Fuzzy IF-THEN Rules Extraction For Medical Diagnosis Using Genetic Algorithm

ALEXANDER ROTSHTEIN, MORTON POSNER
Dept. of Industrial Engineering and Management
Jerusalem College of Technology – Machon Lev
21 Havaad Haleumi, 91160, Jerusalem
ISRAEL

HANNA RAKYTYANSKA
Dept. of Applied Mathematics
Vinnitsa State Technical University
95 Khmelnitske sh., 21021 Vinnitsa
UKRAINE

Abstract: - In this paper the formal procedure of fuzzy IF-THEN rules extraction from histories of diseases is proposed. The suggested procedure envisages the optimal solution growing from a set of primary IF-THEN rules variants using the genetic cross-over, mutation and selection operations. The efficiency of the genetic algorithm is illustrated by an example of ishemia heart disease diagnosis.

Key-Words:- Fuzzy logic, linguistic approximation, fuzzy rules extraction, genetic algorithm

1 Introduction

In a lot of areas of medicine there are huge experimental data collections and it is necessary to transfer these data into the form convenient for decision making. Several well-known methods like mathematical statistics, regression analyses etc. are usually used for data processing. But decision makers in medicine are typically not statisticians or mathematicians. So it is important to present the results of data processing in the easily understandable form for decision makers without special mathematical background.

Fuzzy IF-THEN rules [1] allow to make the result of data analyses easily understandable and well interpretable. During fuzzy expert systems development it is supposed that initial knowledge base is generated by an expert from the given area of medicine [2, 3]. That is why the quality of these systems depends on the skill of medical expert.

The aim of this paper is (1) to propose the formal procedure of fuzzy IF-THEN rules extraction from histories of diseases and (2) to compare the results of medical diagnosis using extracted IF-THEN rules and the similar rules proposed by an expert. The suggested procedure is based on the optimal solution growing from a set of primary IF-THEN rules variants using the genetic cross-over, mutation and selection operations.

The efficiency of proposed genetic algorithms is illustrated by an example of ishemia heart disease (IHD) diagnosis.

2 Diagnostic Model Structure

According to the current clinical practice, the complication of IHD will be defined at the levels as follows (from the lowest to the highest): d_1 is the neurocirculatory dystonia (NCD) of the light case of complication; d_2 is the NCD of the average case of complication; d_3 is the NCD of the heavy case of complication; d_4 is the stenocardia of the first functional disability degree; d_5 is the stenocardia of the second functional disability degree; d_6 is the stenocardia of the third functional disability degree.

The above mentioned levels $d_1 \div d_6$ are considered as the types of diagnosis which should be identified.

While making the diagnosis of IHD of a specific patient we should take into consideration the next main parameters defined in the laboratory tests (possible variation ranges are indicated in round brackets where c. u. is a conventional unit): x_1 is the double product (DP) of pulse and blood pressure ($128 \div 405$ c.u.); x_2 is the tolerance to physical loads ($90 \div 1200$ kGm/min); x_3 is the increase of DP per one kG of the patient body weight ($0.6 \div 3.9$ c.u.); x_4 is the increase of DP per one kGm of load ($0.09 \div 0.56$ c.u.); x_5 is the max. oxygen consumption per one kG of patient weight ($7.4 \div 40.9$ mlitre/min $\times$ kG); x_6 is the increase of DP in response to submaximal load ($46 \div 352$ c.u.); x_7 is the adenosine-triphosphoric acid - ATP ($34.48 \div 69.49$ mmol/l); x_8 is the adenosine-diphosphoric acid - ADP ($11.9 \div 29.4$ mmol/l); x_9 is the adenosine-monophosphoric acid - AMP ($3.6 \div 27.1$ mmol/l); x_{10} is the coefficient of phosphorylation ($1.0 \div 5.7$ c.u.); x_{11} is the ratio factor of milk and pyruvic acid ($3.9 \div 30.2$ c.u.); x_{12} is the age of the patient ($31 \div 58$ years).

The aim of the diagnosis is to translate a set of specific parameters $x_1 \div x_{12}$ into a decision d_j $\left(j=\overline{1,6}\right)$.

The structure of the model for differential diagnosis of IHD is shown in Fig.1, which corresponds to the following hierarchical tree of logic inference:

$$d = f_d\left(x_{12}, y, z\right) , \qquad (1)$$

$$y = f_y\left(x_1, x_2, ..., x_6\right) , \qquad (2)$$

$$z = f_z\left(x_7, x_8, ..., x_{11}\right) , \qquad (3)$$

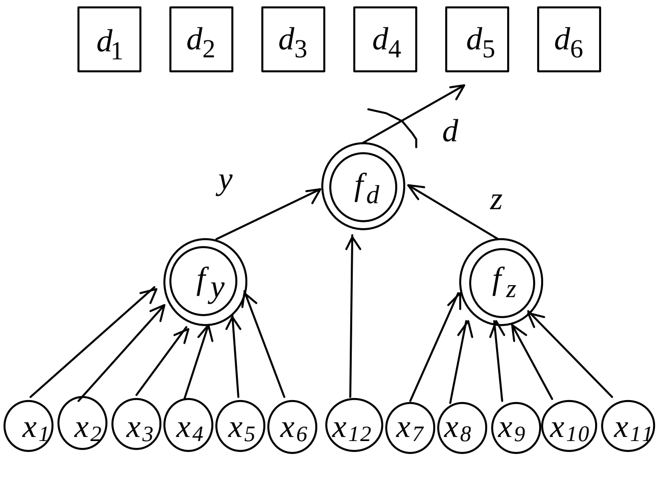

Fig. 1. Diagnostic model structure

where: d is the danger of IHD measured by levels $d_1 \div d_6$, y is the instrumental danger, and z is the biochemical danger measured by the following levels $y_1 \div y_5$, $z_1 \div z_5$: L - low, bA - below average, A - average, aA - above average, H - high.

3 Problem Statement

Let us consider the object (1)-(3) for which the following data are known:

- intervals of inputs (parameters of the patient state) change: $x_i \in \left[\underline{x_i}, \overline{x_i}\right]$, $i=\overline{1,n}$;
- classes of decisions d_j $\left(j=\overline{1,m}\right)$ (types of diagnoses);
- training data (histories of diseases) in the form of M pairs of experimental data "parameters of patient state - type of diagnose" $\left\{X_p, d_p\right\}$, where $X_p = \left\{x_1^p, x_2^p, ..., x_n^p\right\}$ is input vector in p-th pair, $p=\overline{1,M}$.

It is necessary to transfer the available training data into the following systems of the fuzzy IF-THEN rules:

1) *for the instrumental danger y:*

IF $\left[\left(x_1 = a_1^{j1}\right) \text{AND} \left(x_2 = a_2^{j1}\right) \text{...AND} \left(x_6 = a_6^{j1}\right)\right]$
(with weight w_{j1}^y) ... OR
$\left[\left(x_1 = a_1^{jk_j}\right) \text{AND} \left(x_2 = a_2^{jk_j}\right) \text{...AND} \left(x_6 = a_6^{jk_j}\right)\right]$
(with weight $w_{jk_j}^y$),
THEN $y \in y_j$, for all $j=\overline{1,5}$; (4)

2) *for the biochemical danger z:*

IF $\left[\left(x_7 = a_7^{j1}\right) \text{AND} \left(x_8 = a_8^{j1}\right) \text{...AND} \left(x_{11} = a_{11}^{j1}\right)\right]$
(with weight w_{j1}^z) ... OR
$\left[\left(x_7 = a_7^{jk_j}\right) \text{AND} \left(x_8 = a_8^{jk_j}\right) \text{...AND} \left(x_{11} = a_{11}^{jk_j}\right)\right]$
(with weight $w_{jk_j}^z$),
THEN $z \in z_j$, for all $j=\overline{1,5}$; (5)

3) *for the danger of IHD d:*

IF $\left[\left(x_{12} = a_{12}^{j1}\right) \text{AND} \left(y = a_y^{j1}\right) \text{ AND } \left(z = a_z^{j1}\right)\right]$
(with weight w_{j1}) ... OR
$\left[\left(x_{12} = a_{12}^{jk_j}\right) \text{AND} \left(y = a_y^{jk_j}\right) \text{ AND } \left(z = a_z^{jk_j}\right)\right]$
(with weight w_{jk_j}),
THEN $d \in d_j$, for all $j=\overline{1,m}$, (6)

where a_i^{jp} is linguistic term for the estimation of variable x_i in the row with number $p=\overline{1,k_j}$, a_y^{jp} (a_z^{jp}) is linguistic term for the estimation of variable *y (z)* in the row with number $p=\overline{1,k_j}$, and it is supposed that term a_y^{jp} (a_z^{jp}) should be chosen only from estimates y_j (z_j), $j=\overline{1,5}$; k_j is number of conjunction rows corresponding to classes d_j, y_j, z_j; w_{jp}^y, w_{jp}^z, w_{jp} are numbers in the range $[0,1]$ which characterize the weight of the expression with number jp in fuzzy knowledge bases (4)-(6).

4 Optimization Problem

Using the methodology of fuzzy logic approximation proposed in [3] we can transfer the above mentioned systems of IF-THEN rules (4)-(6) into the following hierarchical model:

$$m^{d_j}(d) = \max_{p=\overline{1,k_j}} \left\{ w_{jp} \min\left[m^{jp}(x_{12}), m^{jp}(y), m^{jp}(z) \right] \right\}, \quad (7)$$

$$m^{jp}(y) = \max_{p=\overline{1,k_j}} \left\{ w^{y}_{jp} \min_{i=\overline{1,6}} \left[m^{jp}(x_i) \right] \right\}, \quad (8)$$

$$m^{jp}(z) = \max_{p=\overline{1,k_j}} \left\{ w^{z}_{jp} \min_{i=\overline{7,11}} \left[m^{jp}(x_i) \right] \right\}, \quad (9)$$

$$m^{jp}(x_i) = \frac{1}{1 + \left(\frac{x_i - b_i^{jp}}{c_i^{jp}} \right)^2}, \quad (10)$$

where $m^{d_j}(d)$ is a membership function of diagnose d to a class d_j; $m^{jp}(y)$ ($m^{jp}(z)$) is a membership function of variable *y (z)* to a term a_y^{jp} (a_z^{jp}); $m^{jp}(x_i)$ is a membership function of patient state parameter x_i to a term a_i^{jp}; b_i^{jp} and c_i^{jp} are the tuning parameters for membership function of variable x_i to a term a_i^{jp}.

Relations (7)–(10) can be described in the such short form:

$$m^{d_j}(d) = m^{d_j}(X, W, B, C),$$

where $X = (x_1, x_2, ..., x_n)$ is vector of patient state parameters, $W = (w_1, w_2, ..., w_N)$ is rules weights vector in fuzzy knowledge bases (4)-(6), $B = (b_1, b_2, ... b_q)$ and $C = (c_1, c_2, ... c_q)$ are vectors of parameters of tuning for all fuzzy terms using in fuzzy rules (4)-(6), N is total number of rules-strings, q is total number of terms.

Let us consider restrictions on the number of fuzzy rules (4)-(6) as following:

$$k_1 \le \overline{k_1},\ k_2 \le \overline{k_2},\ ...,\ k_j \le \overline{k_j},$$

where $\overline{k_j}$ is maximum permissible number of conjunction strings in rules of j-th decision class.

That is why the problem of fuzzy IF-THEN rules extraction can be considered as finding of three matrices presented in Tables 1-3. Each element (*b*- and *c*-) of these matrices corresponds to the membership function parameters and can be interpreted as a fuzzy term (low, average, high, etc.)

Table 1. Matrix of IF-THEN rules parameters for model (2)

Rule	IF			Weight	THEN
1	x_1	…	x_6		y
11	(b_1^{11}, c_1^{11})		(b_6^{11}, c_6^{11})	w_{11}^{y}	y_1
…	…		…	…	
$1k_1$	$(b_1^{1k_1}, c_1^{1k_1})$		$(b_6^{1k_1}, c_6^{1k_1})$	$w_{1k_1}^{y}$	
…	…		…	…	
51	(b_1^{51}, c_1^{51})		(b_6^{51}, c_6^{51})	w_{51}^{y}	y_5
…	…		…	…	
$5k_5$	$(b_1^{5k_5}, c_1^{5k_5})$		$(b_6^{5k_5}, c_6^{5k_5})$	$w_{5k_5}^{y}$	

Table 2. Matrix of IF-THEN rules parameters for model (3)

Rule	IF			Weight	THEN
1	x_7	…	x_{11}		z
11	(b_7^{11}, c_7^{11})		$(b_{11}^{11}, c_{11}^{11})$	w_{11}^{z}	z_1
…	…		…	…	
$1k_1$	$(b_7^{1k_1}, c_7^{1k_1})$		$(b_{11}^{1k_1}, c_{11}^{1k_1})$	$w_{1k_1}^{z}$	
…	…		…	…	
51	(b_7^{51}, c_7^{51})		$(b_{11}^{51}, c_{11}^{51})$	w_{51}^{z}	z_5
…	…		…	…	
$5k_5$	$(b_7^{5k_5}, c_7^{5k_5})$		$(b_{11}^{5k_5}, c_{11}^{5k_5})$	$w_{5k_5}^{z}$	

Table 3. Matrix of IF-THEN rules parameters for model (1)

Rule	IF			Weight	THEN
1	x_{12}	$y.$	z		d
11	$(b_{12}^{11}, c_{12}^{11})$	a_y^{11}	a_z^{11}	w_{11}	d_1
…	…	…	…	…	
$1k_1$	$(b_{12}^{1k_1}, c_{12}^{1k_1})$	$a_y^{1k_1}$	$a_z^{1k_1}$	w_{1k_1}	
…	…	…	…	…	
$m1$	$(b_{12}^{m1}, c_{12}^{m1})$	a_y^{m1}	a_z^{m1}	w_{m1}	d_m
…	…	…	…	…	
$m\ k_m$	$(b_{12}^{mk_m}, c_{12}^{mk_m})$	$a_y^{mk_m}$	$a_z^{mk_m}$	w_{mk_m}	

In terms of mathematical programming this problem can be formulated as following. It is necessary to find such vector of membership functions parameters (*b*- and *c*-) and vector of rules weights (*w*-) which satisfy the above mentioned restrictions on the rules numbers and provide minimum distance between theoretical (using fuzzy rules) and experimental (using histories of diseases) results of diagnosis. According to the most popular in identification theory [4] mean square criterion of distance our optimization problem can be formulated as following:

$$\sum_{p=1}^{M}\left\{\sum_{j=1}^{m}\left[m^{d_j}\left(X_p,W,B,C\right)-m_p^{d_j}(y)\right]^2\right\}=\min_{W,B,C}, \quad (11)$$

where

$$m_p^{d_j}=\begin{cases}1, & when\ d_j=d_p\\ 0, & when\ d_j\neq d_p\end{cases}.$$

Since the problem (11) for practically important cases has high dimension and non-linear nature we are using the genetic algorithms optimization technique [5].

5 Genetic Algorithm of Optimization

For application the genetic algorithms technique it is necessary to define the following main notions and operations [5]: *chromosome* - coded versions of solutions, *population* - initial set of solutions versions; *fitness function* - criterion of versions selection; *crossover* - operation of variants-offspring generation from variants-parents; *mutation* - random change of chromosome elements.

To describe the chromosome for parameters of matrices (Tables 1-3) we use the string shown in Fig.2, where r_{jp}^{y}, r_{jp}^{z}, r_{jp} are codes of IF-THEN rule with number jp, $p=\overline{1,k_j}$ in (4)-(6).

To fulfil the crossover operation we are using the exchange of chromosomes parts in each rule r_{jp}^{y}, r_{jp}^{z}, r_{jp} and vector of rules weights. Total number of exchange points equal to $N+1$, that is one for each rule and one for vector of rules weights.

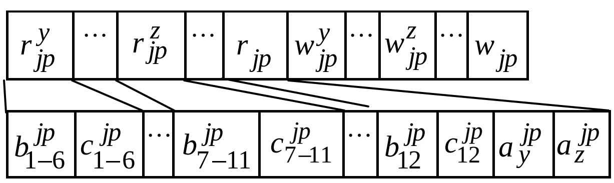

Fig. 2. Coding of parameters matrices

Mutation (Mu) implies random change (with some probability) of chromosome elements:

$$Mu\left(w_{jp}^{y},w_{jp}^{z},w_{jp}\right)=RANDOM\left(\left[0,1\right]\right), \quad (12)$$

$$Mu\left(b_i^{jp}\right)=RANDOM\left(\left[\underline{x}_i,\overline{x}_i\right]\right), \quad (13)$$

$$Mu\left(c_i^{jp}\right)=RANDOM\left(\left[\underline{c}_i^{jp},\overline{c}_i^{jp}\right]\right), \quad (14)$$

where $RANDOM\left(\left[\underline{x},\overline{x}\right]\right)$ is the operation of random number finding which is uniformly distributed on the interval $\left[\underline{x},\overline{x}\right]$.

We consider that weights (w-) of IF-THEN rules can be or 1 (rule available) or 0 (rule not available) and fitness function of chromosomes-solutions is evaluated on the basis of (11) criteria.

If $P(t)$ are chromosomes-parents and $C(t)$ are chromosomes-offsprings on a t-th iteration, then the genetic procedure of optimization will be carried out according to the following algorithm:

Begin
t:=0; To set the initial population $P(t)$;
To evaluate the $P(t)$ using criteria (11);
while (no condition of completion) **do**
To generate the $C(t)$ by operation of cross-over with $P(t)$;
To perform mutation of $C(t)$ by operations (12)-(14);
To evaluate $C(t)$ using criteria (11);
To select the population $P(t+1)$ from $P(t)$ and $C(t)$;
$t:=t+1$;
end;
end.

6 Computer Experiment

The total number of patients with IHD in our study was 65. The aim of computer experiment was to generate three rules for each class of decision (y-, z-, d-) according to the models (1)-(3).

The results of this optimization problem solving are presented in Tables 4-6. According to these tables it is easy to make interpretation of each pairs of parameters using fuzzy terms: L-low, bA – below average, A - average, aA – above average, H – high. For example, according to formula (10), the pairs (176.48, 87.80), (256.11, 25.07) correspond to membership functions shown in Fig.3 which can be interpreted as *below average (bA), average (A).*

After linguistic interpretation we can describe the optimal solutions (Tables 4-6) in the form of fuzzy IF-THEN rules matrices (Tables 7-9).

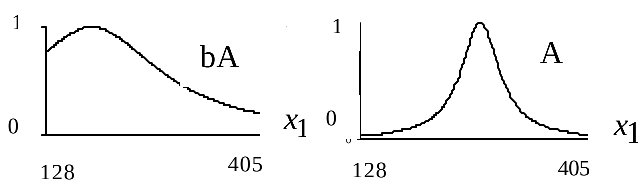

Fig.3. Example of interpretation

Table 4. Parameters of synthesized rules for model (2)

x_1	x_2	x_3	x_4	x_5	x_6	y
(366.22, 21.72) (176.48, 87.80) (145.31, 0.12)	(941.93, 2.11) (667.20, 0.13) (109.43, 50.56)	(3.22, 68.30) (1.84, 64.85) (0.81, 0.26)	(0.43, 0.35) (0.25, 0.002) (0.09, 25.12)	(34.28, 46.38) (17.79, 95.36) (24.23, 0.11)	(275.50, 91.01) (298.45, 50.04) (65.13, 1.08)	L
(368.30, 49.76) (256.11, 25.07) (128.00, 0.30)	(955.80, 32.23) (128.85, 19.79) (92.78, 0.30)	(1.31, 46.84) (2.14, 0.19) (0.60, 1.41)	(0.17, 39.00) (0.32, 99.29) (0.10, 0.22)	(11.42, 62.69) (40.57, 84.19) (7.40, 0.08)	(251.02, 0.007) (179.88, 61.81) (199.77, 7.06)	bA
(184.79, 99.44) (130.77, 14.11) (162.63, 0.20)	(914.18, 63.55) (808.73, 1.70) (306.45, 49.75)	(2.41, 97.90) (0.62, 48.37) (0.66, 0.35)	(0.23, 41.36) (0.40, 54.71) (0.12, 74.83)	(26.33, 75.84) (8.91, 47.99) (8.41, 0.09)	(227.31, 90.78) (140.10, 87.81) (290.80, 73.08)	A
(315.67, 0.65) (188.94, 95.53) (128.00, 12.72)	(123.30, 33.29) (142.73, 1.19) (645.00, 0.21)	(0.88, 96.36) (1.89, 51.36) (0.76, 1.05)	(0.28, 0.58) (0.36, 0.21) (0.10, 0.19)	(33.53, 0.78) (8.91, 2.58) (8.49, 62.61)	(191.35, 99.28) (325.23, 41.56) (208.95, 0.87)	aA
(202.79, 48.80) (290.74, 23.38) (128.00, 1.58)	(597.83, 11.14) (434.10, 11.83) (114.98, 25.82)	(1.47, 30.73) (1.06, 73.89) (0.61, 12.60)	(0.11, 75.40) (0.46, 49.26) (0.09, 0.36)	(16.53, 19.09) (39.90, 75.29) (7.74, 0.44)	(185.23, 51.30) (277.80, 57.23) (46.00, 3.19)	H

Table 5. Parameters of synthesized rules for model (3)

x_7	x_8	x_9	x_{10}	x_{11}	z
(50.32, 33.89) (49.71, 0.78) (35.09, 0.33)	(20.56, 34.79) (22.53, 0.34) (22.84, 0.04)	(13.41, 0.22) (15.47, 93.93) (4.42, 0.005)	(4.50, 52.60) (3.82, 0.19 (1.01, 12.76)	(21.92, 96.15) (16.59, 78.53) (3.90, 12.78)	L
(62.31, 0.29) (61.70, 12.94) (35.01, 0.34)	(26.91, 60.02) (20.87, 0.16) (11.90, 3.39)	(15.88, 46.53) (24.69, 20.64) (3.66, 1.56)	(2.33, 71.15) (2.75, 56.82) (1.01, 0.32)	(23.56, 98.46) (24.74, 75.47) (4.29, 0.37)	bA
(49.10, 0.20) (65.38, 10.18) (56.45, 1.12)	(28.09, 94.26) (27.74, 71.90) (15.71, 0.31)	(16.94, 58.06) (7.30, 26.18) (3.66, 3.50)	(5.32, 0.64) (3.80, 45.65) (2.48, 0.31)	(21.85, 24.64) (20.60, 0.19) (4.10, 0.10)	A
(58.64, 51.82) (47.35, 9.44) (34.66, 62.71)	(16.84, 15.84) (22.36, 0.29) (11.90, 0.24)	(4.60, 0.14) (5.95, 0.07) (5.07, 25.37)	(4.71, 51.30) (3.77, 81.28) (1.00, 0.60)	(24.94, 25.26) (7.91, 15.47) (3.97, 0.17)	aA
(58.72, 39.23) (34.57, 0.33) (34.57, 0.12)	(28.83, 89.91) (15.27, 69.77) (11.90, 0.32)	(24.40, 15.80) (9.24, 47.34) (3.84, 31.70)	(5.32, 92.23) (4.88, 91.19) (1.01, 50.04)	(16.79, 0.29) (6.67, 76.86) (18.76, 0.04)	H

Table 6. Parameters of synthesized rules for model (1)

x_{12}	y	z	d
(38.56, 90.06) (54.83, 94.82) (31.07, 25.25)	H A H	L H H	d_1
(55.30, 5.29) (51.25, 9.85) (31.00, 0.02)	aA bA A	A H bA	d_2
(55.91, 12.41) (49.83, 0.27) (34.38, 0.32)	bA bA bA	A bA bA	d_3
(56.04, 26.81) (31.14, 97.33) (32.01, 0.23)	L bA L	A aA L	d_4
(42.34, 18.74) (46.80, 0.39) (32.96, 0.32)	L aA L	bA aA aA	d_5
(33.30, 2.93) (45.78, 42.60) (31.07, 0.22)	A aA L	aA aA bA	d_6

Table 7. Fuzzy knowledge base for the instrumental danger y

x_1	x_2	x_3	x_4	x_5	x_6	y
aA bA L	aA A L	aA A bA	aA bA L	aA bA A	aA aA bA	L
aA A L	aA L L	bA A L	bA A L	bA L L	aA A A	bA
bA L bA	aA aA bA	A L L	bA aA bA	A L L	A bA aA	A
aA bA L	L L A	bA A L	A A L	aA L L	A L A	aA
bA A L	A bA L	bA bA L	L aA L	bA L L	A aA L	H

Table 8. Fuzzy knowledge base for the biochemical danger *z*

x_7	x_8	x_9	x_{10}	x_{11}	z
A A L	A A aA	A A L	aA A L	aA A L	L
aA aA L	aA A L	A L L	bA bA L	aA aA L	bA
A L aA	L L bA	A bA L	L A bA	aA aA L	A
aA bA L	bA A L	L bA bA	aA A L	aA bA L	aA
aA L L	L bA L	L bA L	L aA L	A bA A	H

Table 9. Fuzzy knowledge base for the IHD danger *d*

x_{12}	y	z	d
bA L L	H A H	L H H	d_1
L aA L	aA bA A	A H bA	d_2
L aA bA	bA bA bA	A bA bA	d_3
L L L	L bA L	A aA L	d_4
A A bA	L aA L	bA aA aA	d_5
bA A L	A aA L	aA aA bA	d_6

7 Comparison of Extracted and Expert IF-THEN Rules

The separate aim of our study was to compare the results of medical diagnosis obtained by formally extracted IF-THEN rules (using genetic algorithm) and the same rules proposed by medical expert in the field of ishemia heart disease [3].

Comparison of diagnoses for 65 patients shows as following (see Table 10). The results obtained by extracted IF-THEN rules are enough close to similar results obtained by fuzzy expert system described in [3]. Future quality improvement of extracted fuzzy IF-THEN rules can be reached by parameters of tuning increasing and using the rules weights in the interval [0,1].

Table 10. Comparison of diagnoses

Levels of coincidences	Expert IF-THEN rules	Extracted IF-THEN rules
Full coincidences of computer decision and real diagnose	56	54
Decisions on a boundary between classes	8	9
Computer decision is far from the real diagnose	1	2

The number of unknown parameters in our computer experiment was 486 and for optimization problem solving we spent about 3 hours on CELERON-450.

8 Conclusion

A specific feature of fuzzy rules bases for medical diagnosis consists of their hierarchical character. In this paper we propose the formal procedure for extraction of hierarchical system of fuzzy rules for medical diagnosis from real histories of diseases. This procedure is based on the optimization problem solving by genetic algorithms. Parameters of optimal solution are forms of fuzzy terms membership functions and fuzzy rules weights. For the interpretation of obtained parameters we used five fuzzy terms: low, below average, average, above average, high. These terms are convenient for linguistic evaluation of a level of patient state parameters. A perspective direction of future research in this field is development of fuzzy rules extraction algorithm with arbitrary linguistic terms using in the medical practice.

The approach proposed in this paper can also be used for data processing in such fields as business, finance, management and others where decision makers are not mathematicians or statisticians and prefer to work with easy understandable and well interpretable expressions.

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