Syntactic Pattern Recognition of the ECG

PANAGIOTIS TRAHANIAS AND EMMANUEL SKORDALAKIS

***Abstract*—An application of the syntactic method to recognition of electrocardiogram (ECG) and to the measurement of ECG parameters is presented. Solutions to the subproblems of primitive pattern selection, primitive pattern extraction, linguistic representation, and pattern grammar formulation are given. Attribute grammars are used as the model for the pattern grammar because of their descriptive power, which is due to their ability to handle syntactic as well as semantic information. This approach has been implemented and the performance of the resultant system has been evaluated using an annotated standard ECG library.**

***Index Terms*—Attribute grammars, ECG patterns, ECG waveforms, pattern recognition, primitive patterns, syntactic pattern recognition.**

I. Introduction

THE electrocardiogram (ECG) is routinely used in clinical practice. Due to the large number of ECG's analyzed each year, it is worthwhile to automate the process to the maximum extent possible. Work toward this end started late in the 1950's [1], [2].

Computerized ECG processing systems, like manual ECG processing systems, perform two distinct tasks. The first is concerned with pattern recognition and parameter measurement. The second is an interpretation task, which utilizes the results of the first task. In typical systems the pattern recognition and parameter measurement task is the hardest. Attempts to automate this task have been made using nonsyntactic methods [2], syntactic methods [3]–[6], and hybrid methods [7]–[10].

Although the syntactic method seems suitable to the problem of ECG pattern recognition and parameter measurement, not much progress has been made to date [11]. In the attempts reported, only specific aspects of this problem have been tackled. A context-free grammar, for peak recognition in ECG's, is described in [3]. Linear [4] and attribute [6] grammars have been proposed for the detection of the QRS complexes. Context-free [5] grammars have been used for the detection of certain ventricular arrhythmias. An attempt to perform arrhythmia analysis using the model of finite-state automata is described in [12]. Filtering of ECG waveforms by the syntactic method has also been studied [13].

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P. Trahanias is with NRCPS Democritos, Institute of Informatics and and Telecommunications, Aghia Paraskevi, Athens 153 10, Greece.

E. Skordalakis is with the Division of Computer Science, National Technical University, Athens 157 73, Greece.

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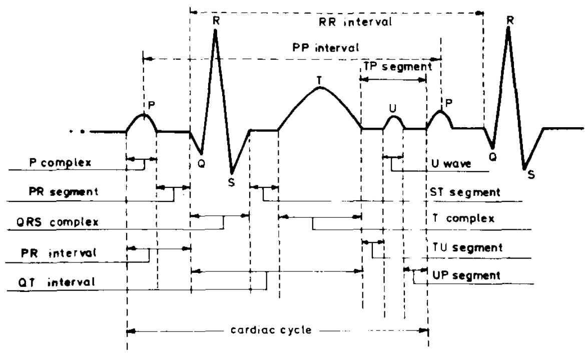

Fig. 1. A cardiac cycle and its constituent patterns.

This paper presents work done in applying the syntactic method to the whole problem of ECG pattern recognition and parameter measurement. Solutions to the subproblems of primitive pattern selection, primitive pattern extraction, linguistic representation, and formulation of a pattern grammar are described.

The paper is organized as follows. The patterns that are to be recognized and the parameters that are to be measured are described in Section II. Our syntactic approach to the problem of ECG pattern recognition and parameter measurement is described in Section III. The implementation of this approach is described in Section IV. Experimental results are given in Section V. The paper concludes with a brief discussion in Section VI.

II. Patterns and Pattern Parameters in ECG's

The ECG is a biosignal which is due to the electrical activity of the human heart that is transmitted to the body surface. One can record this signal using various systems. Currently, two such systems are principally used. The first is the 12-lead system that records 12 subcomponent signals which are called lead I, II, III, AVR, AVL, AVF, V1, V2, V3, V4, V5, and V6, respectively. From these leads, the first six are recorded with electrodes at the limbs, while the other six with electrodes at the chest. The second is the orthogonal 3-lead system that records three subcomponent signals which are called lead X, Y, and Z, respectively. Each ECG lead is composed of a number of cardiac cycles. A typical cardiac cycle is shown in Fig. 1.

The electrocardiographic patterns that constitute a cardiac cycle and must be recognized are the complexes, the interwave segments, and the cardiac intervals (Fig. 1). The complexes are three: the *P complex*, the *QRS com-*

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plex, and the *T complex*. The parameters of these patterns that must be measured are 1) height and duration for the complexes and some of their component waves and 2) duration for the interwave segments and the cardiac intervals. Thus, there are two types of measurements to be performed: *time measurements* and *amplitude measurements*. Moreover, the QRS complexes have to be classified. In most cases they belong to one class but there are cases where they belong to more than one class.

III. The Syntactic Approach in ECG Recognition

A. Primitive Pattern Selection

Line segments have mainly been proposed in the past as primitive patterns [5], [6], [11]. Triangles have also been proposed [8], [10]. The first are low level while the second are difficult to extract.

We have chosen the peak, the straight line segment, and the parabolic segment as primitive patterns [15]. This choice seems to be a natural one because the complexes are composed of peaks and the segments have the shape of a straight line or a parabola.

The peak pattern is shown in Fig. 2. This pattern is that part of a signal which is demarcated by three characteristic points. The first point is called left peak boundary, the second peak extremum, and the third right peak boundary. The sample points between the left peak boundary and the peak extremum form the left arm of the peak. The sample points between the peak extremum and the right peak boundary form the right arm of the peak. In what follows peaks will be symbolized as P_1, P_2, $\cdots$, where P_i is the name of peak i. Each lead of an ECG in digital form is represented as $y_1, y_2, \cdots, y_n$, where y_i is the amplitude in microvolts (μV) of the sample point i.

A set of attributes is assigned to each primitive pattern. The values of these attributes are calculated during the primitive extraction phase and they are utilized during the recognition process. They contribute both to the recognition of the patterns and to the measurement of their parameters. That is, they are used in a quantitative way for qualitative and quantitative purposes.

A set of seven attributes is assigned to each peak P_k. This set is symbolized as $\{x_{lk}, y_{lk}, x_{mk}, y_{mk}, x_{rk}, y_{rk}, e_k\}$, where:

(x_{lk}, y_{lk}) is the left boundary of the peak P_k.
(x_{mk}, y_{mk}) is the peak extremum of the peak P_k.
(x_{rk}, y_{rk}) is the right boundary of the peak P_k.
e_k is the energy of the peak P_k defined as:

$$e_k = \sum_{i=p}^{q} (y_i - y_{i-1})^2, \quad p = x_{lk} + 1, \quad q = x_{rk}.$$

A set of four attributes is assigned to each straight line or parabolic segment S. This set is symbolized as $\{x_{lS}, y_{lS}, x_{rS}, y_{rS}\}$, where:

$x_{lS}, y_{lS})$ is the start point of the segment S.
(x_{rS}, y_{rS}) is the end point of the segment S.

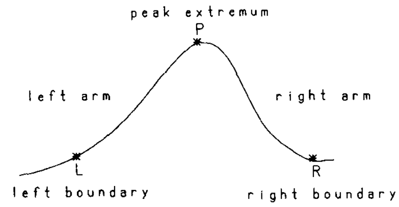

Fig. 2. Illustration of the peak pattern.

B. Primitive Pattern Extraction

The method developed for the extraction of the primitive patterns is discussed in detail in [14] and [15]. This method focuses on the extraction of peaks. The noisy peaks are recognized directly using a set of criteria empirically established. The real peaks are recognized by subtracting the noisy peaks from the set of all peaks. The boundaries of the recognized real peaks are subsequently computed. The algorithm developed for the calculation of the peak boundaries is based on the *a priori* assumption that the curvature is, locally, a maximum at these points. Computationally, the following four steps are executed: 1) a search interval is established, 2) the data points within this interval are approximated by a cubic spline function, 3) the curvature k_t is calculated at each point t of the search interval by the formula $k_t = |y_t''|/(1 + (y_t')^2)^{3/2}$, and 4) the point within the search interval in which the curvature takes its maximum value is taken as the boundary point.

The extraction of the segments is based on the precomputed peak boundaries which are also boundaries of the segments in the following sense: when the right boundary of the peak P_i is very close to the left boundary of the peak P_{i+1} then no segment exists between the peaks P_i and P_{i+1}, otherwise a segment exists which has as left boundary the right boundary of the peak P_i and as right boundary the left boundary of the peak P_{i+1}. By a least-squares fit it can be subsequently decided whether this segment is linear or parabolic.

C. Linguistic Representation

The alphabet of symbols $\Sigma = \{K^+, K^-, E, \Pi\}$ has been adopted for encoding the ECG waveforms, where K^+ denotes positive peak, K^- negative peak, E straight line segment, and Π parabolic segment. Thus, an ECG waveform is linguistically represented as a string of symbols from the alphabet Σ. Each symbol is associated with the values of the corresponding attributes.

D. Pattern Grammar

In syntactic pattern recognition, the task of recognition is essentially reduced to that of parsing a linguistic representation of the patterns to be recognized with a parser that utilizes a certain grammar, called "pattern grammar" [16]. The pattern grammar describes the patterns to be recognized in a formal way, and the formulation of the pattern grammar is always the crucial subproblem in any pattern recognition application that is to be tackled by the syntactic approach.

In the case of ECG's, where we have a large number of different morphologies of the patterns, where added morphologies can be found due to noise, and where measurements of the various parameters have to be performed, powerful grammars capable of describing syntax as well as semantics are needed as a model for the formulation of a pattern grammar. Due to their power in describing structural and statistical features [17], attribute grammars are selected and used in this paper as the model for the formulation of a pattern grammar for ECG's. Other reasons for this selection, which are common to any syntactic approach to pattern recognition, are the following: 1) an increase of parsing speed is obtained as the injection of attributes into symbols (nonterminals and terminals) reduces the grammatical complexity and 2) the technology of processing attribute grammars is fairly mature and many implementations of evaluators do exist. A general description of attribute grammars can be found in [17]. Pattern recognition in the framework of attribute grammars is discussed in [17] and [18].

We have formulated a pattern grammar, based on attribute grammars, for the description of ECG waveforms, using *a priori* knowledge of the ECG structure. This pattern grammar is given in the Appendix. It recognizes the electrocardiographic patterns and measures their parameters as required in the pattern recognition and parameter measurement phase of an ECG processing system. It also performs classification of the QRS complexes. Evaluation of this grammar can be performed by any nondeterministic attribute grammar evaluator that finds the first solution only.

This pattern grammar was formulated in such a way that it can be used to parse error-free input strings as well as erroneous input strings. The grammar is able to cope with errors due to noisy peaks at the interwave segments which have been recognized as real ones during the primitive extraction phase. The syntactic rules are written in such a way that the alternatives for an error-free input string are applied first. If this does not lead to a solution, then the alternatives that assume the presence of erroneous (noisy) peaks are applied.

The attribute grammar notation used includes a global metavariable called "SUCCESS" that takes only the values "true" or "false". When SUCCESS takes the value "false" during the syntactic evaluation of a BNF rule, the parser considers that the matching of the input substring with this rule fails. Thus, SUCCESS directs the parsing (recognition) through the semantics.

The attributes of the terminal symbols (primitive patterns) are also used as synthesized attributes for the nonterminal symbols. In addition to that, eleven more attributes are used for the nonterminal symbols of the grammar, namely:

iw	Number of cardiac waves, inherited.
sw	Number of cardiac waves, synthesized.
ic	Number of QRS classes, inherited.
sc	Number of QRS classes, synthesized.
iqrs(i)	Number of QRS's in class i, inherited.
sqrs(i)	Number of QRS's in class i, synthesized.
ldur	Duration of the left arm of a peak, synthesized.
rdur	Duration of the right arm of a peak, synthesized.
lh	Height of the left arm of a peak, synthesized.
rh	Height of the right arm of a peak, synthesized.
tp_flag	Candidacy of a peak as a P or T (sub)pattern, synthesized. A positive value denotes that the peak is a valid candidate, zero means the peak is not accepted as a candidate, -2 means P complex and -1, T complex.

The inherited attributes of a symbol represent those aspects that derive from the context and are computed in a top-down fashion, whereas the synthesized attributes of a symbol represent those aspects that are built up from the subtree that produces the symbol and are computed in a bottom-up fashion.

The semantic rules that correspond to each syntactic rule are given below each one. To keep the pattern grammar size as small as possible in this paper, the semantic rules that perform amplitude measurements are omitted as are some semantic rules that perform time measurements. Thus, for each syntactic rule $\langle A \rangle_1 \rightarrow X_2 X_3 \cdots X_n$, $X_i \in (V_T \cup V_N)$, where V_T denotes the set of terminal symbols and V_N the set of nonterminal symbols, the semantic rules $x_{l1} := x_{l2}$ and $x_{r1} := x_{rn}$ for the computation of the start and end points of the (sub)pattern $\langle A \rangle$ have been omitted. Similarly, for each syntactic rule $\langle X \rangle \rightarrow x$, $x \in V_T$, the corresponding semantic rules, which pass the attributes of x to the nonterminal $\langle X \rangle$ have also been omitted. For the same reason, a notation is adopted concerning the evaluation of the attributes iqrs(i) and sqrs(i). Where no index is present in these attributes [symbolically iqrs( ) and sqrs( )], it is assumed that a loop exists with the index varying from 1 to K (K being the maximum value of the index).

Although it is easy to follow the logic contained in the pattern grammar of the Appendix, some of the most important tasks it performs are described below in an informal way.

1) QRS Detection and Recognition: A series of n ($1 \leq n \leq 7$) consecutive peaks is recognized as a QRS complex if:

a) $\Sigma_{i=1}^{n} e_i > \epsilon_1$, where ϵ_1 is a threshold value.

b) The angle between the right arm of peak i and the left arm of peak $i + 1$, $i = 1(1)n - 1$, is less than ϵ_2, where ϵ_2 is a threshold value.

The first criterion, which is similar to the nonlinear transformation short-time energy [19] used by other investigators, is adopted here due to its suitability in the syntactic approach and because it gives good results. The sample points taken in the summation are the ones of the corresponding QRS complex, while a constant number of sample points is used in the transformation.

The angle criterion prevents peaks belonging to P or T complexes from being merged with QRS complexes.

The morphology of the QRS is determined by the alternative of the syntactic rule that matches the QRS.

2) P, T Detection and Recognition: One or two consecutive peaks are recognized as a P or T complex, by thresholding their width and amplitude (thresholds ϵ_3 and ϵ_4, respectively), depending on the syntactic rule being evaluated. They are discriminated from other (noisy) peaks by comparing their energies. Noisy peaks in a region between two QRS complexes are required to have less energy than the energy of the P and T complexes in that region. The alternative of the syntactic rule that matches the P or T pattern specifies its morphology. It is noted that P and T complexes occurring before the first and after the last QRS complex found are not recognized. This helps to make the grammar simpler.

3) QRS Classification: The classification of the QRS complexes is performed by a nearest neighbor classification algorithm. The distance between a given QRS complex and a given class of QRS complexes is computed as the average of the distances between the given QRS complex and each QRS complex in the given class of QRS complexes. Both morphological (structural) and quantitative (statistical) features are taken into account in the distance computation. Normalized duration and normalized amplitude are the statistical features used. Morphological features, in the distance computation between two complexes, are taken into account by aligning the complexes so that they fit best [20].

IV. Implementation

The syntactic method to the problem of ECG pattern recognition and parameter measurement, as described above, was implemented and the resultant system named SERAMS (syntactic ECG recognition and measurement system). The structure of SERAMS is shown in Fig. 3.

The ECG acquisition component of this system is responsible for acquiring one ECG at a time in digital form. The primitive pattern extraction component of this system extracts the primitives of each ECG waveform and encodes them so that each waveform is transformed into a string of symbols (linguistic representation), each symbol accompanied by a set of attribute values. The attribute grammar evaluator component of this system takes as input 1) the pattern grammar of the Appendix and 2) the linguistic representation (together with its attributes) of a waveform. It recognizes the electrocardiographic patterns of that waveform and measures their parameters. Finally, the output formatter component of this system formats the results of the recognition and measurement.

SERAMS is coded in Fortran 77 because the primitive pattern extraction component employs mathematical algorithms that require an algebraic language. The attribute grammar evaluator we used is one which is based on the

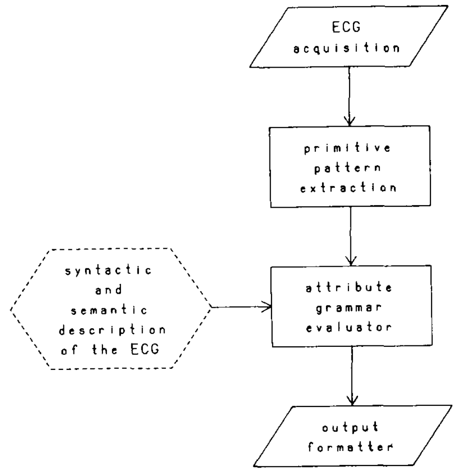

Fig. 3. Structure of the SERAMS system.

Floyd's parser [21]. A Fortran 77 version of it has been made available to us.

V. Experimental Results

Real ECG's, from a standard ECG library known as CSE (common standards for quantitative electrocardiography) library [22], were used in order to tune SERAMS and to test its performance. The CSE library has been specially developed to be used as a reference library. For tuning SERAMS, a very small set of ECG's from the CSE library was used as a training set. With the help of this set, values for the various thresholds were calculated.

A. An Illustrative Example

A sample ECG waveform from the CSE library was analyzed by SERAMS and the results of the various processing steps are presented here for illustrative purposes.

Step 1—ECG Acquisition: This step is performed by the ECG acquisition component of SERAMS. In this particular case, this component read the ECG waveform from the library in digital form. This waveform is shown graphically in Fig. 4(a).

Step 2—Primitive Pattern Extraction: The digitized ECG waveform is the input to the primitive pattern extraction component of SERAMS. This component extracts and encodes the primitive patterns and calculates their attributes, thus transforming an ECG waveform into a string of symbols (linguistic representation).

The corresponding linguistic representation of the waveform is the following string:

$$\Pi K^- K^+ \Pi K^- E K^- K^+ \Pi K^- \Pi K^+ E K^- E K^- K^+ E$$

Each symbol in this representation is accompanied by a set of attribute values, given in Table I. In this table, the symbols are given in the second column while the first column is used for numbering the primitives. The attribute values, associated with each primitive, are given in the next columns. It is noted that the x_m, y_m, and e attri-

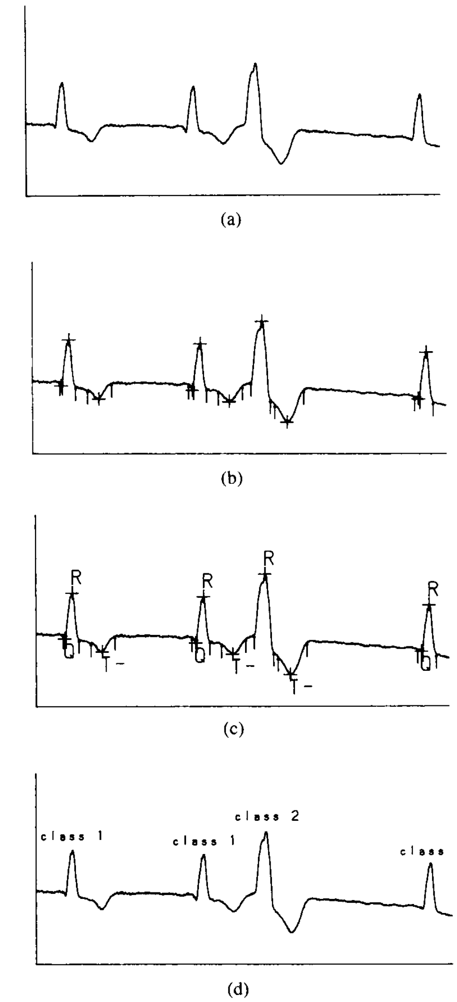

Fig. 4. (a) Initial ECG waveform. (b) Extracted primitive patterns. (c) Recognized ECG patterns. (d) QRS classification.

TABLE I
ENCODED PRIMITIVES AND THEIR ATTRIBUTES FOR THE WAVEFORM OF FIG. 4(a)

PRIMITIVE		ATTRIBUTES						
sequence number	symbol	x_l(ms)	y_l(μV)	x_m(ms)	y_m(μV)	x_r(ms)	y_r(μV)	e(μV^2)
1	Π	1	356			220	367	
2	K$^-$	220	367	234	280	242	379	5050
3	K$^+$	242	379	296	1196	346	273	84016
4	Π	346	273			442	197	
5	K$^-$	442	197	534	14	634	336	10973
6	E	634	336			1248	300	
7	K$^-$	1248	300	1280	190	1288	286	6312
8	K$^+$	1288	286	1344	1117	1392	233	83817
9	Π	1392	233			1484	174	
10	K$^-$	1484	174	1574	-40	1678	282	9332
11	Π	1678	282			1746	356	
12	K$^+$	1746	356	1836	1566	1900	5	163549
13	E	1900	5			1936	-95	
14	K$^-$	1936	-95	2036	-450	2168	195	15682
15	E	2168	195			3052	59	
16	K$^-$	3052	59	3084	15	3094	98	3089
17	K$^+$	3094	98	3148	946	3200	-43	93087
18	E	3200	-43			3320	-122	

TABLE II
RECOGNITION RESULTS FOR THE WAVEFORM OF FIG. 4(a)

ECG complex	morphology	x_l(ms)	x_r(ms)	constituent primitives
QRS	QR	220	346	2, 3
T	T$^-$	442	634	5
QRS	QR	1248	1392	7, 8
T	T$^-$	1484	1678	10
QRS	R	1746	1900	12
T	T$^-$	1936	2168	14
QRS	QR	3052	3200	16, 17

butes do not belong to the set of attributes of the linear and parabolic segments. Because of this, the entries in Table I that correspond to linear or parabolic segments and to any of these attributes are left blank. The linguistic representation given above, together with the associated values of the corresponding attributes, uniquely defines the ECG waveform of Fig. 4(a).

For visual observation, the extracted primitive patterns are shown in Fig. 4(b), where peaks are marked by plus (+) signs and peak boundaries are marked by up arrows (↑).

Step 3—Complex Recognition and QRS Classification: This step is performed by the attribute grammar evaluator component of SERAMS, which utilizes the results of the previous step and the pattern grammar of the Appendix. The recognition results are given in Table II. In this table, the recognized ECG complexes are given along with their morphology, time coordinates of their start and end points, and the sequence numbers (Table I) of the primitive patterns that constitute them.

The recognition of the ECG complexes from the primitive patterns can be inferred by following the rules of the pattern grammar. For example, the application of the third alternative of the seventh rule (without considering higher-level rules) recognizes the first QRS complex after successively applying rules 28 and 25. Similarly, the first *T* complex is recognized by the successive application of rule 22 and fourth alternative of rule 24.

The recognition results are also given in Fig. 4(c) for visual observation. The QRS classification results are given in Fig. 4(d). In this figure, the class membership of each QRS complex is identified by the label above it.

The computer time required to process that ECG waveform on a PRIME 9955 minicomputer system was approximately 1 s for the acquisition and primitive extraction and 1.5 s for the recognition and QRS classification.

B. Performance Evaluation

The CSE library was used for the evaluation of SERAMS, as it is a standard library for testing the performance of ECG measurement programs [22]. The CSE library contains 310 ECG's in digital form together with the measurement results for 1) the onsets of *P* and *QRS*, and 2) the offsets of *P*, *QRS*, and *T*. These results were determined visually by a group of cardiologists using a modified Delfi approach [22] and are considered to represent the true values of the corresponding quantities.

All that has to be done for evaluating the performance of an ECG measurement program, with respect to CSE reference library, is to process with this program the ECG's of the CSE and compare the measurement results obtained by the program for the onsets of *P* and *QRS* and the offsets of *P*, *QRS*, and *T* with the ones provided by the library, according to a specified procedure [23]. This comparison procedure demands 1) the comparison of the results to be done separately for each lead group, 2) the mean of the differences (between the measurements of the program and the ones provided by the library) per lead group to be as close as possible to zero, and 3) the standard deviation of the differences per lead group to be less than a tolerance limit, the value of which is given [23]. The reason that the comparison is performed per lead group is that in the CSE library the leads of each group were recorded simultaneously and therefore their cardiac complexes have the same onsets and offsets. There are five lead groups: group I-III which contains leads I, II, and III, group AVR-AVF which contains leads AVR, AVL, and AVF, group V1-V3 which contains leads V1, V2, and V3, group V4-V6 which contains leads V4, V5, and V6, and group *XYZ* which contains leads *X*, *Y*, and *Z*.

The ECG's in the CSE library were processed by SERAMS and the above comparison procedure was applied. The evaluation results obtained are presented in Table III. As can be observed, the mean of the differences between the measurements of SERAMS and the ones provided by the CSE library (true measurements) is in most cases close to zero and similarly, the standard deviation is in most cases less than the value of the corresponding tolerance limit.

TABLE III
EVALUATION RESULTS OF SERAMS WITH RESPECT TO CSE REFERENCE LIBRARY

parameter	lead group	mean(ms)*	standard deviation(ms)**	tolerance limit(ms)
P onset	I-III	-4.0	8.7	8.0
	AVR-AVF	-2.2	10.2	9.2
	V1-V3	1.2	10.5	12.4
	V4-V6	-3.8	14.2	12.6
	XYZ	-1.6	9.8	8.6
	Average	-2.1	10.7	10.2
P offset	I-III	1.7	10.0	12.8
	AVR-AVF	1.9	7.8	12.0
	V1-V3	-3.9	15.5	14.4
	V4-V6	1.8	14.4	13.6
	XYZ	-0.9	12.0	10.8
	Average	0.1	11.9	12.7
QRS onset	I-III	0.0	7.5	7.8
	AVR-AVF	1.5	7.2	7.8
	V1-V3	-0.6	5.5	5.2
	V4-V6	-0.4	6.4	5.2
	XYZ	-0.8	5.0	6.6
	Average	-0.1	6.3	6.5
QRS offset	I-III	0.6	9.1	12.4
	AVR-AVF	0.3	8.7	13.4
	V1-V3	-0.5	8.0	9.4
	V4-V6	1.2	8.8	12.0
	XYZ	1.6	6.8	10.6
	Average	0.6	8.3	11.6
T offset	I-III	-2.4	19.8	32.8
	AVR-AVF	0.1	19.9	27.6
	V1-V3	-1.5	14.8	28.6
	V4-V6	1.4	19.7	28.8
	XYZ	1.4	18.9	35.2
	Average	-0.2	18.6	30.6

* the mean must be close to zero

** the standard deviation must be less than the corresponding tolerance limit

VI. DISCUSSION

The application of the syntactic approach to ECG pattern recognition and parameter measurement which has been described in this paper has given results that are inferior compared to those reported by some implementations using the nonsyntactic approach [24]. However, the nonsyntactic approach is fairly mature in this particular problem after considerable research work for many years [2]. On the contrary, this is the first implementation of the syntactic approach and there is much room for improvement of the results by further refinement of the method.

We have observed that the primitive pattern extractor does not always accurately delineate the boundaries of the peak patterns. This type of error is propagated in the next stages and is responsible for many inaccurate results. Removing this deficiency would considerably improve the overall performance of the approach. This is not a trivial task, nevertheless it is tractable. Other than this, a very small percentage of noisy peaks are not rejected but recognized as real ones by the primitive extractor. However, this does not affect the system's performance because, as stated earlier, this type of error is corrected by the pattern grammar. Errors due to the grammar, i.e., missing or incorrect recognition of a complex, were rarely observed. The robustness of SERAMS (and of the underlying methods) when using low quality data was not tested as the data in the CSE library have a noise content within acceptable levels. Input data highly contaminated by noise could possibly be suitably filtered within the ECG acquisition part of SERAMS, for improving their quality, before passing them to the recognition procedures.

Other than the accuracy of the results, the syntactic approach possesses some very important characteristics, that its advocates emphasize and were confirmed in the work discussed in this paper. These characteristics are: simplicity, brevity, clarity, understandability, and modifiability of the computer program that implements the syntactic approach. With the exception of the extraction of the primitive patterns and the I/O operations, the rest of the approach is not coded but specified, the pattern grammar being the formal specification. We have here a case of (semi)automatic programming. We do not program, we specify. The dashed lines in Fig. 3 signify this fact. This is the greatest advantage of the syntactic approach. If ways can be found to improve the accuracy of the results, then it is superior to the nonsyntactic approach.

Although the syntactic approach is slower than the nonsyntactic, the speed of processing may be improved by developing a special purpose parser for this specific pattern grammar. Further, the high speed of modern computer architectures may make this problem less significant.

Appendix

A Pattern Grammar for the Description of ECG Waveforms

1. $\langle \text{ECG\_LEAD}\rangle_1 \rightarrow \langle \text{INIT\_PART}\rangle_2\ \langle \text{CARDIAC\_CYCLES}\rangle_3\ \langle \text{FIN\_PART}\rangle_4$
   $sw_1 := sw_4$; $sc_1 := sc_4$; $sqrs(\ )_1 := sqrs(\ )_4$;
   $iw_3 := 0$; $ic_3 := 0$; $iqrs(\ )_3 := 0$;
   $iw_4 := sw_3$; $ic_4 := sc_3$; $iqrs(\ )_4 := sqrs(\ )_3$;
2. $\langle \text{INIT\_PART}\rangle \rightarrow \langle \text{SEGMENT}\rangle\ \langle \text{INIT\_PART}\rangle$
   $\rightarrow \epsilon$
   $\rightarrow \langle \text{PEAK}\rangle\ \langle \text{INIT\_PART}\rangle$
3. $\langle \text{FIN\_PART}\rangle_1 \rightarrow \langle \text{QRS}\rangle_2\ \langle \text{REST\_PART}\rangle_3$
   $sw_1 := sw_2$; $sc_1 := sc_2$; $sqrs(\ )_1 := sqrs(\ )_2$;
   $iw_2 := iw_1$; $ic_2 := ic_1$; $iqrs(\ )_2 := iqrs(\ )_1$;
4. $\langle \text{REST\_PART}\rangle \rightarrow \langle \text{SEGMENT}\rangle\ \langle \text{REST\_PART}\rangle$
   $\rightarrow \langle \text{PEAK}\rangle\ \langle \text{REST\_PART}\rangle$
   $\rightarrow \epsilon$
5. $\langle \text{CARDIAC\_CYCLES}\rangle_1 \rightarrow \langle \text{CARDIAC\_CYCLE}\rangle_2\ \langle \text{CARDIAC\_CYCLES}\rangle_3$
   if $(sw_3 = 0)$ **then** $sw_1 := sw_2$;
   else $sw_1 := sw_3$; **endif**
   if $(sc_3 = 0)$ **then** $sc_1 := sc_2$; $sqrs(\ )_1 := sqrs(\ )_2$;
   else $sc_1 := sc_3$; $sqrs(\ )_1 := sqrs(\ )_3$; **endif**
   $iw_2 := iw_1$; $ic_2 := ic_1$; $iqrs(\ )_2 := iqrs(\ )_1$;
   $iw_3 := sw_2$; $ic_3 := sc_2$; $iqrs(\ )_3 := sqrs(\ )_2$;
   $\rightarrow \epsilon$
   $sw_1 := 0$; $sc_1 := 0$; $sqrs(\ )_1 := 0$;
6. $\langle \text{CARDIAC\_CYCLE}\rangle_1 \rightarrow \langle \text{QRS}\rangle_2\ \langle \text{NON\_QRS}\rangle_3$
   $sw_1 := sw_3$; $sc_1 := sc_2$; $sqrs(\ )_1 := sqrs(\ )_2$;
   $iw_2 := iw_1$; $ic_2 := ic_1$; $iqrs(\ )_2 := iqrs(\ )_1$;
   $iw_3 := sw_2$;
7. $\langle \text{QRS}\rangle \rightarrow [\langle Q\rangle]\ \langle R\rangle\ \langle S\rangle\ \langle R'\rangle\ \langle S'\rangle\ \langle R''\rangle\ [\langle S''\rangle]$
   qrs_calc ;
   $\rightarrow [\langle Q\rangle]\ \langle R\rangle\ \langle S\rangle\ \langle R'\rangle\ [\langle S'\rangle]$
   qrs_calc ;
   $\rightarrow [\langle Q\rangle]\ \langle R\rangle\ [\langle S\rangle]$
   qrs_calc ;
   $\rightarrow \langle \text{QS}\rangle$
   qrs_calc ;
8. $\langle \text{NON\_QRS}\rangle_1 \rightarrow \langle \text{SR}\rangle_2$
   if $(tp\_flag_1 \neq 0)$ **then** SUCCESS: = "false" ; **endif**
   $sw_1 := iw_1$;
   $\rightarrow \langle \text{ST}\rangle_2\ \langle T\rangle_3\ \langle \text{TR}\rangle_4$
   if $(tp\_flag_2 \neq 0 \lor tp\_flag_4 \neq 0)$ **then**
   SUCCESS: = "false" ; **endif**
   if $\neg (e_2 < e_3 \land e_4 < e_3 \land dur_2 \leq dur_4)$ **then**
   SUCCESS: = "false" ; **endif**
   $sw_1 := sw_3$; $iw_3 := iw_1$;
   $\rightarrow \langle \text{SP}\rangle_2\ \langle P\rangle_3\ \langle \text{PR}\rangle_4$
   if $(tp\_flag_2 \neq 0 \lor tp\_flag_4 \neq 0)$ **then**
   SUCCESS: = "false" ; **endif**
   if $\neg (e_2 < e_3 \land e_4 < e_3 \land dur_2 > dur_4)$ **then**
   SUCCESS: = "false" ; **endif**
   $sw_1 := sw_3$; $iw_3 := iw_1$;

$\rightarrow \langle ST\rangle_2 \langle T\rangle_3 \langle ATRIAL\_ACTIVITY\rangle_4$
if $\neg(e_2<e_3 \wedge e_2<e_4)$ **then**
SUCCESS: = "false" ; **endif**
$sw_1:=sw_4$; $iw_3:=iw_1$; $iw_4:=sw_3$;

9. $\langle ATRIAL\_ACTIVITY\rangle_1 \rightarrow \langle FLUTTER\_WAVES\rangle_2$
$e_1:=e_2$; $iw_2:=iw_1$; $sw_1:=sw_2$;
$\rightarrow \langle NON\_COUPLED\_P\rangle_2$
$e_1:=e_2$; $iw_2:=iw_1$; $sw_1:=sw_2$;
$\rightarrow \langle COUPLED\_P\rangle_2$
$e_1:=e_2$; $iw_2:=iw_1$; $sw_1:=sw_2$;
$\rightarrow \langle ATRIAL\_FIBRILATION\rangle_2$
$e_1:=e_2$; $iw_2:=iw_1$; $sw_1:=sw_2$;

10. $\langle FLUTTER\_WAVES\rangle_1 \rightarrow \langle P\rangle_2 \langle FLUTTER\_WAVES\rangle_3$
$e_1:=e_2+e_3$; $iw_2:=iw_1$;
$iw_3:=sw_2$; $sw_1:=sw_3$;
$\rightarrow \epsilon$
$sw_1:=iw_1$; $e_1:=0$;

11. $\langle NON\_COUPLED\_P\rangle_1 \rightarrow \langle TP\rangle_2 \langle P\rangle_3 \langle PP\rangle_4 \langle P\rangle_5 \langle PR\rangle_6$
if $(tp\_flag_2 \neq 0 \vee tp\_flag_4 \neq 0 \vee$
$tp\_flag_6 \neq 0)$ **then**
if $(e_2<e_3 \wedge e_2<e_5 \wedge e_4<e_3$
$\wedge\ e_4<e_5 \wedge e_6<e_3 \wedge e_6<e_5)$ **then**
SUCCESS: = "false" ; **endif**
endif
$sw_1:=sw_5$; $iw_3:=iw_1$; $iw_5:=sw_3$;
$e_1:=\min(e_3,e_5)$;

12. $\langle COUPLED\_P\rangle_1 \rightarrow \langle TP\rangle_2 \langle P\rangle_3 \langle PR\rangle_4$
if $(tp\_flag_2 \neq 0 \vee tp\_flag_4 \neq 0)$ **then**
if $\neg(e_2<e_3 \wedge e_4<e_3)$ **then**
SUCCESS: = "false" ; **endif**
endif
$sw_1:=sw_3$; $iw_3:=iw_1$; $e_1:=e_3$;

13. $\langle ATRIAL\_FIBRILATION\rangle_1 \rightarrow \langle PEAK\rangle_2 \langle ATRIAL\_FIBRILATION\rangle_3$
$sw_1:=iw_1$; $e_1:=e_2+e_3$;
$\rightarrow \langle SEGMENT\rangle_2 \langle ATRIAL\_FIBRILATION\rangle_3$
$sw_1:=iw_1$; $e_1:=e_3$;
$\rightarrow \epsilon$
$sw_1:=iw_1$; $e_1:=0$;

14. $\langle ST\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

15. $\langle TP\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

16. $\langle PR\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

17. $\langle TR\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

18. $\langle SP\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

19. $\langle PP\rangle_1 \rightarrow \langle INTERWAVE\_SEGMENT\rangle_2$
$e_1:=e_2$; $tp\_flag_1:=tp\_flag_2$;

20. $\langle SR\rangle_1 \rightarrow \langle SEGMENT\rangle_2 \langle INTERWAVE\_SEGMENT\rangle_3$
$tp\_flag_1:=tp\_flag_3$;
$\rightarrow \langle PEAK\rangle_2 \langle INTERWAVE\_SEGMENT\rangle_3$
if $(ldur_2>\epsilon_3 \wedge rdur_2>\epsilon_3 \wedge$
$lh_2>\epsilon_4 \wedge rh_2>\epsilon_4)$ **then**
$tp\_flag_1:=1+tp\_flag_3$;
else $tp\_flag_1:=tp\_flag_3$;
endif

21. ⟨INTERWAVE_SEGMENT⟩$_1$ → ⟨SEGMENT⟩$_2$ ⟨INTERWAVE_SEGMENT⟩$_3$
tp_flag$_1$:=tp_flag$_3$; e_1:=e_3 ;
→ ϵ
tp_flag$_1$:=0 ; e_1:=0 ;
→ ⟨PEAK⟩$_2$ ⟨INTERWAVE_SEGMENT⟩$_3$
if ($ldur_2 > \epsilon_3 \wedge rdur_2 > \epsilon_3 \wedge$
$lh_2 > \epsilon_4 \wedge rh_2 > \epsilon_4$) **then**
tp_flag$_1$:=1+tp_flag$_3$;
e_1:=max(e_2,e_3) ;
else tp_flag$_1$:=tp_flag$_3$; e_1:=e_3 ;
endif

22. ⟨T⟩$_1$ → ⟨T_OR_P⟩$_2$
e_1:=e_2 ; sw_1:=sw_2 ;
iw_2:=iw_1 ; tp_flag$_2$:= −1 ;

23. ⟨P⟩$_1$ → ⟨T_OR_P⟩$_2$
e_1:=e_2 ; sw_1:=sw_2 ;
iw_2:=iw_1 ; tp_flag$_2$:= −2 ;

24. ⟨T_OR_P⟩ → K^+K^-
tp_calc ;
→ K^-K^+
tp_calc ;
→ K^+
tp_calc ;
→ K^-
tp_calc ;

25. ⟨R⟩ → K^+
26. ⟨R′⟩ → K^+
27. ⟨R″⟩ → K^+
28. ⟨Q⟩ → K^-
29. ⟨QS⟩ → K^-
30. ⟨S⟩ → K^-
31. ⟨S′⟩ → K^-
32. ⟨S″⟩ → K^-
33. ⟨PEAK⟩ → K^+
→ K^-
34. ⟨SEGMENT⟩ → E
→ Π

Note: [*X*] means that *X* is optional.

Description of the Auxiliary Semantic Routines and Functions

1) Auxiliary Semantic Routine qrs_calc: It performs the following tasks:

a) It sets the value of the metavariable SUCCESS according to:

if $\neg(\Sigma_{i=1}^{n} e_i > \epsilon_1)$ **then** SUCCESS:="false" **endif**
for i:=1 **to** n−1 **do begin**
if $\neg$(angle(i) $< \epsilon_2$) **then** SUCCESS:="false" **endif**
end

where *n* is the number of waves in the QRS complex.

b) It stores the component waves of a QRS complex as well as their attributes.

c) It computes the distances of the QRS complex from the existing QRS classes. Then, it finds the class with the minimum distance as well as the minimum distance. If the minimum distance is less than a preset threshold *t*, it assigns this QRS to that class. Otherwise, it initiates a new class for this QRS.

2) Auxiliary Semantic Routine tp_calc: It performs the following tasks:

a) It sets the value of the metavariable SUCCESS according to:

if $\neg(\Sigma_{i=1}^{q} e_i \le \epsilon_1)$ **then** SUCCESS:="false" **endif**
for i:=1 **to** q **do begin**

if $\neg$ ($\mathrm{ldur}_i > \epsilon_3 \wedge \mathrm{rdur}_i > \epsilon_3$) **then** SUCCESS: = "false" **endif**
if $\neg$ ($\mathrm{lh}_i > \epsilon_4 \wedge \mathrm{rh}_i > \epsilon_4$) **then** SUCCESS: = "false" **endif**
end

where q is the number of waves in the P or T complex.

b) It stores the component waves of a P or a T complex as well as their attributes.

3) Auxiliary Semantic Function angle(i): It computes the angle between the right arm of peak P_i and the left arm of peak P_{i+1}, where the peaks P_i and P_{i+1} are consecutive.

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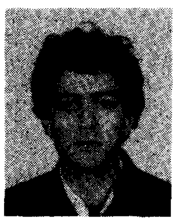

Panagiotis Trahanias received the B.S. degree in physics from the University of Athens, Greece, in 1985 and joined the Institute of Informatics and Telecommunications of the National Research Center for Physical Sciences (Democritos) as a Ph.D. student. He received the Ph.D. degree in computer science from the National Technical University of Athens, Greece, in 1988.

His research interests include pattern recognition, syntactic pattern recognition, waveform analysis, and image processing.

Emmanuel Skordalakis received the B.S. degree in mathematics from the University of Athens, Greece, in 1959, the M.S. degree in numerical analysis and computer science from the University of Manchester, England, in 1966, and the Ph.D. degree in computer science from the University of Patras, Greece, in 1980.

He was an Applications Programmer and then a Research Scientist at the Nuclear Research Center (Democritos) between 1967 and 1986, and is now an Associate Professor at the National Technical University of Athens. His research interests are pattern recognition, waveform analysis, and software engineering.