

PERFORMANCE EVALUATION OF VARIOUS QRS DETECTION ALGORITHMS

**A project report submitted to the
Department of Electronics & Instrumentation Engineering
In the partial fulfilment of the requirements
For the degree of**

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND INSTRUMENTATION ENGINEERING

By

K.VAMSHI (12016T0607)

K.RACHANA (12016T0616)

M.MADHU CHANDRAKANTH (13016T0669L)

Under the guidance of

Sri B. SHASHIKANTH

Dept of E&I Engg.



DEPARTMENT OF ELECTRONICS & INSTRUMENTATION ENGINEERING

KAKATIYA INSTITUTE OF TECHNOLOGY & SCIENCE

(An Autonomous Institute under Kakatiya University)

WARANGAL-506015

ACKNOWLEDGMENTS

This is the time to honour **our guide and the thesis supervisor Sri B. Shashikanth** garu, Assoc. Professor, Dept. of E&I who has encouraged us right from the initial stage to the final in the development of this thesis. We are very grateful to sir for all his support and overall guidance for accomplishment of this work. He made himself up to date with our project progress and not only supported us technically, but also provided moral support.

We owe our deepest gratitude to **Dr. K.Venu Madhav**, Assoc. Professor, Dept. of E&I for valuable guidance as project coordinator. He has given us the freedom to select this project and also brought us this project idea. With his assistance and timely assessment, we made ourselves comfortable in concentrating on how to lead our project in a better way.

We are thankful to **Prof. M.Sreelatha** garu, Assoc. Professor, Dept. of E&I for her valuable suggestions and timely help in the endeavour.

And we convey our sincere thanks to **Dr. K.Srinivas**, Project Head, Dept. of E&I and **Dr. K.Shivani**, Professor & Head, Dept. of E&I, for constantly monitoring our project status and guiding us in a right way for the successful completion of this project..

It's a great pleasure expressing sincere thanks to **Dr. K. Gururaj**, Principal, Kakatiya Institute of Technology and Science, Warangal for his kind gesture.

We would like to record our sincere thanks to all the faculty, staff members and lab assistants, who contributed directly or indirectly to our project in form of their encouragement and support. We are indebted to all their support and suggestions. We also thank our parents for their encouragement.

K.VAMSHI (12016 T 0607)
K. RACHANA (12016 T 0616)
M. MADHU CHANDRAKANTH (13016 T 0669L)

DECLARATION

We declare that the work presented in this project is original and carried out in the Department of Electronics & Instrumentation Engineering, Kakatiya Institute of Technology & Science, Warangal, Telangana and has not been submitted elsewhere for any degree in part or in full.

K.VAMSHI (12016 T 0607)
K. RACHANA (12016 T 0616)
M. MADHU CHANDRAKANTH (13016 T 0669L)

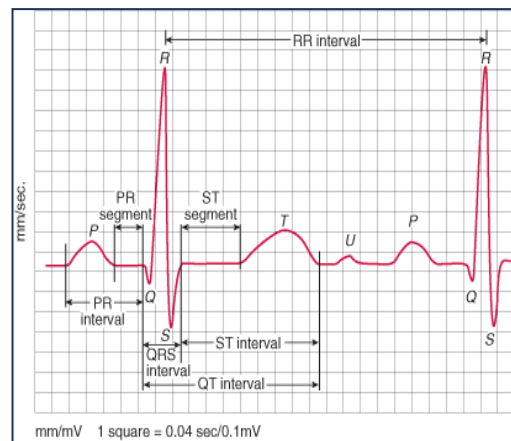
PERFORMANCE EVALUATION OF VARIOUS QRS DETECTION **ALGORITHMS**

ABSTRACT

Biomedical signals carry signatures of physiological events. The part of a signal related to a specific event of interest is often referred to as an epoch. Analysis of a signal for monitoring or diagnosis requires the identification of epochs and investigation of the corresponding events. Once an event has been identified the corresponding wave form may be segmented and analyzed in terms of its amplitude, wave shape, time duration, intervals between events, energy distribution, frequency content and so on. Event detection is thus an important step in biomedical signal analysis.

An electrocardiogram (ECG) is a bioelectrical signal which records the heart's electrical activity versus time. It is an important diagnostic tool for assessing heart functions. The early detection of arrhythmia is very important for the cardiac patients. ECG arrhythmia can be defined as any of a group of conditions in which the electrical activity of the heart is irregular and can cause heartbeat to be slow or fast. It can take place in a healthy heart and be of minimal consequence, but they may also indicate a serious problem that leads to stroke or sudden cardiac death.

As ECG being non stationary signal, the arrhythmia may occur at random in the time-scale, which means, the arrhythmia symptoms may not show up all the time but would manifest at certain irregular intervals during the day. Automatic classification of arrhythmia is critical in clinical cardiology, especially for the treatment of patients in the intensive care unit.



The ECG signal is downloaded from MIT-BIH Arrhythmia database. The pre-processing of ECG signal is performed with help existing algorithms and it is also used for feature extraction of ECG signal. This project implements a simulation tool on MATLAB platform to detect abnormalities in the ECG signal. Computerized Signal Processing with efficient algorithms makes us easier to analyze and characterize obtained ECG Test Signals. Further, research scope is to download the original ECG file, then apply the algorithms one at a time, then transmit and receive the ECG Signal data using DSP Processors or through external sharing means of mobile phone (like Bluetooth, Zig-bee module etc...). This provides accurate ECG data with ease of accessibility.

CONTENTS

1. INTRODUCTION	1
1.1. BACKGROUND	1
1.2. BIOMEDICAL SIGNAL PROCESSING	7
1.2.1 OPTING FOR BMSP PROJECT	7
1.2.2 BIO-MECHANISMS	7
1.2.3 NEED FOR BIO-MEDICAL SIGNAL ANALYSIS	8
2. LITERATURE REVIEW	9
2.1 INTRODUCTION TO ECG	9
2.2 ELECTRICAL ACTIVITY OF THE HEART	10
2.3 QRS DETECTION AND SEGMENTATION	14
2.4 ABNORMALITIES IN ECG AND ECG ARTIFACTS	16
2.4.1 POWER LINE INTERFERENCE	17
2.4.2 BASELINE WANDERING	17
2.4.3 MOTION ARTIFACTS	18
2.5 ECG SIGNAL ACQUISITION - PROCEDURE	18
2.5.1 LEADS & LEAD CONFIGURATION	19
2.5.2 HEART RATE MONITOR – ANALOG CIRCUIT	22
3. SOFTWARE REQUIREMENTS	24
3.1 MATLAB INSTALLED PC	24
3.1.1 OPENING A MATLAB WINDOW	25
3.1.2 SAMPLE WORK ENVIRONMENT	25
3.1.3 CREATING A NEW WORKSPACE	26

3.2	PHYSIONET SOURCE DATABASE	26
3.2.1	MIT-BIH ARRHYTHMIA DATABASE	26
3.2.2	FUNCTIONAL ARCHITECTURE OF DATABASE	27
3.2.3	EXTRACTING A ECG SIGNAL IN .MAT EXTENSION	27
4.	PROJECT IMPLEMENTATION	29
4.1	QRS DETECTION ALGORITHMS EXPLANATION	29
4.1.1	PAN TOMPKINS ALGORITHM	29
4.1.2	EMPIRICAL MODE DECOMPOSITION ALGORITHM	32
4.1.3	TEMPLATE MATCHING ALGORITHM	35
5.	RESULTS	36
5.1	PERFORMANCE PARAMETERS CALCULATIONS	36
5.1.1	EXPECTED RESULTS	36
5.1.2	OBTAINED RESULTS	36
6.	FUTURE SCOPE	37
6.1	RESEARCH LAB WORK-OUTS	37
7.	APPENDICES – MATLAB CODES	38
7.1	PAN TOMPKINS CODE	38
7.2	EMPIRICAL MODE DECOMPOSITION CODE	41
7.3	TEMPLATE MATCH ALGORITHM CODE	45
8.	REFERENCES	46

1. INTRODUCTION

This is an automated era, man efforts are getting replaced by a Machine or a Computer. Self Learning Capabilities of large equipment now can be replaced with a small silicon chip or an IC. Performance of these systems when gets interfaced with Computer makes them faster, efficient and sophisticated. But this trend is tremendously increasing such that an automated/ computerized self learning machine can take over thought process of a man and can control human brain.

In this world, man has to survive first to create a new technology in days to come. So, facts reveal that man has to given priority rather than a machine.

"We knew there is a regular technical revolution going-on in this era. Many new updated versions are being brought out. However, there is no meaning in creating a new technology, if it doesn't help / care for survival of mankind".

COMPUTERS IN MEDICINE & EVOLUTION OF PC

The history of the development of the computer from the first mechanical computers such as those built by Charles Babbage in the 1800s to the modern personal computers, now the IBM PC and the Apple Macintosh is vast. The only computers prior to the twentieth century were mechanical, based on gears and mechanical linkages. In 1941 a researcher named Atanasoff demonstrated the first example of an electronic digital computer. This device was primitive even compared to today's four-function pocket calculator. The first serious digital computer called ENIAC (**E**lectronic **N**umerical **I**ntegrator **A**nd **C**alculator) was developed in 1946 at the Moore School of Electrical Engineering of the University of Pennsylvania.

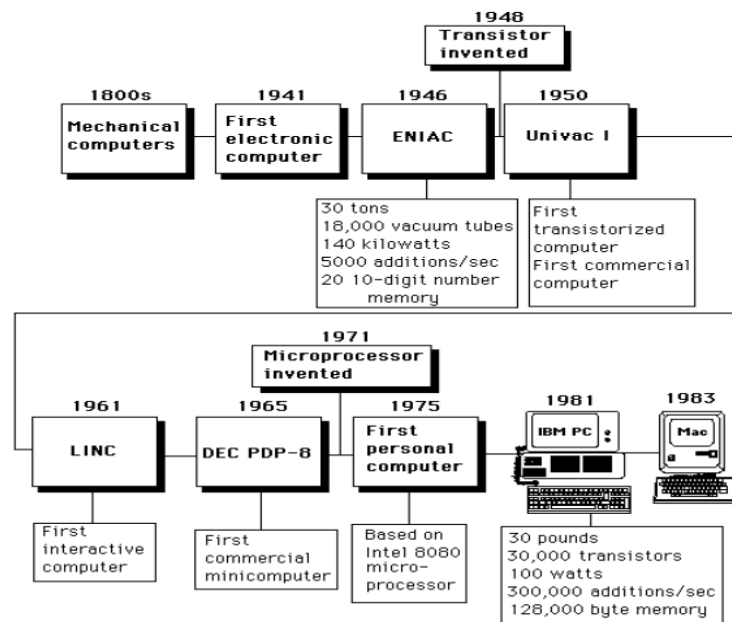
Several other companies including IBM subsequently put transistorized computers into the marketplace. In 1961, researchers working at Massachusetts Institute of Technology and Lincoln Labs used the technology of the time to build a novel minicomputer quite unlike the commercial machines. This discrete component, transistorized minicomputer with magnetic core memory called the LINC (**L**aboratory **I**Nstrument **C**omputer) was the most significant historical development in the evolution of the PC.

Subsequently Digital made a commercial version of the LINC by combining the LINC architecture with the PDP-8 to make a LINC-8. Digital later introduced a more modern version of the LINC-8 called the PDP-12. These computers were

phased out of Digital's product line sometime in the early 1970s. One of the programs that wrote on the LINC-8 in the late 1960s computed and displayed the vector cardiogram loops of patients. Such a program is easy to implement today on the modern PC using a high-level computing language such as Pascal or C.

THE UBIQUITOUS PC

A significant historical landmark was the introduction of the IBM PC in 1981. On the strength of its name alone, IBM standardized the personal desktop computer. Prior to the IBM PC, the most popular computers used the 8-bit Zilog Z80 microprocessor (an enhancement of the Intel 8080) with an operating system called CP/M (Control Program for Microprocessors). For this cost, the number of MIPS (million instructions per second) increases with every new model because of the increasing power of the microprocessor. The first IBM PC introduced in 1981 used the Intel 8088 microprocessor, which provided 0.1 MIPS.



In 1983, about 300 integrated circuits were required in each PC, of which about half were the microprocessor and support logic and the other half made up the 256-kbyte memory. Today half of the parts are still dedicated to each function, but a complete PC can be built with about 18 ICs. In the past six years, the chip count in a PC has gone from about 300 integrated circuits in a PC with a 256-kbyte memory to 18 ICs in a modern 2-Mbyte PC. By the mid-1990s, it is likely that a PC with 4-Mbyte memory will be built from three electronic components, a single IC for all the central processing, a read-only memory (ROM) for the basic input/output

software (BIOS), and a 4-Mbyte dynamic random access memory (DRAM) chip for the user's program and data storage. New architectures on single ICs, such as parallel processors and artificial neural networks with algorithms typically include digital signal processing, together with decision logic in order to analyze biomedical signals as well as medical images.

THE MICROCOMPUTER-BASED MEDICAL INSTRUMENT

The progress in desktop and portable computing in the past decade has provided the means with the PC or customized microcomputer-based instrumentation to develop solutions to biomedical problems that could not be approached before. One of our personal interests has been the design of portable instruments that are light, compact, and battery powered. A typical instrument of this type is truly a personal computer since it is programmed to monitor signals from transducers or electrodes mounted on the person who is carrying it around.

COMPARISON OF PERFORMANCE OF IBM PC AND HUMAN BRAIN

System	Weight (lbs)	Size (ft ³)	Power (watts)	CPU elements	Memory (bits)	Conduction rate (impulses/s)	Benchmark (additions/s)
IBM PC	30	5	200	10 ⁶ transistors (or equiv.)	10 ⁷	10 ⁵	10 ⁶
Brain	3	0.05	10	10 ¹⁰ neurons	10 ²⁰	10 ²	1
Ratio (PC/brain)	10	100	20	10 ⁻⁴	10 ⁻¹³	10 ³	10 ⁶

PORTABLE MICROCOMPUTER-BASED INSTRUMENTS

One example of a portable device is the portable arrhythmia monitor which monitors patient's electrocardiogram from chest electrodes and analyzes it in real time to determine if there are any heart rhythm abnormalities. The device could then accompany the patient home, providing continuous monitoring that is not now practical to do, during the critical times following open heart surgery. One other microcomputer-based device that we contributed to developing is a calculator-size product called the CALTRAC that uses a miniature accelerometer to monitor the motion of the body. There is now an implanted pacemaker uses an accelerometer to measure the level of a patient's activity in order to adjust the pacing rate.

PC-BASED MEDICAL INSTRUMENTS

The economy of mass production has led to the use of the desktop PC as the central computer for many types of biomedical applications. You can configure the PC to have user-friendly, interactive characteristics much like the LINC. The PC captures an image of electrical impedance tomography—EIT. Instead of the destructive radiation used for the familiar computerized tomography techniques, computer controls a custom-built 32-channel current generator that injects patterns of high-frequency (50-kHz) currents into the body. The computer then samples the body surface voltage distribution resulting from these currents through an analog-to-digital converter. Using a finite element resistivity model of the thorax and the boundary measurements, the computer then iteratively calculates the resistivity profile that best satisfies the measured data, solving the computing-intensive algorithms, and presenting the graphical display of the final image. We have used the IBM PC to develop signal processing and artificial neural network (ANN) algorithms for analysis of the electrocardiogram.

SOFTWARE DESIGN OF DIGITAL FILTERS

In addition to choosing a personal computer hardware system for laboratory use, we must make additional software choices. The types of choices are frequently closely related and limited by the set of options available for a specific hardware system. Choices of software at all levels significantly influence the applications that a system can address. Two major software selections to be made are:

- (1) choice of the disk operating system (DOS) to support the development task, and
- (2) choice of the language to implement the application.

DISK OPERATING SYSTEMS

One DOS criterion to consider in the real-time environment is the compromise between flexibility. Unix requires considerable expertise to use all of its capabilities. Therefore it plots high on the graph. PC DOS (or the generic MS DOS) was modeled after CP/M to fall near the compromise line. It became the most-used operating system on 16-bit personal computers, such as the IBM PC and its clones that are based on the Intel 8086/8088 microprocessor or other 80 x 86 family members. Unix or a close clone of it may provide the most accepted answer to the problem of linking PCs together through a local area network (LAN). Unix is not

desirable because of its overhead compared to PC/DOS. In an IBM PC, the DOS is mated to firmware in the ROM BIOS (Basic Input/Output System) to provide a general way to access the system hardware. BIOS firmware is general purpose and has some inefficiency; computers like the NEXT computer are attempting to address some of these issues. It also includes a built-in digital signal processing (DSP) to facilitate implementation of signal processing applications.

LANGUAGES

The best language for this application area would plot at the origin since this point represents a program with the greatest runtime speed and the shortest development time. The diagonal line maps the best compromise language in terms of the run-time speed compared to the software design time necessary to implement an application. Of course there are other considerations for choosing a language, such as development cost and size of memory space available in an instrument. Also most of the languages plotted will not, themselves, solve the majority of real-time problems, especially of the signal processing type

DSP SOFTWARE

The trend is toward using commercial DSP software that provides the entire process of data acquisition, analysis, and presentation. Some common capabilities of commercial DSP software include the following:

1. Support of a wide variety of signal conversion boards.
2. Comprehensive library of DSP algorithms including FFT, convolution, Low-pass, high-pass, and band pass filters.
3. Data archiving abilities. The more sophisticated software allows exporting data to Lotus123, dBase, and other common analysis programs.
4. Wide range of sampling rates.
5. Impressive graphics displays and menu and/or icon driven user interface.
6. User-programmable routines.
7. Support of high-level programming in C, BASIC, or ASCII commands.
8. Customizable report generation and graphing (e.g., color control, automatic or manual scaling).

SPD by Tektronix is a software package designed for Tektronix digitizers and digital oscilloscopes and the PEP series of system controllers or PC controllers. It offers in its toolset over 200 functions including integration and differentiation, pulse measurements, statistics, windowing, convolution and correlation, forward

and inverse FFTs for arbitrary length arrays, sine wave components of an arbitrary waveform, interpolation and decimation, standard waveform generation (sine, square, sinc, random) and FIR filter generation. DADiSP by DSP Development Corporation offers a version that operates in the protected mode of Intel 80286 or 80386 microprocessors, giving access to a full 16Mbytes of addressability. Of interest is the metaphor that DADiSP uses. It is viewed as an interactive graphics spreadsheet. DspHq by Bitware Research Systems is a simple, down-to-earth package that includes interfaces to popular libraries such as MathPak87 and Numerical Recipes.

MathCAD by MATHSoft, Inc. is a general software tool for numerical analysis. Although not exactly a DSP package, its application packs in electrical engineering and advanced math offer the ability to design IIR filters, perform convolution and correlation of sequences, the DFT in two dimensions, and other digital filtering. A more powerful software package, MatLAB by Math Works, Inc., is also a numerical package, with an add-on Signal Processing Toolbox package having a rich collection of functions immediately useful for signal processing and FFT-based frequency domain techniques. Its IIR filter design module allows the user to convert classic analog Butterworth, Chebyshev, and elliptic filters to their digital equivalents. It allows a filter to be designed to match any arbitrarily shaped, multiband, frequency response. Other Toolbox functions include FIR filter design, FFT processing, power spectrum analysis, correlation function estimates and 2D convolution, FFT, and cross correlation.

A version of Commercial DSP Systems 359 this product limited to $32 \times$ ASYST by Asyst Software Technologies supports A/D and D/A conversion, digital I/O, and RS-232 and GPIB instrument interacting with a single package. The OMEGA SWD-RTM is a real-time multitasking system that allows up to 16 independent timers and disk files. LabWindows and LabVIEW are offered by National Instruments for the PC and Macintosh respectively. However, of particular interest is LabVIEW, a visual programming language, which uses the concept of a virtual instrument. A virtual instrument is a software function packaged graphically to have the look and feel of a physical instrument. The screen looks like the front panel of an instrument with knobs, slides, and switches. LabVIEW provides a library of controls and indicators for users to create and customize the look of the front panel. LabVIEW programs are composed of sets of graphical functional blocks with interconnecting wiring. Both the virtual instrument interface and block diagram programming attempt to shield engineers and scientists from the syntactical details of conventional computer software.

1.2. BIO-MEDICAL SIGNAL PROCESSING:

Besides, we have Brain Functioning Mechanism, Muscular Mechanisms, Respiratory Activities... etc. All these Activities involve "Signal Processing" Techniques and we are applying them on Bio-Medical Stream, inter-relating both of them a new flavour of study, "Bio-Medical Signal Processing" has be evolved.

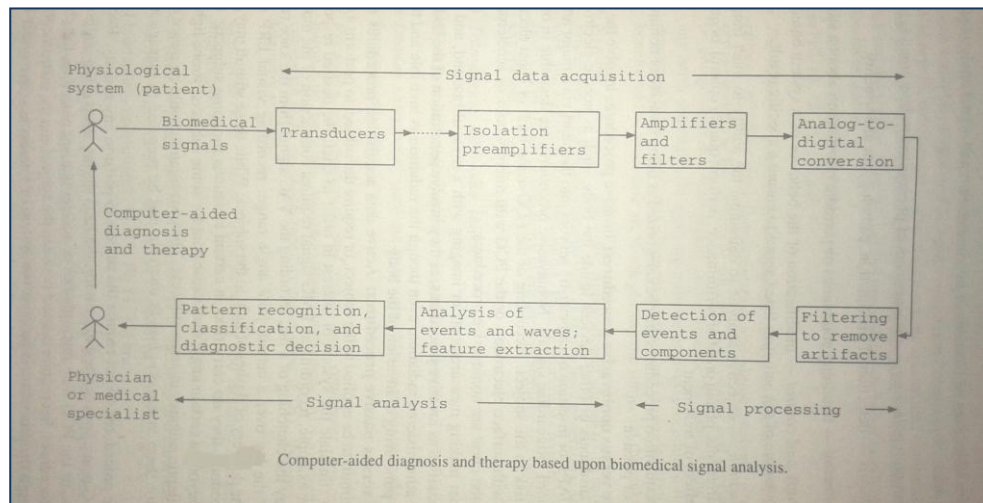


Fig 1.1. Block Diagram Representation of Biomedical System Design

1.2.1 OPTING FOR BMSP PROJECT

As explained earlier man has to be prioritized first, there are many unsolved challenges available on Complex Bio-Machine i.e; Human Mechanisms - origin and their existence. As it involves critical real time mechanisms, the subject victim has to be handled carefully and higher point precision and accurate instruments are used with continuous data monitoring/recording at all successive instants.

No data losses are tolerated as it leads to wrong predictions of observed signals. One such typical human mechanism is Heart Functioning. It can be analyzed by Electrocardiogram (ECG). Electrocardiography is a medical diagnostic procedure used to record the electrical activity of the heart and display it as a waveform. Thus, we decided to work on ECG.

1.2.2 BIO-MECHANISMS

Also we have Electroencephalogram (EEG) for Neuronal Activities of Brain, Electromyogram (EMG) for Muscular Activities, Electrogastrogram (EGG) for gastrointestinal tract, Electro-oculogram (EOG) for recording eye ball movements, Electroretinogram (ERG) for recording potentials generated due to eye illumination and so on...

1.2.3 NEED FOR BIO-MEDICAL SIGNAL ANALYSIS

Study of Bio-Medical Signals helps to categorize the working function of bio-mechanisms, fault test, diagnose the diseases/abnormalities and helps to conclude perfectly for a required treatment of victim (subject) under test. Also, Transmission and Reception of these signals with high accuracy and precision is needed. Computerized Interface makes this task easier.

Difficulties encountered in Biomedical Signal Acquisition and Analysis:

1. Accessibility of variables to measurement
2. Variability of signal source
3. Inter-relationships and interactions among physiological systems
4. Effect of Instrumentation or procedure on the system
5. Physiological Artifacts and Interferences
6. Energy Limitations
7. Patient Safety

2. LITERATURE REVIEW

2.1 INTRODUCTION ABOUT ECG

Electrocardiogram (ECG) is most commonly known, recognized, and used biomedical signal. The etymology of the word Electrocardiogram is derived from the Greek word *electro*, because it is related to electrical activity, *cardio*, Greek word for heart, and *graph*, a Greek root meaning "to write". In English speaking countries, medical professionals often write EKG (the abbreviation for the German word elektrokardiogramm).

Electrocardiogram (ECG) is the recording of cardiac activity and it is extremely used for diagnosis of heart diseases. Good quality ECGs are utilized by physicians for interpretation and identification of physiological and pathological phenomena. The rhythm of heart in terms of beats per minute(BPM) may be easily estimated by counting the readily identifiable waves.

More important is the fact that the ECG wave shape is altered by cardiovascular diseases and abnormalities such as myocardial ischemia and infarction, ventricular hypertrophy, and conduction problems.

The Ionic voltages produced as a result of the electrochemical activity of certain type of cells in living beings are known as 'Bioelectric Potentials'. Transducers are used to convert ionic potentials to electrical voltages. The membrane potentials developed when cell is rest is called as 'Resting Potential' and the potential generated to ionic gradient across membrane is called as 'Action Potential'.

Thus, the process of changing from resting state to action potential is called Depolarization and vice-versa is referred to as Repolarization.

The action potential in the heart originates near the top of the right Atrium at a point called the Pacemaker or sinoatrial (SA) node. The heart beat is the result of simultaneous generated action potentials by pacemakers which propagate in all directions along the surface of both atria. Typically the heart muscle cell propagation rate is 0.2 to 0.4 meters per second.

THE HEART:

The heart is the organ responsible for pumping blood throughout the body. It is located in the middle of the thorax, slightly offset to the left and surrounded by the lungs. The right atrium receives blood returning to the heart from the whole body. That blood passes through the right ventricle and is pumped to the lungs where it is oxygenated and goes back to the heart through the left atrium, then the blood passes through the left ventricle and is pumped again to be distributed to the entire body through the arteries. The heart is a four chambered pump with two atria for collection of blood and two ventricles for pumping out the blood. The resting/filling phase of a cardiac chamber is called diastole and the contracting/pumping phase is called systole.

The right atrium collects impure blood from the superior and inferior vena cavae. During the atrial contraction, blood is passed from right atrium to right ventricle through the tricuspid valve. During ventricular systole, the impure blood in right ventricle is pumped out through the pulmonary valve to the lungs for purification (oxygenation). The left atrium receives purified blood from the lungs, which is passed on during atrial contraction to the left ventricle via mitral valve. The left ventricle is the largest and most important cardiac chamber. The left ventricle contracts the strongest among the cardiac chamber, as it has to pump out the oxygenated blood through aortic valve and the aorta against the pressure of rest of the vascular system of the body. Due to higher level of importance of contraction of the ventricles, the terms systole and diastole are applied to the ventricles by default.

Einthoven's ECG device

An initial breakthrough came when Willem Einthoven, working in Leiden, Netherlands, used the string galvanometer that he invented in 1903. This device was much more sensitive than both the capillary electrometer that Waller used and the string galvanometer that had been invented separately in 1897 by the French engineer Clément Ader. Rather than using today's self-adhesive electrodes Einthoven's subjects would immerse each of their limbs into containers of salt solutions from which the ECG was recorded.

Einthoven assigned the letters P, Q, R, S and T to the various deflections, and described the electrocardiographic features of a number of cardiovascular disorders.

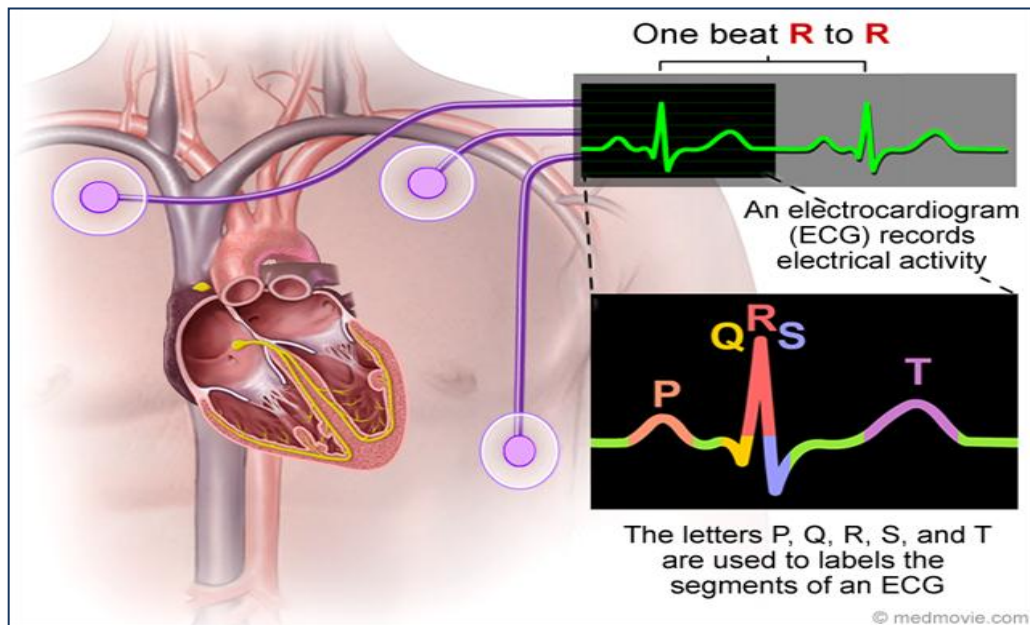


Fig. 2.1 Einthoven's ECG Segments Representation

In 1924, he was awarded the Nobel Prize in Medicine for his discovery. Though the basic principles of that era are still in use today, there have been many advances in electrocardiography over the years.

The instrumentation, for example, has evolved from a cumbersome laboratory apparatus to compact electronic systems that often include computerized interpretation of the electrocardiogram.

2.2 ELECTRICAL ACTIVITY OF THE HEART:

Co-ordinated electrical events and a specialized conduction system intrinsic and unique to the heart play major roles in the rhythmic contractile activity of the heart. The SA node is the basic, natural cardiac pacemaker that triggers its own train of action potentials. The action potential of the SA node propagates through the rest of heart, causing a particular pattern of excitation and contraction.

The sequence of events and waves in a cardiac cycle as follows:

1. The SA node fires.
2. Electrical activity is propagated through the atrial musculature at comparatively low rates, causing slow-moving depolarization (contraction) of the atria. This results in the P wave in the ECG signal. Due to the slow contraction of the atria and their small size, the P wave is slow, low-amplitude wave, with an amplitude of about 0.1-0.3mV and a duration of about 0.08-0.12s.
3. The excitation wave faces a propagation delay at the atrio-ventricular node, which results in a normally iso-electric segment of about 0.08-0.12s after the P wave in the ECG, known as the PQ segment. The pass assists in the completion of the transfer of blood from the atria to the ventricles.

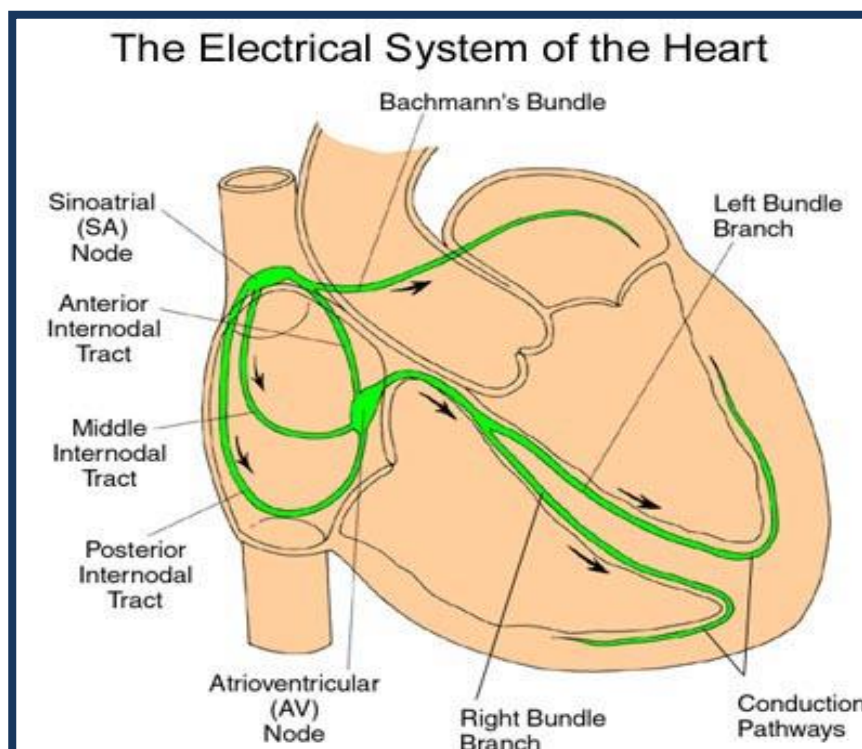


Fig.2.2 Electrical system of Heart

4. The bundle of his, the bundle branches, and the purkinje system of specialized conduction fibres propagate the stimulus to the ventricles at a high rate.
5. The wave of a stimulus spreads rapidly from the apex of the heart upwards, causing rapid depolarization of the ventricles. This results in the QRS wave of the ECG-a sharp biphasic wave of about 1-3mV amplitude and 0.08-0.12s duration.

6. Ventricular muscle cells possess relatively long action potential duration of 0.32s. The plateau portion of the action potential causes a normally iso-electric segment of about 100-120ms after the QRS, known as the ST segment.
7. Repolarization (relaxation) of the ventricles causes the slow T wave, with amplitude of 0.2-1mV and duration of 0.27s.

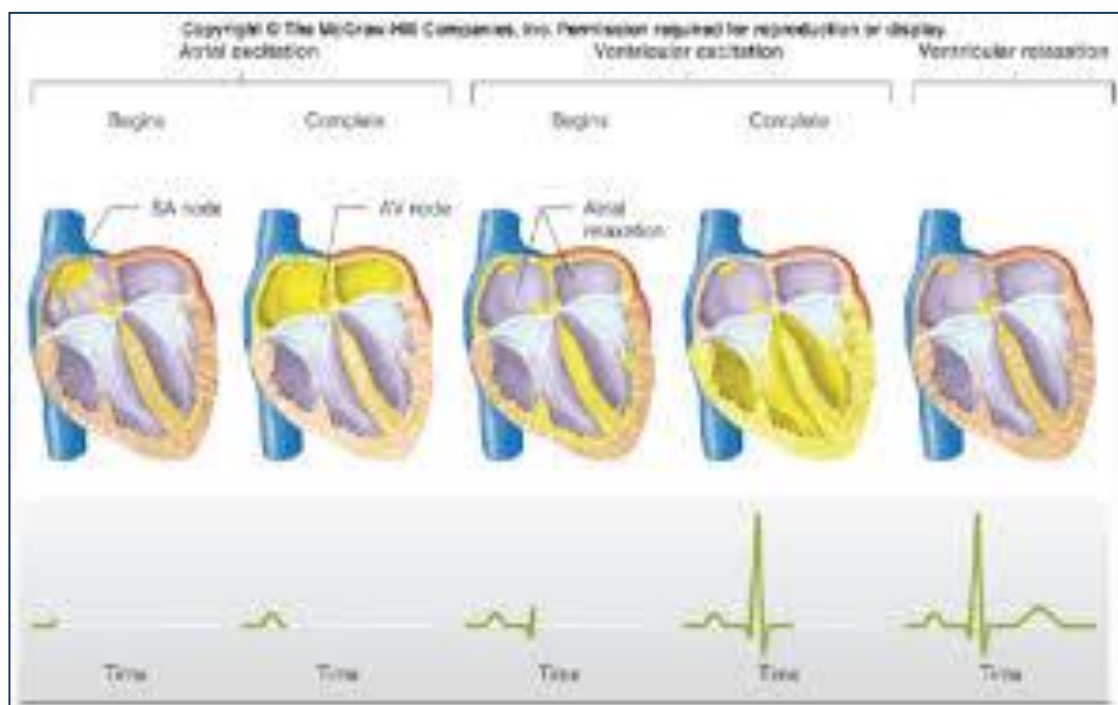


Fig.2.3 Propagation of excitation pulse through the heart – electrical stimulation

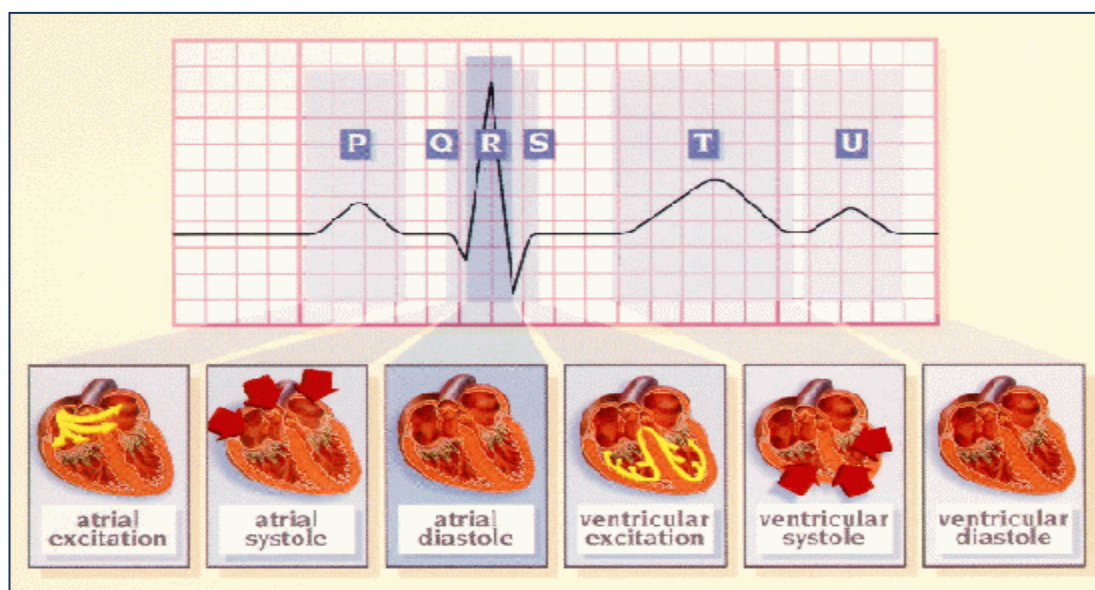


Fig.2.4 ECG Generation Mechanism from heart electrical excitations

2.3 QRS DETECTION AND SEGMENTATION:

ECG SIGNAL:

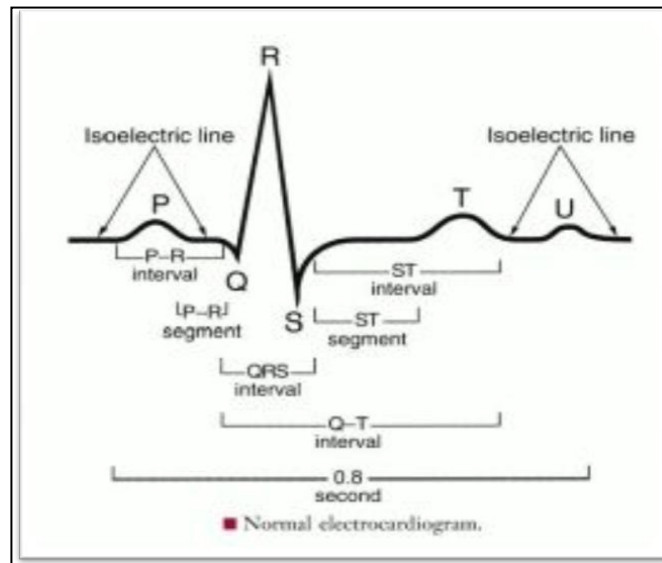


TABLE 2.1: Duration and amplitude of waves in normal ECG

WAVE	DURATION	AMPLITUDE
P wave	0.08-0.12 second	0.1-0.3 mV
QRS complex	0.08-0.12 second	1-3 mV
T wave	0.27 second	0.2-1 mV

PR interval	0.12-0.21 second
ST interval	0.32 second
QT interval	0.4 second

The part of a signal related to a specific event of interest is often referred to as an “epoch”. The ECG records the electrical activity that results when the heart muscle in the atria and ventricles contract.

- Atrial contractions show up as the P wave.
- Ventricular contractions show up as the QRS complex.

- The last common wave in an ECG is T wave. This is the electrical activity produced when the ventricles are recharging for the next contraction(repolarising)

The electrical activity results in P, QRS and T waves that are of different sizes and shapes. When viewed from different Leads, these waves can show a wide range of abnormalities of both the electrical conduction system and the muscle tissue of the hearts four pumping chambers.

P WAVE: Represents atrial depolarization i.e. the time necessary for an electrical impulse from the sinoatrial(SA) node to spread throughout the atrial musculature.

Amplitude: 0.1 to 0.3 mV.

Duration: 0.08 to 0.12 s.

QRS complex: Represents Ventricular Depolarisation. The QRS complex consists of three waves Q wave, R wave and S wave.

- The Q wave is always located at the beginning of QRS complex. It may or may not always be present.
- The R wave is always the first positive deflection.
- The S wave is the negative deflection, follows the R wave.

Amplitude: 1 to 3 mV.

Duration: 0.08 to 0.12 s.

T WAVE: Represents the repolarisation of the ventricles. On rare occasions, a u wave can see following the T wave. The U wave reflects the Repolarisation of the His-purkinje fibres.

Amplitude: 0.2 to 1Mv

Duration: 0.27 sec.

PR Interval: Represents the time taken for impulse to travel from the atria through the AV node, bundle of His, and bundle Branches to the purkinje Fibres.

Duration: 1.12 to 1.21 sec.

ST segment: Represents the End the ventricular depolarization and the beginning of the ventricular repolarisation.

Duration: 0.32 sec.

QT Interval: Represents the time necessary for ventricular depolarization and repolarisation.

Duration: 0.4 sec.

2.4. ABNORMALITIES IN ECG & ECG ARTIFACTS:

Generally the recorded ECG signal is often contaminated by different types of noises and artifacts that can be within the frequency band of ECG signal, which may change the characteristics of ECG signal. Hence it is difficult to extract useful information of the signal. The electrical activity of the heart is sensed by monitoring electrodes placed on the skin surface.

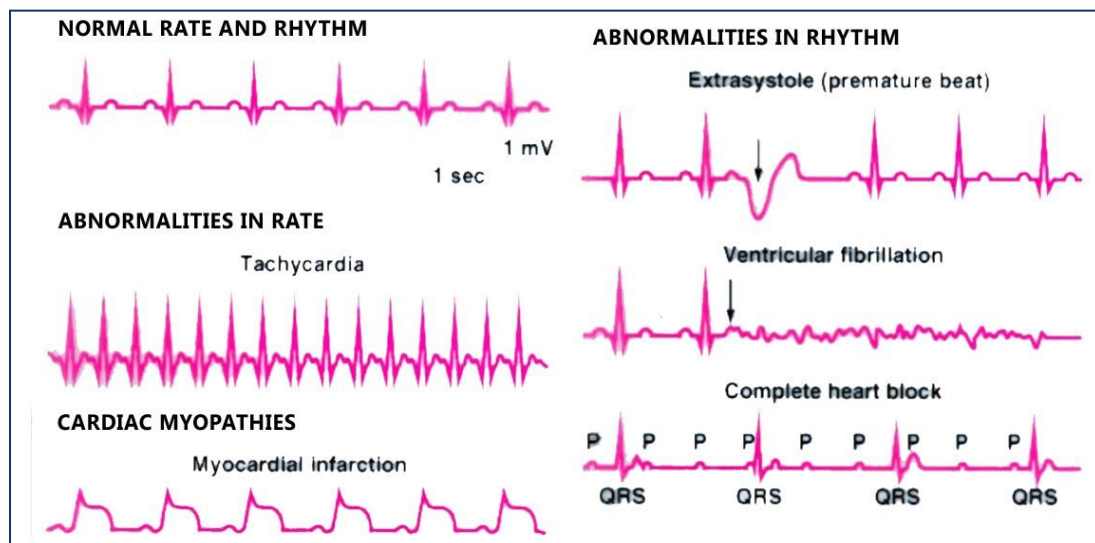


Fig.2.5 Plots showing the abnormal rhythms in ECG

ECG can diagnose the problems of a patient. It can identify the rhythm disturbance which may be Tachycardia due to fast heart beats, Brady cardial due to slow heart beats or irregular pulses. The problems may be due to conduction abnormalities such as left bundle branch block, right bundle branch block, Atrio-Ventricular block.

The poor blood supply to heart muscle is termed as Ischemic Heart Descase and this leads to Angina Pectons (Chest Pain) or Myocardial Infarct (Heart Attack). Hypertrophy occurs due to enlargement of the heart which may be left ventricular, left atrial, right ventricular or right atrial. The metabolic effects may lead to electrolyte abnormalities, wrong medication or thyroid disease.

The electrical signal is very small(normally 0.0001 to 0.003 volts).These signals are within the frequency range of 0.05 to 100hz.unfortunately,other artifactual signals of similar frequency and often larger amplitude reach the skin surface and mix with the

ECG signals. Artifactual signals arise from several internal and external sources. This implies that in practical situations ECG recordings are often corrupted by artifacts. The corruption of ECG signal is due to following major noises:

2.4.1 POWER LINE INTERFERENCE:

Power line interferences contains 60 Hz pickup (in U.S.) or 50 Hz pickup (in India) because of improper grounding. It is indicated as an impulse or spike at 60 Hz/50 Hz harmonics, and will appear as additional spikes at integral multiples of the fundamental frequency. Its frequency content is 60 Hz/50 Hz and its harmonics, amplitude is up to 50 percent of peak-to-peak ECG signal amplitude. This artifact can be removed by using notch filter.

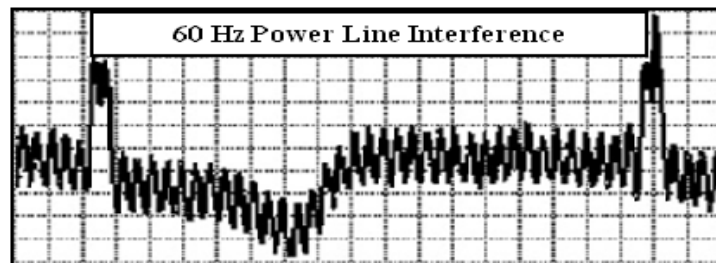


Fig. 2.6 60 Hz Power line interference

2.4.2 BASELINE WANDERING:

Base-line wandering may be caused in chest-lead ECG signals by coughing or breathing with large movement of the chest, or when an arm or leg is moved in the case of limb-lead ECG acquisition. Base-line drift can sometimes caused by variations in temperature and bias in the instrumentation and amplifiers. Its frequency range is generally below 0.5 Hz. To remove baseline drift a high pass filter with cut-off frequency 0.5 Hz is used.

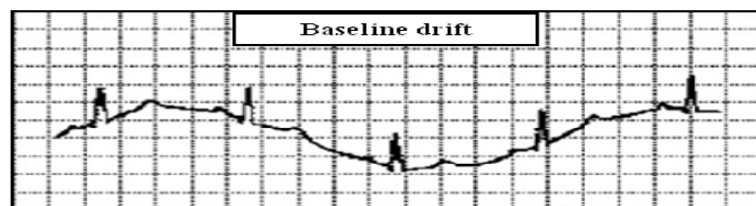


Fig. 2.7 Baseline drifts in ECG signal.

2.4.3 MOTION ARTIFACTS:

Motion artifacts are transient baseline change due to electrode skin impedance with electrode motion. It can generate larger amplitude signal in ECG waveform. The peak amplitude of this artifact is 500 percent of Peak to Peak ECG amplitude and its duration is about 100 – 500 ms. Adaptive filter can be used to remove the interference of motion artifacts. Removing motion artifacts from an electrocardiogram (ECG) is one of the important issues to be considered during real-time heart rate measurements in telemetric health care. Therefore, in a proposed technique, an accelerometer was used to measure the acceleration signal of the vibrations or movement of the trunk as the reference inputs of the adaptive filter. The optimal weight of the adaptive filter which could be adjusted by a least mean square algorithm is used. Experiments with synthetic and real data were performed to demonstrate the efficacy of this proposed method.

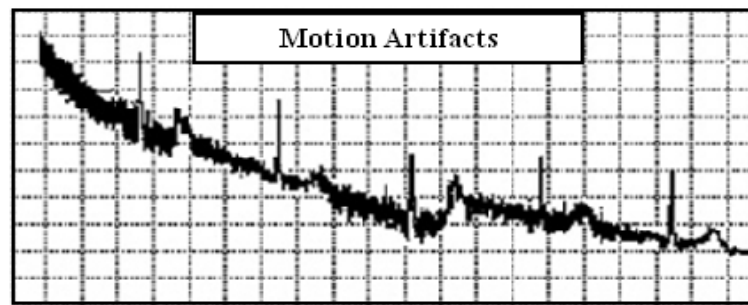


Fig. 2.8 Motion artifacts in ECG signal.

ECG is a high frequency signal, it contains Base Line Wandering, Power Line Interference and other such artifacts are removed first by passing ECG through a Low Pass Filter and Adaptive Thresholding is applied further.

2.5 ECG SIGNAL ACQUISITION - PROCEDURE

In clinical practice, the standard 12-channel ECG is obtained using four limb leads and chest leads in six positions. The right leg is used to place the reference electrode. The left arm, right arm, and left leg are used to get leads I, II, III. The augmented limb leads known as aVR, aVL, and aVF are obtained by using the exploring electrode on the limb indicated by the lead name.

2.5.1. LEADS & LEAD CONFIGURATIONS

A lead is a connection between any two selected points on the surface of the body and electrocardiograph. About 12 different leads are used routinely. These are divided into two types: Bipolar and Unipolar

A) BIPOLAR LEADS

These are three different type leads. Each lead consists of two electrodes –both are exploring electrodes, of which one is +ve and another is –ve. The bipolar leads are as follows:

1. Lead I
2. Lead II
3. Lead III

Lead I:

It measures the potential difference between right and left arms with the left arm being connected to +ve and right arm connected to –ve.

Lead II:

It measures the potential difference between right arm and left foot with the left foot being connected to +ve and right arm connected to –ve.

Lead III:

It measures the potential difference between left arm and left foot with the left foot being connected to +ve and left arm connected to –ve.

According to the Einthoven's law $L1+L2+L3=0$.

B) UNIPOLAR LEADS

Two types of unipolar leads are used routinely. They are:

1. Augmented limb leads.
2. Unipolar chest leads.

In the above leads there are two electrodes, of which one is an active electrode called exploring electrode and another electrode is called indifferent electrode.

i) AUGMENTED LIMB LEADS

These are developed by Goldberger and are not typical unipolar leads. Different augmented limb leads are as follows:

1. aVR
2. aVL
3. aVF

The exploring electrode is kept at the third point.

aVR=PD between right arm and left arm + left foot.

aVL=PD between left arm and right arm + left foot.

aVF=PD between left foot and right arm + left arm.

ii) UNIPOLAR LIMB LEADS

Six chest leads V 1 to V6 are used routinely

Active electrode is kept at any one of the six points on the precardium {V1 to V6}

V1 – right margin of the sternum at the 4th intercostal space.

V2 – left margin of the sternum at the 4th intercostal space.

V3 – midway between V2 and V4.

V4 – 5th intercostal space at left midclavicular line.

V5 – 5th intercostal space at left midaxillary line.

V6 – 5th intercostal space at left midaxillary line.

EINTHOVEN'S TRIANGLE:

The hypothetical equilateral triangle formed by leads I, II, and III is known as Einthoven's triangle. It states that in a volume conductor the sum of the electrical potential at the three peripheral points of an equilateral triangle with the current source in the centre is zero. The centre of the triangle represents Wilson's central terminal. The heart is said to be placed at the centre of the triangle. The six leads measure the projection of the three-dimensional cardiac vector on to the axes.

Einthoven's triangle as applicable to the body which acts as a volume conductor the heart is the current source and the equilateral triangle is formed by the junction of

right upper extremity with the trunk, left upper extremity with the trunk and the junction of left lower limb with the trunk. This is called Einthoven's triangle.

According to the Einthoven's triangle $L1 + L2 + L3 = 0$.

But lead2 is deliberately reversed to get positive waves.

$$\text{Hence } L1 + L3 = L2 \quad (\text{or})$$

$$L1 + L2 - L3 = 0$$

Lead 1 mainly records the activities from the superior aspects of the heart. Lead 2 mainly from the right aspect of the heart, and lead 3 the left ventricular events mainly. The electrodes are placed on the wrists and ankle because the fall of potential along the limb is negligible.

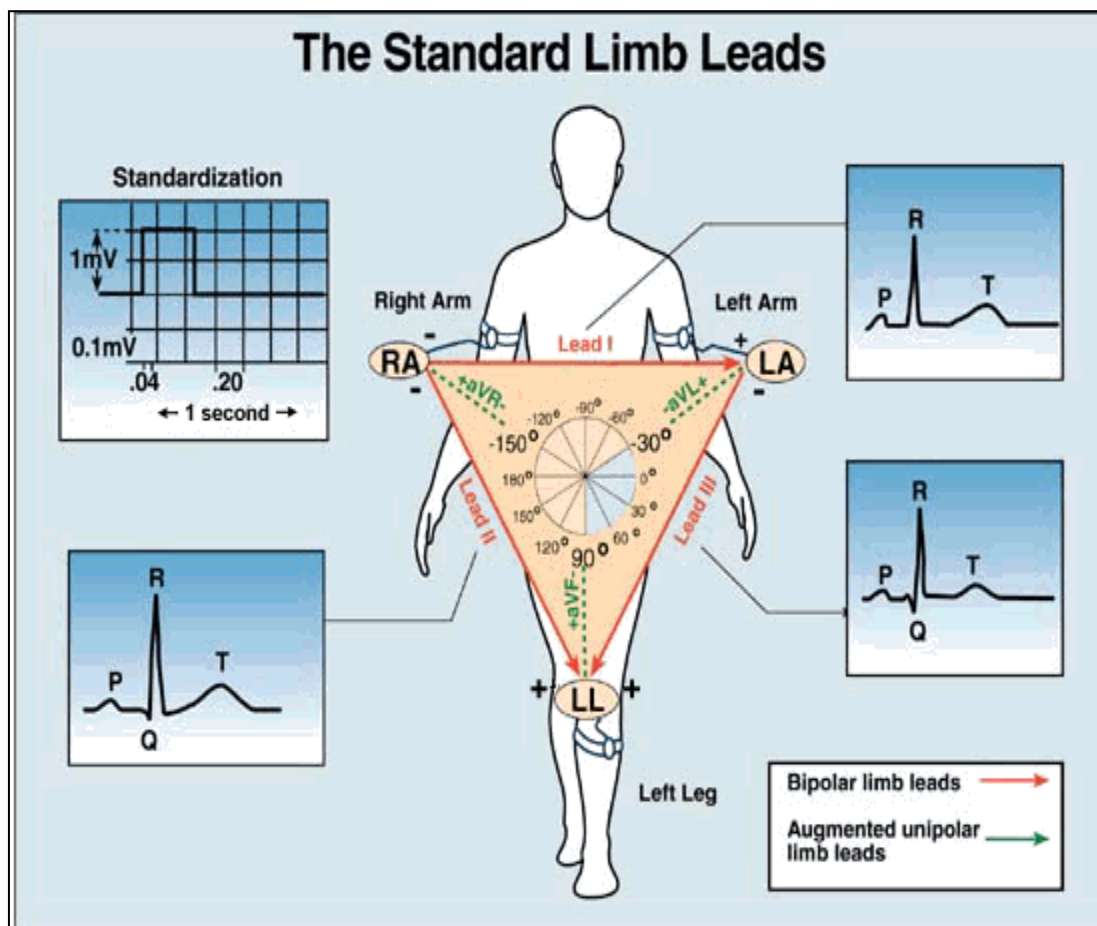
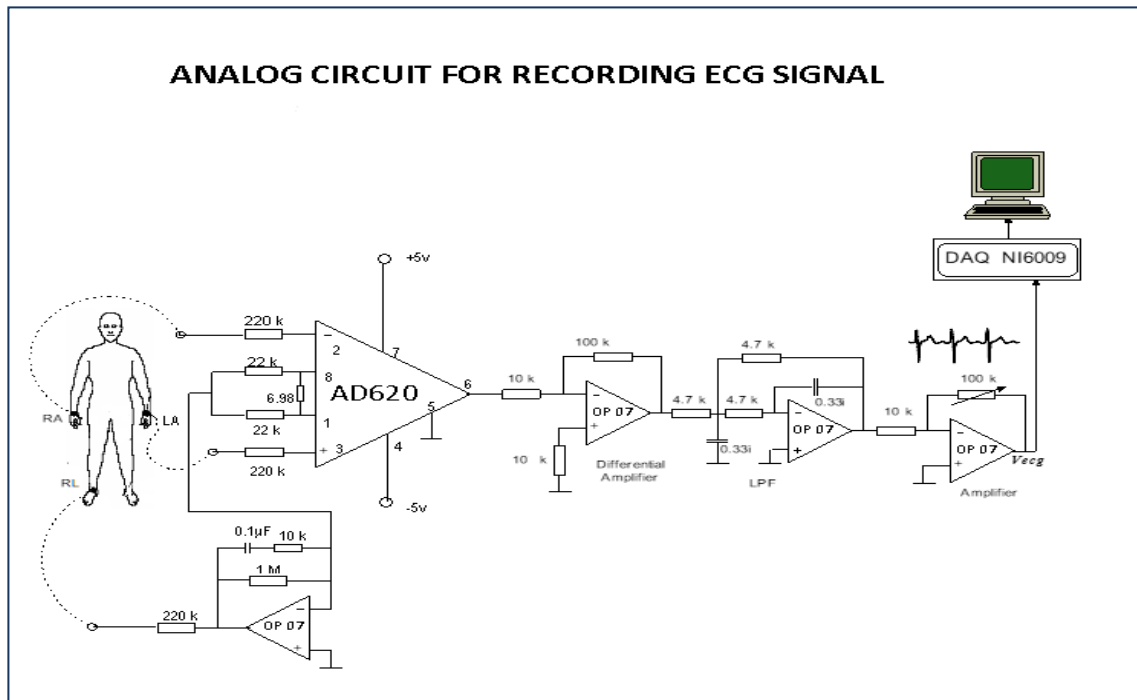


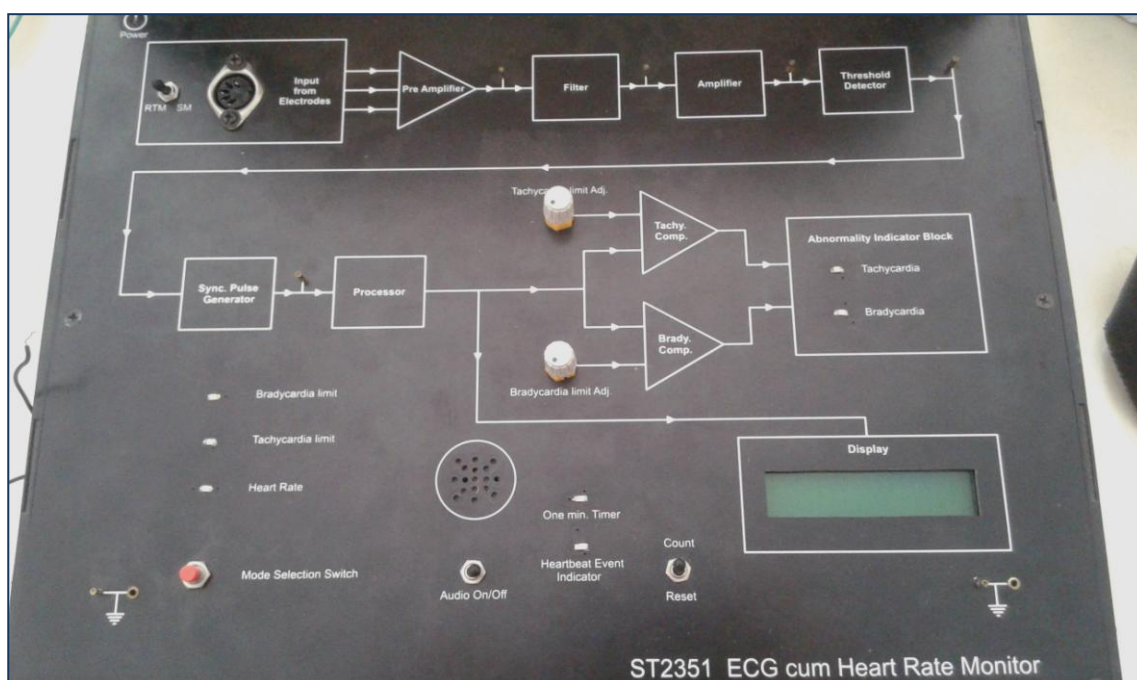
Fig.2.9 Einthoven's triangle

2.5.2. ECG CIRCUIT DESIGN:



Analog circuit for ECG Signal Acquisition

RECORDING ECG SIGNAL: ECG Cum Heart Rate Monitor ST2351 of Scientech Ltd. is used to acquire ECG signal of the subject. The ECG signal is recorded and saved in the PC as Text file.



DATA SETS USED IN EXPERIMENTATION:

ECG signals are recorded from various subjects in different lead configurations, such as limb lead-I, II and III for a period of 10 min. For this a data acquisition system of National Instrumentation NI DAQ 6009 card, which is having a 12 bit resolution is used. These ECG signals are then acquired in LabVIEW environment to a PC by writing suitable Virtual Instrumentation programs and one such recorded ECG signal along with its spectrum are shown in Fig. 5.1, which clearly indicates a peak at 50Hz corresponding to PLI.

DOWN SAMPLING THE ECG:

As ECG signal which was recorded at 1000Hz sampling frequency would contain 1000 samples per each second of data. If we are supposed to process a 10 second ECG data then 10000 samples are supposed to be processed. Therefore to reduce the computational burden the sampling frequency is reduced to 200Hz by down sampling the recorded ECG signal by a factor of 5. Now, the down sampled ECG signal contains only 2000 samples for processing of 10 second ECG data.

DENOISING THE ECG:

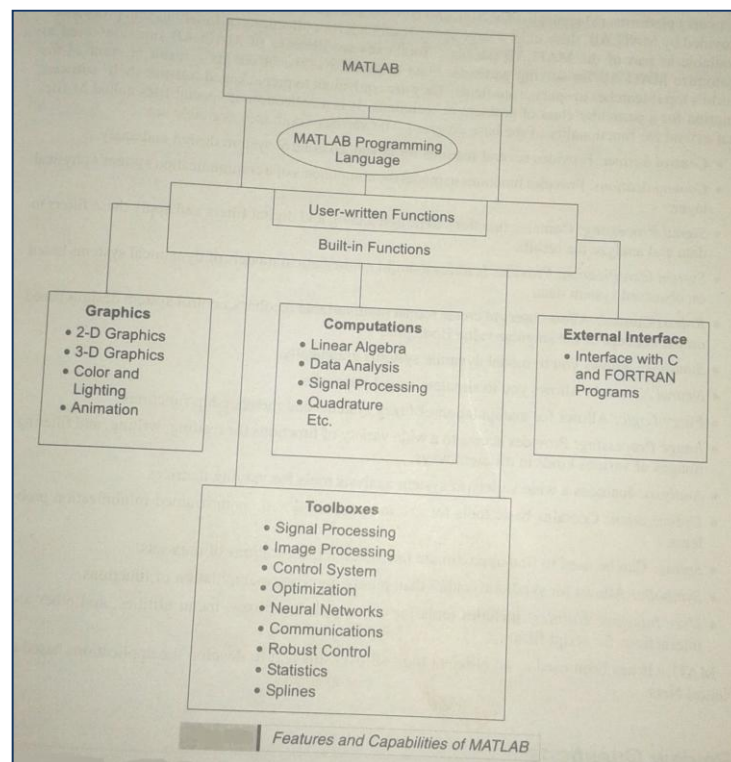
The classical techniques of denoising ECG signals include notch filters, adaptive filters, etc., but these techniques perform well only up to some degree of SNR. All the classical techniques have specific drawbacks which may include loss of important information from the signal, distortion of waveform at QRS complex and many other problems.

In the presented work, a more roguish method called EMD based adaptive noise cancellor is considered and the test results are promising. Comparison of the RMS error values obtained for the proposed method and the preliminary notch filtering technique showed that the EMD based adaptive filter gives better results.

3. SOFTWARE REQUIREMENTS

3.1 MATLAB INSTALLED PC

Dr. Cleve Moler, chief scientist at MathWorks, Inc., originally wrote MATLAB to provide easy access to matrix software developed in LINPACK and EISPACK projects. The first version was written in late 1970's for use in courses in matrix theory, linear algebra and numerical analysis. MATLAB is therefore built upon a foundation of sophisticated matrix software, in which the basic element is a matrix that doesn't require predimensioning.

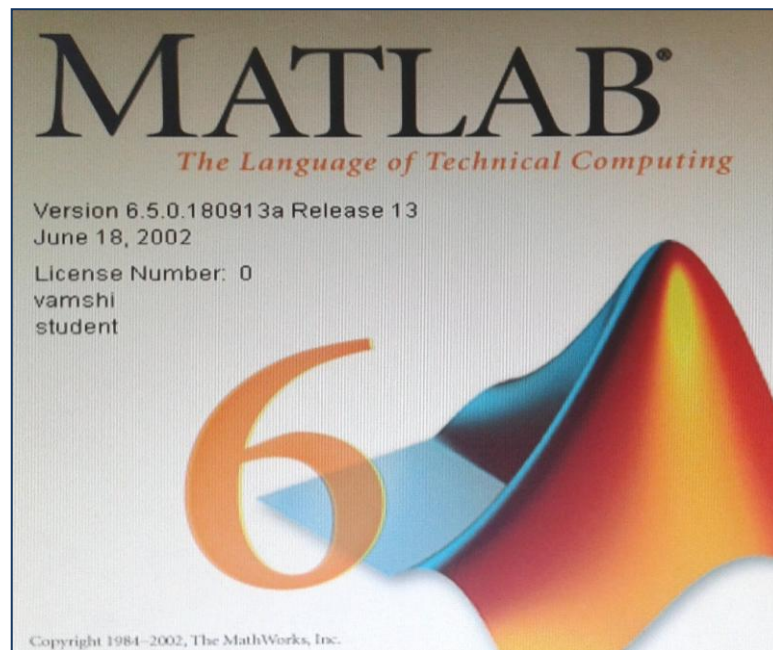


MATLAB Functional Block Representation

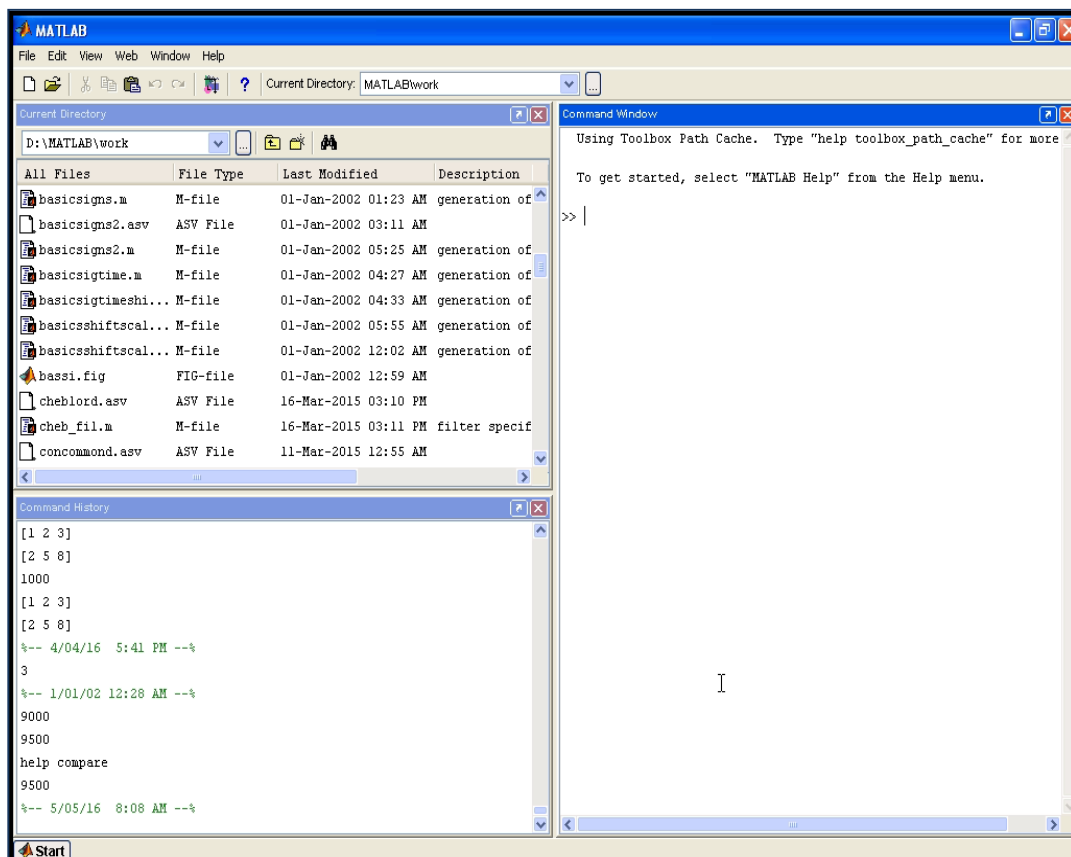
Typical features of MATLAB are:

1. Math and Computation
2. Algorithm development
3. Modeling, emulation and prototyping
4. Data analysis, exploration and visualization
5. Scientific and engineering graphics in 2D and 3D Views.
6. Application Development including Graphical User Interface building
7. MATLAB help for fetching pre-defined functions
8. Importing and Exporting the programs and formatted data
9. Availability of Advanced Toolboxes for Communication Systems, Signal Processing, System Identification, Robust Control, Image Toolbox, Simulink, Neural Networks, Spline, Symbolic, Optimizations and so on...

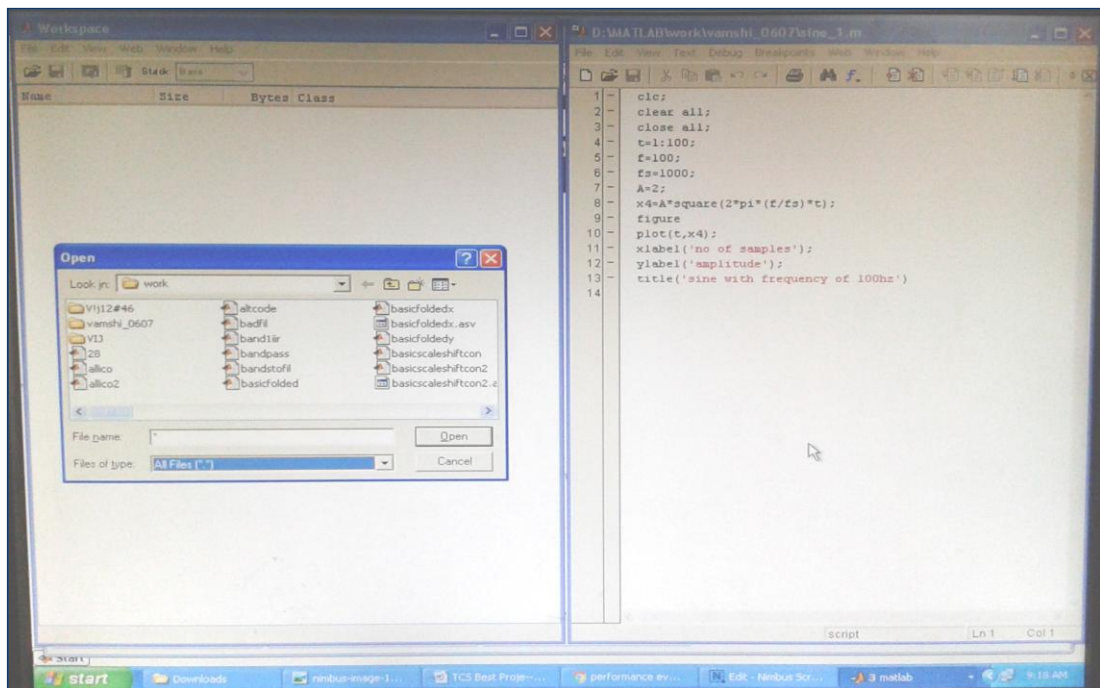
3.1.1. Opening a MATLAB Window



3.1.2. Sample MATLAB Work Environment

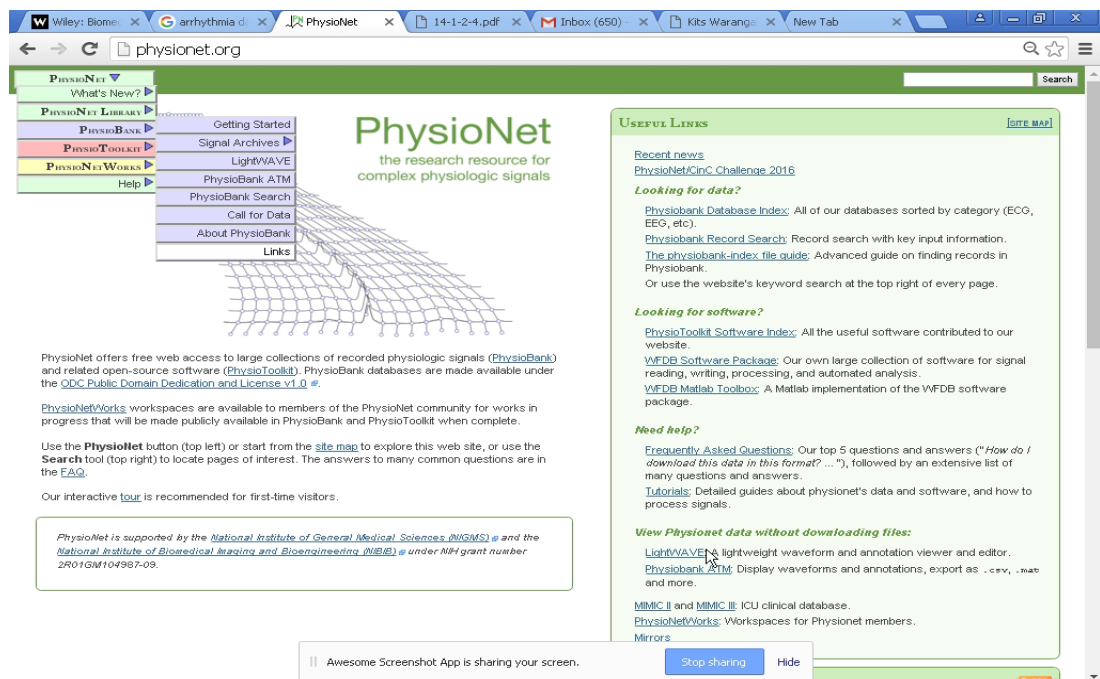


3.1.3. Creating a New Workspace: To write MATLAB Code

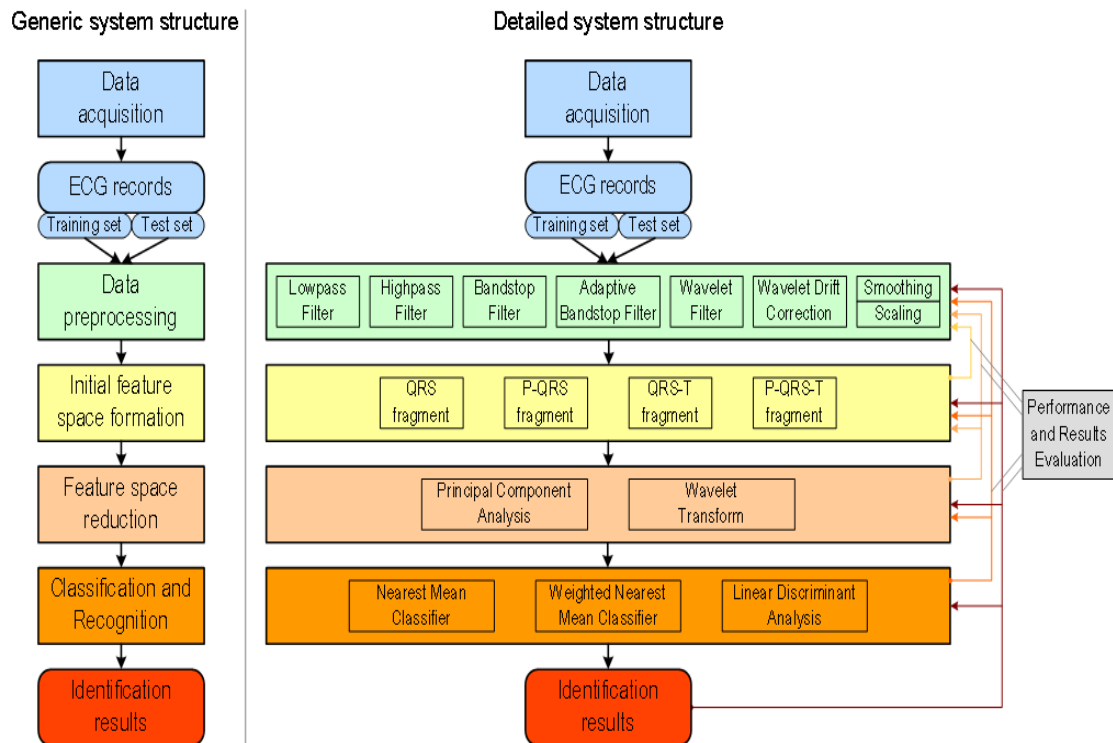


3.2 PHYSIONET SOURCE DATABASE

3.2.1. MIT-BIH Arrhythmia Database



3.2.2. Functional Architecture of Database



3.2.3. Extracting an ECG signal from Database in .mat file format

The screenshot shows the PhysioNet website interface for extracting an ECG signal from the database in .mat file format. The browser window displays the URL `physionet.org/cgi-bin/atm/ATM`.

Selected input: record mitdb/100, annotator str, from 0:00.000 to 0:10.000

The output below was prepared using this command:

```
plotATM.m -r mitdb/100 -f 0 -s 10 -i 1000000 -y100m.info
```

Download these files:

- 100m.mat (binary, 14424 bytes; the matrix of raw signal values)
- 100m.info (text, 332 bytes; signal names and other information about 100m.mat)
- 100m.hes (text, 200 bytes; needed to read 100m.mat using applications in the [WFDB Software Package](#) or functions in the [WFDB Toolbox for MATLAB](#))
- plotATM.m (m-code text; a function that reads 100m.mat and 100m.info and plots the converted data.)

How to read these files in MATLAB or Octave:

Download both 100m.mat and 100m.info. Also download plotATM.m if you have not done so previously.

Each row of 100m.mat contains the samples of one signal. Each column contains a sample of each signal observed at the same time. The time intervals between consecutive columns are equal and specified in 100m.info.

In MATLAB or Octave, run the command

```
[signal, time] = plotATM('100m')
```

to view the signals. Inspect plotATM.m to see how use the information from 100m.info to convert the raw samples from 100m.mat into values in calibrated physical units.

Note: This is a conversion of signals only, not annotations. The amount of data converted is limited to 1 million samples per signal since larger amounts may be difficult to manipulate using MATLAB or Octave.

Send feedback about this page to PhysioNet

Your comments and suggestions are welcome. We encourage you to use our [feedback form](#) to comment on this page. If you would like to receive a reply, please send your comments by email to feedback@physionet.org.

Awesome Screenshot App is sharing your screen. [Stop sharing](#) [Hide](#)

National Institute of Biomedical Imaging and Engineering (NIBIB) and National Institute of General Medical Sciences (NIGMS) logos are visible at the bottom.

Download Required File Extensions

PHYSIONET ▼		PhysioBank Record Search				Search	
Input				Toolbox			
Database: MIT-BIH Atrial Fibrillation Database (afdb) ▼				Export signals as .mat ▼			
Record: 04015 ▼ Signals: all ▼				Navigation			
Annotations: reference rhythm annotations (atr) ▼				<< << < * > >> >>			
Output				Previous record - + Next record			
Length: <input type="radio"/> 10 sec <input type="radio"/> 1 min <input type="radio"/> 1 hour <input type="radio"/> 12 hours <input checked="" type="radio"/> to end							
Time format: <input checked="" type="radio"/> time/date <input type="radio"/> elapsed time <input type="radio"/> hours <input type="radio"/> minutes <input type="radio"/> seconds <input type="radio"/> samples							
Data format: <input checked="" type="radio"/> standard <input type="radio"/> high precision <input type="radio"/> raw ADC units				Help About ATM			

4. PROJECT IMPLEMENTATION

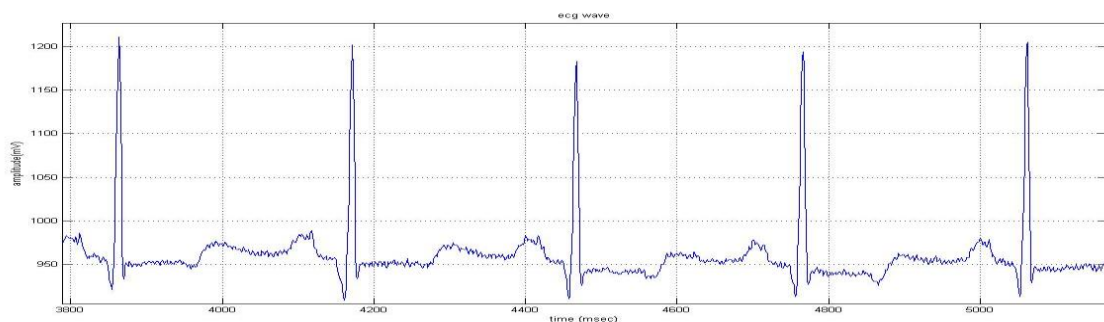
4.1. QRS DETECTION ALGORITHMS – EXPLANATIONS

4.1.1. PAN TOMPKINS ALGORITHM

Step 1: Generate an ECG Signal in MATLAB. (Duration=10000sec=2hr 40mins)

Source Internet: <http://www.physionet.org/>

SELECT: Physiobank> physiobank ATM>



SELECT input: MIT-BIH DATA BASE (mitdb)

SELECT output: length- 2hour 40mins

For Eg: Download: 101.mat, 101.info, 101.he, plot ATM.m

Step 2:

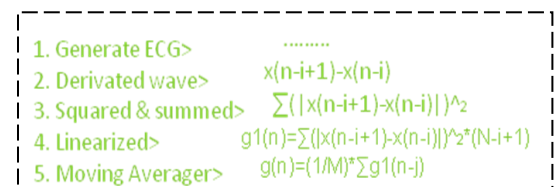
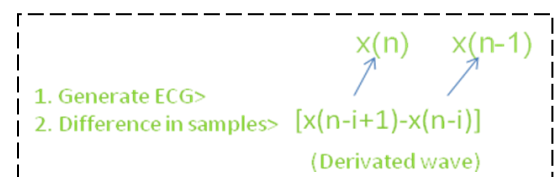
Assuming $x(n)$ =ecg signal, we generate following signals:

$$1. \quad g1(n) = \sum (|x(n-i+1) - x(n-i)|)^2 \cdot (N-i+1)$$

(N-i+1) =linearizer

$$2. \quad g(n) = (1/M) * \sum g1(n-j)$$

M=total avg.samples, M=N=8



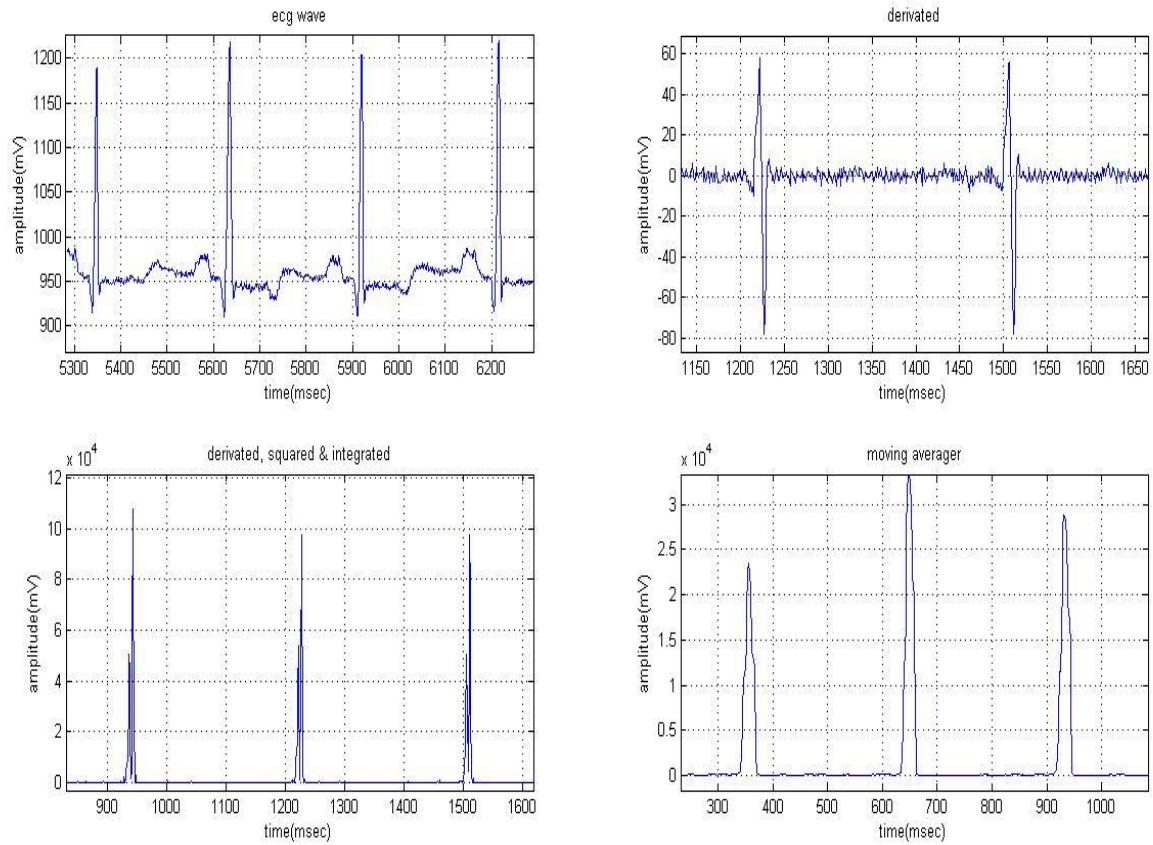
Step 3:

Generating difference equation of two adjacent samples

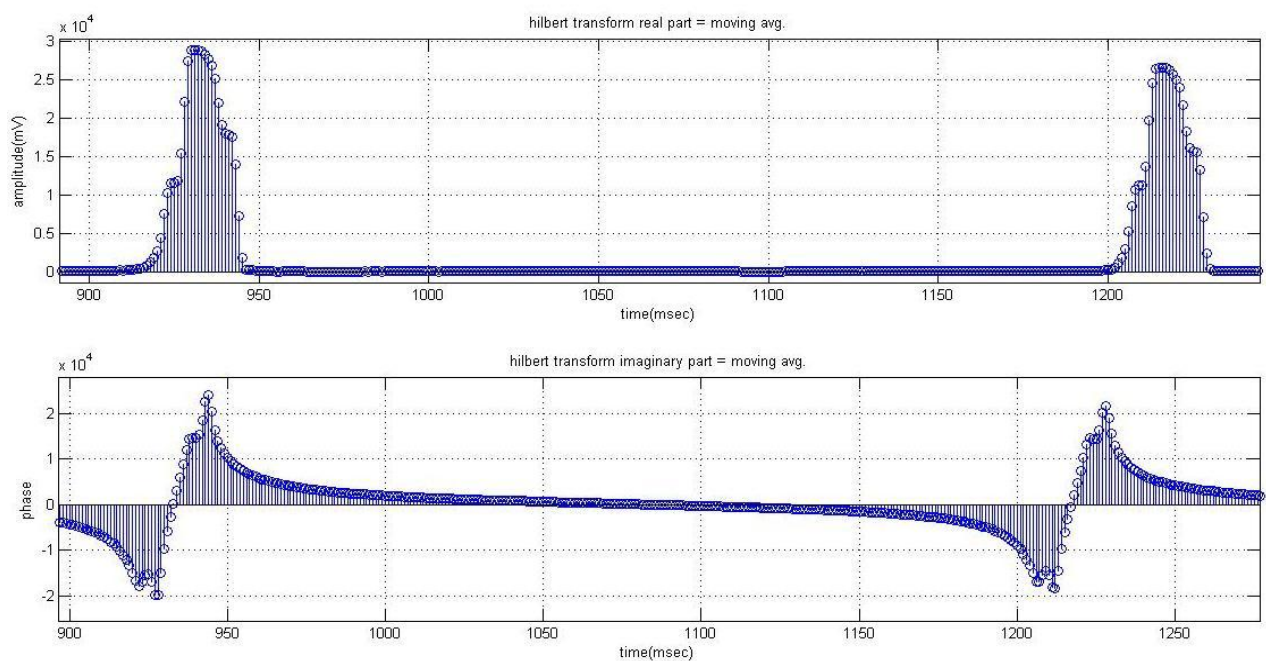
(Differentiator--Low Pass Filter)

Step 4:

Now, obtained signal is Squared and Linearized and Passed through Moving Averager.

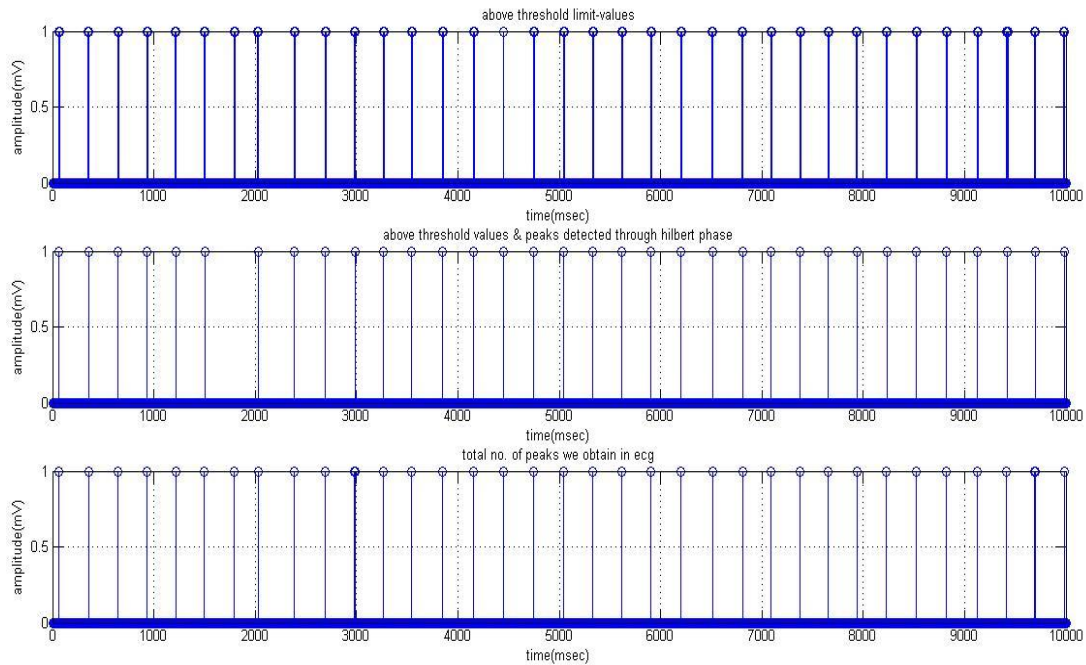


Step 5: Apply Hilbert Transform on 's'. We get Magnitude and Phase plot
(Considering 's' as the signal after passing through a moving averager)



Step 6:

Apply Threshold Limiters on Amplitude Scale of Hilbert Magnitude and Time Scale of Hilbert Phase Plots (we considered, >20000 mV in amplitude Scale and -1500 to 1500msec in Time Scale). Compare R-peaks.



Results:

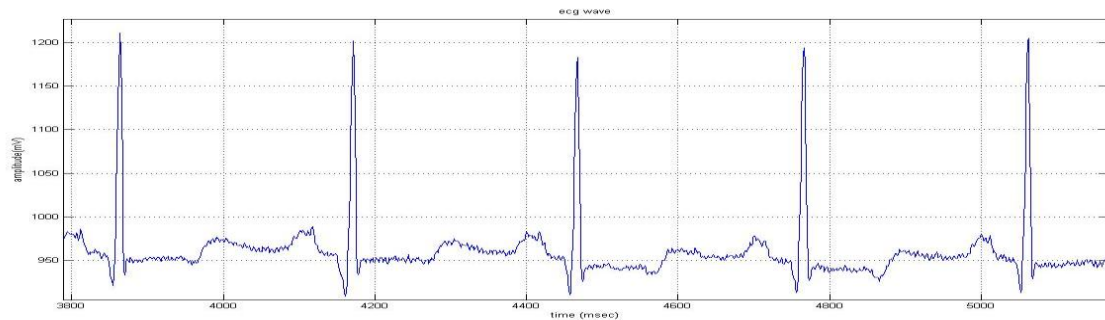
Taking ratio of no. of peaks detected after thresholding and hilberted and no. of total peaks in ECG signal, we get efficiency.

$$\text{Efficiency} = \frac{\text{no. of peaks detected after thresholding and hilberted}}{\text{no. of total peaks in ECG signal}}$$

4.1.2. EMPIRICAL MODE DECOMPOSITION ALGORITHM

Step 1: As this technique does not use any Basic Function, we take the signal itself as initial function...

Step 2: Download ECG Wave & link to MATLAB & Generate next approximating Local



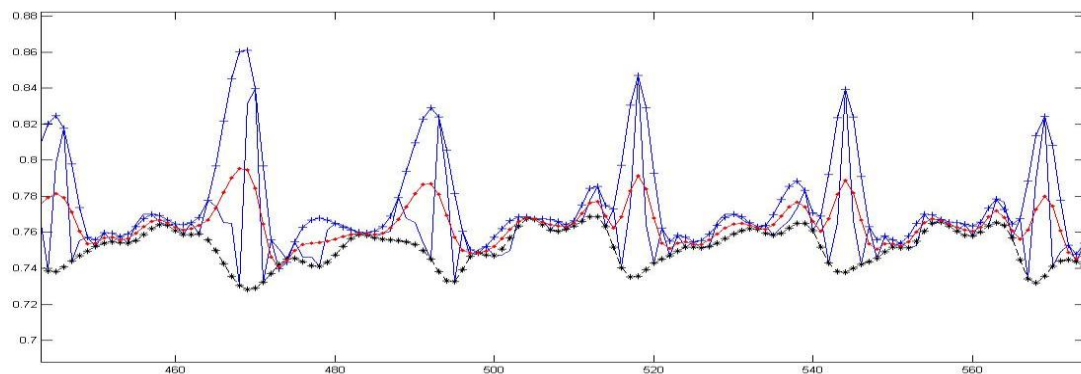
Maxima and Local Minima. Find averaged signal (Now, consider this as Basic Function)

% make endpoints both maxes and mins

% spline interpolate to get max and min envelopes;

maxes = [1 maxes N];

maxenv = pline(maxes,h(maxes),1:N);



mins = [1 mins N];

minenv = spline(mins,h(mins),1:N);

Step 3: Assuming $x(n)$ =ECG signal, generate sub-functions or Intrinsic Mode Functions (IMFs). Subtract this basic function from ECG signal, we get first IMF. Repeat subtraction to get second IMF and repeat this process until we get smoothed frequency IMF function i.e; -IMF.

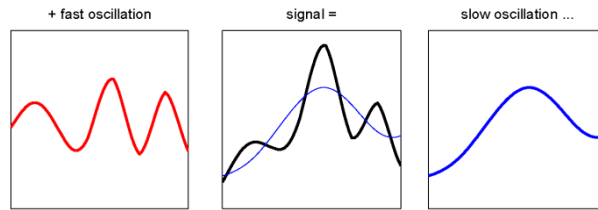
$$m = (\text{maxenv } x(n) + \text{minenv } x(n))/2;$$

$$\text{Residue is } hr = x(n) - m;$$

Advantage: Noise Removal and Signal Retracing.

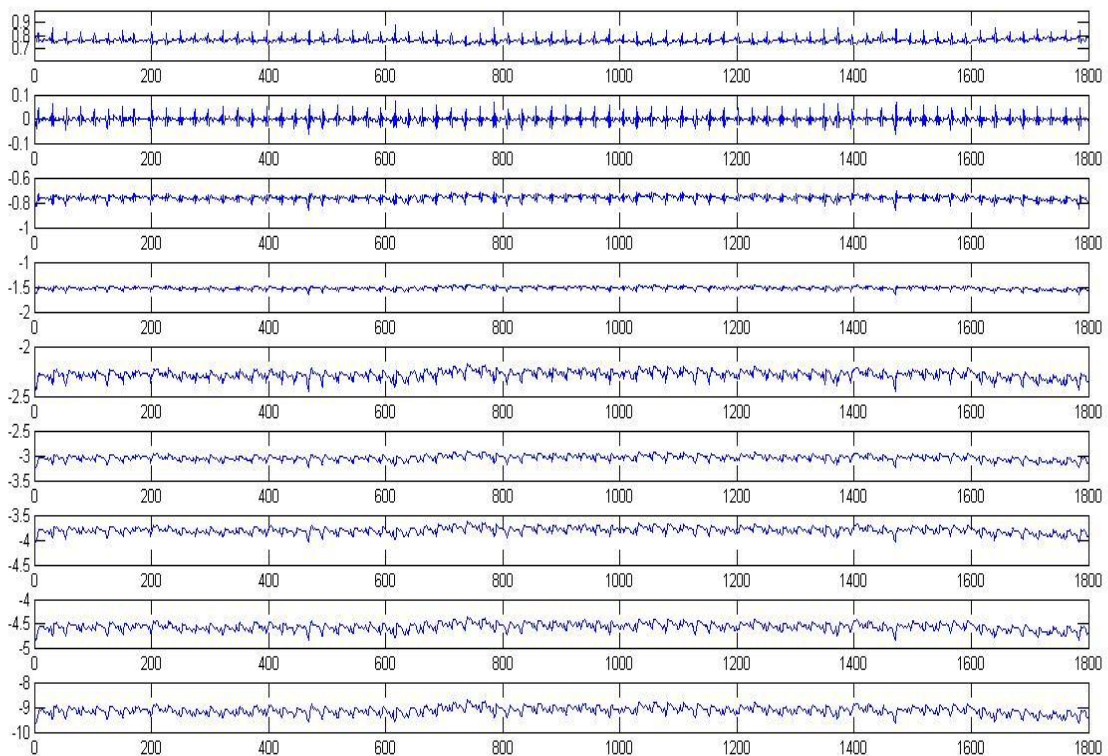
$x(t) = d_1(t) + r_1(t)$
 $d_1(t)$ -''high-frequency'' part (Intrinsic Mode Function)
 $r_1(t)$ -''low-frequency'' part

$$\begin{aligned}
 x(t) &= d_1(t) + r_1(t) \\
 &= d_1(t) + d_2(t) + r_2(t) \\
 &= d_1(t) + d_2(t) + d_3(t) + r_3(t) \\
 &\vdots \\
 &= \sum_{i=1}^N d_i(t) + r_N(t)
 \end{aligned}$$



Step 4: IMFs Waveforms plotted in decreasing order of frequency(from higher frequencies)

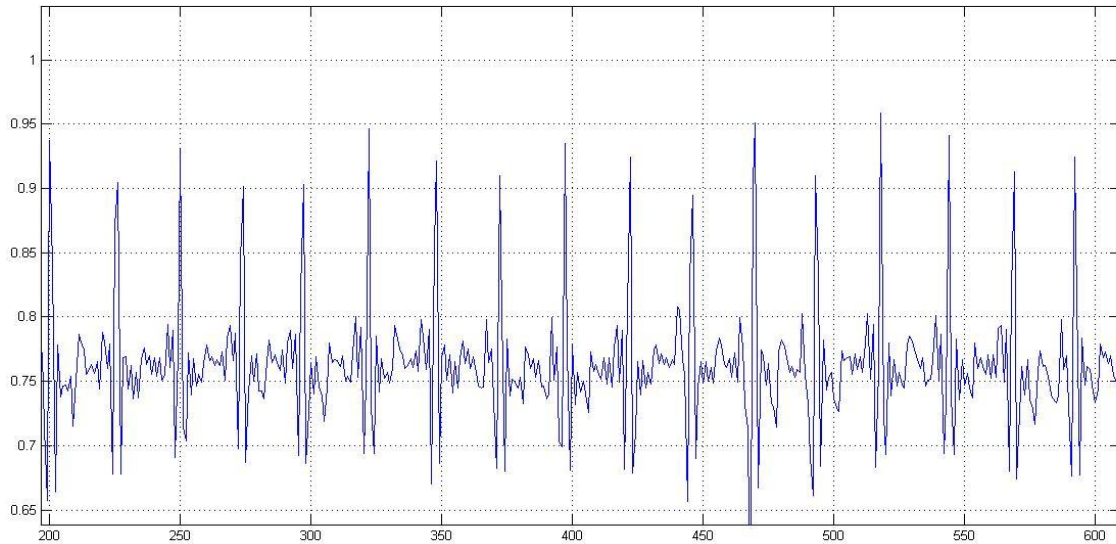
Step 5: Now, make algebraic sum of high frequencies to retrace ECG-QRS Complex (of atmost 5 IMFs). Use any of those, and obtain a signal with higher amplitude peaks, consider them as R-peaks.



Intrinsic Mode Functions(IMFs) with a residue signal

Step 6: Now, using threshold limiters obtain R-peaks.

Step 7: Compare no. of peaks of Retraced Signal with no. of peaks of ECG Signal.



Retraced ECG Signal from summed up IMF Signals

Results:

Taking ratio of no. of peaks of retraced signal and no. of total peaks in ECG signal, we get efficiency.

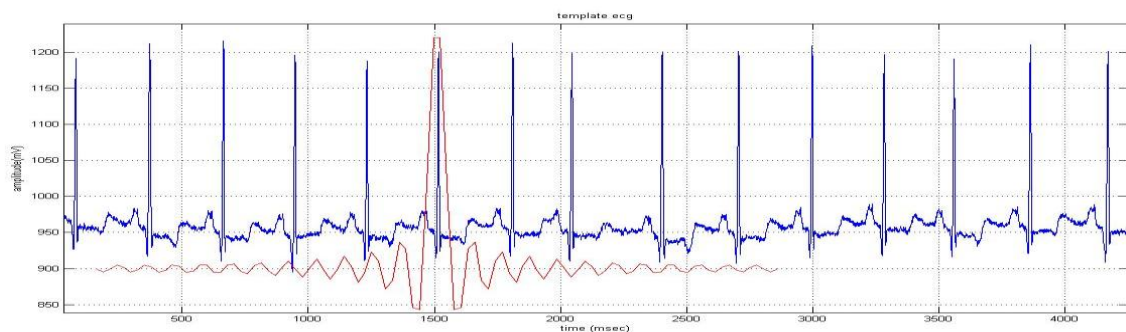
$$\text{Efficiency} = \frac{\text{no. of peaks of retraced signal}}{\text{no. of total peaks in ECG signal}}$$

4.1.3. TEMPLATE MATCHING ALGORITHM

- Step 1:** Creating a PARENT TEMPLATE $x(n)$
- Step 2:** Move the Template over Distorted ECG Wave
- Step 3:** Compare the coefficients of both,
A) when their peaks and time instants matches,
B) also when time intervals matches
- Step 4:** Diff==0; R-peak Found; else, Repeat Step3
Eg: Standard Daubechies Template
- Step 5:** Apply Threshold Limiters, over ECG and Template at a time.
Plot R-peaks.

```
clc; clear all; close all;
load('100m.mat');
x=val(1,:); ecg=x';
figure(1); plot(ecg); grid on;
title('ecg wave'); xlabel('time (msec)');
ylabel('amplitude(mV)'); hold on;

Fc=10; Fb=8; M=500;
t = linspace(-150,150);
y1 = sqrt(Fb).* sinc(Fb*10*t/M);
y2 = sqrt(-Fb).* sinc(Fb*10*t/M);
y=y1+y2;
plot((9*t)+1510,(125*y)+900,'r-'); grid on;
title('template ecg'); xlabel('time (msec)');
ylabel('amplitude(mV)');
```



Recursive Template compared over ECG Signal

Results:

Taking ratio of no. of peaks of Template and no. of total peaks in ECG signal, we get efficiency.

$$\text{Efficiency} = \frac{\text{no. of peaks of Template}}{\text{no. of total peaks in ECG signal}}$$

5. RESLUTS

5.1. EXPECTED RESULTS

We have following algorithms to detect QRS complexes in an ongoing ECG signals:

Derivative Based Algorithm, Pan-Tompkins Algorithm, Filter Banks Techniques, Template Match Method, Empirical Mode Decomposition algorithm, Wavelet Transforms Method

We worked and enable to bring out outputs for three of them:

1. Pan Tompkins Algorithm
2. Empirical Mode Decomposition
3. Template Match Technique

Evaluation of performance is done by calculating parameters like:

- | | |
|----------------------|--------------------------|
| 1. Sensitivity | 2. Specificity |
| 3. Predictivity | 4. Tik-Tac period values |
| 5. Rate calculation. | 6. Signal Accuracy |

Parameters of all three algorithms are calculated and compared, then decided for best fit/efficient algorithm as per need/utility.

5.1. OBTAINED RESULTS

We calculate the Signal Accuracy (Performance parameter) of all three algorithms and those are compared here under:

1. *Output Percentage Efficiency of PT Algorithm ranges between **93.3% and 94.5%.***
2. *Output Percentage Efficiency of EMD Algorithm is in between **94.26 to 95.3%.***
3. *Output Percentage Efficiency of Template Matching Algorithm is estimated as **95.1%.***

6. FUTURE SCOPE

SUBJECT VICTIM UNDER TEST

RESEARCH LAB SEGMENT:	QRS EXTRACTION (LABVIEW) & ONLINE MONITORING
SUBJECT NAME :	VAMSHI
TIME DURATION :	30 MIN TEST
ELECTRODES POSITIONS :	RIGHT ARM, LEFT LEG, RIGHT LEG
DIGITAL OSCILOSCOPE :	ECG WAVE OUTPUT
AUDIO PULSES :	HEART BEATS



Fig: A clip taken during ECG Extraction of our project batch mate in Research Lab

To Test Fault Segments in ECG Online and Diagnose the abnormalities/diseases of Heart using Computerized Interface and for easy transmission and reception of victim's ECG Profile.

7. APPENDICES – MATLAB CODES

7.1 PAN TOMPKINS CODE

```
    Clears the screen -----
clc; clear all; close all;

%    Load ECG, ECG duration is 10000sec signal= 2hr 40mins signal
load('100m.mat');
x=val(1,:);
ecg=x';
figure(1);
plot(ecg); grid on;

title('ecg wave');
xlabel('time (msec)');
ylabel('amplitude(mV)');

N=8; M=8;
k=input('enter the total no.of samples '); % setting input 'k = 9000'
samples
% n=0:1:k;
figure

%    creating differentiated wave -----
n=1:1:2*k;
for i=0:1:7
    x=ecg(n);
    y=ecg(n+i+1);
    z=ecg(n+i);
    y1=y-z;
    %    creating differentiated, squared & integrated wave ----
    x2=y1.*y1;
    x3=abs(x2);
    a(n)=x3*(N+i+1);
end
%    disp(a);
plot(y1); grid on;

title('derivated'); xlabel('time (msec)'); ylabel('amplitude(mV)');
figure;

%    plotting differentiated, squared & integrated wave -----
plot(a); grid on;
title('derivated, squared & integrated');
xlabel('time (msec)'); ylabel('amplitude(mV)');
%    hold on;
figure

%    obtained wave is passed through a moving averager -----
n=1:1:k;
%    j=1:7
%    plot(n, ((a(n-j)/M)));
s1=a(n); s2=a(n+1); s3=a(n+2); s4=a(n+3); s5=a(n+4); s6=a(n+5);

s7=a(n+6); s8=a(n+7); s9=a(n+8); s10=a(n+9); s11=a(n+10);
s12=a(n+11); s13=a(n+12); s14=a(n+13); s15=a(n+14); s16=a(n+15);
s=(s1+s2+s3+s4+s5+s6+s7+s8+s9+s10+s11+s12+s13+s14+s15+s16)/16;
```

CONTD.

```

disp(s); plot(n,s); grid on; hold on;
title('moving averager');
xlabel('time(msec)');
ylabel('amplitude(mV)');
figure

%      type-1: finding Hilbert transform -----
%      finding hilbert magnitude for peaks extraction
v=hilbert(s);
hr=real(v);
subplot(2,1,1); stem(n,hr);
grid on; hold on;

title('hilbert transform real part = moving avg. ');
xlabel('time(msec)');
ylabel('amplitude(mV)');

%      finding hilbert phase for zero crossings
hr2=imag(v)
subplot(2,1,2); stem(n,hr2); grid on; hold on;
title('hilbert transform imaginary part = moving avg. ');
xlabel('time(msec)');
ylabel('phase');

%      finding amplitudes >20000 threshold limit -----
z1=zeros(1,k);
count2=0;
for i=1:1:k
    if hr(i)>20000
        z1(i)=1;
        count2=count2+1;
    end;
end;
disp(count2);
figure;

subplot(3,1,1); stem(z1); grid on; hold on;
title('above threshold limit-values');
xlabel('time(msec)');
ylabel('amplitude(mV)');

%      finding phase changes <1600 and >-1600 within threshold values
%      finding zero crossings -----
z2=zeros(1,k);
count=0;
for i=1:1:k

    if hr(i)>20000;
    if hr2(i)<1600;
        if hr2(i)>-1600;
            z2(i)=1;
            count=count+1;
        end;
    end;
end;
end;

disp(count);
subplot(3,1,2); stem(z2); grid on; hold on;

```

CONTD.

```

title('above threshold values& peaks detected through hilbert phase i.e; Z
C');
xlabel('time(msec)');
ylabel('amplitude(mV)');
%

%      type-2: finding phase R-peaks in threshold values >20000 -----
%      by comparing successive instant samples
z3=zeros(1,k);
count1=0;
hr(k+1)=0;
for i=1:1:k

    if hr(i)>20000;
    if hr(i)>hr(i-1);
        if hr(i)>hr(i+1);
            z3(i)=1;
            count1=count1+1;
        end;
    end;
end;
disp(count1);
subplot(3,1,3); stem(z3); grid on; hold on;

title('total no. of peaks we obtain in ecg');
xlabel('time(msec)');
ylabel('amplitude(mV)');
%

%      finding the relative ratio accuracy defined as 'efficiency'
%      of type-1 algorithm and type-2 algorithms -----
w=((count)/(count1))*100;
disp(w);
%
```

7.2 EMPIRICAL MODE DECOMPOSITION CODE

```
% Clears the screen
clc; close all; clear all;

% Load ECG, ECG duration is 10000msec signal= 2hr 40mins signal
load('100m.mat');
ecg=val(1,:);
ecg1=(ecg)/1244;
figure(1); plot(ecg1);
x = decimate(ecg1,12);
figure(2); plot(x);hold on;

c = x(:)'; % copy of the input signal (as a row vector)
N = length(x);

%-----
% loop to decompose the input signal into successive IMF

imf = []; % Matrix which will contain the successive IMF, and the residue

% while (1) % the stop criterion is tested at the end of the loop

%-----
--
% inner loop to find each imf

h = c; % at the beginning of the sifting process, h is the signal
SD = 1; % Standard deviation which will be used to stop the sifting
process

% while SD > 0.3
% while the standard deviation is higher than 0.3 (typical value)

% find local max/min points
N = length(h);
d = diff(h); % approximate derivative
maxmin = []; % to store the optima (min & max without distinction so
far)

for i=1:N-2
    if d(i)==0 % we are on a zero
        maxmin = [maxmin, i];
    elseif sign(d(i))~=sign(d(i+1)) % we are straddling a zero so
        maxmin = [maxmin, i+1]; % define zero as at i+1 (not i)
    end
end

if size(maxmin,2) < 2 % then it is the residue
    break
end
```

CONTD.

```

% divide maxmin into maxes and mins
if maxmin(1)<maxmin(2)      % first one is a max not a min

    maxes = maxmin(1:2:length(maxmin));
    mins  = maxmin(2:2:length(maxmin));

else                        % is the other way around
    maxes = maxmin(2:2:length(maxmin));
    mins  = maxmin(1:2:length(maxmin));
end

%      make endpoints both maxes and mins
maxes = [1 maxes N];
mins  = [1 mins  N];

%
%%      %-----
%      % spline interpolate to get max and min envelopes; form imf
maxenv = spline(maxes,h(maxes),1:N);
minenv = spline(mins, h(mins),1:N);

plot(minenv,'b+-');
hold on;
plot(maxenv,'k*--');
hold on;

m = (maxenv + minenv)/2; % mean of max and min enveloppes
plot(m, 'r.-');
hold on;
prevh = h; % copy of the previous value of h before modifying it
h = h - m; % subtract mean to h
plot(h,'g');
figure(3);
subplot(9,1,1); plot(prevh);
subplot(9,1,2); plot(h);

% calculate standard deviation
eps = 0.0000001; % to avoid zero values
SD = sum ( ((prevh - h).^2) ./ (prevh.^2 + eps) );

%      end

imf = [imf; h]; % store the extracted IMF in the matrix imf
% if size(maxmin,2)<2, then h is the residue

% stop criterion of the algo.
if size(maxmin,2) < 2
    break
end

h1 = h - m; % subtract mean to h
subplot(9,1,3); plot(h1);

prevh=h;
h2 = h1 - m; % subtract mean to h
subplot(9,1,4); plot(h2);

```

CONTD.


```

        prevh1=h;
h3 = h2 - m; % subtract mean to h
subplot(9,1,5);      plot(h3);

        prevh=h;
h4 = h3 - m; % subtract mean to h
subplot(9,1,6);      plot(h4);

        prevh=h;
h5 = h4 - m; % subtract mean to h
subplot(9,1,7);      plot(h5);

        prevh=h;
h6 = h5 - m; % subtract mean to h
subplot(9,1,8);      plot(h6);

%
%         prevh=h;
%         h = h - m; % subtract mean to h
%         subplot(9,1,9);      plot(h);

%      Retracing the ECG Signal with sharp R-peaks and removed artifacts --
--
h7 = h6 - m; h8 = h7 - m; h9 = h8 - m; h10 = h9 - m; h11 = h10 - m;
h12 = h11 - m;
%      h = h - m;h = h - m;h = h - m;h = h - m;h = h - m;
subplot(9,1,9);      plot(h12);

%
u= h+h1+h2+h3+h4-h5-h6;      figure(4);
plot(u); grid on;
figure

%      retraced ecg from summed signals ----- +
%      setting input k=1800 since it is scaled
k=input('enter the total no.of samples ');

%      setting input w=1800 as sample inputs of ecg
w=input('enter the total no.of samples ecg ');
z3=zeros(1,k);
count1=0;
u(k+1)=0;
%
for i=1:1:(k)
    if u(i)>0.82;
    if u(i)>u(i-1);
        if u(i)>u(i+1);
            z3(i)=1;
            count1=count1+1;
        end;
    end;
end;
disp(count1);
stem(z3); grid on; hold on;

```

CONTD.

```

title('total no. of peaks we obtain in ecg');
xlabel('time(msec)'); ylabel('amplitude(mV)');
% retraced ecg from summed signals, let peak count as 'count1' ----

z4=zeros(1,w);
count2=0;
ecg(w+1)=0;
for j=1:1:(w)
    if ecg(j)>0.93;
        if ecg(j)>ecg(i-1);
            if ecg(j)>ecg(j+1);
                z4(j)=1;
                count2=count2+1;
            end;
        end;
    end;
end;
disp((count2)/110); % as it is decimated, count2 is divided by 110 -----
stem(z4); grid on; hold on;
title('total no. of peaks we obtain in ecg');
xlabel('time(msec)'); ylabel('amplitude(mV)');
%% actual ecg peaks, let peak count as 'count2' ----

s=((count1)/(count2))*100*110; % as it is decimated, count2 is divided by
110
disp(s);

```

7.3. TEMPLATE MATCHING CODE

```
%      Clears the screen -----
clc; clear all; close all;

%      Load ECG, ECG duration is 10000msec signal= 2hr 40mins signal
load('100m.mat');
x=val(1,:);
ecg=x';
figure(1);
plot(ecg); grid on;
title('ecg wave');
xlabel('time (msec)');
ylabel('amplitude(mV) ');
hold on;
%
%      creating a random recursive parent template-1 -----
%      with higher amplitudes and time intervals than ECG
f2=zeros(1,21600);
Fc=10;  Fb=8;
M=500;

t = -10:1:10;
a = sqrt(Fb).*sinc(Fb*10*t/M);
b = sqrt(-Fb).*sinc(Fb*10*t/M);
c=a+b;

for i=0:293:21600
    f1=(12*t);
    f2=(150*c)+980;
    f1=f1+i+370;

    plot(f1,f2,'g-');grid on;      hold on;
end
title('template ecg');
xlabel('time (msec)'); ylabel('amplitude(mV) ');

%      creating a random recursive parent template-2 -----
%      with lower amplitudes and time intervals than ECG
g2=zeros(1,21600);
Fc=10;
Fb=8;
M=500;

t = -10:1:10;
a1 = sqrt(Fb).*sinc(Fb*10*t/M);
b1 = sqrt(-Fb).*sinc(Fb*10*t/M);
c1=a1+b1;

for i=0:293:21600
    g1=(0.4*t);
    g2=(50*c1)+950;
    g1=g1+i+370;
    plot(g1,g2,'r-');grid on;
    hold on;
end
title('template ecg');
xlabel('time (msec)'); ylabel('amplitude(mV) ');
```

8. REFERENCES

1. Journals Explored

- A. "A Real Time QRS Detection Algorithm"
- by JIAPU and WILLIS J. TOMPKINS
//IEEE Transactions of Bio-Medical Engineering, VOL., BME-32, NO.3,MARCH 1985//
- B. "A QRS Detector Based on Empirical Mode Decomposition"
- by WEIFANG ZHU, HEMING ZHAO, XIAOPING CHEN //ICSP2010 Proceedings//
- C. "Detection of QRS Complex in ECG Signal by the EMD" (2011)
- by Z.BOUABIDA, Z.E HADJ SLIMANE, F.BEREKSI REGUIG
//7th International Workshop on Systems, Signal Processing and their Applications//
- D. "ECG Real Time Feature Extraction using MATLAB"
- by SONAL POKHARKAR, AMIT KULKARNI
//International Journal of Technology and Science, VOL V, Issue 1,2015//
- E. "Denoising and QRS Detection of ECG Signals using EMD"
- by B.NARASIMHA, E.SURESH, K.PUNNAMCHANDER, M.SANJEEVA REDDY
- F. "MATLAB Based ECG Signal Classification"
-by JAYLAXMI C MANNURMATH#1, Prof.RAVEENDRAM#2 //IJSETR, VOL 3, Issue 7,July 2014//

2. Textbooks Referred

- A. "Biomedical Signal Analysis" by Rangaraj M. Rangayyan (Wiley India Edition)
- B. "Biomedical Digital Signal Processing" by Willis J. Tompkins (PHI Pvt. Ltd-EEE)
- C. "Fundamentals of Biomedical Instrumentation" by Dr.O.N.Pandey (Katson Books)
- D. "Modern Digital Signal Processing" by Roberto Cristi (Cengage Learning-IND Edition)

MATH WORKS 2012a (Library Help and Online Features Utilities)