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Application of Fuzzy Logic for Decision-Making in Medical Expert Systems

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For certain problems of predictive medicine, early and differential diagnosis in construction of relevant expert systems are best solved using methods of fuzzy decision-making adapted to classification problems. For selection of shape and parameters of membership functions of studied classes of states and methods of their aggregation, the use of the methodology of exploratory analysis followed by unification of particular decision rules into fuzzy groups that provide the best quality of classification is proposed. Recommendations are given for the synthesis of partial fuzzy decision rules and their groups to build a knowledge base of medical expert systems.

Analysis of the literature and the results of own studies lead to the conclusion that a significant number of problems of predictive medicine, early and differential diagnosis, are characterized by high complexity of description formalization of classes of health conditions. In problems of prediction and early diagnosis, various classes greatly overlap in the space of informative features [3, 5, 7-9]. In addition, for a number of socially important problems building of predictive and diagnostic mathematical models is characterized by incomplete and vague representation of the original data. In such circumstances, some researchers recommend using fuzzy decision-making [3, 7, 8, 11, 12, 15].

One of the main problems of practical application of this mathematical apparatus is the difficulty of selecting the shape and parameters of elements of fuzzy decision rules and methods of their aggregation into systems of fuzzy decision rules. Most of these problems can be solved by the application of groups of fuzzy decision rules, with training performed using data of exploratory analysis.

The practice of solving problems of medical prediction and diagnostics showed that under conditions of poor formalization with insufficient statistics and choice of the type of decision rules, unified in groups, it is most appropriate to use Wald sequential analysis, dialog systems of pattern recognition, and fuzzy decision-making in its applications in solving classification problems [3, 4, 6]. In turn, development of the theory of fuzzy decision-making has led to the understanding that for different structures of medical data, different types of fuzzy decision rules (such as minimax operations [5, 8], membership functions with basic variables on the distance to the separating surfaces and reference structures [7], modifications of Shortliffe iterative rules [3], etc.) fit better (in terms of minimization of classification errors).

Studies at the Department of Biomedical Engineering of the South-West State University (BME SWSU) show that it is advisable to perform the choice of elements of fuzzy decision rules and their aggregation with consequent unification into fuzzy groups based on the methodology of exploratory analysis [3, 5].

Synthesis Method

To solve the problems of synthesis of fuzzy decision rules, the BME Department of SWSU developed a special software package for exploratory analysis with recommendations of the selection, types of membership functions, and methods of their aggregation depending on the data structure characteristic for certain types of health problems [3, 5]. It was found that for different groups of informative features involved in solution of the chosen problem, the most suitable (in terms of minimum classification error and professional understanding of experts) are different types of fuzzy decision rules. Furthermore, in the space of all informative features for its various

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hyper-regions, using different classification rules can also be advantageous.

This fact led to the conclusion about the need to develop mechanisms for the synthesis of different types of decision rules with their consequent unification into groups of hybrid solvers.

One of the methodological approaches for such synthesis is proposed in this work in the form of the following sequence.

1. If at the expert level and in the course of exploratory analysis the possibility of formation of feature space or subspace occurs, where each of the features x_i can be represented by a system k of gradations x_{ik}, and it is possible to perform statistical calculation of the frequency of occurrence of the k-th gradation of the i-th feature $P(x_{ik}/\omega_l)$, $P(x_{ik}/\omega_r)$ in alternative classes ω_l and ω_r, the feasibility of using the Wald sequential procedure is studied with the calculation of diagnostic coefficient (DC) by the following formula [1, 4]:

$$\mathrm{DC} = \sum_{i=1}^{n} 10\log\frac{P(x_{ik}/\omega_l)}{P(x_{ik}/\omega_r)}, \tag{1}$$

where ω_l and ω_r — pair of alternative diagnostic classes (diagnoses); x_{ik} — value of the k-th gradation of informative feature x_i ($i = 1, ..., n$); n — feature space dimensionality; $P(x_{ik}/\omega_l)$ — frequency of the k-th gradation of the i-th characteristic in class ω_l, $P(x_{ik}/\omega_r)$ — in class ω_r, respectively.

In the transition to a fuzzy Wald classifier, confidence in classification ω_l — UGV_l is determined by the membership function in ω_l (base variable determined by the DC scale [4]), i.e.

$$UGV_l = \mu_{\omega_l}(\mathrm{DC}). \tag{2}$$

The advantages of this procedure are simplicity of calculations, absence of certain requirements for quantity distribution, and possibility of diagnosis with a predetermined level of reliability even in the absence of some of the measurements. Limitations of this method are: availability of requirements for the volume of the training sample and its representativeness, presence of areas of uncertainty that can be quite broad for values α and β close to one (high quality classification), and independence of features involved in diagnostics. However, even for very high dependence of the features, the number of errors in a serial diagnostic procedure is usually not higher than calculated.

2. If in the course of exploratory analysis, which actively uses different methods of projecting multidimensional data into two-dimensional space, the quality of classification in this space is satisfactory, it is advisable to use the dialog method of constructing two-dimensional classification spaces [6].

In accordance with this method, a two-dimensional projecting space $\Phi = Y_1 \cdot Y_2$ is defined as the Cartesian product of two projecting functions of the form:

$$Y_1 = \varphi_1(A, X);\ Y_2 = \varphi_2(B, X), \tag{3}$$

where φ_1 and φ_2 — functions of projection of multidimensional objects into two-dimensional space Φ; A and B — vectors of adjustable parameters; $X = \{x_1, ..., x_n\}$ — vectors of objects of the multidimensional space of informative features.

On the objects of the training sample in space Φ semi-automatically with experts' involvement, the boundaries separating the alternative classes ω_l and ω_r are formed based on the condition of a minimum number of classification errors in the form of the equation $G_{lr} = F_{lr}(Y_1, Y_2)$.

In transition to two-dimensional fuzzy classification in a two-dimensional space, a clear conclusion of the method of dialog constructing of two-dimensional classification space is transformed into a fuzzy solution by determining the fuzzy membership functions $\mu_{\omega_l}(D_l)$ in ω_l class with a basic variable defined as the distance D_l from the projection of the object into Φ to the two-dimensional borders of the class ω_l described by the equation $G_l = F_l\,(Y_1, Y_2)$.

Confidence in ω_l, obtained by dialog constructing of two-dimensional classification dialog, is defined by the relation:

$$UGD_l = \mu_{\omega_l}(D_l). \tag{4}$$

When using modifications of the classic fuzzy decision-making of Zadeh focused on solving the classification problems, as basic elements they usually use membership functions $\mu_{\omega_l}(D_i)$ and/or $\mu_{\omega_l}(D_j)$ in the studied condition classes ω_l with the basic variables, measured on scales of informative features x_i and/or integrated indicators Y_j calculated by informative indicators $Y_j = f_j(x_1, x_2, ...)$, where f_j — the functional dependence "connecting" all or part of the informative features with Y_j [5, 8, 11, 15].

The most popular aggregation formulas when using membership functions are expressions of the form:

$$UGN_l = \min_i[\mu_{\omega_l}(x_i)];\ UGN_l = \min_j[\mu_{\omega_l}(Y_j)];$$
$$UGN_l = \min_{i,j}[\mu_{\omega_l}(x_i),\ \mu_{\omega_l}(Y_j)]; \tag{5}$$

$$UGN_l = \max_i[\mu_{\omega_l}(x_i)];\ UGN_l = \max_j[\mu_{\omega_l}(Y_j)];$$
$$UGN_l = \max_{i,j}[\mu_{\omega_l}(x_i),\ \mu_{\omega_l}(Y_j)]; \quad (6)$$

$$UGN_l = \max_q \min_i[\mu_{\omega_{lq}}(x_i)];\ UGN_l = \max_q \min_j[\mu_{\omega_{l,q}}(Y_j)];$$
$$UGN_l = \max_q \min_{i,j}[\mu_{\omega_{lq}}(x_i),\ \mu_{\omega_l}(Y_j)], \quad (7)$$

where q – the number of reference hyper-volumes "covering" class ω_l.

Expressions such as (5) should be applied if the subspace or feature space contains such features that none of them requires abandoning ω_l.

The rules from the geometrical point of view can be treated as a classification for ingress of the object into fuzzy hyper-parallelepiped limited by non-zero values of all the membership functions used.

Equation (6) should be used if the presence of any feature is enough to evaluate hypothesis ω_l.

If the feature space contains characteristic groups satisfying the expressions (5) and (6), use of rules of the form (7) is recommended.

Geometrically, this rule usually corresponds to the approximation of geometric images, corresponding to condition classes, by sets of hyper-parallelepipeds with numbers q in the class ω_l.

3. If in the course of exploratory analysis it is shown that between the studied condition classes building a separating hyper-plane of the type $Z_l = F_l(A_{l_i}, x_i)$ is possible, it is advisable to use rules of the form:

$$UGG_l = \mu_{\omega_l}[D_l(Z_l)], \quad (8)$$

where F_l – the function defining the type of the separating surface Z_l (linear, piecewise-linear, quadratic, etc.); $D_l(Z_l)$ – the function of the distance from the studied objects to the dividing surface Z_l [7].

4. If a group or all informative features x_i or complex indicators Y_j are such that each of them increases the confidence in the hypothesis (diagnosis ω_l), the private and/or overall confidence UGS_l in ω_l is determined by the formulas [4, 8, 12]:

$$UGS_l(p + 1) = UGS_l(p) + \mu_{\omega_l}(x_i)[1 - UGS_l(p)];$$

$$UGS_l(p + 1) = UGS_l(p) + \mu_{\omega_l}(Y_j)[1 - UGS_l(p)];$$

$$UGS_l(p + 1) = UGS_l(p) + US_l(p + 1)[1 - UGS_l(p)], \quad (9)$$

where p – number of iteration in calculation of UGS_l; $US_l(p + 1)$ – particular confidence in ω_l by subspace with the number $p + 1$ of a multi-dimensional feature space.

5. If as the informative features electrical characteristics of biologically active points (BAP), for example, their electrical resistance, are used, given the biophysics of these points and the specificity of their output data presented in works of Korenevskiy et al. [13, 14], it is recommended to use a hybrid decision rule consisting of crisp condition and fuzzy decision-making rule of the type:

$$\text{IF } (Y_{jl}\ \forall\ [\text{DSP}]_l\ \delta R_j \geqslant \delta R_j^{\text{thresh}}),\ \text{then}$$

$$\{UGB_l(j + 1) = UGB_l(j) + \mu\omega_l(\delta R_{j+1})[1 - UGB_l(j)]\},$$

$$\text{OTHERWISE } (UGB_l = 0), \quad (10)$$

where Y_{jl} – list of informative points on the disease ω_l; $\forall$ – universal quantifier; $[\text{DSP}]_l$ – list of diagnostically significant points, analysis of which enables marking a pathology out of variety of "output" BAP information; δR_j – relative deviation of resistance of BAP with number j from its nominal value; $\delta R_j^{\text{thresh}}$ – threshold δR_j value determined during synthesis of decision rules; $\mu_{\omega_l}(\delta R_{j+1})$ – a function belonging to class ω_l with the basic variable δR_{j+1}; UGB_l – confidence in diagnosis ω_l; $UGB_l(1) = \mu_{\omega_l}(\delta R_1)$.

In relation to the feature space, the group of fuzzy rules is distributed depending on the particular application [4].

In one case, it is possible that each of the rules handles its own group of features: for example, results of surveys and inspections are aggregated by rule (9); data of traditional laboratory tests by rule (2); data obtained in image processing by rule (8); results of analysis of energy characteristics of biologically active points by rule (10), etc.

In another case, all informative attributes are processed by each rule of the group. Additionally an interim case is possible, when various decision rules use mixed, and possibly intersecting, groups of informative features. Such groups can be created on a different principle: cost of obtaining information; time of measurement; information value; specificity of data structure, etc.

Options for the final aggregation of decision rules can also be different.

With careful strategy when a decision must be made with mandatory "opinions" of all members of the group taken into account, considering possible "doubts" in the direction of alternative (to the class ω_r), it is advisable to use an aggregator of type:

$$UG_l = \min(UGV_l,\ UGD_l,\ UGN_l,\ UGG_l,\ UGS_l,\ UGB_l). \quad (11)$$

If the task "not to miss" objects of class ω_l or if the degrees of confidence in each of decision rules are approximately the same, it is advisable to check the applicability (performance quality) of a decision rule of the form:

$$UG_l = \max(UGV_l, UGD_l, UGN_l, UGG_l, UGS_l, UGB_l). \quad (12)$$

If using each of the regulations adds confidence in the decisions regarding the hypothesis ω_l, it is advisable to use iterative accumulative procedures, such as those of Shortliffe:

$$UG_l(s + 1) = UG_l(s) + UGF_l(s + 1)\cdot[1 - UG_l(s)], \quad (13)$$

where s – number of iterations in the calculation of confidence UG_l in classification ω_l;

$$UGF_l = (UGV_l, UGD_l, UGN_l, UGG_l, UGS_l, UGB_l);$$

$$UG(1) = UGF(1).$$

In practice, there are problems with complex data structure when the in final decision rule it is advisable to combine the options of rule aggregation (11)-(13).

Results and Discussion

Using the above strategy for the synthesis of fuzzy decision rules to solve various medical problems: prediction after operative complications in urology [9], prediction and early diagnosis of heart diseases [14]; assessment of the level of emotional stress and fatigue [2]; prediction, early and differential diagnosis of diseases caused by the influence of harmful environmental factors specific to the Kursk Region, etc. For all solved socially important problems confidence in the correct prediction is greater of 0.85, and for diagnostic problems – of 0.9, enabling recommendation of application of the obtained decision rules in medical practice.

As a detailed example the structure of the collective fuzzy rules, obtained by solving the problems of prediction of disease in people who work in environmentally hazardous areas of the Kursk Region – in the area of Mikhailovsky Ore-Dressing and Processing Plant (MGOK) – can be used. In this area, according to the sanitary-epidemiological services, compared with other areas of Kursk Region, increased morbidity of digestive and respiratory systems is present. During the synthesis, two groups of fuzzy decision rules were obtained. One group, using information on the environmental risk factors (intensity of the constant magnetic field due to the action of the Kursk magnetic anomaly, emissions of MGOK: dust, CO_2, SO_2, NO_2; time of contact with harmful environmental factors, level of the protective properties of the organism determined by the method developed at BME SWSU [10]), defines confidence in risk of digestive and respiratory diseases in the area of MGOK.

The second group of decision rules solves the problem of prediction of digestive and respiratory diseases taking into account lifestyle and individual characteristics of the body (data of surveys, examinations, laboratory tests, and the electrical resistance of BAP "related" to digestive and respiratory diseases).

The decision rules include mathematical models (4), (9), and (10) with the unifying model (13). When tested on control samples of 100 objects in each class (sick in the next three years with digestive (class ω_d) and/or respiratory (class ω_r) disease or not sick (class ω_0)), it was found that confidence in the correct prediction using groups of fuzzy decision rules reaches 0.92. When using mathematical models chosen individually, predictive confidence does not exceed 0.86.

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