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Hybrid technology for collective expertise

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Abstract

This paper outlines a new automatizated technology for collective expertise. The technology provides flexible framework of collective expertise, allows to bring it into accord with the Decision Making Person's conception of the problem, ensures alternative abilities for examination and interpretation of obtained expert information. Information about basic components of the instrumental system for collective expertise **KIOT–1** is presented.

1 Introduction

Expert technologies are succesfully used for solving of many problems in planning and management. They use expert knowledge for decision making in complex problem domains, where another methods are difficult or unusable. We will differentiate two approaches: collective expertise and expert systems.

Collective expertise achieves the result after processing of a number of estimates given by collective of experts. In this case, the main problem is to find consensus (final collective estimate) for different expert estimates, which are often contrary and, in common case, not additive.

Expert system uses symbol structures for representing of expert's knowledge and achieves the result after inference in knowledge base. As a rule, expert systems use knowledge of only expert. The central problem of expert system development and maintance, and in knowledge engineering as a whole, is to transform expert knowledge into the relevant knowledge base.

Remark, that collective expertise and expert systems have today different fields of application. Expert systems have been applied to wide classes of typical problems or typical objects. On the contrary, collective expertise is appropriated for examining of unique phenomenons or problem situations.

Nevertheless, sometimes collective expertise and expert systems could supplement each other. For example, if medical expert system cannot make satisfactory decision, then conference of specialist doctors is organised (some version of collective expertise).

Our purpose was to elaborate a flexible automatizated techology for collective expertise, which is capable to bring obtained information into accord with the Decision Making Person's conception of the problem.

The technology facility should provide:

- forming the right expert group for the task and evaluating the expert's rating;
- aiming the expert group at current problem;
- collecting and examining the expert estimates (including fuzzy values);
- analysing the results of the expertise, revealing contradictions in expert estimates, conflict groups of experts, etc.;
- aggregating the expert estimates and evaluating final result of the expertise;
- providing alternative results of the expertise;
- representing results of the expertise in different ways, including computer graphics;
- arhiving all information and providing exchange with other data bases.

Some of these abilities had approbated in SIREX system [1].

2 Components of collective expertise

2.1 Forming of expert group

When presented with a new task, we must select the most suitable group of experts. There have been numerous expert group forming methods: "ball" method, advancement, documentation, testing, etc. Except the two latters, the methods do not require the computer processing.

Let us choice the documentation as a basic method. All information about experts is placed in data base, for example:

1. Name	N	Ion Verlan
2. Spiciality	S	Informatics
3. Length of service	LS	12 years
4. Specialization	SS	Expert Systems
5. Additional knowledge (5–number index)	AK	Pattern Recognition (4) Knowledge Representation (5) Technical diagnostics (4) Robotics (4)
6. Degree	D	PhD
7. Current rating	CR	87.6

Pic. 1

Remark, that information in column 5 is not strict stated, and all indexes are set by experts.

Then the list of criterions must be fixed, for example:

CR	$\geq$	60
S	=	Informatics
LS	$\geq$	10
SS	=	Indifferent
D	=	Indifferent
AK	=	Indifferent

It is regarded as the inquiry for the data base. Finally, the expert group will be formed on the basis of maximal meeting the all criterions in the aggregate.

2.2 Examination the expert group

Important feature of any expert group is its “uniformity”, e.g. potential tendency of experts from the group to give similar estimates for examined phenomenon.

Let us given group of experts $f_1, \ldots, f_n$ and each of them generates the cortege of values $A_k = \langle a_1, a_2, \ldots, a_m \rangle$, where a is integer. Consider the given corteges $A_k \quad (k = 1, 2, \ldots, n)$ as lines of some matrix T_{kj} and assume, that so–called “function of similarity” $R(\alpha, \beta) \quad (\alpha \neq \beta;\ \alpha, \beta = 1, 2, \ldots, n)$ evaluates the “distance” between two lines of the matrix.

Then we apply the identity

$$\hat{t}_{\alpha\beta} = \begin{cases} 1, & R_{\alpha\beta} \geq R_0 \\ 0, & R_{\alpha\beta} < R_0, \end{cases}$$

where treshold R_0 is fixed apriori.

In result, the initial matrix T_{kj} will be transformed into the binary matrix, denote it $\hat{T}_{\alpha\beta}$.

Matrix $\hat{T}_{\alpha\beta}$ may be shown in the form of symmetrical graph $G(f, T)$, which nodes correspond the experts. Now examining the graph, we can make conclusions about uniformity of the initial expert group. Really, we can contend, that

1) Experts with similar estimates have concentrated in the same connection components of the graph;

2) Inside the connection components experts with similar estimates form full subgraphs;

3) Uniformity of the expert group is determined by powers of different connection components.

We have calculated uniformity of the expert group by the next way:

$$h = \frac{1}{r} \sum_{1}^{r} \gamma_l R_l$$

where γ_l — adjusting weights, r — the number of connection components.

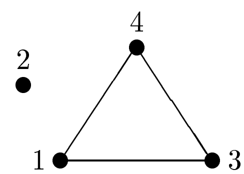
Consider an illustative example.

Let us say that the matrix below (T_{kj}) depicts the values given by four experts after estimation of five parameters of an object (in 5–number scale):

Experts	Estimates				
	a_1	a_2	a_3	a_4	a_5
f_1	2	3	4	4	5
f_2	2	5	2	3	2
f_3	2	4	4	4	4
f_4	3	3	4	3	3

Choicing the Mahalonobis distance ($\rho = 1$) in the capacity of the function of similarity, pass to matrix $\hat{T}_{\alpha\beta}$ with $R_0 = 7$. We have:

	1	2	3	4
1	–	–	2	6
2	–	–	–	–
3	2	–	–	4
4	6	–	4	–



Pic. 2

Graph shown in the Pic. 2 corresponds the matrix $\hat{T}_{\alpha\beta}$. It consist of two connection components: {1,2,3} and {2}. It means that initial expert group consists of two uniform subgroups, including experts f_1, f_2, f_3 and expert f_2 accordingly. Both components are full subgraphs. Experts like f_2, which opinion differents from opinions of all other experts, is called the "heretics".

2.3 The rating of expert

The rating of an expert is the "weight", which indicates the expert's competence. We assume, that rating is dinamic parameter, it varies from expertise to expertise. There is a good analogy for the expert's rating — the rating of chess–player, which indicates professional competence of the player and varies from tournamet to tournament.

Below we consider two algorithms for expert's rating calculation.

Algorithm 1. Let us use the approach from the section 2.2 for examining of the expert group uniformity.

Let beside corteges $A_k \quad (k = 1, 2, \ldots, n)$, we also have the cortege A_0, which randomizes obtained expert estimates. Assume, that criterion of professional skills of the expert A_k is evaluated from the unconformity of corteges A_k and A_0 and consider m–dimensional distance between A_k and A_0:

$$D(A_k, A_0) = \min \sum_{j=1}^{m} (a_{kj} - a_{0j})^2$$

Thus, the calculation of expert's rating is reduced to the following task: it is necessary to form the graph with $(n+1)$ nodes, just like in section 2.2, and then to analyse the nodes for which the Γ_{f_0} is not empty. Weights of arcs joining f_0 with nodes from $\{\Gamma_{f_0}\}$ will be proportionated to unconformity coefficients $\varepsilon_{f_0 f}$.

Finally, the values of ε would be determined by the next way. Calculate summary maximal possible deviation $\varepsilon_{\max}$:

$$\varepsilon_{\max} = \sum_{j=1}^{m} a_{j\max}^2,$$

where $a_{j\max}$ — maximal estimates given by experts.

Then we have:

$$\varepsilon_f = \frac{\varepsilon_{f_0 f}}{\varepsilon_{\max}}$$

Returning to example from section 2.2, we have: $\varepsilon_{f_1} = 0.193$; $\varepsilon_{f_2} = 0.032$; $\varepsilon_{f_3} = 0.064$. In result, we have fixed the expert's rating list:

$$f_1, f_3, f_2,$$

where the expert f_1 has the greatest rating.

Algoritm 2. Let given the set of "experts about experts" estimates in the form of matrix

$$V = \|g_{ij}\|_{i,j=1}^{n} \qquad (g_{ij} = g_j(g_i)),$$

where g_{ij} — the number value of competence of the expert i given by expert j. In some cases, g_{ij} — is the number of experts considering that competence of the expert j is higher then competence of the expert i.

Put into correspondence to the matrix V the following n–dimensional cortege

$$b^{(1)} = \langle\, \sigma_1^{(1)}, \sigma_2^{(1)}, \ldots, \sigma_t^{(1)}, \ldots, \sigma_n^{(1)} \,\rangle$$

where $\sigma_t^{(1)} = \sum_{j=1}^{n} g_{t_j}$; $\quad t = 1, 2, \ldots, n.$

Set for each possible pairs of elements from V the weight coefficients by the next way: 2 if $g_{ij} > g_{ji}$, 1 if $g_{ij} = g_{ji}$, 0 if $g_{ij} < g_{ji}$.

Elements of cortege $b^{(1)}$ indicate the approximate values of experts competences. Introduce the function of step–by–step stabilization:

$$b^{(k+1)} = g(b^{(k)}; \quad \sigma_i^{(k+1)} = \sigma_i^{(k)} + \begin{cases} 2\sigma_j^{(k)}, & b_{ij} > b_{ji} \\ \sigma_j^{(k)}, & b_{ij} = b_{ji}, \end{cases}$$

where $b^{(k)}$ — cortege obtained on the previous step of stabilization $(k = 1, 2, \ldots)$. As shown in [2], such procedure is converged, and the final result is reached when the order of elements will stabilized.

Example. Given matrix for five experts:

	1	2	3	4	5
1	1	2	0	0	0
2	0	1	2	2	2
3	2	0	1	1	2
4	2	0	1	1	0
5	2	0	0	2	1

Initial list of expert's competence coefficients are represented by the following cortege:

$$b^{(1)} = (3, 7, 6, 4, 5)$$

Using the procedure of step-by-step stabilization, we have:

$$\begin{aligned} b^{(2)} &= (17, 37, 26, 16, 19) \\ b^{(3)} &= (91, 159, 114, 76, 85) \\ b^{(4)} &= (409, 709, 542, 372, 419) \\ b^{(5)} &= (1827, 3375, 2198, 1732, 1981) \end{aligned}$$

As we can see, after the fifth step the disposition of expert competences had stabilizated and in result we have:

Expert 1	-	0,164
Expert 3	-	0,198
Expert 5	-	0,178
Expert 2	-	0,304
Expert 4	-	0,156

Remark, that expert 1 and expert 4 have exchanged after stabilization.

2.4 Examining the expert estimates

It is natural, if we demand the expert estimates to be non–inconsistent. Below we describe the correspondent control procedure.

Let the expert has compared in pairs n objects $x_i \quad (i = 1, 2, \ldots, n)$ and ranged them in accordance with fixed quality. Using estimates, given by the expert, we can form the binary matrix $G = \|g_{ij}\|; \quad i, j = 1, 2, \ldots, n$, where

$$g_{ij} = \begin{cases} 1, & \text{if } x_i \prec x_j \\ 0, & \text{if } x_i \succ x_j \end{cases}$$

The $\prec$ symbol means that the strong preference property is kept. This property was fixed by the expert. Hence we have the full graph with orientated arcs. Such graph have not loops. Otherwise, the expert's judgements would be non–transitive. For example, the following list of preferences results the loop: $x_1 \succ x_2 \succ x_3 \succ x_4$. Evaluate the number of simple loops using the next formula[3]:

$$d = \frac{1}{2} \cdot \left[n(n-1)(n-2) \cdot \frac{1}{12} - \sum_{i=1}^{n} \left(\sum_{j=1}^{n} g_{ij} \right)^2 \right].$$

Thus, if the expert's judgements are consistent, then the number of elementary loops equal zero. The case with the maximum number of loops takes place when given estimates are absolute incompatibleness, e.g. when

$$d_{\max} = \begin{cases} \frac{1}{24}(n^3 - 4n), & \text{for even } n \ (n \geq 2) \\ \\ \frac{1}{24}(n^3 - n), & \text{for odd } n \ (n \geq 3) \end{cases}$$

The conformity coefficient ψ definition can be described as

$$\psi = \begin{cases} 1 - \frac{24d}{(n^3-4n)}, & \text{for even } n \ (n \geq 2) \\ \\ 1 - \frac{24d}{(n^3-n)}, & \text{for odd } n \ (n \geq 3) \end{cases}$$

If $\psi = 0$, then estimates of that expert must be ignored.

2.5 Recognizing the conflict expert groups

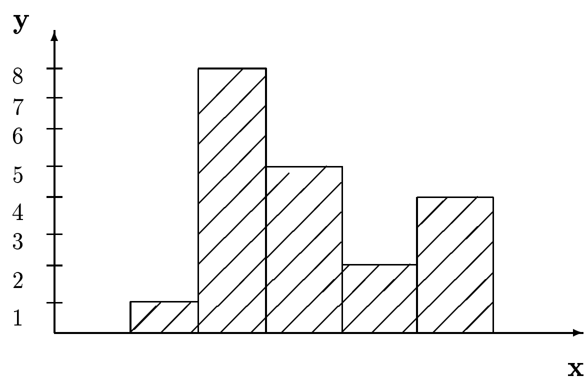
As a rule, the staff of experts is not uniform and includes conflict (in some fixed sense) groups–cliques. For example, when a bargain is contracted, there are three sides–cliques: customers, masters and neutral experts. In our case, to evaluate various expert opinions more exactly, we must take into account the expert cliques existence.

We will differentiate two kinds of expert cliques: "local" and "global". "Local clique" corresponds the single parameter, but "global clique" are determined for the aggregate of parameters.

Picture 3 demonstates an example of the distrubution of expert estimates (a 1–5 scale has been used) for one of parameters of some object. X–Axis corresponds the scale of estimates, Y–axis — the number of experts.

In our example the distribution of estimates is bimodal, that's why we can distinguish two local cliques of experts: first of them is determined by columns $\{1, 2, 3\}$, second — by $\{3, 4, 5\}$.

"Heretic" estimates is defined as estimates given by not numerous groups of experts. To find "heretic" estimates the "threshold of



Pic. 3

heretics" must be fixed. "Threshold of heretics" is defined as the number of experts in group, less than that, its members become "heretics". In example 3, setting the "threshold of heretics" equal 2, we have one "heretic" group of two experts (they set estimate 3) and one single "heretic" (he set 1).

If there are n questions and the number scale is used, then expert's answers fix the n–dimensional vector. In this case, the problem of recognizing the conflict groups is transfered into n–dimensional vector space.

2.6 Aggregating the expert estimates

The purpose of aggregating is to obtain the extended estimates (or even only estimate) of object on the base of initial expert estimates.

Aggregation is correct only if

a) the group of parameters is enough uniform and

b) scales are compatible [4].

The simplest aggregating algorithm is to evaluate the average weighted estimates for group of parameters, where the significance coefficients of parameters are used as weights. The aggregated estimate for group k can be evaluted by formula:

$$R_k = \frac{\sum_{j=1}^{N} R_k^*(P_{kj}) R_k(P_{kj})}{\sum_{j=1}^{N} R_k^*(P_{kj})},$$

where $k \quad (k = 1, 2, \ldots, K)$ — number of the group, P — parameter, j — number of the parameter inside the group $(j = 1, 2, \ldots, N)$, $R(P)$ — significance estimate of parameter P, $R^*(P)$ — average weighted estimate of parameter P. Of course, the aggregating must take into consideration both cliques and single heretics.

Additional difficulties arrise in multicriterial estimation. For example, if we have expert ranges for the set of objects and try to find the aggregated range, then the choice of aggregating method is non–trivial task. Also in the case of qualitative scales estimates (including non–uniform scales).

Let $S_1, S_2, \ldots, S_n$ be the particular criterions and $a_1, a_2, \ldots, a_n$ — their estimates. As a rule, the approach will be used to evaluate the aggregated value by performing the following steps:

- seek appropriate aggregating method (formula) Φ,
- evaluate the aggregated estimate $a = \Phi(a_1, a_2, \ldots, a_n)$.

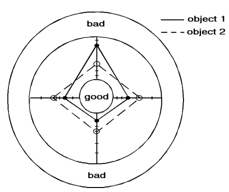
Obtained estimate a is declared as the aggregated estimate for combination of criterions $S = \{S_1, S_2, \ldots, S_n\}$. In that case, it isn't pointed out what the extended criterion S is.

Another approach is to formulate the aggregated criterion S in clear form, and only then evaluate the aggregated estimate a. Initial task would be formulated in terms of attribute problem domain. In that case, it is necessary to define logical relations between particular estimates and aggregated values. Then the aggregated estimate would be obtained as a result of inference in knowledge base. Detailed description of that task and its solution can be found in V.Levchenko and A.Savinov [5].

2.7 Grapic interpretation of results

Our technology stipulates different ways of presenting the intermediate and final results of the expertise. Separate expert estimates, aggregated values for different sets of parameters or aggregated values for different expert groups, full matrixes of estimates, etc. can be displayed on the screen. It is possible to obtain any information about the expert: current rating, the belonging to the "heretic" group, etc. Application of graphics images — for example, circular diagrams [6] and "Chernoff faces" [7] — are of special interest.

In the case of circular diagram (Pic.4) the different radiuses represent different expert scales (in correspondance with the number of parameters). The expert estimate is represented by the point on the circle. Obtained polygon shows the graphic image of the object. Area of the polygon represents the aggregated estimate. Comparing the areas of polygons, we must prefer the object with smallest area. When weighted parameters are considered, the form of polygon can be used as additional information. Remark, that circular diagrams provide the using of fuzzy estimates.



Pic. 4

Another graphical approach – "Chernoff faces" – are the schematic representation (image) of men's face. Values of expert estimates influence the characteristics of the face.

Let given the set X_b of expert estimates $x_j \in X_b \quad (j = 1, 2, \ldots, k)$ aggregated for the group of parameters. Let also we have a set X_a of integral standart characteristics $x_i \in X_A \quad (i = 1, 2, \ldots, m)$ using for "Chernoff face" forming. Each of characteristics can be represented as finite ordered set of visual elements $x_i \in (a_{i1}, a_{i2}, \ldots, a_{iM_i})$ (for example, in accordance with ordered scales of expert estimates), just like in "photorobot". The task is to determine an algorithmic procedure for one–to–one correspondence between X_b and resulted "Chernoff face" basing on semantics of object parameters.

Let form bi–parted graph $G = X_a \cup X_b, \Gamma X_b)$, where X_a and X_b — subsets of its nodes as defined before, ΓX_b — the set of arcs with weights equal $P_{ij} \quad (i = 1, 2, \ldots, k,\ j = 1, 2, \ldots, m)$. Weight coefficients is determined from the values of expert estimates x_j. In the case when $|\Gamma^{-1} x_i| = 1$, the arc between x_i and x_j fixes the some of standart characteristics, and its weight P_{ij} fixes one of the elements $a_{iq} \quad (q = 1, 2, \ldots, M_i)$ of the standart characteristics. If $|\Gamma^{-1} x_i| > 1$, then it is necessary to evaluate the average weight of arc and to apply majority procedure. Standart characteristics corresponding the nodes for which $|\Gamma^{-1} x_i| > \rho$ (ρ have fixed apriori) will consider as basic characteristics. Then the special correction of graphic image will be done and logical contradiction between basic and other characteristics will be revealed. Varying the structure of graph G, values of ρ and standandart characteristics, we can tune the subsystem and form corresponding visual image.

3 Basic components of KIOT system

KIOT was built as opened system allowing to increase its potentialities by addition of new components. **KIOT–1** is the current version of **KIOT** system and consists of the following modules.

KIOT — main constructive module — interpreter of expertise scenario. As important part of **KIOT** the expert system component is used. It was built on the base of the expert system shell **FIACR** [8]. The role of the expert system is

- to see current situation in proper perspective;
- to determine the next step with the due regard for the global purpose of the expertise;
- to execute the next step of the expertise.

EXPTEXT — the dialogue module for initialization of the expertise.

OBLIST — editor of problem domain for current expertise.

EXLIST — editor of data base containing all information about experts.

INESLIST — editor of expert information.

CLUSTER — subroutine library including clasterization algorithmes for expert groups–cliques recognizing.

GENSVOD — subroutine library including algorithmes for aggregation of expert estimates.

ANALYSE — recognizes conflicts in expert information.

INTER — subroutine library of programs for graphic interpretation of results.

STAGES — obtaining the final results of the expertise.

REBASE — administrator for connection with other data bases.

KIOUTPUT — allows to obtain hard copies of documents.

Conclusion

The paper has proposed an overview of perspective approach for collective expertise and its using in complex problem domains. A teoretical framework has been developed and shown to provide flexible collective expertise schema. The framework is generated by expert system from the single constructive steps of an expertise. Basic components of program system realizing the proposed technology is described.

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