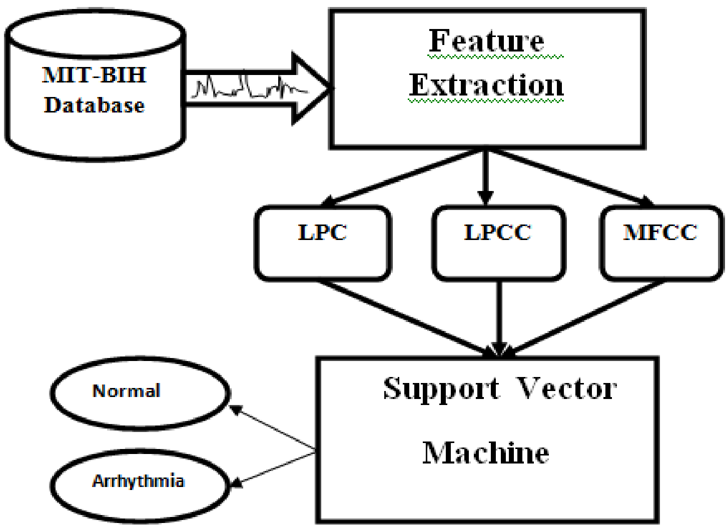

Fig.1. Block Diagram of ECG classification

A. Electrocardiogram

ECG is a test that monitors the electrical activity of the heart over a period of time as detected by electrodes attached to the outer surface of the skin and recorded by a device external to the body. The output of each electrode is called Lead. 12- Lead ECG is normally taken for all the patients. It is used to measure the rate and regularity of the heart beats, as well as the size and position of the chambers and the presence of any damage to the heart and the effects of drugs or devices used to regulate the heart.

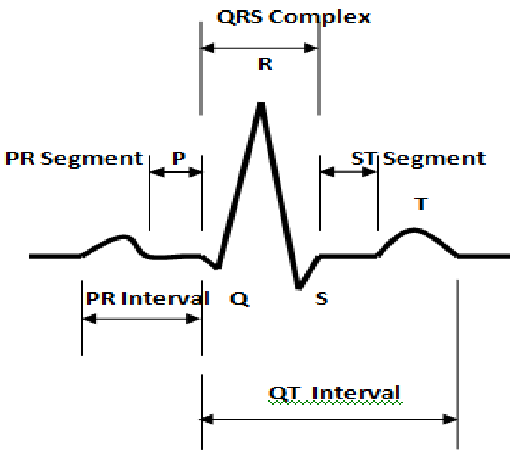

Fig.2. ECG Sample

An ECG wave consists of P, Q, R, S, T waves. P wave is the Atrial depolarisation (Atrial Contraction), T wave is the repolarisation of ventricles (Ventricular relaxation), QRS complex is the depolarisation of ventricles (Ventricular contraction). The QRS complex, ST segment, PR interval, RR interval, PR segment, QT interval is the most important regions in an ECG signal for the diagnosis of different cardiac diseases.

B. Cardiac Arrhythmias

Cardiac Arrhythmia is the irregular heartbeat or abnormal rhythm of the heart which may cause permanent damage to the heart. Basically there are two types of Arrhythmia, Ventricular and Supraventricular. Ventricular arrhythmia happens in the heart's two lower chambers called Ventricles and Supraventricular arrhythmia happens in the heart's two upper chambers called Atrium. Depending upon the heart rate the arrhythmia is classified into Bradycardia, Tachycardia and Fibrillated. An arrhythmia affected heart beat can be very fast, very slow and uncoordinated. The normal range of heart beat is 60-100 beats per minute. Bradycardia is very slow heart rate in which the heart beats less than 60 beats per minute. Tachycardia is very fast heart rate in which the heart beats more than 100 beats per minute. Fibrillation is a fast uncoordinated heart beat.

II. FEATURE EXTRACTION TECHNIQUES

Feature extraction plays an important role in constructing an ECG classification system. The aim is to select features which have large between-class and small within-class discriminative power. Discriminative power of features or feature sets tells how well they can discriminate different classes. Feature selection is usually done by examining the discriminative capability of the features. Feature extraction is done for analyzing and characterizing the ECG signal. Features representing the electrical wave information can be extracted from the ECG signal. It is the process of converting an ECG signal into a sequence of feature vectors carrying characteristic information about the signal. These vectors are used as basis for various types of ECG classification algorithms. It is typical for ECG classification algorithms to be based on features computed on a window basis. These window based features can be considered as short time description of the signal for that particular moment in time.

In this work, a technique is analyzed to automatically classify the ECG signal into Normal and Arrhythmia (Abnormal) category. For these categories, features namely LPC, LPCC and MFCC are extracted to characterize the ECG content. Features representing the information can be extracted from the ECG signal at the segmental level. The segmental features are the features extracted from short segments of the ECG signal. An input wav file is given to the feature extraction techniques. Two feature values are calculated for the given wav file. Features representing the characteristics of the ECG signal can be extracted from the signal for detecting the category change points.

A. Pre-processing

To extract the features from the ECG signal, the signal must be pre-processed and divided into successive windows or analysis frames. The recorded ECG signal of normal and arrhythmia affected (abnormal) patients are taken from the database. The recorded ECG is converted into wave file using a converter and pre-processed before extracting features. This involves detection of begin and end points of the utterance in the ECG waveform, pre-emphasis and windowing of the frame. The process of pre-emphasis provides high frequency emphasis and windowing reduces the effect of discontinuity at the ends of each frame of ECG signal. The ECG samples in each frame are pre-processed using a difference operator to emphasize the high frequency components.

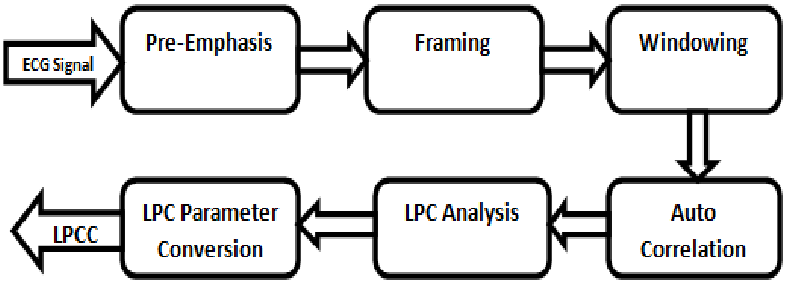

Fig.3. Block Diagram of LPC Computation

This involves detection of begin and end points of the utterance in the ECG waveform, pre-emphasis and windowing of the frame. The process of pre-emphasis provides high frequency emphasis and windowing reduces the effect of discontinuity at the ends of each frame of ECG signal. The ECG samples in each frame are pre-processed using a difference operator to emphasize the high frequency components. In the next step, the continuous ECG signal is blocked into frames of N samples, with adjacent frames being separated by M (M < N). The first frame consists of the first N samples. The second frame begins M samples after the first frame, and overlaps it by N − M samples and so on. This process continues until the entire ECG data are accounted for within one or more frames.

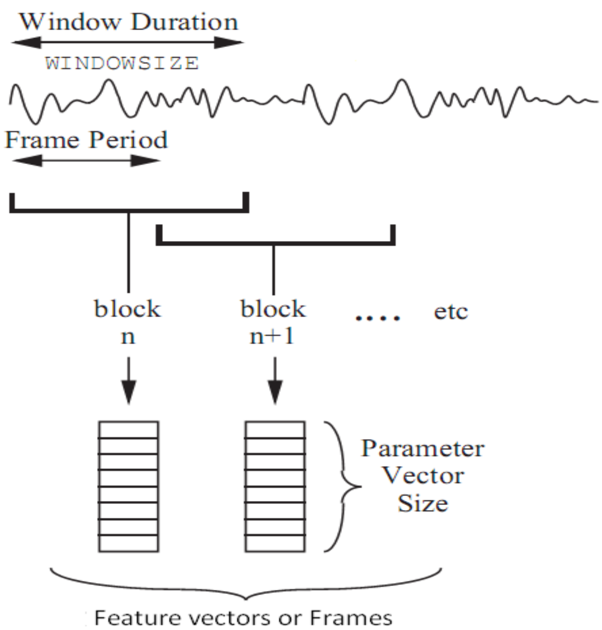

Fig.4. Pre-emphasis and Windowing of the frame

B. Linear Prediction (LP) Analysis

A pth order linear prediction (LP) analysis is used to capture the properties of the signal spectrum. In the LP analysis of ECG, each sample is predicted as linear weighted sum of the past p samples, where p represents the order of prediction [7], [6]. The number of previous samples used for prediction is known as the order of prediction. The weights applied to each of the previous ECG samples are known as linear prediction coefficients (LPC). They are calculated so as to minimize the prediction error.

$$x(n) = \sum_{k=1}^{p} a_k x(n-k) \qquad (1)$$

$$\text{for example if } p = 14$$

$$x(15) = a_1 x(14) + a_2 x(13) + \ldots + a_{14} x(1)$$

$$x(16) = a_1 x(15) + a_2 x(14) + \ldots + a_{14} x(2)$$

$$\ldots \qquad \ldots \qquad \ldots$$

$$x(160) = a_1 x(159) + a_2 x(158) + \ldots + a_{14} x(146)$$

The linear prediction coefficients (LPC) are obtained using Levinson-Durbin recursive algorithm. This is known as LPC analysis. The difference between the actual and the predicted sample value is termed as the prediction error or residual.

C. Linear Prediction Cepstral Coefficients (LPCC)

Feature extraction plays an important role in analyzing and characterizing the ECG content. The window based features can be considered as short time description of the signal for that particular moment in time. The cepstrum is a common transform used to gain information from an ECG signal. It can be used to separate the excitation signal and the transfer function. The cepstrum can be seen as information about rate of change in the different spectrum bands. The recursive relation (2) between the predictor coefficients and cepstral coefficients is used to convert the LP coefficients (LPC) into LP cepstral coefficients $\{c_k\}$.

$$c_0 = \ln\sigma^2 \tag{2}$$

where _2 is the gain term in the LP analysis and d is the number of LP cepstral coefficients.

$$\begin{aligned} c_m &= a_m + \sum_{k=1}^{m-1}\left(\frac{k}{m}\right) c_k a_{m-k}, \quad 1 \le m \le p \\ c_m &= \sum_{k=1}^{m-1}\left(\frac{k}{m}\right) c_k a_{m-k}, \quad p < m \le d \end{aligned} \tag{3}$$

where $c_1, c_2, \ldots, c_d$ are the cepstral coefficients. A 19 dimensional weighted linear prediction cepstral coefficient (LPCC) for each frame is used as a feature vector.

D. Mel frequency cepstral coefficients

The mel-frequency cepstrum has proven to be highly effective in recognizing structure of ECG signals and in modeling the subjective pitch and frequency content of ECG signals. Psychophysical studies have found the phenomena of the mel pitch scale and the critical band, and the frequency scale-warping to the mel scale has led to the cepstrum domain representation. The extraction and selection of the best parametric representation of ECG signals is an significant task in the design of any ECG classification system. (21). A solid representation would be provided by a set of mel-frequency cepstrum coefficients (MFCC), which are the results of a cosine transform of the real logarithm of the short-term energy spectrum expressed on a mel-frequency scale. The calculation o f the MFCC includes the following steps.

i. Mel-frequency wrapping

Human perception of frequency contents of sounds for ECG signal does not follow a linear scale. Thus for each tone with an actual frequency *f*, measured in Hz, a subjective pitch is measured on a scale called the mel scale. The mel frequency scale is linear frequency spacing below 1KHz and a logarithmic spacing above 1kHz. As a reference point, the pitch of a 1 KHz tone, 40dB above the perceptual hearing threshold, is defined as 1000 mels.

Our approach to simulate the subjective spectrum is to use a filter bank, one filter for each desired mel-frequency component. The filter bank has a triangular band pass frequency response and the spacing as well as the bandwidth is determined by a constant mel-frequency interval. The mel scale filter bank is a series of l triangular band pass filters that have been designed to simulate the band pass filtering believed to occur in the ECG system. This corresponds to series of band pass filters with constant band width and spacing on a mel frequency scale.

ii. Cepstrum

The cepstral representation of the ECG spectrum provides a good representation of the local spectral properties of the signal for a given frame analysis, because the mel spectrum coefficients (and their logarithm) are real numbers. Hence, it is converted into time domain using the discrete cosine transform (DCT). The log mel spectrum is converted back to time domain is the final step. The result is called the Mel Frequency Cepstrum Coefficients (MFCC). The discrete cosine transform is done for transforming the mel coefficients back to time domain.

$$C_n = \sqrt{\frac{2}{k}} \sum_{k=1}^{K} (log S_k) \cos\left[n(k-0.5)\frac{\pi}{K}\right], \tag{4}$$

Where, n=1, 2……., L. The block diagram of Mel-Frequency Cepstral co-efficient is shown in fig.5

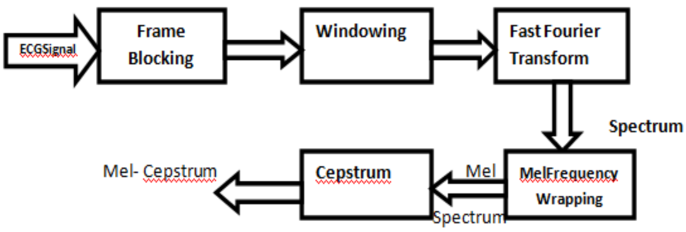

Fig.5. Block Diagram of MFCC computation

III. MODELLING TECHNIQUE FOR ECG CLASSIFICATION

A. *Support Vector Machine (SVM)*

Support vector machine (SVM) [4], [5] is based on the principle of structural risk minimization. SVM learns an optimal separating hyper plane from a given set of positive and negative examples. It minimizes the structural risk, that is, the probability of misclassifying yet-to-be-seen patterns for a fixed but unknown probability distribution of the data. This is in contrast to traditional pattern recognition techniques of minimizing the empirical risk, which optimizes the performance on the training data. For linearly separable data [5], SVM finds a separating hyper plane which separates the data with the largest margin. For linearly inseparable data, it maps the data in the input space into a high dimension space

$$x \in R^I \rightarrow \Phi(x) \in R^H$$

with kernel function $\Phi(x)$, to find the separating hyper plane. In [6], SVM is used to segment the clip into different categories. SVMs are evaluated as popular tools for learning from the given data. The reason is that SVMs are more effective than the traditional pattern recognition approaches based on the combination of a feature selection procedure and a conventional classifier [3].

SVM [4] is a statistic machine learning technique that has been successfully applied in the pattern recognition area [7], [8] and, is based on the principle of structural risk minimization (SRM) [5]. SVM constructs a linear model to estimate the decision function using non-linear class boundaries based on support vectors. If the data are linearly separated, SVM trains linear machines for an optimal hyper plane that separates the data without error and into the maximum distance between the hyper plane and the closest training points. The training points that are closest to the optimal separating hyper plane are called support vectors.

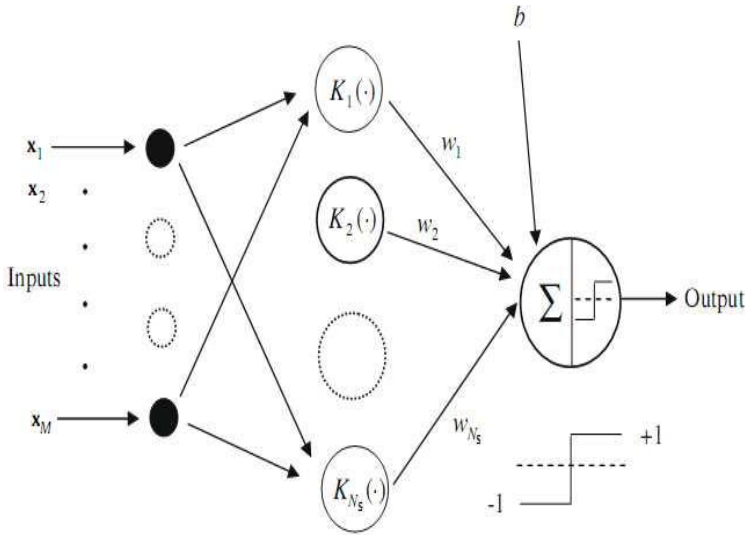

Fig.6. Architecture of the SVM (Ns is the number of support vectors).

Fig.6. shows the architecture of the SVM. SVM maps the input patterns into a higher dimensional feature space through some nonlinear mapping chosen a priori. A linear decision surface is then constructed in this high dimensional feature space. SVM constructs a linear model to estimate the decision function using non-linear class boundaries based on support vectors.

IV. EXPERIMENTAL RESULTS

A. Datasets

Experiments were carried out using the dataset taken from the MIT-BIH database. The ECG signals of normal and arrhythmia patients are collected from MIT-BIH (Massachusetts Institute of Technology- Beth Israel Hospital) database in the recording format and it is converted into wav format using a converter. Since the sampling rate is 360 Hertz, the duration of training data are 5,10,15,20 seconds respectively. About 100 recordings with 5,10,15,20 seconds of each category were taken for training and testing the SVM model.

CATEGORIES	LPC	LPCC	MFCC
NORMAL	90%	93%	93.5%
ARRHYTHMIA	91.5%	93.5%	94%

Fig.7. Comparison of ECG Features

B. Modelling using SVM

Support vector machine is trained to distinguish the ECG signal features of both categories. For training, 100 feature vectors are extracted from two categories of ECG signal for 5 seconds duration each. Hence, this results in 200 feature vectors each of 14 dimensions, 19 dimensions and 39 dimensions for LPC, LPCC and MFCC respectively. The same process is repeated for 10 secs, 15 secs and 20 secs. The derived support vectors are used to categorize the ECG data. For testing, 100 ECG feature vectors (5 secs of an ECG wav file) are given as input to SVM model and the distance between each of the feature vectors and the SVM hyper plane is obtained. The average distance is calculated for each model. The average distance gives better performance than using distance for each feature vector. The ECG content can be discriminated into two categories in terms of the designed support vector classifier. The category of the ECG is decided based on the maximum distance. The same process is repeated for other features, and the performance is studied. Two SVM models were created for the categories. The inputs are given to different Gaussian functions and the performance is studied. The classification results for the three features are shown in Fig.6. The performance of the system is evaluated, and the method achieves about 93.5% classification rate. From the experimental results it is observed that the accuracy of SVM with Mel Frequency Cepstral Co-efficient features (MFCC) can provide a good result.

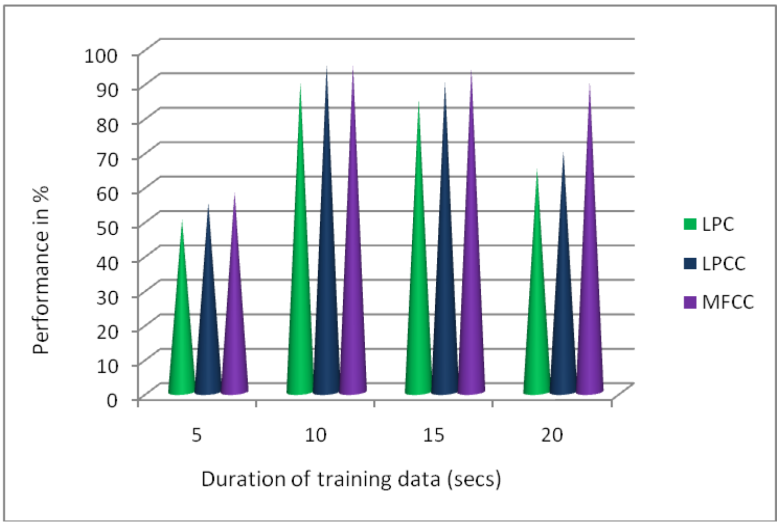

Fig. 8. Performance of SVM for ECG classification

V. CONCLUSION

In this work, a system is designed to automatically categorize the ECG signals based on LPC, LPCC and MFCC features. SVM is the model engaged for classification. Cardiac arrhythmia classification is done by using the ECG recordings of numerous patients collected from the MIT-BIH Arrhythmia database. The system showed an accuracy of 94% classification rate. This study proposes a straightforward, prompt and reliable classification method for analysing the ECG signals. The proposed method is effortlessly performed and requires no difficult mathematic computations. The records of ECG in the MIT-BIH arrhythmia database are experimented to demonstrate the efficacy of the proposed method. The observation from the result shows that SVM with MFCC features provide the better performance. The total classification accuracy (TCA) for the experiments was about 94%. The proposed method can be a useful aid for discovering the abnormality of the heart. In future this work can be extended to diagnose various diseases using different feature extraction and modelling techniques.

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