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A Data Acquisition System for QRS Detections

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Abstract: ***In this paper,*** **a data acquisition system for QRS detections** ***in 12-lead electrocardiogram (ECG) diagnosis is proposed. This system collect data learns rules, synthesizing decision trees by inductive inference from examples. An extended form of Quinlan's algorithm is used. There is also possibility of continual improving the knowledge base maintained, by learning new rules and merging them with the old ones. As a start point for the knowledge base learned, the rules of an already developed expert system are used.***

Keywords: Data acquisition system, QRS detections, HRV, electrocardiograms (ECGs).

1. Introduction

Learning is a basic feature of intelligence. A significant approach in the machine learning field is based on acquiring structured knowledge in the form of concepts, discrimination nets, or production rules. The latter kind of machine learning is very important, because the knowledge acquisition from the human experts is very often impossible to be done quickly enough. Conventional expert systems require the user to code decision-making rules like IF...THEN...ELSE statements, while the human mind does not naturally think in IF...THEN...ELSE terms, but decides depending on examples gathered by experience. So, there is need of learning systems (computer programs) which can acquire knowledge from examples and extract it in the form of decision trees, i.e. computer programs. (The rules corresponding to a decision tree form an expert system.)

The techniques of synthesizing the optimal (by execution time means) decision tree are in brief as follows. Bayes [1], Schumacher-Sevcik [2], Lew [3], developed dynamic programming techniques (complexity O (3n)), applied on "expanded" decision tables. Verhelst [4] used tree pruning techniques. Papakonstantinou [5] improved Verhelst's algorithm, using dynamic programming too. Verhelst's and Papakonstantinou's algorithms have a smaller computational cost (though O (3n) too - the theoretically minimum for every possible algorithm is O (2n)) and are applied on "complete" decision tables.

The need for smaller complexity algorithms, even just near, not absolutely optimal, which can acquire knowledge not from a well formed decision table but from a set of casual or not examples of the objects we want to classify in the future (using the acquired knowledge i.e. the expert system), and the need to confront other problems (e.g. noise), had as result the developing of new techniques such as the information theory based ones [6].The knowledge acquiring can be done once, before the expert system's operation starts. But it's much better to improve continually the knowledge base, by learning new rules and merging them with the old ones. As an initial knowledge base, we can use the rules of an already developed expert system [9, 13].

2. A Data Acquisition System for QRS detections using Quinlan's algorithm

2.1 Quinlan's algorithm

J. R. Quinlan developed the ID3 algorithm [6]. A classification rule (decision tree) is synthesized, which can determine the class of any object from its values of the attributes. To this purpose is given a training set of objects whose attribute values and classes are known. A decision tree has class names as leaves. The other nodes represent attribute tests with a branch for each possible outcome. The decision tree must classify correctly all the training set objects, and to be sufficiently successful on other objects classification. In our case (and almost in any case) good is simple. The simplest such tree is that we are seeking for.

A reasonably good tree is synthesized, not always the best. A tree for a subset C of the training set is synthesized at first. If this tree classifies correctly the other training objects too, the procedure has finished. Otherwise some of the not correctly classified objects are added into C, and the procedure repeats for the new subset.

Synthesizing the tree for C is iterative too. If C=∅ or C contains objects of the same class, the tree is a leaf with the name of this class. Otherwise an attribute A is selected, with possible values A_1... Aí, and the tree has as root the test T of A and as branches the subtrees for the subsets C_1,...,$C_í$, in which C is partitioned with regard to its elements values of A. The selection of attribute A is based on information theory. If there are 2 classes, P and N, and P contains p elements of C and N contains the rest n elements, the attribute A is selected, the knowledge of the value of which gives more information gain (A) for the class. It is gain (A) =I (p, n)-E (A), where

$$I(p,n) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{n}{p+n} \quad (1)$$

is the entropy (uncertainty, information average) of the tree for C and

$$E(A) = \sum_{i=1}^{í}\frac{p_i+n_i}{p+n}I(p_i,n_i) \quad (2)$$

is the entropy under condition of the tree with given the value of A, where p_i and n_i the numbers of the elements of

C_i which belong to the classes P and N, respectively. If for k $\in\{1,...,í\}$ is $C_k=\varnothing$, the tree for C_k is a leaf, which fails to name a class, or, better, gives to C_k the name of the more frequent class in C.

2.2 QRS parameters

The QRS complex is a name for the combination of three of the graphical deflections seen on a typical electrocardiogram (ECG). It is usually the central and most visually obvious part of the tracing. It corresponds to the depolarization of the right and left ventricles of the human heart. In adults, it normally lasts 0.06 - 0.10 s; in children and during physical activity, it may be shorter.

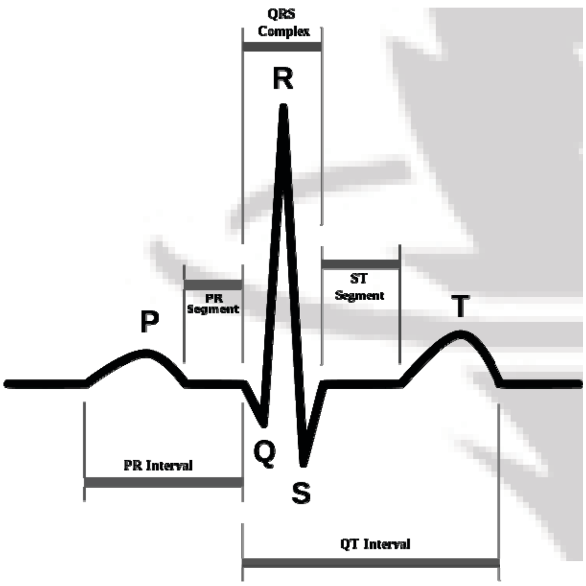

Figure 1: ECG signal with QRS parameters

Typically an ECG has five deflections, arbitrarily named "P" to "T" waves. The Q, R, and S waves occur in rapid succession, do not all appear in all leads, and reflect a single event, and thus are usually considered together. A Q wave is any downward deflection after the P wave. An R wave follows as an upward deflection, and the S wave is any downward deflection after the R wave. The T wave follows the S wave, and in some cases an additional U wave follows the T wave.

Diagram showing how the polarity of the QRS complex in leads I, II, and III can be used to estimate the heart's electrical axis in the frontal plane.

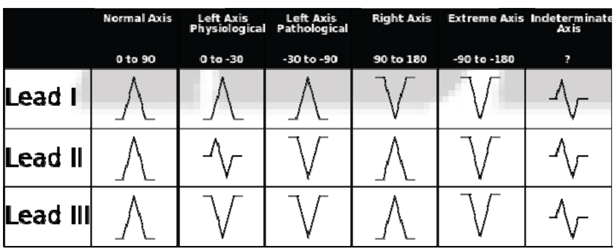

Figure 2: QRS complex in leads I, II, and III

The already developed expert system uses 2 types of attributes; real variables and Boolean variables. In order to apply the data acquisition system algorithm, we transform all variables into Boolean ones. In Real variables we have 2 types of QRS attributes; QRS duration and QRS axis. These can be transformed, for our purposes, into the following described table 1:

Table 1: QRS Duration and Axis

No	*Name of QRS types*	*Greater than*	*Values*
1	QRS duration	0.0987	sec
2	QRS duration	0.1	sec
3	QRS duration	0.11982	sec
4	QRS duration	0.12	sec
5	QRS axis	-45	degree
6	QRS axis	90	degree
7	QRS axis	109.9	degree

In Boolean variables we have 25 types of QRS attributes. These can be transformed, for our purposes, into the following Boolean variables as described in table 2:

Table 2: QRS parameters

No	*Name of QRS types*	*Greater than*	*Values*
1	Duration of Q	0.03	sec
2	Existence of ST	-	-
3	Short ST	-	-
4	Sharp T	8	mm
5	T negative with amplitude	<=2	mm
6	T negative, isoskeles, with amplitude	<=2	mm
7	P negative in I	-	-
8	Duration of P	0.1	sec
9	Amplitude of P in III	3	mm
10	P axis	75	Degree
11	Positive P	negative P	in V1
12	Existence of R	-	in V1
13	Existence of QS	-	in V1
14	Existence of RSR	-	in V1
15	T negative in II	-	
16	T negative in III	-	-
17	Amplitude of S	amplitude of R	in V1
18	T negative in V1, V2, V3	-	-
19	Existence of R	-	in III
20	Existence of R	-	in AVF
21	T negative	-	-
22	Peak of ST	1	mm
23	Fall of ST	1	mm
24	Amplitude of R in V5	27	mm
25	Sum of the amplitudes of RS in I, II, III	<=15	mm

2.3 A data acquisition system for QRS detections

Many methods have been used for describing the ECG diagnostic criteria [9]. At one end is the utilization of the natural language and at the other end the utilization of a computer program with built-in diagnostic criteria. The first approach is suitable for human reading, while the second one for computer reading. Generally speaking, there are two different approaches to the computerization of the ECG diagnosis. One utilizes the binary logic as in [10] and the other involves some statistical procedures as in [11]. The binary logic is usually described in the form of decision tables which provide very clear and compact means for expressing complex relations.

The NTUA Knowledge Expert system shell [14, 15] has been used for the formal description of the ECG diagnostic criteria, which led to the development of an expert system for the interpretation of the 12-lead ECG [16]. This approach is suitable for both human and machine reading, offering diagnostic capabilities, interactive modifications, debugging, explanation and other facilities.

This work started in an effort to formally describe and compare the empiric knowledge used by the different physicians of the department of Clinical Therapeutics, Alexandra Hospital of Athens. The first effort was to utilize decision tables. Soon it was clear that this method was not attractive to the medical personnel, because they had to understand and follow passively complicated decision tables.

The next effort was to use the M.1 expert system shell [12], describe the knowledge in a form of English-like rules and let the medical personnel experiment with the expert system developed so far in this way. By asking "why" and "how" questions, it was possible to find what was wrong in the rules given and make modifications in a straight-forward way [13]. After the NTUA Knowledge Expert system shell has been developed by the National Technical University of Athens [14,15], this system has been used to develop an expert system for the 12-lead ECG interpretation. The reaction of the medical personnel was enthusiastic.

Our intention now is to use the knowledge base of the expert system above as an initial base for the knowledge acquisition and management system we describe in this paper. The classes at our case are all possible diagnoses (rather all that can be done if the values of the specific ECG attributes are known). As such we can select these of the already developed expert system, but this can be changed easily in the future.

The information gain criterion of the data acquisition system algorithm has to be extended, in order to support not only 2 but any number of classes. This can be done as follows. Suppose we have the classes K_1... Km and $k_1,...,k_m$ elements of C belong to $K_1,...,K_m$ respectively. The attribute A is selected, the knowledge of the value of which gives more information gain (A) for the class. It is gain

$$(A)=I\,(k_1... km)-E\,(A) \tag{3}$$

where

$$I(k_1,\ldots,k_m) = -\sum_{i=1}^{m} \frac{k_i}{n}\log_2\frac{k_i}{n} \tag{4}$$

is the entropy (uncertainty, information average) of the tree for C ($n=k_1+...+k_m$ is the number of elements of C) and

$$E(A) = \sum_{j=1}^{i} \frac{k_{1j}+\ldots+k_{mj}}{n} I(k_{1j},\ldots,k_{mj}) \tag{5}$$

is the entropy under condition of the tree with given the value of A, where $k_{1j},...,k_{mj}$ the numbers of the elements of C_j (these having the j-th possible value for attribute A), which belong to the classes $K_1,...,K_m$ respectively.

3. Results

Performance of individual rules is measured over time, and new learned rules are continually merged and sorted with old ones, based on their empirically determined accuracy. The system has interactive features; for every new case it advices the user, using the more successful suitable rule of its knowledge base. The user can accept the proposal, or take his own decision. The system stores the case to be used as a training example for learning new rules. It updates also the performance statistics for each current rule.

The learning procedure is as follows:

1. Update the performance statistics for each current rule, to include performance on all new training example ECGs.
2. Window set = the most recent nw training example ECGs.
3. Training set = nt examples selected at random from the window set.
4. Test set = window set minus training set.
5. Learn a decision tree to make an ECG diagnosis, using the data acquisition system algorithm applied to the training set.
   - Convert each path of the learned decision tree into a rule.
   - Remove any rule precondition that do not result in decreased rule performance over either the training set or test set. (In order to improve generality, rule preconditions are pruned when this improves rule performance.)
   - For each new rule, record the number of positive and negative examples it matches from the window set.
   - Merge new rules into the previous rules, remove duplicates, and sort the list of the rules based on their measured accuracy.

A significant problem though is the difficulty of building such a "good" expert system, because of the complexity of the subject (number of ECG attributes and classes). There is need of a very large training set, in order to cover so many cases. We can therefore use the method of continual learning, in order to succeed continual improvement of an initially not so good expert system.

We have to pay great attention to the size of the training set and to the variety of its elements (ECG samples). If the training set is very small, the synthesized decision tree hasn't general power, it's just a description of the training set (doesn't capture structure inherent in the problem, i.e. the meaningful relationship between an object's class and its attribute values). (The extreme case is a training set with only one example element; this element corresponds directly to a rule.) The training set has therefore to be great enough, if we want to extract simple rules with general power. Using the continual learning technique, we can start with a small training set, augmented from time to time as more and more

ECG samples become available.

4. Conclusion and Prospects

- Machine learning by inductive inference (knowledge acquiring and extracting in a structured form) is feasible and effective.
- The rules learned are intelligible to users and can be continually evaluated.
- The expert system learned is useful for providing interactive advice or for educational purposes, but not sufficiently accurate for autonomous decision-taking. The latter is obvious for applications related with the human health.
- The performance measurement of every rule and the continual merging of new rules to old ones are feasible and effective.
- The great complexity of the ECG (number of attributes and classes) has as result the need of further research in order to improve the system described.

Topics where further research can be done:

- ECG attributes used. One would like the learning system to consider all attributes possible in its search for general rules. However, as one increases the number of attributes one must also increase the number of training examples in order to maintain a fixed level of learning performance (more data is required to select reliably among the larger set of candidate hypotheses). Perhaps a method like R. Caruana's "greedy attribute selection" [8] that selects automatically which attributes to use for future learning by determining which attributes would have led to the most successful learning in the past, could be used.
- ECG classes (diagnoses) used.
- Attribute selection criterion.
- Further modification of the ID3 algorithm, in order to support real-value attributes.
- Further improvement of the algorithms used.
- Any further improvement and refinement.

References

[1] A.J. Bayes, "A dynamic programming algorithm to optimize decision table code", Australian Computer. J. 5, 2, pp. 77-79, 1973.
[2] H. Schumacher, K.C. Sevcik, "The synthetic approach to decision table conversion", Communications of the ACM, Vol. 19, No. 6, June 1976.
[3] A. Lew, "Optimal Conversion of extended-entry decision tables with general cost criteria", Communications of the ACM, Vol. 21, No. 4, April 1978.
[4] M. Verhelst, "The conversion of limited-entry decision tables to optimal and near-optimal flowcharts: Two new algorithms", Communications of the ACM, Vol. 15, Number 11, pp. 974-980, Nov. 1972.
[5] G. Papakonstantinou, "A recursive algorithm for the optimal conversion of decision tables", Angewandte Informatik, Vol. 22, No. 9, pp. 350-354, 1980.
[6] J. R. Quinlan, "Induction of decision trees", Machine Learning 1, pp.81-106, 1986.
[7] T. Mitchell, R. Caruana, D. Freitag, J. McDermott, D. Zabowski, "Experience with a learning personal assistant", Communications of the ACM, Vol. 37, No. 7, July 1994.
[8] R. Caruana, D. Freitag, "Greedy attribute selection", Proceedings of the 11th International Conference on Machine Learning, July 1994.
[9] J. Willems, "Common standards for quantitative electrocardiography" J. Med. Eng. Techn. 9: 209-217
[10] J. Wartak et al., "Computer program for diagnostic evaluation of Electrocardiograms", Computer Biomedical Research 4: 225-238, 1971.
[11] M. Laks et al., "Computer linkage of the clinical history to electrocardiographic language permitting the use of Bayes' theorem", Proc. Computer in Cardiology, Boston 1986.
[12] "M.1 reference manual (version 1.3)", Framentec SA., 1986.
[13] E. Giakoumakis et al., "Formalization of the ECG diagnostic criteria using an expert system shell", Proc. Computer in Cardiology, IEEE, 1988.
[14] K. Flokos, "NTUA Knowledge Expert", Diploma Thesis, National Technical University of Athens, 1990.
[15] NTUA, "The NTUA Knowledge Expert user's manual (version 1.1)", National Technical University of Athens, 1991.
[16] Ph. Bourlas, E. Giakoumakis, D. Koutsouris, G. Papakonstantinou, P. Tsanakas, "The Cardio-Logos system for ECG training and diagnosis", Accepted in Technology and Health Care, Elsevier Science B.V., 1995.