Mechanisms and Machine Science 70

Stanisław Zawiślak
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Engineer of the XXI Century

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Chapter 23
On Data Mining Technique for Differential Diagnostics Based on Data of Arterial Oscillography

O. Mintser, V. Martsenyuk and D. Vakulenko

Abstract The work is devoted to development and application of the decision tree induction algorithm for the problem of differential diagnostics and assessment of adaptation possibilities of patients (cardiovascular, nervous, endocrine, respiratory system diseases) and healthy (in the position of lying and sitting) on the basis of the data of arterial oscillography. Software implementation uses C5.0 algorithm. For each type of research, as well as their totality, separate decision trees are constructed. The classification error as well as attribute usage are gotten and analyzed.

Keywords Decision tree · Data mining · Medical diagnostics · Arterial oscillography

23.1 Introduction

Computer-based medical diagnostic systems (CBMDS), using various types of inference methods, are widely used in many fields of medicine [1–7]. In the process of their designing and implementation not only classic statistical methods are used (multidimensional logistic regression, discriminant analysis, Bayesian classifiers or the method of k-Means), but also data mining and artificial intelligence (including neural networks, fuzzy logic, bayesian networks, supporting vector machines, classification and regression trees) [1, 2, 3, 4, 8, 9, 5, 6, 7]. Their purpose includes support for screening, diagnostic processes (including laboratory procedures) and therapeutic procedures (including drug dosages and pharmacoeconomics), as well as manage-

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ment of the health care system in chronic diseases. It is estimated [2, 3, 6] that the use of CBMDS in about 60–70% of analyzed cases improved significantly the quality of healthcare in clinical practice, in about 60% of management systems for chronic diseases, in more than 65% of pharmaceutical systems and improved significantly the patient satisfaction. An important problem both from a clinical and an economic point of view is the assessment of the risk of events, such as hospitalization or death. The use of CBMDS reduced the risk of misdiagnosis by an average of 16%.

In most of the currently existing hospital information systems, decision-making regarding diagnostics and therapy is a complex and complicated process in each patient. The decision-making process is bounded by limitations imposed by the health care system, clinical conditions, available information, patient preferences, medical staff and the management of a given medical facility. Clinical conditions include, on the one hand, the nature and complexity of the problem (the case) being analyzed, and on the other hand the health policy and economic rigor of the physician in the institution. Patient preferences are the most important when there is no clearly marked further course of action in the decision process (there are many possibilities of decision as to the method of diagnosis and treatment). It is necessary to take into account the patient's satisfaction and its further quality of life resulting from the decision taken. The final decision requires not only an economic analysis of diagnostic and therapeutic procedures, but also the socio-economic situation of the patient.

One of the most widely used approach used in CBMDS is based on application of decision tree induction algorithm. Classification trees (also known as decision ones) are a family of statistical methods, using diagrams (so-called undirected acyclical coherent graphs) to sequentially divide the data space into classes (subspaces) with similar properties. The history of decision trees began with the publication of the book by Breiman et al. presenting the CART (Classification and Regression Tree) model. Another important approach was the Quinlan book, which discussed the construction and implementation of the so-called the C4 algorithm, which is a modification of the algorithm proposed by Breiman. Current version of the algorithm is C5.0

23.2 Material and Method

We present the mathematical problem of decision tree induction in the following way. Let D be the set containing N tuples of learning data. Here any ith tuple $\left(A_1^i, A_2^i, \ldots, A_p^i, C^i\right)$ includes attributes $A_1, \ldots, A_p$ as input data and the class attribute C as an output. The attributes $A_1, \ldots, A_p$ can accept both numerical and categorized values. The class attribute C receives one of the K discrete values: $C \in \{1, \ldots, K\}$. The goal is to predict the value of class attribute C using decision tree on the basis of the values of the attributes $A_1, \ldots, A_p$. Moreover it is necessary to maximize accuracy of prediction of the class attribute, i.e. probability $P\{C = c\}$ on terminal nodes for arbitrary $c \in \{1, \ldots, K\}$. Algorithms of decision tree induction split automatically on nodes the values of numerical attributes A_i into two intervals: $A_i \leq x_i$ and $A_i > x_i$, the values of categorized attributes A_j are spitted into two subsets: $A_j \in S_j, A_j \notin S_j$.

The splitting numerical attributes is based, as a rule, on measures based on entropy, or the Gini index. The partitioning process is recursively repeated until an improvement in the prediction accuracy is observed. The last step involves excluding nodes to avoid overfitting the model. As a result, we need to get a set of rules that go from the root to each terminal node, contain inequalities for numeric attributes and inclusion conditions for the categorized ones.

Our goal is to apply the method of tree induction for software implementation within the decision support system based on the data of arterial oscillography.

Method of the decision tree induction is based on the following recursive procedure [10, 4]

Generation of decision tree
Input data: D is the set of learning tuples $\left(A_1^i, A_2^i, \ldots, A_p^i, C^i\right)$.
Output data: decision tree
Method:

1. Create node N.
2. If all tuples from D belong to common class C then return node N as node with class name C.
3. If list of attributes (hence D) is empty then return node N as leaf with the name of the most extended class in D.
4. Apply *Algorithm of attribute selection* from list of attributes for the set D in order to search the "best" splitting attribute.
5. Remove splitting attribute from the list of attributes.
6. For any splitting condition j for splitting attribute consider D_j, i.e. the set of tuples from D satisfying to splitting condition j.
7. If D_j is empty then join to node N the leaf labeled with the name of the most extended class in D_j, else join to N the node which is returned by the recursive call of the method *Generation of decision tree* with input data D_j and the list of attributes.
8. End of cycle of step 6.
9. Return node N.

As a base of *Algorithm of attribute selection* on the jth step of recursion we use the following information measure:

$$Gain(A_i) = Info(D_j) - Info_{A_i}(D_j). \tag{23.1}$$

Here

$$Info(D_j) = -\sum_{k=1}^{K} p_k^j \log_2(p_k^j) \tag{23.2}$$

is information which is necessary to classify the tuple $(A_1, A_2, \ldots, A_p)$ in D_j,

$$Info_{A_i}(D_j) = \sum_{l=1}^{K_i} \frac{\#(D_j^l)}{\#(D_j)} Info(D_l) \tag{23.3}$$

is information which we need to classify $(A_1, A_2, \ldots, A_p)$ in D_j after splitting D_j into subsets D_j^l with respect to the values of attribute A_i.

In the expression (23.2) the probability that any tuple from D_j belong to the set C_{k,D_j} is estimated as $p_k^j = \frac{\#\left(C_{k,D_j}\right)}{\#\left(D_j\right)}$ where C_{k,D_j} is the set of tuples from D_j for which the class attribute $C = k$. Here $\#(\bullet)$ is the number of elements in set.

In the expression (23.3) $\frac{\#(D_j^l)}{\#(D_j)}$ is the estimate of probability that any tuple from D_j belong to the set D_j^l where D_j^l is the set of tuples from D_j for which attribute $A_i = a_i^l$. Here attribute $A_i \in \{a_i^1, a_i^2, \ldots, a_i^{K_i}\}$.

Thus, $Gain(A_i)$ estimates decrease of information which is needed to classify any set of tuples in D_j when taking into account the known value of the attribute A_i. Therefore, from available attributes for each node of the decision tree for splitting condition we need to select the attribute A_{i^*} with the greatest value $Gain(A_{i^*})$. As a result of such selection for completing classification process in D_j we need the least amount of information.

For the purpose of application of the decision tree induction algorithm we have used the data of arterial oscillography which was executed for 276 people, among them 216 patients aged 25–55 years, who had undergone the rehabilitation at the Sanatorium of V. Hnatiuk Ternopil National Pedagogical University (Ukraine) [8, 11]. We have divided some of these patients into the following groups. Namely, 62 patients with arterial hypertension (AG) stage II; 10 patients with chronic obstructive pulmonary disease (COPD), respiratory failure (RF); 45 of them at the phase of incomplete remission; 38 patients with type 1 diabetes mellitus; 27 patients with coronary heart disease II-FK; 5 patients with coronary heart disease I-FK; 50 and 13 healthy people in sitting and lying position respectively. The structure of attributes that were used in data mining algorithm is presented in Table 23.1.

23.3 Results and Discussion

In case of *healthy sitting and lying persons* (63 persons) we obtained decision tree presented in Fig. 23.1.

Table 23.1 Attributes for decision tree induction which is based on indices of arterial oscyllography

Denotion of attribute	Specification of attribute	Type of attribute values
$A_1 \ldots A_9$	Morphological analysis	Real value
A_{10}	Fractal dimension	Real value
$A_{11} \ldots A_{49}$	Temporal analysis	Real value
$A_{50} \ldots A_{475}$	Spectral analysis	Real value
$A_{50} \ldots A_{335}$	Power spectrum with Fourier transform of oscillations	Real value
$A_{405} \ldots A_{455}$	Power spectrum with Fourier transform of intervalogram	Real value
$A_{336} \ldots A_{406}$	Power of current frequency and phase due to Hilbert-Huang oscillations	Real value
$A_{456} \ldots A_{475}$	Power of current frequency and phase due to Hilbert-Huang transform of intervalogram	Real value

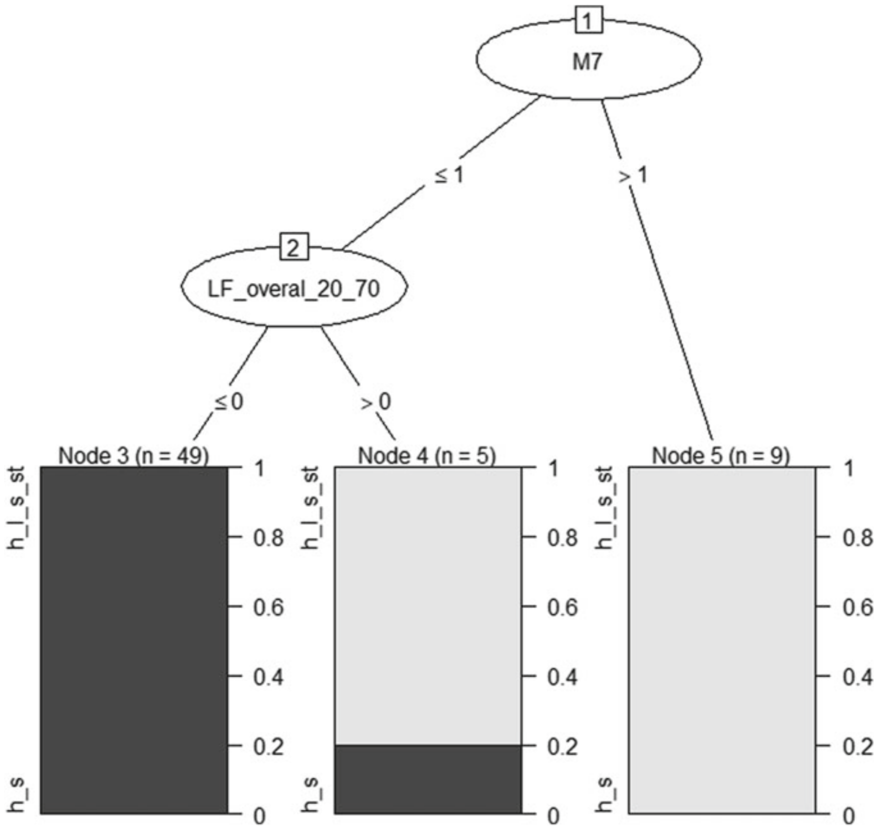

Fig. 23.1 Decision tree based on data of morphological, fractal, temporal and spectral methods of arterial oscyllography for healthy sitting and lying persons (63 persons)

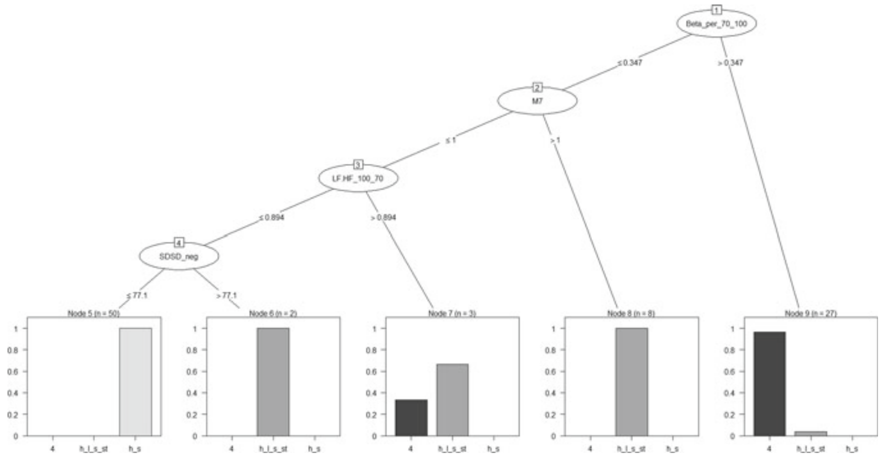

Fig. 23.2 Decision tree based on data of morphological, fractal, temporal and spectral methods of arterial oscillography for healthy sitting, lying persons and patients with coronary artery disease II-FK (lying position) (90 persons)

Analyzing a decision tree based on measured blood pressure, with further analysis of indicators (attributes) obtained from arterial oscillograms in two groups of healthy persons which were sitting and lying (Fig. 23.1), it is evident that the level of information in the first place is excitement of shoulder tissue as a result of compression with a cuff. At values M7 > 1 with probability $P = 100\%$ (9 cases) the person was in a lying position. At values M7 ≤ 1, the value of the power spectrum is calculated for the Fourier transform in the range from 0.04 to 0.15 Hz in the interval from reaching the value of diastolic pressure to 70% of the amplitude of the arterial oscillogram. If the value LF_20–70 $\leq 3.79\text{e}{-6}$ (49 cases), the patient with the probability $P = 100\%$ is sitting and under condition of LF_20–70 $\geq 3.79\text{e}{-6}$ (5 cases), of which 4 patients are in the lying position and one in sitting position with a probability of $P = 80\%$.

The indicator's informativeness evaluation (usability) is carried out. The indicator M7 usage is 100%, and for LF_20–70 is 85.71%.

The diagnostic error using a tree (Fig. 23.1) was investigated. Total error of classification for the data being analyzed is 1.6% (i.e., 1 in 63 cases). In this case, one case in the lying position is mistakenly diagnosed, which is added to the group of patients in the sitting position.

In case of healthy sitting, lying persons and patients with coronary artery disease II-FK (lying position) we obtained decision tree presented in Fig. 23.2.

Analyzing the decision tree based on the performed measurements of arterial pressure, with further analysis of the indicators (attributes) obtained from arterial oscillograms in three groups in a sitting position, lying and patients with coronary artery disease II-FK (Fig. 23.2), it is evident that according to informativity on the first place is the index of the power spectrum from 0 to 50 Hz for the Fourier transform in the range of Beta waves from 13 to 25 Hz in the range from 70% of the amplitude to reaching 100% of the amplitude of the pulsations of the arterial oscillogram. At values %Beta_70–100 > 0.347, in 26 out of 27 patients with coronary artery disease were diagnosed (patient's position when measuring blood pressure was lying down), while in one patient, coronary artery disease was not diagnosed with probability $P = 96.3\%$. At the values %Beta_70–100 $\leq$ 0.347, the value of M7 should be taken into account. At M7 > 1 with a probability of $P = 100\%$ (8 cases) the patient is in the lying position. At M7 $\leq$ 1, the value of the LF/HF ratio of 100% of the amplitude (peak pulsation time) should be estimated until the 70% amplitude of the pulsations of the arterial oscillogram is reached. If LF/HF_100–70 > 0.894 in 2 of 3 cases, the patient was in a lying position and in one sitting position with a probability $P = 66.7\%$. In the case LF/HF_100–70 $\leq$ 0.894, the SDSD (mean squared deviation of intervals between negative intervals) should be estimated. In the case SDSD_neg $\geq$ 77.1 (50 cases) patients are lying with probability $P = 100\%$, while patients are sitting if SDSD_neg < 77.1 (2 cases) with probability $P = 100\%$.

We evaluated the informativeness of indicators (usability). The usage of indicator %Beta_70–100 is 100%, M7 is 70%, LF/HF_100–70 is 61.11%, and SDSD_neg is 57.78%.

The diagnostic error using the decision tree (Fig. 23.2) was investigated. The total error in the data under study is 2.2% (that is, 2 cases out of 90). In this case, one case from 27 assigned to the coronary artery disease II-FK was from the healthy ones in the lying position, was mistakenly diagnosed. One case from 13 in the case of lying position was classified as the patient with coronary artery disease II-FK.

In case of patients with diabetes mellitus (number group 14), pneumonia DN-I (number group 15) and cerebrovascular accident with left ventricular hemiparesis (stroke) (number group 7) decision tree is presented in Fig. 23.3. Here we have analyzed 109 persons.

Analyzing decision tree which is constructed based on measurements of arterial pressure with the following analysis of indices (attributes) which were obtained from arterial oscillograms for three groups of patients with diabetes mellitus, pneumonia and cerebrovascular accident with left ventricular hemiparesis (109 persons) (Fig. 23.3), we can see that the most informative is the indicator of the weight of the spectrum power from 0 to 50 Hz for the Fourier transform in the range of Beta waves from 13 to 25 Hz of the arterial oscillogram. For values %Beta $\leq$ 4.45e−005, it is recommended to evaluate the Kerdo index value. If Index_Kerdo $\leq$ 62, then we have leaf number 3 (10 people), where 8 of them have diabetes and one person with chronic obstructive pulmonary disease and another one with cerebrovascular accident (probability $P = 80\%$). For patients with Index_Kerdo > 62 (25 persons) we have 24 patients with cerebrovascular accident and one patient was diagnosed with diabetes with (probability $P = 96\%$).

At values %Beta > 4.45e−005 it is recommended to estimate the power of the spectrum of the instantaneous frequency by the Hilbert-Huang transform in the range from 4 to 6 Hz from 100% of the amplitude to reaching 70% of the amplitude of the pulsations of the arterial oscillogram.

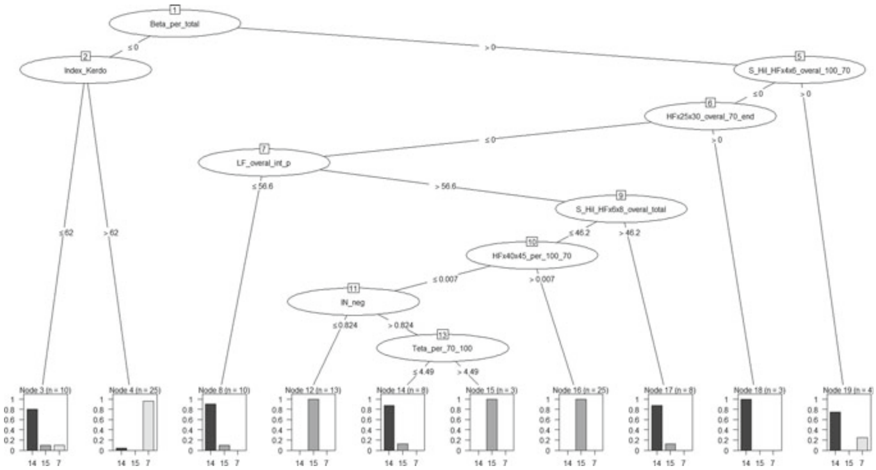

Fig. 23.3 Decision tree based on data of morphological, fractal, temporal and spectral methods of arterial oscillography for patients with diabetes mellitus (number group 14), pneumonia DN-I (number group 15) and cerebrovascular accident with left ventricular hemiparesis (stroke) (number group 7) using data of 109 persons

At S_Hil(4 × 6)_100–70 > 0 for the four people satisfying this condition, three patients of them were diagnosed with diabetes mellitus, and one patient with cerebrovascular disorder (probability $P = 75\%$). For S_Hil(4 × 6)_100–70 ≤ 0 algorithm recommends checking the power of the spectrum over the Fourier transform in the range from 25 to 30 Hz at the interval from 70% of the amplitude of the pulsations of the arterial oscillogram to the end of the measurement.

At HF(25 × 30)_70-end > 2.73e−009 in three cases there were patients with diabetes ($P = 100\%$), and at HF(25 × 30)_70-end ≤ 2.73e−009 it is suggested to evaluate the spectral power for the Fourier transform in the range from 0.04 to 0.15 Hz on the basis of the analysis of positive intervals of the arterial oscillogram.

For values LF_int_p ≤ 56.6 (10 persons) 9 people were with diabetes mellitus and 1 person was with pneumonia (probability $P = 90\%$). In the next step the algorithm proposes for values LF_int_p > 56.6 to check the value of the power of the spectrum of the instantaneous frequency by the Hilbert-Huang transform in the range from 6 to 8 Hz of the arterial oscillogram.

At S_Hil(6–8) > 46.2 (8 patients) 7 patients were diagnosed with diabetes mellitus and one with pneumonia (probability $P = 87.5\%$). At values S_Hil(6–8) ≤ 46.2 the comparison of the power of the spectrum from 0 to 100 Hz for the Fourier transform in the range from 40 to 45 Hz is based on the analysis of positive intervals of the arterial oscillogram from 100% of the amplitude to reaching 70% of the amplitude of the pulsations of the arterial oscillogram %HF(40–45)_(100–70).

In the case %HF(40–45)_(100–70) > 0.00747 25 patients were diagnosed with pneumonia ($P = 100\%$), and at %HF(40–45)_(100–70) ≤ 0.00747, an assessment of the values of index of stress at negative intervals (temporal analysis) IN_neg is required. At IN_neg ≤ 0.824, pneumonia was diagnosed for 13 people. At IN_neg > 0.824 it is proposed to evaluate the weight of the spectral power from 0 to 100 Hz for the Fourier transform in the Teta wave range from 1 to 4 Hz of the arterial oscillogram from 70% to 100% of the pulsed arterial oscillogram %Teta_70–100.

At %Teta_70–100 ≤ 4.49 using leaf number 14 we can see 7 persons with diabetes mellitus and one with pneumonia (probability $P = 87.5\%$). At %Teta_70–100 > 4.49 15 people had chronic obstructive pulmonary disease (pneumonia) $P = 100\%$.

An estimate of the informativeness of the indices (usability) was made. The indicator %Beta was used in 100% cases, S_Hil(4–6)_100–70 in 67.89% cases, HF(25 × 30)_70-end in 64.22% cases, LF_int_p in 61.47% cases, S_Hil(6–8) in 52.29% cases, % HF (40–45)_(100–70) in 44.95% cases, Index_Kerdo in 32.11% cases, IN_neg in 22.02% cases, %Teta_70–100 in 10.09% cases.

The diagnostic error using the decision tree (Fig. 23.3) was investigated. The total error is 6.4% (that is, 7 of 109 cases). In this case, 4 patients with pneumonia and 2 patients with cerebrovascular accident with left ventricular hemiparesis were added mistakenly to the group of patients with diabetes mellitus. All patients with pneumonia were diagnosed correctly.

23.4 Conclusions

Blood pressure measurement is a simple, accessible (both for healthcare professionals and patients) method of examination. It is a mandatory procedure for examination of patients, in sport medicine, private practice [12]. Shoulder cuff compression during arterial pressure measurement can be considered as a functional load that can be used to assess the adaptive capacity of the body of patients and healthy persons. Arterial oscillography provides an opportunity to investigate and evaluate the changes that arise, as well as to be used for primary diagnosis of premorbid conditions, assessment of the features of disease, the choice of methods and evaluation of the effectiveness of treatment.

The use of a decision tree based risk assessment in clinical practice may facilitate decision-making on the therapeutic treatment of certain diseases and bring valuable socio-economic benefits.

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