Patterns in Cyber-Physical Systems

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Abstract A robotic cyber-physical object is an informationally connected set of physical components, onboard measurement systems, onboard executive systems, an onboard computer system with implemented control algorithms, and a control station with displays and controls. Such an object must have the self-sufficient behavior that guarantees the fulfillment of a certain mission. The behavior intellectualization requirement makes us reconsider the logical and mathematical abstractions that are the basis for building their onboard control systems. The problem of developing such systems based on pattern theory is relevant. It is shown that this ensures the effective experience transfer into a cyber-physical system and ensures the compatibility of the theological approach and the cause-and-effect approach. There are the identification and pattern model construction problems are considered. It is proposed to use four information processing points for this purpose, and a method of logical inference on patterns is developed.

Keywords Decision making · Purposeful systems · Fuzzy judgement · Choice situation · Cyber-physical system

1 Introduction

A cyber-physical object is an informationally connected set of physical components, onboard measurement systems, onboard executive systems, an onboard computer system, with implemented control algorithms, and a control station with displays

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and controls. Such an object must have self-sufficient behavior that guarantees the fulfillment of a certain mission. It is possible to achieve the desired increase in the effectiveness of such complexes in an undetermined and poorly formalized environment mainly by improving the intelligent component of their control system. However, it should be noted that the vast majority of research in this area remains at the theoretical level [1–10]. There is a gap between primitive behavioral models of artificial entities, for example, in swarm robotics, their interaction models, and expectations from practice [11–13].

By now, it has become clear that it is possible to achieve the desired sharp increase in the efficiency of robotic systems, mainly by directing designers' and scientists' efforts to improve the control system intelligent component: (1) a set of algorithms for onboard control systems; (2) algorithms for the activities of the crew that controls a cyber-physical system. These components form the "cooperative intelligence" of a cyber-physical system, which allows creating a functionally integral object from a set of separate systems of onboard equipment aimed at performing the task of the current session of a functioning robotic system.

An autonomous intelligent system (hereinafter referred to as an agent) showing human-like behavior is a system that includes the following components (Fig. 1):

- onboard measuring devices (or a set of onboard measuring devices) that function as sensors which allow obtaining information about the environment state and their own state;
- onboard execution units (or a set of onboard execution units) that function as effectors which help the system to affect the external environment and itself;
- means of communication with other systems;
- "onboard intelligence", which can include onboard computers, their software, as well as control center operators that are the carrier of a set of algorithms for solving problems of the subject area obtained due to training and experience

Such a system exists in time and space, interacts with other agents, with the environment when performing combat tasks and obligations using available mods

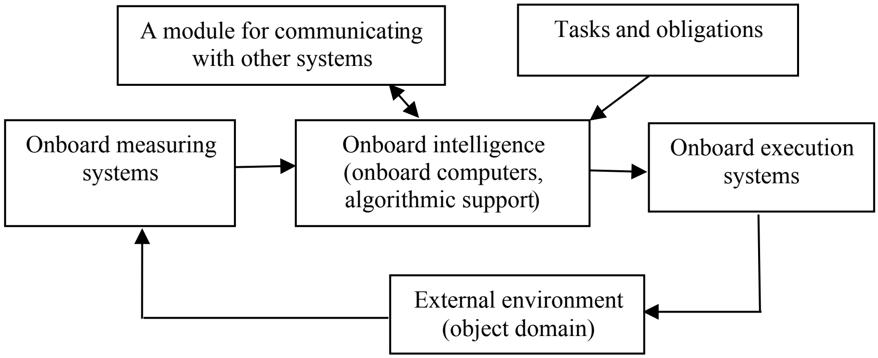


Fig. 1 An enlarged diagram of an intelligent autonomous system

of action. The agent performs the assigned tasks based on an understanding of his condition and subjective ideas about the state of the environment and the combat situation development, as well as the information received through a communication module. The agent is able to predict changes in the environment affected his actions and evaluate their usefulness.

2 Requirements for the Autonomy and Intelligence of Combat Cyber-Physical Systems

The role of automated systems when performing combat tasks should be considered from the standpoint of their impact on a human. They should help a commander by making his work easier and more efficient. At the same time, a commander must be an element of a control system (*human in the loop control*) of the cyber-physical system. Their interaction should ensure the experience transfer both from a human to the system and in the opposite direction, thereby providing the adaptive behavior. For example, the main difficulty for any autonomous system is the recognition of situations in the environment. The complexity and multiplicity of situations that arise during the mission performance make it impossible to identify them based on the results of multiple tests and form a knowledge base on their basis. Consequently, it is necessary to implement an additional monitoring scheme for the cyber-physical system to identify situation classes and successful modes of action in order to form behavioral models (patterns) based on data obtained in real conditions [14, 15]. This scheme guarantees a controlled evolution of self-sufficiency when solving tasks by combat units that include autonomous cyber-physical systems.

3 Initial Assumptions and Hypotheses

Usually, the situations that an autonomous system faces are difficult enough for their constructive formalization by traditional formal methods, but they are described well by natural language means. There also is their resolution experience and description, for example, by fuzzy logic means. The bearer of such experience is called a leader. Leaders share their experience through communication tools in the chosen language. Let us accept the hypothesis that human experience/behavior should be considered as a function of the interaction between a situation and a human. A situation can be interpreted as a component of the cause for its subjective reflection in a person. A person chooses a certain behavior based on a subjective representation of a situation, influences a situation, and changes it. At the same time, the processes occurring in a human mind when performing certain actions lead to expanding his ability structure (knowledge, experience). A cyber-physical system behavior model should also take into account this phenomenon of mutual influence. With this approach, the concept of "typical situation" (TS) turned out to be constructive [16, 17]. This part of a cyber-physical system operation is functionally closed and has a clearly defined meaningful purpose. It appears as a whole in various (real) sessions, being detailed in them according to the conditions and the available ways of resolving problematic sub situations arising in TS [11]. When a cyber-physical system is fully intellectualized, TS, and the modes of action form an individual behavioral pattern as a reaction to it. A person, while mastering his experience, also aims to aggregate it by creating pattern models. Therefore, a pattern model should be considered as a unit of human experience, for which a person has a certain degree of confidence in obtaining the desired states in a situation similar to a typical one (cluster). V. Finn has shown that an ideal intelligent system should have 13 types of abilities. At the present stage, only a part of these abilities can be implemented and only in interaction with a person. For example, "this is a product of the sequence "goal-plan-action", the ability to reflect, the ability to integrate knowledge, the ability to clarify unclear ideas, the ability to change the knowledge system when receiving new knowledge". He notes that it is impossible to exclude a person from this mode. Therefore, an intelligent system for military purposes cannot be completely autonomous and must be considered as a partner human–machine system with a pattern as the unit of knowledge.

Definition. A pattern is the result of the activity of a natural or artificial entity associated with an action, decision-making, its implementation, etc., which was carried out in the past and is considered as a template (sample) for repeated actions or as a justification for actions according to this pattern.

4 The Model of a Behavioral Pattern Fuzzy Description

Behavior in TS is associated with a choice that occurs in a purposeful state situation [12]. Let us consider a behavioral model in the form of a fuzzy description of a choice situation model. It is proposed to build a possible variant of such construction using "paradigm grafting" of ideas from other sciences, for example [12, 18]. A purposeful state consists of the following components:

- a subject who making the choice (agent), $k \in K$.
- choice environment (S), which is a set of elements and their essential properties, a change in any of which can cause or produce a change in a purposeful choice state. Some of these elements may not be system elements and form an external environment for it. The impact of the external environment is described using a set of variables.
- Available modes of actions $c_j^k \in C^k,\ \ j = \overline{1, n}$ of the k-th agent that are known to him and can be used to achieve the i-th result (also called alternatives). Each mode of this set has a set of parameters called control actions.
- Possible results for environment S that are significant for an agent—$o_i^k \in O^k,\ i = \overline{1, m}$. The results are assessed using a set of parameters called the output parameters of a purposeful state situation.

- A method for assessing the properties of the results obtained after choosing a mode of action. Obviously, the assessment of the result should reflect the result value for an agent and thus reflect their personality.
- Constraints reflecting the requirements imposed by the choice situation on output variables and control actions.
- A domain model, which is a set of relationships that describe the dependence of control actions, parameters, and disturbances with output variables.
- An agent constraint model. It is described in detail in [17]. Regardless of a constraint description type, we will assume that the agent has a certain degree of confidence about the possibility of changing a part of constraints towards expanding a set of possible choice options (alternatives).

For the described components, let us introduce measures to assess the purposeful state.

1. We will assume that the agent is able to distinguish factors that are environmental characteristics $X^k = \left\{ x_i^k,\ i = \overline{1, N}\right\}$. The agent evaluates the influence of each factor using a linguistic variable $\mu_x^k(x_i^k) : x_i^k \to [0, 1]$. Let us introduce a parameter for the agent to assess his situational awareness in a purposeful state situation

$$Es^k = \frac{\sum\limits_{i=1}^{N} \mu_x^k(x_i^k) x_i^k}{\sum\limits_{i=1}^{N} \mu_x^k(x_i^k)} \tag{1}$$

   We can define the following constraint:

$$\sigma^k(Es^k) \geq \sigma_0^k,$$

   where σ_0^k is a certain threshold level of agent's awareness due to using his own information sources.
2. We will assume that in order to describe the influence of the selected factors on the results $o_i^k,\ i = \overline{1, m}$, the agent uses an approximation in the form of the following production rules:
   If x_1 is A_{r1}^k and if x_2 is A_{r2}^k and … and if x_N is A_{rN}^k, then

$$o_i^k = f_{ir}^k(x_1, x_2, ..., x_N),\ \ r = \overline{1, R},\ \ i = \overline{1, m} \tag{2}$$

   where R is the number of production rules, r is the current production rule number, $o_i^k = f_{ir}^k(x_1, x_2, ..., x_N)$ is an explicit function that reflects the agent's idea of the causal relationship of input factors with possible results for the r-th rule; A_{ri}^k are fuzzy variables defined on $X^k = \left\{ x_i^k,\ i = \overline{1, N} \right\}$.
   Mathematical models, a verbal description, graphs, tables, algorithms, etc. might be used as a function $f_{ir}^k(\cdot)$.

Since c_j^k it is a function of the external environment state parameters taken into account and system properties, a set of assumptions about their possible values forms a scenario of the possible state of the external environment, the system functionality. The implementation of scenarios, for example, using the rules (2) allows forming an idea of possible results o_i^k. The ambiguity in choosing a mode of action might be described as the degree of confidence in the need to apply it to obtain a result o_i^k. This estimate can be described by the linguistic variable

$$\psi_j^k = \psi_j^k(c_j^k \in C^k | s_i \in S \to o_i^k) \in [0, 1].$$

This measure is an agent's individual characteristic, which can change after training and gaining experience, as well as a result of the communication interaction of agents with each other and with an operator. Therefore, $\psi_j^k = \psi_j^k(c_j^k \in C^k | s_i \in S, I^k \to o_i^k) \in [0, 1]$, where I^k is the information available to the agent at the time point t_k.

3. Choosing a mode of action c_j^k when the agent makes a decision in a purposeful state situation to achieve a result o_i^k is associated with building a quantitative assessment of the chosen solution properties, as shown in [12]. The list of properties and parameters is based on experience, knowledge, intelligence, and the depth of his understanding of a decision-making situation. A correct description of the properties and parameters of a mode of action is one of the main conditions for the choice c_j^k that will lead to the result o_i^k. The choice of the list of properties and their parameters that characterize them depends on the agent (his personality). Let us represent the possible results for a given environment for an agent's choice in the form $o_i^k \in \left\{ o_{ij}^k, j = \overline{1, J} \right\}$, where o_{ij}^k is a set of possible results when choosing the j-th mode of action, $i \in I$ is a set of results that the k-th agent takes into account. It's obvious that $o_{ij}^k = o_{ij}^k(s_i), s_i \in S$.
4. The value of the o_i^k results. Since $o_{ij}^k = o_{ij}^k(s_i)$ and $s_i = S(c_j^k)$, the value of the i-th type of result is estimated by the following linguistic variable $\phi_i^k(o_i^k(c_j^k)) \in [0, 1]$. The function $\phi_i^k(o_i^k(c_j^k))$ for the result o_i^k will be a monotonic transformation since $\phi_i^k(\cdot)$ it translates the range of the function $o_i^k(c_j^k)$ into the set of linguistic variable values. Since the base value of the linguistic variable corresponds to fuzzy variables, this transformation transfers the range of the function o_i^k into the range of the base fuzzy variables.

5 A Model for Choosing an Agent When Implementing a Pattern

The three linguistic variables $\mu_i^k(x_i^k)$, ψ_{ij}^k, E_{ij}^k introduced above form a model of the agent's ideas about the purposeful choice situation.

Since c_j^k it can be described in terms X_i^k and the agent has an idea of the dependence in the form of a rule base that links c_j^k the value of the possible i-th result o_i^k, it is possible to determine the value of the purposeful state by the i-th result o_i^k for the k-th agent according to the rule [6, 17]:

$$E\phi_i^k = \frac{\sum_{j\in J} \phi_{ij}^k(o_{ij}^k(c_j^k)) \cdot o_{ij}^k(s^k)}{\sum_{j\in J} \phi_{ij}^k(o_{ij}^k(c_j^k))}.$$

In a similar way, we can assess the purposeful state value for the k-th agent by the efficiency of the i-th type of result:

$$EE_i^k = \frac{\sum_{j\in J} EE_{ij}^k(o_i^k(c_j^k)) \cdot \psi_i^k(c_j^k)}{\sum_{j\in J} \psi_i^k(c_j^k)}.$$

The agent's assessment of the desirability of a purposeful state by the i-th result and the effectiveness of its achievement in a choice situation is given in the form of a linguistic variable [19]

$$\chi_{i1}^k = \chi_1^k(E\phi_i^k) \in [0, 1], \qquad \chi_{i2}^k = \chi_2^k(EE_i^k) \in [0, 1] \tag{3}$$

We can define the following restrictions:

$$\sum_i \chi_{i1}^k(E\phi_i^k) \geq \chi_1^0 \ \ and \ \ \sum_i \chi_{i2}^k(EE_i^k) \geq \chi_2^0$$

where χ_1^0 *and* χ_2^0 are the agent's expectations from the mission that reflect the balance between costs and achieve results o_i^k.

The model of the agent's choice situation in TS is the set of structural and functional properties that (in his opinion) the choice situation has and which affect his satisfaction or dissatisfaction with the situation.

There is another group of factors that determine the result implementation: will, risk proneness, self-esteem, motivation. These factors make it possible to talk about such an indicator as confidence $\rho_i^k(o_i^k)$ in obtaining a result o_i^k in a situation of choice when using one of the possible modes of action $c_j^k \in C^k$.

Based on the hypothesis of rational behavior, the agent forms a decision according to the rule

$$\begin{aligned}
&P_i^k(s \in S) = Arg \max_{c_j^k}(\sum_{j\in J} E\phi_i(o_i^k(c_j^k)) - EE_i^k(o_i^k(c_j^k))) \\
&c_j^k \in C^k(I_t^i), \ \ I_t^i \subseteq M, \ \ o_i^k \in O^k \\
&\sum_i \chi_{i1}^k(E\phi_i^k) \geq \chi_1^0, \quad \sum_i \chi_{i2}^k(EE_i^k) \geq \chi_2^0 \\
&\sigma^k(Es^k(X)) \geq \sigma_0^k
\end{aligned} \tag{4}$$

Since the choice is related to the agent's ideas about the choice situation, it is necessary to include the knowledge base (2) in (4).

The relations (4) describe the agent's (cyber-physical system) behavioral pattern when striving to achieve the i-th result. The agent considers (4) a pattern as a way of describing a problem, a principle, and an algorithm for its solution, which often arises, and its solution might be used many times without reinventing anything.

The value indicators of the purposeful state for the result $E\phi_i^k$ and the purposeful state value for the efficiency EE_i^k are elements of the integral value indicator of the purposeful state for the k-th individual $\sum_i E\phi_i^k \cdot EE_i^k$. Given his confidence degree in obtaining a result ζ_i^k, an expected specific value indicator will be the following:

$$EV_k = \frac{\sum_i (E\phi_i^k - EE_i^k) \cdot \zeta_i^k}{\sum_i \zeta_i^k} \quad (5)$$

This means that if two subjects are in the same situation of choice, then the difference in their behavior should be manifested in specific value estimates by the result and effectiveness and in the degree of confidence in achieving the goal.

The relationships (4–5) mean that when the agent wants to achieve some result, he has several alternative ways of achieving it with the methods of varying efficiency, and his confidence in obtaining the desired result is significant.

Such a model of autonomous agent's individual behavior supposes forming a knowledge base by learning based on experimental experience, which makes it possible to implement the "cooperative intelligence" evolution due to an artificial cognitive process similar to that of natural entities [1, 20]. It should be noted that this capability is absent in knowledge-based systems since it lacks a computer model of adaptive behavior. Thus, the general principles of the agent's reasoning are quite traditional and include the following three main phases (Fig. 2):

- Perception—receiving data and building a scene model in a loaded world;

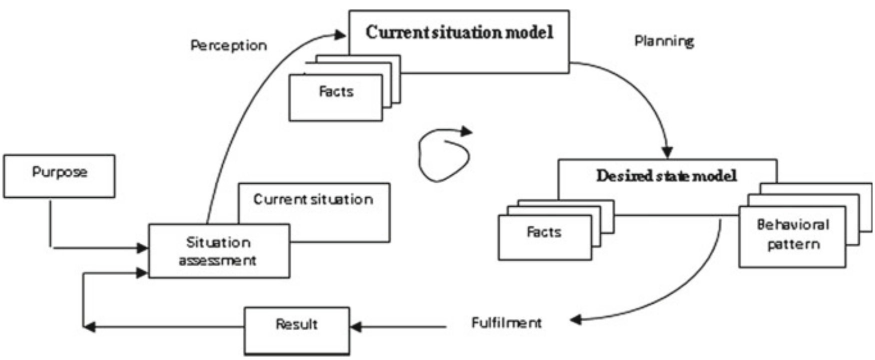


Fig. 2 The intelligent agent's reasoning scheme (TOTE model)

- Cognition—analysis and forming a scenario of the subject's actions to achieve the set goals;
- Execution of the intended scenario with a constant comparison of expected and observed results.

Unlike other similar systems, the system under consideration implements these phases through two basic mechanisms closely related to each other: abstraction and concretization.

6 Modeling Patterns. Basic Modeling Points

6.1 Modeling Patterns

Pattern modeling involves a limited natural language subset including modeling of case-based reasoning, which forms a specific part of human experience—meta-experience. To implement the described approach, there is a developed software system that allows modeling the environment (context) and the agent's behavior pattern from different points. We have selected four basic perception points for collecting and interpreting information in order to identify a behavioral pattern model. They are: the first point (a person's own point of view), the second point (situation perception from another person's point of view), the third point (situation perception from an uninterested observer's point of view), the fourth perception point implies considering the situation from the point of view of the involved system.

Since we assume that each point uses different visions of a situation and possible modes of action, the integration and coordination of viewpoints, allows the agent to expand his understanding of the purposeful state situation and a behavioral pattern.

Modeling from the first point assumes that a person with experience in fulfilling a mission implements it in the system independently and examines the pattern(s) used in this case. A testee shows his behavior by performing voice control of an "avatar" (see Fig. 3).

Rectangles and the way of their positioning on the avatar are shown in red. The disadvantage of this method is that the accuracy of object recognition decreases, but at the same time, this method saves hardware resources and time for calculating intersections. This scheme for determining intersections will be used similarly to implement a hit in a fire contact situation. A testee performs actions in accordance with the scheme shown in Fig. 4.

The implementation of the agent model visual function represents seeing objects through simple forms, for example, in this case, they are cubes and their vertices, as well as ignoring objects that are not of value to the model, for example, walls and others.

The eye is implemented as an empty object that is used as an endpoint for constructing a visual ray located at the head level. To be realistic, it will also be animated for the cases of head rotation during character animation.

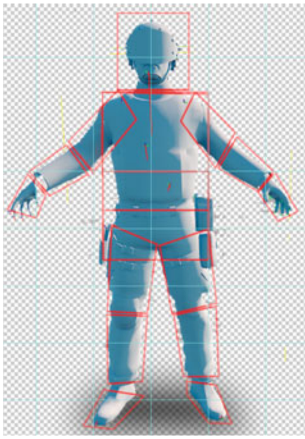
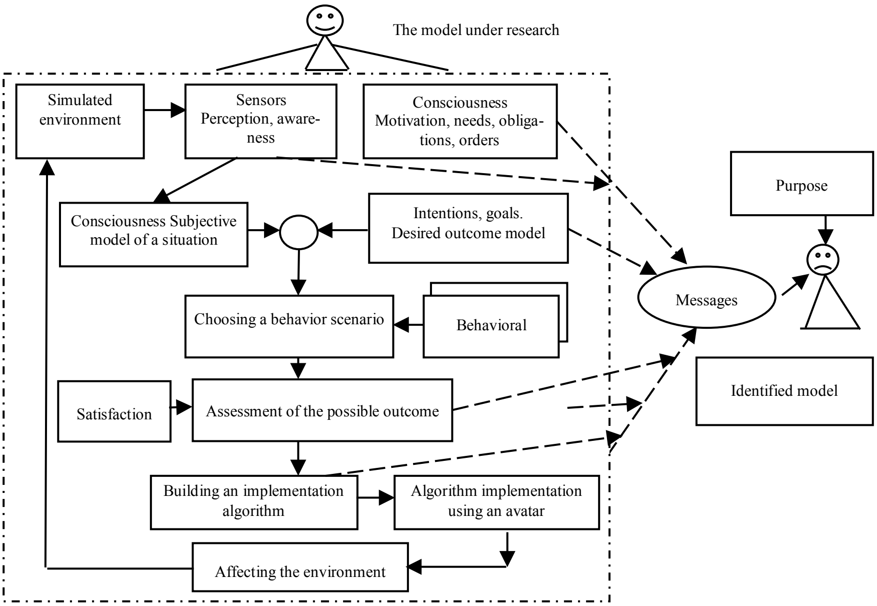


Fig. 3 A simplified representation of an avatar 3D model



These functions are for sorting, and therefore for speeding up object processing.

Fig. 4 A reflexive approach scheme for identifying a behavioral pattern from the first position is information flows

The entire visual part is reduced to 3 main functions:

1. determining whether the object is in sight;
2. determining the distance to the object;
3. constructing vectors from a simplified object model to an object responsible for the agent's eyes.

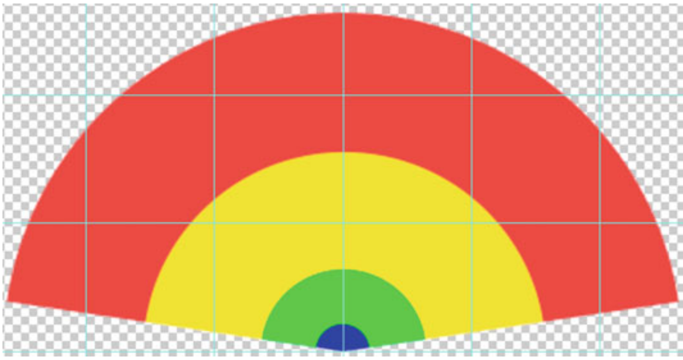


Fig. 5 The eye visibility scope

These functions are for sorting, and therefore for speeding up object processing.

6.2 The Function of Object Detection in the Eye Visibility Scope

The function makes it possible to see those objects that are in the eye visibility scope, thereby reducing the cost of detailed processing of all objects. A schematic implementation of the scope is shown in Fig. 5. The agent's location in the world is blue. The viewing angle is 120°.

6.3 The Function of Object Detection Within Eyesight

Another function for sorting objects and saving calculation time is an area divided into priorities (see Fig. 5).

Green is a high priority; objects in this area will always be selected. Now it is 20 m. Also in this zone, the objects will be named.

The yellow and red priority zones will be selected if there are no objects in the green priority zone. Now, these zones are 50 and 100 m, respectively.

In the future, it might be improved and in terms of time consumption, the objects that are located farther from the eye may require longer focusing time.

6.4 The Function of Object-Eye Intersection Detection

The function works on the principle of finding the intersection between the points of the rough object model and an “eye”. A ray is built between two points; if the ray hits an object, an “eye” does not see this point. If an “eye” sees at least one point of the object, then the entire object is visible.

The action pattern analysis is performed from the researcher’s point of view. It is important to emphasize that in order for the agent to describe already performed activities according to his own pattern (Fig. 4), the subject in question must leave his previous activity point and move to a new point that is external in relation to both already performed actions and the future projected activity. This is called the first level reflection: considering the agent’s previous position, his new point will be called the reflexive one, and the knowledge generated in it will be reflexive knowledge since it is taken in relation to the knowledge developed in the first point. The above reflexive output scheme will be the first abstract model characteristic of reflection in general.

The second position possibly assumes a full imitation of the agent’s behavior, when a researcher tries to think and act as close as possible to the agent’s thoughts and actions using the model obtained in the first point. This approach allows understanding at an intuitive level the essential but unconscious aspects of the modeled agent’s thoughts and actions, thus to refine a model. Modeling from the third point is to observe the modeled agent’s behavior as a disinterested observer. The third point assumes constructing a model of a mode of action from the point of view of a specific scientific discipline related to the agent’s subject domain. The fourth position presupposes an intuitive synthesis of all received ideas in order to obtain a model with maximum values of specific value indicators by a result and efficiency.

This approach involves implicit and explicit information. It is possible that the agent knows or understands the essence of some activity but is not able to perform it (conscious incompetence). Conversely, the agent is able to perform some actions well but does not understand the way to do them (unconscious competence). Having a perfect command of skill implies both the ability “to do what you know” and the ability “to know what you do”. Nevertheless, many behavioral and psychological elements that ensure the success of agents’ actions remain unconscious and only intuitive. As a result, they are unable to describe the mechanisms of any abilities directly. Moreover, some agents deliberately avoid thinking about what they are doing and how they are doing it due to fear that this knowledge will interfere with intuitive actions. Therefore, one of the modeling goals is to identify *unconscious competence,* and make it conscious in order to understand it better, improve and transfer a skill.

Cognitive and behavioral competences are modeled either “implicitly” or “explicitly”. *Implicit modeling* involves taking the second point in relation to the subject of modeling in order to achieve an intuitive understanding of the subjective experiences of a given person. *Explicit modeling* involves taking the third point in order to describe an explicit structure of the modeled agent's experience so that it can be transmitted to others. Implicit modeling is primarily an inductive process for accepting and perceiving the structures of the surrounding world. Explicit modeling is a deductive process for describing and implementing this perception. Both processes are necessary for successful modeling. Without an implicit stage, there can be no effective intuitive base for building an explicit model. On the other hand, without an explicit phase, the modeled information cannot be translated into techniques or means and be transmitted to others. Implicit modeling itself helps a person develop personal, unconscious skills in relation to the desired behavior (this is how young children usually learn). However, creating a technique, mechanism or skill that can be taught or transmitted to others, requires explicit modeling.

Experimental studies involved relatively simple behavioral and cognitive patterns models, for example, when controlling an autonomous underwater vehicle, assessing the combat readiness of special reaction forces, and others. The implementation of the proposed procedures has resulted in models with synthesized: (a) intuitive understanding of the agent's abilities, (b) direct observation of the agent's work, and (c) researcher's explicit knowledge in the agent's subject domain.

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References

1. Gorodetskii, V.I.: Self-organization and multiagent systems: II. Applications and the development technology. J. Comput. Syst. Sci. Intern. **51**, 391–409 (2012)
2. ACL—Agent Communication Language, https://fipa.org/specs/fipa00061/SC00061G.pdf. Last Accessed 19 01 2016
3. AgentBuilder—an integrated software toolkit that allows software developers to quickly develop intelligent software agents and agent-based applications, https://www.agentbuider.com. Last Accessed 19 01 2016.
4. Bernon, C., Gleizes, M.P., Peyruqueou, S., Picard, G.: ADELFE: a methodology for adaptive multi-agent systems engineering. In: Proceedings 3th Internship Workshop on Engineering Societies in the Agents World pp. 156–169 (2002)
5. Bonomi, F., Milito, R., Zhu, J., Addepalli, S.: Fog computing and its role in the internet of things. In: Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing (MCC 2012), pp. 13–16. NY, USA (2012)
6. Burrafato, P., Cossentino, M.: Designing a multi-agent solution for a bookstore with PASSI methodology. In: Giorgini, P., Lesperance, Y., Wagner, G. Yu, E. (Eds). Proceedings of Conference on Agent-Oriented Information Systems Intern 119–135 (2002)
7 Caire, G., Coulier, W., Garijo, F.J., Gomez-Sanz, J.J. (2002). Agent oriented analysis using MESSAGE/UML. In: Eds Agent-Oriented Software Engineering II 2222, pp. 119–125. Springer-Verlag LNCS
8. Cohen, P., Levesque, H.: Teamwork. Nous **25**, 487–515 (1991)
9. Cougaar Agent Architecture, https://cougaar.org/wp/documentation/tutorials/. Last Accessed 19 Jan 2016

10. Deloach, S.: Analysis and Design using MaSE and agentTool. In: Proceedings 12th Midwest Artificial Intelligence and Cognitive Science Conference on (MAICS). Miami University Press (2001).
11. Fedunov, B.E.: Constructive semantics for developing onboard intelligence algorithms for anthropocentric objects. J. Comput. Syst. Sci. Intern. **5** (1998)
12. Vinogradov, G.P.: Modeling decision-making by an intelligent agent. Softw. Syst. **3**, 45–51 (2010)
13. Vinogradov, G.P., Kuznetsov, V.N.: Modeling client behavior considering subjective ideas about the situation of choice. Artif. Intell. Decision-Making **3**, 58–72 (2011)
14. Deloach, S., Garcia-Ojeda, J.: The O-MaSE Methodology. In: Cossentino, M., Hilaire, V., Molesini, A., Seidita, V. (eds.) Handbook on Agent-Oriented Design Processes, 253–285. Springer-Verlag, Berlin-Heidelberg (2014).
15. Filatova, N., Bodrina, N., Sidorov, K., Shemaev, P., Vinogradov, G.: Biotechnical System for the study of processes of increasing cognitive activity through emotional stimulation. In: Kovalev, S., Tarassov, V., Snasel, V., Sukhanov, A. (eds.) Proc. 4th International Scientific Conference on IITI'19. Advances in Intelligent Systems and Computing, 1156 pp. 548–558. Springer Nature Switzerland AG 2020 (2020).
16. Zadeh L.: The concept of a linguistic variable and its application to approximate reasoning. Inf. Sc. **8**, 199–251, 301–357 (1975); **9**, 43–80 (1976)
17. Borisov P.A., Vinogradov G.P., Semenov N.A.: Integration of neural network algorithms, nonlinear dynamics models, and fuzzy logic methods in prediction problems. J. Comput. Syst. Sci. Intern. **1**, 78–84 (2008)
18. Dilts, R.: Modeling with NLP. Meta Publ. (1998).
19. Vinogradov, G.P.: A subjectve rational choice. JPCS **803**, 012176 (2017)
20. Gorodetskii, V.I.: Self-organization and multiagent systems: I. Models of multiagent self-organization. J. Comput. Syst. Sci. Intern. **51**, 256–281 (2012).