A Thesis

on

ECG DATA COMPRESSION FOR TELECARDIOLOGY

for the award of the degree of

DOCTOR OF PHILOSOPHY

submitted to the

Thapar University
Patiala, PUNJAB, INDIA

by

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under the supervision of

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By

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CERTIFICATE

Certified that Mr. Mandeep Singh has carried out the research work presented in this thesis titled, *"ECG Data Compression for Telecardiology"* for the degree of Doctor of Philosophy of the Thapar University, Patiala, Punjab, India under our supervision. The thesis embodies results of the original work and studies carried out by Mr. Mandeep Singh himself and contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else.

We approve its submission for the award of the degree of the Doctor of Philosophy of the Thapar University, Patiala.

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Last but not the least, I am thankful to Almighty who gave me strength and health for completing the work. I dedicate this work to Giani Seetal Singh ji, the Divine Incarnate…

(Mandeep Singh)

LIST OF ABBREVIATIONS

2-D	Two Dimensional
ABSURD	Average Beat Subtraction with Residual Differencing
AHA	American Heart Association
AIIMS	All India Institute of Medical Sciences
ANM	Auxiliary Nurse Midwife
ANN	Artificial Neural Network
API	Application Programming Interface
ART	Adaptive Resonance Theory
ASCII	American Standard Code for Information Interchange
ASEC	Analysis by Synthesis ECG Compressor
ATPG	Automatic Test Pattern Generation
AV	Atrio-Ventricular
AZTEC	Amplitude Zone Time Epoch Coding
BIH	Beth Israel Hospital
CCU	Coronary Care Unit
CD-ROM	Compact Disc - Read Only Memory
CHC	Community Health Centre
CME	Continuing Medical Education
CORTES	Coordinate Reduction Time Encoding System
CR	Compression Ratio
CSMA/CD	Carrier Sense Multiple Access with Collision Detection
CT	Cosine Transform
CT	Computerized Tomography
CTC	Cycle to Cycle
CVQ	Classified Vector Quantization
CWT	Continuous Wavelet Transform
DAMPS	Digital Advanced Mobile Phones
DBMS	Database Management System
DCT	Discrete Cosine Transform
DDC	Direct Data Compression

DDPRD	Dynamically Derived Percentage Root-mean-square Difference
DICOM	Digital Imaging and Communication
DPCM	Differential Pulse Code Modulation
DTE	Data Terminal Equipment
DTW	Dynamic Time Warping
DWT	Discrete Wavelet Transform
EAS	Electronic Article Surveillance
EBP	Error Back Propagation
EBP-NN	Error Back Propagation in Neural Networks
ECG, EKG	Electrocardiograph
EEG	Electroencephalogram
EMG	Electromyogram
EOF	End-of-File
EOG	Electrooculogram
EOT	End-of-Transmission
EPR	Electronic Patient Record
EZW	Embedded Zero-Tree Wavelet
FBI	Federal Bureau of Investigation
FDDI	Fiber Distribution Data Interface
FOI-2DF	First Order Interpolation with Two Degrees of Freedom
FT	Fourier Transform
GNU	GNU's Not Unix
GP	General Practitioner
GPL	General Public License
GPRS	General Packet Radio Service
GSM	*Groupe Spécial Mobile*
GUI	Graphical User Interface
GW-AVQ	Gold Washing-Adaptive Vector Quantization
HR	Heart Rate
HT	Harr Transform

HTML	HyperText Markup Language
ICD	Implantable Cardioverter Defibrillators
ICEG	Intracardiac Electrogram
IEC	International Electrotechnical Commission
ISDN	Integrated Services Digital Network
ISN	Information System Network
ISO	International Organization for Standardization
ISRO	Indian Space Research Organization
ITTP	Integrated Telecardiology and Telehealth Project
JAMES	Java Agent Model for Enhanced Services
JPEG	Joint Photographic Expert Group
KLT	Karhunen - Loeve Transform
LAD	Left Axis Deviation
LADT	Linear Approximation Distance Thresholding
LAN	Local Area Network
LBBB	Left Bundle Branch Block
LIP	List of Insignificant Points
LIS	List of Insignificant Sets
LMS	Least Mean Square
LOT	Linear Order Transformation
LROR	Linear Reverse Order Restoration
LSP	List of Significant Points
LSPIHT	Layered Set Partitioning In Hierarchical Trees
LTA	Linear Transformation Algorithm
LTP	Long-Term Prediction
ltstdb	Long–Term ST Database
LZ	Lempel- Ziv
MC-LTP	Multi-Channel Long Term Prediction
MI	Myocardial Infarction
MIT	Massachusetts Institute of Technology
mitdb	MIT-BIH arrhythmia test base
MPRD	Modified Percentage Root-mean-square Difference
PDA	Personal Digital Assistants
PEC	Parameter Extraction Compression

PGIMER	Post Graduate Institute of Medical Education and Research
PHP	PHP Hypertext Preprocessor
PRD	Percentage Root mean square (rms) Difference
PSNR	Peak-Signal-to-Noise-Ratio
PVC	Premature Ventricular Contraction
QMF	Quadrature Mirror Filters
RAD	Right Axis Deviation
RAM	Random Access Memory
RBBB	Right Bundle Branch Block
RMSE	Mean Square Error or Root Mean Square Error
SA	Sinoatrial
SAPA	Scan Along Polygon Approximation
SAR	Sub-Auto-Regression
SCP	Standard Communication Protocol
SGPGIMS	Sanjay Gandhi Postgraduate Institute of Medical Sciences
SNR	Signal to Noise Ratio
SPIHT	Set Partitioning In Hierarchical Trees
SQL	Structured Query Language
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
TC	Transformation Compression
TCP/IP	Transport Control Protocol and the Internet Protocol
TDM	Time Division Multiplexing
TETRA	Terrestrial Trunked Radio

TIET	Thapar Institute of Engineering & Technology
TP	Turning Point
TRIM	Turning-Point Recursive Improvement Method
URL	Uniform Resource Locator
VAG	Vibroarthrographic
VAT	Ventricular Activation Time
VCG	Vectorcardiograph
VCS	Video Conferencing System
VF	Ventricular Fibrillation
VQ	Vector Quantization
VQ FSVQ	Finite-State Vector Quantization
VSAT	Very Small Aperture Terminal
VT	Ventricular Tachycardia
WAN	Wide Area Network
WDD	Weighted Diagnostic Distortion
WHO	World Health Organization
WHT	Walsh-Hadamard Transform
WLAN	Wireless Local Area Network
WT	Walsh Transform
WWW	World Wide Web
XML	eXtensible Markup Language

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ABSTRACT

The electrical signal generated by heart and acquired from the body surface is known as Electrocardiogram (ECG). It is used to know the status of heart to diagnose its malfunctioning at an early stage, so that corrective action can be taken to prevent any major non-reversible failure. For critical cardiac patients, persons under cardiac surveillance, ambulatory patients and for creation of ECG database, continuous recording of ECG is required. The recorded data becomes so voluminous that it becomes practically impossible to handle it without compression. The importance of data compression further increases by the fact that the rate at which cardiac patients are increasing all over the world, we do not have a matching number of cardiologists to provide the required healthcare, especially in remote and rural areas. One way to overcome this problem is to transmit ECG, along with other vital statistics of a patient, over internet to a cardiologist for expert advice. For one day's continuous recording, the amount of multichannel ECG data exceeds several gigabytes. Moreover if this data is to be transmitted over a telephone line or a slower digital communication network, the time of transmission goes beyond the human patience. Compressing the data is the only solution to this problem. The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant signal morphology on reconstruction.

Our work starts with literature survey of the techniques used for compression of ECG signal, and identifies a wavelet compression method of Set Partitioning In Hierarchical Trees (SPIHT) as superior to any other technique reported so far. We have proposed two additional steps in the SPIHT algorithm, which are "Blank-fire removal" and "Polishing". These additional steps increase the compression ratio and reduce the percentage root-mean-square difference, while retaining all features of the existing SPIHT algorithm. The performance of existing SPIHT has been compared with that of the modified SPIHT algorithm on the same database set i.e. ECG signals from MIT-BIH arrhythmia test base (mitdb) (sampling rate 360 per second), with the same wavelet filters and using the same distortion measure. Out of a total of 84 signals tested, 59 signals (70.2%) have shown an improvement in the compression ratio in the range of 3.24% - 20.22%, averaging to 7.95% improvement, while the remaining 25 signals (29.8%) have maintained the same compression ratio as given by the existing

SPIHT algorithm. Not even a single case has shown deterioration in compression ratio. Improvement in distortion has been found in all 84 signals (100%) ranging from 3.26% to 19.23%, averaging to 9.99% reduction in PRD.

To handle lengthy ECG records, a set of executable files has been developed in C++ environment. Data downloaded from the Long–Term ST Database (ltstdb) has been used to test the executable files. Some peculiar programming problems were encountered while encoding the compressed data bit streams to ASCII characters. Since ASCII character for decimal value 13 in MS-DOS, Windows, and various network standards, is used as part of the end-of-line mark, while ASCII character for decimal value 26 and 255 are used for marking end-of-text and end-of-file (EOF) respectively, they disrupt the normal file reading process. These characters are identified in the bit stream itself and are subsequently modified to circumvent this problem. The concepts of "fragmentation" and "looping" are used to handle long records.

The number of refinement passes determines the extent to which a signal can be safely compressed using SPIHT algorithm. With every refinement pass, the distortion in the reconstructed signal decreases, but this also results in decrease in the compression ratio. A criterion for the number of refinement passes in SPIHT algorithm is therefore required to achieve optimal compression ratio, while retaining all clinically significant morphological features. A study carried out to find this number has revealed that for the same number of refinement passes, different signals give vastly different PRD. Thus recommending a fixed number of refinement passes is not possible. However, if we take into account the presence of "blank-fire" in the compression, a criterion can be evolved. We recommend five refinement passes in absence of "blank-fire", and six in its presence. This has resulted in largely improved consistency in the distortion. The proposed refinement criterion has been validated by visual inspection of the signals by a physician, as well as by a statistical analysis over a larger database. Implementing the improved SPIHT algorithm, with the proposed refinement criterion over 42 sets of two-lead ECG signals, the original and the reconstructed signals were randomly presented to a physician, in sets of 12-15 pairs of signal. The interpretations of these ECGs were same for all 42 reconstructed signals (100%) as for the original ones.

We have also proposed a new form of root-mean-square distortion measuring parameter called Dynamically Derived Percentage Root-mean-square Difference (DDPRD), which gives its numerical value proportional to the distortion measured by other existing parameters. If the original signal is scaled by any factor, or the baseline is shifted in any direction or a baseline wander with zero dc value is introduced in it, subsequent to reconstruction, the numerical value of distortion measured by DDPRD remains unaffected. While all other existing parameters fail to give the same numerical value when the ECG test signal is subjected to scaling/baseline shift/baseline wander, DDPRD shows immunity to the mentioned changes in original signal.

Taking valuable suggestions from a panel of reputed physicians, a user-friendly, interactive and dedicated telecardiology based website has been designed. The website has been designed using HTML as the front end user GUI, MySQL for maintaining the related database, and PHP as the interface programming language. Password protected login to the website can be done as a manager or a client or an expert. The site has built-in security features against unauthorized intrusions in the site. The jobs are prioritized as per the requirement of the client and the transfer of credits from client's account to expert's account is done as per the priority, i.e. more for high priority jobs and vice or versa. Ensuring online availability of experts and making fiscal transactions from clients and to experts is responsibility of the manager. The manager also does new registrations as a client or as an expert after verifying their credentials. The website has been designed keeping in mind the practical requirements and convenience of both client and expert, with an objective of bridging the gap between the client and the expert. The concept of 24 hour availability of authentic experts in the required area of specialization like cardiac medicine and cardio thoracic surgery, facility to compress and decompress long records, prioritizing the jobs instead of having a general queue, enhanced security features, safe fiscal transaction through a manager and a platform for settling disputes, if any, are some of the features of the developed website, which are not available on general chat sites.

It may be concluded that the present work has contributed significantly in the area of ECG data compression for telecardiology, offering an opportunity to deliver better healthcare services for entire population of the world.

CONTENTS

INTRODUCTION

1.1 TELEMEDICINE

In a large developing country like India, with a population of over 100 crore (i.e. one billion), we do not have a matching number of required medical experts. This scene is worse for a under-developed country like Bangladesh where Doctor-Population ratio is as low as 1:5282 [Chowdhury, 2000]. Moreover, whatsoever expertise is available in the country, it is largely concentrated within posh hospitals in big cities. A majority of the population in rural and sub-urban area is thus deprived of the easy access to medical competence. Shifting a patient under critical circumstances to a distant hospital is time-consuming, expensive and many a times practically not possible. Telemedicine offers an opportunity to deliver healthcare services for entire population of the world, and also promises utilizations of resources from distant places, even beyond the borders.

Also referred to as "Tele-health" or "e-health", Telemedicine is defined as "*the use of electronic information and communications technologies to provide and support health care when distance separates the participants*" [Alberts and Liebowitz, 1996]. Depending upon the type of activity involved, Telemedicine can further be classified as Teleradiology (deals with Radiographic images), Telepathlogy (deals with Pathologic images, Histopathologic slides), Telesurgery (deals with screening the surgical candidates without having them to travel to surgical centers, demonstrating the procedures to students, and with post operation follow-ups) etc. For cardiac patients we require Telecardiology to provide relief and patient care.

With the developments in computer hardware and software, telecommunication tools and Internet facility, a good amount of research is being carried out in different parts of the world for efficient solutions through Telemedicine, including Telecardiology.

1.1.1 Telecardiology

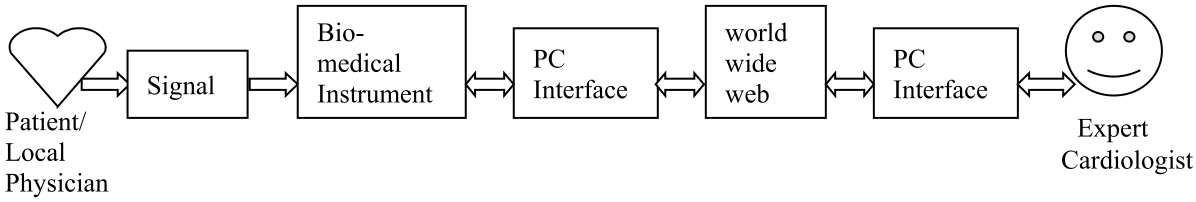


Figure 1.1: Block diagram of Telecardiology

The different components of a Telecardiology system are depicted in figure 1.1. Every living human being requires a continuous circulation of blood to carry various elements like oxygen, nutrients and other materials to different organs of the body for their proper functioning, growth and repair. Heart pumps the blood incessantly throughout the life. If the heart stops beating, death is inevitable. For that reason, it is essential to diagnose any malfunctioning of heart at an early stage, so that the corrective action can be taken to prevent any major non-reversible failure. With every beat of the heart, some signals are generated. These signals are auditory signals that are sensed by a stethoscope or phonocardiograph (PCG), or electric signals that are recorded by Electrocardiograph (ECG, EKG) or vector cardiograph (VCG). In addition, the blood pressure in various arteries also varies cyclically with every beat of the heart. A continuous record of blood pressure too can lead to detection of some of the problems in heart. The bio-medical instrument used to sense any of these parameters can either give an instantaneous display of the measured parameter or a permanent record in the form of a graph.

However, in telecardiology, this cardiac record of the patient, along with his/her clinical history (like his/her age, weight, dietary habits, nature of job etc.) needs to be sent to the expert who is geographically located at a distant place. With the advent of fast and efficient digital means of communication, this can perhaps be done only if the signal/history is available in digitized form. A PC interface with the existing electronic bio-medical instrument can do this work. Though many means of digital communication are available, a handy and versatile Internet facility (world wide web) can be one of the ideal choices for this application. Of course, we need a PC interface at the expert-end too, to receive the data from the Internet and to send his/her opinion back to the patient/local physician.

1.2 CARDIAC SIGNALS

To understand the cardiac signals, a brief description of anatomy and working of heart is essential. The heart is divided into four chambers (figure 1.2). The two upper chambers, the left and right atria, are synchronized to act together. Similarly, the two lower chambers, the ventricles, operate together. The right atrium receives blood from the veins of the body and pumps it into the right ventricle. The right ventricle pumps the blood through the lungs where it is oxygenated. The oxygen-enriched blood then enters the left atrium, from which, it is pumped into the left ventricle. The left ventricle pumps the blood into the arteries to circulate throughout the body.

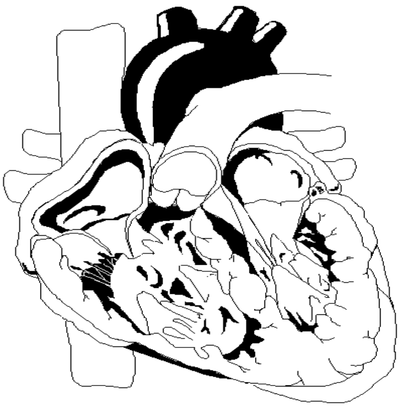


Figure 1.2: The internal structure of heart

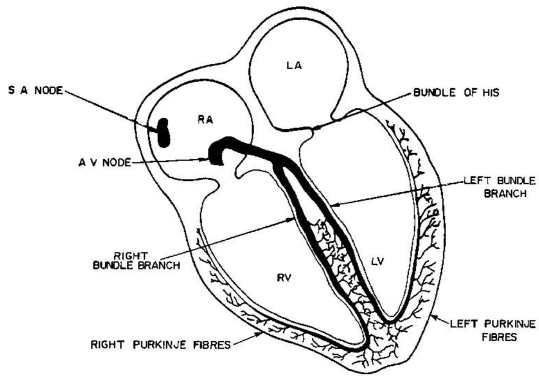
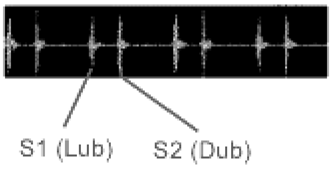


Figure 1.3: The schematic diagram of heart

The contraction of any muscle requires electrical stimulation. This is true for the different cardiac muscles of the heart too. The electrical signal for these contractions originates near the top of the right atrium at point called sinoatrial (SA) node (figure 1.3). It is also called the pacemaker and is a group of specialized cells that spontaneously generate action potentials at regular rate. To initiate the heart beat, the action potentials generated by the SA node propagate in all directions along the surface of atria. The wave terminates at a point near the center of the heart called the atrio-ventricular (AV) node. At this point, some special fibers act as a "delay line" to provide proper timing between the action of the atria and ventricles. Once the electrical excitation has passed through the delay line, it rapidly spreads to all parts of both the ventricles by the *bundle of His.* The fibers in this bundle, called *Purkinje fibers*, divide into two branches to initiate action potentials simultaneously in the powerful musculature of the two ventricles. The ventricles relax thereafter, to complete one cycle. This cycle is repeated over and over again.

The simplest of all the signals that can be used to detect any malfunctioning of heart is its sound. It can be heard using a plain stethoscope or can be recorded in the form of a trace on the paper by phonocardiogram (PCG).



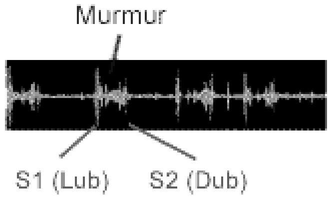


Figure 1.4: Normal Heart Sound   Figure 1.5: Heart Sound with Murmur

Every contraction of atria and ventricles produce characteristic sounds known as lub-dub sounds. When the heart is normal, the trace of this sound recording is shown as in figure 1.4. Any sound, other than these lub-dub sounds, becomes clearly visible on a phonocardiogram as shown in figure 1.5. These sounds are known as murmurs.

Normally only the highest (systolic) and the lowest (diastolic) blood pressure in measured. But in some cases, a continuous variation of blood pressure needs to be monitored. The procedure is painful and requires catheterization and the recording so obtained in shown in figure 1.6.

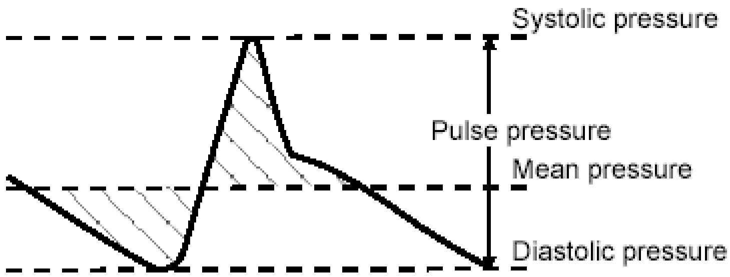


Figure 1.6: Blood pressure recording

The bio-potentials generated by the muscles of the heart result in an electrical signal called electrocardiogram and is abbreviated as ECG or EKG signal. The electrocardiogram reflects the electromechanical activity of the cardiac system. It is one of the most important physiological parameter to be measured for knowing the state of cardiac system. Figure 1.7 shows a typical ECG as it appears when recorded from the surface of the body. Each of the prominent features has been designated by an alphabet i.e. P, Q, R, S, T and U. These can be identified with events related to pattern of propagation of the action potential.

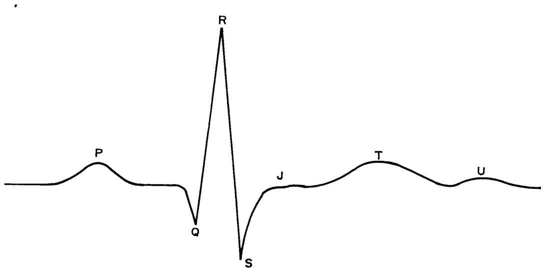


Figure 1.7: A typical Electrocardiogram waveform

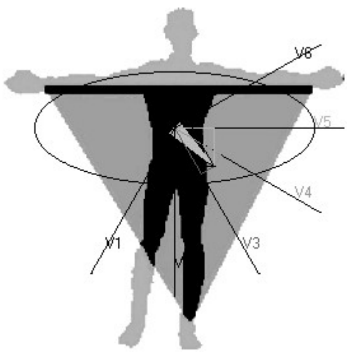


Figure 1.8: Electric Heart Vector

The electric field generated at the heart is a vector whose magnitude and spatial orientation varies during each cycle (figure 1.8 and 1.9). The orientation of the heart within the thorax also determines ECG shape. The main heart axis may normally vary between + 60° and – 110° with the horizontal zero line. Conversely ECG signal can be used to determine this orientation. Vector cardiogram (VCG) is the recording of this variation of electric field with time, derived from ECG signal.

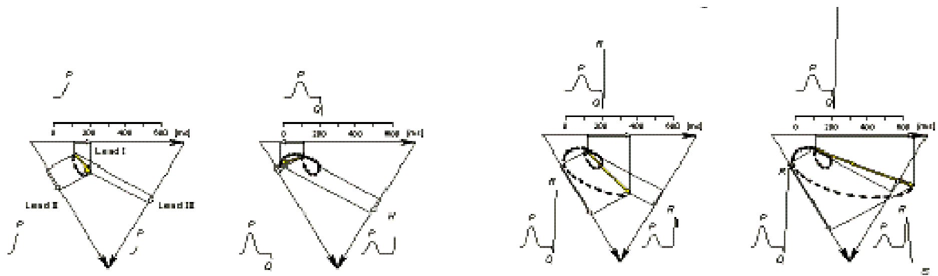


Figure 1.9(a): Propagation of the activation and the projection of the leads

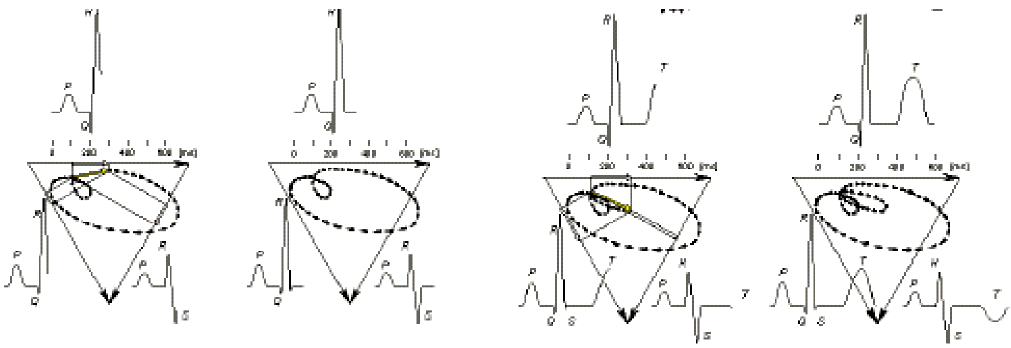


Figure 1.9(b): Propagation of the activation and the projection of the leads

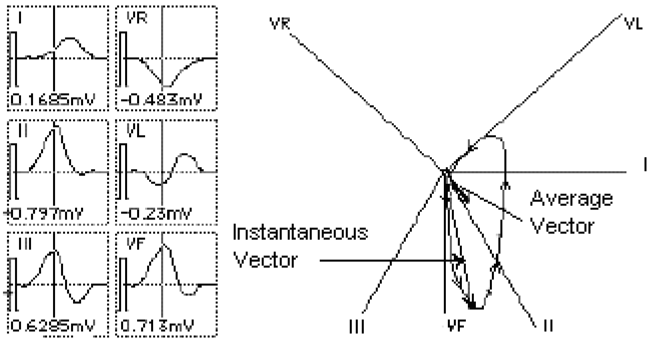


Figure 1.9(c): Six lead signal construction from vector cardiogram instantaneous

All these bio-signals along with associated data like heart rate, systolic and diastolic blood pressure and temperature etc., play a vital role in diagnosing the heart disorder.

1.3 ELECTROCARDIOGRAM (ECG/EKG)

A healthy human heart undergoes a continuous series of alternate excitation (depolarization) and recovery (polarization) of cardiac muscles in a fixed sequence. The record of its electrical activity is called electrocardiogram.

Starting from sinus node (the site of initiation of the electrical impulse in the cranial portion of the right atrium), this electrical activity is represented by a tracing showing the various phases of the activity above or below an isoelectric line (positive above and negative below) over time in a progressive fashion. The electrical field then reaches the AV node (in the right atrium) and then into the His-Purkinje bundle, where it spreads through both the left and right ventricular bundles (located on each side of the interventricular septum respectively) where from it spreads out to each of the ventricles of the heart.

The patient is connected to an electrocardiographic machine with six electrodes on the front of the chest over the heart area (labeled V1-6) and four (labeled RA, LA, RF, LF) on the ankles and wrists, for recording this electrical activity. The normal pattern of the ECG allows analysis to determine whether there is any abnormality in any particular patient's ECG. The initial activity is labeled as a P wave, followed in succession by QRS, T and U waves. The P wave represents the electrical excitation of the atria, which causes contraction of both atria. The QRS complex represents the electrical excitation of the ventricles, which initiates the ventricular contraction (systole) shortly after the Q wave. The T wave represents the return of the ventricles from excitation to a normal state marking the end of systole.

The specialized muscle fibers that make up the pacemaker, return to normal after spreading the electrical signal throughout the ventricles, in the T wave. The PR interval, which usually does not exceed 0.20 seconds, is the interval between the onset of the P wave and the onset of the QRS. The QRS duration is from 0.08-0.10 seconds [Klabunde, 2004]. The activity of the P wave is separated from the QRS and the QRS from the T wave by an isoelectric line (zero voltage). The heart rate of the individual is determined by counting the number of QRS complexes occurring per second.

1.3.1 Peaks and Intervals in ECG

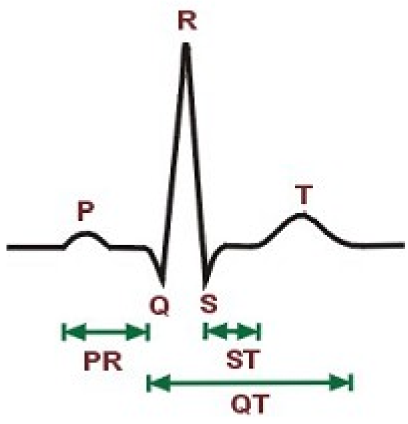


Figure 1.10: ECG trace

The electrical currents that are generated for depolarization and repolarization of heart spread throughout the body and can be measured by an array of electrodes placed on the body surface. The recorded tracing, called an electrocardiogram (ECG, or EKG), is shown in figure 1.10.

The sequence of depolarization and repolarization of the atria and ventricles is represented by the different waves of the ECG. The wave of depolarization that spreads from the SA node throughout the atria is represented by the P wave and is usually 0.08 to 0.1 seconds (80-100 ms) in duration.

Within the AV node the conduction velocity of the impulse is greatly retarded. The time taken by impulse here is represented by a brief isoelectric (zero voltage) period after the P wave. The P-R interval, which normally ranges from 0.12 to 0.20 seconds in duration, is the period of time from the onset of the P wave to the beginning of the QRS complex. This interval represents the time between the onset of atrial depolarization and the onset of ventricular depolarization. If the P-R interval is >0.2 sec, a conduction defect (usually within the AV node) is present (first-degree heart block).

The ventricular depolarization is represented by QRS complex. The duration of the QRS complex is relatively very short (0.06 to 0.1 seconds) thereby indicating that ventricular depolarization normally occurs very rapidly. Prolonged QRS complex (> 0.1 sec), indicates impaired conduction within the ventricles. This can occur under two circumstances. One, with bundle branch blocks and second whenever a ventricular foci (abnormal pacemaker site) becomes the pacemaker driving the ventricle. Such an ectopic foci nearly always results in impulses being conducted over slower pathways within the heart, thereby increasing the time for depolarization and the duration of the QRS complex.

ST segment is the isoelectric period following the QRS. It is the time at which the entire ventricle is depolarized and roughly corresponds to the plateau phase of the ventricular action potential. A depressed or elevated ST segment is important in the diagnosis of ventricular ischemia or hypoxia.

The T wave represents ventricular repolarization and is longer in duration than depolarization, as the conduction of the repolarization wave is slower than the wave of depolarization.

The Q-T interval represents the total time for ventricular depolarization and repolarization to occur and therefore roughly estimates the duration of an average ventricular action potential. Depending upon heart rate, this interval can range from 0.2 to 0.4 seconds. At high heart rates, ventricular action potentials shorten in duration, which decreases the Q-T interval. A relatively prolonged Q-T interval can be diagnostic for susceptibility to certain types of tachyarrhythmias. To know this, the Q-T interval is divided by the square root of the R-R interval (interval between two ventricular depolarizations) and is expressed as a "corrected Q-T (Q-Tc)". This makes assessment of the Q-T interval independent of heart rate. Normal corrected Q-Tc intervals are less than 0.44 seconds [Klabunde, 2004].

Several ECG tracings are recorded simultaneously from different electrodes placed on the body to produce different characteristic waveforms.

1.3.2 ECG Leads

Human body acts as a volume conductor. Thus, as the heart undergoes depolarization and repolarization, electrical currents spread throughout the body. These electrical currents are commonly measured by an array of electrodes placed on the body surface. By convention, electrodes are placed on each arm and leg, and six electrodes are placed at defined locations on the chest. These electrode leads are connected to a device that measures potential differences between selected electrodes to produce the characteristic electrocardiographic tracings.

The electrocardiogram (ECG) leads are of two basic types: bipolar and unipolar. Bipolar leads (standard limb leads) utilize a single positive and a single negative electrode between which electrical potentials are measured, whereas unipolar leads (augmented leads and chest leads) have a single positive recording electrode and utilize a combination of the other electrodes to serve as a composite negative electrode.

The ECG leads are of three types, viz., Limb Leads (Bipolar), Augmented Limb Leads (Unipolar) and Chest Leads (Unipolar).

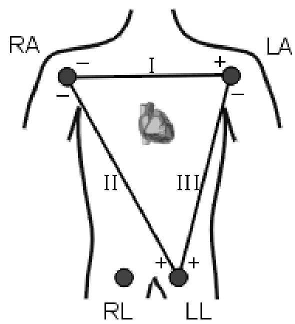


Figure 1.11: Bipolar Leads

1.3.2.1 Standard Bipolar Limb Leads

Figure 1.11 shows bipolar recordings, utilizing standard limb lead configurations. By convention, lead I measure the potential difference between the two arms and have the positive electrode on the left arm, and the negative electrode on the right arm. An electrode on the right leg serves as a reference electrode for recording purposes in this and the other two limb leads. Lead II has the positive electrode on the left leg and the negative electrode on the right arm while lead III has the positive electrode on the left leg and the negative electrode on the left arm. An equilateral triangle (with the heart at the center) is roughly formed by these three bipolar limb leads and is called Einthoven's triangle in honor of Willem Einthoven, who developed the electrocardiogram in 1901 (figure 1.12). The limb can simply be viewed as a long wire conductor originating from a point on the trunk of the body. Thus it makes no difference in the recording whether the limb leads are attached to the end of the limb (wrists and ankles) or at the origin of the limb (shoulder or upper thigh).

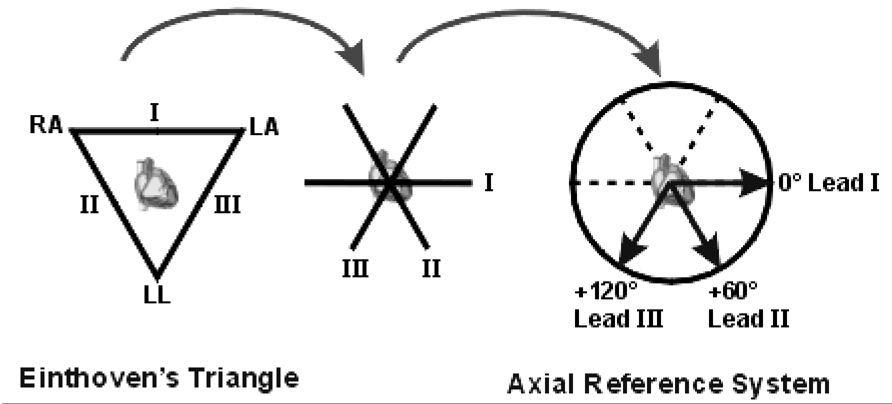


Figure 1.12: Einthoven's Triangle

A depolarization wave heading toward the left arm gives a positive deflection in lead I because the positive electrode is on the left arm. When a wave of depolarization travels parallel to the axis between the right and left arms, maximal positive ECG deflection occurs in lead I. If depolarization wave heads away from the left arm, the deflection is negative. A wave of repolarization moving away from the left arm is recorded as a positive deflection. In leads II and III both, the positive electrode is located on the left leg. So similar statements can be made for these leads like, depolarization wave traveling toward the left leg produces a positive deflection in both leads II and III because the positive electrode for both leads is on the left leg.

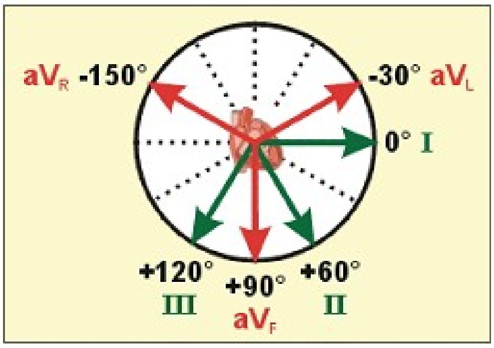


Figure 1.13: Axial Reference System

Figure 1.13 shows the three limbs of Einthoven's triangle (assumed to be equilateral) broken apart, collapsed, and superimposed over the heart. Here the positive electrode for lead I is said to be at zero degrees relative to the heart (along the horizontal axis). The positive electrode for lead II will be +60º relative to the heart, and the positive electrode for lead III will be +120º relative to the heart as shown to the right. This new construction of the electrical axis is called the axial reference system. In this system, a wave of depolarization traveling at +60º produces the greatest positive deflection in lead II, while a wave of depolarization-oriented at +90º relative to the heart produces equally positive deflections in both lead II and III. Similarly, lead III will shows no net deflection if the wave of depolarization is heading at 30º relative to the heart, as it is perpendicular to lead III.

1.3.2.2 Augmented Unipolar Limb Leads

There are three augmented unipolar limb leads in addition to the three bipolar limb leads described above. In these leads, there is a single positive electrode that is referenced against a combination of the other limb electrodes. That is the reason they termed as unipolar leads. The positive electrodes for these augmented leads are located on the left arm (aV_L), the right arm (aV_R), and the left leg (aV_F). In practice, these are the same electrodes used for leads I, II and III. The ECG machine does the actual switching and rearranging of the electrode designations. As shown in figure 1.13, the aV_L lead is at -30º relative to the lead I axis; aV_R is at -150º and aV_F is at +90º. The three bipolar leads, coupled with the augmented unipolar three leads, constitute the six limb leads of the ECG. These augmented leads record electrical activity along a single plane, termed the frontal plane relative to the heart.

Direction of the electrical vector at any given instant in time can be defined by using the axial reference system and these six leads. Thus a depolarization wave from right-to-left along the

0º axis will show greatest positive amplitude in lead I. Similarly a depolarization wave directed downwards at 90º to the axis will show greatest positive amplitude in aV_F and so on.

1.3.2.3 Unipolar Chest Leads

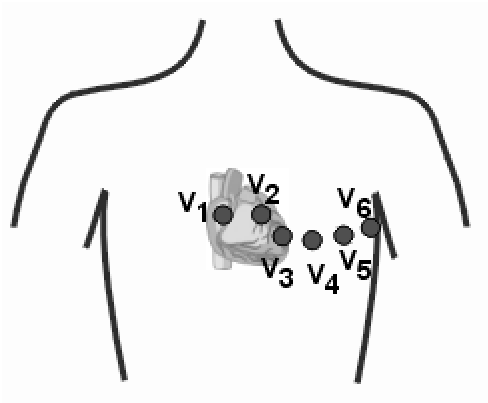


Figure 1.14: Chest Leads

The unipolar chest leads are six positive electrodes placed on the surface of the chest over the heart in order to record electrical activity in a plane perpendicular to the frontal plane (figure 1.14) and are named V_1 - V_6. Same rules of interpretation are applied as for the limb leads, i.e. a wave of depolarization traveling toward a particular electrode on the chest surface will elicit a positive deflection.

In nutshell, the twelve ECG leads provide different views of the same electrical activity within the heart. For that reason, the waveform recorded is different for each lead.

1.3.3 Standard ECG Database

The algorithms developed in this work for ECG data compression have been tested and evaluated on multi lead ECG databases, with known diagnostics. These ECG records have been acquired from MIT/BIH data libraries [Goldberger *et. al.,* 2000].

1.3.3.1 Massachusetts Institute of Technology / Beth Israel Hospital (MIT/BIH) Database

This is a rich database of several hundred ECG recordings, extending over 200 hours [Moody, 1992]. Each recording contains one to three signals and ranges from 20 seconds to

24 hours in duration. Most of the signals have been annotated on beat-to-beat basis. In August 1989 a CD-ROM was produced containing the original MIT-BIH Arrhythmia Database (developed between 1975 and 1979, and first released in 1980), as well as a large number of supplementary recordings assembled for various research projects between 1981 and 1989. The CD-ROM contains approximately 600 megabytes of digitized ECG recordings, most with beat-by-beat annotations, having a total duration in excess of 200 hours [Moody and Mark, 1990]. In September 1991, this data was made available on Internet (http:/www.physionet.org) on PhysioNet, which is a web-based resource supplying well-characterized physiologic signals and related open-source software to the biomedical research community. From September 2000, the data archive named PhysioBank, containing roughly 35 gigabytes of recorded signals and annotations was made available via PhysioNet [Moody *et. al.,* 2000].

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Each record was independently annotated by two or more cardiologists; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database. This directory contains the entire MIT-BIH Arrhythmia Database. About half (25 of 48 complete records, and reference annotation files for all 48 records) of this database has been freely available here since PhysioNet's inception in September 1999 [Goldberger *et. al.,* 2000].

1.4 TRANSMISSION PROTOCOLS

Protocols are agreements on how communication components and Data Terminal Equipment (DTE) are to communicate with each other [Uyless, 1998]. (DTE is a generic term used to describe the end user machine, which is usually a computer or a terminal). Simply stated, a protocol is an agreement on how to converse. Many levels and forms of protocols exist, which often lead to some confusion amongst the users. For example, the voltage levels of logical one and logical zero form an electrical protocol. Another form of protocol is usually software or micro-code-oriented and placed into effect with these codes. For example, the protocol control character of end-of-transmission (EOT) signifies that the transmission by one user is over. Both the communicating devices must know this. Otherwise this may lead to a big confusion.

There are many protocols being followed for controlling a local area network. Some of them, just to name a few are, Carrier Sense Multiple Access with Collision Detection (CSMA/CD), Information System Network (ISN), Fiber Distribution Data Interface (FDDI) etc.

In an application like Telecardiology, where the two participants may be continents apart, working on two entirely different networks, having different protocols, communication between them is not feasible. To overcome this problem, one standard protocol for all the users on this planet was developed – the Transport Control Protocol and the Internet Protocol (TCP/IP).

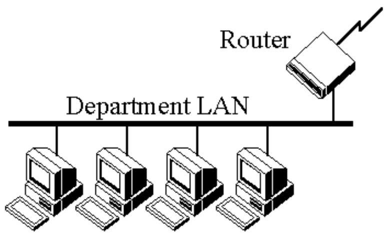


Figure 1.15: Router for LAN

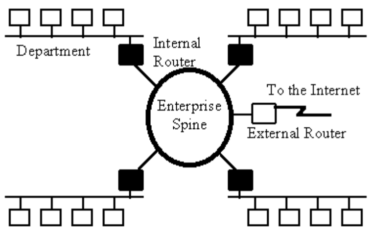


Figure 1.16: Topology for several subnets

The Internet Protocol was developed to create a Network of Networks (the "Internet"). Individual machines are first connected to a LAN. TCP/IP shares the Local Area Network (LAN) with other users. One device called router or gateway provides the TCP/IP connection between the LAN and the rest of the world (Figure 1.15).

To insure that all types of systems from all vendors can communicate, TCP/IP is absolutely standardized on the LAN. In case the network consists of several subnets, the topology followed is shown in figure 1.16. Figure 1.17 shows the relationship of sub-networks and gateway to layered protocol.

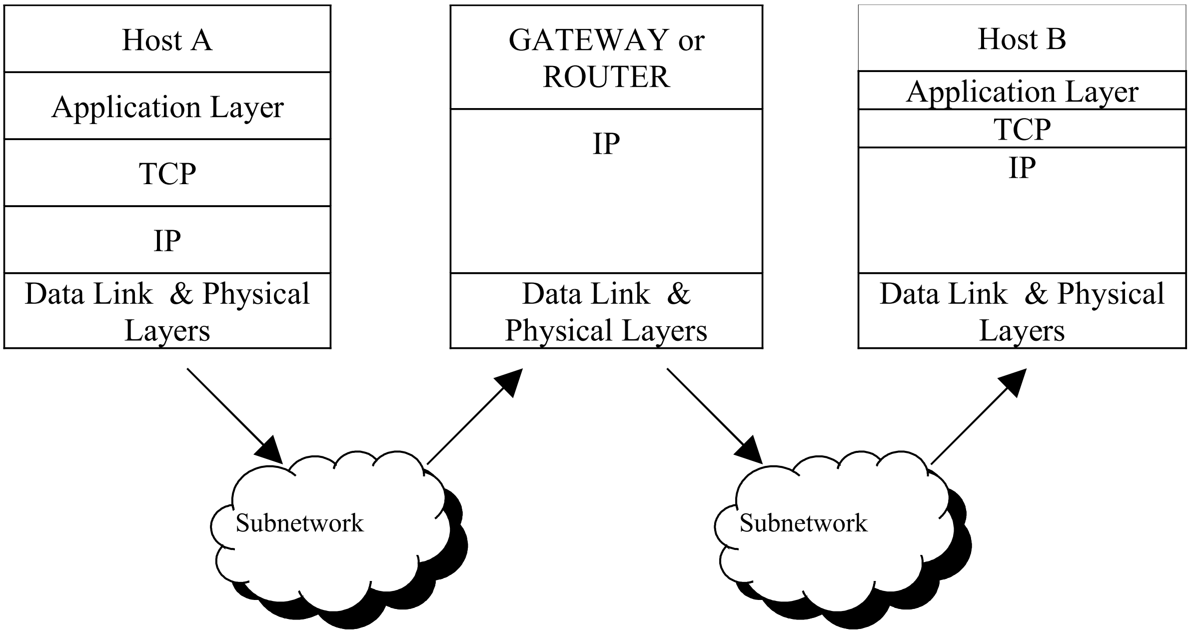


Figure 1.17: TCP/IP operations

TCP/IP operates with a wide variety of other protocols. The protocols that rest over TCP are examples of the application layer protocols, providing services such as file transfer, electronic mail etc. One such application layer protocol can be developed for implementing the scheme of Telecardiology, where signals and text can be exchanged between the two participants.

1.5 DATA COMPRESSION

1.5.1 Need of compression in Telecardiology

For monitoring the cardiac condition of a patient, there are many signals that need to be analyzed like ECG, VCG, PCG, BP Profile, and Heart rate etc. The most significant of all these is ECG signal. For critical cardiac patients, ambulatory patients, astronauts and person under cardiac surveillance, the ECG is recorded continuously and the recorded data becomes so voluminous that it becomes practically impossible to handle them without compression. The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant signal morphology on reconstruction. Conceptually, data compression is a process of detecting and eliminating redundancies in a given set of information. Since the size of the data reduces considerably, compression of the data results in resourceful deployment of memory space for permanent storage of digitized ECG in computer. Also it helps in efficient transmission of multichannel-digitized electrocardiogram for Telecardiology.

1.5.2 Lossless or lossy compression techniques

Compression techniques can be broadly classified as Lossless techniques or Lossy techniques. As the name suggests, there is absolutely no loss of information in lossless compression. This kind of techniques is widely used for compressing textual data, where a loss of even single bit is not tolerated. However, for compression of digitized ECG signal, mostly lossy techniques are used. Use of lossless technique for ECG compression, like Lempel- Ziv (LZ) in adapted form (LZ77) is more of an exception than a rule [Horspool and Windels, 1994]. Dictionary based techniques are normally used for lossless textual compression. But again utilizing the cyclic nature of ECG signal, these techniques too are reported [Barlas and Skordalakis, 1996]. Though, the reconstruction process of lossless methods perfectly recovers the original signal data but in lossless method of data compression techniques the value of compression ratio (CR) is normally very less (hardly 2:1 to 3:1) hence, usually not preferred for the ECG data compression.

1.5.3 Types of lossy compression techniques

ECG data lossy compression technique are further classified as:

i. Direct Data Compression (DDC)
ii. Transformation Compression (TC)
iii. Parameter Extraction Compression (PEC)
iv. Artificial Neural Network (ANN) Techniques

1.5.3.1 Direct Data Compression (DDC)

Most of the direct data compression techniques rely on utilizing prediction or interpolation algorithm. A prediction algorithm employs a prior knowledge of some previous sample, while an interpolation algorithm employs a prior knowledge of both previous and future samples. Normally, these techniques attempt to reduce redundancy in data sequence by examining a successive number of neighboring samples and a preset error or threshold is employed to eliminate data sample. If one selects a small value for the threshold, then the obtained retrieved signal will be of a high quality, but the data reduction will be low, and vice or versa. Amplitude Zone Time Epoch Coding (AZTEC), modified AZTEC, Fan, Scan Along Polygon Approximation (SAPA), Coordinate Reduction Time Encoding System (CORTES), Turning Point (TP) are commonly used direct data compression techniques [Jalaleddine *et al.,* 1990]. Filtering and sub sampling techniques are sometimes used for real-time Holter ECG analyzer. Using this technique, compressed ECG data for 25 hours of a single channel was stored in 1.5 Mbytes of Random Access Memory (RAM) [Smith and Platt, 1988]. Many researchers used combination of various algorithms, for improved compression like combination of AZTEC and SAPA algorithm [Singh and Zhu, 1990]. Mckee *et al.* used fixed point arithmetic to provide an order of magnitude improvement in performance over then existing floating point implementations for Fan/SAPA-2 algorithms [Mckee *et al.,* 1994]. Data compression by entropy coding is obtained by means of assigning variable-length code words to a given quantized data sequence according to their frequency of occurrence. This compression method attempts to remove signal redundancy that arises whenever the quantized signal levels do not occur with equal probability. Cassen and English used entropy coding along with other compression technique [Cassen and English, 1997] . Szilagyi *et al.* developed an adaptive entropy coder to obtain 10 times less redundancy than an optimized Huffman coder [Szilagyi *et al.,* 1997]. Nave and Cohen gave compression system that was based on the sub-auto-regression (SAR) model, also known as the long-term prediction (LTP) model. The 'periodicity' of the ECG signal was employed in order to further reduce redundancy, thus yielding high compression ratios [Nave and Cohen, 1993].

1.5.3.2 Transformation Compression (TC)

Transformation techniques involve preprocessing the input signal by means of a linear orthogonal transformation and properly encoding the transformed output (expansion coefficients) and reducing the amount of data needed to adequately represent the original signal. However, the basic idea is to represent a given data sequence by a set of transformation coefficients utilizing a series expansion technique. The reconstruction of the signal is done by inverse transformation with a certain degree of error. Some of the commonly used TC techniques are Karhunen - Loeve Transform (KLT), Fourier Transform (FT), Cosine Transform (CT), Walsh Transform (WT), Harr Transform (HT), the optimally Warped Transform sub-band coding and the Wavelet Transform. In transformative compression techniques, the earlier work on discrete cosine transform combined with sub-band coding yielded compression ratios as high as 8 to 13: 1 [Allen and Belina, 1993]. Compression using wavelet transforms was mostly reported from 1995 onwards [Djohan *et al*., 1995; Sastry and Rajgopal, 1995; Soraghan *et al.,* 1995]. Saha and Ramakrishnan applied Discrete Wavelet Transform (DWT), based on Daubechies-4 basis functions on the normalized beats, after shifting each of them to the origin. Linear Prediction was then applied to predict those DWT coefficients of the current beat from the corresponding coefficients of a certain number of previous beats, transmitting only the residuals of selected coefficients, resulting in improved compression [Saha and Ramakrishnan, 1997]. Molina *et al.* developed compression algorithm, based on the Walsh-Hadamard Transform (WHT), which is suitable for real-time operation with minimal computational needs [Molina *et al*., 1997]. Later, an algorithm based on a combination of the Karhunen-Loeve Transform (KLT) and multirate sampling for ECG compression was introduced [Blanchett *et al*., 1998]. Much work on different aspects of compression using wavelet transforms has been reported [Nagarajan *et al*., 1996; Nakashizuka *et al*., 1997; Nguyen-Phi and Weinrichter, 1997; Ahmed *et al.*, 2000; Alshamali and Al-Smadi, 2001; Cherkassky and Kilts, 2001; Istepanian *et al.,* 2001a].

1.5.3.3 Parameter Extraction Compression (PEC)

In PEC methods, namely peak-picking [Cohen *et al.*, 1990], syntactic methods [Trahanias and Skordalakis, 1990] and linear prediction methods [Ruttimann and Pipberger, 1979], the extraction of a set of useful parameter from the original signal is carried out and the same are used in the reconstruction process. The Peak picking compression techniques are generally on the sampling of a continuous signal at peak (maxima and minima) and extraction of signal parameter that convey most of the signal information. These parameters include the amplitude and location of maxima and the minima points, slope changes, zero-crossing intervals, and points of inflection in the signal.

1.5.3.4 ANN Techniques

Nowadays Artificial Neural Networks (ANN) are being extensively used for pattern recognition and classification problems. The important features of ANN based techniques are that they (i) exhibit adaptation or learning (ii) pursue multiple hypothesis in parallel (iii) may be fault tolerant (iv) may process degraded or incomplete data and (v) seek answers by carrying out transformations. For training artificial neural networks, two models are normally used - supervised and unsupervised. For supervised learning, the Error Back Propagation (EBP) algorithm has been found to be most suitable, and for unsupervised learning, the self organizing feature map algorithms are normally used. Kohonen's self organizing feature network and Adaptive Resonance Theory (ART) network are based on clustering procedures and are hence best suited for classification. For ECG data compression, supervised learning based on EBP algorithm has been found to be best suited.

Artificial Neural Networks with more than one hidden layer were used for ECG compression as early as in 1992 [Habboush *et al*., 1992]. Sandham *et al*., used ANN algorithms like simple competitive learning network, Fuzzy Min-Max clustering and Fuzzy Adaptive Resonance Theory [Sandham *et al*., 1995].

1.5.4 Evaluation of a compression technique

Normally, Percentage Root mean square (rms) Difference (PRD) measures distortion between the original and reconstructed ECG signal. But PRD, the commonly used figure of merit, may not directly reveal whether the clinically significant ECG waveform information is preserved or not. Zigel *et al.* introduced Weighted Diagnostic Distortion (WDD), which is based on comparing the PQRST complex features (such as: P wave duration, P wave amplitude, P wave shape, QT duration, ST elevation, etc.) to measure distortion. [Zigel *et al.,* 1996; Zigel *et al.,* 2000b]. Visual inspections by a physician, however, will always remain a foolproof way of establishing clinical validation of original and reconstructed ECG signal.

1.6 SCOPE OF PRESENT WORK

There are many situations encountered by physicians when they have to consult other physicians so as to come to the most effective line of treatment for their patients. A patient complaining of chest pain has to be critically examined for any heart related problems. His ECG is to be transmitted to cardiologist for diagnosis [Mishra, 2005b]. A lot of time can be saved under these situations, if the ECG record is transmitted in the compressed form. No cardiac data compression technique has so far been internationally standardized. Scope exists in improvement of the available cardiac compression techniques.

Though there are many references of Telecardiology being practiced in India at various centres, the procedure is more like videoconferencing rather than in the form a dedicated website, designed to take care of cardiology cases [Srikanth, 2003].

Keeping the above in mind the work presented here was carried out with the following objectives

a) To develop a Telecardiology system to efficiently handle the cardiac data from the patient to cardiology expert and vice versa, both being distant apart

b) To develop efficient data compression methods to handle the cardiac data of varied nature. Focus here shall be on large duration ECG data

c) To bring the developed Telecardiology system to a stage suitable for use in cardiac care environment

1.7 ORGANIZATION OF THE THESIS

The work presented in this thesis has been covered in eight chapters. Chapter one starts with a brief introduction to the concept of telemedicine particularly in the area of telecardiology. The topics like cardiac signals, Electrocardiogram and its standard database; transmission protocols and different classes of data compression techniques have then been discussed. The relevant research work carried out by different researchers has been presented in chapter two.

The third chapter deals with introduction to wavelet transform, its advantages over fourier transform, different types of wavelets, continuous and discrete wavelet transforms, and different applications of wavelets in the area of bio-medical engineering. It then covers wavelet compression for ECG signals, choice of wavelets for data compression, embedded zero tree wavelet coding, Set Partitioning In Hierarchical Trees (SPIHT) wavelet compression method and relative superiority of SPIHT wavelet compression.

Modified SPIHT wavelet compression has been discussed in fourth chapter. The two new steps namely, blank-fire removal and polishing were supplemented in the existing SPIHT algorithm. Its effect in increasing the compression ratio, and decrease in distortion of the reproduced signals have been discussed. Handling of long data files, the problems associated with it and the proposed solutions have then been given in this chapter.

Chapter five starts with diagnostic parameters, reporting and interpretation of ECG signal, followed by the proposed refinement criterion in ECG Compression, its statistical analysis and its clinical validation. A new distortion parameter has been proposed in chapter six. The effect of scaling, baseline shift and baseline wander in ECG signals on distortion measurement has been investigated.

A website designed for telecardiology proposing the concept of prioritizing and credit transfer is presented in chapter seven. The conclusion of the overall work, significant findings and the further scope of the work are given in the last chapter.

LITERATURE SURVEY

ECG data needs to be compressed both for the purpose of efficient storage as well as for speedier transmission over long distances. To this effect, several algorithms have been developed in the past four decades [Saxena *et al.*, 1997]. The databases used for testing the developed algorithms and the methods for checking the distortion in the reconstructed signals, however, were not identical in most of the reported works [Bedini *et al.,* 1990]. Comparison of the results therefore could not be done in absolute terms. Keeping these aspects in mind the literature survey thus has been carried out, as per the category of the data compression technique used. As the objective of the work is to compress the ECG data for the telecardiology purpose, literature survey has also been carried out on the facts available on telemedicine in general and telecardiology in specific.

2.1 LOSSLESS ECG DATA COMPRESSION TECHNIQUES

ECG signal compression techniques can be generally categorized as either lossless techniques or lossy techniques. In case of lossless techniques, such as Huff coding, not even a singe bit is lost [Huffman, 1952]. These kinds of techniques are widely used for compressing textual data. On the other hand, for compression of digitized ECG signal, use of lossy techniques is more prevalent. Some of the lossless technique used for ECG compression, like Lempel- Ziv (LZ) in adapted form (LZ77) is more of an exception than a rule [Horspool and Windels, 1994; Koski, 1997]. Though dictionary based techniques are generally used for lossless textual compression, but again utilizing the cyclic nature of ECG signal, these techniques too were reported for ECG compression [Barlas and Skordalakis, 1996]. As compression ratio (CR) in lossless techniques is rather low (hardly 2:1 to 3:1), these are usually not preferred for the ECG data compression. A few algorithms for lossless ECG compression were presented that made use of lifting wavelet transform. The lifting wavelet transform was introduced by D.L. Donoho, W. Sweldens and P. Shroder in nineties [Donoho, 1990; Sweldens, 1996; Sweldens and Shroder, 1996] The transform was implemented in its integer-to-integer version, thus quantization of wavelet coefficients and rounding off of errors was avoided [Kuzume and Niijima, 1998; Duda *et al.*, 2001]. Arnavut proposed a lossless ECG compression Linear Transformation Algorithm (LTA), which was based on a Linear Order Transformation (LOT), [Arnavut, 2001]. Even in the most recent work reported on lossless ECG compression using wavelet based vector quantization approach, the average compression ratio was only 3.068 [Miaou and Chao, 2005].

2.2 DIRECT ECG COMPRESSION TECHNIQUES

Direct data compression techniques mostly rely on utilizing interpolation or short-term prediction algorithm. An interpolation algorithm employs a prior knowledge of both previous and future samples while a prediction algorithm employs a prior knowledge of some previous sample. These techniques normally attempt to reduce redundancy in data sequence by examining a successive number of neighboring samples and a preset error or threshold is employed to eliminate data sample. If one selects a small value for the threshold, then the obtained retrieved signal will be of a high quality, but the data reduction will be low, and vice or versa. Modified AZTEC, Fan, Scan Along Polygon Approximation (SAPA), Coordinate Reduction Time Encoding System (CORTES), Turning Point (TP) are commonly used direct data compression techniques [Jalaleddine *et al.,* 1990].

One of the very first popular ECG compression algorithms, Amplitude Zone Time Epoch Coding (AZTEC), was proposed by Cox et al. and was originally developed for preprocessing the real time ECG for rhythm analysis [Cox *et al.,* 1968]. A simple ECG compression algorithm that gave a fixed compression ratio of 2: 1, without diminishing the large amplitudes of QS complexes, was Turning Point algorithm. However, this algorithm had a major drawback - the saved points were not equally spaced in time [Mueller, 1978]. A hybrid of AZTEC and Turning Point algorithm, retaining the advantages of both was developed and named as Coordinate Reduction Time Encoding System (CORTES) [Tompkins and Webster, 1981; Abenstein and Tompkins, 1982].

Number of data reduction techniques based on First Order Interpolation with Two Degrees of Freedom (FOI-2DF) were proposed, like fan algorithm [Gardenhire, 1964] and Scan Along Polynomial Approximation (SAPA) algorithm in three different varieties viz. SAPA-1, SAPA-2 and SAPA-3 of which SAPA-2 was found to be the best [Skalansky and Goanlez, 1980; Ishijima *et al.,* 1983]. Later it was realized that the SAPA-2 algorithm was same as the older fan algorithm [Barr *et al.,* 1985].

Filtering and sub sampling techniques are sometimes used for real-time Holter ECG analyzer. Smith and Platt reported storing compressed ECG data compression for 25 hours of a single channel in 1.5 Mbytes of RAM, using this technique [Smith and Platt, 1988].

ECG data compression based on Hermite functions modeling was also proposed. In order to apply the procedure, four signal windows were selected in each beat, corresponding to the principal ECG features: P wave, QRS complex, ST segment and T wave. However, in order to model the ECG signal with the Hermite functions, several preprocessing steps had to be applied like, QRS detection and waves boundary detection, baseline wander removing and linear approximation [Jane *et al.,* 1993].

Many researchers used combination of various algorithms, for improved compression like combination of AZTEC and SAPA algorithm [Singh and Zhu, 1990]. Mckee *et al.* used fixed point arithmetic to provide an order of magnitude improvement in performance over then existing floating point implementations for Fan/SAPA-2 algorithms [Mckee *et al.,* 1994].

In 1994, El-Sherief *et al.*, evaluated and compared four commonly used ECG data compression techniques viz., turning point, Amplitude Zone Time Epoch Coding (AZTEC), Coordinate Reduction Time Encoding System (CORTES), and Fan/SAPA (scan-along polygonal approximation). These techniques were evaluated based not only on their percent root-mean-square error but also on the significant clinical information/features that were retained/lost in the decompressed ECG signals. Results showed that the turning point with compression ratio up to 4:1 provided the best reproduction of the total P-QRS-T configuration with minimal loss of important clinical information [El-Sherief *et al.,* 1994].

Another such comparative study was made where SAPA, Average Beat Subtraction with Residual Differencing (ABSURD) and Turning-Point Recursive Improvement Method (TRIM) were evaluated for their ECG compression performances on MIT – BIH database [Hamilton and Tompkins, 1991a; Hamilton and Tompkins, 1991b; Hamilton, 1992]. A variant of Average Beat Subtraction method was proposed as Standard Communication Protocol for Computerized Electrocardiography (SCP-ECG) [Zywietz *et al.,* 1991] and later the method was further refined by Paggetti *et al* [Paggetti *et al.,* 1994].

Udupa and Murthy originally developed the Linear Approximation Distance Thresholding (LADT) algorithm for preprocessing in syntax-directed ECG rhythm analysis [Udupa and

Murthy, 1980]. The LADT algorithm had shown more efficient performance than other piecewise linear approximation algorithms in respect to compression ratio and the quality of reconstructed ECG. However, the LADT algorithm could not be applied to the real-time ECG data compression due to the complexity of the computation. For fast realization of the LADT algorithm, use of an error threshold table that could be applied in real-time ECG data compression was introduced [Gang *et al.,* 1994].

A scheme based on Vector Quantization (VQ) for the data-compression of multi-channel ECG waveforms was proposed. N-channel ECG was first coded using m-AZTEC, a modified, multi-channel extension of the AZTEC algorithm. As in AZTEC, the waveform was approximated using only lines and slopes; however, in m-AZTEC, the N-channels were coded simultaneously into a sequence of $N + 1$ dimensional vectors, thus exploiting the correlation that existed across channels in the AZTEC duration-parameter. Classified Vector Quantization (CVQ) of the m-AZTEC output was then performed to exploit the correlation in the other AZTEC parameter, namely, the value-parameter. CVQ preserved the waveform morphology by treating the lines and slopes as two perceptually distinct classes. Both m-AZTEC and CVQ provided data-compression and their performance improved as the number of channels increased [Mammen and Ramamurthi, 1990]. Subsequently this technique was modified where ECG rate-distortion bound was first estimated, which was the theoretical limit on the compression of the ECG data. A ECG data-compression scheme was presented based on codebook quantizer and Finite-State *VQ* (FSVQ), which were suitable for coding a correlative signal [Wang and Yuan, 1997].

Furht and Perez used several statistical parameters to calculate the variable threshold in AZTEC technique and proposed this to be applied for design of pacemaker follow-up system for the on-line transmission of ECG from the implanted Pacemaker to the computers system located in the clinic [Furht and Perez, 1998].

It was demonstrated by Haugland *et al.,* that exact optimization algorithms outclass heuristical approaches by a wide margin with respect to reconstruction error. As opposed to traditional time-domain algorithms, where some heuristic is used to extract representative signal samples from the original signal, the exact optimization algorithm by Haugland *et al.,* formulated the sample selection problem as a graph theory problem. Thus well known optimization theory could be applied in order to yield optimal compression. Haugland *et al.,* had applied linear interpolation for reconstruction of the signal. Later the optimization algorithm was generalized such that reconstruction could be made by second order polynomial interpolation in the extracted signal samples. The polynomials were fitted in a way that guaranteed minimal reconstruction error, and the method proved good performance compared to the case where linear interpolation was used in reconstruction of the signal [Nygaard *et al.,*1991; Haugland *et al.,*1997; Nygaard and Haugland, 1998] .

Another scheme for data compression based on vector quantization was Gold Washing (GW) Adaptive Vector Quantization (AVQ) (GW-AVQ). The adaptive nature of the algorithm provided the robustness for wide variety of the signals. However, the performance of GW-AVQ was highly dependent on a preset parameter called distortion-threshold (dth) which could be determined by experience or trial-and-error. An algorithm was proposed that allowed assigning an initial dth arbitrarily and then automatically progress toward a desired dth according to a specified quality criterion, such as the PRD for ECG signals. A theoretical foundation of the algorithm was also presented. The algorithm was particularly useful when multiple GW-AVQ codebooks and, thus, multiple dth's were required in a sub-band coding framework [Miaou and Yen, 2000; Miaou and Yen, 2001; Miaou *et al.*, 2002].

Another method of truncated Singular Value Decomposition (SVD) was proposed for ECG data compression. The signal decomposition capability of SVD was exploited to extract the significant feature components of the ECG by decomposing the ECG into a set of basic patterns with associated scaling factors. The signal information was mostly concentrated within a certain number of singular values with related singular vectors due to the strong inter-beat correlation among ECG cycles. Therefore, only the relevant parts of the singular triplets needed to be retained as the compressed data for retrieving the original signals. The insignificant overhead could be truncated to eliminate the redundancy of ECG data compression [Wei *et al.,* 2001].

An ECG wave some time needs to be pre-processed, before it could be compressed. Those techniques that exploit the cyclicity of the signal require QRS of the wave to be detected. This can be done in a number of ways, viz. by syntactic method [Mehta *et al.,* 1996], by artificial neural networks [Vijaya *et al.,* 1997] or by wavelet transforms [Saxena *et al.,* 2002]. A model of ECG compressor that made use of the cyclicity of the signal, was presented by Todd and Andrews [Todd and Andrews, 1999]. Kyoso and Uchiyama proposed a microprocessor based transmitter that utilized ECG data reduction by ECG base line drift canceller, waveform detector and wave analyzer, transmitting only the diagnosis information [Kyoso and Uchiyama, 2000].

Huang and Kinsner proposed frame (beat) compression scheme using a block encoding and window variance techniques where the ECG frame was classified using Dynamic Time Warping (DTW) [Huang and Kinsner, 2002].

Boonyaves *et al.* proposed ECG compression using Multi-quadratic interpolation (Multi-quadratic is the approximation value between significant points of signal). The Multi-quadratic was a linear Combination of square root quadratic function. The data using Multi-quadratic for ECG signal consisted of maximum points, minimum points and changes in slopes points [Boonyaves *et al.*, 2004a; Boonyaves *et al.*, 2004b].

In one of the most recent research works, Kumar *et al.,* proposed some modifications in the direct ECG compression techniques like AZTEC, SAPA etc., to make it suitable for telemedicine purposes. Suitability of the system was checked over Transport Control Protocol (TCP), Internet Protocol (IP), Local Area Network (LAN) and Wide Area Network (WAN) [Kumar *et al.,* 2006].

2.3 TRANSFORMATIVE ECG DATA COMPRESSION TECHNIQUES

Transformation techniques engage preprocessing the input signal by means of a linear orthogonal transformation and properly encoding the transformed output (expansion coefficients) and reducing the amount of data needed to adequately represent the original signal. The reconstruction of the signal is done by inverse transformation with a certain degree of error. Some of the commonly used Transformative techniques are Karhunen - Loeve Transform (KLT), Fourier Transform (FT), Cosine Transform (CT), Walsh Transform (WT), Harr transform (HT), and the Wavelet Transform.

One of the earliest works in ECG compression using transformative methods was reported in 1977. The technique invoked two applications of the discrete Karhunen - Loeve transform. The first application reduced the effects of respiration and the various orientations of different patients' hearts, and required the solution of a 3 X 3 matrix eigen value, eigenvector problem for each beat. The second application involved expressing the transformed cardiogram in a Karhunen-Loeve series, and required the solution of the eigen value, eigenvector problem for a large matrix. However, the solution which was to be obtained only once for all time, could be performed off-line. The same eigenvectors could be used for all patients [Womble *et al.,* 1977].

In early 1990's, use of discrete cosine transform for ECG data compression using sub-band coding was reported [Aydin *et al.,* 1991], that was further improved by using dynamic threshold allocation and variable sub-band coding for enhanced performance [Allen and Belina, 1992; Allen and Belina, 1993]. Cetin *et al.*, reported similar work using Karhunen - Loeve transform and Discrete Cosine Transform (DCT) [Cetin *et al.*, 1993]. Another transformative compression technique based on polynomial transform was reported that had performance better than DCT [Philips and Jonghe, 1992].

In another application of discrete cosine transform for ECG data compression, a method was presented which employed a Two Dimensional (2-D) transform. The 2-D transform method utilized the fact that ECG signals generally show two types of redundancies—between adjacent heartbeats and between adjacent samples. A heartbeat data sequence was cut and beat-aligned to form a 2-D data array. Although any 2-D compression method could then be applied, transform coding using the 2-D Discrete Cosine Transform (DCT) [2-D DCT] was employed there as an example [Lee and Buckley, 1999].

An algorithm based on a combination of the Karhunen-Loeve transform (KLT) and multirate sampling for ECG compression was introduced [Blanchett *et al.*, 1998]. Molina *et al.,* developed compression algorithm based on the Walsh-Hadamard Transform (WHT), which was found suitable for real-time operation with minimal computational needs [Molina *et al*., 1997]. Use of Fast Walsh Transform and Fast Fourier Transform for ECG compression and its clinical acceptability was also reported in the same year [Kulkarni *et al.*, 1997a; Kulkarni *et al.*, 1997c].

Olmos *et al.,* analyzed the effect of noise in orthogonal expansions of ECG signals. When the observed signal was embedded in additive noise, distortion measurements, such as the mean-square error, were not a monotonic decreasing function of the number of transform coefficients, due to the noise presence. Two different ways to estimate the transform coefficients were analyzed and compared with: inner product and adaptive estimation with the Least Mean Square (LMS) algorithm. For stationary signals, superior performance was obtained by the adaptive system when low values of the step-size were used. For non-stationary signals, values of the LMS step-size depending on the noise characteristics and the signal-to-noise ratio were proposed. Theoretical results were contrasted with a simulation study with actual ECG signals from MIT-BIH Arrhythmia database and three kinds of noise: simulated Gaussian white noise, and two records of physiological noise that essentially contained electrode motion artifacts and muscular activity [Olmos *et al.,*1999].

Discrete wavelet transforms have also been found particularly useful for signal compression problems in engineering [Staszewski, 1998; Tanaka *et al.,* 1997; Desforges *et al.,* 1998], their application for ECG data compression was reported as early as in 1994 [Cetin *et al.*, 1994] quickly followed by many others in the subsequent year [Djohan *et al*., 1995; Sastry and Rajgopal, 1995; Soraghan *et al.,* 1995].

In 1996, Bradie made a preliminary investigation of a wavelet packet based algorithm for the compression of single lead ECG. The algorithm combined the efficiency and flexibility of wavelet packet expansions with the methodology of the Karhunen-Loeve transform (KLT) and was tested for selected records from the MIT-BIH arrhythmia database. When compared with the KLT applied to the same data, the wavelet packet algorithm generated significantly lower data rates (better compression ratio) with less than one-third the computational effort [Bradie, 1996].

Saha, and Ramakrishnan applied Discrete Wavelet Transform (DWT), based on Daubechies-4 basis functions on the normalized ECG beats, after shifting each of them to the origin. Linear Prediction was then applied to predict only those DWT coefficients of the current beat from the corresponding coefficients of a certain number of previous beats, transmitting only the residuals of selected coefficients resulting in improved compression [Saha and Ramakrishnan, 1997; Ramakrishnan and Saha, 1997]. Wavelet and wavelet packet-based compression algorithms based on Embedded Zero-Tree Wavelet (EZW) coding were developed for electrocardiogram (ECG) signals [Hilton, 1997]

Chen and Itoh proposed an ECG compression method based on ortho-normal wavelet transform and an adaptive quantization strategy, by which a predetermined Percent Root mean square Difference (PRD) could be guaranteed with high compression ratio and low implementation complexity [Chen and Itoh, 1998].

Galvão *et al.,* introduced the concept of “biased wavelets”, which were functions that were localized in time and in frequency but, unlike conventional wavelets, had an adjustable nonzero mean component. Under mild conditions, it was shown that a conventional mother wavelet could be used to construct a family of biased wavelets, which spanned the set of finite-energy functions. Numerical tests suggested that the introduction of the adjustable "bias" considerably improved the representation capabilities of wavelet expansions. A problem of electrocardiographic data compression was used for illustration purposes using MIT–BIH ECG Compression Test Database [Galvão *et al.,* 1999].

For compression of ECG data by wavelet transform, a study was made on the choice of wavelet for optimal results [Besar *et al.*, 2000]. Addison *et al*., explored the use of two low-oscillation complex wavelets - Mexican hat and Morlet- as powerful feature detection tools for data analysis and proposed a signal compression technique in which the pertinent signal information was contained within a few modulus maxima coefficients [Addison *et al*., 2000].

Ahmed *et al.*, pointed out that the best performance can be obtained if the signal was decomposed up to the fourth level using non-orthogonal wavelet transform. They also reported higher compression ratio for the same PRD for MIT-BIH database as compared to American Heart Association (AHA) database. Higher sampling rate (360 samples per second) in MIT-BIH as compared to 250 samples per second in AHA database was the reason cited for that [Ahmed *et al.*, 2000].

In significant improvement in compression efficiency over the work reported by its contemporaries, a wavelet electrocardiogram (ECG) data codec based on the Set Partitioning In Hierarchical Trees (SPIHT) compression algorithm was proposed. The SPIHT algorithm [Said and Pearlman, 1996] had achieved notable success in still image coding. It was modified for the one-dimensional case and applied to compress ECG data. Experiments on selected records from the MIT-BIH arrhythmia database revealed that the proposed codec was significantly more efficient in compression and in computation than previously proposed ECG compression schemes. The coder also attained exact bit rate control and generated a bit stream progressive in quality or rate [Lu *et al.*, 1999; Lu *et al.*, 2000]. SPIHT- based ECG data compression was also employed for mobile telecardiology using 3G cellular phone standards [Huang and Miaou, 2001]

In another method a coding technique for the compression of ECG signals using the wavelet transform was used which was based on generating a binary stream of 1's and 0's that encoded the structure of wavelet coefficients. This binary stream was compressed using a modified run length encoding. The effects of signal length, finite word length representation of the wavelet coefficients and threshold levels selection on the quality of the reconstructed signal were investigated. It was concluded that no improvement in the compression performance parameters resulted if the signal length exceeds 4096 samples [Abo-Zahhad and Rajoub, 2001].

Wavelet transforms have been used not only for ECG compression, but also for de-noising the signal [Cherkassky and Kilts, 2001]. A combined compression and denoising method was designed for mobile telecardiology scenarios, where reliability as well as spectral efficiency was essential. The signal was segmented into beats and a beat template was subtracted to them. Beat templates as well as residual signals were coded with a wavelet expansion. De-noising and compression were achieved by selecting a subset of wavelet coefficients [Alesanco *et al.*, 2003].

In extension to SPIHT another algorithm called Layered Set Partitioning In Hierarchical Trees (LSPIHT) algorithm, was presented for telemedicine applications. In the LSPIHT, the encoded bit streams were divided into a number of layers for transmission and reconstruction. Starting from the base layer, by accumulating bit streams up to different enhancement layers, medical data could be reconstruct with various Signal to Noise Ratios (SNRs) and/or resolutions. Receivers with distinct specifications could then share the same source encoder to reduce the complexity of telecommunication networks for telemedicine applications [Hwang *et al.,* 2003].

JPEG2000 (Joint Photographic Expert Group) is a wavelet transform based latest international standard used for compression of still images. Bilgin *et al.*, illustrated the use of existing hardware and software JPEG2000 codecs (coder- decoder) for ECG compression, thereby eliminating the need for specialized hardware development. The desirable characteristics of the JPEG2000 codec, such as precise rate control and progressive quality, were retained in the presented scheme [Bilgin *et al.*, 2003].

Another compression technique employing wavelet transform applied iterative threshold until a fixed percentage target of wavelet coefficients to be zeroed was reached. This followed lossless Huffman coding for enhanced compression [Benzid *et al.*, 2003].

Koski *et al.*, proposed a method of so-called successive approximation quantization used with wavelets for ECG compression. The extent to which the lossy compression methods altered values of medical parameters (medical information) computed from signals was also investigated. It was found that ECG signals sampled at 400 Hz could be compressed to one fourth of their original storage space, but the values of their medical parameters changed less than 5% due to compression, which indicated reliable results [Koski *et al*., 2004].

Alesanco *et al.,* communicated error effects in wavelet compression codecs for real-time ECG monitoring in a wireless telecardiology application. Two different strategies for ECG coding were presented and the error effects in the received ECG signals were discussed. Both quantitative (RMS error index) and qualitative (cardiologist opinions) were presented in order to decide if it was useful to monitor retrieved information from ECG packets received with errors or erroneous packets should be discarded [Alesanco *et al.*, 2005].

In one of the recently proposed ECG compression methods, three major approaches based on Time Division Multiplexing (TDM) and multilevel wavelet decomposition followed by parametrical modeling were combined. Before applying these techniques, a pre-processing step was required, which consisted of detecting and aligning different beats. A high compression ratio could be achieved by preserving the major medical information within the ECG using several normal and abnormal signals from various databases to evaluate the performance of the proposed technique [Nait-Ali et *al.*, 2006].

There was an interesting case of researchers reporting extraordinary performance of wavelet based compression of ECG signal [Abo-Zahhad and Rajoub, 2002], that was cross checked and found to be improperly substantiated, merely on account of inappropriate use of distortion measure while comparing the results with those of the other researchers [Alshamali and Al-Fahoum, 2003]. Apart from using the corrected form of PRD, some work was also reported on evaluation of the parameters of diagnostic importance and their interpretation in multi-lead ECG analysis using heuro-logistic approach. The computerized interpretation thus made was found to be in agreement with the visual interpretation given by medical experts [Maheshwari *et al.*, 1998]. To measure the distortion in reconstructed ECG signals, weighted diagnostic distortion (WDD) was proposed. The WDD was based on PQRST complex diagnostic features (such as P wave duration, QT interval, T shape, ST elevation) of the original ECG signal and the reconstructed one. Unlike other conventional distortion measures like PRD, the WDD contained direct diagnostic information and thus was more meaningful and useful [Zigel *et al.*, 1996; Zigel *et al.*, 1997 ;Zigel *et al.*, 2000a; Zigel *et al.*, 2000b].

In one of the most recent research publications, a wavelet-based ECG compression algorithm with a low delay property for instantaneous, continuous ECG transmission suitable for telecardiology applications over a wireless network was proposed. The proposed algorithm reduced the frame size as much as possible to achieve a low delay, while maintaining reconstructed signal quality. To attain both low delay and high quality, it employed waveform partitioning, adaptive frame size adjustment, wavelet compression, flexible bit allocation, and header compression. The performances of the proposed algorithm in terms of reconstructed signal quality, processing delay, and error resilience were evaluated using the Massachusetts Institute of Technology University and Beth Israel Hospital (MITBIH) and Creighton University Ventricular Tachyarrhythmia databases and a code division multiple access-based simulation model with mobile channel noise [Kim *et al*., 2006]. Interestingly, the results were not compared with SPIHT algorithm, and once again inappropriate distortion measure was employed as pointed out earlier by Alshamali and Al-Fahoum [Alshamali and Al-Fahoum, 2003].

2.4 PARAMETER EXTRACTION TECHNIQUES

In some of the parameter extraction methods like linear prediction methods [Ruttimann and Pipberger, 1979], peak picking methods [Imai *et al.,* 1985; Cohen *et al*., 1990] and syntactic methods [Trahanias and Skordalakis, 1990], the extraction of a set of useful parameter from the original signal is carried out and the same are used in the reconstruction process. The peak picking compression techniques are generally based on the sampling of a continuous signal at peak (maxima and minima) and extraction of signal parameter that convey most of the signal information. These parameters include the amplitude and location of maxima and the minima points, slope changes, zero-crossing intervals, and points of inflection in the signal.

Data compression by entropy coding is obtained by means of assigning variable-length code words to a given quantized data sequence according to their frequency of occurrence. This compression method attempts to remove signal redundancy that arises whenever the quantized signal levels do not occur with equal probability. Cassen and English used entropy coding along with other compression technique [Cassen and English, 1997]. Szilagyi *et al.*, developed an adaptive entropy coder to obtain 10 times less redundancy than an optimized Huffman coder [Szilagyi *et al.,*1997].

Nave and Cohen gave compression system that was based on the Sub-Auto-Regression (SAR) model, also known as the Long-Term Prediction (LTP) model. The 'periodicity' of the ECG signal was employed in order to further reduce redundancy, thus yielding high compression ratios [Nave and Cohen, 1993]. The single-channel LTP algorithm was then generalized to the multichannel case and was called the MC-LTP algorithm. This algorithm compressed PQRST beats using a pattern codebook with "typical" beats [Cohen and Zigel, 1998].

Later in 1999 Coggins and Jabri made use of backward prediction compression algorithm for ECG compression. This was mainly designed for Implantable Cardioverter Defibrillators (ICDs) by direct sensing and electrically stimulating of the heart muscle. ICDs are used to detect, diagnose and treat the potentially fatal heart arrhythmias known as Bradycardia, Ventricular Tachycardia (VT), and Ventricular Fibrillation (VF) in cases where these arrhythmias are resistant to surgical and drug-based treatments. Since the ICD is implanted, power consumption, reliability, and size were severe design constraints. A data-compression algorithm described was optimized for low power consumption and high reliability implementation. Reliance on a patient's morphology or that of a population of patients was avoided by adapting to the Intracardiac Electrogram (ICEG) amplitude and phase variations and by using adaptive scalar quantization [Coggins and Jabri, 1999].

Einarsson proposed an algorithm for reversible data compression based on predictive coding. From the input data, a sequence of integer-valued residuals was generated by a linear or nonlinear operation. Performing a modular operation on its symbols reduced the size of the alphabet for the residuals. The reconstruction process recovered the original data exactly. The modular operation resulted in a smaller size codebook and prevented data expansion when the source did not match to the code. This was an improvement over the work done earlier by Pahlm *et al.,* [Pahlm *et al.*, 1979; Einarsson, 1999].

In extension to the predictor algorithms, Diaz-Gonzalez *et al.,* gave an ECG compression algorithm using a Max-Lloyd quantizer, to optimize the low resources of an ECG acquisition and transmission system (telemetry system) for dolphins and human divers. The algorithm scheme was based on a first-order Differential Pulse Code Modulation (DPCM) and used a Max-Lloyd quantizer to code the difference between the current and predicted samples. The use of the non-uniform quantizer instead of a uniform quantizer resulted in low distortion in the reconstructed signals. Due to its low computational complexity, the compression process could be accomplished on-line during the ECG acquisition process [Diaz-Gonzalez *et al.,* 2004].

2.5 ARTIFICIAL NEURAL NETWORK (ANN) BASED ECG DATA COMPRESSION TECHNIQUES

The important features of ANN based techniques are that they (i) exhibit adaptation or learning (ii) pursue multiple hypothesis in parallel (iii) may be fault tolerant (iv) may process degraded or incomplete data and (v) seek answers by carrying out transformations.

For training the artificial neural network, basically two models are normally employed-supervised and unsupervised. For supervised learning, the Error Back Propagation (EBP) algorithm has been found to be most suitable, and for unsupervised learning, the self organizing feature map algorithms are normally used. Kohonen's self organizing feature network and Adaptive Resonance Theory (ART) network, which are based on clustering procedures, are best suited for classification. For ECG data compression, supervised learning based on EBP algorithm has been found to be best suited.

In early work using ANN for ECG compression, Iwata *et al.,* proposed a data compression algorithm for Holter recording with ANN. A dual three-layered (one hidden layer) neural network system that had a few units in the hidden layer was used for this purpose. The network was tuned up with supervised signals that were the same as input signals. The back-propagation was used as the learning algorithm. Network 1 was used for data compression and Network 2 was always learning with current signals. If the ECG waveform changed, the neural network also replaced so that it could follow those changes. Once the network was tuned up, the common waveform features were encoded with the interconnecting weights of the network. The activation levels of the hidden units then expressed the respective features of the waveforms for each consecutive heart beat. Original waveforms were reproduced from the activation level of the hidden units and the interconnecting weights. Thus, the interconnecting weights of the network and the activation levels of the hidden units for each consecutive heart beat needed only to be stored in the memory, instead of the entire data sequence. Since the number of hidden layer units was extremely limited, data compression was accomplished by storing the activation levels rather than the original signal [Iwata *et al.,* 1990]. Habboush *et al.* suggested that a neural network with more than one hidden layer could perform more efficient ECG compression than using the linear methods under the same constrains [Habboush *et al.,* 1992]. Later Sandham *et al*., used ANN algorithms like simple competitive learning network, Fuzzy Min-Max clustering and Fuzzy Adaptive Resonance Theory (ART) [Sandham *et al*., 1995].

A study was made on the compression performance with variation in number of hidden layers and number of elements in each layer. It was concluded that the best compression is achieved with two hidden layers and with four elements in each layer. It was also observed that the method along with compressing the signal, improved the quality of signal by removing high frequency noise in it [Saxena *et al.,* 1997].

In another work using ANN for ECG compression, a three-layer feedforward neural network structure was employed. Each heartbeat was divided into three major waves, i.e. P, QRS complex and T waves. Two hidden units connected the inputs and outputs of each wave respectively. The hidden units also connected the inputs and outputs in conjunction of the neighbouring waves. The advantage of this method was that it could enhance the capability of recovering the waveforms without increasing computation burden, it could also efficiently avoid the failure of redisplaying the waveforms when the P and T waves were unstable in waveform or highly noised, thus strengthening the robustness and feasibility of ECG compression techniques using neural networks [Luo *et al.,* 1999].

2.6 HYBRID ECG DATA COMPRESSION TECHNIQUES

Some ECG compression algorithms combine two or more techniques for achieving better results. In one such proposed method, the input signal was divided into blocks and each block went through a discrete wavelet transform; then the resulting wavelet coefficients were linearly predicted. In this way, a set of uncorrelated transform domain signals was obtained. These signals were compressed using modified run-length and Huffman coding techniques. The error corresponding to the difference between the wavelet coefficients and the predicted coefficients was minimized in order to get the best predictor [Abo-Zahhad *et al.,* 2000; Al-Shrouf *et al.,* 2003]. Thus transformative method, using wavelet transform was combined with parameter extraction method using linear predictor for optimal results. In another such work, non-specific patterns were searched in time-frequency coefficients in highest three octaves in P-QRS-T region. By sending or storing one pattern number per beat instead of whole set of coefficients, high compression ratio was achieved especially in long Holter recording signals. The time-frequency coefficients were obtained using wavelet transforms, thus combining transformative method with classical pattern-matching technique

[Augustyniak and Tadeusiewicz, 2000]. A similar effort was made by combining wavelet and modified run-length scheme for compression of ECG signals. The ECG signal was subjected to discrete wavelet transform and the resulting coefficients were encoded using a modified run-length coding technique [Alshamali and Al-Smadi, 2001].

2.7 TELEMEDICINE

Telemedicine, as defined given by World Health Organization (WHO) is “the delivery of healthcare services, where distance is a critical factor, by all healthcare professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of healthcare providers, all in the interests of advancing the health of individuals and their communities” [Pathni, 2005].

In Israel or in the Baltic countries, there is one doctor for fewer than 300 citizens, while in Ethiopia there is one doctor for every 35,000 people. This is a serious problem in healthcare delivery and availability, but it also makes the recruitment of teachers for medical schools difficult. Adding the ‘brain drain’, with which these countries are plagued, increases this problem [Alkan, 2000]. With more than 11 million home bound patients that have travel and access problem, TeleHomeCare virtual visits can provide a big relief [Finkelstein *et. al.,* 1999].

In islands and other remote areas where regular medical facilities are not available, telemedicine can provide great improvements to the healthcare delivery and bring high-quality care. The little hospitals, especially the outpatient departments, are not always equipped to face all clinical cases. The patients have to be regularly transferred to the mainland, even only for diagnosis [Clark, 2004]. The small dimension of the health service structures is related to the little population of the islands. This problem is more perceived during the summer season with the tourist increment of population. Bracale *et al.,* reported a cardiological and radiological video-teleconsulting system, which connected the two islands (Procida and Ischia) to mainland hospitals (Pozzuoli and Giugliano). The telemedicine network allowed a 24-hour connection between the main hospitals of Pozzuoli and Giugliano and the islands' health centres. This telemedicine solution aimed to provide a prompt and qualified health service in the islands, and to reduce the risks and the costs of patient transportation to the mainland. Technology assessment activities were carried out in order to evaluate and measure the performances of the specific telemedicine solution during its operative work and the preliminary results were promising. This project represented a pilot and demonstration site for future applications of telemedicine in emergency [Bracale *et al.*, 2000].

Clarke *et al.,* presented a similar pilot project AIDMAN, in which health clinics in remote areas of Greece were connected with mainland hospitals in Athens and London, to provide routine cardiological service, through a high-speed satellite network. Primary care teams managed high quality, cheap and easy to deploy noninvasive cardiological investigation tools, Holter ECG and blood pressure, exercise testing and echocardiography, in health clinics. All preliminary investigations were to be carried out in the remote clinic with the reports being forwarded over the link to the cardiologist for review. Consultation with the cardiologist would also be conducted over the link using video conferencing. Onward referral to specialist care, in that case London, was preformed over the same satellite network. Only when invasive procedures were to be carried out the patient needed to travel. The system had numerous advantages: the patient received immediate investigation; intervention and treatment was prompt; unnecessary travel was avoided. Another significant advantage in the video consultation involving cardiologist, patient and the patient's doctor was, the doctor could act as an advocate, making the consultation more effective. It also resulted in effective education process for the inexperienced doctor [Clarke *et al*., 2000].

Nakajima *et al*., reported promising potential benefits to many of the developing countries scourged persistently by the plague of resource constraints and harsh natural topography. The report discussed the possibility of the transmission of medical images from a remote understaffed health center to any bigger hospital for specialized and enhanced diagnosis through the use of Internet protocol. The study dealt with the possibility of introducing tele-ECG over IP, which could go a long way in enhancing the diagnosis of cardio-vascular diseases in the remote areas of Trashiyangtse and Lhuntse in East Bhutan [Nakajima *et al*., 2003 ; Sadiq *et al*., 2004].

The reach of telemedicine has not been limited to this planet only. Attempt is now made by an international network of physicians to treat injured or ailing astronauts by Internet-connected equipment, monitoring the vital signs [Moore, 2001].

The potential of telemedicine can be best illustrated by the statement of Dr. Devi Shetty, a cardiac surgeon and the Chairman of Narayan Hrudayalya, a hospital that has served thousands through telemedicine: "In terms of disease management, there is [a] 99% possibility that the person who is unwell does not require [an] operation. If you don't operate you don't need to touch the patient. And if you don't need to touch the patient, you don't need to be there. You can be anywhere, since the decision on healthcare management is based on history and interpretation of images and chemistry … so technically speaking, 99% of health-care problems can be managed by the doctors staying at a remote place—linked by telemedicine" [Bagchi, 2006]. There is even a report of robotic assisted microsurgery, where the surgeon does not directly touch the subject. Rather the motion of the hands of surgeon are optically detected, the tremor removed, precision enhanced and the surgical tool operated thereupon [Bose *et al.,* 1992]. With faster communication becoming available in near future, tele-surgery may become a practical way to perform even surgical operations from a distance. Efforts are being made to develop networked computing applications according to some evolving international standards, such as HL7 [Ganguly and Ray, 1998]. More recently eXtensible Markup Language (XML) data-encoding standards have been recommended as a powerful tool for dealing with common restrictions to the use and integration of tele-monitoring systems. These standards provide a reliable way not only for managing different forms of bio-signals coming from different sources but also for merging them in semantically structured and meaningful documents [Giacomo and Ricci, 2005].

Many researchers presented design approaches to transmit compressed, or uncompressed ECG signals using GSM(*Groupe Spécial Mobile*), or Digital Advanced Mobile Phones(DAMPS) [Pavlopouloss, 1998; Istepanian *et al*., 1999a; Feedman, 1999]. A special study was made for realization of telecardiology over Terrestrial Trunked Radio (TETRA) networks; transmitting wavelet based compressed ECG data [Alshamali, 2003].

Acute myocardial infarction is the condition in which prompt thrombolytic (breakdown of blood clots by pharmacological means), treatment is critical to the health of the patient and can significantly improve prognosis (doctor's prediction of how a patient's disease will progress, and whether there is a chance of recovery). Chronaki *et al*., proposed a telecardiology consultation system, which played an important role in providing a General Practitioner (GP) with direct access to a specialized cardiologist. The telecardiology consultation folder linked the patient's health care record, shared related medical information and kept a record of the interaction between the cardiologist and the GP. The system proposed was based on WebOnCOLL, an Internet based collaboration platform for the healthcare and tele-working domains. The use of open standards in WebOnCOLL enabled seamless integration with electronic health care record segments and interoperability with the evolving regional healthcare information infrastructure [Chronaki *et al*., 1998].

Mea *et al.,* introduced the agent paradigm from its theoretical basis to the technological issues, and described an agent-based approach to telemedicine, specifically applied to telepathology applications. The system was based on an agent-based model and template using Java, called Java Agent Model for Enhanced Services (JAMES), which was used to implement a prototype multipurpose telepathology application based on federated agency architecture.

A similar work was reported by Ganguly *et al*., in which one of the aspects of telecardiology known as tele-electrocardiography, deployed Electrocardiography machines to transmit ECG over networks. As different parts of the tele-electrocardiography system worked on different computing environments and software interoperability being major issue, software agent technology was proposed that supported heterogeneous computing environment. As this technology reacted dynamically to adverse conditions, it was suitable for development of fault tolerant distributed systems. Additionally, agent technology represented the intentions, desires and resources of the participants - so it could be effectively used in on-line healthcare application. The features of software agent technology were potentially suitable for the development of interoperable telemedicine systems [Ganguly *et al*., 2000)]

Use of 3G(third generation cellular standards for mobile telemedicine had been proposed by several researchers [Miaou and Huang, 2001; Woodward *et al.,* 2001]. Elena *et al.,* gave the design of a portable ECG to allow the on-line remote monitoring and real time cardiac diseases diagnostics of patients from the specialist. The prototype was satisfactorily implemented optimizing signal processing and power consumption using General Packet Radio Service (GPRS) /GSM (*Groupe Spécial Mobile*) modem and a Surface Mount Technology (SMT) low voltage microprocessor board [Elena *et al*., 2002].

To support mobile telemedicine, another dimension is in development of the wearable technology that act as a “platform” for sensors and monitoring devices that can non obtrusively monitor the health and well being of individuals (directly and/or remotely). This wearable yet comfortable, systems that can continue the transformation of healthcare—all aimed at enhancing the quality of life for humans [Yang, 2000; Park and Jayaraman, 2003; Reisner *et al.*, 2004].

There are several reports of the telemedicine programmes in developed countries like the Nordic countries (Denmark, Finland, Iceland, Norway and Sweden) [Olsson, 1995], Canada [Otto, 1999] and United Kingdom [Sibson, 1999]. In one of such reports, Istepanian gave an overview of some of the ongoing telemedicine programs in the United Kingdom. The issues of the future integration of telemedicine activities within the National Health Service that promise better access to healthcare with higher efficiency, mobility, and lower cost were also discussed. Many advances in telemedicine in general and telecardiology in specific were also reported [Istepanian ,1999; Istepanian *et al*., 1999b; Istepanian *et al*., 2001b].

Scalvini *et al.,* developed a telephone linked care technology and applied it as a supplement for ambulatory visits, as a means to offer a specific cardiac diagnosis during a general family doctors' visits. The family doctors used a mobile electrocardiogram (Card Guard 7100), which was able to transmit the ECG signal via any fixed or mobile telephone to a center where a cardiologist was present for the analysis of the ECG and for an interactive opinion [Scalvini *et al*., 1999].

Use of standard-based low-cost Video Conferencing System (VCS) in telemedicine and epidemiological applications was evaluated and an acceptable quality of medical images such as Computerized Tomography (CT), Magnetic Resonance Imaging (MRI) or X-ray was reported. The use of low-cost standard VCSs in telemedicine was recommended as a good substitute for real meetings [Klutke *et al*., 1999]. Moving away from the main stream telecardiology, the Internet and the World Wide Web (WWW) were proposed as tools to improve medical and cardiovascular research [Santoro, 2002].

Pattichis *et al*., gave on overview of wireless telemedicine system presenting some successful case studies in electronic patient record, emergency telemedicine, teleradiology, and home monitoring [Pattichis *et al.,* 2002].

A scalable wireless telemedicine system that was capable of simultaneously monitoring large number of patients (acquiring patient's ECG data) was reported, presenting a simple but useful technique for overcoming temporary "surges" in the environment where large number of patients (beyond the normal capacity of the monitoring system) must be monitored. The solution was based on modification to data transmission over the wireless network [Nussbaum and Wu, 2003].

A store and forward telemedicine service for acute trauma at the Queen Victoria Hospital, which is a tertiary referral centre for plastic surgery in the United Kingdom, was reported describing the development of such a system and the technical and legal difficulties experienced during the initial stages [Jones *et al*., 2004].

Nollo *et al.,* reported telecardiology network for rural area in Italy, where General Practitioners (GP) were equipped by standard 12 lead electrocardiograph with internal modem for the connection to the consultant station placed at the closer Coronary Care Unit (CCU). The connection between GP to the cardiologist was organized in asynchronous way, with the incoming list of on-processing ECG available 24 hour a day. The network had been in progress since 1997 and was then available for 15000 patients with a use rate of more than 50 ECGs per week [Nollo *et al*., 2000]. Neri *et al*., discussed Digital Imaging and Communication (DICOM) image transmission and interactive telediagnosis tools over the European network [Neri *et al*., 1998]. A report on usability analysis of a telemedicine system for interventional cardiology suggested the system to be cost effective and reliable [Rahms *et al*., 1995].

A practical website for telecardiology was proposed by Saxena *et al.,* along with a software which enables the uploading of ECG data from a patient, so that the physician could monitor the state of the patient from a distance and at the same time may consult other experts for a second opinion. Only the authorized physician after proper registration could examine records, and diagnosis or prescription sent back to the referring site. Further consultation with the patient through a 'chat' facility was also possible [Saxena *et al.,* 2000c].

2.7.1 Telemedicine in India

The facts on India's healthcare situation are grim. There is only one hospital bed for every 1333 citizens. India has one doctor for every 15,500 people. But most doctors live in cities, whereas 70 percent of the subcontinent's population of just over 1 billion lives in rural areas. Figures on the percentage covered by health insurance vary from 3 to 9 percent. The basic unit of the public system is the Public Health Center, which is typically staffed by one or two general practitioners and 10 or so nurses. Each of the centers has a few beds for simple in-patient procedures and perhaps X-ray and lab facilities. There are only about 23,000 of these for some 600,000 villages. Above them in the healthcare hierarchy are district hospitals and, in a few cities, multi-specialist hospitals. To get care, those who can afford it, typically spend days traveling [Harris, 2002]. Telemedicine would have a perfect breeding ground in a country with these statistics.

Citing a model for rural India, Cecchini suggested the role of Information and Communications Technology (ICT) in improving health care delivery to the poor. His model employed Telemedicine to diminish the cost and hardship of long distance travel for medical attention and diagnosis. Use of E-mail and medical related web pages could deliver recent medical findings to health workers lacking research and technological facilities at minimal cost. Furthermore, ICT could simplify medical data collection, record management and paper filing [Cecchini, 2002]. Equipment choice must be given priority to preventive care. Besides the general equipment design features of ruggedness, low weight and others, they must have connectivity for telemedicine [Guha, 1992]. Auxiliary Nurse Midwives (ANMs) shoulder most of the responsibility for healthcare delivery in vast and densely populated rural areas. As an offshoot of telemedicine programmes, availability of handheld computers, or Personal Digital Assistants (PDAs) would allow ANMs participating in the India Healthcare Delivery project to reduce redundant paperwork and data entry, freeing up time for healthcare delivery to the poor. Their duty is to administer immunization, offer advice on family planning, educate people on mother-child health programs, and collect data on the rural population's growth, birth, and immunization rates. Each ANM serves 5000 people, typically residing in different villages and hamlets, often located several kilometers apart. ANMs usually spend between 15 and 20 days per month on data collection and registration. PDAs used to facilitate data collection and transmission, would potentially save up to 40 percent of ANMs' work time. Redundant data entry prevalent in paper registers would be eliminated and reports would be generated automatically. These gains in efficiency would multiply the impact and reach of limited resources, thus expanding access to basic services [Cecchini, 2003]. Kulkarni also proposed a simple model comprising of a personal website of a doctor and a low cost bio-medical kit for patient input parameters required for diagnosis. Patient could interact with doctor through webcam and Internet and doctor too could inspect the patient visually. However this model could be applied only for common diseases [Kulkarni, 2002].

In slight variation from the conventional telemedicine models, Kundu *et al*., proposed a limited area model. The healthcare environments are by nature mobile where doctors and nurses do not have fixed workspace and have to move from one place to other. Regular and exceptional events are generated in daily hospital routine such as normal checkup of patients and attending emergency cases. For better and time effective management of such situation medical personnel always need to keep in touch with the patient's medical information. A system was developed that had the potential to support mobile-diagnosis and treatment within a hospital premises. The system allowed doctors to get patient's information in his handheld device using Wireless LAN (WLAN). The physical transmission of patients' information to the mobile device was also supported however, to get them outside the range of WLAN connections. The system was tested and experimented in the laboratory conditions at the Indian Institute of Technology, Kharagpur [Kundu *et al.,* 2005].

Singh in his report gave a pragmatic view of the advantages (improved care by reducing professional isolation of health care specialists) and disadvantages (increased expectations, physician licensing issues, resistance to the technology and costs associated with the installation) of telemedicine for rural India [Singh, 2005]. As far as the advantages are concerned, a somewhat similar report on telemedicine for rural health care in Turkey was also given by Sozen *et al* [Sozen *et al.,* 2003]. To make telemedicine in rural India cost effective, use of mobile ad hoc networks was suggested [Srivastava and Sahu, 2004], while a similar report for rural telemedicine suggested use of wireless packet based IP systems [Trotter and Kawasumi, 2004].

There are number of telemedicine related projects currently being run in India. Indian Space Research Organization (ISRO), as part of its commitment for social sector development had been applying space technology for healthcare and education, under GRAMSAT (rural satellite) programme. Apollo was first to set up a Rural Telemedicine Centre in the village of Aragonda in the state of Andhra Pradesh. Apollo experimented with Telecardiology more than 5 years back through the usage of Transtelephonic ECG machines, which were set up in various smaller hospitals whereby a doctor based in the Tertiary hospital could monitor his patients from a distance. Simulations of Teleconsultations between Apollo Hospitals, Hyderabad, Chennai and Dubai for cases specific to Cardiology, Neurosurgery & Orthopedics were done. Sanjay Gandhi Postgraduate Institute of Medical Sciences (SGPGIMS), Lucknow is a tertiary care referral hospital that has been actively involved in telemedicine since 1999. It is connected with three medical colleges of Orissa i.e. Cuttack, Berhampur and Burla through Very Small Aperture Terminal (VSAT). The telemedicine centre of SGPGIMS is connected via satellite to similar facilities in All India Institute of Medical Sciences (AIIMS), New Delhi and Post Graduate Institute of Medical Education and Research (PGIMER), Chandigarh under a project of Ministry of Information Technology. A Telemedicine & Videoconferencing Network has also been set up at School of Telemedicine, SGPGIMS [Mishra *et al.,* 2004; Mishra 2005a; Mishra, 2005c].

Pal *et al*., reported some more telemedicine projects in India. One of them was Online Telemedicine Research Institute (OTRI), Gujarat. When on January 27, 2001 an earthquake devastated the western city of Bhuj leaving thousands dead and many more homeless within a day, the OTRI in Ahmedabad, about 300 km from Bhuj, established satellite telephone links and set up all the equipment necessary to provide emergency medical care through telemedicine. The satellite phones were soon replaced by VSAT with phone lines and Integrated Services Digital Network (ISDN), and much of the imaging and data transfer were mediated by Pentium based personal computers. A full-fledged telemedicine system was used for teleconsultation in pathology, radiology, and cardiology over ISDN lines, and between district hospitals near Bhuj and others in Ahmedabad.

The Amrita Telemedicine Programme reported that on 13 January 2003, the programme's first remote telesurgery procedure was performed. The Amrita Emergency Care Unit at Pampa (Kerala, India) was able to save the life of a pilgrim by a telesurgical procedure using the local telemedicine facility. The cardiothoracic surgeon guided the procedure remotely, and the pediatric cardiologist at Pampa performed the procedure [Amritanandamayi Devi, 2005]

Mobile telemedicine units were also rushed to the coasts and islands of India after the 2004 tsunami to provide medical consultation and relief to the affected people [Indian Space Research Organization, 2005].

Pal *et al.,* reported about the Asia Heart Foundation, a not-for-profit charitable organization, that was established with the objective of providing cardiac care to the general populace. The Asia Heart Foundation’s telemedicine initiative “Integrated Telecardiology and Telehealth Project” (ITTP) aimed at taking cardiac care to the nation’s deprived rural and remote population, thereby “bridging the critical knowledge gap” in cardiac care services provided in rural and metro areas. All of ITTP's telemedicine units were linked to its Community Health Centres (CHCs) in Calcutta and Bangalore. Several state governments provided the basic infrastructure and the Foundation's doctors did all treatments. Encouraged by the success of the first ITTP project at Siliguri, India, a second ITTP project was also started in the same state in July 2001. With strong support from state governments and ISRO, ITTP is reported to offer the largest telemedicine network in India [Pal *et al*., 2005].

Telemedicine projects in India not only involve tele-consultations, but also tele-education of the medical students [Stamm and Cunningham, 2005]. In one such endeavor, a link was established between Sanjay Gandhi Postgraduate Institute of Medical Sciences (SGPGIMS), a university academic medical center located in Lucknow in the northern part of India, and three medical colleges of Orissa (in Cuttack, Berhampur and Burla), located 1500 kilometers away in the eastern coast of India. Communication solution for this point-to-point connectivity with 384 kbps bandwidth was provided with VSAT, supported by Indian Space Organization (ISRO). End equipments at each points consisted of PC based videoconference system having low-end camera (Polycom via video model) with tele-pathology and tele-radiology accessories. Regular sessions have been carried out between these centers for tele-education, tele-consultation and tele-follow-up for the benefit of treatment of patients, training and teaching of doctors and Continuing Medical Education (CME). [Singh *et al.*, 2004].

Sood and Bhatia described a telemedicine software developed in Mohali, India. Christened as 'Sanjeevani' the software enabled teleconsultations (primarily tele-radiology, tele-pathology and tele-cardiology) in the following manner:- When the patient-end doctor felt the need for a second opinion, he/she would use Sanjeevani, to consolidate relevant clinical information of that patient into an Electronic Patient Record (EPR) and then sought an opinion of the specialist using tele-consultation. After the connection to the specialist-end was established, the electronic patient record had to be uploaded. The specialist also had Sanjeevani installed. Using the software, the specialist then examined the clinical information, and suggested a course of action. If need arose, the doctors on both the ends arranged for a video conferencing to arrive at the diagnosis in a collaborative manner and decided upon the course of treatment in a participative manner. This advice was then formalized after the specialist sent back his opinion to the patient-end doctor. The services included patient demographics, general information, patient's medical-history, other information or data including clinical data like ECG, radiographs, pathological reports, clinical images, appending queries and advice, conducting a video conferencing etc. Sanjeevani generated various reports regarding diagnosis, treatment chart, next visit to hospital etc. as desired by the doctor [Sood and Bhatia, 2005].

3.1 INTRODUCTION

The first block of any measuring system is invariably a sensor or a transducer that comes in contact with the measurand. The electrical signal so obtained is a faithful record of the time varying measurand. Obviously this signal is in time domain. However in many applications, the meaningful information is prominently manifested only when the frequency contents of the signal are analyzed. Examples of this can be readily seen in Electrocardiogram (ECG), Electroencephalogram (EEG), Electromyogram (EMG), vibration pick-up signals etc. Thus a time domain signal (where simply amplitude is plotted against the time scale) needs to be transformed to know its frequency contents. The simplest of all the transforms is Fourier Transform (FT). Here the transformed signal is simply plotted against the frequency axis instead of time axis. As an illustration, let us take a record of 50 seconds of any vibration signal. This is a time domain signal. Its Fourier transform will give us the amplitudes of all frequencies (practically limited to the highest frequency available) in the signal. Thus we get simple amplitude versus frequency plot. But there is a serious flaw in this transformation. This frequency plot is the representation of the total signal content of 50-second duration irrespective of the time localization. That is the amplitude versus frequency plot will remain the same whether high frequency component occurred at earlier, middle or later part of the 50-second duration. Obviously reconstruction of the signal in time domain is not possible on this account. Thus, FT has the limitation that it cannot represent the signal in time domain and frequency domain simultaneously, thus limiting the number of application of the transform.

3.2 SHORT TIME FOURIER TRANSFORM

The Short Time Fourier Transform (STFT) eliminates the problem of loss of time domain signal. It results in a signal represented along time-frequency-amplitude axes as shown in figure 3.1. This means that it gives us the information about the frequencies that exist in the signal and also at what time they occurred. STFT uses a window function to get the resulting signal as a function of both time and frequency. A window function is a unit function, which when multiplied by the signal, results in the product of only that part of the signal which resonates with the window function.

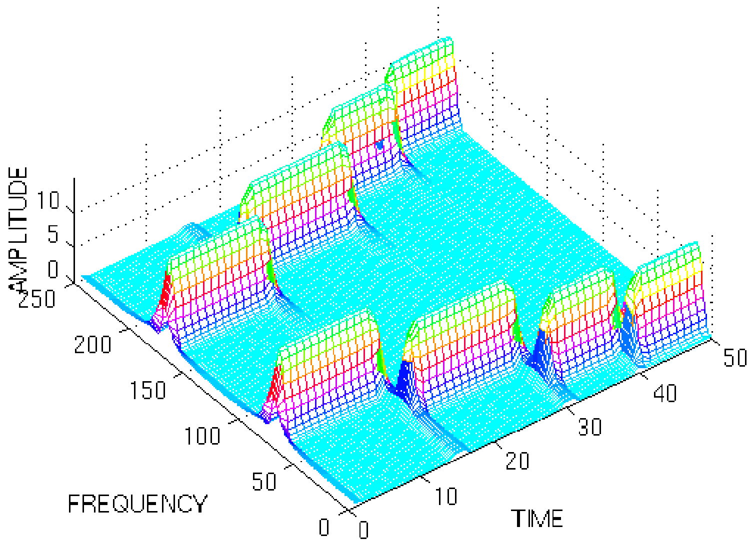


Figure 3.1: Time-frequency-amplitude axes of an STFT representation

The window function is multiplied with the signal at each point at a given instant. Due to the same window width for the whole signal the resolution of STFT is same at every point on the signal. This results in loss of information, which affects the further processes to varying degrees. This loss mainly occurs because mostly the information in the signal is present only at particular frequencies and occurs at particular instances. As the resolution is same everywhere, the part of the signal where negligible information is present, is transformed at same resolution as the part that carries more information (which should have higher resolution). This is because when same window is used, the area it covers remains same for the whole signal. To remove these losses, it is necessary that the width of the window function vary according to the part of the signal under consideration. This forms the basic property of wavelet transform and gives it the multi-resolution property.

3.3 WAVELET TRANSFORMS

The wavelet transform is a time-scale representation technique, which utilizes correlations with the translations and dilations of a mother wavelet function to describe a signal. The translation operation allows signal features to be isolated in time, while the dilation operation allows features existing at different scales to be identified [Bradie, 1996]. Wavelets are mathematical functions that decompose data into different frequency component and then help in the study of each component with a resolution matched to its scale. If we look at a signal with a large window we would notice gross features. Similarly, if we look at a signal with a small window, we would notice detail features. Accordingly wavelet transform uses short windows for high frequencies and long windows for low frequencies. In wavelet transform, the window function varies for the signal from point to point. In this, the window function depends mainly upon two parameters-translation and scale. The translation parameter when varied shows the signal at different time instances at which window function is multiplied with the signal. The scale parameter varies mainly with the width of the window and is directly proportional to it. The resolution depends upon the width of the window and thus on the scale. The scale is a function of inverse of frequency, i.e. higher frequencies correspond to low scale and lower frequencies correspond to the high scale. It can be thought as in maps, low scales show a detailed view while high scales show global view. Similarly low frequency (high scale) gives global information while high frequencies (low scale) give detailed information. This is due to the fact that in most of the signals, low frequencies are present at almost all times and high frequencies are present for very short duration (also carry maximum information). Thus, at low scales we need high resolution than as compared to high scale.

Scaling as a mathematical function either dialates a signal or compresses it. In terms of mathematical functions, if f(t) is a given function, f(st) corresponds to a contracted (compressed) version of f(t) if s > 1 and to an expanded (dilated) version of f(t) if s < 1. However, in the definition of the window function also called wavelet as given in equation (3.1) below, the scaling term is used in the denominator, and therefore, the opposite of the above statements holds, i.e., scales s > 1 dilates the window function, whereas scales s < 1 compresses the window function. On the other hand, translation is a time function which indicates the position of the window i.e. at which point of the signal, the window function is multiplied.

Window function, also called as wavelet, can be described by the equation:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right) \quad \text{--------------(3.1)}$$

where τ corresponds to translation parameter, s to the scale parameter and '*' stands for complex conjugate. Mathematically wavelet can be written as:

$$CWT_x^{\psi}(\tau,s) = \Psi_x^{\psi}(\tau,s) = \frac{1}{\sqrt{|s|}}\int x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \quad \text{------------(3.2)}$$

where CWT stands for Continuous Wavelet Transform i.e. it gives the result in analogous form. As can be seen, it depends upon the two parameters: the scale and the translation. It is given by the convolution of the signal and the window function i.e. integrating the product of the window function (ψ(t)) the signal (x(t)) at its each point for all times.

The computation starts with s=1 and then s is decreased and increased up to the band limit of the signal (the frequency band of the signal). The wavelet is placed at the beginning point of the signal which corresponds to the time, t=0. Then, the wavelet function is multiplied by the signal at this point and then integrated over all the times. This is then multiplied by the term $1/\sqrt{s}$ for normalization, so that the resultant signal will have same energy at every scale.

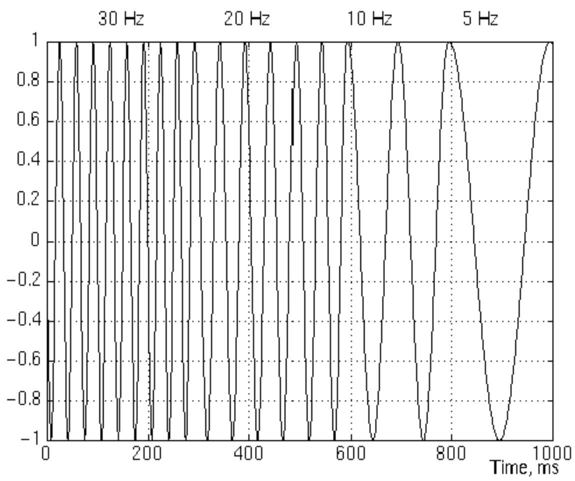


Figure 3.2: A non-stationary signal

Then, the wavelet is shifted by τ amount to the point t=τ and again the whole process is applied. Thus, by repeated application of the process at every point of the signal for one single value of scale gives us one row of the resultant signal. Thus, by giving small increments to the scale value, we can get the plot of the resultant signal. For example, take a non-stationary signal as shown in the figure 3.2, and apply the above process to it. The resultant signal is as shown in figure 3.3.

As seen in the figure 3.2 of the non-stationary signal, highest frequency (30Hz) is present initially. Thus, in the figure 3.3, peaks can be seen at lower scales (high frequency) and at translation value between 0 to 20 (translation is a function of time). In this duration, we have zero amplitude at any other scale value. As the frequency decreases (scale increases), we can see peaks at the respective scales and the translation values.

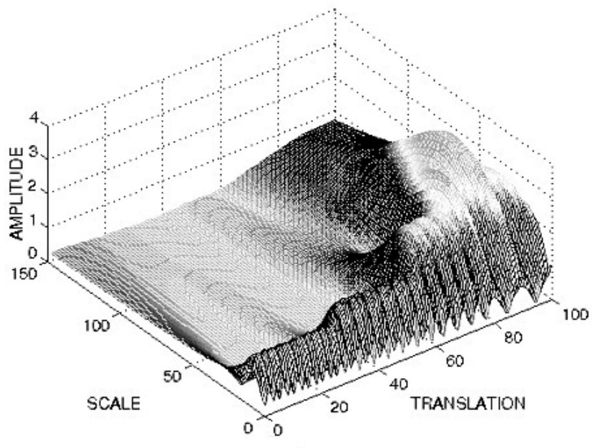


Figure 3.3: Continuous wavelet transform of the non-stationary signal

In CWT, FT, STFT etc., the computations involve analytic equations and complex integrations, which are done by computer and may take lots of time. Therefore, when in CWT we have to increment τ and s, we cannot do it continuously. Though the information loss is negligible because the increments of parameters can be made infinitesimally small, but when we reconstruct the original signal from its CWT, the information in hand is redundant for such operations. Although the discretized continuous wavelet transforms enables the computations of the continuous wavelet transform by computers, it is not a true discrete transform. Therefore, CWT is slightly modified for better computation and to remove the redundancy of the CWT signal for reconstruction of original signal. This modified form of CWT is known as Discrete Wavelet Transform (DWT). The DWT is easier to implement when compared to the CWT. The DWT provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time.

3.4 DISCRETE WAVELET TRANSFORM (DWT)

It may be recalled that the continuous wavelet transform was computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. For this, the signal is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations. The scale is changed by up-sampling and down-sampling/sub-sampling operations. Up-sampling a signal by two corresponds to doubling the sampling rate of a signal by adding usually a zero or an interpolated value, between every two samples of the signal. Similarly, sub-sampling a signal by two corresponds to reducing the sampling rate to half, by removing every other sample of the signal. DWT coefficients are usually sampled from the CWT on a dyadic grid, i.e., $s_0 = 2$ and $t_0 = 1$, yielding $s=2^j$ and $t = k*2^j$.

The procedure of obtaining DWT starts with passing the signal through a half band digital low-pass filter with impulse response h[n]. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter, which is defined as follows:

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k] \quad \text{-------------(3.3)}$$

The signal is passed through a half band low-pass filter, which removes all frequencies that are above half of the highest frequency in the signal. Since the highest frequency is now reduced to half, according to the Nyquist's rule half the samples can be eliminated. Discarding every other sample, thereby sub-sampling by two, does this. This sub-sampling operation doubles the scale. Half band low-pass filtering removes half of the frequencies, which can be interpreted as losing half of the information thereby reducing the resolution to half. Summing up the procedure, the low-pass filtering halves the resolution, but leaves the scale unchanged while the subsequent sub-sampling doubles the scale.

Mathematically, this procedure can be expressed as

$$y[n] = \sum_{k=-\infty}^{\infty} h[k] \cdot x[2n-k] \quad \text{-------------(3.4)}$$

In simpler words, the DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. The transform employs two sets of functions, called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The signal is decomposed into different frequency bands by successive high-pass and low-pass filtering of the time domain signal. The original signal x[n] is first passed through a half-band high-pass filter g[n] and a low-pass filter h[n] followed by sub-sampling by 2, constituting one level of decomposition and can mathematically be expressed by the following equations :

$$y_{high}[k] = \sum_{n} x[n] \cdot g[2k - n] \text{ -----------(3.5)}$$

$$y_{low}[k] = \sum_{n} x[n] \cdot h[2k - n] \text{ -------------(3.6)}$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high-pass and low-pass filters, respectively, after sub-sampling by 2.

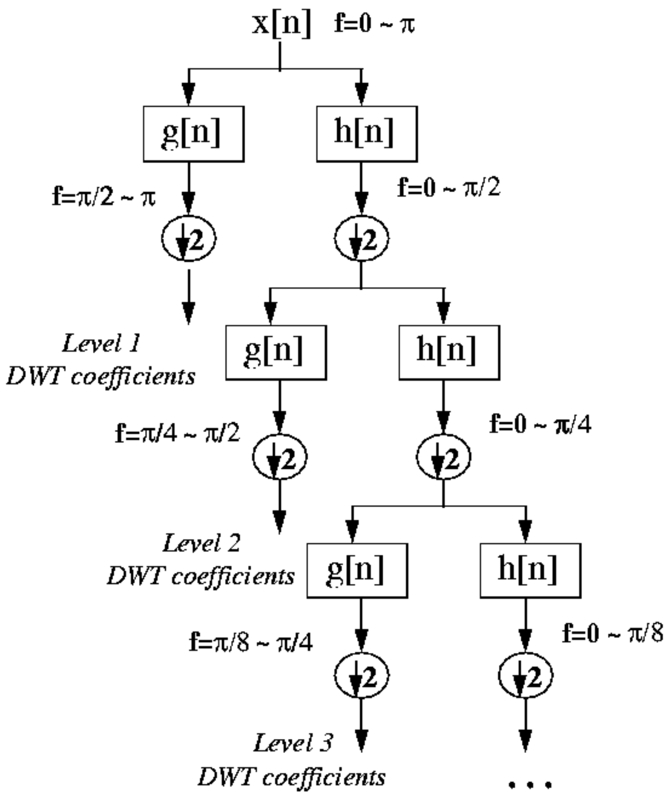


Figure 3.4: Decomposition of signal by high-pass and low-pass filters

Since only half the number of samples now characterizes the entire signal after decomposition, the time resolution halves. At time same time, the frequency band of the signal now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half, thus frequency resolution doubles. This procedure of sub-band coding can be repeated for further decomposition and at every level; the filtering and sub-sampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence double the frequency resolution). This procedure is illustrated in figure 3.4, where x[n] is the original signal to be decomposed, and h[n] and g[n] are low-pass and high-pass filters respectively. The bandwidth of the signal at every level is marked on the figure as "f". It is worth mentioning that the DWT will have the same number of coefficients as the original signal. This transform differs from the Fourier transform in one aspect, that is, the time localization of these frequencies will not be lost. However, resolution of time localization will depend on the level at which they appear. If the main information of the signal lies in the high frequencies, the time localization of these frequencies will be more precise (since they are characterized by more number of samples) and vice or versa. Thus, this process offers a good time resolution at high frequencies, and good frequency resolution at low frequencies.

3.4.1 Data reduction using discrete wavelet transforms

The frequency bands that are not very prominent in the original signal will have very low amplitudes, and that part of the DWT signal can be discarded without any major loss of information, allowing data reduction. A typical 256-sample signal that is normalized to unit amplitude is shown in figure 3.5(a). The vertical axis is the normalized amplitude whereas the horizontal axis is the number of samples. Figure 3.5(b) shows the 8 level DWT of the signal in figure 3.5(a). The highest frequency band in the signal correspond to the last 128 samples in this signal, the second highest frequency band correspond to the previous 64 samples and so on. As seen in figure 3.4(b) only the first 64 samples, which correspond to lower frequencies of the analysis, carry relevant information and the rest of this signal has virtually no information and hence can be discarded without any loss of information, thereby providing a very effective data reduction scheme.

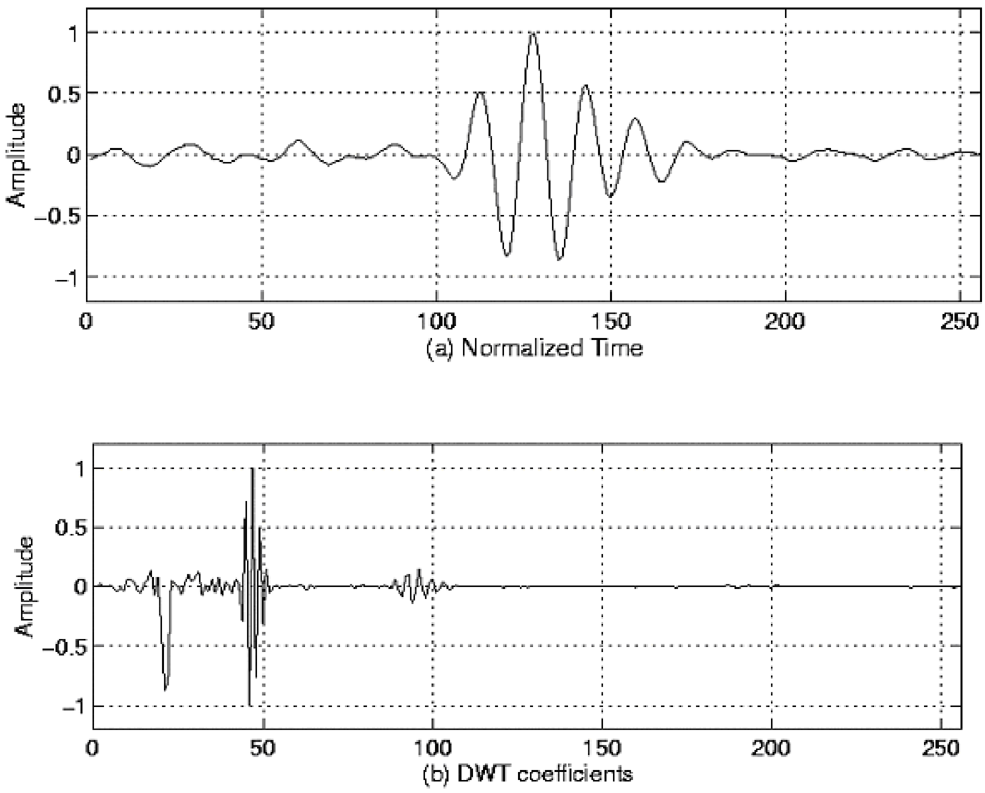


Figure 3.5: Example of a DWT

The high-pass and low-pass filters are related by equation (3.7)

$$g[L-1-n] = (-1)^n \cdot h[n] \text{ ------------------(3.7)}$$

where g[n] is the high-pass, h[n] is the low-pass filter, and L is the filter length (in number of points). Filters satisfying this condition are known as the Quadrature Mirror Filters (QMF). The two filtering and sub-sampling operations can be expressed by equations (3.5 and 3.6).

$$y_{high}[k] = \sum_n x[n] \cdot g[2k-n] \text{ -----------(3.5)}$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k-n] \text{ ------------(3.6)}$$

3.4.2 Reconstruction of the signal from wavelet coefficients

Since half-band filters form ortho-normal bases (synonymous to perpendicular, giving scalar product equal to zero) the reconstruction of the signal is achieved simply by reversing the order. The signals are up-sampled by two at every level, passed through the synthesis filters g'[n], and h'[n] (high-pass and low-pass, respectively), and then added. Interestingly, the analysis and synthesis filters are identical to each other, except for a time reversal, that is, they are relate to each other as $g'(n) = (-1)^{n-1} g(n-1)$; $h'(n) = (-1)^{n} h(n-1)$ [Hilton, 1997].

If the filters are not ideal half-band (it is not possible to realize ideal filters), then perfect reconstruction cannot be achieved. However, under certain conditions it is possible to find filters that provide perfect reconstruction. The most famous ones are the ones developed by Ingrid Daubechies, and they are known as Daubechies' wavelets [Daubechies, 1988; Polikar, 1996].

In order to practically implement this scheme, the signal length must be a multiple of power of 2, to perform successive sub-sampling by 2. The length of the signal determines the number of levels that the signal can be decomposed to. For example, if the signal length is 1024, ten levels of decomposition are possible.

3.4.3 Wavelet packets

By carrying out the decomposition (sub-band coding) not only on the low-pass side but on both sides i.e., zooming into both low and high frequency bands of the signal separately as shown in Figure 3.6, we get what are known as "wavelet packets" [Bradie, 1996].

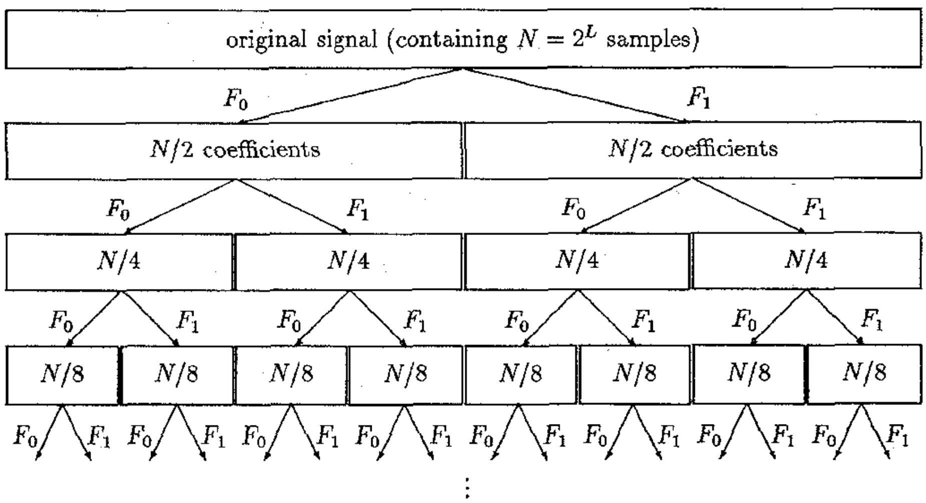


Figure 3.6: Construction of wavelet packet tree

Even the symmetry of decomposition shown in figure 3.6, may not be followed in wavelet packets. The wavelet packets are a generalization of the wavelet transform that allow for arbitrary tree-shaped band-pass filtering and can be adapted to the characteristics of the particular signal being analyzed [Coifman and Meyer, 1990].

3.5 APPLICATIONS OF WAVELET TRANSFORM

In the last few years, the new analytic tool has found a litany of applications. Wavelet theory is rapidly becoming the foundation of applied analysis. It is being used for all kinds of signal processing, from image compression to sound enhancement to statistical analysis. Given below are a few illustrative applications of wavelet transform, the complete list is just forbidding.

3.5.1 Fingerprint image compression

The Federal Bureau of Investigation (FBI) has adopted a wavelet-based standard for digital fingerprint image compression. At compression ratios of about 20:1, the new standard will facilitate the rapid transmission of information that is crucial for effective police work. The FBI's fingerprint standard is just one way that wavelets are making an impact [Cipra, 1993].

3.5.2 Signal-noise decomposition of time series

The continuous wavelet transform can provide a unique decomposition of a time-series into 'signal-like' and 'noise-like' components. From the overall wavelet spectrum, two mutually independent skeleton spectra can be extracted thus allowing the separate detection and monitoring in even non-stationary time-series. The idea of the method is to keep, from the overall wavelet expansion of the time-series, only the wavelet components of locally maximal amplitude at any given time or scale, thus obtaining the instantly maximal and scale maximal wavelet skeleton spectrum respectively [Polygiannakis *et al.,* 2003].

3.5.3 On-line vibration analysis of condition monitoring of bearings

The technique of wavelet transform enables us to observe the evolution in time of the frequency content of a signal. This property makes it very suitable for the detection of vibration transients. The rapid computation of the CWT, together with auto-correlation enhancement, is developed for the detailed on-line vibration analysis. Thus, the raw vibration signal can be continuously processed and monitored, with warning or alarm signals being generated when pre-programmed levels are exceeded [Luo *et al.,* 2003].

3.5.4 Image restoration for compact X-ray microscopy

A wavelet-based de-noising procedure significantly improves the quality and contrast in compact X-ray microscopy images. A non-decimated, discrete wavelet transform (DWT) is applied to original, noisy images. After applying a thresholding procedure to the finest scales of the DWT, by setting to zero all wavelet coefficients of magnitude below a prescribed value, the inverse DWT to the thresholded DWT produces denoised images. It has been found that the denoising procedure has potential to reduce the exposure time by a factor of 2 without loss of relevant image information [Stollberg *et al.,* 2003].

3.5.5 Bio-signal compression for tele-medicine

A bio-signal is acquired by use of transducers or electrodes in the form of an array of elements at regular sampling intervals. Wavelet transform of the signal is taken on dyadic scale. A threshold is decided and zeroes replace all the samples with the value less than threshold. The remaining samples are replaced by a discrete positive or negative value. If all the descendents of a zero down the scale are also less than a threshold, a tree is formed. This gives tremendous compression, with reasonably good reconstructed signal upon taking the inverse wavelet transform. This compression technique helps in reducing the storage space as well as the bandwidth requirement for tele-medicine applications [Lu *et al.,* 2000].

3.5.6 Electronic design automation tool

ATPG, or Automatic Test Pattern Generation is an electronic design automation tool that attempts to find an input (or test) sequence that, when applied to a digital circuit, enables testers to distinguish between the correct circuit behavior and the faulty circuit behavior caused by a particular fault. The effectiveness of ATPG is measured by the fault coverage achieved for the fault model and the number of generated vectors, which should be directly proportional to test application time. ATPG efficiency is another important consideration. It is influenced by the fault model under consideration, the type of circuit under test (full scan, synchronous sequential, or asynchronous sequential), the level of abstraction used to represent the circuit under test (gate, register-transistor, switch), and the required test quality. A simulation-based sequential automatic test pattern generation (ATPG) method for single stuck-at faults using the wavelet transform and Linear Reverse Order Restoration (LROR) compaction has been recently proposed. Sequential ATPG is such a difficult problem that nearly all industrial circuits are tested using full-scan design and combinational ATPG [Devanathan and Bushnell, 2006].

3.5.7 Study of brain dynamics

The use of coherence is a well established standard approach for the analysis of biomedical signals. Being entirely based on frequency analysis, i.e., on spectral properties of the signal, it is not possible to obtain any information about the temporal structure of coherence, which is useful in the study of brain dynamics. Extending the concept of coherence as a measure of linear dependence between realizations of a random process to the wavelet transform a new approach to coherence analysis which allows to monitor time–dependent changes in the coherence between EEG channels has shown that wavelet coherence detects features that were inaccessible by application of Fourier coherence [Klein *et al.,* 2006].

3.5.8 Event detection in implantable cardiac rhythm management devices

An increasing problem in today's society is the large number of noise sources which, to various degrees, interfere with implantable cardiac devices such as pacemakers and defibrillators. The increasing number of electrical equipment like mobile phones (which are relatively safer), Magnetic Resonance Imaging (MRI), and Electronic Article Surveillance (EAS) systems, pose potential threats to the functionality of implantable devices Event detection based on an Intracardiac Electrogram (ECEG), as recorded by implanted devices, introduces new demands which disqualify existing ECG-based QRS detectors. In an implantable device, decisions must be made in real time with a maximum delay of about 40 ms to pace safely. An efficient, low-complexity detector has been developed using the dyadic wavelet transform with integer filter coefficients for event detector for implantable devices and has shown excellent results for in terms of probabilities of missed events and false alarms achieved on electrograms corrupted by the different noise types [Astrom *et al.,* 2006].

3.5.9 Monitoring level of Anesthesia during surgery

The role of anesthesiologist is to provide optimal working conditions to surgeons, and to ensure the patient safety and comfort. For this, anesthesiologists employs a variety of drugs to alter cognitive processing, regulate cardio-respiratory functions, and block muscle movement. One major aspect of the practice is to use these drugs in such quantities that avoid pharmacological toxicity as well as warrant unconsciousness and the absence of response to surgical stress. An analysis of single channel EEG with wavelet transforms can reliably establish the depth of anesthesia, which otherwise is quite a daunting task [Zikov, 2006].

3.5.10 Early detection of knee disorders

Most of the knee joint disorders are caused by the degeneration and damage of the cartilages and are common in the elderly population, athletes, and outdoor sports enthusiasts. These disorders are often painful and incapacitating. There is no successful treatment for a degenerative knee joint pathology except for a complete knee replacement. It is, therefore, vital to detect the early stages of a degenerative knee joint pathology so that appropriate treatment can slow down the degenerative process giving an extended functioning of the knee joints. Hence, the main focus of the diagnostic procedures is in screening and detecting knee joint disorders in the early stage. Arthroscopy is one of the well-known diagnostic procedures for screening knee joint disorders. It is a semi invasive procedure where a fiber optic cable is inserted into the knee joint and the physician looks at the joint through an arthroscope. Due to the semi invasive nature, arthroscopy is not suitable for repeated assessment or follow-up studies for monitoring purposes. Vibration signals [vibroarthrographic (VAG)] are emitted from the knee joint during the swinging movement of the knee. These VAG signals contain information that can be used to characterize certain pathological aspects of the knee joint. A noninvasive method for screening knee joint disorders using the VAG signals has recently been developed that uses wavelet packet decompositions and a modified local discriminant bases algorithm to analyze the VAG signals and to identify the stage of knee disorder. [Umapathy and Krishnan, 2006]

3.5.11 Classification of mammographic micro-calcifications

Breast cancer is the leading cause of death among women. Breast cancer can be detected earlier by mammography than any other non-invasive examination. About 30% to 50% of breast cancers demonstrate tiny granule like deposits of calcium called micro-calcifications. It is difficult to distinguish between benign and malignant cases based on an examination of calcification regions, especially in hard-to-diagnose cases. Chitre *et al.,* investigated the potential of using energy and entropy features computed from wavelet packets for their correlation with malignancy. Two types of Daubechies discrete filters were used as prototype wavelets. The classification results indicate the potential of using features derived from wavelet packets in discriminating micro-calcification regions into benign and malignant categories [Chitre *et al.,* 1995].

3.5.12 Edge detection in infrared and visual images

Wavelet transforms are currently being used for a number of applications such as cue feature and noise extraction from images and acoustic signals. Meitzler *et al.*, applied an algorithm that used wavelets for finding the clutter in infrared and visual images. Once the clutter was found, the probability of edge detection was calculated [Meitzler *et al.*, 1996].

3.6 WAVELET COMPRESSION FOR ECG SIGNAL

An electrocardiogram (ECG / EKG) is a recording of the electrical activity of the heart and is used to investigate the heart diseases. It is a voltage signal, which is picked up from external surfaces of human body. The ECG is usually digitized at 500 samples per second and is recorded simultaneously in 12 channels. With 11 bits resolution analog to digital converter, an ECG record for mere 10 minutes would require 12*500*11*10*60 bits, i.e. 39600000 bits or roughly 37 MB of memory. For ambulatory monitoring of a patient, say for 24 hours, the required storage capacity for this raw data is about 5400 MB. Moreover if this data is to be transmitted over a telephone line [Watts and Macfarlane, 1977] or a slower digital communication network, the time of transmission goes beyond the human patience. Therefore, the data compression is the only solution to this problem. Detection and removal of redundant ECG data is yet to reach a stage of perfection till today. For achieving higher compressions, lossy techniques are in use, but the decompressed signal is not the exact reproduction of the original signal. The lossy techniques are categorized as direct compression and transformative techniques. In direct compression, redundancies are detected by direct analysis of actual signal samples. In transform methods, the signal is transformed to some other time-frequency representation like wavelets, which are better suited for detecting and removing redundancies.

For the last four decades a large number of ECG data compression techniques have been reported. The techniques, which analyze the actual signal samples, are classified as direct compression techniques, whereas those, which first transform the time domain signal to some other domain, are known as transformative techniques. Some of the direct compression techniques are: ECG differential pulse code modulation and entropy coding, Amplitude Zone Time Epoch Coding (AZTEC), Turning Point (TP), Co-ordinate Reduction Time Encoding System (CORTES), fan and Scan Along Polygonal Approximation (SAPA) algorithms, peak picking and Cycle to Cycle (CTC) compression methods [Jalaleddine *et al.*, 1990], compression using Non-redundant Templates [Saxena *et al.,* 2000], and compression by Error Back Propagation in Neural Networks (EBP-NN) [Saxena *et al.,* 2003a]. A combination of these methods is also sometimes applied for the compression [Saxena and Giri, 1997]. Some of the transformative methods include compression using Fast Fourier Transform [Kulkarni *et al.,* 1997a], Fast Walsh Transform [Kulkarni *et al.,* 1997c], and the widely used Wavelet Transform. Transformative compression techniques in general, and wavelet transform methods in particular, are reported to give better results [Lu *et al.,* 2000]. Compression on ECG signal has acquired a renewed importance with the advent of tele-cardiology [Saxena *et al.,* 2003c]. Quality of the transmitted ECG signal in tele-cardiology system has to be assured by all means [Saxena *et al.,* 1997; Saxena *et al.,* 2003b; Kulkarni *et al.,* 1997b]. All advances in ECG signal compression techniques seek to increase the compression ratio, while keeping the distortion at acceptable levels.

The wavelet transform decomposes a signal into a weighted sum of basis functions that are dilated and translated versions of a prototype function called the mother wavelet. If the scaling factor is taken as two, then wavelet decomposition acts like a cascaded octave band-pass filter. One of the efficient ways to compute the forward wavelet transform is to convolve the signal with a pair of appropriately designed quadrature mirror filters (QMF's) and then down-sample by a factor of two. The QMF pair, which decomposes the signal, consists of a low-pass filter L and a high-pass filter H that split the signal's bandwidth in half. The coefficients are recombined to synthesize the signal by means of the inverse wavelet transform. It is implemented by up-sampling by a factor of two and filtering with the synthesis QMF pair Go and G1. The impulse responses of the decomposition and synthesis QMF pairs are related by $Go(n) = (-1)^{n-1} H(n-1)$; $G1(n) = (-1)^{n} L(n-1)$ [Hilton, 1997].

Let us take an example of an ECG signal with 2048 samples, sampled at the rate of 250 samples per second (figure 3.7). 9/7 tap filters are used to decompose this signal in sub bands. The coefficients of L = [0, 0.0378, -0.0238, -0.1106, 0.3774, 0.8527, 0.3774, -0.1106, -0.0238, 0.0378] and H = [0, -0.0645, 0.0407, 0.4181, -0.7885, 0.4181, 0.0407, -0.0645, 0, 0] and for reconstruction, the coefficients are Go = [0, -0.0645, -0.0407, 0.4181, 0.7885, 0.4181, -0.0407, -0.0645, 0, 0] and for G1 = [0, -0.0378, -0.0238, 0.1106, 0.3774, -0.8527, 0.3774, 0.1106, -0.0238, -0.0378]. The output of low pass and high pass filter after sub sampling are shown in figure 3.8 and figure 3.9 respectively.

Comparing figures 3.7 and 3.8, we find that the two signals are almost same, but with the shift in base line. Another thing of importance is that figure 3.8 is for 1024 samples. This is the result of sub sampling. It means that if sampling frequency of original signal was 250 samples per second, the equivalent sampling rate of sub band has reduced to only 125 samples per second. This implies that time resolution of sub-band has reduced to half. But on the other hand, if the frequency of range of original signal was 0-500 Hz (double the sampling frequency, as per Nyquist's Criterion) that of Low pass filter output is 0-250 Hz. This indicates that the frequency resolution has doubled. Because it contains low frequency component, it is also known as approximate signal. Same conclusion of the time resolution getting halved and the frequency resolution getting doubled is true for high frequency sub-band as well. The only difference being that frequency range for high pass sub band is 250-500 Hz. Because of the higher frequency component, this output is also known as detailed signal.

This all process is known as first level decomposition. While the detailed signal after first decomposition is retained as such, the approximate signal is further decomposed, making time resolution a quarter of the original signal and frequency resolution four times that of the original signal. This is known as second decomposition. This process is repeated for a certain number of times. Six level decompositions result in one approximate signal (32 samples) and six detailed signal samples (32 + 64 + 128 + 254 + 512 + 1024 samples). The total samples remain 2048. For reconstruction, the lowest level 32 samples of approximate signal samples ad 32 samples of detailed signal samples are up sampled by placing zeroes in between the successive samples, filtering with Go and G1 and adding to get reconstructed approximate signal of 64 samples. This is further combined with 64 samples of detailed signal to get to higher level reconstruction. This process is repeated for all layers until the full size signal is reached to complete the inverse transform.

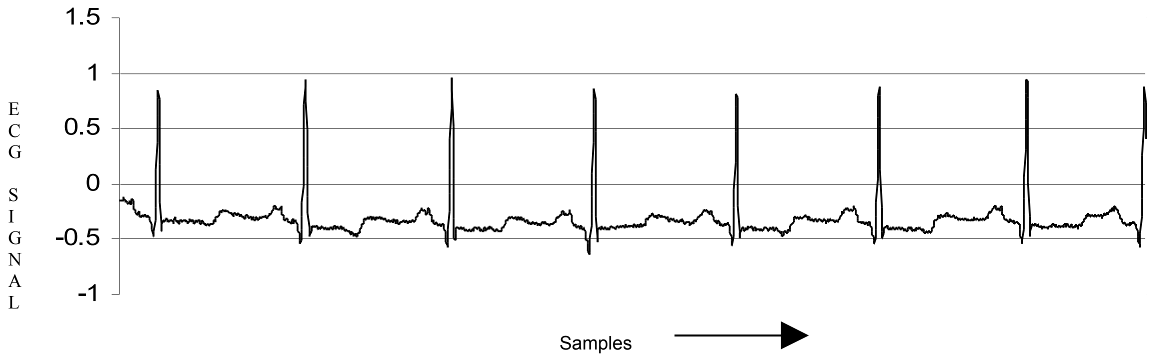


Figure 3.7: Original ECG signal (2048 samples)

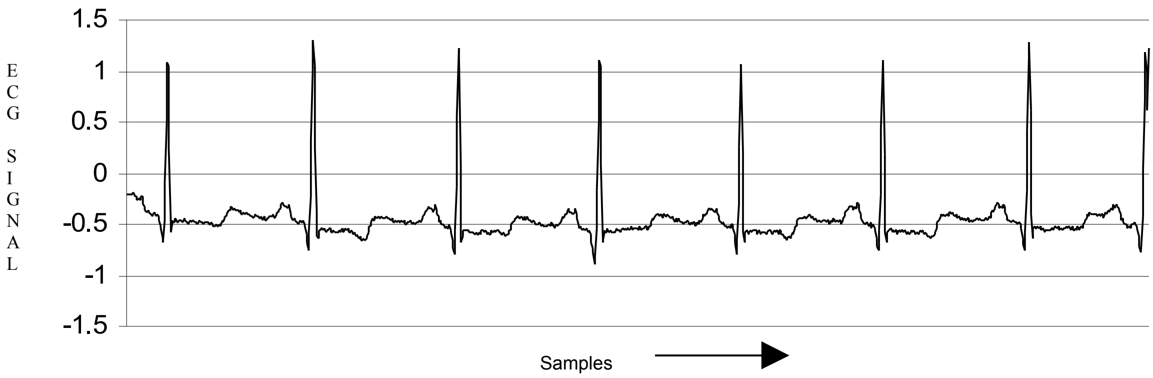


Figure 3.8: Low pass filter output of ECG signal (1024 samples)

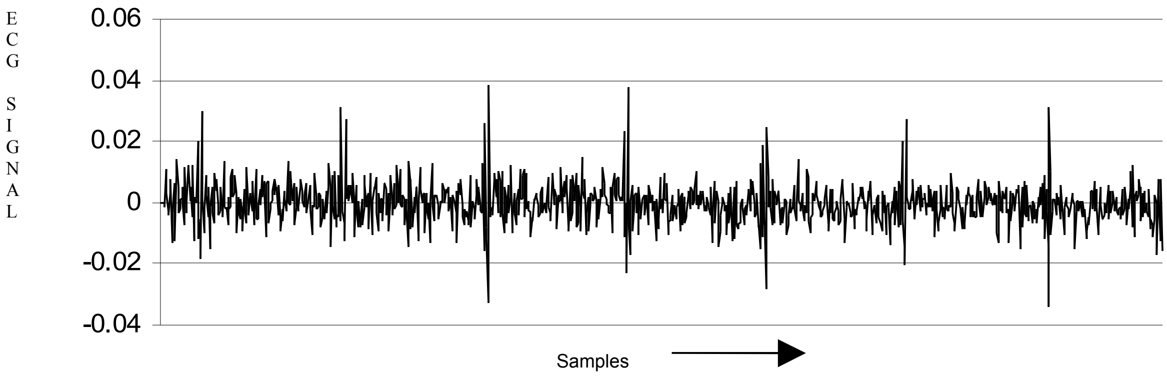


Figure 3.9: High pass filter output of ECG signal (1024 samples)

One of the important features of the wavelet transform is its good localization, in both frequency and time domains. It has fine frequency resolution and coarse time resolution at lower frequency, and coarse frequency resolution and fine time resolution at higher frequency. In order to compress the ECG data, the wavelet transform is used to identify and remove the redundancy in the signal. The signal is first transformed into the wavelet domain, coefficients that small enough are set to zero, such that no significant information is lost on signal reconstruction. Figure 3.9 shows that most of the coefficients lie in $\pm$ 0.02 range and can be safely set to zero to bring in enormous compression.

3.6.1 Choice of wavelets for ECG compression

For obtaining effective and efficient data compression, the choice of different analysis-synthesis filter pairs, which correspond to different wavelet bases, is especially significant [Besar, 2000]. In realization, the number of decompositions, the frame size, and the filter pair need to be suitably selected. The number of decompositions determines the coarsest frequency resolution of the transform and should be at least four for sufficient compression. The frame size is taken to be a power of two that exceeds the number of decompositions. This means that for six decompositions, the minimum frame size should be $2^7 = 128$. The frame size be short enough for acceptable coding delay and memory usage but should be large enough to contain several periods of the ECG signal. Choosing six layers of wavelet decomposition and 2048 sample frames fulfills the requirements. Choice of potential perfect reconstruction filter pairs demands a tradeoff between computational complexity, obviously smaller for the shorter filters, and compression performance, generally better for longer filters. Among all filters tested by Hilton, biorthogonal 9/7 tap filters had the best compression performance for wavelet coding of ECG signals [Hilton, 1997]. These filters being quadrature mirror filters, are symmetric, symmetric (reflective) data extension scheme at the boundaries of the frames is employed to obtain perfect reconstruction at the boundaries in the absence of coding.

3.6.2 Embedded zero tree wavelet coding compression method

In 1993 Shapiro gave an image coding technique that used the concept of zero trees of wavelet coefficients [Shapiro, 1993]. Of the wide variety of encoding methods that have been developed for wavelets, the Embedded Zero-Tree Wavelet (EZW) encoding was one of the most powerful one. The EZW algorithm obtained the best-reconstructed signal quality for a given bit rate under the constraint that the encoding was embedded. With an embedded encoding, all encodings of the signal at a lower bit rate were embedded as prefixes of the bit stream for the target bit rate, and therefore, the transmission and decoding of compressed data could be stopped at any point and a signal can be reconstructed. Inspired by image codec given by Said and Pearlman, Hilton gave an EZW algorithm for ECG data compression [Said and Pearlman, 1996; Hilton, 1997]. The EZW algorithm can be broadly divided in three main parts:

1) Prioritized transmission of the location and sign of a signal's "significant" wavelet coefficients
2) Compactly encoding the locations of non-significant coefficients by exploiting the self-similarity of the wavelet transform across scales
3) Successive approximation of significant coefficient magnitudes via ordered bit plane transmission of coefficient data

Comparing a coefficient's magnitude with a set of octavely decreasing thresholds, its significance is determined; if magnitude of coefficient is greater than or equal to a particular threshold then it is significant with respect to that threshold. The forward wavelet transform decorrelates a signal and its information is concentrated into a relatively small number of coefficients with large magnitude. These large coefficients are more important to the reconstructed signal quality than the small coefficients as they contain more energy than the smaller ones. For that reason, the EZW prioritization scheme transmits the large (significant) coefficients before transmitting the smaller coefficients. This is accomplished by making multiple passes over the wavelet coefficients, lowering the threshold by a factor of two in each pass. In each pass, the coder refines the magnitude value of each coefficient determined to be significant during previous passes and then searches through the coefficients previously considered to be insignificant, encoding information regarding the significance of each with respect to the new threshold. It was observed that if a wavelet coefficient at a coarse scale is insignificant with respect to a given threshold, it is highly likely that all the wavelet coefficients in the same spatial location at finer scales, i.e., the descendants of in the hierarchical pyramid, will also be insignificant with respect to the threshold. If this is indeed true, we say that is the root of a zero-tree. The EZW coder takes advantage of this concept of zero-trees to reduce the amount of information transmitted. By identifying and encoding that zero-tree roots, possibly numerous insignificant descendants are compactly specified, thereby greatly compressing the ECG data.

3.6.3 Set Partitioning In Hierarchical Trees (SPIHT) wavelet compression method

The SPIHT algorithm is used to encode the wavelet coefficients obtained after the wavelet transform. Set partitioning sorting algorithm is used for partial ordering of the transform coefficients by magnitude, followed by ordered bit plane transmission and utilization of self-similarity across different layers of decomposition. The encoder first codes the ECG data, and then the coded data is stored/transmitted. After retrieval of the coded signal, a decoder decodes it. The set-partitioning rule for encoder should essentially be the same for the decoder. The SPIHT algorithm was first given by Said and Pearlman for compressing images [Said and Pearlman, 1996] and later adapted for ECG compression by Lu *et al.*, [Lu *et al.,* 2000]. The algorithm is as follows:

The ECG data is decomposed to half the signal bandwidth into approximate signal (Low frequency) and detailed signal (High frequency) by QMF filters. The approximate signal is further decomposed successively. The coefficients are arranged in the form of a tree as shown in figure 3.10. Corresponding to every point in a layer (called parent) there are two points in the next layer (called offsprings), with the down arrows indicative of the parent-offspring relation. In a usual ECG signal, low frequency bands contain most of the energy. Thus higher decomposition coefficients are larger in magnitude.

For any given set of coefficients, the highest absolute coefficient is selected (say max_coeff), and the largest integer n is chosen, satisfying the relation 2^n < max_coeff. Any coefficient in the subset is said to be significant, if its absolute value is greater than 2^n.
A zero is sent to the decoder if the entire subset is insignificant, If not, a one is sent to the decoder. The subset is then split according to the temporal orientation tree. This process is repeated until all the significant sets are broken down to a single significant point each. This process is called sorting pass.

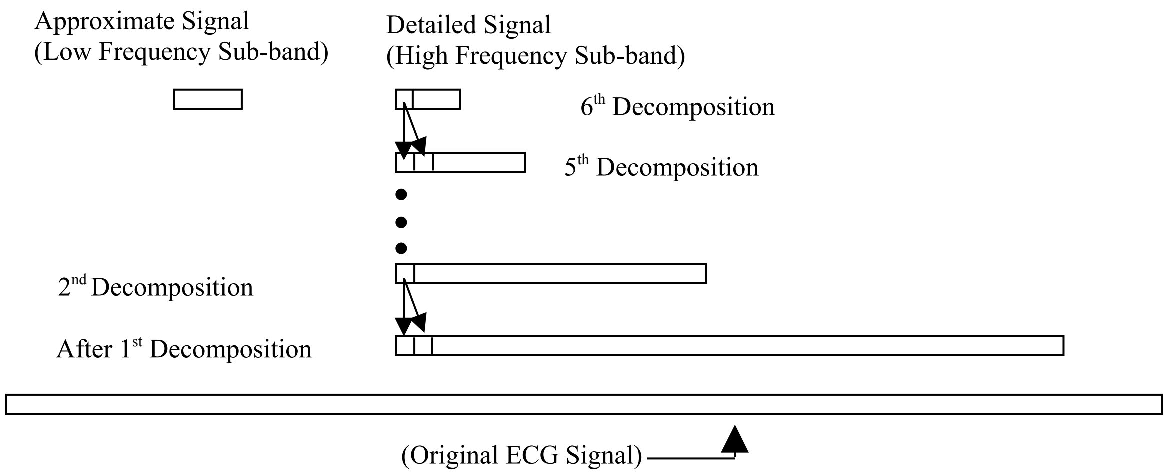


Figure 3.10: A tree structure defining temporal relationship in the wavelet domain

Three lists of the indices of the coefficients are prepared.
(i) The list of insignificant points (LIP)
(ii) The list of insignificant sets (LIS)
(iii) The list of significant points (LSP)

The bits related to the LSP entries and outcomes of the magnitude tests in binary form are transmitted. The entries in the LIP and LIS, which have the same parent into an entry atom, are grouped together. Sorting pass gives a subset of the significant coefficients for the threshold (2^n). While refining, the most significant bit of every coefficient found significant at a higher threshold, is sent to decoder. By this method, all bits of the points found significant till that sort, are transmitted. Value of n is decrement by one and the process is repeated until the desired compression is achieved. The same process is run in the decoder side.

The encoding and decoding comprise of simple operations: comparison to threshold, movement of coordinates to lists, and bit manipulations. No complex calculations are needed for modeling and training prior to coding. Only single search for the initial threshold is required. It always finds the most significant bits of the largest coefficients and sends them before those bits of smaller coefficients. It locates large descendent sets with maximum magnitude smaller than the final threshold and represents them with a single zero. The method is thus simple, self-adapting and efficient [Lu *et al.,* 2000].

3.6.4 Relative superiority of SPIHT wavelet compression method

From the early efforts to compress ECG data using simple Turning Point (TP) algorithm, that gave a fixed compression ratio of 2:1, there have been number of improvements in this field. For this it is important to first understand the definition of two most important terms used for evaluating a compression algorithm. While compression ratio is simply a ratio of the length of the original signal to that of the compressed signal, PRD has taken different definitions in different research reports. The most acceptable definition of PRD is given by the formula

$$PRD = \sqrt{\frac{\sum_i [x_o(i) - x(i)]^2}{\sum_i [x_o(i) - K]^2}}$$

where x_o and x represent original and reconstructed data respectively and K is an estimate of mean noise, usually defined as the mean value of the original signal. However some researchers do not take into account an estimate of mean noise (K) in the definition, therefore, PRD reported by them is obviously much less. Thus is it important to use the same definition of PRD, preferably taking an estimate of mean noise (K), while comparing the performance of any algorithm.

Cetin *et al.,* reported 3.7% to 6.19% PRD for CR ranges of 6.19 to 7.98 using multi-rate signal processing and transform domain coding techniques [Cetin *et al.,* 1993]. Ramakrishnan and Saha reported 9.89% to 13.34% PRD for CR range of 13:1 to 22:1, using encoding by wavelet-based linear prediction [Ramakrishnan and Saha, 1997]. These are much inferior to the results of Lu *et al.,* as they reported 3.57% to 6.49% PRD for CR ranges of 12 to 20 using

SPIHT [Lu *et al.,* 2000]. Table 3.1 shows comparative PRD of MIT-BIH patient 117 for CR of 8, as reported by Hilton, Djohn *et al.,* and Lu *et al.,* [Hilton, 2000; Djohn *et al.,*1995; Lu *et al.,* 2000].

TABLE 3.1: Comparative PRD of MIT-BIH patient 117 for CR of 8.

Algorithm	PRD(%)
Lu	1.18
Chagas	1.22
Hilton	2.6
Djohan	3.9

Zigel *et al.,* gave Analysis by Synthesis ECG Compressor (ASEC) and established its superiority to direct compression techniques like AZTEC, SAPA-2, and Long Term Prediction (LTP) [Zigel *et al.,* 1997]. For MIT-BIH patient 119, sampled at 360 Hz and 11 bits per sample, for bit rate of 183 bits per second, Zigel *et al.,* reports PRD of 5.5%, while for the same case and at the same bit rate the PRD reported by Lu *et al.,* is only 5% [Zigel *et al.,* 1997; Lu *et al.,* 2000].

Later Chagas *et al.,* used Embedded Zero-tree Wavelet (EZW) encoding to report results significantly superior to others, but only comparable to Lu *et al.*, (see table 3.1) [Chagas *et al.,* 2000]. In the most recent work by Kim *et al.,* the proposed algorithm claims better result (lower PRD) as compared to EZW algorithm, using PRD definition without an estimate of mean noise (K), but interestingly, no comparison was made with SPIHT algorithm [Kim *et al.,* 2006]. Thus it can be safely concluded that SPIHT algorithm for ECG compression given by *Lu et al.*, is superior to all other algorithms reported so far.

3.7 CONCLUSIONS

In many applications, the meaningful information in any time domain signal is prominently manifested only when the frequency contents of the signal are analyzed. Fourier transform of the signal gives us the amplitudes of all frequencies. However, it has the limitation that it cannot represent the signal in time domain and frequency domain simultaneously. This transform, therefore is applicable only for stationary signals. Since ECG signal is not a stationary signal, Fourier transform of ECG signal cannot be used for its analysis. The Short Time Fourier Transform (STFT) eliminates this problem by giving us the information about the frequencies that exist in the signal and also at what time they occurred. But this transform still has one limitation. As the resolution is same everywhere, the part of the signal where negligible information is present, is transformed at same resolution as the part that carries more information. Since the frequency component of ECG signal is not uniformly distributed over time, STFT cannot be used of ECG analysis. This limitation is overcome in Wavelet Transforms. Wavelet Transforms are especially valuable because of their ability to elucidate simultaneously local spectral and temporal information from a signal in a more flexible way than the STFT by employing a window of variable width. Thus they produce a time–frequency decomposition of the signal which separates individual signal components more effectively than the traditional STFT. This flexible temporal–spectral aspect of wavelet transform allows a local scale-dependent spectral analysis of individual signal features. In this way both short duration, high frequency and longer duration, lower frequency information can be captured simultaneously. This makes them particularly useful for the analysis of transients, aperiodicity and other non-stationary signal features where, through the interrogation of the transform, subtle changes in signal morphology may be highlighted over the scales of interest. All these features of wavelet transform makes it an ideal choice for analysis of ECG, the signal under investigation. Because of the versatility of wavelet transforms, it finds many applications in other fields too, like finger print storage, condition monitoring of bearings, event detection in implantable devises, estimating depth of anesthesia, detection of knee disorders etc. Of the many techniques used or ECG compression, wavelet transform method is one of the most popular and efficient one. It further has many variants like EZW, SPIHT etc. Research review reveals that SPIHT technique for ECG compression is the best reported so far. Any new algorithm or modification in the existing algorithm for ECG compression, therefore has to be evaluated taking SPIHT as the reference.

MODIFIED SPIHT WAVELET COMPRESSION

4.1 INTRODUCTION

The wavelet transform is a time-scale representation technique, which utilizes correlations with the translations and dilations of a mother wavelet function to describe a signal. Wavelets are mathematical functions that decompose data into different frequency components, and then help in the study of each component with a resolution matched to its scale. The scale factor can be interpreted as the scale in maps, very large scale means global view, while very small-scale means detailed view. In a generalized statement it can be stated that the result in wavelet analysis is to see both the forest and the trees [Graps, 1995]. Using this mathematical genie, many data reduction techniques have been proposed for time varying signals in general and ECG in particular. The most efficient method of ECG compression using wavelet transform is by Set Partitioning In Hierarchical Trees (SPIHT) algorithm [Lu *et al.,* 2000]. Implementing this algorithm on MIT-BIH arrhythmia test base (mitdb) available at http://physionet.org (physiobank) [Goldberger *et al.,* 2000], we found all the claims of Lu *et al.,* about the self-adaptiveness, simplicity and efficiency to be generally factual. While agreeing to the superiority of SPIHT wavelet compression algorithm to other techniques, we found some areas which could be further improved, without sacrificing the existing advantages. The two main additions, termed as "blank-fire removal" and "polishing", are elaborated in the subsequent sections.

4.2 BLANK-FIRE REMOVAL

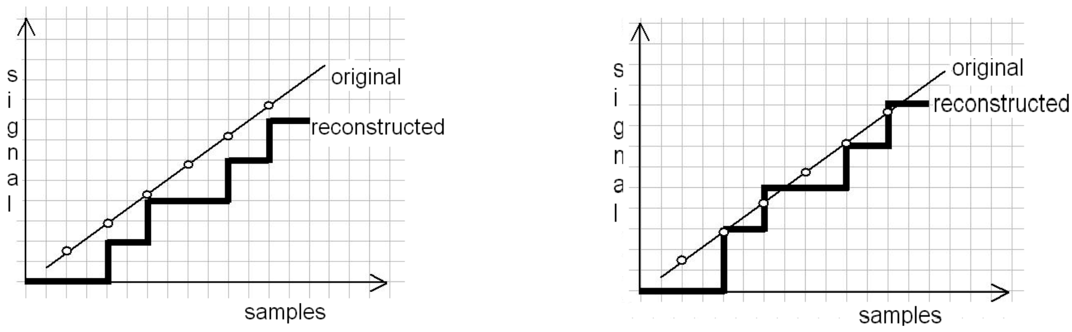
For implementing SPIHT wavelet compression of ECG signal, the ECG data is decomposed to half the signal bandwidth into approximate signal (Low frequency) and detailed signal (High frequency) by QMF filters. The approximate signal is further decomposed successively. The coefficients are arranged in the form of a tree as shown in figure 3.10. Corresponding to every point in a layer (called parent) there are two points in the next layer (called offsprings), with the down arrows indicative of the parent-offspring relation. In a usual ECG signal, low frequency bands contain most of the energy. Thus higher decomposition coefficients are larger in magnitude.

While searching for the largest coefficient, there are two major subsets. One subset of approximate signal (32 samples) let us call it as “L_coeffs” and another subset of six detailed signal samples (32 + 64 + 128 + 254 + 512 + 1024 samples), say “H_coeffs”. We found experimentally that in many cases the largest of L_coeffs was quite different from the largest of H_coeffs. So instead of taking a common threshold (2^n) for both subsets, if two different thresholds are transmitted, we get improved compression ratio. The ratio of threshold for L_coeffs and that for H_coeffs, is many a times 2, and sometimes even 4. The improvement in compression ratio is even better for 4. Improvement in compression ratio is observed even when this ratio is 0.5. In no case we observed any deterioration in compression ratio. Only when the ratio is the same, no improvement occurs. The logic of improvement is simple. Say threshold for L_coeffs is 2 while the threshold for H_coeffs is 1, thereby the ratio being 2. In the first sort, all coefficients in H_coeffs will be less than the threshold. But still 32 bits will have to be transmitted. This transmission of 32 bits that carry absolutely no information is termed as a “Blank-Fire”. Sending a separate threshold for H_coeffs can save these bits. For ratio 4, 64 bits are saved. Again for ratio 0.5, (though rare to spot) the saving is of 32 bits, by the same logic.

4.3 POLISHING

It was found that after going through all sorting and refining passes, at the decoder end if half of the last threshold is added to all positive significant points consolidated till last pass, and subtracted from all negative significant points consolidated till last pass, the distortion reduces considerably. The insignificant points are left untouched. Since this additional step is carried out at the decoder end, it in no way adds any data to the coded stream of bits. The only expense to implement this step is very small amount of computational time. The logic of this step is straightforward. Going back to the principle of digitization, every time any continuous signal is digitized, this leads to an error commonly known as quantization error. SPIHT algorithm is basically a digitizing method, that converts the fine levels of digitized data into the coarsest digital level in the very first pass, and the level is refined to half in each subsequent step. Thus the step of polishing is an effort to reduce this quantization error to as much as half of what is introduced by SPIHT. This is graphically depicted in figure 4.1(a) and figure 4.1(b). Note that in figure 4.1(a), the signal is quantized to two graph blocks. In figure 4.1(b), one graph block is added to all significant points. The first point in the graph is insignificant, and is thus left unaffected. The same is true for negative significant points.

Instead of adding, we subtract one graph block. The result will be same as mirror image of figure 4.1(a) and figure 4.1(b) around their x-axes.



(a) (b)

Figure 4.1: Original and reconstructed signal using (a) SPIHT without Polishing (b) SPIHT with Polishing

4.4 RESULTS AND DISCUSSION

To test the performance of modified coding schemes, the data from the MIT-BIH arrhythmia database has been used. All ECG data used here are sampled at 360 Hz, and the resolution of each sample is 11 bits/sample, so that total bit-rate of these data is 3960 bps. Results of Blank-fire removal are reported in table 4.1, for all the patients of MIT-BIH arrhythmia database set used by Lu *et al.,* [Lu *et al.,* 2000] that are available on physionet physiobank [Goldberger *et al.,* 2000]. Both signal for patients 100, 101, 102, 103, 107, 118 and 119 were analyzed for the blocks of 2048 samples. To further validate our results, different blocks of 2048 samples were taken from both the signals for patients 105, 108, 109, 111, 112, 212, 219, and 222. We have taken the actual bit length of the coded stream to calculate compression ratio. To measure distortion in the reconstructed signal, we used the well-accepted PRD given by

$$PRD = \sqrt{\frac{\sum_i [x_o(i) - x(i)]^2}{\sum_i [x_o(i) - K]^2}}$$

where xo and x represent original and reconstructed data respectively and K is an estimate of mean noise, usually defined as the mean value of the original signal.

We have taken five passes of sorting where the ratio of thresholds is detected as 1, and six passes for all other threshold ratios.

TABLE 4.1: Comparative Results of "Blank-fire Removal"

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
100	MLII	1-2048	2	19.04	15.53	20.13	15.53*
100	V5	1-2048	2	15.51	13.62	16.21	13.62*
100	MLII	32770-34817	4	21.48	14.07	24.46	14.07*
100	V5	32770-34817	2	19.97	10.50	21.17	10.50*
101	MLII	1-2048	2	19.09	14.09	20.18	14.09*
101	V1	1-2048	4	13.6	24.52	14.74	24.52*
102	V5	1-2048	1	20.55	14.57	20.55	14.57**
102	V2	1-2048	1	25.54	7.87	25.54	7.87**
103	MLII	1-2048	1	18.76	9.00	18.76	9.00**
103	V2	1-2048	1	20.22	11.58	20.22	11.58**
107	MLII	1-2048	2	22.85	11.86	24.43	11.86*
107	V1	1-2048	2	19.81	8.27	20.99	8.27*
118	MLII	1-2048	2	20.2	16.8	21.43	16.8*
118	V1	1-2048	2	15.71	13.43	16.44	13.43*
119	MLII	1-2048	2	20.76	10.27	22.07	10.27*
119	V1	1-2048	4	25.54	15.43	29.88	15.43*
119	MLII	6586- 8633	1	28.09	14.83	28.09	14.83**
119	V1	6586- 8633	2	24.98	12.90	26.88	12.90*
105	MLII	38140- 40187	2	17.09	12.92	17.96	12.92*
105	V1	38140- 40187	4	16.22	12.34	17.86	12.34*
108	MLII	3176- 5223	4	24.41	15.37	28.34	15.37*
108	V1	3176- 5223	1	29.07	11.90	29.07	11.90**

* Improved CR for same PRD
** No Change in CR and PRD

TABLE 4.1: Comparative Results of "Blank-fire Removal" (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
108	MLII	9979- 12026	4	16.64	17.04	18.38	17.04*
108	V1	9979- 12026	1	15.94	15.27	15.94	15.27**
109	MLII	1- 2048	2	23.35	13.98	25.00	13.98*
109	V1	1- 2048	4	24.92	9.07	29.03	9.07*
109	MLII	2981- 5028	2	19.12	8.64	20.20	8.64*
109	V1	2981- 5028	1	21.72	8.69	21.72	8.69**
109	MLII	9981- 12028	2	22.09	12.82	23.56	12.82*
109	V1	9981- 12028	2	21.05	9.40	22.39	9.40*
111	MLII	1- 2048	1	22.39	15.45	22.39	15.45**
111	V1	1- 2048	1	24.73	10.88	24.73	10.88**
111	MLII	16001- 18048	1	21.17	13.94	21.17	13.94**
111	V1	16001- 18048	2	21.31	10.80	22.69	10.80*
111	MLII	19001- 21048	4	20.01	9.84	22.57	9.84*
111	V1	19001- 21048	1	25.92	11.39	25.92	11.39**
112	MLII	1- 2048	8	18.99	14.82	21.66	14.82*
112	V1	1- 2048	8	18.44	29.24	21.23	29.24*
112	MLII	14501- 16548	8	17.46	15.71	20.99	15.71*
112	V1	14501- 16548	8	18.49	18.98	21.35	18.98*
212	MLII	1- 2048	2	15.55	10.33	16.27	10.33*
212	V1	1- 2048	1	24.09	12.18	24.09	12.18**
212	MLII	22771- 24818	1	16.79	11.30	16.79	11.30**
212	V1	22771- 24818	4	17.59	27.64	19.54	27.64*

* Improved CR for same PRD
** No Change in CR and PRD

TABLE 4.1: Comparative Results of “Blank-fire Removal” (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
219	MLII	1- 2048	2	19.90	10.96	21.09	10.96*
219	V1	1- 2048	2	16.96	9.31	17.83	9.31*
219	MLII	33120- 35167	2	19.69	8.51	20.86	8.51*
219	V1	33120- 35167	4	21.41	14.51	24.38	14.51*
219	MLII	36629-38676	2	20.08	11.64	21.29	11.64*
219	V1	36629-38676	2	19.21	13.21	20.32	13.21*
219	MLII	437400-439447	2	18.90	8.79	19.97	8.79*
219	V1	437400-439447	4	21.11	13.74	23.99	13.74*
222	MLII	700- 2747	4	19.12	17.27	21.46	17.27*
222	V1	700- 2747	2	14.52	10.62	15.14	10.62*
222	MLII	2776- 2823	4	23.37	13.27	26.95	13.27*
222	V1	2776- 2823	1	24.15	12.65	24.15	12.65**
222	MLII	5111-7158	2	15.56	11.82	16.23	11.82*
222	V1	5111-7158	1	18.45	12.07	18.45	12.07**
222	MLII	11350- 12397	2	12.85	11.83	13.34	11.83*
222	V1	11350- 12397	2	13.75	12.11	14.31	12.11*
222	MLII	15937 – 17984	2	19.14	12.85	20.24	12.85*
222	V1	15937 – 17984	1	22.46	12.21	22.46	12.21**
222	MLII	28267- 30314	2	15.89	10.37	16.64	10.37*
222	V1	28267- 30314	1	18.54	13.08	18.54	13.08**
222	MLII	30861- 32908	2	12.99	10.69	13.49	10.69*
222	V1	30861- 32908	1	14.30	11.64	14.30	11.64**

* Improved CR for same PRD
** No Change in CR and PRD

TABLE 4.1: Comparative Results of "Blank-fire Removal" (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
222	MLII	35623- 37670	2	24.04	12.58	25.81	12.58*
222	V1	35623- 37670	2	21.50	14.06	22.89	14.06*
222	MLII	38818- 40865	4	19.90	11.98	22.44	11.98*
222	V1	38818- 40865	1	18.60	11.27	18.60	11.27**
222	MLII	48328 – 50375	2	15.91	12.46	16.66	12.46*
222	V1	48328 – 50375	1	18.96	12.09	18.96	12.09**
222	MLII	53218 – 55265	2	17.37	14.38	18.27	14.38*
222	V1	53218 – 55265	2	17.61	12.29	18.54	12.29*
222	MLII	56117-58164	1	13.38	11.11	13.38	11.11**
222	V1	56117-58164	1	15.67	12.73	15.67	12.73**
222	MLII	62769- 64816	2	15.37	10.87	16.06	10.87*
222	V1	62769- 64816	1	18.73	11.97	18.73	11.97**
228	MLII	1-2048	2	13.43	11.96	13.96	11.96*
228	V1	1-2048	1	21.23	11.38	21.23	11.38**
228	MLII	6201- 8248	0.5	23.86	9.20	24.92	9.20*
228	V1	6201- 8248	0.5	17.61	8.01	18.18	8.01*
232	MLII	1-2048	2	11.65	17.16	12.05	17.16*
232	V1	1-2048	2	16.43	13.21	17.24	13.21*

* Improved CR for same PRD
** No Change in CR and PRD

The results of polishing on the same test database are given in table 4.2. We found that PRD reduced in all the cases without exception.

TABLE 4.2: Comparative Results of "Polishing"

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
100	MLII	1-2048	2	19.04	15.53	19.04	14.17*
100	V5	1-2048	2	15.51	13.62	15.51	12.14*
100	MLII	32770-34817	4	21.48	14.07	21.48	12.26*
100	V5	32770-34817	2	19.97	10.50	19.97	9.49*
101	MLII	1-2048	2	19.09	14.09	19.09	12.53*
101	V1	1-2048	4	13.6	24.52	13.6	22.9*
102	V5	1-2048	1	20.55	14.57	20.55	12.94*
102	V2	1-2048	1	25.54	7.87	25.54	6.45*
103	MLII	1-2048	1	18.76	9.00	18.76	7.82*
103	V2	1-2048	1	20.22	11.58	20.22	9.99*
107	MLII	1-2048	2	22.85	11.86	22.85	10.15*
107	V1	1-2048	2	19.81	8.27	19.81	6.68*
118	MLII	1-2048	2	20.2	16.8	20.2	15.29*
118	V1	1-2048	2	15.71	13.43	15.71	12.11*
119	MLII	1-2048	2	20.76	10.27	20.76	8.66*
119	V1	1-2048	4	25.54	15.43	25.54	13.98*
119	MLII	6586- 8633	1	28.09	14.83	28.09	13.33*
119	V1	6586- 8633	2	24.98	12.90	24.98	11.31*
105	MLII	38140- 40187	2	17.09	12.92	17.09	11.70*
105	V1	38140- 40187	4	16.22	12.34	16.22	11.49*
108	MLII	3176- 5223	4	24.41	15.37	24.41	14.08*
108	V1	3176- 5223	1	29.07	11.90	29.07	10.67*

*Improved PRD for same CR

TABLE 4.2: Comparative Results of "Polishing" (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
108	MLII	9979- 12026	4	16.64	17.04	16.64	15.92*
108	V1	9979- 12026	1	15.94	15.27	15.94	14.15*
109	MLII	1- 2048	2	23.35	13.98	23.35	12.27*
109	V1	1- 2048	4	24.92	9.07	24.92	7.92*
109	MLII	2981- 5028	2	19.12	8.64	19.12	7.48*
109	V1	2981- 5028	1	21.72	8.69	21.72	7.57*
109	MLII	9981- 12028	2	22.09	12.82	22.09	11.19*
109	V1	9981- 12028	2	21.05	9.40	21.05	7.93*
111	MLII	1- 2048	1	22.39	15.45	22.39	13.87*
111	V1	1- 2048	1	24.73	10.88	24.73	9.67*
111	MLII	16001- 18048	1	21.17	13.94	21.17	12.17*
111	V1	16001- 18048	2	21.31	10.80	21.31	9.63*
111	MLII	19001- 21048	4	20.01	9.84	20.01	8.64*
111	V1	19001- 21048	1	25.92	11.39	25.92	10.03*
112	MLII	1- 2048	8	18.99	14.82	18.99	13.26*
112	V1	1- 2048	8	18.44	29.24	18.44	27.50*
112	MLII	14501- 16548	8	17.46	15.71	17.46	14.27*
112	V1	14501- 16548	8	18.49	18.98	18.49	17.87*
212	MLII	1- 2048	2	15.55	10.33	15.55	8.75*
212	V1	1- 2048	1	24.09	12.18	24.09	10.02*
212	MLII	22771- 24818	1	16.79	11.30	16.79	9.88*
212	V1	22771- 24818	4	17.59	27.64	17.59	26.74*

*Improved PRD for same CR

TABLE 4.2: Comparative Results of “Polishing” (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
219	MLII	1- 2048	2	19.90	10.96	19.90	9.52*
219	V1	1- 2048	2	16.96	9.31	16.96	8.29*
219	MLII	33120- 35167	2	19.69	8.51	19.69	7.47*
219	V1	33120- 35167	4	21.41	14.51	21.41	12.84*
219	MLII	36629-38676	2	20.08	11.64	20.08	10.33*
219	V1	36629-38676	2	19.21	13.21	19.21	11.73*
219	MLII	437400-439447	2	18.90	8.79	18.90	7.59*
219	V1	437400-439447	4	21.11	13.74	21.11	11.92*
222	MLII	700- 2747	4	19.12	17.27	19.12	15.65*
222	V1	700- 2747	2	14.52	10.62	14.52	9.92*
222	MLII	2776- 2823	4	23.37	13.27	23.37	12.32*
222	V1	2776- 2823	1	24.15	12.65	24.15	12.13*
222	MLII	5111-7158	2	15.56	11.82	15.56	11.16*
222	V1	5111-7158	1	18.45	12.07	18.45	11.16*
222	MLII	11350- 12397	2	12.85	11.83	12.85	10.65*
222	V1	11350- 12397	2	13.75	12.11	13.75	11.24*
222	MLII	15937 – 17984	2	19.14	12.85	19.14	12.02*
222	V1	15937 – 17984	1	22.46	12.21	22.46	11.52*
222	MLII	28267- 30314	2	15.89	10.37	15.89	9.62*
222	V1	28267- 30314	1	18.54	13.08	18.54	12.23*
222	MLII	30861- 32908	2	12.99	10.69	12.99	9.66*
222	V1	30861- 32908	1	14.30	11.64	14.30	10.41*

*Improved PRD for same CR

TABLE 4.2: Comparative Results of "Polishing" (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
222	MLII	35623 - 37670	2	24.04	12.58	24.04	12.01*
222	V1	35623 - 37670	2	21.50	14.06	21.50	13.31*
222	MLII	38818- 40865	4	19.90	11.98	19.90	11.16*
222	V1	38818- 40865	1	18.60	11.27	18.60	10.6*
222	MLII	48328 – 50375	2	15.91	12.46	15.91	11.52*
222	V1	48328 – 50375	1	18.96	12.09	18.96	11.15*
222	MLII	53218 – 55265	2	17.37	14.38	17.37	13.35*
222	V1	53218 – 55265	2	17.61	12.29	17.61	11.55*
222	MLII	56117-58164	1	13.38	11.11	13.38	10.00*
222	V1	56117-58164	1	15.67	12.73	15.67	11.59*
222	MLII	62769- 64816	2	15.37	10.87	15.37	9.90*
222	V1	62769- 64816	1	18.73	11.97	18.73	11.17*
228	MLII	1-2048	2	13.43	11.96	13.43	10.89*
228	V1	1-2048	1	21.23	11.38	21.23	10.26*
228	MLII	6201- 8248	0.5	23.86	9.20	23.86	8.11*
228	V1	6201- 8248	0.5	17.61	8.01	17.61	6.97*
232	MLII	1-2048	2	11.65	17.16	11.65	15.93*
232	V1	1-2048	2	16.43	13.21	16.43	12.30*

*Improved PRD for same CR

4.4.1 Combining blank-fire and polishing

The improvement in the results, on account of both these steps of "blank-fire removal" and "polishing" are additive. The first results in increased CR (in 70.2% cases) and PRD remains the same, while the second results in reduced PRD (in all cases) and CR remains the same. By implementing both the steps, improvement occurs in both CR (in 70.2% cases) as well as in PRD (in all cases). This is illustrated in table 4.3.

TABLE 4.3: Comparative Results of “Blank-fire Removal” and “Polishing”

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
100	MLII	1-2048	2	19.04	15.53	20.13	14.17*
100	V5	1-2048	2	15.51	13.62	16.21	12.14*
100	MLII	32770-34817	4	21.48	14.07	24.46	12.26*
100	V5	32770-34817	2	19.97	10.50	21.17	9.49*
101	MLII	1-2048	2	19.09	14.09	20.18	12.53*
101	V1	1-2048	4	13.6	24.52	14.74	22.9*
102	V5	1-2048	1	20.55	14.57	20.55	12.94**
102	V2	1-2048	1	25.54	7.87	25.54	6.45**
103	MLII	1-2048	1	18.76	9.00	18.76	7.82**
103	V2	1-2048	1	20.22	11.58	20.22	9.99**
107	MLII	1-2048	2	22.85	11.86	24.43	10.15*
107	V1	1-2048	2	19.81	8.27	20.99	6.68*
118	MLII	1-2048	2	20.2	16.8	21.43	15.29*
118	V1	1-2048	2	15.71	13.43	16.44	12.11*
119	MLII	1-2048	2	20.76	10.27	22.07	8.66*
119	V1	1-2048	4	25.54	15.43	29.88	13.98*
119	MLII	6586- 8633	1	28.09	14.83	28.09	13.33**
119	V1	6586- 8633	2	24.98	12.90	26.88	11.31*
105	MLII	38140- 40187	2	17.09	12.92	17.96	11.70*
105	V1	38140- 40187	4	16.22	12.34	17.86	11.49*
108	MLII	3176- 5223	4	24.41	15.37	28.34	14.08*
108	V1	3176- 5223	1	29.07	11.90	29.07	10.67**

*Improved PRD, Improved CR
**Improved PRD for same CR

TABLE 4.3: Comparative Results of “Blank-fire Removal” and “Polishing” (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
108	MLII	9979- 12026	4	16.64	17.04	18.38	15.92*
108	V1	9979- 12026	1	15.94	15.27	15.94	14.15**
109	MLII	1- 2048	2	23.35	13.98	25.00	12.27*
109	V1	1- 2048	4	24.92	9.07	29.03	7.92*
109	MLII	2981- 5028	2	19.12	8.64	20.20	7.48*
109	V1	2981- 5028	1	21.72	8.69	21.72	7.57**
109	MLII	9981- 12028	2	22.09	12.82	23.56	11.19*
109	V1	9981- 12028	2	21.05	9.40	22.39	7.93*
111	MLII	1- 2048	1	22.39	15.45	22.39	13.87**
111	V1	1- 2048	1	24.73	10.88	24.73	9.67**
111	MLII	16001- 18048	1	21.17	13.94	21.17	12.17**
111	V1	16001- 18048	2	21.31	10.80	22.69	9.63*
111	MLII	19001- 21048	4	20.01	9.84	22.57	8.64*
111	V1	19001- 21048	1	25.92	11.39	25.92	10.03**
112	MLII	1- 2048	8	18.99	14.82	21.66	13.26*
112	V1	1- 2048	8	18.44	29.24	21.23	27.50*
112	MLII	14501- 16548	8	17.46	15.71	20.99	14.27*
112	V1	14501- 16548	8	18.49	18.98	21.35	17.87*
212	MLII	1- 2048	2	15.55	10.33	16.27	8.75*
212	V1	1- 2048	1	24.09	12.18	24.09	10.02**
212	MLII	22771- 24818	1	16.79	11.30	16.79	9.88**
212	V1	22771- 24818	4	17.59	27.64	19.54	26.74*

*Improved PRD, Improved CR

**Improved PRD for same CR

TABLE 4.3: Comparative Results of "Blank-fire Removal" and "Polishing" (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
219	MLII	1- 2048	2	19.90	10.96	21.09	9.52*
219	V1	1- 2048	2	16.96	9.31	17.83	8.29*
219	MLII	33120- 35167	2	19.69	8.51	20.86	7.47*
219	V1	33120- 35167	4	21.41	14.51	24.38	12.84*
219	MLII	36629-38676	2	20.08	11.64	21.29	10.33*
219	V1	36629-38676	2	19.21	13.21	20.32	11.73*
219	MLII	437400-439447	2	18.90	8.79	19.97	7.59*
219	V1	437400-439447	4	21.11	13.74	23.99	11.92*
222	MLII	700- 2747	4	19.12	17.27	21.46	15.65*
222	V1	700- 2747	2	14.52	10.62	15.14	9.92*
222	MLII	2776- 2823	4	23.37	13.27	26.95	12.32*
222	V1	2776- 2823	1	24.15	12.65	24.15	12.13**
222	MLII	5111-7158	2	15.56	11.82	16.23	11.16*
222	V1	5111-7158	1	18.45	12.07	18.45	11.16**
222	MLII	11350- 12397	2	12.85	11.83	13.34	10.65*
222	V1	11350- 12397	2	13.75	12.11	14.31	11.24*
222	MLII	15937 – 17984	2	19.14	12.85	20.24	12.02*
222	V1	15937 – 17984	1	22.46	12.21	22.46	11.52**
222	MLII	28267- 30314	2	15.89	10.37	16.64	9.62*
222	V1	28267- 30314	1	18.54	13.08	18.54	12.23**
222	MLII	30861- 32908	2	12.99	10.69	13.49	9.66*
222	V1	30861- 32908	1	14.30	11.64	14.30	10.41**

*Improved PRD, Improved CR

**Improved PRD for same CR

TABLE 4.3: Comparative Results of “Blank-fire Removal” and “Polishing” (continued)

Patient	Signal	Sample	Ratio	SPIHT		Modified SPIHT	
				CR	PRD	CR	PRD
222	MLII	35623 - 37670	2	24.04	12.58	25.81	12.01*
222	V1	35623 - 37670	2	21.50	14.06	22.89	13.31*
222	MLII	38818- 40865	4	19.90	11.98	22.44	11.16*
222	V1	38818- 40865	1	18.60	11.27	18.60	10.6**
222	MLII	48328 – 50375	2	15.91	12.46	16.66	11.52*
222	V1	48328 – 50375	1	18.96	12.09	18.96	11.15**
222	MLII	53218 – 55265	2	17.37	14.38	18.27	13.35*
222	V1	53218 – 55265	2	17.61	12.29	18.54	11.55*
222	MLII	56117-58164	1	13.38	11.11	13.38	10.00**
222	V1	56117-58164	1	15.67	12.73	15.67	11.59**
222	MLII	62769- 64816	2	15.37	10.87	16.06	9.90*
222	V1	62769- 64816	1	18.73	11.97	18.73	11.17**
228	MLII	1-2048	2	13.43	11.96	13.96	10.89*
228	V1	1-2048	1	21.23	11.38	21.23	10.26**
228	MLII	6201- 8248	0.5	23.86	9.20	24.92	8.11*
228	V1	6201- 8248	0.5	17.61	8.01	18.18	6.97*
232	MLII	1-2048	2	11.65	17.16	12.05	15.93*
232	V1	1-2048	2	16.43	13.21	17.24	12.30*

*Improved PRD, Improved CR
**Improved PRD for same CR

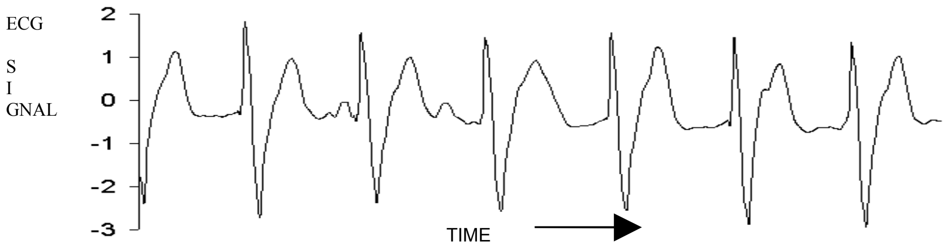
All above results have been carried out for higher CR values (less refinement passes). If a particular signal is taken, say 107[a], its performance for modified SPIHT vis-à-vis existing SPIHT for more number of passes resulting in lower CR and lower PRD is given in table 4.4. Visual inspection of the original and reconstructed signals using modified SPIHT at higher CR of 17.94 and 24.43 for patient 107 signal [a] can be done by comparing figures 4.2(a), 4.2(b) and 4.2(c). The quality of signal reconstruction can be well seen in the figures.

TABLE 4.4: Comparative results of modified SPIHT on patient 107 signal [a] at different CR

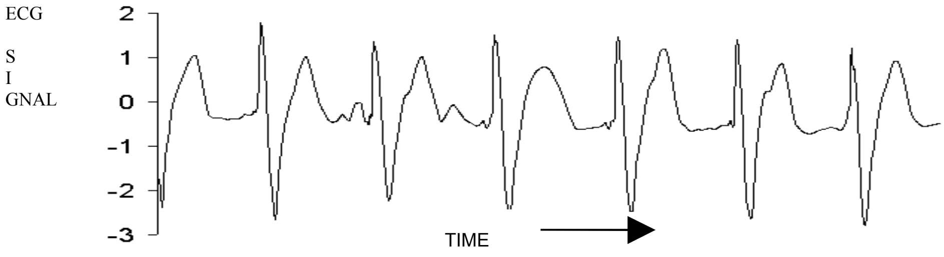
Passes	SPIHT		Modified SPIHT	
	CR	**PRD**	**CR**	**PRD**
6	22.85	11.86	24.43	10.15*
7	17.07	6.96	17.94	5.95*
8	13.07	4.34	13.57	3.82*
9	9.87	3.11	10.16	2.82*
10	6.98	2.39	7.12	2.26*

*Improved PRD, Improved CR

(a)



(b)



(c)

Figure 4.2: ECG signal of patient 107[a]

(a) Original ECG Signal (b) Reconstructed signal with CR=17.94 (c) Reconstructed signal with CR=24.43

In the last chapter we have established with the research review till date, the relative supremacy of SPIHT wavelet compression algorithm for ECG signals, given by Lu *et al.,* [Lu *et al.,* 2000]. Thus it can be concluded that it is sufficient to compare the results of modified SPIHT algorithm only with SPIHT algorithm given by Lu *et al.,* [Lu *et al.,* 2000].

4.5 HANDLING LONG DATA FILES

4.5.1 Need to handle long files

Monitoring patients with serious cardiovascular problems is invaluable in preventing further crises and achieving a faster and thus more effective attention. For this, non-invasive cardiological tests such as dynamic electrocardiography, have proven useful in clinical practice. A Holter monitor is portable device for continuously monitoring the electrical activities of the heart for 24 hours or even more. These long recordings are useful for observing occasional cardiac arrhythmias that would otherwise be difficult to detect in shorter period of time. Just like in standard ECG recording machine, a Holter monitor has standard electrodes that are connected to the body surface (preferably over the bones to avoid artifacts on account of muscular activity) of the patient at designated positions and the monitor itself is held under the belt of the patient. Earlier Holter monitors used audio magnetic cassettes with normal recording duration of 60 or 90 minutes (C60 or C90). These cassettes were run at very slow speed so as to record the electrical activity for 24 hours, without the need to change the cassettes very now and then. Modern Holter machines record this activity onto digital flash memory devices. It is but obvious that this humungous data needs to be suitably compressed before it can be stored and finally decompressed upon being uploaded onto the computer for automatic analyses like counting ECG complexes, calculating average heart rate, minimum and maximum heart rate, and finding specific areas that require attention of a physician. Interestingly, apart from the data recorded by the monitor, the patient too is advised to keep a diary of daily activities like eating, sleeping, running or any other symptoms felt by the patient and the times at which these symptoms occur. These events recorded in the diary of the patient are cross-referred by the physicians to rapidly pinpoint the areas of problem in the vast amount of data recorded during the monitoring period.

Realizing the importance of Holter monitor for detection and prevention of cardiovascular problems, many researchers have tried to improve it efficacy. Compression algorithms have been designed or modified, specifically to be employed in Holter monitors [Smith and Platt, 1988]. Use of Neural Networks for data compression for Holter monitor has also been reported [Iwata *et al.,* 1990]. Some Holter designs have the facility of real time processing and make use GSM mobile telephony standards to monitor patient's heart anywhere, anytime [Guillen *et al.,* 2000]. To sum up, a standard ECG recording for a few seconds may not be able to detect the occasional changes in the heart's electrical activity. Therefore it is important to have a long recording of the electrical activity for say, 24 hours or more.

4.5.2 Implementing Modified SPIHT for ECG signal compression

The present research work aims at ECG data compression for telecardiology. Taking the pre-recorded ECG signals that are available in text format at http://physionet.org (physiobank) [Goldberger *et al.,* 2000], SPIHT algorithm was implemented to verify the claims made by Lu *et al.,* about its efficacy, simplicity and self adaptiveness. Later the two additional steps namely "Blank-fire-removal" and "Polishing" were incorporated to document the improved efficiency of the algorithm. Using Turbo C++ complier an executable file **ddcode.exe** was created that picks up a block of 2048 samples of one lead from the text file containing the ECG signal in the format shown in table 4.5. It compresses the 2048 samples of ECG signal in the text form from a file named **data.txt** and outputs an American Standard Code for Information Interchange (ASCII) file named **ECGCODE.txt** as the compressed code. The execution of ddcode.exe takes place in the following way:

The signal is first transformed into the wavelet domain and the coefficients, which are small enough, are set to zero such that no significant information is lost on signal reconstruction. For obtaining effective and efficient data compression, the choice of different analysis-synthesis filter pairs, which correspond to different wavelet bases, is especially significant [Besar *et al.,* 2000]. In realization, the number of decompositions, frame size, and filter pair need to be selected suitably. The number of decompositions determines the coarsest frequency resolution of the transform and should be at least four for sufficient compression. The frame size is taken to be a power of two that exceeds the number of decompositions. This means that for six decompositions, the minimum frame size should be $2^7 = 128$. The frame size be short enough for acceptable coding delay and memory usage but should be large enough to contain several periods of the ECG signal. Choosing six layers of wavelet decomposition and 2048 sample frames fulfills the requirements. Choice of potential perfect reconstruction filter-pairs demands a tradeoff between computational complexity and compression performance.

TABLE 4.5: First 90 ECG signal samples of patient 100 of mitdb database (360 samples per second)

Time (sec)	MLII (mv)	V5 (mv)
0	-0.145	-0.065
0.003	-0.145	-0.065
0.006	-0.145	-0.065
0.008	-0.145	-0.065
0.011	-0.145	-0.065
0.014	-0.145	-0.065
0.017	-0.145	-0.065
0.019	-0.145	-0.065
0.022	-0.12	-0.08
0.025	-0.135	-0.08
0.028	-0.145	-0.085
0.031	-0.15	-0.085
0.033	-0.16	-0.075
0.036	-0.155	-0.07
0.039	-0.16	-0.07
0.042	-0.175	-0.065
0.044	-0.18	-0.055
0.047	-0.185	-0.05
0.05	-0.17	-0.05
0.053	-0.155	-0.04
0.056	-0.175	-0.04
0.058	-0.18	-0.055
0.061	-0.19	-0.075
0.064	-0.18	-0.08
0.067	-0.155	-0.085
0.069	-0.135	-0.07
0.072	-0.155	-0.08
0.075	-0.19	-0.08
0.078	-0.205	-0.09
0.081	-0.235	-0.095

Time (sec)	MLII (mv)	V5 (mv)
0.083	-0.225	-0.09
0.086	-0.245	-0.095
0.089	-0.25	-0.11
0.092	-0.26	-0.12
0.094	-0.275	-0.145
0.097	-0.275	-0.135
0.1	-0.275	-0.105
0.103	-0.265	-0.095
0.106	-0.255	-0.105
0.108	-0.265	-0.12
0.111	-0.275	-0.135
0.114	-0.29	-0.125
0.117	-0.29	-0.125
0.119	-0.29	-0.115
0.122	-0.29	-0.115
0.125	-0.285	-0.125
0.128	-0.295	-0.14
0.131	-0.305	-0.14
0.133	-0.285	-0.13
0.136	-0.275	-0.125
0.139	-0.275	-0.14
0.142	-0.28	-0.145
0.144	-0.285	-0.15
0.147	-0.305	-0.15
0.15	-0.29	-0.13
0.153	-0.3	-0.115
0.156	-0.28	-0.125
0.158	-0.29	-0.135
0.161	-0.3	-0.16
0.164	-0.315	-0.195

Time (sec)	MLII (mv)	V5 (mv)
0.167	-0.32	-0.2
0.169	-0.335	-0.205
0.172	-0.36	-0.225
0.175	-0.385	-0.255
0.178	-0.385	-0.3
0.181	-0.405	-0.29
0.183	-0.455	-0.235
0.186	-0.485	-0.13
0.189	-0.485	-0.035
0.192	-0.425	0.05
0.194	-0.33	0.12
0.197	-0.22	0.2
0.2	-0.07	0.31
0.203	0.12	0.435
0.206	0.375	0.535
0.208	0.62	0.58
0.211	0.78	0.475
0.214	0.84	0.21
0.217	0.765	-0.085
0.219	0.52	-0.23
0.222	0.17	-0.25
0.225	-0.165	-0.215
0.228	-0.365	-0.18
0.231	-0.435	-0.185
0.233	-0.425	-0.16
0.236	-0.37	-0.15
0.239	-0.33	-0.15
0.242	-0.325	-0.18
0.244	-0.335	-0.18
0.247	-0.345	-0.16

Computational complexity is lesser for shorter filters while compression performance is better for longer filters. Among all filters tested by Hilton, biorthogonal 9/7 tap filters had the best compression performance for wavelet coding of ECG signals [Hilton, 1997]. These filters, being quadrature mirror filters, are symmetric. The symmetric (reflective) data extension scheme at the boundaries of the frames is employed to obtain perfect reconstruction at boundaries in the absence of coding.

The Modified SPIHT algorithm is used to encode the wavelet coefficients obtained after the wavelet transform. Set partitioning sorting algorithm is used for partial ordering of the transform coefficients by magnitude, followed by ordered bit plane transmission and utilization of self-similarity across different layers of decomposition. The encoder (**ddcode.exe**) first codes the ECG data, and then the coded data (**ECGCODE.txt**) is stored/transmitted. After retrieval of the coded signal, a decoder decodes it. The set-partitioning rule for encoder should essentially be the same for the decoder. Step-wise execution for this is given below:

(i) The ECG data is decomposed to half the signal bandwidth into approximate signal (Low frequency) and detailed signal (High frequency) by QMF filters

(ii) The approximate signal is further decomposed successively. The coefficients are arranged in the form of a tree as shown in figure 3.10. Corresponding to every point in a layer (called parent) there are two points in the next layer (called offsprings), with the down arrows indicative of the parent-offspring relation. In a usual ECG signal, low frequency bands contain most of the energy. Thus higher decomposition coefficients are larger in magnitude

(iii) For any given set of coefficients, the highest absolute coefficient is selected (say max_coeff), and the largest integer n is chosen, satisfying the relation $2^n <$ max_coeff. Any coefficient in the subset is said to be significant, if its absolute value is greater than 2^n. Here the concept of "blank-fire removal" is incorporated. While searching for the largest coefficient, there are two major subsets. One subset of approximate signal (32 samples) let us call it as "L_coeffs" and another of six detailed signal samples (32 + 64 + 128 + 254 + 512 + 1024 samples), say "H_coeffs". So instead of taking a common threshold (2^n) for both subsets, two different thresholds (i.e. L_threshold and H_threshold) are transmitted to compressed bit stream, to get improved compression ratio. A separate bit stream for H_coeffs, using H_Threshold is formed called cmp_code_H, while another bit stream for L_coeffs, using L_Threshold is formed called cmp_code_L. A zero is to be sent to the compressed code bit stream if the entire subset is insignificant, if not, a one is to be sent. The subset is then split according to the temporal orientation tree. This process is repeated until all the significant sets are broken down to a single significant point each. This process is called sorting pass. Three lists of the indices of the coefficients are prepared

(a) The list of insignificant points (LIP)

(b) The list of insignificant sets (LIS)

(c) The list of significant points (LSP)

The bits related to the LSP entries and outcomes of the magnitude tests in binary form are transmitted. The entries in the LIP and LIS, which have the same parent into an entry atom, are grouped together. Sorting pass gives a subset of the significant coefficients for the threshold (2^n). While refining, the most significant bit of every coefficient found significant at a higher threshold, is sent to coded bit stream. By this method, all bits of the points found significant till that sort, are transmitted

(iv) Value of n is decrement by one and the process is repeated until the desired compression is achieved

(v) So we now have four text files; two bit stream codes i.e. cmp_code_H (**code.txt**) & cmp_code_L (**code_L.txt**) and two Thresholds i.e. H_Threshold (**thr.txt**) & L_Threshold (**thr_L.txt**)

(vi) All these four text file all coded in the form an ASCII file named **ECGCODE.txt** by another executable file named **coder.exe**

The same process is run in reverse order on the decoder side. First an executable file named **decoder.exe** reads the encoded ECG data (**ECGCODE.txt)** and outputs four text files, namely, **code.txt, code_L.txt**, **thr.txt** and **thr_L.txt**. Then reading these four files, another executable file named dddecode.exe gives the reconstructed ECG data in a file named **recon.txt**. The concept of "polishing" is incorporated as an additional step by dddecode.exe as explained earlier.

4.5.3 Problems with ASCII coding in file reading

We see that of the four text files generated by **ddcode.exe,** two contain a single integer e.g. 4, (**thr.txt** and **thr_L.txt**) and the other two have bit stream string like "1001110101010111" (**code.txt** and **code_L.txt)**. Since we are designing coder for an application in telecardiology over Internet, concatenating these files in the same format would result in loss of compression, as each character in ASCII takes 8 bits of space. This means the compressed string of bit stream containing 16 bits of compressed bit stream like "1001110101010111" would actually occupy 16*8= 128 bits. Apart from concatenation, these bit stream digits are grouped in packs of eight bits and each pack is transmitted/stored as an ASCII character. This is done by the executable file **coder.exe**. The file **coder.exe,** when executed, first reads files **thr.txt**, **thr_L.txt**, **code.txt** and **code_L.txt**. First nibble of the first byte of **ECGCODE.txt** contains coded H_Threshold read from **thr.txt,** while the second nibble of the first byte contains coded L_Threshold read from **thr_L.txt.** Again to use lesser number of bytes and to cover the entire range of possible thresholds, we have employed a mathematical expression for binary code = $(\log_{10}(\text{Threshold})/\log_{10}(2)) + 8$. Thus if threshold is 2, binary nibble will be 1001, for 1 it will be 1000, for 0.5 it will be 0111 and so on. This theoretically covers the range of thresholds from 128 to 1/128. Of course no ECG signal (in millivolt) will ever have threshold beyond these limits. This makes first character of eight bits. The next three characters (24 bits) are split in two groups of three nibbles (12 bits) each. The first group of three nibbles indicates length of bits in **code.txt**, while the second one indicates indicate length of bits in **code_L.txt.** The file **ECGCODE.txt** will be read to the point up to sum of these lengths and then the reading terminates by itself. This is followed by stream of bits in **code.txt** and **code_L.txt**, again grouped in eight bits for an ASCII character. If however, the combined length of these streams is not exact multiple of eight, the remaining bits by default are made zero.

While executing this scheme, we came across a rather interesting phenomenon. After the code **ECGCODE.txt** was transmitted to the decoder, it failed to read certain coded characters in the ASCII stream. Careful and repeated trails revealed that this happened for three groups of eight bits *viz*., for the decimal value 13 (binary value 00001101), 26 (binary value 00011010) and 255 (binary value 11111111). ASCII character for decimal value 13 in MS-DOS, Windows, and various network standards, is used as part of the end-of-line mark, while ASCII character for decimal value 26 and 255 are used for marking end-of-text and end-of-file (EOF) respectively [Wikipedia contributors, 2006]. This means that whenever any command for reading an ASCII string is executed and it comes across these characters, the reading of the files terminates all by itself, thereby disrupting the entire procedure.

4.5.4 File writing/reading with modified characters

To circumvent this tricky situation of unwarranted termination of string reading operation, it was decided to eliminate the very use of these three characters. To ensure their absence in the string, a check is performed at the writing stage itself. Printable character "*" in ASCII has decimal value of 42. Whenever binary combination of 8 bits results in decimal value of 13, 26, 42 or 255 occurs, the character written had decimal value of five less than the original. That is to elaborate, decimal value 13 becomes 8, 26 becomes 21, 42 becomes 37 and 255 becomes 250. Moreover the printable character "*" (ASCII decimal value 42) is put in the string before putting the modified (reduced by five) ASCII character. At the time of decoding, whenever the string read operation identifies "*" it immediately comes to know that the proceeding character is a modified one, and while converting it to bit stream, it automatically adds five to restore the original value. And again to ensure that the bit combination should never be decimal value 42 (corresponding to ASCII value "*"), this character too was added to the list of culprits (problematic characters). For valid termination of read operation, the combined length of cmp_code_H (**code.txt**) and cmp_code_L (**code_L.txt**) is taken as reference. The string of ASCII characters (**ECGCODE.txt**) so concatenated look some what like this " hÓh¢ñÝ}__Yoƒšn*_z¼P"8€<Æ€_×šÕÝ_Ü*_P_ŽÈ_ □ ÷Ã_ *%¶á ". Using this technique, the programme was executed a number of times with different set of test data, never to find the problem of unwarranted termination again.

4.5.5 Fragmenting and looping for handling longer data

The above process of concatenating and coding the bit streams was done only for block of 2048 samples of ECG data. As already discussed, for Holter monitor like applications, the data storage is for 24 hours or even more. Sampled at a moderate 250 samples per second for a single lead, one-minute data has 15,000 samples. And for one hour signal the number of samples would be 900,000 i.e. close to a million. When it comes to handling several million samples, we have to take care of large numerical values to be handled in counters and file indices while programming in C++ environment. For coding a large text file containing a million plus samples of ECG data, the following sequence of steps are adopted:

(i) Write text a file named **counter.txt,** the contents of the file indicate an integer "Count_char"

(ii) Set the content of counter.txt i.e. Count_char to zero

(iii) The long ECG data containing text file is renamed **longdata.txt** for the sake of convenience, though any other name would do equally well

(iv) Start reading **longdata.txt** after skipping Count_char characters and read the next 2048 samples and store it in file named **data.txt**. When dealing with large numbers, skipping characters is easier than skipping formatted samples

(v) Increment **counter.txt** by number of characters read while reading 2048 samples. If the samples are less than 2048, quit

(vi) Run **ddcode.exe** followed by **coder.exe** as explained earlier. A text file **ECGCODE.txt** will be formed

(vii) Check for the existence of a text file named **ECGCODL.txt.** If it does not exist, rename **ECGCODE.txt** as **ECGCODL.txt** else append **ECGCODE.txt** to **ECGCODL.txt** with a separator "**" (ASCII character with decimal value 42 and listed in forbidden character group, as discussed earlier)

(viii) Go to step no. (iv). Termination of this loop will take place at step (v)

The encoded long ECG data is now available in a text file named **ECGCODL.txt** for further transmission or storage as the case may be. **ECGCODL.txt** contain numerous encoded segments separated by "**" group of characters. While encoding **ECGDATA.txt**, it is worthwhile to note that the combination "**" is not possible, hence the choice of this grouping. On the decoder end the same steps are executed in the reverse order. The step sequence is given below:

(i) Set an integer Count_seg to zero and store it in a text file name **counter.txt**

(ii) The characters of **ECGCODL.txt** are read one by one after skipping Count_seg segments and simultaneously stored in text file **ECGCODE.txt** overwriting any existing file of the same name, till the program encounters "**". Note no counting of characters is required at the decoder end. If the file does not encounter EOF then increment counter by one, else quit

(iii) Run **decoder.exe** and **dddecode.exe.** A text file **recon.txt** will be formed Append **recon.txt** to **reconL.txt** if **reconL.txt** already exits, else rename **recon.txt** as **reconL.txt**

(iv) Go to step (ii). The loop will terminate at step (ii) on encountering EOF

Thus the entire long reconstructed ECG data is now available in text file named **reconL.txt.** Not to intimidate the end user with these large numbers of executable files, a single batch file (**encode.bat**) is formed for coding long ECG data, (which also works if the record happens to be not so long) and another single batch file (**decode.bat)** at the decoder end for decoding now not so long compressed code, back to equally long reconstructed ECG signal. The compression ratio reported in table 4.1 – 4.3 is based on actual bit size. If, however, the text size of ECG signal is taken in uncompressed and compressed form, the compression ratio increases manifold (up to five times). And this higher text size compression ratio has the real potential in telecardiology over Internet.

4.5.6 Test data

The whole set of executable files is thoroughly tested on long ECG records downloaded from the Long–Term ST Database (ltstdb) available at http://physionet.org (physiobank) [Goldberger *et al.,* 2000]. Downloading of the text data is itself an arduous task, which takes many days at limited Internet speed, thereby once again validating the relevance of our research topic. The Long-Term ST Database contains 86 (43 available at http://physionet.org) lengthy ECG recordings of 80 human subjects, chosen to exhibit a variety of events of ST segment changes, including ischemic ST episodes, axis-related non-ischemic ST episodes, episodes of slow ST level drift, and episodes containing mixtures of these phenomena. The database was created to support development and evaluation of algorithms capable of accurate differentiation of ischemic and non-ischemic ST events, as well as basic research into mechanisms and dynamics of myocardial ischemia. The individual recordings of the Long-Term ST Database are between 21 and 24 hours in duration, and contain two or three ECG signals. Each ECG signal has been digitized at 250 samples per second with 12-bit resolution over a range of ±10 millivolts. Each record includes a set of meticulously verified ST episode and signal quality annotations; together with additional beat-by-beat QRS annotations and ST level measurements.

However, not considering the clinical significance of the data, we chose this database simply impressed by its size, to test our program for handling lengthy ECG records.

4.6 CONCLUSIONS

SPIHT algorithm is the most efficient method of compressing an ECG signal, which gives higher compression ratio for lesser percentage root-mean-square difference [Lu *et al.,* 2000]. It is easy to compute, is self-adaptive and gives the required compression. Two additional steps in modified SPIHT algorithm, that is “Blank-fire removal” and “Polishing”, further increase the compression ratio and reduce the percentage root-mean-square difference, while retaining all features of the existing SPIHT algorithm. The comparison is made on the same database set, with the same wavelet filters and using the same distortion measure. The modified SPIHT is checked on the block of 2048 data samples of ECG. A total of 84 ECG signals from MIT-BIH arrhythmia test base (mitdb) (sampling rate 360 per second) have been tested using modified SPIHT algorithm. 59 signals (70.2%) have shown an improvement in the compression ratio in the range of 3.24% - 20.22%, averaging to 7.95% improvement, while the remaining 25 signals (29.8%) have maintained the same compression ratio as given by the existing SPIHT algorithm. Not even a single case has shown deterioration in compression ratio. Improvement in distortion (i.e. reduction) has been found in all 84 signals (100%) ranging from 3.26% to 19.23%, averaging to 9.99% reduction in PRD.

In many applications of dynamic electrocardiography, such as Holter monitor, the recordings are for the duration of 24 hours or even larger. The numbers of samples in such cases run to several millions. A set of executable files is developed in C++ environment to handle these lengthy records and tested on data downloaded from the Long–Term ST Database (ltstdb) available at http://physionet.org (physiobank) [Goldberger *et al.,* 2000]. While encoding the bit streams to ASCII characters, some peculiar programming problems were encountered, especially in file reading of ASCII strings for certain characters. ASCII character for decimal value 13 in MS-DOS, Windows, and various network standards, is used as part of the end-of-line mark, while ASCII character for decimal value 26 and 255 are used for marking end-of-text and end-of-file (EOF) respectively and disrupt the normal file reading process. These characters are identified and subsequently modified in the bit stream itself, to solve the problem. Long records are handled using the concepts of fragmenting and looping.

REFINEMENT CRITERION AND ITS CLINICAL VALIDATION

5.1 DIAGNOSTIC PARAMETERS OF ECG

The electrical currents that are generated for depolarization and repolarization of heart spread throughout the body and can be measured by an array of electrodes placed on the body surface. Shown in figure 5.1 is the recorded ECG tracing for a normal subject from standard lead II. The first deflection labeled P corresponds to atrial depolarization, followed by a series of deflections, labeled QRS, arising from ventricular activation and finally a T wave corresponding to ventricular repolarization. To extract meaningful information from this ECG trace, there are some important diagnostic features that need to be identified and measured.

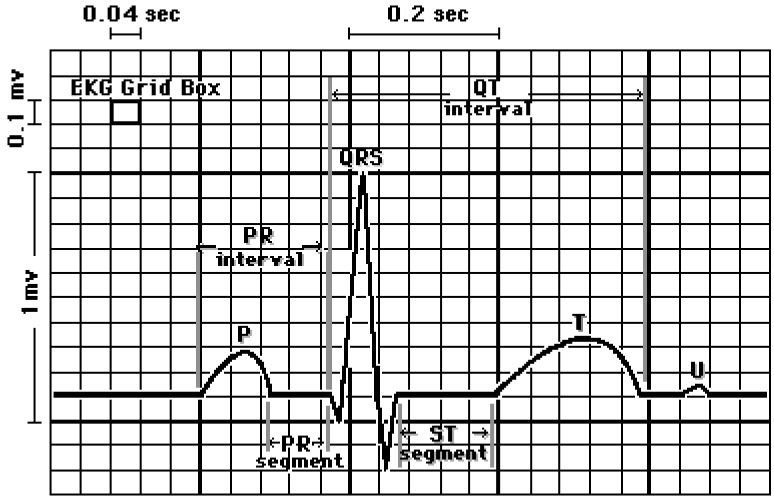


Figure 5.1: ECG trace with its salient features

Most elementary of these features is **Heart Rate** (HR). Heart Rate is determined from R-R interval, which is the interval between two successive R peaks. Heart Rate is usually measured in beats per minutes. Obviously Heart Rate = 60/(R-R interval in second). This formula is valid only for regular ventricular rhythm. For irregular ventricular rhythm, time period for a fixed number of R waves (say five waves) is measured to calculate average R-R interval.

An analysis of beat-to-beat variations in heart rate and blood pressure provides an important tool for understanding cardiovascular regulation. The availability of this non-invasive tool to explore the changing dynamics of individual cardiovascular regulation profile might lead to a deeper understanding of the role of the neural mechanisms in cardiovascular medicine and may help improve the efficiency of targeted medical treatment. However, variations in beat-to-beat heart rate have also been reported in relation to ageing, even in subjects without heart disease [Singh *et al.*, 2006].

P-duration is determined from onset of p-wave to its termination, while **P-R interval** is measured from onset of P-wave to that of QRS complex. **P-amplitude** is measured as the height of P-wave from baseline. **QRS-interval** is defined from onset of Q wave to termination of S-wave. **Ventricular Activation Time (VAT)** is the time taken by the impulse to traverse the myocardium from the endocardial to the epicardial surface and is measured from beginning of Q wave to peak of R-wave. **R-amplitude** is measured as the height of R-wave from baseline. **Q-T interval** is measured from start of Q wave to end of T wave and is measure of electrical systole. **T-amplitude** is measured as the height of T-wave from baseline.

All ECG machines run at a standard rate of 25mm/s and use paper with standard 5mm size squares. As shown in figure 5.1, each large square (5 mm) represents 0.2 second or 200 millisecond. This means there are five large squares in one second and therefore 300 per minute. Similarly along y-axis, one large square represents 1 mV of signal amplitude. This standardization greatly helps in determining the diagnostic parameters. For example, Heart Rate can be simply estimated by checking the number of large squares between two QRS complexes. If there is only one large square between two QRS complexes, then Heart Rate is 300/minute, for two large squares, it is 150 and so on. This is shown in figure 5.2 and tabulated in table 5.1 [Hampton, 2003; Dubin, 2006].

TABLE 5.1: Quick estimation of Heart Rate

R-R interval (in large squares)	Heart Rate (beats per minute)
1	300
2	150
3	100
4	75
5	60
6	50

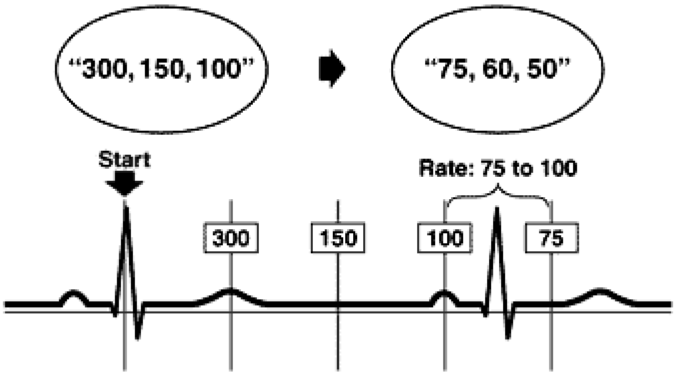


Figure 5.2: Quick estimation of Heart Rate

Same technique is applied to estimate other intervals, using 40 ms for each small square. As we know that P-R interval is the time taken for excitation to spread from the SA node, through the atrial muscle and the AV node, down the bundle of His and into ventricular muscle, the normal P-R interval is 0.12-0.2 s (120-200 ms). This very conveniently gets translated into 3-5 small squares. A physician is trained to read the ECG trace counting these squares, rather than going in for actual timing intervals. This is possible only because of standardization of the ECG recordings. Practical understanding of the routine twelve lead ECG and the display on cardiac monitors provides an invaluable diagnostic skill for physicians and every physician is expected to possess a reasonable level of expertise and skill in electrocardiography. In emergencies, the ECG is the mainstay for evaluating minute-to-minute changes in vital cardiac function during life-and-death crises. For the same reason, the cardiac monitors displaying the heart's electrical messages are standardized equipment used in critical care and emergency areas. Instant interpretation of ECG from either a monitor or a paper record is of utmost importance to save the life a patient under critical conditions. A typical twelve-channel ECG recording with 1 mV, 0.2 s calibration pulse is shown in figure 5.3.

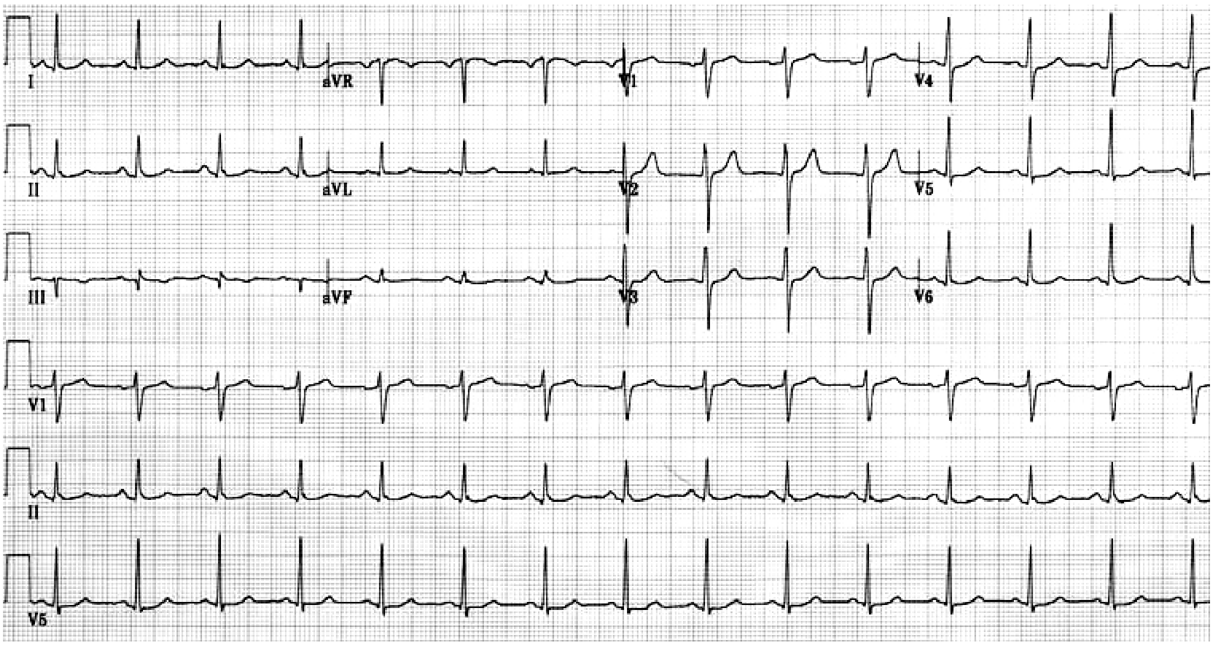


Figure 5.3: Twelve-channel ECG record with 1 mV, 0.2 s calibration pulse

5.2 REPORTING AN ECG

An ECG is reported by taking into account systematically the diagnostic features from a multi-channel (say 12 channel) ECG record. Its description is almost invariably given in the strict sequence as below:

(a) Rhythm
(b) Conduction Intervals
(c) Cardiac Axis
(d) Description of QRS complexes
(e) Description of ST segments and T waves

The ECG reported in this fashion is much easier to interpret. Using these diagnostic parameters, computerized processing of ECG has also been reported [Desai and Saxena, 1984]. Definition of conduction intervals is already covered in the diagnostic parameters. The remaining four items are briefly discussed as under:

5.2.1 Rhythm

The primary function of heart is to pump blood to the various parts of the body by sequential contraction of cardiac muscles. The contraction of any muscle, including cardiac muscles, requires electrical stimulation. In Heart, the electrical signal for these contractions normally originates near the top of the right atrium at point called sinoatrial (SA) node. When depolarization begins in the SA node, the heart is said to be in the sinus rhythm. However, depolarization can begin in other places too. The rhythm is then named after that part of the heart where the depolarization begins, and an arrhythmia is said to be present [Gilmour, 2004]. Points other than sinoatrial node, where the cardiac rhythms can begins are Atrial muscle, AV node and Ventricular muscle.

Starting of these rhythms at these unusual places is rather in the overall interest of the human being. If the SA node fails to depolarize, control is taken over by either atrial muscles or the region around AV node. If however they also fail to respond or the conduction is blocked, ventricular focus takes over. Since these rhythms are slower than the normal, these are called 'bradycardias'. If the rate of depolarization of SA node slows down and control is taken over by Atrium of the heart, the rhythm is called 'atrial escape'. In general 'escape' beats means late beats and 'premature' means early beats. Main characteristic of Atrial escape rhythm is different appearing and late P wave, as seen in figure 5.4. If the cardiac rhythm begins around AV node, the rhythm is called 'nodal' or 'junctional' escape. Here the P wave is conspicuously missing but the QRS complex is normal. Figure 5.5 shows all nodal escape beats. Missing P-wave and wide and bizarre QRS complex, as shown in figure 5.6, characterize ventricular escape beats.

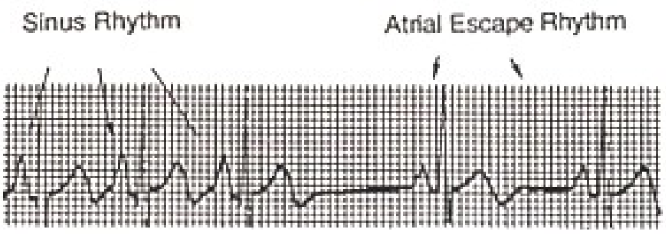


Figure 5.4: Atrial Escape rhythm.

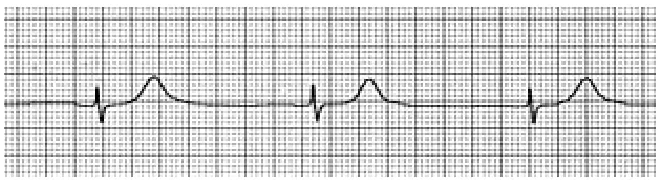


Figure 5.5: Nodal escape rhythm

Figure 5.6: Ventricular escape rhythm

Many a times, a part of heart depolarizes earlier than it should, then the accompanying great beat is called an extrasystole. If this premature contraction originates form abnormal location, the beat is termed as “ectopic”. Like escape beats, extrasystoles may arise from atrial muscles, AV node or ventricular muscles. Atrial extrasystoles have abnormal P-waves (figure 5.7), nodal extrasystoles either have no P-wave or it appears immediately before or immediately after QRS complex (figure 5.8) the shape of QRS complexes in all the cases is normal [Schamroth, 1990]. Ventricular extrasystoles arise within an ectopic focus within the ventricular muscle; the QRS complex is wide, bizarre, and unrelated to a preceding P wave (figure 5.9). Ventricular extrasystole is also known as Premature Ventricular Contraction (PVC).

Figure 5.7: Atrial extrasystole

Figure 5.8: Junctional (nodal) extrasystoles

Figure 5.9: Ventricular extrasystole

Another type of rhythm is flutter. In a type of flutter called atrial flutter, the atrial rate is more than 250 /minute and there is no flat baseline between the P-waves as shown in figure 5.10. The trace thus has a saw-tooth like appearance.

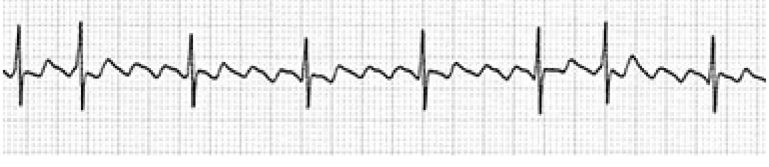


Figure 5.10: Atrial flutter

All rhythms discussed till now involved synchronous contraction of muscle fibres, tough at different speeds (fast or slow). When the individual muscle fibres start contacting independently, they are said to be in “fibrillation”. Traces of atrial fibrillation and ventricular fibrillation are shown in figure 5.11 and figure 5.12 respectively. The main difference between atrial and ventricular fibrillation is marked by total absence of QRS complex in the trace, thereby producing a disorganized wave.

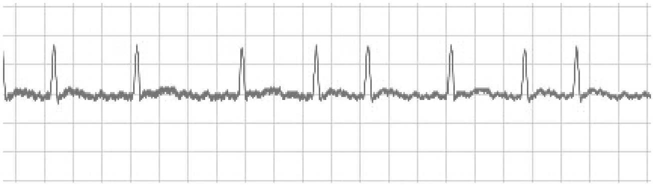


Figure 5.11: Atrial fibrillation

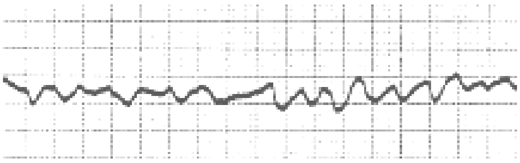


Figure 5.12: Ventricular fibrillation

5.2.2 Cardiac Axis

The electric field generated at the heart is a vector whose magnitude and spatial orientation varies during each cycle. The main heart axis, which is taken as the average vector for the electric field that may normally vary between - 60° and + 110° with the horizontal zero line. While ECG trace is seen as the projection of this vector on the designated lead as shown in figure 5.13, the recorded ECG signals can be used to reconstruct this vector and know the axis of the average vector.

As shown in figure 5.13, the leads V_R and Lead II look at the heart from opposite directions. Seen from the front, as the depolarization vector moves through ventricles the deflections in lead V_R are normally negative and that in lead II are normally positive.

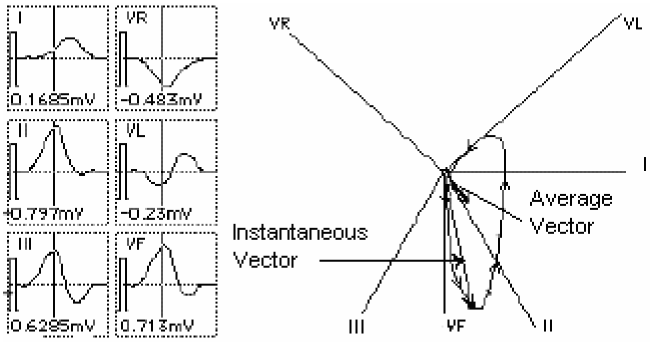


Figure 5.13: Electric field vector and the ECG traces

This is evident in figure 5.13 and in figure 5.3 for multi-channel recording of ECG. The average depolarization vector, which is termed as cardiac axis, has normal limts of -30° to +90°. This is shown in figure 5.14

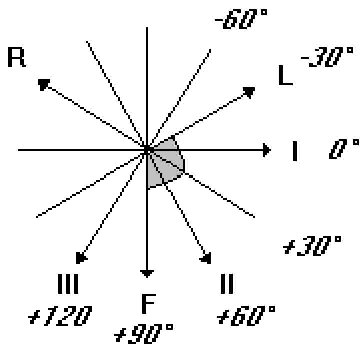


Figure 5.14: Limits of normal cardiac axis

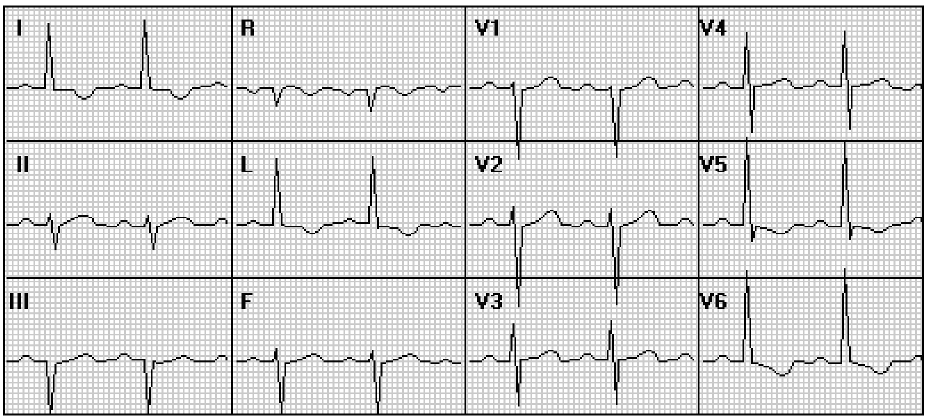


Figure 5.15: Left axis deviation

When the left ventricle becomes hypertrophied, the axis may swing to the left. This results in QRS complex becoming predominantly negative in lead III. When the normal limit of -30° is crossed, deflection becomes predominantly negative in Lead II also. This condition is known as Left Axis Deviation (LAD) and is shown in figure 5.15. The problem however, is usually due to conduction defect rather than due to increased mass in the left ventricle muscle.

A simpler way to estimate the cardiac axis is to know that the axis is at right angle to the lead in which R and S wave are of equal size (refer figure 5.14). Similarly when the patient is associated with pulmonary conditions that put strain on the right side of the heart, or is having congenital heart disorder, the right ventricle becomes hypertrophied. The lead I becomes predominantly negative while lead II becomes predominantly positive, resulting in Right Axis Deviation (RAD).

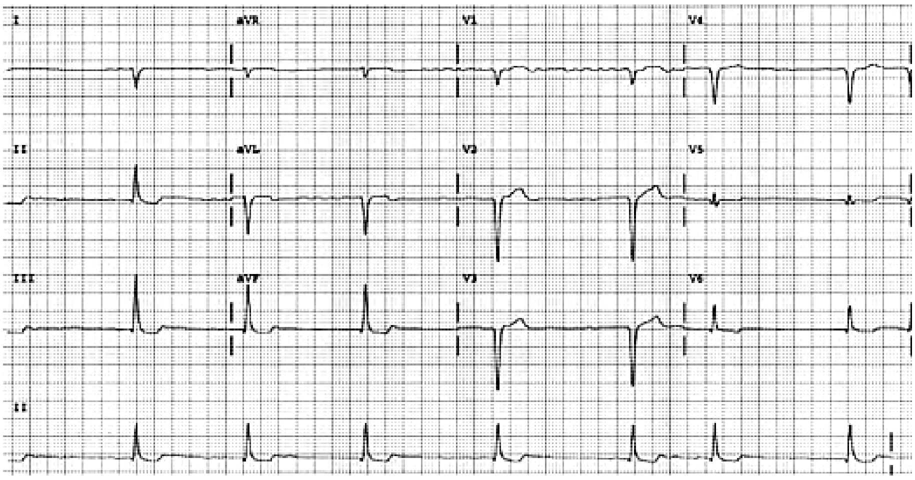


Figure 5.16: Right axis deviation

5.2.3 Description of QRS complexes

The QRS complex is said to be normal in adults, if the following conditions are fulfilled:

(a) Its duration is smaller than three small squares i.e. 120 ms

(b) S wave is greater than R wave in V1

(c) Height of R wave is less than 25 mm i.e. 2.5 mV

(d) Left ventricular leads (V5 and V6) may have Q waves, but should be less than 1mm across i.e. 40 ms duration and 2 mm deep, i.e. 0.2 mV in amplitude

Any deviation from these standards warrants physicians attention and has to be reported accordingly. Abnormally wide QRS complex indicate slow pathway, increased height of QRS complex indicate increase in the muscle mass in either ventricle, leading to increased electrical activity, a deeper and wider Q wave as seen in figure 5.17, indicates Myocardial Infarction (MI) or what is commonly known as heart attack and so on. With Right Ventricular Hypertrophy, the large R wave of V1 gets progressively smaller from V2 to V3 to V4 etc. [Dubin, 2006] and is shown in figure 5.18

Figure 5.17: Wider and deeper Q wave indicating infarction

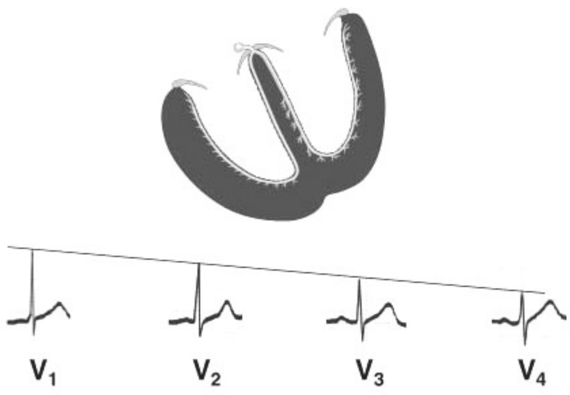


Figure 5.18 : R-wave amplitude and Right ventricular hypertrophy

5.2.4 Description of ST segments and T waves

As seen in figure 5.1, the ST segment lies between the QRS complex and the T-wave. Ideally is should be isoelectric, i.e. the same level as the part between the T-wave and the next P–wave. However, this segment may be depressed or elevated as shown in figures 5.19 and 5.20.

Figure 5.19: Elevated ST segment

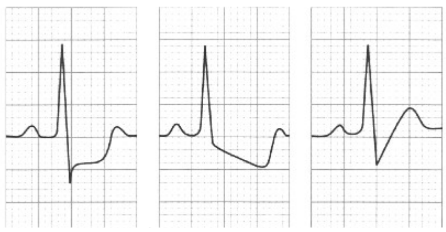


Figure 5.20: Depressed ST segments

Elevated ST segment indicates acute myocardial injury, either due to recent myocardial infarction or due to pericarditis. The lead in which it occurs is indicative of the part of heart that is affected. Horizontally depressed ST segment indicates ischaemia, i.e. restriction in blood supply, with the resultant damage or dysfunction of tissues.

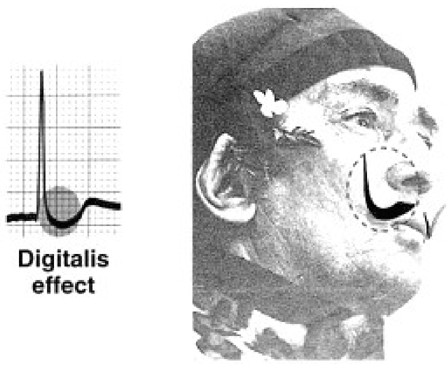


Figure 5.21: Down-sloping ST segment

Digoxin is a cardiac glycoside extracted from a plant Digitalis, that has finger shaped flowers and is prescribed for various heart conditions like atrial fibrillation, atrial flutter etc. Its use causes a gradual down-sloping of the ST segment, to give it the appearance of famous Spanish painter Salvador Dali's mustache, as shown in figure 5.21 [Dubin, 2006].

T-wave, which is normally upright, may be get inverted in some cases. T wave inversion in V1 and aV_R is taken as normal. In young people, T-wave inversion in V2 is also taken as normal. T-wave inversion in other waves is caused by myocardial infarction. MI also results in elevated ST-segment, which returns to normal level after 24 hours, but the T-wave inversion is permanent. Left ventricular hypertrophy also causes T-wave inversion in V5, V6, II and aV_L leads. An inverted T-wave is shown in figures 5.19 and 5.22.

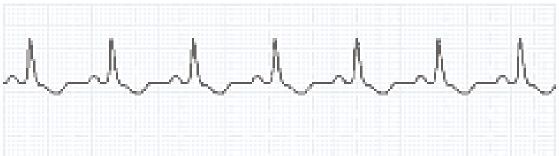


Figure 5.22: Inverted T-wave

5.3 INTERPRETATION OF ECG

Interpreting an ECG is more of an art that has to be acquired in years of practice. An experienced cardiologist may interpret an ECG in a cursory glance, what may take several minutes for a novice physician, though the basis is the same for both of them. After observing the rhythm, conduction intervals, cardiac axis QRS complexes, ST-segment and T-waves, the most important thing is to interpret whether the record is normal or abnormal. In case the record shows some abnormality, the underlying pathology needs to be identified. There are numerous rules that need to be judiciously applied to interpret an ECG. Some of them have been knowingly discussed in the previous section. Stressing on prominent Q waves, isoelectric ST segment and inverted T-waves discussed above, a self explanatory ECG report with its interpretation is given below as an illustration:

An ECG reports (a) Sinus rhythm

(b) Normal PR interval

(c) Normal axis

(d) QRS complex – Q waves in leads II, III, aV_F

(e) ST segment isoelectric

(f) T wave inversion in leads II, III and aV_F

Interpretation: Inferior myocardial Infarction, probably an old one.

A greater detail is beyond the scope of the present work, and is left to the physicians to correctly interpret the ECGs. In our work the main emphasis is on correct reproduction of diagnostic features in the reconstructed ECG signal as compared to the original signal. It is desired that the interpretation of ECG signal should not change upon compressing and reconstructing the ECG signal. This is called human visual inspection for clinical validation and is best done by a physician.

5.4 NEED OF REFINEMENT CRITERION IN ECG COMPRESSION

The most efficient ECG wavelet compression method uses SPIHT algorithm in the following manner [Lu *et al.,* 2000]:

(i) The ECG signal is decomposed in two half-frequency bands; a lower and an upper half

(ii) While the upper half is retained as such, the lower half is again decomposed

(iii) The process decomposition is repeated for a fixed number of times, six times

(iv) We now have six high frequency sub bands and only one low frequency sub band in the form of wavelet coefficients

(v) A common threshold 2^n is chosen in such a way that the highest value of 'n' has 2^n lesser than the highest coefficient

(vi) Comparing the current threshold value to the coefficients forms set of zeroes and ones; zero for the coefficient lesser than the current threshold and one for the coefficient greater than the current threshold

(vii) The current threshold is subtracted from greater coefficients, leaving the lesser coefficients untouched

(viii) Value of the current threshold is reduced to half and step (iv) onwards is repeated for a finite number of times

(ix) The set of zeroes and ones is passed on to the decoder, along with the value of 'n' and the process is reversed to get the reconstructed signal

Step (vi) and (vii) form one **refinement pass.** With each refinement pass, the distortion in the reconstructed signal reduces, the diagnostic parameters in the reconstructed signal approach that in the original signal, but at the same time the size of the compressed code also increases, thereby decreasing the compression ratio. Thus there is a need to find the optimum number of refinement passes, making a tradeoff between distortion and compression ratio. In a bid to find this number, the test data from MIT/BIH mitdb database [Goldberger *et al.,* 2000] was subjected to three, four, five, six and seven refinements. First 2048 samples from both the leads of patient 100, 101, 102, 103, 107, 118 and 119 were considered. The results for the diagnostic parameters and PRD, along with the graphical presentation of the signals are given in the subsequent pages. For diagnostic parameters, the following are considered (a) Heart rate in beats/minute (b) P-wave amplitude in millivolt (c) PR-interval in second (d) QRS interval in second (e) R-wave amplitude in millivolt (f) QT interval in second (g) Ventricular activation Time (VAT) in second (h) T-wave amplitude in millivolt (i) Percentage Root mean square Difference (PRD) in %age. Since the first 2048 samples may contain up to eight waves, the diagnostic parameters were extracted mostly from the first complete wave present in the trace.

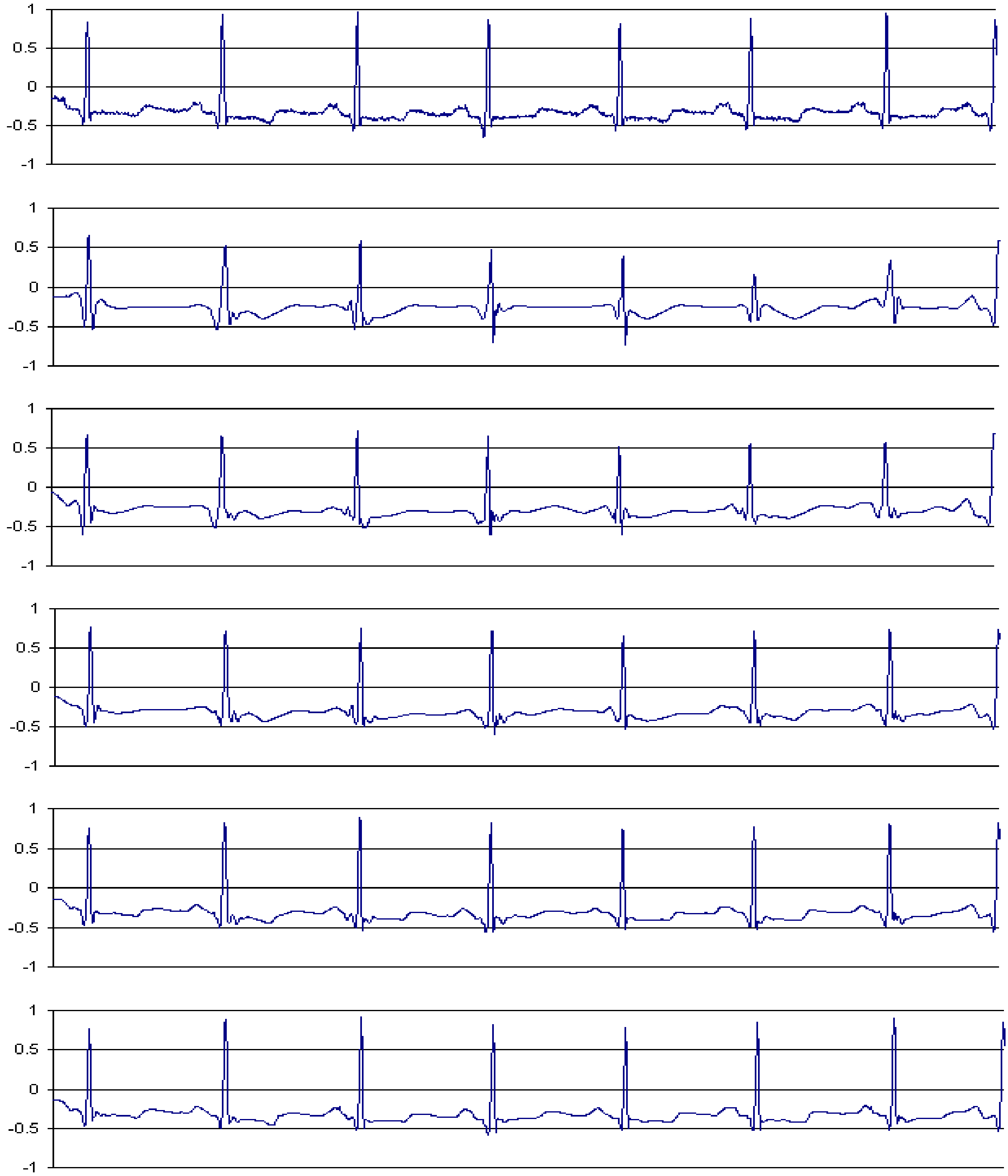


Figure 5.23: Patient 100 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

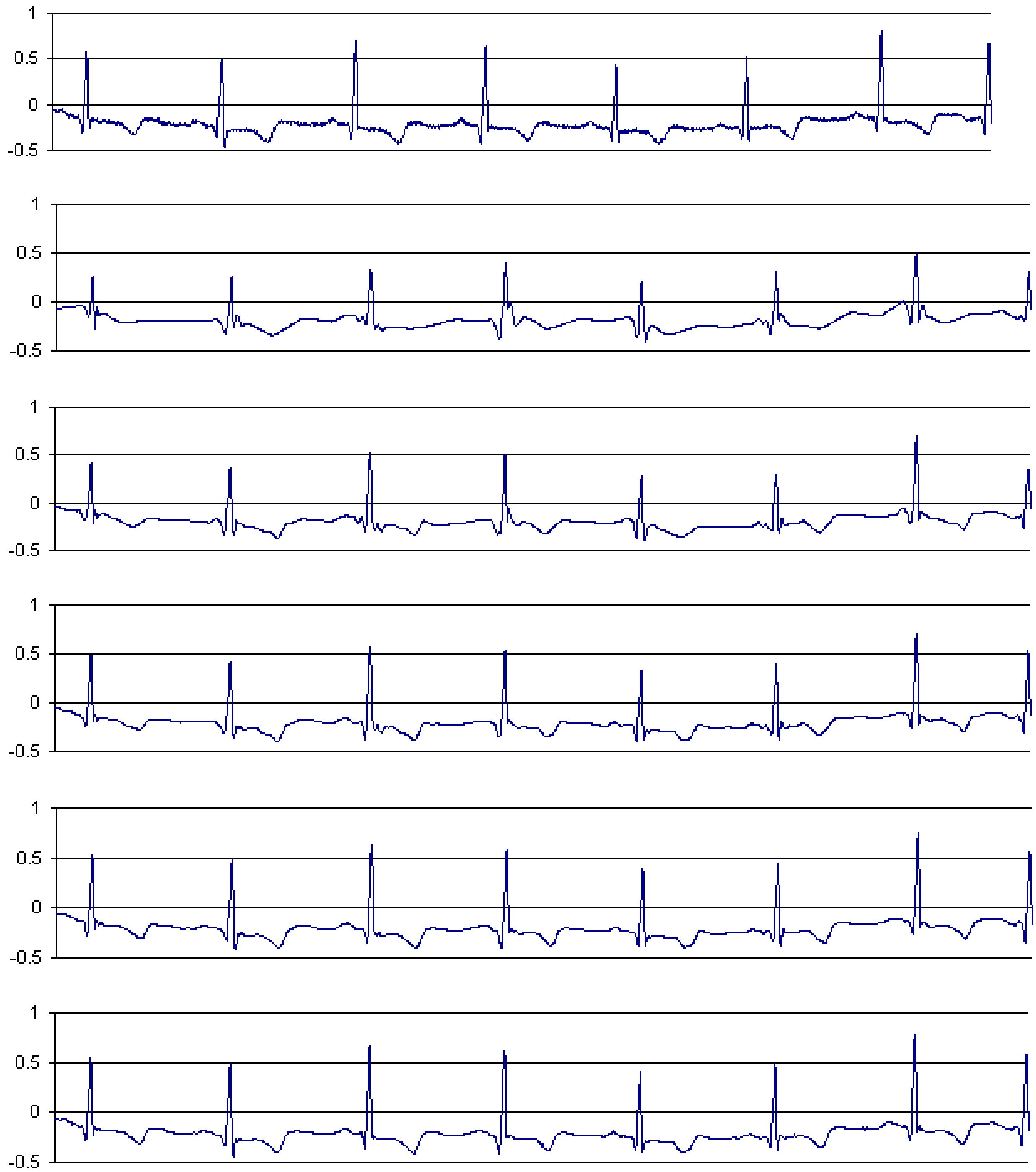


Figure 5.24: Patient 100 Lead V5 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.2: Diagnostic parameters for Patient 100 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	76.8	0.25	0.13	0.16	0.09	1.39	0.54	0.05	0.14	-
3 refine	76.8	0.14	0.11	0.12	0.13	0.89	0.63	0.09	0.14	66.05
4 refine	76.8	0.15	0.13	0.13	0.13	0.98	0.60	0.08	0.08	40.24
5 refine	76.8	0.15	0.13	0.16	0.11	1.11	0.56	0.06	0.10	25.95
6 refine	76.8	0.22	0.13	0.16	0.10	1.25	0.54	0.06	0.14	15.53
7 refine	76.8	0.23	0.13	0.16	0.09	1.31	0.54	0.05	0.15	9.65

Table 5.3: Diagnostic parameters for Patient 100 Lead V5

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	76.8	0.10	0.11	0.16	0.09	0.75	0.52	0.05	0.08	-
3 refine	76.8	0.06	0.05	0.05	0.09	0.50	0.54	0.05	0.07	56.48
4 refine	76.8	0.07	0.07	0.07	0.09	0.62	0.53	0.05	0.08	35.22
5 refine	76.8	0.06	0.08	0.09	0.09	0.64	0.53	0.05	0.09	21.47
6 refine	76.8	0.09	0.09	0.15	0.09	0.78	0.52	0.05	0.09	13.62
7 refine	76.8	0.09	0.09	0.14	0.09	0.73	0.52	0.05	0.08	9.63

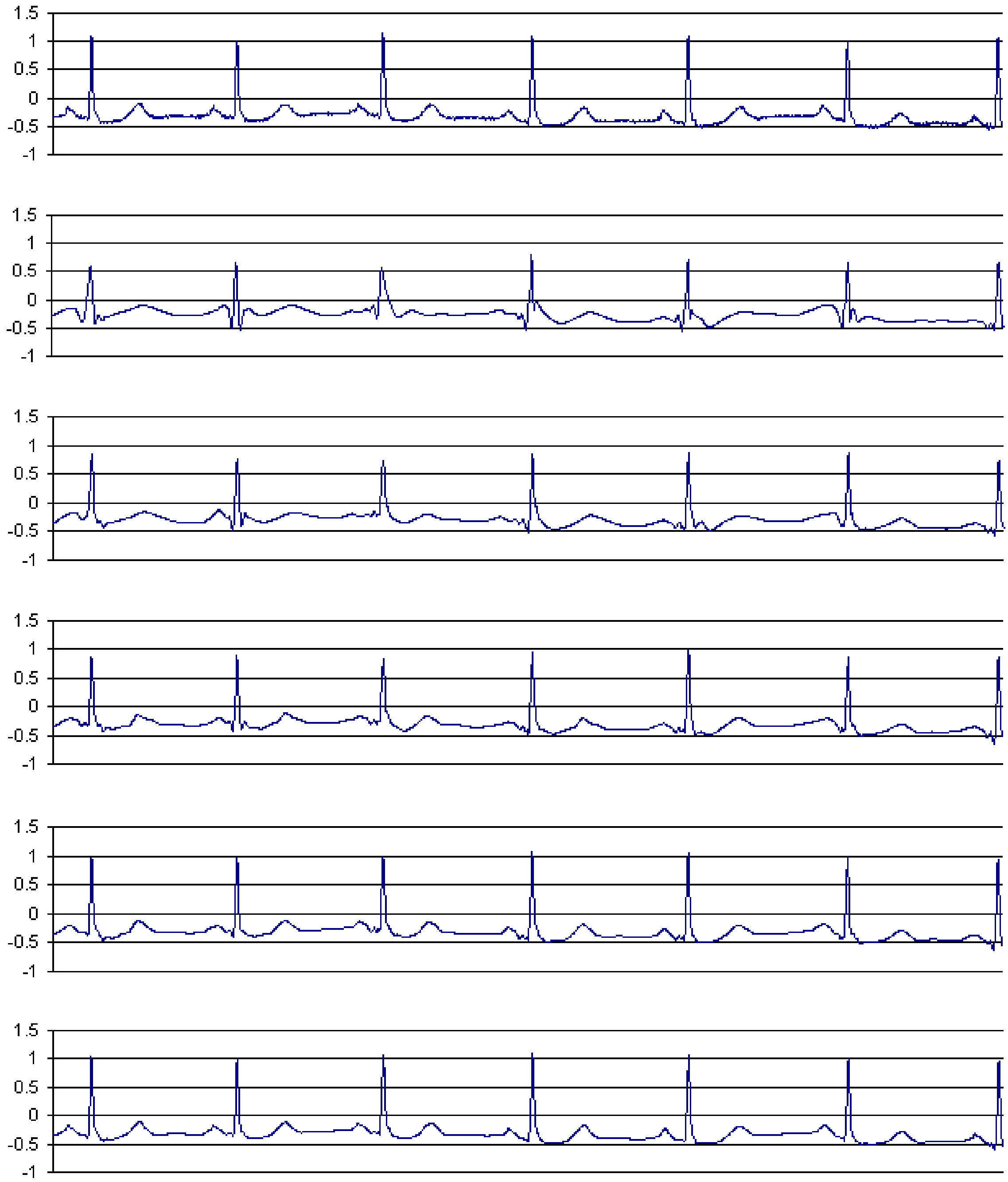


Figure 5.25: Patient 101 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

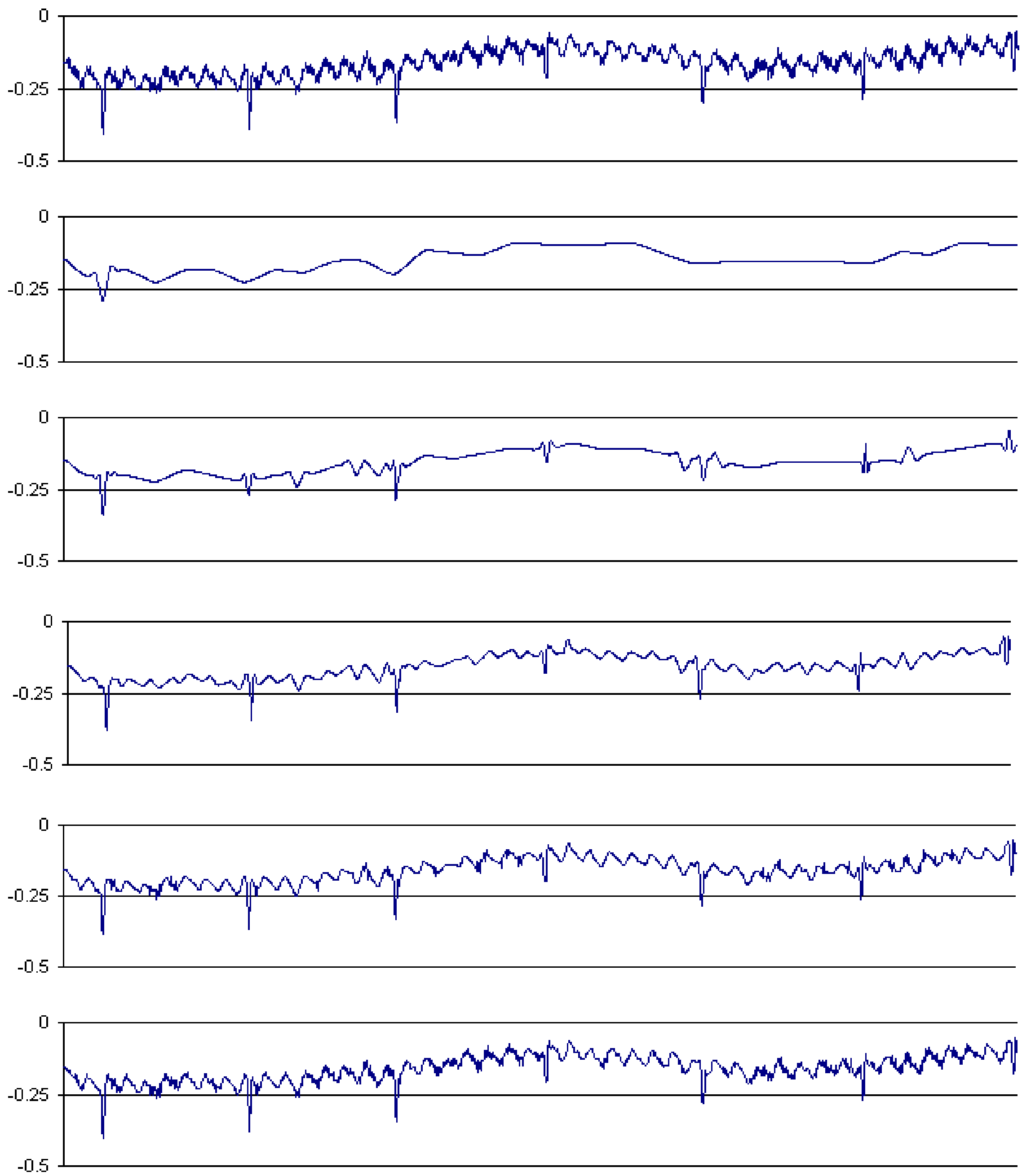


Figure 5.26: Patient 101 Lead V1 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.4: Diagnostic parameters for Patient 101 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD
original		0.16	0.12	0.15	0.09	1.34	0.41	0.03	0.20	-
3 refine	66.4	0.18	0.16	0.16	0.11	0.95	0.58	0.04	0.18	62.95
4 refine	66.4	0.22	0.15	0.16	0.09	1.12	0.54	0.04	0.18	37.91
5 refine	66.4	0.14	0.13	0.15	0.09	1.22	0.47	0.04	0.22	23.08
6 refine	66.4	0.14	0.13	0.16	0.09	1.31	0.41	0.03	0.23	14.10
7 refine	66.4	0.15	0.13	0.16	0.09	1.34	0.40	0.03	0.23	9.16

Table 5.5: Diagnostic parameters* for Patient 101 Lead V1

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	66.4	-	-	-	-	-	-	-	-	-
3 refine	-	-	-	-	-	-	-	-	-	65.86
4 refine	66.4	-	-	-	-	-	-	-	-	49.92
5 refine	66.4	-	-	-	-	-	-	-	-	35.99
6 refine	66.4	-	-	-	-	-	-	-	-	24.55
7 refine	66.4	-	-	-	-	-	-	-	-	15.34

*Because of low strength and irregularity in the signal, regular parameters could not be extracted

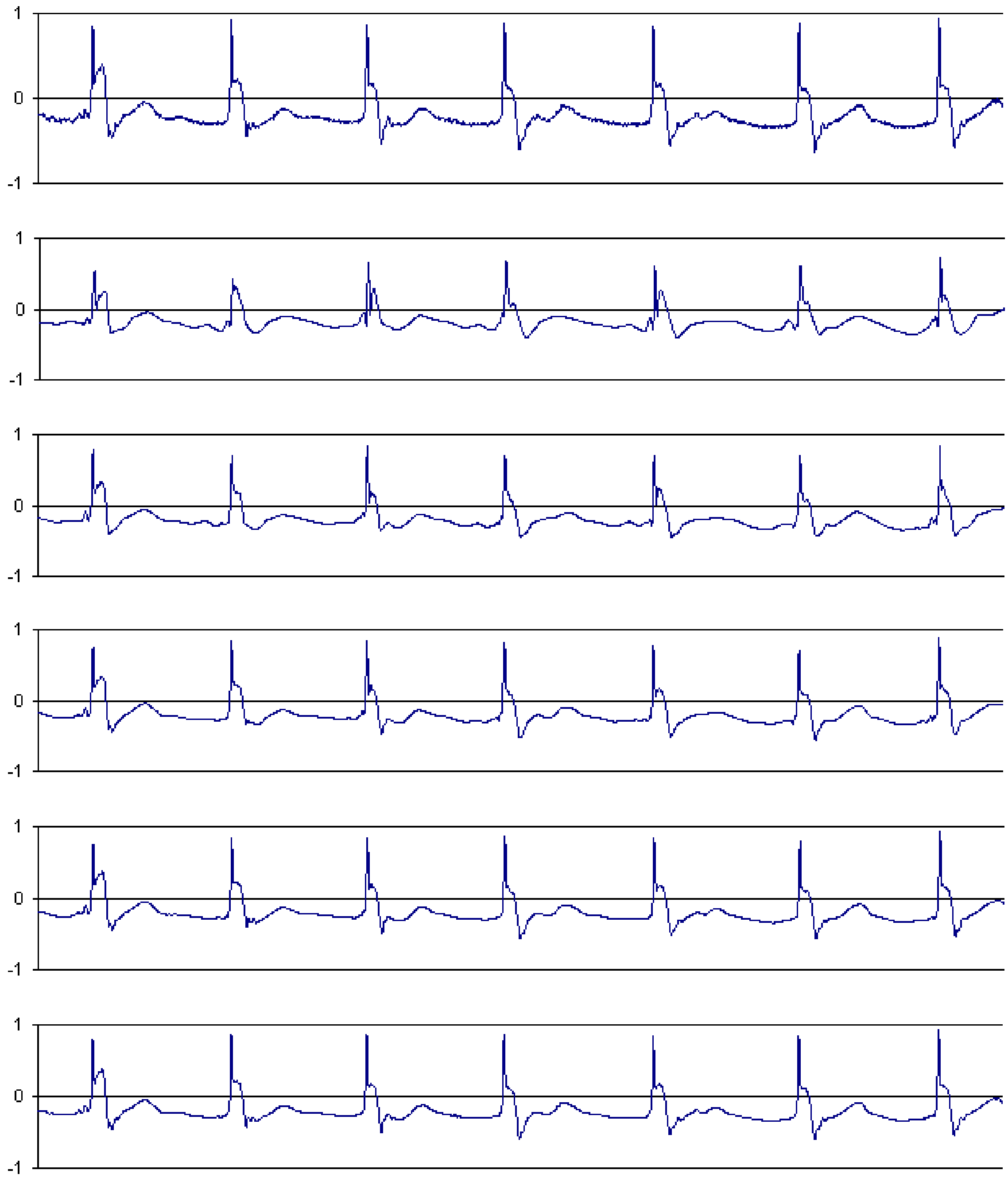


Figure 5.27: Patient 102 Lead V5 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

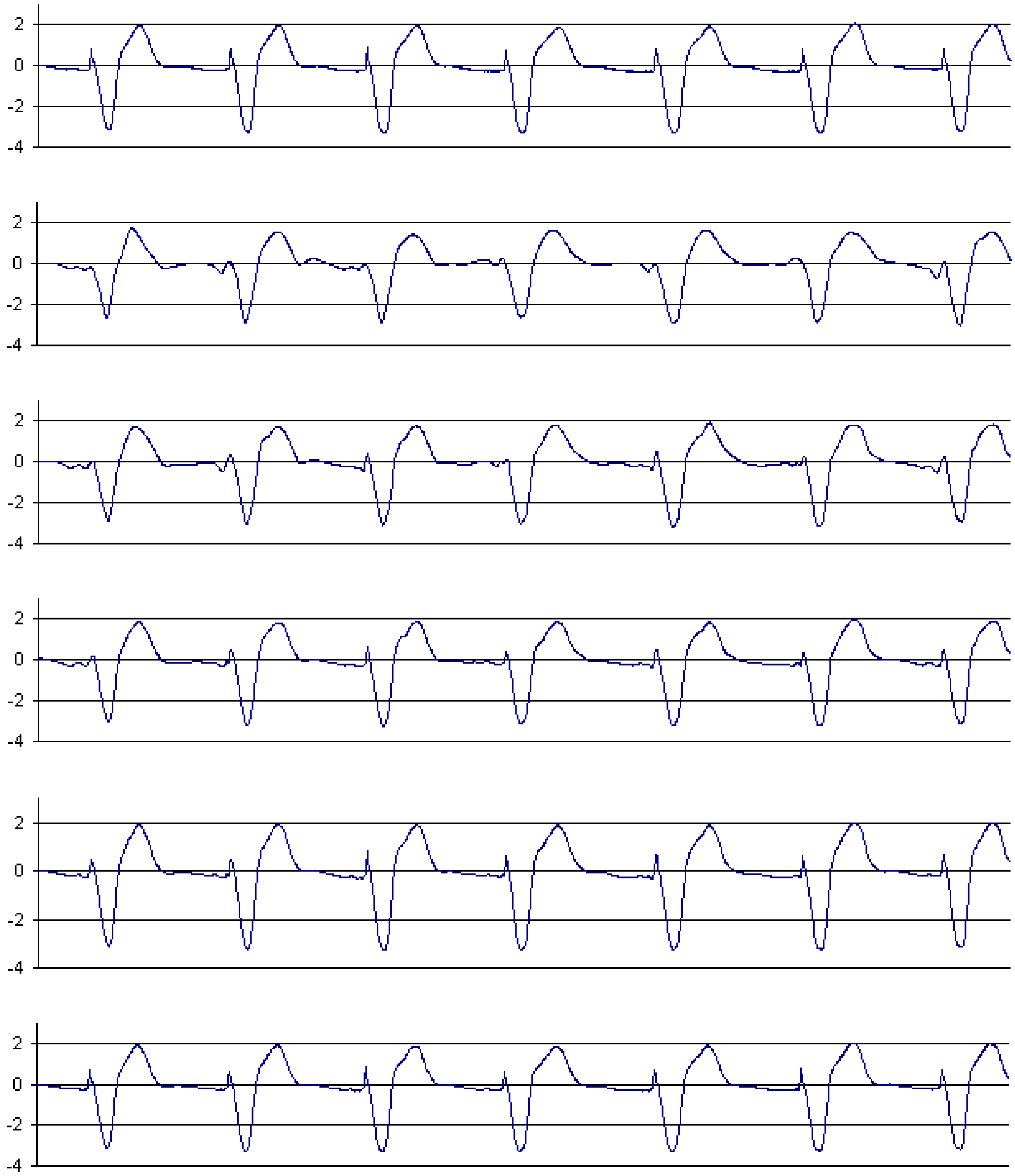


Figure 5.28: Patient 102 Lead V2 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.6: Diagnostic parameters for Patient 102 Lead V5

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	72.2	0.00	NA	NA	0.13	1.16	0.42	0.02	0.16	-
3 refine	72.2	0.04	0.11	0.18	0.23	0.69	0.58	0.02	0.16	43.62
4 refine	72.2	0.03	0.12	0.17	0.14	0.96	0.57	0.04	0.12	24.85
5 refine	72.2	0.00	NA	NA	0.13	1.14	0.42	0.03	0.16	14.57
6 refine	72.2	0.00	NA	NA	0.13	1.14	0.42	0.03	0.17	9.54
7 refine	72.2	0.00	NA	NA	0.13	1.15	0.42	0.03	0.16	6.11

Table 5.7: Diagnostic parameters for Patient 102 Lead V2

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	72.2	0	NA	NA	0.20	0.82	0.44	0.03	2.06	-
3 refine	72.2	0.25	0.48	0.48	0.26	0.29	0.49	0.08	1.77	25.49
4 refine	72.2	0.16	0.14	0.14	0.25	0.54	0.48	0.07	1.92	14.40
5 refine	72.2	0	NA	NA	0.22	0.60	0.45	0.04	1.98	7.87
6 refine	72.2	0	NA	NA	0.21	0.63	0.45	0.03	2.02	4.46
7 refine	72.2	0	NA	NA	0.21	0.61	0.45	0.03	2.01	2.68

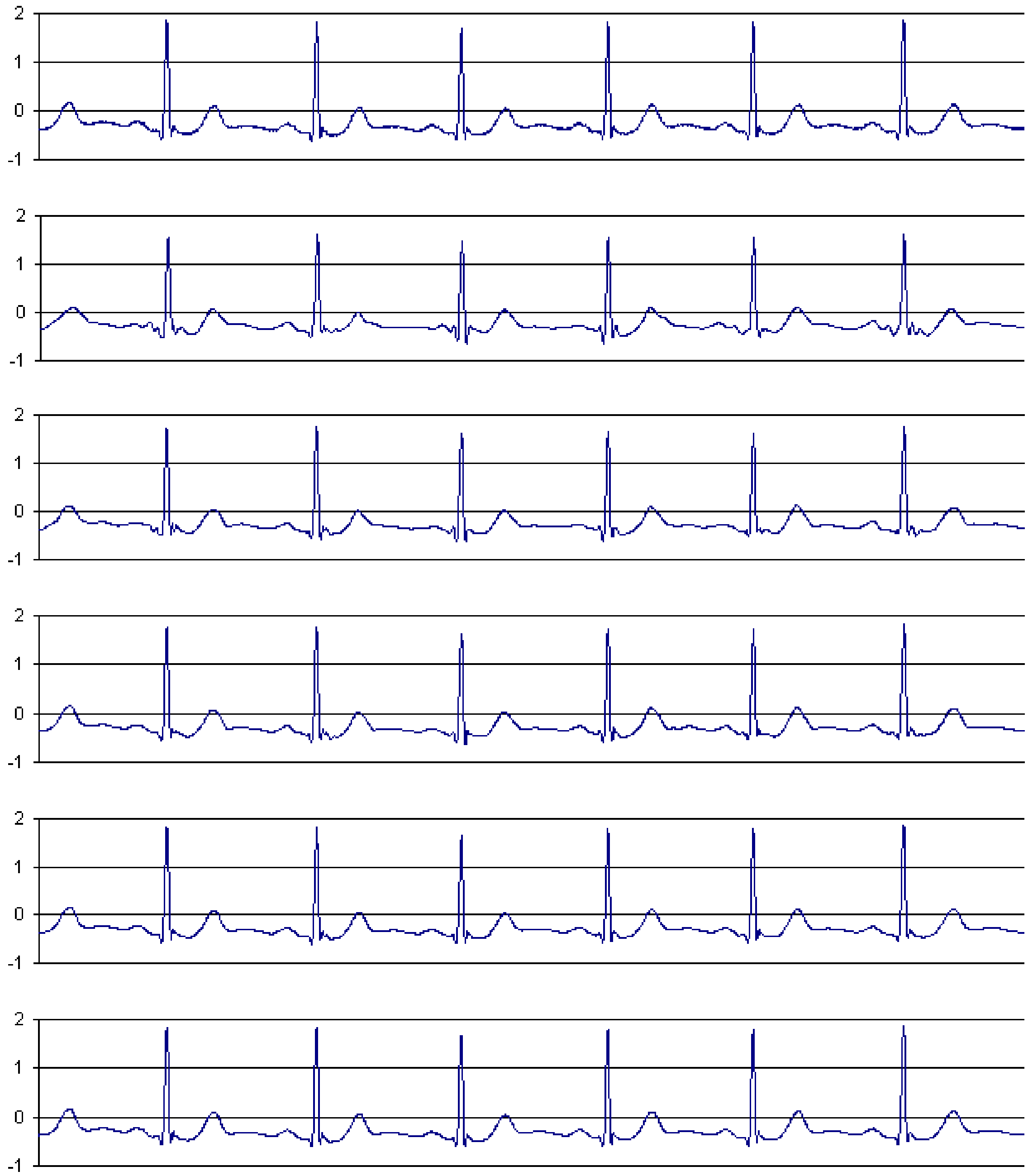


Figure 5.29: Patient 103 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

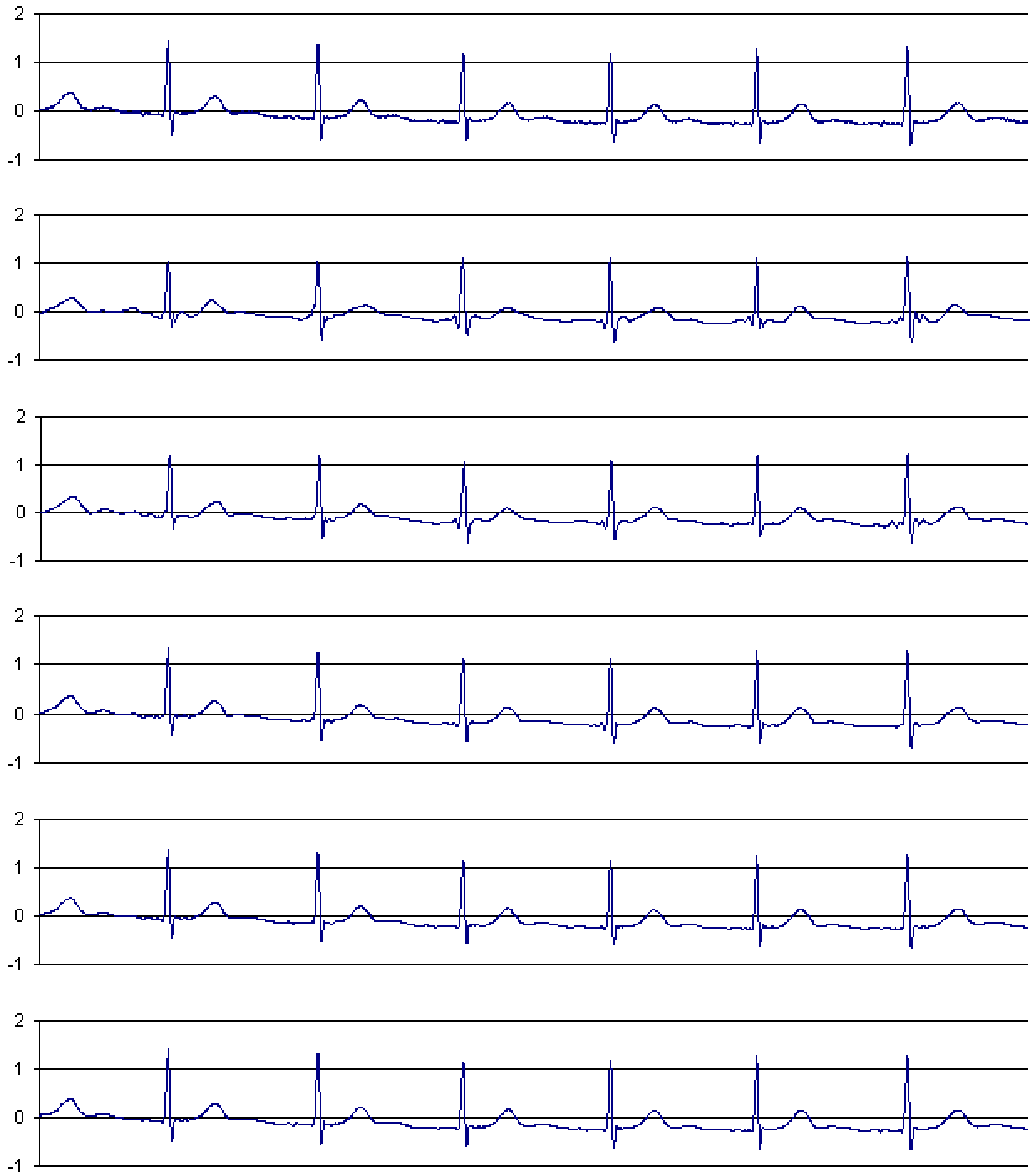


Figure 5.30: Patient 103 Lead V2 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.8: Diagnostic parameters for Patient 103 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	70.6	0.15	0.14	0.20	0.08	2.24	0.39	0.04	0.50	-
3 refine	70.6	0.14	0.16	0.22	0.09	1.98	0.28	0.05	0.38	27.74
4 refine	70.6	0.11	0.15	0.21	0.09	2.10	0.40	0.04	0.41	15.04
5 refine	70.6	0.13	0.14	0.20	0.08	2.19	0.39	0.04	0.46	9.00
6 refine	70.6	0.14	0.14	0.20	0.08	2.22	0.39	0.04	0.47	5.40
7 refine	70.6	0.14	0.14	0.20	0.08	2.23	0.39	0.04	0.48	3.69

Table 5.9: Diagnostic parameters for Patient 103 Lead V2

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	70.6	0	NA	NA	0.07	1.43	0.37	0.03	0.29	-
3 refine	70.6	0.08	0.09	0.15	0.14	1.04	0.45	0.11	0.23	33.67
4 refine	70.6	0.03	0.06	0.13	0.14	1.18	0.44	0.10	0.21	19.70
5 refine	70.6	0	NA	NA	0.08	1.31	0.38	0.04	0.25	11.58
6 refine	70.6	0	NA	NA	0.08	1.34	0.38	0.04	0.27	7.40
7 refine	70.6	0	NA	NA	0.08	1.41	0.38	0.04	0.28	5.10

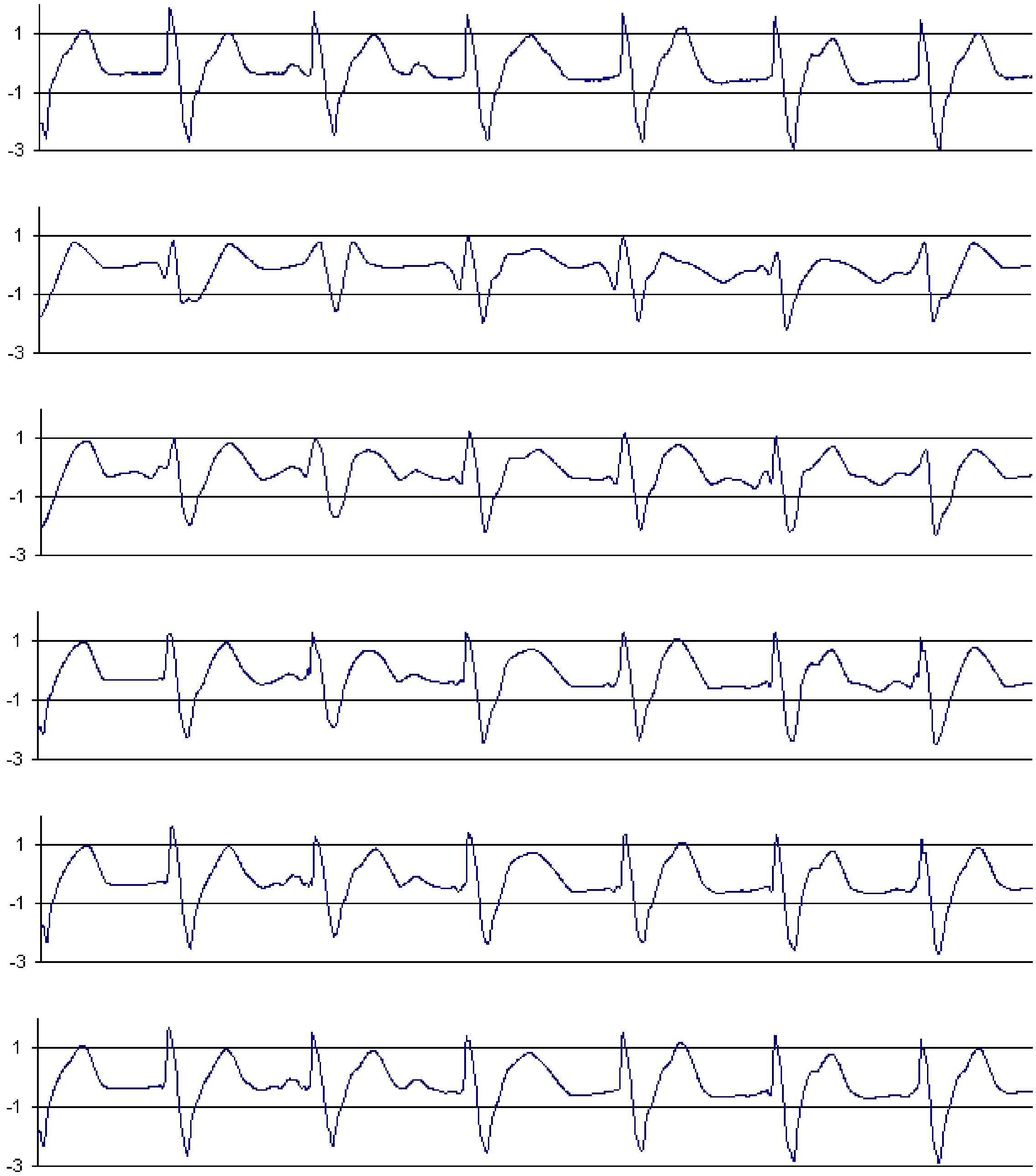


Figure 5.31: Patient 107 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

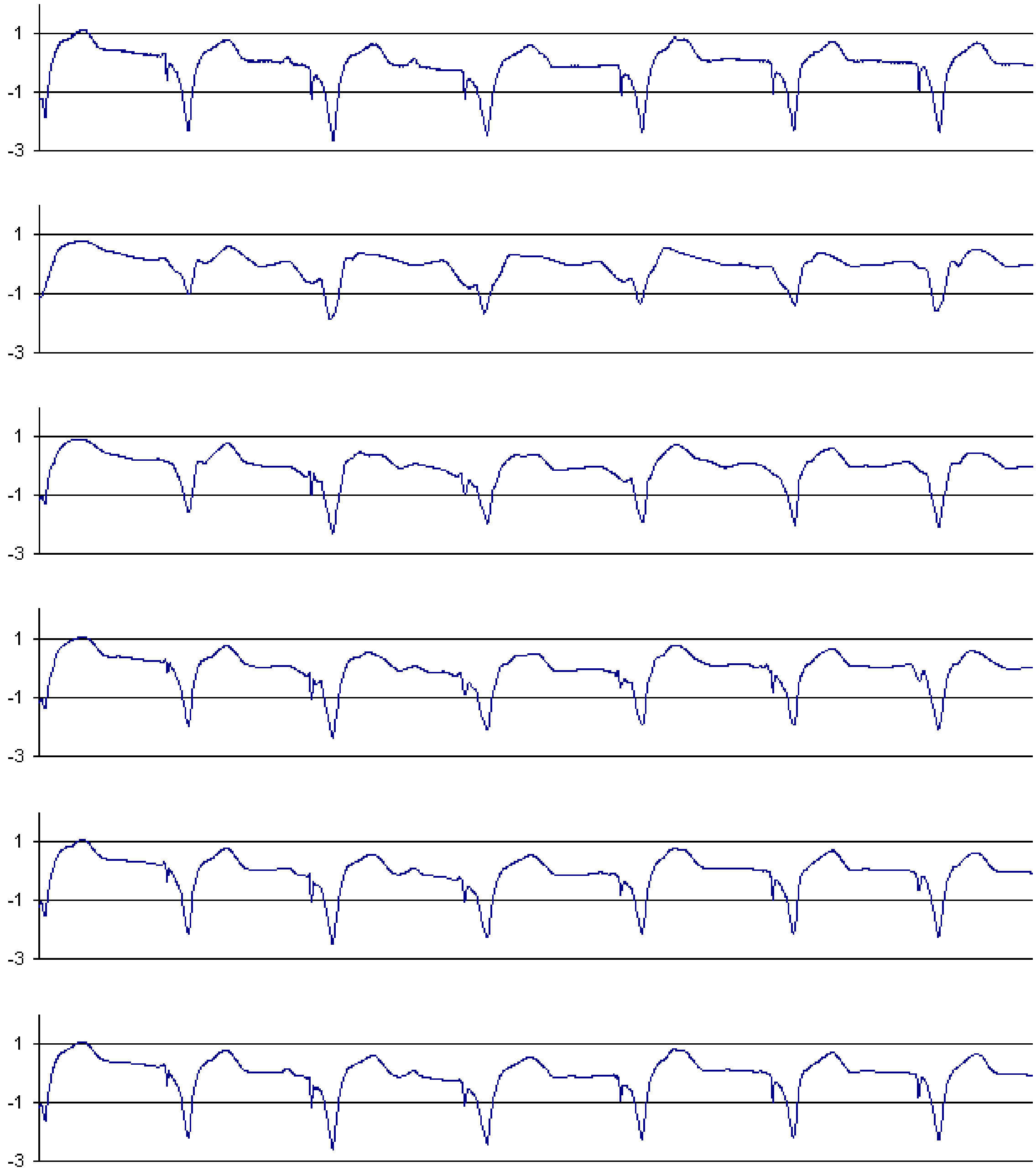


Figure 5.32: Patient 107 Lead V1 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.10: Diagnostic parameters for Patient 107 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	69.8	0	NA	NA	0.21	2.36	0.55	0.04	1.40	-
3 refine	69.8	0.16	0.13	0.13	0.18	0.89	0.56	0.08	0.76	56.76
4 refine	69.8	0.95	0.12	0.17	0.24	1.12	0.59	0.08	1.02	33.40
5 refine	69.8	0	NA	NA	0.26	1.75	0.59	0.06	1.26	19.64
6 refine	69.8	0	NA	NA	0.22	2.05	0.56	0.05	1.34	11.85
7 refine	69.8	0	NA	NA	0.22	2.09	0.56	0.05	1.37	6.96

Table 5.11: Diagnostic parameters for Patient 107 Lead V1

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	69.8	0.10	0.02	0.03	0.22	-0.27	0.50	0.02	0.56	-
3 refine	69.8	0.06	0.10	0.10	0.17	-0.51	0.51	0.06	0.46	40.38
4 refine	69.8	0.04	0.11	0.14	0.15	-0.19	0.48	0.01	0.57	22.83
5 refine	69.8	0.06	0.05	0.07	0.22	-0.08	0.51	0.03	0.55	14.84
6 refine	69.8	0.09	0.03	0.04	0.22	-0.19	0.51	0.02	0.57	8.27
7 refine	69.8	0.09	0.03	0.04	0.22	-0.16	0.51	0.02	0.59	5.29

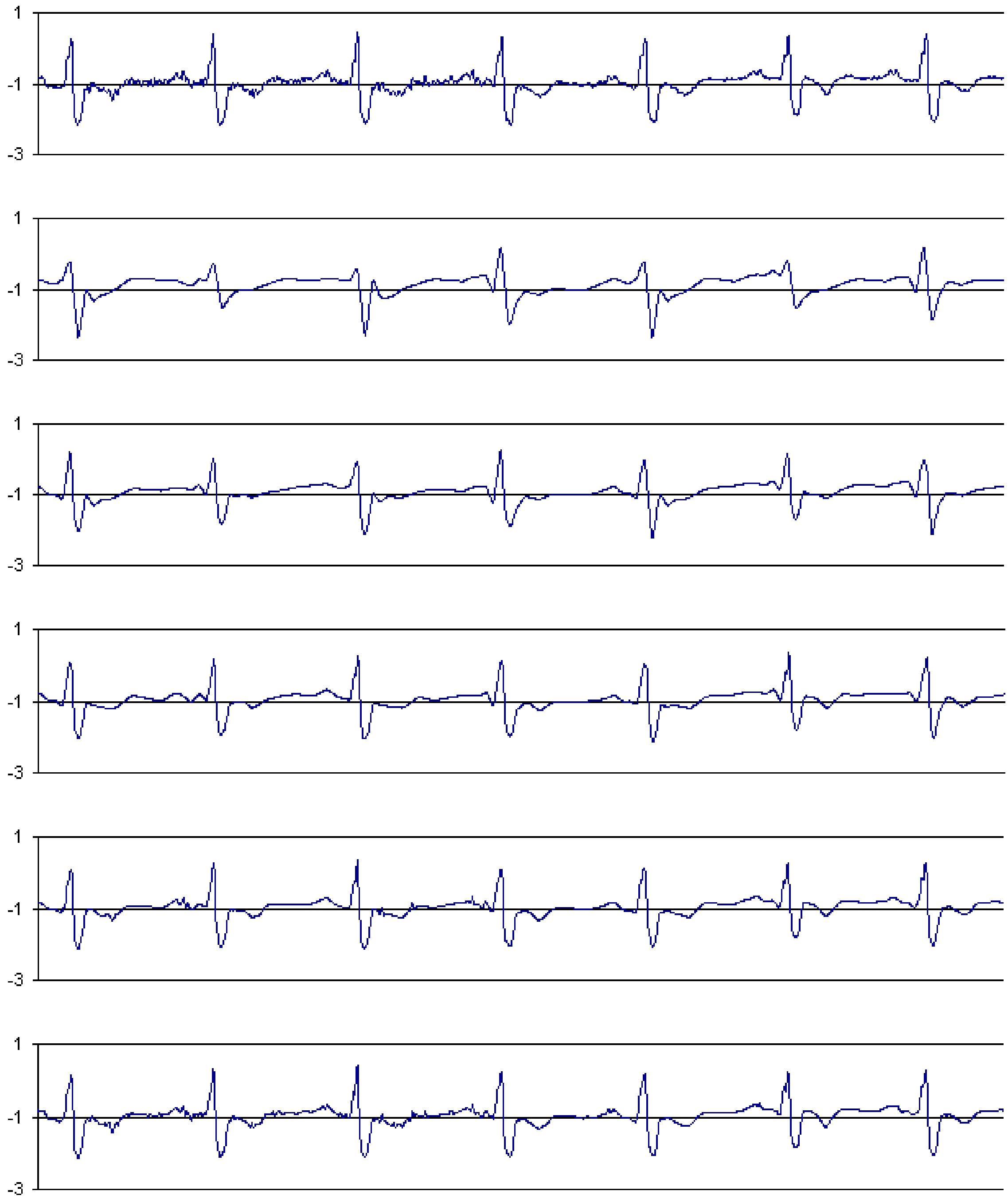


Figure 5.33: Patient 118 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

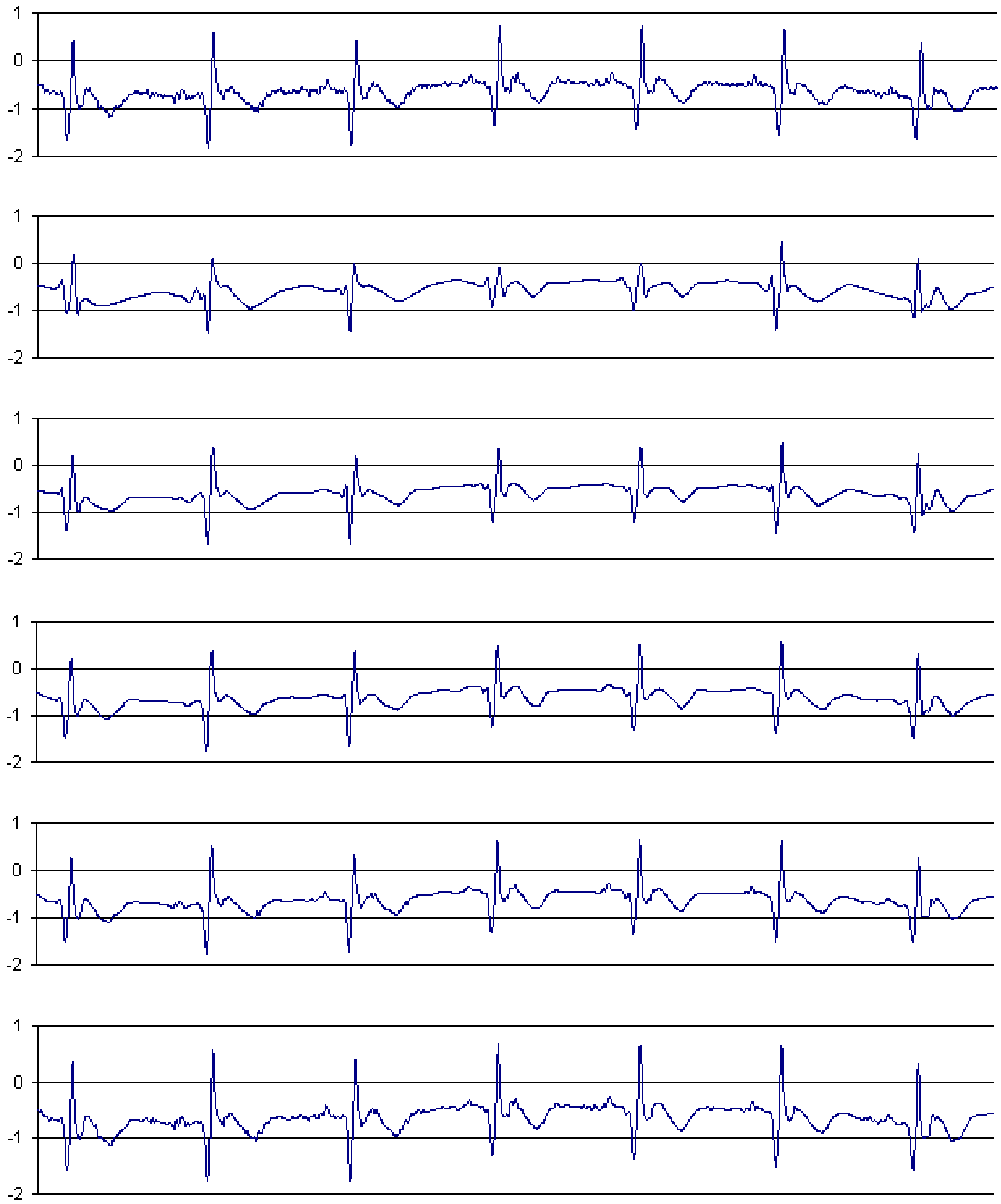


Figure 5.34: Patient 118 Lead V1 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.12: Diagnostic parameters for Patient 118 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	71.6	0.30	0.13	0.18	0.19	1.36	0.40	0.08	-0.31	-
3 refine	71.6	0	NA	NA	0.23	0.41	0.44	0.08	-0.26	61.96
4 refine	71.6	0.08	0.15	0.20	0.19	0.86	0.32	0.09	-0.22	40.58
5 refine	71.6	0.22	0.17	0.22	0.18	1.13	0.41	0.08	-0.21	25.43
6 refine	71.6	0.26	0.14	0.19	0.19	1.28	0.40	0.08	-0.27	16.80
7 refine	71.6	0.26	0.13	0.18	0.19	1.32	0.40	0.08	-0.29	10.30

Table 5.13: Diagnostic parameters for Patient 118 Lead V1

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	71.6	0.11	0.08	0.18	0.12	1.33	0.47	0.06	-0.31	-
3 refine	71.6	0.13	0.07	0.09	0.09	0.79	0.45	0.05	-0.26	54.14
4 refine	71.6	0.07	0.07	0.07	0.09	1.05	0.45	0.05	-0.24	33.18
5 refine	71.6	0.00	NA	NA	0.11	1.06	0.39	0.06	-0.26	21.71
6 refine	71.6	0.10	0.08	0.18	0.12	1.27	0.46	0.06	-0.28	13.43
7 refine	71.6	0.13	0.10	0.18	0.11	1.32	0.46	0.06	-0.29	8.42

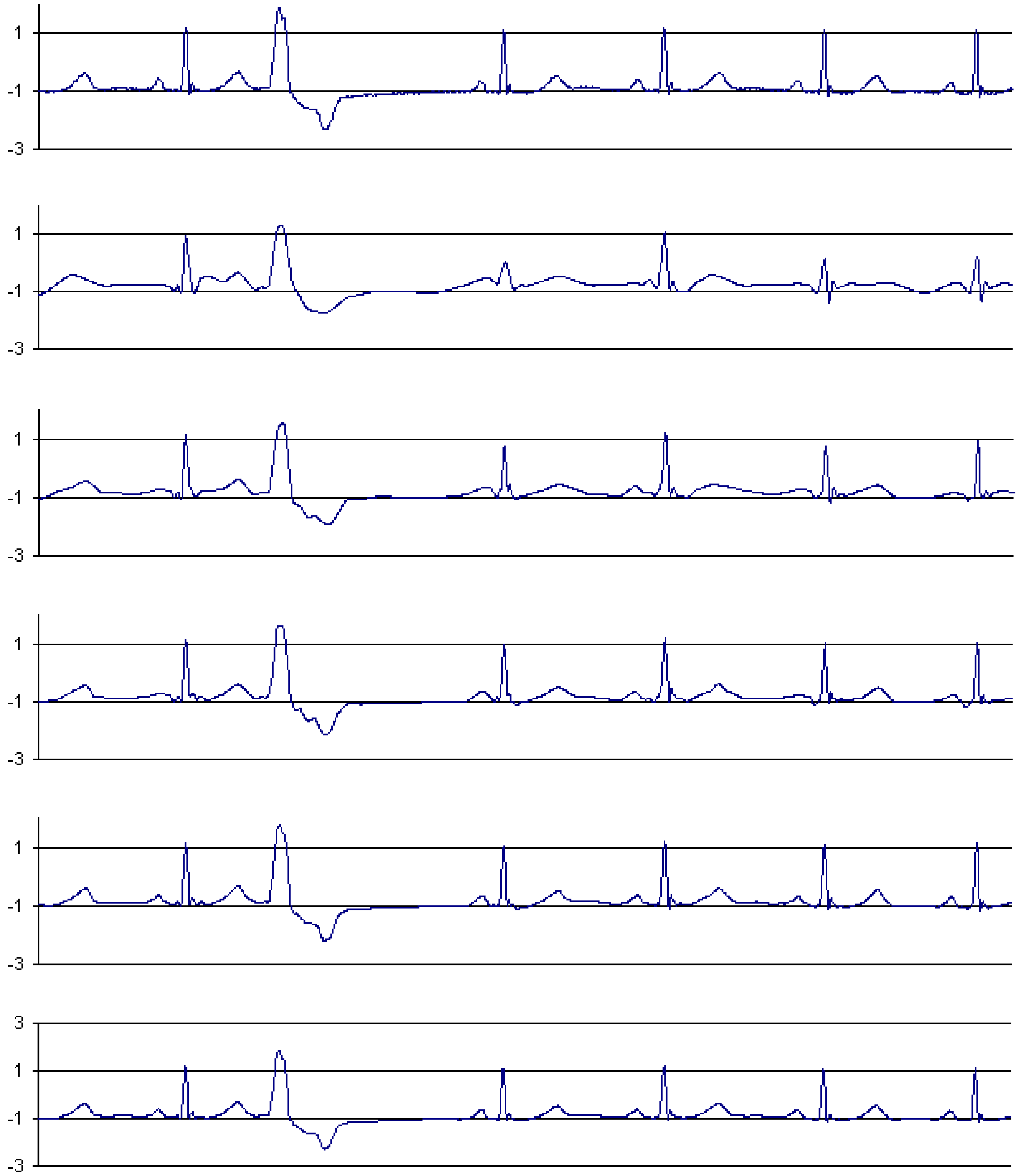


Figure 5.35: Patient 119 Lead MLII (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

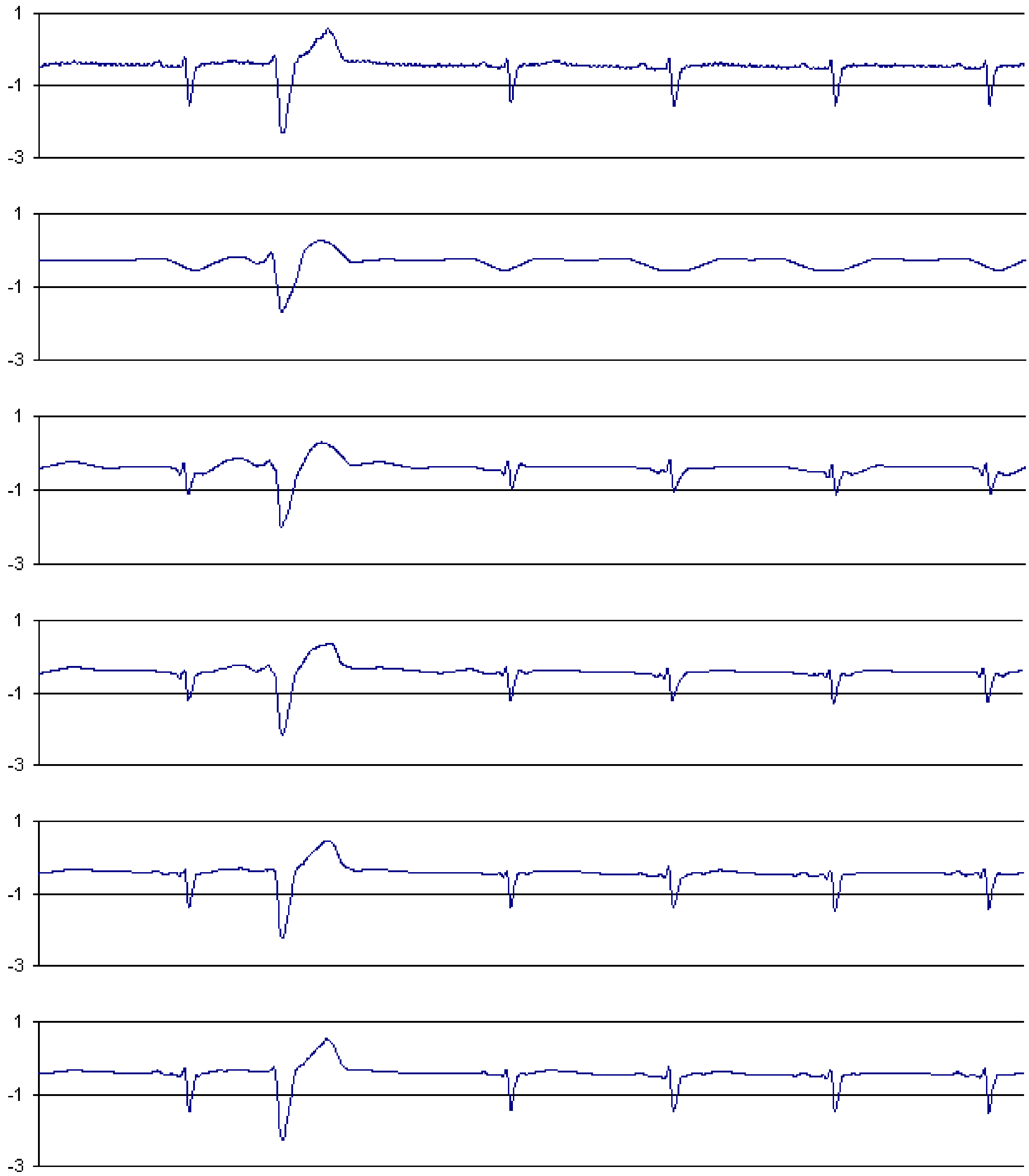


Figure 5.36: Patient 119 Lead V1 (from top) (a) original ECG signal (b) reconstructed signal after 3 refinements (c) reconstructed signal after 4 refinements (d) reconstructed signal after 5 refinements (e) reconstructed signal after 6 refinements (f) reconstructed signal after 7 refinements

Table 5.14: Diagnostic parameters for Patient 118 Lead MLII

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	65.0	0.29	0.09	0.16	0.08	2.13	0.43	0.04	0.64	
3 refine	65.0	0.01	0.14	0.17	0.13	1.61	0.44	0.04	0.40	50.64
4 refine	65.0	0.07	0.15	0.19	0.13	2.02	0.44	0.04	0.50	29.39
5 refine	65.0	0.17	0.13	0.17	0.09	2.06	0.44	0.04	0.52	18.52
6 refine	65.0	0.24	0.09	0.16	0.08	2.09	0.44	0.04	0.56	10.27
7 refine	65.0	0.26	0.09	0.16	0.08	2..10	0.44	0.04	0.57	6.34

Table 5.15: Diagnostic parameters for Patient 118 Lead V1

	HR (BPM)	P-amp (mV)	P-dur (s)	PR-int (s)	QRS-int (s)	R-amp (mV)	QT-int (s)	VAT (s)	T-amp (mV)	PRD (%)
original	65.0	0.10	0.07	0.18	0.12	0.22	NA	0.02	0	
3 refine	65.0	0	NA	NA	NA	0	NA	NA	0	81.41
4 refine	65.0	0	NA	NA	0.13	0.05	0.47	0.05	0.13	44.34
5 refine	65.0	0	NA	NA	0.13	0.08	0.47	0.06	0.15	26.21
6 refine	65.0	0.05	0.08	0.15	0.11	0.18	NA	0.03	0	15.43
7 refine	65.0	0.06	0.08	0.17	0.09	0.20	NA	0.03	0	9.87

After careful observations from the two lead signal from first 2048 samples of patients 100, 101, 102, 103, 107, 118 and 119 from MIT/BIH mitdb database [Goldberger *et al.,* 2000], we conclude that with each refinement, the quality of reconstructed signal improves. This is reflected in the reduced value of PRD as well as the diagnostic parameters in the reconstructed wave approaching the one in the original wave. One thing remarkable about this compression algorithm is that R-R interval remains unaffected even for much lesser (only three) refinement passes. However, in different signals, the extent of distortion in reconstructed signal is different even for the same number of refinements. Nothing in concrete can be deduced from this study as far as the number of refinements required for the acceptable quality of reconstructed signal is concerned. This number varies from case to case and need inspection every time.

5.5 BLANK-FIRE AND NUMBER OF REFINEMENTS

In modified SPIHT wavelet compression method, it is proposed that instead of taking a common threshold (2^n) for low frequency coefficients L_coeff and high frequency coefficients H_coeff, separate thresholds are transmitted, we get improved compression ratio. The ratio of threshold for L_Coeff and that of H_coeff is many a times 2. The logic behind this improvement can be explained by taking an example. Let the threshold for L_coeffs is 2 while the threshold for H_coeffs is 1, thereby ratio being 2. In the first sort, all coefficients in H_coeffs will be less than the threshold. But still 32 bits will have to be transmitted. This transmission of 32 bits that carry absolutely no information is termed as a “Blank-Fire”. Sending a separate threshold for H_coeffs can save these bits. This “Blank-Fire” not only reduces the compression ratio, but also jeopardizes the number of refinement passes to be implemented to achieve a certain level of quality in the reconstructed signal. This means five refinement passes with out any “blank-fire” are equivalent to six refinement passes with a “blank-fire”. Taking clue from this logic, we propose the refinement pass criterion. First the ratio of thresholds for L_coeffs to that of H_coeffs is determined. Ratio one indicates no “blank-fire”, while ratio 2 or 0.5 is indicative of one “blank-fire”. Careful study of quality improvement with the number of refinement passes revealed that while for this threshold ratio equal to one (no “blank-fire”) five refinements are sufficient, but for all other ratios other than one (containing a “blank-fire”), we need six refinement passes. Keeping this as the refinement criterion, we tested the quality of reconstruction by taking PRD, diagnostic parameters and the opinion of a physician after visual inspection of signal into account.

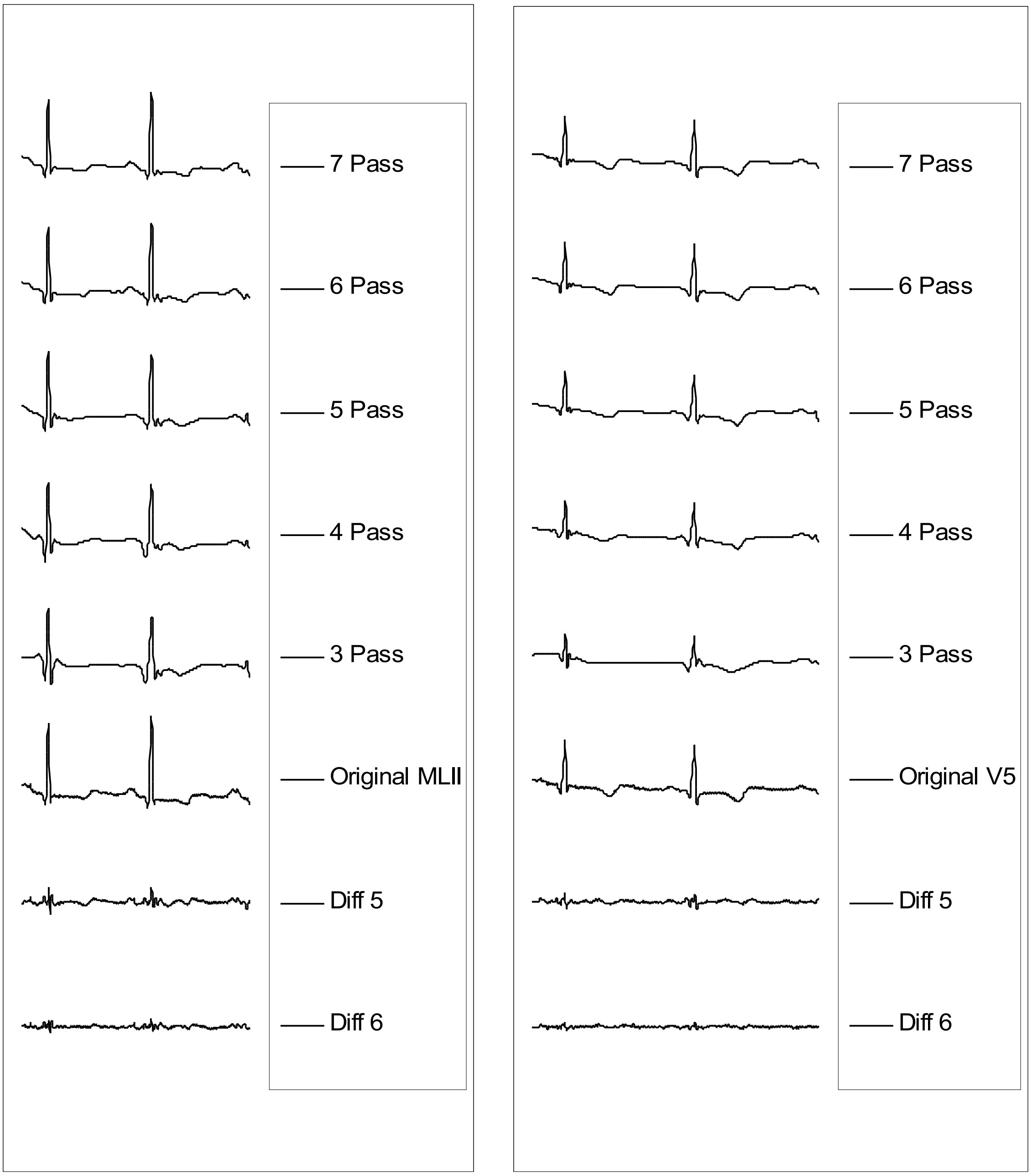


Figure 5.37: Original, reconstructed and difference signals of patient 100

Figure 5.37 shows original signal, reconstructed signal after 3, 4, 5, 6 and 7 refinement passes. It also shows the difference (algebraic subtraction on point to point basis) between the original signal and the reconstructed signal after 5 refinement passes ("Diff 5") and after 6 refinement passes ("Diff 6"). For both these signals, the threshold ratio is 2. Visual inspection reveals that five refinements are not sufficient. We need six refinements to get a good quality reproduction of the original signal and going in for the seventh refinement in this case is really an "overkill". Similar traces for patients 101, 102, 103, 107, 118 and 119 are given in the subsequent figures.

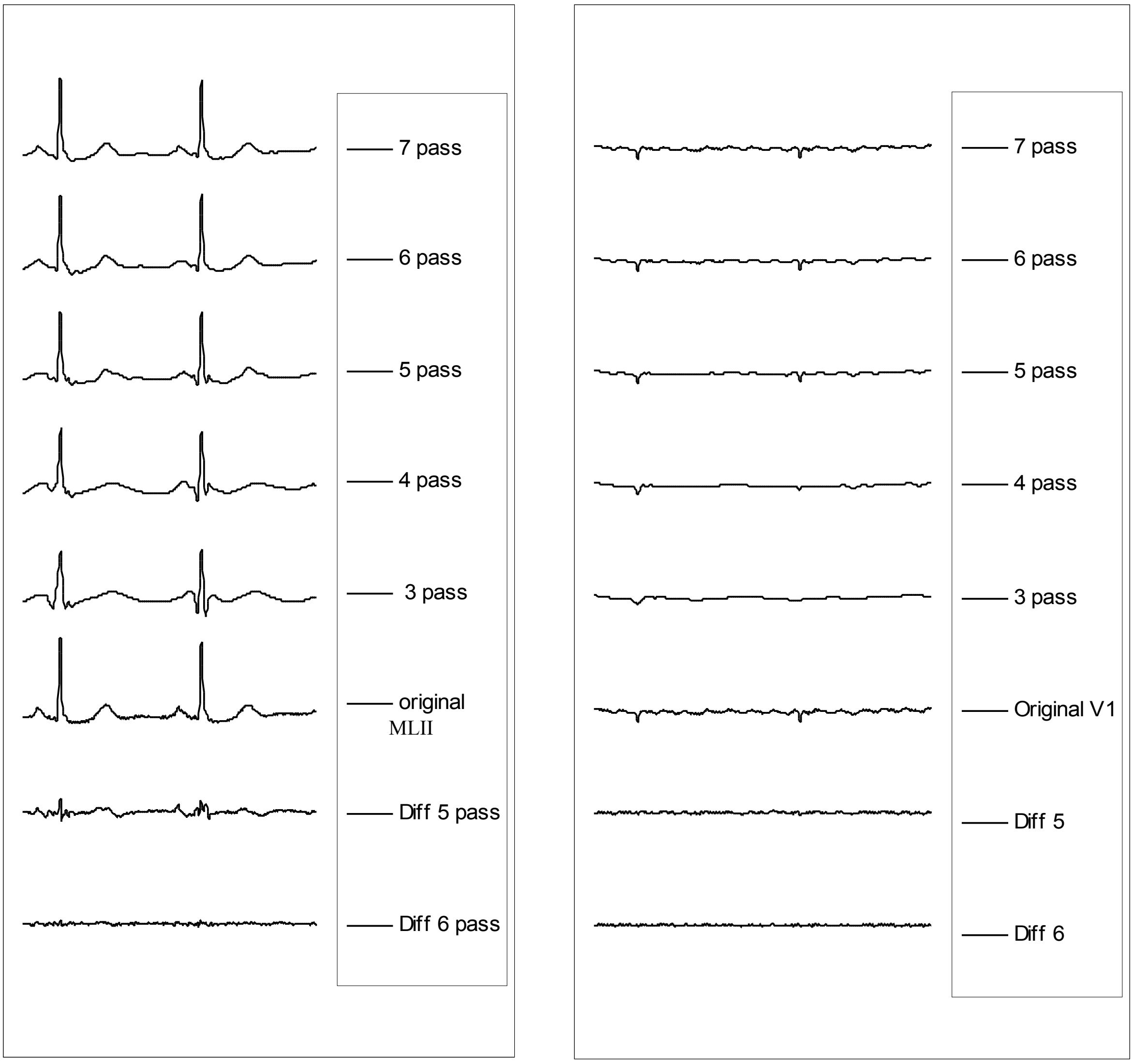


Figure 5.38: Original, reconstructed and difference signals of patients 101

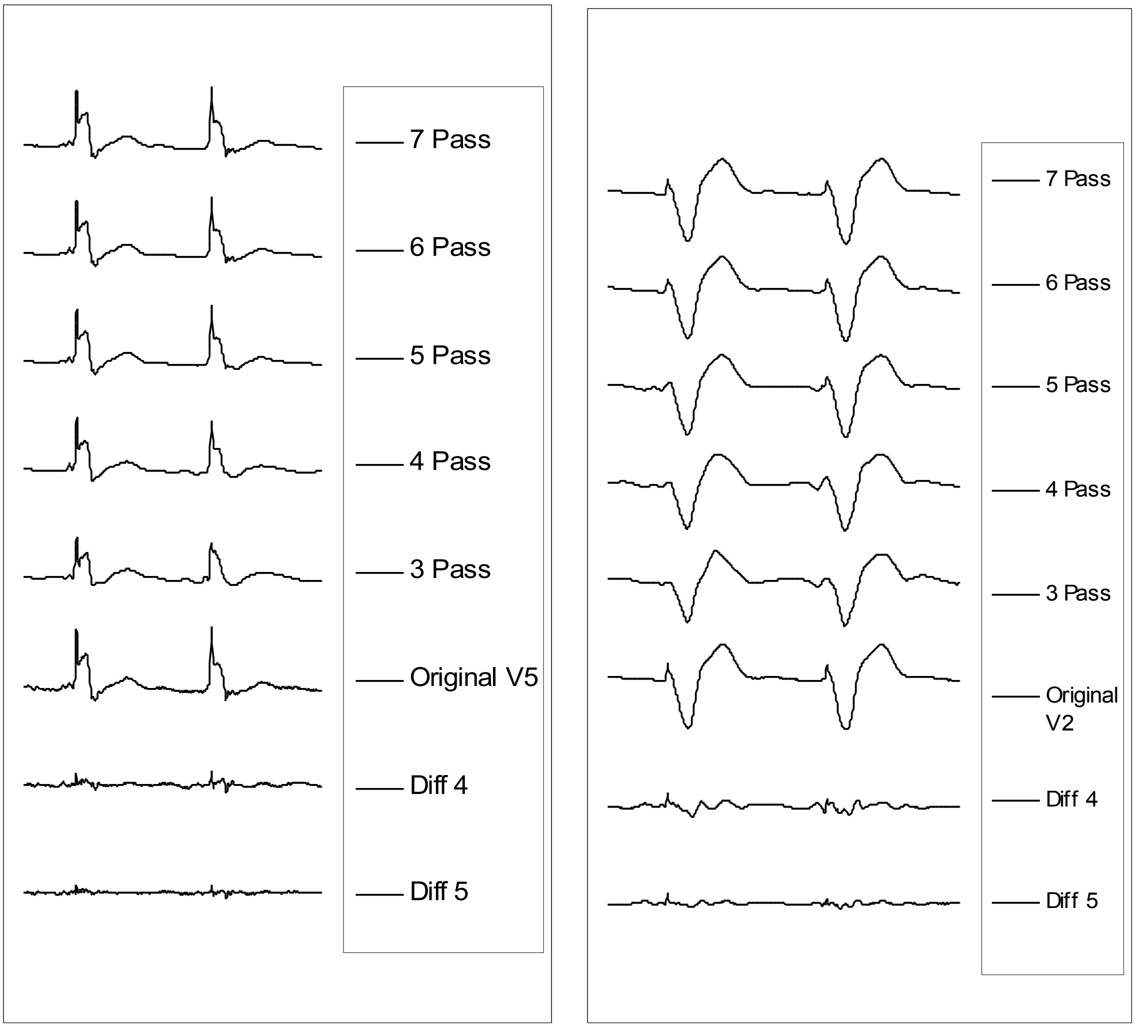
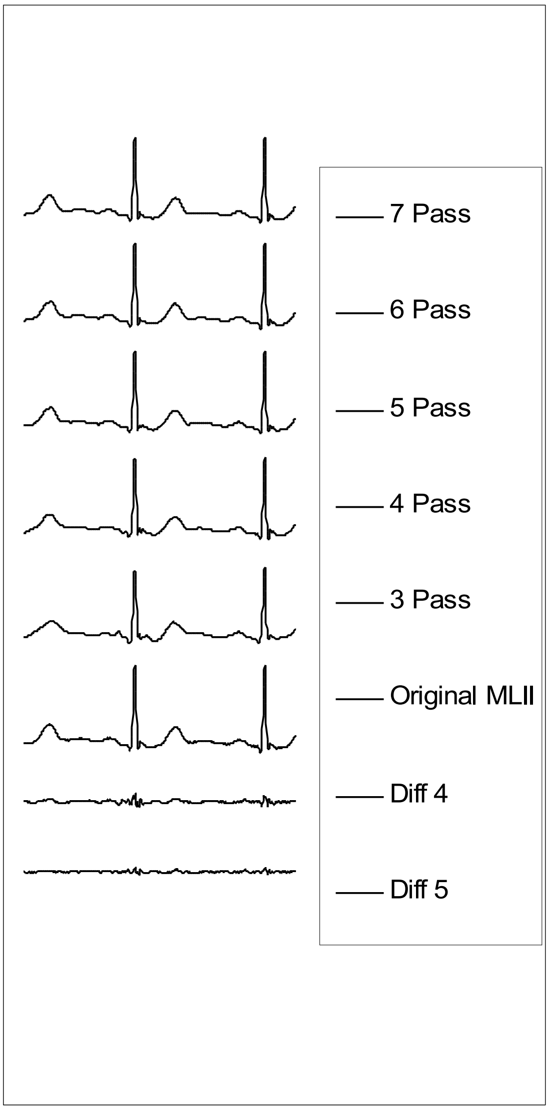


Figure 5.39: Original, reconstructed and difference signals of patients 102



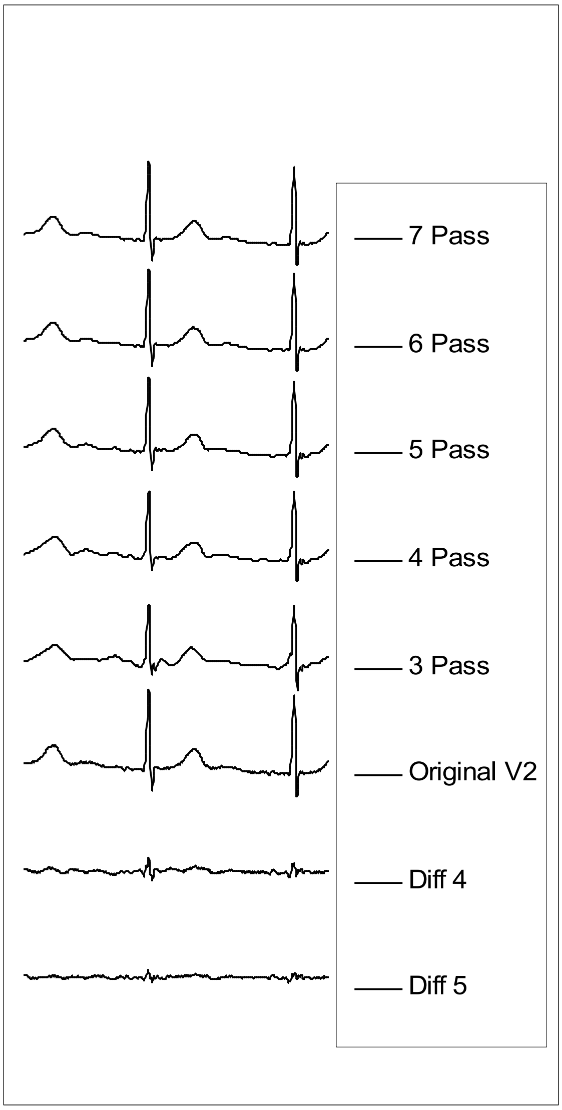


Figure 5.40: Original, reconstructed and difference signals of patients 103

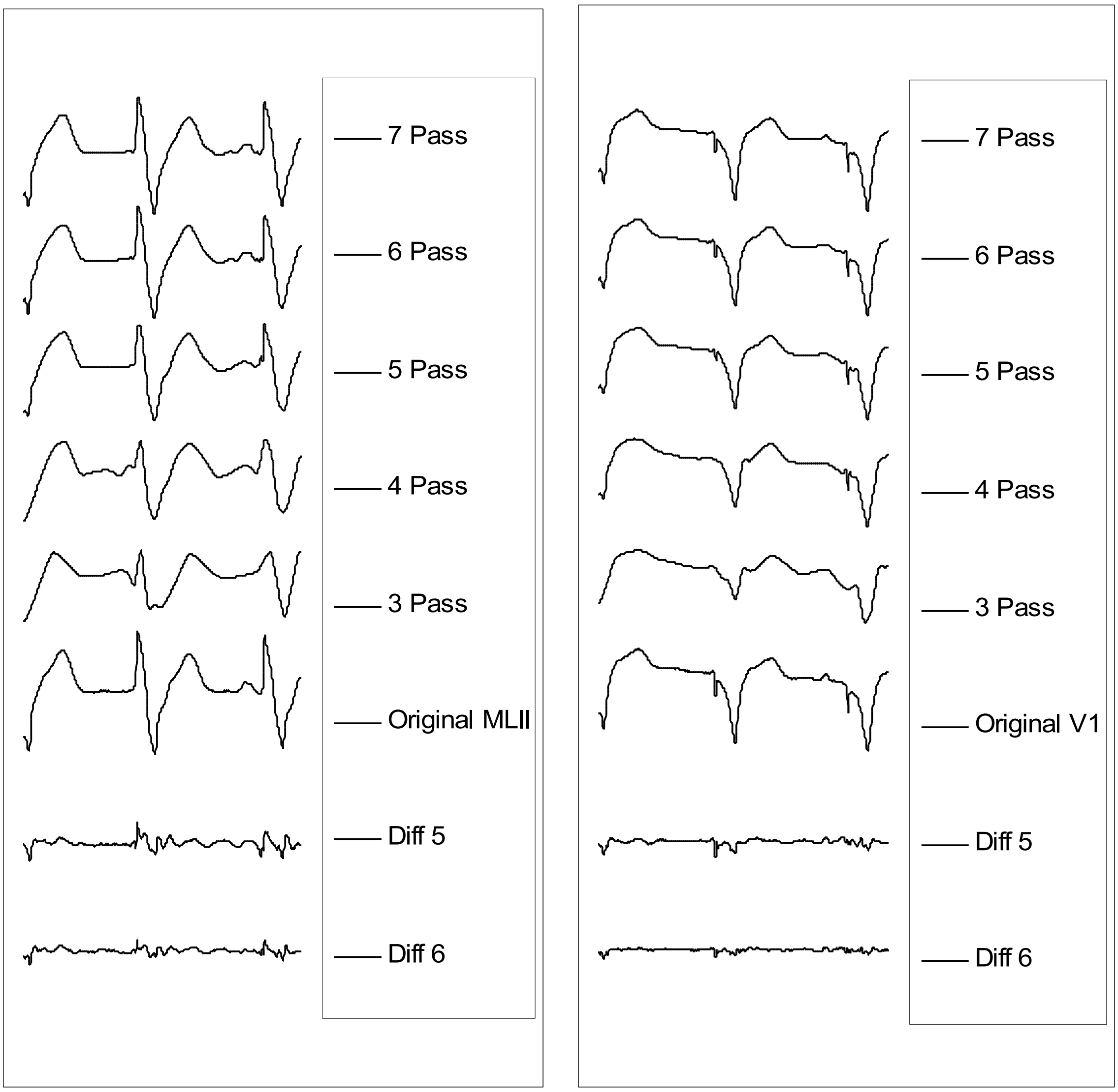


Figure 5.41: Original, reconstructed and difference signals of patients 107

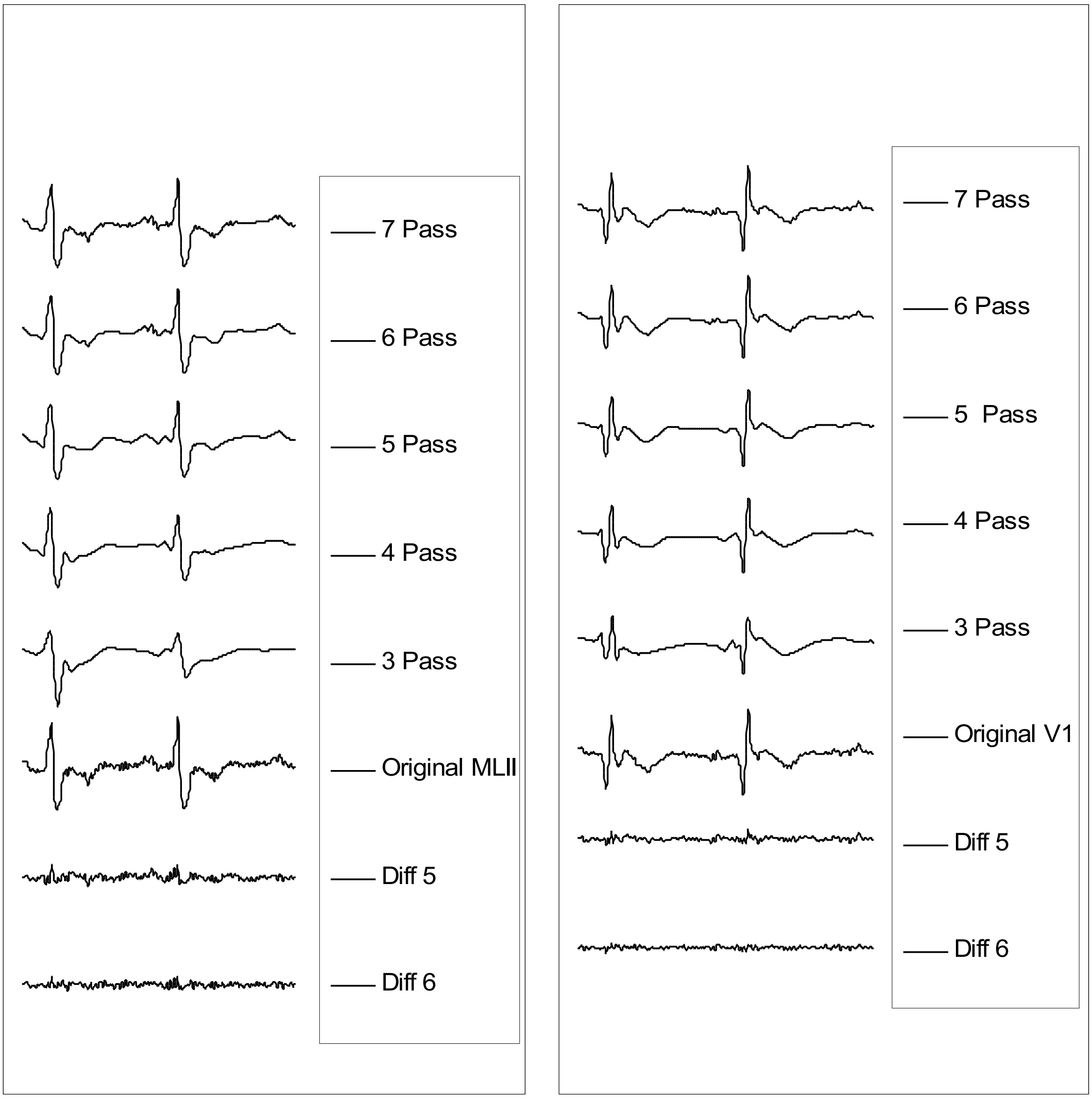


Figure 5.42: Original, reconstructed and difference signals of patients 118

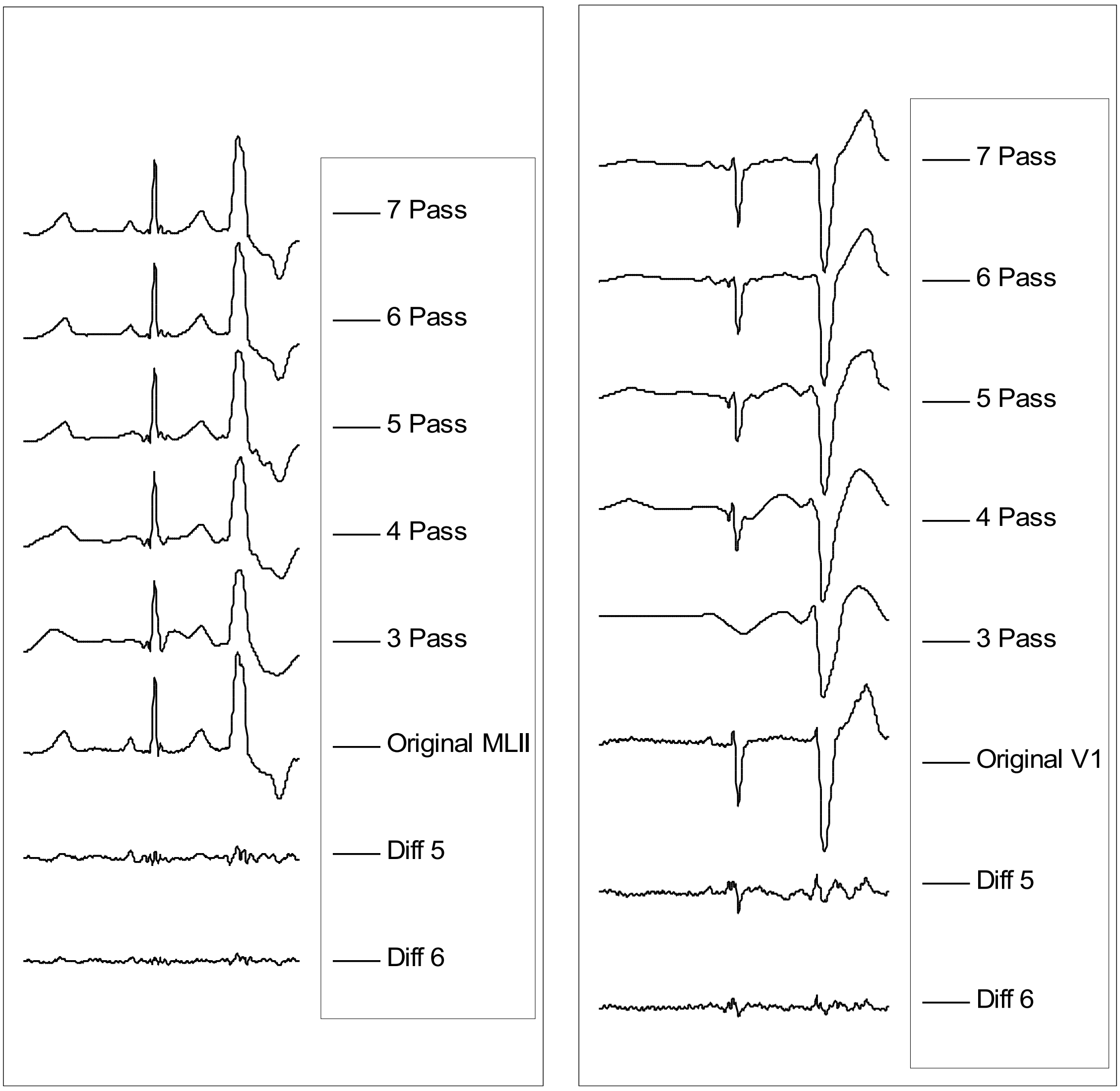


Figure 5.43: Original, reconstructed and difference signals of patients 119

For the ECG signals that were refined 3-7 times, the reconstructed signals were recorded for the PRD, their diagnostic parameters tabulated in tables 5.2 – 5.15, their compression ratios computed and the signals were presented to physician for its clinical acceptability. The results are given in table 5.16.

Table 5.16: Number of refinements and its clinical acceptability

Patient	Signal	Thres hold Ratio	No. of Passes	CR	PRD	Physician's remarks
100	MLII	2	3	49.51	66.05	Not Acceptable
100	MLII	2	4	34.93	40.24	Not Acceptable
100	MLII	2	5	25.86	25.95	Not Acceptable
100	MLII	2	6	19.04	15.53	Acceptable
100	MLII	2	7	13.90	9.65	Overkill
100	V5	2	3	46.84	56.48	Not Acceptable
100	V5	2	4	30.28	35.22	Not Acceptable
100	V5	2	5	21.29	21.47	Not Acceptable
100	V5	2	6	15.50	13.62	Acceptable
100	V5	2	7	11.36	9.63	Overkill
101	MLII	2	3	48.97	62.95	Not Acceptable
101	MLII	2	4	33.52	37.91	Not Acceptable
101	MLII	2	5	25.09	23.08	Not Acceptable
101	MLII	2	6	19.09	14.10	Acceptable
101	MLII	2	7	14.17	9.16	Overkill
101	V1	4	3	63.28	65.86	Not Acceptable
101	V1	4	4	40.59	49.92	Not Acceptable
101	V1	4	5	26.01	36.00	Not Acceptable
101	V1	4	6	13.60	24.52	Acceptable
101	V1	4	7	6.89	15.34	Overkill

Table 5.16: Number of refinements and its clinical acceptability (continued)

Patient	Signal	Thres hold Ratio	No. of Passes	CR	PRD	Physician's remarks
102	V5	1	3	43.08	43.62	Not Acceptable
102	V5	1	4	28.52	24.85	Not Acceptable
102	V5	1	5	20.56	14.57	Acceptable
102	V5	1	6	14.96	9.54	Overkill
102	V5	1	7	10.50	6.11	Overkill
102	V2	1	3	53.89	25.49	Not Acceptable
102	V2	1	4	36.69	14.40	Not Acceptable
102	V2	1	5	25.54	7.87	Acceptable
102	V2	1	6	19.04	4.46	Overkill
102	V2	1	7	14.36	2.68	Overkill
103	MLII	1	3	37.05	27.74	Not Acceptable
103	MLII	1	4	25.17	15.04	Not Acceptable
103	MLII	1	5	18.76	9.00	Acceptable
103	MLII	1	6	14.32	5.40	Overkill
103	MLII	1	7	10.71	3.69	Overkill
103	V2	1	3	40.89	33.67	Not Acceptable
103	V2	1	4	27.34	19.70	Not Acceptable
103	V2	1	5	20.22	11.58	Acceptable
103	V2	1	6	15.40	7.40	Overkill
103	V2	1	7	11.35	5.10	Overkill
107	MLII	2	3	62.40	56.76	Not Acceptable
107	MLII	2	4	42.67	33.40	Not Acceptable
107	MLII	2	5	30.82	19.64	Not Acceptable
107	MLII	2	6	22.85	11.86	Acceptable
107	MLII	2	7	17.07	6.96	Overkill

Table 5.16: Number of refinements and its clinical acceptability (continued)

Patient	Signal	Thres hold Ratio	No. of Passes	CR	PRD	Physician's remarks
107	V1	2	3	61.05	40.38	Not Acceptable
107	V1	2	4	39.59	22.83	Not Acceptable
107	V1	2	5	27.71	14.84	Not Acceptable
107	V1	2	6	19.81	8.27	Acceptable
107	V1	2	7	14.98	5.30	Overkill
118	MLII	2	3	56.89	61.96	Not Acceptable
118	MLII	2	4	39.38	40.58	Not Acceptable
118	MLII	2	5	28.63	25.43	Not Acceptable
118	MLII	2	6	20.20	16.80	Acceptable
118	MLII	2	7	13.00	10.30	Overkill
118	V1	2	3	47.33	54.14	Not Acceptable
118	V1	2	4	32.79	33.18	Not Acceptable
118	V1	2	5	23.97	21.71	Not Acceptable
118	V1	2	6	15.71	13.43	Acceptable
118	V1	2	7	10.31	8.41	Overkill
119	MLII	2	3	54.81	50.64	Not Acceptable
119	MLII	2	4	39.11	29.39	Not Acceptable
119	MLII	2	5	28.88	18.52	Not Acceptable
119	MLII	2	6	20.76	10.27	Acceptable
119	MLII	2	7	15.97	6.34	Overkill
119	V1	4	3	62.93	81.41	Not Acceptable
119	V1	4	4	42.91	44.34	Not Acceptable
119	V1	4	5	33.03	26.21	Not Acceptable
119	V1	4	6	25.54	15.43	Acceptable
119	V1	4	7	20.28	9.87	Overkill

From table 5.16 it can be safely concluded that the refinement criterion of having five refinement passes if the threshold ratio is one and having six refinement passes otherwise, has total clinical acceptability. Using this criterion, the difference of reconstructed signal with original is of generic noise rather than having any ECG feature of diagnostic value. As a matter of fact, the reconstructed signal is more acceptable to a physician than even the original signal as it is devoid of the high frequency noise. In fact large PRD in some cases was only due to removal of this noise in the reconstructed signal.

5.6 STATISTICAL ANALYSIS

To support the refinement criterion, we extended the analysis on a larger database including more cases with threshold ratio equal to one.

Compression ratio and PRD were recorded using the following three norms (i) Five refinement passes, irrespective of the threshold ratio (ii) Six refinement passes, irrespective of the threshold ratio (iii) Five refinement passes if the threshold ratio is one, six refinement passes otherwise. The results are presented in table 5.17.

It can be clearly seen in the table that standard deviation in percentage of mean compression ratio is 15.39 % for five refinements and 18.33% for six refinements, using the proposed criterion, the standard deviation in percentage of compression ratio is 18.66%. Thus there is no considerable improvement or deterioration in consistency in the compression ratio using the proposed criterion. However, the standard deviation in percentage of mean PRD is 39.00% for five refinements and 41.62% for six refinements, using the proposed criterion the standard deviation in percentage of mean PRD radically reduces to 28.63%. This reduction in standard deviation in the PRD is indicative of the enhanced consistency in distortion; thereby supporting the proposed criterion for the number of refinement passes.

Table 5.17: Statistical analysis for consistency in PRD for the proposed criterion

Patient No	Lead	Threshold Ratio	5 Passes		6 Passes		5 Passes if Ratio =1, else 6 Passes	
			CR	PRD	CR	PRD	CR	PRD
100	MLII	2	25.86	25.95	19.04	15.53	19.04	15.53
100	V5	2	21.29	21.47	15.50	13.62	15.50	13.62
101	MLII	2	25.09	23.08	19.09	14.10	19.09	14.10
101	V1	4	26.01	36.00	13.60	24.52	13.60	24.52
102	V5	1	20.55	14.57	14.96	9.54	20.55	14.57
102	V2	1	25.54	7.87	19.04	4.46	25.54	7.87
103	MLII	1	18.76	9.00	14.32	5.40	18.76	9.00
103	V2	1	20.22	11.58	15.40	7.40	20.22	11.58
107	MLII	2	30.82	19.64	22.85	11.86	22.85	11.86
107	V1	2	27.71	14.84	19.81	8.27	19.81	8.27
111	MLII	1	22.39	15.45	16.07	10.08	22.39	15.45
111	V1	1	24.73	10.88	17.79	7.30	24.73	10.88
118	MLII	2	28.63	25.43	20.20	16.80	20.20	16.80
118	V1	2	23.97	21.71	15.71	13.43	15.71	13.43
119	MLII	2	28.88	18.52	20.76	10.27	20.76	10.27
119	V1	4	33.03	26.21	25.54	15.43	25.54	15.43
212	MLII	2	21.66	17.84	15.55	10.33	15.55	10.33
212	V1	1	24.09	12.18	17.61	7.76	24.09	12.18
228	MLII	2	21.79	18.18	13.43	11.96	13.43	11.96
228	V1	1	21.23	11.38	14.85	7.11	21.23	11.38
MEAN			**24.61**	**18.09**	**17.56**	**11.26**	**19.93**	**12.95**
SD			**3.79**	**7.05**	**3.22**	**4.69**	**3.72**	**3.71**
% SD of MEAN			**15.39**	**39.00**	**18.33**	**41.62**	**18.66**	**28.63**

5.7 CLINICAL VALIDATION

The modified SPIHT algorithm for ECG wavelet compression introduces two additional steps viz., “Blank-fire Removal” and “Polishing”. Further a criterion for the number of refinement passes in SPIHT algorithm is proposed, as discussed in the previous section. Using this criterion on the modified SPIHT algorithm, 42 sections of two lead ECG signals from MIT/BIH mitdb database with wide variety of diagnostic truths including normal signals, premature ventricular contractions, atrial flutter, paced rhythm, Right Bundle Branch Block (RBBB), first and second degree heart block, first degree A/V block with Left Bundle Branch Block (LBBB), atrial fibrillation, ventricular bigemini and trigemini, right atrial enlargement, paroxysmal atrial tachycardia, atrial bigemini, junctional rhythm etc. were selected. The original signals as well as the reconstructed signals (42 set each, total amounting to 84 sets of two lead signals) were presented to the same physician in a random fashion, after assigning fictitious numbers to them. The signals were presented in small sets of 12-15 pair of signals, spanning over several days. The interpretation of the physician for clinical validation of modified SPIHT algorithm containing “Blank-fire removal” and “Polishing” along with the proposed refinement criterion is given in table 5.18. The traces of these signals are attached in Appendix I.

We see from table 5.18 that the interpretations given by the physician are invariably same for the original signals and the reconstructed signals, even though the two were presented in a random fashion with a difference of several days. This validates our improved SPIHT algorithm for ECG wavelet compression along with the proposed criterion for the number refinement passes to be implemented.

Table 5.18: Clinical validation of reconstructed ECG signals by physician

Fictitious record number	Patient number	Original/ Reconst.	Sample number	Physician's Interpretation
223	100	Original	1-2048	Normal sinus rhythm (shown for demo)
223(2)	100(2)	Original	32770-34817	Ventricular premature complex
224	101	Original	1-2048	Atrial flutter
225	102	Original	1-2048	Paced rhythm
226	103	Original	1-2048	Within normal limits
230	107	Original	1-2048	Complete heart block with paced rhythm
241	118	Original	1-2048	Right bundle branch block
244	119	Original	1-2048	Ventricular premature complex
244(2)	119(2)	Original	6586-8633	Ventricular premature complex
228	105	Original	1-2048	Within normal limits
231	108	Original	1-2048	First degree heart block with ventricular premature complex
231(2)	108(2)	Original	9979-12026	First degree heart block with ventricular premature complex
232	109	Original	1-2048	First degree heart block with Left bundle branch block
232(2)	109(2)	Original	2981-5028	First degree heart block with Left bundle branch block
232(3)	109(3)	Original	9981-12028	First degree heart block with Left bundle branch block
234	111	Original	1-2048	First degree A/V block with Left bundle branch block
234(2)	111(2)	Original	16001-18048	First degree A/V block with Left bundle branch block
234(3)	111(3)	Original	19001-21048	First degree A/V block with Left bundle branch block
235	112	Original	1-2048	ST depression in LII with first degree A/V block
235(2)	112(2)	Original	14501-16548	ST depression in LII with first degree A/V block
335	212	Original	1-2048	Right bundle branch block
335(2)	212(2)	Original	22771-24818	Within normal limits
342	219	Original	1-2048	Atrial fibrillation with T inversion
342(2)	219(2)	Original	33120-35167	Ventricular trigemini

Table 5.18: Clinical validation of reconstructed ECG signals by physician (continued)

Fictitious record number	Patient number	Original/ Reconst.	Sample number	Physician's Interpretation
342(3)	219(3)	Original	36629-38676	Atrial fibrillation with T inversion
342(4)	219(4)	Original	437400-439447	Ventricular bigemini
345	222	Original	1-2048	Within normal limits
345(2)	222(2)	Original	2776-4823	Junctional rhythm
345(3)	222(3)	Original	5111-7158	Right atrial enlargement
345(4)	222(4)	Original	11350-13397	Paroxysmal atrial tachycardia with A/V block (variable)
345(5)	222(5)	Original	15937-17984	Paced rhythm
345(6)	222(6)	Original	28267-30314	Atrial bigemini
345(7)	222(7)	Original	30861-32908	Paroxysmal Atrial tachycardia with A/V block (variable)
345(8)	222(8)	Original	35622-37669	Junctional rhythm
345(9)	222(9)	Original	38818-40865	Within normal limits
345(10)	222(10)	Original	48328-50375	Atrial bigemini
345(11)	222(11)	Original	437400-439447	Ventricular trigemini
345(12)	222(12)	Original	56117-58164	Atrial flutter
345(13)	222(13)	Original	62769-64816	Second degree heart block (mobiz type I)
351	228	Original	1-2048	First degree heart block
351(2)	228(2)	Original	6201- 8248	First degree heart block with ventricular bigemini
355	232	Original	1-2048	Noisy signal beyond comprehension
421	100	Reconst.	1-2048	Normal sinus rhythm(shown for demo)
421(2)	100(2)	Reconst.	32770-34817	Ventricular premature complex
422	101	Reconst.	1-2048	Atrial flutter
423	102	Reconst.	1-2048	Paced rhythm
424	103	Reconst.	1-2048	Within normal limits
428	107	Reconst.	1-2048	Complete heart block with paced rhythm
439	118	Reconst.	1-2048	Right bundle branch block
440	119	Reconst.	1-2048	Ventricular premature complex
440(2)	119(2)	Reconst.	6586-8633	Ventricular premature complex

Table 5.18: Clinical validation of reconstructed ECG signals by physician (continued)

Fictitious record number	Patient number	Original/ Reconst.	Sample number	Physician's Interpretation
426	105	Reconst.	1-2048	Within normal limits
429	108	Reconst.	1-2048	First degree heart block with ventricular premature complex
429(2)	108(2)	Reconst.	9979-12026	First degree heart block with ventricular premature complex
430	109	Reconst.	1-2048	First degree heart block with Left bundle branch block
430(2)	109(2)	Reconst.	2981-5028	First degree heart block with Left bundle branch block
430(3)	109(3)	Reconst.	9981-12028	First degree heart block with Left bundle branch block
432	111	Reconst.	1-2048	First degree A/V block with Left bundle branch block
432(2)	111(2)	Reconst.	16001-18048	First degree A/V block with Left bundle branch block
432(3)	111(3)	Reconst.	19001-21048	First degree A/V block with Left bundle branch block
433	112	Reconst.	1-2048	ST depression in LII with first degree A/V block
433(2)	112(2)	Reconst.	14501-16548	ST depression in LII with first degree A/V block
533	212	Reconst.	1-2048	Right bundle branch block
533(2)	212(2)	Reconst.	22771-24818	Within normal limits
540	219	Reconst.	1-2048	Atrial fibrillation with T inversion
540(2)	219(2)	Reconst.	33120-35167	Ventricular trigemini
540(3)	219(3)	Reconst.	36629-38676	Atrial fibrillation with T inversion
540(4)	219(4)	Reconst.	437400-439447	Ventricular bigemini
543	222	Reconst.	1-2048	Within normal limits
543(2)	222(2)	Reconst.	2776-4823	Junctional rhythm
543(3)	222(3)	Reconst.	5111-7158	Right atrial enlargement
543(4)	222(4)	Reconst.	11350-13397	Paroxysmal Atrial tachycardia with A/V block (variable)
543(5)	222(5)	Reconst.	15937-17984	Paced rhythm
543(6)	222(6)	Reconst.	28267-30314	Atrial bigemini
543(7)	222(7)	Reconst.	30861-32908	Paroxysmal Atrial tachycardia with A/V block (variable)
543(8)	222(8)	Reconst.	35622-37669	Junctional rhythm

Table 5.18: Clinical validation of reconstructed ECG signals by physician (continued)

Fictitious record number	Patient number	Original/ Reconst.	Sample number	Physician's Interpretation
543(9)	222(9)	Reconst.	38818-40865	Within normal limits
543(10)	222(10)	Reconst.	48328-50375	Atrial bigemini
543(11)	222(11)	Reconst.	437400-439447	Ventricular trigemini
543(12)	222(12)	Reconst.	56117-58164	Atrial flutter
543(13)	222(13)	Reconst.	62769-64816	Second degree heart block (mobiz type I)
549	228	Reconst.	1-2048	First degree heart block
549(2)	228(2)	Reconst.	6201- 8248	First degree heart block with ventricular bigemini
553	232	Reconst.	1-2048	Noisy signal beyond comprehension

5.8 CONCLUSIONS

The extent to which a signal can be safely compressed using SPIHT algorithm depends upon the number of refinement passes. The lesser the number of refinement passes, more is compression, but more is the distortion in the reconstructed signal. One thing remarkable about SPIHT compression algorithm is that R-R interval in reconstructed signal remains unaffected even for much lesser (only three) refinement passes. This property of SPIHT algorithm can be utilized for compressing long arrhythmia cases to much higher compression ratios, where only R-R interval is required, not considering changes in other morphological features.

To achieve optimal compression ratio, while retaining all clinically significant morphological features, a criterion is required for the number of refinement passes in SPIHT algorithm. A study carried out to find this number reveals that different signals give vastly different PRD (a measure of distortion) even for the same number of refinement passes. Thus recommending a fixed number of refinement passes is not possible. However, if we take into account the presence of "blank-fire" in the compression, a criterion can be evolved. We recommend five refinement passes in absence of "blank-fire", and six in its presence. This has resulted in largely improved consistency in the distortion. The same has been validated by visual inspection of the signals by a physician, as well as by a statistical analysis over a larger database.

Finally implementing the improved SPIHT algorithm, with the proposed refinement criterion over 42 sets of two-lead ECG signals, the original and the reconstructed signals were randomly presented to a physician, in sets of 12-15 pairs of signal. The interpretations of these ECGs were same for all 42 reconstructed signals (100%) as for the original ones, thereby validating our improved SPIHT algorithm for ECG wavelet compression along with the proposed criterion for the number refinement passes to be implemented.

A NEW DISTORTION PARAMETER

6.1 INTRODUCTION

Human heart is a four-stage pump that facilitates incessant flow of blood to all cells of the body. It has an inbuilt intricate electrical system for its proper functioning. Many of the heart malfunctions are detected by measuring the electric field vector so traversing in the heart. The various components of the vector are plotted as one-dimensional array with respect to time and are collectively known as Electrocardiogram (ECG). A typical sampling frequency for ECG is taken as 360 samples per second and as many as 12 channels are recorded simultaneously. For one day's continuous recording, the amount of data crosses several gigabytes. Moreover if this data is to be transmitted over a telephone line or a slower digital communication network, the time of transmission goes beyond the human patience. Compressing the data is the only solution to this problem. A high compression is invariably accompanied by some loss that needs to be appropriately quantified. Many parameters used by ECG compression researchers for distortion measurement have been evaluated and a new distortion measuring parameter is introduced in this work.

6.2 VARIOUS DISTORTION MEASURES

In ECG reconstructed signals after compression, the loss is usually quantified in some form of mean square error between the original and the reconstructed signal. The aim of every compression scientists is to maximize compression while keeping a check on the mean square error. Unfortunately, there is no one standard form of mean square error measurement. Some of the commonly used distortion measurement parameters are as follows:

6.2.1 Mean Square Error or Root Mean Square Error (RMSE)

$$MSE = \frac{\sum_{i}^{N} [x_o(i) - x(i)]^2}{N} \qquad RMSE = \sqrt{\frac{\sum_{i}^{N} [x_o(i) - x(i)]^2}{N}}$$

where x_o and x represent the original and reconstructed data respectively, and N is the number of samples in the original signal. These are the absolute measure of distortion, used by ECG compression researchers to quote their results [Besar *et al.,* 2000; Cherkassky and Kilts, 2001]. The problem with these types of distortion measuring parameters is that if the signal is scaled by any factor (say two), these parameters also get multiplied by the same factor. This drawback is removed by normalizing the parameter.

6.2.2 Peak-Signal-to-Noise-Ratio (PSNR)

$$PSNR = 20\log_{10}\frac{\max|x_o(i)|}{\sqrt{\frac{1}{N}\sum_{1}^{N}\left(x_o(i) - x(i)\right)^2}}$$

where x_o and x represent the original and reconstructed data respectively, and N is the number of samples in the original signal. This distortion measure is widely used to measure distortion in reconstructed images, but is rarely used for ECG signal [Ahmed *et al.,* 2000]. A word of caution: this parameter is inversely related to distortion, that is, its numerical value decreases as the distortion in reconstructed signal increases.

6.2. 3 Percentage Root-mean-square Difference (PRD)

$$PRD = \sqrt{\frac{\sum_i [x_o(i) - x(i)]^2}{\sum_i [x_o(i)]^2}}$$

where x_o and x represent the original and reconstructed data respectively. One of the most commonly used parameters [Jalaleddine *et al.,* 1990; Nave and Cohen, 1993; Nagarajan *et al.,* 1996; Hilton, 1997; Nguyen-Phi and Weinrichter, 1997; Saha and Ramakrishnan, 1997; Chen and Itoh, 1998; Ahmed *et al.,* 2000; Alshamali and Al-Smadi, 2001; Istepanian *et al.,* 2001a; Al-Shrouf *et al.,* 2003; Kim *et al*., 2006; Nait-Ali *et al*., 2006], came under fierce attack, as this reports artificially low distortion for baseline shifted ECG signals. This is also sometimes called Normalized Root Mean Square Error (NRMSE).

6.2.4 Normalized Percentage Root-mean-square Difference (NPRD)

$$NPRD = \sqrt{\frac{1}{N}\frac{\sum_i^N [x_o(i) - x(i)]^2}{[\max(x_o) - \min(x_o)]^2}}$$

where x_o and x represent the original and reconstructed data respectively, and N is the number of samples in the original signal. This distortion measuring parameter is immune to base line shifts, but somehow it did not gain much acceptance and is sparsely reported [Huang and Kinsner, 2002].

6.2.5 Modified Percentage Root-mean-square Difference (MPRD)

Many researchers call this parameter as PRD only, but the formula reflects the difference from PRD mentioned at 6.2.3

$$MPRD = \sqrt{\frac{\sum_i [x_o(i) - x(i)]^2}{\sum_i [x_o(i) - K]^2}}$$

where x_o and x represent the original and reconstructed data respectively and K is an estimate of mean noise, usually defined as the mean value of the original signal. Like NPRD, this parameter too is immune to baseline shifts and is the most commonly used parameter as on the day [Cassen and English, 1997; Chagas *et al.,* 2000; Lu *et al.,* 2000; Al-Shrouf *et al.,* 2003; Alshamali and Al-Fahoum, 2003].

6.2.6 Normalized Maximum Amplitude of Error (NMAE)

$$NMAE_i = \frac{\max|x_{0i} - x_i|}{\max(x_{0i}) - \min(x_i)}$$

This expression is for the i^{th} cycle, where x_{oi} is the original sampled data in the i^{th} cycle, x_i is the reconstructed data in the i^{th} cycle. The mean value of NMAE of a subject can be obtained by averaging over all cycles [Saha and Ramakrishnan, 1997]. This method of distortion measurement requires identification of cycle, which necessitates QRS complex detection, and hence is not in the scope of the present work.

6.2.7 Other methods of distortion measurement

None of the methods stated above exactly correspond to the result of a clinical subjective test, but as they are easy to calculate and compare, so are widely used in the ECG data compression literature. Kulkarni *et al.,* have suggested that the loss of information in the peaks of ECG reconstructed signal has critical clinical significance for classifying certain cardiac diseases, like myocardial infarction and hypertrophy [Kulkarni *et al.,* 1997]. So smaller mean square error for a given compression method may not establish its clinical superiority. Large amplitude errors in the high frequency region (QRS complex) may be clinically acceptable, whereas smaller errors in the iso-electrical regions may conceal P-waves. Ishijima *et al.,* and Jane *et al.,* recommend finding peak information in the ECG component waves and determining the boundaries of both the reconstructed and original signals for comparison [Ishijima *et al.,* 1983; Jane *et al.,* 1993]. Zigel *et al.,* introduced a different metric called Weighted Diagnostic Distortion (WDD), which is claimed to be better matched to diagnostic distortion than mean square error, but requires complex parameter extraction to calculate [Zigel *et al.,* 1997; Zigel *et al., 2000a*]. Because of the intricate calculations and computations required in these distortion measures, they have not been very widely accepted and thus lie beyond the scope of present comparison.

6.3 The Comparison

To compare the performance of various distortion measuring parameters, like RMSE, PSNR, PRD, NPRD, and MPRD, we have taken the first 2048 ECG samples of patient 107, signal lead MLII from MIT-BIH arrhythmia database physionet physiobank [Goldberger *et al., 2000*]. The original signal is shown in figure 6.1. The signal was compressed and reconstructed with the compression ratio of 18 and 24 using improved SPIHT algorithm.

Figure 6.1: Original ECG for patient 107, lead MLII

Figure 6.2 : Reconstructed ECG for patient 107, lead MLII, CR =18

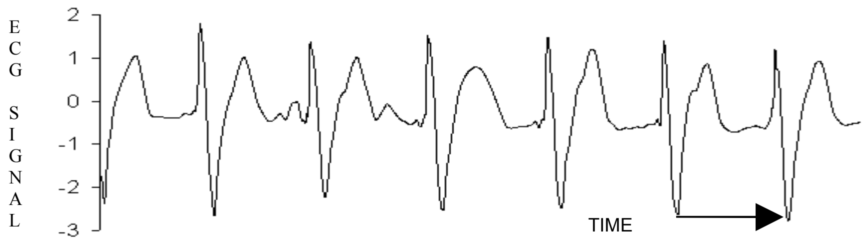


Figure 6.3: Reconstructed ECG for patient 107, lead MLII, CR =24

The two reconstructed signal are shown in figure 6.2 and figure 6.3. It is obvious that distortion with higher compression ratio will be more. But this measure of distortion should not change with the following in the original signal and subsequently in the reconstructed signal:

a) Scaling (multiplying the entire signal with say 2) (figure 6.4)
b) Base line shift (figure 6.5)
c) Base-line wander having no dc value (figure 6.6).

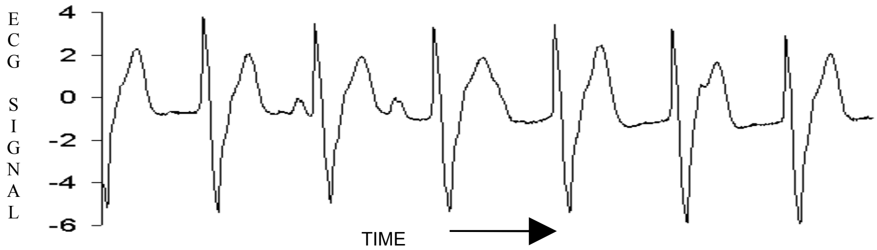


Figure 6.4: Original ECG for patient 107, lead MLII, scaled two times

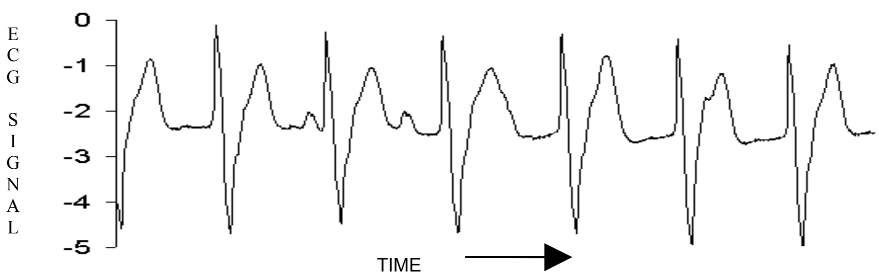


Figure 6.5: Original ECG for patient 107, lead MLII, with base-line shifted by two units

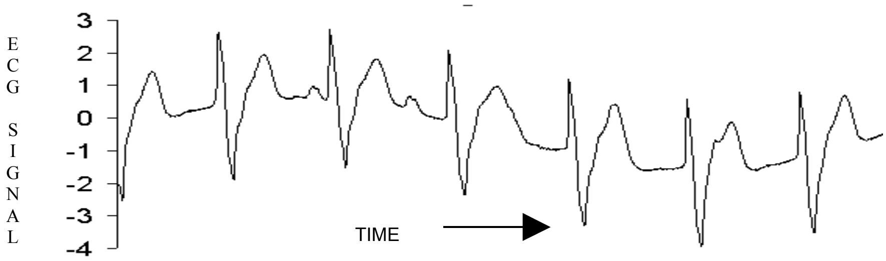


Figure 6.6: Original ECG for patient 107, lead MLII, with baseline wander having no dc value

6. 4 THE RESULTS

Using RMSE, PSNR, PRD, NPRD and MPRD, the distortion is measured comparing the original signal with reconstructed signal. The results are reported in table 6.1. This table is used as reference for knowing the effect of scaling, baseline shift and baseline wander on all the parameters.

Table 6.1: Parameters of original signal

	CR=18	CR=24
RMSE	0.0505	0.0862
PSNR	35.3590	30.7199
PRD	5.7056	9.7315
NPRD	1.0414	1.7765
MPRD	5.9517	10.1531

6.4.1 Effect of scaling

We multiplied the original signal, along with the reconstructed signals (CR=18 and CR=24) by two, to know the effect of scaling. RMSE, being the absolute distortion measuring parameter, also doubled. This indicates the need to normalize distortion parameter. All other parameters being normalized, did not show any change on the scaled signals. This is shown in table 6.2.

Table 6.2: Effect of scaling

	CR=18	Change		CR=24	Change
RMSE	0.1010	100%		0.1723	100%
PSNR	35.3590	0%		30.7199	0%
PRD	5.7056	0%		9.7315	0%
NPRD	1.0414	0%		1.7765	0%
MPRD	5.9517	0%		10.1531	0%

6.4.2 Effect of baseline-shift

We subtracted 2 units from the original signal, and from the reconstructed signals (CR=18 and CR=24), to know the effect of baseline shift. The numerical value of PRD reduced drastically, thereby indicating requirement of further refinement in its formula. NPRD and MPRD were however found immune to baseline shift, proving their superiority over PRD. The results are shown in table 6.3

Table 6.3: Effect of baseline shift

	CR=18	Change		CR=24	Change
RMSE	0.0505	0%		0.0862	0%
PSNR	39.8428	12.68%		35.2037	14.6%
PRD	2.0983	-63.22%		3.5795	-63.22%
NPRD	1.0414	0%		1.7765	0%
MPRD	5.9517	0%		10.1531	0%

6.4.3 Effect of baseline-wander

Many a times, due to respiration, or other reasons, the baseline keeps on wandering. The baseline is characterized by a low frequency noise, which the ECG signal rides on. Some researchers suggest considering the effect of this base line wander while measuring the distortion [Zigel *et al.,* 1996]. This makes distortion measurement akin to parameter extraction, and hence a tedious process. Thus a baseline wander with zero dc value was superimposed on both the original and reconstructed signals (CR = 18 and CR = 24). Other than the absolute unit RMSE, all parameters were significantly affected, indicating artificially low distortion. The results are shown in table 6.4.

Table 6.4: Effect of baseline wander

	CR=18	Change		CR=24	Change
RMSE	0.0505	0%		0.0862	0%
PSNR	37.8504	7.05%		33.2112	8.1%
PRD	4.2581	-25.37%		7.2640	-25.34%
NPRD	0.7573	-27.28%		1.2918	-27.28%
MPRD	4.3580	-26.78%		7.4343	-26.78%

6.5 THE NEW PARAMETER

We can see that all the parameters, viz. RMSE, PSNR, PRD, NPRD, MPRD are affected by either scaling or baseline shift or baseline wander or their combination. This necessitates proposing a new parameter that while maintaining the proportion of its numerical value to the distortion as in the existing parameters, should be immune to scaling, baseline shift and baseline wander. The best and the most frequently cited parameter being MPRD, further modification is proposed in this formula. We put forward a distortion parameter called Dynamically Derived Percentage Root-mean-square Difference (DDPRD) similar to PRD but taking running average of say 4 samples before and four samples after the current sample, including the current sample.

$$DDPRD = \sqrt{\frac{\sum_i [x_o(i) - x(i)]^2}{\sum_i [x_o(i) - R]^2}}$$

where x_o and x represent the original and reconstructed data respectively and R is the running average.

$R = (x_o[i-4] + x_o[i-3] + x_o[i-2] + x_o[i-1] + x_o[i] + x_o[i+1] + x_o[i+2] + x_o[i+3] + x_o[i+4])/9.$

The results are shown in table 6.5. DDPRD clearly fulfils the requirements set for the new parameter. It can be seen that this parameter, while maintaining the proportion of it numerical value to the distortion as in the existing parameters, is immune to scaling, baseline shift and baseline wander.

Table 6.5: Results with DDPRD

	CR=18	%age Change		CR=24	%age Change
Original signal	77.8129	-		132.7418	-
Scaling by 2	77.8129	0%		132.7418	0%
Baseline shift	77.8129	0%		132.7418	0%
Baseline wander	77.8131	~0%		132.7421	~0%

6.6 CONCLUSIONS

Dynamically Derived Percentage Root-mean-square Difference (DDPRD) is the new form of root-mean-square distortion measuring parameter, which gives its numerical value proportional to the distortion measured by other existing parameters like RMSE, PSNR, PRD, NPRD and MPRD. If the original signal is scaled by any factor, or the baseline is shifted in any direction or a baseline wander with zero dc value is introduced in it, subsequent to reconstruction, the numerical value of distortion measured by DDPRD remains unaffected as shown in table 6.6. While all other existing parameters fail to give the same numerical value when the ECG test signal is subjected to scaling/baseline shift/baseline wander, DDPRD shows immunity to the mentioned changes in original signal. This is pictorially represented in table 6.7.

Table 6.6: Consolidated results (percentage change)

	Scaling		Baseline shift		Baseline wander	
	CR18	CR24	CR18	CR24	CR18	CR24
RMSE	100%	100%	0%	0%	0%	0%
PSNR	0%	0%	12.68%	14.6%	7.05%	8.1%
PRD	0%	0%	-63.22%	-63.22%	-25.37%	-25.34%
NPRD	0%	0%	0%	0%	-27.28%	-27.28%
MPRD	0%	0%	0%	0%	-26.78%	-26.78%
DDPRD	0%	0%	0%	0%	~0%	~0%

Table 6.7: Consolidated results (acceptability)

	Scaling	Baseline shift	Baseline wander
RMSE	**X**	✓	✓
PSNR	✓	**X**	**X**
PRD	✓	**X**	**X**
NPRD	✓	✓	**X**
MPRD	✓	✓	**X**
DDPRD	✓	✓	✓

TELECARDIOLOGY WEBSITE DESIGN

7.1 INTRODUCTION

A majority of the population in rural and sub-urban area has little access to medical competence. Shifting a patient under critical circumstances to a distant hospital is time-consuming, expensive and many a times practically not possible. Telemedicine can provide great improvements to the health care delivery in remote areas, where it can bring high-quality care, often not or poorly available. Telemedicine may be as simple as two health professionals discussing a case over telephone, or as sophisticated as using satellites to transmit a consultation between healthcare providers located in two countries, using videoconferencing equipment. Medical data can contain images like X-Rays, MRI, CT Scans, Ultra-sound, Blood slide microphotographs, ECG recordings, Audio–Video clippings etc. Transfer of these images and text data may utilize a variety of telecommunications technology like telephone lines, ISDN, internet, intranets, LAN, WAN and satellites. Basic ingredients remaining the same, "Telemedicine" gets rechristened as "Telecardiology", when dealing with cardiac patients. Though there are many references of Telecardiology being practiced in India at various centres, the procedure is more like videoconferencing rather than in the form a dedicated website, designed to take care of cardiology cases [Srikanth, 2003].

There is need to have a website for Telecardiology, wherein with simple equipment like digital ECG recorder and a PC with moderate speed Internet connectivity would greatly help a local physician or a General Practitioner (GP) to have an access to expertise of cardiac specialists located at distant hospitals, even beyond the political borders. The need to compress an ECG data, especially for continuously monitored long records, to effectively increase the speed of data transfer over Internet with limited speed, a set of executable files for compression of ECG data is installed at the local physician's PC, while another set of executable files for decompression of ECG data is installed at the Cardiologist's PC. The details of these executable files have already been discussed in Chapter 4.

With the developments in Internet and World Wide Web (WWW), majority of teleconsultations, including those for telecardiology have shifted from propriety networks to www, because it not only provides a universal network, but also gives a system-independent platform as all the sub-networks of the Internet support TCP/IP. Since the www supports multimedia information, including text, images, audio and video it is possible for telecardiology system to present multimedia medical information over the www [Bai *et al.,* 1998]. This chapter presents the design model of a user-friendly, interactive and dedicated telecardiology based website along with its number of self-explanatory screenshots. The website is evaluated by a panel of physicians, and their valuable suggestions incorporated therein.

7.2 FRONT-END, BACK-END AND INTERFACE

The terms front-end and back-end in their most general form refer to the initial and the end stages of a process flow. Generally, front end is responsible for collecting input from the user in a possible large variety of forms, and processing it in such a way that it conforms to the specifications that conform to its use by back-end. The connection of front-end to the back-end is a sort of interface. In software design, the separation of system software in front-end and back-end is a kind of abstraction done to reduce and factor out details, so that one can focus on a few factors at a time. Use of subroutines in computer programming is a typical example of abstraction.

We have made use of HyperText Markup Language (HTML) as front end of designing the Graphical User Interface (GUI) of the web pages. HTML is a markup language designed for creation of web pages with hypertext and other information to be displayed with a web browser. A markup language combines text and the extra information about the text. The extra information is about the structure or the presentation of the text to be displayed, is expressed using markups, which are intermingled with the text itself. A hypertext is a user interface for displaying documents, "branch or perform on request". A common form of hypertext document contains number of cross-references (called hyperlinks) to other documents. Selecting a hyperlink causes a computer to quickly display the other document. The most famous implementation of hypertext is World Wide Web. Contrary to a common belief, the Internet and World Wide Web are not synonymous. While internet is a collection of interconnected computer networks, linked by copper wires, fibre-optic cables and other wireless connections, the Web is a collection of interconnected documents linked by hyperlinks and Uniform Resource Locators (URLs) and is accessible using the Internet. HTML is now an international standard [International Organization for Standardization / International Electrotechnical Commission (ISO/IEC) 15445: 2000]. A typical HTML document would look like the following:

```
<html>
  <head>
    <title>Password Update</title>
      </head>
  <body>
WELCOME TO TELECARDIOLOGY <BR>
•
•
•
•
.<form  action="Home.php" method="POST">
<input type = "submit" name = "back2h" value="Back to Home Page ">
</form>
<hr>
</body>
</html>
```

We use MySQL as the database back end for maintaining the related database on Linux platform. MySQL is a multi-user, multi-threaded Structured Query Language (SQL) Database Management System (DBMS). MySQL AB (Aktiebolag, a Swedish term for corporation) makes MySQL available as free software under GNU General Public License (GPL). Interestingly, GNU is a recursive acronym for GNU’s Not Unix, because its design is Unix like, but contains no actual Unix code. There are Application Programming Interfaces (APIs) available that allow applications written in numerous programming languages to access MySQL databases, including: C, C++, C#, Lisp, Perl, PHP, Python etc. An Application Programming Interface (API) is the interface that a computer system, library or application provides in order to allow requests for services to be made of it by other computer programs, and/or to allow data to be exchanged between them.

We chose PHP as the interface programming language. PHP is a recursive acronym for PHP Hypertext Preprocessor. Originally designed as a high-level tool for producing dynamic web content, PHP is used mainly in server-side applications. Server-side scripting is a web server technology in which a user's request is fulfilled by running a script directly on the web server to generate dynamic HTML pages. It is usually used to provide interactive web sites that interface to databases or other data stores. This is different from client-side scripting where scripts are run by the viewing web browser, usually in JavaScript. The primary advantage to server-side scripting is the ability to highly customize the response based on the user's requirements, access rights, or queries into data stores. The web server executes server-side scripts when the user requests a document. They produce output in a format understandable by web browsers (usually HTML), which is then sent to the user's computer. The user cannot see the script's source code (unless the author publishes the code separately), and may not even be aware that a script was executed. In short, PHP runs on a web server, taking PHP code as its input and creating web pages as output.

7.3 CLIENT, EXPERT AND MANAGER

Our website designed for implementing telecardiology categorizes its users in three types: clients, experts and manager. While there can be many clients and experts which may log on the website, there is only one manager to manage various activities on the site. Different persons may be authorized at different times to log in under a common name and password for managing the site. A client is a person that seeks advice on some medical issue. A registered client in our case is a general practitioner wanting expertise in cardiology. A layperson is not authorized to have direct contact with a cardiologist, as the lack of the required vocabulary itself may prove fatal. A common person may not be able to distinguish the term “chronic” from “acute” while describing her symptoms. Similarly the verdict given by the cardiologist may be misinterpreted, if the client is not a medical professional. Moreover taking ECG recording on the subject, interfacing a digital ECG machine with PC, monitoring the blood pressure etc. requires some level of skill. Considering these facts, a layman without any medical pre-qualifications, is not recommended for registration as a client. Verification of these antecedents is to be done by the manager.

To register as an expert, one has to pass through more stringent examination. Here, apart from professional qualification, the current employment status, experience duration and general reputation of the cardiologist is to be reviewed by a panel of assessors and only upon their recommendation will the manager be able to register the expert. In our case the expert may have expertise broadly in either cardiac medicine or in cardio thoracic surgery. A set of rules and regulations are to be followed by both clients as well as experts. In case of any serious violation, the manger has right to deregister the defaulting party. The manager also has a role of arbitrator to play, in case of any dispute between the client and the expert.

7.4 PRIORITIZING AND CREDIT TRANSFER

The request emanating from the client can be classified in three categories (i) Urgent (ii) Routine and (iii) Economy. With a queue of jobs at the expert's end, it very natural of the expert to first attend the urgent queries, followed by the routine queries, giving least priority to the economy queries. The client has right to upgrade an economy query to routine or even to urgent query, in case the waiting period is too long. A deliberate delay on part of expert is detectable by manager, who can any time view all the pending jobs of all the experts. The site has a provision of fiscal transaction from client to expert in the form of credits. A client can buy credits from the manager after making the due payment. The client in making the set of queries to the experts, uses these credits. Thus the credits get transferred from client's account to the expert's account. Conversely, the experts can encash these credits from the manager from time to time, say on weekly basis and get the due payment. The price differential in credits for clients and those for experts is used for providing the entire service.

We have proposed four credits for urgent queries, two for routine queries and only one credit for economy queries, as the name suggests. The transfer of credits takes places once the query session starts and is valid for a minimum of 24 hours. There is no limit on the number of queries in a given session. However all queries must relate to only a single case. It is obvious that the expert will easily detect if the queries don't relate to the same case. He has all the right to withhold his advice in case he feels the client is trying to bungle the things. A client is given large number of alternate names like "Philip", "Philip2", "Philip3" and so on, as the client is a general practitioner, who may like to discuss a number of cases parallelly. An expert is at liberty to give his personal contact details like, his mobile number, email address and post address, but the client has no right on these details. In case the client is not satisfied with the response of the expert, he may approach the manager for the same. The manager will first try to settle the dispute on mutual terms. Otherwise the manager has the right to give his verdict by which either the client has to bite the dust or the expert has to refund the credits transferred to his account. In case when both the parties are unyielding, credits are refunded to the client from the site's exigency fund. All credits are to be purchased in advance by the client. In case of insufficient credits in the account of a client, his query shall not be entertained. For example if a client has only three credits in his account, he can go for one economy and one routine job, but cannot request an urgent job, without purchasing more credits. Any client or expert can always check the balance credits, at a click of a mouse at a proper place.

7.5 THE DATABASE

For maintaining the related database, MySQL is used as the database back end on Linux platform. The entire data is stored in three tables viz., "password", "cure" and "mail". The field and type of these are given in tables 7.1- 7.3.

Table 7.1: MySQL table "password"

Field	Type
Name*	char(25)
Password	char(15)
Category	char(10)
Credits	int(6)
Log	char(4)
Specialization	char(25)

*Key Field

Table 7.2: MySQL table "cure"

Field	Type
Client	char(25)
Expert	char(25)
Query	char(255)
Response‡	char(255)
Q_no	int(4)
Date	date
Type	char(20)

‡Default value "dummy"

Table 7.3: MySQL table "mail"

Field	Type
Name	char(25)
Email	char(25)
Message	char(255)

MySQL table "password" shown in table 7.1 has a key field 'Name'. It means no two records can have same 'Name'. Whenever an expert or a client is registered, a name and default password is allocated to him. The password can be changer later by the user but the name remains the same throughout the lifetime of user. Client can have multiple login accounts with successive names like “Philip”, “Philip2”, “Philip3” etc. as discussed earlier also, but an expert can register with only name after due verification by the manager. Only one name is given for the manager with a rather complicated password, which may be shared by different authorized persons to manage the site. The field ‘Password’, as the name suggests stores the password. Two records may have same ‘Password’ and the user may change the password any number of times. ‘Category’ can be either “Expert” or “Client” or “Manager” and is decided at the time of registration. There is no reason to change this field, unless the client in due course of time qualifies to be an expert. In that case he has to deregister as a client and reregister as an expert.

The field ‘Credits’ is not valid for manager. It has the record of credit balance due to an expert or a client. At the time of registration, the default value of ‘Credits’ is zero. A client buys certain number of credits from the manager by making due payment by fiscal transaction through credit card, cheque, draft or other money transfer tools. The price of credits is fixed for clients and it slightly higher than that for the experts. For example, a credit may be for $1 for the client and $0.9 for the expert. Experts earn credits when they give their expert advise to the clients. After earning a certain number of credits, an expert may decide to encash the credits and get the money by any of the money transfer tools like credits account, cheque, draft etc. The differential of price in the credits for the client and the expert, i.e. $0.1 is retained as service charge for maintaining the site and providing the relevant service. While transfer of credits from client’s record to expert’s record takes place automatically, the manager has the rights to increase the credits of clients upon receiving the money and decrease the credits of the experts on giving the money the expert. In addition, in case of any dispute, for example, client being not satisfied by the response of the expert, the manager has the right to probe into the dispute and reach for a mutual agreement, the credits transferred from client’s record to expert’s record are reversed. In case both the parties are adamant on their stand, the expert gets the payment as usual, at the same time client gets refund from the exigency fund maintained by the site. Recall $0.1 per credit retained by the site, has this component also.

The field ‘Log’ can have only two values i.e. “in” or “out”. Every time any user logs in, ‘Log’ value becomes “in”. On signing out, it becomes “out”. The advantage of maintaining ‘Log’ status for expert is that the clients can view the names of experts currently logged in. On the other hand, the advantage of maintaining ‘Log’ status for the client is that once a client logs out, any unscrupulous person who tries to sneak into client's account by using back arrow key on the web-browser tool bar, is not given access to it, unless it follows a proper login path making use of valid password. This strategy is followed for manager's login too, for enhanced security and prevention of misuse of the back arrow key on web-browser's tool bar. Apart from use of back-arrow key, another loophole in the security is, if the user exits without proper signing out procedure and the unauthorized person tries getting into the user's account by typing in the web page address in the address bar. This loophole is plugged by using "Session" in PHP programming. On exiting without sign out, the "Session" automatically ends and typing in the web page address in the address bar of the web-browser's tool bar will only result in a message "IMPROPER LOGIN". Another aspect of maintaining login status experts is for the manager to ensure that at least one expert in each field of specialization is always available online. He has to coordinate with the experts to achieve this availability.

The field 'Specialization' is only for experts and can have value as either "Cardiac Medicine" or "Cardio thoracic Surgery". This field gets its value only at the time of registration and remains unchanged like 'Name' field, for the lifetime of the expert.

The fields of MySQL table "cure" shown in table 7.2 are quite self-explanatory in nature. The client whose name is stored in 'Client' poses a query that is stored in 'Query' to an expert whose name is stored in 'Expert'. The identity of query is in the form of an integer stored in 'Q_no', the response given by the expert is stored in 'Response', the date on which the query is posed is stored in 'Date' and the type of query i.e. "normal" or "routine" or "economy", is stored in 'Type'. Till the time any response is given by the expert, the 'Response' field in not NULL and contains a default string "dummy" in it. Four credits are transferred for "urgent" query, two for "normal" and only one for "economy" query. Moreover once a query is posed, all subsequent queries for a minimum of twenty-four hours (two dates ahead) are treated as a part of the original query posed. Thereafter the queries become "old" and the "Q_no" for all old queries becomes "0". The old queries may be retained for future reference or the client may delete them.

The third MySQL table "mail" shown in table 7.3 is totally unrelated to the other two tables. This keeps record of the mails sent to the manager by any person before logging in as client or user. Any passerby wanting any relevant information or wanting to register, is free to mail any message to the manager. The name and the email address of the person posing any message to the manager is stored in ‘Name’ and ‘Email’, while the message is stored in ‘Message’ field. The manager regularly check the mails and responds at the given email address, as most of us do, before deleting them from the mailbox.

7.6 WEB PAGES

Our website has only five web pages. (i) Telecardiology home page (ii) Password update page (iii) Manager’s page (iv) Client’s page and (v) Expert’s page. Instead of having a large number of web pages, we have tried to present the relevant information by pop-ups within the same page.

The home page has two primary functions: to log in and to send message to the manager. The screenshot of this page is given in figure 7.1. The person desirous of logging in has to first choose his category as a manager or a client or an expert by clicking at the appropriate radio button. In case no category is selected, or the selected category is wrong, the user is prompted to login with proper selection of the category. In case of a login attempt of an unregistered user, the message displayed is “USER DOES NOT EXIST”. In case of incorrect password, the message flashed is “Password is incorrect”. Only when the category, registered name and password match, the user is given an option to go to the relevant page or to go in password update. In case of any problem with logging in or otherwise, a message to manager can always be posted from this home page as shown in screenshot in figure 7.1. The flow chart for command execution of the home page is given figure 7.2.

In case the user opts to go in for password update, the page for the change opens. Figure 7.3 shows screenshot of password update page, that simply asks for the old password, followed by new password and then again confirming the new password, to safeguard any typing error in the new password. Again, when the old password matches with the stored password, and the two new passwords are the same, the stored password is updated. The flow chart for the password update is given in figure 7.4.

If the category selected is “Manager”, then on successful login, manager’s page opens. Screenshot and the flow chart for manager’s page are given in figures 7.5 and 7.6. respectively. If the category selected is “Client”, then on successful login, client’s page opens. Screenshot of client’s page and the flow chart for client’s page are given in figure 7.7

and 7.8 respectively. Similarly, screenshot for expert's page and its flow chart are shown in figures 7.9 and 7.10 respectively.

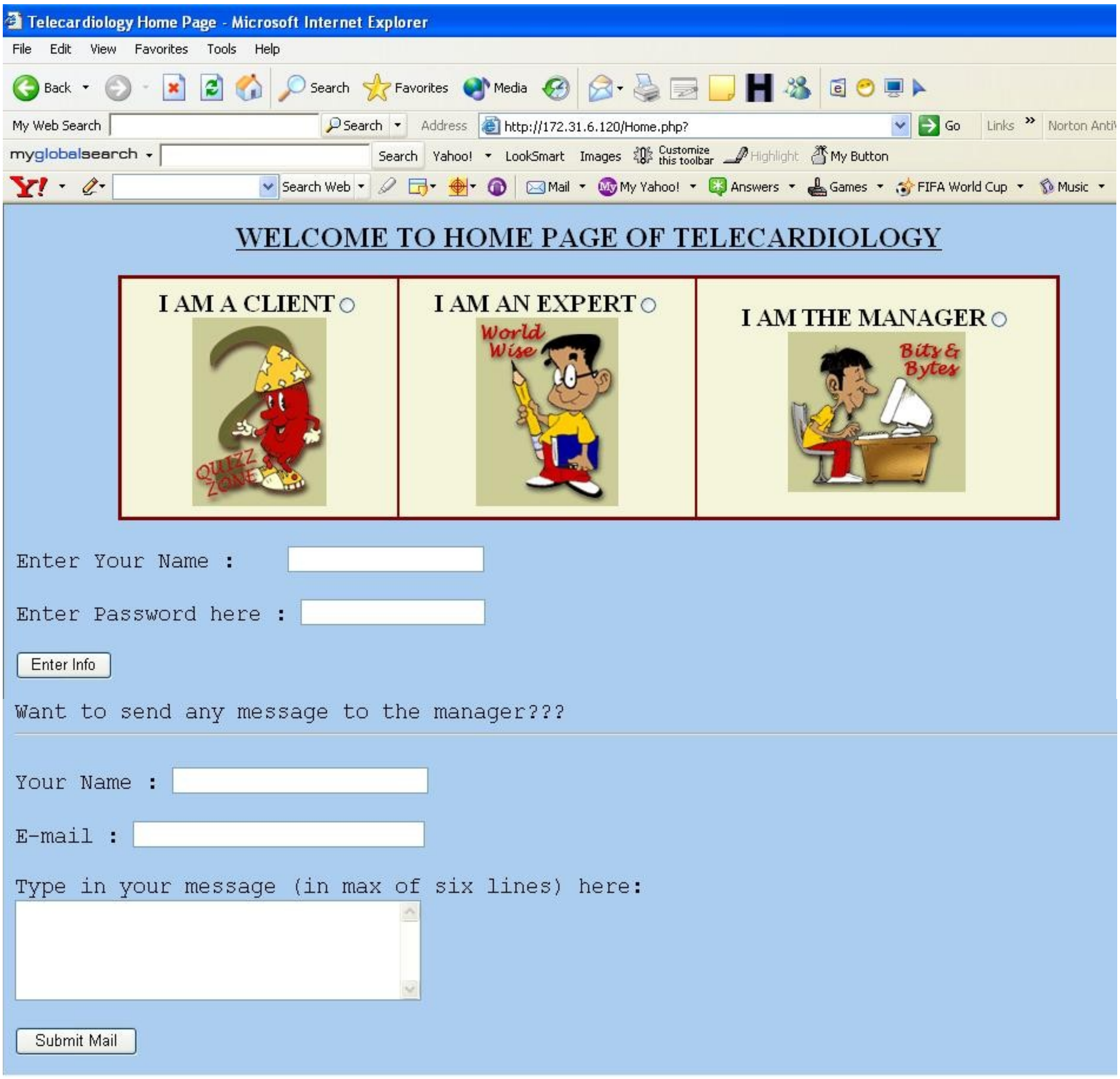


Figure 7.1: Screenshot of Telecardiology Home Page

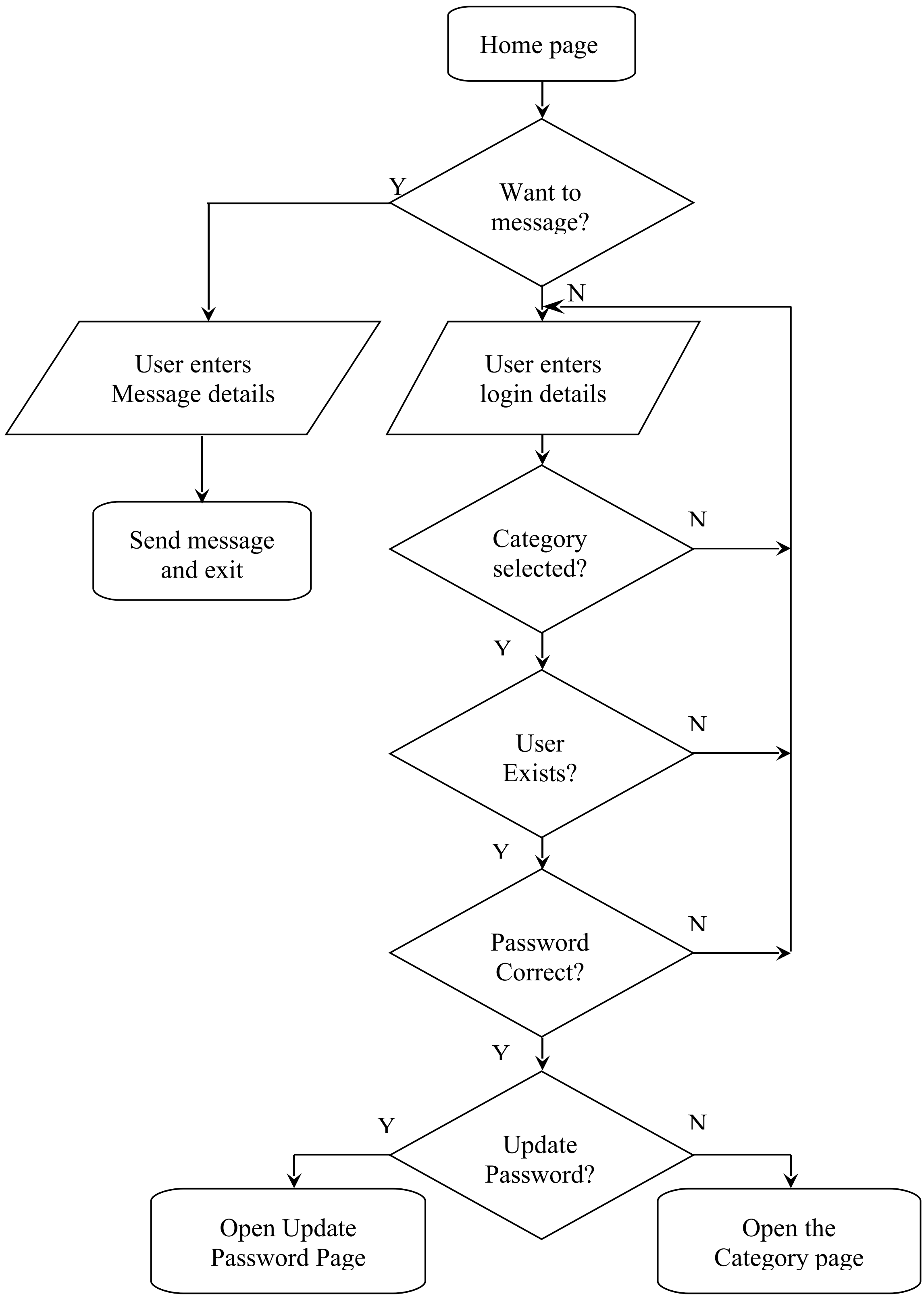


Figure 7.2: Flow chart of command execution in home page

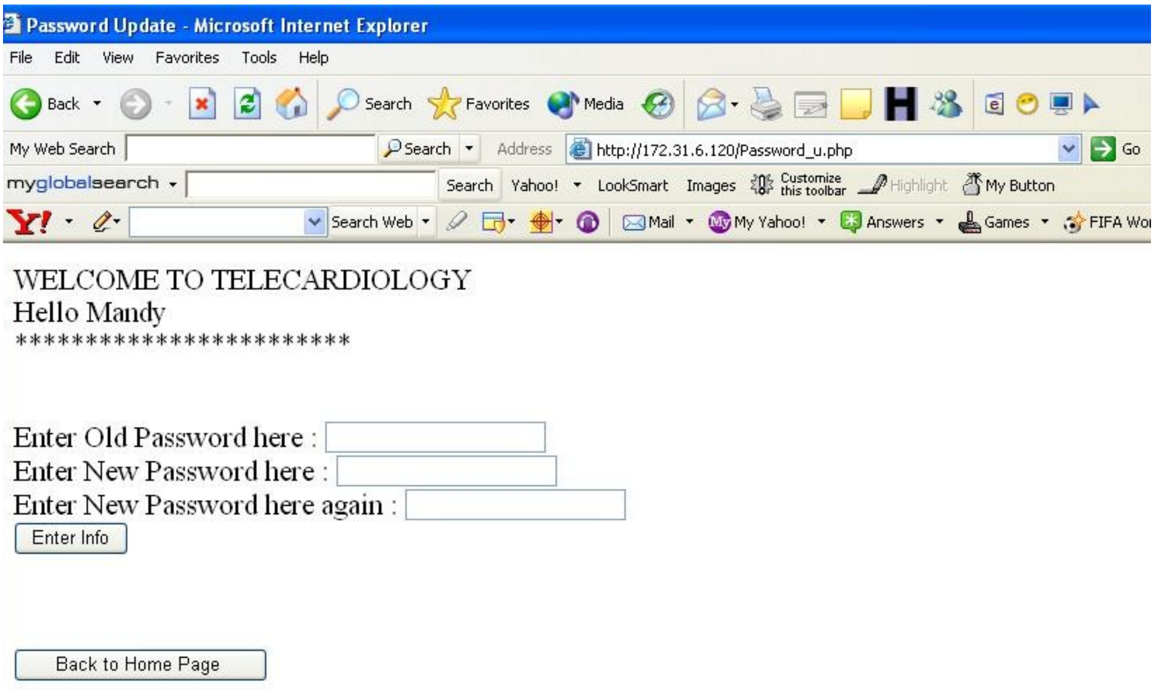


Figure 7.3: Screenshot password update page

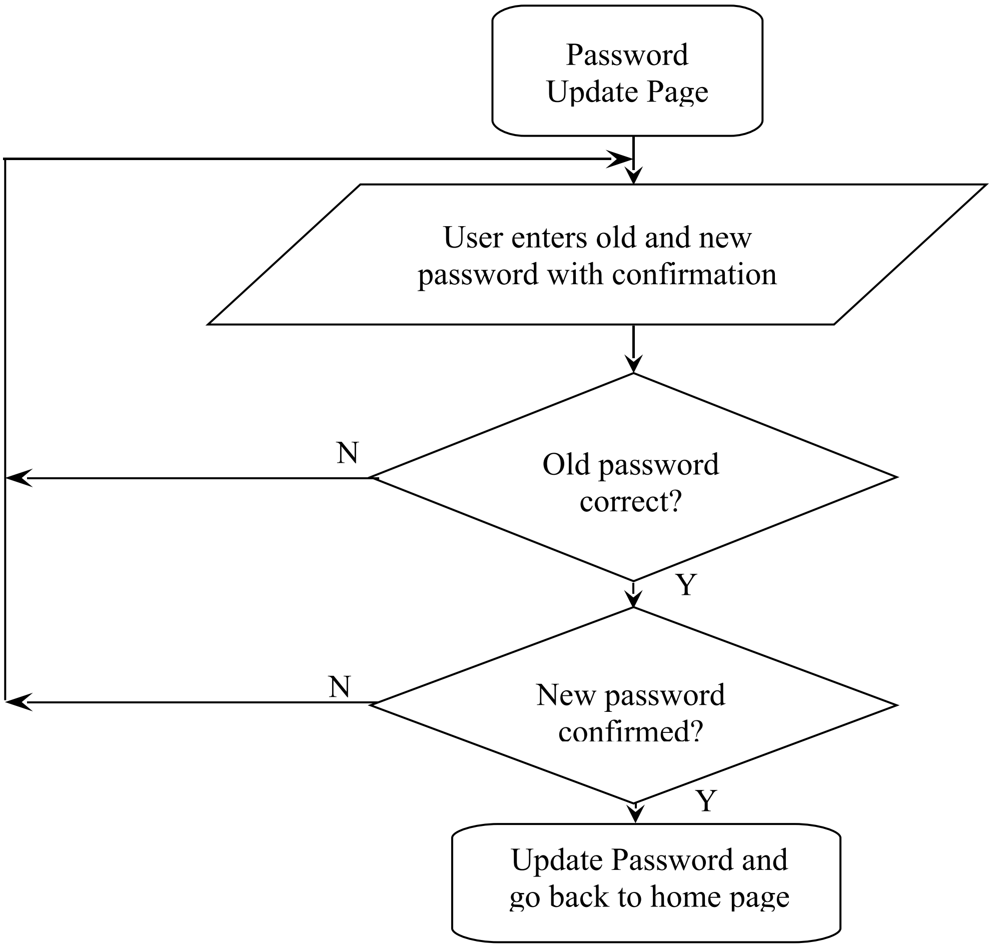


Figure 7.4: Flow chart of command execution in password update page

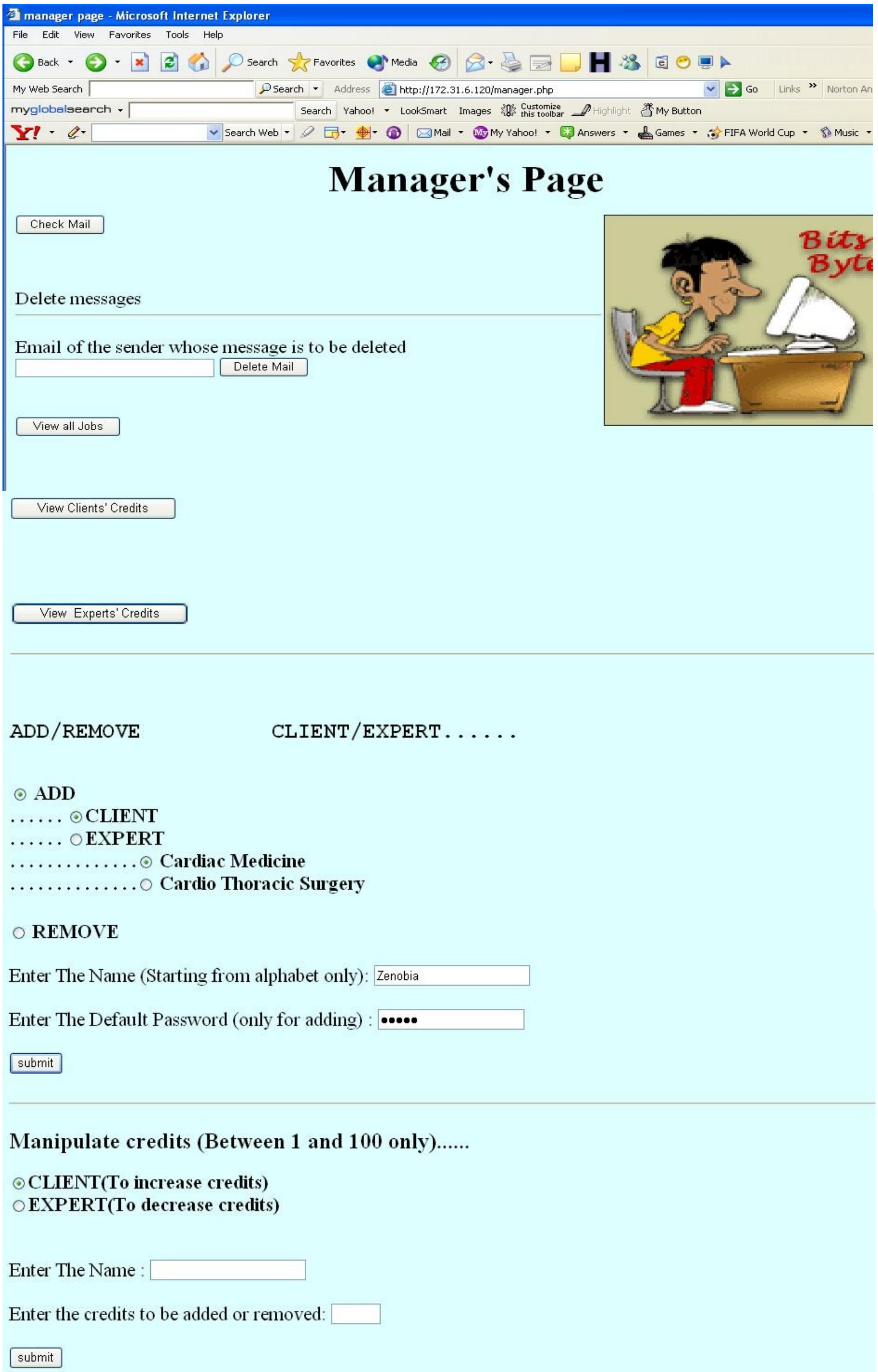


Figure 7.5: Screenshot of Manager's Page

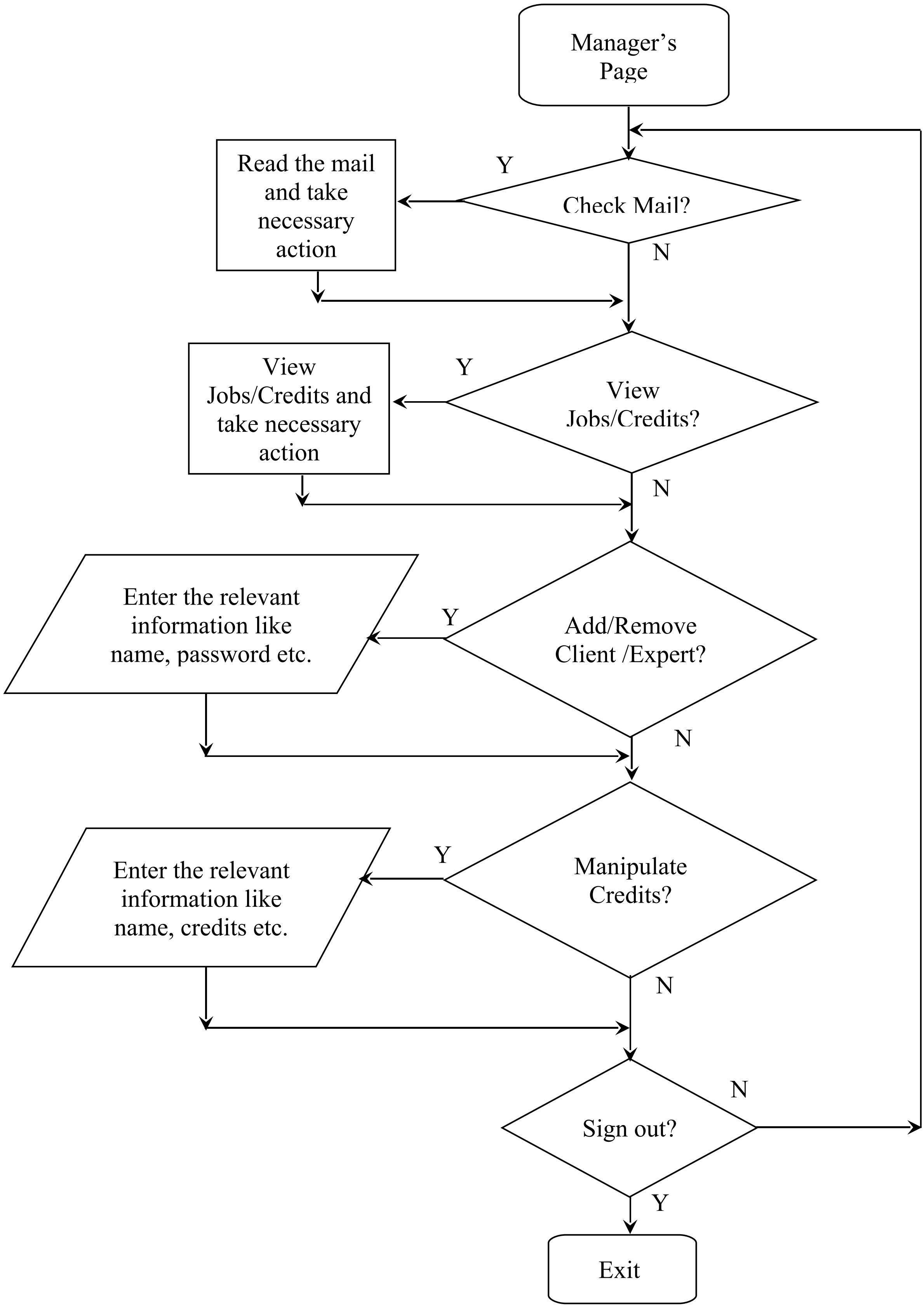


Figure 7.6: Flow chart of command execution in manager's page

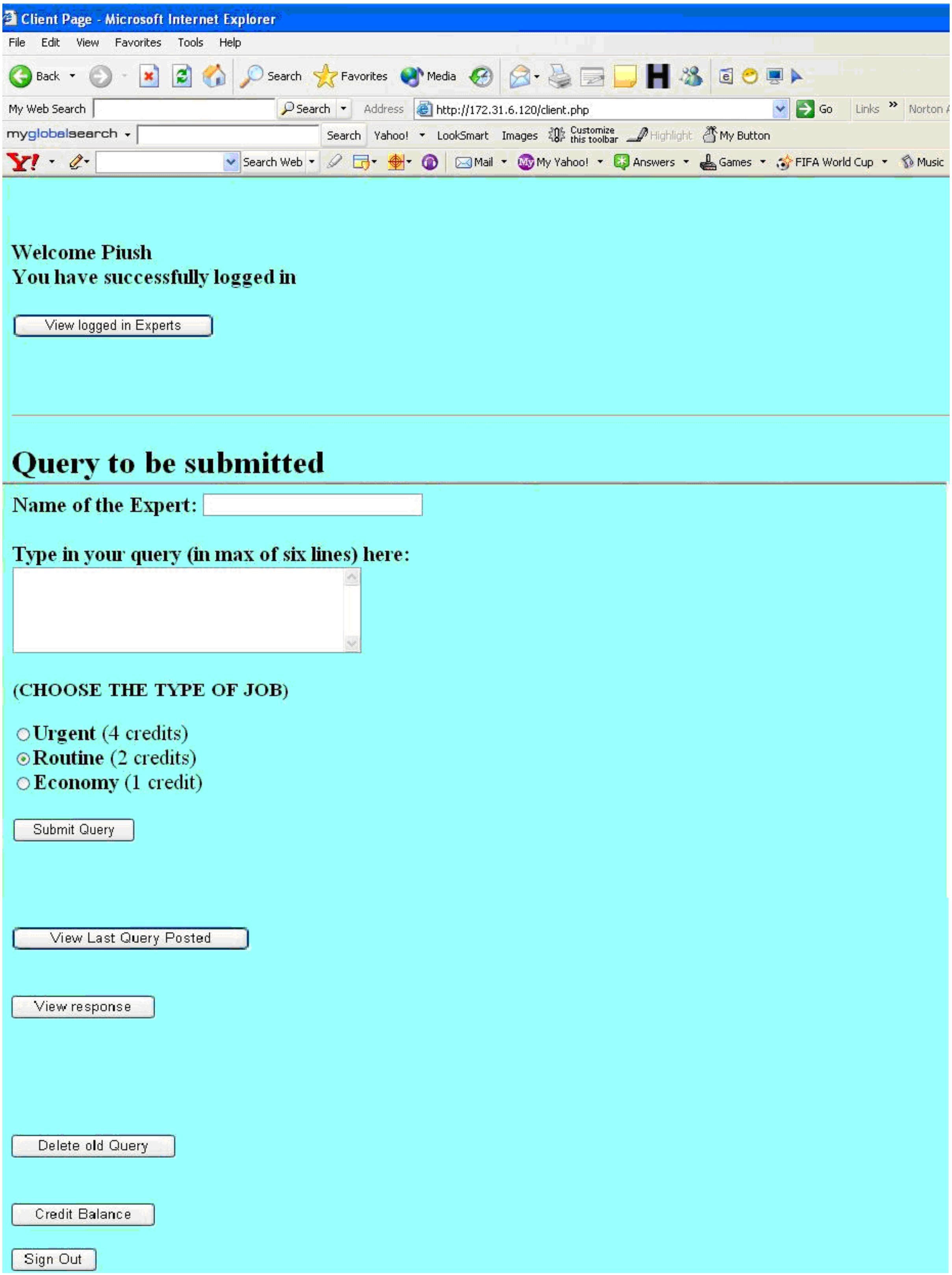


Figure 7.7: Screenshot of Client's Page

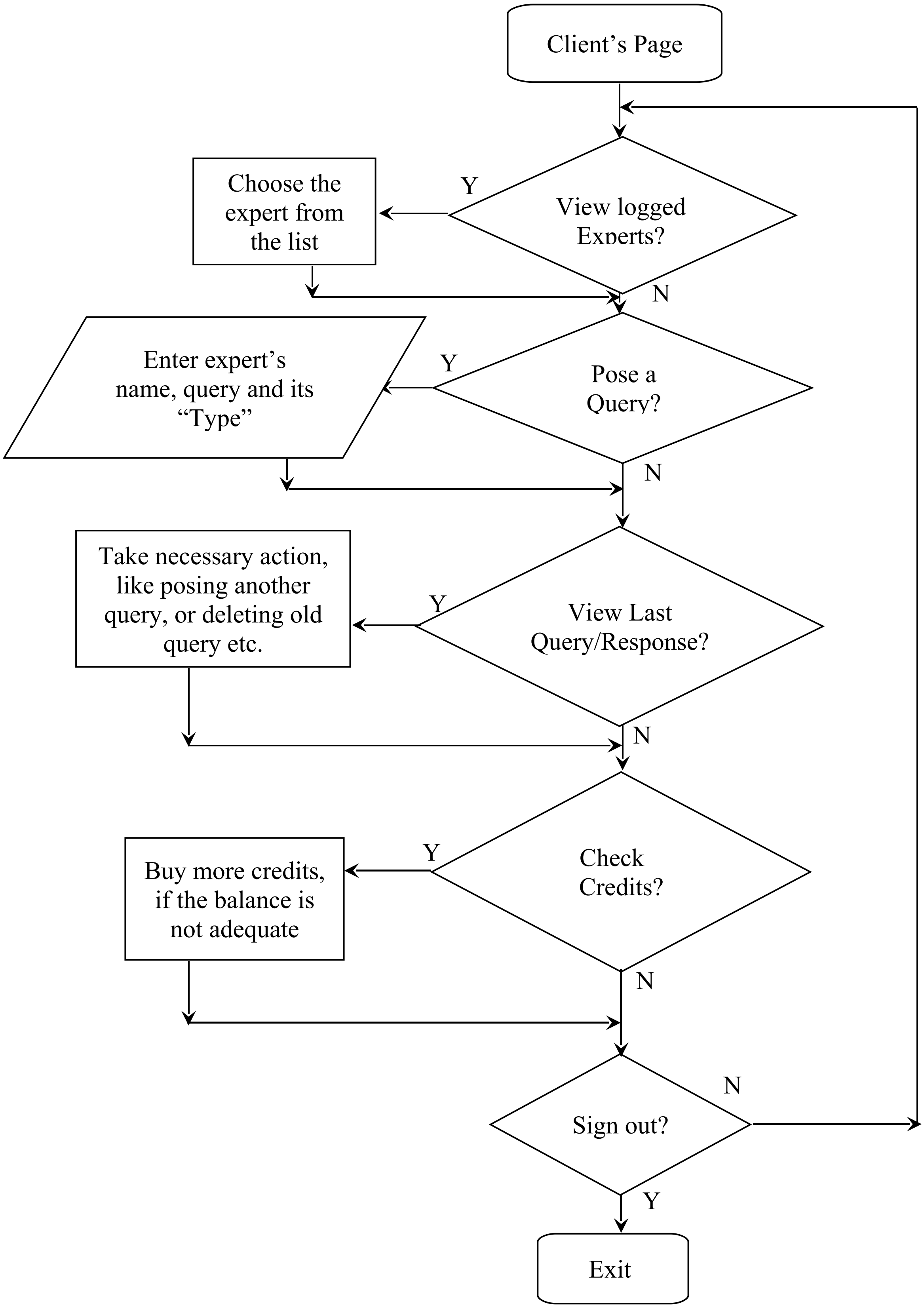


Figure 7.8: Flow chart of command execution in client's page

Figure 7.9: Screenshot of Expert's Page

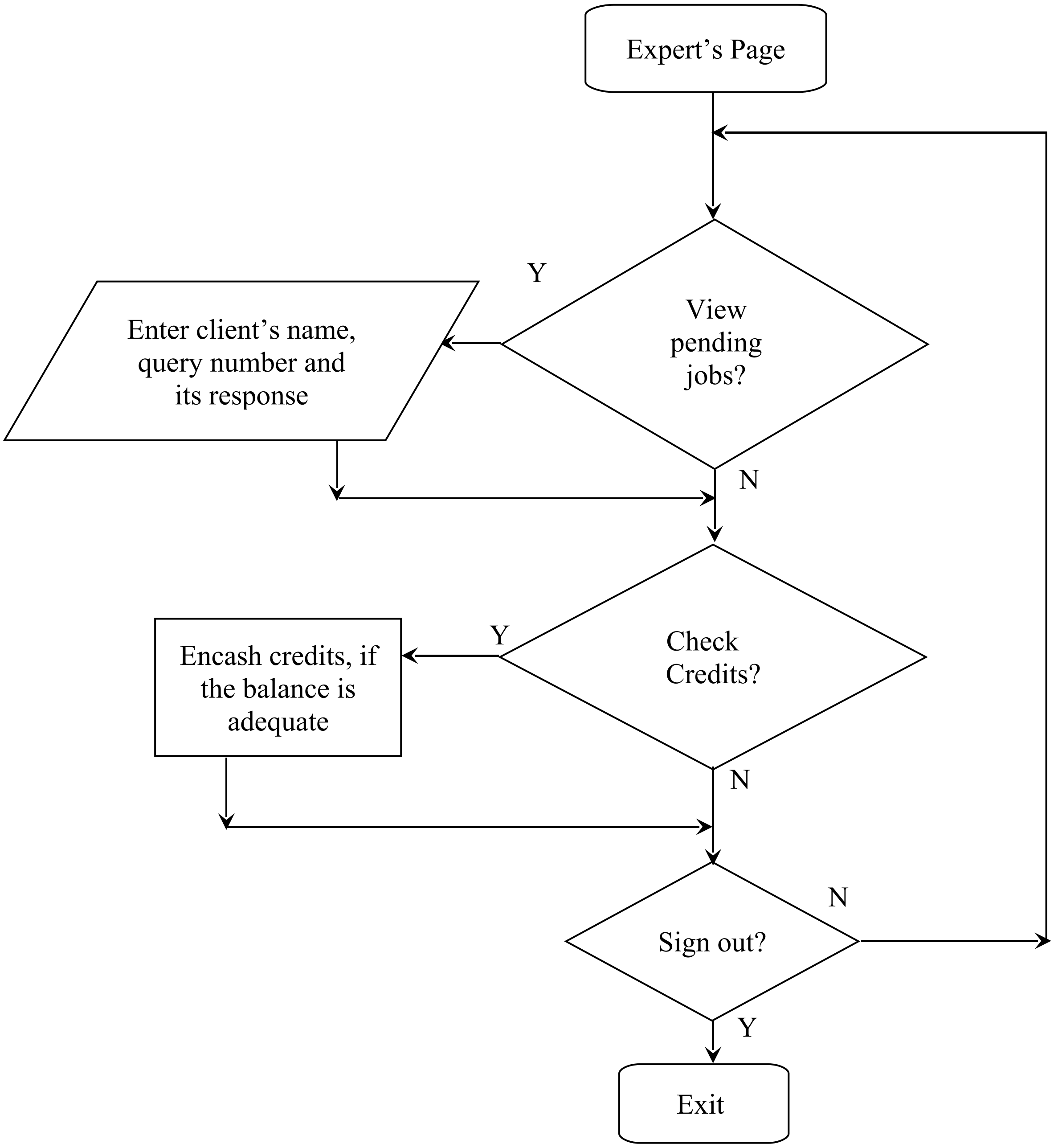


Figure 7.10: Flow chart of command execution in expert's page

Subsequent screenshots show how a dialogue between a client and expert takes place. Figure 7.11 shows a screenshot of client's page where a client named "Piush" views list of logged-in experts, and poses a query to an expert named "Zenobia".

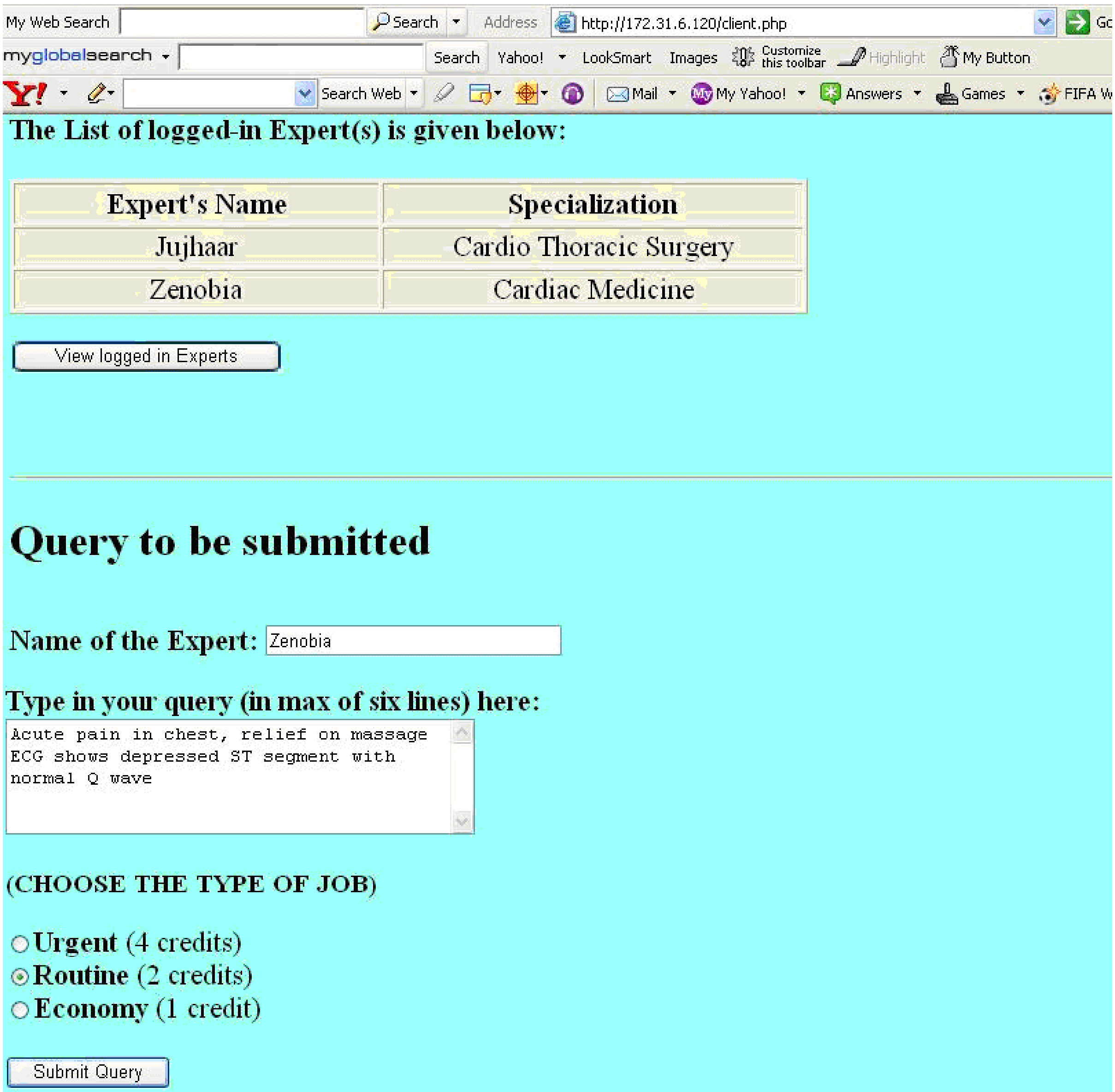


Figure 7.11: Screenshot of a client posing a query to an expert

Figure 7.12 shows the screenshot of expert's page, wherein the query is communicated to the expert and the expert responds to the query. A record of all this communication between the client and the expert is available to the manager. Figure 7.13 shows a screenshot of manager's page showing a dialogue between a client and an expert.

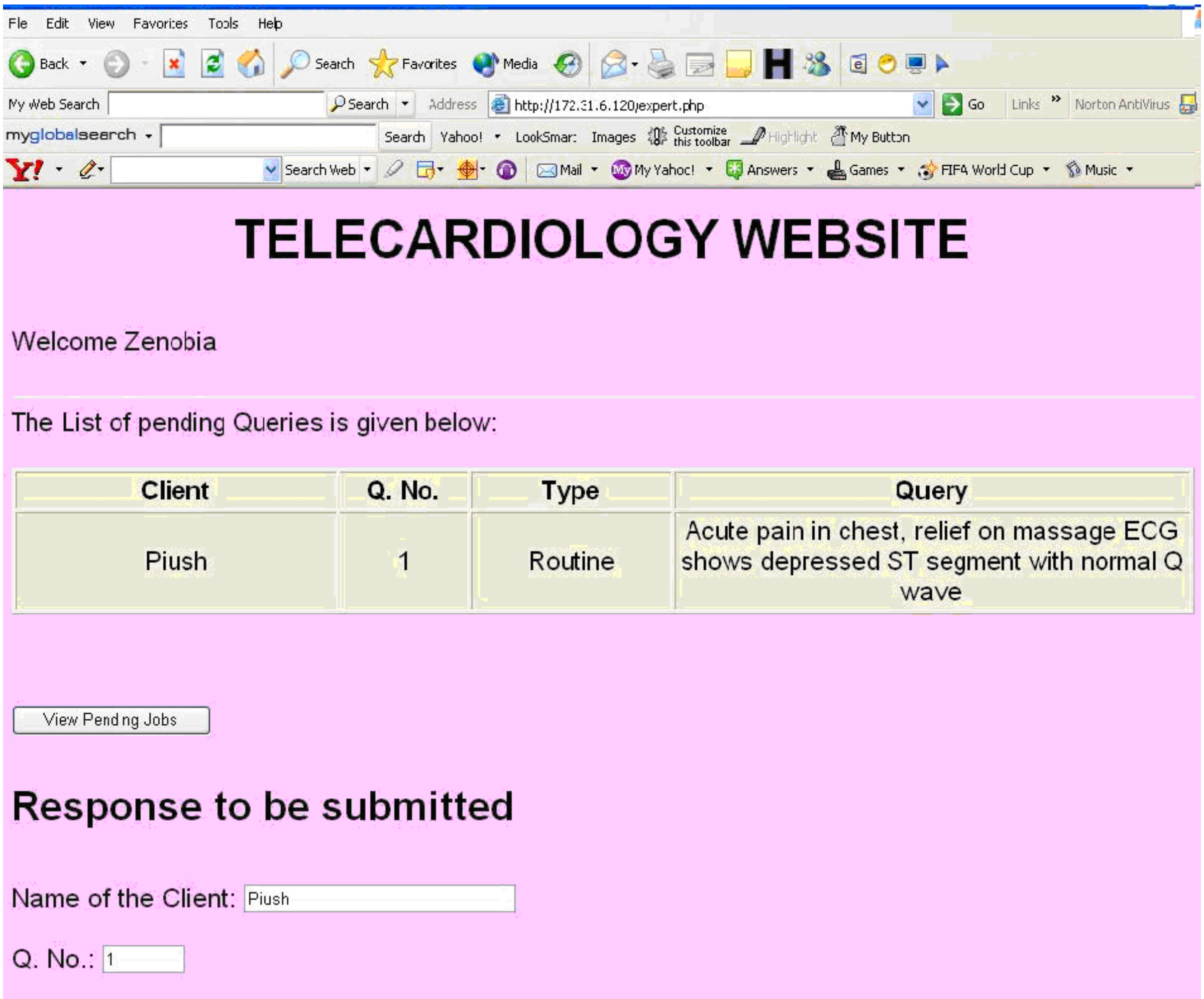
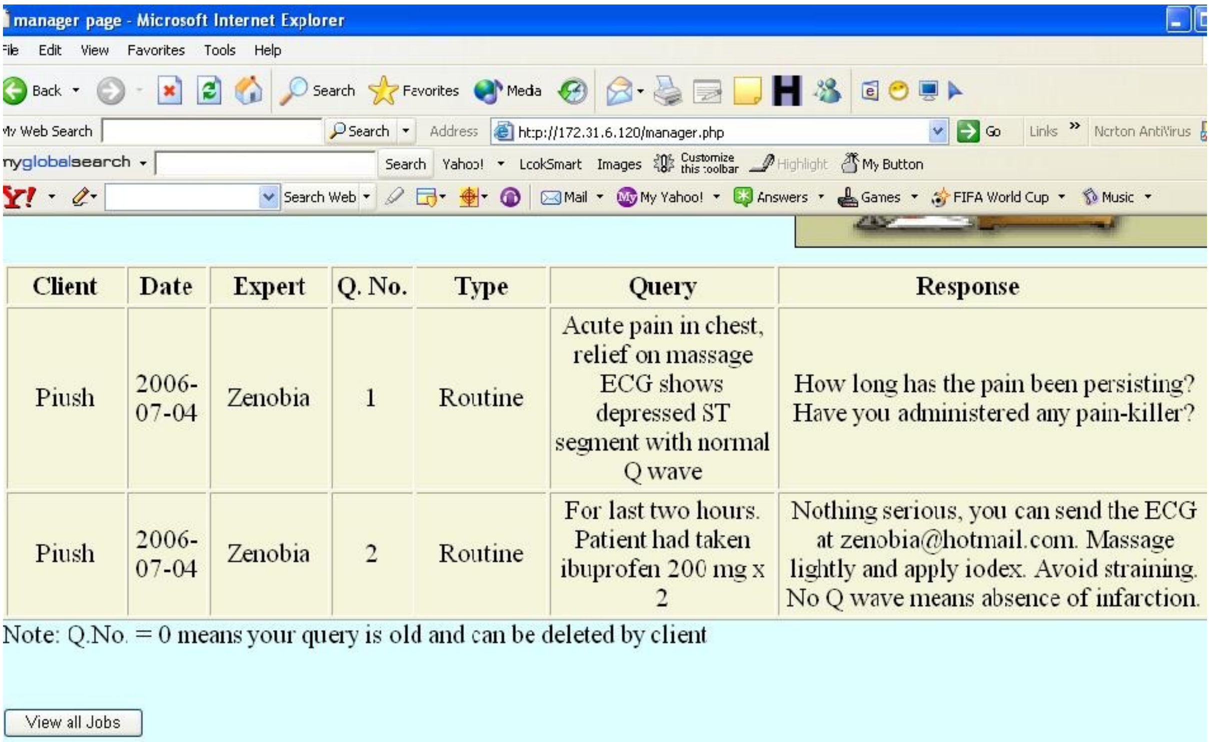


Figure 7.12: Screenshot of an expert responding to client's query



Client	Date	Expert	Q. No.	Type	Query	Response
Piush	2006-07-04	Zenobia	1	Routine	Acute pain in chest, relief on massage ECG shows depressed ST segment with normal Q wave	How long has the pain been persisting? Have you administered any pain-killer?
Piush	2006-07-04	Zenobia	2	Routine	For last two hours. Patient had taken ibuprofen 200 mg x 2	Nothing serious, you can send the ECG at zenobia@hotmail.com. Massage lightly and apply iodex. Avoid straining. No Q wave means absence of infarction.

Note: Q.No. = 0 means your query is old and can be deleted by client

Figure 7.13: Screenshot of manager's page showing a query-response session

7.7 CONCLUSIONS

With doctor population mainly concentrated in posh cities, semi-urban and rural areas are deprived of the medical expertise. Telemedicine is an endeavor to provide this much needed expertise. A general practitioner can get medical advice from experts in majority of the cases and be almost as effective as the expert himself. For cardiologist, ECG is one of the main diagnostic means to determine the status of heart. This ECG record needs to be compressed before it can be transmitted to expert. To enhance the overall speed of communication a set of executable files to compress and decompress ECG signal is installed at the general practitioner's and expert's site respectively. The compressed data file is in the form of ASCII string with built-in threshold values, and thus cannot be read by any other decoding software. The data in a way gets encrypted, providing a high degree of confidentiality against unauthorized access.

A user-friendly, interactive and dedicated telecardiology based website is designed, taking valuable suggestions from a panel of reputed physicians. The website is designed using HTML as the front end user GUI, MySQL for maintaining the related database, and PHP as the interface programming language. Password protected login to the website can be done as a manager or a client or an expert. The site has built-in security features against unauthorized intrusions in the site. The jobs are prioritized as per the requirement of the client and the transfer of credits from client's account to expert's account is done as per the priority, i.e. more for high priority jobs and vice or versa. Ensuring online availability of experts and making fiscal transactions from clients and to experts is responsibility of the manager. The manager also does new registrations as a client or as an expert after verifying their credentials. Several screenshots of the website show its features and functioning of clients, experts and manager. The website has been designed keeping in mind the practical requirements and convenience of both client and expert, with an objective of bridging the gap between the client and the expert. The concept of 24 hour availability of authentic experts in the required area of specialization like cardiac medicine and cardio thoracic surgery, facility to compress and decompress long records, prioritizing the jobs instead of having a general queue, enhanced security features, safe fiscal transaction through a manager and a platform for settling disputes, if any, are some of the features which are not available on general chat sites.

CONCLUSIONS AND SCOPE FOR FUTURE WORK

8.1 CONCLUSIONS

Telemedicine offers an opportunity to deliver healthcare services for entire population of the world, and also promises utilizations of resources from distant places, even beyond the borders. With the developments in computer hardware and software, telecommunication tools and Internet facility, a good amount of research is being carried out in different parts of the world for efficient solutions through Telemedicine, including Telecardiology, which deals with cardiac patients. A healthy human heart undergoes a continuous series of alternate excitation (depolarization) and recovery (polarization) of cardiac muscles in a fixed sequence. The record of its electrical activity is called electrocardiogram (ECG). ECG provides valuable information regarding the status of heart and is an indispensable diagnostic tool. Ever since the computer-aided analysis of ECG came into existence, compression of digital ECG record started receiving attention of the researchers. With the advent of Telecardiology, the compression of ECG signal has started playing a significant role in increasing the overall efficacy of the tele-system by enhancing its speed. The focal theme of ECG signal compression is to reduce the volume of data without distorting the signal morphology on reconstruction. Following are the main conclusions on the basis of the work carried out in this thesis:

1. Of the many techniques used for compression of ECG signal, a wavelet compression method of Set Partitioning In Hierarchical Trees (SPIHT) is superior to any other technique reported so far. This is evaluated in terms of Compression Ratio (CR) and Percentage Root-mean-square Distortion (PRD) using PRD definition with an estimate of mean noise (K), into account. Moreover, it is easy to compute, is self-adaptive and gives the required compression. Any new algorithm, or any modification in the existing technique has to be therefore evaluated against this method.
2. Two additional steps in modified SPIHT algorithm are proposed, that is "Blank-fire removal" and "Polishing". These additional steps further increase the compression ratio and reduce the percentage root-mean-square difference, while retaining all features of the existing SPIHT algorithm. The comparison is made on the same database set, with the same wavelet filters and using the same distortion measure. A total of 84 ECG signals from MIT-BIH arrhythmia test base (mitdb) (sampling rate

360 per second) have been tested using modified SPIHT algorithm. 59 signals (70.2%) have shown an improvement in the compression ratio in the range of 3.24% - 20.22%, averaging to 7.95% improvement, while the remaining 25 signals (29.8%) have maintained the same compression ratio as given by the existing SPIHT algorithm. Not even a single case has shown deterioration in compression ratio. Improvement in distortion (i.e. reduction) has been found in all 84 signals (100%) ranging from 3.26% to 19.23%, averaging to 9.99% reduction in PRD.

3. In many applications of dynamic electrocardiography, such as Holter monitor, the recordings are for the duration of 24 hours or even larger. The number of samples in such cases runs to several millions. A set of executable files is developed in C++ environment to handle these lengthy records and is tested on data downloaded from the Long–Term ST Database (ltstdb) available at http://physionet.org (physiobank) [Goldberger *et al.,* 2000]. While encoding the bit streams to ASCII characters, some peculiar programming problems were encountered, especially in file reading of ASCII strings for certain characters. ASCII character for decimal value 13 in MS-DOS, Windows, and various network standards, is used as part of the end-of-line mark, while ASCII character for decimal value 26 and 255 are used for marking end-of-text and end-of-file (EOF) respectively and disrupt the normal file reading process. These characters are identified and subsequently modified in the bit stream itself, to solve the problem. Identification and modification of troublesome characters solved the problems. Long records are handled using the concepts of fragmenting and looping.
4. The extent to which a signal can be safely compressed using SPIHT algorithm depends upon the number of refinement passes. The lesser the number of refinement passes, more is compression, but more is the distortion in the reconstructed signal. One thing remarkable about SPIHT compression algorithm is that R-R interval in reconstructed signal remains unaffected even for much lesser (only three) refinement passes. This property of SPIHT algorithm can be utilized for compressing long arrhythmia cases to much higher compression ratios, where only R-R interval is required, not considering changes in other morphological features.

5. To achieve optimal compression ratio, while retaining all clinically significant morphological features, a criterion is required for the number of refinement passes in SPIHT algorithm. A study carried out to find this number reveals that different signals give vastly different PRD (a measure of distortion) even for the same number of refinement passes. Thus recommending a fixed number of refinement passes is not possible. However, if we take into account the presence of "blank-fire" in the compression, a criterion can be evolved. We recommend five refinement passes in absence of "blank-fire", and six in its presence. This has resulted in largely improved consistency in the distortion.
6. The proposed refinement criterion is validated by visual inspection of the signals by a physician, as well as by a statistical analysis over a larger database. Finally implementing the improved SPIHT algorithm, with the proposed refinement criterion over 42 sets of two-lead ECG signals, the original and the reconstructed signals were randomly presented to a physician, in sets of 12-15 pairs of signal. The interpretations of these ECGs were same for all 42 reconstructed signals (100%) as for the original ones, thereby validating our improved SPIHT algorithm for ECG wavelet compression along with the proposed criterion for the number refinement passes to be implemented.
7. We propose Dynamically Derived Percentage Root-mean-square Difference (DDPRD) as the new form of root-mean-square distortion measuring parameter, which gives its numerical value proportional to the distortion measured by other existing parameters like RMSE, PSNR, PRD, NPRD and MPRD. If the original signal is scaled by any factor, or the baseline is shifted in any direction or a baseline wander with zero dc value is introduced in it, subsequent to reconstruction, the numerical value of distortion measured by DDPRD remains unaffected. While all other existing parameters fail to give the same numerical value when the ECG test signal is subjected to scaling/baseline shift/baseline wander, DDPRD shows immunity to the mentioned changes in original signal.
8. For cardiologist, ECG is one of the main diagnostic means to determine the status of heart. This ECG record needs to be compressed before it can be transmitted to expert. To enhance the overall speed of communication, a set of executable files based on improved SPIHT algorithm to compress and decompress ECG signal is installed at the general practitioner's and expert's site respectively. The compressed data file is in the form of ASCII string with built-in threshold values, and thus cannot

be read by any other decoding software. The data in a way gets encrypted, providing a high degree of confidentiality against unauthorized access.

9. A user-friendly, interactive and dedicated telecardiology based website is designed, taking valuable suggestions from a panel of reputed physicians. The website is designed using HTML as the front end user GUI, MySQL for maintaining the related database, and PHP as the interface programming language. Password protected login to the website can be done as a manager or a client or an expert. The site has built-in security features against unauthorized intrusions in the site. The jobs are prioritized as per the requirement of the client and the transfer of credits from client's account to expert's account is done as per the priority, i.e. more for high priority jobs and vice or versa. Ensuring online availability of experts and making fiscal transactions from clients and to experts is responsibility of the manager. The manager also does new registrations as a client or as an expert after verifying their credentials. The website is designed keeping in mind the practical requirements and convenience of both client and expert, with an objective of bridging the gap between the client and the expert.
10. The concept of 24 hour availability of authentic experts in the required area of specialization like cardiac medicine and cardio thoracic surgery, facility to compress and decompress long records, prioritizing the jobs instead of having a general queue, enhanced security features, safe fiscal transaction through a manager and a platform for settling disputes, if any, are some of the features of the developed website, which are not available on general chat sites.
11. Finally it is concluded that Telecardiology is an endeavor to provide the much-needed expertise for cardiac patients in semi-urban and rural areas. A general practitioner can get medical advice from cardiologists over Internet using Telecardiology website and can be almost as effective as the expert himself.

8.2 SCOPE FOR FUTURE WORK

"There is nothing new to be discovered in physics now, all that remains is more and more precise measurement" quoted Lord Kelvin (William Thomson) in 1900, resisting the new scientific revolution that was beginning, so different from the science he knew. In this light, we refrain from making any statement related to saturation having reached in the field of data compression, even though no significant improvement, other than the one being currently proposed, in ECG compression has been reported since Lu *et al.,* used SPIHT algorithm in

2000 [Lu *et al.*, 2000]. Scope for future work in this area includes incorporation of the data compression of ECG signal in design of wireless Holter, beaming out packets of compressed data directly on to the physician's desktop, wherein an automated ECG analyzer warns the physician on his cellular phone of any emergent situation that may arise.

With improved data compression technique at hand, the same may be exploited for building a database by mass screening rural population. This data base can be used for statistical analysis of Indian rural population, as no such analysis has been done so far.

The website for telecardiology can be enriched by incorporating live audio and video conferencing facilities. The site can be made more interactive by incorporating an expert system, that updates itself from the expert advice of cardiologists on case to case basis. The same expert system, when it has been sufficiently trained, may be used for online classification of ECG. This will help both, the general practitioners, as well as the cardiologist.

There is a lot of scope for enhancing security features, like incorporating biometrics which include finger scan, hand scan, iris scan, signature analysis, etc. to authenticate the identity of Telecardiology user. The medico-legal aspect of Telecardiology also needs to be formalized as it involves trans-border medical advice. With further integration of wireless, Internet and computing technology, there is only one word for the future scope of Telecardiology: IMMENSE.

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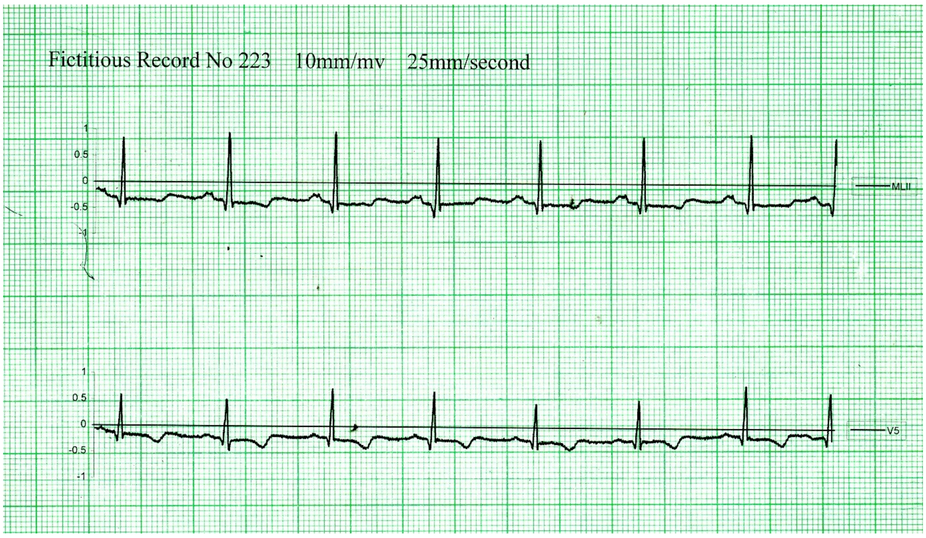
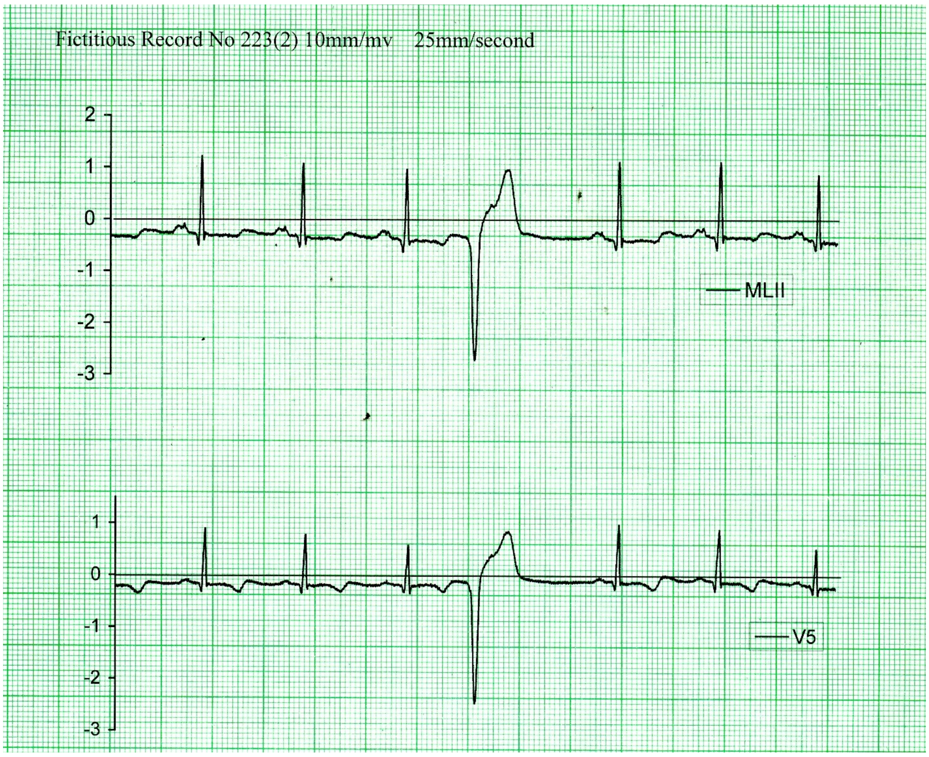
LIST OF PUBLICATIONS FROM THIS RESEARCH WORK

1. Singh, M., Kumar, V., Saxena, S.C., “Modified SPIHT wavelet compression for ECG signal” *Journal of Medical Engineering & Technology, Vol. 31, No. 1, January/February 2007, 29 – 35*

2. Singh, M., Kumar, V., Saxena, S.C., “Refinement Criterion for SPIHT based ECG Signal Compression” *Accepted in IETE Technical Review, New Delhi*

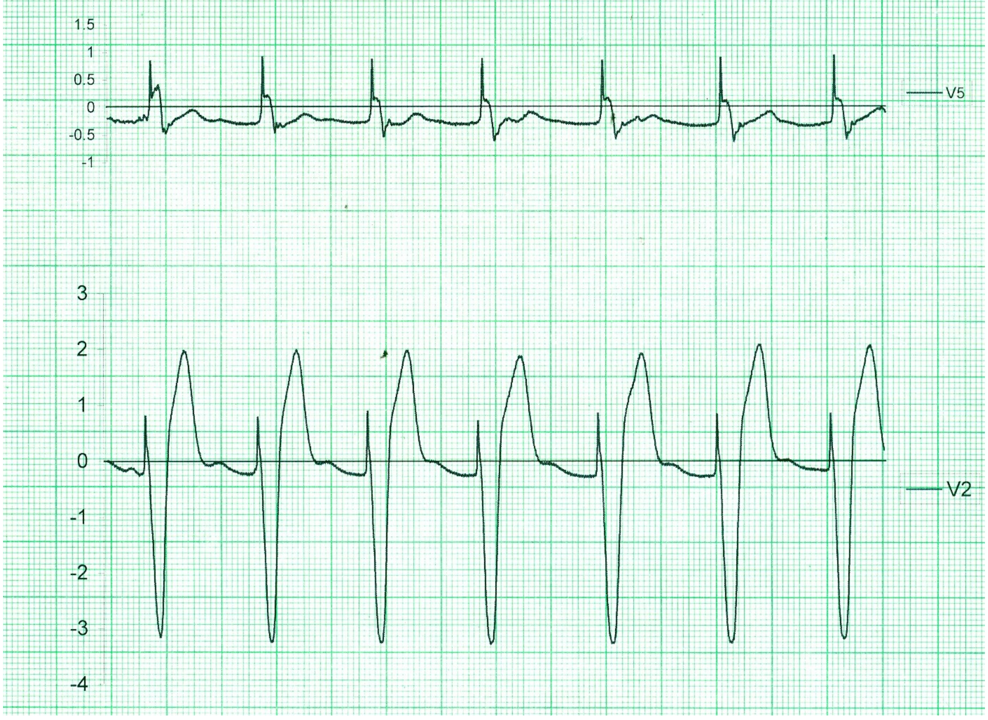
APPENDIX – I

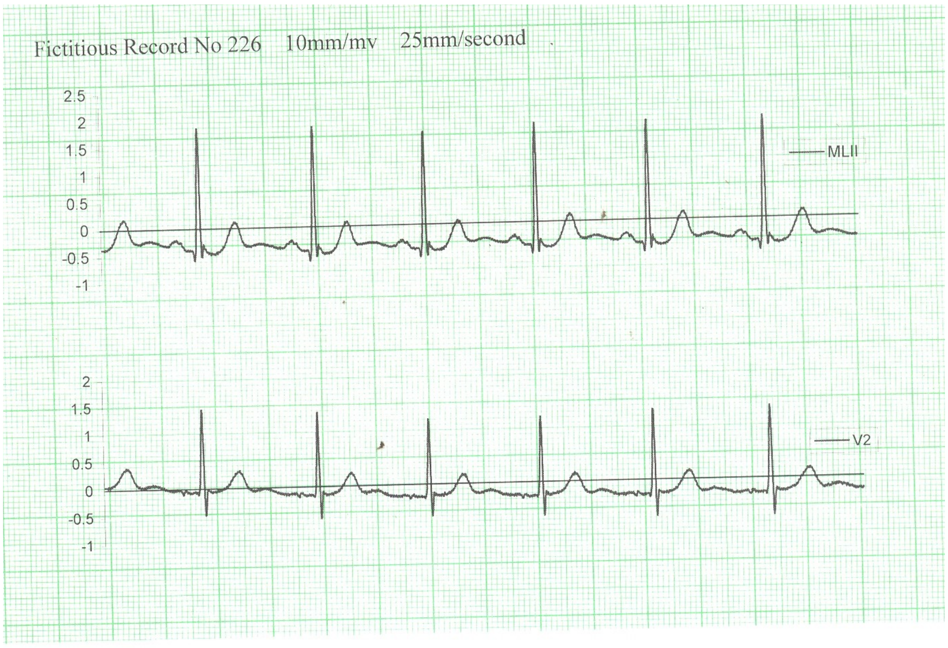

Fictitious Record No 223 10mm/mv 25mm/second
1
0.5
0
-0.5
-1
MLII
1
0.5
0
-0.5
-1
V5

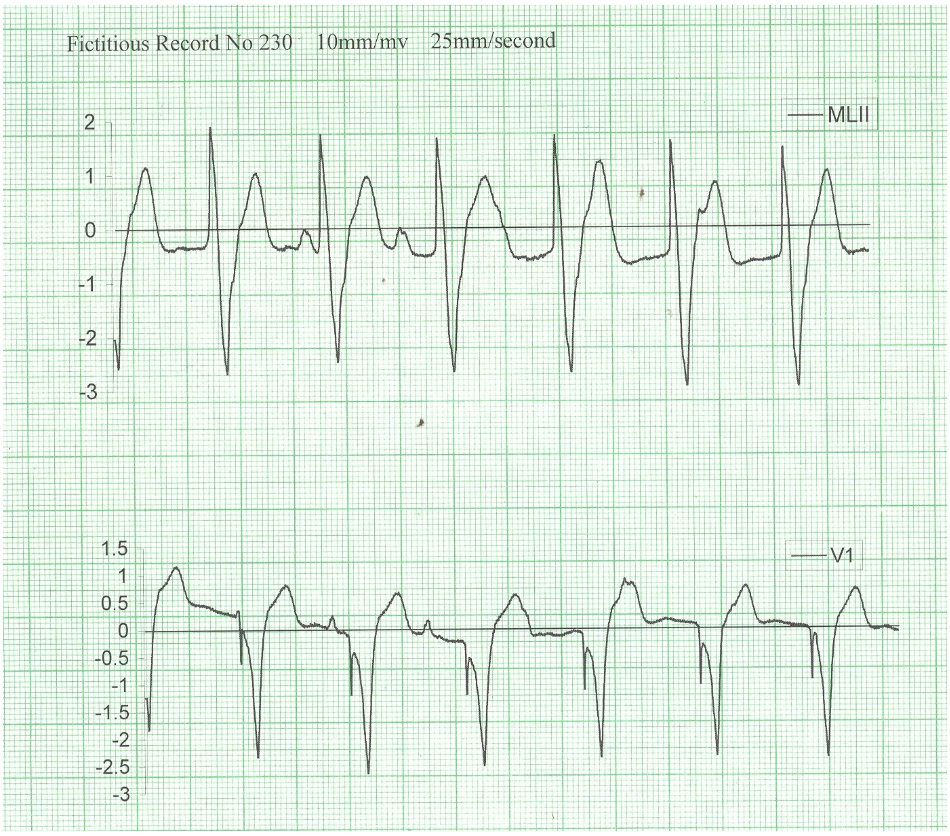

Fictitious Record No 223(2) 10mm/mv 25mm/second
2
1
0
-1
-2
-3
MLII
1
0
-1
-2
-3
V5

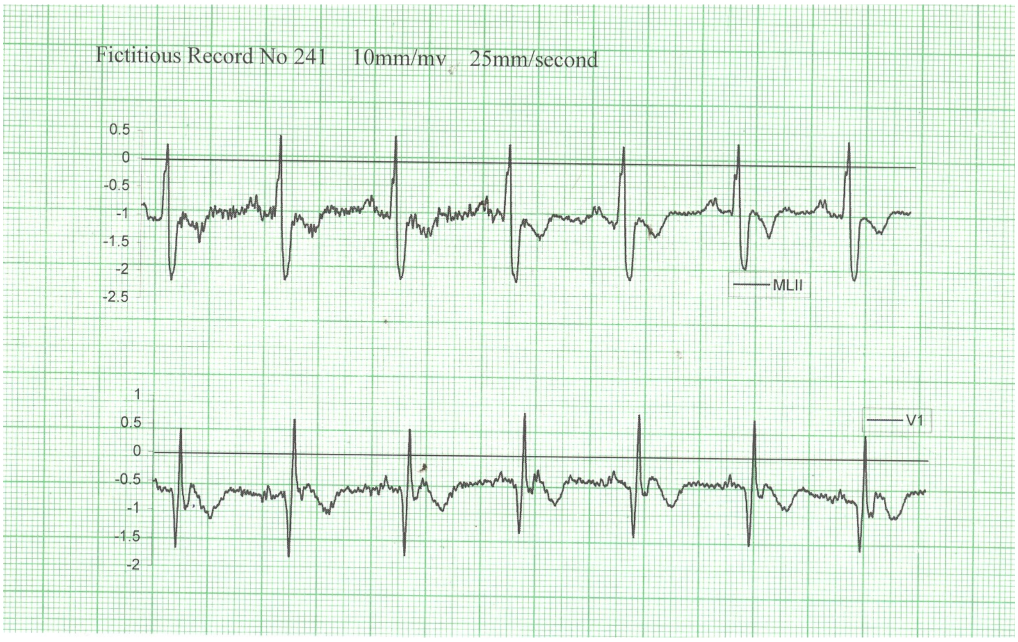
Fictitious Record No 224 10mm/mv 25mm/second

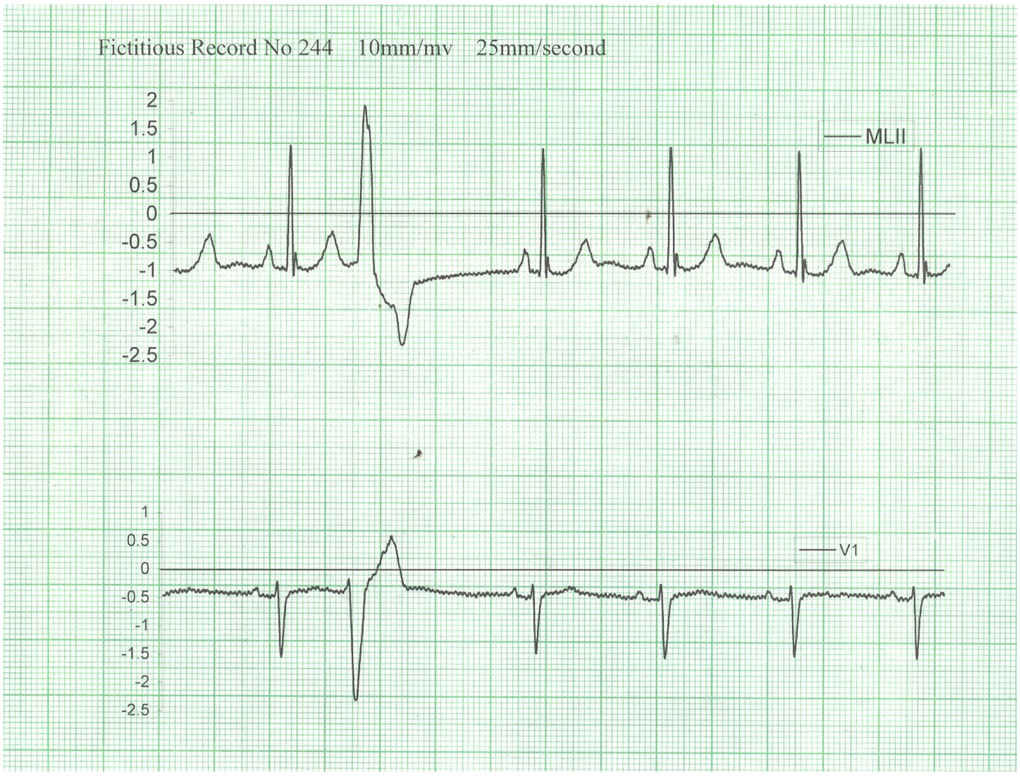
Fictitious Record No 225 10mm/mv 25mm/second



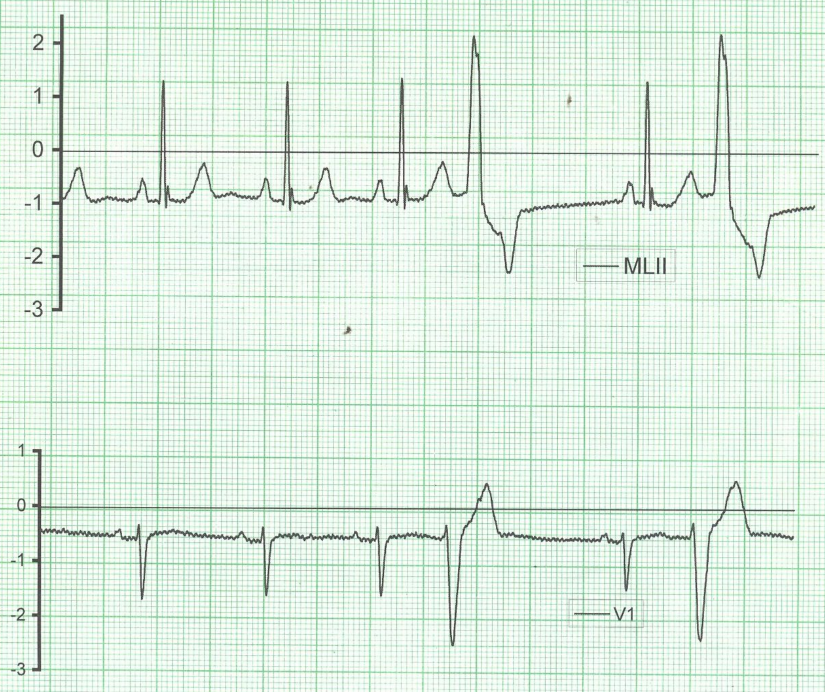

Fictitious Record No 226 10mm/mv 25mm/second
2.5
2
1.5
1
0.5
0
-0.5
-1
MLII
2
1.5
1
0.5
0
-0.5
-1
V2


Fictitious Record No 230 10mm/mv 25mm/second
2
1
0
-1
-2
-3
MLII
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
V1

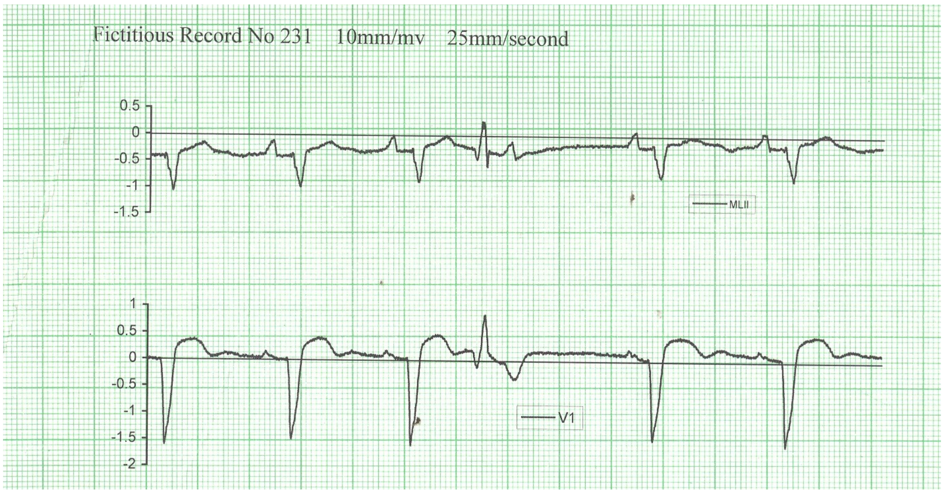

Fictitious Record No 241 10mm/mv 25mm/second
MLII
V1

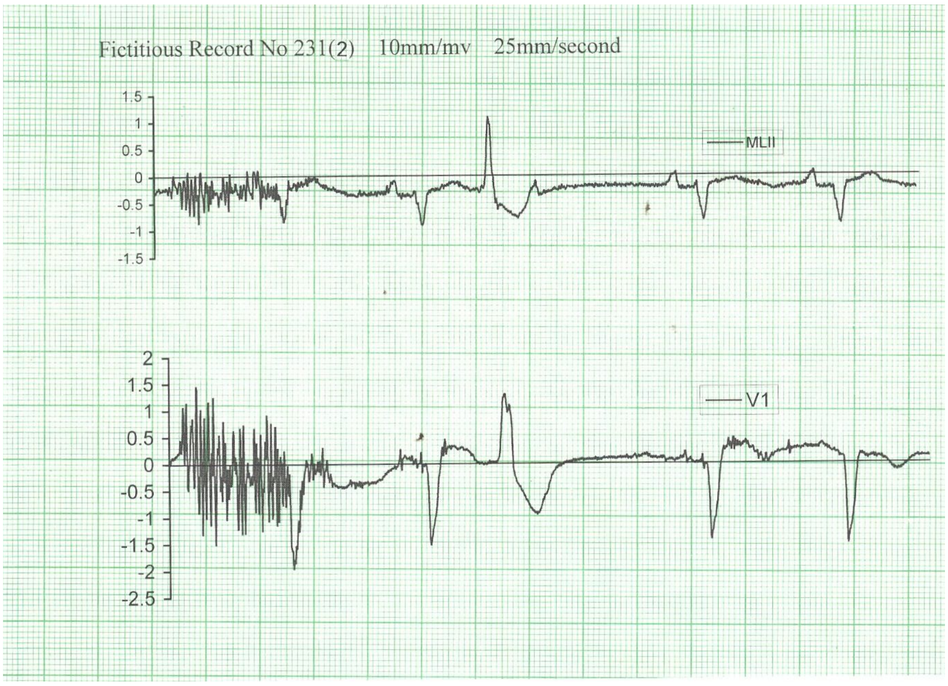

Fictitious Record No 244 10mm/mv 25mm/second
MLII
V1

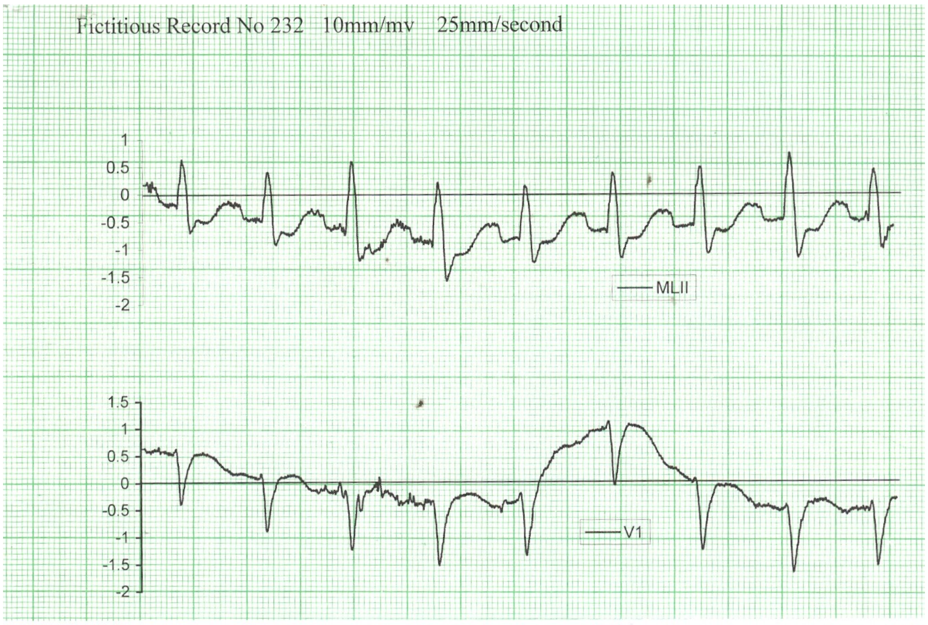
Fictitious Record No 244(2)   10mm/mv   25mm/second

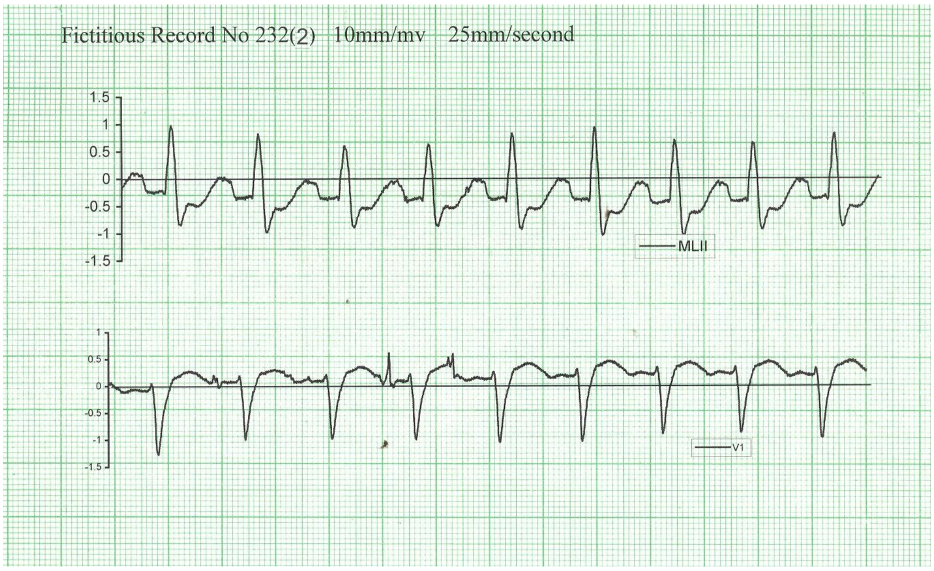


Fictitious Record No 228   10mm/mv   25mm/second

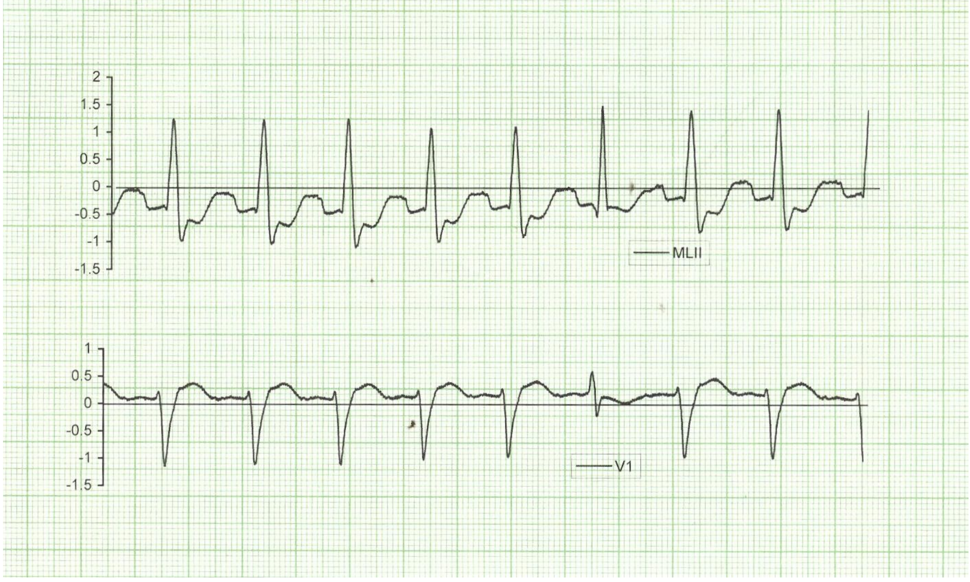

Fictitious Record No 231 10mm/mv 25mm/second
0.5
0
-0.5
-1
-1.5
MLII
1
0.5
0
-0.5
-1
-1.5
-2
V1


Fictitious Record No 231(2) 10mm/mv 25mm/second
1.5
1
0.5
0
-0.5
-1
-1.5
MLII
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
V1

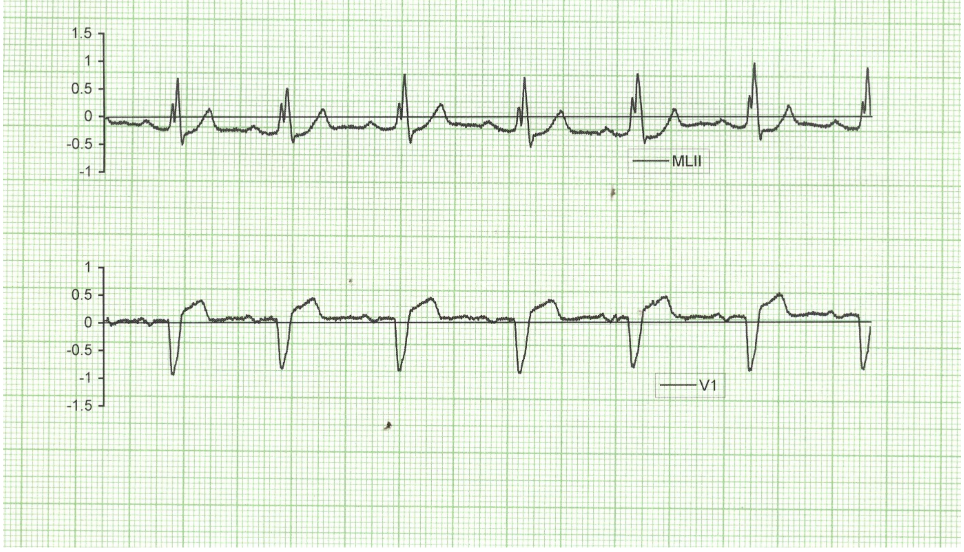

Fictitious Record No 232 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 232(2) 10mm/mv 25mm/second
MLII
V1

Fictitious Record No 232(3)   10mm/mv   25mm/second



Fictitious Record No 234   10mm/mv   25mm/second

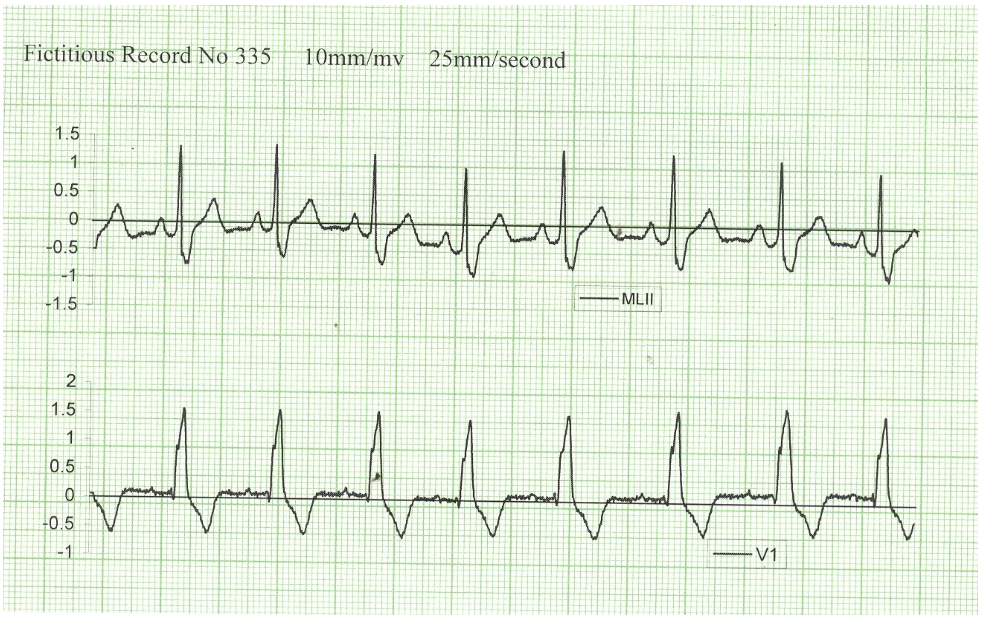


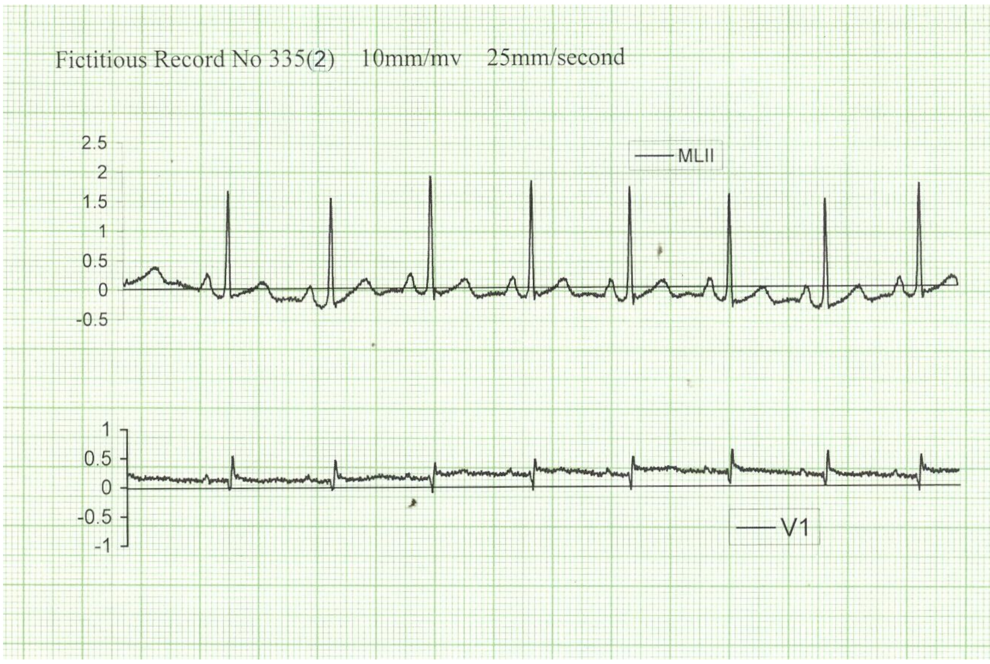
Fictitious Record No 234(2) 10mm/mv 25mm/second

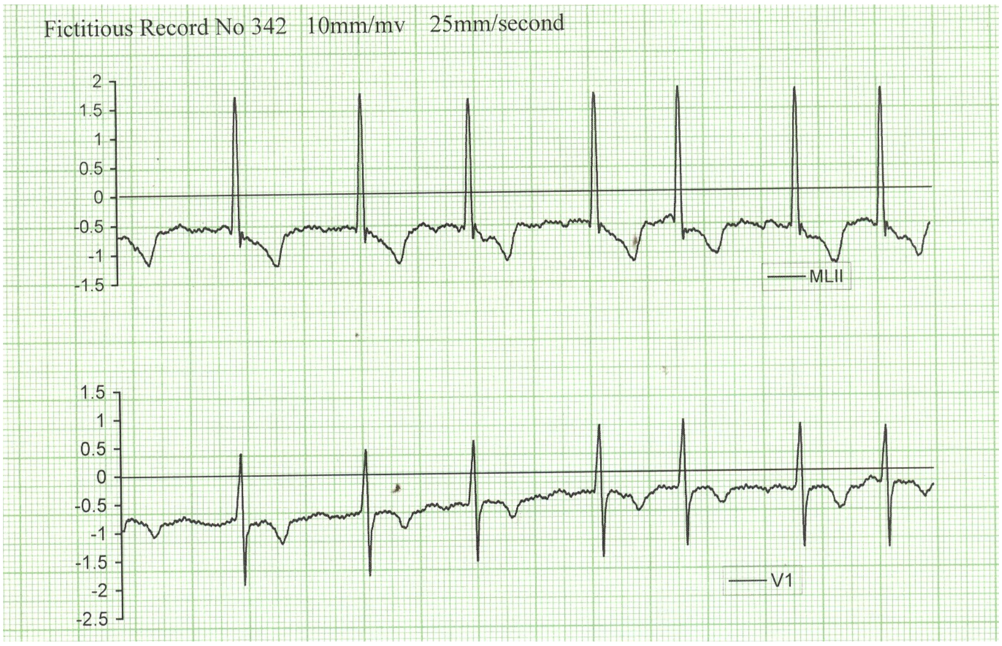
Fictitious Record No 234(3) 10mm/mv 25mm/second

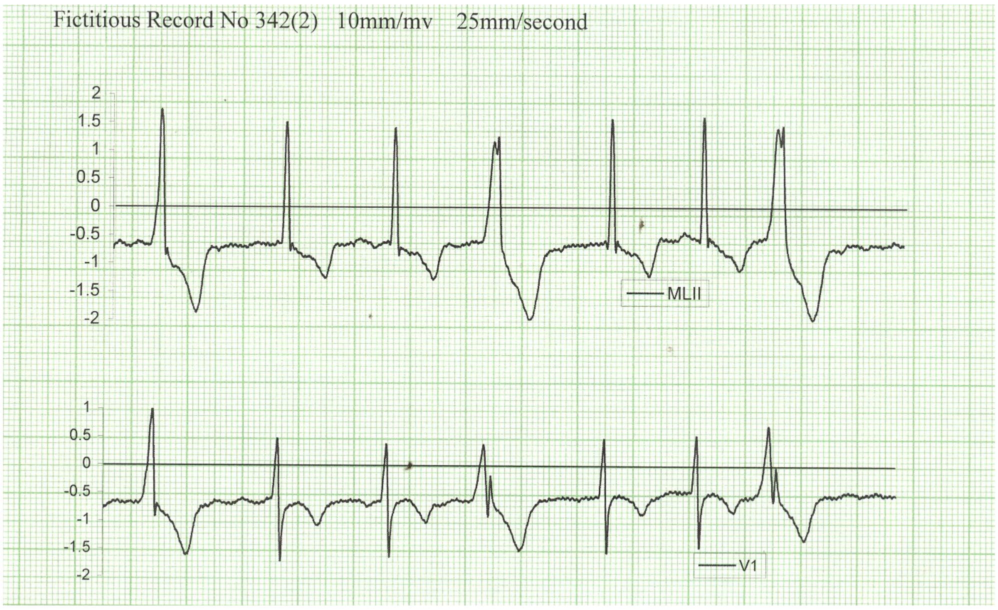
Fictitious Record No 235   10mm/mv   25mm/second

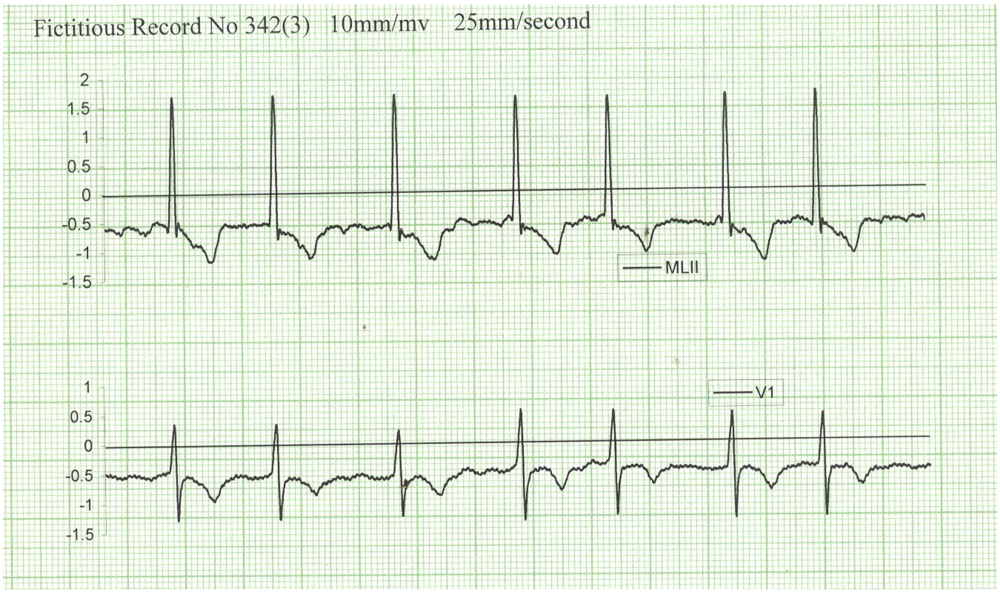
Fictitious Record No 235 (2)   10mm/mv   25mm/second

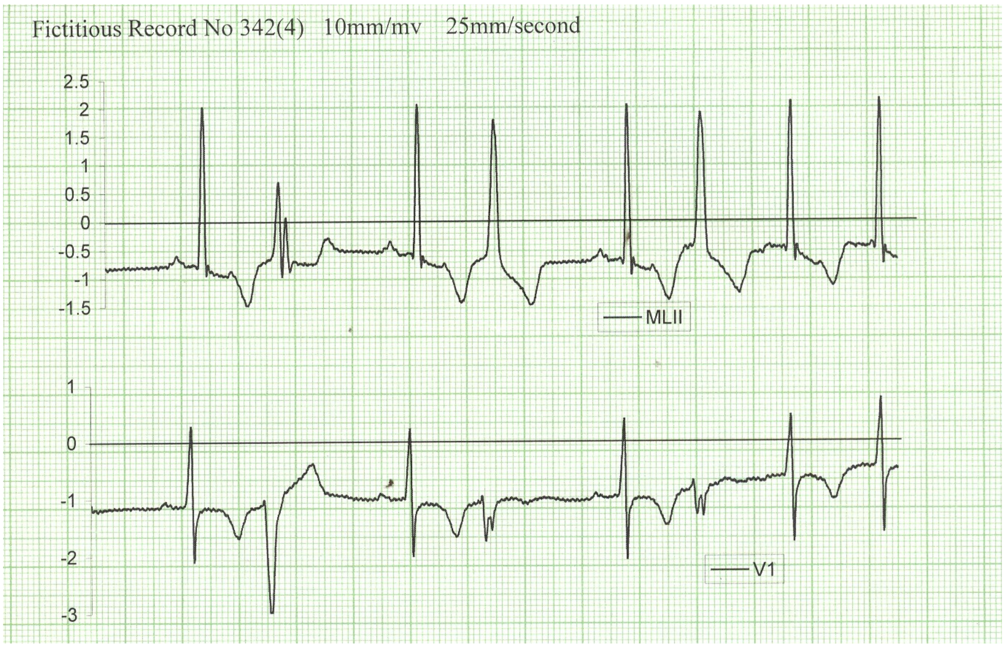

Fictitious Record No 335 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 335(2) 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 342 10mm/mv 25mm/second
MLII
V1

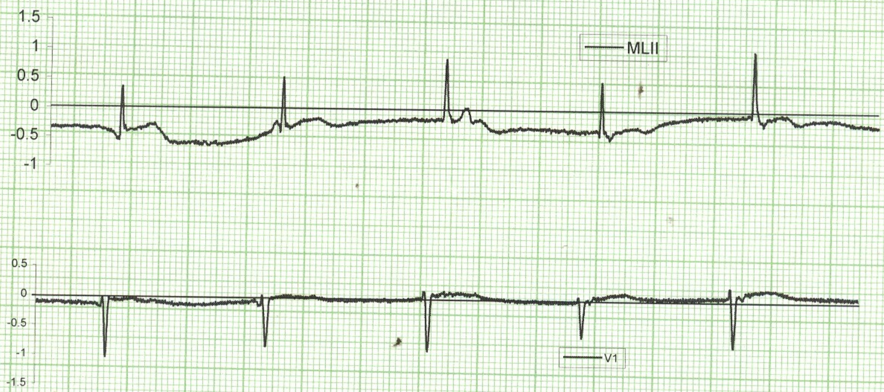

Fictitious Record No 342(2) 10mm/mv 25mm/second
MLII
V1

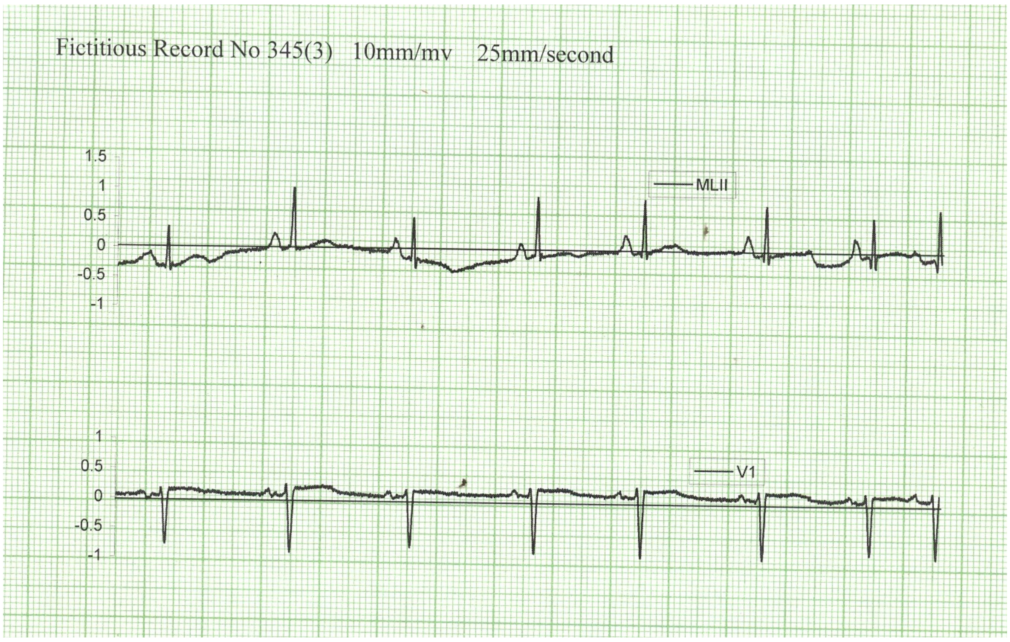

Fictitious Record No 342(3) 10mm/mv 25mm/second
2
1.5
1
0.5
0
-0.5
-1
-1.5
MLII
1
0.5
0
-0.5
-1
-1.5
V1

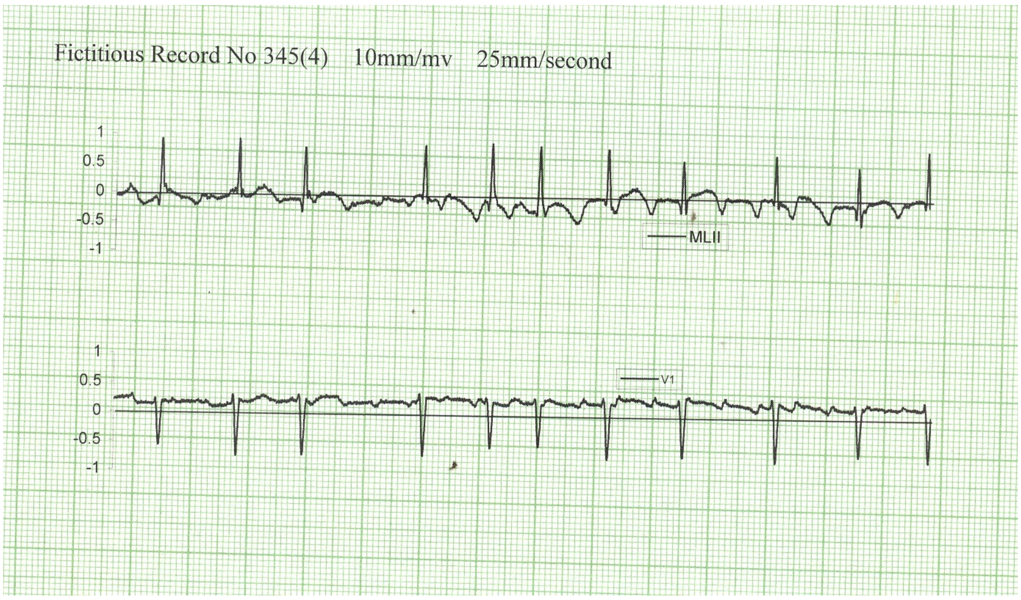

Fictitious Record No 342(4) 10mm/mv 25mm/second
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
MLII
1
0
-1
-2
-3
V1

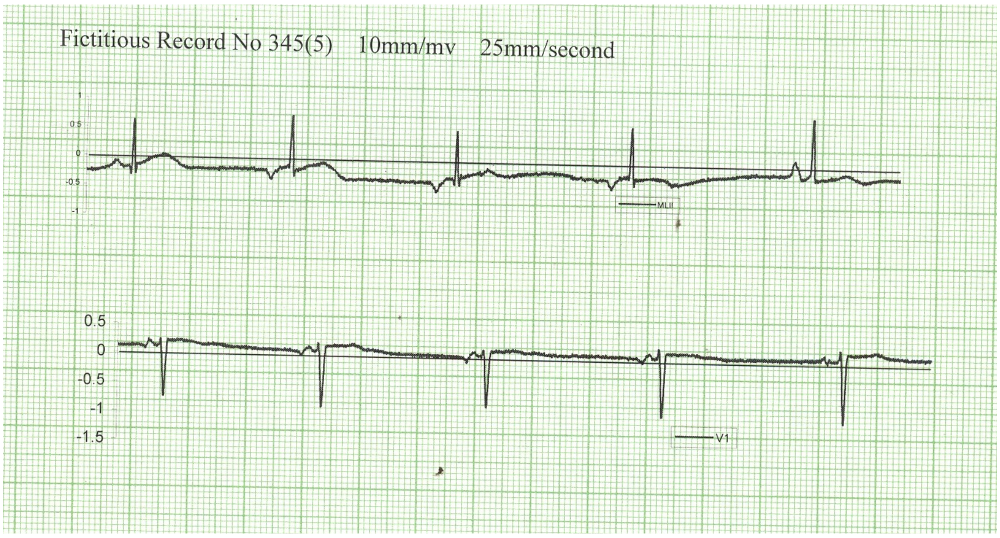
Fictitious Record No 345   10mm/mv   25mm/second

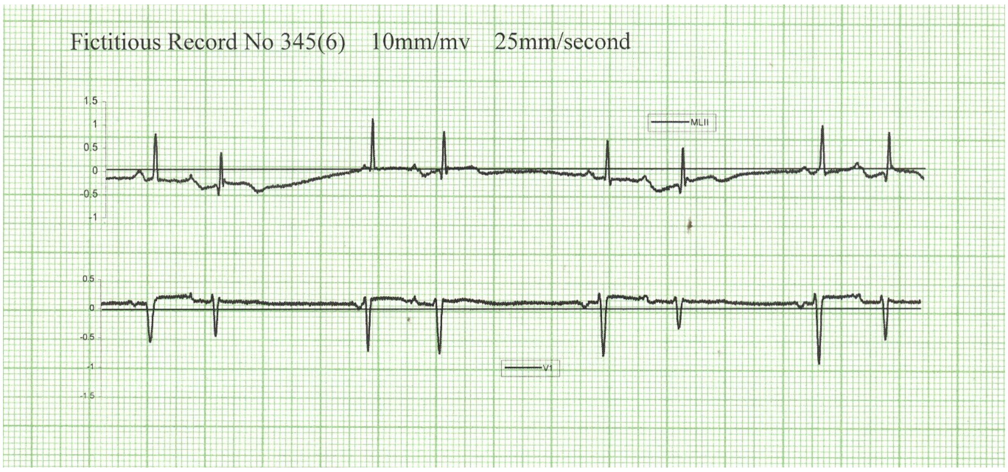
Fictitious Record No 345(2)   10mm/mv   25mm/second

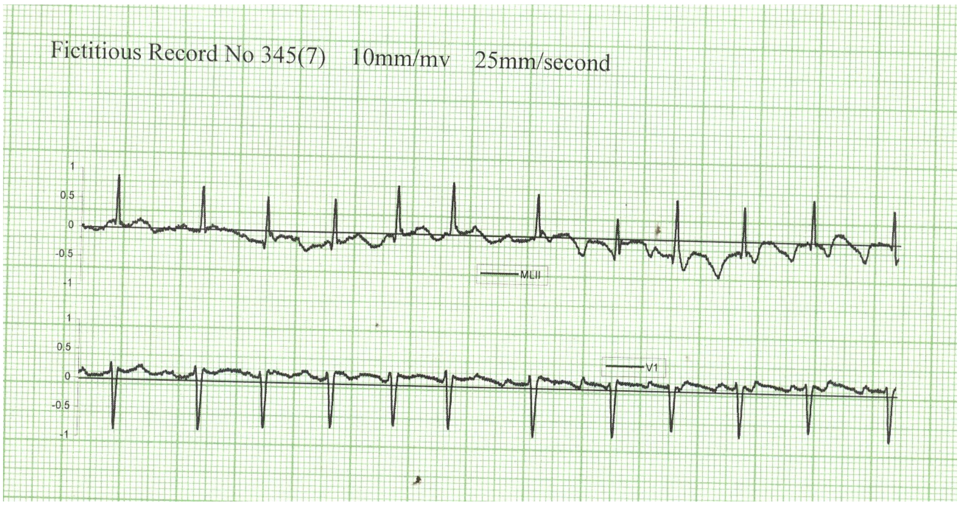


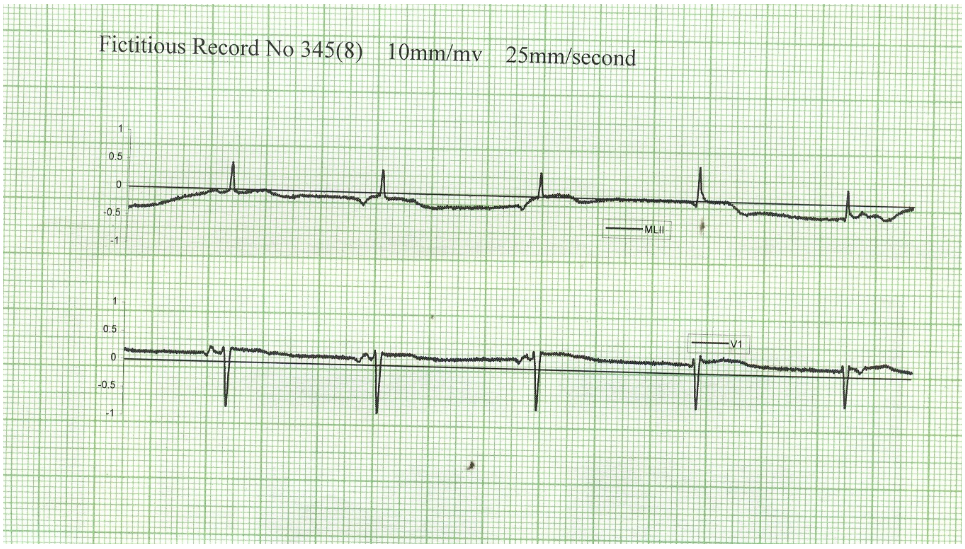

Fictitious Record No 345(3) 10mm/mv 25mm/second
MLII
V1
1.5
1
0.5
0
-0.5
-1

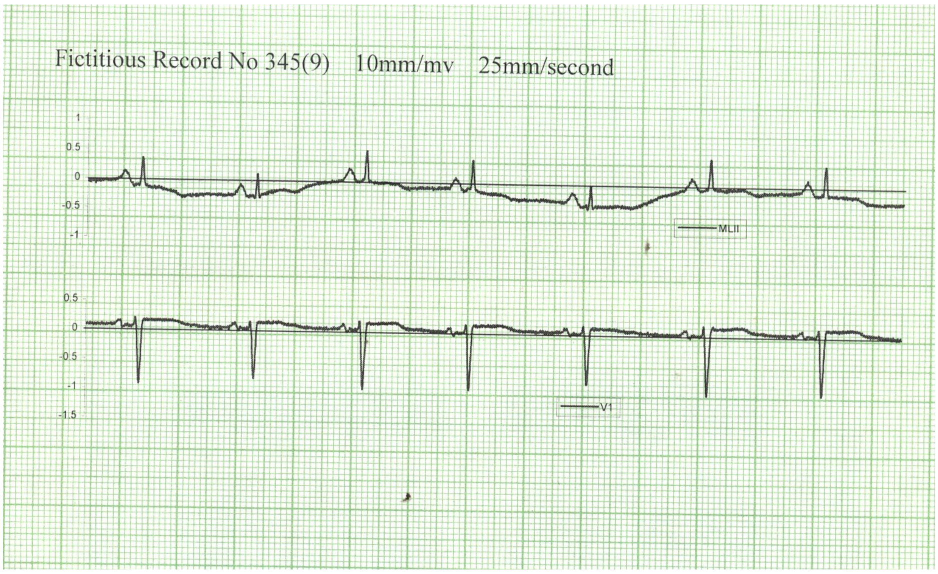

Fictitious Record No 345(4) 10mm/mv 25mm/second
MLII
V1
1
0.5
0
-0.5
-1


Fictitious Record No 345(5) 10mm/mv 25mm/second
MLII
0.5
0
-0.5
-1
-1.5
V1

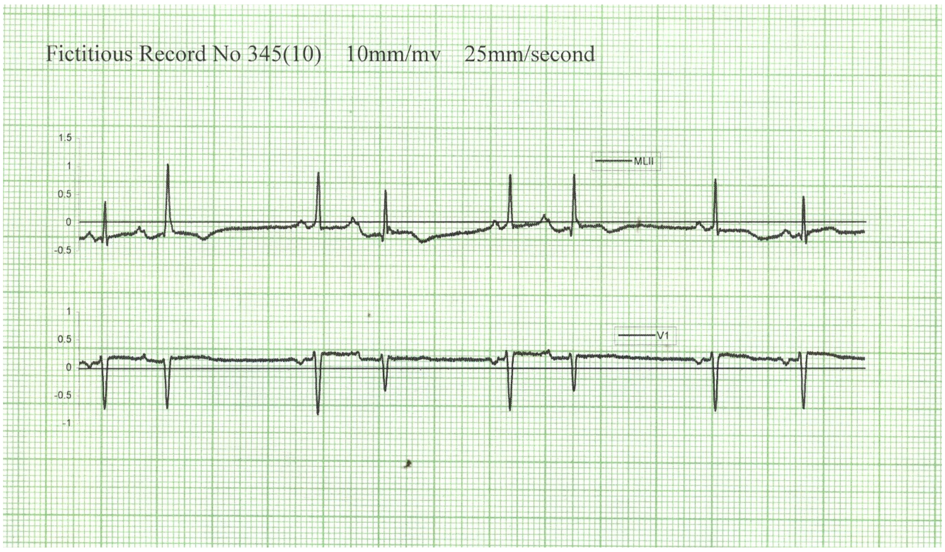

Fictitious Record No 345(6) 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 345(7)   10mm/mv   25mm/second
MLII
V1
1
0.5
0
-0.5
-1

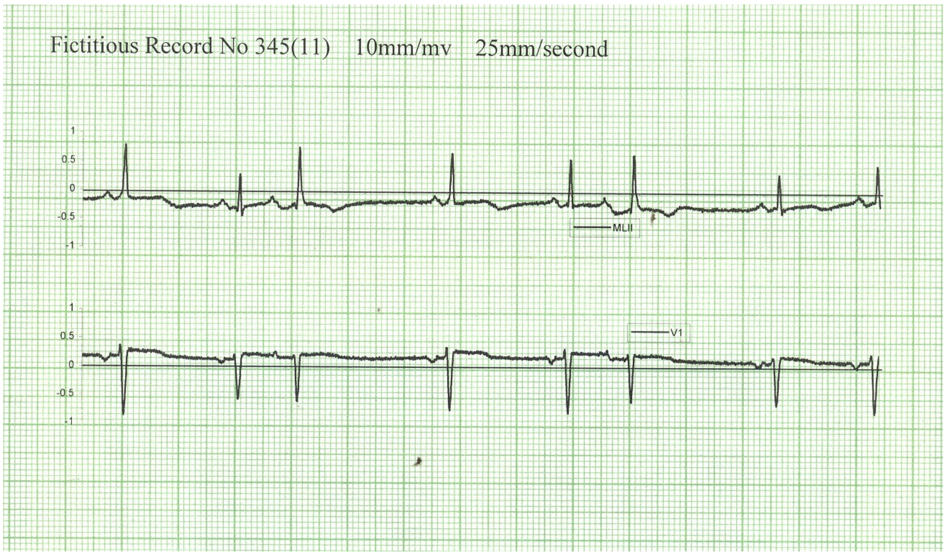

Fictitious Record No 345(8)   10mm/mv   25mm/second
MLII
V1
1
0.5
0
-0.5
-1

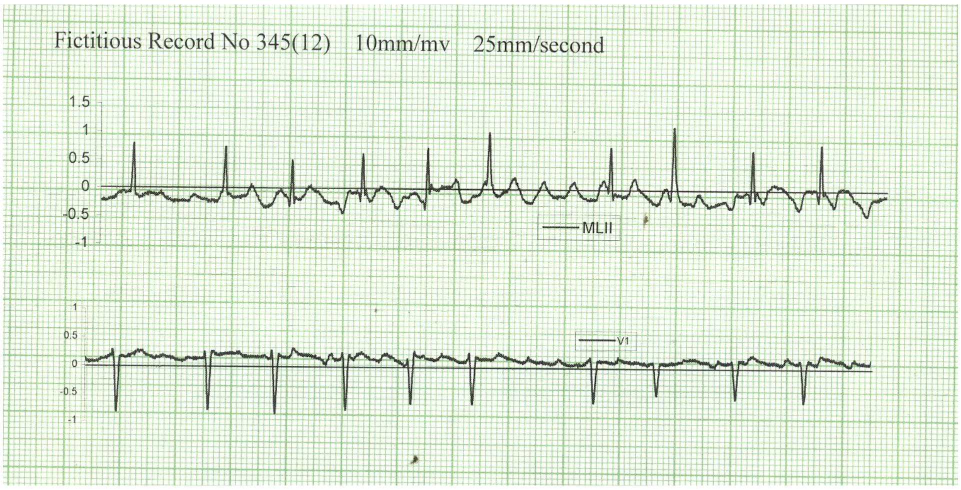


Fictitious Record No 345(9) 10mm/mv 25mm/second
1
0.5
0
-0.5
-1
MLII
0.5
0
-0.5
-1
-1.5
V1

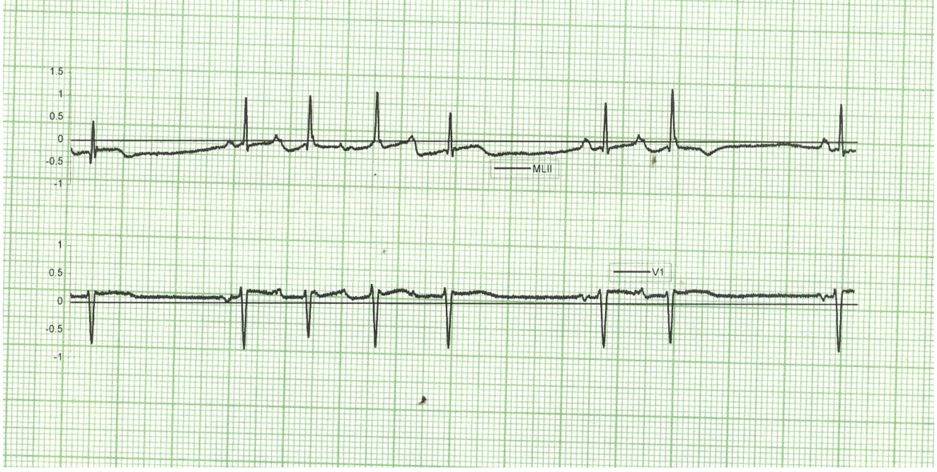


Fictitious Record No 345(10) 10mm/mv 25mm/second
1.5
1
0.5
0
-0.5
MLII
1
0.5
0
-0.5
-1
V1

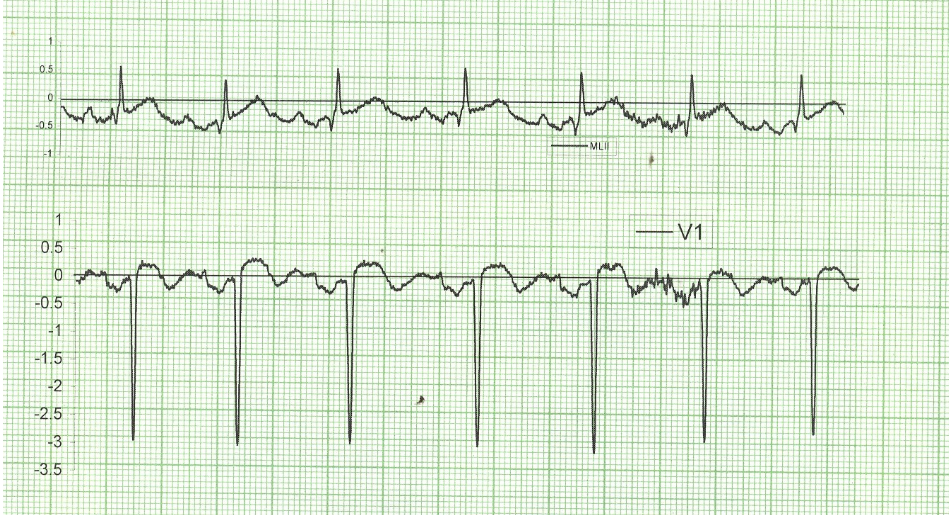

Fictitious Record No 345(11) 10mm/mv 25mm/second
1
0.5
0
-0.5
-1
MLII
1
0.5
0
-0.5
-1
V1

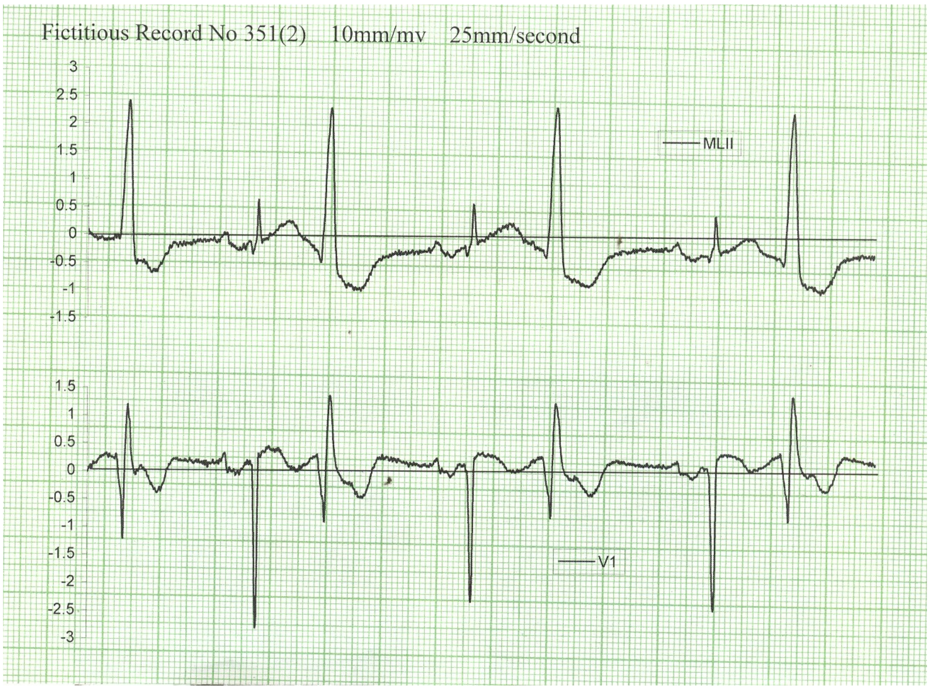

Fictitious Record No 345(12) 10mm/mv 25mm/second
1.5
1
0.5
0
-0.5
-1
MLII
1
0.5
0
-0.5
-1
V1

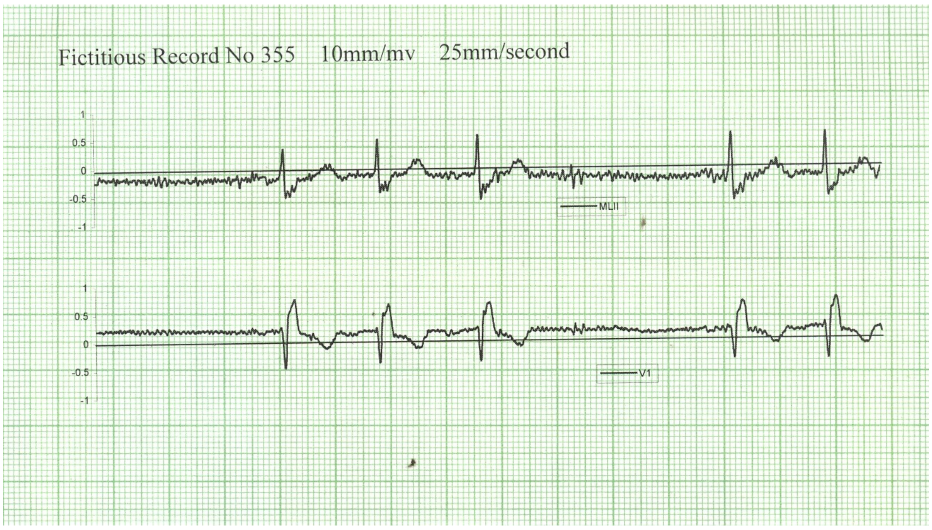
Fictitious Record No 345(13)   10mm/mv   25mm/second



Fictitious Record No 351   10mm/mv   25mm/second

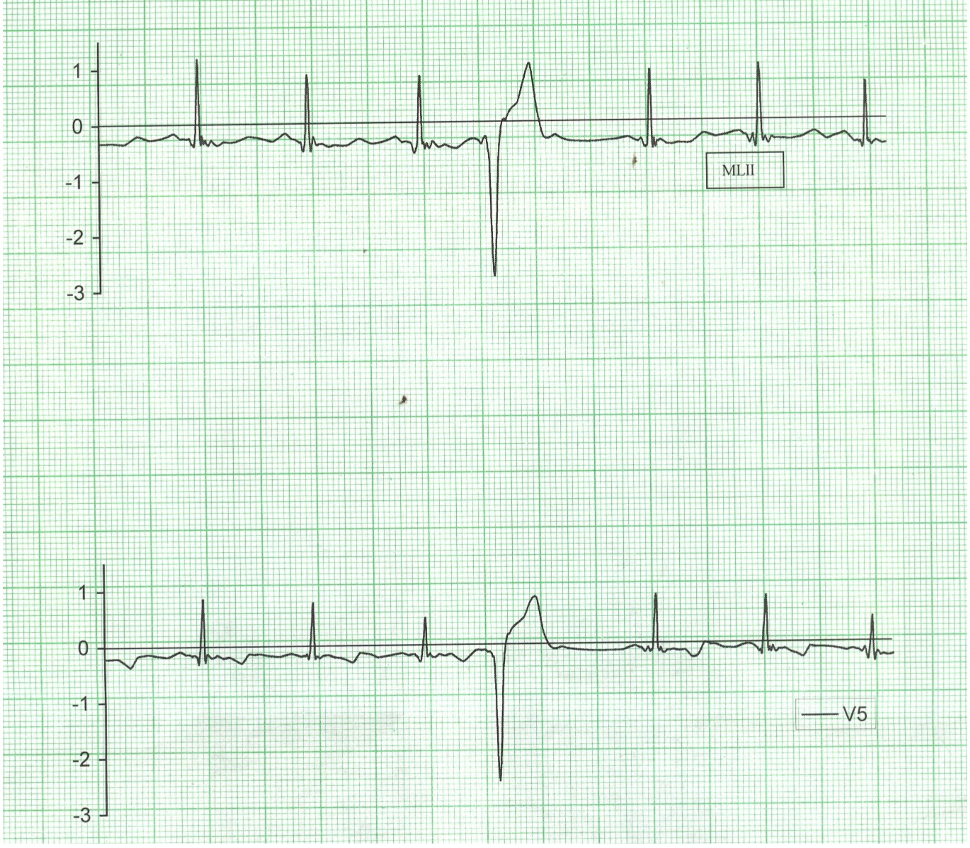



Fictitious Record No 351(2) 10mm/mv 25mm/second
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
MLII
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
V1


Fictitious Record No 355 10mm/mv 25mm/second
1
0.5
0
-0.5
-1
MLII
1
0.5
0
-0.5
-1
V1

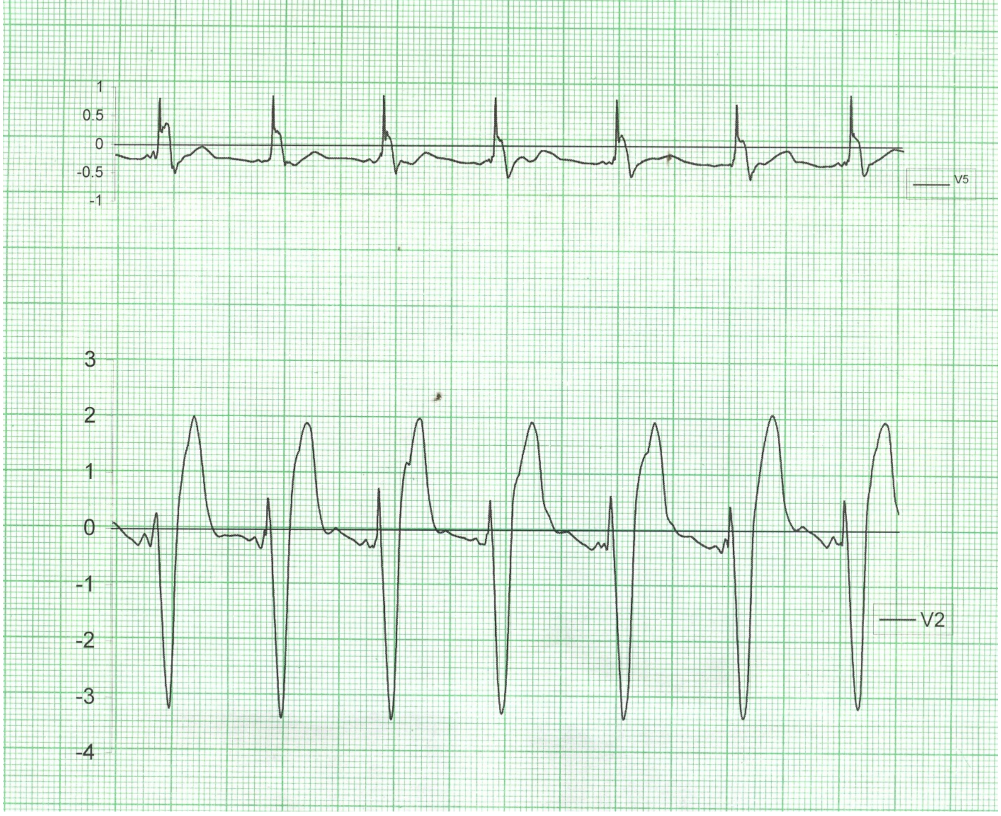
Fictitious Record No 421 10mm/mv 25mm/second

Fictitious Record No 421(2) 10mm/mv 25mm/second

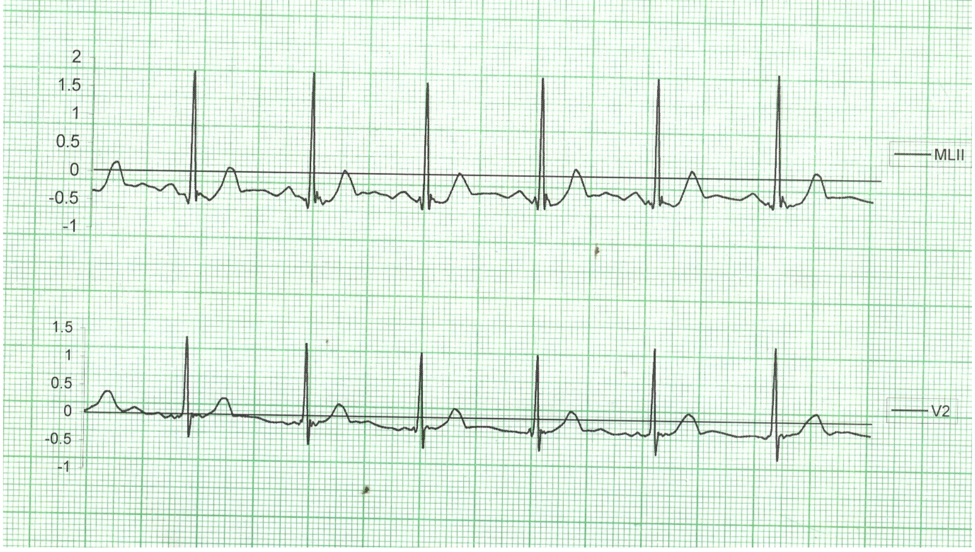


Fictitious Record No 422 10mm/mv 25mm/second

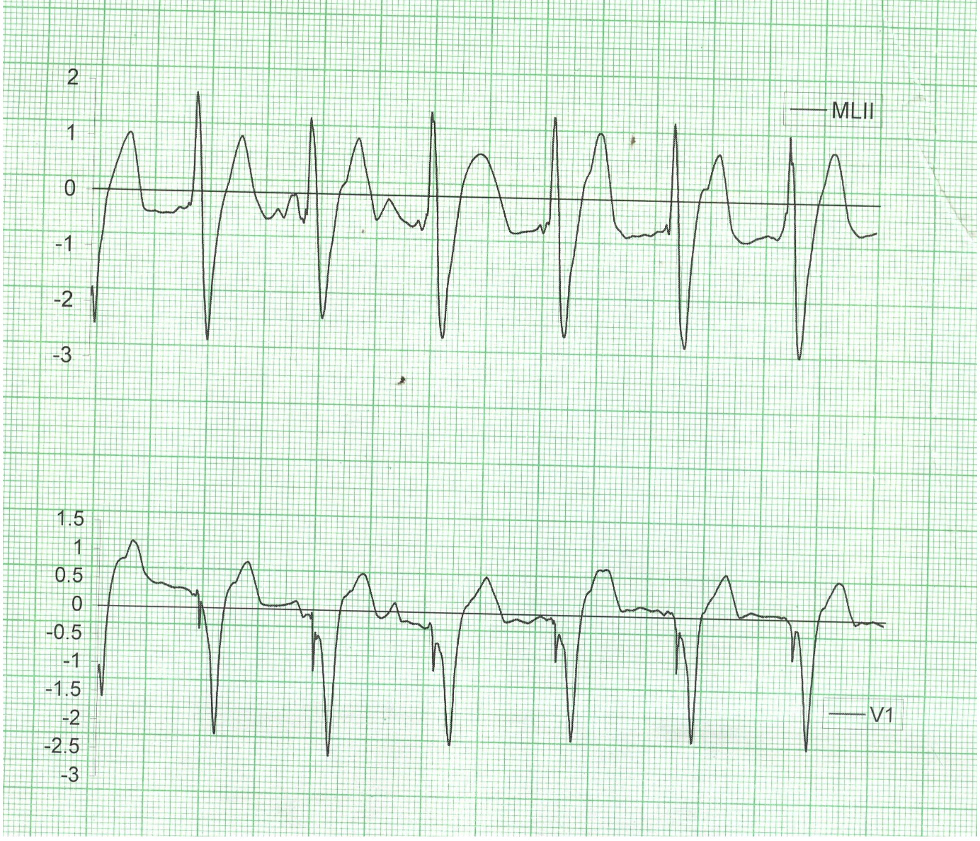
Fictitious Record No 423 10mm/mv 25mm/second

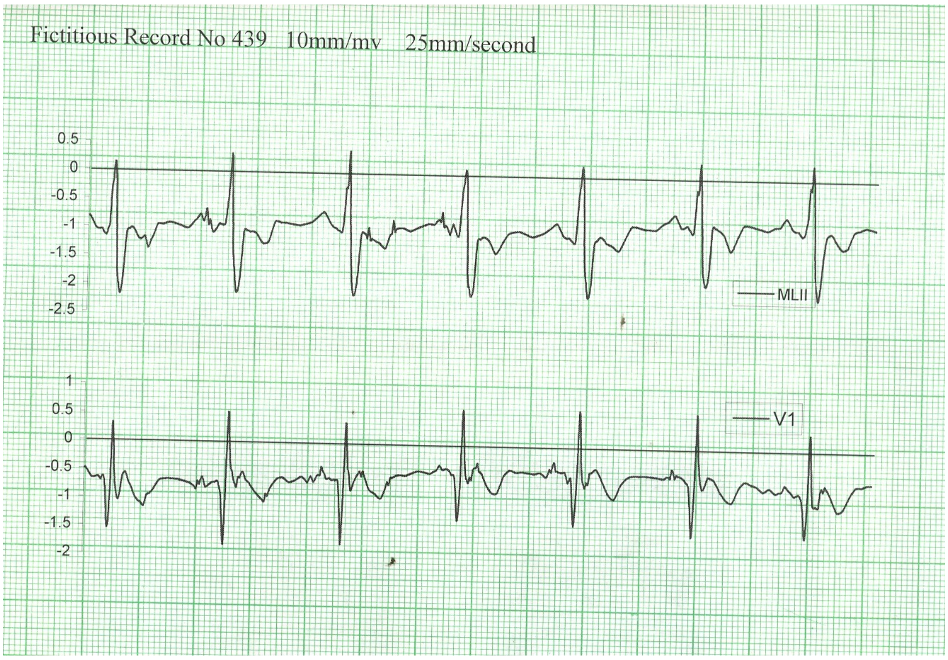


Fictitious Record No 424 10mm/mv 25mm/second



Fictitious Record No 428 10mm/mv 25mm/second



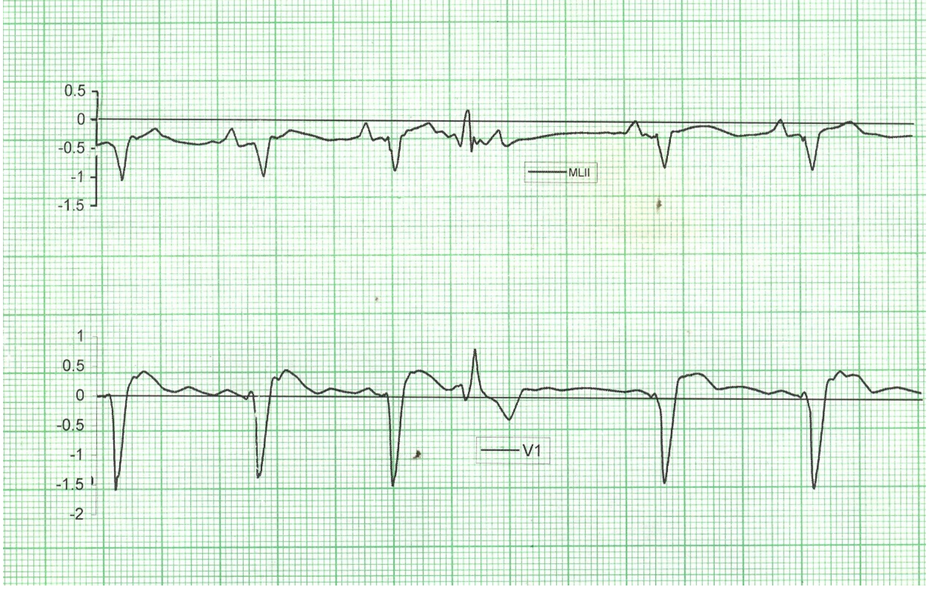

Fictitious Record No 439 10mm/mv 25mm/second
0.5
0
-0.5
-1
-1.5
-2
-2.5
MLII
1
0.5
0
-0.5
-1
-1.5
-2
V1


Fictitious Record No 440 10mm/mv 25mm/second
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
MLII
0.5
0
-0.5
-1
-1.5
-2
-2.5
V1

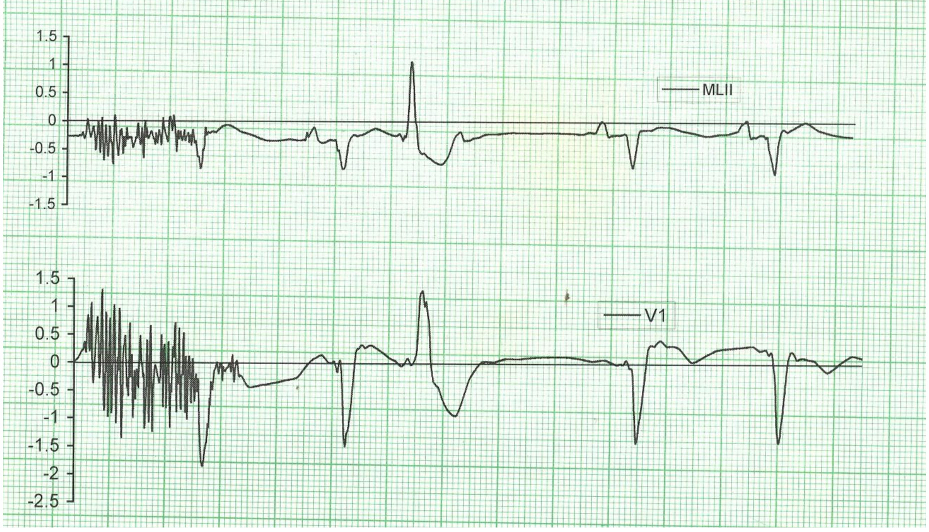
Fictitious Record No 440(2)   10mm/mv   25mm/second

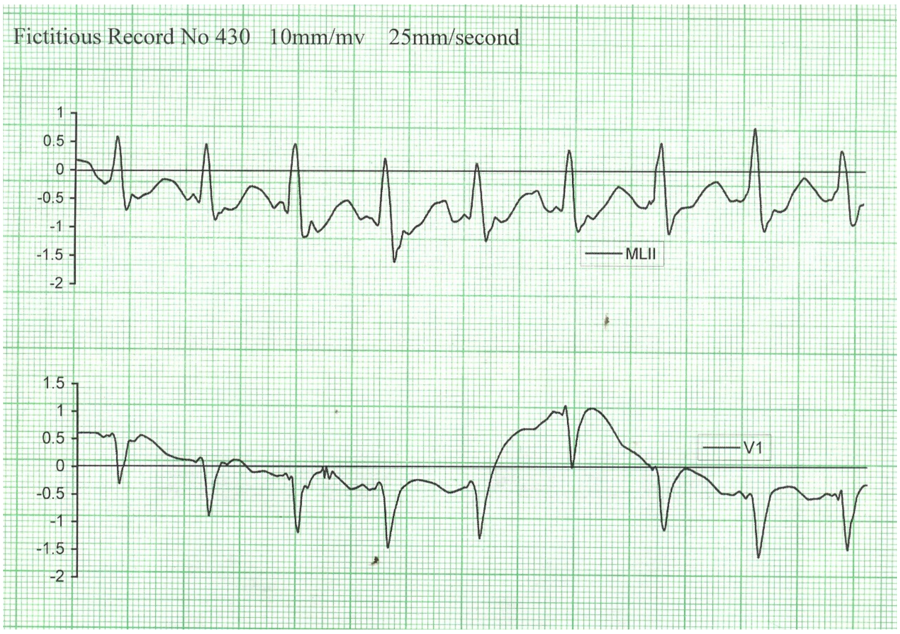
Fictitious Record No 426   10mm/mv   25mm/second

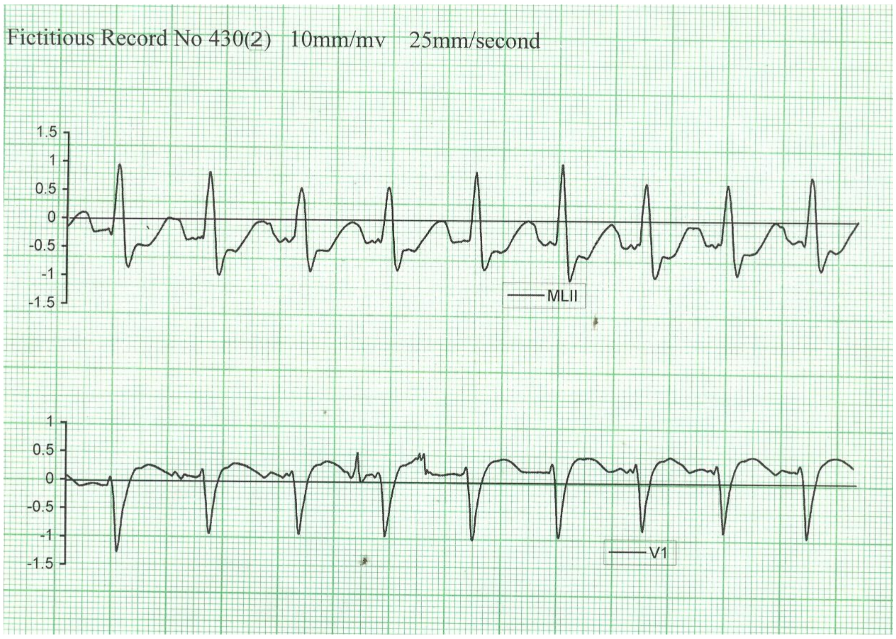
Fictitious Record No 429 10mm/mv 25mm/second



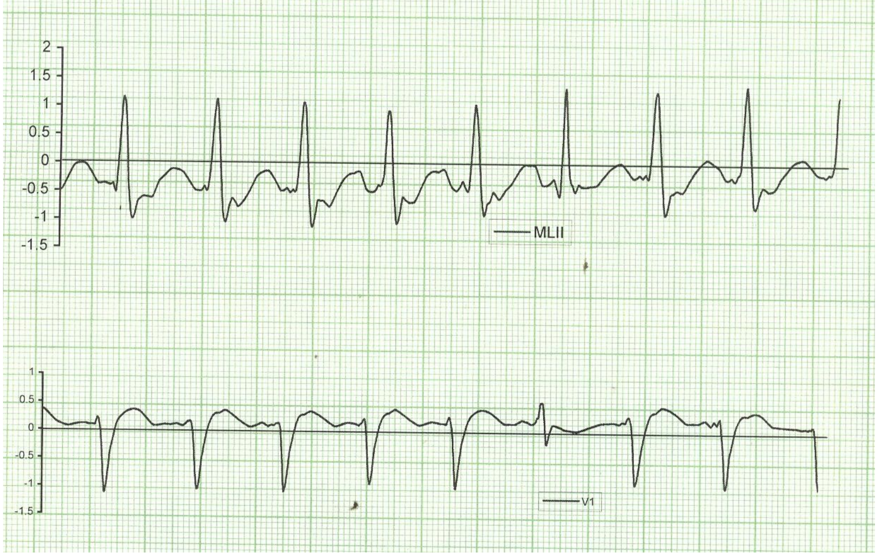
Fictitious Record No 429(2) 10mm/mv 25mm/second



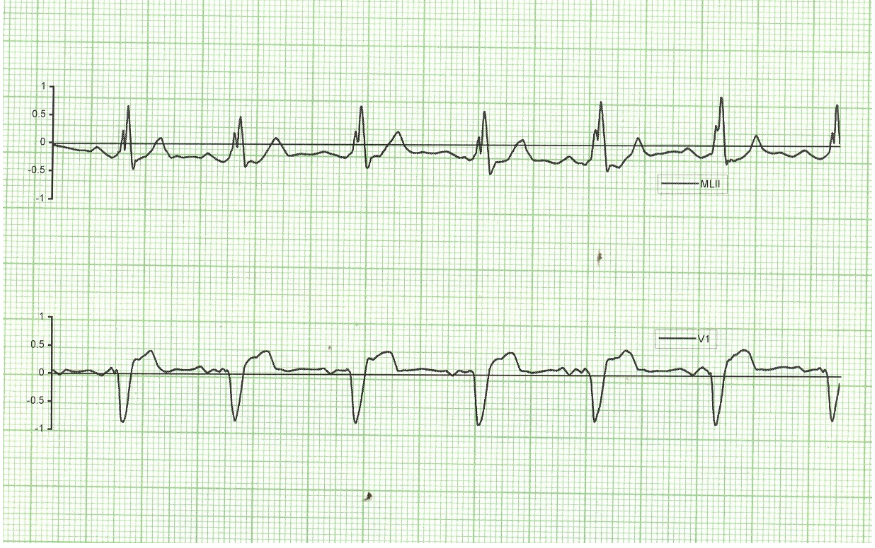

Fictitious Record No 430 10mm/mv 25mm/second
MLII
V1

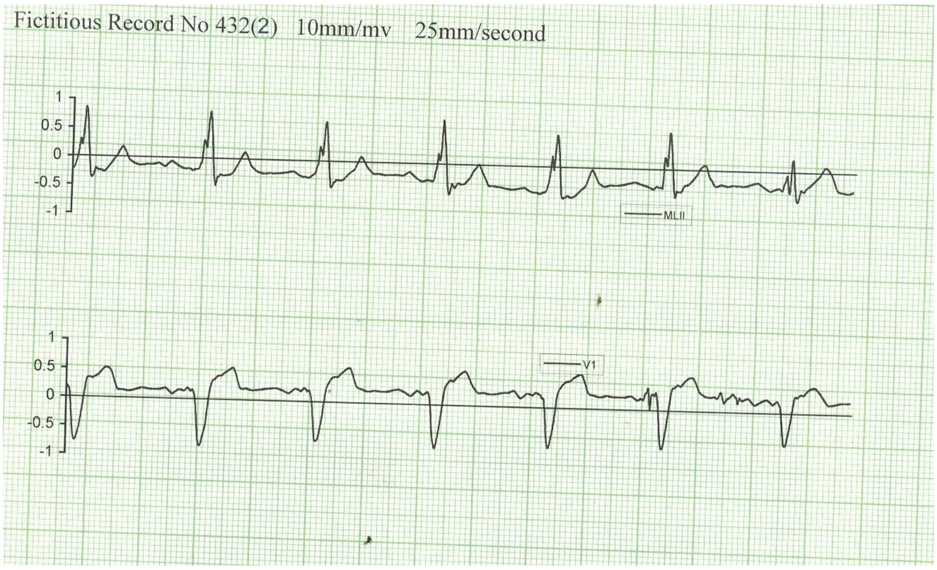

Fictitious Record No 430(2) 10mm/mv 25mm/second
MLII
V1

Fictitious Record No 430(3)   10mm/mv   25mm/second

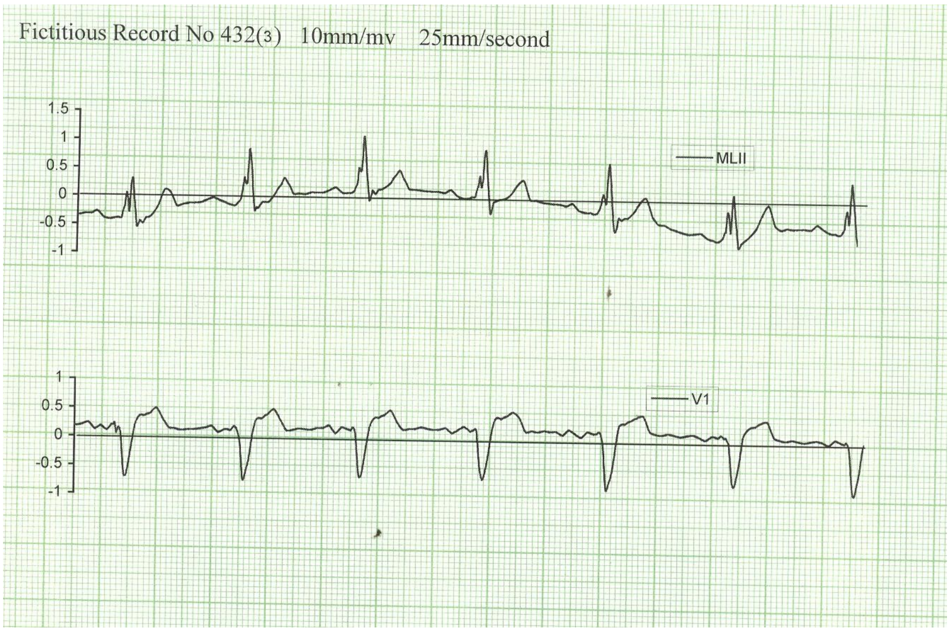


Fictitious Record No 432   10mm/mv   25mm/second



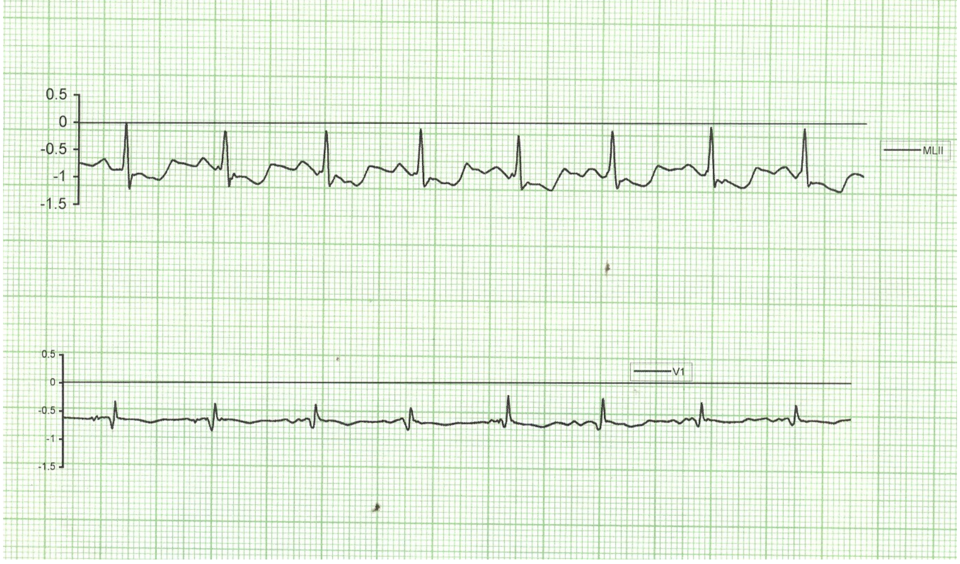


Fictitious Record No 432(2) 10mm/mv 25mm/second

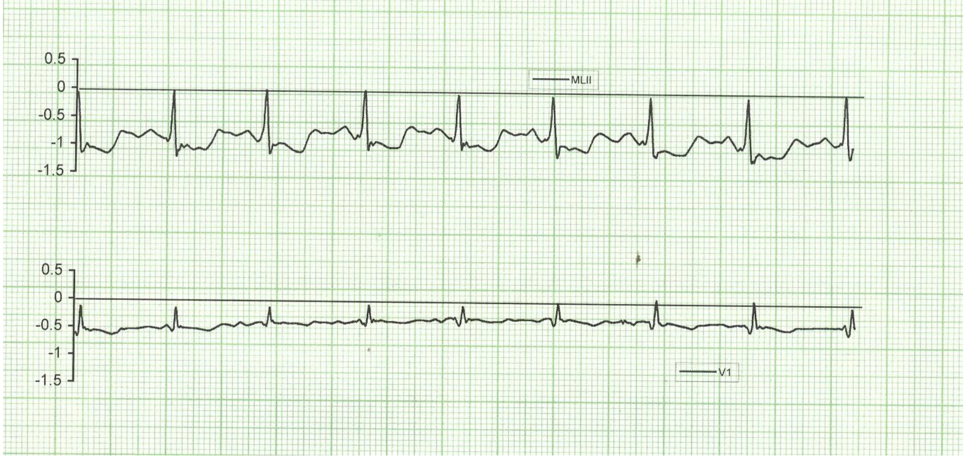


Fictitious Record No 432(3) 10mm/mv 25mm/second

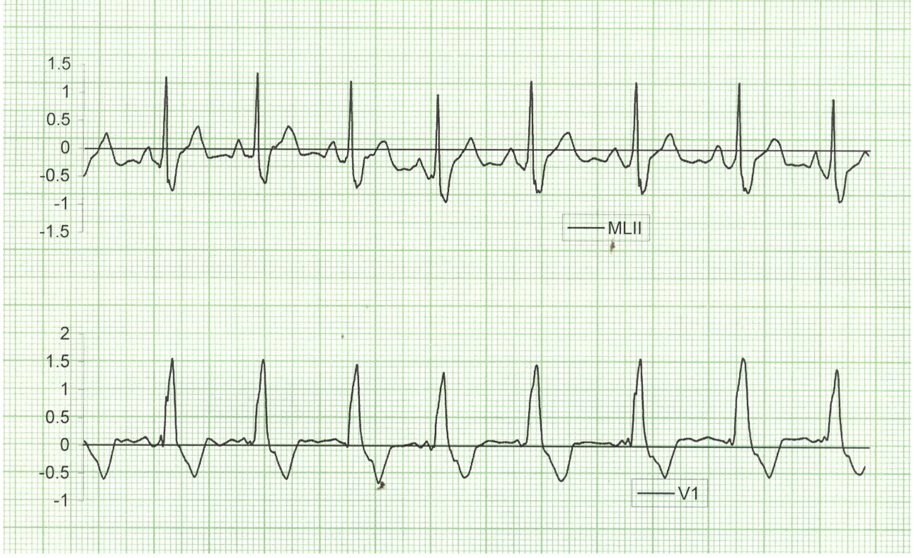
Fictitious Record No 433   10mm/mv   25mm/second



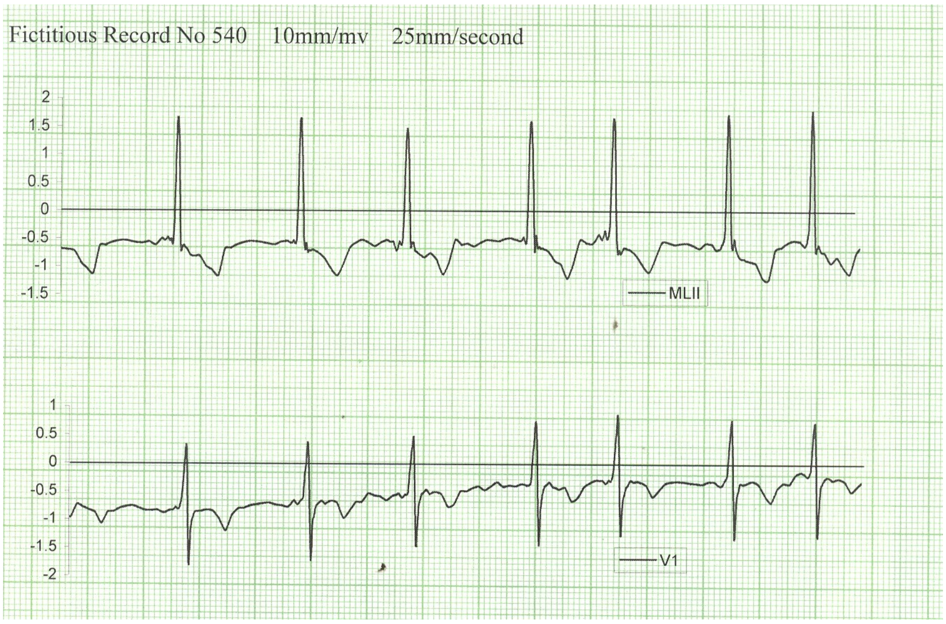
Fictitious Record No 433 (2)   10mm/mv   25mm/second

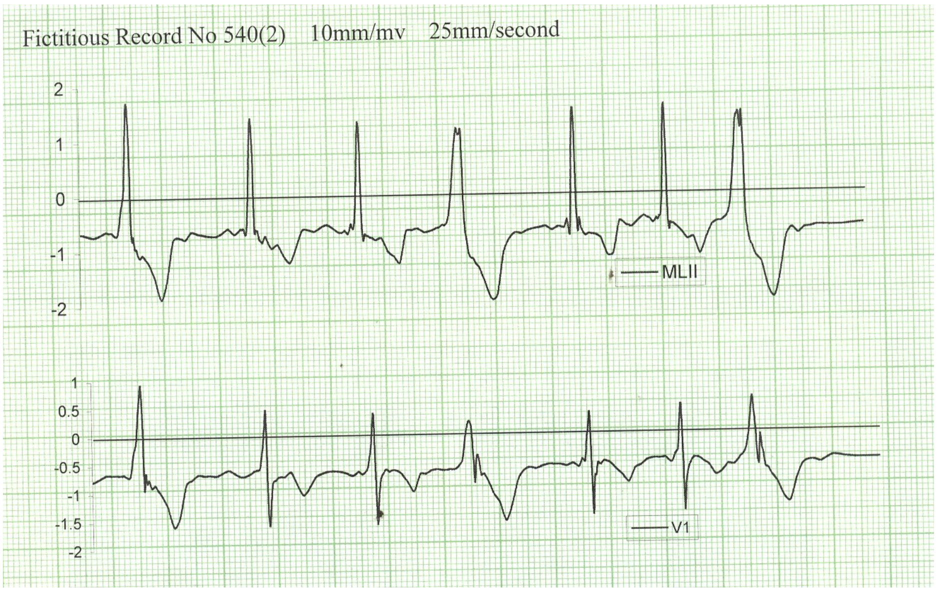


Fictitious Record No 533 10mm/mv 25mm/second

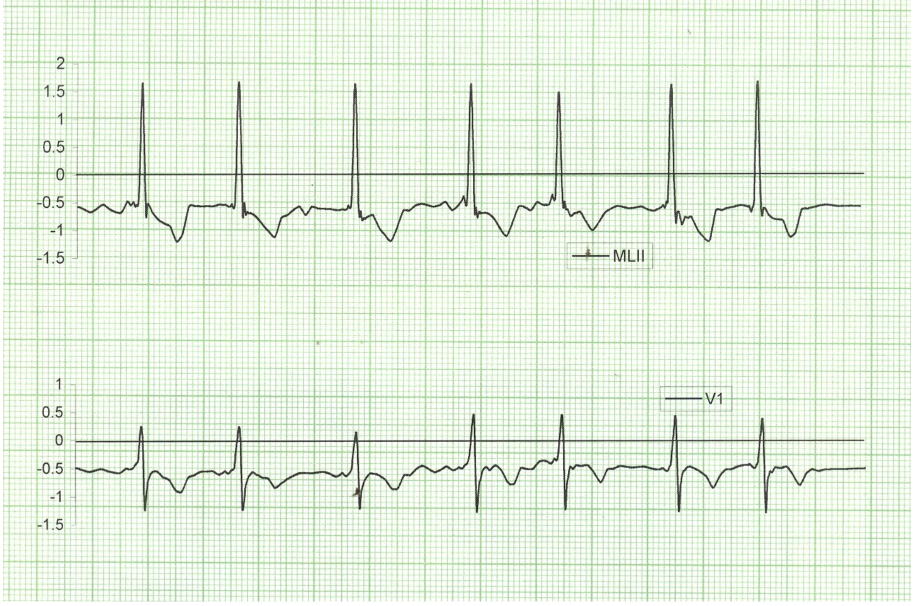


Fictitious Record No 533(2) 10mm/mv 25mm/second

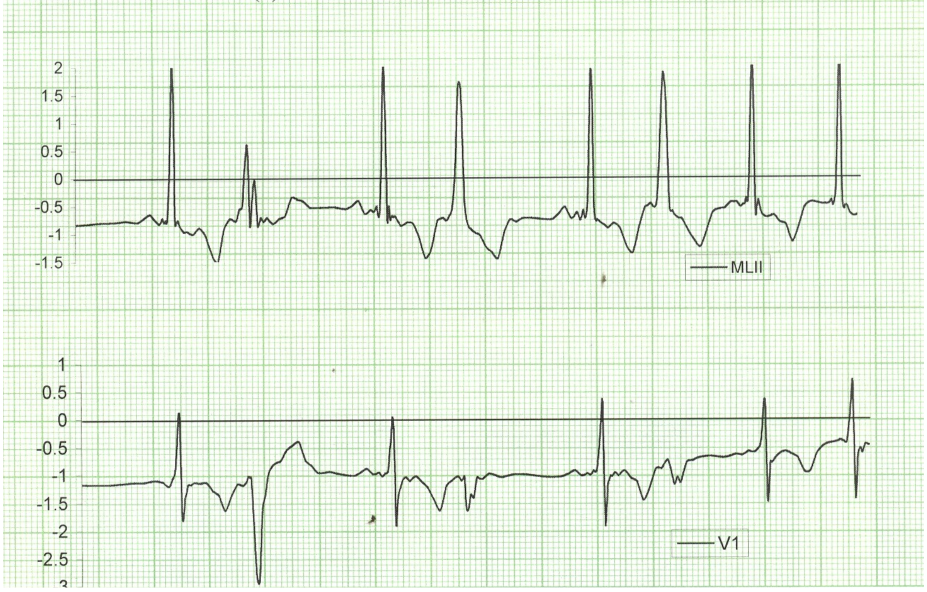

Fictitious Record No 540 10mm/mv 25mm/second
2
1.5
1
0.5
0
-0.5
-1
-1.5
MLII
1
0.5
0
-0.5
-1
-1.5
-2
V1


Fictitious Record No 540(2) 10mm/mv 25mm/second
2
1
0
-1
-2
MLII
1
0.5
0
-0.5
-1
-1.5
-2
V1

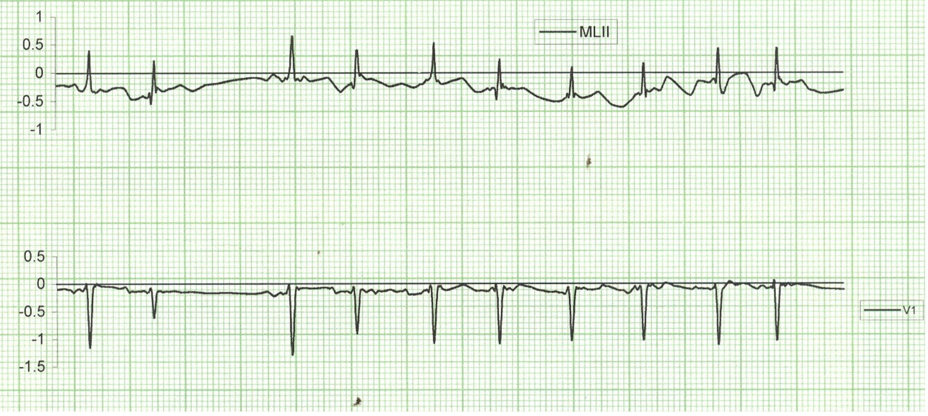
Fictitious Record No 540(3)   10mm/mv   25mm/second



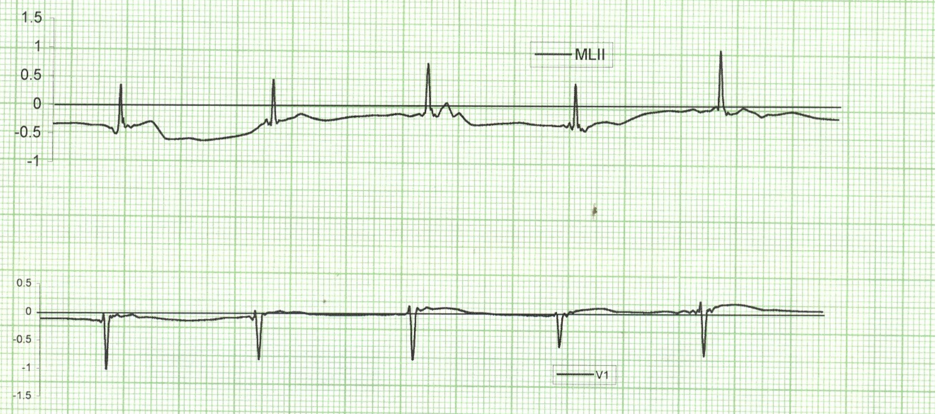
Fictitious Record No 540 (4)   10mm/mv   25mm/second



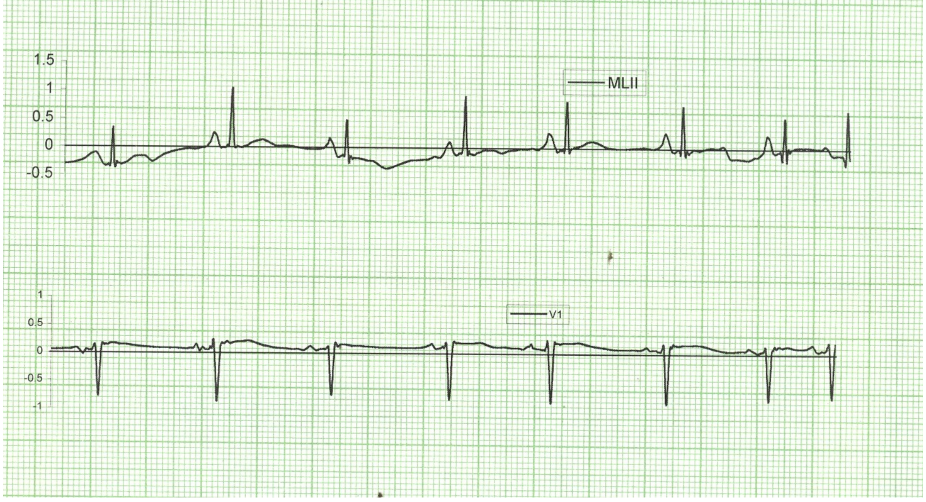
Fictitious Record No 543   10mm/mv   25mm/second



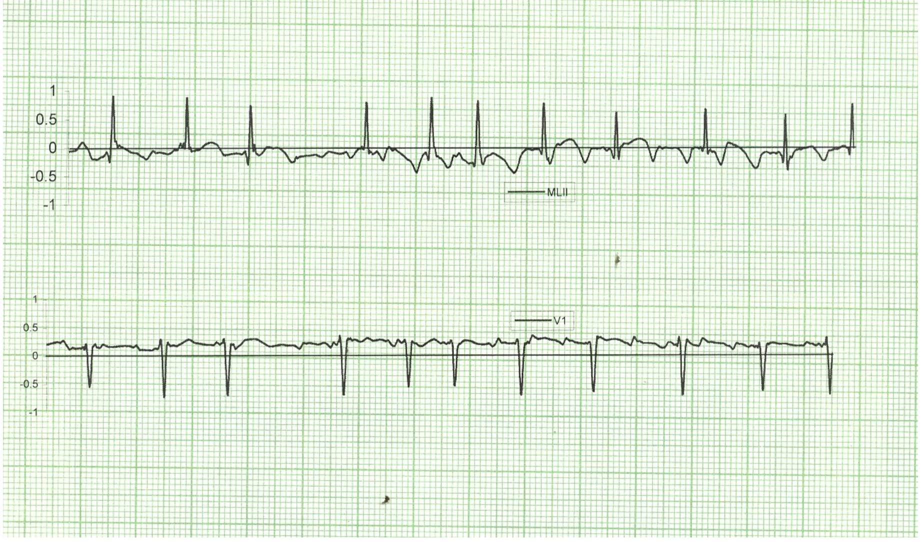
Fictitious Record No 543(2)   10mm/mv   25mm/second



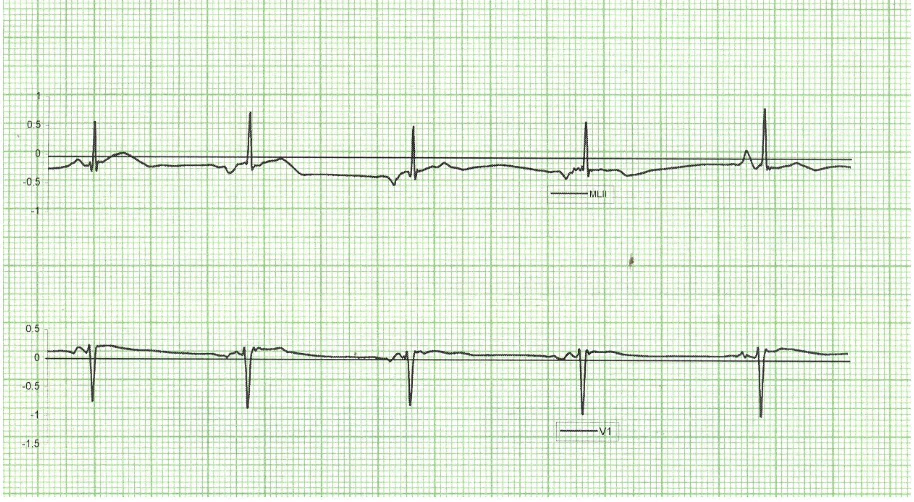
Fictitious Record No 543(3) 10mm/mv 25mm/second



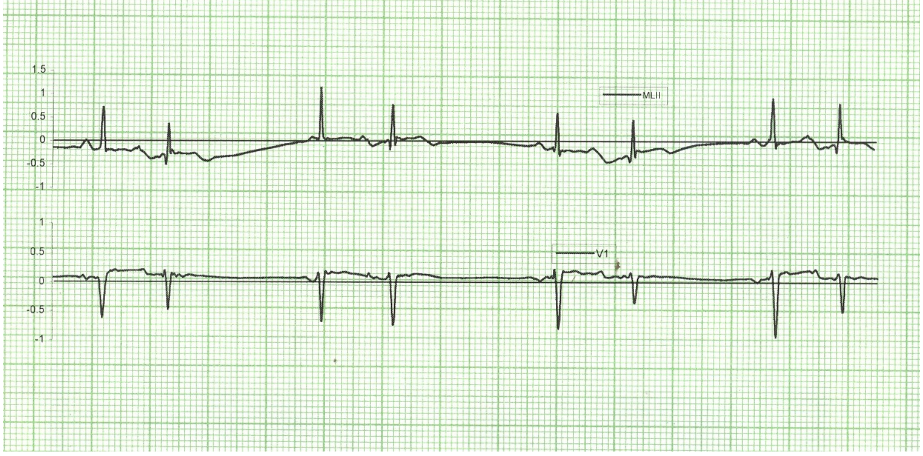
Fictitious Record No 543(4) 10mm/mv 25mm/second



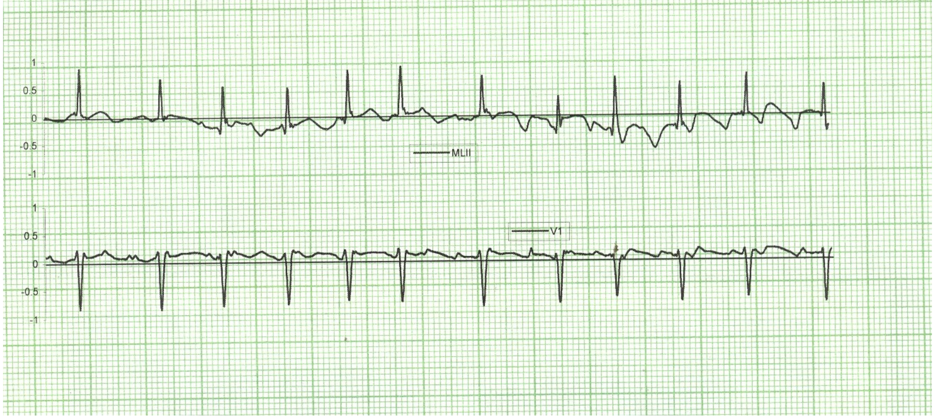
Fictitious Record No 543(5)   10mm/mv   25mm/second



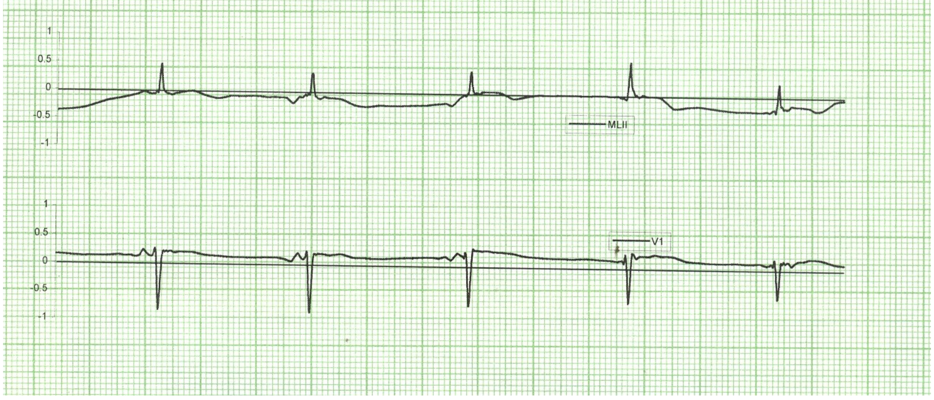
Fictitious Record No 543(6)   10mm/mv   25mm/second

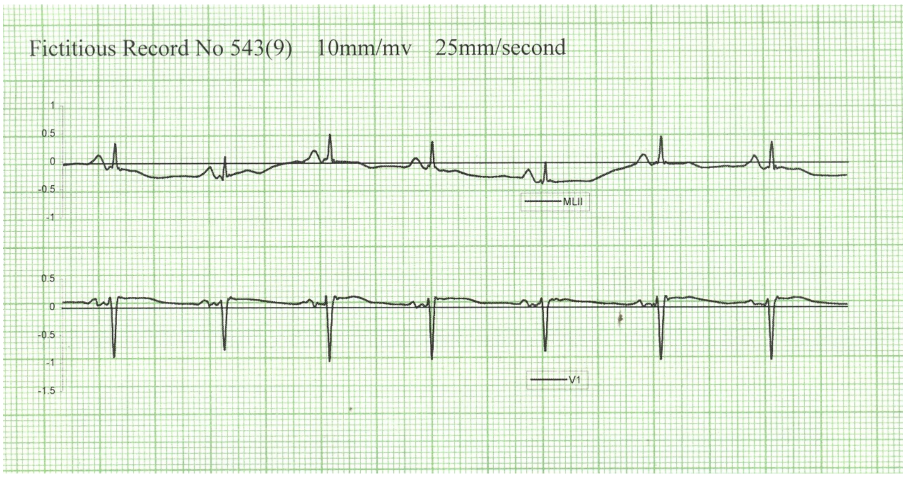


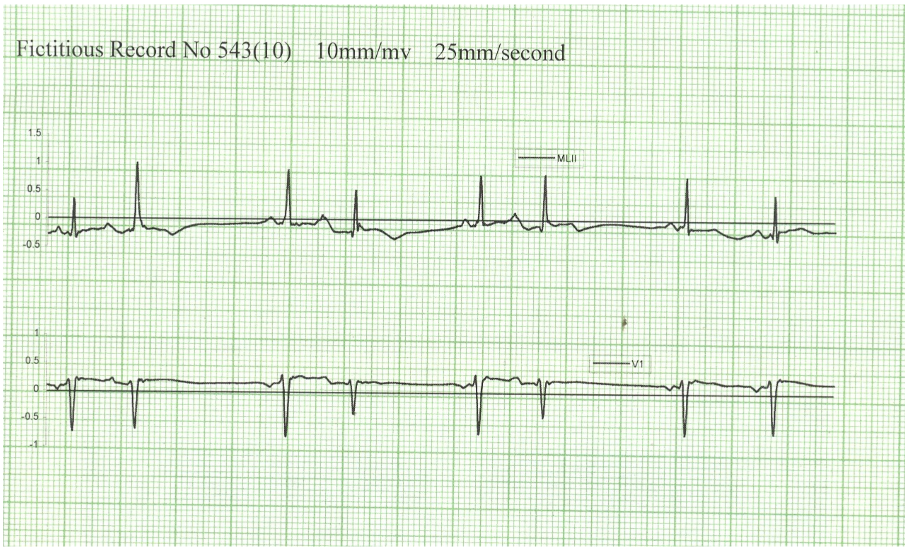
Fictitious Record No 543(7)   10mm/mv   25mm/second



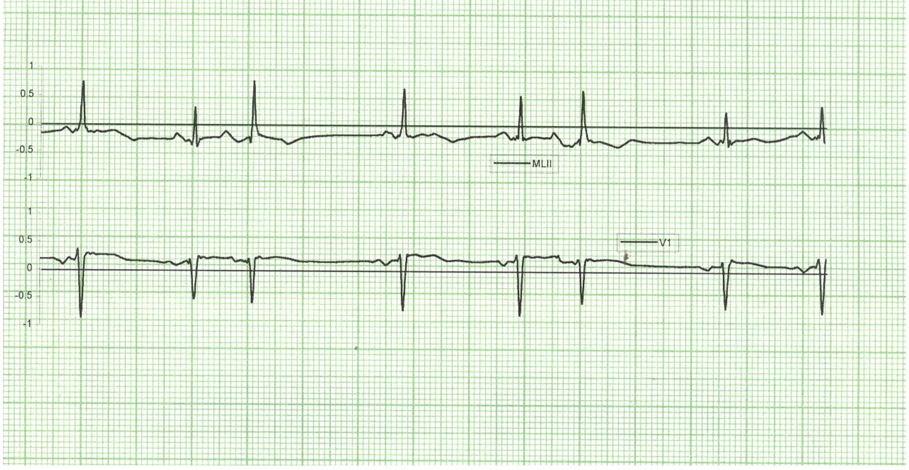
Fictitious Record No 543(8)   10mm/mv   25mm/second



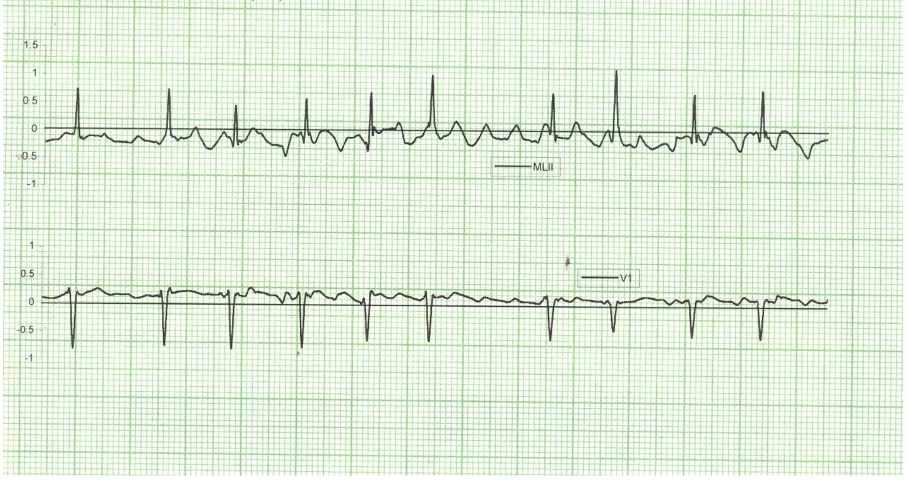

Fictitious Record No 543(9)   10mm/mv   25mm/second
MLII
V1

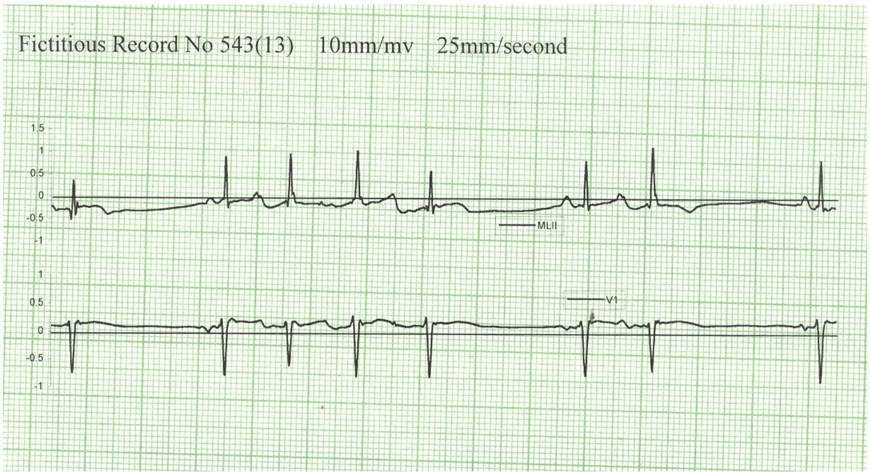

Fictitious Record No 543(10)   10mm/mv   25mm/second
MLII
V1

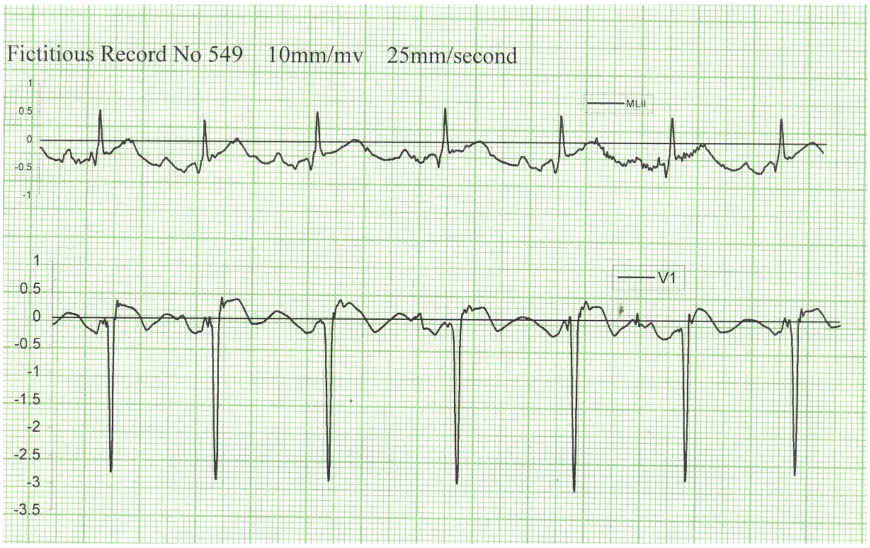
Fictitious Record No 543(11)   10mm/mv   25mm/second

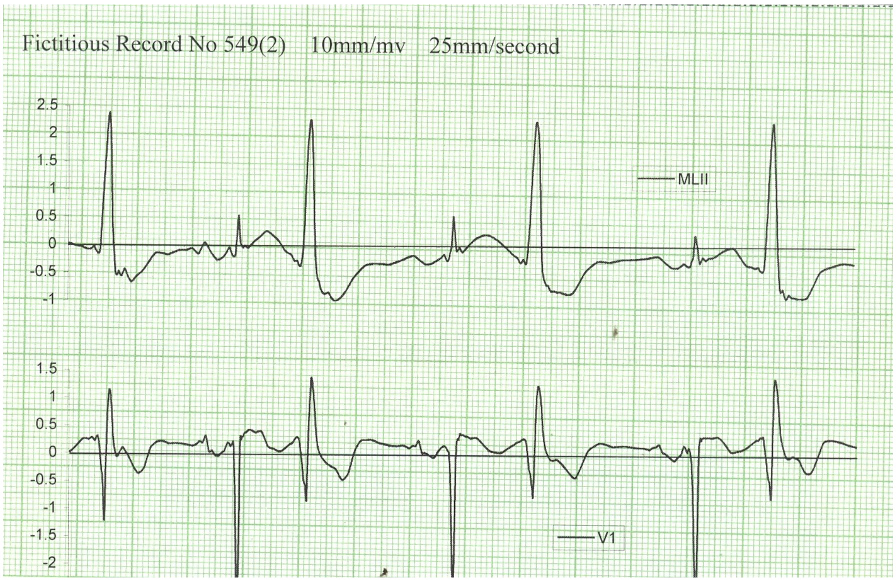


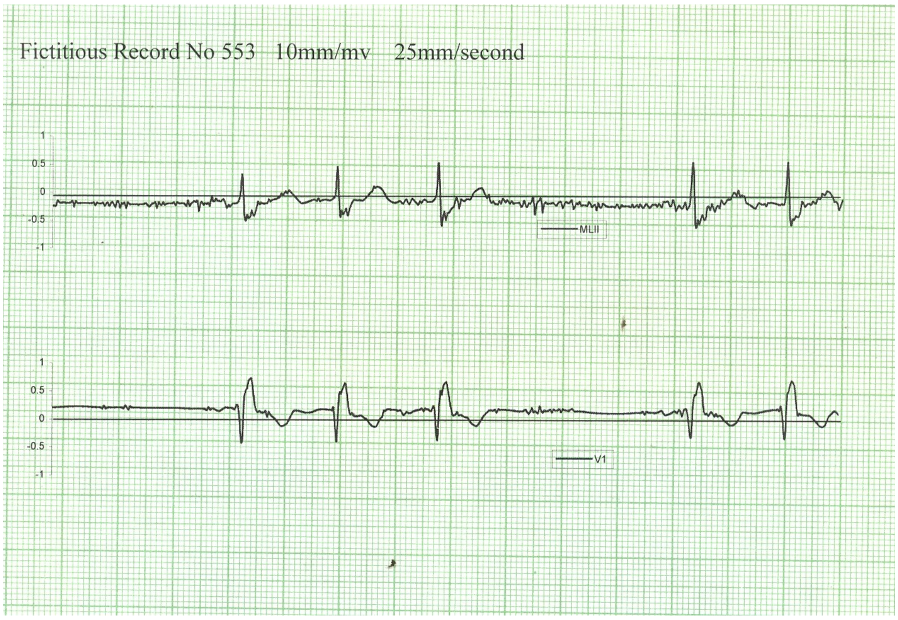
Fictitious Record No 543(12)   10mm/mv   25mm/second




Fictitious Record No 543(13) 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 549 10mm/mv 25mm/second
MLII
V1


Fictitious Record No 549(2) 10mm/mv 25mm/second
2.5
2
1.5
1
0.5
0
-0.5
-1
MLII
1.5
1
0.5
0
-0.5
-1
-1.5
-2
V1


Fictitious Record No 553 10mm/mv 25mm/second
1
0.5
0
-0.5
-1
MLII
1
0.5
0
-0.5
-1
V1