The use of logical-linguistic apparatus to describe the functioning of medical systems

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Abstract. The article describes the developed medical systems. The basis of systems is the mathematical apparatus of fuzzy logic. The advantage of logical-linguistic models is their universality. The components of the model are easily upgradeable. The article discusses examples of models related to medicine. The first model is used to recognize cough sound signals. The sound signals database includes sound signals for coughing patients of a medical institution of the pulmonology department. The developed model has been tested in a hospital, and is also used in the educational process of several higher educational institutions. To develop the second model, statistical data related to the field of eye diseases were used. Based on the collected data, a model has been developed to support adoption in the diagnosis of eye diseases.

At present, it is difficult to imagine our life without expert systems (ES). ES are intended for information support of decision making in the professional activities of various specialists. ES contains knowledge in a specific subject area, accumulated as a result of a person’s practical activity, which she uses to make recommendations or solve problems in this area. ES differ from data processing systems using the symbolic way of describing systems, as well as symbolic inference and heuristic search for solutions. The tasks that are solved with the help of ES, we characterize as follows:

- the impossibility of an algorithmic solution (due to poor formalizability of tasks or the huge cost of computer time);
- inconsistency, incompleteness, possible fallacy of the source data and knowledge in the subject area;
- the enormous dimensionality of data and knowledge, poorly presented in any visual form; dynamically changing composition of data and knowledge (due to their constant replenishment, change and development);
- the need for widespread use in the decision process of heuristic and empirical procedures formulated by experts;
- the need to participate in the decision process of a person (user) who, by answering additionally asked questions, brings additional information and chooses alternative ways of making a decision.

Such tasks are found everywhere, for example:
• in medicine: when monitoring the status of patients with pulmonary diseases; diagnosis of eye diseases;
• in the recognition of technical texts;
• in technological processes: assessment of the quality of manufactured products at bakeries, the selection of suppliers and consumers of perishable dairy products; etc.

In the case of solving recognition problems, the use of ES based on fuzzy logic makes it possible to optimally combine deterministic and heuristic approaches to their solution.

Since unambiguous algorithmic conclusions, as a rule, are absent, it is necessary to be able to control the progress of the logical conclusions of the ES, the corresponding system is called the “explanation subsystem”.

The following main components (subsystems) of ES are distinguished:

• knowledge base;
• knowledge base editor;
• machine (mechanism) of inference;
• user interface based on pseudo natural language;
• subsystem of explanations.

Note that the first three subsystems are mandatory for any ES.

Fuzzy systems are characterized by:

1 probability of using fuzzy input data: such as values that continuously change over time, values that are unambiguously impossible to set (these include the results of statistical surveys conducted by advertising companies, etc.);
2 the possibility of fuzzy formalization of the evaluation and comparison criteria: operating with the criteria "majority", "possible", mainly ", etc.;
3 the probability of conducting qualitative assessments of both the input data and the output results: you operate not only on the data values, but also on their degree of reliability and its distribution;
4 the possibility of carrying out rapid modeling of complex dynamic systems and their comparative analysis with a given degree of accuracy: using the principles of system behavior described by fuzzy methods, firstly, a lot of time is not spent figuring out the exact values of the variables and compiling the describing equations, secondly, it appears the ability to evaluate different options for output values.

![Logical-linguistic model](image)

**Figure 1.** Typical structure of the logical-linguistic model.
For the first time, the concept of a logical-linguistic model was quite fully formulated in the works of D.A. Pospelova. The typical structure of the logical linguistic model is presented in the diagram (figure 1). It includes the formal SF system, the SI interpretation subsystem, and the SA adaptation subsystem, interacting with the external environment M.

The formal system $S_f$ of the logical-linguistic model, like any other formal system, is defined by the four

$$S_f = \langle T, \Phi, A, \Theta \rangle$$

(1)

where T are the terms (alphabet) of the formal system, that is, the set of basic (not further disintegrated) elements used in this system for constructing formulas; $\Phi$ is the syntax of the formal system, that is, the rules for constructing the correct formulas in a given system; $A$ - axioms, that is, correctly constructed formulas reflecting statements and statements, which are considered a priori true in this system; $\Theta$ - the rules for deriving new formulas, which allow for the initial given system of axioms to generate all the correct formulas possible in $S_f$.

Model 1 when used in various systems can be modified for a specific area of application.

To develop a criterion for the final classification based on the data described above, it is proposed to use a fuzzy inference mechanism, which includes three stages: introducing fuzzy (fuzzification), fuzzy inference, composition and bringing to clarity, or defuzzification (figure 2).

![Figure 2. Fuzzy logical input system.](image)

To make it fuzzy, we introduce linguistic variables and describe them.

Denote by $MF_c(\xi)$ – degree of belonging to the fuzzy set C (set of coughs). Then a fuzzy set $C = \{MF_c(\xi)/\xi, MF_c(\xi) \ [0,1]\}$. Value $MF_c(\xi) = 0$ – means lack of belonging to a lot of coughs, 1- full membership.

To describe fuzzy sets, the concepts of fuzzy and linguistic variables are introduced. As linguistic variables for fuzzy logic, the criteria described in [1]:

We describe the fuzzy variable by the set $(N, T, X, G)$, where $N$ – criterion name, $X$ – universal set (area of reasoning $[0,1]$), $T$ – fuzzy set on $X$ (cough, noise), $G$ – syntax rule (IF the criterion is met THEN “cough is possible” OTHERWISE “noise”).

The description of linguistic variables is presented in table 1.

| Variable from set | $N$ | $T$ | $X$ | $G$ |
|-------------------|-----|-----|-----|-----|
| Parameter №.      |     |     |     |     |
| 1                  | Correlation coefficient | Coughing, noise | [0;1] | IF $r_{x1,y1j} \geq R_1$, TO «Cough» ELSE «Noise» |
| 2                  | Correlation coefficient | Coughing, noise | [0;1] | IF $r_{x2,y2j} \geq R_2$, TO «Cough» ELSE «Noise» |
| 3                  | Correlation coefficient | Coughing, noise | [0;1] | IF $r_{x3,y3j} \geq R_3$, TO «Cough» ELSE «Noise» |
| 4                  | Correlation coefficient | Coughing, noise | [0;1] | IF $r_{x4,y4j} \geq R_4$, TO «Cough» ELSE «Noise» |
To bring the obtained experimental data to a general view, normalization was carried out on a scale of intervals.

For fuzzy inference, the following algorithm was used.

For each criterion, phasing was carried out and constructed for each linguistic variable membership function. As a result, we obtain degrees of membership for each rule (2):

\[ A_{ik}(x_k), \quad i = 1..m; \quad k = 1..n, \quad (2) \]

where \( A_{ik} \) - degree of truth; \( x \) – processed sound segment; \( i \) - criterion number; \( k \) - segment number. For each linguistic variable, we construct a membership function.

To construct the membership function, we considered experimental data obtained by processing sound recordings by means of each criterion individually. The data obtained were normalized on a scale of intervals, to normalize the data in a certain range from 0 to 1, where 0 - does not belong to the set of coughs, 1 - completely belongs. According to normalized data, the number of hits in each interval was checked (0 - 0.1; 0.1 - 0.2; ...; 0.9 - 1). Then, the number of sound segments falling into each interval was calculated and the value was determined relative to coughing and noise. The constructed membership functions for each criterion are separately presented in [2].

After obtaining the results for each criterion, we project the “truncated” membership functions on the defuzzification graph of each parameter.

A fuzzy conclusion was carried out with the determination of the level of “clipping” according to the graph of the membership function of each of the criteria. Then, based on the projection of the “truncated” membership functions onto the dephasification schedule of each criterion. Stage of defuzzification. The middle center method or the centroid method was used.

Next, a composition of the obtained “truncated” membership functions was carried out. For this, the maximum composition of fuzzy sets was used (3).

\[ \mu_{total}(\xi) = \max (B_i(\xi)), \quad (3) \]

where \( \mu_{total} \) is the membership function of the resulting fuzzy set; \( B_i \) are the “truncated” membership functions; \( \xi \) is the argument of the membership function.

Figure 3. The final fuzzy conclusion.

The process of the final fuzzy conclusion on Mamdani is presented in figure 3.
The membership function of this graph is described below (4)

\[ \mu_{\text{total}}(x) = \begin{cases} 
0, & x \leq 0.6 \\
4x - 2.4, & 0.6 < x \leq 0.625 \\
0.1, & 0.625 < x \leq 0.7 \\
27x - 18.94, & 0.7 < x \leq 0.725 \\
0.78, & 0.725 < x \leq 0.85 \\
4.8x - 3.3, & 0.85 < x \leq 0.875 \\
0.9, & x > 0.875 
\end{cases} \]  

(4)

The graph in Figure 3 shows the area in which the probability of coughing is 92.5% [3].

To support decision-making in diagnosing eye diseases, we describe a fuzzy variable with the set \((T, S, P)\), where \(T\) are age-related diseases, \(S\) are primary symptoms, \(P\) are possible causes of the underlying disease, in this case, eye disease is considered.

We construct the membership function based on statistical medical data. As a result of processing the statistics of an eye disease, we have a list of symptoms of this disease, as well as numerical values of the frequencies of their appearance for each specific disease. Having identified the minimum and maximum values, we break the entire scale of symptoms into elementary intervals with a fixed step.

The frequency of a particular symptom in each elementary interval of the disease is determined by the following formula (5):

\[ f_j = \frac{k_j}{n}, \]  

(5)

where \(i\) – fixed split interval, \(j\) – symptom in question; \(k\) – how many times was diagnosed; \(n\) – the number of applicants, \(f\) – frequency of a particular symptom falling into the disease interval.

Denote by \(X = X_1 \times X_2 \times X_3\) – many patient input characteristics \(x_1 \in X_1 = \{t_1, t_2, t_3, t_4, t_5, t_6, t_7\}\) – patient age, where \(t_1 = 0-1\) years, \(t_2 = 1-3\) years, \(t_3 = 3-14\) years, \(t_4 = 14-25\) years, \(t_5 = 25-40\) years, \(t_6 = 40-60\) years, \(t_7 = >60\) years; \(x_2 \in X_2 = \{s_1, s_2, s_3, s_4, s_5, s_6\}\) – primary symptoms, where \(s_1\) – temperature / fever, \(s_2\) – swelling in the eye area, \(s_3\) – visual acuity reduction, \(s_4\) – lacrimation, \(s_5\) – dry eye, \(s_6\) – cosmetic defect; \(x_3 \in X_3 = \{p_1, p_2, p_3, p_4\}\) – causes of disease, where \(p_1\) – infection, \(p_2\) – eye injury, \(p_3\) – congenital disease, \(p_4\) – disease of other organs; \(Y = \{y_1, y_2, y_3, y_4, y_5\}\) – many classes of diseases, where \(y_i = \{(x, \mu_{y_i}(x)) | x \in X\}\) – fuzzy disease set with membership vector function (6)

\[ \mu_{y_i}(x) = \begin{pmatrix} \mu_{i1}(x_1) \\ \mu_{i2}(x_2) \\ \mu_{i3}(x_3) \end{pmatrix}. \]  

(6)

A diagnosis can be represented as a selection mechanism on a set based on fuzzy logic (7, 8).

\[ \forall \, x \in X \rightarrow \{\mu_{y_i}(x)\}_{i=1}^S \rightarrow y = C_{\mu}(Y) \subseteq Y, |y| = 1 \]  

(7)

\[ C_{\mu}(Y) = \{y \in Y | \max_i (\mu_i(x)) = \min_j (\mu_{ij}(x_j))\} \]  

(8)

The degree of membership of a certain value is calculated as the ratio of the number of experiments in which it occurred in a certain interval of the scale to the maximum number of experiments for this value in all intervals:

\[ c_{ij_{\max}} = \max(c_{ij}) \]  

(9)

where \(c_{ij}\) – elements of the disease data table according to the age scale, then the membership function is calculated according to the following formula:
\[
\mu_i(x) = \frac{c_j}{c_{j\max}} \tag{10}
\]

1) The operation of logical conjunction is used to determine the degree to which the symptom or disease of the patient belongs to the area of the disease (for example, whether it is age-related disease or infectious).

2) The operation of logical disjunction is used to determine the maximum value for assessing the degree of belonging of a symptom to the area of the disease.

Consider the example of two patients.

A patient: age of 14 years; primary symptom: decreased vision; possible cause: eye injury.

To determine the degree of belonging of the symptoms characterizing the patient’s condition to the \(i\)-th area of the disease, we perform the logical conjunction operation according to the obtained values for each area of the disease in accordance with the following relation (11):

\[
\mu_{ij}(x_j) = \min \left( \mu_{ij}(x_j) \right) \tag{11}
\]

\[
\begin{align*}
\mu_{1\min} &= \min \{0,2; 0; 0\}=0,2 \\
\mu_{2\min} &= \min \{0,11; 0; 0\}=0,11 \\
\mu_{3\min} &= \min \{0; 0,93; 0,71\}=0,71 \\
\mu_{4\min} &= \min \{1; 0,2; 0\}=0,2 \\
\mu_{5\min} &= \min \{0,11; 0,33; 0\}=0,33
\end{align*}
\]

The second operation, namely, the logical disjunction operation, is used to determine the maximum value for assessing the degree of belonging of the patient’s condition to the corresponding area of the disease, which is carried out by a comparative analysis of the resulting sets of estimates. Then, for all values of the selected input variables of the mathematical model of the fuzzy inference, we obtain (12):

\[
\max(\mu_i(x)) = 0,71 \tag{12}
\]

max(\(\mu_i(x)\)) = \(\mu_{3\min}\), therefore, the patient has an area of disease 3 (Diseases of the eyelids).

Drawing up a model of the knowledge base in the form of fuzzy rules.

A fuzzy knowledge base is used for the interaction between input and output parameters and the implementation of decision support [4]. A fuzzy knowledge base is a finite set of fuzzy rules (NPs). In relation to the illustrated areas of diseases and based on all values of the selected input variables of the mathematical model of fuzzy inference.

NP: if \(\mu_{\max} = \mu_{1\min}\), to area of disease 1; 
NP: if \(\mu_{\max} = \mu_{3\min}\), to area of disease 3; 
NP: if \(\mu_{\max} = \mu_{5\min}\), to area of disease 5; 

In our example

\[
\max(\mu_i(x)) = \mu_{3\min} \tag{13}
\]

therefore, the patient has an area of disease 3 (Eyelid disease) - min is not negative.

Patient: age 5 years; primary symptom: fever, dry eye; possible cause: diseases of other organs.

Since we have two symptoms of the same scale, it is necessary to perform a logical conjunction operation to obtain a membership function \(\mu_{ia}\).
Then \( \mu_{\text{min}} = \min\{0,2; 0; 0\}=0,2; \mu_{2\min} = \min\{2; 0,68; 0,35\}=0,35; \mu_{3\min} = \min\{0; 0,39; 0\}=0,39; \mu_{4\min} = \min\{0,2; 0,2; 0,5\}=0,2; \mu_{5\min} = \min\{0,68; 0; 1\}=0,68; \max(\mu_i(x))=0,68; \max(\mu_i(x)) = \mu_{5\min} \), therefore, the patient has an area of disease 5 (Ophthalmic diseases) [4].

Thus, a mathematical apparatus based on fuzzy logic and a direct chain of reasoning has been developed. Using fuzzy logic, a decision support model for the diagnosis of the disease belongs to the class of eye diseases. Computer simulation of algorithms was carried out [5]. Thus, the model narrows the scope of the disease and eliminates the number of symptoms. In addition, it with a sufficient degree of probability for the primary symptoms allows you to indicate whether the patient's condition belongs to a particular class of the disease [5].

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