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Fuzzy Semantic Networks as a Knowledge Representation Model of Autonomous Intelligent Systems

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Abstract—This paper considers the main characteristics of goal-oriented behavior displayed by autonomous intelligent systems in conditions of a problem environment different in the degree of a priori uncertainty. A model is developed for declarative knowledge representation in autonomous intelligent systems regardless of the specific subject area based on active and passive fuzzy semantic networks. The operations of comparing fuzzy semantic networks with each other are considered, which enable the organization of effective decision making in the process of planning goal-oriented behavior under conditions of uncertainty. The operations of decomposition, composition, and generalization of fuzzy semantic networks were developed, which serve to organize the behavioral planning for autonomous intelligent systems in the process of solving complex problems, accompanied by a formal description of current situations of a problem environment with a large dimension.

Keywords: autonomous intelligent system, uncertainty conditions, problem environment, knowledge representation, fuzzy semantic network, planning of behavior

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INTRODUCTION

A characteristic feature of autonomous intelligent systems (AISs) for different applications is the ability to plan goal-oriented behavior in a priori underdetermined conditions of a problem environment (PE). The reason for this is that it is practically impossible to construct a detailed PE model that allows using the principles of knowledge processing that are widespread in modern artificial intelligence systems [1–3] [4]. This suggests an objective need for knowledge representation in a general form, regardless of a specific subject area, possessing the property of adaptability and endowing AIS with the ability to plan goal-oriented behavior under uncertainty. It should be noted that the mathematical apparatus of fuzzy sets is widely used for the generalized presentation of data in control systems for complex objects. This made it possible to solve the following main problems:

– using linguistic variables (LV) [5], to obtain qualitative and quantitative estimates of individual indicators that characterize the current state of a complex object, and based on this as well as on expert data, to form fuzzy control algorithms for the process of its functioning [6];

– to construct mathematical models in the form of a vaguely defined dependence both between individual indicators that determine the current state of a complex control object [7, 8] and a system of equations that characterize the relationship between various indicators of its efficiency and control parameters [9].

However, the specificity of AIS behavior is such that in the process of goal-oriented activity, attaining a given goal usually requires transformation of the current PE situation associated with the need to change both the states of the objects located in it and the relationships that have developed in the environment between these objects. Thus, the above-mentioned results obtained based on the use of fuzzy sets for generalizing data do not provide an AIS with the ability to organize goal-oriented behavior in an a priori undocumented PE. This necessitates developing such a generalized model based on the apparatus of fuzzy sets for representing declarative and procedural AIS knowledge, regardless of a specific subject area that would allow describing complex PE situations and, on this basis, solving various problems that require planning and implementation of goal-oriented behavior.

One such model for representing AIS declarative knowledge is a fuzzy semantic network (FSN). An FSN as a model of knowledge representation of an autonomous intelligent robot was considered for the first time in [10, 11]. FSN application as a model for representing AIS knowledge was further developed in [12, 13]. However, in order to provide higher functionality and endow the AIS with the ability to solve practical problems in unstable a priori undocumented PEs, the following items are required:

— obtaining a more information-intensive description of an FSN than in [10–13] considering the events that occur in the environment that lead to a change in the state of objects in it and the relationships between them;

— expanding the assortment and clarifying the content of operations performed on FSN in the decision-making process with allowance for the changes in the PE.

This paper addresses these topical issues.

1. THE STRUCTURE AND CONTENT OF LABELING FOR VERTICES AND ARCS OF FUZZY SEMANTIC NETWORKS

In the general case, the description of situations for unstable PE, when building a declarative model of AIS knowledge representation, should include the following:

— environment objects $O = \{o_{j_1}(X_{j_1})\}, j_1 = 1, 2, \dots, m_1$, where X_{j_1} is a set of characteristics that define the state, attributes, skills, and properties of the objects $o_{j_1}(X_{j_1}) \in O$ [14];

— events that occur in the PE $D = \{d_{j_2}(X_{j_2})\}, j_2 = 1, 2, \dots, m_2$, where X_{j_2} is a set of characteristics describing the events $d_{j_2}(X_{j_2}) \in D$;

— spatial, temporal, causal, and other types of relationships $R = \{r_{j_3}\}, j_3 = 1, 2, .., m_3$ that develop in the environment between objects and events that occur in it.

The AIS is an active subject endowed with a technical vision system, which is able to move in the PE and work out a set of actions $B = \{b_{j_4}\}, j_4 = 1, 2, .., m_4$ on various objects $o_{j_1}(X_{j_1}) \in O$ in order to perform goal-oriented transformations of its situations.

We consider the case where the formal description of PE situations is performed in the form of an FSN. Structurally, an FSN is an oriented multigraph $G = (V, E)$ where $V = \{v_{i_1}\}, i_1 = 1, 2, \dots, n_2$ and $E = \{e_i\}, i_2 = 1, 2, \dots, n_2$ are sets of vertices and arcs, respectively. In the general case, an FSN can be passive or active. All vertices of the passive FSN are defined by specific PEs $o_{j_1}(X_{j_1}) \in O$, and arcs are determined by the relationships between these objects as well as by events that occur in the environment and transfer its objects from one state to another. Therefore, one type of FSN arc $e_{i_2} \in E$ FSN, i.e., that defined by relationships $r_{j_3} \in R$, can be incident to two nodes of the network G labeled by different PE objects. Another type of arc $e_{i_2} \in E$ is labeled by events $d_{j_2}(X_{j_2}) \in D$ that occur in the PE and are incident to two vertices of the network G that are defined by the same object of problem environment $o_{j_1}(X_{j_1}) \in O$ but are in different states. Thus, events $d_{j_2}(X_{j_2}) \in D$ that occur in the PE should be understood as its actions of different natures, which independently transfer AIS objects $o_{j_1}(X_{j_1}) \in O$ located therein from one state to another.

Vertices $v_{i_1} \in V$ of an active FSN are labeled by characteristics $X^*_{j_1}$, which are arbitrary objects the problem environment should possess in the current state in accordance with the problem to be solved by the AIS, so that they can be labeled with these objects in a specific PE situation. In other words, the vertices of the active FSN $v_{i_1} \in V$ defined by the set of characteristics $X^*_{j_1}$ are labeled during decision-making process by specific objects of the problem environment $o_{j_1}(X_{j_1}) \in O$ if the condition $X^*_{j_1} \subseteq X_{j_1}$ is fulfilled for them.

The arcs $e_{i_2} \in E$ of an active FSN, in accordance with their assignment, are labeled as follows:

— either by the terms $T^k_{j_3}, k = 1, 2, \dots, m_5$ of LV and the intervals of numerical values corresponding to them, which in a fuzzy form of representation define the relation $r_{j_3} \in R$ in an active fuzzy semantic network. In other words, arcs of an active FSN of this type are labeled by intervals of numerical values that determine their relationship, into which their specific values should fall, observed in the current PE conditions between the specified objects $o_{j_1}(X_{j_1}) \in O$ in accordance with the problem being solved by the AIS at the current time;

— or by characteristics $X^*_{j_2}$ enabling the AIS to establish events in the PE, manifestation of which results in a certain change in the current state of the objects.

Each edge of the FSN G defined by the set of characteristics $X^*_{j_2}$ can be labeled by a specific event $d_{j_2}(X) \in D$ that occurs in the PE, subject to the condition $X^*_{j_2} \subseteq X_{j_2}$. Thus, the set $X^*_{j_2}$ is defined by the characteristics of the same name, which are similar to each other in terms of the result produced by the impact on objects $o_{j_1}(X_{j_1}) \in O$ of PE events $d_{j_2}(X_{j_2}) \in D$. For instance, let the events $d_{j_2}(X_{j_2}) \in D_1, j_2 = 1, 2, \dots, 5$ make a similar impact on various objects of the PE. Then, for these events the set of characteristics $X^*_{j_2}$ will be defined as follows: $X^*_{j_2} = \bigcap_{j_2=1}^{5} X_{j_2}$.

It should be noted that if similar events $d_{j_2}(X) \in D_1$ occur in the PE fairly often, then an extended description of its situations, considering the changes in the states of objects $o_{j_1}(X_{j_1}) \in O$ that occur in it, allows the AIS, by passive observation, to expect the necessary transformations of the current situations of the problem environment. In addition, in this case, the AIS self-learning tools with active-passive logic of behavior allow it, on the basis of the FSN, to automatically supplement its knowledge about the patterns of changes that occur in the PE [14].

Different edges $e_{i_2} \in E$ in a passive fuzzy semantic network are labeled either by the values of relationships $r_{j_3} \in R$ that are satisfied between the objects in the current PE conditions or by other events $d_{j_2}(X_{j_2}) \in D$ that occur in the environment. Thus, passive FSNs describe current PE situations.

Active FSNs are designed to build a formal model for a generalized description of various PE situations that are similar to each other and a procedural model of AIS knowledge representation regardless of a specific subject area, for example, in the form of a typical frame of behavior microprograms [15]. In this connection, it should be noted that after labeling the vertices and edges of an active FSN in accordance with the content of their labels by legal objects, relations, and PE events, it becomes passive and determines the current situation of the problem environment $s_{j_5} \in S, S = \{s_{j_5}\}, j_5 = 1,2,\ldots,m_5$ where S is a set of legal situations in the PE.

2. COMPARISON OPERATIONS FOR FUZZY SEMANTIC NETWORKS

One of the main operations performed on various FSNs during a decision-making process is comparing them with each other. We consider the case where the boundary estimates $[x^*_{j_3}(k), x^*_{j_3}(k+1)]$ and $[x^*_{j_6}(k), x^*_{j_6}(k+1)]$ of the terms $T^k_{j_3}$ and $T^k_{j_6}, k = 1,2,\ldots,n_3$ defined on the scales of numerical values of the basic variables of various LV [5] that provide a fuzzy representation of the values of the ratios $r_{j_3} \in R$ and characteristics $x^{j_2}_{j_6} \in X^*_{j_2}, j_6 = 1,2,..,m_6$ of similar PE events, respectively, are set clearly based on the functionality of the AIS (e.g., based on the working area and carrying capacity of the AIS manipulator and the resolution of the AIS technical vision, etc.). In this case, fuzzy values of various relationships $r_{j_3} \in R$ and characteristics $x^{j_2}_{j_6} \in X^*_{j_2 6}$ in a generalized form can be represented, accordingly, by the following pairs:

$$\left\langle \mu(x_{j_3}), T^k_{j_3} \right\rangle \text{ and } \left\langle \mu(x^{j_2}_{j_6}), T^k_{j_2} \right\rangle,$$

where $\mu(x_{j_3})$ is the degree of membership of the actual value of the base variable x_{j_3} to the interval of numerical values of the term $T^k_{j_3}$, LV of the same name with the ratio $r_{j_3} \in R$; $\mu(x_{j_2})$ is the degree of membership of the actual value $x^{j_2}_{j_6}$ of the characteristic $x^{j_2}_{j_6} \in X^*_{j_2}$ to the interval of numerical values of the term $T^k_{j_6}$ of the LV of the same name with this characteristic; and $x^{j_2}_{j_6}$ is a characteristic that participates in the description of similar PE events $d_{j_2}(X_{j_2}) \in D$, for which the condition $X^*_{j_2} \subseteq X_{j_2}$ is satisfied.

As an example, we suppose it is required to construct an LV for the relation $r_{j_3} \in R$: distance between PE objects with a set of values of the base variable $x_{j_3}, x_{j_3} \in [0, 500]$ m. As an AIS let us consider an intelligent drone manipulator equipped with a system of technical vision. In this case, the range of admissible values $[0, 500]$ m of the base variable x_{j_3} formed by LV is divided into the following three fuzzy subintervals defined by the following terms:

- $T^1_{j_3}$, nearby, for which the lower $x^*_{j_3}(1) = 0.2$ m and upper $x^*_{j_3}(2) = 1.2$ m. Boundary estimates of the subinterval of numerical values are respectively determined based on the dimensions of the dead zone and the working zone of the drone manipulator;
- $T^2_{j_3}$ is close, for which the lower boundary value of the subinterval of numerical values coincides with the upper boundary estimate $x^*_{j_3}(2) = 1.2$ m of the previous term $T^1_{j_3}$, and the upper boundary value $x^*_{j_3}(3) = 100$ m is taken equal to the resolution of the technical vision of the drone-manipulator;
- $T^3_{j_3}$ is far; this term corresponds to all values of the base variable x_{j_3} that satisfy the condition $100 < x_{j_3} \leq 500$ m.

Thus, if, in order to achieve the subgoal of the current step of behavior, the drone manipulator needs to capture the PE object $o_{j_1}(X_{j_1})$, then this object must have the following set of characteristics X_{j_1} = {the weight of the object must not exceed the manipulator's carrying capacity; either the overall dimensions of the object must be less than the operating width of the manipulator's working body or the object must have a component of the corresponding dimensions, by which it can be gripped by the manipulator}. In this case, the drone manipulator can encounter the following three situations:

– The distance between the object $o_{j_1}(X_{j_1})$ and drone manipulator in the PE is in the interval of the numerical values of the term nearby. In this situation, AIS considering its knowledge that any PE object located nearby and having a set of characteristics X_{j_1} can be captured, makes a decision to capture the object $o_{j_1}(X_{j_1})$.

– The drone manipulator perceives an object $o_{j_1}(X_{j_1})$ in the PE, i.e., it is close. In this case, the AIS makes a decision about the need to find a safe route for approaching the target.

– The object $o_{j_1}(X_{j_1})$ is beyond the resolution of the technical vision of the drone manipulator; the AIS then makes a decision about the need to find the location of the object in the PE.

From the given example, it follows that decision making based on the proposed model for representing declarative AIS knowledge is based on comparing passive and active FSNs.

It should be noted that the results of measuring various relationships between objects $o_{j_1}(X_{j_1}) \in O$ in the PE, as well as the characteristics of events $d_{j_2}(X_{j_2}) \in D$ that occur in it, which are carried out by the AIS technical vision system, have a quantitative representation. In this connection, it becomes necessary to transfer from the quantitative values of the basic variables $x_{j_3}, x_{j_6}^{j_2}$ of the LV corresponding to their fuzzy representation, in the form of pairs $\langle \mu(x_{j_3}), T_{j_3}^k \rangle$ and $\langle \mu(x_{j_6}^{j_2}), T_{j_2}^k \rangle$, respectively. The AIS intelligent solver uses the following rules to perform these transformations and compare various relationships and characteristics that describe PE events. The degree of membership $\mu(x_{j_3})$ of values of base variables x_{j_3} of relationships $r_{j_3} \in R$ to the sets of numerical values of terms $T_{j_3}^k$ is determined according to Rule 1.

Rule 1. If the condition

$$x_{j_3}^*(k) < x_{j_3} \le x_{j_3}^*(k+1), k = 1, 2, \ldots, m_5,$$

is satisfied then $\mu(x_{j_3}) = 1 - \dfrac{x_{j_3}}{x_{j_3}^*(k+1)}$ and $x_{j_3} \to \langle \mu(x_{j_3}, T_{j_3}^k) \rangle$. Otherwise, $\mu(x_{j_3}) = 0$, where $\to$ is a sign indicating that the quantitative value of the base variable x_{j_3} of the LV corresponds to a pair $\langle \mu(x_{j_3}, T_{j_3}^k) \rangle$.

Similarly, using Rule 1, the degrees of membership for pairs $\langle \mu(x_{j_6}^{j_2}), T_{j_2}^k \rangle$ are determined based on the numerical values $x_{j_6}^{j_2}$ of the characteristics $x_{j_6}^{j_2} \in X_{j_2}$ of events $d_{j_2}(X_{j_2}) \in D$ that occur in the PE.

In order to compare two values $x_{j_3}^1$ and $x_{j_3}^2$, for instance, the same relation $r_{j_3} \in R$ represented by the pairs $\langle \mu(x_{j_2}^1), T_{j_3}^k(1) \rangle$ and $\langle \mu(x_{j_2}^2), T_{j_3}^k(2) \rangle$, respectively, it is convenient to use the degree of their fuzzy equality $\rho(x_{j_3}^1, x_{j_2}^2)$, which is calculated according to Rule 2.

Rule 2. If the condition $\left(\left|\mu(x_{j_2}^1) - \mu(x_{j_2}^2)\right| \le \mu_0\right) \oplus (T_{j_3}^k(1) = T_{j_3}^k(2))$ is satisfied, then $\rho(x_{j_3}^1, x_{j_2}^2) = 1$. Otherwise, if the condition $\left(\left|\mu(x_{j_2}^1) - \mu(x_{j_2}^1)\right|\right) \mu_0) \oplus (T_{j_3}^k(1) = T_{j_3}^k(2))$ is true, then $\rho(x_{j_3}^1, x_{j_2}^2) = \mu(x_{j_2}^1) \leftrightarrow \mu(x_{j_2}^2)$. Otherwise, if the condition $(T_{j_3}^k(1) \ne T_{j_3}^k(2))$ is met, then $\rho(x_{j_3}^1, x_{j_2}^2) = 0$, where $\left|\mu(x_{j_2}^1) - \mu(x_{j_2}^1)\right|$ is the absolute value of the difference; $\oplus$ is a symbol indicating the need to simultaneously fulfill the left and right parts of the checked condition; and $\leftrightarrow$ is the operation of fuzzy equivalence defined by [15], which is performed by the expression

$$\min(\max(1 - \mu(x_{j_2}^1), \mu(x_{j_2}^2)), \max(\mu(x_{j_2}^1), 1 - (x_{j_2}^2))).$$

In the general case, the adequacy of the results of comparing fuzzy values of base variables of LV, represented by pairs obtained according to Rule 2, can be substantiated and interpreted as follows.

(1) Two values $x_{j_3}^1$ and $x_{j_3}^2$ of the same relation $r_{j_3} \in R$ represented by the pairs $\langle \mu(x_{j_2}^1), T_{j_3}^k(1) \rangle$ and $\langle \mu(x_{j_2}^2), T_{j_3}^k(2) \rangle$, respectively, at $\rho(x_{j_3}^1, x_{j_2}^2) = 1$, are equal to each other with an acceptable error. This is due to the fact that they fall in the vicinity of the same point on the base scale of numerical values of the corresponding LV.

(2) Under $0 < \rho(x_{j_3}^1, x_{j_2}^2) < 1$ the compared estimates $x_{j_3}^1$ and $x_{j_3}^2$ are vaguely equal to each other since they fall into the range of values of the same term.

(3) Finally, in the case where $\rho(x_{j_3}^1, x_{j_2}^2) = 0$, the compared estimates are not equal to each other, since they fall within the ranges of numerical values of different terms, i.e., they have different fuzzy meanings.

The last comparison suggests that there is a difference between the compared values of the relationships of the same name, for example, in an active and passive FSN, there is a difference, which needs to be eliminated by the AIS, for example, in order to achieve its goal.

Using the results of comparing various values of relationships $r_{j_3} \in R$ or characteristics of events $d_{j_2}(X_{j_2}) \in D$ obtained based on Rule 2 with each other, it is possible to estimate the degree of their difference $\rho^{-1}(x^1_{j_3}, x^2_{j_2})$, which is determined by Rule 3.

Rule 3. If $T^{k_1}_{j_3} = T^{k_2}_{j_3}$, then $\rho^{-1}(x^1_{j_3}, x^2_{j_2}) = 1 - \rho(x^1_{j_3}, x^2_{j_2})$; otherwise $\rho^{-1}(x^1_{j_3}, x^2_{j_2}) = |k_1 - k_2|$, where k_1, k_2 are sequential numbers of terms in the intervals of numerical values of which the compared estimates $x^1_{j_3}$ and $x^2_{j_3}$, respectively, fall.

Thus, if we set the threshold value h of the degree of difference $\rho^{-1}(x^1_{j_3}, x^2_{j_2})$, at which the AIS decides that there is a difference between the compared estimates $x^1_{j_3}$ and $x^2_{j_3}$, then on this basis it is possible to identify all the differences between the compared PE situations described using the FSN.

It should also be noted that the considered rules make it possible to proceed to constructing operations for comparing passive and active FSNs in the course of deriving AIS decisions. To do this, we preliminarily define the following concepts: structural equivalence of FSNs, fuzzy isomorphism of FSNs, and isomorphism of one FSN vaguely embedded into another network.

Definition 1. Arbitrary FSNs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ are structurally equivalent if they are equal without labels or the corresponding graphs are isomorphic, where, for example G_1, G_2 are passive and active FSNs, respectively.

Definition 2. Passive $G_1 = (V_1, E_1)$ and active $G_2 = (V_2, E_2)$ FSNs are called vaguely isomorphic if the following conditions are satisfied for them:

(1) They are structurally equivalent.

(2) For all structurally equivalent pairs of vertices $\langle v^1_{i_1} \in V_1, v^2_{i_1} \in V_2 \rangle$ the condition $X^*_{j_1} \subseteq X_{j_1}$ holds, where $X^*_{j_1}$ is a set of characteristics that labels the vertex $v^2_{i_1} \in V_2$ in an active network G_2 and X_{j_1} is a set of characteristics of an object $o_{j_1}(X_{j_1}) \in O$, which labels the vertex $v^1_{i_1} \in V_1$ in the passive network G_1.

(3) For all structurally equivalent pairs of arcs $\langle e^1_{i_1} \in E_1, e^2_{i_1} \in E_2 \rangle$ labeled by relationships there holds the condition $x^*_{j_3}(k) < x_{j_3} \le x^*_{j_3}(k+1)$, where $x^*_{j_3}(k), x^*_{j_3}(k+1)$ are respectively the lower and upper boundaries of the interval of numerical values of the term, which labels the arc $e^2_{i_1} \in E_2$in the active network $e^2_{i_1} \in E_2$, and $x_{j_3}$is the quantitative assessment of the relationship that defines the arc $e^1_{i_1} \in E_1$ in the passive network G_1.

(4) For all pairs of structurally equivalent arcs $\langle e^1_{i_1} \in E_1, e^2_{i_1} \in E_2 \rangle$ defined by PE events, the condition $X^*_{j_2} \subseteq X_{j_2}$ is satisfied, where $X^*_{j_2}$ is the set of characteristics labeling the arcs in the active network G_2 and X_{j_2} is the set of PE characteristics, which defines arcs $e^1_{i_1}$ in the passive network G_1.

Then, the degree $\rho(G_1, G_2)$ of fuzzy isomorphism for two compared FSNs G_1 and G_2 can be obtained as follows:

$$\rho(G_1, G_2) = \min_{i_2=1}^{n_3} \rho_{i_2}(e^1_{i_2}, e^2_{i_2}), \tag{1}$$

where $\rho_{i_2}(e^1_{i_2}, e^2_{i_2})$ is the fuzzy equality degree of the labels for a pair of structurally equivalent edges determined by Rule 2.

Estimation of the degree of fuzzy isomorphism makes it possible to establish the presence of differences between the labels of the arcs of the compared FSNs as follows. In the case where the degree $\rho(G_1, G_2) = 0$, the compared networks are not vaguely isomorphic and there is at least one difference between the labels of structurally equivalent arcs therein, which should be eliminated in order to transform one network into the other. Thus, under the obvious difference between the compared fuzzy semantic networks, such a difference should be understood as the one that is observed in the case when the estimates of the base variable of the LV fall into different subintervals of numerical values.

At $0 < \rho(G_1, G_2) < 1$ the decision is made that the compared FSNs are vaguely isomorphic. However, if in the estimate $\rho(G_1, G_2)$ degrees of fuzzy equalities $\rho(e^1_{i_2}, e^2_{i_2}) < h$ are observed, then there is an unobvious difference between the labels of structurally equivalent pairs of arcs $\langle e^1_{i_2}, e^2_{i_2} \rangle$, which should also be eliminated to transform one network into the other.

If the degree $\rho(G_1, G_2) = 1$, this suggests that the compared networks are vaguely equal, i.e., there are no differences between the labels of structurally equivalent pairs of edges in them.

It should be noted that the estimation of the degree of fuzzy isomorphism of two compared FSNs according to Eq (1) does not allow AIS to solve problems having, for example, the following content: Determine to what extent the passive network G_1 in its content of the labels of edges is closer to the network G_2 than the network G_3 on the condition that there are differences in the labels of pairwise structurally equivalent arcs in these networks. This is due to the fact that, regardless of the number of obvious differences that exist between the labels of structurally equivalent arcs in them, the condition $\rho(G_1, G_2) = \rho(G_3, G_2) = 0$ holds true. In the process of planning the behavior of AIS for decision making in this case, we can also use the following average estimate of the degree of fuzzy isomorphism of compared FSNs:

$$\rho^*(G_1, G_2) = \sum_{i_2=1}^{n_2} \rho(e_{i_2}^1, e_{i_2}^2) \Big/ n_2. \tag{2}$$

Then, if the following condition is satisfied

$$(\rho(G_1, G_2), \rho(G_3, G_2) \neq 0) \oplus (\rho^*(G_1, G_2) > \rho^*(G_3, G_2)) \tag{3}$$

for the degrees of the fuzzy isomorphism and determined by formula (1), and for the degrees of the fuzzy isomorphism $\rho(G_1, G_2)$ and $\rho(G_3, G_2)$ calculated by Eq (2), it can be argued that there are more differences between G_1 and G_2 than between G_1 and G_3. This, in turn, allows the AIS to organize FSN-based self-learning in an efficient manner under a priori undescribed PE conditions. In other words, this enables the AIS to automatically form complex programs of appropriate behavior, consisting of elementary acts of the form G_1 & $b_{j_4} \to G_2$, where G_1 is a fuzzy semantic network corresponding to the current PE situation, which is transformed into a situation determined by the network G_2 as a result of processing (tuning) $b_{j_4} \in B$ action by the AIS.

In the process of self-learning, elementary acts G_1 & $b_{j_4} \to G_2$ are memorized in the generated conditional program of AIS behavior only when there are fewer differences between G_1 and G_3 than between fuzzy semantic networks G_2 and G_3 [14], where G_3 is a network corresponding to the target PE situation. For AIS processing (tuning) of trial actions in the self-learning process, these actions in the procedural model of the AIS knowledge representation are defined in the format $\langle G_{j_4}^1, b_{j_4}, G_{j_4}^2 \rangle$, where there is a fuzzy semantic network that characterizes the conditions that must be met in the PE for the effective processing of an action b_{j_4}; $G_{j_4}^*$ stands for the FSN defining the results of refining (tuning) an action in the current situation in the PE. This allows the AIS to identify effective actions $b_{j_4} \in B$ in the course of self-learning based on checking the conditions of the following decision rule.

Rule 4. If the FSN $G_{j_4}^1$ is isomorphically embedded in a fuzzy semantic network describing the current PE situation, then a decision is made about the possibility of processing (tuning) the action in the current conditions of the problem environment and the next transition is carried out. Otherwise, the action b_{j_4} is excluded from the number of appropriate actions in the current conditions of PE.

If replacing the labels of vertices and arcs in FSN G_1 by the values of labels of the same-named vertices and arcs of the network $G_{j_4}^2$ results in the G_2 network in which the number of differences with the network G_3 is smaller than the number of differences between networks G_1 and G_1, then a decision is made on the feasibility of processing (refining) the action in the current environment conditions, where G_3 is a fuzzy semantic network corresponding to the current target PE situation. In this case, the generated conditional program of behavior, stores an elementary act $\langle G_1, b_{j_4}, G_2 \rangle$ etc., and the self-learning process continues until a chain of actions is identified that allows the transformation of the current PE situation into the target situation specified by the AIS.

Definition 3. If, for the passive fuzzy semantic network $G_1 = (V_1, E_1)$ corresponding to the current situation of PE and the active FSN $G_2 = (V_2, E_2)$, based on which a standard element for representing AIS procedural knowledge is developed, the conditions stipulated in paragraphs 2–4 of Definition 2 and $(V_2 \subset V_1) \oplus (E_2 \subset E_1)$ are satisfied, then the network G_2 is isomorphically vaguely embedded in the network G_1, which is denoted as $G_1 \sim G_2$.

Definition 4. If a passive fuzzy semantic network $G_1 = (V_1, E_1)$ and an active FSN $G_2 = (V_2, E_2)$ satisfy the requirements of paragraphs 2–4 of Definition 2 and $(V_2 \subset V_1) \oplus (E_2 \subset E_1)$, and for all pairs of the same-name vertices and arcs therein the degree of the fuzzy equality is defined by unity, then the network G_2 is vaguely embedded equal to the network G_1, which is denoted as $G_1 \subset G_2$.

Definition 5. The active network $G_2 = (V_2, E_2)$ is a generalization of the passive FSN $G_1 = (V_1, E_1)$ if they are vaguely isomorphic.

Thus, the active network $G_2 = (V_2, E_2)$ provided that it is a generalization of various passive networks $G_1 = (V_1, E_1)$ corresponding to different current situations in the PE, actually defines the restrictions imposed by AIS actions on various objects of the problem environment. In other words, the fulfillment of conditions in the PE that satisfy the requirements for the constraints on the labels of vertices and edges of an active FSN allows the AIS to determine effective actions $b_{j_4} \in B$ on its objects and, on this basis, to automatically form a plan for its goal-oriented behavior.

Therefore, the definition of fuzzy isomorphism between various fuzzy semantic networks is one of the key operations associated with knowledge processing during the decision-making process. In order to perform this operation on pairs $\langle G_1, G_2 \rangle$ including active and passive FSNs, it is feasible to represent these networks as adjacency matrices $M = |m_{i_1 j_7}|, i_1 = j_7 = 1, 2, \ldots, n_1$, the elements of which are determined based on the following rule.

Rule 5. If in an arbitrary FSN G vertices v_{i_1}, v_{j_7} are adjacent and the arc incident to them is determined by the ratio, then elements $m_{i_1 j_7}$ of the adjacency matrix of this network are defined by the following pairs: $m_{i_1 j_7} = \langle \mu(x_{j_2}), T_{j_3}^k \rangle$. Otherwise, $m_{i_1 j_7} = 0$.

Let the passive network $G_1 = (V_1, E_1)$ be defined by the adjacency matrix $M_1 = |m_{i_1 j_7}^1|, i_1 = j_7 = 1, 2, \ldots, n_1^1$ and let the active network $G_2 = (V_2, E_2)$ be defined by the adjacency matrix $M_2 = |m_{i_1 j_7}^2|, i_1 = j_7 = 1, 2, \ldots, n_1^2$. In this case, tools that can help to establish the presence of fuzzy isomorphism between the networks G_1 and G_2 are reduced to performing the following basic operations.

(1) comparing the dimensions of networks $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$;

(2) simultaneous permutation of identically labeled columns and rows, for example, in a matrix M_1 in accordance with the position of the columns and rows of the same name in the matrix M_2;

(3) defining, according to Rule 2, the degree of fuzzy equality between the values of the elements occupying the same positions in the matrices M_1 and M_2;

(4) calculating by formula (4) and analyzing the magnitude of the degree $\rho(G_1, G_2)$ of fuzzy isomorphism of the compared fuzzy semantic networks.

It should be noted that the complexity of the method based on the above tools used to determine the fuzzy FSN isomorphism is of the order $O[\beta(n_1)^2]$, because in this case the labeled graphs are compared, where β is the factor of proportionality.

3. SPECIAL OPERATIONS ON FUZZY SEMANTIC NETWORKS

One of the topical problems associated with the organization of goal-oriented behavior planning in conditions of an underdetermined PE is the reduction in the dimension of the problems that are solved and the generalization of the accumulated experience of behavior based on special operations on FSN. The main operations of this type include cutting one network out of another network, concatenating fuzzy semantic networks, and generalizing FSNs. These operations allow one to solve complex problems in various PE conditions based on typical elements of AIS procedural knowledge representation built on the basis of active FSNs, which, as a rule, have a small dimension.

The Operation of Cutting an Active Fuzzy Semantic Network out of a Passive Network with a Large Dimension

Let, in accordance with the complex problem being solved by the AIS, the passive FSN $G_1 = (V_1, E_1)$ that describes the current PE situation have a large dimension. In this case, it is advisable to break the general complex problem solved by the AIS into simpler subproblems which correspond to certain sections of the PE. The dimension of these areas of the environment should be such that, for the passive fuzzy semantic networks $G_z = (V_z, E_z), G_z \subset G_1, z = 1, 2, .., n_4$ describing them in the AIS procedural knowledge representation model, there would be typical behavior programs [12], for which the initial environmental conditions necessary for the successful processing of these programs were determined by active networks G_z^* that are vaguely equal to the passive networks G_z. In this case, breaking the original complex problem into typical subproblems can be done by sequentially cutting out all active FSNs G_z^* from the passive network G_1.

Let the active network G_2 be vaguely isomorphic embedded into the passive network G_1. In this case, cutting the network G_2 out of the network G_1 is reduced to eliminating the network of structurally equivalent vertices and arcs therein from the latter network, with the exception of boundary vertices.

Definition 6. Boundary vertices in the networks $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ are pairs of structurally equivalent vertices $\langle v_{i_1} \in V, v_{i_1}^* \in V \rangle$, for which in the network G_2 there are arcs $e_{i_2}^* \in E_2$ incident to the vertices $v_{i_1}^* \in V_2$, for which there are no arcs in the network G_1 structurally equivalent to them.

The Operation of FSN Concatenation is performed between the active FSN $G_z^* = (V_z, E_z), z = 1, 2, .., n_4$ in order to construct an active network G_2, which is vaguely isomorphic to the passive network G_1 defining the current situation in the PE having large dimensionality. This makes it possible to define such procedural elements of knowledge representation that enable AIS to automatically develop the plan of goal-oriented behavior providing it with the solution of a complex problem in the current conditions of the PE.

As an example, concatenation of two active networks G_2^1, G_2^2 occurs and denotes the network $G_2^3 = G_2^1 \otimes G_2^2$, which is obtained as a result of gluing the networks G_2^1, G_2^2 along the vertices of the same name in them.

The Operation of FSN Generalization is performed on passive FSN describing current PE situations similar to each other. Let a set of vaguely isomorphic passive FSNs $G_z = (V_z, E_z), z = 1, 2, .., n_4$, be specified. Then, the generalization of these networks results in the emergence of an active FSN $G_2 = (V_2, E_2)$ whose vertices $v_{i_1} \in V_2$ are labeled by the following set of characteristics $X_{i_1}^* = \bigcap_{z=1}^{m_z} X_{i_1}^z(j_1)$, where $X_{i_1}^*(j_1)$ is the set of characteristics of objects $o_{j_1}(X_{j_1}) \in O$ which labels structurally equivalent vertices $v_{i_1} \in V_z$ in the networks $G_z = (V_z, E_z)$ and m_z denotes the number of structurally equivalent vertices of the i_1 type in the networks $G_z = (V_z, E_z)$.

Taking the fact into account that structurally equivalent arcs $e_{i_2} \in E_z$ in the networks $G_z = (V_z, E_z)$ are labeled by pairs $\langle \mu(x_{i_2}), T_{i_2}^z \rangle, i_2 = 1, 2, .., n_z$, the arc $e_{i_2} \in E_2$ structurally equivalent arc to them in the active network $G_2 = (V_2, E_2)$ being formed is determined by the term $T_{i_z}^k$ and its boundary estimates $[x_{j_3}^*(k), x_{j_3}^*(k+1)]$ on the base scale of values of the corresponding LV; n_z is the number of structurally equivalent view arcs of the type i_2 in networks $G_z = (V_z, E_z)$.

CONCLUSIONS

Summarizing the above, the following main conclusions can be drawn.

(1) The proposed model for representing declarative knowledge allows one to adequately describe the current situations of an unstable PE using passive FSNs and to build a procedural knowledge representation model of an AIS, regardless of a specific subject area based on passive fuzzy semantic networks. This, in turn, gives the AIS the ability to organize automatic scheduling of goal-oriented behavior in a priori underdetermined conditions of a problem environment.

(2) The developed operations for comparing various FSNs with each other allow an AIS to effectively organize decision making, both in the planning of goal-oriented behavior in underdetermined PE conditions and in the process of self-learning in a priori undescribed conditions of the problem environment, revealing on this basis the patterns that occur in it.

(3) The use of the proposed special operations on the FSN provides an AIS with the ability to plan goal-oriented behavior in a complex PE characterized by a large dimension of the situations that describe them.

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