SITUATIONAL CONCLUSION MECHANISM BASED ON THE DYNAMIC SEPARATIONS IN THE FRAGMENTS OF THE KNOWLEDGE BASE

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Abstract
Технология ситуационных интеллектуальных машин (СИМ) относится к технологиям «мягкой» обработки информации. Она находит применение в задачах синтеза интеллектуальных систем автоматического контроля (ИСАУ). Так как ИСАУ работают в реальном масштабе времени, к ним предъявляются высокие требования по быстродействию, что требует проведения исследований механизма вывода на знаниях. В статье рассматривается механизм. Основанный на методе ситуационного вывода на нечётких знаниях. В основе его положена модифицированная марковская стратегия вычисления глобальной индуции-продуцкции на динамически выделенном фрагменте базы знаний. В фрагмент включаются только те правила, которые потенциально могут иметь изменения в поле ситуации. Приводится формализация указанного формализма.

In the technology of information processing software, the technology of situational intelligent machines (SIM) play very important role /1/. It is used in the synthesis of intellectual systems of automatic control (ISAC). Since the ISAC works in the real time and on-line mode, a high level of time sensitivity is required for the system. This demands the intensive research in the mechanism of knowledge based conclusion. In the following article the real time-scale method of situational conclusion on the basis of fuzzy knowledge is studied. In the Modified Markov's Strategy the global induction-production is made on the basis of the dynamic separation of the knowledge base (KB) in some fragments. In the fragments are included only those rules which will potentially change the current situation. In the present article the formalism of this strategy is offered.

Fundamentals of knowledge representation in SIM: The main paradigm of SIM lies in the fact that the knowledge here is represented in the form of situation and the knowledge based conclusion is represented in the form of mechanism of formation of models of different levels of abstractions. The model of a situation is created on the basis of a set of concepts and facts, which can be considered as different levels of generalization based on the unstructured description of a situation $^{0}\underset{\sim}{C}$, obtained from a control and measuring system. Thus, the model of a situation can be represented as a structured fuzzy set /2/

$$\underset{\sim}{C}(t+kT) = \{^{0}\underset{\sim}{C}(t+kT), {}^{1}\underset{\sim}{C}(t+kT), {}^{2}\underset{\sim}{C}(t+kT), \ldots, {}^{m}\underset{\sim}{C}(t+kT)\} \qquad (1)$$

where $^{1}\underset{\sim}{C}(t+kT), {}^{2}\underset{\sim}{C}(t+kT), \ldots, {}^{m}\underset{\sim}{C}(t+kT)$ are models of a situation of the first, second, …, $m-$ th levels of generalization.

The formation of $^{1}\underset{\sim}{C}(t+kT), {}^{2}\underset{\sim}{C}(t+kT), \ldots, {}^{m}\underset{\sim}{C}(t+kT)$ is carried out automatically in real time on the basis of $^{0}\underset{\sim}{C}(t+kT)$ according to the rules of induction from the knowledge base. The rules of indution or declarative knowledge about the structure of a situation, and production rules forming the control by the way of their "application" to $\underset{\sim}{C}(t+kT)$ are determined on the given set of indution operations /3/.

Declarative knowledge forming the model of the situation $\underset{\sim}{C}(t+kT)$ in (1), is described by the indution rules as follows:

$$\begin{aligned}\underset{\sim}{\Pi}({}^{j}c_r) = \{[(\{{}^{1}G^{i}_{\sim MIN}\}_{i=1}^{n_1},\{{}^{1}G^{i}_{\sim MAX}\}_{i=1}^{n_2},\{{}^{1}G^{i}_{\sim MAX-MIN}\}_{i=1}^{n_3},\{{}^{1}G^{i}_{\sim SUM}\}_{i=1}^{n_4}),\\ (\{{}^{0}\hat{C}_{\sim i},{}^{1}G^{i}_{\sim MIN}\}_{i=1}^{n_1},\{{}^{0}\hat{C}_{\sim i},{}^{1}G^{i}_{\sim MAX}\}_{i=1}^{n_2},\{{}^{0}\hat{C}_{\sim i},{}^{1}G^{i}_{\sim MAX-MIN}\}_{i=1}^{n_3},\{{}^{0}\hat{C}_{\sim i},{}^{1}G^{i}_{\sim SUM}\}_{i=1}^{n_4})],\\ \dots \qquad (2)\\ [(\{{}^{j}G^{i}_{\sim MIN}\}_{i=1}^{p_1},\{{}^{j}G^{i}_{\sim MAX}\}_{i=1}^{p_2},\{{}^{j}G^{i}_{\sim MAX-MIN}\}_{i=1}^{p_3},\{{}^{j}G^{i}_{\sim SUM}\}_{i=1}^{p_4}),\\ (\{{}^{j-1}\hat{C}_{\sim i},{}^{j}G^{i}_{\sim MIN}\}_{i=1}^{p_1},\{{}^{j-1}\hat{C}_{\sim i},{}^{j}G^{i}_{\sim MAX}\}_{i=1}^{p_2},\{{}^{j-1}\hat{C}_{\sim i},{}^{j}G^{i}_{\sim MAX-MIN}\}_{i=1}^{p_3},\{{}^{j-1}\hat{C}_{\sim i},{}^{j}G^{i}_{\sim SUM}\}_{i=1}^{p_4})].\end{aligned}$$

The rule (2) gives the definition of the fragment of the situation ${}^{j}C_r \subset {}^{j}C$ i.e. describes the knowledge about how to determine concept or fact ${}^{j}C_{\sim r}$ through the source information ${}^{0}\underset{\sim}{C}(t+kT), {}^{1}\underset{\sim}{C}(t+kT)$ etc.

Knowledge in the form of production rules forming a model of control $\underset{\sim}{U}(t+kT)$, as well as the declarative rules (2) are represented by the fuzzy sets

$$\underset{\sim}{\Pi} = \{\underset{\sim}{\hat{C}},\underset{\sim}{\hat{U}},G_{\sim SUM}\}, \qquad (3)$$

where $\underset{\sim}{\hat{C}}$ - the measurement standard of a fragment of a situation for which a rule is applicable; $\underset{\sim}{\hat{U}}$ - fuzzy control or increment of membership-funtions; $G_{\sim SUM}$ - reflection-map given on intersection $C \times U$.

The formation of the model of a situation $\underset{\sim}{C}(t+kT)$ /2,3/ is actually the operation of determining the indution rules (2) of the declarative knowledge $\pi_D = \{\Pi({}^{j}c_r)\}_{r=1,j=1}^{r=R,j=m}$ according to the following expressions:

MAX- indution $$\underset{\sim}{\mu_Y}(y) = \begin{cases} \underset{x\in G^{-1}\{y\}}{MAX}[\rho_\alpha(x)], \text{if } G^{-1} \neq \varnothing \\ 0 \qquad , \text{if } G^{-1} = \varnothing \end{cases};$$

MIN – indution $$\underset{\sim}{\mu_Y}(y) = \begin{cases} \underset{x\in G^{-1}\{y\}}{MIN}[\rho_\alpha(x)], \text{ if } G^{-1} \neq \varnothing \\ 0 \qquad \text{if } G^{-1} = \varnothing \end{cases};$$

MAX-MIN – indution $\underset{\sim}{\mu_Y}(y) = \underset{x\in X}{MAX}(MIN[\mu_G(y \| x), \underset{\sim}{\rho_\alpha}(x)])$;

SUM- indution
$$\mu_Y(y) = \frac{1}{N}\sum_{x\in X} MIN[\mu_G(y \parallel x), \rho_\alpha(x)], \tag{4}$$

where $\rho_\alpha(x)$ - x is a component of the vector $\rho_\alpha(\underset{\sim}{X}, \underset{\sim 1}{X})$, describing the degree of proximity of two fuzzy sets $\underset{\sim}{X}$ and $\underset{\sim 1}{\bar{X}}$; $\rho_\alpha(\underset{\sim}{X}, \underset{\sim 1}{\bar{X}}) = \overline{\left| \underset{\sim}{X} - \underset{\sim 1}{X} \right|}_\alpha$.- complement of an usual approximately fuzzy set of α - level, which is found as an absolute difference between two fuzzy sets $\underset{\sim}{X}$ And $\underset{\sim 1}{X}$.

Tree for induction-production input: In correspondence with the structure of the situation (1) the structure of the knowledge base can be formed. Set of the induction rules and production of a knowledge base is divided into the subsets (fragments) : $\{^1\pi, ^2\pi, ..., ^m\pi\}$.

The rule $\underset{\sim}{\Pi}(^1c_r)$ is included in the fragment of the first level, i.e. $\underset{\sim}{\Pi}(^1c_r) \in {}^1\pi$, if the expression (2) takes the following form for it

$$\underset{\sim}{\Pi}(^1c_r) = \{[(\{^1\underset{\sim}{G}^i_{MIN}\}_{i=1}^{n_1}, \{^1\underset{\sim}{G}^i_{MAX}\}_{i=1}^{n_2}, \{^1\underset{\sim}{G}^i_{MAX-MIN}\}_{i=1}^{n_3}, \{^1\underset{\sim}{G}^i_{SUM}\}_{i=1}^{n_4})$$
$$(\{^0\underset{\sim i}{\hat{C}}, {}^1\underset{\sim}{G}^i_{MIN}\}_{i=1}^{n_1}, \{^0\underset{\sim i}{\hat{C}}, {}^1\underset{\sim}{G}^i_{MAX}\}_{i=1}^{n_2}, \{^0\underset{\sim i}{\hat{C}}, {}^1\underset{\sim}{G}^i_{MAX-MIN}\}_{i=1}^{n_3}, \{^0\underset{\sim i}{\hat{C}}, {}^1\underset{\sim}{G}^i_{SUM}\}_{i=1}^{n_4})]\}, \tag{5}$$

where $^jc_r \subset {}^jC$.

The rule $\underset{\sim}{\Pi}(^jc_r)$ is included in the fragment of the rules of the j-th level, i.e. $\underset{\sim}{\Pi}(^jc_r) \in {}^j\pi$, if it is represented in the general form (2), $^jc_r \subset {}^jC$ and at least one of the levels $\{^0C, ^1C, ^2C, ..., ^mC\}$ for example, $i, i \lhd j$ satisfies the condition $c_r \in {}^i\hat{C}_n$, where $^i\hat{C}_n \subset {}^iC$.

Here ^jc_r is the concluding (output) element of the rule and c_l is the element of the rule entering in the standard fragment of the situation.

In this way the subsets of the rules $\{^1\pi, ^2\pi, ..., ^m\pi\}$ (the fragments of KB) are hierarchically ordered. The rules belonging to the different fragments can be dependent on each other.

The rule $\underset{\sim}{\Pi}(^jc_r)$ e.g. of the type $\underset{\sim}{\Pi}(^jc_r) = \{^{j-1}\underset{\sim}{\hat{C}}, {}^j\underset{\sim (\bullet)}{G}\}$ is directly dependent on a rule $\underset{\sim}{\Pi}(^lc_r) = \{^{l-1}\underset{\sim}{\hat{C}}, {}^l\underset{\sim (\bullet)}{G}\}$ if $^lc_m = c_k$, $c_k \in {}^{j-1}\hat{C}$, i.e. c_k is the element which forms the rule $\underset{\sim}{\Pi}(^jc_r)$ and c_k is formed by the rule $\underset{\sim}{\Pi}(^lc_m)$.

The process of construction of induction-production net of conclusion is reality the process of dividing the set of rules in the hierarchically ordered fragments and establishing the dependence amongst the rules (the relation on the set of pairs of rules belonging to different fragments). Formally the net of conclusions represented in the form of set of hierarchically ordered fragments of the KB $\{^1\pi, ^2\pi, ..., ^m\pi\}$, and the set of relations $O = \{O^{i,j}(^i\pi(^ic_r), ^j\pi(^jc_j))\}_{i,j=1}^m$, where the relation $O^{i,j}$ is given on the intersection of sets of the rules of fragments $^i\pi$ and $^j\pi$.

In the pic.1 the graphical illustration of the tree for induction-production conclusion is represented.

Conclusion-subtree for an arbitrary subset of elements $^0\hat{C}\subset{}^0C$: Let at the moment of time $(t+kT)$ in comparison with the moment $(t+(k-1)T)$ the value of the membership function of only one element was changed, for example $c_2\in{}^0C$. (see pic.1) This modification in the processing of a rule Π_1 will result in a modification of the membership-function of an element $^1c_1$, and the last event in the processing of a rule Π_6 will change the value $\mu(^2c_1)$. The membership-functions of remaining elements $\hat{C}=\{(^1c_2,{}^1c_3,{}^1c_4,{}^1c_5),{}^2c_2,\}$ will not be changed, as the rules $\Pi_2,\Pi_3,\Pi_4,\Pi_5,\Pi_7$ are processed using former values of membership-functions of elements. Computation related with the productions of the rules $\Pi_2,\Pi_3,\Pi_4,\Pi_5,\Pi_7$, according to the equations (4), and (5) in the given case does not produce new result.

In connection with the above said increase in the efficiency of the induction-production mechanism of a conclusion, it is expedient for each moment of real time to determine a subset of elements $^0\hat{C}\subset{}^0C$, the membership functions of which have been changed the values, and to form dynamically the corresponding conclusion-subtree.

Here we notice two aspects. The first aspect - preliminary formation of the whole conclusion-tree and its conclusion-subtrees for each element on the basis of unordered set of the rules. The second aspect - dynamic formation of the conclusion-subtree on the basis of the given subset of elements $^0\hat{C}$.

At first we shall consider the algorithm of preliminary formation of a conclusion-tree(subtrees).

1. According to the definition given in section 3, is formed the knowledge base: the hierarchical fragments of the KB $\{^1\pi,{}^2\pi,...,{}^m\pi\}$ and the subsets of the relation for each i-th fragment $O^i=\{O^{i,j}(^i\pi(^ic_r),{}^j\pi(^jc_j)),\forall^ic_r\in{}^iC\}$ are separated.

2. For each of $c\in{}^0C$, are formed the set of subsets $\pi(c)=\{^1\pi(c),{}^2\pi(c),...,{}^m\pi(c)\}$, where the subset $^i\pi(c)$ includes the directly dependent rules which are included in the fragments $^j\pi, j\prec i$. The process of formation of $^i\pi(c)$ is based on the analysis of the subset of relation $O^i\in O$.

The dynamic formation of the conclusion-subtree in real time for the given subset of element $^0\hat{C}$ is simply the union of subsets theoretically:

$$\pi(^0\hat{C})=\bigcup_{\forall c\in{}^0\hat{C}}\pi(c)=\{\{\bigcup_{\forall c\in{}^0\hat{C}}{}^1\pi(c)\},\{\bigcup_{\forall c\in{}^0\hat{C}}{}^2\pi(c)\},...,\{\bigcup_{\forall c\in{}^0\hat{C}}{}^m\pi(c)\}\}$$

The mechanism of the situational conclusion forms the model of the situation rule $\underset{\sim}{C(t+kT)}$ at the moment of time $(t+kT)$ only on the set of rules $\pi(^0\hat{C})$, what substantially reduces the number of computations.

Conclusion : The strategy and algorithm of the knowledge based conclusion presented in the given article are used in the situational intelligent machines /4/ and possess considerable advantage in speed and actuality of conclusion over the classical method of fuzzy conclusion used in the fuzzy control systems.

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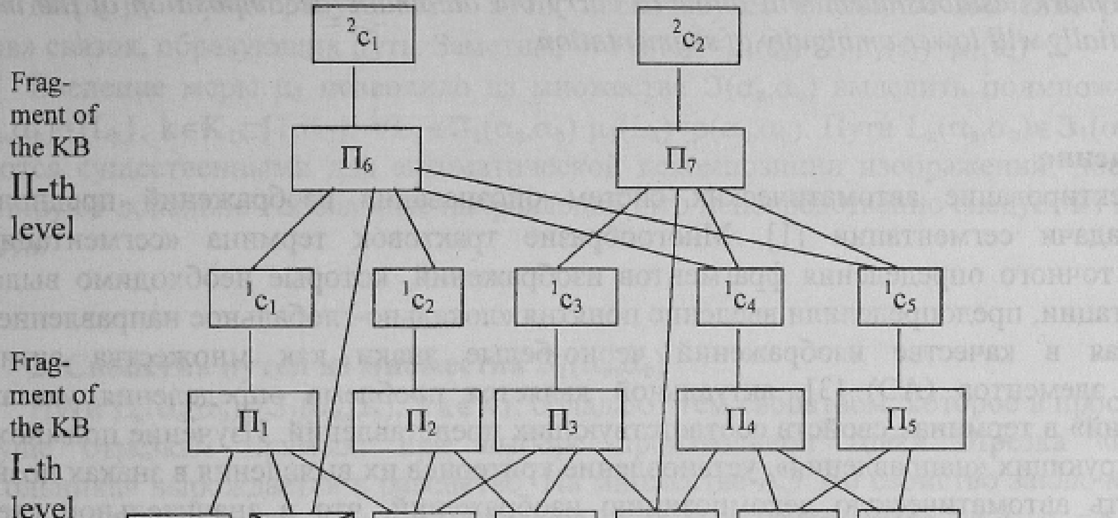

Pic.1 Tree of multilevel models