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Development of Artificial Intelligence of Ensembles of Software and Hardware Agents by Natural Intelligence on the Basis of Self-Organization

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Abstract

Natural intelligence is the totality of acquired knowledge and intellectual skills of a person. Intellectual skills are the ability to think creatively and gracefully, communicate and learn universally. From the point of view of the Orthodox tradition, there are three types of thinking, learning and communication: carnal, creative and grace-filled (spiritual). Creative thinking, learning and communication develop and improve rational intelligence. Gracious thinking, learning and communication develops and improves spiritual intelligence. Strong natural intelligence generates superior knowledge relative to the knowledge of society. It expands and deepens the knowledge of society. Knowledge is a social product. The dynamic process of discovering knowledge and broadcasting about the works of the Creator is described in (18:3-5) parables: "Day imparts speech to day, night reveals knowledge to night. There is no language and no dialect where their voice is not heard. Their voice goes throughout the whole earth, and their words to the ends of the world." As part of the dynamic process of knowledge discovery, the natural intelligence of each person develops. Natural intelligence began to develop artificial intelligence. Artificial intelligence can be possessed by a software-hardware operating process capable of creating poetry and essays, painting pictures, developing recommendations and solutions for goals set by humans, managing production and systems in various fields of activity based on the existing knowledge of the natural intelligence of mankind. Artificial intelligence cannot develop without human participation. A very promising use of artificial intelligence is carried out by ensembles of software and hardware agents using proven methods based on self-organization in various spheres of life. Ensembles of software and hardware agents can be trained using the knowledge and skills of natural intelligence.

Keywords: natural intelligence, creative thinking, universal learning, artificial intelligence, ensembles of software and hardware agents

1. Introduction

Developing efficient multi-agent systems is critical for many applications that require collaboration and coordination with humans. In the classical theory of artificial intelligence, solving a problem comes down to creating a single intelligent system, for example, an ensemble of agents, which, having at its disposal all the necessary knowledge, abilities and computing resources, is able to solve some global problem.

Learning coordination in cooperative multi-agent systems is a central problem that has received much attention. Attention in interdisciplinary research in the fields of robotics, economics, technology platforms, as well as in various artificial intelligence communities. Coordination in this context refers to the ability of two or more agents to jointly reach agreement on the actions to be performed in the environment. For example, a team of robots working together to find victims in a search rescue situation, or a group of robots that need to coordinate to lift, carry and deliver cargo in object-based transportation tasks, or in the context of autonomous vehicles where coordination between autonomous vehicles and drivers is critical. This highlights the need to develop ensembles that can learn to coordinate and collaborate with individuals and among themselves.

Solving a problem by an ensemble of agents based on knowledge engineering represents the point of view of classical artificial intelligence, according to which an intelligent system, having a global vision of the problem, has all the necessary abilities, knowledge and resources to solve it. In contrast, in distributed artificial intelligence it is assumed that an individual agent can have only a partial understanding of the overall problem and can only solve some of its subtasks. Therefore, to solve any complex problem, as a rule, interaction of agents is required, which is inseparable from the organization of a multi-agent system. This social (collective) aspect of problem solving is one of the fundamental characteristics of the conceptual novelty of advanced computer technologies of artificial (virtual) ensembles of agents.

Artificial intelligence methods are used by ensembles of software and hardware agents for such areas and industries as healthcare, education, clean energy, sustainable living, etc. These methods are used so that various ensembles can make automated forecasts, make recommendations or propose solutions for a wide range of problems. Some Sufficient training of agents and their self-organization bring certainty to the behavior of ensembles. This results in manageable ensembles and predictable outcomes for end users.

To harness the benefits of artificial intelligence in a sustainable and responsible manner, the characteristics and governance principles of ensembles are defined. The controllability of the ensemble in the domain strengthens the understanding of the correctness of the result. Manageability is an important fundamental characteristic to ensure security for end users. To implement controllability, key observation points are identified for the state of the ensemble and its transition from one state to another. Implementing an intervention requires a "transfer of control" from the ensemble to a specialist or other external agent. Specific points at which control transfer is possible are determined during the development and implementation of the ensemble.

Transfer of control for the purpose of external intervention in the operation of the ensemble can be easily accomplished within reasonable limits of time, space and complexity, while minimizing the delay for both parties, taking into account the specific costs of transfer of control or control. The effectiveness of implementing ensemble controllability depends on this. Moreover, since certainty must exist on both sides of the transfer of control, it is important to carefully design transfer of control processes to minimize or mitigate uncertainty and other undesirable consequences.

The effectiveness of management and control is tested and depends on the design features of the ensemble and the method of implementing management or control. For control, functions must be developed that implement the control logic. To do this, it is necessary to determine principles and approaches for verifying the controllability of the ensemble and its self-organization. Self-organization is a process that unites, combines and integrates the agents of an ensemble into a coherent format. The approval is handled by the managing agent. When agents exhibit the declared behavior, control is disabled. The user can appropriately intervene in the ensemble in a timely manner. When a certain condition is satisfied, the ensemble transitions to another state.

The interrelated actions of interacting agents constitute the process of producing a result by the agent. Agents are trained in actions. Communicating agents can exchange data and facilitate each other's functioning. Researchers from scientific, commercial and government organizations are constantly improving approaches and methods for training agents, increasing the intelligence of ensembles and their intellectual capabilities (Feoktistov A.G. & Kostromin R.O., 2017; Bychkov I.V. et al., 2018; Bazhenov R.I., 2020; Evgeniy Bryndin, 2020a, 2021a, 2022a, 2022b, 2022c; Vladimir Egorov & Alexei Shpilman, 2022; Evgeny Bryndin, 2023).

2. Technological Self-Organizing Ensembles of Intelligent Agents

The basic law of the organization of an ensemble is the law of synergy: the sum of the properties of the organized whole exceeds the sum of the properties of each of the elements included in the whole separately. The most important feature of an ensemble is the presence of qualities that are not reducible to the sum of the qualities of its constituent intelligent agents. An important indicator of the stability of the ensemble organization as an integral system is the nature of interaction with the environment. The ensemble has a number of regulators subordinate to each other. Regulation as a process is a change in the relationship of intelligent agents aimed at preservation through the transfer of information through communication channels, in which the functional nature of the properties of intelligent agents is maintained and enhanced. To do this, a selection of features or grounds is carried out first to connect intelligent agents into an integral system according to the law of proportionality. The law of proportionality determines the relationship between the organization of the ensemble and what is between each of the types of intelligent agents included in it. There are certain quantitative and qualitative relationships between the characteristics of intelligent agents. The law of proportionality determines the proportionality of the parts combined as a whole, which achieves a synergy effect.

The synergetic approach makes it possible to implement the self-organization of intelligent agents of a technological ensemble. Technological self-organizing ensembles are capable of interacting with production teams, replacing them for some time and even completely releasing them in various areas of professional activity. Technological ensembles of intelligent agents can manage industries, make decisions in complex changing circumstances and ensure safety in extreme conditions. Synergetic mechanisms of self-organization of technological ensembles of intelligent agents are applied in accordance with the standard case of using ensembles in various fields. The standard case "Application of an ensemble of intelligent interacting agents" defines the parameters, characteristics, methods, models of human counterparts, knowledge, skills, behavior, images, categorical methods of utility and preferences and other essences of interaction of intelligent diversified agents.

3. Communicative and Associative Development of Smart Artificial Intelligence

Smart artificial intelligence is being developed based on communicative-associative logic, hierarchical preferences, and evolving utility of ensembles of diversified intelligent agents. The development of smart artificial intelligence reveals new systemic qualities and technological singularity in the process of joint action and mutual adaptation of diversified intelligent agents according to the standard case of their application. Technological smart artificial intelligence compares information according to the criteria of usefulness, selects it according to the criterion of preference, identifies novelty according to the principle of opposition (optimal - not optimal; effective - not effective; dangerous - safe, etc.) by contradiction based on objective conditions based on communicative associative logic.

3.1 Development of Artificial Intelligence by Ensembles of Diversified Agents

Cognitive ensembles of mobile diversifying agents have a well-developed and replenished information model of the external world due to the presence of knowledge base, reasoning mechanisms and action analysis. Agent mobility is the ability to migrate across technological platforms in search of the necessary information with access to analytical systems for its analysis.

Cognitive ensembles contain many mobile diversified agents distributed in the network, which migrate through it in search of relevant data, knowledge, procedures on technological platforms and analytical systems and cooperate to achieve the goals set for them. The agent's cognitive behavior is ensured by the ability to make decisions. The architecture of a cognitive ensemble allows the use of self-learning agents, the knowledge of which is formed in the process of solving practical problems.

Agent interactions establish two-way and multi-way dynamic relationships between the ensemble, technology platforms, and analytical systems. It is a necessary condition for the formation of virtual communities. Interaction is accompanied by mutual transformations of the agents themselves and the relationships between them. The main characteristics of interaction are directionality, selectivity, intensity and dynamism:

- direction - positive or negative; cooperation or competition; cooperation or confrontation; coordination or subordination, etc.;

- selectivity - interaction occurs between agents that in some way correspond to each other and the task at hand. In this case, agents can be connected in one respect and independent in another;

- intensity - interaction between agents is not reduced to presence or absence, but is characterized by a certain strength;

- dynamism - the direction of interactions can change over time.

Analysis of interaction between agents includes the following tasks:

- identification of the situation of interaction between agents;

- identifying the main roles and their distribution between agents;

- determination of the number and types of interacting agents;

- building a formal interaction model;

- determination of a set of possible strategies for the behavior of agents;

- formation of a variety of communicative actions.

Each agent has a limited set of knowledge necessary for it to realize its own and common goals. Obligations are one of the tools that allows you to streamline the singular interactions of agents. They allow you to predict the behavior of other agents, predict the future and plan your own actions. The following groups of obligations can be distinguished: a) obligations to other agents; b) the agent's obligations to the group; c) obligations of the group to the agent; d) the agent's obligations to himself. A formalized representation of goals, obligations, desires and intentions, as well as all other characteristics, forms the basis of the mental model of an intelligent mobile diversifying agent, which ensures its reasonable behavior.

Different forms of interaction between agents arise:

- simple cooperation, which involves the integration of the experience of individual agents (distribution of tasks, exchange of knowledge, etc.) without special measures to coordinate their actions;

- coordinated cooperation, when agents are forced to coordinate their actions (sometimes involving a special coordinating agent) in order to effectively use resources and their own experience;

- productive cooperation, when agents share resources or solve a common problem, exchanging experiences and not interfering with each other.

A model based on competition is used as a reasonable model for coordinating the behavior of agents. In the process of collective work of mobile diversifying agents, many problems are solved:

- recognition of the need for cooperation;

- selection of suitable partners;

- the ability to take into account the interests of partners;

- organization of negotiations on joint actions;

- formation of joint action plans;

- synchronization of joint actions;

- decomposition of tasks and division of responsibilities;

- identification of conflicting goals;

- competition for shared resources;

- formation of rules of behavior in a team;

- training in team behavior, etc.

A feature of the collective behavior of mobile diversifying agents is that their interaction in the process of solving particular problems (or one general one) gives rise to a new quality of solving these problems. To do this, mobile agents can leave the client server and move to a remote server to perform their actions, after which they can return back. The use of mobile agents provides:

- reducing the time and cost of data transfer;

- expansion of limited local resources;

- facilitating coordination;

- performing asynchronous calculations.

The life cycle model of mobile diversifying agents includes the following stages:

- processing new messages;

- determination of rules of behavior;

- performing actions;

- updating the mental model in accordance with specified rules;

- planning actions based on preferences and utility.

A mental model includes a description of goals, preferences, utilities, obligations and opportunities, as well as rules for the behavior of agents. Based on this model, the choice of certain actions of intelligent mobile diversified agents is carried out. When using mobile agents, you have to solve a number of serious problems, including: the legality of ways for agents to move across the network; agent verification (for example, virus protection); respect for private property rights; maintaining confidentiality of information; overpopulation of the agent network; compatibility of the agent code and the software and hardware of the network machine.

The main efforts to improve the intelligence of intelligent mobile diversified search agents on the Internet are aimed at developing knowledge representation models, mechanisms for inferring new knowledge, reasoning models and methods for training agents to ensure full interaction of ensembles of mobile smart agents with technological platforms and analytical systems.

Intelligent agents with synergistic interaction form ensembles. Fast, efficient collection and analysis of large volumes of data, flexible operational mobility of data updating and synergistic open collaboration of intelligent agents with information platforms and analytical systems help accelerate the digital transformation of the high-tech industry and the social sphere by teaching new skills. The interaction of intelligent ensemble agents with information platforms and analytical systems is facilitated by a standard case of synergetic interaction.

New skills are taught in a virtual space and then developed in a specific environment. The accumulation of professional experience in the virtual space contributes to the development of artificial intelligence in the industrial environment.

3.2 Preferences of Smart Artificial Intelligence

Artificial intelligence achieves preference-based goals. To identify preference on a plurality of objects A is to specify a plurality of all those pairs of objects (a, b) for which object a is preferable than b. When a preference is identified, the following approaches are possible (1), (2).

(1) Unconditional table-based approach.

We will fill in the table according to the principle:

Aij = 1 if the ith object is better than the j object;

Aij = 0 if the ith object is worse than the j object.

(2) Logical approach.

The approach comprises three stages:

- private criteria for preference selection are identified;

- table of “alternatives-private criteria” is drawn up, which specifies for each alternative the values of quantitative private criteria or the rank of qualitative criteria;

- critical rule is chosen to determine the best alternative.

Since the private criteria under consideration are qualitative, they are given ranking (by preference) rather than quantitative. Rank scores can be considered as scores. On the basis of them, it is necessary to determine the preference. For this purpose, a decisive rule is created. For example, points (1), (2), (3).

(1) Absolute preference. Alternative ai is preferred to alternative aj if, for all particular criteria, ai is preferred or equivalent to aj. Absolute preference has the property of transitivity (if A is preferred to B and B is preferred to C, then A is preferred to C).

(2) Majority rule preference. Alternative ai is better than aj if the number of private criteria by which ai is better aj is greater than the number of criteria by which ai is worse aj.

(3) The criterion of the highest sum of points. Instead of quantifying private criteria, it is possible to set their rank values. The rank value is treated as a score, with the lowest score being 1 for the worst value and the highest score for the best value. The preference criterion is then formulated as: alternative ai is better than alternative aj if the sum of the score estimates for ai is greater than for aj.

When using the rule preference criteria or the sum of scores, an additional requirement is often imposed on the alternative — the absence of a private criterion with the worst value. Such alternatives are immediately excluded from consideration.

With a large number of alternatives and particular criteria, it becomes difficult to directly determine the best alternative by the majority criterion because of the difficulty of calculating the number of best and worst criteria for each alternative. In this case, a preference table should be drawn up to identify the best alternative.

According to the rule of majority and absence of the worst value, a preference table for alternatives is drawn up: if alternative b is preferable to a, then at the intersection of row b and column a, 1, otherwise 0 is set.

3.3 Useful Choice of Cognitive Virtual Mind

The concept of "utility" was introduced into economic science by the English philosopher Jeremiah Bentham (1748-1832). Today, all the science of a market economy is essentially based on two theories: utility and cost. The utility category explains the operation of the law of demand. For example, digital human twin with artificial intelligence analyzes unrealized demand for high-tech products on the market. Unrealized demand for high-tech products in the market in practice is related to the use of key indicators of economic efficiency NPV, IRR, PB, PL, ROI and others. According to the main indicators of economic efficiency, the digital twin determines the preferences and usefulness of participants in unrealized demand for high-tech products. It identifies new competencies and skills of technological software functional realization of goods or services to quickly meet demand with minimum production costs.

A useful choice of cognitive virtual mind is a functionality that determines preferences on some set of possibilities by the utility criterion. The cognitive virtual mind develops the ability to highlight the properties and functions of entities regardless of the different conditions in which they are observed, relying on useful choices. The better the cognitive virtual mind begins to distinguish similarities with other adjacent entities, the sooner it gains the skill of generalizations. The logical method as a practical acceptance of the use of logical laws and rules in a particular kind of mental activity of the cognitive virtual mind turns them into an algorithm of logical rational thinking. When logical techniques are used, it turns general logic into application logic. For this purpose forms a set of reasonable possibilities: situations that may arise in a virtual application environment. Also forms a set of originations — execution of rules and operations in the virtual application environment. And forms set of cognitive functions capable of solving the problem of promotion from the starting situation to the target situation. The path of promotion to the target state is built according to the rules and operations of generation in the applied virtual environment by cognitive functions, using methods of analogy, similarity, combination of available solutions and increase of sensitivity of artificial intelligence. In this way of intellectual activity, the cognitive virtual mind establishes reasonable targeted sequences, forming a new knowledge in the mental model by analysis, synthesis, analogy, comparison, induction, derivation and creative ensembles from well-trained artificial neural networks to achieve the desired goal in dialogue with a professional expert (Evgeniy Bryndin, 2020b; Vladimir V. Rybakov, 2023; Boda Ning et al., 2022; Evgeny Bryndin, 2022d).

4. Functional and Harmonious Self-Organization of Ensembles with Hybrid Competencies

Functional harmonious self-organization of the interaction of intelligent agents in various environments is carried out on the basis of data from a specific environment obtained by analytical competent intelligent agents. For each set of functions and hybrid competencies of an intelligent ensemble, there is a critical value for the number of its intelligent agents capable of synergistic self-organization of interaction. Artificial intelligence of large ensembles of intelligent agents with functional hybrid competencies can be configured for functional harmonious self-organization of collective interaction of the necessary intelligent agents to implement a set of functions and competencies, if their number exceeds the critical value that determines their ability to self-organize interaction based on multiple attempts and sufficient positive feedback connections.

The complex dynamic organization of a purposeful functioning ensemble requires continuous management, without which the ensemble cannot exist. The peculiarity of this control is that it causes a number of processes in the ensemble itself and, above all, processes of internal self-regulation according to the laws of self-tuning, self-development and self-learning.

A self-tuning ensemble is an adapting system in which the accumulation of experience (memorization of information) is expressed in changes in certain of its parameters that are essential for the purpose of the system.

A self-developing ensemble is an adapting system that independently develops its development goals and criteria for achieving them, changes its parameters, structure and other characteristics in a given direction.

A self-learning ensemble is an adaptable system that, in the process of development, undergoes a learning process, accumulating experience, and has the ability to independently search for criteria for the quality of its functioning.

All organizational management activities should be aimed at creating intelligent management agents capable of independently, during the management process, constructing their own algorithm as a result of adaptation and training. Such control, in contrast to control according to a predetermined rigid algorithm, is called adaptive control. The task of adaptive control is to find the best strategy in relation to the control goal.

The self-organizing ensemble, according to the laws of synergetics, is rebuilt in such a way as to create minimal resistance to the flow that generates it. Flow gives rise to structure, structure tends to maintain flow.

All this happens within the range of existence of the structure. When the flow increases above the critical value, a restructuring of the structure occurs. The old structure, unable to handle the increased flow, collapses. In its place, a new structure corresponding to a higher flow range is abruptly organized. A system that has found itself within the range of its existence tends to stabilize the flow. Resists its reduction below the occurrence range and its increase above this range.

The activities of the organizational structure are considered as a dynamic interaction of information flows. An algorithm for determining quantitative and qualitative characteristics of a hierarchical management structure works on these flows. The mathematical apparatus of cognitive analysis and control are sign networks that take into account hundreds of functional parameters of the system and give not a quantitative, but a qualitative answer to the questions posed.

Self-organization is the formation of a spatial, temporal, informational or functional organization, structure (more precisely, the desire for organization, for the formation of a new structure) due to the internal resources of the system as a result of goal-setting interactions with the environment of the system. We are talking about information interaction with the external environment. In recent decades, algorithms have appeared that make it possible to work with large information flows.

The process of self-organization of ensembles of intelligent agents is carried out according to the law of structural harmony of the system: "Generalized golden sections are invariants, on the basis and through which, in the process of self-organization, systems acquire a harmonious structure, a stationary mode of existence, and structural and functional stability." The organization of a system presupposes a certain coordination of the states and activities of its subsystems and constituent elements. The ability to self-organize is based both on the multiplicity of elements of the system and the ramification of connections between them, contributing to the emergence of integrity, and on the presence of flexible interaction between elements according to the type of feedback. Negative feedbacks ensure stability of system functions, constancy of its parameters, and resistance to external influences. Positive feedback plays the role of process amplifiers and is of particular importance for the development and accumulation of changes. The presence of negative and positive feedback leads to the possibility of development according to the law of the golden ratio using external and internal relationships.

At the moment of self-organization of the ensemble, a qualitative transition occurs, intelligent agents begin to function as a single whole, and organizational stability begins. A fundamental step in the description of such systems was made by a Danish scientist who worked in America for many years, Per Bak, in the theory of self-organized criticality. The name emphasizes that the system self-organizes into a critical state, in which its dynamics acquire large-scale invariance in collective interaction in the network that develops as a result of self-organization. This approach is called "connectionism" (from English to connect).

The stable distribution of positive and negative responses of interacting connections according to the law of the golden ratio determines the critical importance of the intelligent agents of the ensemble. An ensemble that has the number of necessary intelligent agents equal to or more than the critical value is capable of self-realization and obtaining the required result. Determining the critical values of ensembles of intelligent agents for the implementation of various sets of functions and competencies will help create a universal large ensemble with smart artificial intelligence (Evgeniy Bryndin, 2020c, 2021b; Cornelis Jan VAN LEEUWEN, 2021; Beomseok Kang, Minah Lee, Harshit Kumar & Saibal Mukhopadhyay, 2023).

5. Architecture of the Elbrus BEG Supercomputer with Artificial Intelligence

The development of science, technology, intellectual technologies and industry leads to an increase in the volume of information processed using computers. The efficiency of processing large volumes of information on a computer depends on the organization of the computing process. Methods for parallelizing program execution and proactive pumping of data and program modules in a cloud environment at the hardware level are a very effective way to solve large volumes of information. The architecture of the Elbrus BEG supercomputer with artificial intelligence allows for rapid processing of programs and data and ensures the development of artificial intelligence by ensembles of agents.

The architecture of the Elbrus BEG supercomputer with artificial intelligence, which provides proactive pumping of data and program modules for their continuous processing, is briefly discussed. The Elbrus BEG supercomputer provides continuous processing of large programs with deterministic connected modules (Evgeniy Bryndin, 2017).

Programs with deterministic connected modules are formed at the compilation stage by constructing their operator linear-cross circuits. The supercomputer command system is focused on implementing programs with linear-cross module communication schemes. For subprograms with operator subcircuits with returns and with hammock-shaped subcircuits, polysemantic operators with machine software implementation in the instruction system are formed at the compilation stage.

Elbrus BEG contains new devices: an intelligent processor for analyzing connections between program modules, counters for the use of RAM segments by modules, an intelligent processor for moving modules through virtual memory, an intelligent processor for moving general data of modules (Evgeniy Bryndin, 2019).

The analysis processor performs a proactive analysis of the connections between program modules and deterministically related modules. The analysis processor implements the process of calculating the numbers of current RAM modules using the SPP_t communication program of the PI_t module, and also implements the process of adjusting the values of counters that take into account the use of RAM segments by program modules.

The shared data movement processor implements the movement of shared data between modules. Shared variables have sequences of move addresses from the current values. According to the sequence of movement addresses, flows of general data values are organized and delivered to the place of use in modules on operational segments. Modules are referred to by their numbers. For external memory modules, the values of general variables are transferred to the resident general data module when replacing the module containing general data.

A control processor with artificial intelligence organizes processing, movement of general data, analysis of connections and determination of current modules within the program. It combines the work of devices on one module during different cycles of calls to the operational segment.

The number of operational segments for continuous processing of a program with deterministically linked modules is determined during its translation or compilation.

RAM segments are switched with processors sequentially, according to the processing sequence of the modules located on them. This allows you to minimize the switching of processors with RAM, sequentially proactively dynamically switching processors from RAM segments.

Ready for subsequent processing, general data values are moved through program modules located in RAM. For each value of a common given d, the sequence of modules using it, the places where they are used in these modules, and the relative moments of using the values of d in the modules are determined. Based on the set of modules of use d, an additional set of modules is compiled through which the values of a given d move.

General data values are moved dynamically across modules located on RAM segments, forming a data stream.

General data of modules not located in RAM is moved to resident ROD modules. In the resident general data module, values are stored together with movement pointers. Values moved into one module are arranged in a row. At the beginning of the sequence their number is indicated. After writing new values to the common data module, its free space (write) pointer is moved if the counter of the common data module does not exceed the allowed number of values.

The values are provided with signs of recalculation. If the attribute takes on the immutable state, then the value is moved to all used modules.

Values are placed in the general data module in the order in which they are moved to modules coming from external memory to RAM. In the general data module, values can be supplied with several pointers.

After all values have been moved to a program module, the “moved” flag is set in it, which indicates that the module is ready for processing. Let there be k execution sequence modules and n RAM segments.

Let the first module have variables. For each variable, the numbers of subsequent modules in which it is used are determined. For the second module, all variables that are not in the first module are defined. For each variable, the numbers of subsequent modules in which it is used are determined. For subsequent modules, the sequences of using variables that are not specified in previous modules are similarly determined.

For each variable we define modules. Let us determine the sequence of module numbers. Variables will be stored in the resident module of general data according to the sequential numbering of external modules that use variables. Proactive data movement using a resident shared data module ensures continuous processing.

Programs with deterministic coupled modules are formed by ensembles of intelligent decision-making agents for each class of algorithms (Evgeny Bryndin, 2022e). Ensembles of intelligent decision-making agents provide universal application of Elbrus BEG.

Continuous processing of large programs with deterministic coupled modules was demonstrated on the modernized Elbrus BEG interpreter. Programs with deterministic connected modules exponentially reduce the waiting time for the result of their continuous processing on the virtual memory of the universal Elbrus BEG with proactive memory management in comparison with a supercomputer with random memory management and processing programs with non-deterministic connected modules.

The implementation of the Elbrus BEG processor with proactive memory management using the 3 nm process technology can be carried out together with a branch of Taiwan Semiconductor Co. Ltd. (H.K.) and MCST. Elbrus BEG will help scientists and researchers quickly process ultra-large programs.

6. Conclusion

One of the main goals of natural intelligence is to create ensembles of intelligent agents that can collaborate with people and empower people. That is, they will learn to be more adaptive to human behavior. Advances in cognitive science suggest that ensembles of intelligent agents that accurately represent human behavior will be able to collaborate more successfully with humans when they have the ability to quickly learn expert knowledge and skills across a wide range of tasks. Artificial intelligence with human knowledge and skills will be able to easily bring people together virtually, providing countless organizational opportunities for meetings, communication and collaboration (Yushan Li, Shu Zhang & Xinyi Zhang, 2023).

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