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Digital Ecosystems: Interconnecting Advanced Networks with AI Applications

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Current Opportunities and Prospects of Artificial Intelligence in Evolutionary Development

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Abstract. The current possibilities of using artificial intelligence (AI) systems in various fields of human activity are considered. Some problems with AI systems that require further research are shown. A presentation of the development of AI systems from initial structures to highly organized systems with distributed parameters is given. Examples of AI systems at medium levels of organization relevant for practical implementation are presented. The regularities of the organization of technical systems in solving specific problems in practice are determined. Directions for increasing the intellectual level of the systems being created are noted. The prospects for the development of AI systems are presented.

Keywords: Artificial intelligence · Organization of control system · Automation · Intellectualization · Man-machine systems

1 Introduction

The evolutionary development of biological systems provides the main ways to create artificial intelligence in technical devices. The breakthroughs for the implementation of artificial intelligence in the last decade were deep learning techniques and the ability to work with large databases [1–3]. The creation of practical systems with elements of intelligence goes from systems for simple tasks of inference of decisions and purposeful actions to systems for making complex decisions in non-deterministic and non-stationary environments. When creating effective control systems for practical tasks, the presence of a developed intellect is not always required. Making current decisions can be vital and require quick reactions without taking all situational conditions into account. There is an

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optimal level of intelligence for each organization under a variety of external temporal and spatial conditions of existence. However, if the scope of these conditions is expanded, the introduction of intelligence elements into the system can be of significant importance [4, 5].

The most general fundamental idea of consideration is the anthropic concept of the organization of control systems, which consists in the requirement of functional similarity between the developed systems and the control systems of biological organisms and humans. In this case, it is the similarity in the functional sense that stands out, and the issues of technical element-by-element implementation are relegated to the background [6].

Another fundamental idea is the target conditionality of information transformations, including preliminary processing of the characteristics of the object and the environment, obtaining a forecast of the current situation, and searching for a possible solution. Target conditionality implies the presence of a generalized target space for the characteristics under consideration.

The proposed consideration is aimed at the phased implementation of the ability to comprehensively perceive information about the outside world, the ability to generalize observations, to establish patterns, to forecast, and to take purposeful actions and movements.

The purpose of the review is to present the foundations of the methodology for the organization of man-machine and automatic control systems that operate under conditions of uncertainty and conflict. The proposed methods and technologies of the organization include: determining the essential characteristics for a specific practical task of managing dynamic objects; building realistic models of decision-making and control processes; and generating behavior strategies [7, 8] (on the examples of developing target information and control systems for advanced aviation, sea, and land vehicles).

The specific features of this methodology are defined as follows: [6, 8]. The control process is considered discrete or situational. The intervals of discreteness are determined by the goal-achieving interaction of the object and the subject of control, as well as the influence of the external environment. In this case, usually the most significant influence on the discreteness of the control process is exerted by the human operator and, accordingly, his characteristics and practical experience. The next significant reason for the discreteness of the control process is the presence of noise components in the control object and the environment. The third factor, in terms of the degree of influence on the discreteness of the control process, can be considered the inaccuracy of the initial and current data on the characteristics of the object and the control environment. A specific feature of this methodology is that it also takes into account the interaction between a person and a control object, even if a fully automatic control system is considered. At the same time, automatic control is organized taking into account the ideas of a person about a possible control process and the experience of his work, taking into account the possibilities of monitoring and correcting the decisions obtained. Thus, the solutions obtained directly or indirectly correlate with the requirements of a person and the necessary information characteristics of management processes. Also essential in the development of individual optimal systems are individual targets and human experience in the management process.

2 A Brief Review of Promising Trends in the Modern Development of Artificial Intelligence Systems

The rapid development of AI systems over the past decade is associated with increased technical capabilities for sufficiently fast processing of large amounts of information and access to various digital databases distributed in computer networks. The successes of AI in the areas of image and sound recognition, generation of graphic information from a text description, building communication systems, performing complex tasks in various natural languages, and much more are impressive and even cause concern for the development of human civilization.

The time is approaching when technical devices will be able to perform even creative functions better than a person. Most likely, this process is irreversible, and it is necessary to adapt to the new conditions of development, using them to expand the possibilities for the long-term existence of civilization.

Let us note further some impressive achievements of recent years. At the same time, there is a need for various forms of manifestation and implementation of AI for autonomous technical systems [9–12]. Let us briefly present some opinions from researchers and Internet users.

Among researchers, there is still no dominant point of view on the criteria of intellectuality, the systematization of the goals and tasks to be solved, or even a strict definition of science. There are different points of view on the question of what is considered intelligence. There is no single answer to the question of what artificial intelligence does. Almost every author who writes a book about artificial intelligence starts with some intuitive definition in it, considering the achievements of a certain science in its light.

At the moment, in the field of artificial intelligence, there is an involvement in many subject areas that are more practical than fundamental to artificial intelligence. Some of the most famous systems are:

- ChatGPT is an artificial intelligence chatbot from OpenAI based on the GPT-3.5 large language model; able to work in interactive mode in natural languages;
- Deep Blue - chess program developed by IBM, won the world chess champion;
- AlphaGo—Go game developed by Google DeepMind, won a Go match against Korean 9-dan professional Lee Sedol;
- Watson - a promising development of IBM, capable of perceiving human speech and performing probabilistic search, using a large number of algorithms; To demonstrate her work, she took part in the American game Jeopardy!, where the system managed to win both games.

The GPT neural network (Generative Pre-trained Transformer) is one of the most powerful and efficient among all existing ones. GPT uses deep learning methods to create texts on any topic and is able to generate unique texts. The GPT neural network achieves amazing results for creating social media content and surprises with its efficiency and accuracy. This is one of the clearest examples of how technology can help us in our lives. GPT does not just generate random texts. It processes large amounts of data and creates texts that are not only unique but also evoke emotions in readers. The GPT neural network can create unique texts on topics ranging from travel to science. These texts can be applied in psychology, medicine, and more narrow areas of science, responding to any audience requests. Generative modeling and autocoding allow you to create texts that capture the imagination and leave vivid impressions.

Research into the potential of deep learning includes developing recommender systems for e-commerce, object detection for autonomous vehicles, and generative models that can create anything from realistic images to coherent text.

On February 24, 2023, Meta AI released LLaMA, an LLM that outperforms GPT-3 in most ways despite having significantly fewer parameters. Less than a month later, on March 14, OpenAI released GPT-4, a larger, more powerful, and multimodal version of GPT-3. The exact number of GPT-4 parameters is not known, but it is assumed that their number is in the trillions.

On March 15, researchers at Stanford University released Alpaca, a lightweight language model that has been further trained in instruction-following demonstrations. A few days later, on March 21st, Google launched its ChatGPT competitor, Bard. On May 10, Google released its latest LLM, PaLM-2.

More and more companies are implementing these models in their products. For example, Duolingo announced the launch of Duolingo Max, based on GPT-4, with the goal of providing individual language lessons to every user. Slack also introduced an AI-powered assistant called Slack GPT that can compose answers or summarize discussions. In addition, Shopify has introduced a ChatGPT-based helper for the company's Shop app, which helps customers identify the products they want with a variety of prompts.

Modern AI-based chatbots are seen as an alternative to therapists. For example, the US Replika app offers users an intelligent companion who cares about them, is always ready to listen and talk, and is always by their side. The app has a wide audience of customers, ranging from children with autism to single adults who just need a friend.

At the beginning of the year, Microsoft introduced its GPT-4-based search assistant, which is tuned for search and has become a serious competitor to Google's dominance in the search business.

Over the last ten years of AI development, there have been changes that have had a significant impact on business and human interaction. The progress made with generative LLMs is related to their number of parameters. In a series of GPT models that started with 117 million parameters (GPT-1) and, after each subsequent model, increased by about an order of magnitude and peaked at GPT-4 with potentially trillions of parameters. However, OpenAI CEO Sam Altman believes that in the future, the number of parameters will increase, but the focus will be on increasing the capabilities, utility, and security of the models.

Powerful AI tools are now available to the general public and are no longer limited to the controlled environment of research labs. It is now important to move forward carefully and ensure that AI tools are safe and consistent with the global interests of humanity.

Generative AI has become a groundbreaking technology that has the potential to revolutionize industries. This advanced AI application allows machines to autonomously create and generate original content. As the technology gains momentum, it is expected to split into two categories: horizontal AI with general-purpose applications and vertical AI with industry-specific solutions. The introduction of generative AI holds great promise for streamlining workflows, automating creative processes, and unlocking new opportunities across sectors. Generative AI harnesses the power of advanced deep learning models to create new and original content. Generative AI learns from large datasets; the learning process involves collecting patterns, styles, and correlations, which allow the model to generate new content.

As generative AI advances, the difference between horizontal and vertical models becomes more significant. Horizontal AI, exemplified by popular models such as ChatGPT and Google Bard, has generalized capabilities applicable to many industries. Vertical AI models are being developed specifically for specific industries, offering a more targeted and immediate ROI.

Generative AI is a transformative force that can change industries with industry-specific solutions. The distinction between horizontal and vertical AI underscores the importance of individualized approaches to exploiting the full potential of this revolutionary technology. Organizations must explore the possibilities of generative AI, integrate it into their workflows, and use its capabilities to achieve a high level of success in today's business.

Deep learning has led to breakthroughs in several AI tasks, including speech recognition and image recognition. The ability to automate predictive analytics is generating interest in using machine learning for product and service manufacturers. Expanded support for product development and improvement, functional workflow optimization, and sales optimization are driving businesses across industries to invest in deep learning applications. In addition, the latest machine learning approaches have greatly improved the accuracy of models, and new classes of neural networks have been developed for applications such as image classification and text translation.

Improvements in the algorithms of deep learning methods have significantly increased their efficiency. The increase in data volumes has facilitated the creation of neural networks with several deep layers, including streaming data from the Internet of Things and textual data from social networks and doctor's notes. Considerable computing power is needed to solve deep learning problems given the iterative nature of deep learning algorithms, whose complexity increases as the number of layers increases. The hardware that runs deep learning algorithms must also support the large amounts of data needed to train networks.

Computing advances in graphics processing units (GPUs) and distributed cloud computing have placed incredible computing power at the disposal of users. This development is being led by hardware vendors such as NVIDIA, Intel, and AMD, improving the distributed computing speed of user-defined functions and making them compatible with the most commonly used open source frameworks such as Tensorflow, Cognitive Toolkit, Chainer, Caffe, and PyTorch. Therefore, open-source deep learning capabilities are becoming increasingly popular among enterprises. These platforms allow users to build machine learning models efficiently and quickly.

The US Department of Energy is providing approximately $30 million for cutting-edge research in machine learning and AI for both complex systems management and scientific research. The initiative covers two separate thematic areas. One topic is devoted to the development of machine learning and artificial intelligence for predictive modeling and research-oriented modeling in the physical sciences. Machine learning and AI are considered promising new alternatives to traditional programming methods for computer modeling and simulation. The second topic is devoted to the main research areas of machine learning and artificial intelligence for decision support in the management of complex systems.

The US Department of Transportation has developed new safety regulations to help eliminate blind spots behind vehicles and see people behind them. According to statistics from the National Highway Traffic Safety Administration, about 292 deaths and 18,000 injuries occur in all-vehicle reversing accidents. Such regulations are expected to encourage the adoption of advanced driver assistance systems (ADAS), thereby opening up opportunities for regional deep learning markets. In addition, the regions are also seeing an increase in automakers' investment in developing advanced solutions, which contributes to the growth of the market.

Micron Technology Inc. is working with technology company Continental to explore and adapt Micron's deep learning accelerator for next-generation automotive machine learning applications. Automotive infotainment systems, ADAS, communication systems, and powertrain management systems are becoming more sophisticated. Micron and Continental are working on developing an application-specific version of the deep learning accelerator technology that must be scalable and flexible while still delivering the high performance and low power consumption needed to support standard models.

The market for generative artificial intelligence is developing at a fast pace. At the end of 2022, the volume of the global market for generative artificial intelligence technologies will reach approximately \$40 billion. This is 75% more than in 2021, when the costs in the corresponding segment were estimated at \$23 billion. Such data are provided in a study by Bloomberg Intelligence, the results of which were published on June 1, 2023. Analysts say the emergence of advanced consumer services based on generative AI, such as ChatGPT and Google Bard, is fueling the industry's rapid growth. In 2023, the costs in this area, according to experts, will reach \$67 billion; in 2024, \$137 billion; and in 2025, \$217 billion. In 2032, spending will exceed \$1.3 trillion. Thus, the average annual growth rate of compound interest over ten years will be around 42%.

For the first time since 2021, Matt Turk, a partner at US venture capital firm FirstMark Capital, and colleagues presented the 2023 MAD (machine learning, artificial intelligence, and data) landscape. This is an interactive map that reflects the changes that have taken place in the market over the past year due to the economic crisis and other global factors. As the authors of the map note, a whole generation of data and AI startups have had to adapt to a new reality.

According to the authors of the landscape, the vast majority of organizations represented in it are venture capital-backed startups. In addition, the landscape showcases products (for example, from cloud providers) or open source projects. In total, there are 238 logos on the map, but some names are duplicated since the company can work in several directions at the same time.

In previous years, landscapers have paid a lot of attention to companies in the growth stage, depending on the funding stage. In 2023, a lot of young startups were included in the list. There is a new category called "LLMOps" (Large Language Models Opps), which includes startups focused on specific infrastructure needs for large language models.

The category "Horizontal AI" has been renamed "Horizontal AI/AI General Intelligence" to reflect the emergence of a whole group of organizations that openly declare the development of such AI as their ultimate goal.

A separate category "Advanced AI" reflects the efforts to introduce artificial intelligence into everyday life. For example, it features Edge Inpulse, a startup that develops solutions to simplify the deployment of machine learning applications not in the cloud but on lower-level systems running on microcontrollers (chips for controlling electronic devices). This allows you to create various smart devices, such as gadgets for the smart home system.

Investor Oliver Molander, in his blog on Medium, noted the imperfections of the landscape. According to him, North American startups are more represented in the categories, but strong European players are not indicated. He also points out that the Horizontal AI/AI category includes companies focused more on large language models and generative AI (for content creation) than general AI (for a wide range of tasks).

3 Ways to Create Control Systems with Intelligence of Various Levels

The evolutionary development of biological systems occurs for quite a long time relative to the lifetime of an individual. Generations change, and the structural and functional properties of organisms are fixed, which contribute to their existence and their further development under changing external conditions. A critical factor in the process of evolution is the ratio of the rates of change in the environment and body systems. Various types of organizations are created, adapted to the conditions of the environment. In a broad sense, the presence of intellectual functions in a biological or technical system also appears as an adaptation to changing environmental conditions. Intelligence can increase the number of environmental states in which the system exists and develops; however, it requires additional resources and time to search for optimal solutions. The intellectualization of control systems is aimed at expanding the total set of initial microsituations, where from the control task is achieved. In practice, it is usually not possible to obtain positive solutions in the entire range of initial values due to the presence of noise components of various nature in information data, restrictions on the computational and energy resources of the system, and restrictions on the time. Intellectualization of control processes, including full automation of individual links, basically expands the initial area from which the required result is achieved. However, especially time constraints may reduce or undo the expansion of the initial area and less intelligent but fast solutions will be required. Thus, the intelligence and overall efficiency of the control system may not always have the same direction.

On the evolutionary path of the development of natural intelligence, the efficiency of using relatively simple control structures is also preserved. The presence of intelligent functions does not always increase the survivability and efficiency of the system under changing environmental conditions. Therefore, it is not paradoxical that, with sharp changes in external conditions, simpler forms of organization can be preserved. Intelligence, as the ability to find certain target solutions in rudimentary forms, can also be observed in relatively simple systems.

Further development of intellectual functions includes the ability to remember and reflect on the functioning of the system when external conditions change. A pronounced manifestation of the presence of intelligence is considered to be the ability to build models of the external world and predict the results of possible actions. When constructing technical systems with elements of intelligent functions, as well as in wildlife, it is necessary to take into account their intended purpose and efficiency of functioning at specified time intervals. Practical tasks may require efficient control systems with different levels of intelligence.

The use of the presented ideas is aimed at automating complex control processes; however, it does not exclude the joint use of classical representations of the control process using transfer functions. The main focus in classical representations is on finding transfer functions between a known input value (or values) and an output control. Usually, the input value is considered continuous over a certain interval of change, and the value of the control element obtained using analytical functions is put in correspondence with it. In these representations, the human operator is usually defined by a set of these functions. In control systems built in this way, the human operator is either a tracking device that generates control signals to bring a certain value to a given position or a control device that intervenes in the control process only in special situations. Basically, the dynamic characteristics of the human operator are described in this way, not his creative capabilities. The proposed representations are aimed at filling the space of control situations where there is no obvious correspondence between the input data and the position of the output control bodies. Preliminary processing of incoming information is required, which is usually not described by a set of classical analytical functions. To search for information transformations in these cases, various methods of pattern recognition theory, probability theory, fuzzy set theory, self-organization theory, etc. are used [1, 13]. Thus, the main attention is paid to the search for transformations of input information for making complex management decisions.

A possible approach to the organization of new and improved technical control systems is the methodological provision of microsituational analysis and synthesis of the functioning of the target system in a dedicated environment [6, 8]. The allocation of the target environment is formed taking into account the problem being solved. In the world in which everything happens, a part is allocated where the interaction of the controlled object with external conditions takes place, and an environment is allocated in which the target task is implemented. There is a determination of the dimensions of significant target characteristics and conditions of the environment; the following are distinguished: the control object, the control system, input and output characteristics, and patterns of human functioning. Based on these data, the target situations are described, and the sets of target microsituations included in the situations are determined. Next comes the definition of target functioning in situations and microsituations.

In most of the problems considered in building automated and automatic control systems, the following division of situational states can be represented as follows:

- microsituations in which elementary control actions are implemented (it is also worth noting the presence of transitional micro-situations responsible for the change of control when a new situation arises);
- situations - logical sets of control actions that implement the target task;
- macrosituations (complex sets of target situations).

A global macrosituation may include a certain set of situations, each of which is characterized by a certain stable set of control actions (sometimes this set can be called a stereotype of the behavior of a human operator). In order to analyze the control process carried out in a certain situation and the subsequent synthesis of an automated system, discrete components of the control process, called microsituations, are considered. In a certain sense, the microsituation defines an elementary act of control in which a control action is generated based on the input information. The concept of temporal discreteness in information receipt is also associated with the concept of a microsituation. The temporal discreteness of most of the considered control systems is decisive for taking into account the discreteness of input and output signals. If there are several control channels in the system for which the human operator determines the control action, among the entire set of microsituations, microsituations can be distinguished in which the attention of the human operator switches from one control channel to another (or the conditional significance of the control channels changes).

The essence of the method of microsituational analysis lies in a holistic, systematic consideration of the process of organizing the structure and functions of control systems, taking into account the targets, characteristics of the environment, and means of obtaining and processing incoming information. The essence of the microsituational synthesis method is to create, on the basis of a preliminary analysis, initial functional structures and basic elements that provide opportunities for improving the control system and implementing its target functioning.

The methods of situational analysis and synthesis of control structures are based on the use of general patterns of control of complex nonlinear dynamic systems and the study of the perception and processing of information by a human operator [7]. The processes of human recognition of complex dependencies of the environment are analyzed, and the issues of ensuring human creative activity through mathematical and computer modeling, etc. are considered. Various authors put their own specifics into the term situational control, which consists, for example, of a certain description of the relationship between objects in the external world. In this presentation, the use of the terms microsituational analysis and synthesis is associated with the discrete allocation of certain situations at various levels, in which there is a functional similarity of the control process.

When solving practical problems that most often arise in modern conditions, there is usually a certain human-machine control system that ensures, to a certain extent, the fulfillment of target requirements. The task of further improving such a system is to search for information transformations that could increase the overall efficiency and reliability of the system by automating individual operations for making managerial decisions by a human operator both at the stage of processing input information and at the stage of executing the decisions obtained. Ideally, this could be a fully automatic system with control functions and the ability to actively change control decisions by a person.

The tasks of macrosituational analysis and synthesis also exist at the stage of the development of new tools and control systems, when the composition of the input information and the devices that record it are not initially determined and the control mechanisms that change the state of the system in the environment are not explicitly indicated. There is only a list of requirements for the system to achieve the target settings. This is a rather complex creative task that is solved in the management of economic, environmental, social, and other multi-purpose systems.

The sequence of organization and search for solutions for target man-machine systems [14].

- General formulation of targets.
- Identification of the characteristics of the target space and the control object.
- Analysis of the activity of a human operator in the implementation of general and particular targets.
- Analysis of the selected environment in the space of the target functioning of the system - target reduction of the control environment.
- Analysis of the control object in the space of the target functioning of the system - target reduction of the control object.
- Creation of the basic structure of the management system in the implementation of targets.
- Allocation of resources for efficient and reliable implementation of targets.
- Creation of opportunities for expanding databases and knowledge, adaptation, training and retraining in the implementation of target settings.
- Holistic integration of resources and decision making structure.
- Achieving the adequacy of the functioning of the technical part of the control system and the human operator in a specific subject area.

4 Specificity of Control in Distributed Systems

The construction and development of the structure and properties of complex control systems lead to the specialization of individual blocks of the system, the automation of their functioning within certain limits. Systems with the presence of such blocks and a certain degree of conditionality can be considered control complexes. When building blocks for such complex systems, the basic principles of organization for complex systems should be taken into account. In an extended interpretation, these blocks represent subsystems in which particular goals (or subtasks) are solved that are necessary for the implementation of a global goal. Such blocks have functional and structural patterns similar to the hierarchical organization of biological organisms. This situation can also be observed in the organization of remote control systems and distributed systems, in which, for example, there is a significant separation between the object and the control system due to the remoteness of information sources, databases, and knowledge. For the successful operation of this type of complex at remote objects, it is required to create private reduced models of the object and the environment, which have databases and knowledge for local forecasts and estimates [8, 15].

At present, the development of the structure of network-centric systems of various applied natures, the development of technologies for performing complex tasks with available free resources, and the development of specialized network complexes for concentrating resources on services of increased demand are gaining importance. If delays occur in the control loop, their compensation requires knowledge of the inertial characteristics of the object, the environment, and the patterns of the functional activity of the human operator [8, 16]. The possibilities of control in such situations are determined by the extent to which the real state of the object in the environment differs from the one calculated, taking into account the specified knowledge in the control cycle.

The specificity of remote control may be the need for a certain distribution of control system functions between the base and remote parts [8, 17]. Depending on the number of significant variables that affect the movement of an object, their accuracy characteristics, and the remoteness of the base part of the control system, various structures for organizing the control process are required. It is necessary to preliminarily determine the composition, accuracy, and distribution of the simulated components on the object and the base part of the system.

Patterns of organization of remote control for different durations of delays in the system

- When the delays are less than the time of the limiting dynamic characteristics of the human operator (critical for the operation of automatic devices, usually less than 0.05 s), models of the object dynamics and a forecast of the object state are built on the remote control system.
- When the delays are comparable with the time of the limiting dynamic characteristics of the human operator (usually 0.05–0.5 s), the dynamics of the human operator's control activity is adjusted to compensate for delays, or automation devices are used to predict the trajectory of the control object.
- When the delays are comparable to the time of a stable prediction of the control object's trajectory (under different conditions, they can reach several minutes or more), predictive models of the trajectory motion and dynamics of the control object and the environment are used.
- When delays are significant (depending on conditions from several minutes to hours, for example, when controlling in near space) and the state of the control object and the environment cannot be reliably predicted, it is required to transfer models of human control activity and knowledge bases to a remote control object, starting from simple logical patterns to complex models of intellectual activity, and at certain moments these models must be corrected.

On Fig. 1 shows the interaction between the object and the system when organizing remote control. The presence of essential components of the system and the control object remote from each other, as well as control and corrective information flows, is noted. Depending on the requirements for the management process, control and corrective information flows are formed with different temporal intensity. In each admissible cycle of information exchange, in accordance with the figure, not only control can be carried out, but also the adjustment of knowledge bases, the environment model, the object model and the model of the decision-maker at the object and in the control system.

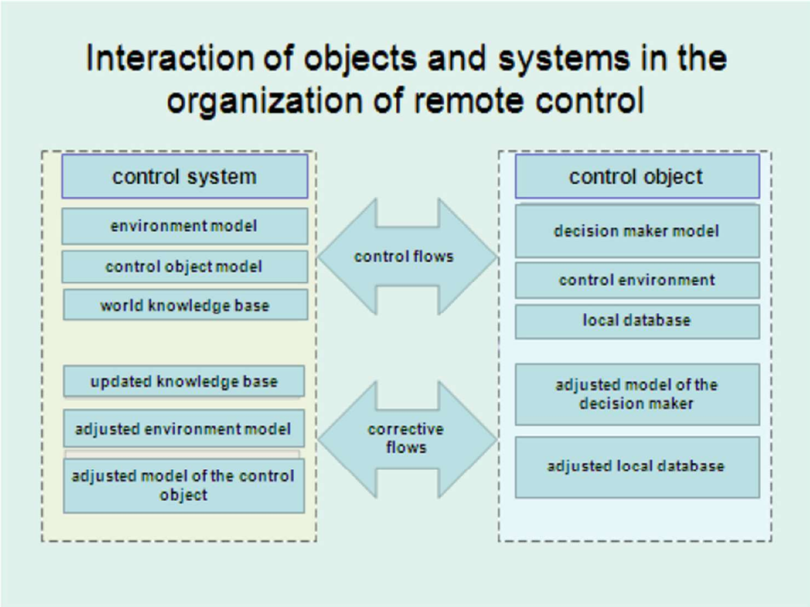

Fig. 1. Interaction of structural elements and information exchange of data between the object and the system in remote control.

When building effective distributed remote control systems, the following stages should be distinguished.

- Statement of the task of remote control, determination of general requirements for the functional characteristics of the object and control system.
- Formation of time requirements for functional agents of the control system.
- Determination of the characteristics of the existing network structure, which can be used to solve the considered problem of remote control.
- Determination of time characteristics when using various protocols of network information exchange.
- Based on the performed analysis, the distribution of the structure of control blocks in a distributed object and control system.
- Improving the efficiency of managing a remote site through additional knowledge about the characteristics of the object and environment.
- Refinement and optimization of information exchange protocols in the network.
- Introduction of new information devices for receiving and processing information into network structures.
- Creation of an evolving network infrastructure with the ability to adapt and add promising technical solutions.

Current areas of research on distributed control systems:

- Achieving automation of the sharing of heterogeneous distributed databases and knowledge.
- Achievement of automatic and automated remote control of dynamic objects in real time.
- Strengthening the intellectual capabilities of training systems and decision support systems using distributed human and machine resources.
- Construction of hybrid human-machine intelligent complexes and systems for processing databases and knowledge.

5 Comparative Efficiency of Different Control Algorithms

When developing new control algorithms, it is required to evaluate their effectiveness in solving the target task using the developed models of interaction in a dedicated environment. Next, you need to analyze and compare the results obtained for further refinement and verification in real-world conditions [6]. An example of the interaction of two aircraft in a conflict situation (a bomber and a fighter solving the interception problem) is considered. In accordance with the above provisions, three algorithms for intercepting are implemented and simulated: algorithm (1) for pointing into a moving specified area; algorithm (2) for pointing into a predicted area of intercept without taking into account the dynamic limitations of the fighter; and algorithm (3) for pointing into a predicted area of intercept with taking into account the dynamic limitations of the fighter. The simulation results are presented in the form of horizontal areas of the initial positions of the fighter (relative to the target), from where the interception (defeat) of the bomber is achieved, according to each of the three indicated algorithms in Figs. 2, 3 and 4.

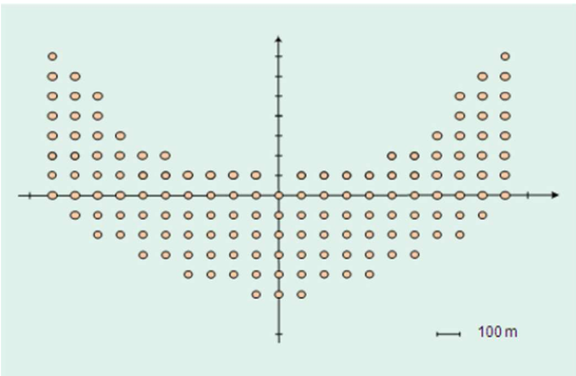

Fig. 2. The area of the initial positions of the aircraft, from which, under given restrictions, the achievement of the target task is achieved using the control algorithm 1

An analysis of the areas from which interception is achieved for various algorithms shows the effectiveness of each algorithm (as measured by the number of initial positions of the fighter relative to the target object). According to the complexity of information

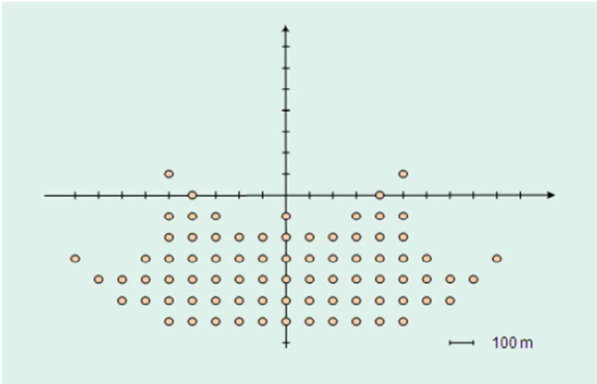

Fig. 3. The area of the initial positions of the aircraft, from which, under given restrictions, the achievement of the target task is achieved using the control algorithm 2

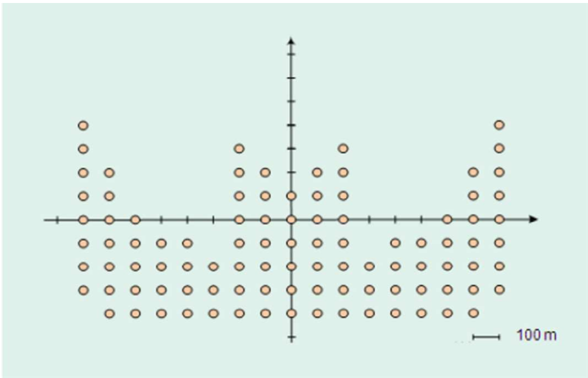

Fig. 4. The area of the initial positions of the aircraft, from which, under given restrictions, the achievement of the target task is achieved using the control algorithm 3

transformations (a conditional indicator of intelligence), the algorithms are ranked in the direction of their increase, from algorithm 1 (with a minimum of complexity) to algorithm 3 (with a maximum of complexity). For the problem under consideration, the imposed time constraints are a critical factor, and the efficiency of simple, quick solutions can be higher. Analogues of such situations are observed in wildlife and in human reactions with developed analytical abilities.

As can be seen from the figures, there are positions where the interception task is performed by only one of the considered algorithms. The combination of algorithms 1–3, depending on the current position, can increase the overall efficiency of the task by approximately 50%. Thus, it is possible to carry out a preliminary analysis and comparison of various algorithms regarding their effectiveness and build new combined control systems.

In addition to the considered example, the methodology of microsituational analysis and synthesis was successfully used in the development, construction, and testing of aircraft landing control systems in difficult and emergency situations, systems for warning and avoiding collisions with ships, and user interfaces for these systems [14].

6 Conclusion

The development of intelligent systems is similar to the evolutionary development of biological organisms. In various areas of human functioning, certain technical systems are required that are optimized in terms of time characteristics and degree of intelligence.

The creation of intelligent technical systems optimized for certain target tasks requires a holistic consideration of the system's functioning in the environment. To do this, a micro-situational analysis of the functioning of the system and the synthesis of algorithms to achieve the goal can be carried out. The specificity of each task determines the time intervals for making decisions and the possible elements of intellectualization necessary for the targeted functioning of the technical system and interaction with a person. At the same time, there is a tendency towards more complete automation of the technical system and the autonomy of its functioning, taking into account safety for humans and the environment.

A good example in the present is the creation of autonomous cars, aircraft, and other vehicles. The priority resolution of conflict situations in the world for their participants increasingly depends on the availability of such means.

The introduction of AI systems affects more and more areas of human life, and systems are becoming indispensable assistants. In the future, the role of an assistant may change to that of an equal interlocutor and, possibly, an initiator in the formulation of actual tasks. Refinement of existing AI systems will reduce the difference in the functioning of a person and AI systems and create in a technical system a semblance of emotional states and awareness of its capabilities for functioning in the environment.

The rapid development of AI systems over the past decade is bringing about the moment when technical systems will perform complex creative tasks better than highly qualified specialists. The functions of organizing the process of finding the required solutions, qualitative assessment, and verification of results will remain with the person.

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