Patterns in Intelligent Systems

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Abstract

One of the most important directions in control theory is the development of the theoretical foundations for creating artificial entities capable of acting autonomously. A number of IEEE standards formulates the requirements for such systems. Such object should have the property of self-sufficient behavior that guarantees the fulfillment of some mission. A number of papers note the existence of a gap between the developed behavioral and interaction models of artificial entities based on the theory of multi-agent systems, distributed artificial intelligence, swarm robotics, and practical expectations. The gap and the requirement of autonomy and intellectualization of artificial entities' behavior make us to reconsider logical and mathematical abstractions in the basis of their onboard control systems. The paper proposes a solution to the problem of constructing such systems based on the pattern theory. It shows the implementation of effective experience transfer and the compatibility of the theological approach and the causal approach. The paper considers the problems of identification and construction of pattern models. It proposes to use four positions of information processing for these purposes and describes the developed method of logical inference based on patterns.

Keywords 1

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1. Introduction

A subject domain with a general name "autonomous intelligent systems" becomes leading among various fields of applying artificial intelligence methods. It was believed that the multi-agent system (MAS) theory and agent-based modeling [4, 5, 6] would be a theoretical basis capable of integrating the achievements of various fields when creating such systems. It has been affirmed that there was a possibility of creating so-called "autonomous agents" that can be integrated into systems capable of solving complex problems jointly. An agent was considered as "an entity that receives data in some environment"; the data reflected "events occurring in the environment, interprets them and executes commands that affect the environment" [15]. Naturally, there were works with the attempts to use MAS results, for example, when developing cyber-physical objects (CPO), which are an information-related set of physical components, onboard measuring systems, onboard executive systems, an onboard computer system, and a control point with an information control field. The requirements for such objects include the self-sufficient behavior property that guarantees the fulfillment of a certain mission in an uncertain and poorly formalized environment. The implementation of agents with declared properties in them would create the possibility of a sharp increase in efficiency by improving an intelligent component of their control system: 1) algorithms of onboard CPO control systems; 2) algorithms of operators who control a CPO. Together, they form the CPO "business intelligence" [1, 2, 3], which ensures the execution of missions according to its functional purpose. However, it should be noted that the overwhelming number of studies in this area remains at the theoretical level. There is a gap between primitive

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behavioral models of artificial entities (for example, in swarm robotics), their interaction models and practical expectations [15, 16]. This is due to the computational complexity problems in the practical implementation of the rational action theory provisions in systems consisting of many selfish agents and agents capable of cooperation.

2. The requirements for the autonomy and intelligence of cyber-physical systems

The main difficulty for any autonomous intelligent system is the fact that with the expansion of its application areas, the number of possible situations in which it may be expands dramatically. Uncertainty, poor environment structuredness and the multiplicity of situations that arise during a mission make it impossible to identify them based on the results of multiple tests and to form a complete rule-based knowledge base. The task of identifying and developing a knowledge base for fulfilling a mission in possible situations becomes immeasurable. Recent advances in deep learning only partially dismantle this problem, since they require a certain number of repetitions of the identified situation. A person not only identifies it, but also “analyzes” its, forms and uses the so-called patterns, which dramatically increases the efficiency of the learning process and knowledge extraction [16]. As a result, human knowledge is characterized by internal interpretability, structuredness, and coherence, which is the basis for the ability for purposeful behavior.

The role of CPO in performing tasks should be considered from the point of their impact on a person. They should help him by making his work easier and more efficient. At the same time, a person must be an element of the control system (human in the loop control). Their interaction should ensure experience transfer both from a human to a machine and in the opposite direction, thereby ensuring adaptive behavior. This assumes the research and development of systems containing the so-called “business intelligence”. It is necessary to implement an additional monitoring scheme for a cyber-physical system to identify classes of situations and successful modes of action quickly to form effective behavioral models (patterns) based on real data. This scheme might guarantee a controlled evolution of self-sufficiency when solving tasks, for example, by combat units that have autonomous robotic systems.

3. Initial assumptions

The technology of using CPO assumes the development of at least three systems when solving the problem of their “intellectualization” [7]:

- off-board intelligent systems for preparing the CPO for the current combat mission, which should: a) ensure that all the information necessary for the successful completion of the session (goals, tasks, maps, communication algorithms, adjustment receiving methods, etc.) is transferred on a CPO board; b) training of a robotic system escort crew;
- onboard intelligent control systems that ensure mission fulfillment in the autonomous mode;
- intelligent systems for analyzing CPO session results. The results of their work are the basis for accumulating an effective and up-to-date pattern base, as well as for forming requirements for the CPO functional and hardware components.

When developing onboard intelligent control systems, the concept of “typical situation” (TS) turned out to be constructive. A typical situation is a functionally closed part of the CPO work with a clearly defined meaningful purpose, which appears in various (real) sessions as a unit, being detailed in them according to the conditions and by the available ways of resolving problematic subsituations arising in a TS [3, 7, 8, 9, 14].

Typically, an autonomous system faces situations that are difficult for their constructive formalization using traditional formal methods, but they are well described by natural language means and there is experience of their best resolution by humans. The one who has the best experience is called a leader. Leaders' experience is shared through communication tools in the chosen language.

Let us accept the hypothesis that human experiences/behavior should be considered as a function of the interaction between a situation and a human. The purposeful action of a human depends both on situation signs and on his personality traits (motivation degree, the structure of abilities, knowledge, etc.). A situation can be interpreted as a component of the cause that creates a subjective reflection of it in a human. When a human chooses a certain behavior based on a subjective representation of a situation, he affects the situation by changing it. At the same time, the processes occurring in a human conscience when performing certain actions lead to the extension of his ability structure (knowledge, experience). That is, the stable human traits manifested in his actions through behavior and experiences can influence the situation by changing it. Conversely, a situation can reversely affect a human stable traits when he changes his values, norms, modes of action and experience while interpreting a situation. An agent's behavioral model should also take into account this phenomenon of mutual influence of a robotic system and a situation.

Certain cognitive models of purposeful actions regulate the activity. These models include an idea of the time sequence of performing certain types of actions. The agent purposefully affects the objects of the environment by implementing modes of action. The basis for developing modes of action are agent's subjective ideas about a purposeful state situation [10]. We will assume that the observed agent’s activity is a function of the programs developed by him, which in turn are the result of his inherent cognitive processes and which serve to fulfill the assigned tasks or to achieve the desired results with varying degrees of efficiency. Thus, the activity plan and its implementation is an internal programming product. Its result is a program (algorithm) of actions that uses the operations available to the agent. It allows the agent to transform an observed situation into a desired (target) one through its implementation. The person evaluates the feasibility of a created algorithm with the linguistic variables “conviction” and “efficiency”. 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). Pattern modeling is performed with a limited natural language subset including case based reasoning, which forms a specific part of human experience – meta-experience. The problem of identifying these programs should be solved by analyzing language patterns and non-verbal communication. The implementation of CPO intellectualization should involve its inclusion in the activity and agreeing with an operator. With the complete CPO intellectualization, TS and the modes of action, as a reaction to it, form an individual behavioral pattern.

Definition. A pattern is a result of the activity of a person (group of people) associated with an action, making a decision, behavior, etc., carried out in the past, and considered as a template (sample) for repeated actions or as a justification for actions according to this template. In other words, thanks to a pattern mechanism in the mode of perception and thinking simultaneity, patterns existing in nature and society are revealed. This is a behavior project, in contrast to a precedent that is considered a way of behavior as a reaction to a situation or a case [ru.wikipedia.org]. A person, while mastering his experience, aims to aggregate it by creating pattern models.

4. A fuzzy description of a behavior pattern model

In [8] it is shown that a human makes a choice based on subjective ideas about the situation of choice and when he is characterized by the so-called purposeful choice state. This section discusses how a person builds a subjective representation model and assesses his awareness degree based on the processes of perception, awareness and understanding, how he connects understanding a situation with a motive, determines a behavioral goal and a model for choosing a behavioral pattern. The material in this section is based on the papers [8, 12, 13, 17].

The purposeful state consists of the following components:

- A subject making a choice (agent), $k \in K$.
- A choice environment (S), which is many elements and their essential properties, a change in any of which can cause or produce a change in the state of a purposeful choice. Some of these elements may not be system elements and form the external environment for it. The impact of the external environment is described using variables, some of which can remain unchanged over a certain time interval T, and some can change. The first type of variables is called parameters, and the second one is perturbations. Values of both types of variables are generally considered to be independent of an agent.

- Available modes of action $c_j^k \in C^k, j = \overline{1,n}$ of the k-th agent, which are known to him and can be used to achieve i-th result (also called alternatives). Each mode of this set is characterized by a set of parameters called control actions.
- Possible results for S environment that are significant for the agent $o_i^k \in O^k, i = \overline{1,m}$. The results are estimated using the output parameters of a purposeful state situation.
- The method of estimating the properties of the results after choosing a mode of action. Obviously, result estimates should reflect the value of the result for an agent and thereby reflect its personality.
- Constraints reflecting the requirements imposed by a situation of choice on output variables and control actions.
- A domain model that is a set of relations describing the dependence of control actions, parameters and disturbances with output variables.
- An agent constraint model that is described in detail in [14]. Regardless of the type of description of restrictions, we assume that an agent has a certain degree of confidence about the possibility of changing a part of restrictions by expansion of a set of possible options (alternatives) of choice.

Let us denote U as a set of control parameters, P – a set of parameter vectors, Ω – a set of external disturbance vectors. The model of the purposeful choice state situation is described by F as follows:

$$\mathrm{F} : \mathrm{U} \times \mathrm{P} \times \Omega \to \mathrm{O}, \tag{1}$$

The relation (1) is a domain model, which is the basis of the agent's idea on the control object operation.

Let us introduce measures for the described components that will be used to estimate a purposeful state.

1. We assume that the agent is able to distinguish factors – environmental characteristics $Z^k = \{x_i^k, i = \overline{1,N}\}$. The agent assesses the influence of each factor using a linguistic variable, the influence degree of the factor $\mu_x^k(x_i^k): x_i^k \to [0,1]$. We introduce a parameter for the agent to assess its situational awareness in a purposeful state situation

$$Es^k = \frac{\sum_{i=1}^{N} \mu_x^k(x_i^k) x_i^k}{\sum_{i=1}^{N} \mu_x^k(x_i^k)}.$$

We can define the following restriction:

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

where σ_0^k is some threshold level of agent's awareness from the using its own information sources.

2. We assume that to describe the influence of the selected factors on the results $o_j^k, i = \overline{1,m}$, the agent uses 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

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

where R is the number of production rules, r is the current production rule number, $o_i^k = f_{ir}^k(x_1, x_2, \dots, x_N)$ is an explicit function that reflects agent's idea of a causal relationship of input factors with possible results for the r-th rule; A_{ri}^k are fuzzy variables defined on $Z^k = \{x_i^k, i = \overline{1,N}\}$.

Mathematical models, a verbal description, graphs, tables, algorithms, etc. can be used as $f_{ir}^k(\cdot)$ function.

Since c_j^k is a function of the external environment state parameters, system properties taken into account, 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 the possible results o_i^k. The ambiguity in choosing a mode of action can be described as the degree of certainty of the need for its application to obtain the result o_i^k. This estimate can be described by a linguistic variable $\psi_j^k = \psi_j^k\left(c_j^k \in C^k \middle| s_i \in S \to o_j^k\right) \in [0,1]$.

This is an agent's individual characteristic, which can change after training and gaining experience, as well as after the communication interaction of agents with each other and with an operator. Therefore, $\psi_j^k = \psi_j^k\left(c_j^k \in C^k \middle| s_i \in S, I^k \rightarrow o_j^k\right) \in [0,1]$, where I^k is the information that the agent has at the time t_k.

3. When an agent makes a decision in a purposeful state situation to achieve a result o_j^k, the choice of a mode of action c_j^k is associated with constructing a quantitative estimation of the properties of a chosen solution, as shown in [6, 14]. The list of properties and parameters is based on experience, knowledge, intelligence and how well it understands a decision-making situation. The correct description of the properties and parameters of the mode of action is one of the main conditions for the choice c_j^k to lead to the ac result o_j^k. The choice of a list of properties and parameters depends on the agent (its personality). This is the agent's contribution to the decision-making process.

Let us imagine the possible results for agent's choice environment is given in the form $o_j^k \in \{o_{ij}^k, j = \overline{1,J}\}$, 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 taken into account by the k-th agent. It's obvious that $o_{ij}^k = o_{ij}^k(s_i), s_i \in S$.

4. The value of the results o_i^k. Since $o_{ij}^k = o_{ij}^k(s_i)$, and $s_i = S(c_j^k)$ $s_i = S(c_j^k)$, the value of the i-th type of the result can be estimated by the following linguistic variable $\varphi_i^k\left(o_i^k\left(c_j^k\right)\right) \in [0,1]$. The function $\varphi_i^k\left(o_i^k\left(c_j^k\right)\right)$ for the result o_i^k will be a monotonic transformation, since $\varphi_i^k(\cdot)$ translates the range of the function $o_i^k\left(c_j^k\right)$ into the set of values of the linguistic variable. Since fuzzy variables correspond to the basic value of the linguistic variable, this transformation transfers the range of the function o_i^k to the range of basic fuzzy variables.

5. The effectiveness of the mode of action in terms of the result is the confidence that this result is obtained by this mode of action at known (or assumed) costs of its implementation. The confidence degree E_{ij}^k that a certain mode of action c_j^k will lead to a result o_j^k in the environment S if the agent chooses it is the following: $E_{ij}^k = E_{ij}^k\left(o_i^k \middle| A \text{ choses } c_j^k \text{ in } S\right) \in [0,1]$.

It is a linguistic variable and expresses an agent's individual assessment of choice consequences in terms of costs.

5. Agent's choice model [17]

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

Since c_j^k can be described in X_i^k terms and the agent has an idea of dependence as a rule base that links c_j^k and the value of the possible i-th result o_i^k, it is possible to determine the value of a purposeful state by the i-th result o_i^k for the k-th agent according to the rule [6, 14]:

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

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

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

The agent evaluates the desirability of a purposeful state according by i-th result and the effectiveness of its achievement in a situation of choice is given in the form of a linguistic variable

$$\chi_{i1}^k = \chi_1^k\left(E\varphi_i^k\right) \in [0,1], \chi_{i2}^k = \chi_2^k\left(EE_i^k\right) \in [0,1]$$

The validity of this statement corresponds to the definition introduced by Zadeh [11] about the types of fuzzy sets. According to that definition, a fuzzy set is a set of type *n*, *n* = 1, 2, 3, ..., if the values of its membership function are fuzzy sets of type *n*-1.

We can define the following restrictions:

$$\sum_i \chi_{i1}^k \left(E\varphi_i^k\right) \geq \chi_1^0 \; and \; \sum_i \chi_{i2}^k \left(EE_i^k\right) \geq \chi_2^0$$

where χ_1^0 and χ_2^0 are agent's expectations of a mission, which reflect the balance between costs and results o_i^k.

Since s_i is a function of the awareness of the *k*-th purposeful agent $s_k = s_k(I_k)$ and there is an iterative procedure for exchanging views between agents, the following assumption is true:

$$I_{t+1}^k = \omega[\omega_k] I_t^k \tag{3}$$

where t is an iteration number during interactive formation of a consistent forecast. This is an assumption about growing awareness of the k-th agent depending on an iteration number. ω is an iterative mapping (generally point-multiple), so that at the initial awareness level I_0^k, any sequence generated by the inclusion $I_t^k \subseteq I_{t+1}^k$ will be bounded and all its limit points are in $M \subset R^n$. This assumption is valid due to the fact that an agent forms a certain stable point of view during communication and analysis. A parameter σk shows agent's ability to take new points of view and to review the awareness structure. The introduction of this parameter allows causing the transformation of the agent's choice situation model through producing a change in one or more components or representation parameters during communication or interactive interaction.

Thus, the contribution of a purposeful agent to the situation of choice is shown:

In evaluating a significance degree of $\varphi_i^k(x_i^k)$ situation factors and through them a situation awareness in the form (3).

In evaluating the value of results $o_i^k - \varphi_i^k(o_i^k)$.

In evaluating the admissibility of applying the *j*-th mode of action to achieve the *i*-th result $\psi_j^k(c_j^k)$.

In evaluating the effectiveness $E_{ij}^k(c_j^k)$ of achieving the result o_i^k by the *j*-th mode of actionc_j^k, which help the agent to estimate its own costs of achievement of the result.

The first and the fourth groups of estimates reflect agent's knowledge of a subject domain, the level of its various training types (skills, etc.).

The second and third groups allow describing agent's value system and evaluating a congruence degree of agent's and system values, which largely determine the its performance.

The model of agent's choice situation is a set of structural and functional properties that belong to the choice situation and affect its satisfaction or dissatisfaction with a situation, according to its beliefs.

There is another group of factors that determine the implementation of a result. They include will, risk appetite, self-esteem, motivation. Taking these factors into account, we can talk about such indicator as confidence in obtaining a result o_i^k in a situation of choice $p_i^k(o_i^k)$ when using one of the possible mods of action $c_j^k \in C^k$.

According to the hypothesis of rational behavior, the agent forms a decision:

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

Since the choice is related to agent's ideas about the choice situation, it is necessary to include the knowledge base (3) in (4).

Relations (4) describe agent's behavior pattern (cyber physical system) when striving to achieve *i*-th result. An agent considers (4) as a pattern, i.e. a way of describing a problem, its solution principle and algorithm. A solution for such problem might be used many times without reinventing anything.

The above characteristics assume that assessing the factor influence degree, the degree of confidence in the need to choose a mode of action, the value of a result, the effectiveness of a mode of action for each result are four personality (individuality) indicators. All other characteristics are derived from them by known methods of the theory of fuzzy sets.

The above indicators: a purposeful state value by the result $E\varphi_i^k$ and a purposeful state value by efficiency EE_i^k – are elements of an integral indicator of a purposeful state value for k-th individual $\sum_i E\varphi_i^k \cdot EE_i^k$. Taking into account its degree of confidence in obtaining the result ζ_i^k, an indicator of the expected specific value is the following:

$$EVk = \frac{\sum_i (E\varphi_i^k - EE_i^k) \cdot \zeta_i^k}{\sum_i \zeta_i^k} \tag{5}$$

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

The purposeful state of a purposeful agent has the following characteristics:

the agent is in a selection state: U(•) > 0;

there is at least one potential result o_i^k; if there are other potential results, then their purposeful state values by a result are not equal;

for an agent, there are at least two potential modes of action $c_1^k \; and \; c_2^k$ such that $\psi_{i1}^k > 0 \; and \; \psi_2^k > 0$;

the effectiveness of the modes of action $c_1^k \; and \; c_2^k$ is such that the sum of the estimates of purposeful state values by the effectiveness of obtaining results o_i^k in these two ways are not equal $\sum_i EE_{i1}^k(o_i^k(c_1^k)) \neq \sum_i EE_{i2}^k(o_i^k(c_2^k))$.

There is at least one potential result o_i^k with a value greater than a certain threshold value φ_i^{k0} for an agent, and its degree of obtaining confidence is also higher than a certain threshold value ζ_i^{k0}.

These rules mean that there is an agent wanting to get some result. For this purpose, it has several alternative ways of achieving it with different effectiveness, and its confidence in obtaining the desired result is significant.

6. An approach to identifying anв building a pattern model

There is a developed software system for implementing the described approach. The system allows modeling the environment (context) and an agent' (leader's) behavioral pattern from different points. We have identified four basic perception positions 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 of 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 position is that a person who has experience in fulfilling a mission implements it in the system independently and explores the pattern used in this case. The subject realizes his behavior by performing voice control of the "avatar" and performs actions in accordance with the scheme in which the context of the implementation of his pattern is reproduced. The analysis of the results of the action pattern is carried out from the point of view of the researcher, who takes a first-level reflective position. The knowledge generated in it will be reflective knowledge, since it is taken in relation to the knowledge developed in the first position.

Modeling from the first point assumes that a person with experience in fulfilling a mission implements it in the system independently and examines a pattern used in this case. A testee shows his behavior by performing voice control of an “avatar” and performs actions in accordance with the scheme with the implemented pattern context. The action pattern results are analyzed from the researcher’s point of view, who takes a first-level reflective point. The generated knowledge will be reflective knowledge, since they are taken in relation to the knowledge developed in the first point.

The second position possibly assumes a full imitation of 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.

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 a 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 fearing that this knowledge will interfere with intuitive actions. Therefore, one of the modeling goals is to identify *unconscious competence* and make it to conscious in order to understand it better, improve and transfer a skill.

Modeling from the third point assumes constructing a pattern model from the point of view of a specific scientific discipline related to the agent’s subject domain. Cognitive and behavioral competence are modeled either implicitly or explicitly. *Implicit modeling* involves taking the second point in relation to the subject of modeling in order to achieve intuitive understanding of subjective experiences of a given person. *Explicit modeling* involves taking the third point in order to describe the modeled agent’s experience of a specific scientific discipline. Implicit modeling is an inductive process for specific situations to be integrated into a pattern structure. Explicit modeling is a deductive process for modeling behavior in specific private situations using a pattern. 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 translate into techniques or means and be transmitted to others.

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.

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.

7. Conclusion

Intelligent technologies that use the pattern theory have significant prospects since they solve computational complexity problems. The presented formal model of a behavioral pattern for the autonomous object control system describes the mechanisms for forming subjective representations and assessments of choice situation components, a choice model that takes into account motives and obligations. It is shown that building a model involves identifying the carrier of the most successful behavioral model (leader). Obtaining and analyzing information for identifying a model is based on four points of its perception and extraction. Information collecting is based on active experimentation. Processing the results involves the synthesis of: a) an intuitive understanding of the agent's abilities, b) direct observation of the agent's work, c) the explicit knowledge of the researcher in the subject area of the agent. The described approach was used when designing a control system for a group of autonomous unmanned underwater vehicles for performing search and rescue missions.

Processing the results involves the synthesis of: a) intuitive understanding of the agent's abilities, b) direct observation of the agent's work, c) researcher’s explicit knowledge in the agent's subject domain. The described approach has been used to design a control system for a group of autonomous unmanned underwater vehicles for performing search and rescue missions.

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