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Identification of Myocardial Infarction from Multi-Lead ECG signal

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ABSTRACT
Electrocardiogram (ECG) is the cheap and noninvasive method of depicting the heart activity and abnormalities. It provides information about the functionality of the heart. It is the record of variation of bioelectric potential with respect to time as the human heart beats. The classification of ECG signals is an important application since the early detection of heart diseases/abnormalities can prolong life and enhance the quality of living through appropriate treatment. Since the ECG signals, while recording are contaminated by several noises it is necessary to preprocess the signals prior to classification. Digital filters are used to remove noise from the signal. Principal component analysis is applied on the 12 lead signal to extract various features. The present paper shows the unique feature, point score calculated on the basis of the features extracted from the ECG signal. The point score calculation is tested for 40 myocardial infarction ECG signals and 25 Normal ECG signals from the PTB Diagnostic database with 94% sensitivity.
Keywords **-** ECG, MI, PCA, Point score, QRS

I. INTRODUCTION

The ECG is a recording of the electric potential generated by the electrical activity of the heart. The ECG thus represents the extracellular electrical behavior of the cardiac muscle tissue [4]. It describes different electrical phases of a cardiac cycle and represents a summation in time and space of the action potentials generated by millions of cardiac cells. The state of the cardiac health is generally reflected in the shape of ECG waveform and the heart rate. The variability of the human heart beat is unexpected. In the Time domain the ECG signal is identified by different waves viz., P, Q, R, S, T and U. The letters P, Q, R, S, and T were selected in the early days of ECG history and were chosen arbitrarily. The ECG waveform is as shown in fig. 1.1. The P wave represents atrial depolarization. The Q, R & S waves together make up a complex, QRS complex, which represents ventricular depolarization and T wave corresponding to the period of ventricular repolarisation. The interval between S wave and the beginning of the T wave is called the ST segment. In some ECGs an extra wave can be seen at the end of the T-wave, called as U wave. Its origin is uncertain, though it may represent repolarisation of the papillary muscles. If a U wave follows a normally shaped T wave it can be assumed to be normal. If it follows a flattened T-wave it may be pathological.

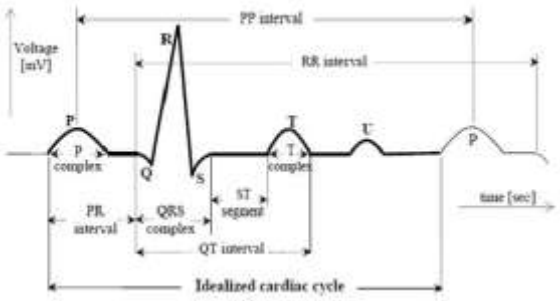

Fig.1.1 ECG wave in Time Domain

II. LITERATURE SURVEY

The extraction of high-resolution cardiac signals from a noisy electrocardiogram (ECG) remains an important problem in the biomedical engineering community. The numerous noncardiac ECG contaminants, such as electromyography noise, overlap with the cardiac components in the frequency domain, particularly in the 0.01 Hz to 100 Hz range. In [10] the proposed method is based on an approximation filter whose characteristics are dynamically changed depending on the ECG signal slope. This procedure requires evaluation of the slope regardless of the EMG noise component. An approximate relation is established between slope values and the number of samples over which the approximation is to be accomplished. Band pass filtering is therefore inadequate to suppress such contaminants [10], [21]. Feature extraction is the

determination of a feature or a feature vector from a pattern vector. In order to make pattern processing problems solvable one needs to convert patterns into features, which become condensed representations of patterns, ideally containing only salient information. Feature extraction methods could be based on either calculating statistical characteristics or producing syntactic descriptions. Various techniques and transformations proposed earlier in the literature for extracting features from an ECG signal and a comparative study of various methods proposed by researchers in extracting the feature from ECG is presented [22]. The Data is collected from Physionet. It is considered as the research resource for complex physiologic signals. It is a unique web based resource funded by NIH intended to support current research and stimulate new investigations in the study of complex biomedical and physiologic signals. ECGs are collected from PTB (Physikalisch-TechnischeBundesanstalt), the National Metrology Institute of Germany. The ECGs in this database were collected from healthy volunteers and patients with a different heart. The database contains 549 records from 290 subjects out of which 148 were suffering from Myocardial Infarction. Each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs. Each signal is digitized at 1000 samples per second, with 16 bit resolution. The base is 0 and the gain of the signal is given as 2000.

III. SIGNAL PROCESSING

The extraction of high-resolution cardiac signals from a noisy electrocardiogram (ECG) remains an important problem in the biomedical engineering community. The numerous noncardiac ECG contaminants, such as electromyography noise, overlap with the cardiac components in the frequency domain, particularly in the 0.01 Hz to 100 Hz range. In many Signal processing applications it is desired to remove the distortions or noise, leaving the original signal unchanged. Applications like communications, biomedical engineering etc. are major areas of using the Notch filters. The frequency response of the digital notch filter satisfies the following constraints.

$$H(e^{j\omega})_{\omega=0,\pi} = 1 \ \ and \ \ H(e^{j\omega})_{\omega=\omega 0} = 0$$

A second order IIR notch filter is used for removing the Powerline interference in the ECG signal. The given signal is contaminated with noise at 50 Hz and also with the baseline wander. The notch filter is designed to remove the 50 Hz power line interference and the low pass filter is used to remove the baseline wander. The quality factor is set to 1.8. The passband ripple and the stopband ripple of the FIR low pass filter is set to 3 and 70 respectively. The filter gives very promising results when tested with signals after adding the 50Hz noise and baseline drift of 0.2 Hz. The results are verified by calculating SNR using the formula $SNR = 10\ log10\ [\frac{\sum_{i=1}^{n}[s(i)]^2}{\sum_{i=1}^{n}[s(i)-x(i)]^2}]$ where s(i) is the recorded/ noisy signal and x(i) is the filtered signal. The SNR using the Notch filter for the PTB database is 0.2 to 1.9dB.

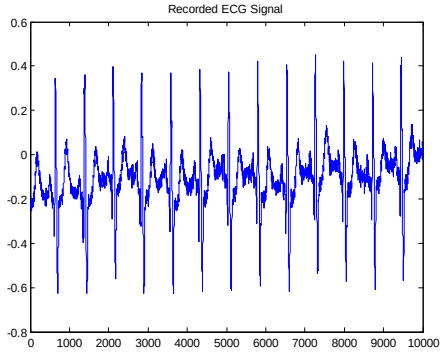

Fig. 1.2 Recorded ECG signal lead 1 from the PTB

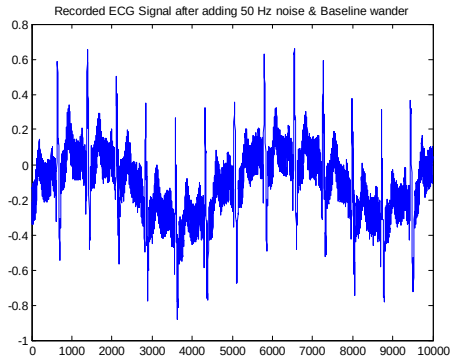

Fig. 1.3 ECG signal after adding PLI and Baseline Wander

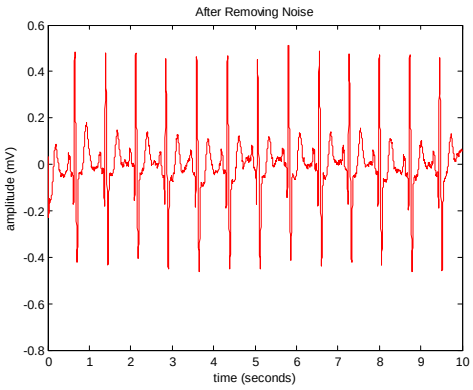

Fig. 1.4 ECG signal lead 1 after Notch filter

IV. FEATURE EXTRACTION

The QRS complex is the most prominent feature in electrocardiogram because of its specific shape; therefore it is taken as a reference in the feature extraction. Detection of R wave is very useful in

analyzing ECG features, thus form the basis of ECG feature extraction. Modern era of medical science is supported by computer aided feature extraction and disease diagnostics in which various signal processing techniques have been utilized in extracting features from the biomedical signals and analyzes these features. Principal component analysis (PCA) is a statistical technique whose purpose is to condense the information of a large set of correlated variables into a few variables termed as principal components, while not throwing overboard the variability present in the data set. The principal components are derived as a linear combination of the variables of the data set, with weights chosen so that the principal components become mutually uncorrelated. Each component contains new information about the data set, and is ordered so that the first few components account for most of the variability. The features extracted from the given signal using PCA are given as follows

Table 1.1 Features extracted for the signal Patient002/s0015lrem using PCA

Lead	Q amplitude	R amplitude	S amplitude	T amplitude	Q durat--ion
I	-0.0184	0.2128	-0.3125	-0.0146	29
II	-0.0862	0.3526	-0.3533	0.1837	33
III	-0.0898	0.1686	-0.1794	0.2779	33
avR	-0.2777	0.3388	-0.0148	0.0217	31
avL	-0.0095	0.0757	-0.1415	-0.0467	8
avF	-0.0888	0.2512	-0.2497	0.2307	37
V1	-0.5938	0.4370	-0.0346	0.0466	33
V2	-0.7384	0.3192	-0.0626	0.0696	34
V3	0.1164	-0.0336	-1.1861	0.0359	36
V4	0.0741	0.1579	-0.9644	0.0471	40
V5	0.0256	0.3025	-0.7785	0.0511	40
V6	-0.0475	0.3969	-0.3545	0.0126	16

Along with the above features, since we have found the locations for P, Q, R, S, T we can also calculate different intervals like PR interval, QT interval, QRS interval etc.

V. CALCULATING SCORE USING POINT SCORING SYSTEM

The accuracy of any diagnostic method can be improved if the ECG signals are acquired simultaneously for 12 leads instead of acquiring sequentially from each lead. For determining the presence and location of Myocardial Infarcts, 12-lead ECG is the standard because it is easily available, noninvasive, inexpensive and easily repeatable

Table 1.2: Scoring pattern for myocardial infarction [23].

Position criteria	Anterior			Lateral			Inferior		
	V2	V3	V4	I	V5	V6	II	III	aVF
Q/R>=1/3 & Q>=36 (34,32)ms	3	3	3	3	3	3	3	2	3
Q/R>=1/3 & Q>=28 (26,24)ms	2	2	2	2	2	2	2	1	2
Q/R>=1/4 & Q>=24 (22,20)ms	1	1	1	1	1	1	1	0	1
All three leads T<-0.1mV	3			3			3		
two leads T<-0.1mV	2			2			2		
one lead T<-0.1mV	1			1			1		

If the total score ≥ 4 cannot rule out infarction
total score ≥ 6 possibility of infarction
total score ≥ 8 definite infarction

Threshold values for Q durations are aligned in the following order: criteria for adults aged over 18 years, for those aged between 12-17 years and for those aged below 11 years.

Table 1.3: Point Score calculation for Patient002/s0015lrem from PTB database

Lead	Amplitude Ratio Q/R	Q Duration	T Amplitude	Remark
I	0.0865	29	-0.0146	Score > 8 Definite Infarction
II	0.2444	33	0.1837	
III	0.5327	33	0.2779	
avF	0.3536	37	0.2307	
V2	2.3129	34	0.0696	
V3	3.5663	36	0.0359	
V4	0.4694	40	0.0471	
V5	0.0847	40	0.0511	
V6	0.1197	16	0.0126	

Table 1.4 Classification Sensitivity using point score as feature

Type	Number of Signals	TP	FN	Se (%)
Normal	25	23	2	94%
MI	40	38	2	
Total	65	61	4	

Where TP - True Positive
FN - False Negative
SE - Sensitivity

$$SE\ (\%) = \frac{TP}{TP+FN} \times 100$$

VI. CONCLUSION

The nature and amplitude of P, Q, R, S, T waves in the ECG signal changes depending on the lead. Multi-lead ECGs improves the accuracy in the diagnosis of heart diseases. The proposed model with the improved feature vector has been introduced to classify ECG signals. The point score is computed depending on QRS complex and T amplitude. The improved feature vector enhances the performance to recognize and classify the ECG with better accuracy for Myocardial Infarction signals. The present study evaluated the utility of a point scoring system in classification of ECG signals with myocardial infarction as compared to the Normal ECG Signals. The sensitivity of the test is 94%.

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