HEART DISEASES ANALYSIS THROUGH ECG SIGNAL PROCESSING: A REVIEW

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Abstract: ECG signal analysis is more important to diagnose different heart related diseases effectively with reduced manual effort. This paper outlines a brief survey over different ECG analysis techniques to perform the effective disease detection among the heart related diseases. Mainly the complete approaches are categorized as Preprocessing techniques and feature techniques and classification techniques. The main objective of preprocessing techniques is to make the ECG signal compatible to the detection system. Feature extraction techniques aims at efficient feature extraction to achieve efficient detection accuracy and further the classification techniques aims to make the system robust. Different datasets are tested over the available approaches to test the performance and performance evaluation is done through Accuracy measurement.

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

1. INTRODUCTION

In general, the diagnosis of heart related issues such as the proper or malfunctioning are detected through the Electrocardiogram (ECG) signal [1-5]. 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. 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 figure.3.

A. Preprocessing

Since real ECG signals are noisy (i.e. white and mains noise) and contaminated with artefacts (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 has an 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. Lannoy et. al., [25] used two median filters to remove the baseline wander. One median filter of 200-ms 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. Bazi et. 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-Moran et al. [32] used the raw wave *i.e.*, no preprocessing is applied.

B. Feature Extraction

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 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.

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 heartbeat. Dhani [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]. Sani et.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. Amrutha devi [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.

C. 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], 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.

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. Mitra et.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.

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. Nitin aji bhaskar [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. Qin et.al., [79] combined the DWT with SVM to perform arrhythmia beat classification.

III. CONCLUSION

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. 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.

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