CHAPTER-5

ECG ANALYSIS - A REVIEW

The electrocardiogram (ECG) has become a widely used diagnostic tool in clinical practice. ECGs can be divided into three categories : (1) "rest ECGs", which are recorded from ambulatory patients at rest for the purpose of an easy and rapid assessment of the cardiac status of the patients as well as for monitoring the effect of treatment; (2) "exercise ECGs", which are obtained from patients while performing a (predefined) excersise protocal for the purpose of (mainly) confirmation of ruling out the presence of coronary artery disease and (3) "arrhythmia monitoriy ECGs", which is recorded either from critically ill patients in coronary and intensive care units or from ambulatory patients for the purpose of (mainly) detecting arrhythmias [43].

Attempts to computerize the process of interpretation of ECGs have started very early, specifically in the late 50's. These attempts have resulted in the development of seperate computerized ECG processing systems for each ECG category described above. The "rest ECG processing systems", [59,139,140], "exercise ECG processing systemes, [100,110,111], and "arrhythmia ECG monitoring systems", [101] were developed.

The computerized ECG processing used in hospital and medical offices always try to imitate the cardiologist. Thus these systems perform two distinct tasks. The first is a pattern recognition and a pattern parameter measurement task. The second

is an interpretation task. In these systems the pattern recognition task is the hardest of all.

Three different approaches have been used for tackling the pattern recognition task : the "non-syntactic", the "syntactic" and the "hybrid" approach. The non-syntactic approach employes techniques from classical signal processing such as matched filters, template correlation, frequency domain analysis, etc. as well as heuristic techniques. The syntactic approach employes techniques from the syntactic pattern recognition field. The hybrid approach is a mixture of the non-syntactic approach and the syntactic approach and employes some techniques from the artificial intelligence field.

In this chapter the work done in the field of automatic ECG processing based on the syntactic approach as well as artificial inteligence are reviewed. However, revisal of non-syntactic approaches for ECG analysis will also be highlited.

As the computer assisted ECG analysis problem deals with a huge number of sampled data, the following tasks need importance while reviewing the automatic ECG processing.

1) Data reduction

2) Feature extraction

3) Interpretation or diagnosis of diseases.

5.1 Data reduction

For the purpose of processing by digital computers, patterns are usually digitized (in time or in space) first, and then represented by more compact forms (compressed data) using coding or approximation schemes. Considering that, a pattern is an

one dimensional function (e.g. waveform), it can be reconstructed exactly by the samples taken at a regular interval of time.

There are a number of approximation schemes proposed by different researchers for the ECG data reduction [31,69,167]. These include data reduction mainly by the reduction of the sampling rate and the straight line interpolation scheme. The reduction of sampling rate reduces the number of sampled points as well as the bandwidth of the transmission line so long the sampling theory is not violeted. This could result insignificant loss of key points, especially for QRS complexes with large amplitudes and high slopes.

In the straight line interpolation, a sample point is predicted by interpolating the two adjacent samples. When the difference between the interpolated and the actual values exceeds a preditermined criterion, only then the sample point is taken into account. This method can also be applied to determine a sample point in which the predication by interpoletion is done considering several of the preceding samples.

Cox, Nolle, Fozzard and Oliver Jr. [73] suggested an algorithm for the ECG data reduction in the year 1968. The method is known as the amplitude-zone-time-epoch-coding (AZTEC). The algorithm takes the raw ECG data and converts it into sequences of sample points with plateaus and slopes. This algorithm's data compression ratio is observed to be about 80% (5:1) with correctly chosen algorithm variable. The resen behind the result is that only the amplitude and length of a plateau or the final elevation and duration of a slope are under consideration. However this reduction in data often introduces significant discontinuity and

distortion in the reconstructed wave form. Other porblems include occassional complete loss of the P wave,amplitude loss of the QRS complex, loss of PR and ST segment durations and amplitudes and widening.

The 'turning point' algorithm developed by Mueller and Tompkins et.al [112,170,173] is an easy way to achieve a 50% data reduction while retaining the important data points to preserve ECG features. Here, the most recent sampled point x(nT) becomes the reference. The trend of the data is analyzed by comparing the amplitudes of the two previous data points x(nT-T) and x(nT-2T) to the most recent data point. Where T is the duration between the sampled points. Depending upon the nature of the pathway between x(nT) and x(nT-2T), either x(nT) or x(nT-2T) is saved and the other point is discarded. Turning point algorithm conveys information about a change in direction of the sampled data (i.e. turning point). Selection of these turning points causes localized time base distortion of one sample interval, but it has less distortion that can be visualized using conventional ECG recording techniques. Turning points are easily detected from the slope betweem the points. The method retains peaks and valleys of the signal while eliminating only "constant slope" points which do not represent crucial information in the signal. This method produces short term distortion since the saved points do not always represent equal time intervals but there is no long term distortion.

The combination of the 'turning point' and 'AZTEC' algorithm was used by Abenstein and Tompkins [87] in their "coordinate reduction-time-encoding system" (CORTES) data since

turning point algorithm retains the information of peaks and valleys it is used to the higher frequency part of the signal where as AZTEC to the isoelectric region of the ECG.

The CORTES algorithm preserves the QRS morphology, still there are discontinuties in the iso-electric region, therefore needs some smoothing. Parabolic filter may be applied to the AZTEC portion of the CORTES signal to reduce this distortion but the loss of peak and valley amplitudes will be the new hazard.

A method for compression of the ECG data by prediction of interpolation and entropy encoding was suggested by Ruttimann and Pipberger [168]. In this method, the records with relatively poor signal quality (due to noise) tend to require longer word length of the sample in average, and also a significant amount of execution time is required.

Udupa et.al. [86] presented a relatively new syntactic approach to ECG rhythm analysis. They used the differences in shape and structure between arrhythmic and normal ECG patterns, and generated distinctly different descriptions in terms of preselected set of pattern primitives. The sampled ECG signal was approximated by line segnals. The line segments were specified with their length and slope values. They used seven symbols to describe seven classes of slope values (e.g. horizontal, small, negative small, intermediate, negative intermediate, large negative large of which the last four symbols are called major). The given signal was represented as a string of such symbols based on the length and angle of the line segments. The signal was compacted by reducing the length of the generated string. The reduction was done by considering the following two facts.

1. Isolated major slope symbols may be deleted from the string as their large slope values does not affect the duration appreciably.

2. Alterneting sequence of positive and negative (or vice-versa) major slope symbols may by replaced by its half number of horizontal slope symbols. This data compression procedure is good enough to reconstruct the signal but takes a significant amount of execution time.

G. Papakonstantinou et. al, [54] developed a syntactic algorithm suitable for the detection of QRS patterns. This algorithm is described using a special type of grammar called attribute grammar [52]. The terminal symbol for this grammar are of the form (T,i,n). The ECG data are approximated by line segments, where T stands for line segments of large(small), positive(negative) slopes ,i and n are attribute values of the corresponding line segments. Here i denotes the x coordinate of the begining of the corresponding line segment, and n is the number of sample points comprising the segment.

The piecewise linear approximation to the initial ECG data was obtained through the algorithm described in [78]. Here, a waveform is defined as a sequence of the coordinates of its sample points (x_1,y_1), (x_2,y_2), ... ,(x_n,y_n), such that $x_i,y_i \geq o$ for $1 \leq i \leq n$. Starting with the point (x_1,y_1) of the waveform, angles v_1 and l_1 with initial values $\pi/2$ and $-\pi/2$ respectively are defined. The algorithm proceeds stepwise. For each sample point (x_i,y_i) two lines are drawn defined by the points $[(x_1,y_1), (x_i,y_i+\epsilon)]$ and $[(x_1,y_1),(x_i,y_i-\epsilon)]$, respectively where ϵ is a small predetermined value.

These lines form angles a_i, b_i with the x-axis. For each point (x_i, y_i) the angles v_i and l_i are defined as follows,

$$v_i = \text{minimum of } v_{i-1}, a_i$$

$$l_i = \text{maximum of } l_{i-1}, b_i$$

If $v_i > l_i$ and the point (x_i, y_i) is inside its "current cone", i.e. in the area defined by the lines $[(x_1, y_1), \tan v_i]$ and (x_1, y_1), $\tan l_i]$ then the point (x_i, y_i) is a valid one. If a point (x_j, y_j) is not a valid one, then the line between the points (x_1, y_1) and (x_{j-1}, y_{j-1}) is the piecewise linear approximation between these two points and (x_{j-1}, y_{j-1}) becomes the starting point of the next line segment with $v_{j-1} = \pi/2$ and $l_{j-1} = -\pi/2$.

The result of the processing according to the above approximation scheme is a string of line segments and their end points. Note that the end points of the line segments found are sample points which may not be consecutive as in the raw data and thus a reduction of data is obtained.

The kth line segment is :

$$\text{line segment}_k = \{(x_k^b, y_k^b), (x_k^e, y_k^e)\}$$

where (x_k^b, y_k^b) is the start point of the line segment k and (x_k^e, y_k^e) is the end point of the line segment k.

The algorithm described here requires floating point divisions for the computation of slopes. However a modification of the algorithm is suggested which avoides the time consuming operations, still it requires a subsequent amount of processing time.

Methods of linear approximation are widely used in data compression. Another such approximation has been proposed by Ewa Pietka [37] while presenting a feature extraction algorithm to the

ECG analysis. The system consists of two stages. The first one leads to description of the signal in a language-like structure by an interchangable use of two linear approximation methods. In the second part a set of rules are applied to the extraction of ECG features.

The algorithm if the approximation is based on the 'fan' method. In this method a line segment is widened until the distances between the following samples and the line segment do not exceed a threshold value. If it exceeds the value, the end of the line segment is fixed. A quite long runtime, particularly for a long line segment, is an important weakness of this method. In an ECG signal, more than half of the signal reflects a low activity potential of a heart muscle. The shorten the time of approximation, a much faster comparitive method has been applied in which the error is defined as a potential difference between the first sample and each of the following ones. These two methods have been used interchangably. The fan method approximates the waves, while the comparitive one approximates the base line. Combination of these methods decreases the number of line segments and shortens the time of performance.

As a resut of the approximation process the signal is described as a set of pairs. The elements of each pair are : the angle of a line segment and its length. The method of coding the signal into a string of slope symbols depends on the value of the line segmnts' angle. Each of the angles (nine intervals) is associated with a symbol.

6.2 Feature extraction

Morphological changes in the shape of the ECG waves are visible signs of heart muscle illness. Small changes in QRS or P or T morphology may cause disproportionately great changes in various features. As an example, some cases of a bundle branch block may be considered in which a ripple on the QRS slope is of diagnostic importance. The duration or amplitude may not exceed the physiological range and the abnormality would may go undetected. The synatactic approach allows consideration of either numerical values or shape parameters and requires undertaking the time-consuming problem of grammar inference for each class of patterns [37,148].

Different methods are available for classifying the heart diseases based on a number of features extracted from the ECG [37,46,93,115]. Methods are also there for locating QRS wave [107,112,113,118,128,130,131] P-wave [24,48,157,158], and T wave [123,142,144]. These methods are based on non-syntactic approach of pattern recognition. Wolthuis et.al. [142] presented predictive equations for finding the location and occurence of T-waves in the exercise ECG [148]. Stallman and Pipberger [48] proposed a method for finding ECG features based on spatial velocity. Okada [118] describes an algorithm for the QRS complex detection using digital filter technique. Ahlstrom and Tompkins [112] used bandpass filters for QRS detection. They also proposed a derivative-based QRS detection algorithm using microprocessors.

Few syntactic algorithms for ECG waveform processing have been reported in the literature. These algorithms are based on pattern grammars. The pattern grammars utilized are mainly

linear, context-free and attribute grammars. Skordalakis [43] reviewed the work in the field on syntactic ECG processing in the year 1986. He reviewed the different pattern grammars along with the set of pattern primitives used by defferent researchers for the ECG processing. Four different sets of pattern primitives and five pattern grammars are described in his paper. Of these four are based on the slope of the respective line segments and one is based on the energy of the ECG derivatives. The types of primitives and grammars, discussed in the paper [43], will be given now. In the brief discussion it is assumed that the ECG waveform is in the form :

$$(y_1,t_1),(y_2,t_2).....(y_n,t_n)$$

where

y_k is the amplitude of the ECG signal at the time instance t_k, k = 1(1)n and that the corresponding line segments are in the form : S_1, S_2, ...S_m.

where $S_k = ((y_k^b, t_k^b), (y_k^e, t_k^e)$, k = 1(1)m.

(y_k^b, t_k^b) is the start point of the line segment k,

(y_k^e, t_k^e) is the end point of the line segment k.

The first set

Horowitz (150,153) selected the following pattern primitives.

$$V_T = \{(a,b)\mid a \in \{/,\backslash,0\}, b \in \{+,-,*\}$$

The first element of each pair signifies wheather the slope of the corresponding line segment is positive (/), negative (\), or zero (0). The second element signifies wheather the begining of the corresponding line segment is above (+), below (-), or on (*) the base line.

Each line segment S_p, $p = 1(1)m$ is encoded into a string of pairs $(a,b) \in V_T$ as follows:

$$a = \begin{cases} / & \text{if } A_p > \epsilon_1 \\ \backslash & \text{if } A_p < -\epsilon_1 \\ 0 & \text{if } |A_p| \leq \epsilon_1 \end{cases}$$

$$b = \begin{cases} + & \text{if } y_p^b - \text{baseline} > \epsilon_2 \\ - & \text{if } y_p^b - \text{baseline} < -\epsilon_2 \\ * & \text{if } |y_p^b - \text{baseline}| \leq \epsilon_2 \end{cases}$$

where

A_p is taken from the equation $y = A_p t + B_p$

ϵ_1 slope threshold

ϵ_2 baseline threshold.

baseline is the y coordinate of the corresponding baseline. This encoding scheme requires the equation of each line segment in addition to its end points.

The pattern grammar, developed by Horowitz, was used to recognize the peaks in the waveforms. This grammar is a context-free grammar employing the primitives described as above. Details of the grammar can be found in [150,153].

This grammar does not address the whole problem of pattern recognition in ECG waveforms.

<u>The second set</u>

This primitive set was selected by Belforte et.al. [50] and it is the set :

$$V_T = \{a,b,c\}.$$

The encoding of the ECG signal was done by considering the energy

of the ECG derivatives. The energy of the first derivative (i.e. the square of the first derivative) is calculated giving a transformed signal. Then, in this transformed signal the peaks are calculated and used for encoding the ECG signal into a string of the symbol $x \in V_T$ according to

$$x = \begin{cases} a \text{ if } \epsilon_3 \leq P_a & \text{and } P_d > \epsilon_4 \\ b \text{ if } \epsilon_2 \leq P_a < \epsilon_3 & \text{and } P_d > \epsilon_4 \\ c \text{ if } \epsilon_1 \leq P_a < \epsilon_2 & \text{and } P_d > \epsilon_4 \end{cases}$$

where

P_a is the amplitude of a peak

P_d is the deration of a peak

$\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4$ are threshold values such that $\epsilon_1 < \epsilon_2 < \epsilon_3$.

The goal of the pattern grammar developed by Belforte et.al. was to detect the QRS complexes in ECG wave forms. The grammar developed is a linear grammar and was developed using an automatic inference procedure.

<u>The third set</u>

This primitive set was selected by Udupa et.al. [86] and it is the set :

$$V_T = \{s, i, l, \underline{s}, \underline{i}, \underline{l}, h\}$$

These symbols stand for small, intermediate, large, negative small, negative intermediate, negative large and horizontal slopes of the line segments respectively.

Each line segment S_p, $p = 1(1)m$ is encoded into a substring W_{j_p} of the symbol $x \in V_T$ as follows:

$$w_{j_p} = x^{k_p}$$

where

$$x = \begin{cases} s \text{ if } \theta_H < \phi_p \le \theta_S \\ i \text{ if } \theta_S < \phi_p \le \theta_I \\ l \text{ if } \quad \phi_p > \theta_I \end{cases}$$

$$x = \begin{cases} \underline{s} \text{ if } -\theta_H > \phi_p > -\theta_S \\ \underline{i} \text{ if } -\theta_S > \phi_p \ge \theta_I \\ \underline{l} \text{ if } \quad \phi_p \le -\theta_I \end{cases}$$

$$x = 1 \text{ if } -\theta_H \le \phi_p \le \theta_H$$

$$k_p = \left[\frac{\text{length of } S_p}{\text{UNIT}} \right]$$

ϕ_p is the angle of the line segment S_p with the horizontal axis. θ_H, θ_S, θ_I are three angles which provide threshold values for characterizing a line segment according to its slope.
[y] denotes the nearest integer value of y. UNIT is a value for the unit length.

The purpose of the pattern grammar developed by Udupa et.al.was to describe a family of diseases e.g. six specific ventricular arrhythmias (normal, PVB, bradycardia, tachycardia, sinus arrhythmia, etc.). A BNF grammar was developed for combined pattern recognition task and the interpretation task and it used the pattern primitives as discussed above.

The fourth set

The grammars described by Udupa et.al. are inappropriate for describing time varying aspects of the electrocardiographic

patterns. Despite that Udupa's effort addressed a broader part of the syntactic ECG processing problem.

The grammar developed by Skordalakis et.al. [40] revealed that attribute grammars [52] can be employed for the description of normal ECGs. He demonstrated that grammars with a semantic description capability, such as attribute grammars, are a proper tool for the description of ECG patterns. Although no solution to the problem of ECG pattern recognition was given. He used the same pattern primitives as used by Udupa et.al.

The fifth set

Papakonstantinou et. al. [54] selected the following pattern primitives :

$$V_T = \{(LP,i,n), (SP,i,n) (SN,i,n),(LN,i,n)\}.$$

Here the triplet of symbols are used in the place of each terminal symbol. The first elemnt of each triplet is one of the four symbols LP,SP,SN and LN, which stands for large positive slope line segment, small positive slope line segment, small negative slope line segment and large negative slope line segment respectively.The second element of each triplet is an altribute value of the corresponding line segment, specifically it is the t-coordinate of the begining of this line segment. The third element of each triplet is an attribute value of the corresponding line segment, specifically it is duration of this line segment.

Each line segment S_k, $k = 1(1)n$ is encoded into a triplet $(TS_k, i_k, n_k) \in V_T$ as follows.

$$TS_k = \begin{cases} \text{LP for a line segment with slope } s_k \text{ such that } s_k \geq \delta \\ \text{SP for a line segment with slope } s_k \text{ such that } o \leq s_k < \delta \\ \text{SN for a line segment with slope } s_k \text{ such that } -\delta \leq s_k < o \\ \text{LN for a line segment with slope } s_k \text{ such that } s_k \leq \delta \end{cases}$$

where $i_k = t_k^b$, $n_k = t_k^e - t_k^b$,

$$s_k = (y_k^e - y_k^b) / (t_k^e - t_k^b)$$

and δ is a threshold value.

Papakonstantinou utilized attribute grammars to solve a particular subproblem (QRS detection) of the ECG pattern recognition problem.

Skordalakis concluded that the electrocardiographic patterns have context sensitive characteristics as well as time varying size and shape and therefore it is difficult to devise a grammar for the description of these patterns.So grammars with semantic description ability are needed.

Pietka [37], in the year 1991, proposed a feature extraction algorithm to the ECG analysis. The system consists of stages. The first one leads to description of the signal in a language like structure by an interchangable use of two linear approximation methods. In the second part a set of rules is applied to fix the on and offset of the ECG waves and their parameters. She has used attribute grammars with semantic rules. The semantic rules are applied to evaluate the parameters of particular waveforms i.e durations and amplitudes of the ECG waves, and durations of the baseline segments.

The algorithm consists of four procedures.

i) The P procedure analyses the P and T waves; the starting point is the onset of the P or the T wave. The output consists of the values of amplitudes and durations, the shape paramenters and the offset of the P or the T wave.

ii) The Q procedure fixes the onset of the QRS complex as a fiducial point.

iii) The QRS procedure analyses the QRS complexes; starting point is the offset of the P wave. The output consists of values of parameters of the complex and its offset.

iv) The PR procedure analyses the PR, ST and TP intervals and fixes their offsets.

After finding the starting point the procedures are performed. *The algorithm* was tested on the basis of a set of ECG signals consisting of normal, super ventricular premature beats (SVPV), ventricular beats (VB), ventricualr premature beats (VPB), left bundle branch block (LBBB), right bundle branch block (RBBB) patterns. The length of each signal was about 5 sec. A measurement vector was defined on the basis of the identified on- and offsets of the waveforms (determined by the four different procedures). This measurement vector was used as input to the classification stage.

5.3 Classification

For the many years the automatic classification of ECGs was done by considering two basic approaches [69]. The first approach was based on the boolean logic combined with decision trees or decision tables. The second approach includes the formation of a measurement vector from the evaluated ECG signal.

Both the techniques have been applied with varying degree of success. A review on classification of the ECGs may be found in [148]. The gist of the review is given in the following paragraph.

Several proposed methods of ECG interpretation may be found in the literature [20,67,68,70,104,108,109,145]. Vector cardiography system, which use one of the several proposed three -orthogonal lead systems, were presented in [3,41,84]. Fourier frequency analysis methods have been investigated in [8,44,88,123,134]. Lack of spectral information is the only drawback of this method. The amplitude and time duration of different waves of the ECG are considered as basic criteria by most cardiologists [14,72,109]. A shape criteria, such as correlation, should contain more information than amplitude and time duration. Different correlation techniques are used by different researchers for interpretation of the ECG [25,56,57,108,119]. It is found that in order to classify a broad spectrum of heart diseases occuring in diverse areas of the heart, more ECG leads waveforms are required [71,165,172]. So huge amount of crosscorrelation co-efficents and sebsequently large amount of computations are required. Decision tables ware used for diagnostic evaluation of ECG [5,89,166]. The method has several advantages. The most important is that a complex problem of medical diagnosis can be expressed in a greatly simplifind form. Again, the decision tables can be translated into a computer language. Decision table format is so simple and straight forward that the physician can prepare them with very little training and practically with no knowledge of computers and programming. The

first decision tables are usually difficult to prepare but once these are formed, logical structuring facility develops rapidly. However,the main drawback of the decision tables is that it requires huge amount of storage locations and the patient data vector has to be formed every time whenever any decision has to be taken.

A syntactic approach for diagnosis of cardiac diseases has been presented in [149]. The method uses the 'patient data matrix', which contains all the measured ECG parameters, to classify ECG diseases. Pattern primitives are selected on the basis of diagnostic criteria. On checking the patient data matrix, an input string composed of the primitves is generated. Context free language in Chomsky normal form is developed using diagnostic rules for describing five selected cardiac diseases besides the normal ECG. The Cocke-Younger-Kasami algorithm is used to parse the input string. Ultimately, the parsing table will show the occurrence of different diseases if they are manifested in the patient's ECG.

This method has some weakness. It requires all clinical attributes (symptoms, signs, laboratory findings) must be either present or absent in a particular diagnostic category. Again there is no mathematical justification for the optimality of the selection of the set of pattern primitives. Finally, since the increase in parsing time with the length of an input string is more than linear, it is not desirable to process all diseases at a time.

The AI approach

In the early 1970's researchers at several institutions

simultaneously began to investigate potential clinical applications of artificial intelligenc (AI) techniques [36]. Among the earliest symbolic inference programs in medicine, was the diagnostic interviewing system of Kleinmuntz [15]. Initial prototype consultation programs using AI concepts were developed in opthalmology (CASNET [155]),infectious diseases (MYCIN [38]), internal medicinie (INTERNIST [62]), renal diseases [154], and dermatology [4].

There is some notable success in autometed ECG interpretation using AI techniques. Birman [92] presented a rule based learning for ECG analysis in the year 1982.

Mylopoulos et. al. described a knowledge based system for ECG interpretation (PSN [74]). The procedural semantic networks, or PSN project began at the University of Toronto in 1976 as a language design and implementation project. Two large knowledge based systems built at the University of Toronto use PSN as a knowledge representation language. The Alven project, begun in 1976, was implemented with a much expanded knowledge base and facilities that would make it suitable for clinical testing. Research on extending Alven's representation and control structure for application to electrocardiography began in 1979, resulting in a prototype design and implementation of the CAA systems (the Causal Arrhythmia Analysis). Since detection of arrhythmias typically requires ECGs gathered over 24 hours, the CAA system attempted to apply physiological knowledge of the heart conduction system together with signal knowledge to the task of recognizing and describing arrhythmias. Alven is an expert computer-vision system for assessing the performance of the human heart's left

ventricle.

The CAA stratified knowledge base includes a morphological knowledge base, which describes such aspects of ECG waveforms as their slope and duration, and a physiological knowledge base, which maintains information about the cardiac conduction system. Conduction events are related to their morphological counterparts through a projection mechanism.

Wave recognition starts with the detection of prominent waveforms in ECG signals, resulting in a starting set of hypotheses. Alven's recognition strategy is then applied to this set to generate and evaluate additional morphological hypothesis. As these hypotheses are generated, the system seeks to establish corresponding physiological hypothesis through projection links relating a morphological event class to a collection of possible physilogical event class with binding conditions for each. Since the overall arrhythmia recognition process must start with a rhythm hypothesis, which includes a sequence of beats, the system uses this process to examin each projected class and decide wheather the class must be included in the current global hypothesis as a component hypothesis. Using this process, the system recursively hypothesizes consecutive beat events and rates the degree of consistency by testing them against the corresponding wave sequence. Shibhara [163] provides detailed account of CAA.