ECG Signal Processing for Recognition of Cardiovascular Diseases: A Survey

Waqas Ahmed
Bahria University, Islamabad
Pakistan
waqas_qasi2000@yahoo.com

Shehzad Khalid
Bahria University, Islamabad
Pakistan
shehzad_khalid@hotmail.com

ABSTRACT: *Electrocardiogram (ECG) is nearly a periodic signal widely used for the detection and diagnosis of cardiac abnormalities. Recently with the inception of computer based techniques, automated analysis of shape and pattern of ECG waveform has facilitated physician to obtain fast and accurate diagnosis of cardiac disorders. Abnormalities related to sinus rhythms can be detected by using ECG signal beat classification, whereas Ischemic Heart Disease and Myocardial Infarction can be detected by deviation in ST segment or inversion of T wave in ECG signal. This paper discusses techniques proposed earlier in the literature for noise removal, feature extraction and classification of ECG signals.*

Keywords: Electrocardiogram (ECG); Myocardial Ischemia (MI); Heart Beat Classification; Wavelet Transform (WT); Artificial Neural Network (ANN); K-Nearest Neighbor (KNN), Support Vector Machine (SVM)

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1. Introduction

Electrocardiogram (ECG) is a non-invasive tool for the detection and diagnosis of cardiovascular diseases, which are among one of the leading causes of morbidity and deaths around the world. CVDs accounts for approximately 31% of all the global deaths [1]. ECG is a non stationary signal which is a widely used for mapping heart electrical activity by using electrodes attached to the skin. The ECG examination of nearly 30% of European Union population is conducted per year for the diagnosis of heart related diseases. Such vast practicing of ECG examination is due to its simplicity and effectiveness in diagnosing cardiovascular diseases. The ECG waveform depicts information about the health of patients. Therefore by analyzing the underlying information of different shapes and patterns in ECG signals, cardiologists can easily interpret the different conditions of the heart which may vary from having a minor threat to being life threatening.

According to [2], ECG signal classification involves four major stages: ECG Preprocessing, P-QRS-T wave fiducial points detection, feature extraction and Classification stage as shown in figure 1. In preprocessing stage ECG signal is processed for the removal of artifacts added during signal acquisition. P,-QRS-T wave detection stage aims to detect heartbeats in ECG signal, and to find out the relevant segments for feature extraction. The feature vector formed during feature extraction stage must contain the minimum number of discriminating features for successful classification. The Classification stage comprises of one or more classifier to recognize the classes for data given in the feature vector. Choice of specific classifier may result in better classification rate than its variants for a particular heart disease.

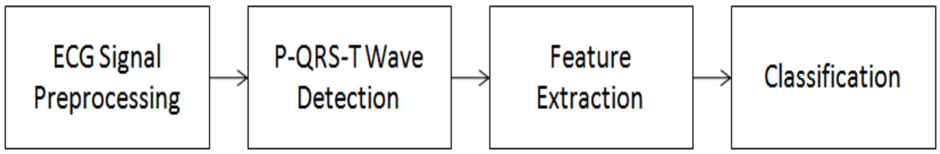

Figure 1. ECG Signal Processing Stages

Sinus arrhythmias are mainly due to irregular electrical activity in the heart which results in improper pacing of heart. Computer based ECG signal processing techniques effectively detects and classify abnormalities related to cardiac rhythms. Some of the major heart beat problems investigated in literature are Sinus Tachycardia, Sinus Bradycardia, Left and Right Bundle Branch Block (RBBB, LBBB), Premature Atrial Contraction (PAC), Atrial Fibrillation, Premature Ventricular Contraction (PVC) and Ventricular Fibrillation. Most of arrhythmias do not indicate presence or absence of severe health risk; however their proper detection is significant for proper diagnosis of cardiac disorders. Furthermore, Ischemic Heart Disease and Myocardial Infarction (MI) can be detected by ST segment deviation and T wave inversion on ECG waveform. Different types of Myocardial Infarction can be localized by making use of 12 lead ECG data because each lead views heart from a unique angle [4]. This paper analyzes and reviews the already presented approaches in literature, for the detection and recognition of cardiovascular diseases with the help of ECG signal processing.

2. Pre processing

The artifacts present in the ECG distort actual signals and degrade its processing capability for accurate diagnosis of disease. Therefore, these artifacts should be removed from signal or the impact of these artifacts must be reduced to an extent that their presence does not affect overall accuracy. These artifacts mainly include baseline wandering, motion artifacts, power line interferences (PLI), Electromyographic (EMG) noises and other high frequency noises.

2.1 Baseline Wandering Removal

In literature, many diverse techniques have been employed for the removal of baseline drift. Adaptive filter (AF) based technique for the removal of baseline drift is used in [5-6]. Whereas finite impulse response (FIR) high passes zero phase, forward-backward filtering with cutoff frequency of 0.5 Hz is applied by [7]. FIR high pass filter of order 56 and 100 is applied to remove baseline drift in [8]. While FIR high pass filter with Kaiser window having filter order 100 and cutoff frequency of 0.5 Hz for the removal of low frequency baseline wandering is utilized in [9]. In another approach, baseline drift of ECG signal is removed by employing two median filters [2]. Baseline wandering is also removed by transforming the ECG signal into time-frequency representation using wavelet transform. Wavelet decomposition based techniques for the removal of BW are proposed in [11, 12].

Baseline drift can also be removed by applying curve fitting on the ECG signal [13,14]. Meyer et al. [13] presented cubic spline curve fitting whereas Papaloukas et al. [14] presented linear spline curve fitting techniques for the removal of baseline drift. A technique using median with polynomial fittings is also applied by [3] for the removal of baseline drift.

There are a lot of other techniques like empirical mode decomposition (EMD) [15-16], mean-median filtering using discrete wavelet transform [10] and projection pursuit gradient ascent [17], exist in literature for baseline drift removal. Figure 2 shows mean and median values of the errors in μV for different baseline removal methods [6]. These clearly show that wavelet based baseline removal methods display prominent performance.

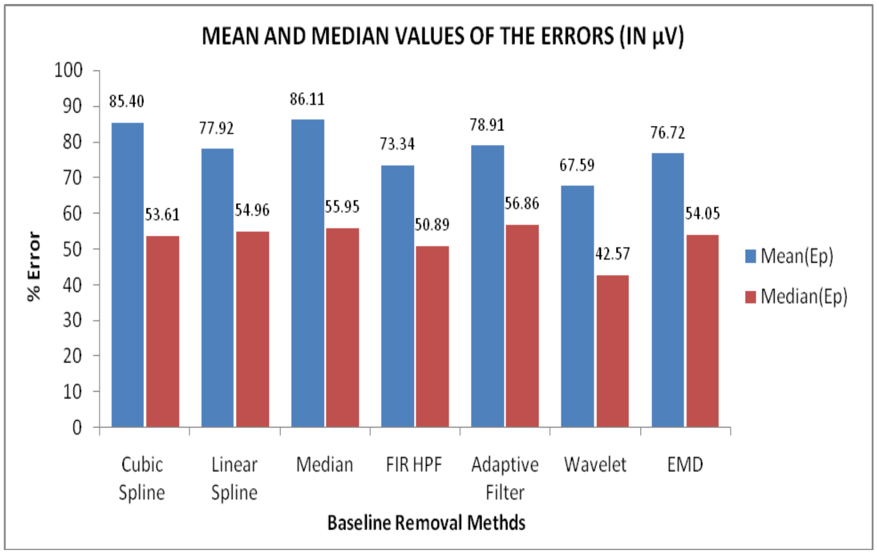

Figure 2. Mean and Median Values of the Errors [12]

2.2 Noise Removal

ECG signal is contaminated by different kind of noises which corrupts the actual health information encoded in the signal and may leads to false diagnosis. These noises includes Power line interferences (PLI) and electromyographic (EMG) noises. Theses noises must be removed or their impact should be reduced before any further processing on ECG signals.

Power line interferences (PLI) can be removed by using linear notch filter, which filter out the noise present at 50/60 Hz frequency from the ECG signal [21]. On the other hand, Levkov et al. [22] implemented non linear filter by using subtraction procedure for the removal of PLI. Adaptive filters based approaches are also been used in literature for the removal of power line interferences [18]. Low pass, high pass and notch filters are cascaded in [9] to remove EMG noise, baseline drift and power line interferences. Also, wavelet based de-noising technique is employed in [23] for the removal of PLI and EMG noises.

3. QRS Detection

In ECG signal processing, QRS detection is one of the most important tasks for ECG feature extraction. QRS complex detection begins with R peak localization. Other important fiducial points can be easily determined by utilizing already detected R peak locations. Moreover, the task of QRS detection is complex due to presence of noises, P wave and T wave components. Variation in heart rate and QRS complex duration due to heart related diseases also impose the use of adaptive techniques for the detection QRS complex. Variety of QRS detection approaches have been proposed in literature which includes: filter based techniques [24]; QRS detection algorithm based on derivatives [25]; wavelet transform based QRS detection [26]; neural networks based QRS detection method [27]; algorithm based on hidden morkov model [28]; genetic algorithm based QRS detection technique [29]; phasor transform based QRS detection algorithm [30], and QRS detection using support vector machines [31].

4. Feature Extraction and Classification

The task of feature extraction is of non trivial which aims to find out the possible smallest set of features for maximum discrimination between different classes. In literature, features for heart disease classification are classified into three classes:

1) Time based Features
2) Frequency domain based Features
3) Time Frequency based features.

Whereas, classifiers used for recognition of cardiovascular diseases varies with approaches, which includes Artificial Neural Network (ANN), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), Fuzzy Logic System, K-Nearest Neighbor (KNN), and ensemble based classifiers. In this section, we briefly review the features and classifiers used in literature for heart disease recognition. A comparison of feature extraction and classification techniques for heart beat classification and myocardial infarction detection are summarized in Table 1 and Table 2 respectively.

4.1 Time based Features

Time based features mainly have time interval in milliseconds representing RR interval, PR interval, PP interval etc. Also, the duration or amplitude of P wave, T wave and QRS complex are used as time based features in ECG signal analysis. These features mostly do not provide high performance due to low sensitivity.

Mores at el. [32] uses four features extracted from ECG wave form. In this study they utilize 1) width of QRS complex, 2) sum of areas under positive and negative curves, 3) total sum of absolute values of sample variations in the QRS complexes and 4) amplitude of QRS complex to classify normal and premature ventricular contraction (PVC) beats using Mahalanobis distance as classifier. They attained sensitivity of 90.74% and positive predictive value of 96.55% using 44 records of MIT-BH database. In another approach, two features set based on 28 features are extracted from RR interval, P wave, QRS complex and T wave after the ECG segmentation in [2]. In this study classification of normal, PVC and fusion beats were obtained by linear discriminant Analysis (LDA) and Neural Network (NN) classifiers and achieved accuracy of 89.1% using both feature set. In this method feature extraction may be affected by noise and errors in calculation of onset and offset of QRS complex. Also these features have higher intra-class variations due to which this method is unable to provide very good severability among different types of QRS complexes.

Pandit at el. [33] in their proposed method extracted 11 features from P-QRS-T waves and applied Artificial Neural Network (ANN) and Ensemble classifier using European ST, QT and MIT-BIH Arrhythmia databases. In this work they achieve average accuracy of 98.73% and 99.40% using ANN and Ensemble classifier respectively.

Arif at el. (2010) [34] presented a myocardial infarction (MI) detection and localization method using back propagation neural network (BPNN). They used time based feature for MI detection and achieved sensitivity and specificity of 97.5% and 99.1% respectively. Whereas, for localization of MI PCA based 117, the dimensional feature vector is extracted from ST-T (0.5 seconds) segment and Q wave (0.06 seconds) region. The localization results in beat classification accuracy of 93.7%. In this approach, BPNN gives poor results due to overlapping features in case of inter related MI categories.

Arif at el. (2012) [35] utilizes 36 time based features along with K Nearest Neighbor (KNN) classifier for the detection and localization of myocardial infarction (MI). The MI detection specificity and sensitivity of 99.9% is achieved using KNN classifier. Moreover, they also used pruning algorithm for reducing storage and time for nearest neighbor search which results in the reduction of data by 93% and achieved sensitivity and specificity of 97% and 99.6% respectively. Also, localization accuracy of 98.3% was achieved for different types of myocardial infarction.

Recently, Park et al. [52] applied Random Forests for the classification of five different heartbeat classes. They extracted temporal and morphological features along with three amplitude difference features and attained the overall accuracy of 98.68% using MIT-BIH database.

4.2 Frequency domain based Features

Frequency based features are mostly computed through Fourier transform. These features have increased sensitivity but time resolution is lost during transformation process therefore it cannot specify in which portion of time the change has been occurred.

Minami at el. [36] proposed technique for the discrimination of ventricular tachycardia, ventricular fibrillation and normal sinus rhythm by observing the QRS complex changes in ECG. Their proposed technique consists of three stages. In first stage, they extracted QRS complex of each heart beat by finding the R peak using local maxima. Then in second stage, Fourier transform is applied on the QRS window of 256 ms to calculate power spectrum consisting of five spectral components. In last stage, neural network having five inputs and two output nodes is utilized for the classification. They obtained classification sensitivity and specificity of 98%.

In another study Gothwal et al. [37] detected six types of cardiac arrhythmias using Fourier transform and ANN. In their proposed work, they transformed the ECG signal into Fourier domain to remove lower frequency component which mostly represents noise. After the noise removal, features are extracted by using QRS estimates and then ANN is employed to classify cardiac arrhythmias. This method gave accuracy of 98% for cardiac arrhythmia detection on 40 records of MIT-BH arrhythmia database.

4.3 Time-Frequency based features

The new feature extraction method based on time-frequency domain has the combined advantages of both already mentioned approaches. It provides frequency analysis with time resolution for analyzed features. Mostly wavelet transform (WT) is used for time-frequency analysis because of its computational simplicity and interpretability in similar way as that of Fourier transform. In a comparative study carried out by Dokur at el. [38], it is demonstrated that performance of wavelet transform exhibits better result as compared to Fourier transform for the classification of ten different types of arrhythmias using MIT-BH arrhythmia database. The choice of use of specific type and order of wavelet depends on nature of application e.g. denoising of the ECG signal using debauches wavelet may give better signal to noise ratio as compared to denoising of ECG signal with symlet wavelet.

Al-Fahoum at el. [39] used wavelet transform for beat classification and extracted six energy descriptors using wavelet coefficients over a beat interval. In this study different types of wavelets were used for the classification of four types of beats. The extracted features through debauches-4 wavelet transform achieved highest accuracy of 97.5 % using Radial Basis Function (RBF) Neural Network classifier. Prasad et al. [40] have presented a method for the classification of beats using symlet-6 wavelet transform. In this study, 12 different types of beats were classified with Neural Network classifier. The feature set included 23 derived coefficients and 2 RR interval features. This method achieved highest classification accuracy of 96.77% using MIT-BH arrhythmia database. In another study, Yu et al. [41] proposed beat classification method based on wavelet transform and probabilistic neural network classifier. They achieved the highest classification accuracy of 99.65%.

Fayyaz A. Afsar et al. [42] used 1-Nearest Neighbor classifier with wavelet based features for ECG beat classification. In the proposed approach, they extracted 11 features including one instantaneous RR interval feature to classify 6 different types of beats. They also applied Principle Component Analysis (PCA) technique to reduce the feature set from 11 to 6 features and achieved classification accuracy of nearly 99.5% with both proposed methods (with and without PCA).

Fayyaz. A. Afsar et al. [43] also proposed a Pruned Fuzzy K Nearest Neighbor approach for cardiac arrhythmia recognition. In this method they extracted 11 features including one instantaneous RR interval feature using wavelet transform. They used 6 features after applying PCA with Pruned Fuzzy K-NN classifier and achieved nearly 97% classification accuracy for 9 different types of arrhythmias recognition. Faziludeen at el. [44] also extracted 25 wavelet and 3 RR intervals based features from the ECG signal and classified three kinds of beats using Support Vector Machine.

This method achieved accuracy of 98.46%, 98.47% and 99.92% for left bundle branch block (LBBB), normal (NSR) and premature ventricular contraction (PVC) beats respectively. Another method utilizing a mixture of features has been proposed by M. K. Das at el. [45], which uses two features extraction methods for the classification of 5 different types of beats in MIT-BH arrhythmia database. This approach achieves classification accuracy of 96.9% and 97.5% for their proposed methods using multilayer perceptron neural network (MLPNN).

L. N. Sharma at el. [46] proposed MI detection and localization approach based on multiscale energy and eigenspace (MEES) features. They used six-level wavelet decomposition to extract 72 dimensional feature vectors. In this study only, lower frequency subbands A6, D6, D5, and D4 are used. The multiscale energy for A6, D6, D5, and D4 subbands are calculated from each lead of 12 lead ECG. Then multiscale eigen analysis is performed to constitute the 24 remaining features of 72 dimensional feature set. In this regard, covariance matrix for each decomposition level is formulated and eigen decomposition is performed to get eigenvalues and eigenvector for approximation and detail subbands respectively. For each of already mentioned subbands 6 dominant eigenvalues values are used as features because most of the energy is retained by them. Correlation based feature selection is also applied in this method on 72 dimensional feature set to select the optimum features subset. Support vector based classifier with RBF kernel achieved highest accuracy, sensitivity and specificity of 99%, 93% and 96% respectively. The localization accuracy of 99.58% is achieved by using proposed MEES features with multiclass SVM classifier with RBF kernel. In another study, Banerjee et al. [47] employed cross wavelet transform with threshold based classifier for MI detection. They claimed overall accuracy of 97.6% using their proposed method.

Features	Author	Year	Classifier	Dataset	Accuracy
Time Domain Based Features (P,QRS,T wave Amplitude, Interval etc)	Moraes et al. [32]	2002	Mahalanobis distance	MIT-BIH	Se. 90.74% PPV 96.55%
	De Chazal et al. [2]	2003	LD & ANN	MIT-BIH	Acc. 89.00%
	Pandit et al. [33]	2014	ANN Ensemble Classifier	MIT-BIH, QT, ST-T	Se. 98.73% PPV 99.40%
	V. R. Kumar et al. [51]	2015	ANN, PSO	MIT-BIH	Acc. 92.49%
			ANN, GSA	MIT-BIH	Acc. 94.47%
	Park et al. [52]	2015	Random Forrest	MIT-BIH	Acc. 98.68%
Frequency Domain Based Features (FFT Coefficients)	Minami et al. [36]	1999	ANN	-	Se. 98.00%
	J. Gothwal et al. [37]	2011	ANN	MIT-BIH	Acc. 98.48%
Time-Frequency Domain Based Features (DWT Coefficients)	Al-Fahoum et al. [39]	1999	Radial Basis Neural Network	MITDB, YUDB, MMSDB	Acc. 97.50%
	Prasad et al. [40]	2003	Neural Network	-	Acc. 96.77%
	Yu et al. [41]	2007	Probabilistic NN	MIT-BIH	Acc. 99.00%
	Afsar et al. [42]	2008	1-Nearest Neighbour	MIT-BIH	Acc. 99.50%
	Afsar et al. [43]	2009	Pruned Fuzzy KNN	MIT-BIH	Acc. 96.75%
	Faziludeen at el. [44]	2013	SVM	MIT-BIH	Acc. 98.50%
	M. K. Das at el. [45]	2013	MLPNN	MIT-BIH	Acc. 97.50%

Table 1. Feature Extraction Approaches Used in Literature For The Classification of Heart Beats

Features	Author	Year	Classifier	Dataset	Accuracy
Time Domain Based Features	Papaloukas et al. [49]	2001	Rule Based	ESC-ST-T	Se. 92.10% PPV 93.80% Se. 91.09% PPV 80.09%
	Goletsis et al. [48]	2004	Multi-criteria Sorting Method	ESC-ST-T	Se. 91.00% Sp. 91.00%
	Exarchos et al. [50]	2007	Fuzzy rule based classifier	ESC-ST-T	Se. 91.00% Sp. 92.00%
	Arif et al. [34]	2010	BNN	PTB Database	Se. 97.50% Sp. 99.10% Acc. 93.70%
	Arif et al. [35]	2012	KNN	PTB Database	Se. 99.97% Sp. 99.90%
Time-Frequency Domain Based Features (DWT Coefficients etc)	S. Banerjee at el. [47]	2014	Threshold-based classifier	PTB Database	Se. 97.30% Sp. 98.80% Acc. 97.60%
	Sharma et al. [46]	2015	SVM (RBF)	PTB Database	Se. 93.00% Sp. 99.00% Acc. 96.00%

Table 2. Feature Extraction Approaches Used in Literature For Detection of Myocardial Infarction & ST Segment Deviation

All the aforementioned approaches for the feature extraction have been used in literature for: ECG beat detection, classification of arrhythmias and for detection of ischemic ST segment deviation for diagnosis of coronary heart disease. A brief overview of feature extraction approaches are presented in Table 1 and Table 2.

5. Conclusion

In literature, a variety of approaches are presented for the recognition of heart related diseases using ECG signal processing and machine learning techniques. This paper provides an overview of ECG denoising techniques along with in depth review of feature extraction and recognition approaches used for heart beat classification and myocardial infarction detection. It is noticed that the recorded ECG signal may contain different types of artifacts which should be removed before further processing. In this study, it is found that baseline wandering, power line interferences and electromyographic noises are effectively removed by employing wavelet based approaches. Also, it is noticed that the accurate detection of onset and offset of QRS complex is of prime importance because most of research uses time interval based features for the detection cardiovascular diseases which heavily rely on the reliable detection of QRS complex, P and T waves. We have noticed that overall time frequency based features gives better performance for classification of different types of hearts beats. Moreover, mixture of features are also used in recent research which includes time interval based feature as well as wavelet based features for better classification of heart related diseases. In most of the modern research taking place, artificial neural network (ANN) and its variants are used for the classification of biomedical signals. Support vector machine (SVM) along with K-Nearest Neighbor (KNN) classifier also provide promising classification results in case of arrhythmia and myocardial infarction detection. Therefore, it can be seen that this type of research accounts for further study. In addition to this, recognition system can be developed for fast and reliable diagnosis of cardiovascular diseases, which can extend the number of heart diseases that can be recognized with better classification accuracy.

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