Construction of Intellectual Informative Systems

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Abstract. A short summary of literature on the description of fundamental methods and techniques, the implementation of schemes and computer programs for the construction of software for the implementation of self-developing intelligent multimedia models is given. They are based on the concept of multiagency, development in systems of artificial origin. In addition, neural fuzzy software agent systems are used. Consider increasing the intellectual value of advanced multimedia models using methods based on agent-ordered methods. For an agent the functional model of the mixed type, in that clear and unclear rules are used in playback modification of behavior, is built. To analyze complex factors and conditions, functional dependencies over relations are used, as well as symbolic formulas for fuzzy logic over fuzzy symbols and forms. With the help of transformations over attribute values, diagrams of the rules for outputting the alphabet of the calculus are described. Their essence in functional transformations. The abilities of theoretical-categorical representation of models of similar intellectual agents and further formalization of the evolutionary formation of agent groups are discussed. In the future, it is assumed to study the potential of a theoretical and formal representation of the nature of neural fuzzy elements with various modifications of their components. It is also intended to build mappings that can convert elements of one format to elements of another format. The goal of all research is to develop new transformations.

Keywords: Multimedia Systems, Intellectual Agents, Fuzzy Logic, Conversion Agent, Neural Networks.

1 Introduction

Currently, multimedia systems are complex local multi-level batch associations [1]. The large streams of information pass through them. These systems are the link between the input and output effects [2], [3].

Multimedia multitasking. Intelligent systems, as one of the subspecies of multimedia systems, can also manage information [4]. Often managed from one location, or by one decision maker. In addition, the task of summarizing systems helps solve problems of the decision maker in managing multimedia processes, and also allows you to build structures that model the functioning of multimedia systems [5-6].

The study of these issues is devoted to the work of a number of domestic and foreign authors [2-7]. Their works describe the problems of analysis, synthesis, modeling and construction of information telecommunication systems. Also named a number of reasons for solving these problems:

- systems consist of a large number of interconnected subsystems and elements interconnected and subordinate to a single development goal;
- the functioning of any element and subsystem within one system is not separate from the others and depends on the position of each of them in the system;
- some individual elements and subsystems within one system may develop inconsistently with each other, so their behavior may be described by complex functional dependencies;
- the behavior of some subsystems and elements within one system has a stochastic direction, and also in some cases assumes an odd nature.

2 Materials and methods

The article uses intelligent systems to solve problems of modeling and building information telecommunication systems and describes their state using logical-mathematical dependencies. They will be called agent-oriented systems in the future [8].

In the real world, when information systems are paramount, and therefore the role of the person is significantly abolished, information intelligence agents come to the fore. To solve the resulting problems, these agents are combined into groups, which also allows them to best adapt to new environmental conditions.

Information intelligent agents are widely found in the works of domestic and foreign authors [9-10], [11-14], who developed and built models of neural fuzzy intellectual agents. In conditions of very small discrete states, the models of intelligent agents considered in these research projects showed optimal fundamental and applied results. Error correction method, error signal feedback correction method, error backward propagation method - all these modern neural network training methods were used in these models.

However, the practical implementation of these models is still quite difficult to implement due to the growth in geometric progression of process states. To simplify the process of building such models, you need to consider multilevel neural models of agents with fuzzy task conditions. Such models are also self-learning and adapt well to the conditions of a booming heterogeneous information environment [15].

Over time, due to the reasons associated with an increase in modifications to information communication systems, a delay in determining the outcome of intelligent agents, difficulties appear in managing neural models. All this makes us study uncertainty in the behavior of intellectual agents, patterns in the development and self-development of intellectual agents using fuzzy neural models.

Of interest is a number of studies describing technical systems of artificial origin from the point of view of formalizing their processes of self-improvement and self-organization. For example, modeling formal conditions of activity, where the main function of phenomena is the function of adaptation [10]. In these works, the rules for the phased development of processes are widely used. Models are built using logical laws and using information technologies. Practical implementation of models is tested on information manipulators or real robots. All this testifies to the accuracy and truth of this scientific direction.

The basis of these works is an approach that describes phenomena from the point of view of their biological component. The fixture function is well represented using formalized criteria. Criteria are information technology rather than biological in nature.

In addition, a new course arose aimed at considering the artificial origin of the mind, which was called "Artificial Life". It appeared in the late 80s. XX century and its goal was to describe and model self-organizational phenomena in biotechnical systems.

The basis of this direction is work in which technical and genetic systems are described using an NK-automatic scheme [12]. The circuit consists of n-components, each of which is described by its own state, and has k inputs-outputs connected to each other.

This direction is also very developed in the Russian Federation, the adherents of which build and study biotechnical models of behavior of various forms of life.

These models are based on an algorithm for building artificial life, concentrating on the phased development of simple organisms. These organisms are not involved in the formation of mental models. Biotechnical models themselves are most often built using computer software packages in a hardware or software technical environment.

As a result, the study of artificial systems is currently an urgent task. The study and construction of such systems using neural models with fuzzy logic is especially in demand.

3 Results

In the structure of an artificial system, there are a huge number of different modules that can both depend on and not depend on other elements of the system. All are designed to process, store and transmit information. When interacting with other elements of the system, modules can both influence and not affect the development of the first. These modules act as intelligent agents and have all the necessary properties to solve the agent-oriented problem.

Текст When describing the work of these intelligent agents, it turns out that all external influences that appear in the system in the form of signals, signs and signs can be considered as certain messages and presented as functional logical dependencies. This action is called the input language of the intelligent agent. Conversely, all actions that the agent exerts on the external environment can also be described using functional logical dependencies. They can also be generalized into the output language of the intelligent agent [16].

The resulting functional dependencies can be converted by application packages and other software methods into different physical signals. The types of signaling can be different, both synchronous and asynchronous. Also suitable is the physical encoding of the signal.

Further, based on the obtained dependencies, the architecture of the neural network is built, which can take on both a clear and fuzzy character. Input and output signals can be measured with a certain degree of accuracy and significantly simplified by describing them with simple dependencies.

But if we consider modern information systems where it is necessary to optimize behavior under environmental conditions, then it is possible to receive messages and signals with a less clear value. By drawing an analogy, these can be variables whose values are contained in fuzzy sets. Schematically, the input and output of intelligent agent messages is shown in Fig. 1.

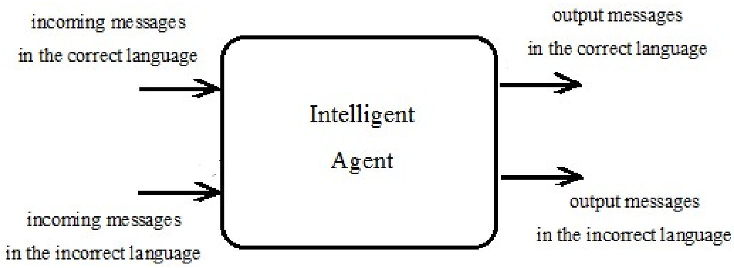

Fig. 1. Intelligent agent operation.

The intelligent agent proposed for consideration is responsible for the recognition of both correct and incorrect input information and interaction with other agents. Therefore, to create a universal model of interaction of a combined intelligent agent, we use the well-known scheme of states of an intelligent agent in a multi-agent information system.

Imagine a theoretical-multiple model of an intelligent agent in the following form $LI =< SN, C_A, K, AF >$ - this is a tuple of relational relations, in which SN – the system number, C_A – attributes, K – agents associated with the subject, AF – the function of the action [17].

Pointing and descriptive attributes will be $C_A = \{C, \hat{C}\}$, composed of which are the exact and fuzzy attribute values, respectively. In turn, for the exact value of the attribute it will be true $C_i =< NC_i, SC_i, VC_i >$, and for the fuzzy one $\hat{C}_j =< N\hat{C}_j, X_j, \mu_j(x), x(t) >$, where, NC_i, $N\hat{C}_j$ - the considered properties; SC_i - defining set; VC_i - value at some time moment t; $\mu(x)$ - a membership function with a domain of definition X_j; $x(t)$ - an element from a set U corresponding to a given time t.

Let us denote: $\{R,\tilde{R}\}$ - a set of elements that reflect the nature of incoming messages; $\{T,\tilde{T}\}$ - a set of messages outgoing from an agent. This allows translating the state model of an intelligent agent into mathematical language.

Thus, for the mathematical model of an intelligent agent, sequential operations are performed on the entered sets: $\{C,\hat{C}\}$, $\{R,\tilde{R}\}$, $\{T,\tilde{T}\}$. The transition states in the behavior model are specified in the set $\{S\}$ by the following classes: the reception of the elements of the set $\{R,\tilde{R}\}$ and the impossibility of reception - $\{R,\tilde{R}\}$.

To find out the nature of the content of messages received by the agent and the number of clear and fuzzy attribute values, we define a set of predicates $\{\Pr\} = (\Pr 1, \Pr 2, ..., \Pr \varphi)$ in the state model of an intelligent agent, which in first-order logic constitute a set of admissible predicates.

It is possible to analyze complex conditions and relationships for incorrect input information using predicate theory and fuzzy logic, respectively, formulas F and $\tilde{F}$.

To formalize the predicate calculus, we compose the alphabet of the predicate calculus K_{AF}: $A = (\{C,\hat{C}\},\{R,\tilde{R}\},\{T,\tilde{T}\},\{S\},\{\Pr\},\&,\vee,(,),\neg,\rightarrow,@,\nabla,\varnothing,0)$.

The alphabet for subject variables will have the form $P = (p,q,f,hA)$, p, q - elements of sets $\{R,\tilde{R}\}$, $\{T,\tilde{T}\}$, respectively, that is, information at the input and output, f - logical formulas of predicates $\Pr$, as well as logic of fuzzy statements, hC - properties of an intelligent agent $hC_A = \{hC, h\hat{C}\}$.

Let us compose the axioms of the calculus in the form: $Cx = (\varnothing @ S_0 @ hC_A(0) @ \varnothing @ \varnothing)$, where is $\varnothing$ - the absence of data on the state of the variable, and $hC_A(0) = \{hC(0), h\hat{C}(0)\}$ consists of arrays: $hC(0) =< NC_1, SC_1, VC_1(0) >$; $< NC_2, SC_2, VC_2(0) >$; ... $< NC_n, SC_n, VC_n(0) >$; $h\hat{C}(0) =< N\hat{C}_1, X_1, \mu_1(x_1), x_1(0) >$; $< N\hat{C}_2, X_2, \mu_2(x_2), x_2(0) >$; ..., $< N\hat{C}_m, X_m, \mu_m(x_m), x_m(0) >$. Here, at the initial operation time of the intelligent agent, $VC_i(0)$ - is the exact value of the i - th attribute at time $t = 0$, $x_j(0)$ is the fuzzy value of the j - th attribute at time $t = 0$.

To complete the construction of the predicate K_{AF} calculus under consideration, we assign the inference rules in the form of a scheme of axioms: $R_i = (R_l, \tilde{R}_k)$, $T_j = (T_p, \tilde{T}_q)$, $F_j = F_j(F_e, \tilde{F}_r(W_r))$, where W_r - the value of the degree with which the logical formula is true. Depending on the specified degree of truth, the fuzzy function will be active, and, therefore, used to apply the rule [18].

The number of inference rules that satisfy these schemes for each action model is diverse. For example, the laws that transfer elements from a state S_0 to the corresponding states of the form 1 and 2 are determined by logical schemes $\frac{R_i, p@S_0@hC(0)@q@f}{p@S_i@hC(R_i)@q,T_i@f,F_i}$ and $\frac{R_i p@S_0@hC(0)@q@f}{\nabla p@S_i@hC(R_i)@q,T_i@f,F_i}$. Note that the operator ∇ was introduced to denote the state of refusal in processing incoming information R_i. In these schemes, it is likely that $T_i=\varnothing$ and $F_i=\varnothing$ (T_i - messages at the output, F_i - a formula) - this is convenient as a variant of minimizing the number of outputting circuits [19].

The transition of states from type 1 to type 1, both with a truth table F_i and without it, is described by the schemes $\frac{R_i p@S_i@hC@q@f}{p@S_j@hC(R_i)@q,T_j@f,F_j}$ and $\frac{R_i p@S_i@hC@q@f,F_i}{p@S_j@hC(R_i)@q,T_j@f}$. It must be borne in F_i mind that it is possible to clarify the degree of truth of the negation, that is, to draw up a formula $\neg F_i$. Then the verified formula F_i will not be displayed. If an intelligent agent has an infinitely repeating task execution period, then the formula required for use is again determined by the previous schemes $\frac{R_i p@S_i@hC@q@f}{p@S_j@hC(R_i)@q,T_j@f,F_j}$.

Without analyzing the formula F_i, the transition to a new state is described by the scheme $\frac{R_i p@S_i@hC@q@f}{\nabla p@S_j@hC(R_i)@q,T_j@f,F_j}$, and the scheme $\frac{R_i p@S_i@hC@q@f,F_i}{\nabla p@S_j@hC(R_i)@q@f}$ is analyzed F_i.

Return to state 1 from 2 characterizes structures of the form $\frac{\nabla p@S_i@hC@q@f}{p@S_j@hC(R_i)@q,T_j@f,F_j}$ and $\frac{\nabla p@S_i@hC@q@f,F_i}{p@S_j@hC(S_i)@q,T_j@f}$.

Logical structures $\frac{\nabla p@S_i@hC@q@f}{\nabla p@S_j@hC(S_i)@q,T_j@f,F_j}$ and $\frac{\nabla p@S_i@hC@q@f,F_i}{\nabla p@S_j@hC(S_i)@q,T_j@f}$ indicate a return from state 2 to the same state. It should be noted that in the transition circuits, a stop is determined during the transition to a state S_j where there is no case of a new output and, accordingly, a return to the original state S_0 occurs.

As can be seen from the schemes for the inference axioms, they define calculation functions $hC(S_i) = \{hC(S_i), h\hat{C}(S_i)\}$ that can be compared with the transformations of attribute values $VC_1(t)$, $VC_2(t)$,…, $VC_n(t)$ and $x_1(t)$, $x_2(t)$, …, $x_n(t)$.

Using the above, it is possible to divide intelligent agents into types, for example, such as active and passive, precise and fuzzy. Each of which can be primitive and non-primitive, parametric and an agent with a shell [20].

4 Discussion

The developed approach to providing fuzzy logic methods in the development of multi-agent systems is to help create a set of intelligent agents capable of self-development and solve a common system problem, to organize effective interaction between agents at different levels of the hierarchy of information systems.

To organize a clear structure of interaction between agents according to certain rules, each intelligent agent is assigned a clear role based on its capabilities. And here it is possible to use both canonical number systems and number systems of a higher level. That is, the set of processed input information, objects and parameters can be ordered using the theory of structural calculus.

The developed model of a fuzzy neural structure allows agents to evolve, accumulate information and skills when interacting with the external environment of information, and increase their scope without including decentralized artificial intelligence.

In the algorithm for creating this model, the following roles of an intelligent agent are used, characterized by the level of artificial intelligence and the way of behavior:

- reflection - the presence of a response to the constant movement of the environment and information coming from other intelligent agents;
- focus on existing knowledge - the further behavior of agents in achieving the goal is based on the previously laid down knowledge about the environment and recognition of the situation when making decisions;
- goal-setting and self-learning - the ability to accumulate knowledge, having a large amount of data in the form of a previously introduced base and a system of goals, behavior patterns and algorithms in unclearly specified conditions [21].

Thus, the role of the possibility of formalizing the input data in a clear or fuzzy way for building a functional model of a mixed type of the considered neural structures increases.

5 Conclusion

The indisputable advantage of agent-based models in solving technological and commercial problems allows them to be used in information systems to improve models of intelligent agents. This allows obtaining self-organizing and fault-tolerant intelligent information systems.

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