

Learning algorithm for an intelligent decision making system based on multi-agent neurocognitive architectures

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INTRODUCTION

The main fundamental problem of creating artificial intelligent decision-making systems is their inability to solve the unstructured tasks of the world on a par with humans.

The goal of the study is to develop an AI system that would have an architectural resemblance to the brain and in which the decision-making process is similar to human.

The task is to develop an algorithm for teaching intelligent decision-making systems based on self-organization of the invariant of multi-agent neurocognitive architectures.

The object of research is the process of learning intelligent systems.

The subject of research is the possibility of learning an intellectual system based on the invariant of multi-agent cognitive architectures.

1 Multi-agent neurocognitive approach to creating intelligent systems

The decision-making process by a person include: situational analysis and the synthesis of the solution.

Each of these stages is a cognitive function of the brain, which is defined as the highest mental function. In neuropsychological studies, it is noted that the brain, when implementing any mental function (including cognitive functions), works as a paired organ, i.e. involved distributed neural networks, which include many areas in both hemispheres of the brain.

These principles underlie the multi-agent neurocognitive approach to creating intelligent systems. In [1, 2], algorithms for constructing some cognitive functions based on multi-agent architecture are described.

An intelligent system based on a multi-agent neurocognitive architecture, consisting of software agents-neurons, we called an intelligent agent. The intelligent agent receives information from the external environment through the sensor system in the form of an event (1)

$$S_{trk}^j = \{N_i^j: N_i^j = \bigcup_{k=1}^n \nu(N_i^{j+1})\}. \quad (1)$$

In expression (1), the symbol N_i^j denotes agent, where i is the agent's name, j is the agent's type, symbol ν (Ain-function) denotes a functional relationship between agents that arises after they fill their valences and is called a multi-agent existential mapping.

The situation that occurred at the time t_k is recorded as a sequence of events (1) in the time interval $[t_s, t_f]$ with the corresponding emotional assessment ε_{tk} :

$$S_{trk}^{trf} = (S_{trk}^i \wedge S_{trk+1}^j \wedge S_{trk+2}^k \wedge \dots \wedge S_{trk}^l \wedge \varepsilon_{tk}). \quad (2)$$

Knowledge is written as (3)

$$k_i^{trf} = (S_{trk}^{trb} \wedge S_{trk}^{trf}, a_{trk}^{trf}), \quad \tau_a \leq \tau_b \leq \tau_c \leq \tau_d \leq \tau_f, \quad (3)$$

where S_{trk}^{trb} is the initial situation (cause), S_{trk}^{trf} is the final (desired) situation (consequence), a_{trk}^{trf} is the action.

Correlation coefficient:

$$b = \frac{V^{sp}}{V^s} = 1, \quad (4)$$

where V^{sp} is the positive events number, V^s is the total events number. Then, taking into account (4), (3) can be rewritten in the form

$$k_i^{trf} = \begin{cases} S_{trk}^{trb} \wedge S_{trk}^{trf}, a_{trk}^{trf}, b \geq 1, \\ S_{trk}^{trb} \wedge S_{trk}^{trf}, a_{trk}^{trf}, b < 1. \end{cases} \quad (5)$$

2 An invariant of the organizational and functional structure of the process of intellectual decision-making based on multi-agent neurocognitive architecture

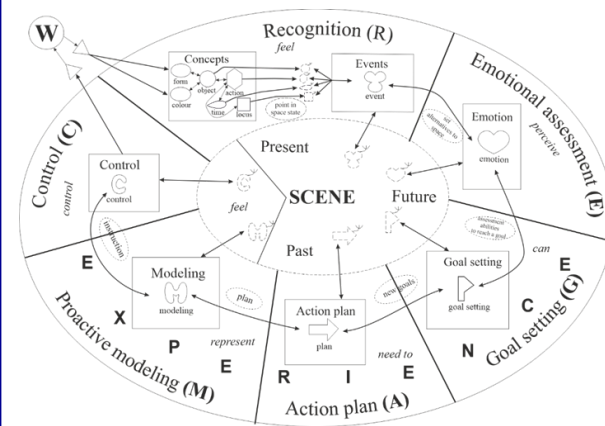


Fig. 1. Invariant of the organizational and functional structure of the intellectual decision-making process on the basis of multi-agent neurocognitive architecture

4 Software implementation of a self-learning intelligent agent

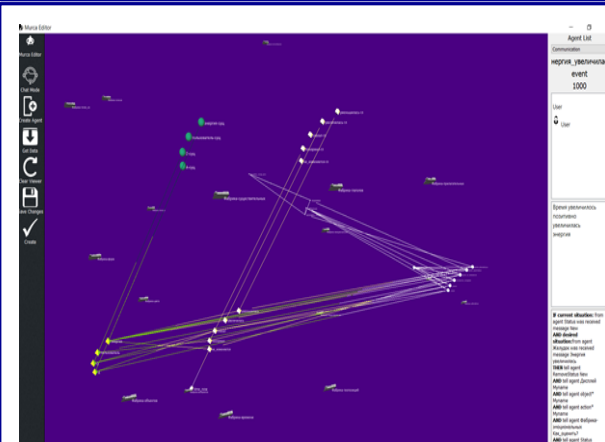


Fig. 3. Software implementation of an intelligent agent nutritional behavior

3 Training of an intelligent agent based on an invariant of neurocognitive architecture

The goal setting function of an intelligent agent is to maximize its energy to increase life expectancy. To monitor the energy level, knowledge about which is contained in the conditionally called agent Stomach, the interoceptor Sensor-stomach has been implemented, which signals changes in the energy value with a certain frequency. The neurocognitive architecture of an intelligent agent implements the ability to generate agents of different types on demand, using special actors, conventionally called Factories. The corresponding factories generate conceptual, emotional, goal setting, modeling, planning agents who ascertain the current situation, assess it, set goals, build a model to achieve this goal and control actions. As a result of the implementation of multi-agent contracts and the execution of the learning algorithm in the neurocognitive architecture of the intelligent agent, knowledge is formed, according to which the agent, in the event of a "hunger", will be able to signal this to the user and, having received energy, state "saturation".

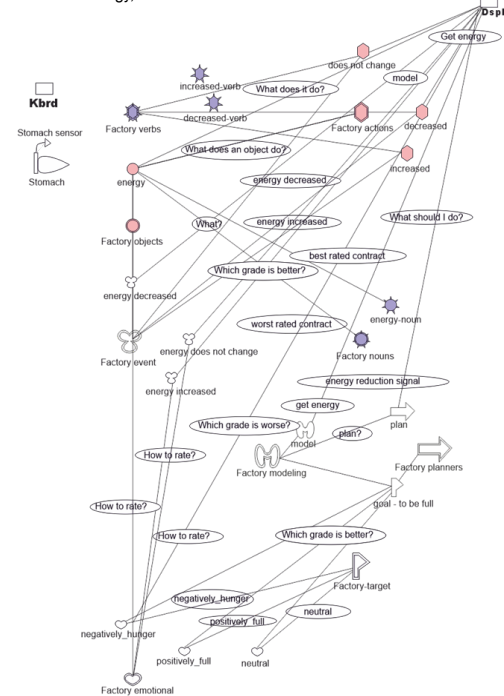


Fig. 2. Architecture of an intelligent agent learning process based on an invariant of neurocognitive architecture

CONCLUSIONS

1. The formalism of an intelligent decision-making system based on multi-agent neurocognitive architectures, which has an architectural similarity to the human brain, is presented.
2. An invariant of the organizational and functional structure of the intellectual decision-making process based on the multi-agent neurocognitive architecture is developed.
3. An algorithm for teaching intelligent decision-making systems based on the self-organization of the invariant of multi-agent neurocognitive architectures is presented. Using this algorithm, an intelligent agent was trained and the architecture of the learning process was built on the basis of an invariant of neurocognitive architecture.

ACKNOWLEDGMENTS & REFERENCES

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