ANALYSIS OF ELECTROCARDIOGRAM AND CARDIO-VASCULAR AND PULMONARY SYSTEMS

A THESIS

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in
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By

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "Analysis of Electrocardiogram and Cardio-Vascular and Pulmonary Systems" in fulfilment of the requirement for the award of the Degree of Doctor of Philosophy, submitted in the Department of Electrical Engineering of the University is an authentic record of my own work carried out during a period from September 1980 to June 1983 under the supervision of Dr.S.C.SAXENA, Reader in Electrical Engineering.

The matter embodied in this thesis has not been submitted by me for the award of any other degree.

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Candidate's Signature

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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ABSTRACT

This thesis deals with the work done in the areas of analysis of electrocardiogram and cardiovascular and pulmonary systems. Electrocardiogram is extensively used by cardiologists in clinical interpretations for knowing the functioning of the heart. Electrocardiogram has good correlation with the mechanical activity of the heart which is responsible for the flow of blood throughout the circulatory system. The pulmonary system is responsible for maintaining the proper level of Oxygen content inside the blood. Proper functioning of the cardiovascular system is dependent on the state of the cardiovascular and pulmonary systems.

The work done for this thesis can be divided into two major sections:

(i) Analysis of electrocardiogram

(ii) Analysis of cardiovascular and pulmonary systems.

New methods have been developed for the analysis of electrocardiogram. Existing models with modifications have been used for the analysis of cardiovascular and pulmonary systems.

ANALYSIS OF ELECTROCARDIOGRAM

The first section deals with the accurate representation of ECG signal, derivation of diagnostically significant parameters, and development of the methodology for classification of cases according to nature of abnormality in ECG patterns. Twelve lead

ECG system has been used for this work. Measurement error and lead proximity corrections are applied to lead potentials using Burger triangle representation. Peak potentials at leads I,II and III have been used to find the Frontal plane Peak Resultant vectors (FPR) for various segments of ECG pattern. The precisions achieved for amplitude and phase are 0.0000002 mV and 0.000004 degree, respectively. From the set of normal cases, the different ranges of variation for various parameters are established. The relative values of parameters showed very good clustering in the normal pattern space.

Sine, cosine, unit impulse, exponential and Gaussian functions have some limitations as the basis functions for the model representation of ECG waves. Therefore, a set of new mathematically defined basis functions is proposed for various segments of ECG wave. These basis functions have specified shapes. The coefficients of the polynomial expressions defining the various basis functions are computed and stored once for all. The main variations in the ECG patterns are horizontal and vertical elongation and/or contraction of various segments. There are also relative phase shifts among the segments and also lead to lead variations. All these have been properly taken into account in this model. In addition to the permanently stored model parameters the number of parameters required to generate the corrected pattern at the six frontal plane leads are less than or equal to eighteen. The set of ECG patterns has been defined by a mathematical expression. The ECG pattern at any frontal plane lead with measurement and lead proximity corrections can be generated by this model

expression. There is a considerable data compression resulting in less memory storage requirement in computers.

Simple and composite binary codes have been developed for representing the diagnostic parameters as symptoms. The parameters within and beyond the normal range are represented by a 0 and 1, respectively. For composite binary code, the parameters are represented as 11, for values within normal range, 01, for values below normal range and 10, for values above normal range. Symptom patterns are specified for four categories namely, normal case, myocardial infarction, right ventricular hypertrophy and left ventricular hypertrophy. Depending upon the matching or mismatching of a symptom of a case with the specified symptom, the multiplier may be taken as 1, 0 or -1 for the respective symptom. Linear programming has been used to find the weight factors of symptoms with respect to different categories. The cases are classified into their respective categories by computing and comparing weighted sums of symptoms for a case with respect to different categories. The weighted sum is expressed as,

$$Y(I) = \left(\sum_{j=1}^{N} W(J) * MM(I,J) \right.$$

where, j corresponds to the symptom number, MM the symptom multiplier, I the category, and W the weight factor.

The development of the methodology and computation of coefficients to be stored once for all has been carried out on DEC-20 computer. The computation for the final interpretation became quite simple and showed a possibility of microprocessor

implementation. The software implementation of the method on a 8085 based microprocessor system is also given in this work.

The method developed here using only three of the twelve leads is simple and efficient for ECG interpretation. The sample cases of myocardial infarction, left ventricular hypertrophy, right ventricular hypertrophy, and normal categories have been properly discriminated by this method. The microprocessor implementation shows that the method is well suited for bedside online analysis in hospitals.

ANALYSIS OF CARDIOVASCULAR AND PULMONARY SYSTEMS

The invasive measurements in the cardiovascular system are to be limited in number due to discomfort to the patient. This restricts the number of measurable physiological parameters. Therefore, with limited number of measured quantities a large number of diagnostically significant additional parameters for the system are found out using parameter estimation techniques. Clark et al.(1980) presented a modified Wind Kessel model of left heart systemic circulation system and proposed a method for its parameter estimation. This model has been used with modification in the present work for studying the effect of variation of aortic valve resistance, resistances and compliances of proximal and distal parts of left heart systemic circuit, peripheral resistance, inertance of long fluid columns and aortic valve switching functions for systolic and diastolic periods. Maxima, minima and average values of responses are computed and considered for comparison purposes. The work has been done to establish

correlation among abnormalities of cardiovascular system, affected parameters and system responses. Simulation of certain abnormal states and associated mechanism is also possible. During the analysis a new source of mechanical arrhythmia has been observed. The means to arrest this arrhythmia are also discussed in this work.

Large number of lumped parameter models of respiratory system has been developed so far. The respiratory system has been modelled using R-C or RLC parameters. In the present work RC and RLC models have been used for the analysis. The parameters have been estimated by the solution of the system equations for these models.This model analysis reduces the invasive measurements considerably. The loss of diagnostic information is compensated by the estimation of additional parameters. The results of the analysis are useful for knowing the state of overall pulmonary system and comparison of cases of different categories.

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CHAPTER I

INTRODUCTION

1.1 GENERAL

Biosystems and signals are complex in nature. It is not possible to collect all the information about them directly by measurement. The measurements in general and invasive measurements in particular are to be limited as they may be tedious, time consuming, expensive, uncomfortable and at times harmful to the patient. Therefore, model analysis is carried out for getting the consistent and instructive picture of these complex systems. The analysis also reveals useful information and establishes useful relationships which are useful in medical decision making.

Mathematical description of biosystems and their mathematical models establish useful correlations. It is now possible to model complex systems taking more complexities with minimum assumptions due to advances in the area of computational methods and digital computers. The impact of recent development in information processing is considerable. Computer modelling and simulation has been recognised as a very useful tool in biomedical research and education. From a qualitative discipline, the life science has now emerged as a more quantitative discipline with a strong theoretical basis. Computer modelling and simulation promote the interaction between experimental and theoretical works and allows more information to be extracted from experimental results. The increasing cost for laboratory experiments and

decreasing cost for computer analysis have made this approach more attractive.

Clinical diagnosis is made more accurate, free from bias of similar cases, more reliable, and reproducible with the help of computers. Proper balancing of expenses, time, and inconvenience against the returns optimizes the economy of tests and therapies. Pattern recognition techniques define the mathematical relationship between measurable features and classification. Computerised interpretation uses principles of pattern recognition. In parametric methods parameters of probability density functions are found. In nonparametric or distribution free methods the assumptions are not made about the nature of distributions.

In this thesis, the biosignals and systems namely electrocardiogram and cardiovascular and pulmonary systems have been selected for the analysis. These are interrelated signal and systems.

1.2 BIO-SIGNALS AND SYSTEMS

Blood is the most vital fluid for the human body. Its circulation involves heart as the pumping device and systemic circulation bed as the load. The electrocardiogram reflects the activity and state of the heart. The pulmonary system is responsible for maintaining proper level of oxygen in the blood. Proper functioning of the circulatory system is dependent on the well being of the cardiovascular and pulmonary systems.

1.2.1 Cardiac System and Electrocardiogram

As shown in figure 1.1, human heart consists of four chambers : right atrium (RA), right ventricle (RV), left atrium (LA), and left ventricle (LV)[116]. RA and RV are connected through tricuspid valve (T). LA and LV are connected through mitral valve (M). At the beginning of the cardiac cycle relaxed atria and ventricles are filled with blood from venous return. A-V valves are open and pressures in all the four chambers are almost same. Impulse generation at the SA node initiates the contraction of atrial muscle, raising the atrial pressure, which is followed by the ventricular pressure. The atrial contraction lasts for about 0.1 second in a total cycle length of 0.8 second. As it passes off, atrial and ventricular pressures fall. Meanwhile exciting pulse spreads from SA node, across the atrial muscle to the A-V node and via bundle of His and Purkinje tissue as shown in figure 1.2[81]. The ventricular contraction makes ventricular pressure greater than the atrial pressure closing A-V valves. As the ventricular pressure exceeds the arterial pressure, the semilunar valve opens. During ejection phase arterial and ventricular pressures follow closely to each other. At the end of ventricular systole of about 0.3 second ventricular pressure drops sharply. Arterial pressure is sustained by elastic recoil of vessel wall and as it exceeds the ventricular pressure semilunar valve closes. Initial isometric part of ventricular diastole (0.08 sec) ends in opening of A-V valve, because the arterial pressure exceeds the ventricular pressure. Then there is a rapid filling of ventricle (0.1-0.12 sec) followed

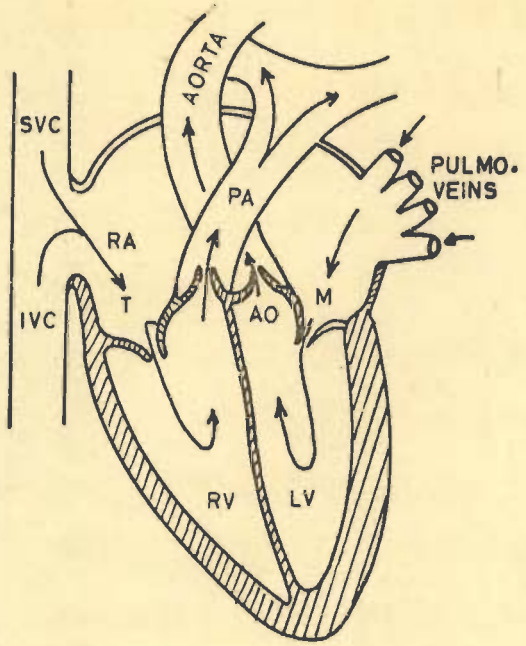


FIG1.1. PHYSIOLOGY OF HEART

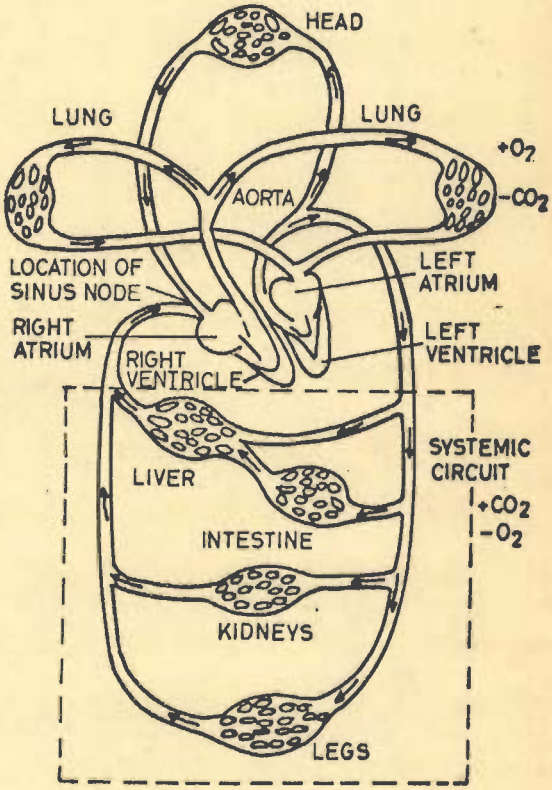


FIG.1.3. CARDIOVASCULAR SYSTEM

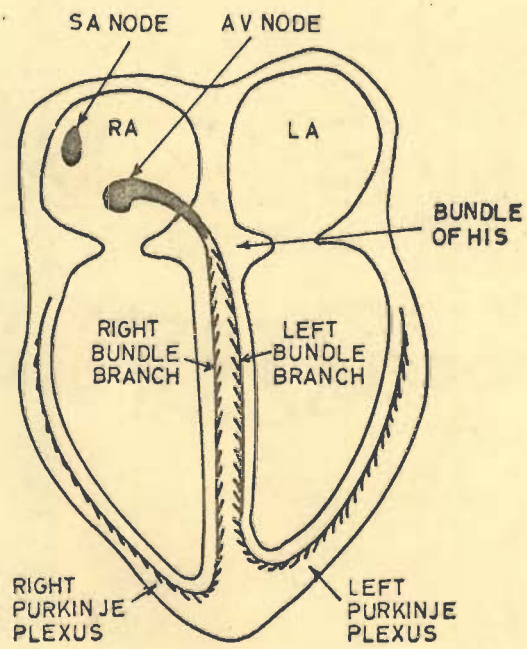


FIG.1.2. CONDUCTION SYSTEM
OF HEART

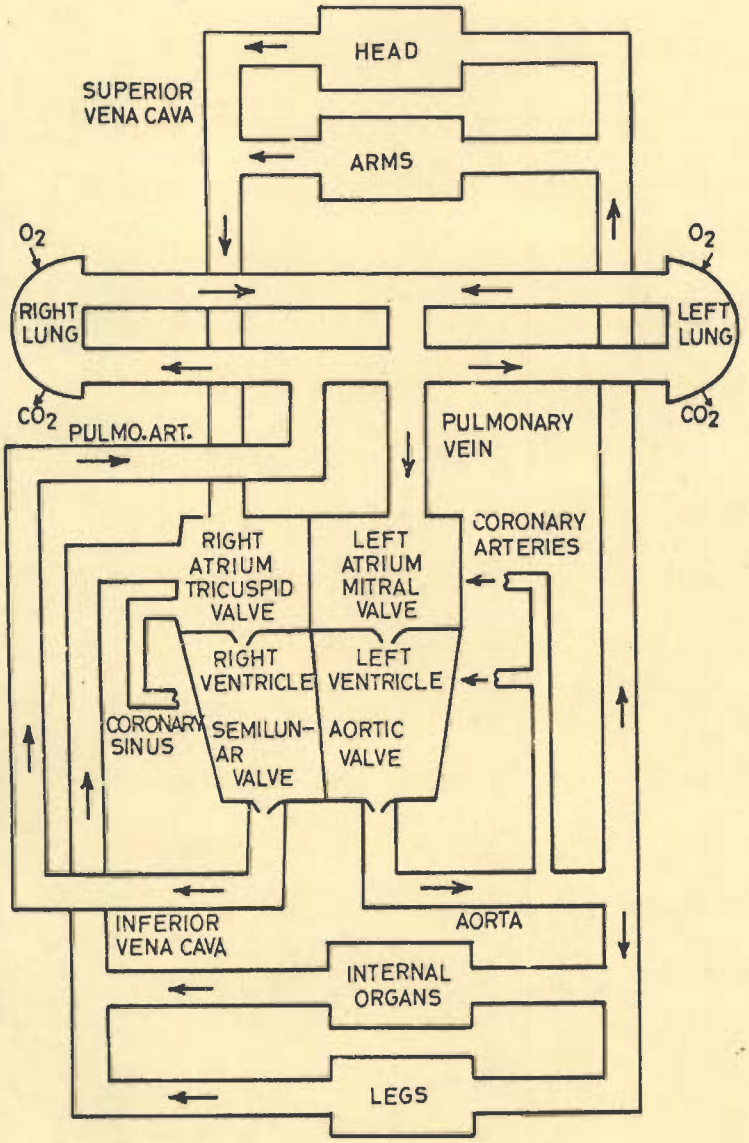


FIG.1.4. CARDIOVASCULAR CIRCULATION

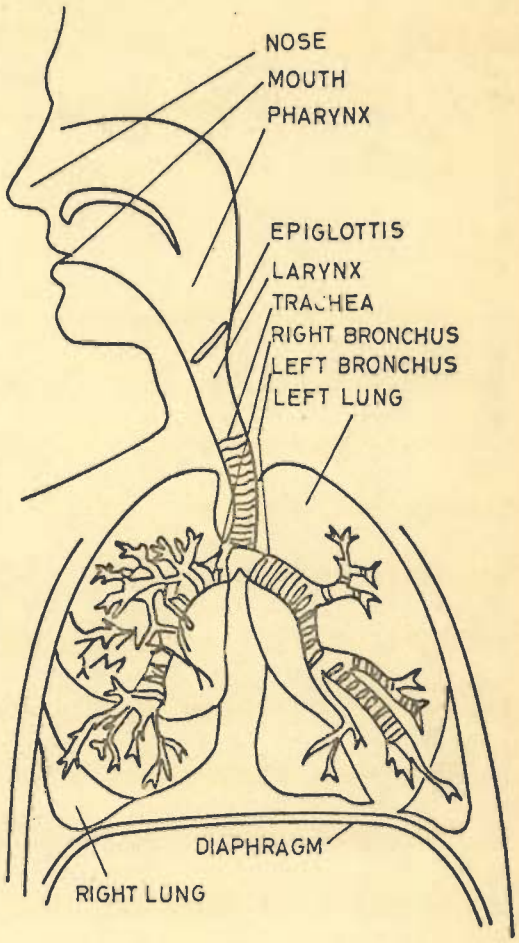


FIG.1.5. RESPIRATORY TRACT

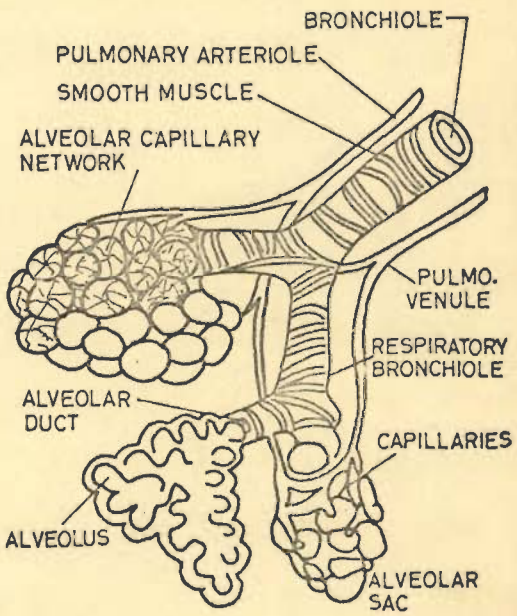


FIG.1.6. ALVEOLI AND CAPILLARY NETWORK

by slow filling (0.19 sec) due to continued venous return, filling both atrium and ventricle, and readjusting the end diastolic volume of ventricle. The ventricular diastole lasts about 0.5 second [81,116].

Auricular systole starts with the discharge of SA node. P wave of electrocardiogram corresponds to auricular systole and atrial depolarisation. QRS wave corresponds to ventricular depolarisation. QRS interval represents intra ventricular conduction time (0.06-0.1 sec). Atrial repolarisation is very slow and buried in the ventricular depolarisation complex. T wave represents ventricular repolarisation. Depolarised state of ventricles is represented by ST segment. QT interval represents the time required for the completion of ventricular depolarisation and repolarisation (electrical systole). The interval from the end of T wave to the beginning of QRS complex represents electrical diastole of the ventricles. PR interval is the duration between the onset of atrial and ventricular depolarisation. It corresponds to the time of travel by the impulse from SA node to the ventricles [81].

Thus the ECG represents the electrical activity of the heart which has good correlation with its own mechanical activity. It indicates systolic and diastolic periods, conduction delay, opening and closing of valves, and the sequence of various events. The amplitude of ECG segment potential depends on the shape, size and orientation of the tissues responsible for its generation. The various timings on the ECG depend on the state of the conduction mechanism. The relative phase shift among the segments

depends on relative disposition of the tissues in space. In case of right and left ventricular hypertrophy, there is enlargement of respective portion of the ventricle. So, there is increase in corresponding segment potentials. Due to predominance of right or left ventricle there may be right or left axis deviation. In myocardial infarction, the damaged tissues are unable to generate and transmit the action potential. Therefore, ECG is a very useful diagnostic aid about the state of heart as it reflects various types of abnormalities.

The development in electrocardiography started with capillary electrometer by Lipman in 1872 and string galvanometer by Einthovan in 1901. Einthovan, Lewis and Wilson did useful work in the early days of electrocardiography [73,123-126,236-240]. Frank lead system is commonly used corrected lead system [78-79]. Burger et al. applied scalene triangle correction to Wilson's tetrahedron [31-34]. With the introduction of computers a number of methods are developed for the analysis of electrocardiogram [2,13,92,118,138,143,155,209,219,245,246]. In last twentyfive years a lot of work has been done for the computer assisted interpretation of ECG in the various parts of the world [6,21-23, 41,57,71,91,106,117,131,135,166,168,172,177,185,197,201,202] Presently, microprocessor based systems are also being developed for the purpose of recording, monitoring and analysis of ECG.

1.2.2 Cardio-Vascular and Pulmonary Systems

There is a very large number of living cells for the muscular activity through out the body. They consume Oxygen as

the fuel from the blood and return carbon dioxide. One side of the heart pumps blood for the systemic circulation and the other side for pulmonary circulation.

The systemic circuit has a higher resistance resulting in larger pressure gradient between the arteries and veins. Left ventricle pumps blood at peak systolic pressure of about 120 mm of Hg and diastolic pressure of about 80 mm of Hg. Left heart is effectively a pressure pump. The pulmonary circuit has a lower resistance and smaller pressure difference between arteries and veins. Right ventricle pumping blood at about 25 mm of Hg is effectively a volume pump. Blood has to depend on the lungs for the exchange of carbondioxide and Oxygen.

The details of the circulatory system are shown in figure 1.3. The schematic representation of the same is shown in figure 1.4 [59]. Superior vena cava leads from the upper extremities of the body and inferior vena cava from the bodily organs and extremities below the heart. Through these two main veins and coronary sinus the blood enters the right atrium. It flows to right ventricle from right atrium through tricuspid valve.The blood is pumped by right ventricle to the two lungs through semilunar pulmonary valves and pulmonary artery. In the alveoli of the lungs, the red blood cells get rid of carbon dioxide and get charged with oxygen. The pulmonary artery is divided many times to form arterioles of very small cross sections. The necessary blood for the exchange of carbondioxide and oxygen is supplied to the alveolar capillaries by these arterioles. On the other side of the lung mass capillaries feed in to venules.Combination

of venules form larger veins which combine to form a pulmonary vein carrying Oxygenated blood to left atrium. It flows to aorta, through left ventricle and aortic valve. While reaching the extremities, the arteries undergo many bifurcations. In the last stage leading to arterioles, the cross section decreases and the number of branches increases. The arterioles feed in to the capillaries. Here, exchange of oxygen and carbondioxide takes place between the blood and the cells. The low velocity of blood facilitates this exchange. Starting from capillaries, the combination of branches results in venules, small veins, larger veins; and superior and inferior vena cava [47,59].

The metabolic process consumes oxygen and liberates carbondioxide. The tissue cells are not in direct contact with the environment. The cells are bathed in a fluid. The cells can exchange oxygen and carbon dioxide with this fluid. The circulatory blood exchanges carbondioxide and oxygen with the tissue fluid. The exchange of gases between the blood and external environment takes place in the lungs. The inflow of air to the lungs and outflow to the atmosphere takes place through the respiratory system.

The details of the pulmonary system are shown in figures 1.5 and 1.6 [59]. The respiratory tract includes the nasal cavities, pharynx, larynx, trachea, bronchi, and bronchioles. The lungs are elastic bags and are located in a closed thoratic cavity. The right lung has three lobes and left lung has two. Epiglottis above the larynx prevents liquids and solids from entering the respiratory tract. The diameter and length of

trachea are 1.5-2.5 cm and 11 cm, respectively. The right and left bronchi enter in to respective lungs. Successive branching forms bronchioles and finally respiratory bronchioles, where some alveoli are attached as small airsacs in the walls of the lungs.

During inspiration, the muscular changes increase thorax volume. The negative pressure developed initiates inflow of air. During expiration, the release of muscles and elasticity of lungs reduce thorax volume, and develop a positive pressure that creates outflow of air.

The cardiovascular and pulmonary systems have interdependence. Proper functioning of one system is essential for the proper functioning of the other. Some symptoms of cardiovascular abnormality lead back to the pulmonary disorder and vice versa.

Modelling of the cardiovascular system started with the Wind Kessel model [80]. A large number of models or modifications in the models are proposed later on [7,15,29,30,49,50,67,89,93, 122,181,199,206,229]. The efforts of the modelling of pulmonary system started with Rohrer [184]. Some of the models are related to respiratory airways [74,88,97,136,161,196,244]. There are certain models devoted to only gas exchange in the pulmonary system [19,111,186,224,225]. Some interaction models have covered both the external airways and internal gas exchange [3,76,101,192, 193].

1.3 ORGANISATION OF THE THESIS

The work embodied in this thesis deals with the analysis of electrocardiogram, and cardiovascular and pulmonary systems.

The major portion is devoted to analysis of electrocardiogram. The first chapter deals with the importance of model analysis and the details of electrocardiogram and cardiovascular and pulmonary systems.

The second chapter deals with the analysis of electrocardiogram. In the beginning the developments in the field of electrocardiographic analysis are reviewed. Various methods of representation for the ECG are discussed. The methods of data compression, selection of lead system and method of recording the 12 lead ECG are discussed. A method is developed for the representation of ECG by Frontal plane Peak Resultant vectors (FPR) using Einthovan and Burger triangle representations. An algorithm is developed for measurement error and lead proximity corrections. In the next section of this chapter, a model based on new basis functions is developed for the representation of electrocardiogram. At first, coefficients of the polynomial expression representing various basis functions for the different segments are computed. These polynomial expressions for the basis functions are combined to develop mathematical model for the overall ECG pattern. The reconstruction of the group of ECG patterns at the six frontal plane leads by a common model expression is also illustrated.

Computer assisted interpretation of electrocardiogram is given in Chapter III. In the beginning, clinical criteria are given for ECG interpretation. The review part covers the various methods of wave recognition, and the development of various ECG interpretation programs. In the next section of the chapter, a

method is developed for the computation of diagnostic parameters, their effective representation in signal space, and definition of normal pattern space. Using this approach, electrocardiograms are screened in to normal and abnormal categories. Composite binary codes are developed and used for generation of symptom patterns. Symptom multipliers and weighted sums of symptoms are used for the discrimination of training cases of different categories. Method of computation of weight factors is also discussed. A method is also developed for the detailed classification of electrocardiograms. The last section of the chapter shows the implementation of the method developed, on microprocessor.

The fourth chapter deals with the analysis of cardiovascular system. After brief review of the models developed so far, the cardiovascular system is analysed using a recently proposed model. Model analysis is used to investigate the effect of variation of aortic valve resistance, resistance and compliance of proximal part, inertance of blood column, compliance of distal part, peripheral resistance; and improper opening and closing of aortic valve. Correlation is established among model parameters, some abnormalities and affected response. The scope of model simulation of abnormalities of cardiovascular system is also highlighted. Effort is made to correlate the cardiac arrhythmia, abnormal set of model parameters, and model responses. It is also discussed as how this arrhythmia can be arrested.

The analysis of pulmonary system is carried out in the fifth chapter. Two methods have been used for parameter estimation. One method is a nonlinear iterative technique and the other one

is a simple noniterative technique. Effort is made to establish the basis of comparison for the normal and abnormal cases. The main problem in the diagnosis of pulmonary system is with the abnormalities in the lower airways. So, more stress is given to the estimation of diagnostically significant model parameters for the lower airways.

The last chapter deals with general conclusions, discussion and scope for future work.

CHAPTER II

ANALYSIS OF ELECTROCARDIOGRAM

2.1 INTRODUCTION

The electrocardiogram is recorded from the surface of human body. The recording is affected by the placement of electrodes and also by some human and instrumental errors. It necessitates proper correction before making its use for interpretation. This chapter deals with the work done towards ECG data correction and representation using mathematical expressions. A correction algorithm is developed. A method is developed for the effective and accurate representation of electrocardiogram. Burger triangle with measurement error and lead proximity corrections is used to compute frontal plane peak resultant vectors for individual ECG segments. A model based on new basis functions is also developed to yield diagnostically significant parameters suitable for categorization in addition to reconstruction of electrocardiogram.

2.2 HISTORICAL DEVELOPMENTS

Development of electrocardiography started with the introduction of capillary electrometer by Gabriel Lippman in 1872. But permanent photographic recording became possible only after its modification by Marey in 1876 [113]. The surface potential measurement was introduced by Augustus Desire Waller [226] and Jimmie. The diagnostic significance of these measurements was first recognized by Willem Einthovan. A high precision string

galvanometer was developed by Einthovan in 1901. The labelling of ECG segments was also introduced. The Einthovan triangle and Einthovan's laws for frontal plane leads are commonly used by the cardiologists all over the world. Some useful work was contributed by Thomas Lewis between 1910-1913 [123-126]. Frank Wilson is known for his contributions in electrocardiography from 1920 to 1947 [236-240]. In 1913, Einthovan et al. introduced the cardiac vector and described the method for determining the mean electrical axis of the QRS complex [73]. A vectorcardiogram from simultaneously recorded leads was constructed by Williams in 1914 [234]. The first vector loop was constructed in 1920[139]. The heated stylus with waxed paper for ECG recording was introduced by Haynes in 1936 [102]. Cathode ray tube was introduced to vector cardiography in 1937 [194]. The heart vector and lead vector were correlated by Burger and Van Millan during 1946-1948 [31-33]. Burger et al. also introduced scalene triangle in 1956 [34]. Frank lead system [78-79] shown in Figure 2.1 is very commonly used corrected system. It is based on detailed torso model and requires only seven electrodes with a built in resistive network. It is orthogonal and has a good anatomical correlation [78]. Rijalant System [183] with 72 electrodes, inspite of sound scientific footing, had problems in clinical practice [113]. Schmitt's system uses 14 electrodes. The X component of cardiac vector is derived from the right and left arm electrodes along with components derived from chest and back electrodes placed at the level of 5th intercostal space. The Y component is obtained from the head and left leg electrodes, and the Z component from

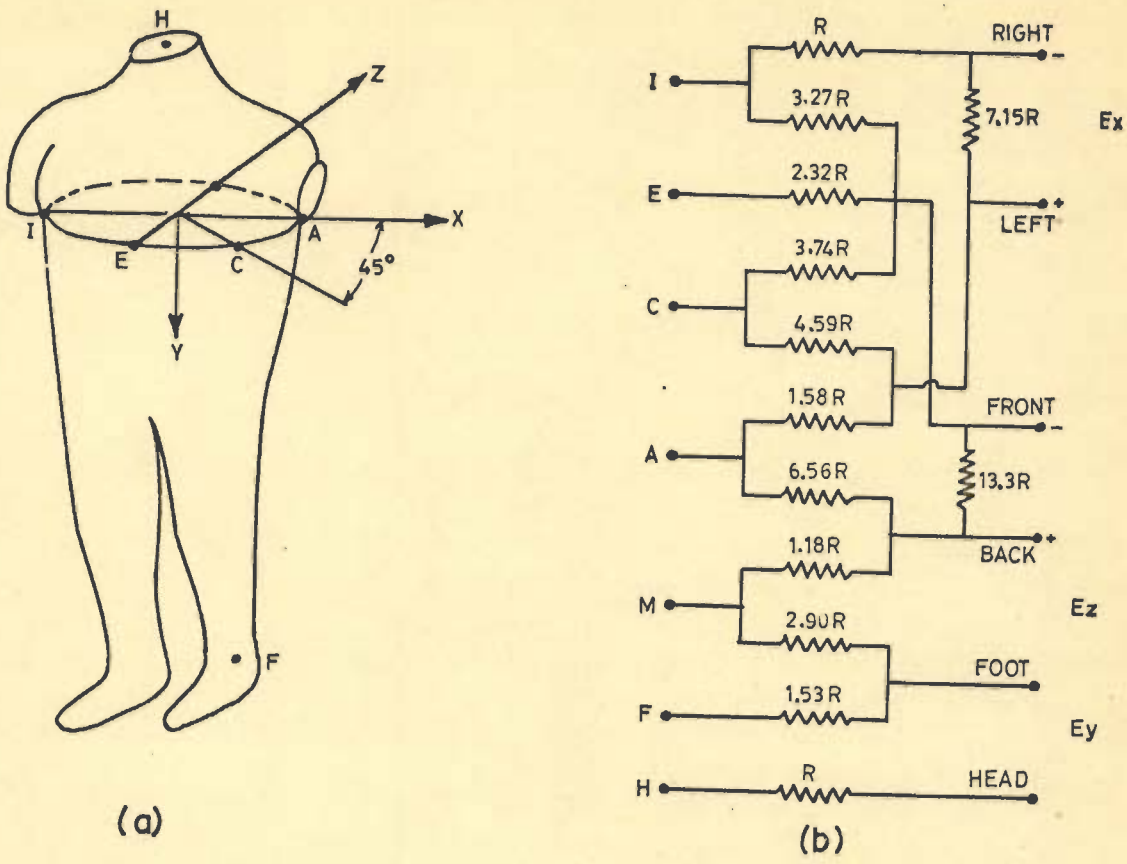


FIG.2.1.(a,b). FRANK'S VECTOR CARDIOGRAPHIC LEAD SYSTEM

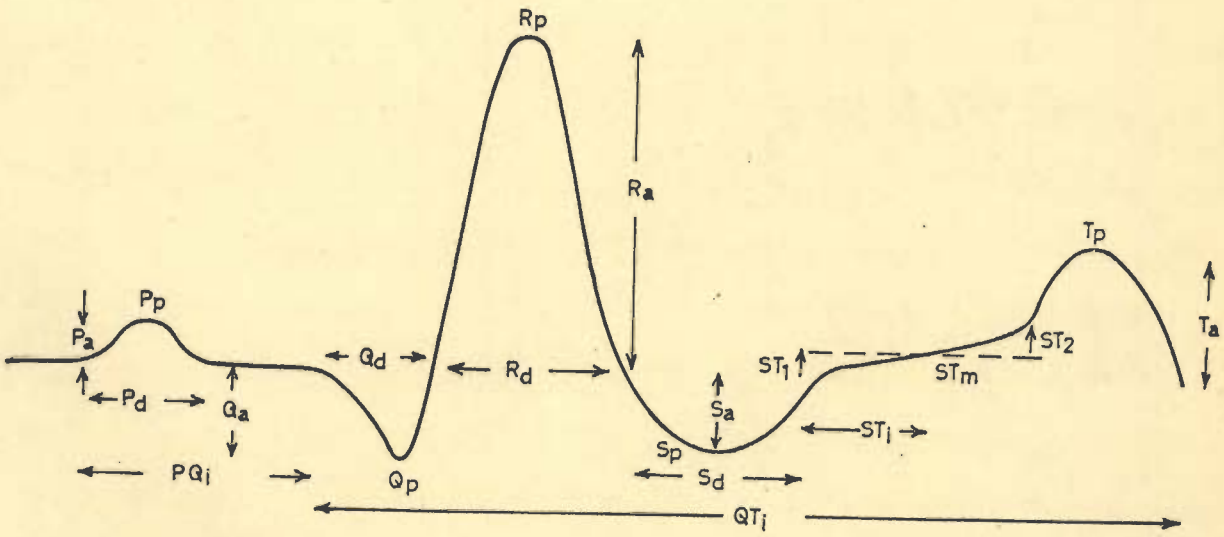


FIG.2.2. ECG PARAMETERS

8 electrodes located on the chest and back at the 3rd and 6th interspace[113]. The lead field concept was substituted for lead vector type correlation coefficients by McFee and Parungao in 1961 [144].

2.3 METHODS OF ELECTROCARDIOGRAM ANALYSIS

The application of computer has brought revolution in the analysis of electrocardiogram (ECG). In case of forward problem of electrocardiography, the electrical generators at the heart are considered as functions of time over complete cardiac cycle and effort is made to determine the electrical potentials over the same span at the body surface. In case of inverse problem, the electric potentials at the body surface are assumed to be known over the complete cycle and effort is made to determine electrical generators at each instant of time in the heart. The known geometry and conductivity of human torso and surface potentials simply do not result in unique solution for the generators. The orientation and number of dipoles and their time sequence of operation are to be assumed [211]. The principle problem in electrocardiography is to find the means to recover the dipolar information, which represents 75-80 % of the electric field [4]. The recovery of the remaining nondipolar information is difficult. It requires registration of unipolar leads from 100-250 points of the thoratic surface. Although, surface potential mapping with multiple electrodes is more informative, but unavailability of commercial instrumentation system, lack of interpretation and classification techniques, and relatively

high overall cost are in the way of its routine application [104,213]. Some methods of ECG analysis try to correlate the large number of ECG potentials measured on the body surface to one or more generators at the heart. In the other approach, models are used to simulate the ECG patterns at one or more leads. The model parameters are representative of a particular ECG pattern. In some cases the model parameters have good diagnostic significance and form the basis of classification algorithms. Some methods of ECG analysis are discussed here.

2.3.1 Intrinsic Component Theory

The intrinsic component theory is known as Eigen value and factor analysis problem. In this approach, spatially non-orthogonal, stationary sets of current sources and sinks are considered [245]. The amplitude variation in a set follows a single pattern of intrinsic component orthogonal (uncorrelated), to other components in the time domain.

Let,

H = correlation matrix

h_{ij} = elements of H, ith row and jth column

h_{ij}^* = complex conjugate of h_{ij}

$x_i(t)$ = ith ECG measurement with complex conjugate $x_i(t)^*$

λ_k = kth Eigen value

e_{ik} = ith element of kth Eigen vector with complex conjugate e_{ik}^*

$< \tilde{x}_i | x_j > = \int x_i(t)^* . x_j(t)\, dt$

= temporal correlation of ith and jth ECG measurements.

$V(p,t)$ = ECG voltage at point P

$C_k(p)$ = coefficient relating kth intrinsic component and ECG measurement at point P.

For n measured components of ECG, $x_1, x_2, \ldots, x_n$ a signal correlation matrix H is formed as follows.

$$H = \begin{bmatrix} < \tilde{x}_1 | x_1 > & < \tilde{x}_1 | x_2 > & \ldots\ldots & < \tilde{x}_1 | x_n > \\ < \tilde{x}_2 | x_1 > & < \tilde{x}_2 | x_2 > & \ldots\ldots & < \tilde{x}_2 | x_n > \\ \ldots\ldots\ldots\ldots & \ldots\ldots & \ldots\ldots & \\ < \tilde{x}_n | x_1 > & < \tilde{x}_n | x_2 > & \ldots\ldots & < \tilde{x}_n | x_n > \end{bmatrix} \quad \ldots (2.1)$$

Matrix element h_{ij} is a correlation between x_i and x_j.

$$h_{ij} = < \tilde{x}_i | x_j > = \int_0^\infty x_i(t)^* . x_j(t)\, dt \quad \ldots (2.2)$$

It is independent of t. Eigen values λ_k's and Eigen elements e_{ik}'s are found such that $\sum_j h_{ij}\, e_{jk} = \lambda_k\, e_{ik}$, $h_{ji}^* = h_{ij}$, and Eigen vectors satisfy the orthonormal conditions.

$$\sum_i e_{il}^* e_{ik} = \delta_{lk} = \text{Kronecker delta}$$
$$= 1 \text{ (for } l = k) \text{ and } 0 \ (l \neq k) \quad \ldots (2.3)$$

The intrinsic component is defined as

$$U_k(t) = \sum_{i=1}^{n} e_{ik}\, x_i(t) \quad \ldots (2.4)$$

Matrix H has m significant Eigen values ($m < n$). The coefficient

$C_k(p)$ relating kth intrinsic component and field point P is a function of space. The voltage at P is expressed as

$$V(p,t) = \sum_{k=1}^{m} C_k(p)\, U_k(t), \text{ where, } C_k(p) = \int_0^{\infty} V(p,t)^* U_k(t)dt \quad \ldots(2.5)$$

Due to orthogonality of intrinsic components in signal space,

$$\langle \tilde{U}_1 | U_k \rangle = \int_0^{\infty} U_1(t)^* U_k(t)dt = 0 \quad \text{for} \quad 1 \neq k \quad \ldots(2.6)$$

The magnitude of intrinsic component is equal to the square root of Eigen value λ_k. Each ECG is considered as a linear combination of m intrinsic components. It is claimed that this representation is better than multipole theory, because the cardiac tissue is a combination of spatially fixed dipoles discharging in an ordered temporal sequence. The approach requires less data and is suitable for digital computation. For normal ECGs, eight most significant Eigen vectors are sufficient for representation of QRST segment with 98.43 % accuracy, but for abnormals more components may be necessary [98].

Using factor analysis, a given set of N electrocardiograms may be represented as [143],

$$f_i = a_i f_I + b_i f_{II} + C_i f_{III} + \ldots. \quad \ldots(2.7)$$

where, f_i is the represented ECG, a's and b's are constants and f_I, f_{II}, ... are functions of time. The values of a's and f_I are found at first by least square error criterion using expression

$$S = \sum_{i=1}^{N} \int (f_i - a_i f_I)^2 dt \quad \ldots(2.8)$$

The residue functions are used to find the successive factors and associated coefficients.

2.3.2 Amplitude and Duration Method

It is a simple method considering amplitudes and durations/intervals at leads II and V_3 as representative of an ECG for a particular case [209]. The sampling rate is 625 samples per second. As shown in Figure 2.2, amplitudes of waves P,Q,R,S, and T and of segment ST, durations P_d, Q_d, R_d, S_d and T_d of respective waves, and intervals PQ_i, ST_i, QT_i and RR_i are measured and stored. The derivatives are also found for various segments.

2.3.3 Latent Components in ECG

In this decomposition technique the components $C_j(t)$ are positive between start and finish, and zero elsewhere [92]. They start in a sequence. At one time, not more than three components are nonzero. The k observed waveforms are represented as

$$D_i(t) = \sum_{j=1}^{M} A_{ij} C_j(t) + E_i(t) \qquad \ldots (2.9)$$

where, A_{ij} is the constant coefficient and $E_i(t)$ is the error. The number of components M depends on the set error criterion. The addition of a component alters the shapes of other components. The decomposition procedure is shown in Figure 2.3. The coefficients are plotted as vectors within a unit circle for horizontal, frontal and left sagittal planes. The computational algorithm is as follows:

Step I : The components are set to unit impulses located at the centroid of the previously derived components. Unit impulse is added at the instant of peak absolute error.

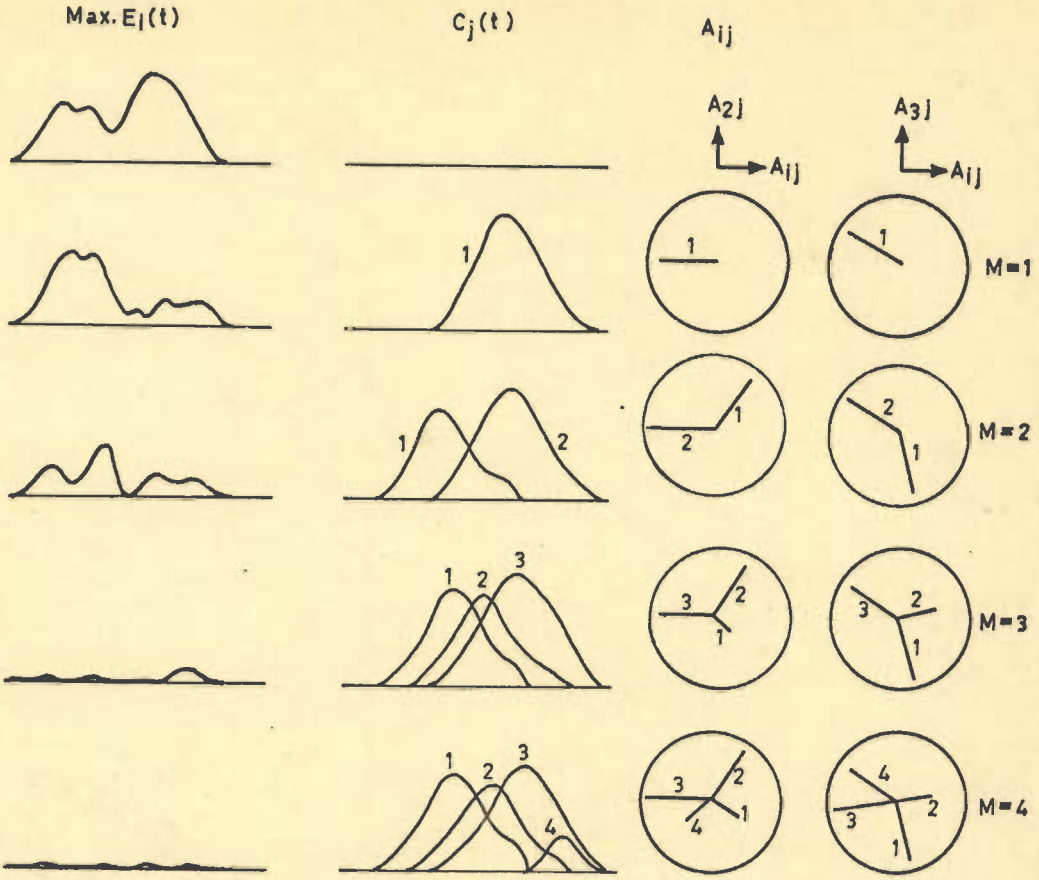


FIG. 2.3. DECOMPOSITION PROCEDURE FOR LATENT COMPONENTS

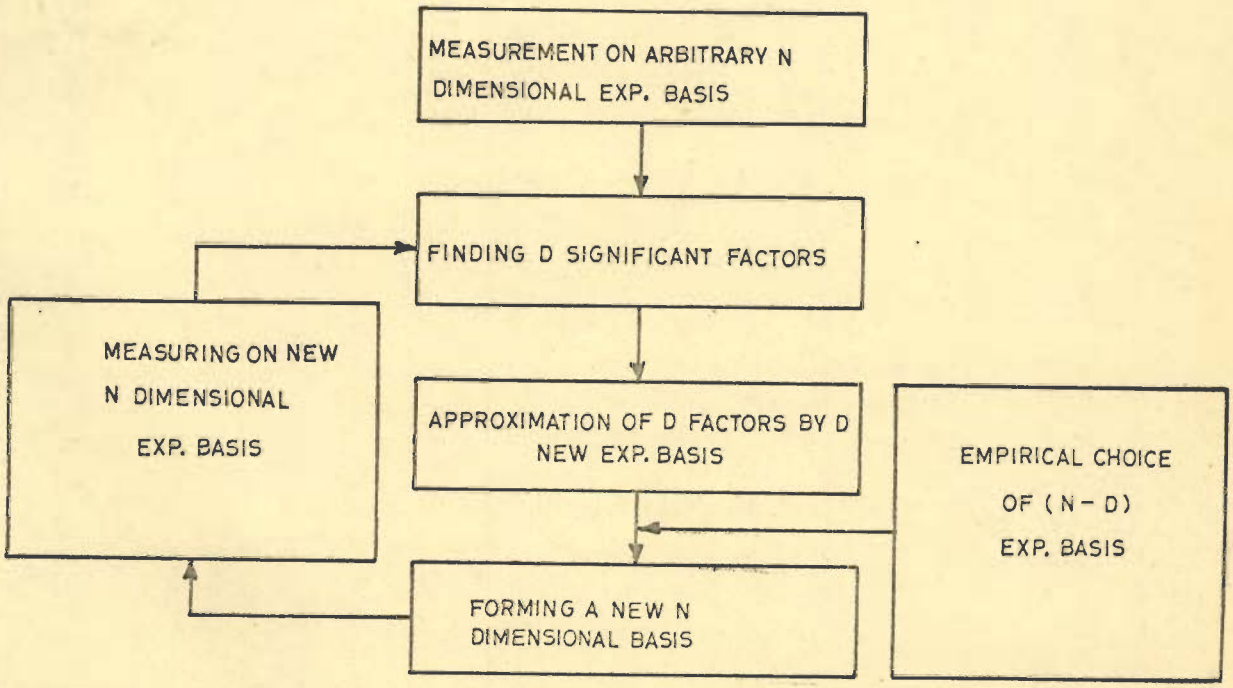


FIG 2.4. ITERATIVE PROCEDURE FOR MATCHED EXPONENTS

Step II : (a) The coefficients are evaluated for least squared error and then are normalised. The component amplitudes are adjusted.

(b) Positive components are extended for minimum squared error. The starting and ending sequence is kept same and the simultaneous components are limited to three.

Step III: Return to step I for peak absolute error larger than the acceptable one, otherwise the decomposition is complete.

2.3.4 Matched Exponents

A set of matched orthonormal exponentials found by an iterative process is used to represent the ECG in this method[246]. The orthonormal exponentials are linear combination of ordinary exponents

$\exp(-\alpha_k t \pm j \beta_k t)$.

where, t is the time, and α_k and β_k are the constants. N real exponentials are chosen to form initial basis for the measured ECG. The number of significant exponentials D is decided by Eigen vector process. They are represented by the Eigen vectors weighted by the square root of the Eigen values. The weighted Eigen vector is a linear combination of N original exponentials. They are then approximated by D new exponential basis, so that all the energy measured in the original N dimensional space is contained within this D dimensional space. The remaining (N-D) basis functions are chosen empirically. The signal is again measured

on this new N dimensional basis and the process is repeated until satisfactory results are obtained. The iterative process is shown in Figure 2.4. The final basis consists of 6 pairs of complex exponentials; the first pair for small Q wave, next three for QRS complex and last two for T wave. The error is limited within ±5 %. The Fourier series requires 28 sine and cosine terms and a constant term. The analog simulation is possible by orthonormal exponential filter [246].

2.3.5 Fourier Series Analysis

Diagnostically significant upper frequency for ECG is still undecided [118]. The fundamental frequency lies between 6.6 and 12 Hz. The frequency components greater than or equal to 80 Hz contribute less than 3 % to the total amplitude [195]. The ECG reconstructed from 34 to 37 Fourier terms has agreement with original ECG within ± 1 % [45]. Use of 60 harmonic components reduces the reconstruction error to 1%. Beyond this order the improvement is very slow [118]. Waveform amplitude information extends only to 200 Hz and waveform duration information lies below 60 Hz [87]. The Fourier series can also be found for individual ECG segments as the significant range is different for different segments. The frequency analysis is also used to specify the minimum value of upper frequency limit for ECG equipments. It is specified between 50 and 1000 Hz by different countries. Therefore, minimum sampling rate of 100 samples per second and quantization interval less than 10 ms are desirable.

The ECG can be represented by a Fourier series in the following form [69]:

$$u(t) = A_o/2 + \sum_{n=1}^{\infty} (A_n \cos n\omega t + B_n \sin n\omega t) \qquad \ldots (2.10)$$

where,

$$A_n = \frac{2}{T} \int_{-T/2}^{T/2} u(t) \cos n\omega t \, dt,$$

$$B_n = \frac{2}{T} \int_{-T/2}^{T/2} u(t) \sin n\omega t \, dt$$

$$u(t) = U_o + \sum_{n=1}^{\infty} U_n \cos (n\omega t + \emptyset n) \qquad \ldots (2.11)$$

where,

$$U_o = A_o/2 \ , \ U_n = \sqrt{A_n^2 + B_n^2} \ ,$$

$$\emptyset_n = \tan^{-1}(-B_n/A_n)$$

$$u(t) = U_o + \sum_{n=1}^{\infty} U_n \sin (n\omega t + \emptyset_n)$$

$$\emptyset_n = \tan^{-1}(A_n/B_n) \qquad \ldots (2.12)$$

The advantage of the approach is that the Fourier coefficients are independent of the number of harmonic components considered. The baseline shift during ECG recording affects only the average value. It is a convenient method for computation on a digital computer. Inspite of reduced error with large number of components, in some regions the shape matching is poor. There may be wide variation in the values of Fourier coefficients from individual to individual and lead to lead.

2.3.6 Cross Correlation Technique

This technique relies more on shape than area, amplitude or duration. It is claimed to be more informative. Matched filters are also used as the analog equivalent of correlation[208]. Digital cross correlation is also used [147,215]. For periodic functions $f_x(t)$ and $f_s(t)$ with N+1 sampled values in sets X_k and S_k, the discrete time correlation is given by

$$\phi_{xs}(T) = \frac{1}{N+1} \sum_{k=1}^{N} X_k \, S_{k+T} \qquad \ldots (2.13)$$

where, T a time delay, $f_s(t)$ is normal or specific disease ECG, and $f_x(t)$ is unknown ECG. The normal heart rate of 75 BPM is considered for linear time normalisation. The mean square value of unknown waveform is made equal to mean square value of reference wave for amplitude normalisation. Each sample value is divided by square root of the ratio of mean square value of unknown ECG to that of the mean square value of the reference ECG. In case of perfect shape matching, cross correlation is reduced to auto-correlation. With the multiple adaptive matched filter system, a variety of operations namely normalisation, weighing, comparison, decision, modification and adaptation are performed on the original data sampled at 600 samples per second. QRS is assigned evenly spaced 30 intervals. This 31 dimensional vector becomes time normalised and synchronised pattern [13].

2.3.7 Template Matching

The approach uses a linear combination of a set of template waveforms to fit in, a set of pattern waveforms [138].

The template of m waveforms sampled at n points and represented by n x m matrix T is considered. The template is used to synthesize a set of k pattern waveforms, represented by n x k matrix P. The m x k matrix W is found to minimise the squared error. The error is normalised to make it independent of amplitude and dimensions of P. The specific patterns of normal Frank lead x- y- z wave forms are used as template in matching normal and abnormal pattern waveforms. The parameters obtained for matching are stored as representative of a particular ECG. The QRS complex is considered in the illustration [138].

2.3.8 Orthogonal Transforms

The Karhunen Loeve Transforms (KLT), Haar Transform (HT), Discrete Cosine Transform (DCT), and Identity Transform (IT) are considered for data compression and compact representation of ECG pattern [2]. The normalised mean squared errors (MSE) for various transforms are compared in table T.2.1 [2].

TABLE - T.2.1

Orthogonal Transforms

No. of components M	Normalised MSE			
	KLT	DCT	HT	IT
8	0.2332	0.2838	0.3404	0.8767
16	0.0773	0.1451	0.1763	0.7813
32	0.0034	0.0293	0.0603	0.6180
64	0.0000	0.0069	0.0088	0.3599
96	0.0000	0.0000	0.0000	0.1608

The value of M equal to 32 to 64 results in data compression of 2:1 to 4:1 (number of points 128) with good accuracy for DCT and HT. The KLT can also be applied to P and QRST segments considered separately [243].

2.3.9 Some Other Approaches

Cadzow et.al.[46] have reported that the continuous periodic signal may be represented by a set of values measured at some interval, forming a parameter vector, $a = (a_1, a_2, \ldots, a_m)$. The linear recursive representation of finite length sequences is discussed. Twelfth order direct recursive match of 91 samples for one period of ECG is illustrated [46]. The compression of data achieved is 91:25. The minimum value of normalised inner products, f(a) is equal to 0.0105 for the whole wave. For DCT with m = 28, f(a) is 0.00963 in the illustration.

The signals are decomposed into their minimum and maximum phase components through homomorphic filtering in homomorphic analysis and modelling. The components are modelled by Poles and Zeros [155]. The best extraction procedures may fail to give good results due to noise and artefacts. The frequency domain techniques are less suitable for diagnostic purposes due to lack of spectral feature variability associated with pathological states [219]. The part of the ECG wave is represented as a combination of 27 linear segments with specified lengths and slopes in a syntactic approach [219]. The piecewise approximation approach [105] is somewhat similar to this approach. The ECG pattern is thought of as a series of triangles or trapezoids separated by some intervals. The line segments on the ECG are

specified by the heights, lengths, and intervals. A spin harmonic model is also developed and applied for the investigation of properties of ECG, location of ECG neutral point, and study of reversal of phases of unipolar ECG records [149,150,151].

2.4 DATA COMPRESSION

The ECG data to be used for the analysis should be acquired and stored or transmitted economically. The higher sampling rates are desirable for ECG to retain diagnostically significant high frequency components. But, the limitations are due to cost of storage and transmission. Digital data transmission is free from noise and is suitable for direct use on digital computers. The transmission of three leads sampled at 250 samples per second with a 10 bit word length creates more than 7500 bits per second which is beyond the capacity of standard dial up telephone lines [227]. Therefore, data compression is essential. The reduction of sampling rate and shortening of word length are rarely used for data compression. In case of expansion of ECG using orthogonal transforms, only coefficients of individual functions are transmitted. The prediction formulae is used for the sampled data in another approach. The error between the predicted and actual value is transmitted. The bit rate can also be minimised by transmission of signal, only if, the ECG potential has changed by a predetermined value Δ. The value of Δ and its time of occurrence are transmitted. In straight line interpolation, the transmission occurs only when the interpolation error exceeds a predetermined criterion. Beat to beat variation is

involved in serial comparison. It is economical to store a few significant parameters describing the variation rather than a series of patterns [114].

Ruttiman and Pipberger digitized the ECG with 12 beat resolution at a rate of 500 samples per second[190-191]. The sample values are stored by integer multiples of 1 μv. The degradation of amplitude measurements increased with digital filtering and time measurements were almost unaffected with the decrease in bandwidth. The rate of 200 samples per second and f response up to 100 Hz are considered sufficient for practical purposes. For further compression, prediction formulae is used. It is reported that the variance does not decrease substantially for a predictor of higher than that of second order. The scheme is suitable for microprocessor implementation. If the transmission is not otherwise protected, adequate error control is mandatory adding to cost. The use of first 40-60 coefficients of KLT results in data compression of 750:40 to 750:60. The reconstruction is good in terms of energy and absolute average error but maximum amplitude errors of 20-30 μv could occur at unpredictable points in the signal. The error may be tolerated up to the limit the diagnostic accuracy is unaffected. In AZTEC (Amplitude Zone Time Epoch Coding) preprocessing the ECG is represented by a series of straight lines with specific slopes. Data reduction is 10:1 [58]. Many of the methods of ECG representation discussed earlier also result in considerable data reduction . The data reduction scheme should not be selected only on the basis of compression ratio. The computing effort, ease in manipulating

the compressed and expanded data, acceptable least squared error and effect on diagnostic accuracy depending on the type of classifier are the deciding factors. According to Bonner [20], the reconstruction which does not show visual difference is sufficient. The effect of inaccuracies due to compression is less than that caused by normal beat to beat and day to day variations and also by noise and baseline shift.

2.5 LEAD SELECTION AND RECORDING

2.5.1 Lead Selection

The attempts to find the best lead system for picking up the total information content of the electrical field of the heart and optimal classification of ECG pattern, are not fully successful. Even the most commonly used lead systems like Einthovan, Goldberger, Wilson, Frank etc. have not fully met this requirement. More than 90 % of ECG recordings in the world are made using the 12 lead ECG system. Many research centres use in addition a corrected orthogonal three (Frank) lead system [247]. The information content of 12 lead ECG and Frank (x y z) lead system is almost same [24,133,142,169]. With respect to lead variability and number of leads orthogonal three lead system is considered better. It is reported that it combines the advantages of scalar and vector electrocardiography and has a 4:1 data reduction [166]. Recently it is reported that different information is available in different lead systems [134]. The hybrid 15 lead system (x y z + 12)[127,214] and a system consisting of nine optimally placed chest leads [119] aim at combining the information of the

two systems. In 1970's, the computer analysis of ECG was carried out at Royal Infirmary , Glasgow using three orthogonal leads derived from modified axial lead system [128]. It was not favoured by the clinicians and it became necessary to incorporate 12 leads in further development [135]. In hybrid lead system, the conventional 12 lead electrodes are retained. One additional electrode at V_{6R} position and another on the left side of the neck are added. In the conventional form twelve lead ECG is reported [70] to be less informative than polar and vector cardiograms. At the same time, there is lack of generally accepted diagnostic criterion for orthogonal lead ECGs and VCGs. It is also reported that VCG supplements ECG but does not replace it. It adds to diagnostic accuracy in only 15 % cases [81]. It has much to offer as a teaching aid. It has a limited clinical value and will not replace ECG in routine application [84]. The vector loop does not contain any additional information which is not present in the two scalar leads producing it. It has not established its diagnostic role so far. The final settlement on lead system may be decided depending upon the diagnostic significance and not only on the faithfulness of reproduction of the equivalent dipole. The justification for the twelve lead ECG lies in its worldwide acquaintance and commercial availability of recording equipment. It stands on a solid basis of clinical experience and is supported by anatomical, physiological and radiological evidences. It ensures some continuity with the existing practice and, hence, gets more support from the clinicians. In India, the ECG data collected is usually by 12 lead system. Even at All India Institute of

Medical Sciences, from where the data is collected, uses 12 lead system in routine use. So 12 lead system is selected for the present work. The aim is to retain the advantages and to overcome the limitations of this system.

2.5.2 Recording

The twelve lead ECG is a sequential record of 12 different leads connected one by one through a selector switch. Leads I,II and III are the bipolar standard limb leads. As shown in Figure 2.5, lead I connects the right (-ve) and left (+ve) arms. Lead II connects right arm (-ve) and left(+ve)leg.Lead III connects left arm (-ve) and left leg (+ve) [228]. In case of unipolar leads one exploring electrode is used to detect the actual potential over a particular point and the other indifferent electrode provides the reference. Wilson's central terminal is used for this purpose. V_R, V_L and V_F are the potentials recorded by the unipolar leads at right and left arms, and left leg with respect to the central terminal. These potentials are relatively small. Goldberger augmented the leads by breaking the connection between the Wilson's central terminal and the extremity whose potential is being recorded as shown in Figure 2.6(a,b) [81]. The augmented potentials are related as $aV_R = 1.5\ V_R$, $aV_L = 1.5\ V_L$ and $aV_F = 1.5\ V_F$. Leads I,II,III,aV_R,aV_L and aV_F are also called frontal plane leads. Figures 2.7(a) and (b) show the Einthovan triangle and hexaxial reference system for the frontal plane leads.

The standard precordial leads include the six unipolar leads V_1 to V_6 as shown in Figure 2.7(c). The negative electrode

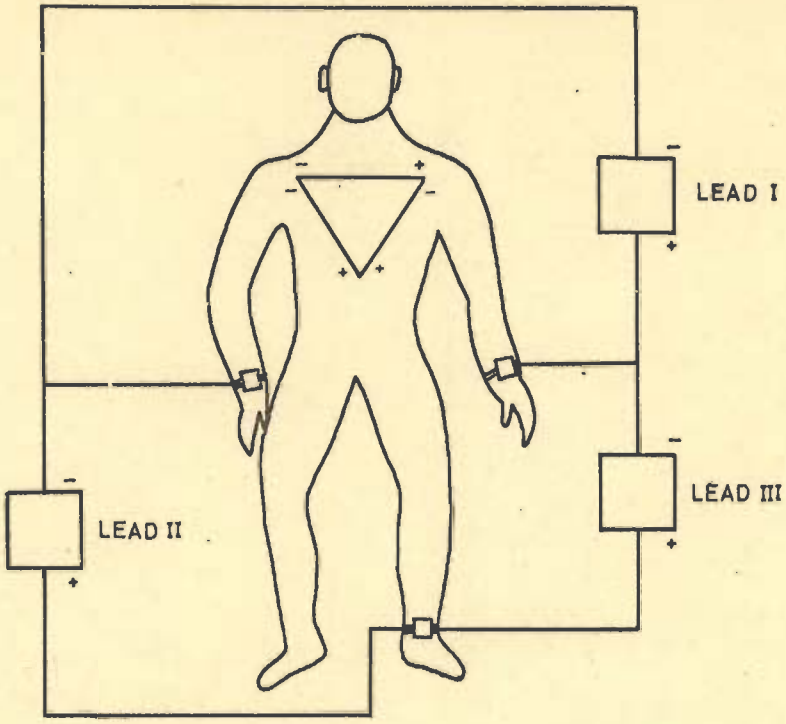


FIG.2.5. PLACEMENT OF FRONTAL PLANE ELECTRODES

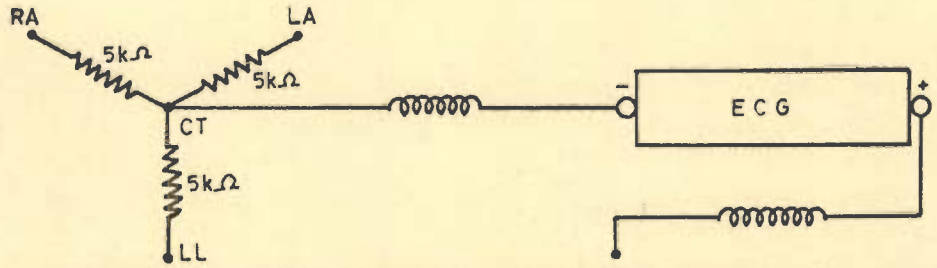


FIG.2.6.(a). WILSON'S CENTRAL TERMINAL AND UNIPOLAR LEADS

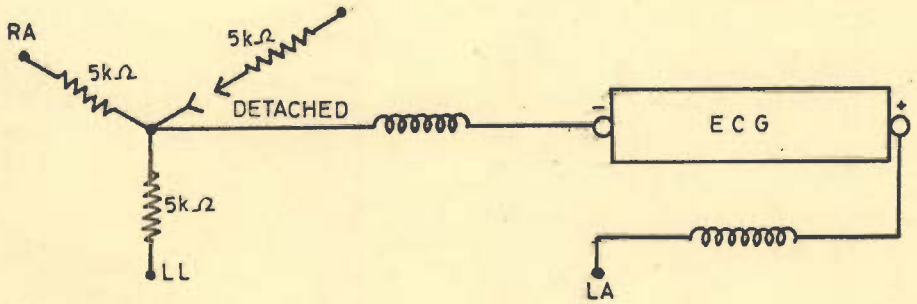


FIG.2.6.(b). AUGMENTED UNIPOLAR LEADS

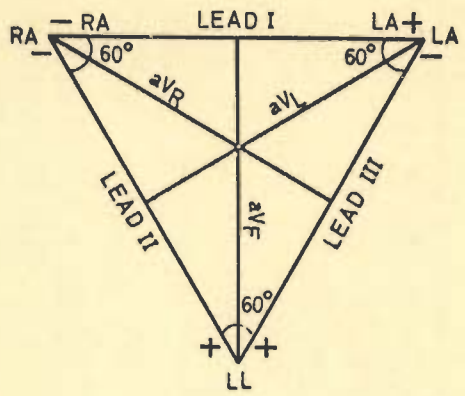


FIG.2.7.(a) EINTHOVAN TRIANGLE

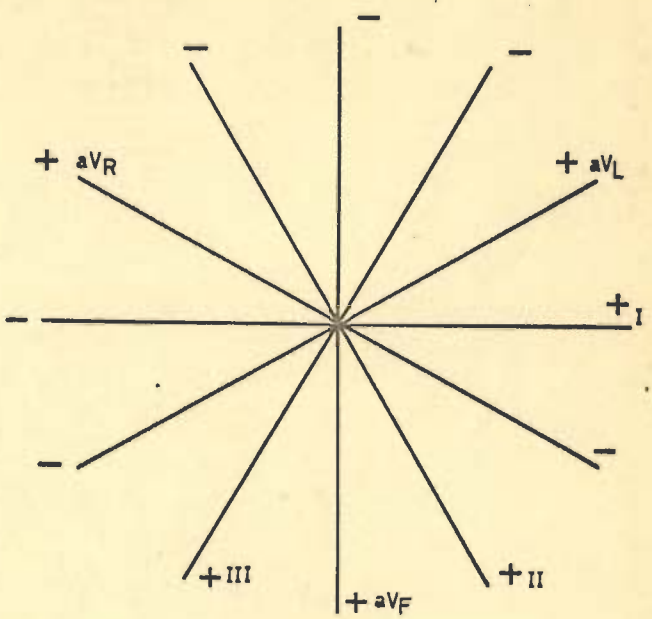


FIG.2.7.(b). HEXAXIAL REFERENCE SYSTEM

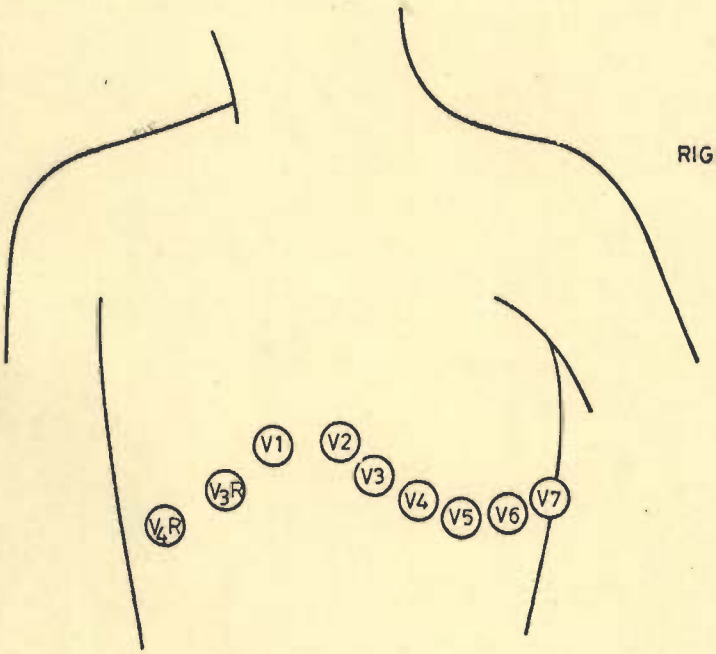


FIG.2.7.(c). LOCATION OF PRECORDIAL LEADS

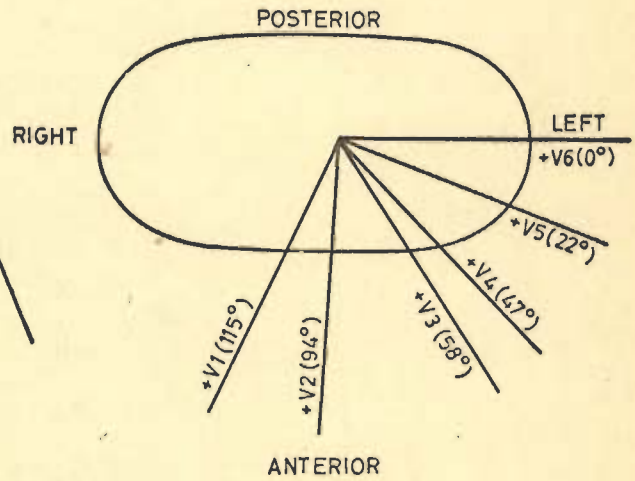


FIG.2.7.(d). PRECORDIAL LEAD AXES

is connected to the central terminal and the positive exploring electrode is connected to the corresponding point on the chest. The spatial relationship for these transverse plane leads based on Abildskov and Wilkinson reference system is shown in Figure 2.7(d).

The type of electrode depends on the application and point of measurement. The electrodes may consist of two rectangular (3.5 cm x 5 cm) or circular (4.75 cm) plates of German silver, nickel silver or nickel plated steel. They are fixed at the site of recording with electrode jelly. Suction cup configuration is suitable as chest electrode. For quick application an electrode, contained in adhesive tape is also used. It consists of a light weight metallic screen backed by a pad for electrolyte paste. The multipoint electrode is more suitable for quick placement and removal in mass screening. Due to absence of electrode pastes and jellies, it is also suitable for application in abnormal environment. The floating electrode with liquid contact is suitable for aerospace studies and exercising subjects. A silver-silver chloride disk mounted behind a stiff baffle with holes filled by electrode jelly has a better contact and high mechanical and electrical stability [84].

The ECG recorder used by the cardiologist has a heated stylus attached to the D'Arsonval movement. The waxed paper moves under the heated stylus. The frequency response up to 80 Hz is easily obtained with the heated stylus and ink recorders. The chart speed is 25 mm/second. The sensitivity is 1 mV/centimeter of deflection. The patient is kept in supine position. The

electrodes are firmly attached to respective locations. After switch on the sensitivity is checked and for particular position of the selector switch when the pointer is steady, the chart is run for the recording. In case of high speed recording, magnetic tape can be used to store the signal. For detailed study it can be played back at a slower speed on a conventional recorder.

2.6 REPRESENTATION OF ELECTROCARDIOGRAM BY FPR

The classification of electrocardiograms is based on certain diagnostic parameters. The accuracy of classification depends on the accuracy and precision of estimation and diagnostic significance of these parameters. This section deals with the improvement in accuracy of estimation of the diagnostic parameters. The ECG parameters are related to the method of representation. The final aim is to develop an interpretation algorithm using minimum number of leads for 12 lead system. The first stage is the estimation of parameters. The Einthovan triangle is based on some assumptions [48].

(i) The body is considered as a homogeneous volume conductor

(ii) Equilateral triangle assumes symmetry of leads I,II, and III.

(iii) A single equivalent dipole is considered at the centre of the volume conductor.

The vector concept is applicable to instantaneous and mean vectors and also to various ECG segments. The area under the segment is found by observation in clinical practice for the location of axis. Calculation of quadrant for QRS vector using

ratio of maximum deflections in leads I and aV_F (and/or II) in the conventional form is reported to be less precise [48]. The heart is a multipolar source, but studies have revealed that 80-90 % of body surface potentials may be attributed to the presence of a single, fixed, equivalent dipole [36]. Therefore, resultant ECG segment vector is a good approximation of the source. The resultant ECG segment vector is used to represent the resultant amplitude and phase of individual ECG segments. In the transverse plane, the relative amplitudes and phases of potentials V_1 to V_6 have much variability as compared to the frontal plane leads. They are affected much by shape and size of the chest and electrode placement. The points of contact are not equidistant from each other and from the heart. Being inversely proportional to the square of the distance, these potentials have a very wide range of variation from lead to lead. One alternative is to locate the neutral axis in the transverse plane by zero crossing or polarity change by the segment potential. The axis of peak resultant vector would be perpendicular to the null axis and towards the positive potential. With respect to the reference axis, if the frontal plane resultant direction is at an angle α, transverse plane resultant direction is at an angle Υ, and the amplitude of the net resultant is A, the resultant in frontal plane is equal to A cos Υ and in transverse plane is equal to A cos α. The equivalent net resultant A at the frontal plane distance is given by

A = Frontal plane resultant/cos Υ.

In the conventional form, it is not convenient to find the transverse plane resultant amplitude or phase and the null method involves the modification of the measurement procedure itself. It is not permitted in the present set up. So, the computation is limited to frontal plane peak resultant vector (FPR). Frequently the segment vector is represented by the area under the segment [14,81,109]. In the present work, the Frontal plane Peak Resultant vector (FPR) derived from the peak values of the segments in the concerned leads is used.

2.6.1 Einthovan Triangle Method

The Frontal plane Peak Resultant vector (FPR) can be found out from the Einthovan's equilateral triangle and hexaxial reference system shown in Figures 2.7(a,b) [60,66]. The following relationships are used:

FPR amplitude (1) = Square root of (square of I + square of $1.1547\ aV_F$) ... (2.14)

FPR phase $\emptyset(1)$ = Arc tan ($1.1547\ aV_F$/I) with respect to lead axis I ... (2.15)

FPR amplitude (2) = Square root of (square of II+square of $1.1547\ aV_L$) ... (2.16)

FPR phase $\emptyset(2)$ = Arc tan ($1.1547\ aV_L$/II) with respect to lead axis II ... (2.17)

FPR amplitude (3) = Square root of (square of III + square of $1.1547\ aV_R$) ... (2.18)

FPR phase $\emptyset(3)$ = Arc tan ($1.1547\ aV_R$/III) with respect to lead axis III ... (2.19)

The FPR vectors are found separately for each segment, P,Q,R,S and T. Here I,II,III,aV_R,aV_L and aV_F are the peak values of segment potentials at the respective leads. The correction factor of 1.1547 is derived from the geometry of the Einthovan triangle and is applied to the augmented leads for making the order of their magnitudes same as that of the bipolar leads. The angles $\alpha(1)$, $\alpha(2)$ and $\alpha(3)$ are found by refering the phase angles $\phi(1)$, $\phi(2)$ and $\phi(3)$ to a common reference lead axis I

Mean FPR amplitude = (FPR amplitude (1) + FPR amplitude (2) + FPR amplitude (3))/3 ... (2.20)

Mean FPR phase = $(\alpha(1) + \alpha(2) + \alpha(3))/3$ ... (2.21)

The variation observed among the three values and their arithmetic mean is more. Therefore, the approach gives a very rough approximation for FPR.

2.6.2 Burger Triangle Method

The Wilson's central terminal is not at zero potential. The lead extremities are neither equidistant from each other nor from the heart. The body tissue resistance may be different in different directions. The bipolar and augmented leads are not orthogonal. So, Einthovan's equilateral triangle was replaced by scalene Burger triangle as shown in Figure 2.8(a). Figure 2.8(b) shows Langner's reference system which explains the phase relationship of various leads derived from Burger triangle with different scales for different leads. The different scales account for the effect of the distance of the point of measurement from the source and variation in conductivity along various paths. Burger

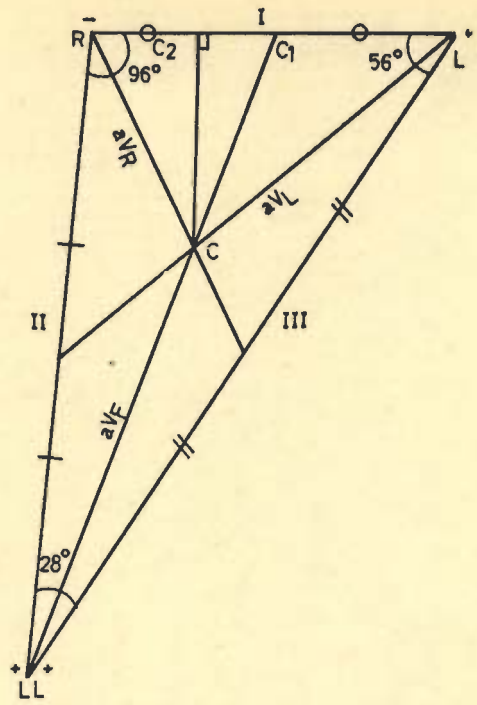


FIG. 2.8(a). BURGER TRIANGLE

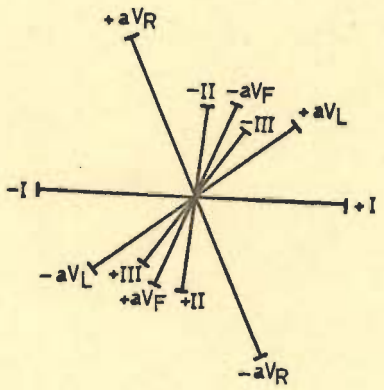


FIG. 2.8.(b). LANGNER HEXAXIAL REFERENCE SYSTEM

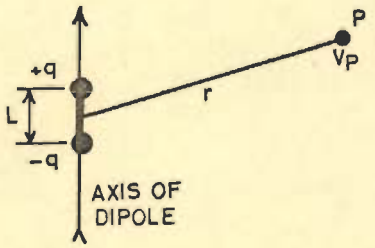


FIG.2.9. LEAD PROXIMITY EFFECT

triangle is claimed to be better representation of the spatial relationship of ECG segments for various leads.

From the Burger triangle and Langner's reference system, the FPR can be derived [62]. If the FPR is at an angle α with respect to reference axis I, then

$$I = FPR \cos \alpha \quad \ldots (2.22)$$

The lead voltages are considered as the projections of FPR vector in respective directions.

$$II = FPR \cos (\alpha + 96^{\circ}), \quad III = FPR \cos (\alpha + 124^{\circ}) \quad \ldots (2.23)$$

$$I/II = \cos \alpha / \cos (\alpha + 96^{\circ})$$

$$= \cos \alpha / (\cos \alpha . \cos 96^{\circ} - \sin \alpha . \sin 96^{\circ})$$

$$= 1/(\cos 96^{\circ} - \tan \alpha . \sin 96^{\circ}) \quad \ldots (2.24)$$

The solution of this equation results in

$$\tan \alpha(1) = Y1/X1 \quad \ldots (2.25)$$

where,

$$Y1 = I \cos 96^{\circ} - II \text{ and } X1 = I \sin 96^{\circ} \quad \ldots (2.26)$$

$$So, \quad \alpha(1) = \text{Arc tan } (Y1/X1) \quad \ldots (2.27)$$

$$\text{and } FPR(1) = I/\cos \alpha(1) \quad \ldots (2.28)$$

Again,

$$II/III = \cos (\alpha + 96^{\circ})/\cos (\alpha + 124^{\circ})$$

$$= (\cos \alpha . \cos 96^{\circ} - \sin \alpha . \sin 96^{\circ})/(\cos \alpha . \cos 124^{\circ} - \sin \alpha . \sin 124^{\circ})$$

$$= (\cos 96^{\circ} - \tan \alpha . \sin 96^{\circ})/(\cos 124^{\circ} - \tan \alpha . \sin 124^{\circ}) \quad \ldots (2.29)$$

$$\text{Resulting in } \tan \alpha(2) = Y2/X2 \quad \ldots (2.30)$$

where,

$$Y2 = (II \cos 124^{o} - III \cos 96^{o}) \quad \ldots (2.31)$$

$$X2 = (II \sin 124^{o} - III \sin 96^{o}) \quad \ldots (2.32)$$

$$\alpha(2) = \arctan (Y2/X2) \quad \ldots (2.33)$$

$$\text{and } FPR(2) = II/(\cos \alpha(2) + 96^{o}) \quad \ldots (2.34)$$

Again,

$$I/III = \cos \alpha/\cos (\alpha + 124^{o})$$

$$= \cos \alpha/(\cos \alpha.\cos 124^{o} - \sin \alpha.\sin 124^{o})$$

$$= 1/(\cos 124^{o} - \tan \alpha.\ \sin 124^{o}) \quad \ldots (2.35)$$

Resulting in

$$\tan \alpha(3) = Y3/X3 \quad \ldots (2.36)$$

where,

$$Y3 = (I \cos 124^{o} - III) \text{ and } X3 = I \sin 124^{o} \quad \ldots (2.37)$$

$$\alpha(3) = \arctan (Y3/X3) \quad \ldots (2.38)$$

$$\text{and } FPR(3) = III/\cos (\alpha(3) + 124^{o}) \quad \ldots (2.39)$$

Here also the lead axis I is taken as the reference axis for the phase angles. The quadrant of the vector is decided on the basis of polarity of X and Y components. The angles are then reduced to absolute values between 0 and 360 degrees. The negative angles are converted to corresponding positive values. Mean Phase angle α is given by

$$\alpha = (\alpha(1) + \alpha(2) + \alpha(3))/3 \quad \ldots (2.40)$$

while taking the mean angle, due care is taken, if the three angles lie on either side of the reference axis. If FPR(1), FPR(2) or FPR(3) is zero, its phase angle has no significance and is ignored. In that case, mean is taken of only the remaining

angles. When all the three resultant amplitudes are zero, the mean phase angle has no significance.

Mean FPR amplitude = (FPR(1)+FPR(2)+FPR(3))/3 ... (2.41)

If $\alpha(1)$ or $(\alpha(2)+96^{\circ})$ or $(\alpha(3)+124^{\circ})$ is equal to or an odd multiple of 90°, it makes FPR(1) or FPR(2) or FPR(3) indeterminate. Therefore, it is ignored while finding the value of mean FPR amplitude.

2.6.3 Measurement and Lead Proximity Corrections

(A) Measurement Error Correction

Burger triangle is a better representation than the Einthovan triangle. For further improvement of Burger triangle representation, measurement error and lead proximity correction algorithms are developed in the following section.

When the potentials are measured consecutively along a series of points returning to the original point, the algebraic sum of all these potentials equals to zero. It leads to Einthovan's law.

$I-II+III = 0$ and $aV_R+aV_L+aV_F = 0$ ... (2.42)

It has nothing to do with the orthogonality of leads or equal distances. The law is applicable to both Burger and Einthovan triangles. The rule is applicable to overall and to instantaneous values of potential. In this analysis, the rule is applied to peak lead potentials. In the ideal case, if the measurements are perfect, the sum in Einthovan's law is zero. But in the measurement and digitisation, some human and instrumental errors are

always there, leading to nonzero sums.

$$SUM\ 11 = I\ 1 - II\ 1 + III\ 1 \qquad \ldots (2.43)$$

where, I 1, II 1 and III 1 are the measured peak potentials for the respective leads for a segment under consideration. If there is no measurement error, SUM 11 equals zero and no correction is required. For nonzero value of SUM 11, the algorithm proceeds further for measurement error correction.

Applying Einthovan's law to the measured peak potentials, another set of peak lead potentials I2, II2 and III2 is computed.

$$I2 = II\ 1 - III\ 1\ ,\ II2 = I\ 1 + III\ 1 \text{ and } III2 = II\ 1 - I\ 1 \qquad \ldots (2.44)$$

These values are different than the measured values I 1, II 1 and III 1, if measurement error is present. Again, there is a non-zero sum.

$$SUM\ 12 = I2 - II2 + III2 \qquad \ldots (2.45)$$

If the measured values I 1, II 1 and III 1 have positive or negative errors ΔI, ΔII and ΔIII,

$$\begin{aligned} SUM\ 11 &= I\ 1 - II\ 1 + III\ 1 \\ &= (I + \Delta I) - (II + \Delta II) + (III + \Delta III) \\ &= (\Delta I - \Delta II + \Delta III) + (I - II + III) \end{aligned} \qquad \ldots (2.46)$$

But, $I - II + III = 0$

So, $SUM\ 11 = \Delta I - \Delta II + \Delta III$ $\qquad \ldots (2.47)$

Again,

$$\begin{aligned} SUM\ 12 &= I2 - II2 + III2 \\ &= (II\ 1 - III\ 1) - (I\ 1 + III\ 1) + (II\ 1 - I\ 1) \\ &= -2(I\ 1 - II\ 1 + III\ 1) \\ &= -2(\Delta I - \Delta II + \Delta III) \end{aligned} \qquad \ldots (2.48)$$

$\therefore$ SUM 12 = -2(SUM 11) ... (2.49)

SUM 11 and SUM 12 may be positive or negative. The true values I,II and III lie between measured values I 1, II 1 and III 1, and computed values I2, II2 and III2. Now assume same order of error magnigude (not same value of error) for the three leads. The results will justify (have justified) the assumption. As the SUM 12 is twice the value of SUM 11 with the negative sign, the order of error magnitude is twice in the second case compared to the first one. The polarities of error are opposite in the two cases. So, the true values can be easily interpolated as follows:

Consider ratio S = SUM 12/(SUM 12 - SUM 11)

= -2 SUM 11/(-2 SUM 11 - SUM 11)

= 2/3 ... (2.50)

The values I,II,III corrected for the measurement error can be found as follows.

I = I2 + S(I 1 - I2) = I2 + (2/3)(I 1-I2) ... (2.51)

II = II2 + S(II 1 - II2) = II2 +(2/3)(II 1 - II2) ... (2.52)

III = III2+ S(III 1-III2) = III2+(2/3)(III 1- III2) ... (2.53)

SUM 13 = I-II+III is computed for a check.

Low value of SUM 13 compared to SUM 11 indicates that the measured error has been corrected properly. If the procedure is continued the error may be reduced further.

Alternatively, consider ratio

S' = SUM 11/(SUM 12 - SUM 11)

= SUM 11/(-2 SUM 11 - SUM 11)

= -1/3 ... (2.54)

The values I,II,III corrected for the measurement error can be found as

$$I = I\,1 + S'(I\,1 - I2) = I\,1 - (1/3)(I\,1 - I2) \quad \ldots (2.55)$$

$$II = II\,1 + S'(II\,1 - II2) = II\,1 - (1/3)(II\,1 - II2) \quad \ldots (2.56)$$

$$III = III\,1 + S'(III\,1 - III2) = III\,1 - (1/3)(III\,1 - III2) \quad \ldots (2.57)$$

Here values of SUM 11, SUM 12, S and S' may be positive and/or negative.

Similarly the measured values of augmented leads can be corrected for the measurement error. If R1, L1, F1 are the measured peak values and R,L,F are the corrected values of the leads aV_R, aV_L, aV_F for a segment under consideration, then

$$SUM\ 21 = R1 + L1 + F1 \quad \ldots (2.58)$$

$$R2 = -(L1+F1),\ L2 = -(R1+F1),\ F2 = -(R1+L1) \quad \ldots (2.59)$$

$$SUM\ 22 = R2 + L2 + F2 \quad \ldots (2.60)$$

$$Ratio\ SS = SUM\ 22/(SUM\ 22 - SUM\ 21) \quad \ldots (2.61)$$

The corrected values for the measurement error are given as

$$R = R2 + SS\ (R1 - R2) \quad \ldots (2.62)$$

$$L = L2 + SS\ (L1 - L2) \quad \ldots (2.63)$$

$$F = F2 + SS\ (F1 - F2) \quad \ldots (2.64)$$

SUM 23 = R + L + F , which is very less compared to SUM 21.

(B) Lead Proximity Correction

As shown in Figure 2.9 for a pair of charge q, separated by distance L, the dipole moment is given by

$$M = qL. \quad \ldots (2.65)$$

The potential V_p at point P in a medium of dielectric constant K is given by,

V_p = Work done per unit charge = W/q_o

$= M \cos \alpha/(K r^2) = K_1 \cos \alpha/r^2$ ... (2.66)

where, r is the distance of point P from the centre of the dipole and α is the angle between the axis of the dipole and line joining point P with centre of the dipole [84]. Thus the potential at a point is inversely proportional to the square of the distance from the source. It also depends on the orientation of the point with respect to the axis of the dipole.

The measured lead voltages may be affected by the distance of point of measurement. But, there is no appreciable change in potential for a distance greater than 15 cm. Therefore, Einthovan considered the points of measurement for leads I,II,III and aV_R, aV_L, aV_F to be equidistant for practical purposes. There after, Burger and Milan [31-34] proposed the scalene Burger triangle and ruled out the independence of lead voltages of the distance of measurement. From the geometry of the Burger triangle

$I/\sin 28^\circ = II/\sin 56^\circ = III/\sin 96^\circ$ ... (2.67)

If I is taken as one unit, then

$II = \sin 56^\circ/\sin 28^\circ = 1.7658951$

$III = \sin 96^\circ/\sin 28^\circ = 2.1183858$

Similarly, $aV_R = 0.9681442$, $aV_L = 1.4014929$ and $aV_F = 1.8849328$. The reciprocals of these relative values specify the lead proximity factors LPF 1 to LPF6 for the frontal plane leads I,II,III, aV_R, aV_L and aV_F respectively.

LPF1 = 1.0 , LPF2 = 0.566285 , LPF3 = 0.4720575 ,
LPF4 = 1.0329039 , LPF5 = 0.7135248 , LPF6 = 0.5305228.

The lead voltages multiplied by the lead proximity factors (LPF) result in lead proximity corrected values. These lead proximity corrected voltages have same orders of magnitudes.

2.6.4 Data Acquisition and Analysis

The twelve lead ECG data required for the present work is collected at All India Institute of Medical Sciences, New Delhi. Three cycles of ECG are recorded for the twelve leads I,II,III, aV_R, aV_L, aV_F and V1 to V6 for all the cases along with the calibrating signal. To facilitate the comparison of analysis with the conventional clinical analysis, the data was collected under normal clinical set up in the cardiac clinic without any sophistication prevailing in the research centre dedicated to ECG analysis. From the research point of view, this is a raw data from which effort is made to extract as much information as possible with the attainable accuracy and precision. The mean value of peak lead potentials in a segment over three consecutive cycles is found for segments P,Q,R,S,T and ST for all the cases. The data collected includes four categories, namely Normal, Myocardial Infarction (MI), Right Ventricular Hypertrophy (RVH) and Left Ventricular Hypertrophy (LVH).

The objective of the first stage is to compare the accuracy and precision of Einthovan and Burger triangle methods with and without measurement error and lead proximity corrections for the representation of ECG patterns in terms of the Frontal plane

Peak Resultant segment vectors (FPR). In the first set Einthovan triangle without measurement error and lead proximity corrections is used to find FPR. In the second set, measured lead values are first corrected for the measurement error and then they are used to find FPR. In the third set, Burger triangle is used without measurement and lead proximity corrections. In the fourth set, only lead proximity correction factors are applied to the Burger triangle before finding the FPR. In the fifth set, at first the measurement error correction is applied to the measured lead values, followed by application of lead proximity correction. The corrected values are considered while finding the FPR using the Burger triangle. In case of Einthovan triangle lead values I, II, III, aV_R, aV_L and aV_F are used to find FPR. The method of computation is explained in earlier section. Lead pairs I, aV_F; II, aV_L; and III, aV_R are used to find three sets of values for FPR amplitude and phase. In case of Burger triangle only lead values I, II and III are used to find the FPR as explained in earlier sections. Lead pairs I, II; II, III; and III, I give three sets of amplitude and phase values. For all the five sets mean amplitudes FPR and phase α are also found. The three amplitude values have some deviation Δ FPR from the mean value of FPR and the three phase values have some deviation $\Delta\alpha$ from the mean value of α. To compare the accuracy and precision of representation of ECG pattern in terms of the Frontal plane Peak Resultant vector, maximum values of Δ FPR and $\Delta\alpha$ are computed for all the five sets.

2.6.5 Results and Discussion

The results of the analysis are shown in Tables T2.2 and T2.3. Table T.2.2 shows the maximum deviations in FPR amplitudes for segments P,Q,R,S, and T for all the five sets and 25 normal cases. Table T.2.3 shows the maximum deviations in FPR phase for three lead pairs. The amplitude deviations are expressed in mv and the phase deviations are expressed in degree. The order of magnitudes for the different sets being the same, the maximum deviations are not converted to percentage or relative values. The comparison is made on the basis of absolute values.

In the first set of Einthovan triangle without corrections, the deviations of amplitude and phase angles are large. In the second set as the measurement error correction is used with Einthovan triangle the amplitude deviation decreases for some cases and increases for the others. As such the phase deviation is reduced in many of the cases but still it is quite large. In the third set when Burger triangle is used without corrections the results improve for some cases and deteriorate for the others. There is not appreciable improvement for the fourth set using only lead proximity correction with the Burger triangle. When both the measurement error and lead proximity corrections are applied to the Burger triangle in the fifth set, there is a drastic improvement in the results as compared to other four sets. The maximum deviation of amplitude is reduced to less than 0.0000002 mv for all the cases and segments. The maximum deviation of phase is reduced to less than 0.000004 degree for all the cases and segments. In most of the cases the maximum deviation

TABLE - T.2.2

Maximum Deviation of Amplitude (Δ FPR) mv

Case code no.	segment	Δ FPR for				
		Set I	Set II	Set III	Set IV	Set V
1	2	3	4	5	6	7
6	P	0.0222669	0.0217025	0.0178645	0.0331952	0.7451 E-08
	Q	0.0116724	0.0142333	0.0000116	0.0040687	0.2980 E-08
	R	0.0158057	0.0242757	0.0378879	0.0266072	0.1788 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0158116	0.0085487	0.0140311	0.0306736	0.1788 E-07
7	P	0.0237658	0.0204063	0.0120859	0.0151821	0.5960 E-08
	Q	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0586978	0.1672390	0.1780060	0.2297700	0.1788 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0179045	0.0330493	0.0050833	0.0323345	0.1192 E-07
8	P	0.0195500	0.0147194	0.0246287	0.0063693	0.7451 E-08
	Q	0.0152679	0.0131166	0.0047682	0.0022770	0.1118 E-08
	R	0.0215664	0.0360153	0.0799020	0.0334345	0.2980 E-07
	S	0.0449999	0.0181379	0.0177971	0.0063033	0.4098 E-08
	T	0.0334006	0.0237687	0.0057617	0.298E-08	0.2980 E-08
9	P	0.0039257	0.0091549	0.0025738	0.0134921	0.2235 E-08
	Q	0.0183330	0.0161111	0.0083243	0.0030275	0.2235 E-08
	R	0.0403607	0.0399124	0.0459211	0.0063616	0.8941 E-08
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0328902	0.0241926	0.0566652	0.0108786	0.1490 E-08

Contd.....

(Table T.2.2 contd....)

1	2	3	4	5	6	7
10	P	0.0198915	0.0135335	0.0227797	0.0153574	0.5960 E-08
	Q	0.0471002	0.0471002	0.0158894	0.745E-09	0.7451 E-09
	R	0.0399312	0.0452589	0.2759368	0.1084990	0.3576 E-07
	S	0.0199695	0.0257877	0.0067330	0.0109481	0.4470 E-08
	T	0.0355179	0.0216127	0.0389253	0.0062121	0.1788 E-07
11	P	0.0055153	0.0134976	0.0178645	0.0331952	0.7450 E-08
	Q	0.0666667	0.0222222	0.0603109	0.0284702	0.2980 E-08
	R	0.0813970	0.1324000	0.0290111	0.1264751	0.0476 E-07
	S	0.1501110	0.0500370	0.0000000	0.0000000	0.0000
	T	0.0330571	0.0492019	0.1374560	0.0172611	0.8940 E-07
12	P	0.0192880	0.0236166	0.0025086	0.0101251	0.8940 E-08
	Q	0.0192450	0.0094303	0.0087802	0.224E-08	0.2235 E-08
	R	0.0489230	0.0524680	0.0907810	0.0504043	0.2980 E-07
	S	0.0265958	0.0650858	0.0476683	0.149E-08	0.1490 E-08
	T	0.0248263	0.0212382	0.0476683	0.149E-08	0.1490 E-08
13	P	0.0138961	0.0164613	0.0097163	0.0082195	0.5960 E-08
	Q	0.0300000	0.0277778	0.0012629	0.0041964	0.1862 E-08
	R	0.0727884	0.0708372	0.1943410	0.0622762	0.1192 E-07
	S	0.0333333	0.0333333	0.0043901	0.112E-08	0.1118 E-08
	T	0.0182973	0.0089739	0.0220188	0.0113410	0.2682 E-07

Contd.....

(Table T.2.2 contd....)

1	2	3	4	5	6	7
14	P	0.0204883	0.0225906	0.0330329	0.0144373	0.5960 E-08
	Q	0.0145786	0.0291640	0.0134660	0.0218962	0.8941 E-08
	R	0.0947695	0.0580229	0.0509802	0.417E-07	0.4172 E-07
	S	0.0461880	0.0153960	0.0000000	0.0000000	0.0000
	T	0.0962687	0.0852544	0.0474564	0.0152043	0.1788 E-07
15	P	0.0460138	0.0516513	0.0352829	0.0127384	0.7451 E-09
	Q	0.0103134	0.0181119	0.0087802	0.224E-08	0.2235 E-08
	R	0.1008500	0.0978245	0.0366295	0.0683999	0.6557 E-07
	S	0.0869092	0.0687012	0.0078902	0.0067492	0.4470 E-08
	T	0.0207166	0.0583545	0.0489011	0.0250761	0.2384 E-07
16	P	0.0074324	0.0098984	0.0486444	0.0108274	0.4768 E-07
	Q	0.0423390	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0131549	0.0348520	0.4675910	0.0353437	0.7153 E-07
	S	0.0384900	0.0128300	0.0000000	0.0000000	0.0000
	T	0.0215039	0.0412791	0.1625030	0.0284056	0.4470 E-07
17	P	0.0309471	0.0178846	0.0139550	0.0114059	0.4470 E-08
	G	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0692099	0.0890844	0.1587100	0.0471075	0.2384 E-07
	S	0.0384900	0.0128299	0.0000000	0.0000000	0.0000
	T	0.0448817	0.0465898	0.0635578	0.298E-08	0.2980 E-08

Contd.....

(Table T.2.2 contd....)

1	2	3	4	5	6	7
18	P	0.0147580	0.0147580	0.0057617	0.298E-08	0.2980 E-08
	Q	0.0359117	0.0098387	0.0301554	0.0142351	0.1490 E-08
	R	0.0155670	0.0641353	0.0294815	0.1036430	0.1132 E-06
	S	0.0359117	0.0098387	0.0251377	0.0251377	0.1862 E-08
	T	0.0523314	0.0650441	0.0590465	0.298E-08	0.2980 E-08
19	P	0.0166564	0.0099015	0.0243231	0.0144108	0.4470 E-08
	Q	0.0166667	0.0055555	0.0125689	0.0125689	0.9313 E-09
	R	0.0526835	0.0174907	0.2886990	0.0957730	0.2980 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0088742	0.0076598	0.0727024	0.0171353	0.3576 E-07
20	P	0.0118385	0.0095917	0.0343602	0.373E-08	0.3725 E-08
	Q	0.0400000	0.0133333	0.0639016	0.0361865	0.2235 E-08
	R	0.0631315	0.0309133	0.0136516	0.119E-07	0.1192 E-07
	S	0.0700517	0.0281528	0.0201974	0.0428593	0.1788 E-07
	T	0.0309248	0.0281241	0.0421345	0.134E-07	0.1341 E-07
21	P	0.0205229	0.0273634	0.0442040	0.745E-08	0.7451 E-08
	Q	0.0333333	0.0111111	0.0532514	0.0301554	0.2235 E-08
	R	0.0218256	0.0975620	0.5623560	0.0443904	0.1192 E-07
	S	0.0359117	0.0098387	0.0532514	0.0301554	0.2235 E-08
	T	0.0316040	0.0118498	0.0761621	0.0421415	0.8941 E-08

Contd.....

(Table T.2.2 contd....)

1	2	3	4	5	6	7
22	P	0.0150858	0.0150858	0.0238342	0.745E-09	0.7451 E-09
	Q	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0911139	0.0539300	0.2446750	0.0898165	0.4172 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0086634	0.0095118	0.0635578	0.298E-08	0.2980 E-08
23	P	0.0054215	0.0088119	0.0067875	0.0088272	0.3725 E-08
	Q	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0073413	0.0063017	0.2182870	0.0042903	0.1192 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0131427	0.0121003	0.0300395	0.0112987	0.2041 E-06
24	P	0.0115200	0.0080611	0.0166488	0.0060549	0.4470 E-08
	Q	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0159840	0.119E-06	0.0243684	0.0336159	0.5364 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0083855	0.0103324	0.1219490	0.0177044	0.2235 E-07
25	P	0.0109326	0.0074187	0.0311781	0.0098553	0.1490 E-08
	Q	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	R	0.0023416	0.0148300	0.0215210	0.0168005	0.1341 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0256077	0.0295890	0.1377990	0.0351652	0.8941 E-08

Contd.....

(Table T.2.2 contd....)

1	2	3	4	5	6	7
26	P	0.0164130	0.0193053	0.0072710	0.596E-08	0.5960 E-08
	Q	0.0271679	0.0426089	0.0131703	0.298E-08	0.2980 E-08
	R	0.0978176	0.1078790	0.0460934	0.238E-07	0.2384 E-07
	S	0.0289188	0.0598653	0.0081128	0.0096157	0.2086 E-07
	T	0.0785704	0.0644037	0.0241717	0.0303642	0.1192 E-07
27	P	0.0143156	0.0026984	0.0458572	0.0163926	0.4470 E-08
	Q	0.0421254	0.0260620	0.0158894	0.745E-09	0.7451 E-09
	R	0.0464013	0.0695269	0.0150562	0.0505048	0.2980 E-07
	S	0.0807550	0.0289984	0.0904663	0.0427053	0.5215 E-08
	T	0.0221111	0.0112729	0.0988585	0.0170693	0.2980 E-07
64	P	0.0178888	0.0052333	0.0105534	0.0029728	0.5215 E-08
	Q	0.0246090	0.0048799	0.0065852	0.149E-08	0.1490 E-08
	R	0.0507635	0.0441209	0.0102619	0.0322970	0.4172 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0104372	0.0247294	0.0033274	0.0163999	0.1192 E-07
65	P	0.0263297	0.0169460	0.0035549	0.0136292	0.4470 E-08
	Q	0.0323915	0.0322479	0.0065321	0.0047034	0.6706 E-08
	R	0.0287002	0.0588940	0.1581150	0.0570880	0.4768 E-07
	S	0.0000000	0.0000000	0.0000000	0.0000000	0.0000
	T	0.0409441	0.0317453	0.0305951	0.0143359	0.8941 E-08
66	P	0.0117575	0.0122666	0.0326253	0.0067308	0.2235 E-08
	Q	0.0112117	0.0094303	0.0087802	0.224E-08	0.2235 E-08
	R	0.0457204	0.0851129	0.1624200	0.0115384	0.7153 E-07
	S	0.0211325	0.0385440	0.0486444	0.0108274	0.4768 E-07
	T	0.0104869	0.00970267	0.0764426	0.0017073	0.1490 E-07

TABLE - T.2.3

Maximum deviation of phase (Δ Alpha) degrees

Case code no.	Segment	Δ Alpha for				
		Set I	Set II	Set III	Set IV	Set V
1	2	3	4	5	6	7
6	P	22.629635	15.654167	4.547447	9.003666	0.0000
	Q	16.368868	13.553622	0.021791	10.568549	0.3815 E-05
	R	8.579838	3.434616	6.022903	4.990704	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	5.200081	2.062111	2.386631	5.300983	0.3815 E-05
7	P	11.838882	12.626057	7.440476	9.079227	0.0000
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	20.241444	10.354332	10.396378	12.517609	0.0000
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	15.367367	8.571735	0.777428	5.346104	0.0000
8	P	11.109104	10.968433	7.648853	2.468323	0.0000
	Q	15.756490	16.333237	29.346515	16.477626	0.5722 E-05
	R	6.263050	4.209106	4.115620	2.168057	0.0000
	S	0.000010	41.516125	17.158805	7.639320	0.1907 E-05
	T	18.998500	18.067543	4.371506	0.000000	0.0000
9	P	16.045600	9.796959	1.117420	6.855995	0.0000
	Q	60.000000	60.000000	6.963405	2.865050	0.9536 E-06
	R	6.532803	6.588120	4.277012	0.683144	0.0000
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	4.265930	6.863163	12.453007	2.834580	0.0000

Contd.....

(Table T.2.3 contd....)

1	2	3	4	5	6	7
10	P	5.826725	6.275684	13.180534	10.445349	0.3815 E-05
	Q	22.195587	22.195587	9.333336	0.000002	0.1907 E-05
	R	6.070072	2.273457	9.075485	4.231735	0.0000
	S	18.998502	15.308952	6.540905	15.178144	0.3815 E-05
	T	4.916126	4.835835	16.138975	0.990982	0.0000
11	P	14.037144	5.956398	5.564358	0.900367	0.0000
	Q	0.000000	60.000000	48.000000	48.000000	0.6199 E-05
	R	9.406506	5.933994	0.753551	3.485806	0.0000
	S	0.000000	60.000000	0.000000	0.000000	0.0000
	T	8.258171	5.645180	7.079907	1.084011	0.3815 E-05
12	P	8.696808	6.444283	0.928387	5.101406	0.3815 E-05
	Q	0.67E-05	3.963230	13.333330	0.29E-05	0.2861 E-05
	R	7.860405	4.417084	8.457878	5.850369	0.3815 E-05
	S	44.034479	22.982759	9.333336	0.19E-05	0.1907 E-05
	T	7.226265	7.551689	9.333332	0.38E-05	0.3815 E-05
13	P	10.854439	8.592098	4.659466	4.515579	0.0000
	Q	30.000000	60.000000	2.679849	12.475496	0.2861 E-05
	R	6.038757	5.010180	7.731522	2.897446	0.0000
	S	30.000000	30.000000	13.333333	0.28E-05	0.2861 E-05
	T	0.668213	3.938885	5.524571	3.149204	0.3815 E-05

Contd....

(Table T.2.3 contd....)

1	2	3	4	5	6	7
14	P	8.213215	6.419994	13.684483	7.785213	0.3815 E-05
	Q	11.001500	6.788778	6.540905	15.178144	0.3815 E-05
	R	1.322319	3.899025	4.971218	0.38E-05	0.3815 E-05
	S	0.000000	60.000000	0.000000	0.000000	0.0000
	T	31.011486	32.211899	6.506020	2.341789	0.0000
15	P	15.963356	13.908478	9.682465	4.589172	0.0000
	Q	19.999999	10.208043	13.333333	0.29E-05	0.2861 E-05
	R	14.438335	12.634312	2.095585	4.664970	0.0000
	S	19.47414	44.508424	39.156704	29.367016	0.6676 E-05
	T	13.015873	7.269852	8.795220	5.669224	0.3815 E-05
16	P	8.101975	5.063973	13.142094	3.495998	0.0000
	Q	30.000000	60.000000	0.000000	0.000000	0.0000
	R	3.849953	2.332850	12.326244	1.051106	0.3815 E-05
	S	0.000000	60.000000	0.000000	0.000000	0.0000
	T	15.674515	9.917896	18.529533	3.251221	0.0000
17	P	5.965527	14.450504	4.446892	3.986664	0.0000
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	8.572868	6.665012	7.714027	2.740410	0.0000
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	10.893402	10.402618	9.333332	0.38E-05	0.3815 E-05

Contd.....

(Table T.2.3 contd....)

1	2	3	4	5	6	7
18	P	14.173267	14.173267	4.371506	0.000000	0.0000
	Q	15.000000	14.173272	48.000000	48.000000	0.6199 E-05
	R	11.837753	6.243778	1.354984	5.554470	0.0000
	S	15.000000	14.173279	14.000000	14.000000	0.190 E-05
	T	11.726273	8.806576	5.193611	0.000000	0.0000
19	P	7.017239	7.161854	11.612839	8.649921	0.3815 E-05
	Q	0.000000	60.000000	14.000000	14.000000	0.1907 E-05
	R	3.875610	1.214066	9.089035	3.934818	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	2.332684	1.673256	5.871601	1.700737	0.0000
20	P	6.468800	5.859192	2.369835	0.38E-05	0.3815 E-05
	Q	0.000000	60.000000	28.000000	28.000000	0.1907 E-05
	R	12.023434	5.164311	1.800781	0.38E-05	0.3815 E-05
	S	24.295118	12.348764	4.733982	10.392771	0.1907 E-05
	T	9.404518	10.095066	5.558323	0.000000	0.0000
21	P	15.393616	9.276848	7.538303	0.000000	0.0000
	Q	0.000000	60.000000	28.000000	28.000000	0.1907 E-05
	R	11.221500	6.430039	13.271667	1.142265	0.3815 E-05
	S	15.000000	14.173268	28.000000	28.000000	0.1907 E-05
	T	2.332134	3.041458	7.984844	7.177387	0.0000

Contd.....

(Table T.2.3 contd....)

1	2	3	4	5	6	7
22	P	8.948284	8.948284	9.333332	0.38E-05	0.3815 E-05
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	4.107662	5.312992	7.438038	2.843155	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	4.391186	2.196266	9.333332	0.38E-05	0.3815 E-05
23	P	13.791706	7.175266	4.607987	6.169468	0.0000
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	0.388220	0.969620	14.263596	0.263237	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	7.701759	4.835400	6.213657	2.602058	0.3815 E-05
24	P	3.878349	5.734211	6.963402	2.865048	0.0000
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	1.415802	0.76E-05	8.578175	1.550194	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	6.138397	3.961102	15.100742	2.409897	0.3815 E-05
25	P	7.262264	6.239075	10.466942	4.628525	0.0000
	Q	0.000000	0.000000	0.000000	0.000000	0.0000
	R	9.972355	4.709274	3.230904	3.120853	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	21.588566	14.140591	19.677040	5.607700	0.3815 E-05

Contd.....

(Table T.2.3 contd....)

1	2	3	4	5	6	7
26	P	10.355656	8.644196	4.430443	0.38E-05	0.3815 E-05
	Q	24.732563	18.474321	13.333330	0.19E-05	0.1907 E-05
	R	14.636204	14.028271	4.371506	0.000000	0.0000
	S	24.632628	13.840799	4.483369	7.216726	0.3815 E-05
	T	15.039555	17.773716	7.440476	9.079227	0.0000
27	P	8.583344	1.808003	11.632675	5.920956	0.0000
	Q	5.446700	31.504789	9.333336	0.19E-05	0.1907 E-05
	R	13.227242	9.959629	1.210976	4.896164	0.0000
	S	15.000000	31.554501	48.000000	48.000000	0.5960 E-05
	T	3.789787	3.697472	10.560570	2.338486	0.0000
64	P	6.068169	3.181229	4.862732	1.529350	0.3815 E-05
	Q	7.589084	2.833101	13.333333	0.19E-05	0.1907 E-05
	R	2.167137	1.904678	0.575890	2.369144	0.0000
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	10.217907	5.945099	3.466251	2.122753	0.0000
65	P	7.326084	13.329952	1.163906	5.296875	0.0000
	Q	9.190260	9.158958	6.124878	5.949208	0.5722 E-05
	R	5.230747	2.905159	16.813202	8.310425	0.3815 E-05
	S	0.000000	0.000000	0.000000	0.000000	0.0000
	T	5.909191	7.870094	5.193337	2.872578	0.3815 E-05
66	P	18.327110	12.162552	9.962738	2.720600	0.0000
	Q	10.893391	3.963230	13.333333	0.28E-05	0.2861 E-05
	R	5.955830	3.375511	10.181550	1.017868	0.3815 E-05
	S	30.000000	18.157867	13.142090	3.496000	0.1907 E-05
	T	2.556351	2.784386	8.012631	0.225449	0.0000

is much less than this value. In about 50 % cases the maximum deviation of phase is reduced to zero in the fifth set.

The general feeling is that the 12 lead ECG system is less informative and less specific in the conventional form. The results of the present analysis show that if Burger triangle with measurement error and lead proximity corrections is applied to the 12 lead ECG data, the FPR amplitude and phase are computed with very high accuracy and precision. In past the failure to correlate the 12 lead potentials to the dipole source might have created doubt about its validity and utility of 12 lead system. It is felt that the consistency of the results attained here should clear this doubt. For segments P,Q,R,S,T,ST separate single dipole sources are conceived. As the frontal plane lead potentials for an ECG segment can be correlated to the single dipole source representation of the electric field at heart with high precision, it is not necessary to go in to the complexity of multipole concept. It is true that the amplitude of internal potential vector (even for frontal plane) will be much larger than the equivalent FPR found here corresponding to the frontal plane lead distance. But, the relative values are more significant. The hypothetical potential vector FPR considered here is unique for a particular set of lead voltages and has a good diagnostic significance. It is true that the points of origin or locations of sources for vectors P,Q,R,S,T, and ST may be different in space. But, compared to the size of the body or lead to lead distances the size of the heart is very small and the inter-source distance is quite negligible. So, each segment vector is

related to a separate source but the point of its location is almost same for the practical purpose.

Another important point is about the number of leads to be recorded and associated cost of amplification, detection, storage and processing. In the analysis illustrated, six leads are used with Einthovan triangle and three leads with Burger triangle representation for the computation of FPR. Here three values of FPR are computed just to highlight the accuracy and precision of the Burger triangle representation with measurement error and lead proximity corrections. In routine application only two leads are sufficient with Burger triangle representation for FPR computation. The remaining four frontal plane leads provide redundant data which can be accurately and easily generated from the FPR amplitude and phase.

2.7 ANALYSIS OF ELECTROCARDIOGRAM USING NEW BASIS FUNCTIONS

2.7.1 Limitations of Other Functions

In the preceding section peak segment potentials at various leads are simply represented by a set of FPR vectors corresponding to various segments. The aim of this section is to represent the set of ECG patterns over the whole cycle at the six frontal plane leads by a single model. Till now, number of approaches has been tried to develop the mathematical model to specify the potential variations in the ECG pattern qualitatively and quantitatively. It is observed that most of the models are successful for singular pattern and a specific lead. Many of these models fail when the question of categorization of diagnostic model parameters comes in.

Bemmel [220] has pointed out that these methods describe the signals and set of parameters in an objective and quantitative manner. It is difficult to understand the mechanical process or abnormal condition of heart and also to have the suitable classification by these methods. In most of the cases, the feature variability has no direct correlation with the pathological states. Sometimes inspite of the least squared error, the shape matching is not satisfactory. Gaussian function, unit impulses, matched exponentials, sine, cosine and many other functions have been tried as the basis functions. The shapes of these basis functions are quite different than the shapes of individual ECG segments P,Q,R, etc. For example, if an effort is made to represent the half wave rectified sine wave or a square wave by a regular sine series,more components may be required and yet the representation may not be satisfactory. Moreover, use of the same basis function is not suitable for all the segments. A set of new basis functions with shape resemblence to respective ECG segments has been proposed here [64].

2.7.2 Development of Proposed Model

The aim in the present work is to develop a mathematical model whose response matches with the corrected values of externally measured lead potential variations over the complete cardiac cycle at the six frontal plane leads. At the same time the wave pattern is to be expressed in terms of diagnostically significant parameters suitable for categorization. Here a set of hypothetical potential vectors is conceived. The movement of the end of these

vectors with respect to time traces the resultant ECG pattern over the cardiac cycle in the three dimensional space. A single basis function is not sufficient to describe the various ECG segments effectively. Therefore, different basis functions are proposed for different segments. The shapes of conventional basis functions are much different than those of various ECG segments. Therefore, here the segmentwise basis functions are derived from the ECG pattern itself. The shape variation of ECG pattern from lead to lead is attributed to their different angular positions in space. The source for potential variations over a particular segment at different leads is same. So, it is justifiable to assume some common source pattern for a segment and to consider the lead potential variations as the segmentwise projections along the respective lead axis. The maximum amplitude of a source potential may vary from individual to individual. Therefore, unit basis functions are proposed. There may be some attenuation of source potential while reaching the points of measurement. The attenuation factor can be assumed constant for a short interval of time and as such there may not be much distortion of the waveform as it reaches the body surface. The variability of ECG segment pattern from individual to individual is mainly in the form of horizontal and/or vertical elongation and/or contraction of basic segment pattern. Therefore, the proposed basis function is assumed to have unit peak value and unit duration. The shape of this basis function is the average shape of a resultant segment for a normal adult subject with amplitude and time normalisation. Friedman [81] has discussed some intrinsic segment patterns

P,Q,R,S,T, and PT responsible for the generation of ECG pattern as shown in Figure 2.10. From the specified normal shapes of various intrinsic components the unit basis functions derived for the present work are as shown in Figure 2.11. The basis functions are assumed to have amplitude variation between 0 and 1 in the positive direction only. In the earlier work by the author [60,65] an effort was made only to specify these functions geometrically and also the possibility of its utility was investigated. In the present work a systematic approach is made for the mathematical representation of these basis functions. The periodic time of the segment basis function is divided in to ten equal parts. The value of data point x along the horizontal axis ranges from 0 to 10. The amplitudes y at all the eleven points are measured for a basis function. These are the relative point values with respect to the peak value of the respective segment on a standard normal average ECG. Curve fitting technique is used to find the mathematical expression for the unit basis function described by the eleven data points. A polynomial expression of the following form is used for its representation.

$$y = A_1 + A_2 X + A_3 X^2 + ... + A_{11} X^{10} \qquad \ldots (2.68)$$

The coefficients A_1 to A_{11} are computed to match the evaluated polynomial to the measured point values. Larger number of data points and higher order of polynomial can also be taken. There is a convergence problem when the order is high. So, some compromise is to be made about the order of the polynomial.

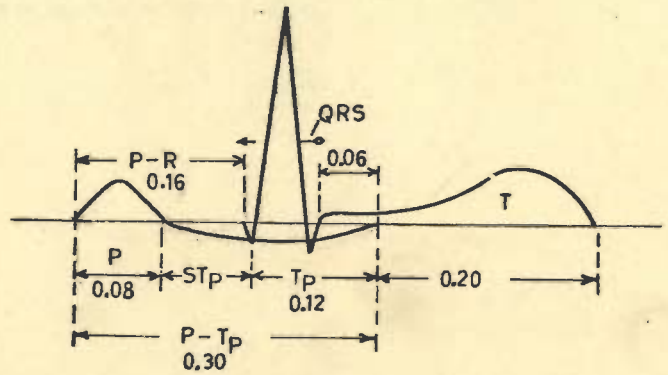


FIG. 2.10. TIME RELATIONSHIP OF ELECTRICAL PROCESSES

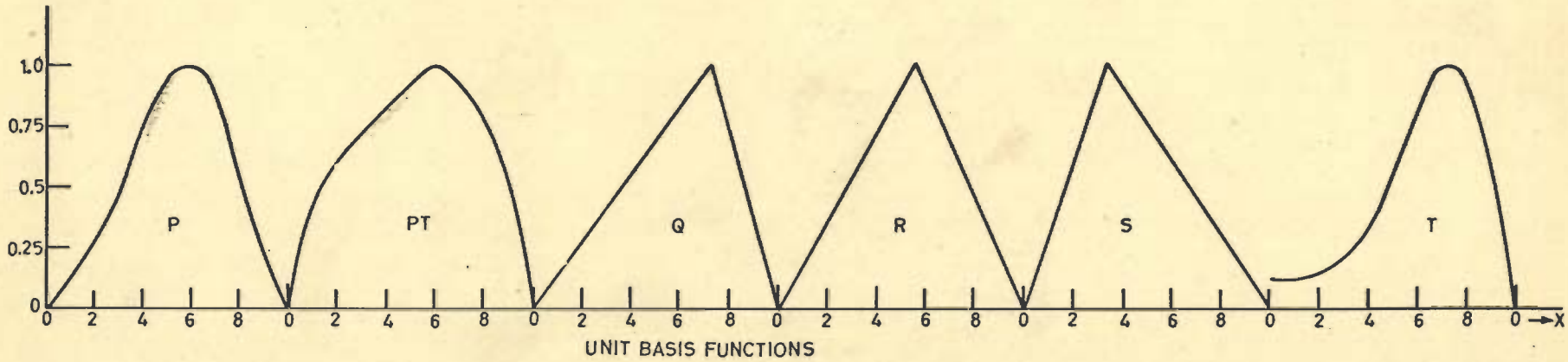


FIG. 2.11

(A) Gauss Seidel Technique

In the first part tenth order polynomial is considered. The values of y are known for x equal to 0 to 10 for a particular basis function. The set of equations are solved using Gauss Seidel iterative technique to find coefficients A_1 to A_{11}. A very large number of iterations are required due to slow and oscillatory type of convergence. The variation of individual coefficients for two successive iterations is checked at each iteration. The maximum percentage variation in the set of coefficients is reduced appreciably after 2000 iterations. Table T.2.4 shows the maximum percentage variation in the set of coefficients for various basis functions. The point errors at all the points except the end points and average point errors are also found for checking the goodness of curve fitting. Maximum and average point errors for respective basis functions are also shown in the same table. The curve fitting is very poor except for functions T and PT. It means that fixed order (10) polynomial may not be reasonable for all the basis functions. Pennington has stated that the optimum order of polynomial for curve fitting may be 50 to 75 % of the number of data points [164]. Therefore, in the second stage different orders of polynomial are considered for various basis functions.

TABLE - T.2.4

Results of Gauss Seidal Iterative Process

Basis Function	Max. % variation of coefficient	Max. % Point error	Av. % Point error
P	0.25116476	19.535824	3.4106465
Q	0.06818139	16.072697	3.3664713
R	0.10005472	33.292577	6.0167916
S	1.91549200	94.889411	18.6098320
T	0.34650913	3.399192	0.8735776
PT	0.23109692	6.628914	1.6013007

(B) Least Square Technique

Here also the same polynomial expression is used to define the various basis functions. Gauss Jordon elimination technique with least square error criterion is applied to the set of eleven data points for each basis function. Coefficients A_1 to A_{N+1} are found for the Nth order polynomial. Fifth order to tenth order polynomials are tried with the basis functions for segments P,Q,R,S,T and PT. The least square algorithm provides the minimum sum of squared errors for a particular order of polynomial, but it may not be absolute minimum. It varies with the order of the polynomial. As a check the percentage errors are computed at all except the end points. The maximum and average of percentage point errors are computed for each order of polynomial for each basis function. The order of polynomial which

results in minimum values of maximum and average values of percentage point errors provide the best fit. Table T.2.5 shows the maximum and average values of percentage error with respect to the true value at the respective points for basis functions of segments P,Q,R,S,T and PT for 5th to 10th order polynomials.

It is observed that for basis function of segment P a nineth order polynomial results in minimum value of maximum percentage point error. Eighth order polynomial results in a slightly more maximum percentage point error and minimum average error. Basis function of Q has the minimum values of maximum and average errors for 8th order polynomial. Similarly polynomials of 9th order for R and 8th order for S and T provide the best fits. Tenth order polynomial has the minimum value of maximum error for PT. Nineth order polynomial has the maximum error slightly more than the 10th order but the minimum for an average error. Thus compared to the results of Gauss Seidal iterative process, the results of Gauss Jordon elimination algorithm with the least square error criterion are better. The orders of the polynomials with the best fit are different for different basis functions.

The pecularity of these basis functions is that each one is defined by an Nth order polynomial,

$$y = A_1 + A_2 x + A_3 x^2 + ... + A_{N+1} x^N \qquad \ldots (2.69)$$

The basis functions for different segments can be specified by specifying the coefficients A_1 to A_{N+1}, which are to be evaluated only once and stored permanently. The mathematical model of the ECG pattern can be represented as

TABLE - T.2.5

Results of Least Square Technique

Basis Function	Order of Polynomial	Maximum Percentage error	Average Percentage error	
P	5	4.5586216	1.6483535	
	6	10.4028670	2.7328321	
	7	76.4064010	14.1396870	
	8	2.5991783	1.1133910	Best fit
	9	2.4294894	1.2199611	
	10	3.9338701	1.5805437	
Q	5	25.8997540	7.7690001	
	6	8.9454485	4.4517780	
	7	No convergence		
	8	5.0451164	2.8854604	Best fit
	9	7.6288878	2.9731436	
	10	10.4603890	4.0738583	
R	5	18.3388640	6.2909451	
	6	25.7281380	6.7402567	
	7	214.8782000	42.3137450	
	8	5.7808527	2.7366557	
	9	5.0208097	2.7484162	Best fit
	10	5.6193459	2.8540876	
S	5	23.0952560	6.7375990	
	6	49.3131760	11.2978320	
	7	No convergence		
	8	7.0357874	4.4484001	Best fit
	9	15.7220640	5.5214513	
	10	13.8168670	5.0380081	
T	5	29.8214260	9.2228542	
	6	5.8636804	2.5050092	
	7	20.9570410	5.6722518	
	8	3.7228825	1.2315937	Best fit
	9	4.3916711	1.5904652	
	10	4.5028768	1.5382368	
PT	5	6.8661824	2.8430353	
	6	12.2752250	2.8069560	
	7	86.7327710	20.4103120	
	8	1.6303272	0.7004408	
	9	1.4639778	0.5201858	Best fit
	10	1.4210738	0.7502444	

$$e = A_p.P.\cos(\alpha_p - \theta_1) + A_{pt}.PT.\cos(\alpha_{pt} - \theta_1)$$
$$+ A_q.Q.\cos(\alpha_q - \theta_1) + A_r.R.\cos(\alpha_r - \theta_1)$$
$$+ A_s.S.\cos(\alpha_s - \theta_1) + A_t.T.\cos(\alpha_t - \theta_1) \quad \ldots (2.70)$$

Where, e is the instantaneous potential at some lead and P,PT,Q,R, S,T segment basis functions expressed by respective polynomials with the corresponding coefficients. These are the functions of x which itself is a function of time. The basis functions are discontinuous functions effective over only a certain interval of time. $A_p, A_{pt}, A_q, A_r, A_s$, and A_t are the amplitude coefficients for respective segments. The proposed model is suitable for defining the resultant ECG pattern in terms of overall resultant cardiac vectors for respective segments. In the present work twelve lead ECG data is used. As mentioned earlier there is much variability in the transverse plane and there is a difficulty of computing transverse plane resultant due to the variation in chest shape and size and variation in electrode placement. Therefore here the application of the model is limited to frontal plane only. In this case the amplitude coefficients are equal to the corresponding frontal plane peak resultant vector amplitudes. The phase angles of FPR with respect to the reference axis taken along lead axis I are $\alpha_p, \alpha_q, \alpha_r$, etc. The computation of FPR amplitude and phase using Burger triangle with measurement error and lead proximity corrections is explained earlier. θ_1 is the phase angle between the reference axis and lead considered. It has some fixed values corresponding to leads I, II, III, aV_R, aV_L and aV_F as defined by the Burger triangle. For known or computed parameters, ECG

pattern at any lead can be described instant to instant over the complete cardiac cycle. The model is also suitable for orthogonal lead system with slight modification.

2.7.3 Justification for the Model

The following points justify the proposed model.

(i) A single model expression is able to describe the ECG pattern of any subject at any frontal plane lead.

(ii) The coefficients A's for the respective basis functions are to be evaluated only once and are stored permanently.

(iii) The relative segment durations or time coefficients account for horizontal elongation or contraction of respective segments along the time axis as follows:

(a) Different values of these parameters for the same subject with the same condition of health account for varying heart rates.

(b) Different values of these parameters for different subjects account for individual variations of segment durations or heart rates. Variation beyond certain normal range may be due to some abnormality.

(iv) Different values of amplitude coefficients account for the vertical expansion or contraction of various segments due to individual physiology and health.

(v) Variation in values of phase angle α for respective segments accounts for the variation in the disposition of the tissues of the heart. Individual to individual variation is due to variation of physiology. Variation for the same

individual at different times may be due to changes in the state of health.

(vi) Basis function PT accounts for the almost horizontal line (idle period) and ST elevation or depression observed in case of some ECG patterns.

(vii) Different values of θ_1 account for lead to lead variation in the frontal plane.

(viii) The unit basis functions proposed are assumed to be unaffected individually. Because, the main variations in the ECG patterns are the horizontal and vertical expansion and/or contractions of various segments and the phase shifts among them with respect to time. All these variations alongwith the lead axis are properly accounted for in this model.

The main advantage of the approach is the simplicity of computation and ease of generalisation of parameters. The number of quantities to be measured, computed and stored or transmitted is reduced appreciably. The ECG interpretation problem also became suitable for implementation on a minicomputer or a micro processor.

The proposed model can be used for twelve lead as well as orthogonal three lead system. The two systems are compared in the earlier section. In computer assisted ECG interpretation programs, the main argument in favour of orthogonal three lead system is 4:1 data compression as compared to 12 lead system. This point is important when the ECG pattern is to be recorded and stored in the analogue or digital form for all the (6 or 12)

leads over one or more cardiac cycles. It would require a very large number of samples to be stored. The sampling rate is decided by the upper frequency of interest. In light of the proposed model, the approach for specifying the ECG pattern is totally different. Now the pattern is not to be specified lead to lead or instant to instant. The resultant (overall resultant or frontal plane resultant) ECG pattern is specified in terms of the model parameters. In the present approach only the FPR amplitudes or amplitude coefficients, durations and relative phase shifts are to be stored. For a remotely located ECG interpretation machine this method needs less than or equal to eighteen parameters to be transmitted. At the receiving end the corrected ECG wave patterns at leads I, II, III, aV_R, aV_L and aV_F can be reconstructed with the help of the model expression and the associated parameters.

2.7.4 Reconstruction of Electrocardiogram

It uses the stored values of coefficient A's of the polynomials defining the various segment basis functions. For a particular ECG pattern, peak amplitudes for various segments at leads I, II, and III are used to find the FPR amplitude and phase. The segment durations are also measured at the three leads. The average durations are used. The values of amplitude coefficients A_p, A_q, A_r, etc. for different segments P, Q, R, etc. are taken same as the values of the FPR amplitudes. The durations T_p, T_q, T_r, etc. are taken same as the respective segment durations. The lead axis angles θ_l for various leads are specified by the Burger triangle. All these parameters are substituted in the model expression.

The instantaneous potential at any lead can be computed by using the detailed expression as follows:

$$
\begin{aligned}
e &= A_p.P.\cos(\alpha_p-\theta_1) && \text{from } t = 0 \text{ to } T_p \\
&= A_{pt}.PT.\cos(\alpha_{pt}-\theta_1) \\
&\qquad \text{from } t = T_p \text{ to } T_p+0.4\,T_{pt} \\
&= A_q.Q.\cos(\alpha_q-\theta_1) + A_{pt}.PT.\cos(\alpha_{pt}-\theta_1) \\
&\qquad \text{from } t = T_p+0.4\,T_{pt} \text{ to } T_p+0.4\,T_{pt}+T_q \\
&= A_r.R.\cos(\alpha_r-\theta_1) + A_{pt}.PT.\cos(\alpha_{pt}-\theta_1) \\
&\qquad \text{from } t = T_p+0.4\,T_{pt}+T_q \text{ to } T_p+0.4\,T_{pt}+T_q+T_r. \\
&= A_s.S.\cos(\alpha_s-\theta_1) + A_{pt}.PT.\cos(\alpha_{pt}-\theta_1) \\
&\qquad \text{from } t = T_p+0.4\,T_{pt}+T_q+T_r \text{ to } T_p+0.4\,T_{pt}+T_q+T_r+T_s \\
&= A_t.T.\cos(\alpha_t-\theta_1)+A_{pt}.PT.\cos(\alpha_{pt}-\theta_1) \\
&\qquad \text{from } t = T_p+0.4\,T_{pt}+T_q+T_r+T_s \text{ to } T_p+T_{pt} \\
&= A_t.T.\cos(\alpha_t-\theta_1) \\
&\qquad \text{from } t = T_p+T_{pt} \text{ to } T_p+0.4\,T_{pt}+T_q+T_r+T_s+T_t \\
&= 0.0 \\
&\qquad \text{from } t = T_p+0.4\,T_{pt}+T_q+T_r+T_s+T_t \text{ to tou} \qquad \ldots (2.71)
\end{aligned}
$$

where, e is the instantaneous ECG potential at a lead, P,PT,Q,R,S,T are the unit basis functions, T_p, T_q, T_r, etc. are segment durations in ms, and tou is cycle length in ms.

A_p, A_q, A_r, etc. amplitude coefficients.

For generalisation of the expressions the basis functions are expressed in terms of x. For actual evaluation of instantaneous ECG potential x is expressed in terms of time t. The basis functions are discontinuous functions, effective over only a certain interval of time. For basis function P, from t = 0 to T_p, $x = 10t/T_p$. In this region only basis function P is effective. At the end of this period basis function PT becomes effective. For basis function PT, from $t = T_p$ to $T_p + T_{pt}$, $x = 10(t-T_p)/T_{pt}$. From T_p to $T_p+0.4\ T_{pt}$ only basis function PT is effective. At the end of this period basis function Q becomes effective.

For Q, from $t = T_p+0.4\ T_{pt}$ to $T_p+0.4\ T_{pt}+T_q$, $x = 10(t-T_p-0.4\ T_{pt})/T_q$. In this region both Q and PT are effective. At the end of this period function R becomes effective.

For R, from $t = T_p+0.4\ T_{pt}+T_q$ to $T_p+0.4\ T_{pt}+T_q+T_r$,

$x = 10(t-T_p-0.4\ T_{pt}-T_q)/T_r$. In this region R and PT are effective. At the end of this period basis function S becomes effective.

For S from $t = T_p+0.4\ T_{pt}+T_q+T_r$ to $T_p+0.4\ T_{pt}+T_q+T_r+T_s$,

$x = 10(t-T_p-0.4\ T_{pt}-T_q-T_r)/T_s$. In this region S and PT are effective. At the end of this period basis function T becomes effective.

For T, from $T = T_p+0.4\ T_{pt}+T_q+T_r+T_s$ to $T_p+0.4\ T_{pt}+T_q+T_r+T_s+T_t$,

$x = 10(t-T_p-0.4\ T_{pt}-T_q-T_r-T_s)/T_t$. In the initial part of this period both T and PT are effective. PT terminates before the termination of T. So, in the later part of this period only T is effective. Start and finish of PT are selected arbitrarily. PT accounts for the almost horizontal line between P and Q segments

and ST elevation or depression observed in some ECG patterns. For most of the normal patterns there may not be ST elevation or depression and the idle period between P and Q segments. So, to simplify the analysis PT can be ignored. But, for the general justification of the model PT is to be considered.

The value of x lies between 0 and 10 for each segment. The cardiac cycle length is divided in to 300 parts. Starting from t = 0, the time is increased in steps of 1/3 % of the cycle length. At each point, the value of x is found. The segment basis function which is effective at the point is also determined. The function is evaluated and instantaneous value of ECG potential is computed. The procedure is repeated for all the points for a lead and then for all the six frontal plane leads. The results are plotted directly using a subroutine PLOT.

2.7.5 Results and Discussion

The results for one case are shown in Figure 2.12(a,b). The recorded ECG is shown in (a) and the model generated ECG is shown in (b). The reconstructed wave corresponds to ECG potentials after the application of measurement error and lead proximity corrections. Most of the methods provide mathematical model for curve fitting or reconstruction of ECG pattern at only one of the leads. The pecularity of the present approach is the common model for the curve fitting or reconstruction of a group of ECG patterns at the six frontal plane leads. The results are very encouraging. It is not necessary to measure, store and transmit hundreds of instantaneous values at the six leads necessitating

FIG. 2.12.(a). RECORDED E C G

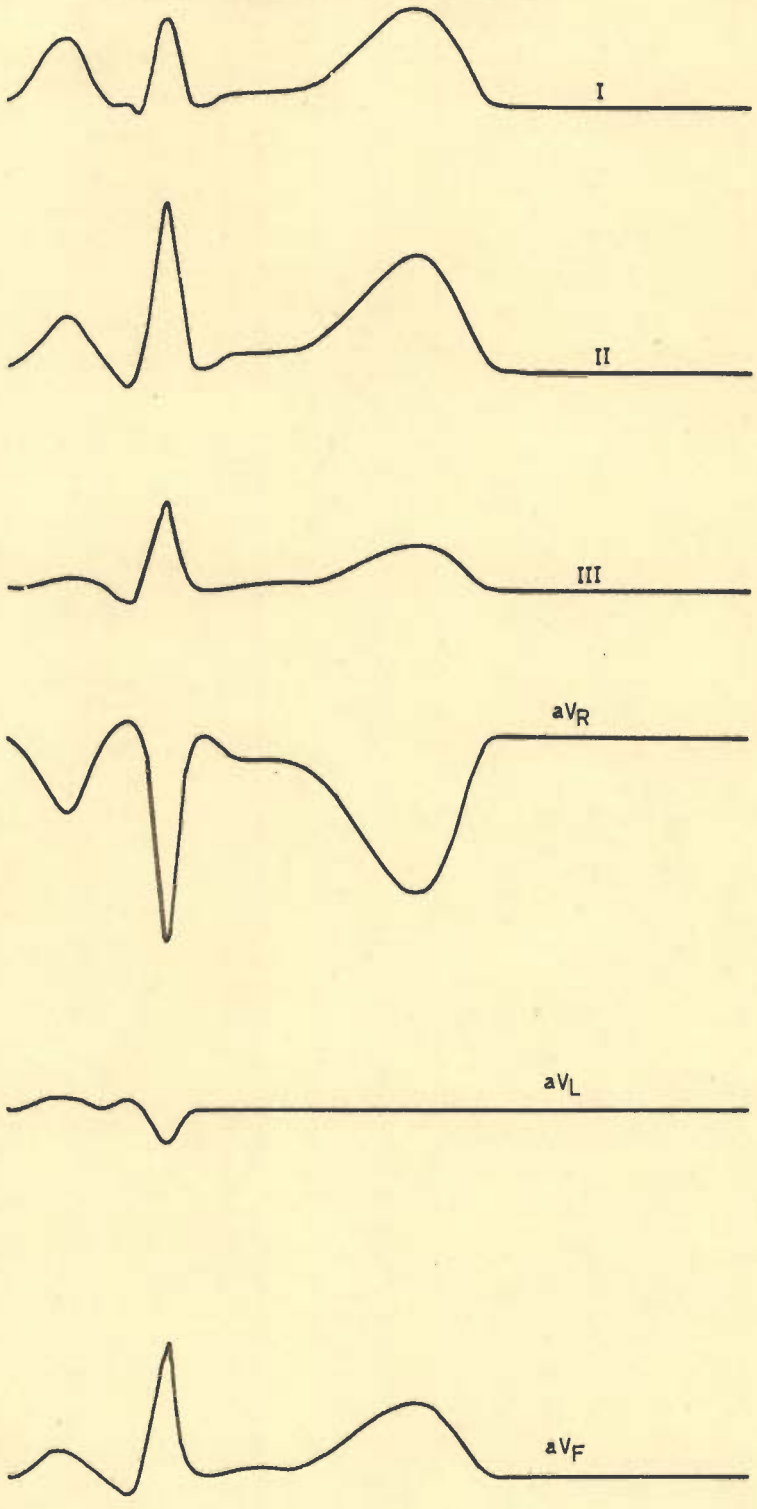


FIG. 2.12.(b). MODEL GENERATED E C G

a very large memory capacity. Only about 18 parameters are to be stored or transmitted. The resulting data compression is worth noting. FPR amplitude and phase used as the model parameters can be computed with very high accuracy and precision. They have very high diagnostic significance.

So long as the cardiologists are not satisfied with the performance of the computer and fully reliable computarized interpretation is not achieved, the overview of computer interpretation by cardiologist has to be continued. For the overview, the reconstruction of 12 lead ECG may be necessary. Even with orthogonal three lead programs sometimes 12 lead ECG is recorded for this purpose. The philosophy of hybrid ECG system is somewhat similar. But if the purpose is served by only three of the 12 leads it is much advantageous. The real advantage of this approach is in its suitability for categorization of model parameters.

CHAPTER III

COMPUTER AIDED INTERPRETATION OF ELECTROCARDIOGRAM

3.1 INTRODUCTION

In normal clinical practice ECG usually becomes available to cardiologist after a clinical diagnosis. So, some cardiologists make purely electrocardiographic diagnosis and others 'custom fit' diagnosis [48]. In computer aided diagnosis of electrocardiogram, computer programs are based on the premise that ECG interpretation should be standardized, and the objective and semiquantitative criteria should be used instead of qualitative interpretation. An advantage of computer aided diagnosis which has not been emphasized enough is enhanced efficiency with which a heart station can operate at purely technical level. It includes storage of data and consistency of ECG interpretation. The economics of computer aided diagnosis involves operating costs, pay roll, overhead, professional fees, etc. With this type of system, there may be more productive utilisation of cardiologist's time and skill for the analysis of complex cases, treatment of critical patients, and development of new methods and criteria. The measurements of amplitudes, durations, and intervals are extremely accurate using computer. As such, computer is a good alternative for a physician practicing in a hospital where there are no expert cardiologists.

This chapter deals with the work done towards computer aided interpretation of ECG. Electrocardiogram is represented in terms of frontal plane peak resultant vector amplitudes and phases for various segments and the normal pattern space is defined for individual parameters in the form of relative values. A method is developed for screening of ECGs in to normal and abnormal categories. Composite binary code is introduced for effective and compact representation of symptom patterns. An ECG interpretation algorithm is developed for the detailed classification in to various disease categories, namely myocardial infarction, right ventricular hypertrophy and left ventricular hypertrophy. The soft ware implementation of the developed interpretation algorithm is also shown on a 8085 based microprocessor system.

3.2 CLINICAL CRITERIA

It is necessary to have some idea about the method of clinical classification before going to computer aided interpretation. With years of experience, the cardiologists have specified some clinical criteria for screening of cases in to normal and abnormal categories and detailed classification. Friedman has reproduced tabulated values for the normals for a large number of cases of different age groups [81]. The mean values and ranges of potential variation for segments Q,R,S and T at all the 12 leads are tabulated for these groups. In another table, corrected values of normal QT intervals for various age groups are also given. The mentioned leadwise segment variations are very wide.

Normal heart rate is somewhere between 60 to 100 beats per minute. P wave has amplitude of 0.05 to 0.25 mv and duration of 0.07 to 0.11 second. It has a phase displacement of 17.5 to 87 degrees in clockwise direction in frontal plane with respect to axis I. The distance between peaks of P notches should not be greater than 0.03 second in normal ECG. The amplitude of normal Q wave is less than 0.2 mv or 25 % of succeeding R in leads I and II and less than 0.6 mv in lead III. The normal QRS wave has duration of 0.08 to 0.09 second and phase displacement of 30° anti-clockwise to 103° clockwise. The frontal plane maximum value of R wave is 2.1 mv. PR interval is 0.10 to 0.22 second. The ratio of P duration and PR interval is 1.0 to 1.6. The corrected QT duration is 0.35 to 0.44 second for adults. The angle between mean QRS and T is less than 45° in frontal plane and less than 60° in anterior posterior plane.

$R_I+S_{III} < 2.5$ mv, $R_I < 1.4$ mv, $R_{II}+R_{III} < 4.5$ mv, $R_{aV_L} \leq 1.1$ mv, $R_{aV_R} \leq 2.0$ mv, $R_{V1} \leq 0.6$ mv, $R_{V1}/S_{V1} < 1.0$, $R_{V5}/S_{V5} = R_{V6}/S_{V6} > 1.0$, $R_{V5} < 2.6$ mv, $R_{V6} < 1.8$ mv, $R_{V5}+S_{V1}$ or $V2 \leq 3.4$ mv, R_{V5} or $V6+S_{V1} \leq 3.0$ mv, R_{V4} or $V5 + S_{V2} \leq 3.5$ mv, R_{max}+deepest S in precordial leads ≤ 4.0 mv, $S_{V1} \leq 2.5$ mv, $S_{V2} \leq 2.9$ mv.

The T wave has amplitude of 0.1 to 0.5 mv and duration of 0.1 to 0.27 second. The segment U is hardly detectable in limb leads. In limb leads of healthy subjects, ST elevation is absent. ST and PR are parts of a continuous curve.

In case of Right Ventricular Hypertrophy (RVH), the right axis deviation makes the axis greater than $+120^{\circ}$. Some of the main symptoms for the indication of RVH are increase in QRS amplitude, anteriorly directed QRS with normal interval, tall R in V1 and unusually large S in V6, inversion of T and depression of ST in right sided chest leads, and/or abnormally deep and wide S in left sided chest leads.

In case of Left Ventricular Hypertrophy (LVH), there is an increase in the amplitude of QRS without much change in direction. The older subjects have more horizontal QRS complex by left axis deviation. Some other main symptoms are posteriorly directed QRS, QRS duration of 0.09 to 0.11 second, S_{V1} or $V2 + R_{V6} > 4.0$ mv, precordial $R+S > 3.5$ mv, $(R_{max} + S_{max}) > 4.5$ mv, ST and T opposite in direction to QRS, and/or abnormally tall R in V_6 and deep S in V_1.

In case of Myocardial Infarction (MI), ST vector points towards the injured region. T and mean QRS vectors for the first 0.04 second points away from the infarct. The QRS interval may be normal or prolonged. The Q wave is not indicative of infarction unless it has duration greater than 0.04 second regardless of its amplitude. After the occurrence of MI, there is ST elevation in some leads and depression in the others. After several weeks, ST becomes normal but the change in T persists. In case of MI there is localised ST elevation (convex upward) in infarcted areas and depression in remote areas. The amplitude of R wave diminishes and at times disappears altogether.

Some idea about the clinical criteria collected from the literature [14,81,109,116,162] is given here. There is ample variability in the criteria from cardiologist to cardiologist and clinic to clinic. The interpretation of same cardiologist may be affected by time, place, training, experience and non-ECG symptoms. The clinical classification is more qualitative and subjective. The identification of LVH by ECG is very difficult. It is reported that the voltage based criterion loses specificity with increased sensitivity.

Vectorcardiography is generally used for QRS loop. It represents 5 % of the tracings taken in general hospitals and is more useful for suspected MI. The leads X, Y and Z have some correspondence with I, aV_F and V_2. The QRS loops are observed for frontal (xy), sagittal (zy) and horizontal (xz) planes. The loop display expands time scale. Most of the patterns can be recognized in the horizontal projection. VCG should not be a routine procedure. There is an unacceptably high cost benefit ratio when it is used indiscriminantly [241].

3.3 STATE OF ART FOR COMPUTER ASSISTED INTERPRETATION OF ELECTROCARDIOGRAM

A new era of electrocardiography started with the introduction of computers for ECG interpretation. In 1957, Veteran Administration (VA), USA, started the development of methods of computerised ECG analysis [167]. The first stage of the work was the development of A/D converters [170,171,212]. The first computer program for classification of normals and abnormals was based

on the ventricular gradient [168]. The other workers also started work in the same direction [45]. At that time, one of the serious problems was automatic identification of onset and end of P,Q,R,S and T segments of ECG. The following section deals with some methods of wave recognition.

3.3. Wave Recognition

Stallman and Pipberger reported probably the first program on automatic wave recognition. Above 60 Hz, signal to noise ratio is low. Filter is used for the elimination of noise before automatic wave recognition [207]

$$\bar{X}(t) = \sum_{T=-N}^{+N} g(T)X(t-T) \qquad \ldots (3.1)$$

$$\bar{Y}(t) = \sum_{T=-N}^{+N} g(T)Y(t-T) \qquad \ldots (3.2)$$

$$\bar{Z}(t) = \sum_{T=-N}^{+N} g(T)Z(t-T) \qquad \ldots (3.3)$$

where, $g(T) = g(-T)$ to avoid phase shifts. The weight of $g(T)$ employed in this case is

$$g(T) = \frac{1}{32}\left(1 + 2\cos\frac{\pi}{16}T\right) \ldots\ldots T = 0, \pm 1, \ldots\ldots, \pm 15.$$

$$g(T) = -1/64 \ldots\ldots\ldots\ldots\ldots\ldots T = \pm 16$$

For $x(t) = \sin N\,(\pi/16)t$ or $\cos N\,(\pi/16)t$, $N = 2,3,\ldots,16$;

$g(T)$ is orthogonal to $x(t)$.

For $x(t) = \sin N\,(\pi/16)t$ or $\cos N(\pi/16)t$ or constant, $g(T)$ leaves $x(t)$ unchanged.

For wave recognition spatial velocity D is considered.

$$D = (\text{square root of } (\Delta x^2 + \Delta y^2 + \Delta z^2))/\Delta t \quad \ldots (3.4)$$

For lead x, rate of change of voltage is given by

$$\Delta x/\Delta t = (x(t+\Delta t) - x(t))/\Delta t. \quad \ldots (3.5)$$

Similarly $\Delta y/\Delta t$ and $\Delta z/\Delta t$ can be found. The beginning and end of a wave can be defined by determination of the points where D crosses certain threshold values. All programs developed since then have employed same general principles for wave detection[179]. The QRS onset is easy to locate, while P wave onsets, and P and T ends vary considerably.

Caceres along with others did a pioneering job in wave recognition [37,41,43,44,209]. The rules and definitions based on conventional criteria were formulated to define wave onset, wave peak, wave termination, significant voltage fluctuations and time intervals as shown in Figure 2.2. The onset of P is the point immediately after the region of minimum slope fluctuation. The end of P is the point following the region of minimum slope on the descending limb of the P wave. The onset of QRS is the first point of increased slope above a minimum of 0.01 mv for 0.01 second. The end of Q and onset of R is the point where the QR segment crosses the base line. The end of R and onset of S is the point at which the trailing edge of R wave crosses the base line. The end of S is the point where the trailing edge of S crosses the base line. ST segment is the unit of time and the average voltage quantity above or below the base line per 0.01 second between the end of S and peak of T. Onset of T is the first positive or negative slope change of 0.01 mv for 0.01 second

from the base line after the end of S. The end of T is the point preceding the area of least voltage fluctuation. The peaks of P,Q,R,S,T are detected in respective regions. Leads II and V3 are used for this purpose [209].

Bonner et al. used level crossing and slopes for wave detection [21]. In the wave detection described by cornfield et al.[57] for Frank lead system, QRS onset is determined by comparing spatial velocity V_t with standard spatial velocity V_t^*. The standard curve is obtained by averaging spatial velocity for a series of records. The time of QRS onset for a new record t_q is defined as the value of t_q which minimises $\Sigma W_t(V_{t-t_q}-V_t^*)^2$ in the neighbourhood of t_q and W_t is inverse of estimated variance around the standard curve. The end of P wave is taken first in a sequence of points preceding t_q at which V_t exceeds 1.12-1.63 μv/ms. P onset is similarly determined. End of QRS is determined using standard spatial velocity curve. Searching back ward from the end of cycle, the first in a sequence of points having V_t greater than threshold is end of T. In the method reported by Smets and Kornreich [200], the pattern is transformed in any positive function like spatial amplitude or spatial velocity amplitude. It is integrated and the times needed for the integral to attain certain percentage of total variation due to the signal are noted. The signal sampled at certain epoch points provides diagnostic parameters. The amplitude of external cross product of VCG at time t+1 by the smoothed VCG at time - is proportional to the surface of the triangle formed by the two vectors. This vector

is used for P wave detection in noisy signals. This method could be helpful in avoiding the delicate problem of strict definition of the limits of the waveform.

Murthy and Rangaraj have reported detection of QRS complexes using first difference in amplitudes of successive ECG samples [154]. Simple transformation is used to get a single peak at the QRS complex.

$$g_1(n) = \sum_{i=1}^{N} |x(n-i+1) - x(n-i)|^2 \, (N-i+1) \qquad \ldots (2.6)$$

where, N is the width of the window within which N past differences are computed, squared and weighted by factor (N-i+1), n the running index of signal, and its transform g_1. The methods based on angle patterns,"the local variance of the amplitude of the external product of consecutive sampled points", combination of spatial velocity and amplitude, integral etc. are used. The spatial velocity and amplitude are parameters of general choice. Low amplitude, low signal to noise ratio, wide range of morphologies associated with onset and offset make P wave identification difficult [145]. A technique is also developed for recording and identifying the P wave from esophagus [112]. Rubel et al. have reported QRS detection based on threshold crossing of spatial velocity function S_{vt} varying from 14 to 40 μv/ms [188]. Shibata has reported a template method developed for P wave detection [198]. Murray et al. have combined clinical criteria with mathematically extracted parameters [152]. Use of atleast two of the three parameters amplitude, slope and area under the curve with

filtering improves QRS detection [75]. In linear approximation, the ECG is considered as a series of triangles or trapezoids separated by intervals described by a series of line segments[105]. This syntactic approach suitable for mini and microcomputers works well for QRS detection. Udupa et al. also reported syntactic ECG representation in terms of Lengths and angles of a series of 27 linear segments [219]. Rubel has also discussed a method using spatial area and spatial velocity [187].

In another approach [242], prediction formulae are used for rough estimation of point of maximum or minimum amplitude for various segments. A window covering twice the standard deviation around this point is considered and exact point of maxima or minima is searched over this window. Okado has developed a five step digital filter which removes components other than QRS complex from ECG [158]. A square wave is produced whose interval corresponds to the segment with QRS complex in original ECG. Bockmann et al. have derived polynomial regression age dependent functions for estimation of standard spatial velocity values [18]. The spatial velocity curves are also derived for the 12 leads.

$$SPV_j = a_{oj} + a_{1j}.Age + a_{2j}.Age^2 + a_{3j}.Age^3 \qquad \ldots (3.7)$$

The adaptive polynomials are given as

$$SPV_j = a_{oj} + a_{1j}.Age + a_{2j}.Age^2 + b_{2j}\ SPVMAX^2 \qquad \ldots (3.8)$$

where, SPV_j is expected value of spatial velocity of QRS onset and offset in different approximation points. Broda et al. found P wave phase more reliable for its detection [28]. Okajima et al.

employed multiple adaptive matched filter [159].

It is possible most of the times to detect the presence of ventricular complexes with level detection methods [210]. A threshold method is always sufficient except for low amplitude waveforms and with small signal to noise ratio. Zero crossing estimated by linear interpolation gives best results. The validity of detector output pulse is tested by the time interval between positive and negative deflections crossing the lower level in digitally filtered signal [220]. In learning population, this time appeared to vary from 10 to 40 ms. If a level of about 40 % is crossed and the interpulse criteria are fulfilled, there is true detection. If a lower level (about 15 %) is crossed and the interpulse criteria are also satisfied, it should be further checked by software. The detector implemented in hardware saves computer time [230,90]. If the waveform is stable spatial velocity template can be used [222]. In another method by Hengeveld and Bemmel [103] illustrated in Figure 3.1(a-f) for detection of P waves, digital bandpass filtering is applied to ECG after cutting away QRS. Before applying filtering, routine rough estimation of end of preceding T wave is made by regression formula

$$QT\ max = (2/9)\ RR + 250\ (ms) \qquad \ldots (3.9)$$

The filtered signals are rectified and two thresholds are applied at 50 and 75 % of maximum amplitude, resulting in ternary signal. The cross correlation is computed with the template. The correlation function has maximum value at P wave. This routine is only applied if an earlier algorithm could not find coupled P

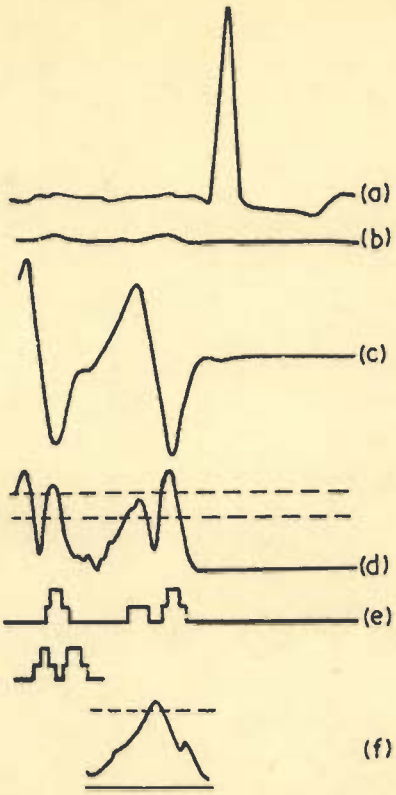


FIG.3.1. WAVE RECOGNITION

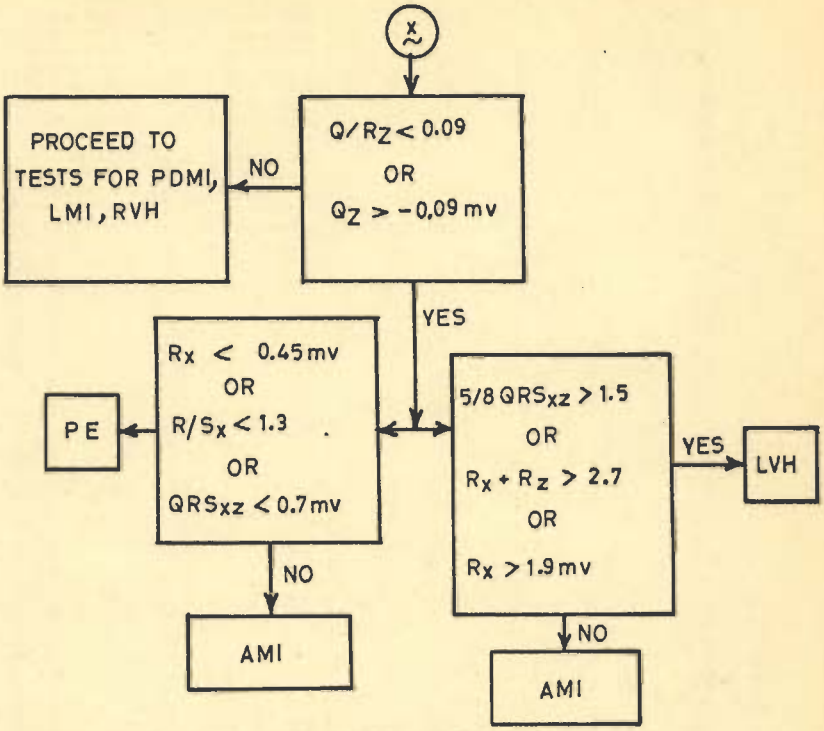


FIG.3.2. Ist GENERATION PROGRAM

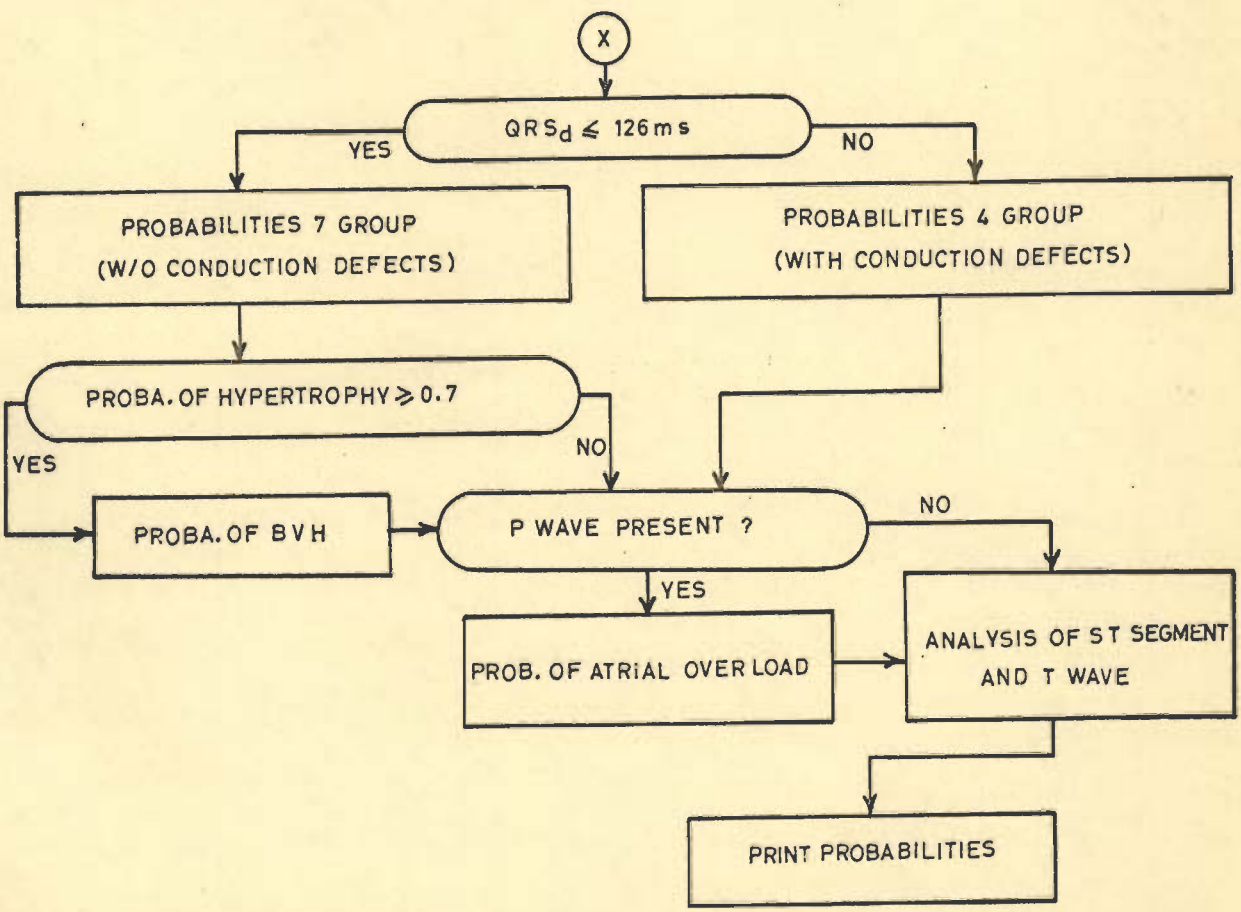


FIG.3.3. IInd GENERATION PROGRAM

waves. Van Bemmel et al. have reported QRS detection as follows [223A].

ECG(i) = $(x_1(i), x_2(i), x_3(i))$ for three simultaneous leads (from 12 or 3 lead system).

Detection function $d(i) = \sum_k T(x_k(i))$ ... (3.10)

T is a transform of $x_k(i)$. The derivative is computed by the two sided first difference.

$$T = |x_k(i+1) - x_k(i-1)|^2 \quad \ldots (3.11)$$

Spatial velocity = square root of (d(i)) ... (3.12)

There exist neither definitions nor recommendations which can be applied on discrete ECG signals and translated in to computer statements. The location of points of onset and offset vary from program to program. Even with logically correct program remarkable differences in performance can be observed with different programs for the same ECG. The European working group is trying to improve and standardise the method [247].

3.3.2 Interpretation Methods

The classification of ECG interpretation programs as first and second generation types is related to the complexity and not the time. The first generation programs simulate clinical methods of classification using decision trees [23,172,177]. When certain measurements are greater than normal, the record is labelled abnormal and is classified according to matching of abnormality with a disease. The number and type of measurements vary

with the program. The advantage of these programs is that the program users are familiar with the criteria and relatively follow the program logic easily. Since there is no general agreement on optimal criteria, diagnostic strategies and program performance vary considerably [167]. Large number of measurements leads to false positives. When a selected group of electrocardiographers was tested in a study by Simonson et al. (1966), the correct interpretation was achieved only in 54 % cases. According to Pipberger [172], the programming of the criteria of ECG experts can lead at best to the same results.

In second generation programs, large number of parameters is employed with multivariate statistical analysis. As compared to human readers, better diagnostic results are reported. But the program logic is difficult to follow, the measurements are not familiar to the program user, and assumption about mutual exclusiveness of diagnostic categories is unrealistic. Unlike decision tree programs, a small variation of singular measurement or noise may not affect the final diagnosis much [167].

So far, a large number of programs has been developed in Europe and North America. Some of these programs are AVA (3.6), TNO (7603), HP-5, ECAN-D, IBM (1 and 2), CIMHUB, THE LYON, HANNOVER, GLASGOW, SIEMENS, PADOVA and THE GIESSEN 12 lead programs, the Modular developed in Utrecht, THE LOUVAIN, HP78, MAYO, MSDL, MOUNT SINAI, DREIFUS, TELEMED and HALIFAX. Some of these programs are based on 12 lead system and some are on orthogonal three lead system [91, 235]. A program based on hybrid lead system is also being developed at Royal Infirmary,

Glasgow. It is not possible to give details of all the programs here. Therefore, only some idea is given about the development of Ist and IInd generation programs.

Caceres did the pioneering work in 12 lead ECG analysis [37,38]. Smith and Hyde [204] developed the Mayo program for VCG analysis which is replaced by a version with greater specificity [106]. Computer analysis of arrhythmia complemented these programs later; Bonner, Pordy and associates [21,22,174] reported on detailed algorithms for identification of cardiac rhythm disturbances. The program was replaced by a more powerful program as tested by Bailey et al.[8]. For analysis of orthogonal ECGs and VCGs, other operational programs are also reported [6,177]. For these first generation programs, when the normal limit for a given ECG measurement is exceeded, this finding may lead to a diagnostic statement or the statement may be qualified by a 2nd or 3rd measurement before a final decision is made, as shown in Figure 3.2. For reasonable specificity number of criteria is to be limited. In the illustration reported [117] the gain in correct classification is 5 % against loss of 11 % in specificity with increased measurements. The computer print out of MSDL program [91] included amplitudes, amplitude ratios, and intervals for 12 leads; axes for P,QRS,T,Q,R,S,STO,ST-T,QRS-T etc.; interpretation and 12 lead plots for visualisation.

IBM developed a program with three cardiologists for interpretation of scalar 12 leads just like clinical interpretation [23]. The five sets of three simultaneously recorded leads (12 + modified x,y,z or V1,II,V6) are used. The last set

is used for rhythm analysis of averaged measurements. The diagnostic criteria accompany the interpretation print out for a check. The measurement matrix includes amplitudes and durations, frontal plane angles for QRS,P,T and QRS area for the twelve leads. It can also be used as a teaching aid.

Whiteman et al.[233] have reported a compact scheme of representing 12 lead data in matrix form. The 12 columns correspond to 12 leads. Different rows provide the results of comparison of various segment amplitudes and durations with the set criteria. The normal values are indicated by 0 and abnormals by 1. The frontal plane vector program computes mean electrical axis with reference to two of the hexaxial reference system at 60^{o}. Leads with the greatest amplitudes are selected. For certain categories, some matrix elements are masked and significant ones are retained. For final interpretation, all tentative diagnostic statements are combined.

The capability of computer to perform more complex analytical procedure is harnessed in multivariate statistical analysis. The Veteran Administration (VA) program is based on Frank leads. The following parameters are obtained for the three leads [166].

(1) Amplitudes of P,Q,R,S and T

(2) Q/R and R/S

(3) Peak to peak time intervals of notched or biphasic waves

(4) Curves of spatial magnitude, orientation and velocity

(5) Spatial maximal vectors for P,QRS, and T

(6) Selected series of instantaneous vectors

(7) Durations/intervals for PR, QRS, Q, R, S, QT.

For time integrals positive areas are added while negative areas are subtracted. Ventricular gradient which is the sum of time integrals of QRS and T indicates net effect of ventricular depolarization and repolarisation. Eigen vectors of spatial P, QRS and T vector loops are also computed. A series of instantaneous vectors leads to optimal separation (more than 90 %). Measurements derived from scalar orthogonal leads, Eigen vectors, time integrals and spatial maximum vectors led to markedly lower recognition rates (45-55 %). They are suitable only for screening of normals and abnormals. The vector difference between unknown patient vector and various means of pathological entities indicates the probability for each of these entities [166].

Cady et al.[45] applied stepwise linear discriminant function analysis on Fourier coefficients derived from a set of orthogonal leads. Fourier coefficients (50 pairs of C_p and S_p) are found for x, y and z leads.

$$f_n = \frac{1}{2} C_o + \sum_{p=1}^{N} C_p \cos \frac{2\pi pn}{2N+1} + \sum_{p=1}^{N} S_p \sin \frac{2\pi pn}{2N+1} \qquad \ldots (3.13)$$

For LVH the discriminant function equation is given as

$$\text{LVH status} = 0.000164 + 0.000843\, S_1^x + 0.000832\, C_1^x - 0.00221\, C_{25}^x - 0.00878\, S_{17}^x - 0.00593\, S_{16}^x - 0.00389\, C_{27}^x \qquad \ldots (3.14)$$

The score for normals ranged from 0.0 to 0.4 and for LVH cases 0.6 to 1.3. The separating line is provided by a score of 0.53.

In a stepwise search procedure, a Fourier coefficient making greatest improvement in fit is added at each step. The discriminant solution gives least square best fit values of weight factors for a particular sample of ECGs.

Linear discriminant function technique is also used with selected set of measurements [72,83]. Adoptive filter [208] initially resolves around training sets of records for various entities. A cross correlation is performed between each new, unknown record and the various training sets. The unknown record is then entered in to the group of best correlation. The selected training set is up dated on the basis of new material. Polynomial Discriminant Method (PDM)[205] is its different form. It is a nonparametric statistical technique in which the pattern classification is based on estimates of probability density functions for each of the possible states. Bayes strategy is used for final classification. Fifteen samples at 5 ms after onset of QRS on each lead and duration of QRS provided 46 measurements. Thirty coefficients (27 linear, 2 squared and a constant term) are found significant. According to Stallman and Pipberger (unpublished observation)[71] the number of training cases greater than 100 results in overlapping and finally merging of groups in adaptive filter approach.

The ECG library of Veteran's Administration has tens of thousand of cases classified on the basis of non ECG symptoms. Matched filter, Fourier and Power spectrum and discriminant function analysis were tested using this data. The later approach proved much successful and was adopted for VA programs [71]. This

approach has since been extended to Bayesian likelyhood ratio reported earlier [56]. It forms the basis for the ECG computer program available to the public which except for the criterion of 126 ms for QRS duration to define conduction defects uses multivariate analysis exclusively [71]. The program computes posterior probabilities for 26 different categories. Figure 3.3 shows the flow chart for the program based on Frank lead system. Some details of this program are reported by Cornfield et al.[57]. The group of seven categories without conduction defect includes (i) Normal (ii) Anterior Myocardial Infarction (AMI), (iii) Posterior MI, (iv) Lateral MI (v) Left Ventricular Hypertrophy (vi) Right Ventricular Hypertrophy and (vii) Pulmonary emphysema. The measured variables are (a) voltage amplitudes on time normalised scale (b) maximum amplitudes for each wave (c) angles for time normalised points on QRS and maximum angle for each projection in that complex (d) durations Q_d, R_d, S_d, T_d (e) time of peak amplitudes for each wave and (f) areas. QRS measurements are obtained from unfiltered records and P, ST-T from smoothed derivatives. About 10-15 significant measurements are retained for each pairwise comparison e.g. normal and AMI. Most of the amplitudes are specified leadwise. Posterior probabilities are computed for all the categories as explained by pipberger et al.[172]. The results are affected strongly by the prior probabilities based on tentative diagnosis marked in the request form depending on non ECG symptoms. When more than one categories are marked combination sets of prior probabilities are applied. The sets of prior probabilities are determined

arbitrarily to minimise misclassifications. The method necessi tates that the marking of tentative diagnosis and selection of prior probabilities are proper. The prior probabilities vary among populations. The prior probabilities used here are percentage of cases in each category in files of well diagnosed cases. Due to very large number of parameters any data base may become inadequate. The number of parameters should not be more than 1/20th the number of training cases [172]. The assumptions about multivariate normality and equal covariance matrices may not be true in reality [57].

The point score technique is claimed to be most successful of recently developed criteria [131]. Romhilt et al. have reported point score technique with 12 lead ECG for detection of LVH cases [185]. Computerized Electrocardiography Laboratory at University of Louisville also uses a point score system for RVH and LVH with 12 lead system [197]. Macfarlane et al.[131] have applied point score technique to orthogonal leads for LVH, RVH and BVH. In this approach, certain point score is assigned to an amplitude, duration, ratio of amplitudes, sum of amplitudes or phase angle exceeding a specified value or value at some other lead. Total score is used for the categorization. Depending on the total score the classification is RVH or probable RVH or possible RVH and LVH or probable LVH or possible LVH.

The type of diagnostic criteria used with the computer are as follows [132]

LVH: QRS vector amplitude $\geq$ 2.5 mv

or R_X > 2.1 mv or S_Z > 1.2 mv

or transverse plane QRS axis 270°-310°.

RVH: $(R/S)_Z$ > 3 or R_Z > 0.85 mv

or (S_X > 0.55 mv and S_X > R_X)

or transverse plane QRS axis 30-270°

or frontal plane QRS axis 90-270°.

MI : (1) Anterolateral:

$(Q/R)_X$ > 1/3 possible MI

and if Q_X duration > 0.03 second consistent with MI

(2) Inferior : Similar to (1) but for lead Y.

(3) Anteroseptal:

Q_Z present and Q_Z duration > 0.02 second

or R_Z < 0.11 mv

$(R/S)_Z$< 0.10 and transverse plane axis of

QRS vector 0.03 second after its onset 180-330°.

In all the three instances ST segment and T wave appearances are used to determine age of infarction.

Royal Infirmary Glasgow group started with simultaneously recorded orthogonal leads in early seventies. Three leads are used simultaneously for amplitude and duration measurements of P,Q,R,S,T in each lead. Certain measurements describing amplitude and phase of resultant electrical force are obtained. Due to reluctance of cardiologists in accepting orthogonal lead program, hybrid system program is under development. Till the

diagnostic criteria for hybrid system are established, mixture of conventional and new criteria for 12 lead system are used. Hybrid ECG is recorded using microprocessor based electrocardiograph in which 15 leads are recorded simultaneously. The program is commercially available from Siemens Elema [135].

The value of generally used two dimensional concept of normality and abnormality is limited [39]. Fuzzy set approach is an attempt to avoid problem of single border line value between normal and abnormal. A grey area between normal and abnormal is conceived [130]. In fuzzy set approach, the measure of belonging to a set is arbitrarily scaled from 0 to 1. Classical sets are particular cases of fuzzy sets where measure of association or otherwise may be 1 and 0 (yes and no). Fuzzy sets and probabilities cover two distinct sources of ignorance. One deals with our ignorance about the patient and the other with our ignorance about the definition of the diagnostic entity. A better approximation of human behaviour and capacity have been obtained with fuzzy sets [202]. In the experiments, the clinicians are reported to be more at ease with subjective probabilities and fuzzy sets than with the more classical frequentist probability and classical sets [201].

3.3.3 Accuracy of Interpretation

The accuracy of classification is very difficult to measure and the methods and philosophy of program evaluation are intensely debated topics. There is also difficulty due to the lack of standardization of diagnostic criteria [5]. Various

claims and conclusions are made about the accuracy and effectiveness of various programs. The sensitivity of a program is the ratio of cases of a category detected by the computer (i.e. Positives) to the actual number of cases of that category. Specificity is the ratio of cases decided by the computer as not belonging to a category (i.e. negatives) to the actual number of cases not belonging to the category.

In 1967, Whiteman et al.[233] have reported complete agreement for 72 % and complete disagreement for 28 % in cases of normals; and complete agreement for 73 % , agreement on abnormality but disagreement on nature of abnormality for 26 % and disagreement for 0.8 % in case of abnormals [233]. In 1968, Romhilt et al. [185] have reported sensitivity of 62.2 % and specificity of 96.7 % for application of point score system to twelve lead data for LVH. In 1970, Gorman and Evans have reported 97.8 % agreement and 2.2 percent disagreement for normals; and 75.1 % agreement, 3.4 % disagreement and 21.5 % partial agreement with 12 lead MSDL system [91]. In 1973, Cornfield et al.[57] have reported 69.4 as the over all percentage correctly classified in seven group analysis. Twelve percent of the normals are misclassified with only 3 % misclassified as infarcts. For infarct cases the correct classification ranged from 70 to 88 % . For LVH and RVH, the values are 50 % and 38 % . When posterior probabilities were calculated using the likelyhood ratios from well diagnosed file, the correct classification rose to 70 % and more.

Bailey et al. made a systematic approach for testing and evaluation of some computer programs. Each ECG is reviewed by a board of 4 cardiologists unaware of the computer interpretation. computer-cardiologist disagreement may be attributed to criteria differences, program errors or reader errors. Specified criteria are followed by the readers. According to 1974 report IBM 71 program had 76 % agreement and 20 % disagreement due to criteria difference and 4 % disagreement due to program errors [12]. In case of version D of PHS program the agreement was 45.5 % , 29 % disagreement due to criteria difference and 25.5 % disagreement due to program errors. In case of Mayo program (1968) the agreement was 47 % , criteria difference disagreement 30.9 % and program error disagreement 22.1 % . With PHS program the error resulted primarily from mismeasurements and deficient program logic. With Mayo program the errors were mainly due to pattern recognition [11]. For checking reproducibility two digital representations of the same ECG were separated by one millisecond. The reproduction of diagnostic statements was 60 % with Mayo('68) program. The reproducibilities for version D of PHS and new IBM programs were 43.3 % and 76 % respectively. The results improved to 49.8 and 79.7 % by analog filtering. The need for human over view and quality checking is reemphasized [10]. In 1975, Pipberger et al. have reported that the results of 12 lead interpretations were correct, partially correct and incorrect by 68 %, 4 % and 28 % respectively. Multivariate analysis with orthogonal leads increased correct classification by 18 % . The misclassifications were reduced from 28 to 9 % . The correct recognition

rate for MI was 85 % against 79 % by conventional analysis [172]. In 1976, Caceres has reported that MSDL Scalar system had agreement of measurement on amplitude, duration and slope of waveforms in the range of 39.7 to 100 % and repeatability of measurements 94 % . For normals the agreement was 98.5 % and for abnormals 82.5 %. IBM 71 program showed 75.5 % agreement between computer and physician with NIH technique [40]. In 1976, Bailey et al. have reported that for AVA 3.4 program by Pipberger et al. reproducibility is 75.1 % without filtering [9]. Heavy analog filtering may improve the diagnostic reproducibility but sometimes results in loss of diagnostic statements. In 1979, Macfarlane [129] has reported sensitivity, specificity and index of merit of 70 %, 97 % and 0.67 for LVH and 53 % , 89 % and 0.42 for RVH using scoring technique with orthogonal leads. In 1981, Macfarlane et al.[131] have reported sensitivity and specificity for LVH,RVH and BVH as 74,94;67,100; and 64,100 % in the training group and 65,91;53,90; and 42,93 % in the test group using scoring technique for orthogonal leads. In 1982, a sample computer output of computerized Electrocardiography Laboratory at University of Louisville the percentage of agreement is 40.9. For hypertrophies range of sensitivity is 42-65 % and that of specificity is 90-93 % [197]. For three mutually exclusive and exhaustive groups, Smets et al.[203] have suggested the use of two sensitivities and one specificity.

3.3.4 Some Remarks

This comparison is not aimed at criticising any of the methods. It highlights the limitation of the computer interpretation in the present form. According to Friedman and Gustafson it merely tries to duplicate what a physician can already do quite well [82]. Only as a last resort agreement and disagreement between computer and majority opinion of group of observers should be used for evaluation [5]. Physician computer difference indicates criteria difference and not the computer system error [42]. The overreading does not answer the question whether the electrocardiographer or the computer is right or wrong [167]. Use of majority opinion of observers should be limited to descriptive statements only [180]. The fact that 12 lead ECG classification with decision tree logic is inferior to orthogonal three leads with multivariate analysis does not mean that the basic information content is different [172]. So far the computer has not become fully reliable. It has remained Computer Assisted Reporting of Electrocardiogram rather than automatic interpretation of ECG. Overview is still inevitable. After sufficient development only some complex ECGs may be required to be reviewed by the cardiologists [130]. The CSE European working group [235] is trying to establish measurement standards in computer ECG analysis. In pilot study (Ist stage) basic library of 250 ECG (Frank and 12 leads) is planned. Referees will locate on and offsets of waves from beats enlarged 10 times vertically and 10-20 times horizontally. The ECGs are to be processed by seven VCG and eleven 12 lead ECG computer programs developed in

Europe and North America. The second stage will use 2500 ECGs. In third stage guidelines for standards of ECG measurements are to be worked out.

According to Caceres unfortunately there has been too much expenditure and effort on studies to determine which program does what best and not enough on studies for constructive changes to ECG criteria that physicians should use, which could then be easily evaluated and added to, by any or all existing ECG programs. The saving in one year by computer assisted ECG interpretation alone is sufficient to purchase the hardware needed to do the entire nation's job. We should not wait any more and lose a huge sum every year in patient savings, lose 60 % of cardiologists' time in ECG reading or lose half of the time of clerical services in the heart station and continue to have inconsistent, unstandardized answers with the observer variability common to all of us [39].

The existing programs should not become frozen. There is still ample room for imaginative innovation in computer systems designed for ECG analysis [167]. The last remark has inspired and encouraged to put some fresh approach in the present work for the analysis of electrocardiogram. It is more useful to combine decision tree (Ist generation) and multivariate statistical analysis (IInd generation) methods. Poor performance of quadratic discriminant analysis is due to lack of adequate sample size for training sets. Linear discriminant analysis presumes that ECG measurements are multivariate and normally distributed, which is not true. So, it seems attractive to use statistical

models which are not based on these assumptions [148].

3.4 SEARCH FOR THE NORMALITY OF NORMAL ELECTROCARDIOGRAM

3.4.1 Method of Representation

Whether it is screening of large population of patients or routine classification, the first task is the classification of the ECG patterns in to normal and abnormal categories. The normal electrocardiogram is not a single unique pattern, otherwise, the job would have been very simple. Actually it covers a wide spectrum of patterns. In the earlier section on clinical criteria, it is seen that usually normal average values of amplitudes and durations at different leads of the 12 (or orthogonal 3) lead system for various segments P,Q,R,S,T and ST are specified. The upper limits for lead potentials at respective leads and segment durations for the normal ECG are also specified. Sometimes sum of deflections at two leads for segment R, sum of deflection R at one lead and deflection S at another lead, and upper limit for the ratio of R and S deflections for a pair of leads are specified. The upright and inverted deflections for some segments at some leads are also specified. The specified ranges of variation of ECG potentials for various segments of different leads are very wide and fail to define the normal pattern space with specificity. Therefore, this is ambiguous definition of normal ECG. Even arithmetic mean $\pm$ 2 times the standard deviation is not able to cover the total range of variation of the concerned parameter. The uncertainty about the criteria reduces the sensitivity and specificity of ECG interpretation. It may be one of

the reasons that ECG only is not considered as a sufficient evidence for clinical diagnosis of cardiac cases. It is supported by physiological and radiological observations, pattern of variation of blood pressure and flow; nature, location and duration of pain; study of heart sounds, pulse rate, colour of part or whole of the body, case history, and clinical observations. Long back Wilson remarked that ECG Science may be exact but its clinical utilisation is often wretched. It is hoped that computer will overcome this limitation.

The aim in this section is to derive and represent diagnostic parameters from 12 lead system to define normal ECG with more specificity and to ensure good clustering of parameters of the normal cases in the normal pattern space. The lead potentials are dependent on phase angle of the potential vector. The concept of potential vector is well known. The spatial vector approach discussed in literature usually considers mean vector. In this case, shift of baseline may give erroneous results. In clinical practice, it is used for rough estimation of axis and rarely for amplitude. Sometimes instantaneous vectors at some specific points in the cardiac cycle are also found. The peak potential vector with orthogonal leads is also used. Sufficient weightage is not given to it as there may be difficulty in its accurate computation or interpretation [166].

The present approach is mainly based on the Frontal plane Peak Resultant vectors (FPR) for the various ECG segments. It has been explained in the earlier chapter that by applying measurement error and lead proximity corrections to the ECG lead

potentials with Burger triangle representation, FPR amplitude and phase can be determined very accurately. The precision achieved is 0.0000002 mv for amplitude and 0.000004 degree for phase. The ECG representation in terms of amplitudes and phases of FPR for the various segments is a very effective and efficient method of representation.

3.4.2 Specification of Normal Pattern Space

Twenty five normal and sixtynine abnormal cases are analysed in this work. The average values for peak segment potentials P,Q,R,S,T and ST at leads I,II,III and segment intervals PQ,QR,RS,ST,TP are measured. Due to the presence of noise and frequent shift of baseline , there is always some difficulty in detecting the instant of zero crossing by the ECG potential. The duration from the beginning to the end of a segment considered normally in clinical practice can not be measured accurately. Therefore, time intervals between peak values of consecutive segments are considered in the present work. The sums and differences of some segment amplitudes are considered in clinical criteria. The algebraic sum of areas is considered while finding the mean spatial vector. Additional parameters Q+R, Q-R, R+S, R-S, S+T and S-T are considered here to account for similar effect. These are the arithmetic sums or differences of respective peak values. FPR amplitudes and phases are computed for P,Q,R,S,T,ST,Q+R, Q-R,R+S,R-S,S+T and S-T using Burger triangle representation with measurement error and lead proximity corrections for all the normal and abnormal cases. The computation procedure has been explained in section 2.6.

The actual values of FPR amplitude and phase are used as the polar co-ordinates for position vector for the point corresponding to a particular segment of a particular case in the pattern space. On the basis of analysed 25 normal cases, the ranges of variation of respective segment amplitude and phase is characterized by boundaries of certain sector in the circular plot as shown in Figure 3.4. The normal ranges of variation for absolute values of FPR amplitudes and phases corresponding to P, Q, R, S, T, Q+R, Q-R, R+S, R-S, S+T and S-T are clearly displayed on the plot by different sectors which specify the normal pattern spaces for respective parameters. The normal range of variation for absolute values of FPR amplitudes for a segment is very wide. The range varies from segment to segment. The arithmetic means and standard deviations are also found for these parameters. The distribution is irregular and even arithmetic mean with $\pm$ 2 times standard deviation is not able to cover the total range of variation for the normal cases. So actual maximum and minimum values are used to specify the range. The normal pattern spaces for some segments are quite apart. Moreover, the generalisation of diagnostic parameters is not convenient at this stage.

In the next stage, the above parameters are converted to relative values. The FPR amplitude of a particular segment for a case is divided by the arithmetic mean NMFPR of corresponding FPR amplitude for all the 25 normal cases to get the relative value of FPR amplitude. The relative value of phase angle for a segment is obtained by subtracting the average value NMα of phase angles for all the 25 normal cases from the actual value of phase

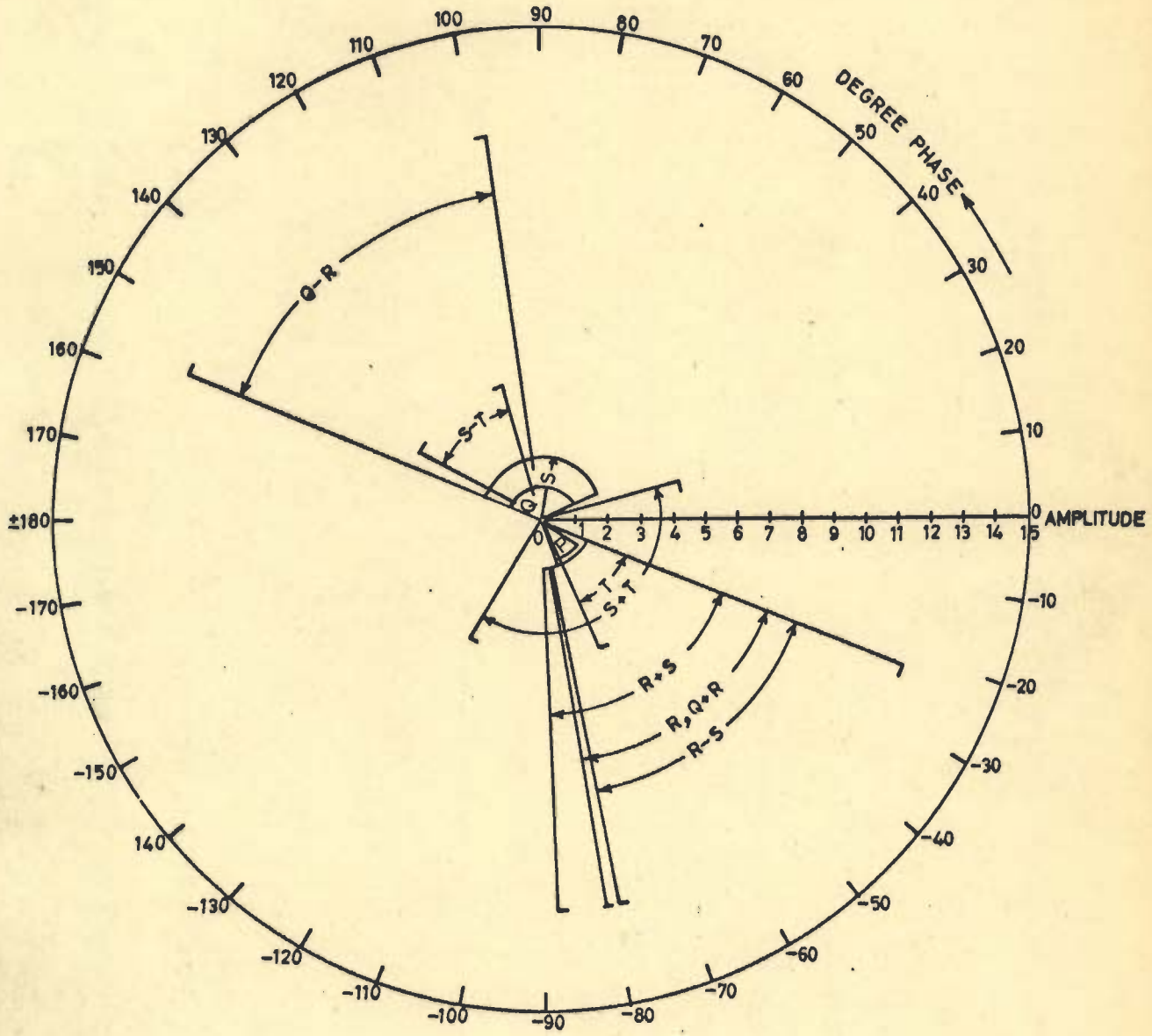


FIG.3.4. NORMAL PATTERN SPACES BASED ON ACTUAL VALUES

angle for a particular case. The use of relative values has made the order of amplitude and phase independent of the segment under consideration. In the normal pattern space, all the relative values for the normal cases cluster around 1 and 0 for amplitude and phase, respectively. The peak to peak segment intervals INT are first converted to percentage of cycle length T. The percentage interval is further divided by the arithmetic mean, NMINT of corresponding percentage intervals for the 25 normal cases to get relative value. The clustering of these parameters for normals is around 1.

$P_a, Q_a, R_a, S_a, T_a, ST_a, Q+R_a, Q-R_a, R+S_a, R-S_a, S+T_a$ and $S-T_a$ are the relative values of FPR amplitudes for P, Q, R, S, T, ST, Q+R, Q-R, R+S, R-S, S+T and S-T. $\alpha_p, \alpha_q, \alpha_r, \alpha_s, \alpha_t, \alpha_{st}, \alpha_{q+r}, \alpha_{q-r}, \alpha_{r+s}, \alpha_{r-s}, \alpha_{s+t}$ and α_{s-t} are the relative values of corresponding FPR phase angles.

$PR_d = PQ_d + QR_d$, $RT_d = RS_d + ST_d$,

$PT_d = PQ_d + QR_d + RS_d + ST_d$ or $PR_d + RT_d$

$PQ_d, QR_d, RS_d, ST_d, PR_d, RT_d, TP_d$ and PT_d are the relative values of respective peak to peak segment intervals.

$\angle P,R$ is the phase difference between P and R segments

$\angle T,R$ is the phase difference between T and R segments

$\angle T,P$ is the phase difference between T and P segments.

With relative values of 32 parameters $P_a, Q_a, R_a, S_a, T_a, ST_a, \alpha_p, \alpha_q, \alpha_r, \alpha_s, \alpha_t, \alpha_{st}$, etc., $Q+R_a, Q-R_a, R+S_a, R-S_a, S+T_a, S-T_a, \alpha_{q+r}, \alpha_{q-r}, \alpha_{r+s}, \alpha_{r-s}, \alpha_{s+t}, \alpha_{s-t}$, $\angle$phase differences $\angle P,R$, $\angle T,R$, and $\angle T,P$, 35 parameters, S_1 to S_N, are computed for the 25 normal and 69 abnormal cases. Upper and lower limits, $NMAX_j$ and $NMIN_j$, for each parameter are

set from the results of the normal cases. They define the normal range of variation for various diagnostic parameters.

Relative values of parameter vectors P,Q,R,S,T,Q+R,Q-R, R+S,R-S and S-T for the normal cases are plotted in Figure 3.5 (a-k). The relative values of phase angle and amplitude of respective parameter vectors are taken on vertical and horizontal axes, respectively. The numerals indicate the code numbers assigned to various cases. These numbers are assigned in some blocks according to the sequence in which the cases are collected. So there should not be any confusion even if the numbers are out of sequence or the sequence is discontinuous. The relative values of segment intervals for normal cases are plotted in Figure 3.6 (a-h). Here, the segment intervals are taken along the horizontal axis. For clarity some points are shifted upward or downward. The vertical scale has no significance. In Figures 3.5 (a-k) and 3.6(a-h) very good clustering of FPR vectors and segment intervals for various segments of ECG patterns for the 25 normal cases is observed in the pattern space. It is possible to define the boundaries of the normal pattern space for various parameters which is very useful for screening of cases in to normals and abnormals.

The diagnostic utility of the approach is verified by the analysis of 69 abnormal cases including 29 cases of Myocardial Infarction (MI), 20 cases of Right Ventricular Hypertrophy (RVH), and 20 cases of Left Ventricular Hypertrophy (LVH). For illustration, the results for R and T vectors with the cases of MI are presented in Figure 3.7(a-b). With the help of the results

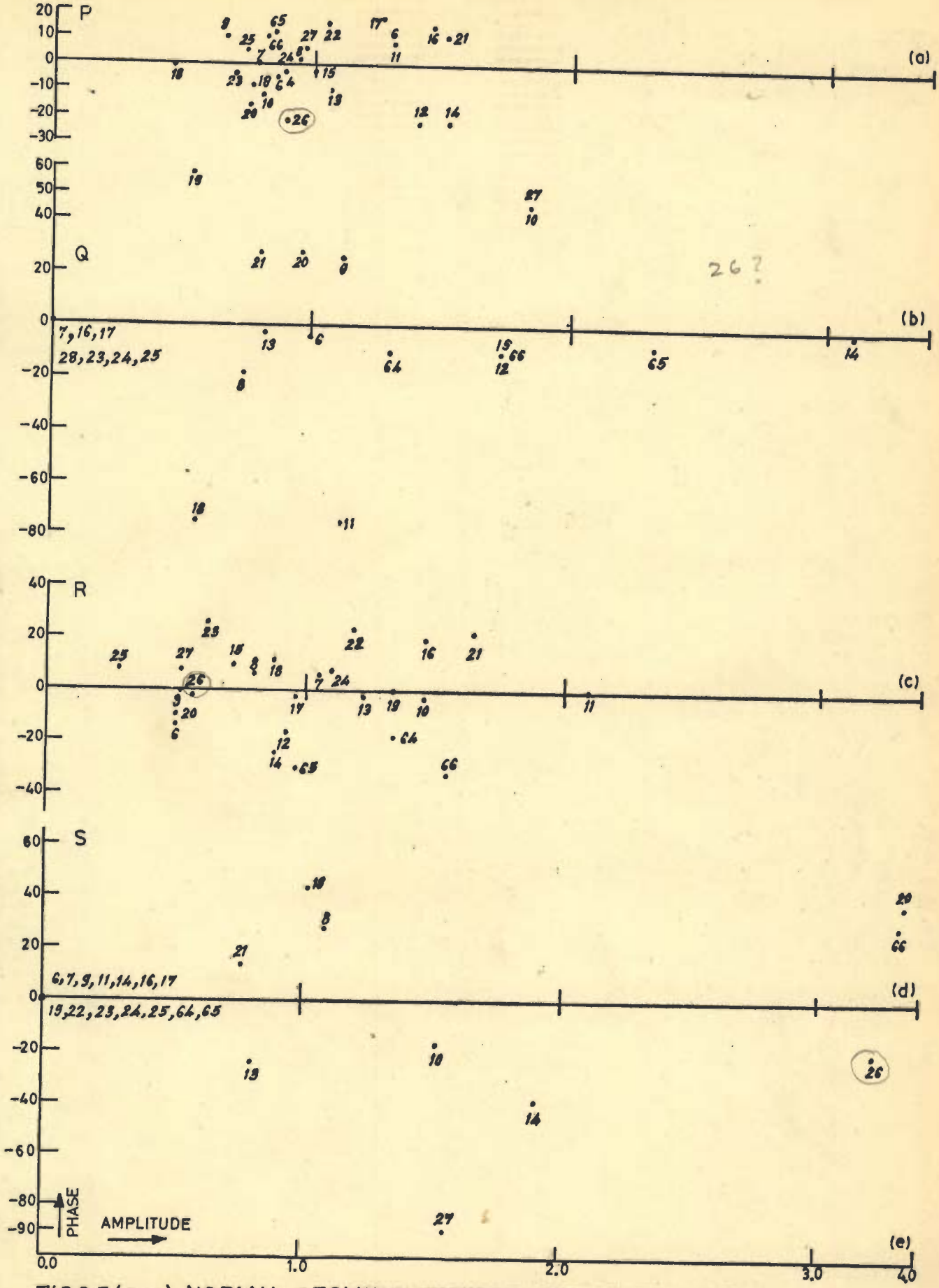


FIG.3.5(a-e). NORMAL SEGMENT VECTORS: RELATIVE VALUES

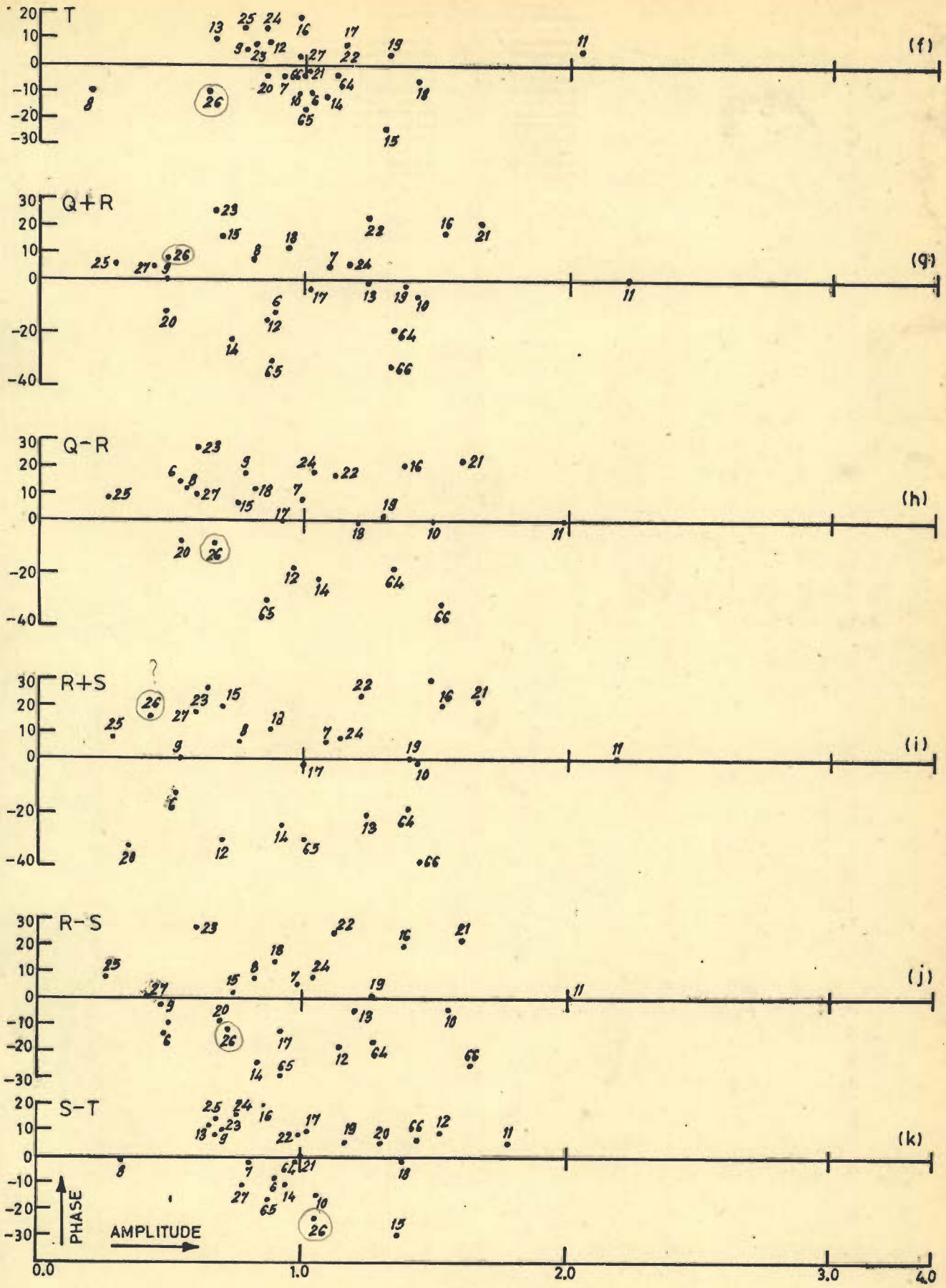


FIG.3.5 (f-k). NORMAL SEGMENT VECTORS: RELATIVE VALUES

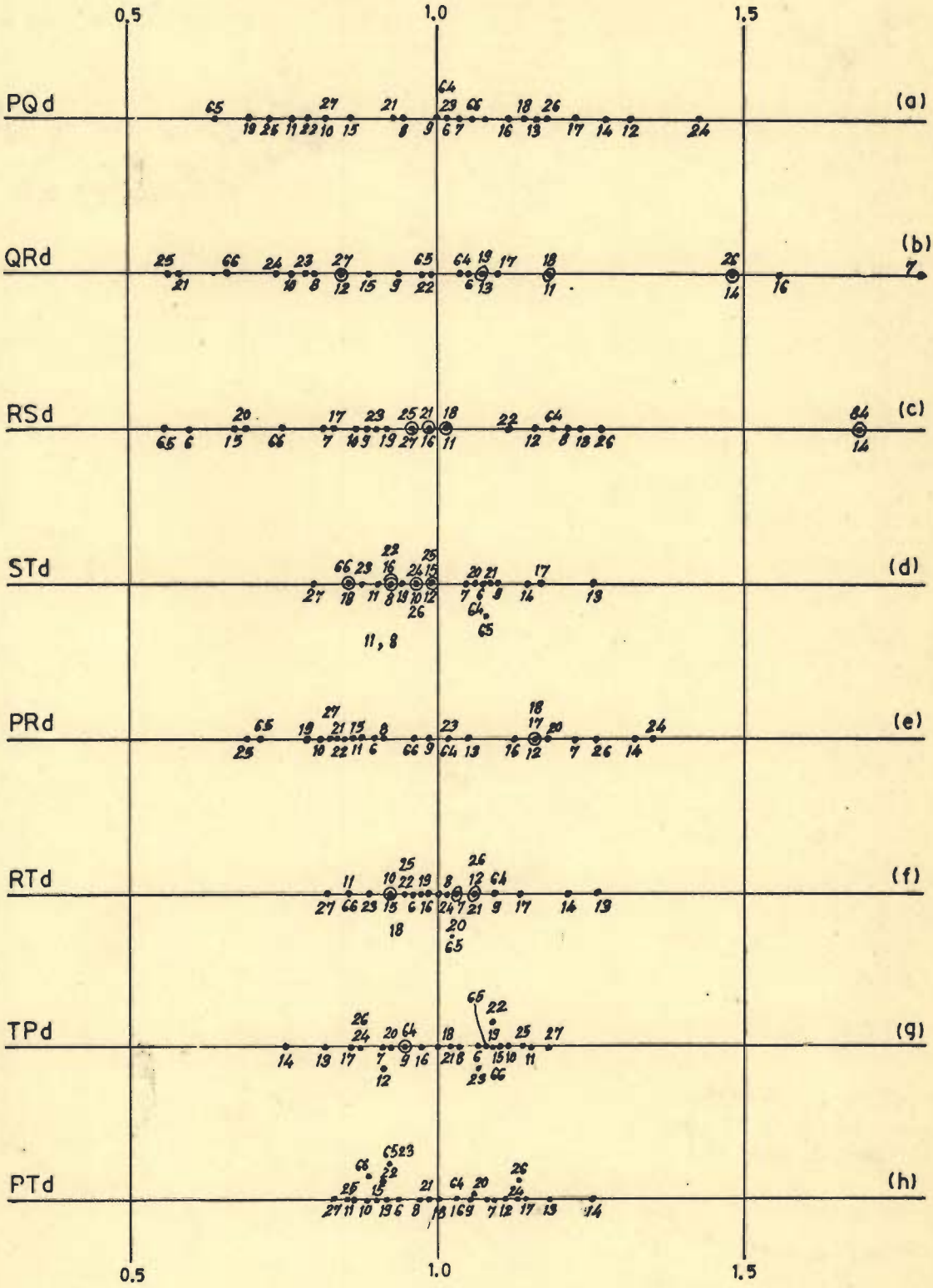
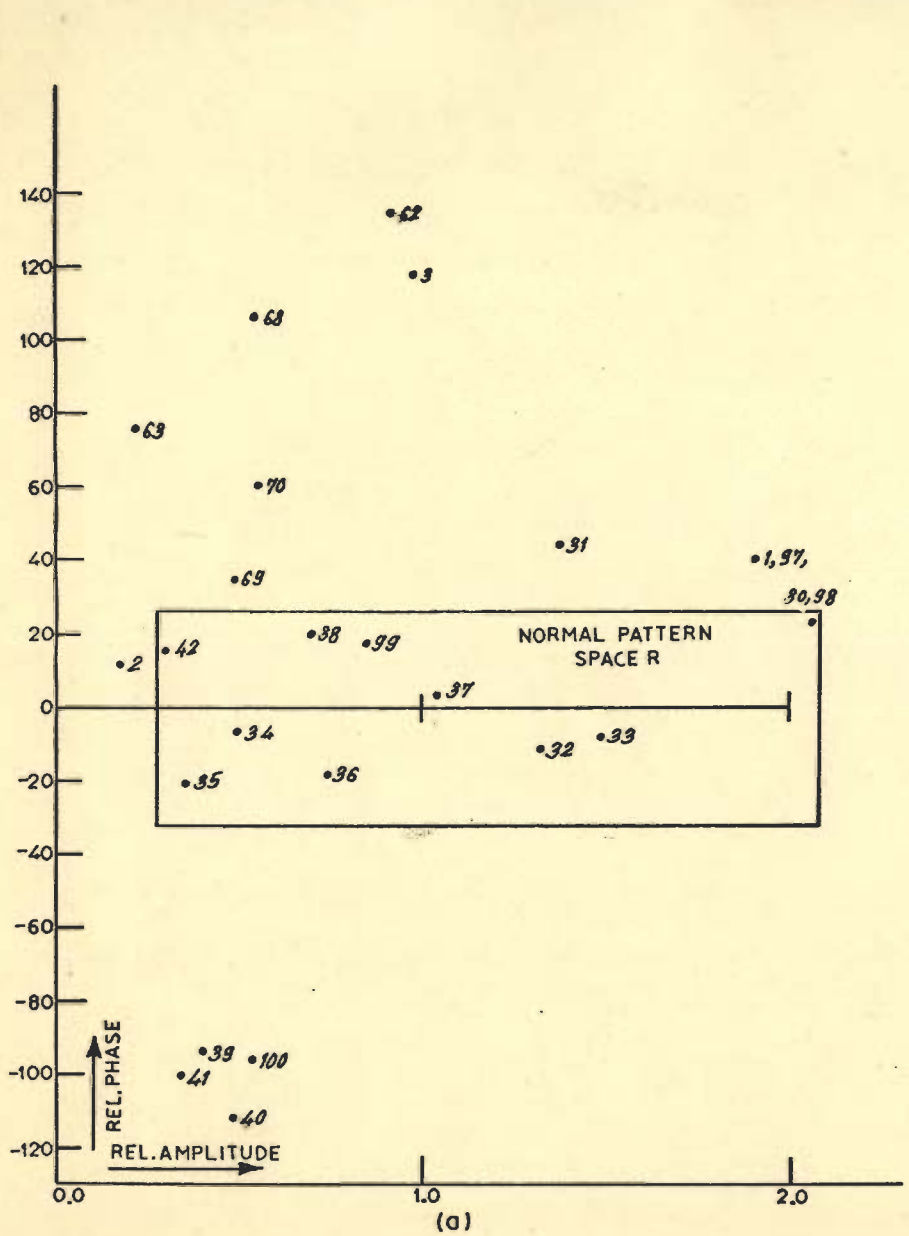


FIG.3.6(a-h). SEGMENT INTERVALS NORMAL CASES(RELATIVE)



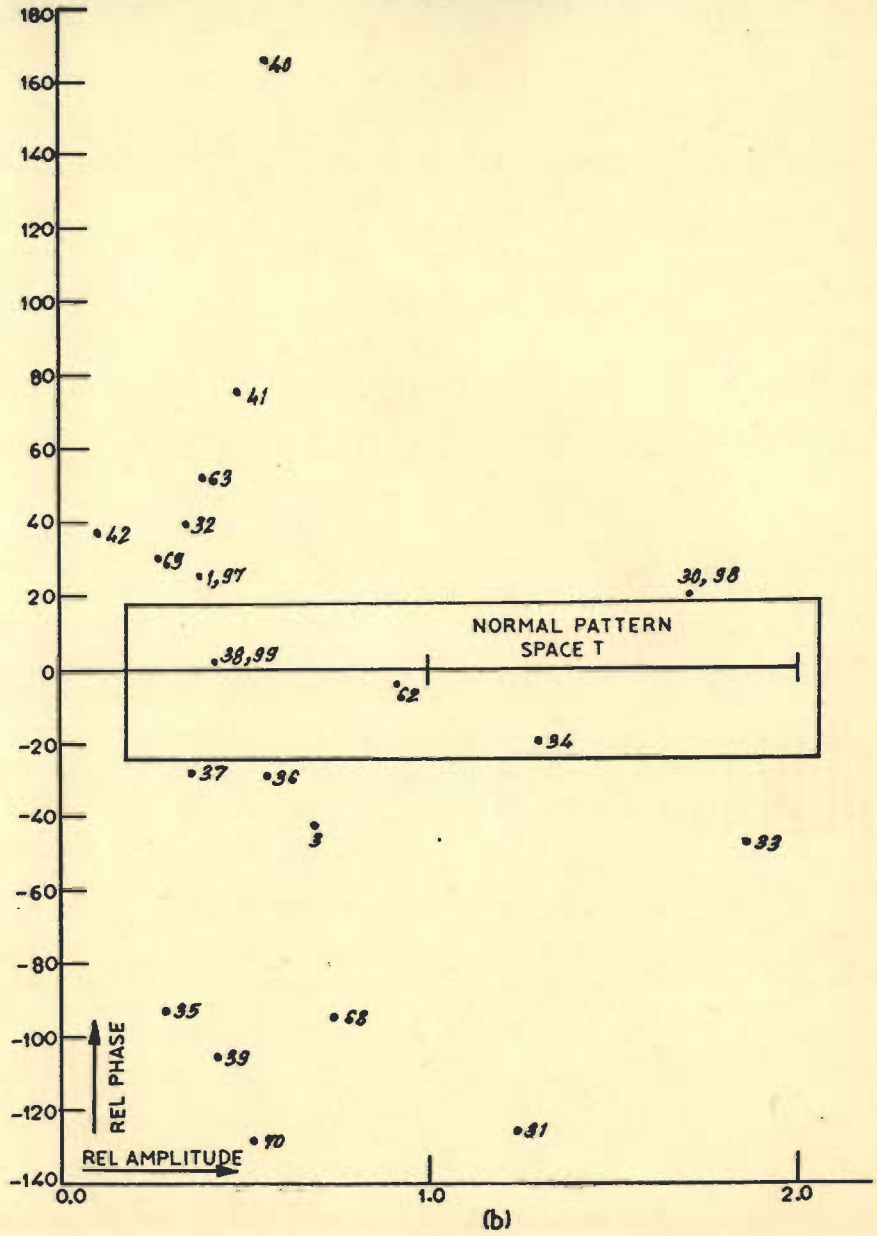


FIG. 3.7 (a, b). M I CASES

for the normal cases, the boundaries of the normal pattern spaces are drawn in these figures. The abnormal parameters are scattered away from the normal reference value (1,0). For a normal case, almost all the parameters are lying within the normal pattern space. For abnormal cases, the affected parameters are lying outside the normal pattern spaces and unaffected parameters are lying within the normal pattern spaces. Large number of parameters lying outside the normal pattern spaces for a case indicates degree of severity of abnormality.

3.4.3 Screening : Normals and Abnormals

Computer algorithms are developed for the classification of ECGs in to normal and abnormal categories. In the first method, actual values of 35 parameter set are considered. Actual values of maxima and minima are used to specify the normal range of variation for the normal parameters. (If arithmetic mean ± 2 times the standard deviation is used for the purpose, many normal cases are classified as abnormals). For all the cases being analysed, the parameters are converted to the binary form. Parameters within the normal range are specified by 0 and beyond the normal range by 1. The sum of these binary symptoms is carried out for each case. For the 25 normal cases, all the symptoms are 0. So the sum of binary symptoms is also zero. For abnormal cases, some symptoms are zero and others are 1. The sum of sumptoms is having some positive value. Higher positive value corresponds to severe abnormality. The results for all the cases are shown in Figure 3.8. The sum of binary symptoms and the case code numbers

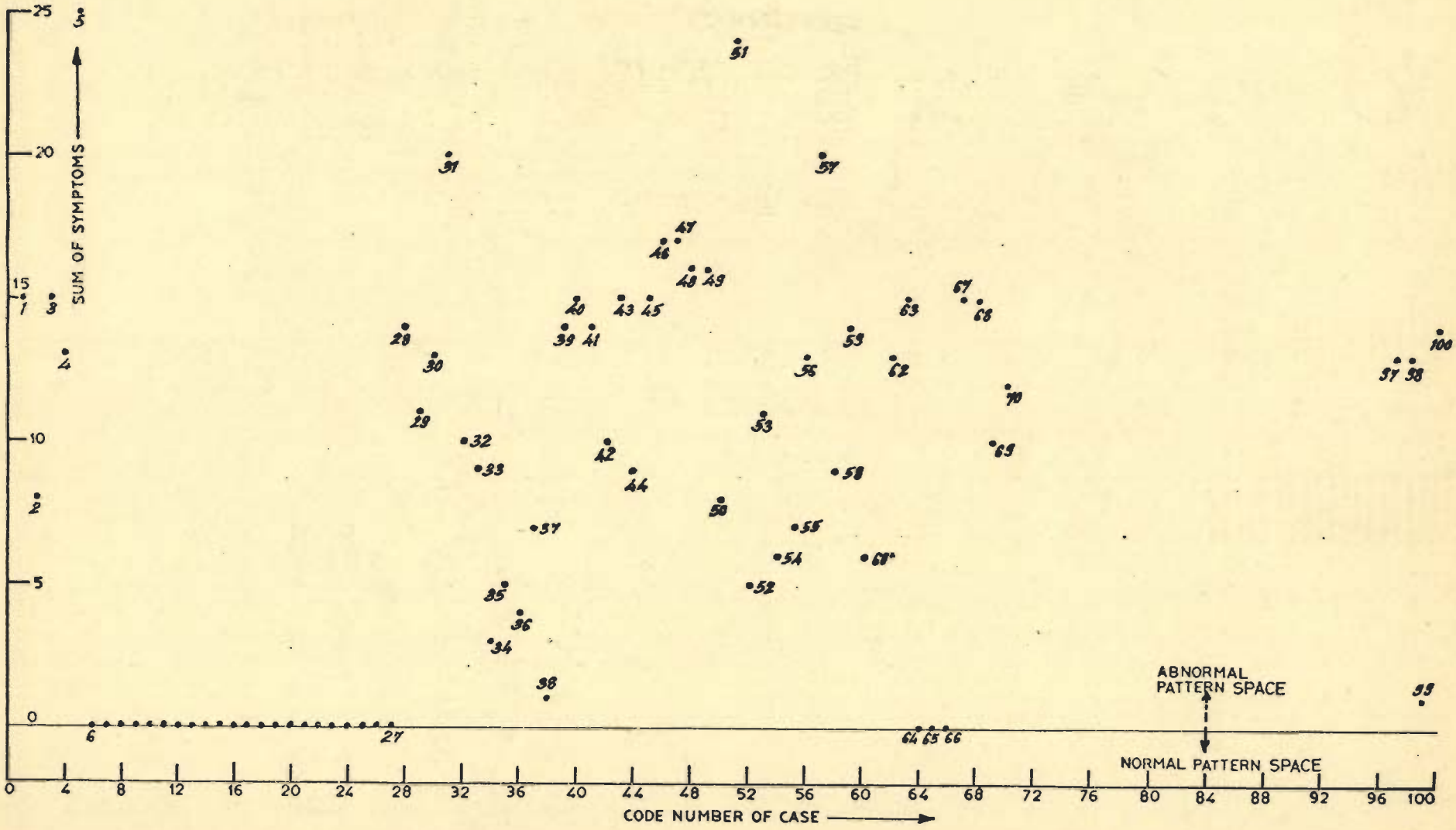


FIG. 3.8. SCREENING WITH ACTUAL VALUES

are taken along vertical and horizontal axes, respectively. Due to the sum being zero all the normal cases lie along the horizontal axis. All the abnormal cases lie above the horizontal axis. For some abnormal cases, the sum is very small. So in the pattern space the separating belt between normal and abnormal categories is very narrow. The threshold sum for classification in to abnormal category is to be set to a low value.

In the second method maxima and minima of relative values, $NMAX_j$ and $NMIN_j$, are used to specify the range. The relative values of parameters S_j for the various cases are converted to binary form (B_j) using the simple binary code. The sum of binary symptoms is computed. The results are plotted in Figure 3.9. The sum of binary symptoms and case code number are considered along vertical and horizontal axes respectively. In this case the grey area is increased. The threshold value for classification can be increased and misclassifications can be avoided. So the relative values are found more suitable for screening.

For screening of ECG patterns in to normals and abnormals, an algorithm 'SCRIN' is developed. The measured parameters for the case to be classified are converted to relative values. They are further converted to the binary code by comparison with the stored values of maxima and minima for the 35 parameters. A case to be classified is represented by a 35 bit binary pulse train. The sum of all the 35 bit values is carried out. If the sum is greater than or equal to specified threshold value, the case is classified as abnormal. If the sum is less than the threshold value, the case is classified as normal. For the abnormal case,

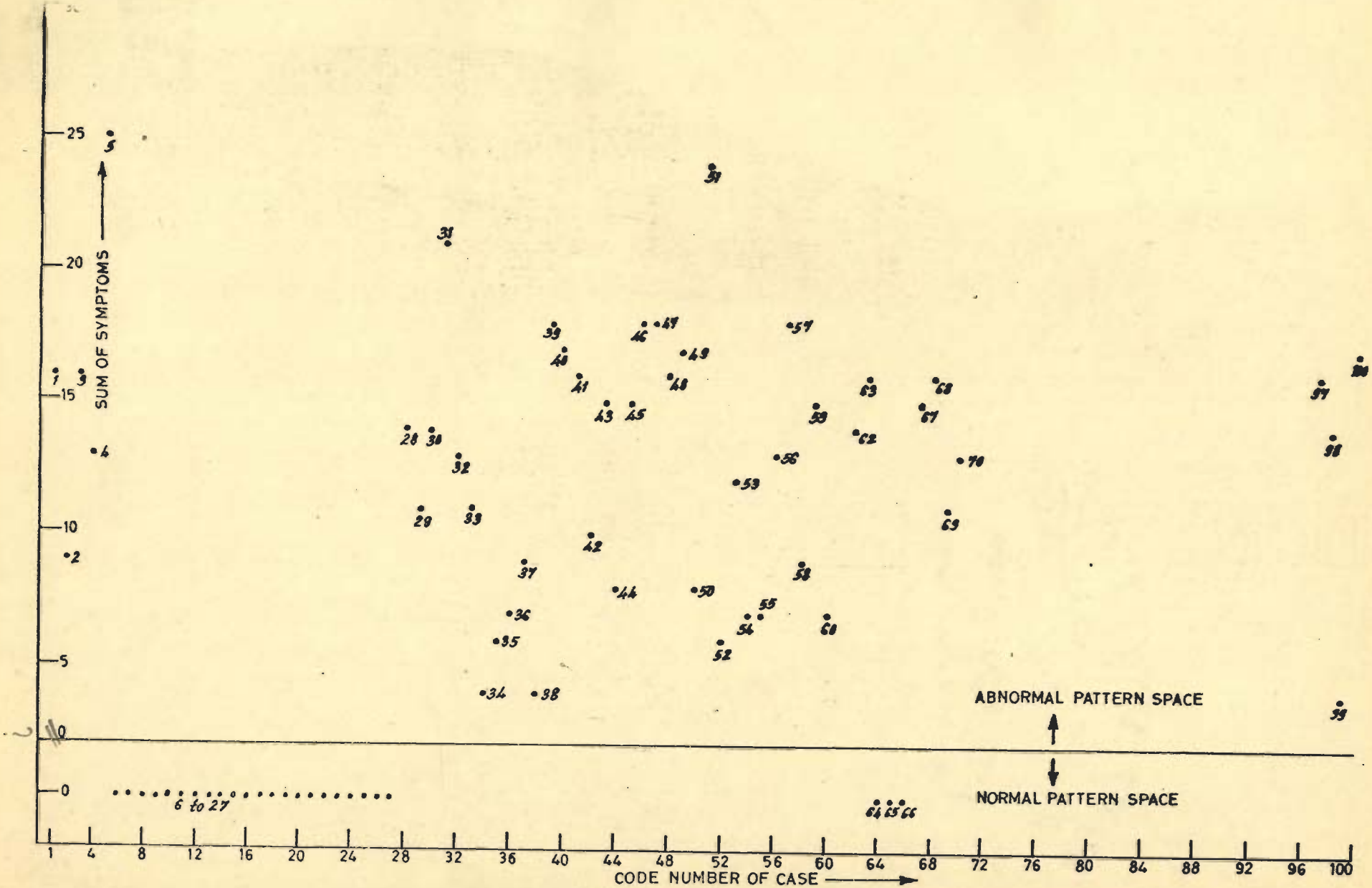


FIG.3.9. SCREENING WITH RELATIVE VALUES

abnormality index is equal to (sum of symptoms/35). This simple algorithm is sufficient for screening. A complex algorithm is developed for detailed classification.

3.5 DETAILED CLASSIFICATION

3.5.1 Composite Binary Code

A three state and two bit composite binary code is developed for detailed classification. The relative value of amplitude or duration or phase within normal range is represented by 11. The relative value above normal range for amplitude or duration and anticlockwise shift beyond the normal range for relative phase angle is represented by 10. The relative value below normal range for amplitude or duration and clockwise phase shift beyond the normal range for phase angle is represented by 01. From the 35 relative parameter values S_j for various cases, symptom patterns with 35 pairs of binary bits CB_j are generated. For all the 25 normal cases, all the 35 pairs of bits are 11.The composite binary pulse trains generated for the 29 cases of MI, 20 cases of RVH, and 20 cases of LVH are shown in Table T.3.1.

At first, pulse trains for 29 cases of MI are studied closely. For the jth symptom, if majority of the 29 cases of MI are having the value 10 and/or, if majority of the 40 cases of RVH and LVH are having the value 01, the jth symptom for MI is specified as 10. Similarly all the 35 symptoms are specified for MI, and a generalised symptom pattern consisting of 35 pairs of binary bits is specified for the category of MI. The same procedure is followed to specify symptom patterns for the

TABLE T.3.1 Symptoms in composite binary code

SYMPTOMS (1-35) $P, Q, R, S, T, ST, \alpha_p, \alpha_q, \alpha_r, \alpha_s, \alpha_t, \alpha_{st}, PQ_d, QR_d, RS_d, ST_d,$ $PR_d, RT_d, TP_d, PT_d, \hat{PR}, \hat{TR}, \hat{TP}, Q+R, Q-R, R+S, R-S, S+T, S-T,$ $\angle Q+R, \angle Q-R, \angle R+S, \angle R-S, \angle S+T, \angle S-T$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Case No.	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35					
1	10	11	11	11	01	10	10	11	10	10	10	01	10	11	01	11	10	11	11	11
	11	11	11	11	11	11	11	11	11	10	10	10	10	11	10					
2	11	11	01	11	01	10	11	11	11	11	11	01	11	11	11	11	11	11	11	11
	11	11	11	01	01	01	01	11	01	11	11	11	11	11	11					
3	11	11	11	11	11	10	10	01	10	11	01	10	11	11	10	01	11	11	11	11
	01	01	01	11	11	11	11	11	11	10	10	10	10	11	01					
30	01	11	11	10	11	10	01	11	11	10	10	01	11	11	11	11	01	11	11	11
	01	11	10	11	11	11	10	11	10	11	11	11	10	11	10					
31	10	10	11	11	11	10	11	10	10	11	01	10	10	10	10	01	11	11	11	11
	01	01	01	11	11	11	11	11	11	10	10	10	10	01	01					
32	11	10	11	11	01	10	11	11	11	11	10	10	10	11	11	01	10	01	11	11
	11	10	10	11	11	11	11	11	11	11	11	11	11	10	10					
33	11	10	11	10	11	10	01	11	11	10	01	01	11	11	11	11	11	11	10	01
	11	01	11	11	11	11	11	10	11	11	11	11	11	11	11					
34	11	11	11	11	11	10	11	11	11	11	11	01	11	11	11	11	11	11	11	11
	11	11	01	11	11	11	11	11	11	11	11	11	11	11	01					
35	11	11	11	11	01	11	11	11	11	11	01	11	11	11	11	11	11	11	11	11
	11	01	01	11	11	11	11	11	11	11	11	11	11	01	01					
36	11	11	11	11	01	10	10	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	11	01	11	11	11	11	11	11	11	11	11	11	11	11					
37	10	11	11	10	01	10	11	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	11	01	11	11	11	11	11	11	11	11	11	11	10	01					
38	11	11	11	11	01	10	11	11	11	11	11	10	11	11	11	11	10	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11					
39	11	11	11	10	01	10	11	11	01	11	01	10	11	11	11	11	10	11	01	10
	10	11	01	11	11	01	11	11	11	01	01	10	01	10	01					
40	11	11	11	11	01	11	11	11	01	11	10	11	10	11	10	11	10	11	01	10
	10	01	10	11	11	11	11	11	11	01	01	01	01	10	10					

Contd...

(Table T.3.1 contd...)

Case No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35					
41	11	11	11	11	01	10	11	11	01	11	10	01	11	11	11	10	11	10	11	11
	10	01	10	11	11	11	11	11	11	01	01	01	01	10	10					
42	11	10	11	11	01	11	11	11	11	11	10	11	11	01	11	11	11	11	11	11
	11	11	10	11	11	11	11	11	11	10	11	10	11	10	01					
62	11	11	11	11	11	10	11	11	10	11	11	10	11	11	10	10	11	10	01	10
	01	01	11	11	11	11	11	11	11	10	10	10	10	11	11					
63	11	11	01	11	01	11	11	11	10	10	10	11	11	11	11	11	11	11	11	11
	01	11	10	01	01	01	01	11	11	10	10	10	10	11	11					
68	11	11	11	11	11	11	10	01	10	11	01	11	11	11	11	11	11	01	10	01
	01	10	01	11	11	11	11	11	11	10	10	10	10	01	01					
69	11	11	11	10	01	11	11	11	10	11	10	11	11	11	11	11	11	11	11	11
	11	11	11	11	11	01	11	11	11	10	10	10	10	01	10					
70	11	11	11	11	01	11	10	10	10	11	01	11	11	11	11	11	11	11	11	11
	11	10	01	11	11	11	11	11	11	10	10	10	10	01	01					
97	10	11	11	11	01	10	10	11	10	10	10	01	10	11	01	11	10	11	11	11
	11	11	11	11	11	11	11	11	11	10	10	10	10	11	10					
98	01	11	11	10	11	10	01	11	11	10	10	01	11	11	11	11	01	11	11	11
	01	11	10	11	11	11	10	11	10	11	11	11	10	11	10					
99	11	11	11	11	01	10	11	11	11	11	11	10	11	11	11	11	10	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11					
100	11	11	11	10	01	10	11	11	01	11	01	10	11	11	11	11	10	11	01	10
	10	11	10	11	11	01	11	11	11	01	01	10	01	10	01					
74	11	11	11	11	01	11	11	11	01	11	10	11	11	11	11	11	10	11	01	10
	10	10	10	11	11	11	11	11	11	01	01	01	01	11	10					
79	10	10	11	10	01	10	11	11	11	11	11	10	11	11	11	10	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	10	01					
80	11	11	11	11	01	11	11	11	01	11	01	11	11	11	11	11	11	11	11	11
	10	01	01	11	11	01	11	11	11	01	01	01	01	01	01					
75	11	10	11	11	01	10	11	11	11	11	10	10	10	11	11	01	10	01	11	11
	11	10	10	11	11	11	11	11	11	11	11	11	11	10	10					

Contd....

(Table T.3.1 contd...)

Case No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35					
43	11	10	11	11	11	11	11	01	01	11	01	11	11	11	11	10	11	10	11	11
	10	10	01	11	11	11	11	11	11	01	01	01	01	01	01					
44	10	10	11	10	11	11	11	11	11	11	11	11	11	11	01	10	11	11	11	11
	11	11	11	11	11	11	10	11	10	11	11	11	11	10	11					
45	11	10	11	10	11	10	11	11	11	11	11	10	11	11	10	10	11	10	01	10
	11	10	11	11	10	11	10	11	10	11	01	01	11	01	11					
46	10	11	11	11	01	11	01	01	01	11	01	11	10	11	11	10	10	10	01	10
	10	10	11	11	11	11	11	11	11	01	01	01	01	11	11					
47	11	11	10	11	11	11	11	01	01	11	11	11	10	11	11	11	10	10	01	10
	11	10	11	10	10	10	10	11	11	01	01	01	01	11	11					
48	11	10	10	10	11	10	11	01	01	11	11	10	11	11	11	11	11	11	11	11
	11	10	11	11	10	10	10	11	10	01	01	01	01	11	11					
49	11	11	11	11	11	10	10	01	01	11	10	10	11	11	11	01	10	01	11	11
	01	01	11	11	11	11	11	11	01	01	01	01	01	10	10					
50	10	11	11	11	11	11	01	11	01	11	11	11	11	11	11	11	11	11	11	11
	11	10	11	11	11	11	11	11	11	01	01	01	01	11	11					
51	10	10	10	10	10	10	11	01	01	11	10	10	11	11	11	11	11	11	11	11
	10	01	10	10	10	10	10	10	10	01	01	01	01	10	10					
28	11	11	11	11	11	10	11	01	01	11	10	10	10	11	11	11	10	11	11	11
	10	10	10	11	11	11	11	11	11	01	01	01	01	11	10					
29	10	10	11	11	11	10	11	01	01	11	11	10	11	11	11	11	11	11	11	11
	10	10	11	11	11	11	11	11	11	01	01	01	01	11	11					
67	10	11	10	11	11	11	11	11	01	11	10	11	11	11	11	11	11	11	11	11
	10	10	11	10	10	10	10	11	11	01	01	01	01	11	10					
88	01	11	11	10	01	11	01	11	01	11	01	11	11	11	11	11	11	11	11	11
	10	10	11	11	11	11	11	11	11	01	01	01	01	10	11					
89	10	11	10	11	11	11	11	11	01	11	10	11	11	11	11	11	11	11	11	11
	10	10	11	10	10	10	10	11	11	01	01	01	01	11	10					
90	10	11	11	11	01	11	11	01	01	11	10	11	10	11	11	10	11	11	11	11
	10	10	10	11	11	11	11	11	11	01	01	01	01	10	10					

Contd...

(Table T.3.1 contd...)

Case No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35					
91	10	11	11	10	11	11	11	11	01	11	11	11	11	10	11	10	11	10	01	10
	10	11	11	11	11	11	11	11	11	01	01	01	11	10	11					
71	11	10	11	10	11	10	11	11	11	11	11	10	11	11	10	10	11	10	01	10
	11	10	11	11	10	11	10	11	10	11	11	01	11	01	11					
77	11	10	11	11	11	11	11	01	01	11	01	11	11	11	11	10	11	10	11	11
	10	10	01	11	11	11	11	11	11	01	01	01	01	01	01					
78	11	11	10	11	11	11	11	01	01	11	11	11	10	11	11	11	10	10	01	10
	10	10	11	10	10	10	10	11	11	01	01	01	01	11	11					
81	11	10	10	10	11	10	11	01	01	11	11	10	11	11	11	11	11	11	11	11
	10	10	11	11	10	10	10	11	10	01	01	01	01	11	11					
4	11	10	11	11	11	11	11	10	10	11	01	11	11	11	11	11	11	11	11	11
	01	10	01	11	11	11	11	11	11	10	10	10	10	01	01					
5	10	11	10	11	11	10	10	01	10	10	01	01	10	10	11	11	10	01	11	11
	01	10	01	10	10	10	10	11	11	10	10	10	10	01	01					
52	10	10	11	11	11	10	11	11	11	11	11	10	11	11	11	11	11	11	11	11
	11	11	11	11	10	10	11	10	11	11	11	11	11	11	11					
53	11	11	10	11	01	11	11	11	11	11	10	11	11	11	11	11	11	11	11	11
	11	10	10	10	10	10	10	11	01	11	11	11	11	10	01					
54	11	11	10	11	11	11	11	11	11	11	10	11	11	11	11	11	11	11	11	11
	11	11	11	10	10	10	10	11	11	11	11	11	11	11	10					
55	11	11	10	11	11	11	10	10	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	10	10	10	10	11	11	11	11	11	11	11	11					
56	10	11	10	11	11	10	11	11	11	11	01	10	11	11	11	11	11	01	11	11
	11	01	01	10	10	10	10	11	11	11	11	11	11	01	01					
57	11	10	10	10	11	10	11	10	11	10	10	10	10	11	11	01	10	01	11	11
	11	10	10	10	10	10	10	10	11	11	11	11	11	01	10					
58	11	11	11	10	11	10	11	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	01	01	11	11	11	11	11	10	11	11	10	11	10	01					
59	10	11	10	11	11	10	01	11	11	11	10	10	11	11	11	11	11	11	11	11
	11	10	01	10	10	10	10	10	11	11	11	11	11	10	10					

Contd...

(Table T.3.1 contd...)

Case No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35					
60	11	11	11	11	01	10	11	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	01	01	11	11	11	11	11	11	11	11	11	11	10	01					
73	10	11	10	11	01	11	11	11	11	11	11	11	11	11	11	11	10	11	11	11
	11	11	11	10	10	10	10	11	01	11	11	11	11	11	11					
76	11	11	10	11	11	11	11	11	10	10	01	11	11	11	11	11	11	11	11	11
	11	10	01	10	10	10	10	11	11	11	11	11	10	01	01					
82	11	11	11	11	01	11	10	11	11	11	01	11	11	11	11	11	10	11	11	11
	10	11	01	11	11	11	11	11	01	11	11	11	11	11	01					
83	11	11	11	11	11	11	11	11	11	11	10	11	10	11	11	11	10	11	11	11
	11	01	10	11	11	11	11	11	11	11	11	11	11	10	10					
84	10	11	10	10	10	10	11	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	01	01	10	10	10	10	10	10	11	11	11	11	10	01					
85	11	11	10	11	11	11	11	11	11	11	01	11	11	11	11	10	11	11	11	11
	11	01	01	10	10	10	10	11	11	11	11	11	11	01	01					
86	11	10	10	11	10	11	10	01	01	11	10	11	10	11	11	11	10	11	01	10
	10	10	11	10	10	10	10	10	10	11	01	01	01	11	10					
87	11	11	10	11	11	11	11	11	11	11	01	11	11	11	11	11	10	11	11	11
	11	01	01	10	10	10	10	11	11	11	11	11	11	01	01					
72	11	11	11	11	01	10	11	11	11	11	01	10	11	11	11	11	11	11	11	11
	11	01	01	11	11	11	11	11	11	11	11	11	11	10	01					

categories of RVH and LVH. These symptom patterns are established just by observation. So it is necessary to check the validity of the symptom patterns. At the same time, all the 35 symptoms may not be significant for all the categories. Moreover, a symptom may be common to more than one category, but the assigned weights may be different with respect to different categories. If the symptom is wrongly specified, (e.g. 10 instead of 01) the weight may be negative. For nonsignificant symptom, the weight may be zero or very small. So, it is very essential to find the weight factors for all the 35 symptoms for all the 3 categories which can establish proper discrimination among the cases of different categories.

3.5.2 Training Phase of Interpretation Algorithm

A training phase is used in the analysis of ECG to arrive at the function required for the discrimination among various categories and to estimate the values of coefficients or weight factors associated with each symptom corresponding to different categories. For discrimination among the cases of different categories, weighted sum of symptoms is considered. For the weighted sum of symptoms, presence or absence of a symptom of the specified type is indicated by a symptom multiplier, whose value may be 1, 0 or -1. Presence of a symptom of a specified type is indicated by 1, absence by 0, and presence of symptom of opposite nature by -1. The logic for symptom multipliers is as shown in Table T.3.2.

TABLE T.3.2

LOGIC FOR SYMPTOM MULTIPLIERS

Sr. No.	1	2	3	4	5	6	7	8	9
Specified Symptom $SS_{j,k}$	11	11	11	10	10	10	01	01	01
Actual Symptom CB_j	11	01	10	10	01	11	01	10	11
Symptom Multiplier	1	0	0	1	-1	0	1	-1	0

The following expressions are considered to establish the discrimination among the training cases of different abnormal categories.

$$YM(I) = \sum_{j=1}^{N} WM(J).MM(I,J) \qquad \ldots (3.15)$$

$$YR(I) = \sum_{j=1}^{N} WR(J).MR(I,J) \qquad \ldots (3.16)$$

$$YL(I) = \sum_{j=1}^{N} WL(J).ML(I,J) \qquad \ldots (3.17)$$

where,

I and J are case and symptom numbers, YM,YR,YL are weighted sums of symptoms with respect to MI,RVH,LVH,

WM,WR,WL are weight factors assigned to different symptoms with respect to MI,RVH and LVH,

MM(I,J), MR(I,J), ML(I,J)are symptom multipliers associated with jth symptom of ith case with respect to MI,RVH,LVH.

Positive value of the weighted sum of symptoms with respect to a category indicates the presence of symptoms of that disease. The negative or zero value indicates absence of symptoms of that category. For the development of the method, well diagnosed 29 cases of MI, 20 cases of RVH and 20 cases of LVH are analysed. For 29 cases of MI, YM(I) should be greater than specified positive threshold value AMIT. For 40 cases of RVH and LVH (non MI), YM(I) should be less than specified negative threshold value (-AMIT). The datafile of training cases is arranged to have first 29 cases of MI, next 20 cases of RVH and next 20 cases of LVH. The following conditions are to be satisfied.

$$YM(I) = \sum_{j=1}^{N} WM(J).MM(I,J) \geq + AMIT \text{ for } I = 1,29 \qquad \ldots (3.18)$$

$$YM(I) = \sum_{j=1}^{N} WM(J).MM(I,J) \leq - AMIT \text{ for } I = 30,69 \qquad \ldots (3.19)$$

These conditions can be satisfied by proper values of weight factors WM(J). For the estimation of weight factors linear programming technique seems more suitable. For the discrimination of MI and non MI cases, the problem can be formulated as follows.

$$(((\sum_{j=1}^{N} WM(J).MM(I,J) \geq AMIT),\ J=1,35),\ I=1,29) \qquad \ldots (3.20)$$

$$(((\sum_{j=1}^{N} WM(J).MM(I,J) \leq -AMIT),\ J=1,35),\ I=30,69) \qquad \ldots (3.21)$$

These constraints can also be expressed as

$$((-AMIT + \sum_{j=1}^{35} MM(I,J).WM(J) \geq 0),\ I=1,29) \qquad \ldots (3.22)$$

$$((-AMIT - \sum_{j=1}^{35} MM(I,J).WM(J) \geq 0),\ I=30,69) \qquad \ldots (3.23)$$

To minimise misclassifications, the sum of weighted sum of symptoms for 29 cases of MI

- sum of weighted sum of symptoms for 40 non MI cases should be minimised without violating the above constraints.

The objective function becomes

Minimise,

$$\sum_{j=1}^{35} \left(\sum_{I=1}^{29} MM(I,J) - \sum_{I=30}^{69} MM(I,J) \right).WM(J) \qquad \ldots (3.24)$$

As all the constraints are inequalities and all coefficients of the objective function tobe minimised are nonnegative,Dual simplex method is more suitable. It can also account for degenracies [120]. For the Dual Simplex method, the problem is formulated as follows: Minimise the objective function

$$\sum_{j=1}^{35} \left(\sum_{I=1}^{29} MM(I,J) - \sum_{I=30}^{69} MM(I,J) \right).WM(J) \qquad \ldots (3.25)$$

Subject to the constraints

$$\left((-AMIT + \sum_{J=1}^{35} MM(I,J).WM(J) \geq 0),\ I=1,29\right) \qquad \ldots (3.26)$$

$$\left((-AMIT - \sum_{J=1}^{35} MM(I,J).WM(J) \geq 0),\ I=30,69\right) \qquad \ldots (3.27)$$

Here 35 weight factors WM(J) are to be estimated which will minimise the objective function and satisfy the 69 constraints. In the Dual simplex method, there is one limitation. The coefficients (weight factors) of the constraint expressions and objective functions to be estimated should be nonnegative. The actual weight factors to be evaluated here may be positive, negative or

even zero. Because, the symptom pattern for the category is generalised just by observation of symptom patterns for the training cases without bias for any medical criteria. Due to this reason, when the attempt was made to find the weight factors with the above formulation it led to 'no feasible' solution. So the problem is modified further. Individual weight factor is taken as a difference of two positive values of weight factors. Depending on the magnitudes of the two, the net value may be positive, negative or zero. The problem is reformulated as follows:

Minimise the objective function

$$\sum_{J=1}^{35}\left(\sum_{I=1}^{29} MM(I,J) - \sum_{I=30}^{69} MM(I,J)\right).WM(J)) - \sum_{j=36}^{70}\left(\sum_{I=1}^{29} MM(I,J) - \sum_{I=30}^{69} MM(I,J)\right).WM(J)) \quad \ldots (3.28)$$

Subject to constraints

$$\left(-AMIT+\left(\sum_{J=1}^{35}(MM(I,J).WM(J)\right)-\left(\sum_{j=36}^{70}(MM(I,J).WM(J))\right)\geq 0\right), I=1,29) \quad \ldots (3.29)$$

$$\left(-AMIT-\left(\sum_{J=1}^{35}(MM(I,J).WM(J)\right)-\left(\sum_{J=36}^{70}(MM(I,J).WM(J))\right)\geq 0\right), I=30,69) \quad \ldots (3.30)$$

Now, 70 weight factors are to be estimated which will minimise the objective function, subject to 69 constraints. The effective values of weight factors are given by

$$(W(J) = (WM(J) - WM(J+35)),\ J = 1,35) \quad \ldots (3.31)$$

e.g. W(1) = WM(1) - WM(36), and so on.

Here all WM(J) are positive and still W(J) can have positive, negative or zero values. This approach led to feasible solution of weight-factors for the 35 symptoms by the Dual simplex method of linear programming. The estimated values of weight factors are further checked by computing the weighted sum of symptoms with respect to MI. For all the cases of MI, the weighted sum of symptoms is found to be greater than the positive threshold value. For all the non MI cases, the weighted sum of symptoms is found to be less than the negative threshold value. Thus 100 % sensitivity and 100 % specificity are achieved for the 69 training cases.

For RVH,

$$YR(I) = \sum_{J=1}^{N} WR(J).MR(I,J) \geq + RVHT \text{ for } I = 30 \text{ to } 49 \qquad \ldots (3.32)$$

and

$$YR(I) = \sum_{J=1}^{N} WR(J).MR(I,J) \leq - RVHT \text{ for } I = 1, 29 \text{ and } 50 \text{ to } 69 \qquad \ldots (3.33)$$

The problem is formulated as follows.

Minimise the objective function

$$\sum_{J=1}^{35} \left(\sum_{I=30}^{49} MR(I,J) - \sum_{I=1}^{29} MR(I,J) - \sum_{I=50}^{69} MR(I,J) \right).WR(J)$$

$$- \sum_{J=36}^{70} \left(\sum_{I=30}^{49} MR(I,J) - \sum_{I=1}^{29} MR(I,J) - \sum_{I=50}^{69} MR(I,J) \right).WR(J) \qquad \ldots (3.34)$$

Subject to constraints

$$\left(-RVHT + \left(\sum_{J=1}^{35} (MR(I,J).WR(J)) - \left(\sum_{J=36}^{70} (MR(I,J).WR(J)) \right) \geq 0 \right), I = 30, 49 \right) \qquad \ldots (3.35)$$

$$(-RVHT-(\sum_{J=1}^{35}(MR(I,J).WR(J)-(\sum_{J=36}^{70}(MR(I,J).WR(J)))\geq 0),I=1,29;50,69) \quad \ldots (3.36)$$

For LVH,

$$YL(I) = \sum_{J=1}^{N} WL(J).ML(I,J)\geq + LVHT \text{ for } I = 50,69 \quad \ldots (3.37)$$

$$YL(I) = \sum_{J=1}^{N} WL(J).ML(I,J)\leq - LVHT \text{ for } I = 1,49 \quad \ldots (3.38)$$

The problem is formulated as follows.

Minimise the objective function

$$\sum_{J=1}^{35}(\sum_{I=50}^{69} ML(I,J) - \sum_{I=1}^{49} ML(I,J)).WL(J)$$

$$-\sum_{J=36}^{70}(\sum_{I=50}^{69} ML(I,J) - \sum_{I=1}^{49} ML(I,J)).WL(J) \quad \ldots (3.39)$$

Subject to constraints

$$(-LVHT + (\sum_{J=1}^{35}(ML(I,J).WL(J))-(\sum_{J=36}^{70}(ML(I,J).WL(J)))\geq 0),I=50,69) \quad \ldots (3.40)$$

$$(-LVHT - (\sum_{J=1}^{35}(ML(I,J).WL(J)-(\sum_{J=36}^{70}(ML(I,J).WL(J)))\geq 0),I=1,49 \quad \ldots (3.41)$$

For RVH and LVH also, 70 coefficients and 35 weight factors are estimated. Using the estimated values of weight factors, weighted sums of symptoms are found with respect to RVH and LVH. For both of them, 100 % sensitivity and 100 % specificity are achieved for the 69 training cases. In training phase, the number of cases is to be limited. During the actual application, the weight factors can be updated by including more and more typical cases of respective category covering the whole range of severity of the disease.

3.5.3 Classification Phase of the Algorithm

The procedure for the classification of an unknown case is as follows. The peak segment amplitudes at lead I,II and III; and peak to peak segment intervals are measured. FPR vectors are computed. The computed parameters are converted to relative values. By comparison with the stored upper and lower limits for relative values of various parameters, composite binary symptom pattern is derived for this case. It is to be decided, whether the case under consideration is normal or abnormal on the basis of this symptom pattern. If the case is completely normal, all the 35 pairs of bits in the symptom pattern would be 11. If the sum of 70 bits is carried out, it would be 70 in the ideal case. If all the 35 symptoms are abnormal, some of the 35 bits would be 10 and some would be 01. In the extreme case, the sum would be 35. The actual sum would be between 35 and 70. The lower extreme corresponds to most severely abnormal case and upper extreme corresponds to ideal normal. The abnormality index can be specified as

$$(\text{sum of 70 bits} - 35)/35.$$

To provide grey area between normals and abnormals, some threshold value can be specified. Abnormality index $\geq$ threshold is used to specify the case as abnormal. If the abnormality index is less than the threshold, the case is classified as normal and classification algorithm is terminated.

For abnormal case, the procedure is continued for detailed classification. Now weighted sum Y(k) is computed for the same case with respect to different categories.

((Y(k) = W(J,K).MM(J,K), J = 1,35), K = 2,4) ... (3.42)

Here, J the symptom number and K is the category. Categories 1,2,3 and 4 are normal, MI,RVH and LVH. W(J,K) specifies the 35 weight factors for the 3 abnormal categories. The weight factors found during the training phase are permanently stored and used as required. By comparison of the actual symptem pattern of the unknown case with the specified symptom patterns for the three abnormal categories, three sets of 35 symptom multipliers are found. They are used to find weighted sums of symptoms with respect to the three categories.

If only Y(2) is positive, the case is classified as MI. If only Y(3) or Y(4) is positive, the case is classified as RVH or LVH, respectively. For more than two sums positive symptoms of two diseases may be present. If none of the sums is positive, some miscellaneous disease may be suspected. For the indication of complex and miscellaneous diseases, additional tests are recommended. If two sums are positive, but one is much larger than the other one, the class with higher sum is considered predominant and the case is classified accordingly.

During training phase, four sets of cases were formed corresponding to one normal and three abnormal categories. As the available data is limited, therefore, for testing of the program, all the 94 cases corresponding to the four categories are mixed up to reshuffle their sequence. From this mixed group normals and abnormals were separated successfully by the program. For detailed classification of the abnormal cases weighted sums

of symptoms of individual cases with respect to three abnormal categories were carried out. The results are as shown in Table T.3.3. The classification on the basis of maximum positive sum is indicated in the last column. It is observed from the table that each of the case is having positive sum only for the category to which it belongs. For the other categories the sum is negative. So all the 94 cases are correctly classified and well discriminated from the other categories.

3.6 MICROPROCESSOR BASED ANALYSIS OF ELECTROCARDIOGRAM

The current research trends in this area are towards the development of new methods for increasing the accuracy of ECG interpretation. At the same time, the quest for new, reliable, reasonably accurate, compact, portable and low cost instrumentation for ECG processing continues. Presently, work in the first direction is carried out on main frame computers and in the second direction using microprocessor based systems.

The cost of microprocessor is going down rapidly. It is reported that a microprocessor with a built in A/D converter costs less than 150 $ [221]. Microprocessor based units are flexible and can be made available at desired locations in the hospitals. The external interference and additional cost inherent in telemetering system are eliminated in bedside signal processing using microprocessor based system. The microprocessor can not compete with the speed and numerical accuracy of main frame computer, but has reasonable accuracy and sufficient capability to cope up with the daily ECG load of a hospital without much sacrifice of

TABLE T.3.3

RESULTS OF DETAILED CLASSIFICATION

Case code no.	WEIGHTED SUM w.r.t.			Classification	Actual category
	MI	RVH	LVH		
1	2	3	4	5	6
1	10.00	-25.00	-31.39	MI	MI
2	109.13	-10.00	-11.98	MI	MI
3	9.83	-13.64	-32.02	MI	MI
4	-14.54	-35.60	9.88	LVH	LVH
5	- 9.95	-11.44	9.85	LVH	LVH
28	-13.06	30.57	-22.95	RVH	RVH
29	-22.49	15.57	-32.22	RVH	RVH
30	10.02	- 9.99	-10.02	MI	MI
31	9.81	-10.03	-10.13	MI	MI
32	10.02	-10.00	- 9.96	MI	MI
33	9.98	- 9.98	- 9.94	MI	MI
34	14.89	-12.25	- 9.96	MI	MI
35	10.02	-15.82	- 9.93	MI	MI
36	9.99	-20.69	- 9.88	MI	MI
37	10.01	-10.02	-60.73	MI	MI
38	15.28	-10.00	- 9.99	MI	MI
39	10.12	-10.03	-32.07	MI	MI
40	10.11	-10.00	-32.83	MI	MI
41	10.16	- 9.97	-21.44	MI	MI
42	9.99	-10.00	-10.00	MI	MI
43	-9.92	10.02	- 9.82	RVH	RVH

Contd....

(Table T.3.3 contd...)

1	2	3	4	5	6
44	-9.94	10.02	-36.39	RVH	RVH
45	-9.92	9.99	-15.21	RVH	RVH
46	-9.75	9.98	-101.96	RVH	RVH
47	-29.64	10.00	- 9.72	RVH	RVH
48	-62.80	10.03	- 9.65	RVH	RVH
49	-29.43	10.03	- 9.85	RVH	RVH
50	- 9.90	19.59	-59.08	RVH	RVH
51	-50.06	+10.04	- 9.71	RVH	RVH
52	-97.37	-17.23	10.18	LVH	LVH
53	-55.29	-10.00	78.24	LVH	LVH
54	-10.55	- 9.99	10.14	LVH	LVH
55	-27.26	-30.03	10.10	LVH	LVH
56	-14.3	- 9.99	10.12	LVH	LVH
57	- 9.92	-14.95	10.07	LVH	LVH
58	-41.72	-10.00	15.89	LVH	LVH
59	- 9.86	-10.01	33.84	LVH	LVH
60	- 9.98	-18.67	10.09	LVH	LVH
62	9.84	-34.12	-10.08	MI	MI
63	66.56	-22.97	-10.22	MI	MI
67	- 9.70	10.03	-35.93	RVH	RVH
68	9.87	- 9.99	-10.18	MI	MI
69	49.62	-29.70	-45.88	MI	MI
70	19.64	-41.99	-14.98	MI	MI
71	-57.02	12.34	- 9.82	RVH	RVH

Contd.....

(Table T.3.3 contd...)

1	2	3	4	5	6
72	-9.98	-18.67	10.09	LVH	LVH
73	-37.15	-10.00	10.21	LVH	LVH
74	10.14	-10.01	-57.41	MI	MI
75	10.02	-10.00	- 9.96	MI	MI
76	- 9.85	-42.69	106.90	LVH	LVH
77	- 9.92	10.02	- 9.82	RVH	RVH
78	-37.10	10.51	- 9.72	RVH	RVH
79	18.35	-24.2	-54.34	MI	MI
80	10.13	- 9.98	-9.82	MI	MI
81	-70.26	10.55	-9.65	RVH	RVH
82	- 9.97	-20.14	10.14	LVH	LVH
83	- 9.96	- 9.99	10.02	LVH	LVH
84	-35.28	-27.15	51.32	LVH	LVH
85	-17.54	-18.62	10.10	LVH	LVH
86	- 9.81	- 9.98	10.30	LVH	LVH
87	- 9.82	-12.39	24.25	LVH	LVH
88	- 9.90	10.01	-62.15	RVH	RVH
89	- 9.70	10.03	-35.93	RVH	RVH
90	-19.77	10.02	-70.12	RVH	RVH
91	-10.05	9.97	-218.78	RVH	RVH
97	10.00	-25.06	-31.39	MI	MI
98	10.0|	- 9.90	-10.02	MI	MI
99	15.28	-10.00	- 9.90	MI	MI
100	10.12	-10.03	- 9.87	MI	MI

accuracy of classification. Macfarlane and Pipberger have shown that various ECG interpretation programs could be implemented on minicomputers. If the same is made true for microcomputers, benifits of unit dedication can be achieved [121]. Use of microprocessor based system for data acquisition is becoming common. One such system using 8 bit microprocessors (8080 or Z80 and 8748) is reported by Rubel et al.[189]. Okamoto has also reported use of Motorola 6800 microprocessor with digital ECG recorder [160] and rhythm analysis. Bemmel has commented that with decreasing cost of microprocessor and central memory, advantages of multilead analysis should be exploited [221]. Macfarlane has observed that development in microprocessor hardware and software keep pace with each other. Hardware is being developed for simultaneous acquisition of multiple leads. Research is also in progress for complete interpretation of ECG through microprocessor based system [130]. Bertrand et al. have reported numerical encoding and transmission of electrocardiogram using microprocessor [16]. Murray et al. [152] have reported a microprocessor based real time ECG contour analysis. First, it determines whether an ECG is normal or abnormal. For an abnormal ECG it further defines the abnormality. Patient data matrix includes $P_a, P_d, Q_a, Q_d, R_a, R_d, S_a, S_d$, PR, QT, RR, etc. for the 12 leads. Certain conditions are checked. The results Yes, No and Irrelevant are converted to binary image matrix using 1,0 and 0, respectively. Due to 8 bit byte of 8080, sets of 8 conditions are checked one by one and presence or absence of symptoms of a category are checked and probabilityof concerned abnormality is indicated. Mahoudeaux

et al. have reported simple microprocessor based system for on line arrhythmia analysis including wave detection [137].

In this section the software implementation on 8085 based microprocessor system of the ECG interpretation method developed in earlier sections is given.

3.6.1 Software Development

The problem is divided in to number of stages. Figure 3.10 shows the general flow chart for the overall system. It includes wave recognition, measurement error and lead proximity corrections, calculation of Frontal plane Peak Resultant vector FPR, calculation of relative values, generation of simple binary symptom pattern, classification of normals and abnormals, generation of composite binary symptom pattern, finding the symptom multipliers, calculation of weighted sum of symptoms, detailed classification, and storage and/or display of diagnosis.

The flow chart for the measurement and lead proximity corrections developed in section 2.6.3 is shown in Figure 3.11. It uses the measured peak values of lead potentials I1, II1 and III1. The peak values I, II, III after measurement and lead proximity corrections are stored in memory. The computation of FPR amplitude and phase developed in section 2.6.2, is shown in the flowchart of Figure 3.12. It uses the stored values of I,II, cos 96^{o}, and sin 96^{o}. The following series expression is used for computation of phase angle α.

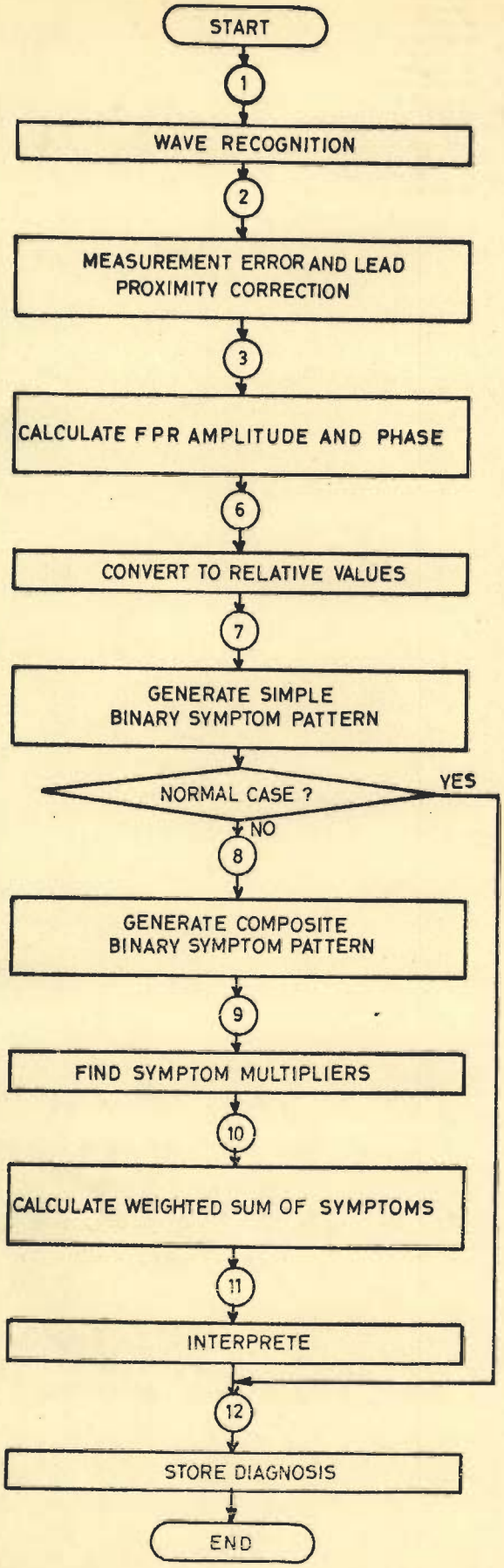


FIG.3.10. GENERAL FLOW CHART

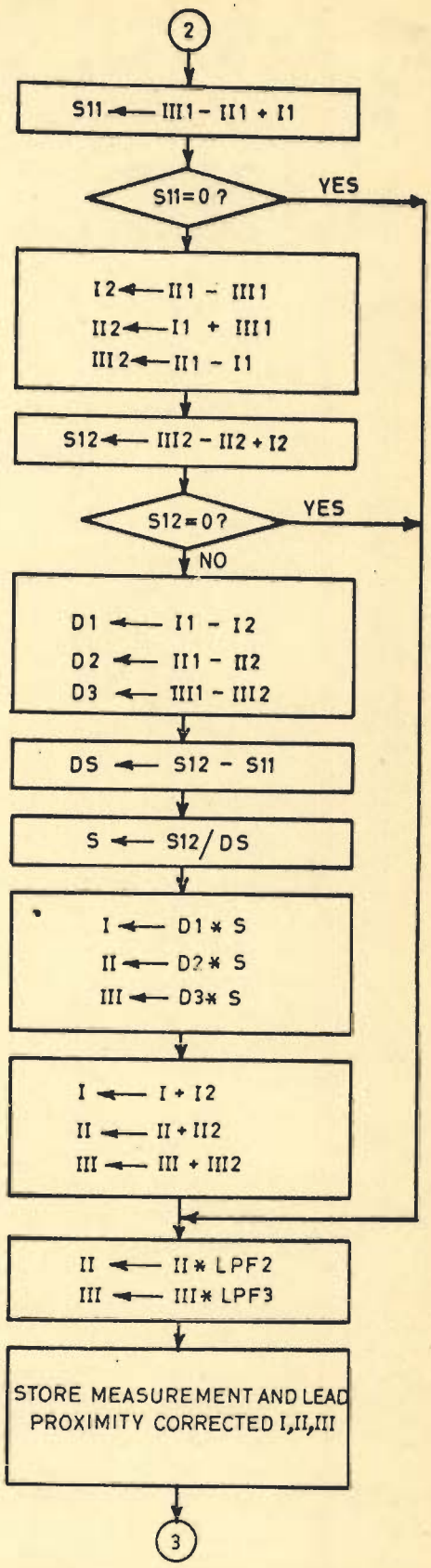
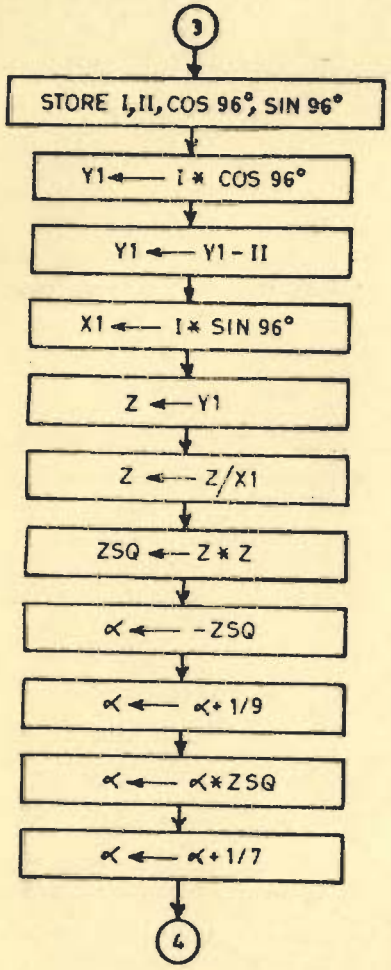
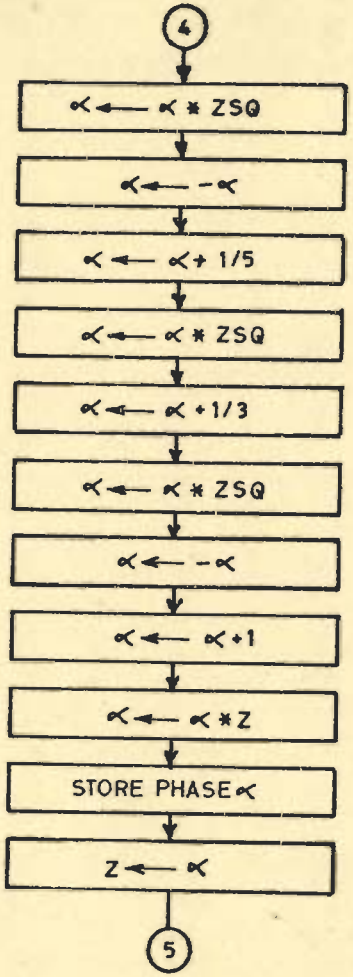


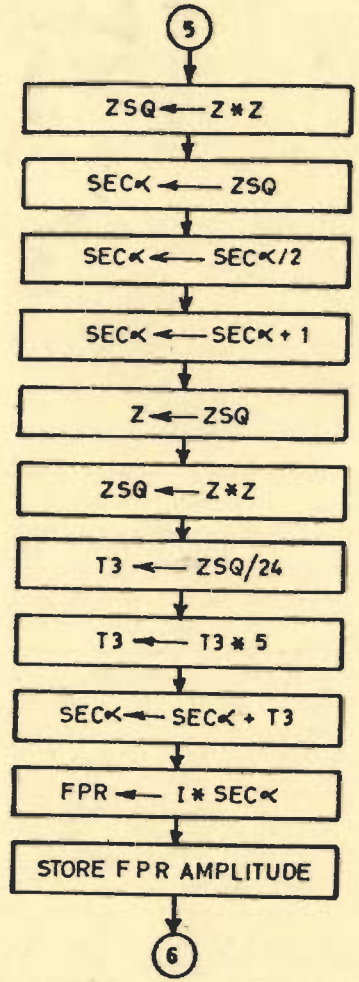
FIG.3.11. MEASUREMENT AND LEAD PROXIMITY CORRECTION



(a)



(b)



(c)

FIG. 3.12 (a,b,c). FPR COMPUTATION

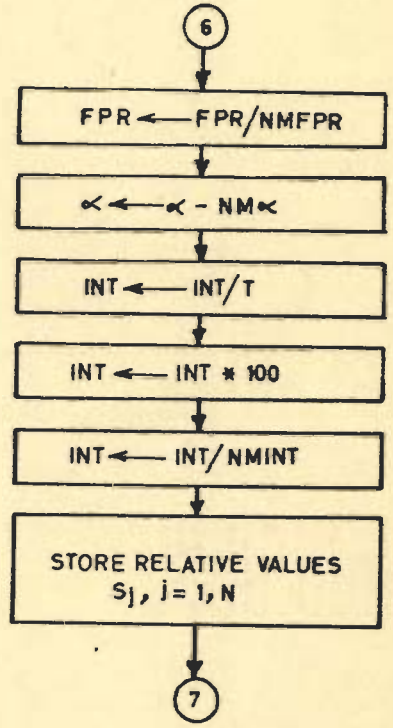


FIG. 3.13. COMPUTATION OF RELATIVE VALUES

$$\alpha = \arctan Z$$
$$= Z(1-Z^2(1/3+Z^2(1/5-Z^2(1/7+Z^2(1/9-Z^2)))))$$
$$= Z(1-ZSQ(1/3+ZSQ(1/5-ZSQ(1/7+ZSQ(1/9-ZSQ))))) \quad \ldots (3.43)$$

where, $Z = Y1/X1$ and $ZSQ = Z*Z$

The values of phase angles for respective segments $\alpha_p, \alpha_q, \alpha_r, \alpha_s, \alpha_t, \alpha_{st}, \alpha_{q+r}, \alpha_{q-r}, \alpha_{r+s}, \alpha_{r-s}, \alpha_{s+t}$ and α_{s-t} are computed and stored.

$$\text{FPR amplitude} = I/\cos\alpha = I \sec\alpha \quad \ldots (3.44)$$

The value of $\sec\alpha$ is computed by expanding it in series as

$$\sec\alpha = 1+(1/2)\alpha^2+(5/24)\alpha^4+\ldots+(-1)^n \cdot \frac{E_{2n}}{(2n)!} \cdot \alpha^{2n}+\ldots \quad \ldots (3.45)$$

where, Euler numbers E are defined as

$$E_o = 1, \quad (E+1)_k + (E-1)_k = 0, \quad k = 1,2,3$$

Amplitudes $P_a, Q_a, R_a, S_a, T_a, ST_a, Q+R_a, Q-R_a, R+S_a, R-S_a, S+T_a$ and $S-T_a$ are computed and stored. The amplitude FPR, Phase α, and peak to peak interval INT are converted to relative value and stored as parameters S_j as shown in Figure 3.13. The necessary computations are explained in section 3.4.2.

The conversion of parameter set S_j to simple binary symptom pattern B_j and screening of cases in to normals and abnormals explained in section 3.4.3 is shown in upper part of Figure 3.14. The generation of composite binary symptom pattern explained in section 3.5.1 and its storage are shown in lower part of Figure 3.14. The method of finding the symptom multipliers for various symptoms with respect to different categories developed in section 3.5.2 is explained by the flow chart of Figure 3.15. The calculation of weighted sum of symptoms for a

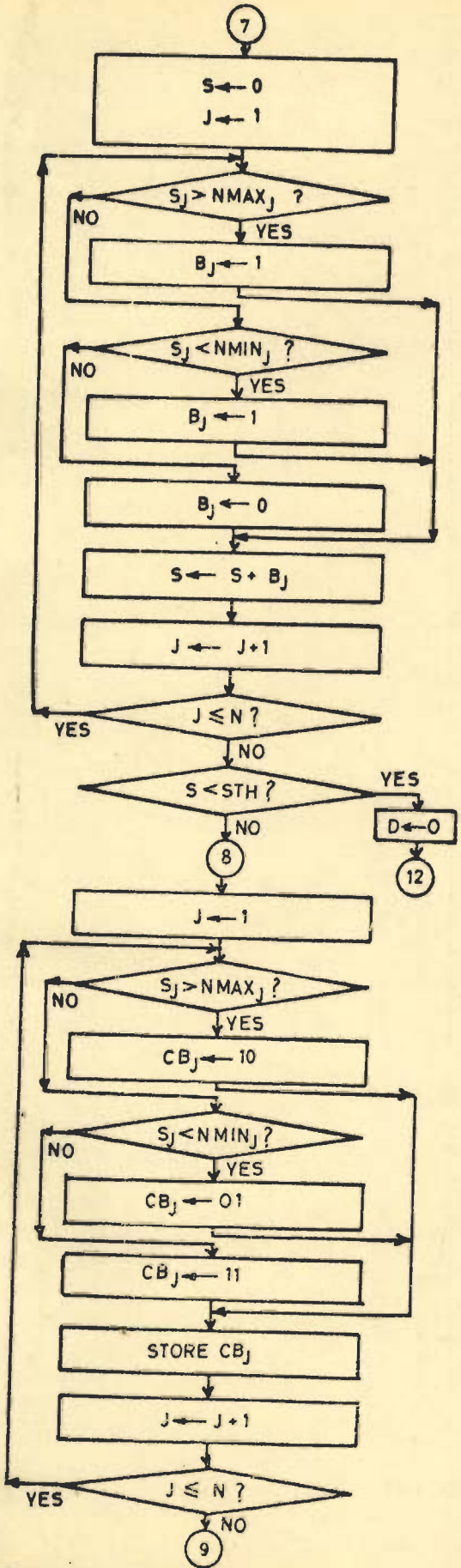


FIG.3.14. BINARY CODE

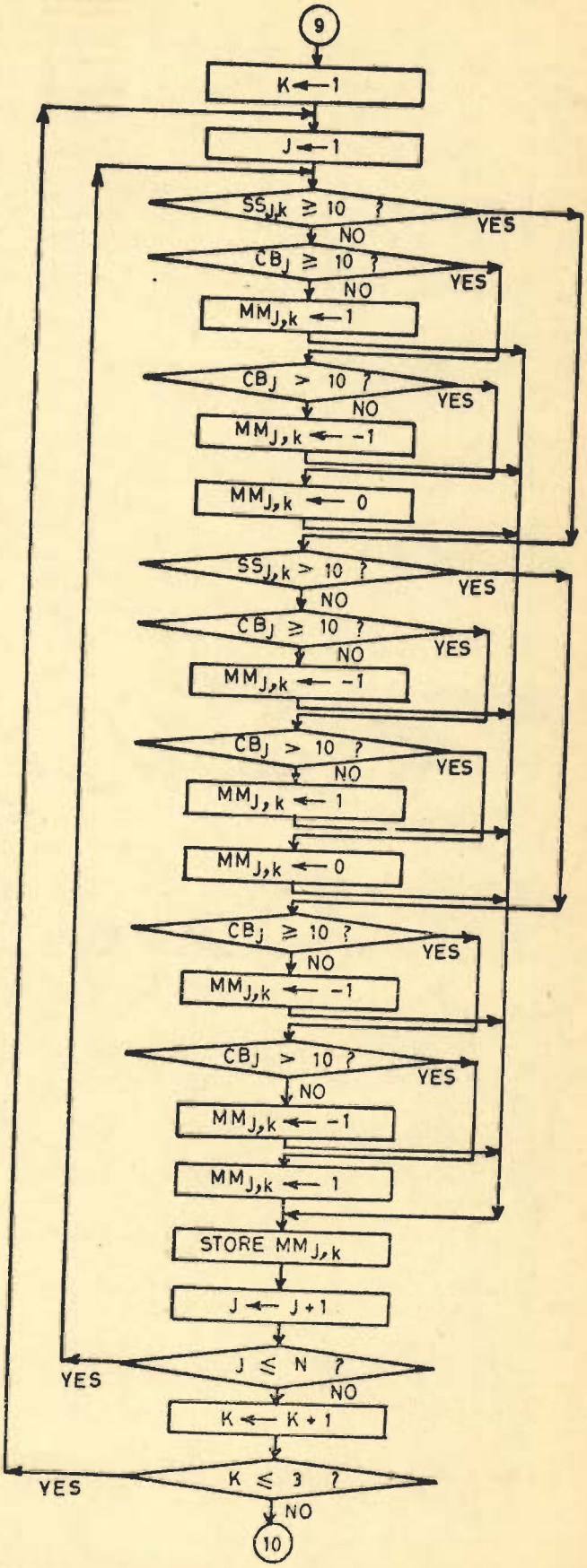


FIG.3.15. SYMPTOM MULTIPLIERS

case to be classified with respect to different categories explained in section 3.5.3 is shown in the flowchart of Figure 3.16. The procedure for the classification of the cases according to weighted sum of symptoms developed in section 3.5.3 is shown by the flow chart of Figure 3.17. D equal to 1,2, and 3 correspond to diagnosis for MI, RVH and LVH respectively. D equal to 12,13,23 and 123 correspond to overlapping symptoms for two or more categories. If there are no appreciable symptoms for any of the three categories, miscellaneous category is indicated by D equal to 64.

Subroutines are developed for the addition, subtraction, multiplication and division of real numbers on 8085 microprocessor. The numbers are stored as $M*2^{\pm E}$. Where, M is mantissa and E is exponent. The exponents are biased by adding 128. For negative numbers 2'S compliments are used. Mantissa and exponents are stored and operated separately. For addition and subraction exponents are equalised. Negative multiplier is complemented in the beginning and the product is complemented at the end. Use of biased exponents and separate storage of mantissa and exponents have practically removed the limitation of 8085 microprocessor on the size of the number.

In the present section it has been shown that microprocessor can be used for ECG interpretation. Its use is no longer limited to wave recognition and arrhythmia analysis. Inspite of the low speed and limited capability the microprocessor based system can meet the daily load of ECG interpretation in a hospital without sacrificing the accuracy of interpretation.

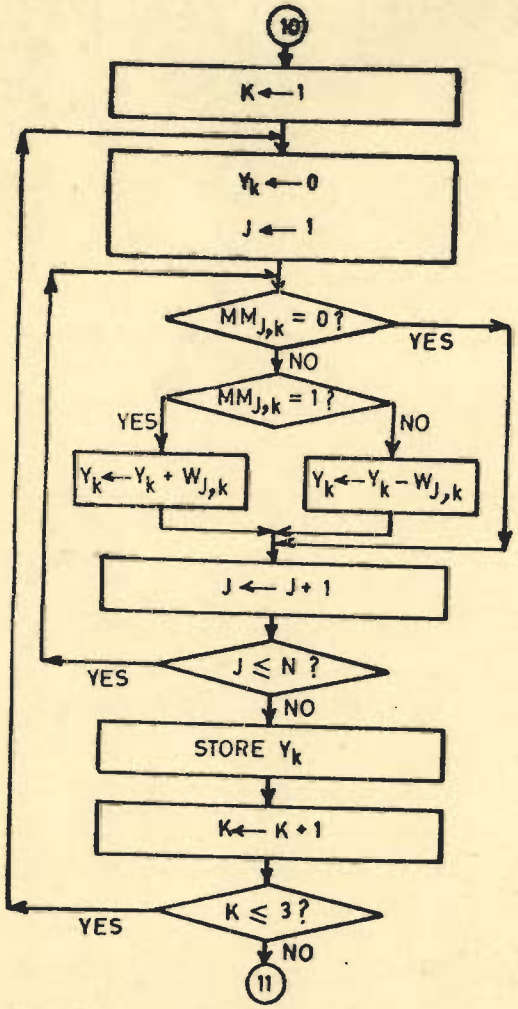


FIG.3.16. WEIGHTED SUM OF SYMPTOMS

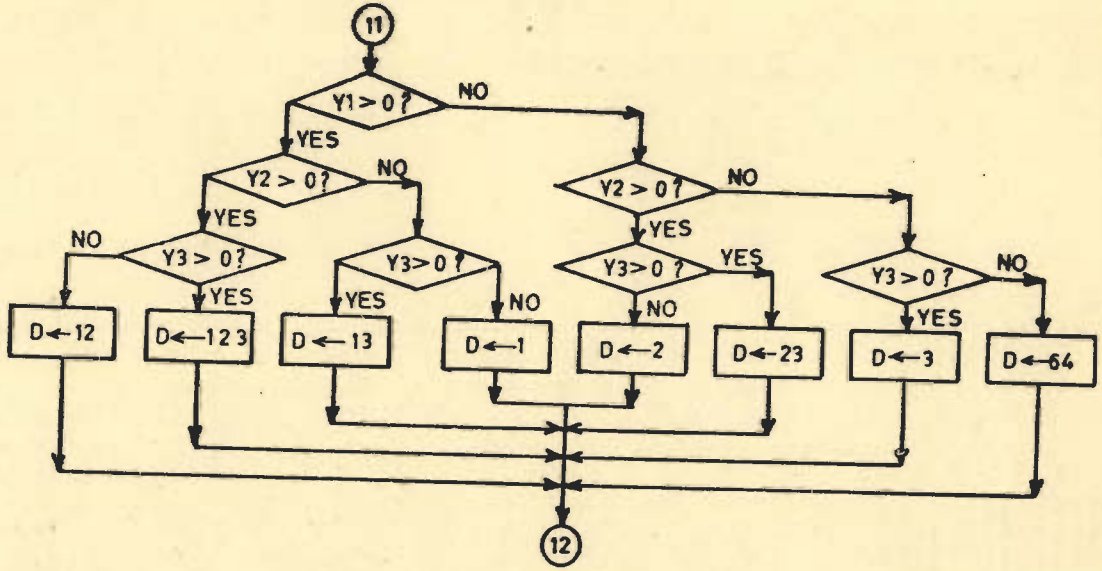


FIG. 3.17. DIAGNOSTIC INTERPRETATION

CHAPTER IV

ANALYSIS OF CARDIOVASCULAR SYSTEM

4.1 INTRODUCTION

Electrocardiogram reflects the electrical activity of heart. It originates with impulse generation at the SA node which initiates the contraction of atrial muscle and starts cardiac cycle. The blood is taken in or pumped out by the heart due to the relaxation and contraction of heart muscles. One side of the heart pumps blood for the systemic circulation and the other side for pulmonary circulation. This chapter deals with the analysis of cardiovascular system. A model is considered for left heart systemic circulation system. The effects of variation of model parameters on system response are investigated. A possible mechanism of cardiac arrhythmia is also analysed.

4.2 CARDIOVASCULAR SYSTEM MODELS

Wind Kessel model proposed by Frank in 1899 and shown in Fig.4.1 is the simplest R-C model [80]. Here aorta and major arteries are considered as an elastic reservoir. Due to over simplification it is unable to account for physically observed undulations in pressure during dicrotic portion of the cardiac cycle. This model was modified by Landes in 1943 [122]. Initially resistance r was added in series with parallel R-C combination. Later on, inertance L was also introduced as shown in Fig.4.2 in series with r to account for the frequency dependence of

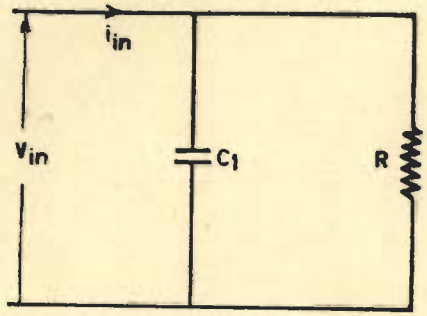


FIG.4.1. WIND KESSEL MODEL

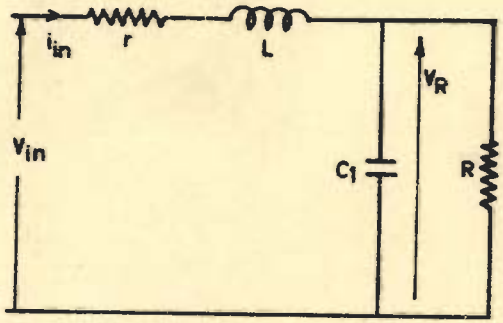


FIG.4.2. LANDES' MODEL

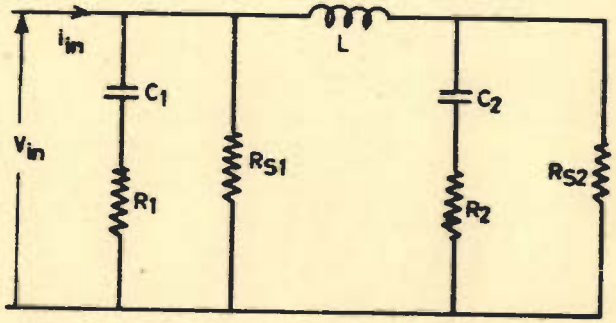


FIG.4.3. MODEL BY SPENCER AND DENISON

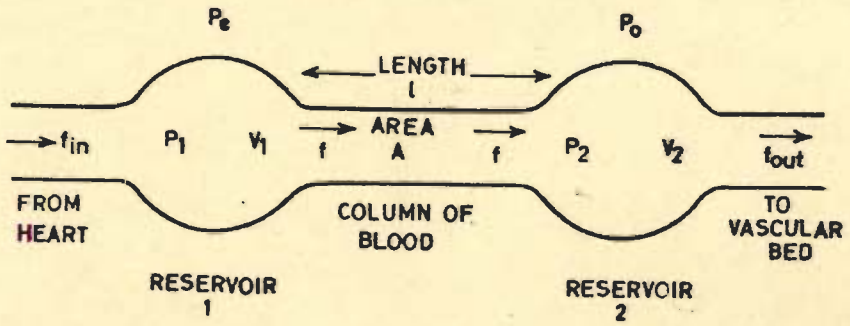


FIG.4.4 MODEL BY GOLDWYN AND WATT

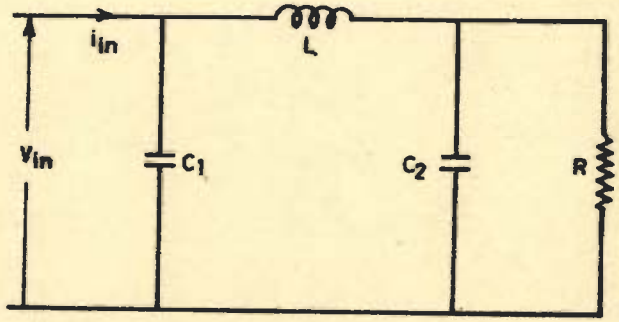


FIG.4.5.

response. Cope considered nonlinear relationship between changes in pressure and reservoir volume in 1960 [55]. Roston considered linear relationship between reservoir volume and pressure [178]. Spencer and Denison proposed a model in 1963 which is shown in Fig.4.3 [206]. They considered two elastic reservoirs with individual peripheral resistances. In 1967, Goldwyn and Watt considered a model as shown in Fig.4.5 [89]. Two elastic reservoirs are connected by a long column of blood. The corresponding physical model of the circulatory system is shown in Fig.4.4. The equations of the system are set up on the basis of conservation of mass. Eigen vectors and Eigen values are found. For a measured pressure curve, the set of coefficients is found by least square technique which are further used to find C_1, C_2 and L in terms of R for one normal and two abnormal persons. Rideout and Dick reduced Navier Strokes equations for fluid flow in distensible tubes to difference form suitable for analog computer implementation in 1967 [182]. Equations for fluid resistance R_m, inertance L_m, and capacitance C_m are derived.

$$R_m = 81\ \mu \Delta Z/(8\pi R^4), \qquad \ldots (4.1)$$

$$L_m = 9\rho \Delta Z/(4\pi R^2) \qquad \ldots (4.2)$$

$$C_m = 2\pi R^3(1-\sigma^2)\ \Delta Z/(Eh) = 3\pi R^3 \Delta Z/(2Eh) \text{ if } \sigma = 1/2 \qquad \ldots (4.3)$$

where, μ is the viscosity of blood, R is the radius of vessel wall, ρ is the blood density, E is the modulus of elasticity for the blood vessel wall, and h is the thickness of vessel wall.

Beneken proposed two forms of model in 1968 [15]. In one of them a lumped circuit representation is considered for

simulation of pressure,flow and volume relationships. The second one is coupled to it for simulation of substances transported by blood. In another type of model perturbation analysis is used. The analog part may be used for the circulatory system and digital part for control loops using a hybrid computer. In 1968, Westerhof [230] gave the following interpretation of the parameters of r-C-R model [122].

(i) r+R = total peripheral resistance
= mean aortic pressure/mean flow.

(ii) The characteristic resistance r is the model representation of characteristic impedance of aorta where pressure and flow are measured. Its value is related to mechanical and geometrical properties of aorta.

(iii) Total compliance C of arterial bed is equal to the change in volume/change in pressure of all arteries lumped together.

Noordergraaf presented a review of some models in 1969 [156]. Wind Kessel representation of arteries considers that all pressure changes are simultaneous in arterial tree, effectively taking wave velocity equal to infinity. From the model of Goldwyn and Watt [89] information of clinical value may be obtained from numerical values of parameters calculated by digital computer through a least square algorithm. If aortic wall is considered viscoelastic and peripheral resistance pressure dependent, the model response improves. The electric network theory is extensively used for analysis. In 1971, Burrus et al.[35] reported the method of identification of parameters of a third order

model of arterial circulatory system [89]. The Z transform of third order digital signal for the network with given a_i and b_i is

$$G(Z) = (a_o+a_1Z^{-1}+a_2Z^{-2})/(1+b_1Z^{-1}+b_2Z^{-2}+b_3Z^{-3})$$
$$= g_o+g_1Z^{-1}+g_2Z^{-2} \qquad \ldots (4.4)$$

The coefficients a_i and b_i are found such that autonomous solution of g_i closely approximates in some sense to the sampled blood pressure curve. Finally, digital filter parameters are converted to corresponding electrical analogue using Z transform [86].

In 1972, Cook and Simes reported a simple analogue heart model for biological system simulation as shown in Fig.4.6 [54]. It is a third order model developed for teaching purpose. The pumping action of heart is represented by a variable capacitor, systemic circulation by RC filter, and aortic and mitral valves by diodes D_2 and D_1. It is assumed that right atrium, right ventricle and left atrium have constant volume. Left ventricle is assumed to be two state time varying fluidic capacitor.During systole left ventricle is represented by a small fixed capacitor and during diastole it is increased by 20 times. The valves are taken as ideal diodes with a pressure drop for forward flow. Aorta is assumed as linear, lossless fluidic capacitor.

In 1972, Rideout reported a hybrid computer model for cardiovascular system simulation involving 27 equations running at real time rate for biomedical engineering education [181]. Models are extended for parameter estimation, studies, hypothesis checking, and clinical applications. In the model shown in

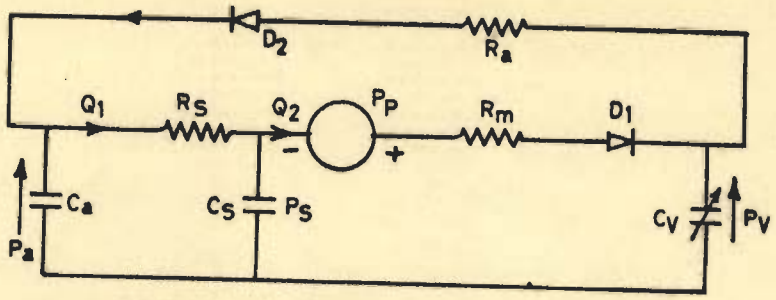


FIG.4.6. COOK AND SIMES MODEL
PULMONARY CIRCULATION

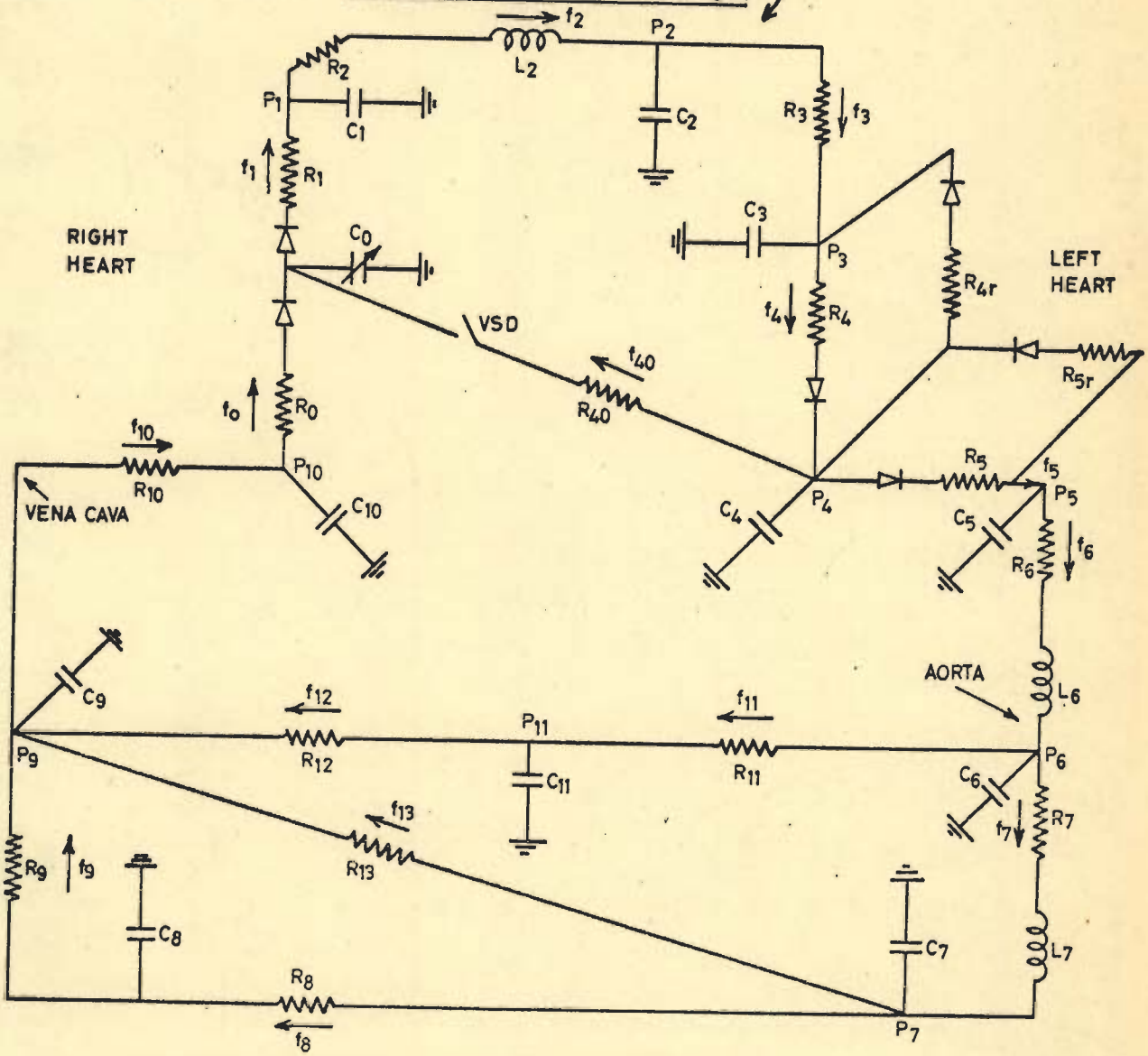


FIG.4.7. SYSTEMIC CIRCULATION: RIDEOUT

Fig.4.7, effort is made to simulate presence and size of various defects like ventricular septal defect (VSD), aortic valve incompetence, mitral valve incompetence, stenosis of any valve, heart rate change, peripheral resistance change, haemorrhage, etc.

In 1973, Green and Clark, represented elastance curves for animals by a mathematical expression [94]. Green et al. developed a model in 1973 as shown in Fig.4.8. The ventricular elastance is characterized as a function of end diastolic volume and time. The model of heart is terminated in a modified Wind Kessel load and accurately simulates mechanical response of the heart to various pre - and after load conditions. The elastance is represented by

$$E_H(V_{ed},t) = \sum_{i=1}^{N} A_i(V_{ed}) \exp\left[-B_i^2 (V_{ed})(t-C_i(V_{ed}))^2 + D\right] \quad \ldots(4.5)$$

where, D is a constant amplitude term. The coefficients of Gaussian distribution are evaluated from the data taken for the dogs. Pressure and volume relationship is assumed as

$$P_v = h_2 V_v^2 + h_1 V_v + h_o \quad \ldots (4.6)$$

Differential equations are numerically integrated via a subroutine that uses fourth order Runge Kutta starter method and continues with Adams-Bashforth, Adams-Moulton predictor corrector pair. In 1973, Wesseling et al. tried L, T and π models for arterial system with analogue computer [229]. The models of T and π type are more accurate in representation while model L is simple for programming. The estimated compliances were higher than the expected values. The peripheral resistance was under estimated.

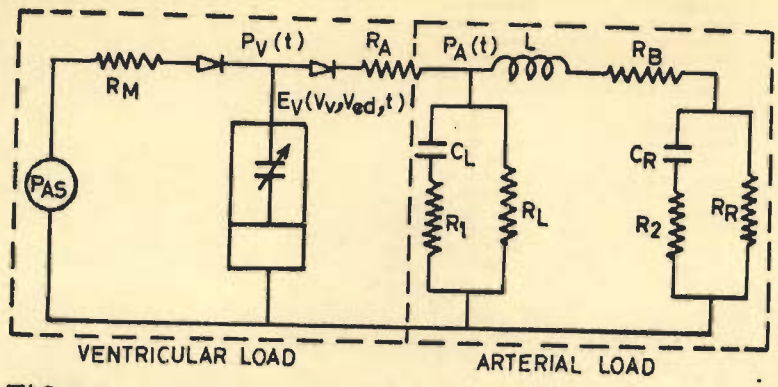


FIG.4.8 GREEN AND CLARK MODEL

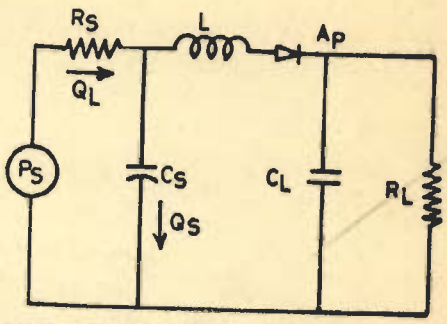


FIG.4.9. MODEL BY BUONCRISTIANI

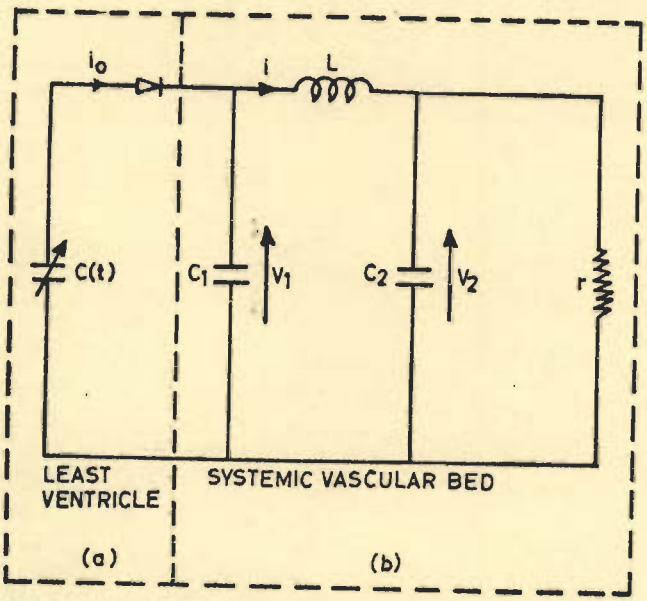


FIG.4.10. DESWYSON MODEL

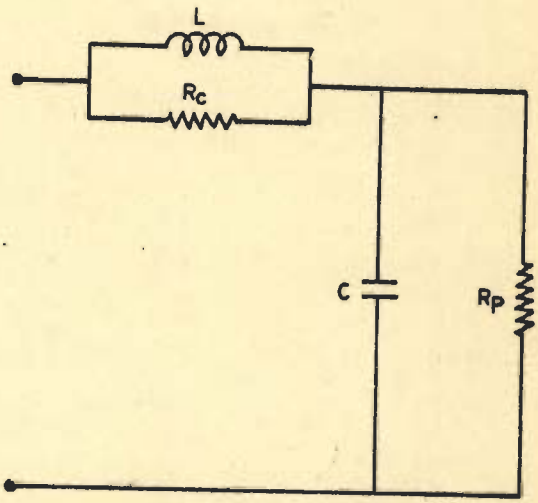


FIG.4.11.4-ELEMENT WINDKESSEL MODEL BY BURATTINI AND GNUDI

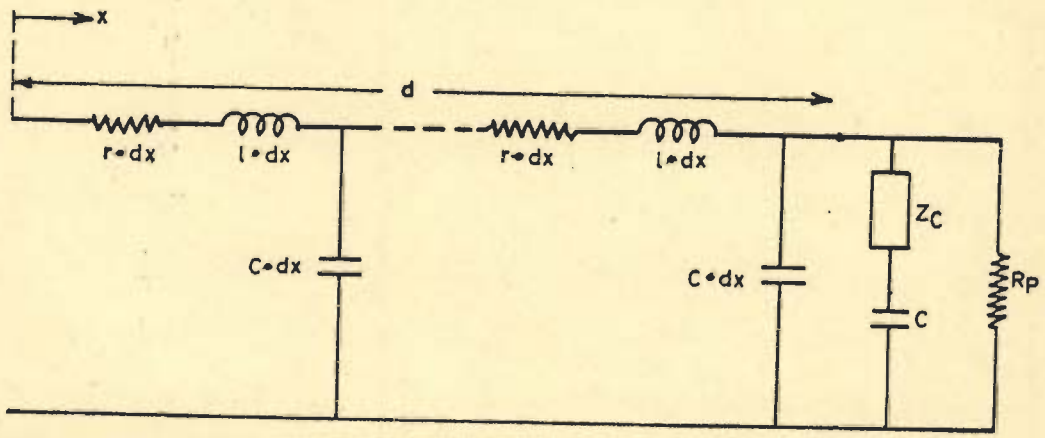


FIG.4.12. TUBE MODEL BY BURATTINI AND GNUDI

Westerhof et al. calculated input impedance of arterial tree by Fourier series for seven dogs in 1973 and justified the Wind Kessel model [231]. The impedance in the control situation may be modelled by means of a three element Wind Kessel consisting of a peripheral resistance and arterial compliance, together with a resistance equal to the characteristic impedance of the aorta. Buoncristiani et al. in 1973 used a model shown in Fig.4.9 [29]. The parameters are estimated for ejection phase only. It is remarked that Fourier series analysis ignores the discontinuity (nonlinearity) due to aortic valve and may lead to nonphysiological results. The model used accounts for second order effects, ventricular compliance, inertia of blood and aortic compliance and has very little nonlinearity. In case of completely distributed parameter model identification of clinically significant model parameters from a single pressure measurement is unrealistic and unnecessarily complicates the model. Detailed models developed by Sims in 1972 [199] and Chang et al. in 1974 [49] are very complex. The limitations on the nature and number of measurements that can be taken conveniently and safely with human subjects, also make these models impracticable.

In 1974, Green and Clark reported a model of ventricular mechanics that reflects changes in inotropic state, end diastolic volume (preload) and time [93]. In 1977, Clark et al. analysed elastance curves for dog and human subjects [51]. For humans, left ventricular volume V is determined by single plane cineangiography.

$$V = 0.667\ A^2\ C^3/L + 7.8\ (ml) \qquad \ldots\ (4.7)$$

where,

A = calculated area of planar projection

L = longitudinal length from aortic valve to apex

C = correction factor.

Maximum values and slopes of various phases of elastance curve are diagnostically significant. In 1977, Deswyson considered the model as shown in Fig.4.10 [67]. Here, V_1 corresponds to aortic pressure, i_o to ejected flow $Q_{ao}(t)$, C(t) to ratio of instantaneous left ventricular volume and pressure, C_1 and C_2 to distensibility of vascular wall, L to mass of blood flowing, R to friction between molecules flowing through vascular bed. The procedure for computation of model parameters for dog data is illustrated in the reference [67]. The peripheral resistance r is taken as the ratio of average pressure and flow. In 1977 Westerhof et al. reported improvement of model response by inclusion of inertance L with proper value [232].

In 1977, Hanmer considered a mathematical model for combination of left ventricle and arterial system [99] Starting from Navier stroke equations a set of five equations is derived for five unknowns namely, velocity of left ventricular contractile element shortening V_{ce}, Ventricle spherical radius R, muscle tension T, arterial pressure P, and average cross sectional blood velocity V. A model of human arterial system based on anatomical branching was reported in 1980 [7]. The uniform thin walled elastic tubes were represented by 128 segments with realistic arterial dimensions and wall proportions. It was observed that there was good agreement with experimental results for pressure,

flow and impedance at various locations. The wave propagation in certain pathological conditions and action of vasoactive agents can be simulated. Noninvasive flow measurement also allows parameter estimation associated with some pathological conditions. In 1980, a model was proposed which was based on finite difference solution of Navier Stroke equations retaining certain nonlinear features of the system using data from the dogs [157]. A model of arterial hemodynamics was reported in 1980, encompassing Wind kessel and Pulse propagation effects [96].

In 1980, Deswysen et al. reported that large flow harmonics make interpretation of input impedance difficult. The useful parameters are total peripheral resistance (modulus of Zin at f=0) and characteristic impedance (average of moduli of Z in between 3 to 10 Hz). The report has also compared earlier models [68]. In 1980, Huisman et al. reported comparison of models used to calculate left ventricular force [107]. Burattini and Gnudi in 1982, proposed two new simple models for the arterial tree input impedance [30]. The first, as shown in Fig.4.11 is a four element Wind Kessel model. The second, is a tube model with a complex load. The electrical analogue of this model is shown in Fig.4.12. Powell algorithm is used for parameter estimation. By choosing the flow as input and best fitting the pressure signal the arterial input impedance works as a lowpass filter. It behaves as a highpass filter by choosing the pressure as an input.

Aguilar et al. simulated variable compliance on analogue computer in 1982 [1]. A simplified electronic model is applied to cardiovascular system to obtain left ventricular pumping

action. The multicompartment model developed by Hardy et al. in 1982 [101] simulates pulsatile blood flow, and transport and exchange of gases. The effect of short term whole body acceleration in aerial combat is mainly investigated.

In 1980, Clark et al. proposed a model of left ventricle and systemic circulation shown in Fig.4.13 [50]. It is a compact discrete component model and contains most of the useful information without unnecessary complexity. It is a modified version of earlier used similar models [35,67,89]. A resistance R_t is included in series with the proximal compliant element C_1 to account for frequency dependent behaviour of the system. The model consists of two parts. The first part is the model of left ventricle and the second part is the model of systemic arterial load. The term elastance of the left heart is explained earlier [51,94,95]. It is an index of contractibility of left ventricle. The instantaneous elastance is the ratio of left ventricular pressure and volume at a particular instant. It is a reciprocal of left ventricular compliance. The left ventricle can be considered as a pressure source with a voltage analog or a flow source with current analog. Here left ventricle is represented by a variable pressure source $P_{LV}(t)$. The systemic load model is a linear third order modified Wind Kessel model. The arterial tree is lumped in to two major compartments, proximal and distal. The proximal compartment is represented by the lumped viscoelastic properties of aorta and large arteries. Here, C_1 and R_t are the corresponding compliance and resistance respectively. The distal compartment of the systemic circulation is represented by

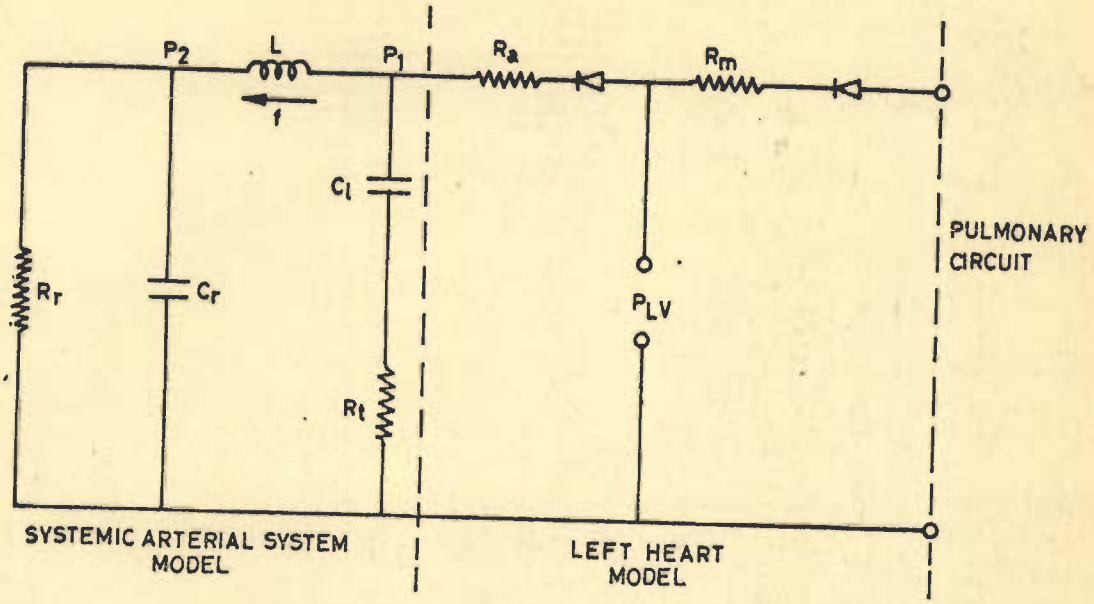


FIG. 4.13

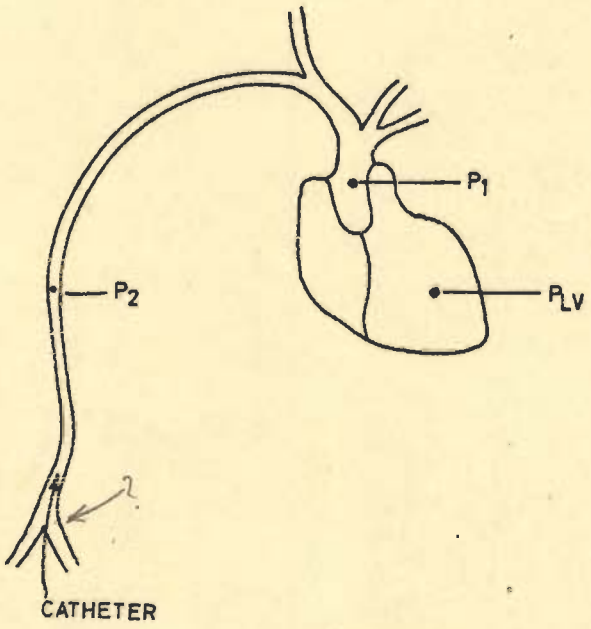


FIG. 4.14

compliance C_r and peripheral resistance R_r. The inertance of the long fluid columns connecting the two compartments is represented by L. Aortic valve is represented by a diode in series with resistance R_a. The switching function S_a specifies the state (open or closed) of the aortic valve. Mitral valve is represented by a resistance R_m. The pulmonary circuit is not considered in this model.

Using this model Clark et al.[50] have developed a two stage identification scheme for the determination of model parameters of the systemic arterial system for a patient undergoing cardiac catheterization. The aortic root pressure P_1, the peripheral pressure at the right proximal brachial artery P_2 and the left ventricular pressure P_{LV} are measured by using solid state catheter tipped transducer and an FM tape recorder as shown in Fig.4.14. Radiopaque die is injected to provide X-ray fluoroscope image of the heart. The analysis of the ventriculogram provides the ventricular outline and ventricular volume is calculated according to a formula adopted from Kasser and Kennedy [115]. The ventricular stroke volume was obtained by difference between the end-diastolic and end-systolic volumes. The system equations are formulated as follows.

$$\begin{bmatrix} \dot{P}_1 \\ \dot{P}_2 \\ \dot{f} \end{bmatrix} = \begin{bmatrix} -W_1 & W_2 & -W_3 \\ 0 & -1/R_rC_r & 1/C_r \\ 1/L & -1/L & 0 \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ f \end{bmatrix} + \begin{bmatrix} S_aW_4 & S_aW_5 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} P_{LV} \\ \dot{P}_{LV} \end{bmatrix} \quad \ldots(4.8)$$

where,

$$W_o = (1+S_aR_t/R_a)\ ,\ W_1 = (R_t/L+S_a/R_aC_1)/W_o,\ W_2 = R_t/LW_o,$$
$$W_3 = 1/C_1W_o,\ W_4 = 1/R_aC_1W_o\ ,\ W_5 = R_t/R_aW_o \qquad \ldots(4.9)$$

Switching function S_a is defined as

$S_a = 1$ if $P_{LV} > P_1$ and 0 if $P_{LV} \leq P_1$.

The pressures are in mm of Hg, flow in litres/minute, resistance in mm of Hg. minutes/litres, compliance in litres/mm of Hg, and inertance in mm of Hg. minutes^2/litre.

The parameters to be identified are C_r, L, R_t, C_1 and initial flow $f(0)$. R_a is presumed to be known and R_r is taken to be the ratio of mean brachial arterial pressure and cardiac output. In the first stage only diastolic part of the cardiac cycle is considered. During this part the systemic arterial system is isolated from the left heart. By assuming nominal value of R_t, parameters L, C_1 and C_r are estimated by Prony method [35]. The mathematical expression for P_2 is [89]

$$P_2(t) = q_1 e^{-q_2 t} + q_3 e^{-q_4 t} \cos(q_5 t + q_6) \quad \ldots (4.10)$$

With a Z-transform

$$P_2(Z) = (a_o + a_1 Z^{-1} + a_2 Z^{-2})/(1 + b_1 Z^{-1} + b_2 Z^{-2} + b_3 Z^{-3} \quad \ldots (4.11)$$

and laplace transform

$$P_2(S) = (N_2 S^2 + N_1 S + N_o)/(S^3 + D_2 S^2 + D_1 S + D_o) \quad \ldots (4.12)$$

At first, constants a_0, a_1, a_2, b_1, b_2, and b_3 are found out. Then constants q_1 to q_6 and N_0, N_1, N_2, D_0, D_1 and D_2 are found [50]

$$N_2 = P_2(0), \quad N_1 = (R_t P_2(0))/L + f(0)/C_r$$

$$N_0 = P_1(0)/LC_r + P_2(0)/LC_1 + R_t f(0))/LC_r$$

$$D_2 = R_t/L + 1/R_rC_r \ , \ D_1 = R_t/(LR_rC_r)+1/LC_1+1/LC_r$$

$$D_0 = 1/(LC_1C_rR_r) \qquad \ldots (4.13)$$

For given values of R_t and R_r, and by elimination of L and C_r from the expressions of D_o,D_1 and D_2, we have

$$C_1^3 + 2K_2C_1^2 + K_1C_1+K_0 = 0 \qquad \ldots (4.14)$$

where,

$$K_2 = (D_2/D_1)/(R_t+R_r) \qquad \ldots (4.15)$$

$$K_1 = (D_1/D_3)/(R_t(R_t+R_r))+K_2^2 \qquad \ldots (4.16)$$

$$K_0 = ((D_3-D_1D_2)/D_3^2)/(R_t(R_t+R_r)^2) \qquad \ldots (4.17)$$

The real root out of three roots of C_1 which produces minimum observational error in $P_1(t)$ and $P_2(t)$, is chosen.

Then, $$C_r = D_1/D_0R_r - (R_t/R_r+1)C_1 \qquad \ldots (4.18)$$

$$L = 1/D_0C_1C_rR_r) \qquad \ldots (4.19)$$

and $$f(0) = C_rN_1-R_tC_rP_2(0)/L. \qquad \ldots (4.20)$$

In the modified Prony method Fibonacci interval elimination search method [17] is used to minimise the observational errors in $P_1(t)$ and $P_2(t)$ during the diastole and optimum value of R_t is found. In the second stage the parameters found in the first stage are used as the starting values. The iterative nonlinear least square Marquardt algorithm [140] is used for the estimation of model parameters. The pressures $P_{LV}(t)$,$P_1(t)$ and $P_2(t)$ over the entire cardiac cycle and calculated values of R_a and R_r are used as input data. Marquardt algorithm adjusts parameter vector

consisting of C_1, R_t, L and C_r to minimise the square of the difference between observed and computed values of $P_1(t)$ and $P_2(t)$. Initial flow f_o is calculated as

$$f_o = P_2(0)/R_r + C_r \, dP_2/dt \quad \text{at} \quad t = 0. \qquad \ldots (4.21)$$

4.3 MODEL ANALYSIS

The equations for change in pressure and flow are written in the following form [61] for the model shown in Fig. 4.13.

$$\dot{P}_1 = (-(R_t/L + S_a/R_a C_1)P_1 + P_2 R_t/L - F/C_1 + S_a P_{LV}/R_a C_1 + S_a R_t \dot{P}_{LV}/R_a)/(1 + S_a R_t/R_a) \qquad \ldots (4.22)$$

$$\dot{P}_2 = - P_2/R_r C_r + F/C_r \qquad \ldots (4.23)$$

$$\dot{F} = P_1/L - P_2/L \qquad \ldots (4.24)$$

In the first part of the analysis, during the cardiac cycle, when P_{LV} is greater than P_1, value of S_a is taken 1; when P_{LV} is less than or equal to P_1, value of S_a is taken zero. In the later part of the analysis different values of S_a are used. The effect of variation of individual model parameters on the response of the cardiovascular system is to be analysed. The actual cardiac cycle length may vary with the individual and time. For a typical normal subject it is taken 800 ms and kept fixed. Its effect is just like normalisation in time domain. The selection of left ventricular pressure $P_{LV}(t)$ as the forcing function corresponds to voltage analogue. In systems approach the model response is compared under various conditions with the known input. For the present work the required pressure wave is

derived using the elastance and volume curves reported by Clark et al.[50]. This pressure wave is considered typical for a normal subject. The present work is concentrating more on the abnormalities on the systemic side, the source being intact. So, assumption of normal typical left ventricular pressure wave as the forcing function is well justified. It also provides a good basis of comparison for the response under various conditions. The cycle length is divided in to 512 equal intervals and the left ventricular pressure wave is digitised at the resulting points. Its first derivative is also found using a subroutine on digital computer. Fourth order Runge Kutta method is used for the numerical solution of the model equations. The point by point solution is used to get the response over the complete cycle. The response includes pressures P_1,P_2 and flow F. For the convenience of comparison maximum, minimum and average values of response over one complete steady cycle are considered. If the variation of response over two consecutive cardiac cycles subsides to less than 0.01 percent, the response is considered steady.

For the first six sets of computation, S_a is taken one for the period when P_{LV} is greater than P_1, and zero for the period when P_{LV} is less than or equal to P_1. Initially a set of normal values is taken for R_a,R_t,L,C_1,C_r, and R_r. In the first set, value of aortic valve resistance R_a is varied from 50 percent to 150 percent of its normal value, in steps of 2.5 %. The other parameters are kept constant. In the second set, resistance R_t is varied keeping the other parameters constant at their respective normal values. Similarly third, fourth, fifth, and sixth

sets are taken corresponding to the variation of L, C_1, C_r, and R_r, respectively. For the seventh set all the parameters are brought to their respective normal values. For the period when P_{LV} is less than or equal to P_1, value of S_a is fixed at zero. In this set variation of S_a for the period when P_{LV} is greater than P_1 is considered. S_a is not varied from instant to instant. In the respective parts of the cycle there is a fixed value of S_a. The aim is to investigate the response for effective value of S_a less than one. For the different cases, value of S_a for the period when P_{LV} is greater than P_1 is successively decreased from one to zero in steps of 0.05, by taking $S_a = 1-0.05I$, and varying I from 0 to 20. For the eighth set all the parameters are kept normal. The value of S_a for the period when P_{LV} is less than or equal to P_1 is considered variable. For different cases its value is successively increased from 0 to 1 in steps of 0.05, by taking $S_a = 0 + 0.05I$, and varying I from 0 to 20. For the nineth set all the parameters are again kept normal. The value of S_a for the period when P_{LV} is less than or equal to P_1 is increased from 0 to 1 and value of S_a for the period when P_{LV} is greater than P_1 is decreased from 1 to 0 by taking $S_a = 0 + 0.05I$ and $S_a = 1 - 0.05I$ respectively. For all the nine sets maxima, minima and average of P_1, P_2 and F during one cycle of steady response are computed. The time required to reach the steady cycle is also computed.

4.4 RESULTS

It is observed that the response is independent of the initial conditions. Except some small regions of discontinuities, the response stabilises and repeats with 0.01 percent accuracy only within a few cycles. The results are plotted in Figs.4.15-19. The variable relative value of parameter is taken along horizontal axis. The maximum, minimum and average values of responses P_1, P_2 and F are taken along vertical axis. The corresponding maxima, minima and average are P_{1H}, P_{2H} and F_H; P_{1L}, P_{2L} and F_L; and P_{1av}, P_{2av} and F_{av}. Effect of variation of R_a and R_t on the response are shown in Figure 4.15. Effect of variation of L and C_1 are shown in Figure 4.16. Effect of variation of C_r and R_r are shown in Figure 4.17. The Figure 4.18 corresponds to the variation of S_a for the period when P_{LV} is greater than P_1. Figure 4.19 shows the effect of variation of increased value of S_a for the period when $P_{LV} \leq P_1$ observed for set (8). It also shows the combined effect of decreased value of S_a for the period when P_{LV} is greater than P_1, and increased value of S_a for the period when $P_{LV} \leq P_1$ observed for set (9). In most of the cases the variation of response with respect to the parameter being varied is almost linear. In some cases after the discontinuity the response curve settles at a slightly different level, the slope remaining almost the same. With respect to variation of S_a the response curves have drooping characteristics in most of the cases.

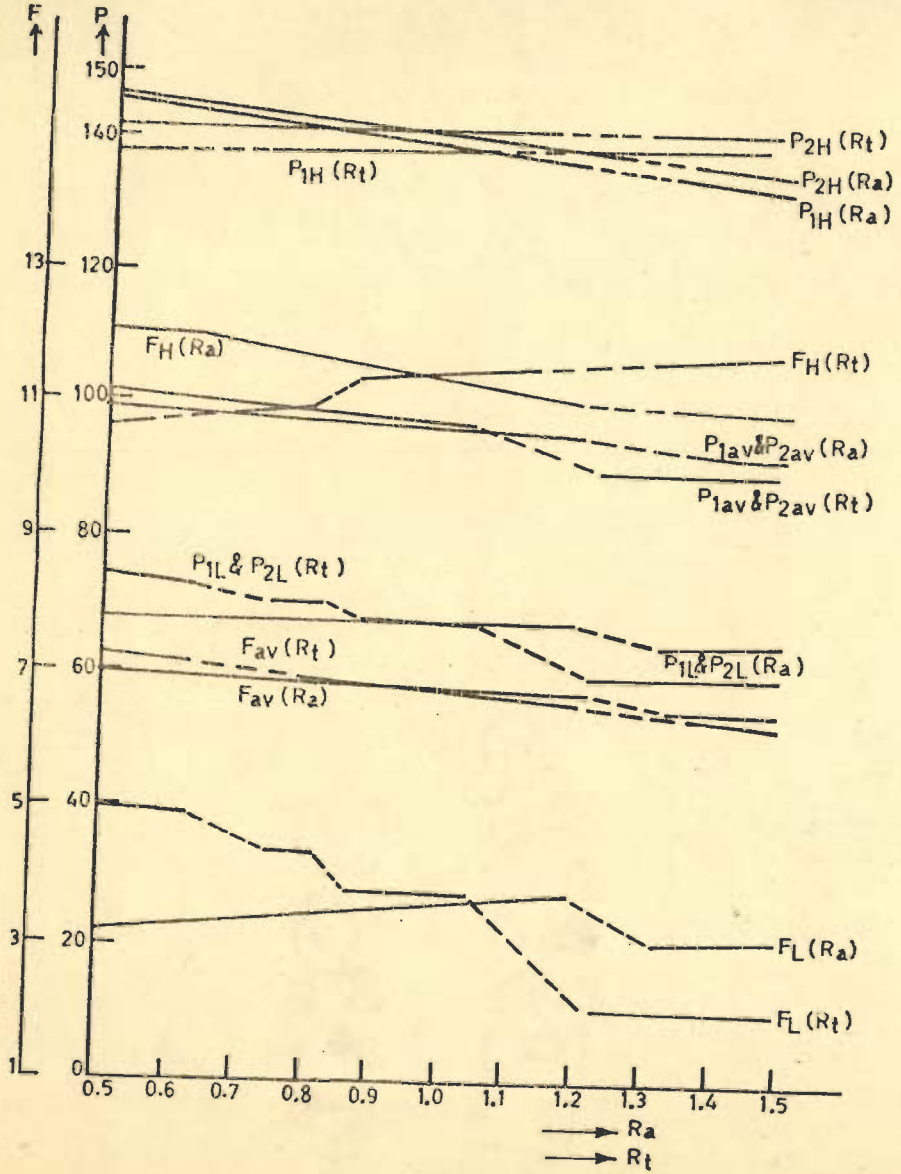


FIG. 4.15

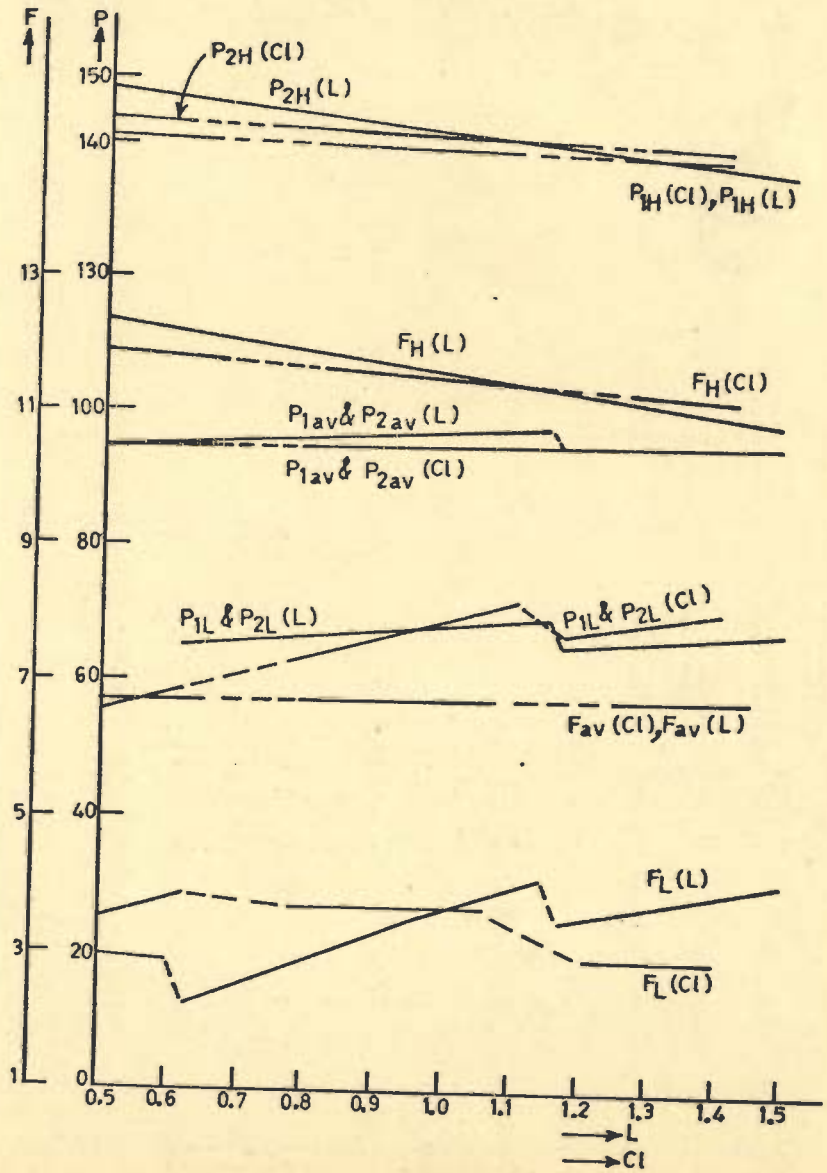


FIG. 4.16

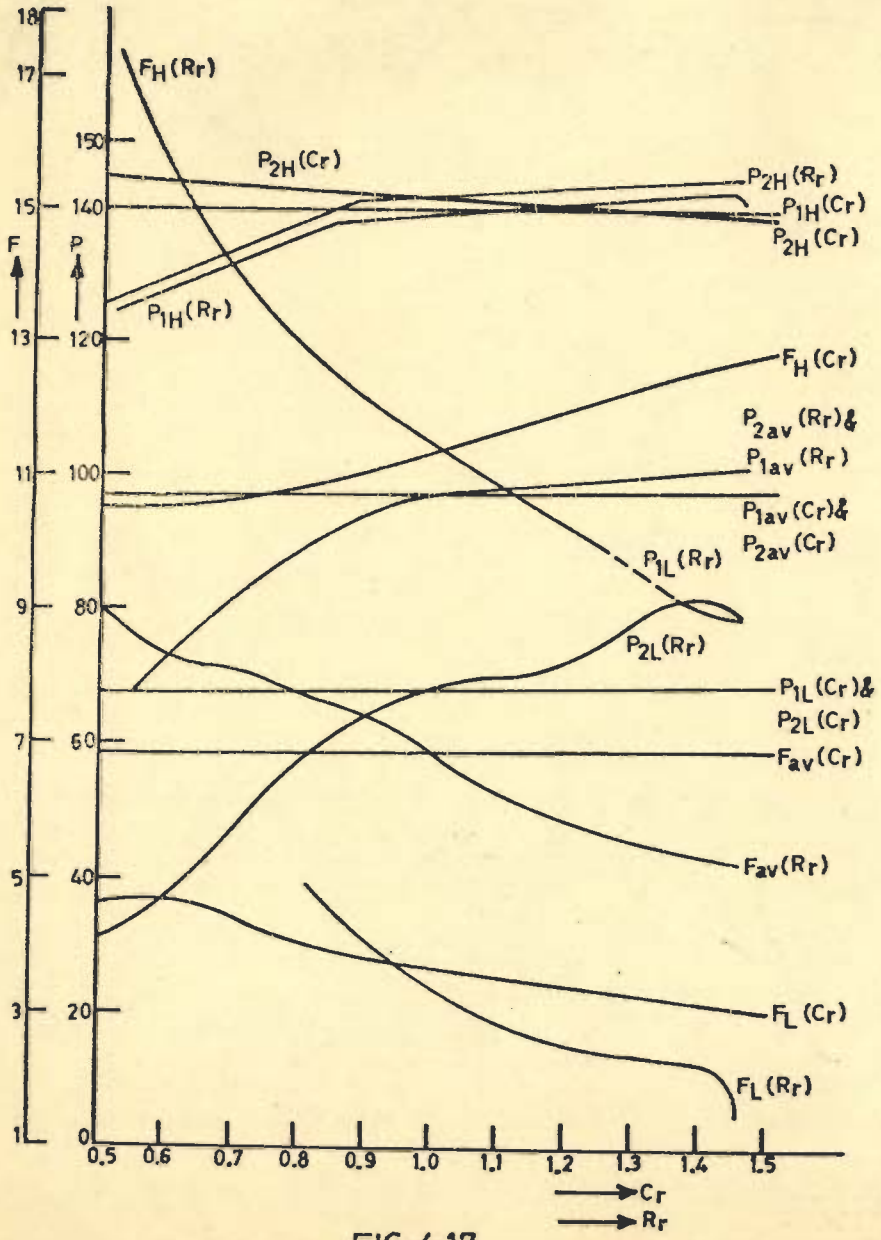


FIG. 4.17

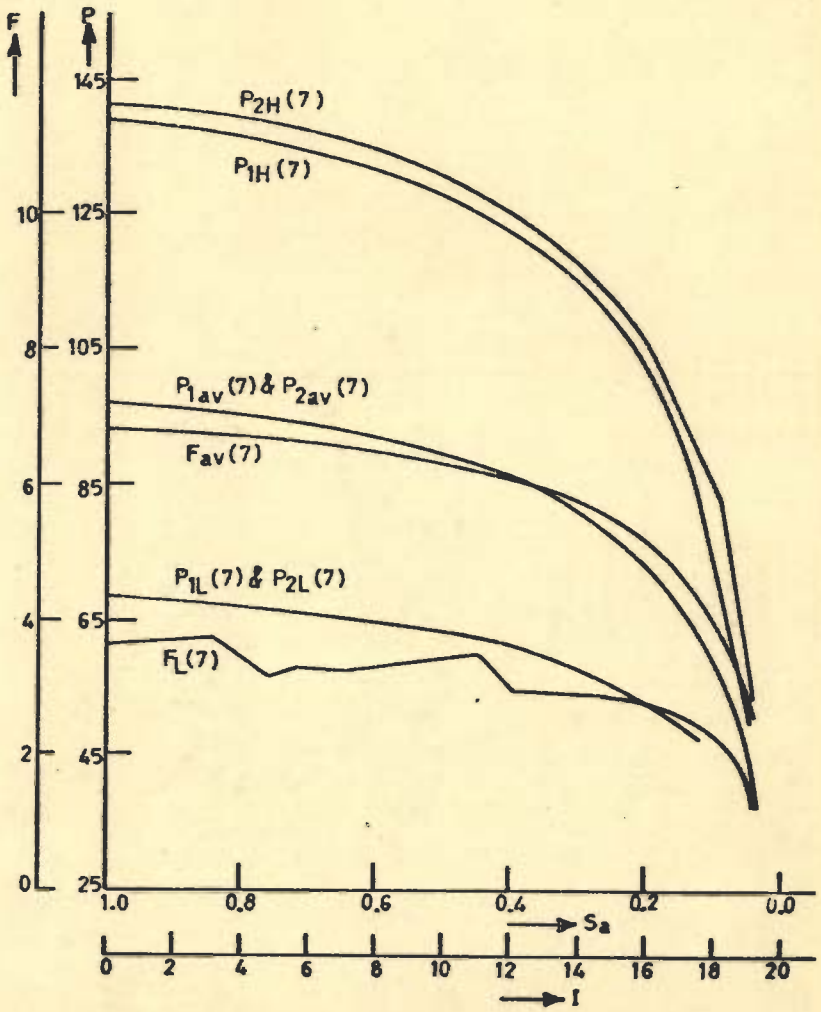


FIG. 4.18

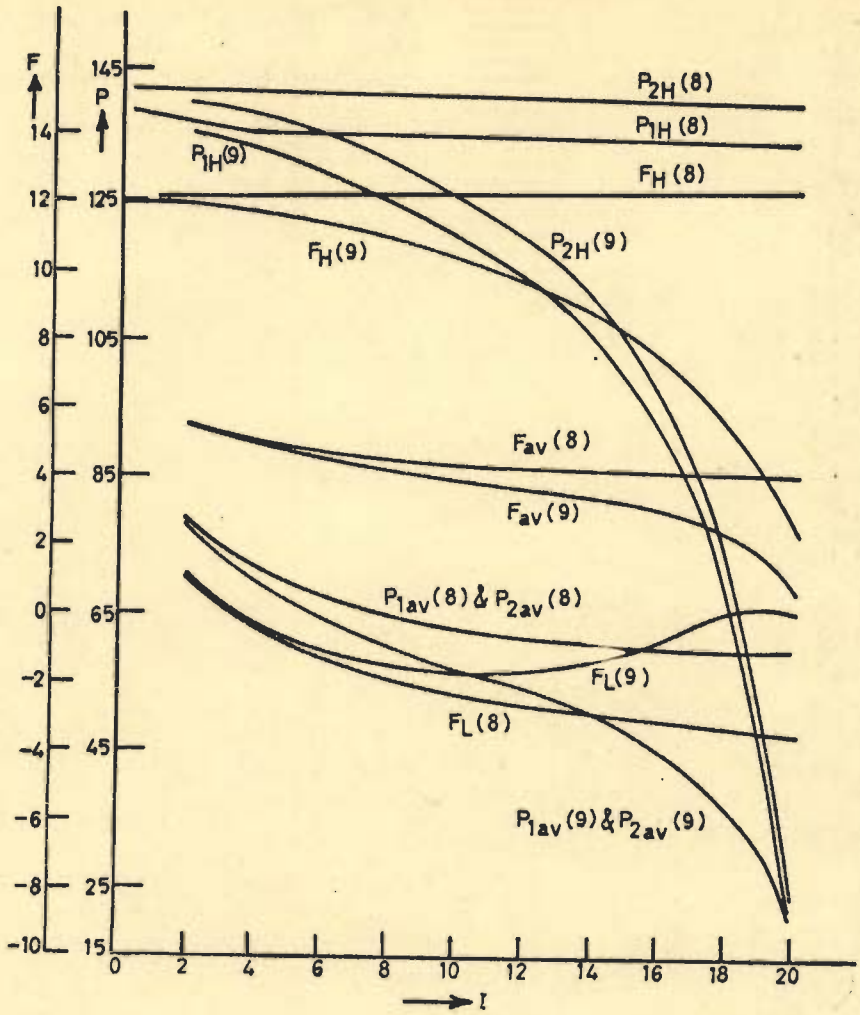


FIG. 4.19

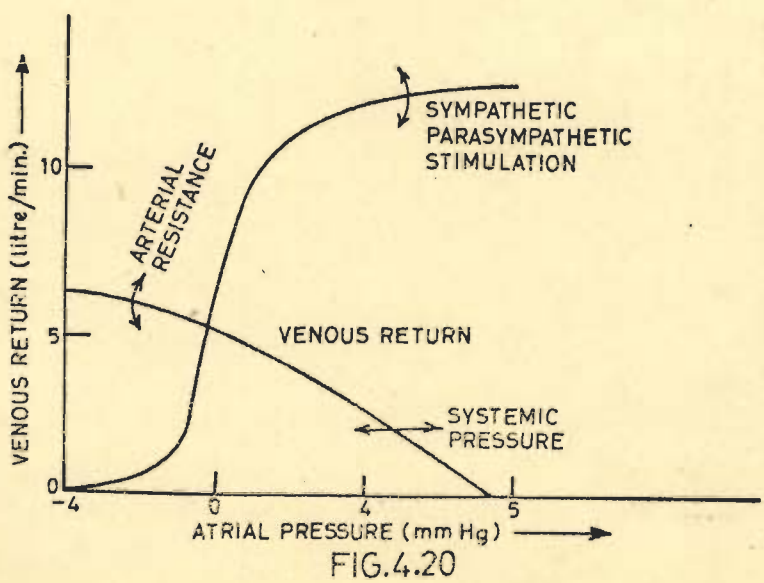


FIG. 4.20

4.5 CLINICAL CORRELATION AND DISCUSSION

It is the intrinsic tendency of an organ to maintain normal blood pressure and flow despite physiological variations. In case of temporary requirement of increased blood flow by a particular organ, vasodilation reduces the local resistance and vice a versa. The blood is diverted from the system to the organ with higher blood requirement. Thus in a healthy subject inherent regulation is able to adjust the system parameters in such a way that the response is normal.

The cardiac system forms a complex closed loop control system involving multiple feedbacks affecting heart and peripheral system. The equilibrium systemic pressure is decided by the intersection of venous return curve with the atrial pressure axis as shown in Fig.4.20. The variation in mean systemic pressure occurs as a result of blood (affecting inertance) and venous compliance changes. The changes in resistance to venous return cause a rotation of venous return curve about the mean systemic pressure end point. The resistance to venous return is influenced by resistance and compliance of peripheral circulation. To meet the demands of the body, the changes occur in both the venous return and cardiac output curves to establish a new operating point. In a closed loop control system some change in input is considered. It results in deviation of the output from the desired value. The deviation is the error signal which is sensed by the sensing device, amplified and used to actuate the correcting system, it offsets the deviation and restores the controlled condition. In the present case the set of model

parameters acts as the correcting device and tries to restore the controlled state. Under normal conditions the controlled state is easily maintained. But, in case of certain abnormalities the system fails to reach equilibrium at the normal set condition and equilibrium is reached at some other point which may be abnormal for the physiological system. Thus controllability of the system depends on the effect of individual parameters. Moreover, it seems that for the investigation of the working of the model it should be isolated from feedback. Because, in the closed loop system the abnormalities in response created by the system parameters may be nullified by the control action. Therefore, in the present analysis effect of individual model parameter is investigated separately. One or more of them are responsible for the different abnormal states. So, resultant response can be predicted.

The opening resistance R_a of aortic valve increases in aortic stenosis. The improper opening of valve reduces the outflow. The effective value of S_a is reduced from one, for the period when P_{LV} is greater than P_1. The dilation of ascending aorta may reduce R_t. Aortic incompetence is a closing defect of aortic valve. The effective value of S_a for the period when P_{LV} is less than P_1 is increased from zero and accounts for regurgitation (back flow during diastole). Hypertension is associated with arteriolar thickening, sclerosis, narrowing of peripheral vessels and at times coarctation of aorta resulting in loss of blood pressure in legs and enlarged collateral vessels. The arteriolar tone increases. In case of elderly patients with

systolic hypertension atheroma of aorta and loss of elasticity takes place. The diastolic hypertension depends on constriction of arterioles. In this case, R_r,R_t and L may increase and C_r and C_l may decrease. In case of hyperthyroidism peripheral vasodilation may decrease R_r and L, and may increase C_r [27,108,141, 218].

The electrocardiogram is a well defined signal suitable for direct recording and online analysis. The pressure and flow involved in circulatory system measured by indirect methods are less suitable for such analysis. As compared to ECG, very little work is done for the computerized analysis of this aspect of the cardiovascular system. It would also be necessary to establish data bank and criteria for the interpretation of cardiovascular system. At this stage it would be premature to attempt at the computerized interpretation of the abnormalities of the cardiovascular system, but the scope can not be denied. The actual system parameters are distributed, some of them may be variable and that too nonlinearly. But assumptions of linearity and lumped parameters are more common and convenient in model analysis. It is true that parameters of cardiovascular system are not independent of each other. At the same time it is also true that some parameters are more adversely affected under certain pathological conditions and some are less affected. Moreover some parameters have predominant effect on the response where as inspite of wide variation some parameters have negligible effect on the response. The effects of some parameters may be opposite in nature. In the simulation of certain pathological states on

the model it may be necessary to adjust many parameters. A simple trial and error procedure for parameter adjustment may involve many steps and plenty of time. So, investigation of the trend analysis is not only helpful but desirable for simulation purpose. The definition of the parameter is based on the relationship between change of parameter and resulting response, keeping the other parameters same. The variation of individual parameters may seem unphysiologic but is necessary for such analysis.

The analysis of model response under various conditions has a good scope for the simulation of abnormalities. For teaching purpose it is possible to create various abnormal states on the model without the presence of actual patient. For clinical diagnosis of cardiovascular system, some invasive measurements add to the discomfort and risk to the patient. So, they may not be permissible in some cases. With the model analysis the invasive measurements can be minimised. If necessary the additional quantities can be computed. Thus, the approach also aids in diagnosis indirectly. If computer analysis of pressure-flow signals and ECG are combined, much better results can be obtained for the diagnosis of cardiovascular system.

4.6 CARDIAC ARRHYTHMIA

4.6.1 A Possible Mechanism

In the cardiovascular system analysis discussed in sections 4.3 and 4.4 [61] one interesting phenomenon was observed. In this analysis one of the model parameters was varied and the observed response was in the form of pressures P_1 and P_2; and flow F.

The response was independent of the initial conditions and settled down to a steady response cycle within a few cycles. But there were some typical sets of parameter values for which the response failed to stabilize even after sufficiently long time (50 times the normal periodic time). In Figures 4.15-17, maxima, minima and average of the responses corresponding to variation of different parameters are shown. The dotted lines in these curves correspond to the regions of discontinuity where the response fails to stabilize. This pecularity of response inspired for further investigation of the problem reported here [63].

The heart can be considered as a biological (fluidic) oscillator. During the normal operation, it beats rhythmically. At this time the values of the system parameters are within some normal range. To maintain the physiological requirement of certain pressures, and flows at various points of the system and to match with the electromechanical action the biological oscillator attains stable operation at some frequency called the normal heart rate. From electrical point of view this frequency is related to the internal pacemaker or impulse generation at the SA node. But, the impulse generation is also related to the myocardial muscular contraction. From the point of view of the biological oscillator, the heart rate (frequency of oscillation) is also dependent on the values of the system parameters. When the system parameters are gradually varied on either side of the initial normal values, the response cycles for pressures and flow attain some stable pattern within a short interval of time. The maxima, minima and average values of pressures P_1 and P_2, and

flow F follow some systematic variation as shown in Figures 4.15-17. For some typical set of parameter values, the response cycles fail to stabilize. The instantaneous values of pressures and flow undergo abnormal variations. If the cardiovascular system is unable to withstand the abnormal stresses developed it may fail. The heart tries to continue to oscillate at initial normal heart rate. The systolic and diastolic periods of the biological oscillator are similar to the charging and discharging periods of capacitors in the electronic oscillator. At the end of a stable response cycle the instantaneous pressures and flow should reach the values which prevailed in the beginning of the cycle. With abnormally changed values of parameters the charging and discharging (rise and decay) periods are not matching properly. Due to the mismatching of the periods the instantaneous pressures and flow fail to reach the initial values at the end of the cycle. There is a cumulative rise or fall in the pressures and flow. The heart becomes unstable and it seems that this may lead to cardiac arrhythmia.

4.6.2 Arresting Cardiac Arrhythmia

Earlier it is mentioned that on the curves relating maxima, minima and average values of pressures P_1 and P_2, and flow F to the variation of parameters, there are certain regions of discontinuity. For R_a, R_t, L, C_1, C_r and R_r certain regions of discontinuity are observed. In case of R_a at a point corresponding to 130 % of the normal value such discontinuity is observed. Initially for this subject the heart had stable operation at

75 beats per minute (BPM) with a periodic time of 800 ms. But, at the same heart rate, for R_a equal to 130 % of the normal value, the systolic and diastolic periods are not matching properly. So, the oscillator is unable to stabilize at 75 BPM. Alternatively if the heart rate is varied the systolic and diastolic periods will change. Because, they are decided by the aortic valve switching function S_a, depending on the relative values of pressures P_{LV} and P_1. So, it is possible that the heart may stabilize at some other frequency (heart rate).

In the present analysis the periodic time of the cardiac cycle is varied from 600 to 1000 ms, corresponding to the heart rates of 100 BPM to 60 BPM. For the purpose of computation as mentioned earlier P_{LV} and $\dot{P}_{LV}$ are used as the forcing functions. Fourth order Runge Kutta method is used for the numerical solution of the model equations. For different values of periodic time (heart rate) maxima, minima and average values of response over a complete steady cycle are computed. Figures 4.21 and 4.22 show the variation of maxima, minima and average values of pressures P_1 and P_2, and flow F on the vertical axis with respect to variation of periodic time (heart rate) for specified values of R_a and L respectively on horizontal axis. The crosses on the curves correspond to the missing points (discontinuities) and zones at which the heart can not stabilize. It is observed from these plots that between 70 BPM and 100 BPM there is a large number of frequencies of oscillation at which the heart can attain stable operation. It is desirable to restore normal operation with the minimum disturbance. It is seen from the results that even a

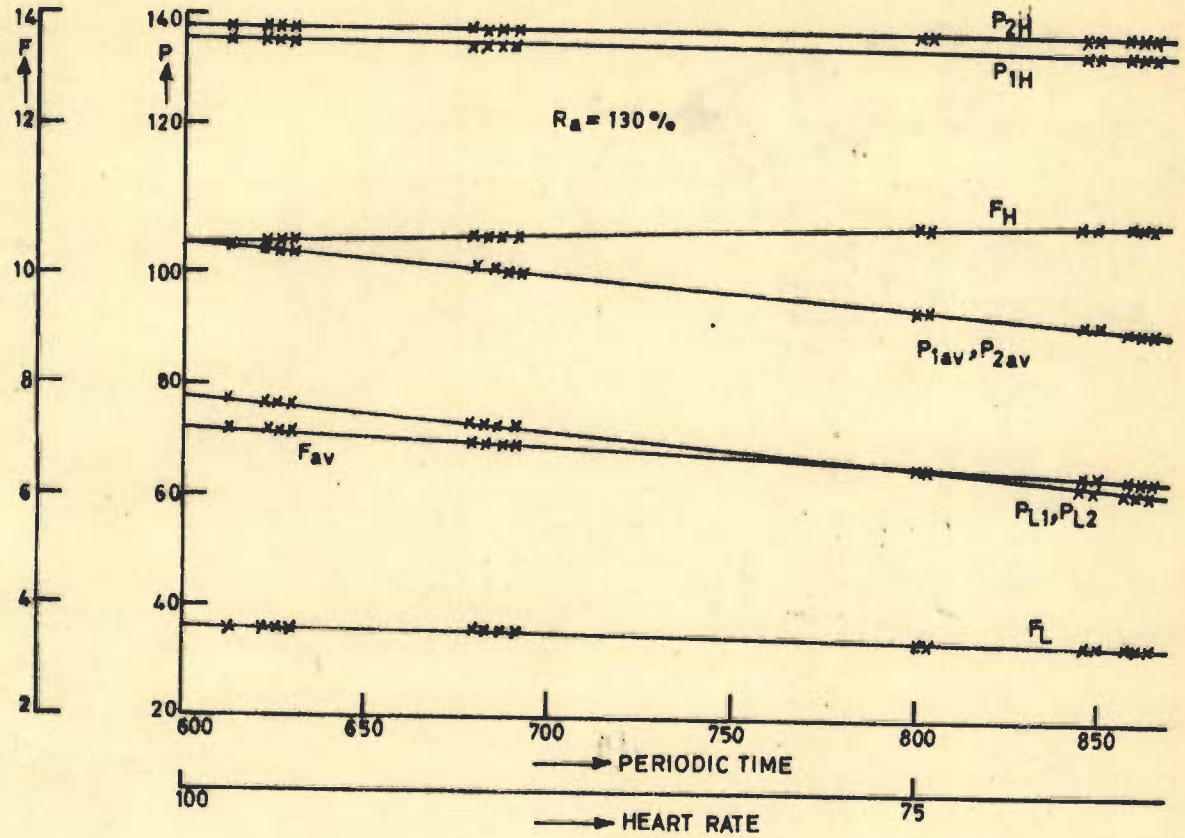


FIG. 4.21

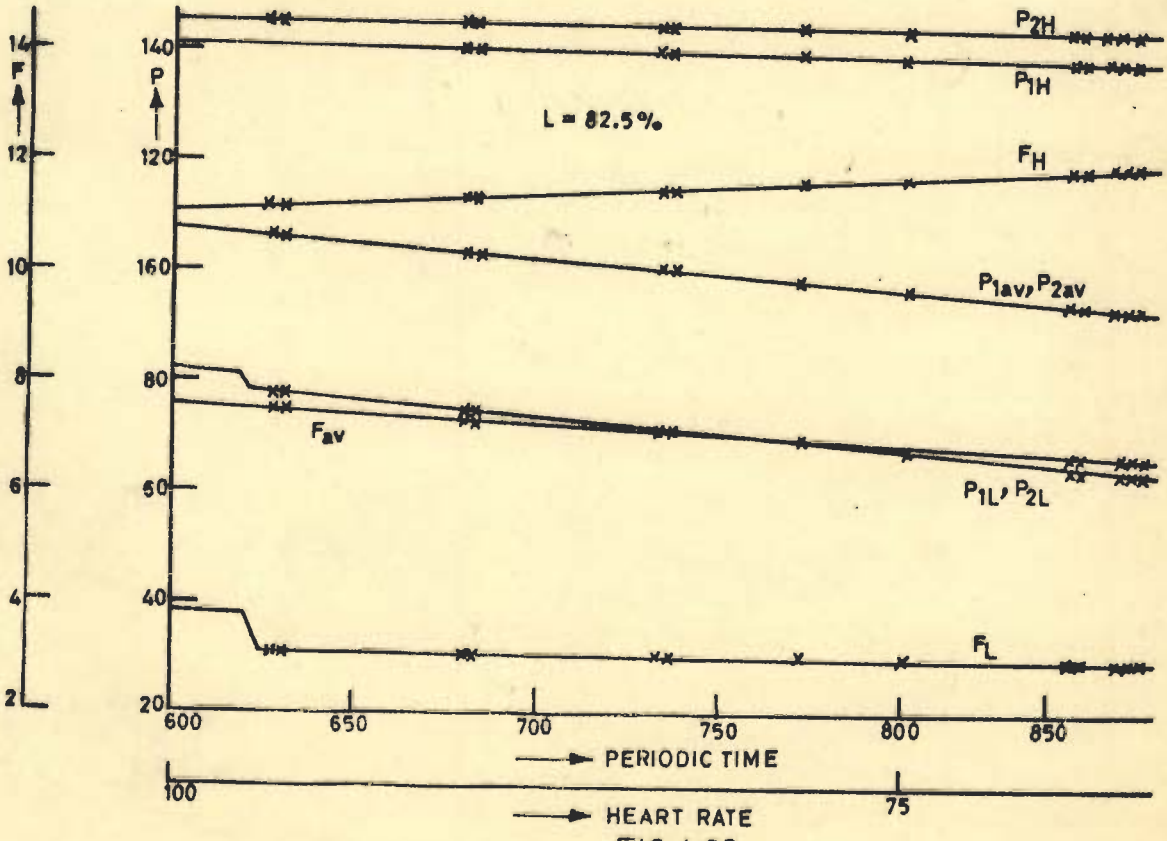


FIG. 4.22

variation of 0.5 % from the initial normal heart rate is sufficient to restore the normal stable operation. In case of a healthy subject the marginal change of heart rate required is easily accomplished by the natural control mechanism. The arrhythmia is arrested before it aggravates or even being noticed. In case of severe abnormality the system may not be self adaptive. The arrhythmia may persist and at times may prove fatal. In such case external intervention is inevitable. There are many medicines which can provide the required small change in the heart rate. Alternatively an external pacemaker may be operated at a frequency slightly higher than the previous value of normal heart rate. It will pull the heart in to synchronism to provide stable operation at a slightly different heart rate. From the Figures 4.21 and 4.22 it is also verified that the maxima, minima and average values of pressures P_1 and P_2, and flow F at this slightly different heart rate (75 BPM $\pm$ 0.5 % of this value) are same as they should be at the previous normal heart rate of 75 BPM, with the corresponding values of the parameters, if the response curves in Figures 4.15 and 4.16 were continuous.

The available literature explains the cardiac arrhythmia in terms of faulty generation and/or conduction of cardiac action potentials. The present analysis envisages a a new possible mechanism leading to cardiac arrhythmia. On the basis of this analysis it is concluded that some typical variation or combination of left heart and systemic circulatory system parameter values may also be a cause of cardiac arrhythmia. The cardiac system can be corrected and brought to its normal operation by using either some medicine or an external pacemaker.

CHAPTER V

ANALYSIS OF PULMONARY SYSTEM

5.1 INTRODUCTION

The circulatory system consists of two parts: systemic circulation and pulmonary circulation. The analysis of cardiovascular system has been carried out in the previous chapter. Pulmonary system is basically responsible for the purification of blood through lungs. The exchange of gases takes place between the blood flowing in pulmonary capillaries and the lungs. The CO_2 is taken out from the blood and O_2 is diffused in the blood as shown in Figures 1.3 and 1.4. The blood rich in O_2 content is later on used by the cardiac system for systemic circulation through left ventricle and aorta. The proper exchange of gases depends upon the state of the pulmonary system. The parameters of the pulmonary system are affected by the abnormalities of the pulmonary system and influence the exchange process. The analysis of the equivalent model for the normal and abnormal conditions of pulmonary system provides a good insight into its working. The work in the present chapter is in this direction.

5.2 PULMONARY SYSTEM MODELS

The lumped parameter models are generally used for the analysis of pulmonary system. In 1915, Rohrer [184] proposed a model of pulmonary system by using the following relationship between alveolar pressure (Palv) and airflow at the mouth ($\dot{V}_{ao}$).

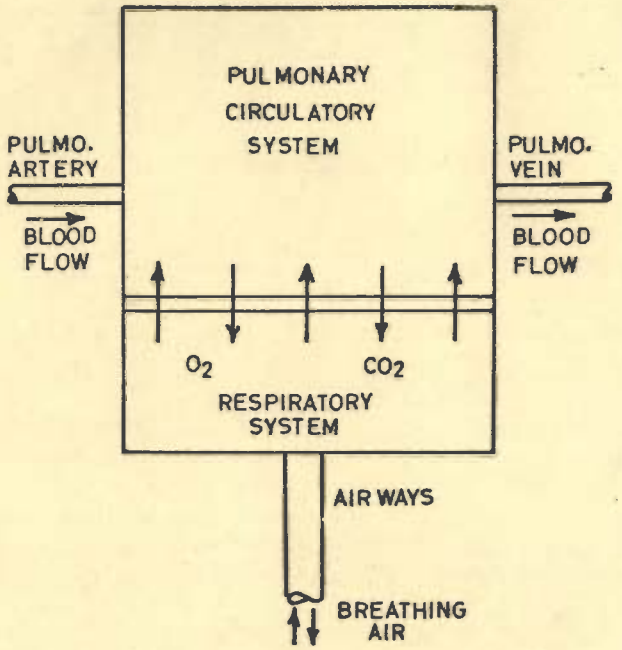


FIG.5.1. PULMONARY INTERACTION

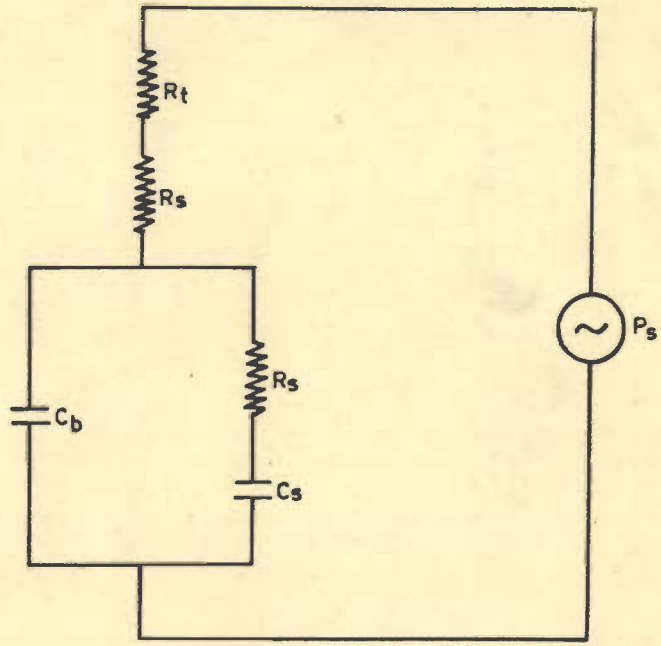


FIG.5.3. RESPIRATORY ANALOGUE

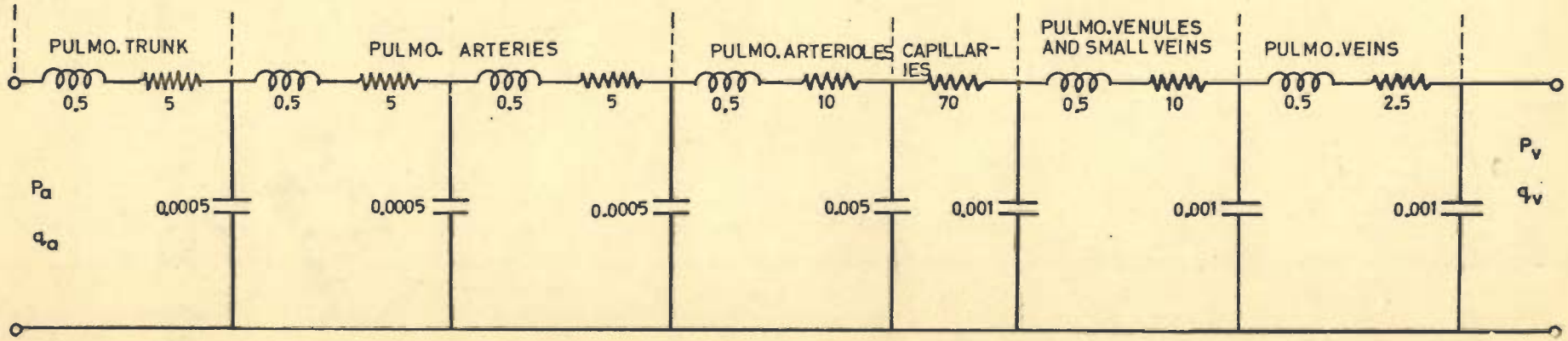


FIG.5.2. PULMONARY CIRCULATORY SYSTEM

$$P_{alv} = K_1 \dot{V}_{ao} + K_2(\dot{V}_{ao})^2 \qquad \ldots (5.1)$$

In 1967, Bouhuys and Johnson [26] revealed that this model satisfies the inspiratory flow conditions but fails to predict flow limitation due to compressed airways during expiration. The models proposed in 1967 by Pride et al. [175] and in 1970 by Yamayashi et al. [244] included the airway resistances which are functions of transmural pressure across the airway walls. The models account for the expiratory flow limitation but not for the expiratory loops. In 1972, Albergoni et al. proposed a two compartment interaction model between the circulatory and respiratory systems [3]. The functional description of the model is as shown in Figure 5.1. It explains the exchange of O_2 and CO_2 between pulmonary blood and alveolar air. To obtain the driving functions of the interaction model, the circulatory and respiratory systems are modelled separately. The circulation part is modelled by an RLC network as shown in Figure 5.2. Right ventricular output pressure P_a is the forcing function resulting in blood flow q_a at the input to the pulmonary system. The outputs are pulmonary vein (or left atrium input) pressure P_v and blood flow in pulmonary vein q_v. Electrical analog of the respiratory system is as shown in Figure 5.3. Variable part of intrathoratic pressure acting as the driving function is assumed sinusoidal.

$$p_s = p_m \sin(2\pi ft + \emptyset) \qquad \ldots (5.2)$$

The tidal volume is taken as the output function.

While passing through the pulmonary system blood leaves part of its CO_2 in pulmonary compartment and receives O_2 bound to

hemoglobin. Hemoglobin increases capability of absorbing O_2. The curve for CO_2 dissociation is almost linear where as that for O_2 is exponential. Blood running through vascular bed exchanges O_2 and CO_2 with alveolar air. A step by step procedure is followed for digital solution of circulatory, respiratory and interacting sections. The versatality of model permits the change of most of the parameters necessary for physiological and pathological conditions during the simulation run.

In 1972, Saidel et al. reported a dynamic lumped parameter mass-balance model of pulmonary oxygen transport [193]. As shown in Figure 5.4, the gas side of the lung is modelled as a series-parallel arrangement of five perfectly mixed variable volume compartments G_1 to G_5. Blood side of lung is modelled as a series of perfectly mixed, constant volume compartments B1 to B4 of pulmonary capillary bed. The compartments used have functional significance rather than anatomical. The model simulations indicate that the oxygen-hemoglobin reaction does not reach equilibrium in the pulmonary capillaries, as assumed commonly in analysis of pulmonary oxygen transport. The model aims at predicting the O_2 concentration of the blood leaving the lung from input conditions, forcing functions and system parameters; and to discriminate normals and abnormals on the basis of oxygen transport ability. Oxygen transport on gas and blood sides of the lungs is simulated solving the system equations using fourth order Runge Kutta algorithm.

In 1973, Golden et al. [88] proposed lumped representation of ventrilatory system and electrical analog as shown in

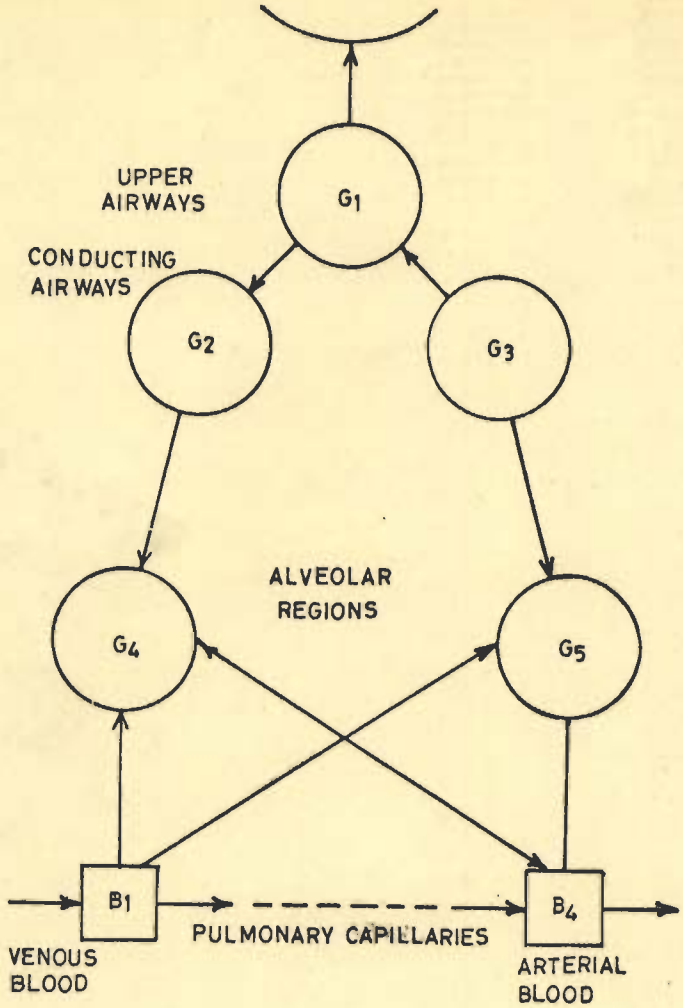


FIG.5.4. MASS BALANCE MODEL

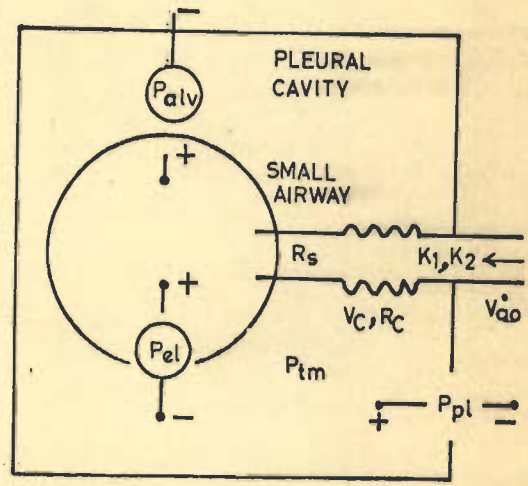


FIG.5.5. VENTILATORY SYSTEM

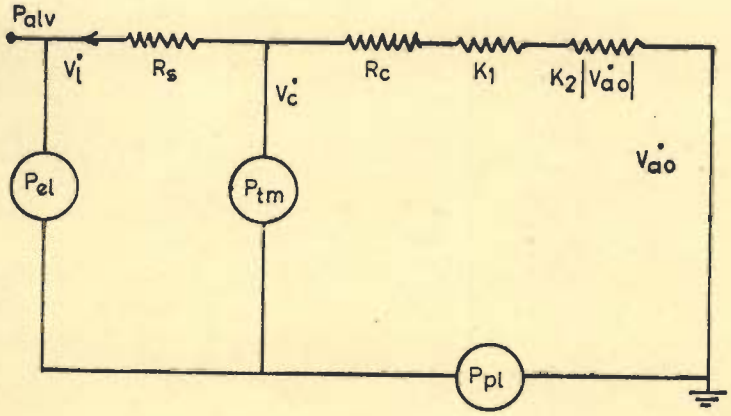


FIG.5.6. ELECTICAL ANALOG

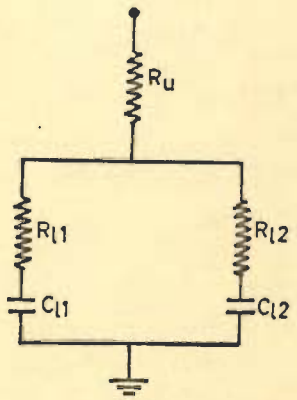


FIG.5.7. 3-COMPARTMENT MODEL

Figures 5.5 and 5.6. For collapsible segment volume and transmural pressure, hyperbolic relationship is assumed. The rigid and collapsible parts of small airways are represented by fixed and variable resistances R_s and R_c respectively. The value of R_c is assumed as

$$R_c = 0.2\ (0.02/V_c)^2 \qquad \ldots (5.3)$$

The collapsible segment volume is V_c. The large airway has a constant component of resistance K_1 and flow dependent component $K_2|\dot{V}_{ao}|$, to account for turbulent flow. Considering flow less than 2 l/s, lung volume and elastic recoil are assumed constant. During inspiration overall airway resistance decides the flow. During expiration airway collapses, small airway resistance and lung elastic recoil decide the flow. Numerical integration is used to simulate panting maneuver with various values of model parameters. The sinusoidal variation of alveolar pressure at frequency 1.6 Hz is considered. The model is also used with plethysmographic data of panting maneuver at high frequency (2Hz) and volume less than 0.1 l. P_{alv} and $\dot{V}_a$ at mouth are recorded. Parameters P_{el}, R_s, K_1 and K_2 are estimated using Gauss-Newton least square algorithm with Levenberg adjustment. The alveolar pressure is used as input. The computed and observed airflow are compared. It is also remarked that inclusion of more parameters in the model may improve the curve fitting, but will not add any insight in to the physiological occurances during a pant.

In 1975, Shaffer developed a 3-compartment pulmonary model as shown in Figure 5.7 and investigated the frequency

response sensitivity for impedance, resistance and capacitance. The lung parameters are determined as function of frequency, peripheral airway contribution to total airway resistance and relative % obstruction of peripheral airways. The frequency sensitivity as an indicator of small airway obstruction is confirmed, but frequency sensitivity is limited to specific range of airway obstruction and breathing frequency. Under certain circumstances this measure may be of little or no clinical value.

In 1976, Olender et al. [161] did an analog computer simulation of expiratory flow limitation using a model as shown in Figure 5.8. It is remarked that large number of parameters involved makes the parameter identification difficult. The constants K_1 and K_2 are adopted from Bouhuys and Jonson [26] and Mead [146]. The resistance of collapsible segment is taken to be

$$R_c = K_3 (K_4/V_c)^2 \qquad \ldots (5.4)$$

where, constants K_3 and K_4 are adopted from literature and V_c is collapsible segment volume. The small airway resistance R_s is related to % vital capacity VC by a graphical relationship adopted from Maclem and Mead [136] and Bouhuys [25]. Ratio of collapsible segment volume to maximum value of collapsible airway volume is also related to transmural pressure by a graphical relationship derived from Murtaugh et al. [153] and Hyatt and Flath [110]. Static lung compliance curve is derived from Colebatch et al. [53] and dynamic compliance curve is derived using static compliance curve and data by Clements et al. [52] and Glaister et al. [85]. Using sinusoidally varying pleural

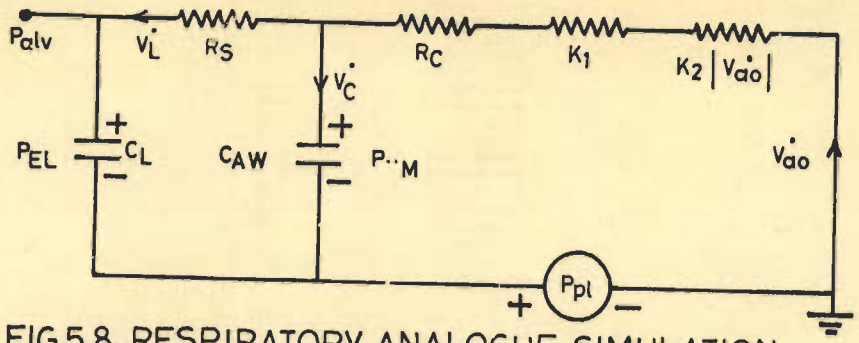


FIG.5.8. RESPIRATORY ANALOGUE SIMULATION

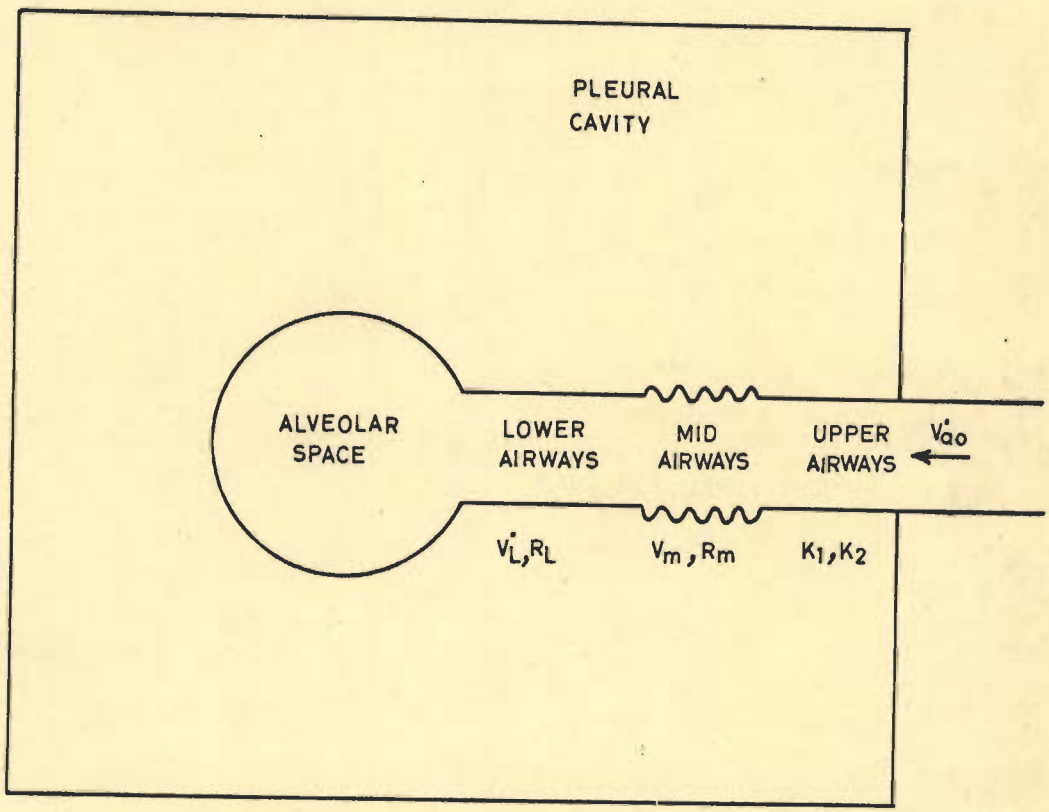


FIG.5.9(a). VENTILATORY SYSTEM

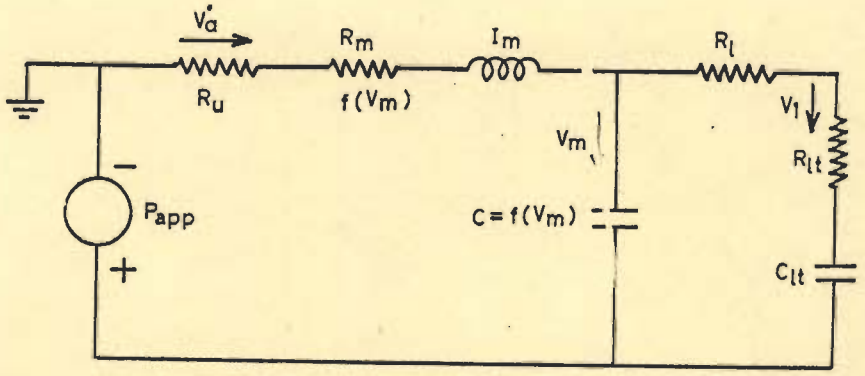


FIG.5.9(b). EQUIVALENT CIRCUIT OF CONDUCTING AIRWAYS.

pressure as the input, effects of variation of various model parameters are investigated on the analog computer.

In 1978, Gupta [97] considered the lumped representation of ventilatory system as shown in Figure 5.9(a). The equivalent nonlinear circuit for the model of the conducting airways is as shown in Figure 5.9(b). The modified David-Fletcher Powell optimization method used for parameter estimation and diagnosis by Feinberg et al. [77] is reported to have unstable and slow convergence with too much computation. Gupta [97] has considered panting maneuver with small volume 50 ml and high f(2-3 Hz). Pleural pressure is used as the forcing function and airflow at the mouth as the response. The effects of blood flow and gas exchange are neglected. The parameters are estimated by least square curve fitting of human data with extended Gauss-Newton method. Some diagnostic interpretation and expiratory looping are illustrated [97].

In 1978, Pederson et al. [163] have investigated the potential of using low intensity penetrating microwave energy in diagnosis and monitoring of pulmonary diseases like edema and emphysema for selected animal models. The lung water in these diseases modifies the conductivity and permitivity of the lung tissue. Both the reflection and transmission measurement techniques are examined. In 1979, Tsai et al. [217] have applied pattern recognition principles to spirometric data. Different categories like Normal, moderately, severely and very severely obstructed are considered. A five element pattern vector is formed by normalised values of FVC,FEV, midmaximum flow rate

MMFR and flow rates with 50 and 25 % vital capacity remaining. A parametric Bayes classifier and one and two layer pairwise Fisher linear classifiers are designed. The rates of recognition up to 81-82 % are achieved. For normal and abnormal classification, the rate of recognition achieved is 94 % .

In 1979, Tsai and Pimmel reported a forced oscillatory method for rapidly measuring total respiratory impedance as a function of frequency for dogs [216]. For humans forced random noise is used. Series combination of resistance R, compliance C, and inertance I forms the total impedance,

$$Z = R + j2\pi f I + E/j2\pi f. \qquad \ldots (5.5)$$

The elastance E is reciprocal of compliance C. The optimum values of parameters are found by least square error criteria.

$$J = \sum_{i=1}^{N} |[U(f_i)+jV(f_i)]-[R+j2\pi f_i I+E/j2\pi f_i]|^2 \qquad \ldots (5.6)$$

where, $U(f_i)$ and $V(f_i)$ are the real and imaginary parts of measured impedance at frequency f_i and N the total number of measurements. The value of J is real. The values of R,I, and C are found by equating $\partial J/\partial R$, $\partial J/\partial I$ and $\partial J/\partial E$ to zero. The forced oscillatory parameters are found as

$$R_{FO} = \frac{1}{N} \sum_{i=1}^{N} U(f_i) \qquad \ldots (5.7)$$

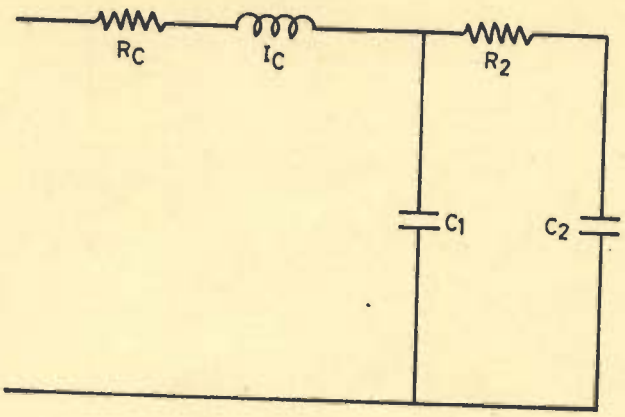
$$I_{FO} = \frac{N}{C} \sum_{i=1}^{N} V(f_i)/2\pi f_i - \frac{a}{c} \sum_{i=1}^{N} 2\pi f_i V(f_i) \qquad \ldots (5.8)$$

$$E_{FO} = \frac{b}{C} \sum_{i=1}^{N} V(f_i)/2\pi f_i - \frac{N}{C} \sum_{i=1}^{N} 2\pi f_i V(f_i) = 1/C_{FO} \qquad \ldots (5.9)$$

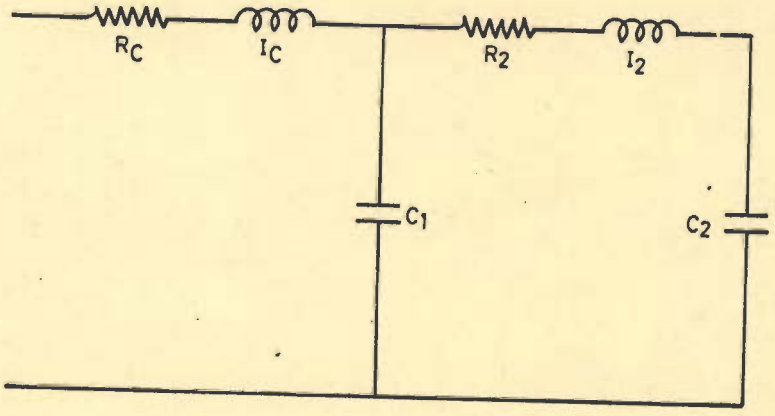
$$a = \sum_{i=1}^{N} 1/(2\pi f_i)^2 \,,\quad b = \sum_{i=1}^{N} (2\pi f_i)^2 \,,\quad c = [\,]^2 - ab \qquad \ldots (5.10)$$

For series-parallel RLC combinations the equations become non-linear and nonseparable. In 1980 Pimmel et al.[165] found total respiratory impedance for six dogs using forced oscillations ranging from 0.9 to 16 Hz. The values of R, L and C are found by linear regression. It is claimed that transient mechanical changes induced by vagal stimulation can be characterised by this technique.

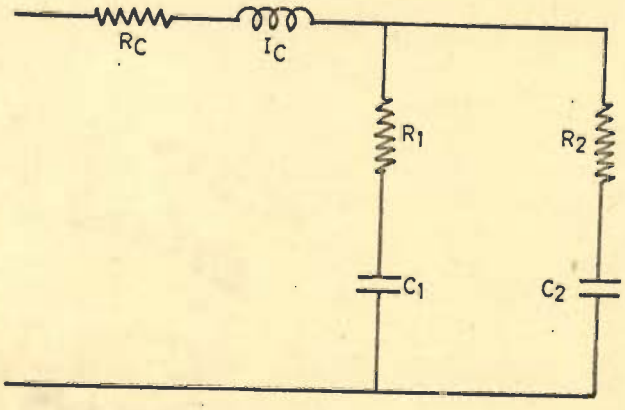
In 1981, Eyles and Pimmel [74] have reported that simple RLC series model explains the impedance data for normals but fails in case of lung disease. Time constant discrepancies between the parallel compartments can simulate the diseased states but parameter estimation involves iterative minimization algorithms. For the forced random noise technique used a loudspeaker is coupled to the respiratory system by a mouthpiece and random signal with bandwidth 4-35 Hz is used for excitation. The induced pressure and flow are recorded and digitised. By spectral analysis complex impedance is found at 1Hz interval. For all the three models as shown in Figures 5.10 a,b and c, one and two stage gradient descent and one and two stage Simplex algorithms are used for the parameter estimation. Here, R_c and I_c represent viscous and inertial properties of central airways. The C_1 and R_2- C_2 paths in model 1 and C_1, R_2- I_2- C_2 paths in model 2 represent an airway and a parenchymal compartment. R_1 - C_1 and R_2- C_2 in model 3 represent parenchymal compartments. The criterion function minimised is



(a) MODEL 1



(b) MODEL 2



(c) MODEL 3

FIG.5.10 (a,b,c). PARALLEL COMPARTMENT MODELS OF RESPIRATORY MECHANICS

$$J = \sum_{f=4}^{35} \left| Z_m(f) - Z_e(f) \right|^2 \qquad \ldots (5.11)$$

In one stage gradient descent algorithm random search subroutine is used to find the starting values. With two stage gradient descent algorithm in second random search R_c and I_c are always fixed and C_1 is fixed for models 1 and 2. This second random search is followed by a second application of gradient descent subroutine in which all the parameters are adjusted. One and two stage simplex algorithms correspond to one and two stage gradient descent methods with Simplex subroutines in place of gradient descent subroutine. (In first random search 47000 and in second random search 3000-5000 sets of parameters are tested). Gradient descent subroutine uses combination of Gauss Newton, Newton Raphson, Optimum gradient and gradient projection methods to gain the advantages and overcome the limitations. Unlike the gradient descent methods in the Simplex algorithm it is not necessary to compute derivatives of criterion function at each iteration. For the data used two stage Simplex algorithm with model 1 offered the best approach for parameter estimation in parallel compartment models. For six parameters no suitable combination is found. It is also reported that different model-method combinations may be optimum for different data.

In addition to the modelling related to the respiratory tract a lot of work is done on gas exchange in the interacting zone. In 1909, Bohr [19] introduced the mathematical basis of calculations of transfer of oxygen between alveolar gas and capillary blood using diffusion principle. The kinematics of

combination of hemoglobin with oxygen was stressed by Roughton and Foster in 1957 [186]. With the introduction of digital computers in the field much more complicated models have been emerged to account for interaction between O_2 and CO_2, chemical reactions of these gases and pulsatality of capillary blood flow. In 1974, Wagner et al. have considered areas with low, zero and high values of ventilation-perfusion ratios $\dot{V}_A/Q$ and unperfused area (dead space) separately [225]. In 1977, Wagner has analysed the factors affecting O_2 and CO_2 exchange [224]. Oxygen transfer to blood is in the dissolved form and bound to hemoglobin. The higher capacity of blood for CO_2, chemical reaction and nearly linear CO_2 dissociation curve slow down equilibrium of CO_2 between alveolar gas and capillary blood. The reduction of mass transfer of O_2 and CO_2 automatically results in fall in venous P_{O_2} and rise in P_{CO_2} and total alveolar ventilation. This restores normal P_{CO_2} but not P_{O_2}.

In 1975, Jaliwala et al. have used a variable metric (or Davidson Fletcher Powell) optimization method of numerical analysis to recover known distributions of intrapulmonary ventilation-perfusion ratios from inert gas data [111]. The hypothetical lungs are simulated by a 50 compartment model. It is reported that the prevailing levels of measurement error represent an important limitation in current techniques for deriving distributions from inert gas measurements. After the analysis of simulation model shown in Figure 5.11, Farrell and Siegel have reported that simulation parameters provide functional indices of ventilation/perfusion disparity, diffusion gradients, venous-arterial pulmonary

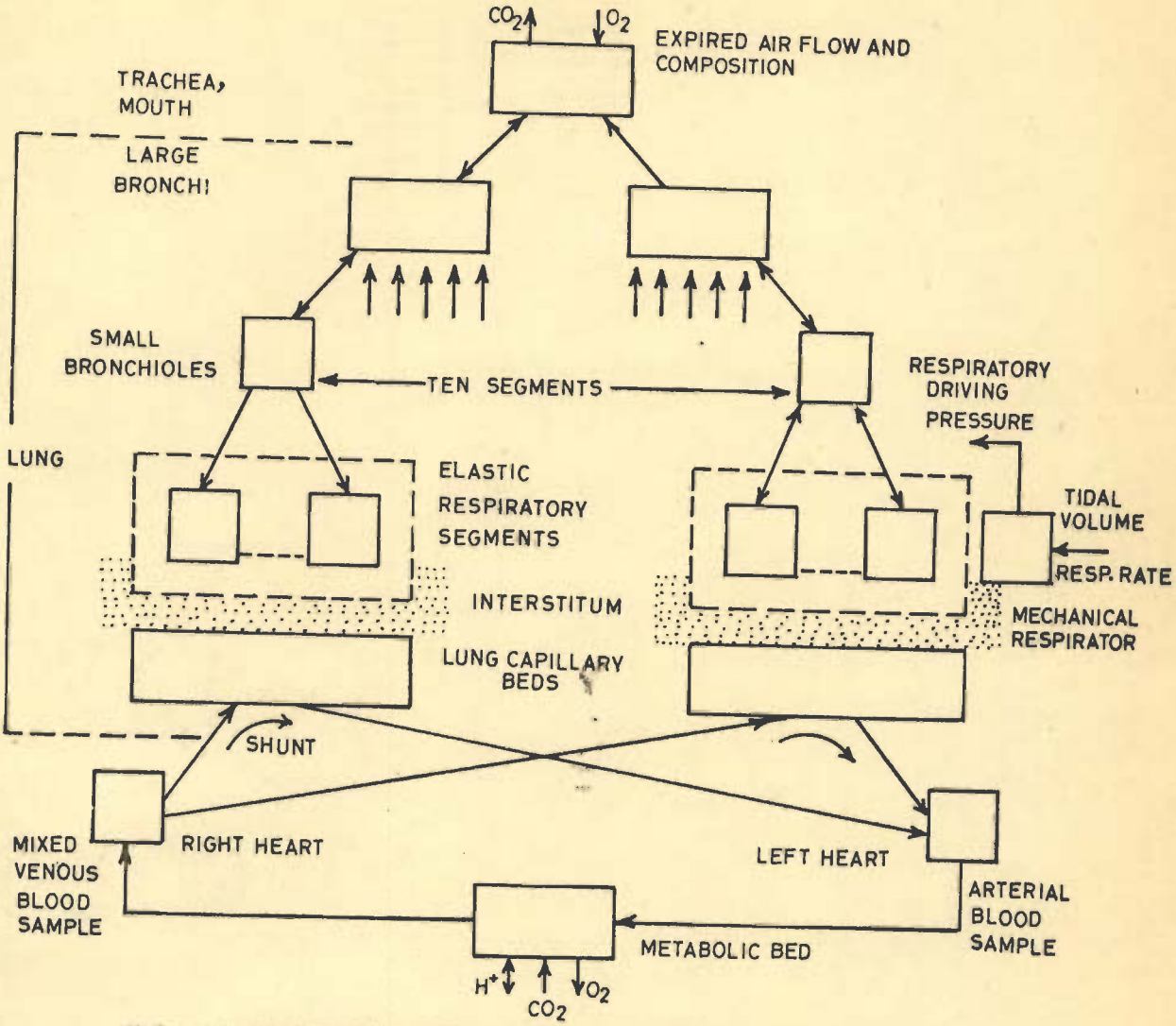


FIG.5.11. CARDIORESPIRATORY SIMULATION

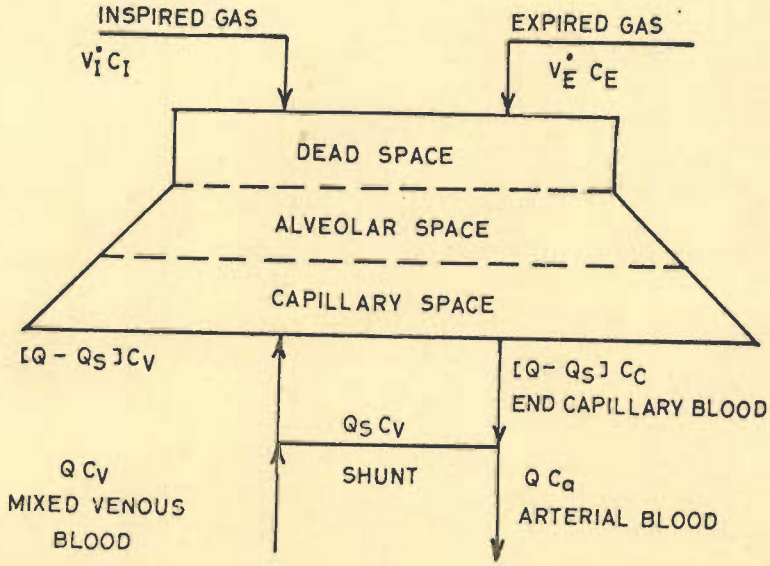


FIG.5.12 GAS EXCHANGE MODEL - SAIDEL

shunt and respiratory dead space [76]. The efficacy of cardio-respiratory support maneuvers in changing blood gas and PH values in clinically ill post coronary bypass patient with an acute respiratory distress syndrome can also be estimated.

In 1981, Poon et al. have proposed a one compartment, continuous time model for dynamic gas exchange in lungs [173]. The dynamics of alveolar gas concentrations (x_i) are critically dependent on blood-gas partition coefficients and inspired concentrations (u_i) of component gases. The Eigen values of the system are all real and negative and can be simultaneously maximised if the most soluble gas of the inspirate alone is inhaled. In 1982, Saidel has presented a mathematical model of inert gas exchange as shown in Figure 5.12, that accounts for a diffusion limitation as well as ventilation-perfusion inhomogeneity [192]. The model suggests that the input of inert gases by inhalation rather than by venous infusion is feasible and sampling of venous blood is unnecessary. So, inert gas study of abnormal pulmonary gas exchange may yield more information and may be more readily applied to clinical studies than currently recognised.

In 1982, Primiano et al. have reported a digital computer program developed to evaluate vital capacity, expiratory reserve volume, and inspiratory capacity from the spirograms [176]. In 1982, Hardy and Collins tried to fit data of flow resistance against transmural pressure for pulmonary vascular system of a dog [100]. A digital many compartment model of the human circulatory system proposed by Hardy et al. simulates pulsatile blood flow, gas transport and exchange, and passive breathing for

human data [101]. The computed CO_2 and O_2 partial pressures vary realistically around measured average partial pressures.

5.3 PULMONARY SYSTEM ANALYSIS

The model shown in Figure 5.13 is used for the analysis of pulmonary system. The model parameters are defined as follows.

R_1 = Fixed part of upper airway resistance

L = Inertance of air

R_C = Collapsible segment resistance

C_{AW} = Collapsible segment compliance.

R_{LA} = Lower airway resistance

F_1 = Airflow at nose

$K|F_1|$ = Turbulent component of upper airway resistance

PTM = Pressure developed across C_{AW}

PALV= Alveolar pressure

PLE = Pleural pressure

PEL = Lung elastic recoil.

The following units are used.

Pressure : cm H_2O

Flow : litres/second

Resistance : cm H_2O/liters/second

Inertance : cm H_2O.Second^2/litre

Compliance : litre/cm H_2O.

By taking flow F_1 through the inertance and pressure F_2 across the compliance as the state variables the state equations are written in the following form.

$$\dot{F}_1 = ((-(X(1) + X(2)*ABS(F_1)*F_1 - F_2 - PLE)/X(3) \quad \ldots (5.12)$$

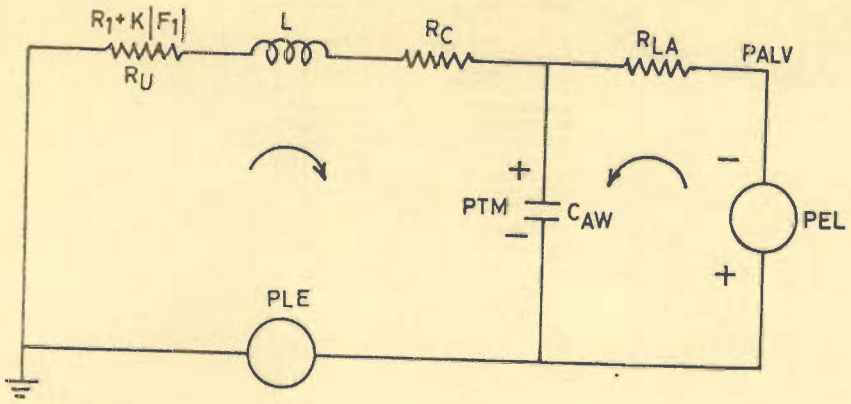


FIG.5.13. RLC MODEL OF PULMONARY SYSTEM

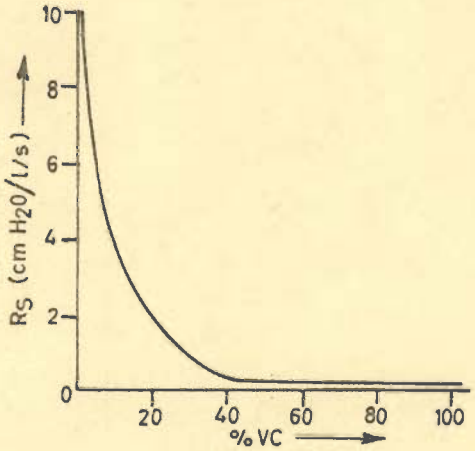


FIG.5.14. RESISTANCE CURVE

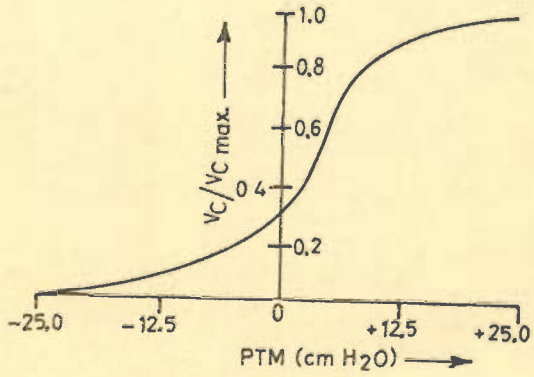


FIG.5.15. AIRWAY COMPLIANCE

$$\dot{F}_2 = (F_1 - (F_2 + PEL)/X(5))/X(4) \qquad \ldots (5.13)$$

where,

$X(1) = R_1 + R_C$

$X(2) = K$

$X(3) = L$

$X(4) = C_{AW}$

$X(5) = R_{LA}$

F_1 = flow with derivative $\dot{F}_1$

F_2 = transmural pressure PTM with derivative $\dot{F}_2$.

The parameters of this model have good correlation with the actual pulmonary system. The estimated parameters of this model can prove to be very useful for the diagnostic purpose. Generally in pulmonary system analysis panting maneuver is considered. It takes very small air volume, assuming lung volume and lung elastic recoil almost constant. Using sinusoidal pressure wave as the forcing function shallow high frequency breathing is considered. In the present analysis actual pressure wave, airflow and variable lung volume are considered. Forced oscillatory response is a totally different approach. It estimates model parameters under different conditions than the normal working of the pulmonary system. The aim in the present analysis is to estimate the parameters of pulmonary system under actual physiological conditions using minimum assumptions. The technique commonly used for this type of problem is regression analysis in which curve fitting is used to obtain values of parameters utilising known input and output. Gauss Newton method is suitable for

nonlinear regression equations but with poor initial guesses for unknown coefficients there is convergence problem. Marquardt method can converge for poor guess but proper selection of λ and computation time are the problems. Powell (SSQMIN ALGORITHM) method is a modification of Gauss Newton technique and is suitable for nonlinear regression equation. So, it was tried in the beginning.

For the parameter estimation of pulmonary system pressure and flow data are required. In this connection All India Institute of Medical Sciences, New Delhi, Medical College at Aurangabad and Pulmonary functions laboratory, Houston were contacted but the effort was in vain. Finally the data available in literature [47,116] for alveolar and pleural pressures and flow of air were used for the analysis. Starting with pressure data, fourth order Runge Kutta method was used to compute flow F_1 and transmural pressure F_2. The initial values of pressure and flow are decided by an iterative process so that the response cycle stabilises and repeats periodically. Least square technique with Powell (SSQMIN ALGORITHM) method is used to fit the computed flow curve with the actual flow curve and effort is made to estimate the parameters.

In this approach there are number of problems. Five parameters and unknown initial pressures and flow make the number of unknowns very large. The noise and inconsistency inherent in the type of data available has aggravated the problem further. So there are convergence and reproducibility problems. Olender et al.[161] and Tsai and Pimmel [216] have also confirmed this limitation. To reduce the number of unknowns R_1+R_c and K were

adjusted externally by trial and error process to minimise the initial sum of squared errors and only three parameters L, C_{AW} and R_{LA} were estimated by Powell algorithm. In this case the convergence is achieved but the estimated parameter values are much sensitive to initial values of L, C_{AW} and R_{LA} and set constant values of $R_1 + R_c$ and K. Moreover, the aim in the present work is not only the parameter estimation of a single case, but to develop a generalised method of parameter estimation suitable for discrimination among the cases of different categories. For this purpose the approach was also applied to the data of an abnormal case. In this case the use of same set of constant values for $R_1 + R_c$ and K, and initial values of L, C_{AW} and R_{LA} did not result in convergence. So the whole objective of establishing basis of comparison for different cases is lost and the method is not suitable at least for the present purpose.

In another approach, a model shown in Figure 5.8 is considered. For simplicity inertance is dropped. The lower airway resistance is considered in two parts. One part having fixed value R_s and another collapsible part having resistance R_c and corresponding compliance C_{AW}. $\dot{V}_{ao}$ is input airflow and $\dot{V}_L$ is flow at the lungs having compliance C_L. K_1 is fixed part of upper airway resistance and $K_2|\dot{V}_{Ao}|$ is its turbulent component. P_{alv}, P_{pl}, PTM and PEL are alveolar, pleural and transmural pressures and lung elastic recoil. V_L is the lung volume with initial value V_{Lo}. V_c is collapsible segment volume, V_{co} initial value and $\dot{V}_c$ flow through collapsible segment.

Pulmonary pressure, pleural pressure and airflow curves are enlarged and digitised. By interpolation with the spline fits 601 data points are generated on each curve. Numerical integration is used to get corresponding values of tidal volume.

Lung elastic recoil PEL = $P_{alv} - P_{pl}$ ... (5.14)

$C_L = (V_L - V_{Lo})/PEL$ ... (5.15)

From the data of Maclem and Mead [136] and Bouhuys [25] the curve relating small airway resistance and lung volume as % of vital capacity is reported [161] to be as shown in Figure 5.14. This curve is enlarged and digitised. The coefficients for the spline-fits in the resulting 52 intervals are computed so that the value can be interpolated at any desired point.

$PTM = PEL + R_S * \dot{V}_L$ ... (5.16)

Lung volume as % vital capacity = (Functional residual capacity FRC + Tidal volume)/vital capacity FRC is taken 2.3 litres and vital capacity is taken 6.5 litres. At a point first vital capacity and then corresponding value of R_s is computed. PEL and $\dot{V}_L$ are already known. So PTM can be found out.

Airway compliance is expressed by a curve relating $V_c/V_{c\,max}$ and PTM [110,153] as shown in Figure 5.15. This curve is also enlarged and digitised. By spline fit corresponding to value of PTM, $V_c/V_{c\,max}$ is computed. $V_{c\,max}$ is reported to be 0.1 litre [161].

$V_c = V_{c\,max} * (V_c/V_{c\,max})$

At this point $\dot{V}_c$ is found by numerical differentiation. Flow at

nose and alveolar flow are related by

$$\dot{V}_{ao} = \dot{V}_c + \dot{V}_L. \qquad \ldots (5.17)$$

Resistance R_c is computed as follows:

$$R_c = -(PTM+P_{pl}+(K_1+K_2|\dot{V}_{ao}|)\dot{V}_{ao})/\dot{V}_{ao}$$

$$= -((PTM+P_{pl})/\dot{V}_{ao}+K_1+K_2.|\dot{V}_{ao}|) \qquad \ldots (5.18)$$

Reported values of K_1 and K_2, 0.5 and 0.2 respectively are taken here [26,146,161].

Total upper airway resistance R_u is computed as

$$R_u = K_1+K_2|\dot{V}_{ao}| \qquad \ldots (5.19)$$

Compliance of the collapsible segment is given by

$$C_{AW} = (V_c - V_{co})/PTM \qquad \ldots (5.20)$$

Using these relationships instantaneous values of R_S, C_L, flow $\dot{V}_{ao}$, R_c, R_u, and C_{AW} are computed. Average values of various parameters for inspiration, expiration and over the whole respiratory cycle are computed for one normal and one abnormal case. The values for the ratio of parameter value of the abnormal case to that for the normal case are shown in Table T.5.1.

5.4 RESULTS AND DISCUSSION

The main difficulty with the pulmonary system is about the diagnosis of the abnormalities in the lower airways. Sputum production, blood-gas tests and forced vital capacity help in detection of mechanical impairment. It is difficult to locate the cause and site of obstruction. Early detection of emphysema,

TABLE T.5.1

Relative values of parameters of abnormal case w.r.t. corresponding values of the normal case

Sr.No.	Quantity	Rel. value
1	Inspiratory lung compliance C_{LI}	1.0175
2	Expiratory lung compliance C_{LE}	0.9025
3	Average lung compliance C_L	0.9560
4	Average flow F	0.8490
5	Small airways inspiratory resistance R_{SI}	1.0000
6	Small airways expiratory resistance R_{SE}	1.0000
7	Small airways average resistance R_S	1.0000
8	Collapsible segment inspiratory resistance R_{CI}	1.9180
9	Collapsible segment expiratory resistance R_{CE}	11.2900
10	Average collapsible segment resistance R_C	6.1650
11	Upper airway av. turbulent resistance R_{1T}	0.8440
12	Total upper airway resistance	0.9800
13	Collapsible segment inspiratory compliance	0.9540
14	Collapsible segment expiratory compliance	1.7050
15	Av. collapsible segment compliance	1.0710

bronchitis and asthama is difficult. In the present analysis, the upper airways are considered intact and the corresponding parameters are assumed constant. The parameters for lower airways and inner part of the pulmonary circuit are computed. With the Powell algorithm due to large number of unknowns, noise and inconsistency of the data there are convergence and reproducibility problems. It has not been possible to establish a generalised method of analysis and basis of comparison for normal and abnormal cases. Earlier Eyles and Pimmel also had concluded on similar lines that simple RLC series model explains the impedance data for normals but fails in case of lung disease. The results of second method are better. Estimated parameters for the abnormal case show considerable deviation from the values for the normal case. Therefore the approach has a good diagnostic utility. Unlike the first method there is no convergence problem in this case. Moreever, here the local inconsistency or noise in the data is not much troublesome as experienced with Powell algorithm. Inspite of very large number of data points the computation time is very small (about 5 second) in this case. It is true that it is not a very sophisticated method, but with some simple computations and very small computation time it provides a good basis of comparison for diagnostically significant parameters. As observed by Eyles and Pimmel different parameter estimation algorithm may be suitable with different types of models and the nature of data.

CHAPTER VI

CONCLUSIONS AND DISCUSSION

6.1 ELECTROCARDIOGRAM

Computer assisted ECG interpretation requires accurate and compact form of representation of ECG pattern with suitability of categorization of diagnostic parameters. In the present work the ECG pattern is represented by the Frontal plane Peak Resultant vectors (FPR) corresponding to different segments. When the measurement and lead proximity correction algorithm developed is applied to Burger triangle representation, FPR amplitudes and phases are computed with very high accuracy and precision. The results contradict the general feeling that 12 lead ECG system is less specific and less informative. One more important point is that it is necessary to measure peak segment potentials at only two leads for FPR computation.

When measurement and storage of instantaneous potentials at hundreds of points over the cardiac cycle at all the leads is considered orthogonal three lead system has inherent advantage of 4:1 data compression compared to 12 lead system. If the proposed model based on new basis functions is used, it is necessary to measure and store less than or equal to about eighteen parameters. With this information it is possible to reconstruct the set of ECG patterns at leads I, II, III, aV_R, aV_L and aV_F with the potentials corrected for measurement error and lead proximity. Compared to 250 x 3 (orthogonal leads) or 250 x 6 (six of 12 leads) samples/

second, the storage of 18 parameters results in notable data compression. Moreover, these parameters have high diagnostic significance and are suitable for categorization. The coefficients of the basis functions are to be evaluated only once for all. The model accounts for horizontal and vertical elongation and/or contraction of various ECG segments and relative phase shifts among them, effect of individual lead axis, and other physiological changes. It has the simplicity of computation and ease of generalisation of diagnostic parameters. The fiducial points on the ECG pattern are clampted to the corrected values computed with high accuracy and precision. Good shape matching is ensured for the individual segments. The deviation of intermediate potentials from the corrected true values may be less compared to beat to beat variation. Moreover the reconstruction of ECG which does not affect the accuracy of interpretation adversely is considered sufficiently accurate for diagnostic purpose. Actually for the interpretation algorithm developed here instantaneous values are not necessary at all.

One of the most important and difficult problem in computer interpretation of ECG is the development of criteria for normal/abnormal and other diagnostic entities. Effort was made to know if any such criteria are fixed by American and British Heart Association. According to information collected from Dr. P.W. Macfarlane, Dr. H.V. Pipberger and Dr. J.J. Bailey (personal communications in September-October 1982) British Cardiac Society, American Heart Association and American College of cardiology have not established such criteria. Dr. Pipberger

further pointed out that there are substantial differences between the different races in electrocardiography. He suggested that to achieve accuracy in the present work criteria for normality should be established based on large samples of Indian population. He also agreed that it might take considerable time. As the research is to be completed in limited time with limited means, just to start with the development of methodology some typical normal cases were collected from All India Institute of Medical Sciences, New Delhi. The relative values of parameters were used to define boundaries of the normal pattern spaces for respective parameters. The use of relative values ensured very good clustering of the cases of the same category in the pattern space and scattering away of cases of different categories. Use of peak to peak segment intervals instead of segment durations between start and end increased accuracy of measurement. An algorithm based on simple binary code is successful in screening the ECGs in to normals and abnormals.

The developed composite binary code provided a very compact method of representing the symptom patterns for various cases. The algorithm started without bias for any medical criteria of ECG interpretation. From the training sets of cases the computer was allowed to decide its own criteria so that the cases of different categories could be discriminated with 100 % sensitivity and 100 % specificity. The generalised symptom patterns for different categories and associated weight factors were decided by the computer itself during the training phase. It can minimise the criteria error if the data bank includes well diagnosed cases.

On the basis of weighted sum of symptoms, all the cases considered are correctly classified and well discriminated from the other categories. The method has combined the first and second generation programs. Multiple measurements and statistical techniques are used but assumptions about multivariate measurements, normal distribution and probability denties are avoided. The value of weighted sum of symptoms indicates the degree of severity of abnormality and provides graded diagnosis instead of two state i.e. yes/no type diagnosis. Thus the advantage of fuzzy set approach is also incorporated. Generation of symptom patterns with composite binary code, derivation of symptom multipliers and weighted sum of symptoms can also be implemented through hardware.

In the present work the interpretation algorithm is very much simplified and arithmatic computations are much reduced. In the final stage of the interpretation the symptom multipliers used have values 1, -1 and 0. The weighted sum of symptoms involves only addition or subtraction of various weight factors (no multiplication or division is involved). So, microprocessor implementation of interpretation algorithm is very much convenient. Use of microprocessors should no longer be limited to data acquisition, wave recognition and arrhythmia analysis. Inspite of the low speed and limited capability, microprocessor based system can meet the daily load of ECG interpretation in a hospital without sacrificing the diagnostic accuracy.

This is not the end of the problem. It is just a beginning for the solution of the problem. It should be kept in mind that this is not the commercial version of the program. This

research work was aimed at the development of an ECG interpretation program with some novel features to overcome some of the limitations of certain methods and to reduce complexity of computations without sacrificing the diagnostic accuracy. It is required that before exposing the program to commercial application and/or testing a rich data bank covering the whole range of normality and abnormality and various degrees of severity for various diagnostic entities should be established. This data bank can be used to define the pattern spaces for individual diagnostic parameters and to update the generalised symptom patterns and associated weight factors for various diagnostic entities.

6.2 CARDIOVASCULAR AND PULMONARY SYSTEMS

The lumped parameter model of the cardiovascular system considered is a useful tool for the analysis of the system with reasonable accuracy. The open loop analysis of the model allows investigation of effect of variation of various model parameters on the system response. Most of the abnormalities of the cardiovascular system are reflected in the variation of model parameters. The simulation of abnormalities like aortic stenosis, aortic valve incompetence, hypertention, etc. is much suitable on this type of model. The reverse flow in aortic incompetence could also be simulated. For teaching purpose it is possible to create various abnormal states on the model without the presence of actual patients. With the model analysis harmful and risky invasive measurements can be minimised and additional information required can be computed. This approach indirectly helps for the

diagnostic purpose. With the limitation of unavailability of data for various abnormalities of cardio-vascular system, the diagnosis part could not be covered but the scope for diagnosis can not be denied. It is felt that if computer analysis of pressure-flow signals and ECG are combined, much better results can be obtained for the diagnosis of cardiovascular system.

Generally, cardiac arrhythmia is explained in terms of faulty generation and conduction of cardiac action potentials. In the present analysis it is observed that abnormal set of parameter values for the cardiovascular system may also lead to cardiac arrhythmia, which can be arrested by some medicine or pacemaker.

Large number of parameters involved in the pulmonary system, noise and inconsistency in the data make the estimation of parameters of the pulmonary system very difficult. In the absence of the availability of actual and accurate data, the use of text book data has aggravated the problem still further. The convergence is difficult even with the Powell algorithm. If the convergence is attained, the estimated parameters are much dependent on the initial values of the variable parameters and values assigned to the fixed parameters. The objective of establishing the basis of comparison for normal and abnormal cases is not met with in this approach. The second noniterative method is simple, involves less computation and computation time. Local inconsistency and noise in data are not as trouble some as with the Powell algorithm. It provides a good basis of comparison for the parameters of the lower airways of the normal and abnormal cases.

The parameters considered have direct correlation with the actual physiological system. So the method has good diagnostic utility.

6.3 SCOPE FOR FURTHER DEVELOPMENT

In the area of computerized ECG analysis, the work was started about three decades back. A good amount of work has been carried out so far, but still, the ECG interpretation programs have not reached perfection. The problems are due to some of the limitations like inaccuracies in automatic wave recognition and loss of information during data compression. The difficulties are partly overcome by advancement in electronic equipment, capabilities of computers and computational methods. Yet there is a lot of scope to carry out work in this area with reference to following aspects.

(i) Wave recognition

(ii) Data compression

(iii) Location of transverse plane axis and computation of overall resultant vector

(iv) Establishment of data banks corresponding to different age, sex and race groups

(v) Updating the criteria to make the method suitable for routine application.

For the cardiovascular system, if necessary data is available, closed loop analysis can be carried out by including venous return. If large number of cases corresponding to different abnormalities are available, it may be possible to devise interpretation algorithms based on the model parameters for

cardiovascular and pulmonary systems. An interpretation algorithm incorporating all the parameters of ECG, cardiovascular and pulmonary systems may give useful information about the interdependence of different abnormalities.

LIST OF PUBLICATIONS

The following is the list of contributions by the author related to this thesis work.

1. Analysis and application of an electrical model of left heart-systemic circulation system for diagnostic purposes. Proc. Ist International Conf. on Applied Modelling and Simulation, AMS 81, Lyon, France, Sept.7-11, 1981, Vol.V, pp.74-77.

2. Comparative ECG analysis using Einthovan and Burger triangles, Journal of Institution of Engineers (I), Vol.62, IDGE 3, 1982, pp.58-66.

3. A new approach based on model analysis for understanding the mechanism of cardiac arrhythmia, Proc. International AMSE Conf. on Modelling and Simulation, Paris-Sud, July 1-3, 1982, Vol.12, MS 82, pp.8-10.

4. Mathematical model of an electrocardiogram based on new basis functions, International Journal of Systems Science, Vol.14, No.2, Feb.1983, pp.223-234.

5. Search for the normality of normal electrocardiogram for diagnostic purposes, Journal of Institution of Engineers (I), IDGE accepted for publication.

6. Parameter estimation of respiratory system, International Conference on Systems Science, Systems Science VIII, Sept.13-16, 1983, Wroclaw, Poland, accepted for presentation.

7. Application of left heart systemic circulation model for simulation of abnormalities, Journal of Institution of Engineers (I), IDGE, accepted for publication.

8. Microprocessor based ECG analysis, Medical and Biological Engineering and Computing, Communicated for publication.

9. Evaluation of diagnostic parameters for the pulmonary system, IXth All India Symposium on Bio Medical Engineering, Pune, November, 1983, Communicated for presentation.

10. Discrimination among various diagnostic entities in computer ECG Processing, International Journal of Systems Science, Communicated for publication.

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