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Real Time ECG Analysis For Prediction Of Sudden Cardiac Death Using PCA Interpretation

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Abstract:*Cardiac arrhythmias are disturbances in the rhythm of the heart, manifested by irregularity or by abnormally fast rates (tachycardias) or abnormally slow rates (bradycardias). However, many patients with arrhythmias report no symptoms, and the condition may first be discovered during a routine examination. In these cases, treatment of the arrhythmia can often return normal function to the ventricles. Also, by identifying these patients having high risk for sudden cardiac arrest, there are the chances for their survival from a fatal arrhythmia by placing a prophylactic implantable cardioverter defibrillator. Considering this situation, an Electrocardiogram (ECG) monitoring system has been designed to interpret the data from the ECG graph and Principle Component Analysis technique has been implemented in a LabVIEW based Virtual Instrument to predict certain chances of sudden cardiac death by analysis of the data acquired from the ECG curve.*
Keywords:*Cardiac arrhythmias; Electrocardiogram; Data Analysis; Principle Component Analysis.*

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INTRODUCTION

The heart is an electrical pump, where the electricity is generated in special pacemaker cells in the upper chamber, or atrium, of the heart. This electrical spark is carried through pathways in the heart so that all the muscle cells contract at once and produce a heartbeat. This pumps blood through the heart valves and into all the organs of the body so that they can do their work.

This mechanism can break down in a variety of ways, but the final pathway in sudden death is the same; the electrical system is irritated and fails to produce electrical activity that causes the heart to beat. The heart muscle can't supply blood to the body, particularly the brain, and the body dies. Ventricular fibrillation (V Fib) is the most common reason for sudden death in patients. Without a coordinated electrical signal, the bottom chambers of the heart (ventricles) stop beating and instead, jiggle. Ventricular Fibrillation is treated with electrical shock, but for it to be effective, the shock usually needs to happen within less than four to six minutes. Automatic external defibrillators (AEDs) are commonly available in public places to allow almost anybody to treat sudden death. Less commonly, the heart can just stop beating. The absence of a heart beat is known as asystole. Cardiac arrhythmias are disturbances in the rhythm of the heart, manifested by irregularity or by abnormally fastrates (tachycardias) or abnormally slow rates (bradycardias). Patients who perceive these abnormalities most frequently observe palpitations, which some describe as the sensation of ‘my heart turning over in my chest’, or awareness that their hearts are beating rapidly or slowly. Premature beats, which may originate in the atria or the ventricles, are the most common cardiac arrhythmia. They occur in subjects with normal hearts and in patients with heart disease of lesser or greater severity. Palpitations are the principal symptoms produced by premature beats, whatever their origin. The sensation is produced by the early contraction of the ventricles followed, after a pause, by a stronger than normal contraction. Other symptoms include weakness, shortness of breath, light headedness, dizziness, fainting (syncope) and, occasionally, chest pain. The symptoms tend to be more severe when the rate is faster, the ventricular function is worse, or the arrhythmia is associated with abnormalities of autonomic tone. Sudden cardiac death (SCD), generally defined as death within one hour of symptom onset or during sleep in a patient who was previously stable, is a clinical syndrome that is a final common pathway of a number of disease conditions and states. Arrhythmic SCD may be due to ventricular fibrillation (VF)/tachycardia (VT) [SCD-VT/VF] or asystole/pulse less electrical activity (PEA).

Epidemiologic studies suggest that there has been a decline in cardiac arrest due to VT/VF and a concomitant increase in PEA/asystole. the surface electrocardiogram (ECG) and ECG-related assessment techniques are being evaluated to determine if they can be used to identify patients at high risk for Sudden Cardiac Arrest (SCA). The ECG is an especially attractive screening tool because of its low cost and noninvasive application. Various classifier techniques could be implemented on the ECG waveform to interpret and analyze various features for recognizing any kind of abnormalities in the functioning of the heart.

LITERATURE REVIEW

Recent years have witnessed a growing interest in developing personalized and non-hospital based care systems to improve the management of cardiac care. The reason behind such interest is due to the fact that cardiovascular diseases represent nowadays the leading cause of mortality in and reducing the time before treatment is crucial to reduce cardiac mortality. [1] have developed a personal cardiac homecare system by sensing Lead-I ECG signals for detecting and predicting SCD events, which also builds in ECG identity verification. A MIT/BIH SCD Holter Database plus our ECG database were investigated. [2] seeks three-dimensional shape metrics of the left ventricle derived from clinical cardiac magnetic resonance images that can predict SCD risk. The present study is a proof-of-concept, where the author has combined image-processing and computational anatomy techniques to develop a processing pipeline to statistically compare localized left ventricular shape metrics between patient groups. The results demonstrate that this approach is able to locate systematic wall thickness differences between the two groups. [3] have improved the overall performances of the QRS detector evaluated the results on the 48 records of the MIT-BIH Arrhythmia Database where each ECG record is composed by 2 leads sampled at 360 Hz for a total duration of about 30 minutes. [4] have presented two dynamic cardiac risk estimation models, focusing on different temporal signatures in a patient's risk trajectory. [5] have focused on the development of an accurate, low cost and user friendly real time ECG acquisition using Virtual Instrumentation to know about general cardiac abnormalities and facilitate the improved medical treatment. [6] have analyzed the performance of four R-wave detection methods that were applied on new born piglet ECG data. These methods are based on: first derivative, wavelet transform, and nonlinear transform. [7] have presented an application of K-Nearest Neighbor (KNN) algorithm as a classifier for detection of QRS-complex in ECG. A digital band-pass filter is used to reduce false detection caused by interference present in ECG signal and further gradient of the signal is used as a feature for QRS-detection. [8] described some of the latest ambient intelligence and pervasive solutions that are being designed and are deployed in the PEM device, and more specifically the BN risk factor stratification module and its integration into the overall Personal ECG Monitor telemedical platform. in [9] have proposed an ECG signal processing method with quad level vector (QLV) for the ECG holter system. [10] have used LabVIEW as the professional development environment of virtual monitoring and control equipment, has good man-machine interface, and easy to setup system and reconstruct system and make custom function. [11] have proposed the application of combined neuronal networks with fuzzy logic systems that allow the quantification and characterization of the HRV, helping the identification of patients with low and high probability (risk) of undergoing a cardiac problem. [12] have proposed an embedded real-time QRS detection algorithm dedicated to PCC systems. After analyzing author suggested QRS complex under PCC environments, this algorithm establishes the correction mechanism of motion artifacts, presents the QRS complex detection algorithm based on the linear time domain statistical analysis and syntactic analysis.

PROBLEM FORMULATION AND IMPLEMENTATION STRATERGY

The problem formulation behind this work is to predict sudden cardiac death by ventricular fibrillation. The idea is to use the technique of Principle Component Analysis (PCA) to perform the same. Also, a potable single channel ECG recoding system is designed for real time signal acquisition and processing. Also, a software based Virtual Instrument is developed to read the data from MIT BIH database for various ECG signals and perform the required analysis and processing techniques to predict the disease that is in this case cardiac arrhythmia by analyzing the peaks of a the ECG curve.

The database is taken as a basis for validation of the results thus obtained. Also, there is an option of acquiring data in real time from the self designed hardware for real time analysis. Preprocessing of ECG signal to remove noise with the help of FFT and IFFT tools is performed in LabVIEW. Finally, a new PCA based hybrid algorithm has been proposed for the detection of ECG signals to calculate the high QRS peak of ECG. Further, Analysis of the result of QRS peak and compare with normal sinus arrhythmia values. Validation of the proposed model is attained by comparing the proposed hybrid algorithm with conventional Adaptive Difference Threshold algorithm.

Methodology Used

The use of classifier systems in medical diagnosis is increasing gradually. There is no doubt that evaluation of data taken from patient and decisions of experts are the most important factors in diagnosis. But, expert systems and different artificial intelligence techniques for classification also help experts in a great deal. PCA technique has been employed in this research to analyze the ECG curve for prediction of SCD. 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 ("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. In signal processing applications, PCA is performed on a set of time samples rather than on a data set of variables. When the signal is recurrent in nature, like the ECG signal, the analysis is often based on samples extracted from the same segment location of different periods of the signal. Signal processing is today found in virtually any system for ECG analysis, and has clearly demonstrated its importance for achieving improved diagnosis of a wide variety of cardiac pathologies. Signal processing is employed to deal with diverse issues in ECG analysis such as data compression, beat detection and classification, noise reduction, signal separation, and feature extraction. Principal Component Analysis has become an important tool for successfully addressing many of these issues, and was first considered for the purpose of efficient storage retrieval of ECGs. Over the years, this issue has remained central as a research topic, although the driving force has gradually changed from having been tiny hard disks to become slow transmission links. Noise reduction may be closely related to data compression as reconstruction of the original signal usually involves a set of eigenvectors whose noise level is low, and thus the reconstructed signal becomes low noise. Such reduction is, however, mostly effective for noise with muscular origin. Classification of waveform morphologies in arrhythmia monitoring is another early application of PCA, in which a subset of the principal components serves as features which are used to distinguish between normal sinus beats and abnormal waveforms such as premature ventricular beats. A recent application of PCA in ECG signal processing is robust feature extraction of various waveform properties for the purpose of tracking temporal changes due to myocardial ischemia. Historically, such tracking has been based on local measurements derived from the ST-T segment, however, such measurements are unreliable when the analyzed signal is noisy. With correlation as the fundamental signal processing operation, it has become clear that the use of principal components offer a more robust and global approach to the characterization of the ST-T segment. Signal separation during atrial fibrillation is another recent application of PCA, the specific challenge being to extract the atrial activity so that the characteristics of this common arrhythmia can be studied without interference from ventricular activity. Such separation is based on the fact that the two activities originate from different bioelectrical sources; separation may exploit temporal redundancy among successive heartbeats as well as spatial redundancy when multi lead recordings are analyzed. Step by step design methodology is illustrated below:

- Collect the standard reference ECG signal for analysis of sudden cardiac death from the database of MIT BIH.

- Preprocessing the ECG signal with the help of FFT algorithm to avoid artifacts and noise.
- Simulate of proposed set and run the setup for detection of sudden cardiac arrest.
- Compare the result with pre-collected reference signal for estimation and to predict the sudden cardiac death.

Flowchart

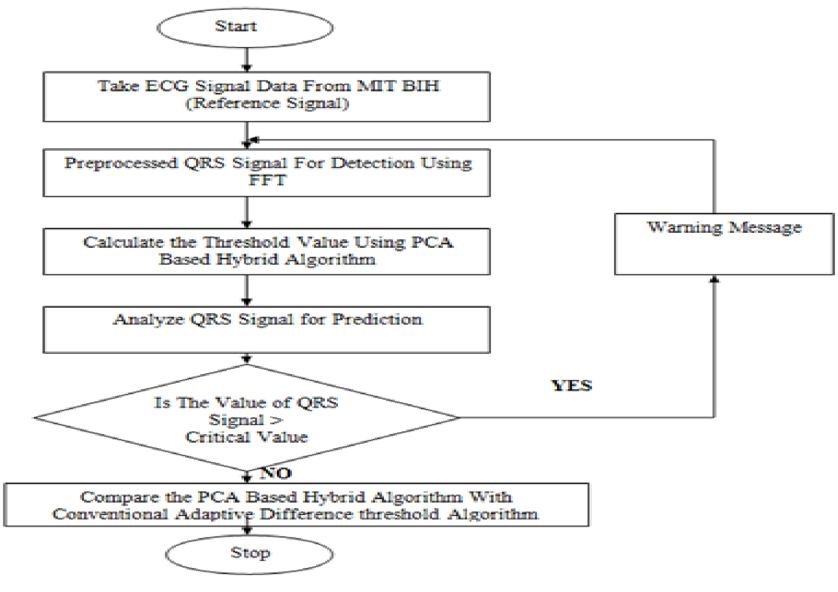

Fig. 1 Flow Chart of Model

Fig.1 shows the flow chart of the proposed hybrid algorithm for the prediction of sudden cardiac death.

Experiemental Setup

The experimental technique involved the implementation of the proposed algorithm in the hardware and software tools using various signal processing and instrumentation systems. The hardware implementation involves the development of the designed ECG electrodes and data acquisition circuit. This data acquired through the external hardware in real time is fed to the computer using serial port that is further accessed by LabVIEW software. A VI is designed in the LabVIEW software that could predict the chances of SCD using PCA implementation on the acquired data and the saved data of many patients from the MIT BIH database.

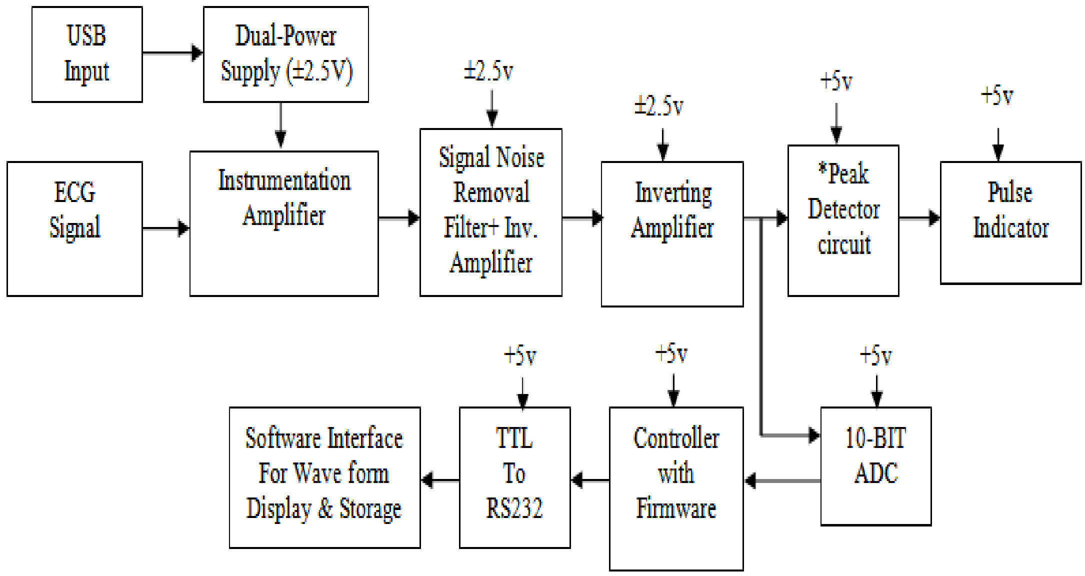

Fig.2 Block Diagram of ECG hardware

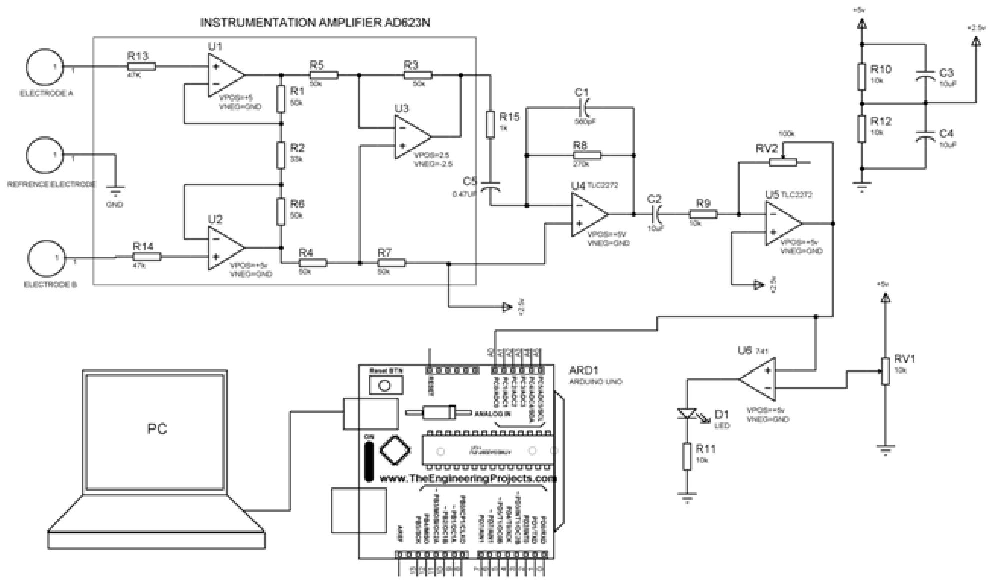

Fig.3Circuit Diagram of ECG Hardware

Figure 2 and 3 represent the block diagram and circuit diagram of the hardware been developed to acquire and process the ECG signals in real time. It involves the acquiring of ECG signals from the electrodes and then further sending them to the instrumentation amplifier for increasing the amplitude of the signal. AD623N instrumentation amplifier is utilized as per the circuit diagram. After amplification, the external noise and other low frequency noise is removed with the filter and inverting amplifier and only the desired ECG signal is amplified. Peak detector and pulse detector is used to further detect the peak of the ECG signal and show it with the blinking of an LED. Also the desired filtered signal is then fed to the computer serial port using a controller with firmware. Electrocardiogram analyzer having Arduino Uno as processing unit and analog front is designed using dual, rail to rail, low output impedance ,low offset single supply Op-amp TLC227 and General purpose op-amp as comparator.

A 10-bit ADC is used to perform the signal conversion process from the analog to digital conversion. The data collected from the data acquisition circuit is fed to the software for further processing and analysis. Various simulations of the above circuit were carried out in Proteus Design Suite. Next step after simulation is to test circuit in real time by developing it on prototype board with the help of function generator as source for test signal and DSO for displaying output signal.

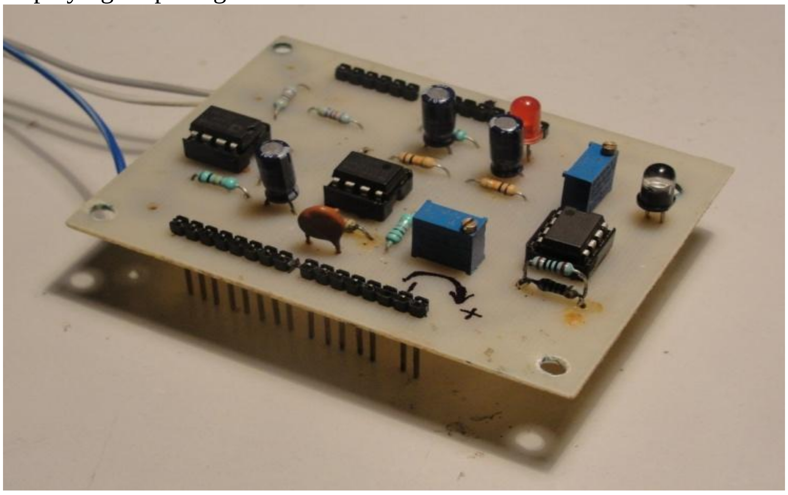

Fig.4 Complete Picture of Final Hardware

After performing the step by step testing process, the final circuit was fabricated on the designed PCB as depicted above in figure 4.

Results And Discussion

The ECG is characterized by a recurrent sequence of five principal waves (see Fig.5), denoted by P, Q, R, S and T, each showing some beat to beat variability. The analysis of this variability can be fundamental in sudden cardiac arrest; the R-R time series (tachogram) may provide essential information for the determination of hidden cardiopathy [32], and the Q-T series have been proposed as a marker of sudden death risk.

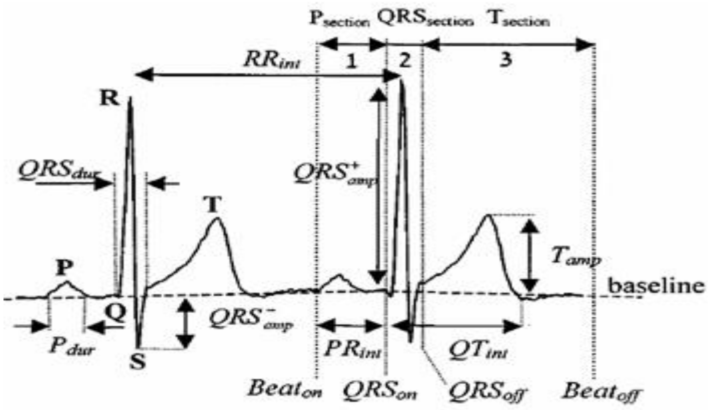

Fig.5 ECG Principal Waves

Fig.5 represents the electrical activity of the heart which may be divided into the following sections. The first little upward notch of the ECG trace is called the "P wave." P wave indicates that the atria (the 2 upper chambers of the heart) are contracting to pump out blood. The next part of the tracing is a short downward section connected to a tall upward section PQ-interval. This next part is called the "QRS complex." This part indicates that the ventricles (the 2 lower chambers of the heart) are contracting to pump out blood. The next short upward segment is called the "ST segment." The ST segment indicates the amount of time from the end of the contraction of the ventricles to the beginning of the rest period before the ventricles begin to contract for the next beat. The QT-interval is the time between the onset of ventricular depolarization and the end of ventricular depolarization. The next upward curve is called the "T wave." The T wave indicates the resting period of the

ventricles and the cardiac muscle is prepared for the next cycle of the ECG. The exchanges in the normal layout of an ECG can indicate one or more conditions related to the heart. When the ECG is studied, it is observed the size and the length of each part, these variations could be significant. PCA is a bilinear modeling method that provides an interpretable overview of the main information contained in a multidimensional table. It is also known as a *projection* method, because it takes information carried by the original variables and projects them onto a smaller number of latent variables called *Principal Components (PC)*. Each PC explains a certain amount of the total information contained in the original data and the first PC contains the greatest source of information in the data set. Each subsequent PC contains, in order, less information than the previous one.
Geometrical Interpretation of the Difference between Samples
Let us consider the whole data table geometrically. Two samples can be described as similar if the values of most of their variables are close to each other. This results in data points that are close to each other in space. On the other hand, two samples can be described as different if their values greatly differ for at least some of the variables. This results in data points occupying distinctly different areas in multidimensional space. This is represented for two groups, A and B in the figure below.

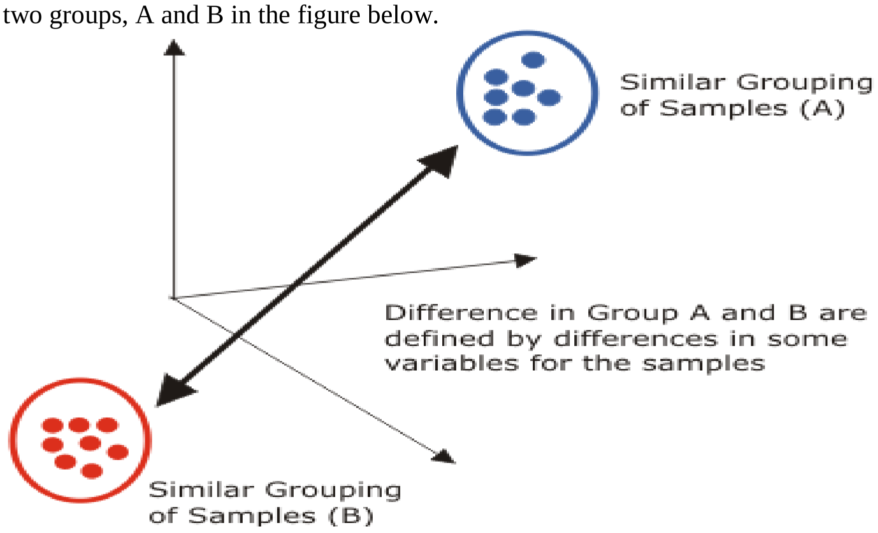

Fig.6 PCA Interpretation of Results

For study of ECG signal parameter, the data is taken from online data base of MIT-BIH Arrhythmia [31]. The data of Normal Sinus Rhythm and sudden cardiac death is studied. Generally the data is plot of amplitude (mill volt) vs. time (millisecond or number of samples). Then form the data amplitude of P, Q, R, S, T waves is recorded. Also, other parameter such as time difference between peaks such as P-Q, Q-R, R-S, S-T, Q-S and Hear rate will be used to predict the sudden cardiac attack. Following cases will be followed to complete data analysis of sudden cardiac death attack.

Step1- Collection of ECG data wave form from MIT-BIH Arrhythmia database. Data for ten different patient of normal sinus rhythm and cardiac arrest patient is collected.
Step2- Generally data available from website is amplitude vs. Number of samples, and some time the data for different patient with different sampling rate.
Step3- Conversion of Horizontal axis of wave form into similar scaled parameter i.e. time parameter
Step4-Extraction of P, Q, R, S, T and P-Q, Q-R, R-S, S-T, Q-S data for Normal sinus rhythm and sudden cardiac arrest patient. For each patient an average of 10 cycles of ECG waveform. Then analysis is performed on this averaged data
Or second Method will be used in which whole set of data as available from website; will be used for Analysis by keeping their similar sampling time.
Step5- Prediction of Sudden cardiac arrest using PCA based cluster to distinguish between ECG data of sudden cardiac arrest and normal sinus rhythm. Unscrambler software will be used for multivariate and principal component analysis of data.
First step was to download data from MIT-BIH Arrhythmia database Website as Shown below the various parameter we need to select in order to download data are.
a) Name of Database (MIT-BIH Normal Sinus rhythm database)
b) Record Number (It represents the Patient)
c) Signal (This represent the Number of Channel in ECG data)
d) Annotation (Reference Beat)

e) Output (we can select signal parameter such as (Total Time, Time format, Second, millisecond, minutes, hour, samples)

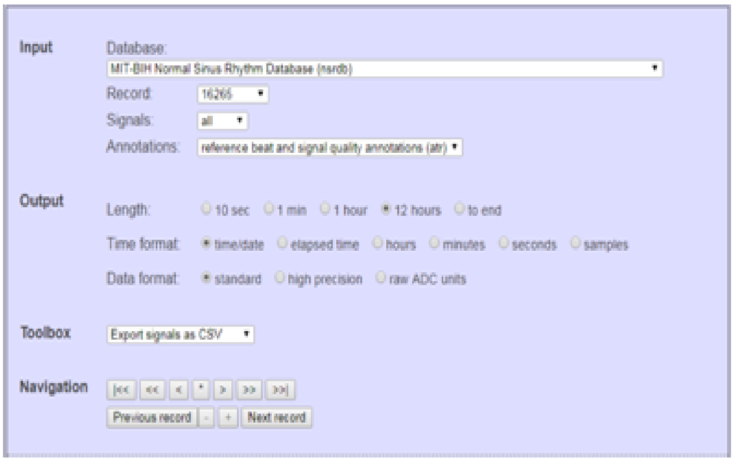

Fig 7 NSR BIH Arrhythmia Database Downloader Dialog Box

(*Reference:* *https://physionet.org/cgi-bin/atm/ATM*)

The ECG data for 20 patient of normal sinus rhythm is collected as shown below, plotted and studied for further analysis.

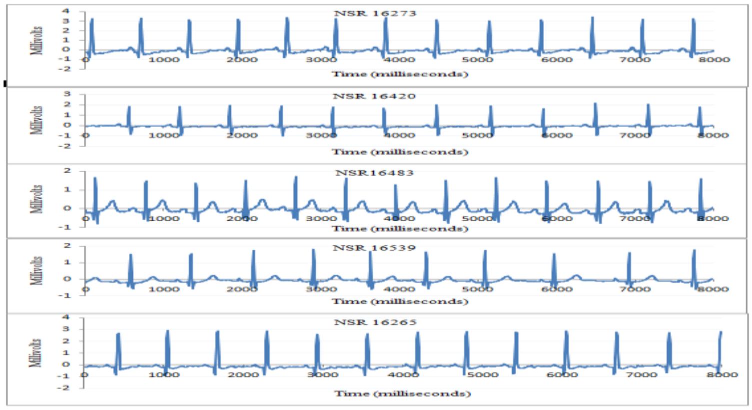

Fig.8 ECG Waveform Normal Sinus Rhythms With Base Line in Millisecond

As shown below in Fig. 9, the PCA applied on raw data and PCA result window from Unscrambler software for the Only sinus rhythm ECG data, we have observed that Most of ECG waveform of different patient representing similar characteristic and is grouped to right side of vertical axis. Some of Data from Selection of data showing abnormal behavior such as Sample No. NSR16273, so that data is removed from sample matrix.

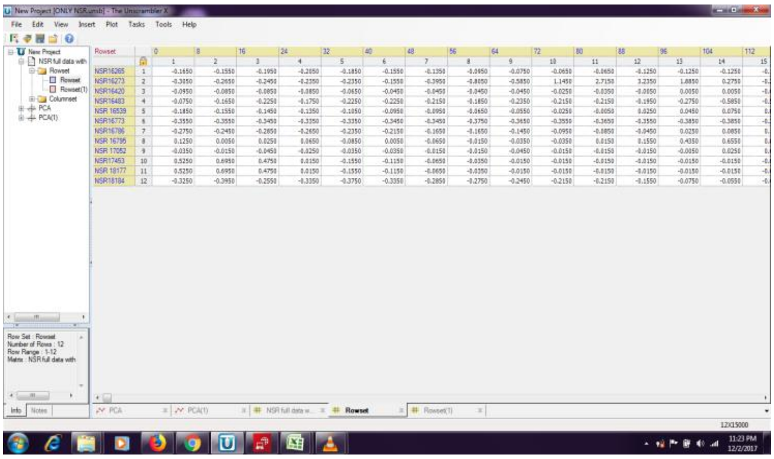

Fig. 9. Data Matrix for NSR

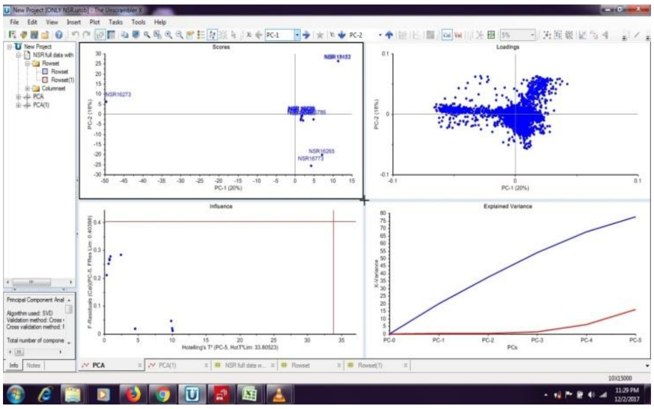

Fig. 10 PCA Analysis of NSR ECG Data

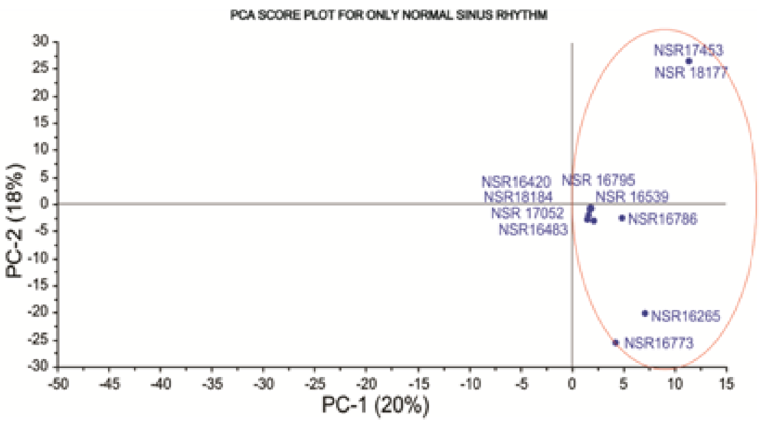

Fig. 11 PCA Analysis of NSR ECG Data

As shown above in PCA plot of NSR ECG data it is found that ECG Data of NSR is only take postion in right quadrant of PCA plot (except some exceptional data), it is also clear that only 48% of total information is represented by PC1 and PC2 , so we need to find other method of performing PCA analysis, before doing that lets check the data analysis of only SCD ECG data. Now next step was to download data for sudden cardiac Arrest from MIT-BIH Arrhythmia database.

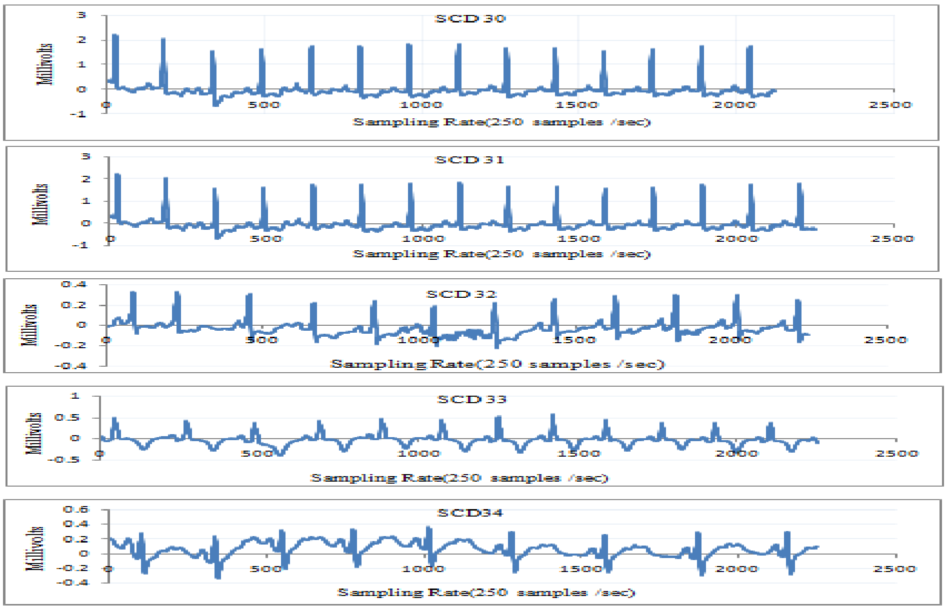

Fig. 12 ECG Waveform Sudden Cardiac Arrest Raw Data

Now the data obtained above yet not suitable for analysis, since in order to extract time information of P, Q, R, S, T waves we need to perform base line correction i.e. we have to convert the ECG signal x-axis data into millisecond format.

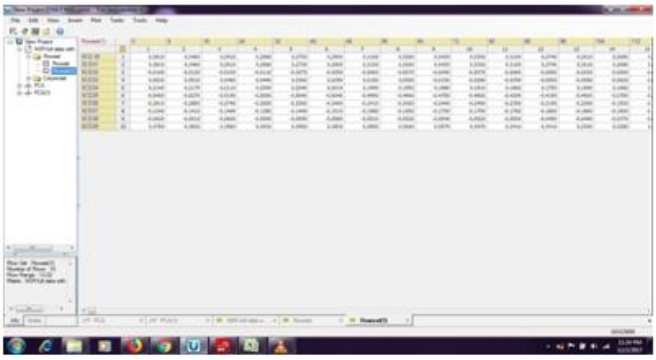

Fig. 13 Data Matrix for SCD Raw Data

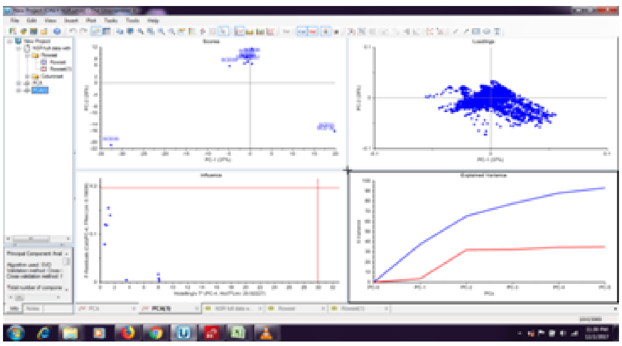

Fig. 14.PCA Analysis of SCD ECG Data

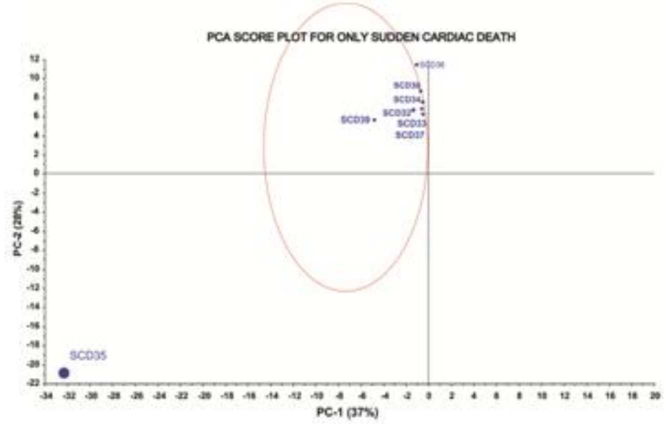

Fig. 15 PCA Score Plot for SCD ECG Data

As shown above in PCA plot of SCD ECG data it is found that ECG Data of SCD is only take postion in Left quadrant of PCA plot (except some exceptional data), it is also clear that only 65% of total information is represented by PC1 and PC2. As we can in cluster data point are closed to each other ,this mean that SCD data of all patient is simlar characterstic.

Hence, it is clear from above , if individual PCA score plot is plotted, we can see data is seprable ,however in order to predict data type, combined data analysis is required.

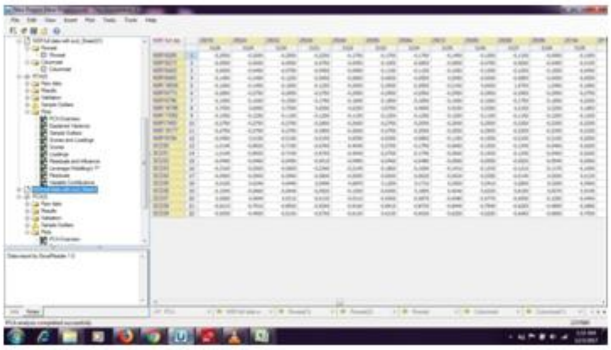

Fig. 16.DATA Matrix of Combined SCD and NSR ECG Data

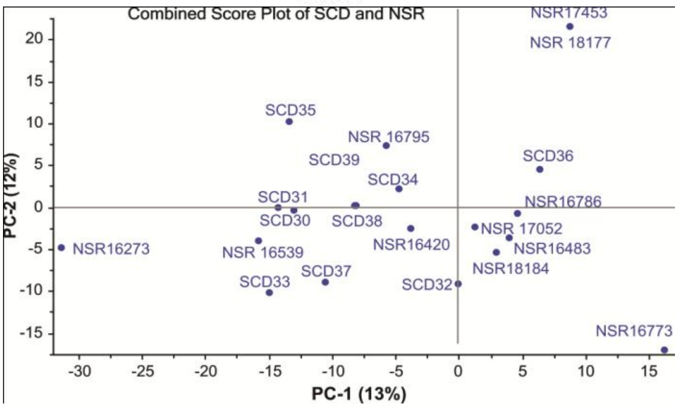

Fig. 17 PCA Score Plot of Combined SCD and NSR ECG Data

As shown in Fig 4.18 the PCA Score plot of combined data of sudden cardiac arrest and Normal sinus rhythm. It is observed from above figure that Most of SCD ECG data, marked red (9 out of 10) lies in Left region of PCA score plot , while the Most of NSR ECG data (7 out of 11) lies in Right region of PCA score plot. As shown below in another rectified enhanced image of PCA score plot of combined SCD and NSR ECG data, PCA model is able to separate SCD and NSR data into some extent , however due to some common parameter to Each signal the data of SCD and NSR is overlapping.

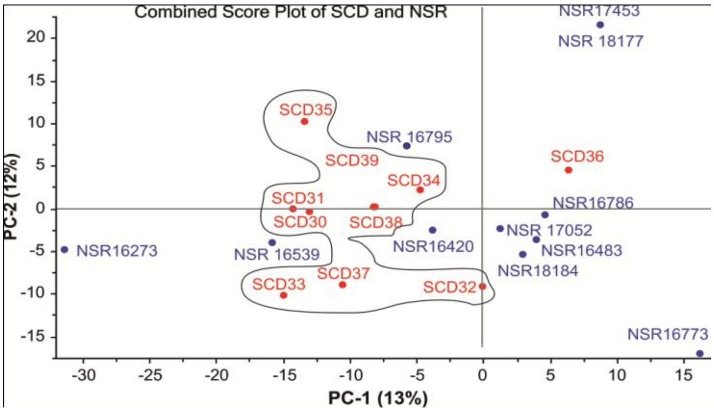

Fig. 18 Enhanced PCA Score Plot Analysis of Combined SCD and NSR ECG Data

This PCA model yet not able to separate the SCD and NSR ECG data so, in next method of analysis instead of using complete set of data, only particular parameter of ECG signal will be used for analysis of ECG Data. This method may avoid overlapping problem of plotting different cluster using PCA.

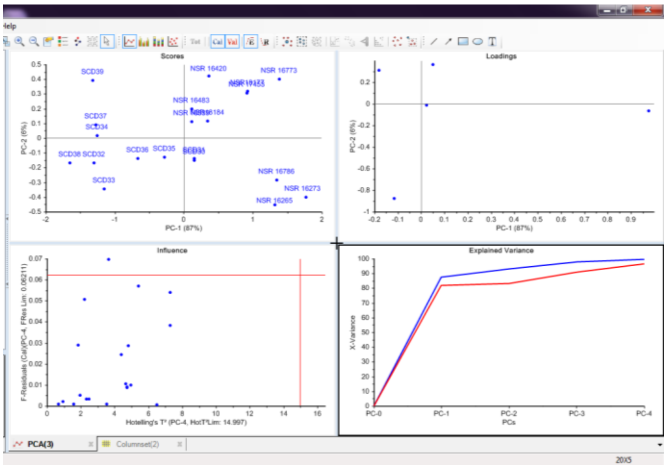

Fig. 19 PCA Plot for Various Samples Collected from MIT BIH Database for Both NSR and SCD Patients.

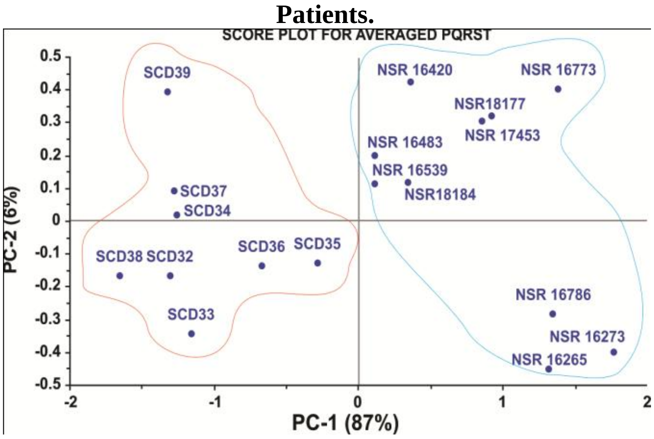

Fig. 20 Score Plot for Various Samples Collected from MIT BIH Database for Both NSR and SCD

Conclusion

Typical QRS detection technique has been employed to detect the SCD caused by ventricular fibrillation based on principle component analysis. A portable and accurate ECG recording system have been designed and implemented to acquire and analyze the ECG signals from heart of various patients in real time and also software based virtual instrument to analyze different waveforms taken from the MIT BIH standard database. Also, a PCA based hybrid algorithm was designed to detect the high QRS peak and thus detect SCD in patients. Also, the data of affected patients and normal patients was compared in terms of its PCA plot and score plot.

It was concluded that patients who suffered SCD have a higher value of QRS peaks as compared to other normal arrhythmia patients and the score plot lied on the negative side of the graph as compared to the normal patients. Also, other than the software based analysis, the hardware model designed could take the patients data in real time and display it on the PC with its PCA analysis.

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