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Analysis of Signal Processing Techniques to Identify Cardiac Disorders

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Abstract: World Health Organization (WHO) report says that most of the countries have highest incidence of hea**rt** related diseases.If no initiative is taken to check the disease that is the most predictable and preventable among all chronic diseases people around the world will have to suffer due to massive heart attack problem.The Electrocardiogram (ECG) is an important bio-signal representing the electrical activity of the heart. It contains important insight into the state of health and nature of the disease afflicting the heart. Processing of cardiac signal and identifying the cardiac disorders is challenging task in biomedical signal processing. This paper deals with different signal processing techniques that are widely in use for determining what sort of a cardiovascular problem a patient is suffering from. Time domain, Frequency domain and Principal Component Analysis have been done on the ECG with the final goal of understanding which of these methods is the best for the identification of cardiac arrhythmias such as Atrial Fibrillation (AF), Cardiac Ischemia (CI) and Sudden Cardiac Arrest (SCA). ECG data has been obtained from the MIT-BIH cardiac arrhythmia database. The work has been done using MATLAB®.

Keywords: Normal sinus rhythm (NSR), Atrial fibrillation (AF), Cardiac Ischemia (CI), Sudden Cardiac Arrest (SCA).

I. INTRODUCTION

In the modern industrialized countries every year millions of people die due to cardiac disorders. The Electrocardiogram (ECG) is an important bio-signal representing the electrical activity of the heart. Processing of cardiac signal and identifying the cardiac disorders is challenging task in biomedical signal processing. The state of cardiac heart is generally reflected in the shape of ECG waveform. Computer based ECG analysis can provide information regarding various Cardiac diseases.This paper introduces the work that has been done to distinguish the Electrocardiogram (ECG) of a normal healthy human from that of AF,CI and SCA patients.

II. ECG WAVE AND INTERVAL

The rhythm of the heart is in terms of beats per minute (bpm) may be estimated by counting the readily identifiable waves. The ECG records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Normally, the frequency range of an ECG signal is 0.05-100 Hz and its dynamic range of 1-10 mV. The ECG signal is characterized by 5 peaks and valleys labeled by the letter P, Q, R, S, T. In some cases we also use another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T-and P-waves. The ECG wave formation during electrical functioning of heart is shown in figure. I

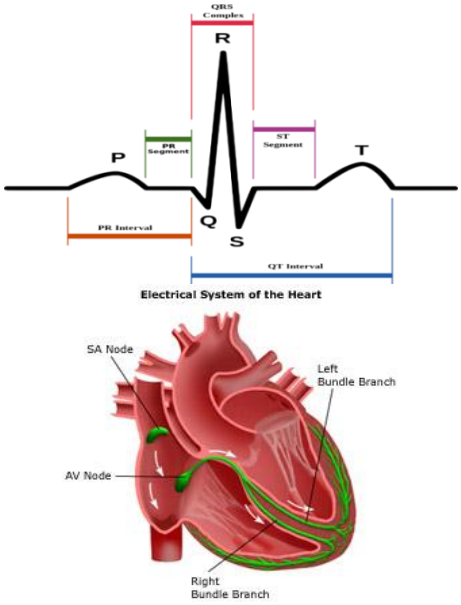

Figure I. Schematic representation of normal ECG Waveform and electrical functioning of heart

A. Arrhythmia

Normally, SA Node generates the initial electrical impulse and begins the cascade of events that result in a heart-beat. For a normal healthy person the ECG comes off as a nearly periodic signal with depolarization followed by depolarization at equal intervals. However, sometimes this rhythm becomes irregular. Cardiac arrhythmia is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart.

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A. Normal Sinus rhythm

The normal rhythm of the heart where there is no disease or disorder in morphology of ECG signal is called Normal Sinus Rhythm (NSR). The heart rate of NSR is generally characterized by 60 to 100 beats per minute and is rhythmic. The regularity of the R-R interval varies slightly with the breathing cycle. A P wave exists for every QRS complex. All QRS complexes are the same size and shape and point in the same direction

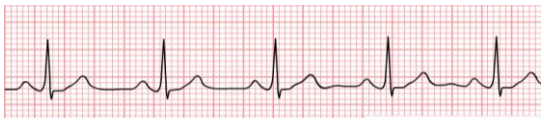

Figure II.Normal sinus rhythm person ECG signal

B. Atrial Fibrillation

Atrial fibrillation occurs when the electric current in the heart is generated from all over the atria at a very high speed, between 300 and 500 impulses a minute. This does not allow the atria to contract in a synchronized fashion. Because of the high number of impulses generated by the heart, and their location, the atria begin to quiver. This is known in medical terms as fibrillation. This causes a fast, irregular heart rate between 80 and 160 beats per minute.

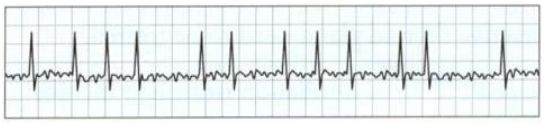

Figure III.Atrial Fibrillation person ECG signal

C. Cardiac Ischemia

Cardiac Ischemia is a condition that occurs when blood flow and oxygen are kept from a particular part of the body. Cardiac Ischemia is the name for this condition when the heart is the body part targeted. Ischemia heart disease is a term that covers heart issues caused by narrowing of the arteries. With arteries narrowed, less blood and oxygen are able to reach the heart muscle.

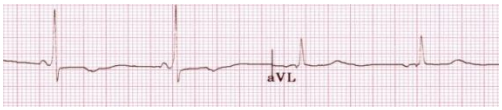

Figure IV.Cardiac Ischemia person ECG signal

D. Sudden Cardiac Arrest

It is a sudden stop in effective blood circulation due to the failure of the heart to contract effectively or at all. Medical personnel may refer to an unexpected cardiac arrest as a sudden cardiac arrest (SCA).

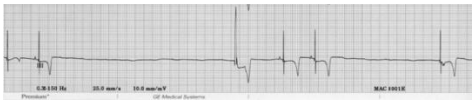

Figure V.Sudden Cardiac arrest person ECG signal

III. NOISE REDUCTION

Data preparation is the manipulation of data into a form suitable for further analysis and processing. Poor quality data typically result in incorrect and unreliable results. Data preparation improves the quality of data and consequently helps to improve the quality of results. Pre-processing stage is used to reduce the noise level and improve the signal-to-noise ratio (SNR).

A. Baseline Wander Removal

Baseline drift usually occurs due to improper measurement during the recording of the ECG signal due to external factors. This type of noise usually occurs below 2Hz. In order to remove this drift in the signal, the signal is filtered using a 3rd order Butterworth low-pass filter operating at a cut-off frequency of 2Hz. The obtained filtered signal is the unwanted noise and is subtracted from the original ECG signal. The baseline corrected signal still has a DC level due to improper bias. This is removed through mean correction technique.

B. Filtering

The ECG signal consists of all frequency components which are not required and this redundant data can be removed through filtering methods. The PQRST segment of the ECG is the main characteristic feature and lies in the frequency range of 2-32Hz. All the frequencies above 32Hz are hence redundant and are removed by applying a 3rd order Butterworth low-pass filter at the cut-off frequency of 32Hz. The resultant signal is void of all frequency components above 32Hz.

C. Resampling

The ECG data obtained from the MIT-BIH database are sampled at a particular sampling frequency over a fixed amount of time. The NSR data obtained was sampled at a sampling frequency of 128Hz, while the AF, CI and SCA data were sampled at a frequency of 250Hz. During the analysis, it is of utmost important that the sampling rate of the signals should be greater than two times the frequency of the input signal according to Nyquist criterion. Hence, the NSR data is resampled to 250 Hz beforehand.

IV. TECHNIQUES USED IN THIS PAPER

A. Time Domain Analysis

Time domain is the analysis of mathematical functions, physical signals or time series of economic or environmental data, with respect to time. In the time domain, the signal or function's value is known for all real numbers, for the case of continuous time, or at various separate instants in the case of discrete time. A time-domain graph shows how a signal changes with time, whereas a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies. Here we use an algorithm called Pan Tompkins algorithm which translates the ECG into time domain by the following steps. Here Pan-Tompkins Algorithm is used to detect the number of R-peaks in30000 samples.

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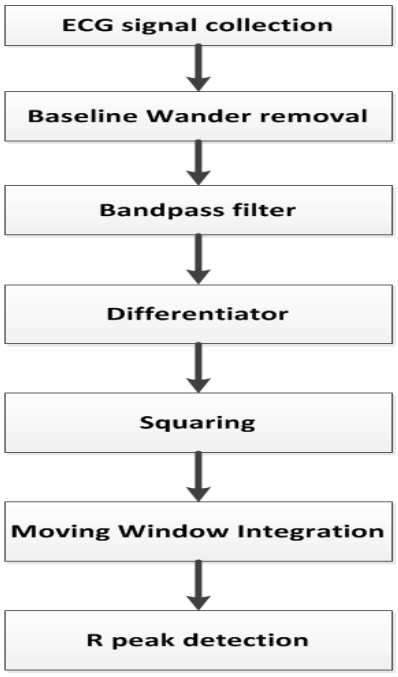

Figure VI. Pan Tompkins Algorithm

As per the algorithm shown in the flow chart and the topics presented in the previous chapter, the first steps in Pan-Tompkins algorithm are related to correcting the measurement issues. As explained earlier, measurement inherently has noise because of various reasons. This noise is, in the end, inevitable, and has to be removed before proceeding to analysis phase. This is done by filtering the frequency components below 2 Hz. Then, the components of EC signal, which are of interest (2-32 Hz) are extracted. NSR samples are resampled to double the initial rate and prepared for subsequent analysis.

Then, the differences between samples corresponding to NSR and the disease under investigation are calculated. Square of this sample wise error is taken for further analysis using a moving window integrator. Parameters from each window are calculated and analysed. Each window is tested for R-peaks and recorded whenever such distinctive desired peaks are found. This is the essence of Pan-Tompkins algorithm.

B. Frequency Domain Analysis

The above examples have introduced the notion of filtering in an operational and intuitive way. In order to make more precise statements on the characteristics of a discrete-time filter we need to move to the frequency domain. What does a filtering operation translate to in the frequency domain? The fundamental result of this Section is the convolution theorem for discrete-time signals: a convolution in the discrete-time domain is equivalent to a multiplication of Fourier transforms in the frequency domain. This result opens up a very fruitful perspective on filtering and filter design, together with alternative approaches to the implementation of filtering devices, as we will see momentarily.

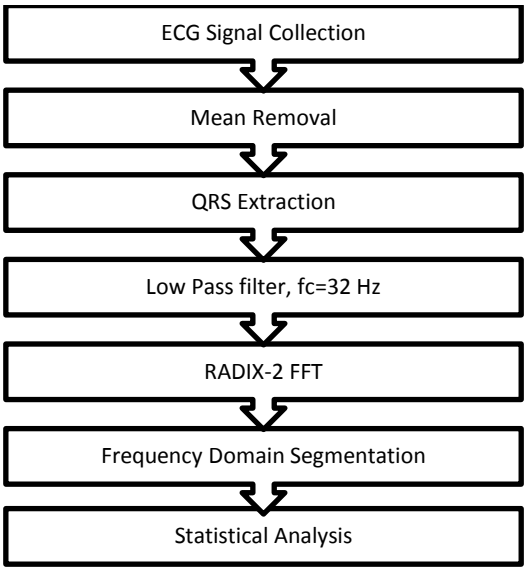

Figure VII. Frequency Domain Analysis

C. Principal Component Analysis

Principal component analysis (PCA) is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of linearly uncorrelated variables. In general terms, PCA uses a vector space transform to reduce the dimensionality of large data sets. Dimensionality reduction is a feature extraction method used to represent the data using fewer variables. The analysis of the reduced dimension set is useful in the identification of trends, patterns and outliers in the data. Some of the other common applications include; de-noising signals, blind source separation, and data compression. PCA transforms the data into a set of uncorrelated feature vectors called the principal components.

The ECG data consisting of large number of samples over a period of time and hence PCA is a highly efficient technique which can be used for ECG signal analysis. Classification of cardiac ischemia using ECG analysis is done using covariance method of PCA by initially providing a set of training samples and comparing the principal components obtained for the test data with those of the training samples.

D. Method of PCA

The main aim is to automate the process of disease identification through principal component analysis to identify cardiac arrhythmia namely; Normal sinus rhythm (NSR), Atrial Fibrillation (AF) and Cardiac Ischemia (CI). Hence the PCA algorithm is provided with three classes of test samples. Each of the classes had 5 ECG signal collected from the MIT BIH Database. The data are mean corrected so that the DC level in the signals is removed and the signal is centred across the origin. The covariance matrix, eigenvectors and Eigen values are computed. The obtained Eigen values are sorted along with their corresponding eigenvectors. The projections of the data sets for all the classes are computed from the feature vector, which is the transpose of the eigenvector matrix.

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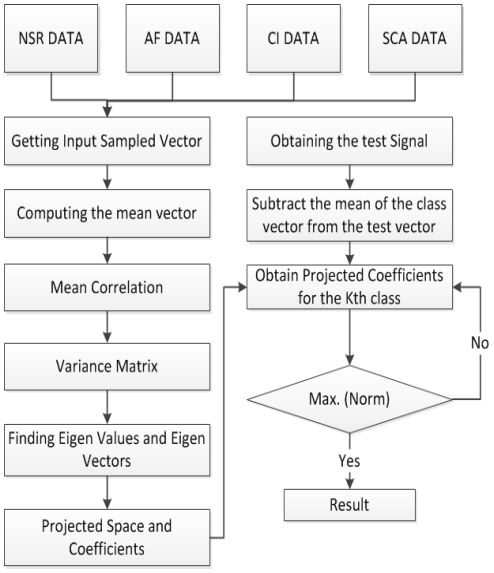

Figure VIII. Block diagram for Principal Component Analysis of ECG analysis.

This process first begins with a learning phase. The algorithm is given a set of inputs one of which is the NSR and the others being those corresponding to the cardiovascular ailments considered in this project. When these inputs are received by the algorithm, it starts to characterize and learn the differences between these conditions statistically. This correlation in between these diseases with NSR is done statistically using covariance matrices, after removing means from all the inputs (DC correction is a requirement by default to remove correlation components between these DC components). Then, Eigen values and vectors for this co-variance matrix are found to create a virtual n dimensional space (depending on the number of Eigen vectors). This completes the learning phase by the end of which there will be 3 different spaces for 3 different diseases under consideration. Intuitively, when a new sample data is given, the algorithm can place the sample vector within this plane and depending on its statistical spatial distribution, can tell which disease is being dealt with.

V. RESULTS

A. Time Domain Analysis

Time domain analysis shows a good variation in the number of R peaks for all three cardiovascular conditions. The statistics presented have been acquired with a data set of 2500 samples. Comparing the disease condition with Normal Sinus Rhythm, a disease condition can be identified. But it is quite apparent that to distinguish between the three conditions, there is a very small margin and that may create some false alarms in identifying disease.

Table I. Number of R- Peaks Comparison between NSR, AF, CI, SCA

S.No	No. of R peaks of ECG data			
	NSR	**AF**	**CI**	**SCA**
1	16	8	6	8
2	15	9	8	6
3	16	7	6	7
4	15	6	6	1
5	16	7	6	6
6	15	9	4	1
7	12	6	1	6
8	12	5	6	1
9	14	7	4	1
10	14	6	6	6
11	13	9	1	7
12	15	6	8	3
13	18	8	4	4
14	14	6	7	2
15	16	6	5	6
16	15	5	7	3
Avg.	**14.75**	**6.85**	**5.31**	**4.12**

When the amplitudes are considered, there is a good difference between average amplitudes of normal sinus rhythm and disease conditions. But measuring amplitudes requires sophisticated instrumentation and sensitive acquisition, to prevent false alarms.

Table II. Amplitude of R-peaks comparison between NSR, AF, CI, SCA

S.No	Amplitude of R peak (in mV)			
	NSR	**AF**	**CI**	**SCA**
1	4.77545	1.09013	0.47726	0.13062
2	1.11567	0.32959	0.27781	0.09696
3	5.87631	0.11064	0.17093	0.18279
4	2.14446	0.12050	0.87073	0.05149
5	1.83494	0.02771	0.52674	2.65147
6	1.80448	0.39779	0.42701	0.05276
7	5.70626	0.28182	0.44321	0.07860
8	4.41893	0.28477	0.662.0	0.05736
9	1.20179	0.47091	0.35383	0.12092
10	0.95706	1.17950	0.78066	0.11746
11	3.52943	0.13940	1.89749	0.18279
12	1.86282	0.02539	0.09611	0.05544
13	2.61550	0.58800	0.01295	0.07860
14	2.19591	0.06402	0.22270	0.05778
15	3.58389	0.05187	0.24021	0.09602
16	1.30129	0.04361	0.63174	0.18674
Avg.	**2.588**	**0.259**	**0.505**	**0.261**

Though, the time domain analysis provides an indication in terms of the average number of R peaks in an ECG signal, it cannot give an indication on the basis of this crucial time difference between consecutive R peaks.

B. Frequency Domain Analysis

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Table III. Energy comparison of diseases with NSR

Range	Energy NSR	Energy CI	Energy SCA	Energy AF
R1	23309996.5	103025.17	83212204	36802636
R2	16016883.4	548802.31	1712789	6473738
R3	5445154.71	173258.99	25239.51	422333.1
R4	53452.8794	11008.753	1353.278	30673.37
R5	23967.4916	2399.9229	1330.007	3088.657

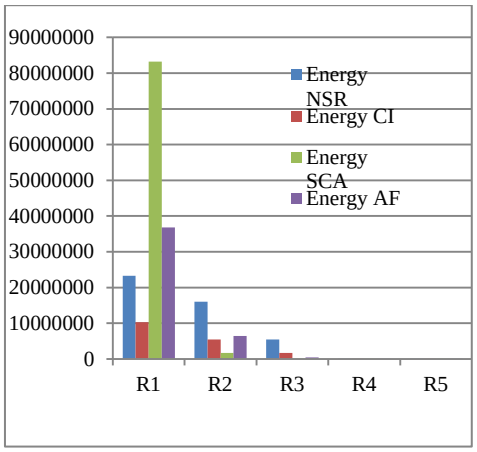

Figure IX.Frequency segment wise energy Comparison for three diseases

From the results obtained, it can be said that the energy per each of the components R1 to R5 varies from normal condition to a disease condition. The energy is usually found to be less when the disease condition is analysed. About 50% of energy per component is lost when the ECG shows irregularities that can be related to all three diseases considered. But this reduction in the energy is not such a good indicator to exactly determine which cardiovascular problem is being dealt with, without false alarms at all. Hence, though frequency domain analysis can be used, it is complex and not fool proof.

C. Principal Component Analysis

Principal component analysis is an automated method for identification of the abnormalities in the ECG signal. The PCA is trained with 5 samples of NSR, CI, SCA and AF. The samples used for the training are given in the table below.

Table IV. Table showing the ECG samples used for training PCA

Disease	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5
NSR	NSR1	NSR2	NSR3	NSR4	NSR5
CI	CI1	CI2	CI3	CI4	CI5
AF	AF1	AF2	AF3	AF4	AF5
SCA	SCA1	SCA2	SCA3	SCA4	SCA5

Test cases have been applied to the PCA algorithm and the norm values of projections in projected space of each class are computed. The results have been tabulated and it is observed that the norm values are the highest for the respective disease each test case.

Table V. Norm of the test signals calculated for Diseases

Test Signal	norm(NSR)	norm (AF)	norm (CI)	norm (SCA)
TEST_1	**17.6268**	17.5814	17.5937	17.2632
TEST_2	29.1677	**29.1970**	29.1723	29.1861
TEST_3	16.6179	16.4438	**16.9456**	16.5610
TEST_4	19.5745	19.7410	19.6624	**19.7732**

VI. CONCLUSIONS

From all the three methods explored, it can be thus said that time and frequency analysis methods both give a part of the crucial information required to uniquely diagnose all the three different cardiovascular problematic conditions. Detection of R peaks and measuring their amplitudes and their average occurrences have been good indicators but require precise measurements. Frequency domain analysis methods gave energy information and frequency deviations that could determine what problem is being dealt with. But the energy information can still not be used as a standalone source for determining these diseases.When motivated to move to Principal Component Analysis, both these domain of time and frequency have been analysed together. It gives a single norm metric that was found to vary quite well in agreement with the disease condition under consideration. And since it uses learning algorithms and operates in Eigen vector spaces, this approach simply places a sample set in a vector space and tries to analyse it accordingly. So, it has a huge space in which sample placement can be quite accurate. So, it can be said that PCA can be a better technique when compared to both time and frequency analysis techniques.

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