ECG SIGNAL DENOISING USING INDEPENDENT COMPONENT ANALYSIS TECHNIQUE

Thesis submitted in partial fulfilment of the requirements

For award of the degree of

MASTER OF TECHNOLOGY

In

Electronics Circuits and Systems

By

ZAEEMA QAYOOM

1800103799

Under the Guidance of

Dr. Imran Ullah Khan

Jr. Associate Professor

Department of Electronics and Communication Engineering.

INTEGRAL UNIVERSITY, LUCKNOW

September, 2020

CERTIFICATE

This is certify that the thesis entitled **"ECG SIGNAL DENOISING using INDEPENDENT COMPONENT ANALYSIS TECHNIQUE" by ZAEEMA QAYOOM** submitted to the Integral University, Lucknow for the degree of MASTER IN TECHNOLOGY, is a record of bonafide research work, carried out by her in the department of electronics and communication engineering under my supervision and guidance. I believe that the thesis fulfils part of the requirements for the award of degree of master of technology. To the best of my knowledge, the matter embodied in this thesis has not been submitted to any other university / institute for the award of any other degree.

Signature of supervisor

Dr. Imran Ullah Khan
Jr. Associate Professor
Department of Electronics and.
Communication Engineering
Integral University, Lucknow

Signature of Co-Supervisor

Mr. Saif Ahmad
Assistant Professor
Department of Electronics and
Communication Engineering
Integral University, Lucknow

Date:

Place: Lucknow, U.P, INDIA 226026

DECLARATION

I **Zaeema Qayoom**, Roll No. 1800103799 certify that this thesis work entitled "**ECG SIGNAL DENOISING using INDEPENDENT COMPONENT ANALYSIS TECHNIQUE"** is submitted by me in partial fulfilment for the Award of the degree of **MASTER OF TECHNOLOGY** in Electronics and Communication Engineering, **Integral University, Lucknow.**

I understand that plagiarism includes:

1. Reproducing someone else's work (fully or partially) or ideas and cleaning it as one's own.
2. Reproducing someone else's work (Verbatim copying or paraphrasing) without crediting.
3. Committing literary theft (copying some unique literary constructed).

I have given due credit to the original authors/sources through proper citation for all the words , ideas , diagrams , graphics , computer programs, experiments results , websites , that are not my original contribution .I have used quotation marks to identify verbatim sentences and given credit to them by citing them in the text of the thesis and giving their details in the references.

I affirm that no portion of my work is plagiarized. In the event of a complaint of plagiarism. I shall be fully responsible. I understand that my supervisor may not be in a position to verify that this work is not plagiarized.

Name: Zaeema Qayoom **Date:**

Enroll.No.1800103799

Department of Electronics and Communication Engineering

Integral University, Lucknow (India)

ABSTRACT

Electrocardiogram (ECG) is the important data of the human body that gives the information measures of the changes in the cardiovascular system. These clinical ECG signals are always corrupted by the electromagnetic field and power line interference which causes misleading results during the diagnosis of diseases by advanced software modules. So, it is important to minimize these data acquisition recording errors in the ECG to make the accurate clinical analysis. We are developing an algorithm that can break three consecutive ECG signal data array into 3 equivalents Empirical Mode Decomposition these decomposed data matrix are passed through the Independent Component Generation algorithm from these components we will select and eliminate the noisy components and thereafter reverse ICA and EMD will be applied to get error free ECG data.

ACKNOWLEDGEMENT

Throughout my MTech work I came across many people who support helped me to complete this research work smoothly and at this moment I would like to take the opportunity to acknowledge them. First and foremost, I would express my deep and sincere gratitude towards my respectable supervisor, **Dr. Imran Ullah Khan** for his invaluable guidance, constant inspiration and motivation along with enormous moral support during my difficult phase to complete this work, without his suggestion and ideas, this thesis would not be asset for me. I am indebted to him for the valuable time he has spread for me during this work.

I am very much thankful to **Prof. (dr). Naimur Rahman Kidwai,** professor and head of the department, electronics and communication engineering, for his continuous encouragement. Also, I am indebted to him for providing me with all the official and laboratory facilities.

I am also thankful to **MR SAIF AHMAD** and all staff members of dept. of electronics and communication engineering, integral university, Lucknow for their generous help in various ways to complete this thesis work.

Last but not least I would acknowledge my family, parents, sisters, brothers and friends for their support, strength and motivation. A special thanks goes to my father **ABDUL QAYOOM DAR** and mother **ZEINAB** for their love and patience. I have realized that without the selfless help from them, I could never achieve this goal. I would like to convey my heartiest regards to my parents for their boundless love and affection.

Place: Integral University, Lucknow **ZAEEMA QAYOOM**

Date: May 2020 **1800103799**

TABLE OF CONTENT

LIST OF FIGURES

LIST OF ABBREVATION

ECG	Electrocardiogram
ICA	Independent Component Analysis
EMD	Empirical Mode Decomposition
AVR	Augmented Vector Right
AVL	Augmented Vector Left
AVF	Augmented Vector Foot
EMG	Electromyography
EEG	Electroencephalogram
CVD	Cardiovascular disease
SCA	Sudden cardiac arrest
MATLAB	Matrix Laboratory
DSP	Digital Signal Processing
ANN	Artificial Neural Network
EKF	Extended Kalman Filter
SNR	Signal to Noise Ratio
DAQ	Data Acquistion
ADC	Analog to digital converter
GUI	Graphical User Interface
DWT	Discrete wavelet transforms
DDWICA	Double density wavelet Independent Component Analysis
BPNN	Back Propagation Neural Network
AAMI	Association for the Advance of Medical Instrumentation
EMD	Empirical Mode Decomposition
PCA	Principal Component Analysis

FECG	Abdominal Fetal Electro Cardio Grams
BPM	Beats per minute
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
LBBB	Left Bundle Branch Block
RBBB	Right Bundle Branch Block
EKF	Extended Kalman Filter
EOG	Electrooculography
FMRI	Functional Magnetic Resonance Imaging
PCA	Principal Component Analysis
ERP	Event Related Potentials
LPF	Low Pass Filter
MAF	Moving Average Filter
MSE	Mean Square Error

CHAPTER 1

INTRODUCTION

1.1 ECG Signal Overview

A pair of floor electrodes positioned without delay at the coronary heart will record a repeating sample of adjustments in electric “movement capacity.” As movement potentials spread from the atria to the ventricles, the voltage measured between those two electrodes will range in a way that gives a “photo” of the electrical hobby of the coronary heart. The nature of this photo may be various by using changing the position of the recording electrodes; exclusive positions offer distinctive views, permitting an observer to gain an extra whole picture of the electric events. The frame is a superb conductor of strength due to the fact tissue fluids contain an excessive concentration of ions that flow (growing a contemporary) in reaction to ability differences. Potential differences generated by way of the coronary heart are for that reason conducted to the frame surface where they can be recorded by floor electrodes positioned at the skin. The recording as a result received is referred to as an electrocardiogram (ECG or EKG). There are kinds of ECG recording electrodes, or “leads.” The bipolar limb leads record the voltage among electrodes located at the wrists and legs. These bipolar leads encompass lead I (right arm to left arm), lead II (proper arm to left leg),and lead III (left arm to left leg). In the unipolar leads, voltage is recorded between a single “exploratory electrode” placed on the body and an electrode that is built into the electrocardiograph and maintained at zero capability (floor). The unipolar limb leads are located on the right arm, left arm, and left leg; these are abbreviated AVR, AVL, and AVF, respectively. The unipolar chest leads are categorized one via six, starting from the midline function (see under).

There is hence a total of twelve preferred ECG leads that “view” the changing sample of the coronary heart’s electric pastime from unique views. This is vital due to the fact positive abnormalities are pleasant visible with particular leads and won't be visible in any respect with other leads. The unipolar limb leads are placed at the right arm, left arm, and left leg; these are abbreviated AVR, AVL, and AVF, respectively. The unipolar chest leads are labeled one thru six, starting from the midline position (see beneath). There are consequently a complete of twelve popular ECG leads that “view” the converting pattern of the heart’s electric activity from unique views. This is vital due to the fact certain abnormalities are exceptional visible with particular leads and may not be seen in any respect with other leads.

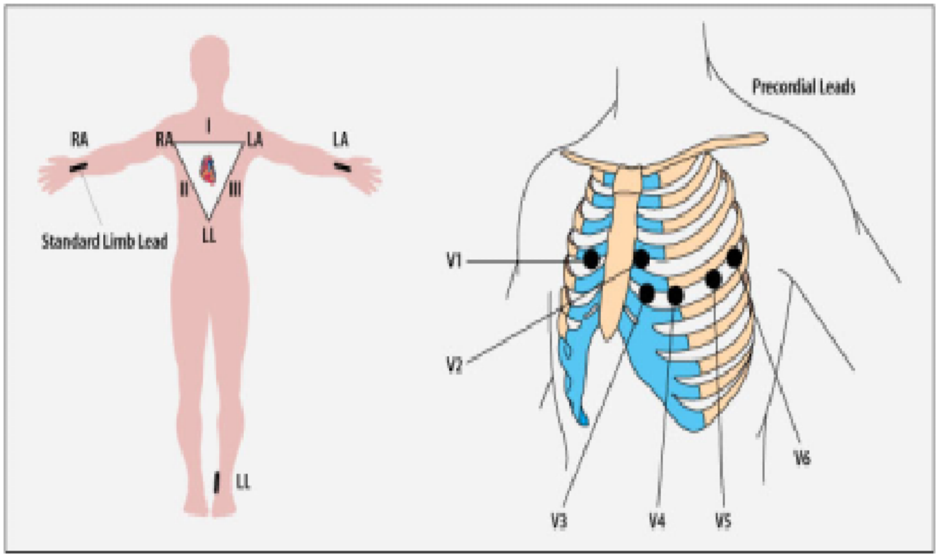


Fig 1.1: The placement of the bipolar leads and the exploratory electrode for the unipolar chest leads in an electrocardiogram (ECG); (RA = right arm, LA = Left arm, LL = left leg.)

Each cardiac cycle produces three wonderful ECG waves, specified P, QRS, and T. It ought to be stated that those waves are not motion potentials; they represent adjustments in capability among two areas at the floor of the heart which are produced through the composite results of motion potentials in lots of myocardial cells. For instance, the spread of depolarization through the atria reasons an ability distinction this is indicated via an upward deflection of the ECG line. When approximately half of the mass of the atria are depolarized, this upward deflection reaches a maximum fee, because the ability difference among the depolarized and unstimulated quantities of the atria is at a most. When the entire mass of the atria is depolarized, the ECG returns to baseline because all regions of the atria have the equal polarity. The unfold of an ordeal depolarization thus creates the P wave. Conduction of the impulse into the ventricles in addition creates a potential difference that results in a pointy upward deflection of the ECG line, which then returns to the base line because the entire mass of the ventricles turns into depolarized. The unfold of the depolarization into the ventricles is thus represented via the QRS wave. During this time the atria repolarize, however this event is hidden by means of the greater depolarization occurring in the ventricles. Finally, repolarization of the ventricles produces the T wave (see illustration below).

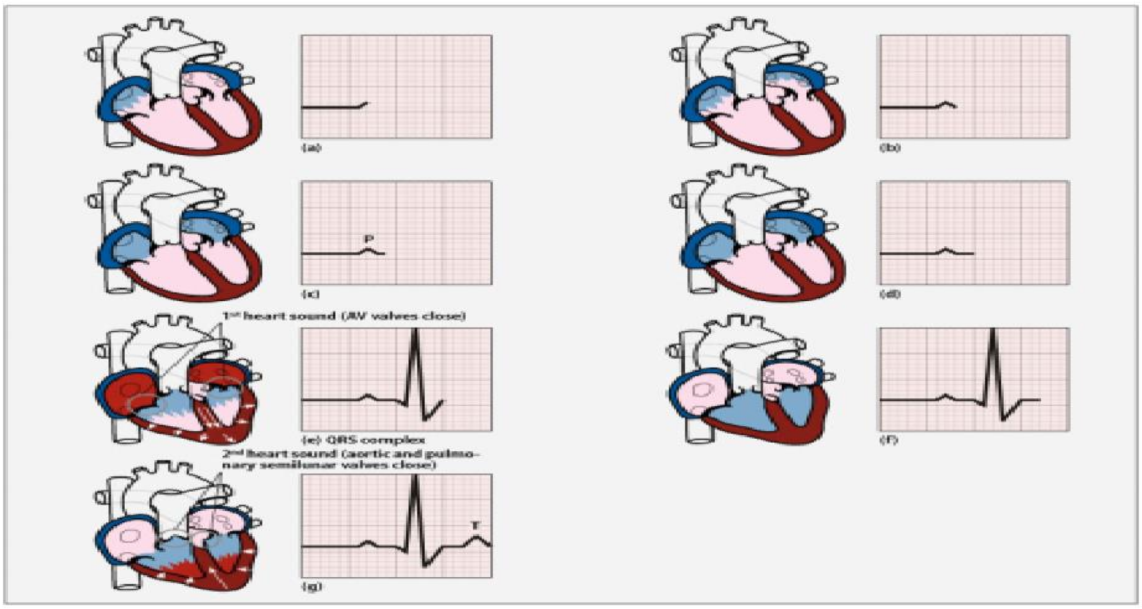


Fig 1.2: The conduction of electrical impulses in the heart, as indicated by the electrocardiogram (ECG). The direction of the arrows in (e) indicates that depolarization of the ventricles occurs from the inside (endocardium) out (to the epicardium), whereas the arrows in (g) indicate that repolarization of the ventricles occurs in the opposite direction.

1.1.1 Correlation of The ECG With Heart Sounds

Depolarization of the ventricles, as indicated by the QRS wave, stimulates contraction by promoting the uptake of Ca++ into the regions of the sarcomeres. The QRS wave is thus seen to occur at the beginning systole. The rise in intra ventricular pressure that results causes the AV valves to close so that the first heart sound (S1, or lob) is produced immediately after the QRS wave (see following illustration).

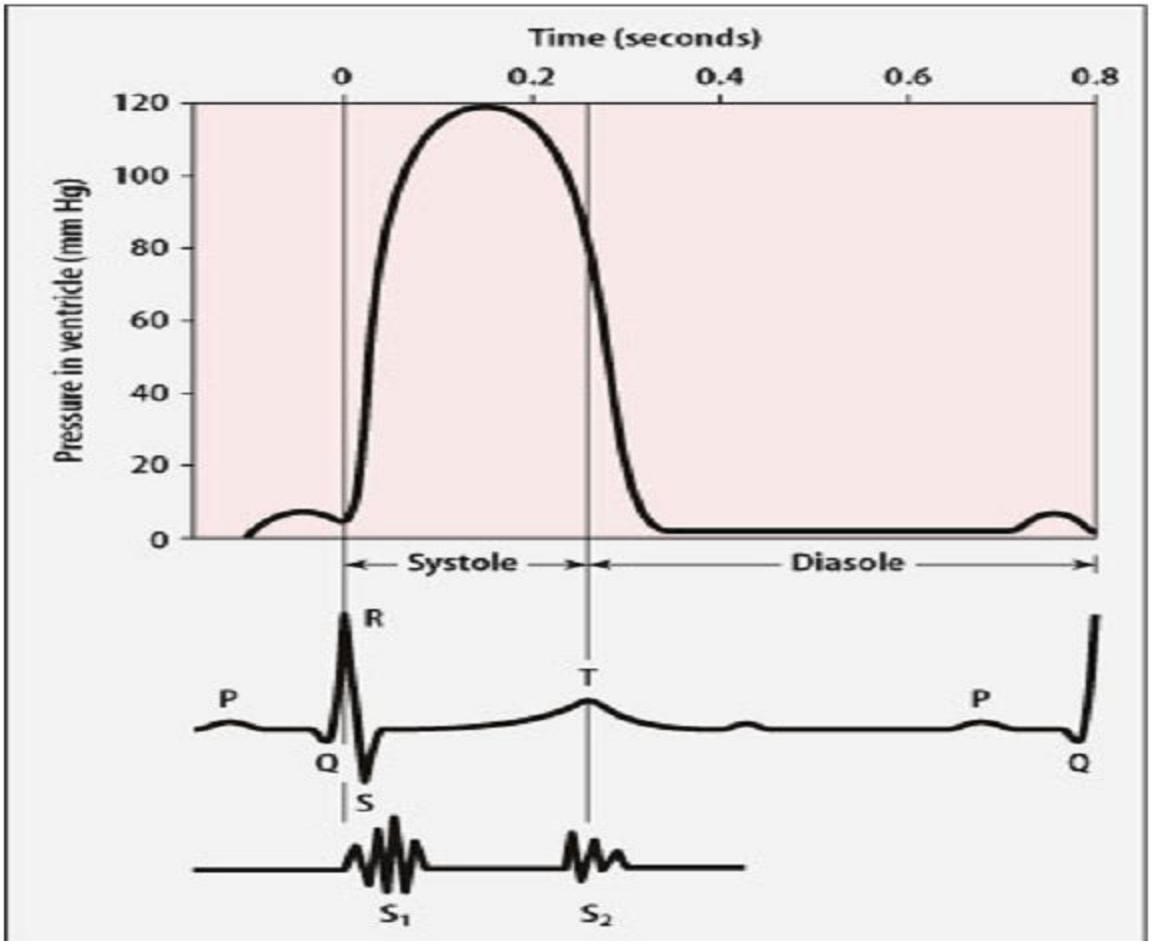


Fig 1.3: The relationship between changes in intra ventricular pressure and the electrocardiogram during the cardiac cycle. The QRS wave (representing depolarization of the ventricles) occurs at the beginning of systole, whereas the T wave(representing repolarization of the ventricles) occurs at the beginning of diastole.

Repolarization of the ventricles, as indicated by the T wave, occurs at the same time that the ventricles relax at the beginning of diastole. There sulting fall in intra ventricular pressure causes the aortic and pulmonary semilunar valves to close so that the second heart sound (S2, or dub) is produced shortly after the T wave in an electrocardiogram begins.

1.2 ECG Data Analysis

In most environments, electrical devices and wiring can be found in the vicinity of the ECG measurement equipment and wiring, and 50/60 Hz power line frequency artifact can be easily introduced to the measured ECG signals. Power line frequency artifact is clearly independent from the ECG signals and often well-separable and removable by ICA. EMG artifacts generated by muscles other than the heart muscle are generally independent of ECG signals. However, in principle, EMG represents a distributed source and cannot be immediately assumed to originate from a single or a small number of discrete sources comparative to the number of ECG leads. Nevertheless, separating EMG artifacts may well be attempted and can be successful in practice. A usual application of ICA is also the removal of ECG artifacts from EMG or electroencephalogram (EEG) signals, as e.g., proposed in (Jung et al., 2000). Baseline wander is a usual artifact seen in ECG signals. It is clearly an independent effect, which may be seen in only one or a few ECG lead signals. It may also appear totally different in different leads and can easily be generated by applying slowly changing pressure to an ECG electrode, among other reasons. In general, the effect is well separable and removable. ECG baseline wander removal by ICA has been proposed by Barati & Ayatollahi (2007), for example. Limb movement, couching, and general restlessness among other similar activities represent a more complex class of artifacts, which may include EMG artifacts and other artifacts due to the movement of wires and stresses on ECG electrode contacts, and maybe other artifacts as well. Removal of such complex artifacts may be attempted but in general the success cannot be predicted a priori. Shoulder movement artifact removal was successfully performed in (Milanesi et al., 2008). Holding hands together or grasping hospital bed metal side railings with both hands may effectively bring the two wrist electrodes to a nearly equal potential, thus making the signals of the standard ECG leads II and III almost equal, and lead III signal may nearly disappear. Such an effect is not caused by an independent source of interference, and cannot be expected to be removable by ICA.

1.2.1 ICA for Noise and Artifact Removal

As described in advance, the primary approach to noise and artifact elimination is to perform ICA followed by means of ECG reconstruction the usage of (2) with the noise and artifact wearing ICs set to zero. Here, a critical step is the recognition of the ICs wearing the artifacts. This may be achieved, e.g., via different statistical or waveform class strategies in time area or in frequency domain, or by way of extra superior methods as described, e.g., by way of He et al. (2006) who also supply numerous illustrative examples. Note that inside the examples in (He et al., 2006) the artifacts and noise to be eliminated are contained in ICs which apparently do not carry ECG contributions, for that reason yielding correct ECG reconstruction which does not regulate the actual ECG waveforms. In this Chapter, recognition of the ICs sporting atrial fibrillation is taken into consideration in the instance, while otherwise IC classification has been done by way of visible remark only. ICA can also be successfully implemented, as an instance, to ECG baseline wander (Barati & Ayatollahi, 2007) and motion artifact removal (Milanesi et al., 2008). In Fig. 1.4.1, a popular ECG is shown with an artifact caused by the issue clenching his left fist. The artifact is evident in all leads besides within the lead II. The measurements have been done with NeuroScan (SynAmp by using Compumedics NeuroScan, El Paso Texas, USA) with the reference at the left ankle. The general chest ECG leads in Fig. 1.4.1 have been determined the use of Wilson's crucial terminal. In Fig. 1.4.2, ICs because of ICA calculated on the ECG signals visible in Fig. 1.4.1, are proven. Since the lead III in Fig. 1.4.1 has been calculated from the leads I and II, there are only eight real measurements in the 9 ICA enter alerts.

Accordingly, ICA discovered best eight ICs (Fig. 1.4.2), as it can at most. In Fig. 1.4.2, the left fist clenching artifact is well contained in IC4, although here the artifact has been detected by visible assessment simplest, and its miles difficult to exclude the opportunity of artifact contributions inside the different ICs. At least IC1, IC2, IC3, IC5, IC6, and IC7, may be seen to carry ECG statistics. IC7 might be taken to show contributions from T wave in addition to a few other ECG contributions at some point of QRS complex, however that is handiest speculative. IC8 may be noise and convey additionally minor ECG facts (noise is comparative to the feasible ECG information). In Fig. 1.4.3, the ECG reconstructed without IC4 is proven.

In visible inspection, the fist clenching artifact has been eliminated, and for the second heart beat shown, the T wave morphology within the lead I' and the info of the QRS complicated morphology within the lead II', both of which are unobservable in Fig. 1.4.1, had been re-covered in Fig. 1.4.3. A reconstructed lead is denoted with a prime in the lead call, addition-ally in the sequel.

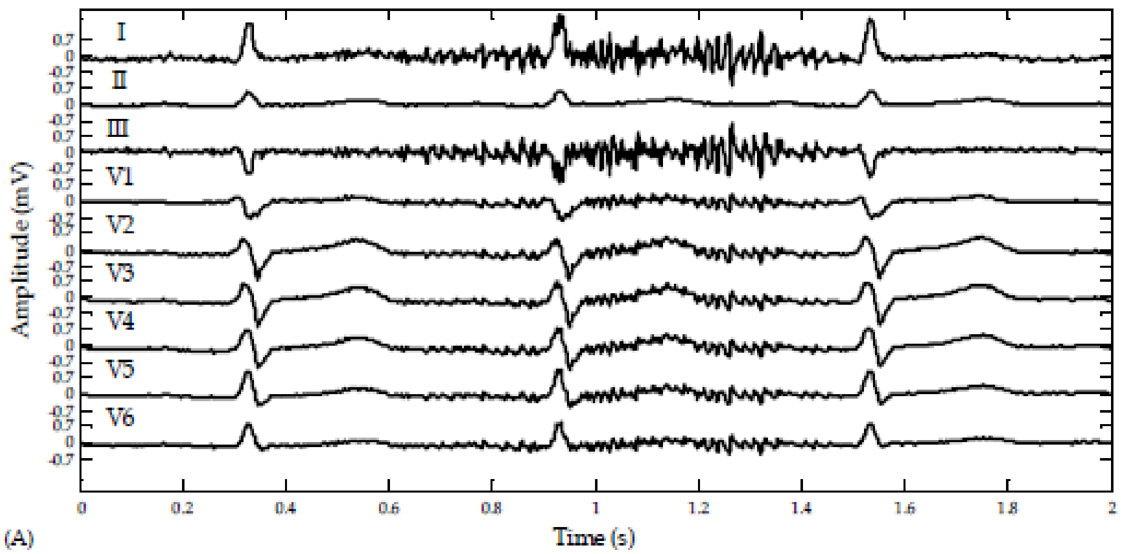


Fig 1.4.1: ECG with left fist clenching artifact visible in all leads but II.

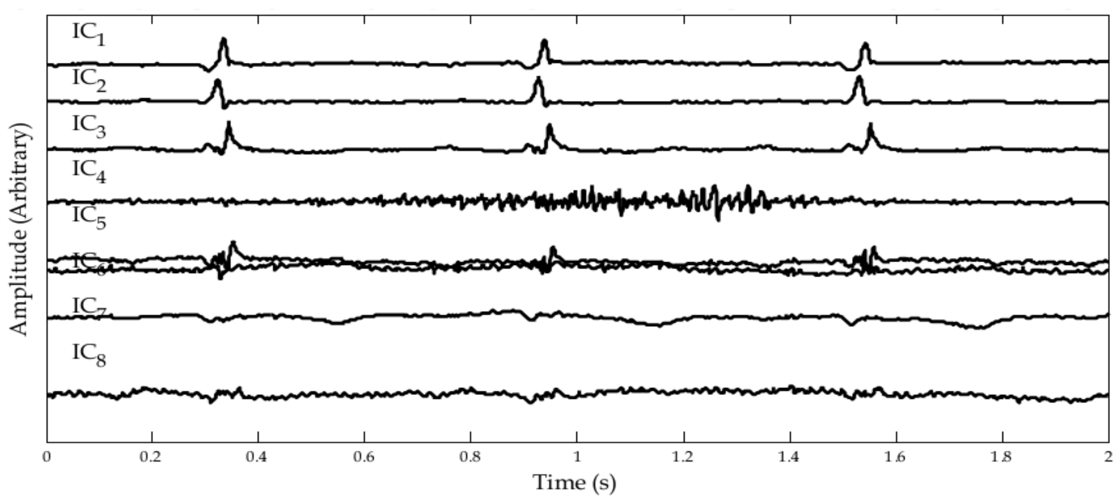


Fig1.4.2: Results of calculating ICA on the signals in (A). Fist clenching artifact has been separated into IC4.

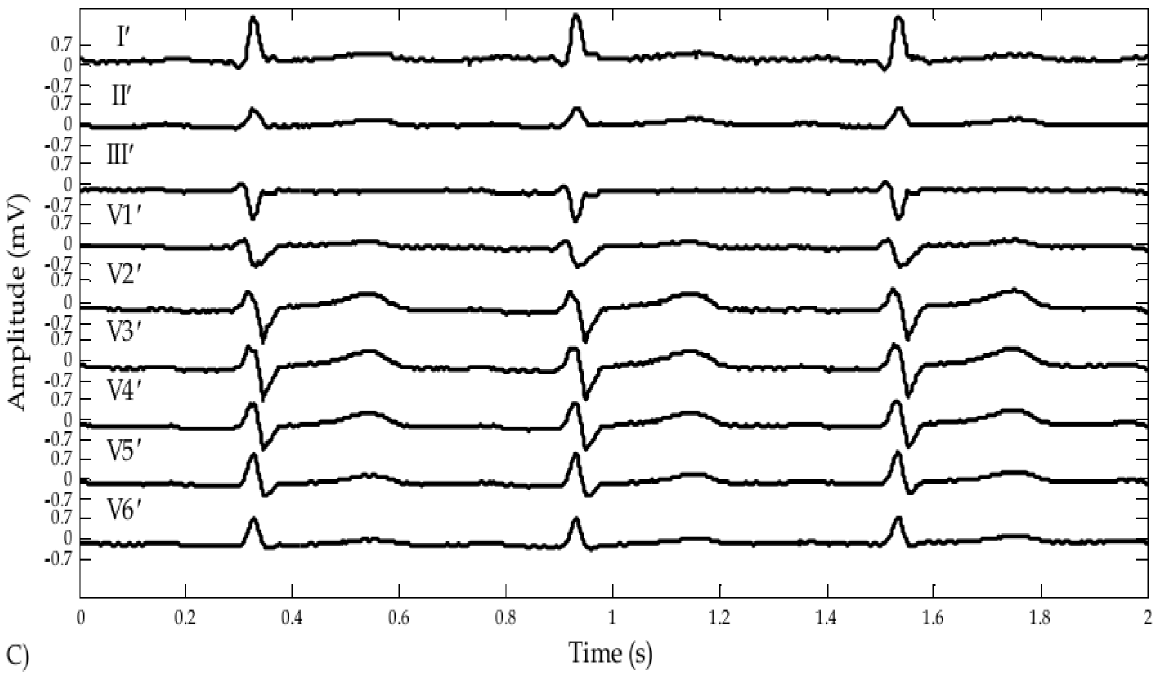


Fig1.4.3 ECG signals reconstructed using all the ICs except IC4.

1.3 ECG Statistical Parameter

The ECG facts the electric activity of the heart, wherein each coronary heart beat is displayed as a sequence of electrical waves characterized through peaks and valleys. Any ECG gives varieties of information. One, the length of the electrical wave crossing the coronary heart which in turn decides whether the electrical interest is ordinary or sluggish or irregular and the second is the quantity of electrical activity passing via the heart muscle which permits to discover whether or not the parts of the heart are too massive or overworked. Normally, the frequency variety of an ECG sign is of 0.05–100 Hz and its dynamic variety – of 1–10 mV. The ECG signal is characterised by five peaks and valleys labelled by way of the letters P, Q, R, S, T. In a few instances we also use some other peak referred to as U. The overall performance of ECG reading system relies upon particularly at the correct and dependable detection of the QRS complex, in addition to T- and P waves. The P-wave represents the activation of the upper chambers of the coronary heart, the atria, whilst the QRS complicated and T-wave represent the excitation of the ventricles or the lower chamber of the coronary heart. The detection of the QRS complex is the most important challenge in automated ECG sign analyses. Once the QRS complicated has been diagnosed an extra distinctive examination of ECG signal which include the coronary heart charge, the ST segment and so on. May be completed [13].In the everyday sinus rhythm (everyday kingdom of the heart) the P-R c language is inside the range of 0.12 to 0.2 seconds. The QRS c language is from 0.04 to 0.12 seconds. The Q-T c program language period is less than 0.42 seconds and the regular rate of the coronary heart is from 60 to 100 beats in line with minute. So, from the recorded form of the ECG, we will say whether or not the heart interest is normal or odd. The electrocardiogram is a graphic recording or show of the time variant voltages produced by the myocardium in the course of the cardiac cycle. The P-, QRS- and T-waves mirror the rhythmic electrical depolarization and repolarization of the myocardium related to the contractions of the atria and ventricles. This ECG is used clinically in diagnosing diverse abnormalities and situations related to the coronary heart.

Amplitude P-wave — 0.25 mV

R-wave — 1.60 mV

Q-wave — 25% R wave

T-wave — 0.1 to 0.5 mV

Duration P-R interval : 0.12 to 0.20 s

Q-T interval : 0.35 to 0.44 s

S-T interval : 0.05 to 0.15 s

P-wave interval : 0.11 s

QRS interval : 0.09 s

The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (Slow heart) and a higher rate is called tachycardia (Fast heart). If the cycles are not evenly spaced, an arrhythmia may be indicated. If the P-R interval is greater than 0.2 seconds, it may suggest blockage of the AV node.

The horizontal phase of this waveform previous the P-wave is targeted as the baseline or the isopotential line. The P-wave represents depolarization of the atrial musculature. The QRS complex is the mixed end result of the repolarization of the atria and depolarization of the ventricles, which arose almost simultaneously. The T-wave is the wave of ventricular repolarization, where because the U-wave, if present is normally believed to be the end result of after potentials within the ventricular muscle. So, the length amplitude and morphology of the QRS complicated is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial contamination and other ailment states [14].

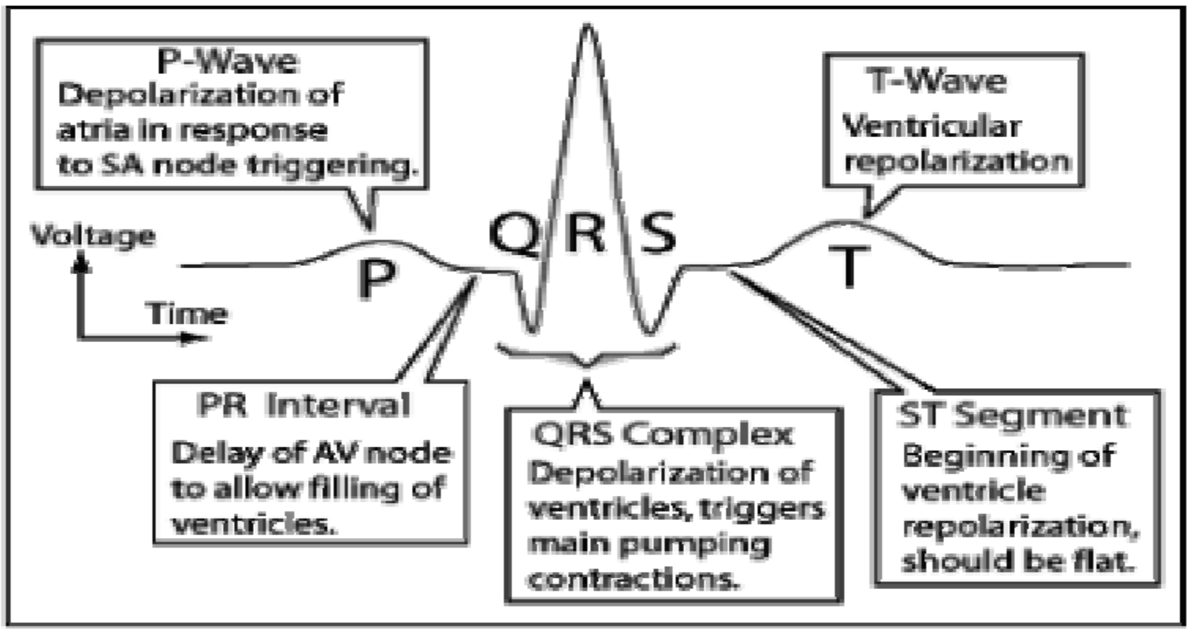


Fig 1.5: The normal ECG waveform**.**

1.4 Problem Statement

Electrocardiogram (ECG) signals plays a vital role in clinical diagnosis especially for diagnosing heart related diseases and disorders such as, cardiovascular disease (CVD), pulmonary disease, sudden cardiac arrest (SCA), etc. ECG signal is generated by a nerve impulse stimulus to a heart. The current is diffused around the surface of the body and build on the voltage drop, which is a normally 0.0001 to 0.003volt and the signals are within the frequency range of 0.05 to 100 Hz. ECG signals are usually recorded at the surface of the body and processed to give important information about the electrical activity of heart. A typical ECG tracing of a normal heartbeat consists of a P wave, a QRS complex and a T wave (Figure 1.6). Usually, the signal which is acquired from the human body is of very low potential and difficult to analyze the signal variance. Hence, necessary amplification is required before processing the ECG signal to derive any give useful information about the cardiac abnormalities.

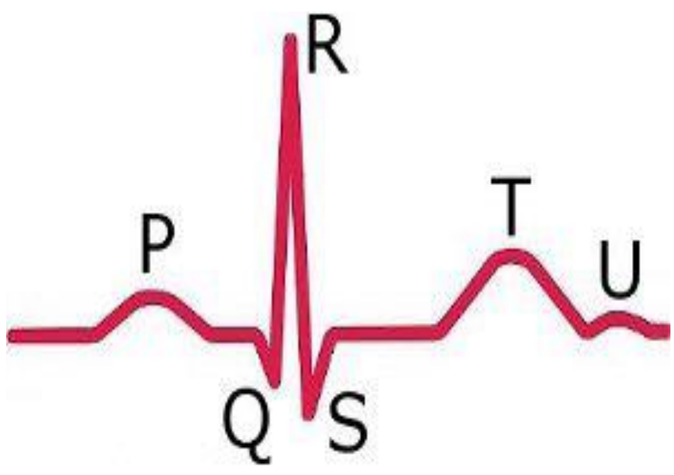


Fig 1.6: The elements of ECG complex

The extraction of high-resolution ECG signals from noisy measurements is among the most tempting open problems of biomedical signal processing. Specifically, the extraction of ECG signals from low SNR measurements is the state of the art in applications such as the noninvasive extraction of fetal ECG signals, recorded from an array of electrodes placed on the maternal abdomen.

1.5 Motivation

Biomedical alerts are observations of physiological sports of organisms, starting from protein sequences, tissue and organ pix, to neural and cardiac rhythms. Biomedical alerts are obtained with the aid of electrodes that report the versions in electrical potential generated via physiological approaches. Each physiological method is associated with sure types of alerts that mirror their nature and activities. Observing those indicators and comparing them to their recognized norms, sicknesses or issues can frequently be detected. When such measurements are found over a period of time, a one-dimensional time-series is acquired which is called a physiological signal. Arrhythmia is a generalized time period used to denote any disturbances within the heart's rhythm. Cardiac Arrhythmia is a strange charge of muscle contractions in the heart. These abnormalities of heart might also reason unexpected cardiac arrest or motive damage to coronary heart. Proper diagnosis of arrhythmia requires an electrocardiogram. The coronary heart offers the driving pressure for the movement of blood. It contains four-chambered pump with two atria for collection of blood and ventricles for pumping out of blood.

The resting or filling segment of a cardiac chamber is called diastole; the contracting or pumping phase is called systole. By decoding the information within the ECG waveform, an extensive variety of heart conditions may be recognized. Therefore, the exceptional of the sign is extraordinarily crucial. Signal processing is carried out within the sizeable majority of structures for ECG evaluation and interpretation. It is used to extract some function parameters [15]. Now a days, biomedical sign processing has been in the direction of quantitative or the goal analysis of physiological systems and phenomena thru sign evaluation [17]. Many researchers have worked closer to reduction of noise in ECG sign [16]. In latest instances, some of strategies have been evolved to locate ECG capabilities together with amplitude and time intervals as well as frequency area representations [18]. Also, numerous researchers have evolved numerous methodologies and algorithms for analyzing and classifying ECG signal. These techniques consist of Digital Signal Processing(DSP), Knowledge-based totally System, Rule-primarily based machine, Fuzzy Logic System, Artificial Neural Network (ANN), and Hybrid System [11]. Other methods consist of Genetic Algorithm, Support Vector Machines, Self-Organizing Map, Wavelet-Domain Hidden Markov Models, Bayesian and different methods with every approach having its own advantages and drawbacks [12]. The intention of this work is to increase a price-powerful pc aided software to investigate ECG indicators with a view to detecting cardiac arrhythmia. In this paper, the unique goal is to increase a version inclusive of technique of pre-processing and observe analytical strategies (DSP with know-how-based) for feature extraction contemplating QRS estimation, amplitude and time variability of ECG signals.

1.6 Objective and Scope of the Project

ECG is the important data of the human body that gives the information measures of the changes in the cardiovascular system. These clinical ECG signals is always corrupted by the electromagnetic field and power line interference which causes misleading results during the diagnosis of diseases by advanced software modules .

So, it is important to minimize these data acquisition recording errors in the ECG to make the accurate clinical analyses. We are developing an algorithm that can break three consecutive ECG signal data array into 3 equivalents Empirical Mode Decomposition these decomposed data matrix are passed through the Independent Component Generation algorithm from these components we will select and eliminate the nosy components and thereafter reverse ICA and EMD will be applied to get error free ECG data.

1.7 Hardware & Software to be Used

We will use MATLAB software of version MATLAB2010.The program script file will be written using basic MATLAB commands that includes arithmetic, logical, branching and loop commands.

1.7.1 Testing Technologies Used

Least Square error, percentage accuracy will be taken for validating testing result.

1.8 What Contribution Would the Project Make?

In most the analysis based on EMD or ICA for ECG signal the researchers have used multi-channel ECG data that require 6 to 8 recording electrodes that become costly we are going to introduce the use signal ECG signal that will be broken into consecutive cycles and among these cycle of single electrode ECG will create the EMD of the signal and then ICA will be applied on generated EMD components. It will be less costly and more accurate due to hybrid of two technologies ICA and EMD.

CHAPTER 2

LITERATURE SURVEY

This chapter covers the year wise development occurring in the field of various computational related advancement in the area covering ECG signals specially their artefact removal using ICA and other equivalent existing methodologies. It covers summarized overview of different methodologies along with their concluding remarks for the last fifteen-year wise research and development.

Aapo Hyvärinen and Erkki Oja (2000), [1] Labored on a fundamental problem in neural community studies, as well as in lots of other disciplines, is locating an appropriate representation of multivariate data, i.e. Random vectors. For motives of computational and conceptual simplicity, the representation is often sought as a linear transformation of the authentic information. In other phrases, every element of the representation is a linear combination of the original variables. Well-reconsider linear transformation methods encompass predominant component analyses, aspect analyses, and projection pursuit. Independent component analysis (ICA) is these days developed approach in which the aim is to find a linear illustration of no gaussian records so that the components are statistically unbiased, or as impartial as possible. Such a representation seems to capture the important shape of the information in many applications, inclusive of function extraction and signal separation. In this work, we give the simple concept and applications of ICA, and our current works at the challenge.

ICA is a completely trendy-cause statistical technique in which found random information are linearly transformed into components which might be maximally independent from each other, and simultaneously have “interesting” distributions. ICA can be formulated because the estimation of a latent variable model. The intuitive notion of maximum non gaussianity may be used to derive specific objective features whose optimization allows the estimation of the ICA model. Alternatively, one can also use greater classical notions like maximum chance estimation or minimization of mutual facts to estimate ICA; really surprisingly, these techniques are (approximatively) equivalent. A computationally very efficient method performing the actual estimation is given by using the Fast ICA set of rules. Applications of ICA may be found in lots of distinct areas such as audio processing, biomedical signal processing, photograph processing, telecommunications, and econometrics.

Huang's facts-pushed method of Empirical Mode Decomposition (EMD) is offered by way of **Gabriel Rilling et. Al., (2003),** [2], and troubles related to its effective implementation are mentioned. A range of algorithmic versions, which includes new stopping standards and an on line version of the algorithm, are proposed. Numerical simulations are used for empirically assessing overall performance elements related to tone identity and separation. The acquired results help an interpretation of the method in phrases of adaptive consistent-Q filter out banks.

EMD is a promising new addition to current toolboxes for nonstationary and nonlinear signal processing, but it nevertheless desires to be higher understood. This work mentioned algorithmic problems aimed toward extra powerful implementations of the method, and it proposed some preliminary overall performance measures. The outcomes mentioned right here are believed to offer with new insights on EMD and its use, but they're simply of an experimental nature and they simply call for similarly studies committed to greater theoretical procedures.

Arnaud Delorme and Scott Makeig, (2004), [3] have developed a toolbox and graphic person interface, EEGLAB, jogging beneath the move-platform MATLAB surroundings (The MathWorks, Inc.) for processing collections of unmarried-trial and/or averaged EEG records of any range of channels. Available capabilities include EEG statistics, channel and occasion data importing, facts visualization (scrolling, scalp map and dipole version plotting, plus multi-trial ERP-picture plots), preprocessing (including artifact rejection, filtering, epoch selection, and averaging), Independent Component Analysis (ICA) and time/frequency decompositions inclusive of channel and element pass-coherence supported by bootstrap statistical methods based totally on statistics resampling. EEGLAB functions are organized into 3 layers. Top-layer capabilities allow users to have interaction with the records through the picture interface without having to apply MATLAB syntax. Menu alternatives permit customers to track the behavior of EEGLAB to available reminiscence. Middle-layer functions permit users to customize records processing the use of command history and interactive 'pop' functions. Experienced MATLAB customers can use EEGLAB facts structures and stand-alone signal processing capabilities to jot down custom and/or batch analysis scripts. Extensive function help and tutorial records are protected. A 'plug-in' facility lets in easy incorporation of new EEG modules into the primary menu. EEGLAB is freely available (http://www.Sccn.America.Edu/eeglab/) under the GNU public license for non-commercial use and open supply development, together with pattern information, consumer academic and sizeable documentation.

Another relative downside of the use of MATLAB to technique excessive-density EEG data is that MATLAB presently converts all floating-point numbers to sixty-four-bit double precision, hence requiring big amounts of fundamental reminiscence to method big facts units. Though hopefully some future MATLAB versions might also allow the choice of processing information in 32-bit floating-point format, we have taken care to address this difficulty in EEG LAB through such as numerous alternatives to decrease reminiscence usage, such as constraining EEGLAB to work on a unmarried dataset, or computing the 'activation' time publications of unbiased components handiest as wished. However, this trouble stays a severe problem for big datasets: parts of the toolbox may also need to be updated to permit very big (e.g., lengthy 256-channel) datasets to be analyzed in the modern Linux 2GB/procedure restrict. One possibility is to use the MATLAB MEX language, an interface between C and MATLAB that lets in a greater variety of statistics types consisting of unmarried precision. Another opportunity is to have EEGLAB load into fundamental reminiscence best a part of the dataset at a time. However, as sixty-four-bit processors emerge as more available, the contemporary data space limits of operating systems and MATLAB need to growth, in which case the closing problem could best be the load of buying the important RAM. Current development of EEGLAB makes a specialty of processing of massive datasets (>1 Gb), semi automatically grouping independent component across topics, and element supply localization. EEGLAB will also be related to our FMRLAB toolbox (http://www.Sccn.United states.Edu/fmrlab) to system simultaneously recording EEG and fMRI data (Duann et al., 2002a). We additionally have all started running with codevelopers to growth the range of EEGLAB features the usage of the 'plug-in' facility, wherein participants may additionally without difficulty contribute non-obligatory EEGLAB code that is without difficulty incorporated into the EEGLAB menu. The plug-in facility is designed in order that plug-in features can be used and disbursed both within EEGLAB and independently. By this mechanism we are hoping to inspire the open supply development of complete EEG (and MEG) signal processing tools under EEGLAB.

Empirical mode decomposition (EMD) has lately been pioneered by **Patrick Flandrin, Gabriel Rilling, and Paulo Gonçalvés, (2004),** [4] for adaptively representing nonstationary alerts as sums of 0-mean amplitude modulation frequency modulation additives. In order to higher apprehend the way EMD behaves in stochastic conditions regarding broadband noise, we report here on numerical experiments primarily based on fractional Gaussian noise. In this kind of case, it seems that EMD acts essentially as a dyadic filter bank corresponding to those involved in wavelet decompositions. It is also mentioned that the hierarchy of the extracted modes can be in addition exploited for getting access to the Hurst exponent.
They reported here on first numerical experiments aimed at supporting the claim that, within the case of dependent broadband stochastic procedures consisting of fractional Gaussian noise, the built-in adaptivity of EMD makes it behave spontaneously as a "wavelet-like" filter out bank. A thrilling derivative of this interpretation is that EMD might also offer a brand-new manner of studying self-comparable approaches. Thorough comparisons (which are past the scope of this letter) with different existing methods are in development. Let us simply mention that blessings very similar to the ones of wavelet-based totally methods are obtained when the use of EMD: specifically, the method takes place to obviously address superimposed smooth developments. From a more widespread perspective, the consequences presented here certainly call for theoretical elements which might give an explanation for the located behaviors (e.g., the -dependence of the filter bank shape), a venture which is made hard by means of the truth that EMD does not admit an analytical definition. The purpose of the prevailing experimental have a look at changed into to be a contribution aimed at a better knowledge of one specific thing of EMD (the manner it decomposes broadband noise), filling

one way or the other the gap among a none the less nonexisting theory and the software of an appealing approach to actual-international situations.

An Extended Kalman Filter (EKF) has been proposed by means of **Reza Sameni, M.B. Shamsollahi, Christian Jutten, and Massoud Babaie-Zadeh (2007**), [5] for the filtering of noisy ECG signals. The technique is based totally on a modified nonlinear dynamic version, formerly introduced for the era of artificial ECG indicators. An automatic parameter selection approach has also been cautioned, to adapt the version with a substantial kind of regular and strange ECG signals. The outcomes display that the EKF output is able to tune the original ECG sign shape even within the noisiest epochs of the ECG sign. The proposed method might also serve as an efficient filtering technique for packages such as the noninvasive extraction of fetal cardiac signals from maternal stomach signals.

In this work an Extended Kalman Filter (EKF) became designed for the filtering of ECG alerts. The EKF's dynamic model turned into based totally on a changed 3-dimensional nonlinear dynamic version formerly added for the technology of artificial ECG signals. This nonlinear version changed into linearized on the way to be utilized in an EKF. The designed filter out was later implemented to noisy ECG signals, and the outcomes display the filter's functionality in tracking and filtering noisy ECG signals. The evaluation of the EKF carried out in this works was pretty qualitative. In realistic applications it is essential to symbolize greater quantitative measures, collectively with problems regarding the stability and convergence of the Kalman filter. The filtering performance is tremendously reliant on the underlying dynamics assumed for the ECG signal. It turned into shown that through the use of a bendy nonlinear dynamical model, together with the EKF, it's far possible to construct a filter which can eliminate environmental noises and artifacts. The proposed technique can serve as a base for the layout of a robust ECG clear out, with giant packages for low SNR ECG signals which include the noninvasive fetal cardiac sign extraction. Future works encompass the aggregate of the proposed EKF version with supply separation strategies, for the extraction of maternal and fetal cardiac indicators from multi-channel surface electrode recordings.

Sim Kuan Goh, Hussein A. Abbass1, Kay Chen Tan, and Abdullah Al Mamun (2014), [6] in step with them Independent Component Analysis (ICA) has been widely used for isolating artifacts from Electroencephalographic (EEG) signals. Still, a few challenging problems remain. First, in actual-time programs, visual inspection of components has to get replaced with an automatic identification approach or a heuristic for artifacts detection. Second, as they may provide an explanation for extra inside the work, they expect to have a clean order relationship among an electrode and a corresponding element. Third, they want to minimize the EEG information loss in the course of artifact removal at the same time as also minimizing the residue of the artifact in the wiped clean signal.

In this work, they endorse a decomposition of the unbiased additives. This decomposition separates each aspect into vectors, one - they name local vector - continues most information from the precise EEG facts encoded by using an electrode, even as the other - they call shared vector - absorbs over- lapping artifact facts. They present a specific Pareto-based totally multi-goal optimization method that change-off similarity between the neighborhood vector and the authentic vector on the only hand, and the uncorrelatedness of all local vectors from all components on the other hand. They display that the proposed method can automatically isolate artifacts from an EEG sign while maintaining most EEG data.

M Murugappan, Reena Thirumani, Mohd Iqbal Omar, and Subbulakshmi Murugappan (2014) [7] in line with them the primary objective of this work is to develop a portable and price powerful information acquisition (DAQ) system for scientific packages. This DAQ includes numerous modules which includes electricity deliver, analog to digital converter (ADC), amplifiers, isolators, filters and interfacing circuits. The whole information acquisition circuit has been evolved using This gadget mainly goals to gather the ECG indicators of frequency between 0.05 Hz and 113 Hz with a gain of 3113. This frequency data from the ECG sign is fairly useful medical programs together with SCA prediction, cardiovascular sickness (CVD) detection, and so on. ECG indicators could be accumulated from the subjects using 3 leads system and given to DAQ for recording the ECG signal. The obtained sign thru this DAQ will then be transferred to the Notebook through NI6008 facts acquisition card. This DAQ interface is used to transform the input analog sign to digital signal output and to keep the ECG statistics within the notebook the usage of LabVIEW software program. This acquired sign from LabVIEW software is used for similarly medical research. We also advanced a Graphical User Interface (GUI) in LabVIEW software to constantly monitor the ECG sign strains and to record the ECG information with better precision. The morphology of the received ECG signal inside the gadget is notably unique and beneficial for medical analysis. Furthermore, this proposed system is used for growing unexpected cardiac arrest (SCA) prediction in our college.

This works ambitions to design and increase a portable, value powerful and clinically possible ECG information acquisition system the usage of LabVIEW software program. The ECG signal has been generated the usage of ECG Simulator and acquired the usage of three lead ECG information acquisition circuit. The generated sign is preamplified using INA118 instrumentation amplifier and filtered at a cut of frequency of 0.05 Hz – 113 Hz. Because, ECG sign does now not have any beneficial statistics past 100 Hz. This filtered sign is similarly amplified using AD620. This amplified input is surpassed to the PC through NI6008 facts acquisition card. This DAQ card is used to convert the analog ECG signals into digital ECG alerts at a decision of 12 bits. Furthermore, the GUI evolved in this works is more interactive and consumer friendly device to without problems collect the ECG facts from the simulator. The proposed hardware circuit is straightforward and powerful to suppress the noises evolved in the course of the information acquisition. This device has a capability to document the ECG sign for non-stop tracking and saved the ECG information in . Xl’s layout in comparison with different present systems.

Presence of artifacts in electroencephalographs (EEG) is foremost hurdles for the best analysis of spectral conduct. For suppression of ocular artifact in EEG this work proposed via **Vandana Roy and Shailja Shukla (2015), [8]** a component primarily based Independent Component Analysis (ICA) model. It includes the generating a set of character components of given sign followed by means of rejection of undesirable artifacts. Further this works offers a unique technique with mixture of ICA, facts sharing and double density wavelet remodel to reject the artifacts from the signal. The Independent Component Analysis (ICA) here is used to segment artifact peaks inside the signal. Then the Discrete Wavelet Transform(DWT) is carried out for multi-degree switch of sign records until the reception of vast end result. The Wavelet ICA suppression not most effective gets rid of artifacts however additionally preserves the spectral and coherence homes of brain indicators.

In this works the trouble of artifacts elimination for EEG sign has been addressed. A two stage ICA and double density wavelet rework has been integrated for automated artifacts removal. Graphical analysis suggests that double density wavelet transform ICA(DDWICA) outperforms higher than ICA. Mean square errors is calculated to assess the overall performance of removal on 19 channel one at a time. A similarly take a look at has been consciousness on quantitative evaluation of ways a whole lot distortion or statistics loss is due to automated artifact removal with spectral power density. The information shows that two-stage preforms higher than ICA based approach.

Electrocardiogram (ECG) is an image recording of the electric interest produced by the coronary heart. The accuracy of any electrocardiogram waveform extraction plays a crucial position in assisting a better diagnosis of any coronary heart related ailments. They offered **Akinlolu A. Ponnle et. Al. (2015) [9],** a computer-aided application version for detection of cardiac arrhythmia in ECG signal, which consists of sign pre-processing and detection of the ECG sign additives adapting Pan-Tompkins and Hamilton-Tompkins algorithms; feature extraction from the detected QRS complexes, and category of the beats extracted from QRS complexes using Back Propagation Neural Network (BPNN). The utility version turned into advanced for ECG signal type below 'Normal' or 'Abnormal' heartbeats to locate cardiac arrhythmia inside the ECG signal. The model became educated with popular arrhythmia database of Massachusetts Institute of Technology Division of Health Science and Technology/Beth Israel Hospital (MIT-BIH), and taking into consideration the Association for the Advance of Medical Instrumentation (AAMI) preferred. The overall performance of the evolved software model for category of ECG indicators turned into investigated the usage of the MIT-BIH database. The accuracy of detection and extraction of the sign additives and capabilities (primarily based most effective at the MIT-BIH database used) suggests that the evolved application model can be hired for the detection of heart diseases in sufferers.

Automatic category of ECG signal enables in spotting coronary heart illnesses with much less time. A pc-aided utility model for the classification of ECG indicators changed into developed and has been investigated the usage of the MIT-BIH database. The model is primarily based on some present algorithms from literature, which were tailored. The advanced device version entails the extraction of a few morphological capabilities of an ECG signal and simulating it with a trained BPNN item. The accuracy of detection of signal additives and functions extraction, show that the advanced laptop-aided application version may be employed for the detection of heart sicknesses in sufferers. Upon implementation on a computer with a GUI, it can serve as a method of diagnosis of condition of a patient's heart from his/her ECG sign at a low price. The of completion and installation of the utility is pronounced in Part II of this work.

Analysis of EEG activity normally increases the problem of differentiating among actual EEG hobby that's brought via **Arjon Turnip, and Dwi Esti Kusumandari (2015),** [10] via an expansion of outside affect. These artifacts may additionally have an effect on the final results of the EEG recording. In this works, wavelet denoising and band bypass clear out for preprocessing and an adaptive primary aspect analysis based recursive least squares set of rules for extraction are proposed to cast off the artifacts. The set of rules is designed to adaptively derive an extraordinarily small variety of decorrelated linear mixtures of a hard and fast of random 0-imply variables even as preserving as a good deal of the records from the authentic variables as viable. The proposed technique changed into examined in actual EEG data received from eight topics. The experimental result show that the proposed technique can correctly put off the artifacts from all topics.
In this works, an adaptive PCA algorithm to automatically extract event-related components and refine uncooked EEG signals has been addressed. The superiority of this technique is adaptive, identifies the artifacts in a sufficiently small variety of iterations and tracks correctly changes inside the supply indicators. Finally, the consequences the usage of the proposed illustrate the effectiveness of the proposed algorithm disposing of the artifacts and different non-even-related sources, and increasing the visibility of the ERPs on all topics.

Abdominal fetal Electro Cardio Grams (FECGs) convey a wealth of facts about the fetus inclusive of fetal Heart Rate (FHR) and sign morphology throughout exclusive tiers of pregnancy. Here **Radana Kahankova et. Al.,[32]** (2017) stated our outcomes on the implementation and evaluation of two non-adaptive sign processing techniques suitable for FECG signal extraction, specifically: The Independent Component Analysis (ICA) and the Principal Component Analysis (PCA) Methods. We used the fetal heart price extracted from FECG signals (in Beats Per Minute - BPM) and Signal-to-Noise Ratio (SNR) as powerful performance assessment metrics for our applied strategies. Our findings demonstrated that given adequate SNR, those methods produced outstanding effects in accurate determination of FHR. Furthermore, we determined out that compared to the PCA Method, the ICA Method produces a lower variance inside the detection of the FHR.
In this works, we've tested ICA and PCA especially for FHR detection. Both techniques confirmed correct effects, but the FHR detection the usage of ICA showed smaller variance of values. Methods fail to works while input SNR degrees from -30 to -35 dB. In some other assessment, we used SNR as the primary parameter. However, this evaluation is feasible best for PCA because ICA adjustments amplitude of extracted additives. This evaluation showed comparable effects-PCA had excessive overall performance besides the range from -30 to -35 dB. The extracted FECG signal become deformed in case of the usage of each algorithm by the maternal residues. These algorithms display very high overall performance, consequently it is feasible to apply them inside the scientific exercise for figuring out FHR for diagnosing fetal hypoxia. This study may be progressed by way of checking out received FECG with the aid of figuring out so-called T/QRS ratio. However, the deformation of T wave in extracted FECG need to be minimal.

Heart diseases are one of the maximum crucial dying causes across the globe. Therefore, early detection of coronary heart sicknesses is essential to reduce the growing dying price. Electrocardiogram (ECG) is extensively used to diagnose many varieties of coronary heart sicknesses together with strange heartbeat rhythm (arrhythmia). However, the non-linearity and the complexity of the unusual ECG alerts make it very difficult to hit upon its traits. Besides, it is able to be time-ingesting to check those ECG indicators manually. To overcome these limitations, **Mohamed Hammad, et al. (2018) [33],** had proposed fast and accurate classifier that simulates the diagnosis of the heart specialist to classify the ECG indicators into regular and extraordinary from an unmarried lead ECG sign and better than different famous classifiers. First, an accurate set of rules is used for correcting the ECG alerts from noise and extracting the foremost capabilities of every ECG sign. After that, we simulated the characteristics of the ECG alerts and created the proposed classifier from these characteristics. Two Neural Network (NN) classifiers, 4 Support Vector Machine (SVM) classifiers and K-Nearest Neighbor (KNN) classifier are hired to classify the ECG signals and in comparison, with the proposed classifier. The overall thirteen functions extracted from each ECG sign used in the proposed algorithm and set as enter to the other classifiers. Our algorithm is confirmed the usage of all information of MIT-BIH arrhythmia database. Experimental results show that the proposed classifier demonstrates better performance than other classifiers and yielded the best average category accuracy of ninety-nine%. Thus, our algorithm has the opportunity to be applied in scientific settings.

This works provides a category technique based on characteristics of ECG to classify ECG indicators records into ordinary and ordinary instructions. Out of 48 statistics from MIT-BIH arrhythmia database, 25 information are selected as a regular elegance and 23 facts are taken into consideration as peculiar class. An accurate set of rules is used for extracting the capabilities of each ECG alerts. The overall thirteen functions extracted from each ECG signal used on this have a look at to classify the signals. The overall performance of the proposed classifier is comprehensively better than that of other NN, SVM and KNN classifiers and the alternative famous techniques. The usual accuracy of the proposed classifier is 99% with a mean computation time identical 0.006203 s. The proposed classifier solved most of classification troubles and overcomes the misdiagnosis troubles that face many cardiologists. Results display that we will use the proposed classifier to carry out actual-time type of ECG signal. Hence, it's far evident that our algorithm has the opportunity to be applied in medical settings, that can serve as a device to help clinicians in confirming their analysis. In the destiny, we will make bigger this works to categories many types of extraordinary ECG signals including left package deal department block (LBBB), proper package deal department block (RBBB) and Paced beats (P) with precise performance results.

Signals acquired from an affected person i.e., bio-indicators are utilized to research the fitness of patient. One such bio signal of paramount significance is the Electrocardiogram (ECG), represents the functioning of the coronary heart. Any strange behavior inside the ECG signal is an indicative degree of malfunctioning of the coronary heart termed as arrhythmia circumstance. Due to the involved complexities which includes loss of human knowledge and high possibility to misdiagnose, long-time period monitoring primarily based on pc-aided analysis (CADIAG) is desired. There exist numerous CADIAG techniques for arrhythmia prognosis with their personal blessings and obstacles. In this work, **Sai Manoj Pudukotai Dinakarrao et al,** (2019) [34], classified the arrhythmia detection procedures that make use of CADIAG primarily based on the utilized approach. A massive range of techniques useful for arrhythmia detection, their performances, involved complexities and assessment amongst distinctive variants of identical method and throughout one-of-a-kind strategies are discussed. The assessment of various techniques in terms of their performance for arrhythmia detection, and its suitability for hardware implementation toward frame wearable gadgets is mentioned on this work. Arrhythmia detection is one of the broadly researched topics. There exist numerous techniques for arrhythmia detection, starting from simple statistical metrics primarily based methods to state-of-the-art machine studying techniques like neural networks, SVMs, Bayesian classifiers and so forth. Based on the present works, it's been discovered that the gadget getting to know methods outperform conventional strategies in arrhythmia detection. However, the complexity of maximum of the conventional techniques is a lot lower as compared to the device learning strategies. In machine learning strategies, neural networks, SVMs (including their editions) gain better performances. However, neural networks are efficient whilst the wide variety of varieties of arrhythmia to hit upon is small (5-6), while SVMs and their variations are green even when the number of styles of arrhythmias to classify is huge but of better complexity. Additionally, SVMs can be efficiently applied while the quantity of statistics is big, and may as well be applied collectively with information discount techniques such as PCAs. Lastly, Bayesian classifiers, though now not green as compared to neural networks, SVMs, are preferred in particular when there exist no labels for the records.

Classification of electrocardiogram (ECG) indicators is compulsory for the automated diagnosis of cardiovascular sickness. With the latest advancement of low-fee wearable ECG device, it turns into more viable to utilize ECG for cardiac arrhythmia type in each day life. In this work, **Yuwei Zhang et. Al. (2019)** [35] proposed a light-weight technique to categories five forms of cardiac arrhythmia, namely, normal beat (N), atrial premature contraction (A), premature ventricular contraction (V), left package deal branch block beat (L), and proper package department block beat (R). The blended approach of frequency evaluation and Shannon entropy is applied to extract appropriate statistical functions. Information gain criterion is employed to pick capabilities that the effects display that 10 tremendously powerful functions can achieve overall performance measures similar to the ones acquired by means of using the complete features. The selected features are then fed to the input of Random Forest, K-Nearest Neighbour, and 48 for class. To examine category performance, tenfold pass validation is used to verify the effectiveness of our method. Experimental consequences show that Random Forest classifier demonstrates sizeable overall performance with the highest sensitivity of 98.1%, the specificity of 99.5%, the precision of 98.1%, and the accuracy of 98.08%, outperforming different consultant procedures for automated cardiac arrhythmia type.

We have proposed a technique for classifying five sorts ECG heartbeats, specifically, N, A, V, L, and R, which come from MIT-BIH arrhythmia database. The db5 mom wavelet is used for sign frequency area evaluation that the sign is denoised and became clean. CFASE feature extraction technique combined with db6 mother wavelet is used for the function extraction. A comprehensive of 24 capabilities are extracted for the pulse type, and the dimension of the whole capabilities is decreased through IG technique to attain quite informative capabilities. The proposed method has yielded the very best sensitivity of 98.1%, the specificity of 99.5%, and the precision of 98.1% and the accuracy of 98.08%. It makes contribution to lessen the computational cost and improves the category efficiency. In the destiny, we plan to growth the class accuracy primarily based on the challenge schooling scheme: (a) growth the variety of samples and analyze various types ECG heartbeats from special databases, (b) extract extra quantity of suitable capabilities for ECG signal category, and (c) the usage of deep studying methods on class for extra distinct forms of ECG heartbeats.

CHAPTER 3

METHODOLOGY

3.1 ECG Signals

The extraction of excessive resolution ECG alerts from noisy measurements is the various most tempting open problems of biomedical sign processing. Specifically, the extraction of ECG indicators from low SNR measurements is the state of the artwork in programs consisting of the noninvasive extraction of fetal ECG indicators, recorded from an array of electrodes placed on the maternal abdomen [27].

On the alternative hand, in current years some research has been conducted closer to the generation of artificial ECG indicators. Regarding the physiological bases of ECG signals, a true ECG version have to recollect the morphology of the PQRST complex, collectively with the RR-wave timing. In a previous work [22], an artificial model has been proposed which has unified the morphology and pulse timing of the ECG sign in an unmarried nonlinear dynamic version. Concerning the simplicity and versatility of this model its miles believed that it may be effortlessly adapted to a broad elegance of regular and bizarre ECG indicators. This model can be further used in dynamic adaptive filters, consisting of the Kalman Filter, for ECG filtering packages. Meanwhile, the dynamic version of [22] is nonlinear and requires the nonlinear counterparts of the conventional Kalman Filter.

In a current painting [23], the authors have evolved an Extended Kalman Filter (EKF) based totally on the referred to dynamic version for noisy ECG filtering. In this paper, the synthetic ECG version has been similarly changed to meet the requirements of the EKF filter. The EKF model parameter selection has also been computerized that allows you to adapt the technique to exceptional ordinary and atypical ECG signals. The outcomes show that the proposed approach can completely music the ECG signal even within the noisy epochs, where the determined ECG signal is almost misplaced in noise.

Electrocardiogram (ECG) alerts performs a vital position in scientific diagnosis specially for diagnosing heart associated illnesses and disorders which include, cardiovascular sickness

(CVD), pulmonary disorder, sudden cardiac arrest (SCA), and so on [27]. ECG signal is generated by means of a nerve impulse stimulus to a coronary heart. The modern is subtle around the surface of the frame and build on the voltage drop, that is a typically 0.0001 to 0.003volt and the indicators are in the frequency range of zero.05 to one hundred Hz [27] [22]. ECG indicators are commonly recorded at the surface of the frame and processed to give crucial information approximately the electrical hobby of heart. A standard ECG tracing of a normal heartbeat includes a P wave, a QRS complicated and a T wave (Figure 3.1). Usually, the signal which is acquired from the human body is of very low potential and difficult to analyze the signal variance. Hence, necessary amplification is required before processing the ECG signal to derive any give useful information about the cardiac abnormalities.

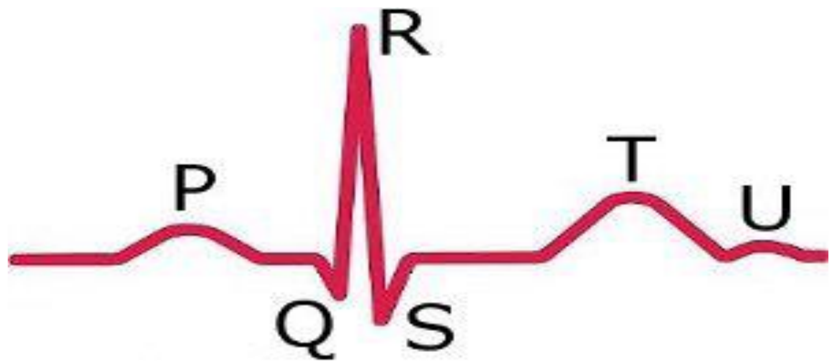


Fig 3.1: The elements of ECG complex

Biomedical signals are observations of physiological activities of organisms, ranging from protein sequences, tissue and organ images, to neural and cardiac rhythms. Biomedical signals are obtained by electrodes that record the variations in electrical potential generated by physiological processes. Each physiological process is associated with certain types of signals that reflect their nature and activities. Observing these signals and comparing them to their known norms, diseases or disorders can often be detected. When such measurements are observed over a period of time, a one-dimensional time-series is obtained which is called a physiological signal. Arrhythmia is a generalized term used to denote any disturbances in the heart's rhythm. Cardiac Arrhythmia is an abnormal rate of muscle contractions in the heart. These abnormalities of heart may cause sudden cardiac arrest or cause damage to heart. Proper diagnosis of arrhythmia requires an electrocardiogram.

An electrocardiogram is a graphic recording of the electrical activity produced by the heart. Electrical activity radiates from the heart in all directions. The ECG signal is recorded by properly pasting a certain number of electrodes on the body [27]. A typical ECG signal of one heart beat is shown in Figure 3.1. The heart provides the driving force for the circulation of blood. It contains four-chambered pump with two atria for collection of blood and two ventricles for pumping out of blood. The resting or filling phase of a cardiac chamber is called diastole; the contracting or pumping phase is called systole. A normal ECG pattern consists of P wave, QRS complex, and T wave. The QRS complex, in turn, includes three separate waves: Q, R and S. All these are generated when the cardiac impulse goes through the ventricles. The P wave depends on electrical currents generated when the atria depolarize before contraction, and the QRS complex is produced by currents arising when the ventricles depolarize prior to contraction. Therefore, P wave as well as the components of the QRS complex corresponds to depolarization waves. The T wave, which is caused by currents arising when the ventricles recover from the depolarization state, is known as the repolarization wave.

By interpreting the details In the ECG waveform, a huge variety of coronary heart situations can be recognized. Therefore, the satisfactory of the signal is extremely crucial. Signal processing is done within the vast majority of systems for ECG analysis and interpretation. It is used to extract some characteristic parameters [22], [23]. Now a days, biomedical sign processing has been toward quantitative or the goal evaluation of physiological systems and phenomena via sign analysis [24], [25].

3.2 Artifacts Removal in ECG Signals

ECG artifacts are the recorded signals which can be non-cerebral in starting place. The ECG indicators are divided into one in every of two categories depending on their beginning: physiological artifacts and non-physiological artifacts [27]. The amplitude a sign is subjected to the pastime of cortical signals taken under consideration. The fashionable categories of artifacts which are entertained consists of: ECG, EMG, EOG, aware or subconscious frame activity, electrodes and so forth. The details of the impact of those classes are given in [22]. Artifacts are ubiquitous i.e. They are present in each ECG tracing. Artifacts on being difficult

to understand the ECG activity and render the ECG uninterruptable. Williams et al. [26] said, “Artifacts can mimic almost any kind of cerebral hobby and lead to serious interpretation.”
The artifact removal methods focus on dismantling the ECG epochs that lies outside the range of threshold values. Most of these methods are statistical in nature and does not consider any portion of signal outside their range. An example of such strategies such as regression offline method [27] and Fourier transform [22] leads in loss of data.
Ocular artifacts are significant observation in ECG [23], It involves skilled resource to remove manually or semi-automated method which influences majority of meaningful data loss for subsequent analysis. The presence of eye blink signals in neural signals is evident and bidirectional in nature. For separation of EOG signals, regression methods are employed for differentiating EOG from ECG.
A component based automated separator of artifacts is required to overcome this issue based on linear decomposition of signals into source components. The components give individual nature of information, where artifacts information combines into separate sources and reconstruction of signals without this source are claimed as artifact free information. P. Levan [19] Hyvarinen A and Oja E [20] on a 30s window size applied Fast ICA Algorithm 8using ECGLAB platform. They developed an automated system for artifact removal based on ICA and Bayesian Classification. Hemant K. Sawant and Zahra Jalali [28] analyzed ECG waves by DWT for frequency domain analysis. P. Senthil Kumar et al. [21] presented a statistical method based on wavelet transform to mimic ocular artifacts in ECG. Haslaile. Abdullah proposed wavelet-based image processing technique at various window size. 1-D double density and 1-D double density complex were tested at window size of 10s, 30s, 60s and 300s for ECG signals.

3.3. Independent Component Analysis

To rigorously define ICA (Jutten and Herault, 1991; Comon, 1994), we can use a statistical "latent variables" model. Assume that we observe n linear mixtures x_1 ,……, x_n of n independent components

$$X_j = a_{j1}s_1 + a_{j2}s_2 + \ldots\ldots + a_{jn}s_n \text{ , for all j.}$$

We have now dropped the time index t; inside the ICA version, we anticipate that each combination x_j in addition to every impartial component s_k is a random variable, as opposed to a right time signal. The located values $x_j(t)$, e.g., the microphone indicators in the cocktail birthday party problem, are then a sample of this random variable. Without lack of generality, we will anticipate that each the combination variables and the unbiased additives have zero suggest: If this isn't real, then the observable variables xi can usually be centered with the aid of subtracting the sample mean, which makes the model zero mean.

The ICA/ECG toolbox of Makeig and associates (1997) protected a collection of MATLAB functions for signal processing and visualization of ECG facts consisting of runica(), a characteristic for automatic infomax ICA decomposition (Makeig et al., 1997), ERP-picture plotting (Jung et al., 1999; Makeig et al., 1999), a way of visualizing time-locked capability variations throughout sets of unmarried trials, and time-frequency decomposition (Makeig, 1993). By 2002, over 5,000 researchers from over 50 nations had downloaded the ICA/ECG toolbox. However, the supplied tools should handiest be used for ECG evaluation by way of knowledgeable users.

A primary device of ECGLAB is to facilitate the manner of making use of and evaluating the outcomes of impartial component analysis (ICA) of ECG statistics. ICA algorithms have established capable of isolating each artifactual and neurally generated ECG resources (Makeig et al., 1999; Jung et al., 2000) whose ECG contributions, throughout the schooling records, are maximally impartial of each other. ICA changed into first implemented to ECG via Makeig et al. (1996) and is now extensively used in the ECG studies network, most customarily to hit upon and put off stereotyped eye, muscle, and line noise artifacts (Jung et al., 1999; Jung et al., 2000). The temporal independence assumption of ICA is with ease understood as a basis for isolating artifact assets, considering their sports will in most cases no longer be reliably phase-locked to each other, given enough training statistics. In practice, however, ICA additionally has proved capable of setting apart biologically potential mind sources whose interest patterns are quite linked to behavioral phenomena. In fact, among the biologically attainable assets ICA identifies in ECG information have scalp maps almost fitting the projection of a single equal modern-day dipole (Jung et al., 2001; Makeig et al., 2002), and are therefore pretty compatible with the projection to the scalp electrodes of synchronous neighborhood area activity within a connected patch of cortex.

ECGLAB carries an automatic model, runica (Makeig, 1997), of the infomax ICA algorithm (Bell and Sejnowski, 1995) with several enhancements (Amari et al., 1996; Lee et al., 1999) each as a Matlab feature and as a stand-by myself binary C software that lets in quicker and less reminiscence-extensive computation. The toolbox also permits the consumer to pick any of over 20 available ICA algorithms which includes JADE (Cardoso and Souloumiac, 1993) and fixed-point ICA (Hyvarinen and Oja, 2000).

Though it isn't always our intention right here to describe ICA in detail, we will try and provide a few insights approximately its nature. In quick, ICA reveals a coordinate frame wherein the statistics projections have minimum temporal overlap. The center mathematical concept of ICA is to limit the mutual information a number of the data projections or maximize their joint entropy. ICA can be considered as an opportunity linear decomposition to major issue analysis (PCA). PCA carried out in the temporal area might in particular make each successive aspect account for as a good deal as possible of the activity uncorrelated with previously decided additives – whereas ICA seeks maximally independent assets. This difference in desires ends in dramatic differences in their effects. PCA components are both temporally and spatially orthogonal, a constraint unrealistic for actual ECG resources, which stand up in domains (spatial areas) of partially synchronous interest in electrically oriented cortical neurons (and in all likelihood glia). Because the density of cortical connections is weighted in the direction of local connections (<<1 cm), specifically within the community of inhibitory cells that preserve cortical oscillations (Pauluis et al., 1999), the partly synchronous domain names giving rise to ECG interest recorded on the scalp need to be specifically compact – although the extent and density of these partly synchronous sports are not recognized. Through easy extent conduction, the projection of synchronous activity within almost any patch of cortex will be giant on the scalp. Any electrode will therefore sum contributions of ECG assets in a massive portion of cortex. ECG supply contributions to scalp electrode potentials rely upon supply strengths and orientations as plenty as supply locations. The scalp projections of actual brain ECG resources, therefore, are nearly continually overlapping and non-orthogonal, opposite to the idea of PCA. Indeed, because of the spatial orthogonality constraint, projections of smaller primary components to the scalp generally resemble checkerboard maps that couldn't constitute coherent interest within a related patch of cortex. Therefore, to locate biologically achievable resources, PCA should be observed by using an axis rotation procedure. Previously proposed tactics, consisting of Promax and Varimax, have been drawn from the issue analysis literature. ICA may be viewed as an extra effective rotation technique, though in exercise ICA is commonly implemented to the original data without PCA preprocessing (for info, see Makeig et al., 1999). ICA seeks to locate component time courses that are at the same time unbiased, that means that factor cross correlations in addition to all of the better-order moments of the signals are 0. ICA is unfastened to adapt to the actual projection styles of ECG mills if their activity time courses are (near) unbiased of one another. ICA is now being implemented to many biomedical sign processing issues which includes decomposing fMRI facts (Duann et al., 2002b) and speech and noise separation (Park et al., 1999). Performing ICA decomposition is maximum suitable when sources are linearly mixed in the recorded indicators, without differential time delays. These assumptions are precisely met for mind (and non-brain) generator tactics summed by volume conduction in scalp ECG statistics. Because ICA does no longer try to maximize the variance of every aspect, ICA additives can also account for extra same portions of the total alerts than PCA components. For example, in 32-channel decompositions ICA component activities normally account for close to 0% to about 5% of the entire alerts. ICA may additionally usefully be carried out to records with 128 or 256 channels, even though significant outcomes also are feasible the use of 32 or fewer channels (Makeig et al., 2002). Some in advance studies applied ICA to collections of ERP records averages (Makeig et al., 1997; Makeig et al., 1999). However, this technique calls for care and warning in interpretation of effects. To separate two or greater strategies, ICA calls for that their independence be expressed in the information. A small set of information averages may not include enough conditions in the training set to demonstrate the independence of the underlying procedures. If, for instance, several techniques are partly section reset in similar approaches, the resulting occasion-locked reaction averages may not express their underlying useful and temporal independence. Data averages, through their nature, incorporate sums of activities occurring at comparable latencies relative to a few classes of activities. When two or more sources always contribute to a hard and fast of reaction averages at the identical latency, ICA, skilled on these averages, may also assign their summed sports to an unmarried factor. Trained at the unaveraged facts but, ICA may additionally use their relative variability in unmarried trials to split them. A 2nd problem with applying ICA to information averages is that the averaging process nearly cancels out the interest of a number of the ECG sources. Thus, applying ICA to the unaveraged ECG facts additionally lets in ICA to split ongoing hobby of ECG assets although they're simplest partially section-locked for short time durations. This is maximum useful when there is an enough quantity of channels to suit the liveliest ECG and artifact processes.

3.4. Empirical Mode Decomposition

EMD algorithm depends on a number of options which have to be controlled by the user and which require some expertise.

3.4.1 Sampling, interpolation and border effects

A basic operation in EMD is the estimation of upper and lower “envelopes” as interpolated curves between extrema. The nature of the chosen interpolation plays an important role, and our experiments tend to confirm (in agreement with what is recommended in [2]) that cubic splines are to be preferred. Other kinds of interpolation (linear or polynomial) generally tend to boom the desired wide variety of sifting iterations and to “over-decompose” indicators by using spreading out their components over adjoining modes. A 2d factor is that, since the set of rules operates in practice on discrete-time signals, a few unique interest must be paid to the reality that extrema should be correctly identified, a pre-needful which calls for a truthful amount of oversampling Finally, a third issue that has to be taken under consideration is related to boundary conditions, with a purpose to decrease blunders propagations because of finite statement lengths. To this stop, we reap top consequences by using mirrorizing the extrema close to the rims.

3.4.2 Stopping Criteria for Sifting

The extraction of a mode is taken into consideration as satisfactory while the sifting procedure is terminated. Two situations are to be fulfilled on this admire [2]: the primary one is that the variety of extrema and the range of zero-crossings should differ at most by way of 1; the second is that the mean between the higher and decrease envelopes have to close to 0 in keeping with a few criterion. The assessment of the way small is the amplitude of the imply needs to be accomplished in evaluation with the amplitude of the corresponding mode, however enforcing a too low threshold for terminating the iteration method leads to drawbacks just like the ones stated previously (over-new release results in over-decomposition). As an improvement to the criteria which have been taken into consideration thus far [2], we recommend in emd.m [9] to introduce a new criterion based totally on 2 thresholds θ_1 and θ_2, geared toward making certain globally small fluctuations within the suggest while deliberating locally huge tours. This quantities to introduce the mode amplitude $a(t) := (e_{max}(t) - e_{min}(t))/2$ and the evaluation function $\sigma(t) := |m(t)/a(t)|$ so that sifting is iterated until $\sigma(t) < \theta_1$ for some prescribed fraction $(1 - \alpha)$ of the total duration, while $\sigma(t) < \theta_2$ for the remaining fraction. One can typically set $\alpha \approx 0.05$, $\theta 1 \approx 0.05$ and $\theta 2 \approx 10\ \theta 1$ (default values in emd.m).

3.4.3 Local EMD

In the classical EMD implementation, sifting iterations practice to the overall duration sign, and they are pursued so long as there exists a neighborhood region where the suggest of the envelopes is not considered as sufficiently small. However, as it has been already mentioned, it seems that over-iterating at the whole signal for the sake of a higher local approximation has the downside of contaminating different parts of the sign, in particular in uniformizing the amplitude and in over-decomposing it by spreading out its additives over adjoining modes. Moreover, the hierarchical and nonlinear nature of the princeps set of rules can by no means assure that the EMD of concatenated alerts will be the concatenation of person EMD's. This observation suggests consequently a first variant upon the preliminary EMD system. This variation, referred to as "local EMD" (local-emd.m), introduces an intermediate step in the sifting process: those local zones where the error remains large are identified and isolated, and extra-iterations are applied only to them. This is achieved by introducing a weighting function $w(t)$ such that $w(t) = 1$ on those connected time supports where $\sigma(t) > \theta 1$, with a soft decay to 0 outside those supports. Thus, simply replaced by $d(t) = x(t) - w(t)m(t)$.

3.4.4 On-line EMD

A 2nd version is based at the commentary that the sifting step relies on interpolations between extrema, and hence most effective calls for a finite range of them (five minima and 5 maxima within the case of cubic splines) for being operated at a given factor. This suggests that the extraction of a mode ought to consequently be viable block wise, without the necessary information of the complete sign (or previous residual). This commentary paved the road for our improvement of an EMD set of rules which operates online and might consequently be carried out to statistics flows (emd_online.m). A pre-needful for the block wise extraction of a method is to use the same variety of sifting steps to all blocks so that it will prevent viable discontinuities Since this would require the information of the complete signal, the quantity of sifting operations is proposed to be constant a priori, and it proved in truth that a few iterations (much less than 10, usually four) are usually enough to extract a significant IMF. The powerful utility of the on-line model of the EMD algorithm that we recommend is received by means of a sliding window working on pinnacle of the neighborhood algorithm described above. The front fringe of the window progresses whilst new information come to be to be had, whereas the rear side progresses by way of blocks when the stopping criterion is met on a block. Based in this principle, an IMF and its corresponding residual can be computed sequentially. The whole algorithm can therefore be applied to this residual, therefore bearing in mind an extraction of the subsequent mode with some put off. An example of how the algorithm works on may be favored by going for walks ex-online.m, an example in which the analyzed signal is the periodization of the three-aspect sign. In this situation, the very last decomposition received on-line on 16000 statistics factors virtually appears because the periodization of the decomposition obtained via decomposing the primary block of 2000 statistics points. Besides the important usefulness of an on-line algorithm for decomposing information flows, one can also factor out its advantage over general (block) algorithms in phrases of computational burden, which fast turns into very heavy when handling long statistics facts.

3.5 ECG Data Recording Mechanism

The development of the model for the application can be divided into the following stages: ECG Signal Pre-processing, Feature Detection, Feature Extraction, and Feature Classification using BPNN. For the signal pre-processing and feature detection, we made use of Pan-Tompkins and Hamilton-Tompkins algorithms [29], and adapted them to suit our application. The algorithms are more popular in QRS detection methods. For the feature classification by BPNN, we adopted MATLAB in-built Levenberg-Marquardt (LM) algorithm. The model accepts and works on already digitally acquired ECG signal, and MATLAB software was used to both implement and evaluate the application model, using MIT-BIH database. Figure 3.2 shows the block diagram representation of the developed ECG beat classifier.

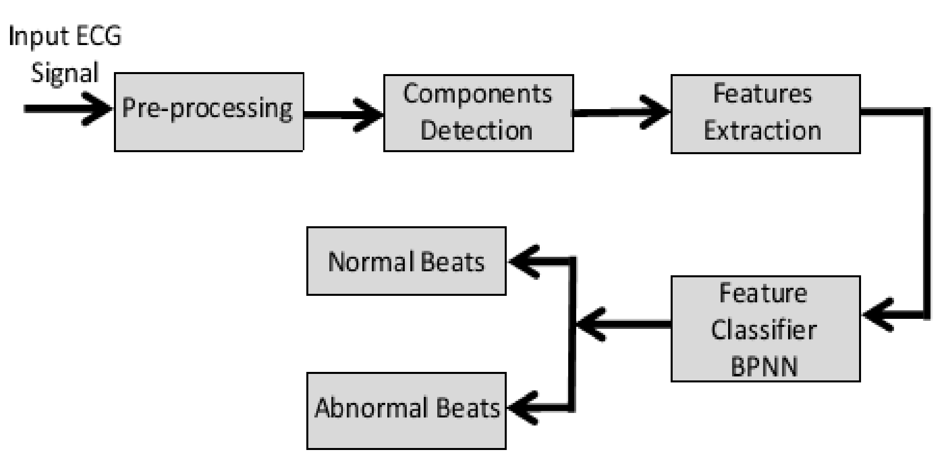


Fig 3.2: Block diagram of the ECG beat classifier.

3.5.1 MIT-BIH Arrhythmia Database

To enable test and comparison of developed algorithms by researchers, common databases are used. The Massachusetts Institute of Technology Division of Health Science and Technology's (MIT/BIH) arrhythmia database contains 48 records, each containing two-channel ECG signals for 30 minutes duration selected from 24-hr recordings of 47 individuals. Many of these databases were developed at MIT and at Boston's Beth Israel Hospital (MIT-BIH), and a website where it can be found is called Physio net [30]. There are 116,137 numbers of QRS complexes in the database. Each recording includes two leads; the modified limb leads II and one of the modified leads V1, V2, V4 or V5. Continuous ECG signals are band pass-filtered at 0.1–100 Hz and then digitized at 360 Hz. Twenty-three of the recordings (numbered in the range of 100–124) are intended to serve as a representative sample of routine clinical recordings and 25 recordings (numbered in the range of 200–234) contain complex ventricular, and supra-ventricular arrhythmias. The database contains annotation for both timing information and beat class information verified by independent experts. Each signal record consists of a period of about 30:06 minutes which is equivalent to 60000 samples. Some records are labeled as 'normal', and some records are labeled 'abnormal'. Among the 'normal' records used are records 100, 101, 103, 105, 106, 109, 111, 112, 113, 115, 116, 119, 122, and 124. Among the 'abnormal records used are records 215, 220, 221, 222, 223, 228, 230, 232, 233 and 234.

3.5.2 ECG Signal Preprocessing

Usually while ECG data is being taken, different types of noise are added to the ECG signal such as electrode motion, power-line interferences, baseline wander, muscles noise etc., and corrupt the original signal. In order to get rid of the noise, a proper filter must be designed [31]. Since very fine features present in an ECG signal may convey important information, it is important to have the signal as clean as possible. A digital ECG signal is read by MATLAB, and is then normalized. The ECG data is then sampled (or re-sampled) at a frequency of 360 Hz (frequency used in the MIT/BIH records). The proposed ECG signal preprocessing model is shown in Figure 3.3. The preprocessing stages consist of low pass filtering, high pass filtering, differentiation, Hilbert transform, squaring and moving average. The low pass and high pass filters are cascaded to form a band pass filter.

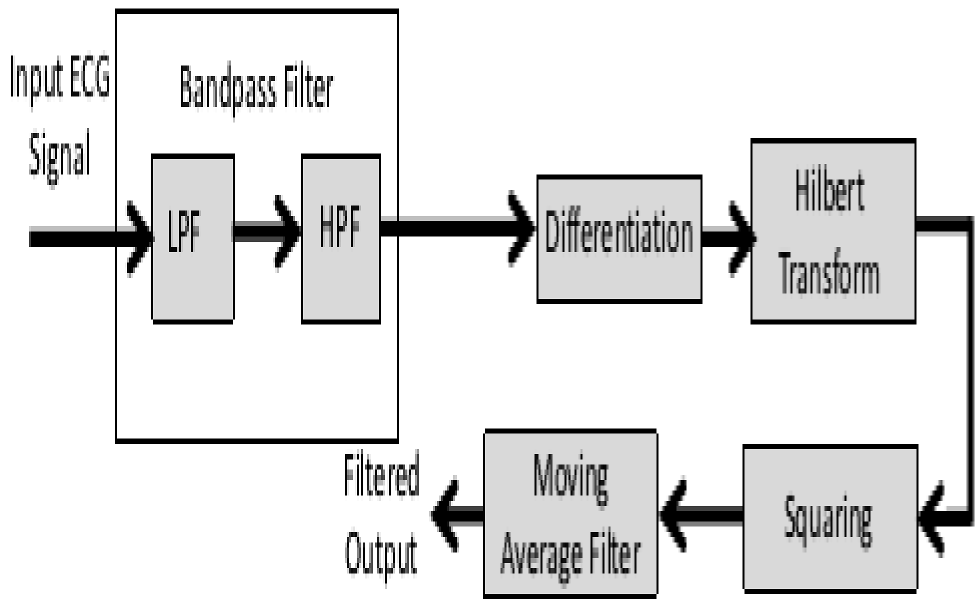


Fig 3.3: Block diagram of the proposed ECG signal preprocessing stage

A Butterworth low skip clear out (LPF) is used to dispose of noise inclusive of the electromagnetic interference and 50Hz electricity line noise. The adopted designed LPF is of order 6, a cutoff frequency of 11 Hz and a sampling frequency of 360 Hz. The distinction equation representing the LPF [29] is

$$y(n) = 2y(n-1) - y(n-2) + x(n) + 2x(n-6) + x(n-12)$$

The IIR LPF was designed in MATLAB and the designed filter object was then used to filter the input ECG signal. The output of the LPF is passed into the high pass filter (HPF) to eliminate motion artifacts. The adopted designed HPF has a cutoff frequency of 5Hz, and the difference equation is given [29] as

$$y(n) = y(n-1) + x(n) + x(n-1) + x(n-5) - x(n-10)$$

The filtered ECG signal is then differentiated to give the slope information by accentuating QRS complexes relative to P and T wave. The differentiator also helps to overcome baseline wandering in the signal. The adopted difference equation used to design the differentiator [29] is

$$8y(n) = 2x(n) + x(n-1) - x(n-4) - 2x(n-5)$$

After the differentiation of the ECG signal, Hilbert Transform is applied to the signal to find the location of R-peak in the ECG signal. The output of the Hilbert transform is squared in order to emphasize the higher frequency component and attenuates the lower frequency component. This helps to suppress the P and T waves.

The squared signal is then passed into the moving average filter (MAF) to produce a waveform with smoothed features by performing moving window integration. The difference equation designed for the MAF is given as

$$y(n) = \frac{x[n-(N-1)]+x[n-(N-2)]+\cdots+x[n]}{N}$$

where N is the length of the MAF, i.e. N-point MAF. In our developed application, we used 3 for the value of N.

3.5.3 Detection of the ECG Signal Components

The next step after preprocessing of the ECG signal is the detection of the R, Q, S, P and T points on the signal waveform. These points were first detected before extracting the features needed for training the neural network object. The flow chart of Figure 3.4 represents the steps of obtaining the points. This was achieved by taking a beat out of the ECG waveform. The beats are extracted using 128 samples centered on R points. Pan-Tompkins and Hamilton-Tompkins algorithms were adapted for this operation to suit our application [29].

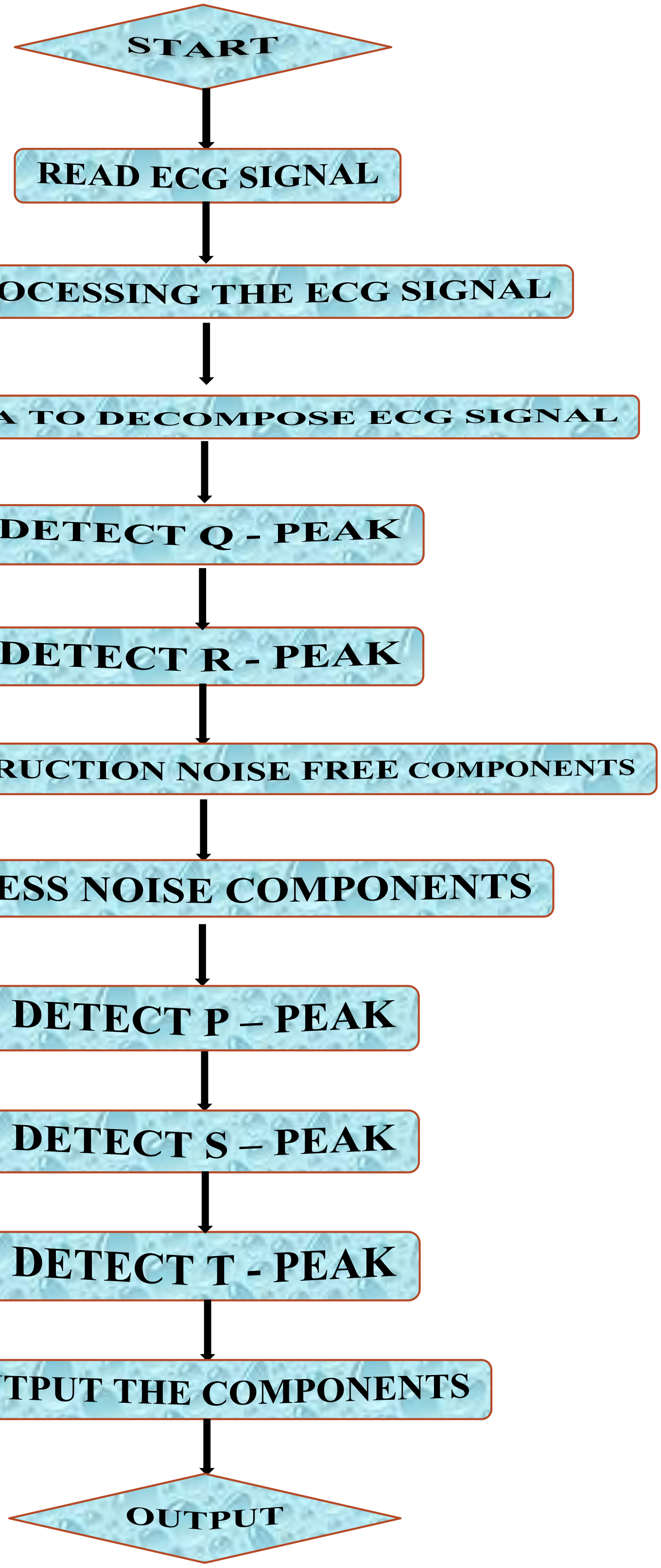


Fig 3.4: Flow Chart of Detection of the ECG signal components.

Basically, in our application, the detection of the points consists of the following steps, which is illustrated in Figure 3.5.

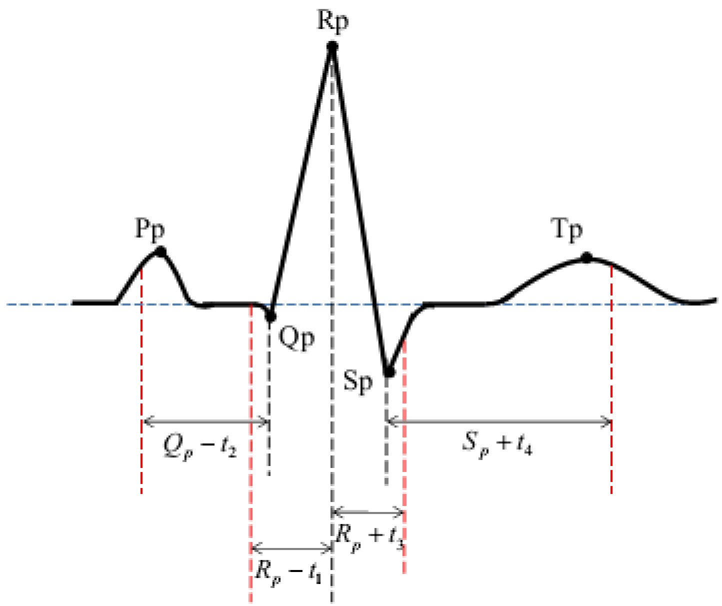


Fig 3.5: Detection of the ECG signal components.

a. Locate the maximum amplitude in the signal beat; this is the R peak. The point at which the R peak is detected is the R point R_p.

b. Shift some steps to the left of R peak, that is R_p - t_1, and locate the minimum amplitude; this is the Q point Q_p. t_1 is the number of steps taken until the signal to the left of R begins to rise i.e. changes direction.

c. Shift some steps to the left of Q_p, that is Q_p - t_2, and locate the maximum amplitude; this is the P point P_p. t2 is the number of steps taken until the signal to
the left of Q_p begins to fall i.e. changes direction.

d. Shift some steps to the right of R_p, that is R_p + t_3, and locate the minimum amplitude; this is the S point S_p. t_3 is the number of steps taken until the signal to the right of R_p begins to rise i.e. changes direction.

e. Shift some steps to the right of S_p, that is S_p + t_4, and locate the maximum amplitude; this is the T point T_p. t_4 is the number of steps taken until the signal to the right of S_p begins to fall i.e. changes direction.

In adapted algorithms, the determination of t_1, t_2, t_3 and t_4 to be adaptive within some predefined time intervals with respect to some pre-determined values based on knowledge of standard normal ECG waveform; as for example, there could be possibility of false peaks to occur due to noise or otherwise between S_p and T_p. The step size is made equal to the sampling interval of the signal.

CHAPTER 4

RESULTS AND DISCUSSIONS

We have considered an ECG data having length of 50000X1 samples. It is an ECG data of healthy person having 10 ECG cycles. The data plot with respect to time axis is shown in figure 4.1 and magnified view of 1st cycle is shown in figure 4.2.

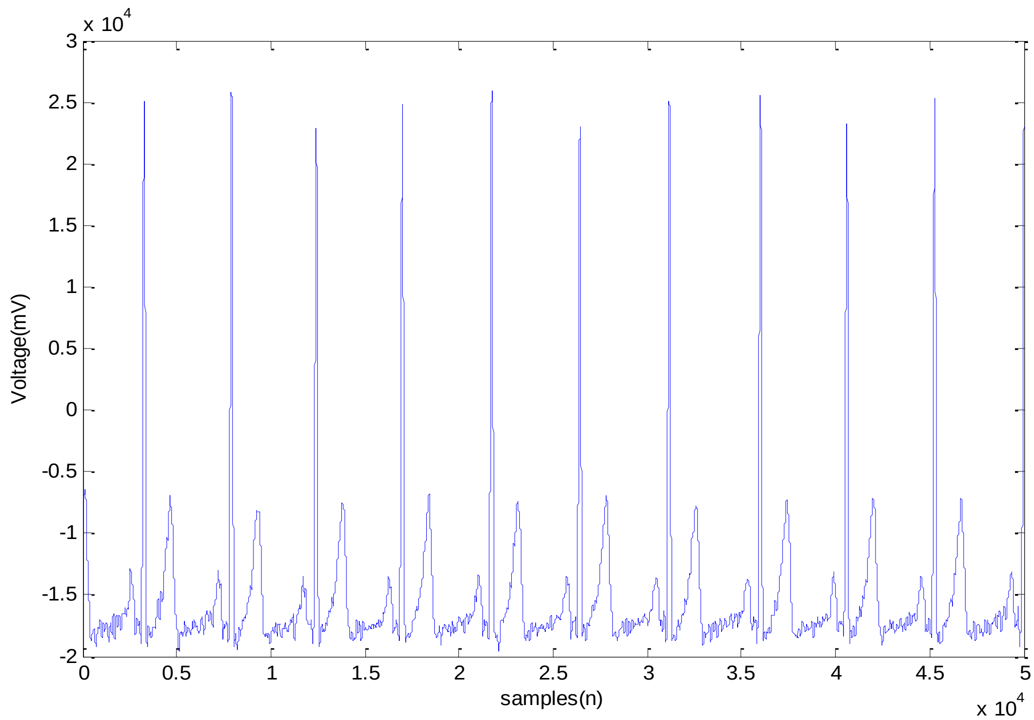


Fig 4.1: ECG waveform of data prior to adding noise.

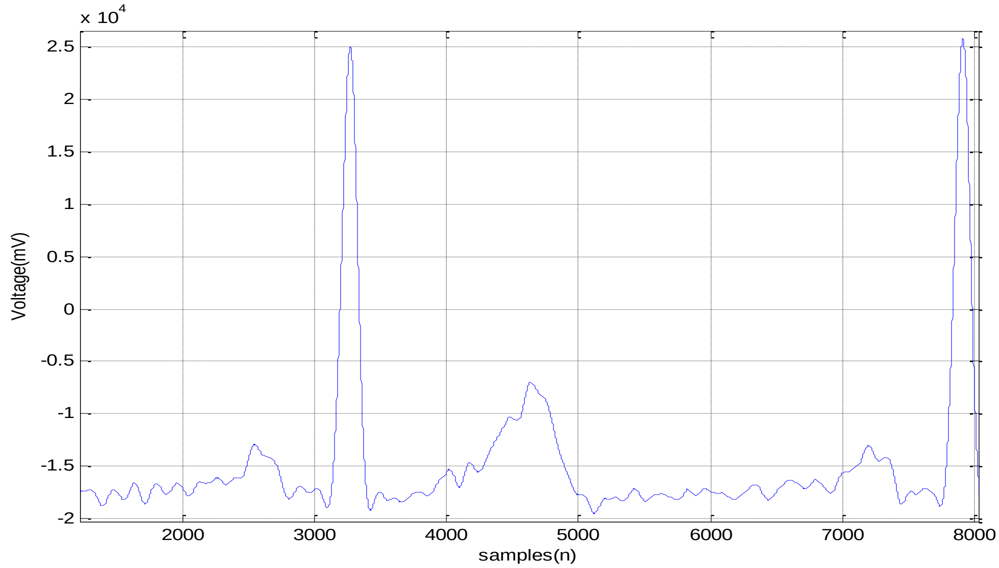


Fig 4.2: Magnified View of 1st ECG waveform of data prior to adding noise

Since above signal shown in figure 4.1 consist of 50000 samples for only 10 cycles it will take large memory space hence processing time. So, the number of samples are reduced by down sampling by 8 times thus total samples we obtained are 50000/8=6250 data points. This down sampled signal is shown in figure 4.3.

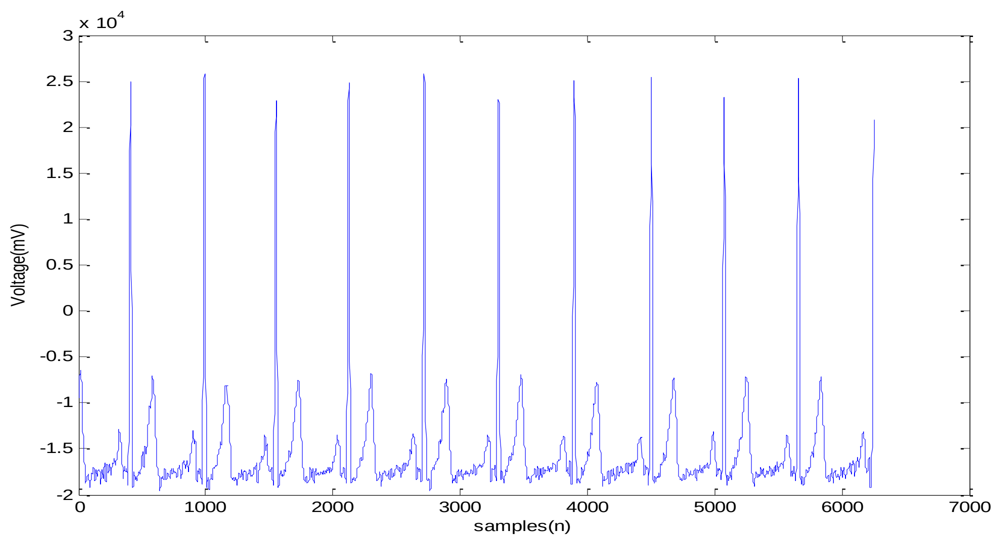


Fig 4.3: ECG waveform of data prior to adding noise after down sampling by 8 times**.**

We can see that there are no significant differences in figure 1 and figure 3 even eliminating the data information by 8 times but along with this denoising processing time will become fast. The above ECG data is to be passed through Empirical mode decomposition (EMD) prior to this we will have to clip multiple portions of above signal to make a multiple dimension data. For clipping out the ECG data we have pointed the peaks location foe the given ECG records as shown in figure 4. 4.From the figure 4.4 we have defined the approximated position of peaks as an array x.

x= [409 998 1552 2127 2716 3300 3896 4520 5075 5659 6250].

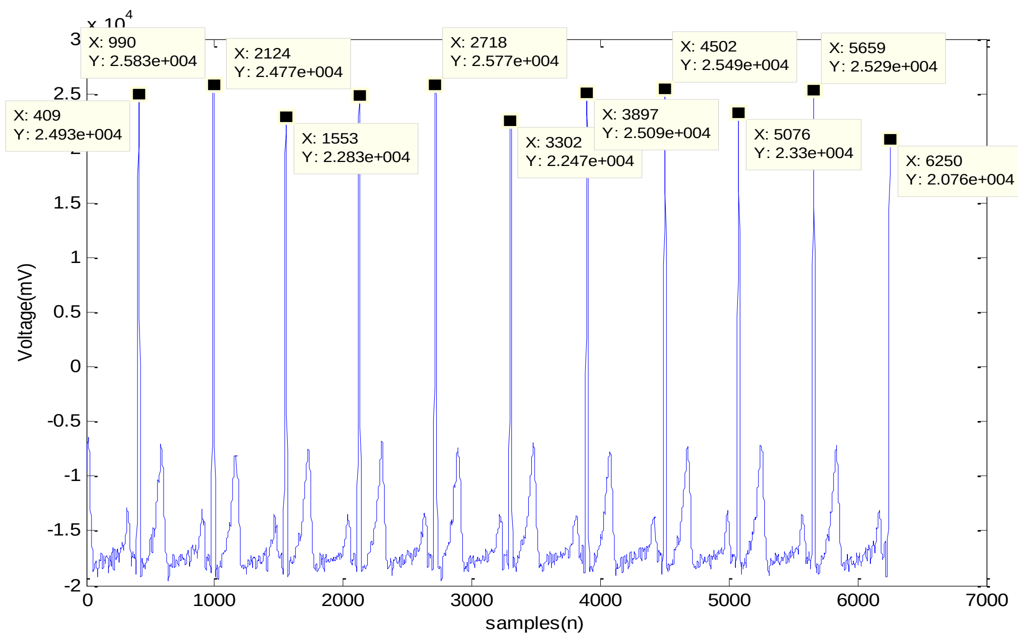


Fig 4.4: ECG data peak location for all 10 cycles. (x: location of peak value, y:value of peak ECG voltage).

Since available database of any biomedical signals are contributed by standard research lab hence, they are extremely high-quality instrument-based measurements values and taken under several precise environment. Due to this these data do not consist of any noise. For testing our denoising algorithm we require to add noise in these data such that they exhibit distortions. We have added noise shows distortions in their waveforms. We have added

Gaussian noise in the signal having noise power 10% of the signal power. The generated noisy signal and its magnified view are shown in figure 4.5 and 4.6.

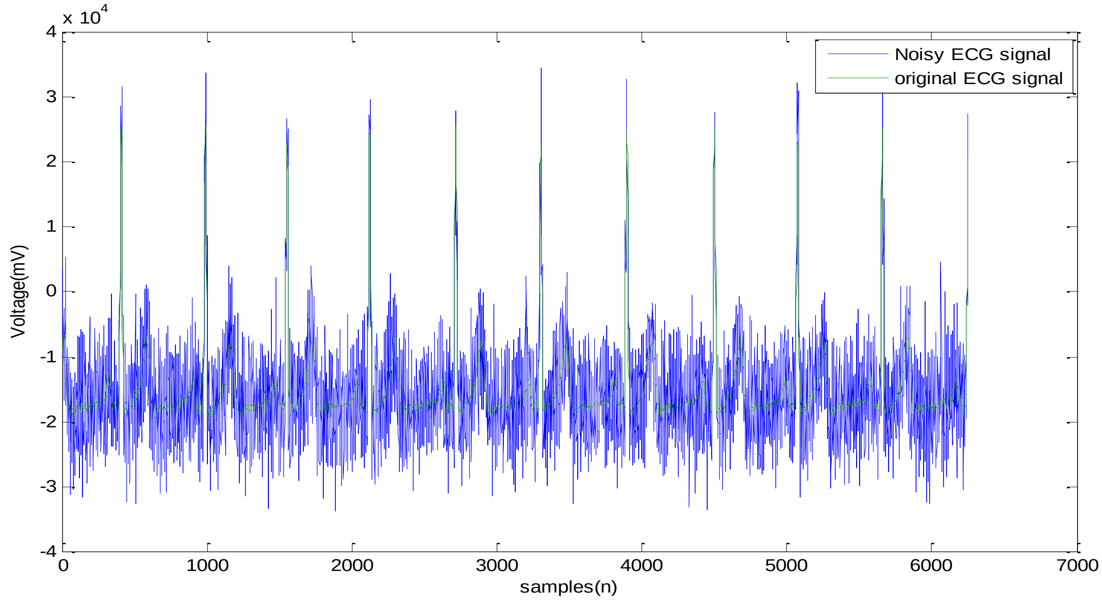


Fig 4.5: Noisy ECG data (blue) and original ECG data (red).

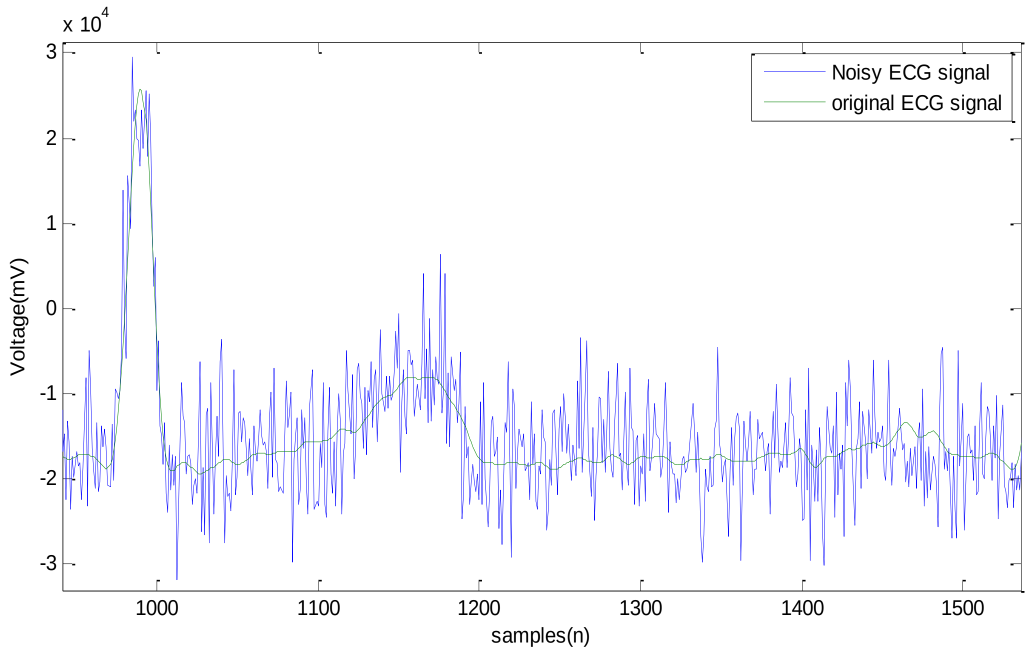


Fig 4.6: Magnified View of Noisy ECG data (blue) and original ECG data (black).

As per the location ECG signal cycles are one by one for performing the EMD of the noisy ECG data cycles. For example, first two cycles are taken by assigning samples from first peak to third peak location given in array x. All the clipped ECG cycles are shown in figure 4.7 below.

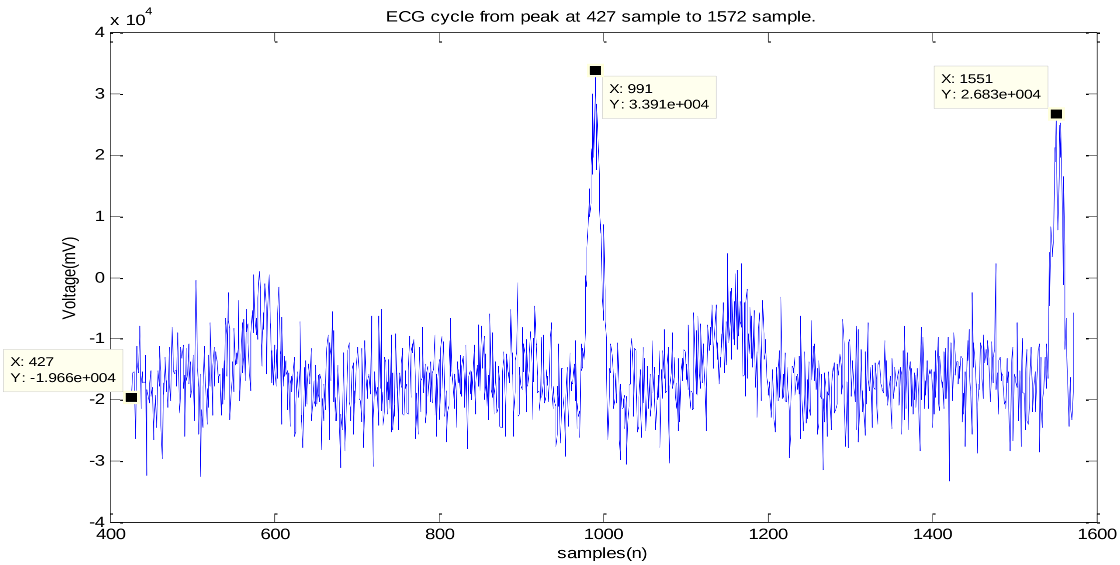


Fig 4.7: Clipped Noisy ECG signal from first two cycles.

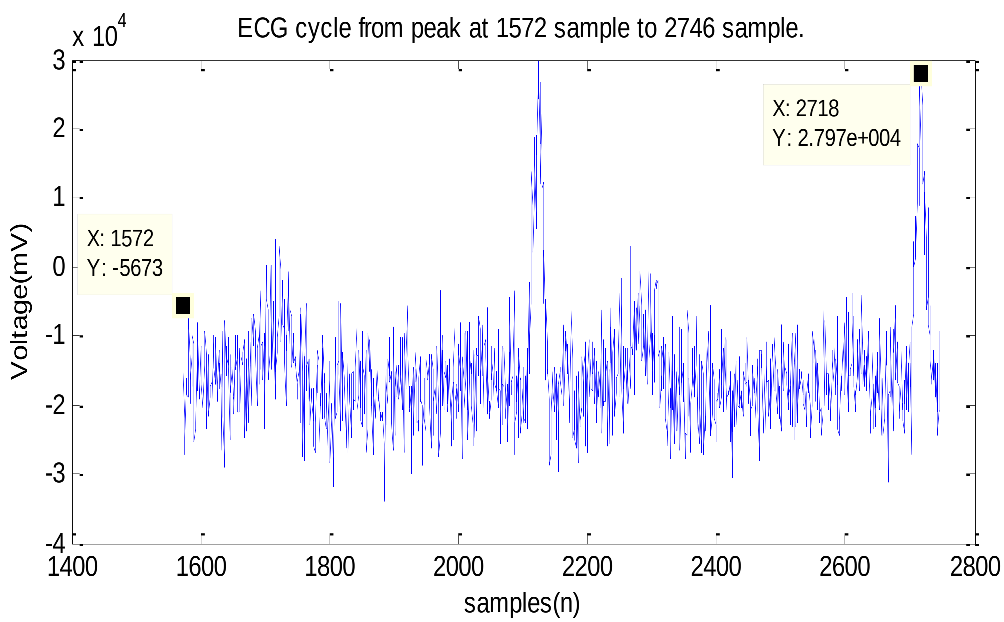


Fig 4.8: Clipped Noisy ECG signal from third to fifth cycles**.**

Similar to cases of figure 4.7 and we have taken the discrete data blocks one by one for the processing under EMD algorithm to obtain these cycles 12 decompositions. All the 12 de-composed components of EMD for the cycles of figure 4.7 are shown in figure 4.9 below. The top left is the ECG signal and remaining 12 are EMD components.

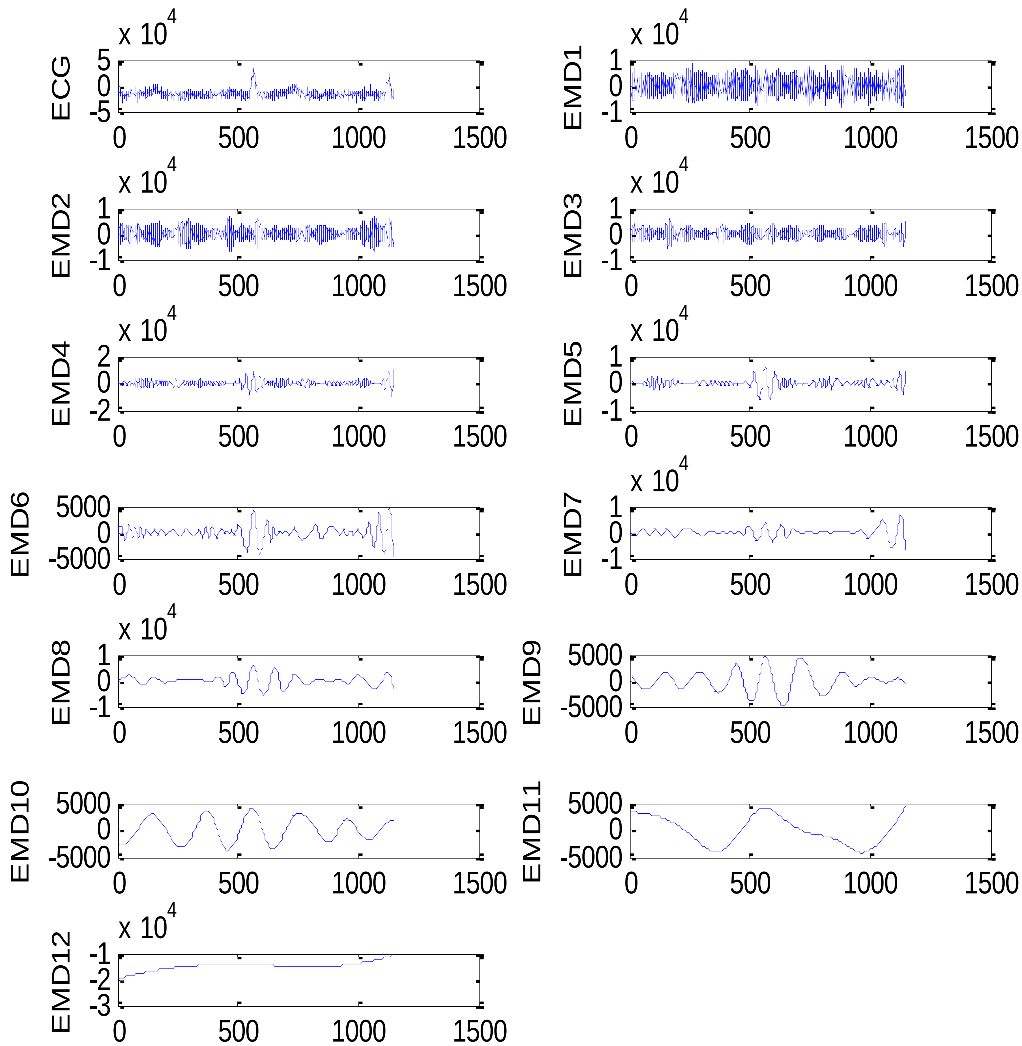
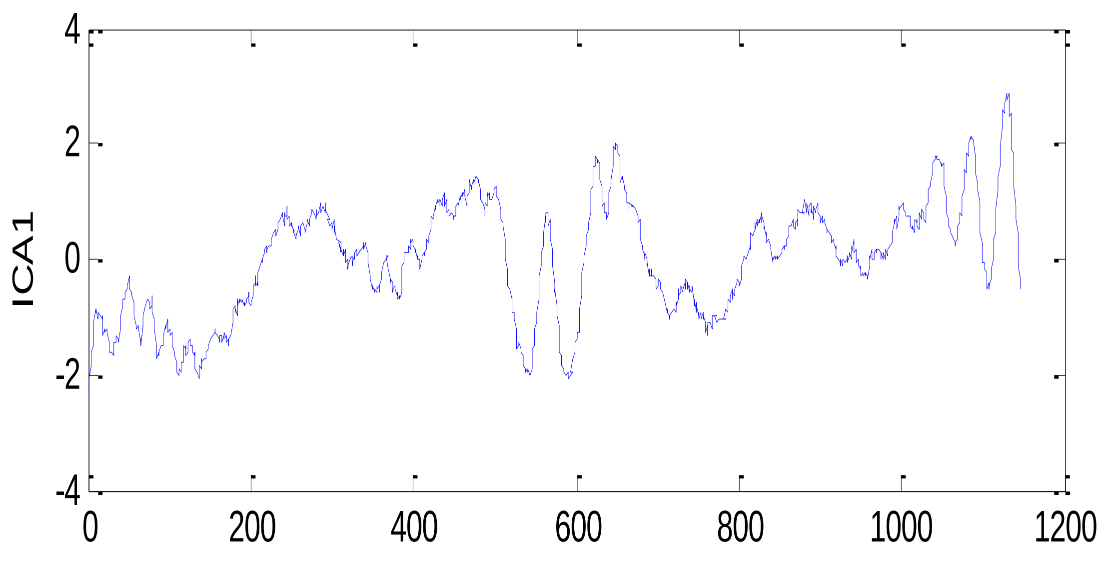
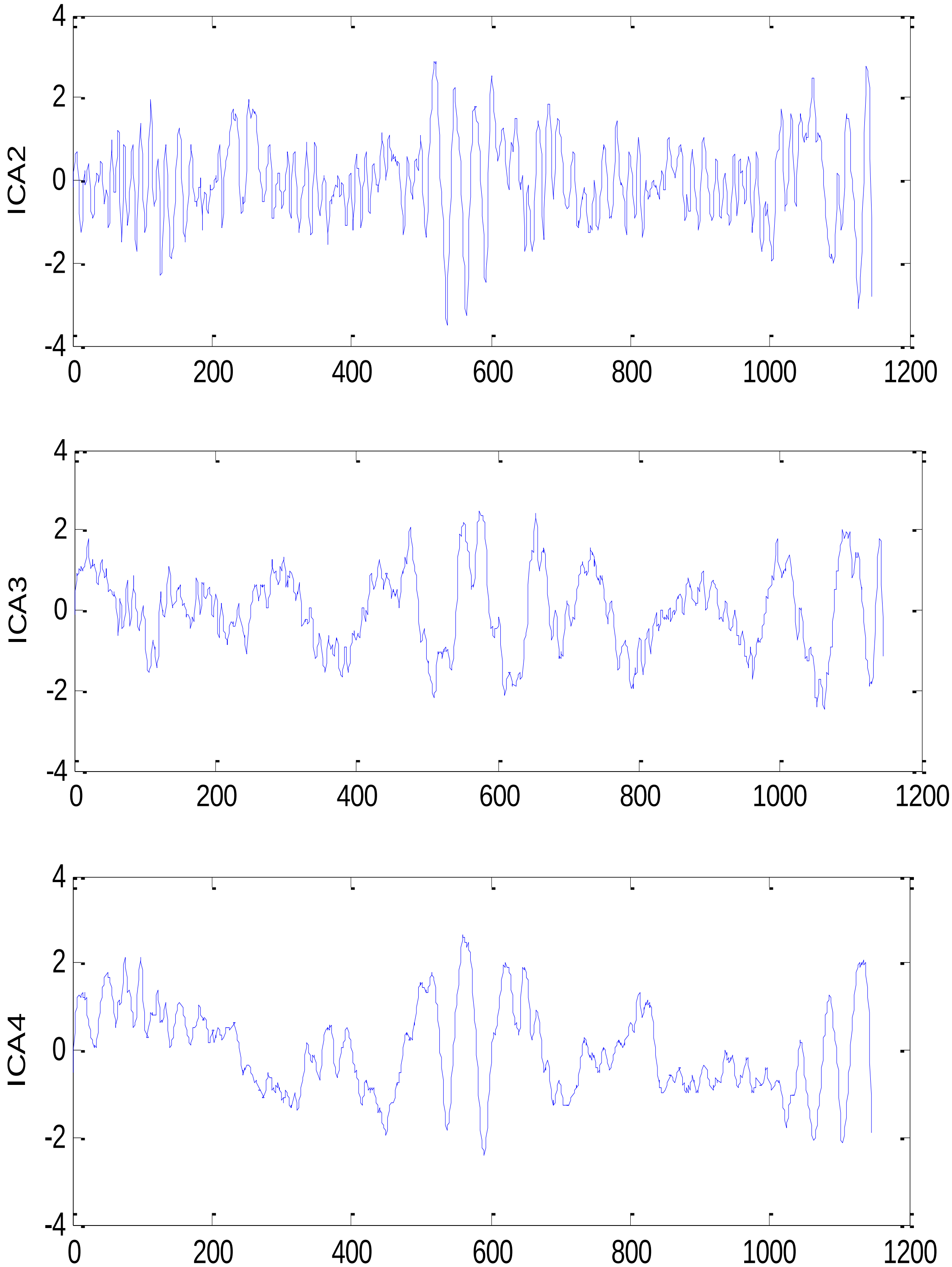


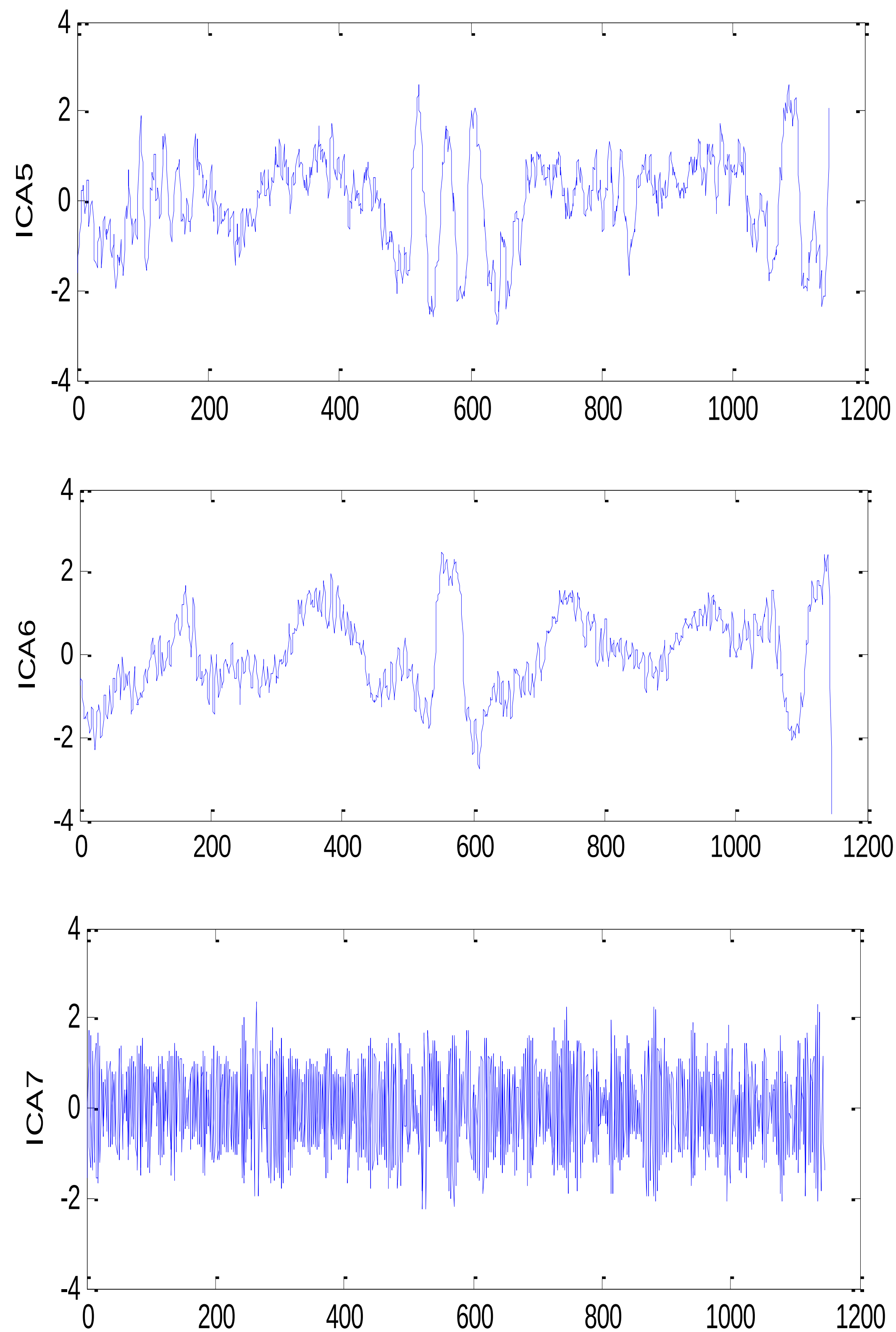
Fig 4.9: Initial two cycles of noisy ECG and its EMD components from EMD1 to EMD12.

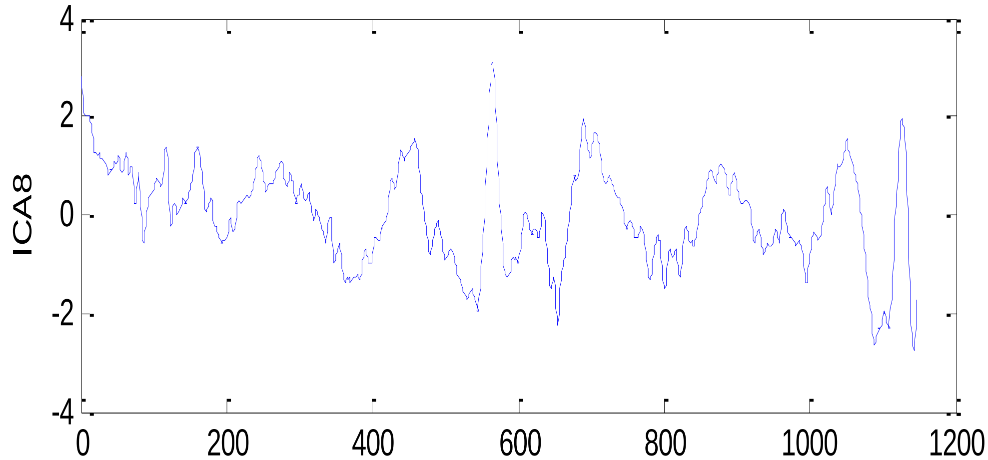
The ECG is decomposed by EMD algorithm as per the significance level of these components hence the EMD has highest significance and the as we move towards EMD12 the signal significance reduces. All these signal are the parts of ECG cycles but they are representing different patterns of the data some are periodic while some are random (EMD 11 ,EMD 10 and EMD 9) while some of them are similar as pure ECG wave (EMD6 ,EMD7 ,EMD and EMD4) but EMD1 and EMD3 are seems to be random and representing noise components and EMD 12 is constant. Hence it indicates that there is higher probability to of discriminating these signals to each other as per there variations but still we are finding that all the components exhibit some amount of similarity it is because they are not independent to each.

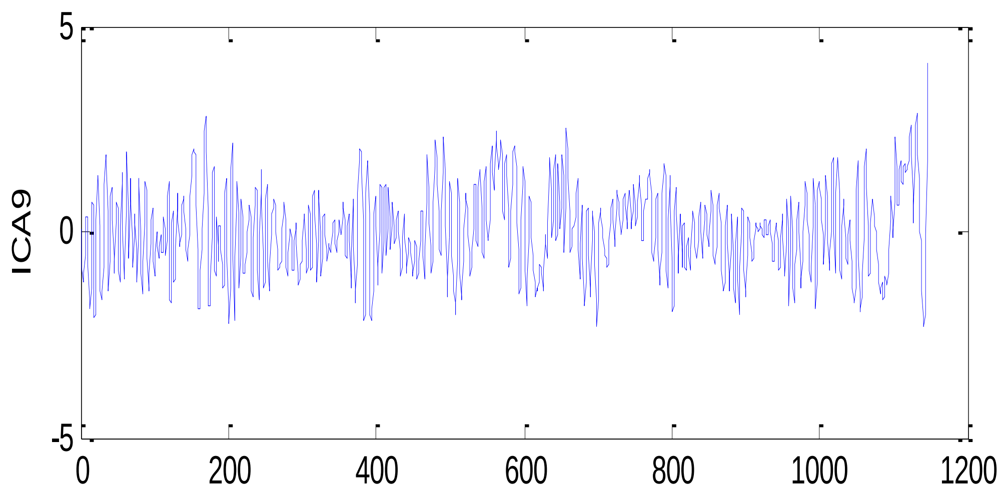
For example, EMD11 looks independent of EMD12 but it is dependent with EMD5 and EMD6 are looks to be similar or dependent to each other. Hence if we find that some of the components are noise components or random errors but they may also preserve some signal information so we cannot eliminate them. That is why we have applied ICA on these EMD components to further decompose them in 12 independent components. Such that noise become totally separated out from ECG data. The ICA components of above EMD1 to EMD12 decompositions are shown in figure 4.10.

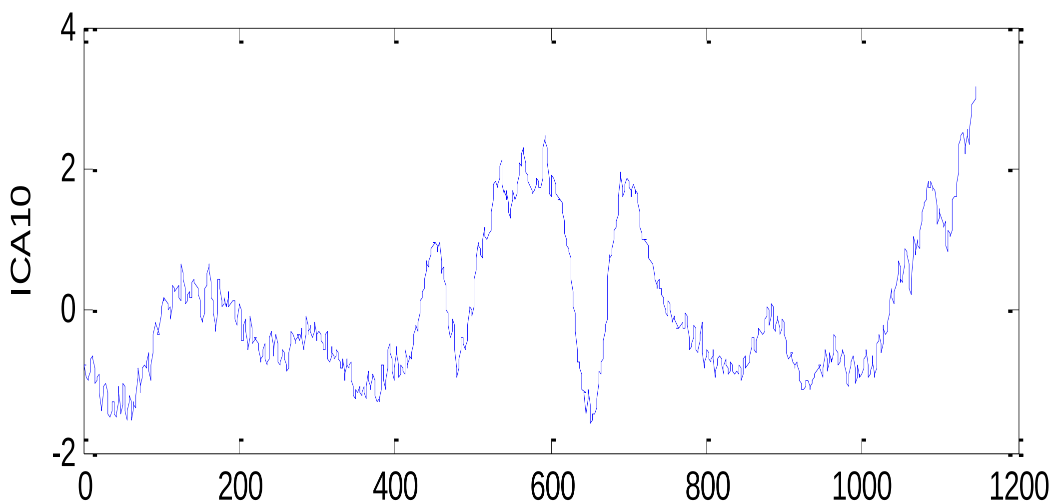



ICA2
ICA3
ICA4
4
2
0
-2
-4
0
200
400
600
800
1000
1200


ICA5
4
2
0
-2
-4
0
200
400
600
800
1000
1200
ICA6
4
2
0
-2
-4
0
200
400
600
800
1000
1200
ICA7
4
2
0
-2
-4
0
200
400
600
800
1000
1200


ICA8
4
2
0
-2
-4
0
200
400
600
800
1000
1200


ICA9
5
0
-5
0
200
400
600
800
1000
1200


ICA10
4
2
0
-2
0
200
400
600
800
1000
1200

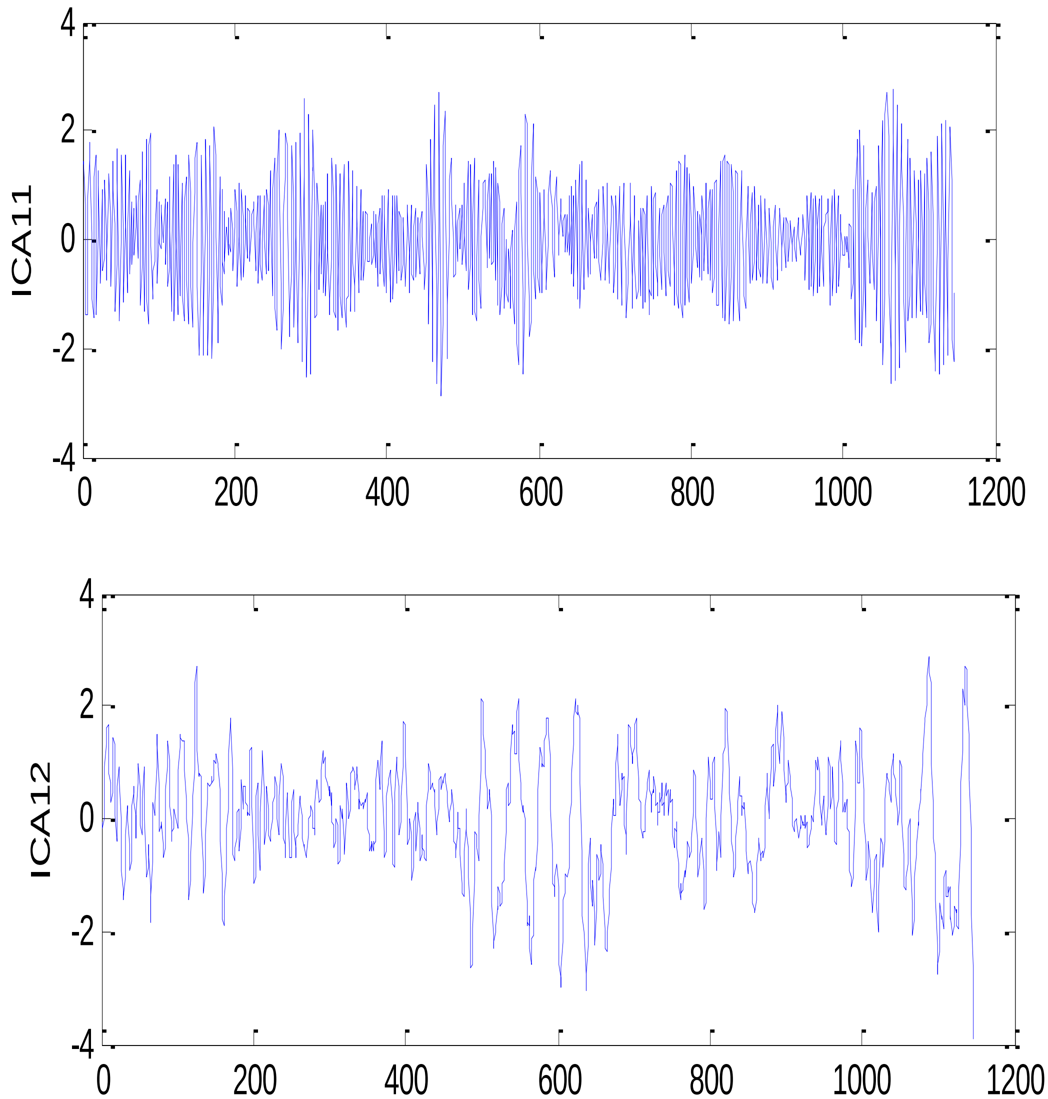


Fig 4.10: ICA components ICA1 to ICA12 for EMD of ECG cycles.

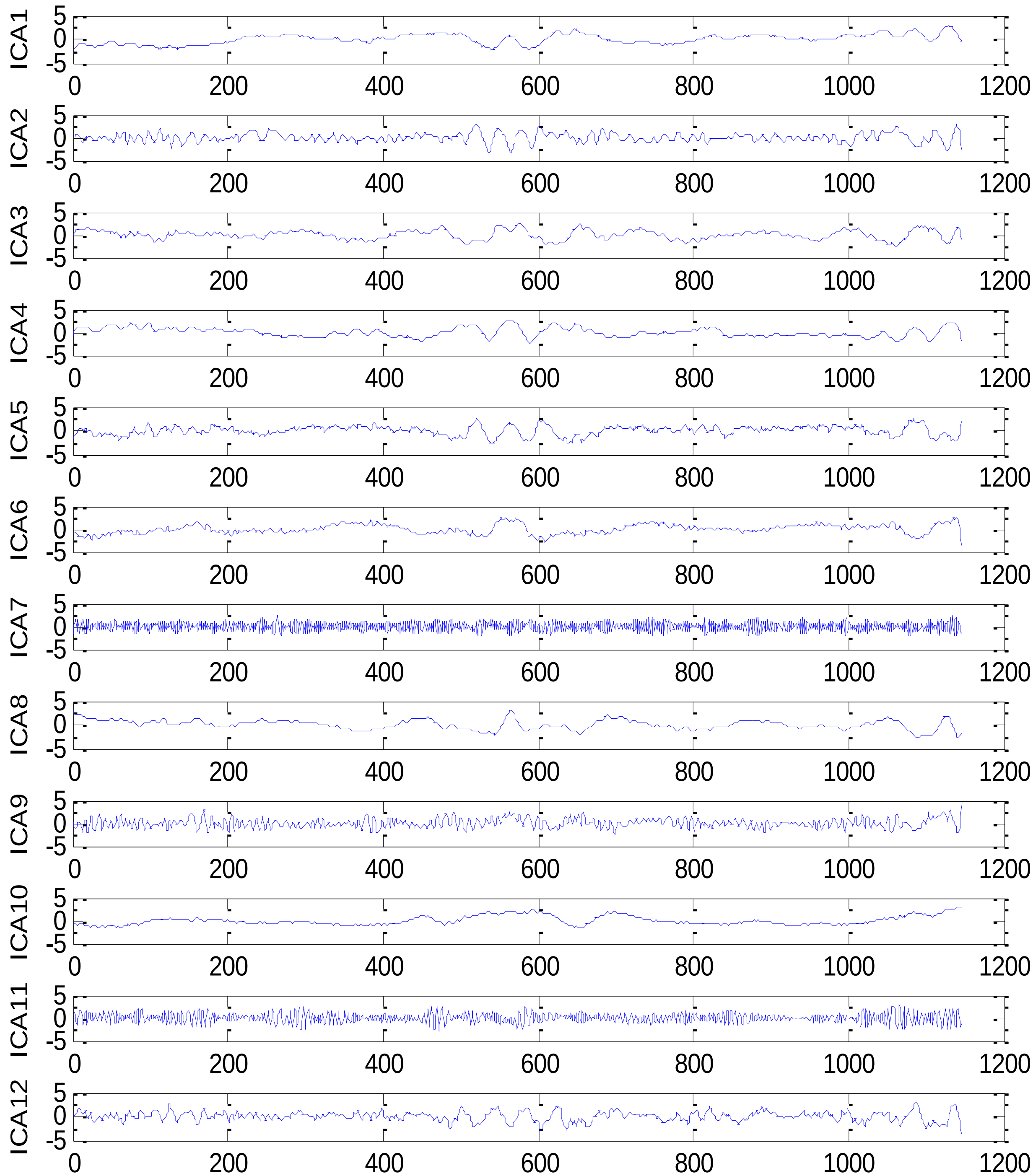


Fig 4.11: Collective view of ICA components ICA1 to ICA12 for EMD of ECG cycles in one window.

The algorithm after performing the ICA decomposition shows all the ICA components in one window along with this it also displays the kurtosis(degree of independence) of all the generated ICA components as given below.

Kurtosis of ICA components are:

(1) 2.4905 (2) 3.4545 (3) 2.4358 (4) 2.4409 (5) 2.7921 (6) 2.6080 (7) 1.9007

(8) 2.9257 (9) 2.7919 (10) 2.7599 (11) 2.7069 (12) 3.2093.

For the random sample, its sample moments, especially the skewness and kurtosis, typically differ somewhat from the specified distribution moments. In above value kurtosis of most the samples are 2.4 to 2.7 but for 2nd , 7th and 12th the kurtosis is differed and 7th ICA component kurtosis value does not match with any other signal value. So, we select the 7th ICA component to be eliminated thereafter reverse ICA is applied to reconstruct EMD component and then EMD components are reconstructed to ECG waveform. The original, noisy and denoised signal are shown in figure 4.12.

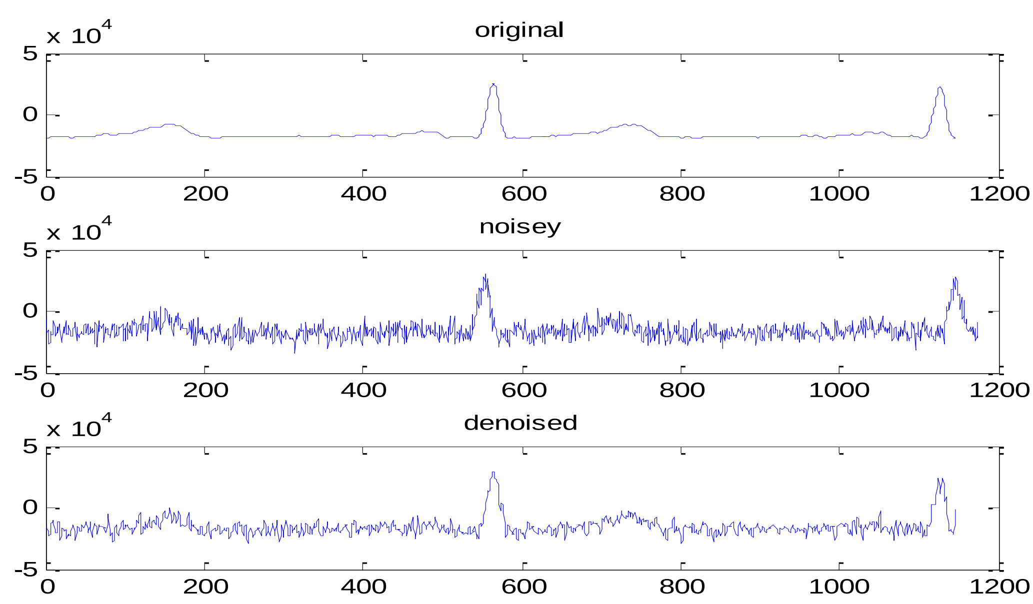


Fig 4.12: Original, noisy and denoised ECG waveform.

As per the above discussion denoising phenomenon is applied at different ECG cycles and the mean square error (MSE) is measured in between original w.r.t noisy and original w.r.t to denoised signal. These results and the values are given one by one.

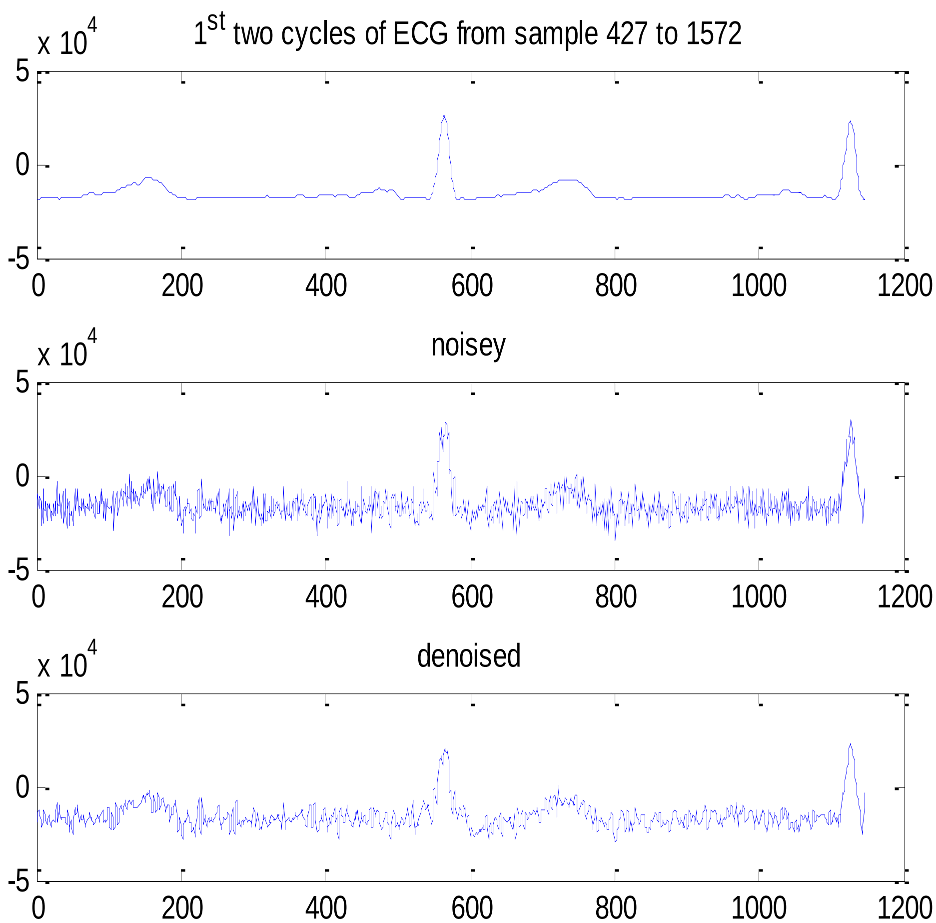


Fig 4.13: Denoising result of 1stcycle of ECG data.

M.S.E original w.r.t to noisy = 2.7082×10^7

M.S.E original w.r.t to denoised = 1.6605×10^7

Comment : Error is reduced after denoising.

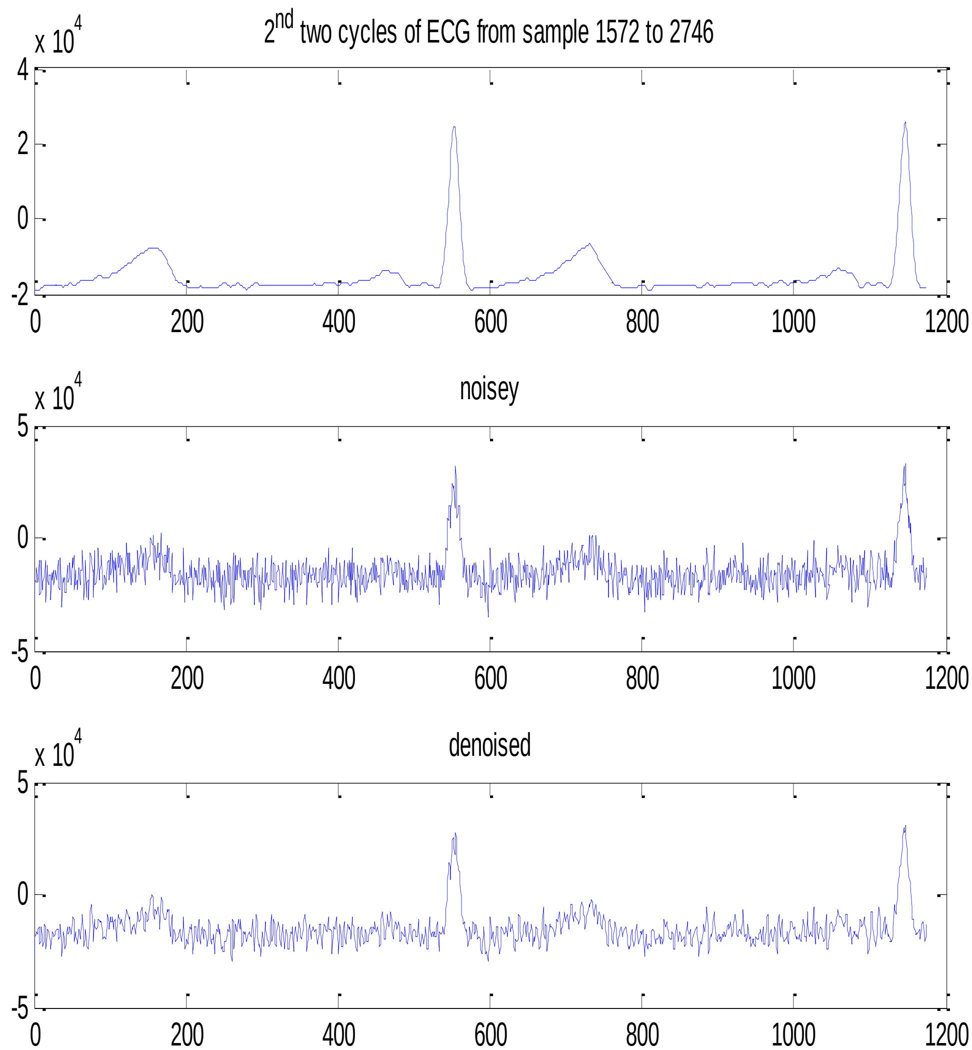


Fig 4.14: Denoising result of 3^{rd} and 4^{th} cycle of ECG data.

M.S.E original w.r.t to noisy = 2.8149 $x10^7$

M.S.E original w.r.t to denoised = 1.5981 $x10^7$

Comment: Error is reduced after denoising.

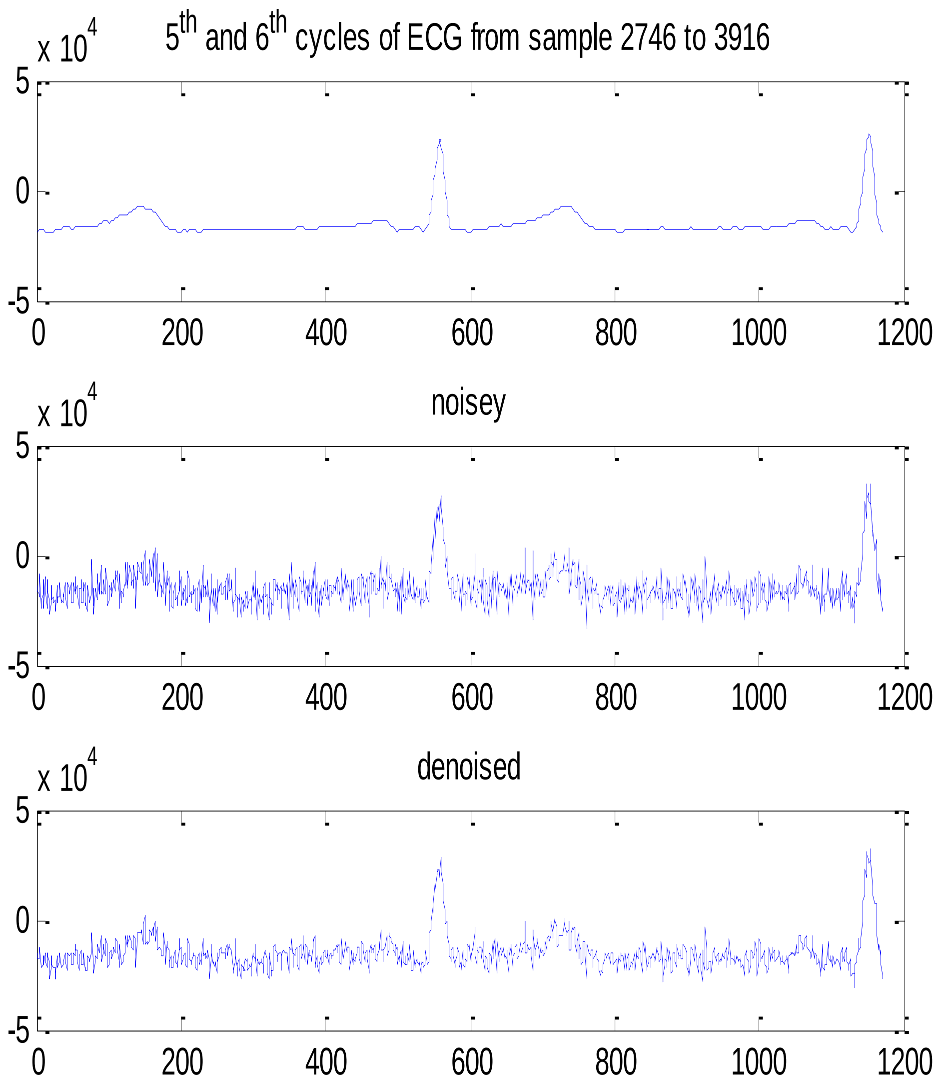


Fig 4.15: Denoising result of 5th and 6th cycle of ECG data.

M.S.E original w.r.t to noisy = 2.626 x10^7

M.S.E original w.r.t to denoised = 1.5893 x10^7

Comment: Error is reduced after denoising.

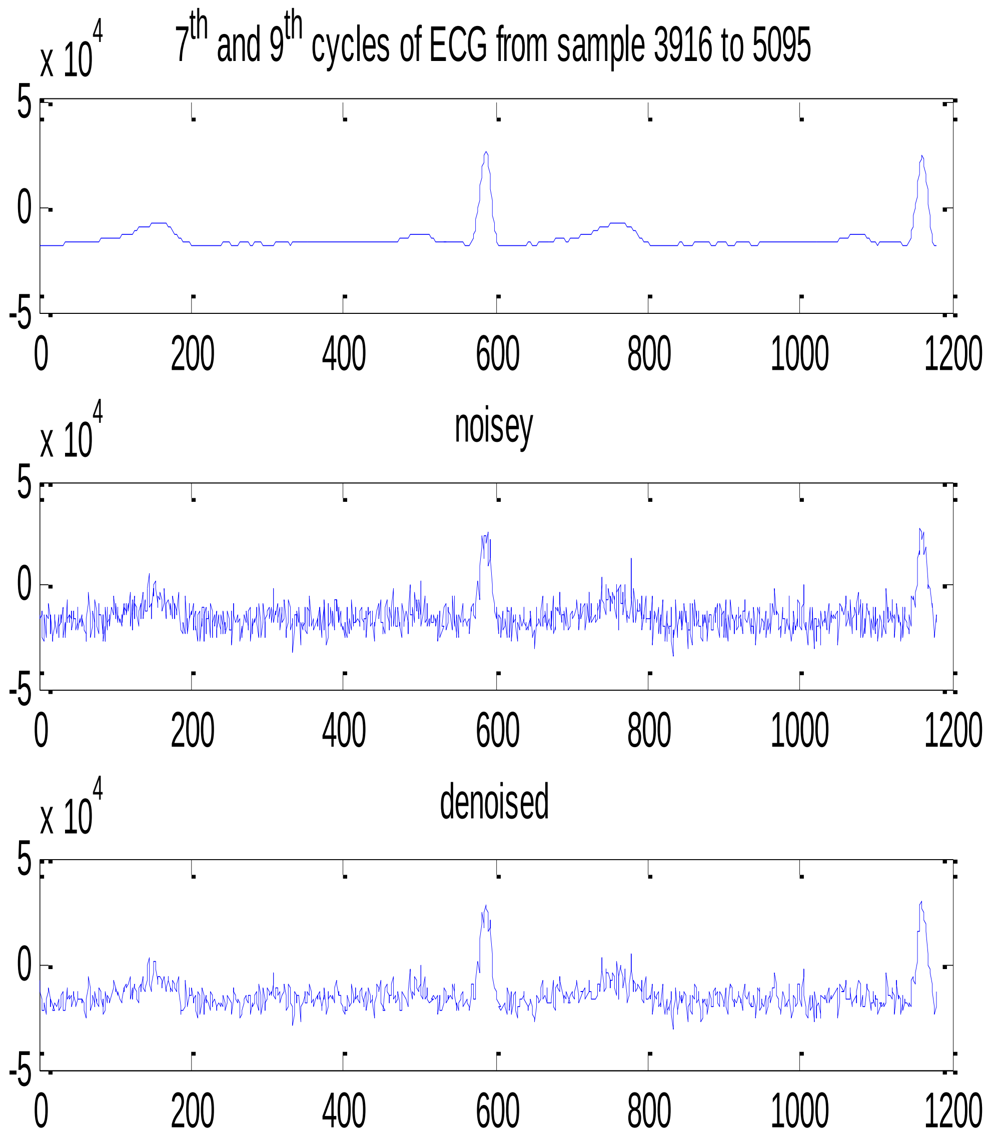


Fig 4.16: Denoising result of 7^{th} and 9^{th} cycle of ECG data.

M.S.E original w.r.t to noisy = 2.7604×10^7

M.S.E original w.r.t to denoised = 1.6257×10^7

Comment: Error is reduced after denoising.

CHAPTER 5

CONCLUSIONS AND FUTURE SCOPES

In this work we consider distortion related problem in diagnosis based on amplitude of ECG applied in common practice. By ECG amplitude analysis we can construct a new set of signals from the signal amplitudes at some defined points of the ECG, such as R peak or ST amplitudes or from time averages of delineated ECG segments. We have developed an algorithm by combining ICA and EMD decomposition techniques for error minimization in ECG database for improving diagnosis quality. ICA has found several applications in signal processing systems aimed at aiding in diagnostics. ECG based diagnostics applications in which ICA has been utilized in the applications of classification of ECG beats, analysis of parameterized ECG signals, heart rate variability analysis, arrhythmia estimation and atrial fibrillation extraction and analysis. In our literature survey we have observed that 12-lead ECG may sometimes be insufficient for efficient ICA based analysis of the phenomenon of interest Zhu et al. (2008) analyzed 72-lead and 98-lead ECG measurements using ICA and were able to separate the P wave, QRS complex, and T wave. Thus, with high-density ECG measurements and ICA based analysis more detailed diagnostics applications might be realizable. In this works we have shown that even using single lead ECG records we can consider ICA decomposition up to 12 level if we apply EMD prior to ICA.

REFERENCES

[1] Aapo Hyvärinen and Erkki Oja, "Independent Component Analysis: Algorithms and Applications", Neural Networks, 13(4-5):411-430, 2000.

[2] Gabriel Rilling et. al., "On Empirical Mode Decomposition and Its Algorithms" IEEE 2003.

[3] Arnaud Delorme and Scott Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis" Journal of Neuroscience Methods 134 (2004), 9-21.

[4] Patrick Flandrin, Gabriel Rilling, and Paulo Gonçalvés, "Empirical Mode Decomposition as a Filter Bank" IEEE Signal Processing Letters, Vol. 11, NO. 2, February 2004.

[5] Reza Sameni, M.B. Shamsollahi, Christian Jutten, and Massoud Babaie-Zadeh, "Filtering Noisy ECG Signals Using the Extended Kalman Filter Based on a Dynamic ECG Model", Computers in Cardiology 2007;32:1017−1020.

[6] Sim Kuan Goh, Hussein A. Abbass1, Kay Chen Tan, and Abdullah Al Mamun, "Artifact Removal from EEG using a Multi-Objective Independent Component Analysis Model" Volume 8834 of the series Lecture Notes in Computer Science pp 570-577 2014.

[7] M Murugappan, Reena Thirumani, Mohd Iqbal Omar, and Subbulakshmi Murugappan, "Development of Cost-Effective ECG Data Acquisition System for Clinical Applications using LabVIEW" 2014 IEEE 10th International Colloquium on Signal Processing & its Applications (CSPA2014), 7 - 9 Mac. 2014, Kuala Lumpur, Malaysia.

[8] Vandana Roy and Shailja Shukla, "A Two Stage Approach with ICA and Double Density Wavelet Transform for Artifacts Removal in Multichannel EEG Signals" International Journal of Bio-Science and Bio-Technology Vol.7, No.4 (2015), pp.291-304.

[9] Akinlolu A. Ponnle et. al., "Development of a Computer-Aided Application for Analyzing ECG Signals and Detection of Cardiac Arrhythmia Using Back Propagation Neural Network - Part I: Model Development" International Journal of Applied Information Systems (IJAIS)Volume 9 – No.3, June 2015.

[10] Arjon Turnip, and Dwi Esti Kusumandari, "Artifacts Removal of EEG Signals using Adaptive Principal Component Analysis" 3rd International Conference on Computation for Science and Technology (ICCST-3) 2015.

[11] Upasani D.E and Kharadkar R.D. 2012, Automated ECG Diagnosis, IOSR Journal of Engineering, Vol. 2 (5), pp. 1265-1269.

[12] Karpagachelvi S., Arthanari M., and Sivakumar M. 2010, ECG Feature Extraction Techniques: A Survey Approach, International Journal of Computer Science and Information Security, Vol. 8, No. 1, pp. 76-80.

[13] C. Li, C. Zheng (1993) Proc. Annual Int. Conf. IEE Eng. in Med. & Biol. Soc., San Diego, California, 330331.

[14] C. Li, C. Zheng, C. Tai (1995) IEEE Trans. Biomed. Eng. 42 21-28.

[15] Ince T., Kiranyaz S., and Gabbouj M. 2009, A Generic and Robust System for Automated Patient-Specific Classification of ECG Signals, IEEE Transactions on Biomedical Engineering, Vol. 56, pp. 1415-1426.

[16] Afonso V. X., Tompkins W.J., Nguyen T.Q. and Luo S., 1999, ECG Beat Detection using Filter Banks, IEEE Transactions on Biomedical Engineering, Vol. 46, pp.192–202.

[17] Correia S., Miranda J., Silva L. and Barreto A. 2009, LabVIEW and MATLAB for ECG Acquisition, Filtering and Processing, In Proceedings of 3rd International Conference on Integrity, Reliability and Failure (IFR2009), Porto/Portugal, 20-24 July 2009, paper ref: S0228_A0402.

[18] Li C., Zheng C., and Tai C. 1995, Detection of ECG Characteristic Points using Wavelet Transforms, IEEE Transactions on Biomedical Engineering, Vol. 42, No. 1, pp. 21-28.

[19] A. Hyvarinen, E. Oja, “A Fast-Fixed-Point Algorithm for Independent Component Analysis”, Neural Computer, vol. 9, no. 7, (1997), pp. 1483 –1492.

[20] P. Levan, E. Urrestarrazu, and J. Gotman, “A System for Automatic Artifact Removal In Ictal Scalp EEG Based On Independent Component Analysis And Bayesian Classification”, Clinical Neurophysiology, vol 117, no. 4, pp. 912- 927, (2006).

[21] P. Senthil Kumar, R. Arumuganathan, K. Sivakumar, And C. Vimal, “Removal of Ocular Artifacts In the EEG Through Wavelet Transform Without Using an EOG Reference Channel”, Int. J. Open Problems Compt. Math., vol. 1, no. 3, pp. 188-200, (2008).

[22] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[23] Z Gao, J Wu, J Zhou, W Jiang, et.al, Design of ECG Signal Acquisition and Processing System, International Conference on Biomedical Engineering and Biotechnology, pp 762-764, 2012.

[24] P O. Bobbie, C Z Arif, H Chaudhari, and S Pujari, Electrocardiogram (EKG) Data Acquisition and Wireless transmission, Proceedings of WSEAS International Conference on System Engineering, pp, 1-7, 2004.

[25] S Warren, Lesson learned from The Application of Virtual Instruments and Portable Hardware to Electrode Based Biomedical Laboratory Exercise, American Society for Engineering Education, 2012.

[26] G. W. Williams, H. O. Luders, A. Brickner, M. Goormastic, D. W. Klass, "Inter Observer Variability in EEG Interpretation", Neurology, vol. 35, no. 12, (1985), pp. 1713-19.

[27] T Wang, H P Shen, C H Lin, and Y L Ou, Detection and prediction of Sudden Cardiac Death (SCD) for Personal Healthcare, Proceedings of the 29th Annual International Conference of the IEEE EMBS, pp. 2575-2578, 2007

[28] H. K. Sawant and Z. Jalali, "Detection And Classification Of EEG Waves", Oriental Journal Of Computer Science & Technology, vol. 3, no. 1, (2010), pp. 207-213.

[29] Pan J. and Tompkins W.J. 1985, A Real Time QRS Detection Algorithm, IEEE Transactions on Biomedical Engineering. BME-32(3), pp. 230-236.

[30] PhysioBank Archive Index, http://www.physionet.org/physiobank/database/

[31] Chavan M. S., Agarwala R. A. and Uplane M.D. 2008, Design and Implementation of Digital FIR Equiripple Notch Filter on ECG Signal for removal of Power Line Interference, WSEAS Transaction on Signal Processing, Volume 4, Issue 4, pp. 221-230.

[32] Radana Kahankova et. al., "Non-Adaptive Methods of Fetal ECG Signal Processing", Biomedical Engineering Volume: 15, Number: 3, 2017, September.

[33] Mohamed Hammad, et al., " Detection of abnormal heart conditions based on characteristics of ECG signals", Measurement 125 (2018) 634–644.

[34] Sai Manoj Pudukotai Dinakarrao et al, " Computer-Aided Arrhythmia Diagnosis with Bio-signal Processing: A Survey of Trends and Techniques", ACM Computing Surveys, Vol. 9, No. 4, Article PP, Publication date: March 2019.

[35] Yuwei Zhang et. al., " Wearable ECG signal processing for automated cardiac arrhythmia classification using CFASE-based feature selection", April 2019, Wiley Expert System.