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Automatic Detection of Cardiac Arrhythmia through ECG Signal Analysis: A Review

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Abstract: *Analyzing the characteristics of an ECG signal plays a vital role in the detection of various Cardiovascular Diseases (CVDs). However the analysis of ECG signal is not a simple task. In this paper a broad survey is carried out over various approaches focused to analyze the characteristics of ECG signal to perform automatic Cardiac Arrhythmia detection. Initially, the details of ECG acquisition, Characteristics of ECG and the possible arrhythmias based on the abnormalities in the ECG signal are discussed. Based on the step by step execution of the system model, all the approaches are classified as preprocessing approaches, feature extraction approaches and classification approaches. These approaches are further classified in different ways based on the methodology used for accomplishment. This paper also discussed about various standard databases which are used for the implementation of developed approaches.*

Keywords: *ECG, Cardiovascular Diseases, Cardiac Arrhythmia, Feature Extraction, MIT-BIH.*

I. Introduction

In recent years, due to the drastic change in the lifestyles of population across the world, various health related problems are propagated enormously. Especially with the 20th century the cardiovascular diseases (CVDs) have become the leading cause of mortality in India. According to the survey carried out by World Health Organization (WHO), in Western populations only 23% of CVD deaths occur before the age of 70 years; in India, this number is 52% [1], [2]. Among the possible CVDs, Cardiac Arrhythmia (CA) is one of the leading heart diseases, is the main cause of about half of deaths due to cardiovascular disease or about 15% of all deaths globally. Cardiac Arrhythmia [3]**,** also known as irregular heartbeat, is a group of conditions in which the heartbeat is irregular, too fast (above 100 beats per minute, called as tachycardia), or too slow (below 60 beats per minute, called as bradycardia). Mainly there are four main types of arrhythmia:

- Extra beats,
- Supraventricular tachycardias,
- Ventricular arrhythmias,
- Brady arrhythmias.

Extra beats include premature atrial contractions, premature ventricular contractions, and premature junctional contractions. Supraventricular tachycardias include atrial fibrillation, atrial flutter, and paroxysmal supraventricular tachycardia. Ventricular arrhythmias include ventricular fibrillation and ventricular tachycardia [4]. Arrhythmias are due to problems with the electrical conduction system of the heart. All the above mentioned arrhythmias are life-threatening, which may cause sudden cardiac arrest and even death if timely therapy is not conducted within a few minutes. A high quality, easily implementable, fast Cardiac Arrhythmia detection algorithm will help achieve a high probability of survival from out-of-hospital heart attack incidents. Hence there is a need of develop an efficient and feasible CA detection technique which helps in the accurate diagnosis.

In general, the diagnosis of heart related issues such as the proper or malfunctioning are detected through the Electrocardiogram (ECG) signal [5]. An ECG signal characterizes the electrical activities of a heart, which are recorded through several electrodes attached to the skin. This quasi-periodic signal contains valuable information on the functioning of a heart and can be used for the detection of heart disease. The automatic detection of arrhythmia and distinguishing them from normal heart rhythms could be very useful for an early detection of heart disease, especially in real time.

Various approaches are proposed in earlier to perform automatic arrhythmia detection based on the characteristics of ECG signal. Since the automatic detection is a computer aided task, provision of most significant features of ECG is very important by which the accurate diagnosis is possible. The earlier approaches focused on various aspects like some focused on preprocessing, some on feature extraction and some on learning techniques. This paper provides a complete literature survey about the earlier developed approaches.

Rest of the paper is organized as follows; Section II gives the basic details of ECG signal. Section III illustrates the details of earlier proposed approaches and section IV concludes the paper.

II. ECG Signal Analysis

1. ECG Acquisition

The heart is a muscle that contracts in a rhythmical manner, pumping blood throughout the body. This contraction has its beginning at the atrial sine node that acts as a natural pace-maker, and propagates through the rest of the muscle. This electrical signal propagation follows a pattern [6]. As a result of this activity, electrical currents are generated on the surface of the body, provoking variations in the electrical potential of the skin surface. These signals can be captured or measured with the aid of electrodes and appropriate equipment. The difference of electrical potential between the points marked by the electrodes on the skin, usually is enhanced with the aid of an instrumentation (operational) amplifier with optic isolation. Then, the signal is submitted to a high-pass filter; and as a second stage, submitted to an anti-aliasing low-pass filter. Finally, it appears in an analogical to digital converter. The graphical registration of this acquisition process is called electrocardiogram (ECG). A simplified block diagram of ECG acquisition is shown in fig.1.

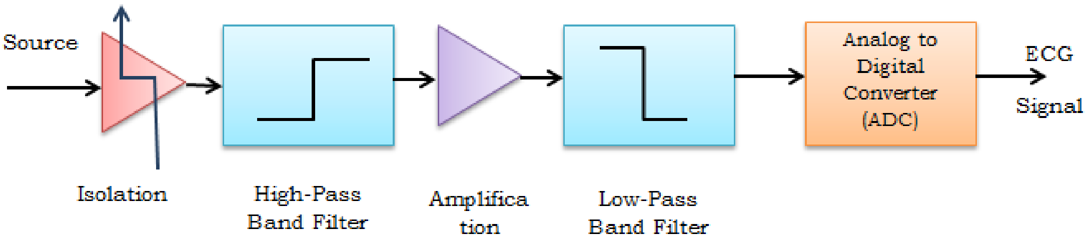


Fig.1: Architecture for acquisition of an ECG

2. ECG Segments

An ECG signal can be segmented into heartbeats. Each heartbeat consists of five standard waves labeled with the letters P, Q, R, S and T [7]. These waves indicate the depolarization and the re-polarization phases of heart muscles. Besides, five more inter-wave timings called PR, PR segment, QRS, QT, ST segment are used. These intervals are indicated on Fig.2.

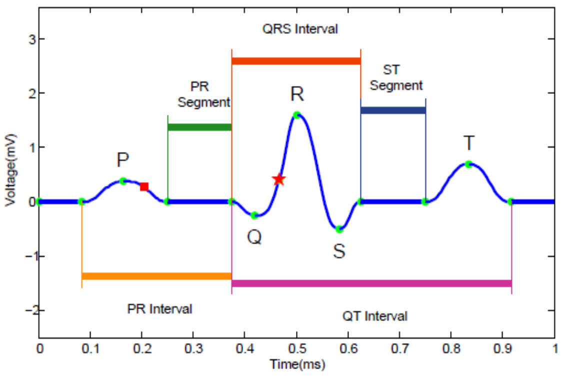


Fig.2: Main characteristics of an ECG curve

Now we give a brief introduction about the role of these clinical features:

P wave: P waves are usually a low-amplitude feature that represents the depolarization of the atria prior to atrial contraction. They are hard to detect, but important to distinguish various cardiac arrhythmias.

QRS complex: It reflects the depolarization of the ventricles. This is the most significant wave of the ECG due to the large muscle mass of the ventricles. So it can be easily detected and often used to determine the heart rate.

T wave: The T wave represents the re-polarization of the ventricles. It is a recovery phase of the cardiac muscle. The shape of this wave carries a lot of information about cardiac abnormalities. So it is important to analyze its geometrical properties such as symmetry, asymmetry and slope.

PR interval: It is the time elapsing between the beginning of the P wave and the beginning of the next QRS complex. It reflects conduction through the AV node1.

PR segment: The PR segment is the flat, usually isoelectric segment between the end of the P wave and the start of the QRS complex. Most of the delay in the PR segment occurs in the AV node.

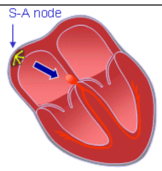
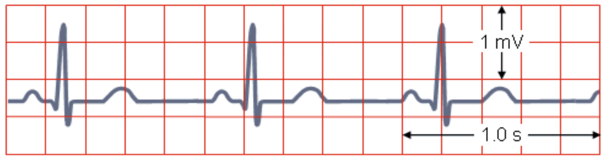
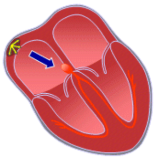
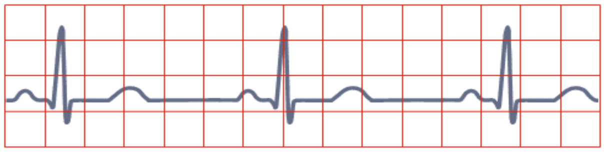
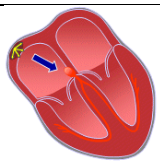
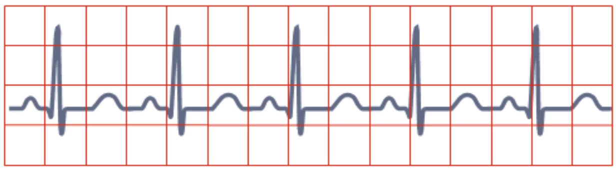
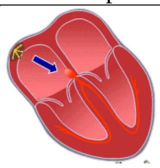
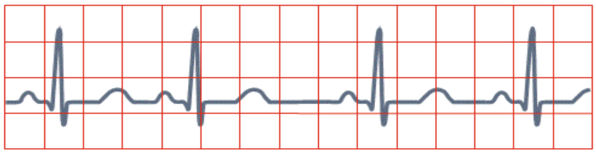
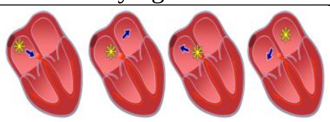
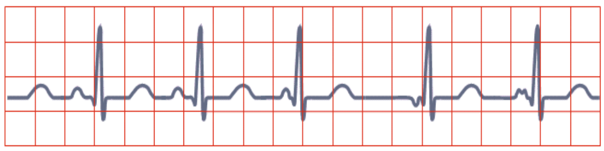
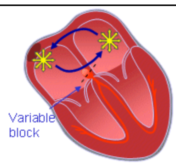
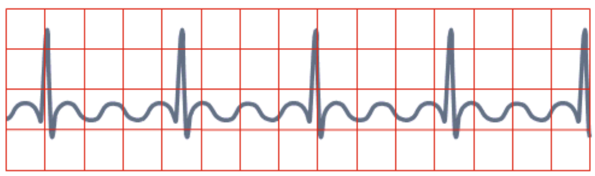
ST segment: Represents the period from the end of ventricular depolarization to the beginning of ventricular re-polarization. ST level shifts are significant markers of cardiac abnormalities

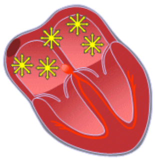
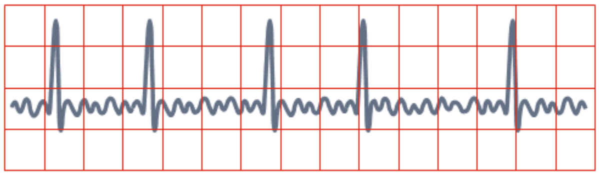
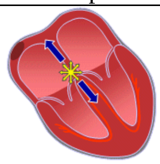
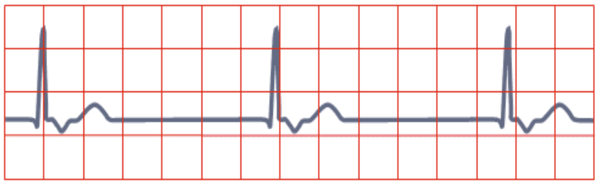
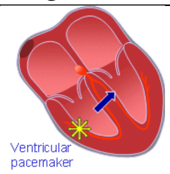
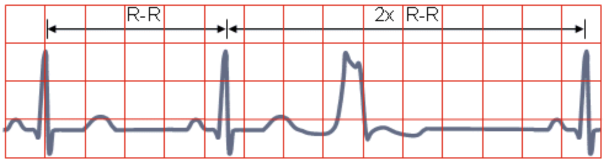
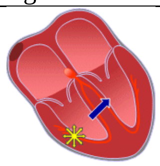
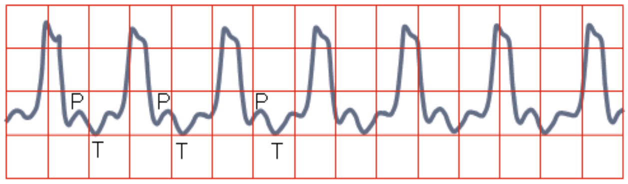
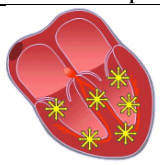
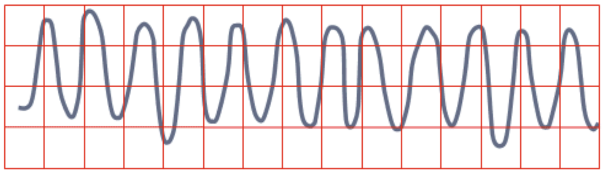
QT interval: It represents the time between the start of ventricular de-polarization and the end of ventricular re-polarization. The QT interval is inversely proportional to heart rate: shortens at faster heart rates and lengthens at slower heart rates.

3. Cardiac Arrhythmias

Since the ECG signal is the main contributor in the diagnosis of CA, different types of abnormalities in the rhythm of ECG declares different types of CAs. Table.1 gives the details of CAs and their respective abnormalities in the characteristics of ECG signal [8].

Table.1: Differentiation between different types of CAs

Name of CA	Heart Condition	ECG Abnormality
Normal Sinus rhythm	 Impulses originates at S-A node at normal rate	 All complexes are normal, evenly spaced, rate 60-100/min
Sinus bradycardia	 Impulses originates at S-A node at slow rate	 All complexes are normal, evenly spaced, rate < 60/min
Sinus tachycardia	 Impulses originates at S-A node at rapid rate	 All complexes are normal, evenly spaced, rate > 100/min
Sinus arrhythmia	 Impulses originates at S-A node at varying rate	 All complexes are normal, rhythm is irregular, longest R-R interval exceeds shortest > 0.16s.
Wandering pacemaker	 Impulses originates from varying points in atria	 Variation in P-wave contour, P-R and P-P interval therefore in R-R interval.
Atrial Flutter	 Impulses travel in circular course in atria	 Rapid flutter waves, ventricular response irregular

Atrial fibrillation	 Impulses have chaotic, random pathways in atria	 Baseline irregular, ventricular response irregular
Junctional rhythm	 Impulses originates at AV node with retrograde and antegrade direction	 P-wave is often inverted, may be under or after QRS complex, Heart rate is slow
Premature ventricular contraction	 A single pulse originates at right ventricle	 Time interval between R peaks is multiple of R-R interval
Ventricular tachycardia	 Impulses originates at ventricular pacemaker	 Wide ventricular complexes, Rate > 120/min
Ventricular fibrillation	 Chaotic ventricular depolarization	 Rapid, wide irregular ventricular complexes

4. Available Databases

Various databases are composed of ECG signals with various types of arrhythmias. The use of five databases is recommended by the standardization:

MIT-BIH [102]: The Massachusetts Institute of Technology – Beth Israel Hospital Arrhythmia Database (48 records of 30 min each). The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. About half (25 of 48 complete records, and reference annotation files for all 48 records) of this database has been freely available

EDB [103]: The European Society of Cardiology ST-T Database (90 records of 2h each). This database consists of 90 annotated excerpts of ambulatory ECG recordings from 79 subjects. The subjects were 70 men aged 30 to 84, and 8 women aged 55 to 71. Each record is two hours in duration and contains two signals, each sampled at 250 samples per second with 12-bit resolution over a nominal 20 millivolt input range.

AHA [104]: The American Heart Association Database for Evaluation of Ventricular Arrhythmia Detectors (80 records of 35 min each). As for the records in the AHA Database, the data consist of a 3-hour recording of two ECG signals, for which the last 30 minutes are annotated beat-by-beat.

CU [105]: The Creighton University Sustained Ventricular Arrhythmia Database (35 records of 8 min each). This database includes 35 eight-minute ECG recordings of human subjects who experienced episodes of sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation.

NST [106]: The Noise Stress Test Database (12 records of ECG of30 min each, plus 3 records with noise excess)

III. Literature Survey

Based on the above discussion, the automatic detection of Cardiac Arrhythmia involves the ECG signal preprocessing, Feature Extraction and Classification phases. The preprocessing phase involves removing the unwanted noises and interferences in the ECG signal. The feature extraction phase involves the extraction of significant features which represents the detailed analysis of ECG and further the classification phase involves the detection of type of arrhythmia based on the features of ECG. Here the literature survey is also carried out in the same fashion. I.e., initially, the earlier proposed approaches focused on the removal of noise are illustrated and followed by the approaches focused on feature extraction and finally the approaches belong to classification. A simple block diagram for the automatic detection of arrhythmia through ECG signal processing is represented in fig.3.

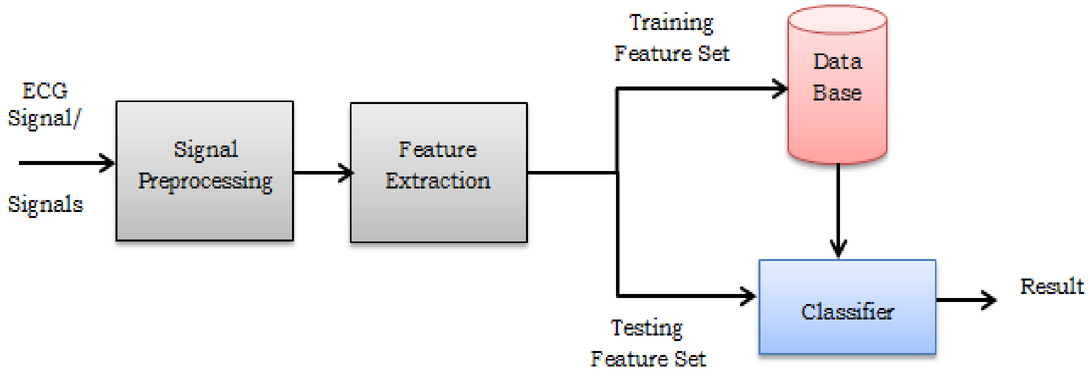


Fig.3: Simple block diagram of Cardiac Arrhythmia (CA) detection through ECG signal processing

1. Preprocessing

Since real ECG signals are noisy (i.e. white and mains noise) and contaminated with artifacts (i.e. electromyography signals due to breathing and chest movement) the first step generally consists of band pass filtering the measured signals.

Among all proposals for reducing noise in ECG signals, the simplest and most widely used is the implementation of recursive digital filters of the finite impulse response (FIR) [9], [10], which was made computationally possible with the advance in microcontrollers and microprocessors. Since these filters allow quick and easy application of reject band filter, they works well for the attenuation of known frequency bands like the noise added due to the electrical network (frequency range is about 50-60 Hz). However the main problem is that the frequency of the noise is not known always. This problem is solved by designing the adaptive filters for various frequencies of the signal. However the undiscriminating use of filters, i.e., low-pass and high pass filters distorts the signal's morphological attributes and makes them as unsuitable for the CA diagnosis. The architectures of [11-13] applied adaptive filters for noise removal form the ECG signal. Least Mean Square (LMS) Filter is an adaptive which a san ability to remove the unknown frequencies. Ravina [14] used the LMS filter to de-noise the ECG signal in an adaptive fashion. However, this technique has constraints and does not offer great advantages over the FIR digital filters.

In the last decade, many methods based on wavelet transforms have been employed to remove noise, since they preserve ECG signal properties avoiding loss of its important physiological details and are simple from a computational point of view [15-22]. Sayadi and Shamsollahi [18] proposed a modification of the wavelet transform called the multi-adaptive bionic wavelet transform and it was applied to reduce noise and baseline variation of the ECG signal. This method presented superior results when compared to the ones based on the traditional wavelet transform. Chen et al. [19] use a wavelet denoising stage based on a discrete wavelet transform, with three levels of decomposition, as the first processing stage for real-time QRS complex detection. Thus a wavelet denoising operation appears to be suitable for on-line operation while maintaining the ECG features for further processing stages. In [21], Savitzky-Golay filter and Discrete Wavelet Transform (DWT) are being used to de-noise ECG signal and a comparison is provided between two methods.

Some more approaches are also proposed including nonlinear Bayesian filters [23], extended Kalman filtering [24] to remove the noise from the ECG and these approaches measured the performance in terms of signal to noise ratio. Lannoyet.al., [25] used two median filters to remove the baseline wander.One median filter of 200ms width to remove QRS complexes and P-waves and other of 600 ms width to remove T-waves. Then the resulting signal is filtered again with 1 12-tap, low-pass FIR filter with 3-dB point at 35 Hz. A similar method is accomplished in [26-28] for the removal noises in ECG.Baziet.al., [29] proposed the use of high pass filter for noise artifacts and a notch filter for power network noise. Lin and Yang [30] uses a second order low pass filter and two median filters. In [31], the signal is subtracted by its mean and then normalized. Escalona-Moranet al. [32] used the raw wave *i.e.*, no preprocessing is applied.

2. Feature Extraction

The feature extraction stage is the key to the success in the heart beat classification of the arrhythmia using the ECG signal. Any information extracted from the heartbeat used to discriminate its type maybe considered as a feature. The features can be extracted in various forms directly from the ECG signal's morphology in the time domain and/or in the frequency domain or from the cardiac rhythm.

Most of the research work focused on the extraction of RR interval. The RR interval is a time period between two successive R peaks. With exception of patients that utilize a pacemaker, the variations perceived in the width of the RR interval are correlated with the variations in the morphology of the curve, frequently provoked by arrhythmias [36]. Thus, the features in the RR interval have a great capacity to discriminate the types of heartbeats and some authors have based their methods only on using the RR interval features [33-35].

Not only has the RR interval features, some approaches focused on the extraction of other features also. Among those QRS interval, or the duration of the QRS complex is the most utilized feature. In [37] the ECG signal is denoised to remove the artifacts and analyzed using Wavelet Transform to detect the QRS complex and arrhythmia. A similar process for arrhythmia detection is carried out in [38] through the detection of QRS complex. ECG data was filtered out first and after removing artifacts, QRS complexes were identified. For each QRS complex its R-peak, slope, sharpness and duration were calculated. Along with these approaches, a new approach is developed in [39] for intuitive and robust real time QRS detection based on the physiological characteristics of the electrocardiogram waveform. The proposed algorithm finds the QRS complex based on the dual criteria of the amplitude and duration of QRS complex. It consists of simple operations, such as a finite impulse response filter, differentiation or thresholding without complex and computational operations like a wavelet transformation. Along with these techniques [40-43] are also focused on the extraction of ECG signal feature alone and combined. In [44], a new method based on the continuous wavelet transform is described in order to detect the QRS, P and T waves. QRS, P and T waves may be distinguished from noise, baseline drift or irregular heartbeats. Firstly, our algorithm is validated using fifty 12 leads ECG samples from the CinC collection. The samples have been chosen in the "acceptable records" list given by Physionet. The detection and the duration delineation of the QRS, P and T waves given by [44] are compared to expert physician results.

A location, width and magnitude (LWM) [80] model is proposed for extracting each wave's features in the ECG. The model is a stream of Gaussian function in which three parameters (the expected value, variance and amplitude) are applied to approximate the P wave, QRS wave and T wave. Moreover, the features such as the P-Q intervals, S-T intervals, and so on are easily obtained. Then, a mixed approach is presented for estimating the parameters of a real ECG signal. To illustrate this model's associated advantages, the extracted parameters combined with R-R intervals are fed to three classifiers for arrhythmia diagnoses. Two kinds of arrhythmias, including the premature ventricular contraction (PVC) heartbeats and the atrial premature complexes (APC) heartbeats, are diagnosed from normal beats using the data from the MIT-BIH arrhythmia database.

Features extracted from the domain of time/frequency [82] together with the features of the RR interval appear as part of the methods that produced the highest accuracies. The simplest way to extract features in the time domain is to utilize the points of the segmented ECG curve, *i.e.*, the heartbeat, as features [45]. However, the use of samples of the curve as features is a technique that is not very efficient, since besides producing a vector of the features with high dimensions (depending on the amount of samples used to represent the heartbeat), it suffers from several problems related to the scale or displacement of the signal with respect to the central point (peak R).

Aiming at reducing the dimension of the feature vector, various techniques have been applied directly on the samples that represent the heartbeat (in the neighborhood of the R peak) as principal component analysis (PCA) [46-48], [84, 85] or independent component analysis (ICA) [49, 50], [85], or the combination of PCA and ICA [51, 52], [85]in which new coefficients are extracted to represent the heart beat. Hani [52] presents a comparative study between the use of PCA and ICA to reduce the noise and artifacts of the ECG signal and showed that PCA is a better technique to reduce noise, while ICA is better one to extract features. The ICA technique enables statistically separate individual sources from a mixing signal. The ECG is a mix of several action potentials and each action potential could be strongly related to an arrhythmia class. The rationale behind ICA for ECG heartbeat classification is to separate the action potentials sources as well as the noise sources. The PCA technique separates the sources according to the energy contribution to the signal.

Another technique based on PCA, the Kernel Principal Component Analysis (KPCA), was used by Devy et al. [53]. In that work, a comparison between PCA and KPCA was performed and it was concluded that KPCA is superior to the PCA technique for classifying heartbeats from the ECG signal. According to Kallas et al. [54], KPCA performs better, due to its nonlinear structure. Asl et al. [55] used Generalized Discriminant Analysis (GDA) to reduce the dimensions of the features of the heartbeat interval type to classify rhythmic arrhythmias. However, the authors did not take care to separate the heartbeats of the same patient used during training and testing (intra-patient paradigm), which is a serious concern discussed further. The inter-patient paradigm should be considered for a more realistic scenario.

Although various techniques have been considered, most of the studies presented in literature use wavelet transform and researchers claim that this is the best method for extracting features from the ECG signal [57, 58]. Saniet.al., [59] has proposed a robust ECG feature extraction technique suitable for mobile devices by extracting only 200 samples between R-R intervals as equivalent R-T interval using Pan Tompkins algorithm at preprocessing stage. The discrete wavelet transform (DWT) of R-T interval samples are calculated and the statistical parameters of wavelet coefficients such as mean, median, standard deviation, maximum, minimum, energy and entropy are used as a time-frequency domain feature. Amruthadevi [60] focused on the suggested Discrete Wavelet Transform (DWT) in processing ECG recordings and also to extract certain attributes. The process of feature extraction and dimensionality reduction can be effectively performed using Principal Component Analysis (PCA). Besides DWT, continuous wavelet transform (CWT) has also been used to extract features from the ECG signals [61], since it overcomes some of the DWT drawbacks, such as the coarse-ness of the representation and instability.[62] Presents a classification method using Support Vector Machine (SVM) algorithm. The noise and some electrical disturbances during measurement also affect the signal feature measurements. So, the signal is transformed into another domain using Wavelet Transformation method (Continuous Wavelet Transform (CWT) to be precise) to extract certain features of the signal and study their pattern while comparing the abnormal ECG signal with that of a normally running ECG signal. However, CWT is not largely used due to the fact that its implementation and its inverse are not available in standard toolboxes (such as MATLAB wavelet Toolbox) and CWT should be carefully discretized for the use as a CWT analyzer.

3. Classification

Once the set of features has been defined from the heartbeats, models can be built from these data using artificial intelligence algorithms from machine learning and data mining domains [64-66] for arrhythmia heartbeat classification.

The four most popular algorithms employed for this task and found in the literature are: support vector machines (SVM) [54] [62], [83], artificial neural networks (ANN) [67], [71], [75], [78] and linear discriminant (LD) [63], and Reservoir Computing with Logistic Regression (RC) [68]. Since the most of the research work is carried out through the ANN and SVM techniques the following section illustrates the proposed approaches based on those three techniques.

3.1 Artificial Neural Network (ANN)

The ANN architectures mostly used for arrhythmia classification are Multilayer Perceptrons (MLP) and Probabilistic Neural Networks (PNN). According to Yu and Chen [69], models constructed with PNN are computationally more robust and efficient than the traditional MLP.A feed forward multilayer neural network (NN) with error back-propagation (BP) [70] learning algorithm was used as an automated ECG classifier to investigate the possibility of recognizing ischemic heart disease from normal ECG signals. The proposed ECG classification in [72] is supervised by ANN. The ECG waveform gives the almost all information about activity of the heart, which is depending on the electrical activity of the heart. In [72] only five features of ECG signal P, Q, R, S, T are focused. This is achieved by extracting the various features and duration of ECG waveform P-wave, PR segment, PR interval, QRS Complex, ST segment, T-wave, ST- interval, QTC and QRS voltage. Mitraet.al., [73] attempts correlation-based feature selection (CFS) with linear forward selection search. For classification, [73] used incremental back propagation neural network (IBPLN), and Levenberg-Marquardt (LM) [76] classification tested on UCI data base. Some more approaches are proposed by combining ANN with other algorithms. According to Osowski et. al., [74], a combination of classifiers not only reduces the overall error in the neural networks, but also reduces the incidence of false negatives.

3.2 Support Vector Machine (SVM)

SVM is found to be a most popular and efficient classifier for the classification of ECG signals to detect cardiac arrhythmias. A novel life-threatening arrhythmias detection algorithm is presented in [77] by combining the SVM with previously proposed ECG parameters A total of 13 parameters were computed accounting for temporal (morphological), spectral, and complexity features of the ECG signal. A filter-type feature selection (FS) procedure was proposed to analyze the relevance of the computed parameters and how they affect the detection performance. Nitinajibhaskar [78] focused to classify an ECG signal as healthy subject or subject diagnosed with Myocardial Infarction (MI) using Artificial Neural Networks (ANN) and SVM (Support Vector Machine). LIBSVM is utilized for the classification with SVM and back propagation artificial neural networks with varying hidden layers and nodes are also implemented for performance analysis. Compared to the extraction of feature sin time domain, the features extracted through the transform domain illustrates gives the more information about the features. Qin et.al., [79] combined the DWT with SVM to perform arrhythmia beat classification. In classification, 12-element feature vectors characterizing six types of beats are used as inputs for one-versus-one support vector machine, which is conducted in form of 10-fold cross validation with beat-based and record-based training schemes.

Since SVM presents a negative behavior for imbalanced classes, database balancing techniques for the training phase, which are little explored for this problem, can be studied in future research, as for example, more sophisticated sampling techniques.

3.3 Logistic Regression

RC computing models are dynamical models aiming to process a time series signal in two parts: represent the signal through a non-adaptable dynamic reservoir and a dynamic readout from the reservoir. More details regarding RC can be found in [87]. Chaurasia V et.al., [88],developed prediction models for heart disease survivability by implementing data mining algorithms CART (Classification and Regression Tree), ID3 (Iterative Dichotomized 3) and decision table (DT) extracted from a decision tree or rule-based classifier to develop the prediction models using a large dataset.

This approach is achieved efficient results and also declared that this can be implemented on hardware due to its less complexity and it is much suitable for heart beat classification.

3.4 Other Techniques

Many other methods for arrhythmia classification have been developed using other machine learning and data mining algorithms, such as nearest neighbors [89, 90], clustering [93], decision tree [95-97]etc.

In [89], an automatic ECG beat is classified into 2 categories-Normal and Premature ventricular contraction using Dempster Shafer Theory (DST). In biomedical signal classification problems, the cost of making an erroneous decision can be high. Deferring a decision rather than taking a wrong decision might be beneficial. This is done by using the evidential *k* nearest neighbors (EKNN) approach which is based on Dempster Shafer Theory for classifying the ECG beats. RR interval features are used. Analysis is done on the MIT-BIH database. Performance evaluation is done by considering error rates. However K-NN algorithm is not much used for the problem of arrhythmia classification, since their efficiency is intimately connected to previous knowledge to perform the classification of each sample that is represented by the complete training set, which leads to a high computational cost during the testing phase.

Clustering techniques are widely used along with Artificial Neural Networks. Some works used unsupervised clustering techniques to agglomerate all of the heart beats in the record of a given patient into clusters [91] and the final classification of each cluster, *i*.e., the heart-beats of that group, is then defined by a human specialist. Abawajy et.al., [92] proposed a novel multistage clustering algorithm that combines various procedures for dimensionality reduction, consensus clustering of randomized samples and fast supervised classification algorithms for processing of the highly dimensional large ECG datasets. An unsupervised method based on relevance analysis to improve ECG heartbeat clustering is described in [94]. A new feature matrix projection method for unsupervised relevance analysis is described. The proposed scheme computes weighting feature values that enable data dimensionality reduction along with a proper feature relevance ranking and uses a least squares optimization of the input feature matrix in a single iteration. Large datasets tend to be sparse thus making it very hard to identify structure in the dataset for clustering based on distance measures. Another challenge is that the dataset often contains noisy and/or irrelevant features that may mislead clustering algorithms. Generally, these challenges are addressed by coupling clustering algorithms with dimensionality reduction approaches. In this regard, a number of advanced consensus functions for clustering ensembles have been developed recently. However, many of the existing consensus functions are computationally expensive so their application for clustering large and highly dimensional datasets such as ECG signals is impracticable.

Methods that use a decision tree allow an interpretation of the decisions made by the model. In [98], arrhythmia beat classification using ensemble decision tree is studied. Bootstrap aggregating (bagging) decision tree is used as a type of ensemble learning. ECG signals from 22 patients including five arrhythmia beats and normal beats are obtained from MIT-BIH arrhythmia database. After the filtering process, 56569 ECG beats are collected and feature are extracted based on morphological properties including RR, FF, RR and FF ratio to previous values (RRR, FFR), RR and FF differences from mean values (RRM, FFM). 25% of 56569 beats is used as test data for bagged decision tree and the rest for training. However, this type of method is not efficient for continuous features (belonging to a set of real numbers) and feature vectors of large dimensions. Thus, methods that use decision trees consider only a few features.

HMM is widely used to audio and speech signal analysis and recognition. Andreaoet al. [99] validated the use of HMM for ECG analysis in medical clinics. A novel ECG classification approach based on HMM model is proposed by Wei Lianget.al.,[100]. In ECG preprocessing, an integral-coefficient-band-stop (ICBS) filter is applied, which omits time-consuming floating-point computations. In addition, two-layered Hidden Markov Models (HMMs) are applied to achieve ECG feature extraction and classification. The periodic ECG waveforms are segmented into ISO intervals; P sub wave, QRS complex and T sub wave respectively in the first HMM layer where expert-annotation assisted Baum-Welch algorithm is utilized in HMM modeling. Then the corresponding interval features are selected and applied to categorize the ECG into normal type or abnormal type (PVC, APC) in the second HMM layer [101].

IV. Conclusion

Cardiac arrhythmia occurs spasmodically at the early stages of heart disease by which the diagnosis will become difficult. If these CA is not detected in early stages, the effect of treatment will become ineffective at the advanced stages. In addition some types of CAs like tachyarrhythmia are associated with sudden dead, occurring less than an hour after the onset of symptoms. Hence the major part of biomedical research is directed towards the development of an effective ECG signal diagnosing equipment to detect the CAs in the early stages only and making the effective heart disease treatment.

This paper focused on the earlier approaches developed with the aim of accurate diagnosis of various CAs through ECG signal. Since the ECG signal carries the most significant information of the status of heart, i.e., proper or malfunctioning, analysis of the entire characteristics of ECG signal gives better results. For this purpose the entire system is divided into three phases such as preprocessing, feature extraction and classification. Initially the approaches which are focused towards the preprocessing of ECG signal are discussed. All these approaches aimed to remove the unwanted noise added in the ECG signal. Further the approaches mainly focused on the feature extraction are discussed. In summary the total feature extraction approaches are categorized as time domain and transform domain. From the survey it was summarized that, compared with time domain features, transform domain features gives the better results in the ECG diagnosis. Finally the approaches mainly focused in the optimization of classification are discussed. These methods include the machine learning algorithms, clustering algorithms and data mining approaches etc. Based upon the above survey, the concluding remarks can be outlined as follows;

Results presented in literature usually use the MIT-BIH database that is extremely unbalanced. However, this aspect has been ignored by authors that use the intra-patient scheme.

Various approaches employed the semi-automatic approaches to enhance the results of diagnosis. These semi-automatic approaches can improve the results around 40% even with less number of features. However the main drawback is that they demand the expert intervention.

Various machine learning approaches have shown that the size/diversity of the database used for the construction of methods impacts more than the choice of the learning algorithm and/or employed techniques.

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