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NEUROCOMPUTER OPERATING IN THE RESIDUE CLASS SYSTEM

Abstract. Objective. The aim is to justify the possibility of creating a data processing neurocomputer (NC) based on the use of one kind of non-positional machine arithmetic residue class system (RCS). **Methodology.** In the basis of research of the problem of NC creation there is a methodology based on the use of methods of synthesis of non-positional code representation structures (NPCRS), as well as on the realization of data processing methods in RCS. The totality of these methods is realized on the basis of using three basic principles of data processing in RCS: independence of processing of numerical values of the residue content; equality of functioning of data processing channels; low-digit data in the numerical representation of the residue content. **Results.** The results of the conducted research confirm the possibility of creation of NC using RCS as a basis for information processing. Formal (semantic) similarity of mathematical models, as well as analytical similarity of artificial neural systems representation with the basic formulas of data processing represented in RCS is presented. The correspondence of the operation of weighted summation in neuron to the operation of addition by modules in RCS is established. It is shown that the activation function of a neuron can be efficiently approximated using multiplication operations by modules in RCS. It is analytically shown that the representation of synapse weights in NPCRS elements allows to realize parallel computations similar to parallel information processing in the human brain. **Scientific Novelty.** For the first time, a comprehensive study of the influence of RCS on such key characteristics of NK neurocomputers as performance in processing large amounts of data, reliability of information storage and transmission, and overall fault tolerance has been carried out. A new approach to the construction of NC based on the use of neural network mathematical basis based on non-positional RCS codes is proposed. The introduction of this mathematical apparatus into the structure of neural networks provides the possibility of achieving higher accuracy and naturalness in modeling the hierarchical organization inherent in biological neural networks of the human cognitive system. **Practical Significance.** The prospects for further research are the development of specific hardware implementations of super-performance and highly fault-tolerant NC based on RCS, as well as the study of the possibility of applying this approach to solve specific problems of artificial intelligence, such as pattern recognition and natural language processing.

Keywords: data processing; artificial intelligence; artificial neuron; residue class system; human cognitive system; neurocomputer; neural network; neural network mathematical basis.

Introduction

The research is devoted to one of the relatively new directions of artificial intelligence (AI) systems development – creation of super-performing, reliable and fault-tolerant neurocomputers (NC) for real-time data processing. At present, the theory of AI systems creation is developing simultaneously in different directions: NC, neural networks (NN), evolutionary computing, fuzzy logic, intelligent applications, distributed computing, etc. Studies on the potential of NN emphasize the presence of a number of distinctive properties that make them an effective tool for modeling and evaluating complex systems [1]. Despite the fact that prominent scientists from many fields of science argue about the possibility of creating AI systems and determining the area of their effective application, no one has any doubts about the importance and prospect of conducting research on this problem. At the present stage of development of cybernetic systems in the process of researches the main purpose of creation of AI was determined - imitation of human thinking activity, i.e. transfer to the computer system (CS), both "non-intellectual" and "intellectual", tasks of mankind [2]. The mysteries of the human mind, and especially of the thinking process, have not yet been fully unraveled. Thinking is a complex cognitive process that includes information processing, concept formation, decision making, problem solving, imagination and other mental operations. It is closely related to other cognitive functions such as perception, memory, attention and speech [3].

The mechanisms of cognitive processes are a complex system of interactions between neurons. The cognitive system functions due to the work of neuronal networks in the brain. The high reliability of the brain is due to the fact that many neuronal populations perform a variety of functions [4, 5]. The polyfunctionality of initial neural structures (INS) allows the cognitive system to compensate for potential malfunctions of individual neurons or structures. This makes it possible to process incoming information accurately and reliably.

AI seeks to replicate some aspects of the cognitive system through computer systems. Both the human brain and AI process information to solve problems. Machine learning techniques allow AI to learn from data, similar to how humans acquire knowledge through learning [6]. AI research allows for the creation of models that mimic various cognitive processes, which helps to better understand how the brain works [7].

The problem of investigating the capabilities of a cognitive system (in particular, information and constructive reliability, performance, memory capacity, etc. [8]) is one of the cardinal tasks of cybernetics in general, and AI in particular. The results of solving this problem can be used to reproduce certain aspects of its functioning in technical and information-control systems of various purposes.

The relevance of neurocomputer development for AI development based on alternative number systems, such as the residue class system (RCS) [9], is due to a number of factors related to the limitations of traditional computing systems and the growing needs of modern AI tasks. Under the assumption of the parallel and distributed nature of information processing in the human brain, the development of AI systems that utilize the RCS model of information processing appears to be a promising direction.

This paper aims to investigate and justify the use of a non-positional numeral system, the residue class system, for information processing in neurocomputer within an AI model, as a potential improvement over traditional positional binary arithmetic.

A review of related scientific publications

The human brain is characterized by simultaneous functioning of all its information structures, which provides deep parallelism of information processing processes, which is not achievable in CS functioning in binary positional numeral system (BPNS). Improvement of models of AI systems on the basis of digital CS functioning in BPNS can have limits, because of which the transition to the solution of AI tasks of a higher class, which require taking into account the global nature of information processing, is impossible on discrete digital machines and systems with any perfect algorithms. This means that the technical evolution of reflecting systems is associated with changes in the material substrate and structure of these systems [10].

In [11] an original principle of construction of hybrid analog-digital information processing systems based on the application of RCS is considered. It allows to parallelize the execution of not only separate operations, but also the elementary operation itself due to the absence of transfers between the digits (residues) of the number represented in RCS, which provides a significant increase in the user performance of data processing systems. The application of RCS for the construction of digital computing systems is proposed in [12], which makes it possible to construct a simple information processing system operating with any predetermined accuracy. It should be noted that the studies [11, 12] are devoted to the implementation of the developed data processing methods in the context of classical computing systems rather than neurocomputer systems.

There is an assumption that the human brain works on the principle of analog CS. However, creation of AI systems directly on the basis of analog principles of processing information presented in BPNS deprives it of some important and necessary qualities. The created hybrid analog-digital systems of information processing in BPNS, although showing their significant efficiency of application, however, require significant improvement, first of all, on the way of parallelization of solved algorithms [13]. Increasing the number of parallel processors leads to the necessity of increasing the amount of equipment, complicates their mathematical support and although it increases the system performance of CS, it leaves the user performance within the same limits.

In this respect, it can be argued that the structural realization of processes identical to the thinking processes in the human brain and requiring the creation of essentially new principles of global information processing could provide an effective solution of AI tasks [14].

As shown in [15], when solving computational and logical problems, modern types of positional CS do not use those advantages that the sensual image of human intellect possesses in comparison with its concept represented in the form of an encoded message. It is connected, first of all, with the locality of information processing, which is characteristic for all existing digital and analog positional computing systems, regardless of the nature of their mathematical support. Partitioning of computable algorithms into separate branches increases the user performance of computing systems, but leaves the local character of processing of this information in each branch of the algorithm.

Overcoming the local character of information processing with the help of computing systems functioning in positional number systems, as shown in [16-18], is practically impossible. Determination of methods of global information processing and their realization in AI systems is one of the main ways of its improvement. The solution of this problem, the development of effective methods of its global coverage cannot be realized only by improving semiotic systems. In this case, the holographic principles of information processing play an essential role.

The literature [19] shows that there is some analogy between the principles and methods of information processing in RCS and the principles of hologram creation. At the same time, there is a reasonable assumption that information retrieval and storage in the human brain is identical to the process of information retrieval and storage from a digital hologram. Let us consider the similarity in the procedures of representation and description of data represented in RCS and in the realization of the procedure of transferring the features of holographic image processing to the coding of arbitrary digital data.

It is known from [20] that the holographic theory has been effectively used in the direction of digital optical information processing for a relatively long time. But within the framework of this study the analogy between the principles and methods of information processing in SOC and the creation of holograms is not carried out.

Optoelectronic techniques are successfully applied in the creation of highly reliable and fast-acting components and CS [21-23]. In particular, reliable and ultrafast optoelectronic matrix processors in RCS have been developed and operate [24]. This is a confirmation that RCS can be one of the possible tools for synthesizing an AI model that aims to become our digital twin of a human being.

One of the alternative ways to create AI models is to use productive rules with fuzzy parameters. The productive representation of knowledge is close to human thinking in its content, and fuzzy logic, unlike Boolean logic, has a blurred, fuzzy form of representation for possible values of system parameters. Such features of fuzzy systems allow creating AI models that will function with fuzzy data on the characteristics of the object of observation [25]. Automation of tuning of such fuzzy systems can be carried out using neural networks by synthesizing a special type of fuzzy system – ANFIS [26]. However, the use of this approach to create AI models has its limitations, which are related to the performance and learning speed of such systems.

Research methodology

Despite the urgency of creating AI models, the transition from cognitive research to their practical realization is constrained by the lack of an adequate information model of AI capable of reproducing the complexity of human cognition within the existing computational limitations. If the AI model can be modified depending on the current level of representation of the structure and principles of functioning of a cognitive system, the power (performance, reliability, fault tolerance, survivability, etc.) of modern CS functioning in BPNS has practically exhausted its possibilities.

In this aspect, a neurocomputer should be created on other principles and other approaches, as well as, possibly, on the use of non-traditional computer arithmetic. Let us first formulate one of the possible definitions of a neurocomputer. A neurocomputer is an information processing device based on formalized principles of natural neural networks or their analogues. The main problem of creating a neurocomputer is to build real physical devices, which will allow not just modeling artificial neural networks on an ordinary CS functioning in a BPNS, but so change the principles of operation of CS that it will be possible to say that they work in accordance with the theory of the artificial neural networks (ANN). Modern neurocomputers have significant high requirements for: processing large data arrays in real time; reliability, fault-tolerance and survivability of functioning; efficiency of restoring full or partial operable state of the neurocomputer; high reliability of calculations [27].

To meet the growing computational needs of neural networks and neurocomputers, it is proposed to use a non-positional numeral system in residue classes. The computational parallelism characteristic of this system allows efficient processing of large amounts of data, and the modular representation of numbers ensures high computational accuracy. In addition, RCS have increased error tolerance, which makes them promising for use in robust systems. These advantages make RCS promising for the realization of new generation neural network models, which take into account the above requirements for modern neurocomputers.

In the course of the research, a new methodology has been developed that allows to create artificial intelligence models that more accurately mimic the work of the human brain. This approach is based on the adaptation of the mathematical apparatus of residual classes. The methodology relies on three original principles of data processing in non-positional machine arithmetic in RCS:

1. Independence of the processing of numerical values of the residues content (residues), constituting NPCRS in RCS. The use of this property allows to synthesize the CSs structure in the RCS as a set of n independent functioning data processing channels (DPC) for RCS with n modules. Each DPC in the system operates independently (autonomously) and in the mode of strict parallelism, which allows to significantly increase the performance of calculations due to the load distribution between different channels. In this case it is possible to parallelize the task solved by a CS at the level of micro-operations, which is not achievable for CS in BPNS. This makes it possible to dramatically increase the performance of arithmetic operations [28].

2. Equality of the functioning of the DPC CS in the RCS. The arbitrary residue contains information about the quantitative value of the initial number corresponding in the BPNS to the NPCRS value in the RCS. The use of this RCS property allows to develop methods and means of ensuring the operable state of the CS in case of failures and malfunctions. The considered property provides CS in RCS with increased reliability, fault tolerance and survivability. In this case, CS in RCS can be referred to the type of nature-fault-tolerant computing structures.

3. *Low-bitness of data in the numerical representation of NPCRS residue contents*. This property makes it possible to use the existing tabular methods and algorithms of single-cycle implementation of integer arithmetic operations in the RCS. This allows to significantly increase both system and user performance of real-time CS.

These principles of data processing in RCS and their combination allow overcoming the limitations of traditional approaches of BPNS and ensure the speed and efficiency of AI tasks fulfillment, as it is done by the human cognitive system. To increase the reliability of the proposed model of artificial intelligence, mechanisms of active redundancy of key modules and hot data redundancy are implemented. This approach allows to ensure the continuity of the system functioning in case of failure of separate components and to reach the level of fault tolerance corresponding to the requirements of the standard [29]. As a result, the application of the principles of parallel processing and redundancy of data representation in RCS allows to realize in the AI model the mechanisms of self-correction based on error detection and correction, as well as the mechanisms of performance recovery in case of failures, which increases the overall fault tolerance and survivability of the system.

Formal statement of the research task

Creating a neurocomputer involves several stages, the main one being the selection of a neural network mathematical basis (NMB). This stage includes determining the mathematical basis that will be used to build the neural network. The choice of NMB depends on the type of the problem to be solved and the requirements to the performance, accuracy and energy efficiency of the NC. The theory, principles and methods of non-positional information processing, namely, the residue class system (RCS) relying on the Chinese Remainder Theorem with reciprocal simple moduli, are used as the NMB for the NC considered in this study.

In this paper we propose a model of neurocomputer, which is based on the use of RCS. In the construction of NPCRS only integers are used. Each integer *N* in the range from 0 to $\prod_{t=1}^{s} b_t - 1$ is represented as a set of residues n_t from dividing this integer *N* by each of the bases b_t, that is

$$n_t = N - \left[N/b_t \right] \cdot b_t \text{, for } t = 1, 2, ..., s \text{ .}$$

The digit of the *g*-th position n_t of an integer *N* is the least non-negative residue obtained from the division of n_t by b_t (n_t modulo b_t), i.e. it is obvious that $n_t < b_t$. Here, in contrast to the generalized positional system, the formation of digits of each digit is carried out independently of each other. From the theory of numbers it is proved that if numbers b_t are mutually prime, then the representation of the whole number *N* described by residues $n_1, n_2, ..., n_s$ is singular. Consequently, based on the principle of code construction in RCS, each residue n_t is a function of the full value of the initial number *N*, reflecting its properties relative to the corresponding base (modulus) and carries information about the whole initial number *N*.

Let $\{Q\}$ be a given amount of numerical information to be processed. In this case, the value

$$\{Q\}_B = (\{q_1\} \| \{q_2\} \| ... \| \{q_i\} \| ... \| \{q_n\})$$

represents the amount of information represented in RCS $Q = (q_1 \| q_2 \| ... \| q_t \| ... \| q_s)$, in the numerical segment *B*, which belongs to the half-interval [0, $\prod_{t=1}^{s} b_t$). It is assumed that $\{q_t\} \Leftrightarrow q_t$, i.e. a certain finite amount $\{q_t\}$ of information unambiguously corresponds to the element of the numerical code q_t, represented as the smallest positive residue from dividing the number *Q* by a positive integer number b_t of RCS bases.

Increase of number and size of the RCS bases leads to increase of accuracy of representation of numerical information that is caused by expansion of a range of possible values and decrease of rounding error. Thus, the addition of new bases to the RCS leads to an increase in the amount of information contained in the representation of the number *N*, which allows a more complete description of the properties of the represented object *Q*.

Experimental research

Let INS serve as an element of information processing by the brain $\{q_t\}$. In this case, it is assumed that each INS of the brain processes a given amount of information $\{Q\}$, corresponding to the numerical code *Q*, according to its specific basis b_t of RCS. Thus, the information $\{Q\}$ arriving to the brain is transformed to a form $\{Q\}_B$ and further processed by parts $\{q_t\}$ of each INS separately. At the same time, a separate part $\{q_t\}$ carries information about the whole initial $\{Q\}$. The condition of unambiguous determination of the processed volume $\{Q\}_B$ of information expressed by the numerical code *Q* is defined by the following expression:

$$\prod_{t=1}^{p} b_{l_t} \geq Q_t, \quad (1)$$

where the base $b_{l_t} \subset (b_1, b_2, ..., b_s)$.

The following condition is satisfied:

$$s \gg p. \quad (2)$$

Inequalities (1) and (2), and inequalities (3):

$$b_t \geq \prod_{k=1}^{c} b_{d_k}, \quad (3)$$

defining the condition of the possibility of replacing by one base several simultaneously failed ones ($b_{d_k} \subset b_t$; $s \geq c$), show (from the point of view of neuropsychology) the possibility of restoring the disturbed (affected) INS of the brain. Modern neuropsychology states that complex forms of mental processes are complex forms of activity that change their structure significantly as they develop, and even for this reason alone, the mechanism of functioning of the brain apparatus represents a complex functionally rearrangeable system [30]. Thus, almost any part of the brain cary can be introduced into one or another functional system and used to reintegrate the disturbed work of the brain apparatus, which ensures high reliability, survivability, and fault tolerance of the brain. Thus, the principle of reintegration of disturbed functional formations and reorganization of brain INS connections corresponds to the main corrective properties of codes in RCS. The need to explain some properties of living organisms in order to use the principles of their existence and functioning in the developed technical systems makes researchers at least tentatively define, using known technical concepts and definitions, the methods of reliability assurance used in the human brain. One of such methods is probably the application of various types of redundancy (structural, informational, etc.) simultaneously both at the level of INS and at the level of separate groups of INS. This method is widely used in technical systems of information processing to increase the reliability of its processing.

This method is most effective in case of constant element-by-element redundancy of INS and in case of dynamic redundancy of separate groups of INS. Most likely, all known types and varieties of redundancy are present in the human brain at the same time.

Let us consider in more detail an important property of RCS, which consists in the possibility to change the ratio between the number of information and control bases in the process of problem solving and at the same time flexibly utilize the reserves of accuracy and reliability of CS. The method of variable scaling is known, which allows reducing the number of digits when representing numerical information in BPNS. Due to this it is possible to introduce additional digits to organize hardware operational control in the presence of restrictions on the increase in weight, dimensions and cost of CS. At the same time it is possible to maneuver the accuracy, speed and reliability of calculations. The specifics of BPNS impose the following limitations on the variable scaling method: before each program cycle, additional shift operations must be performed, reducing the actual performance of CS by approximately 10%; the use of variable scaling requires a large volume of theoretical work to determine optimal scaling coefficients before program development; variable scaling makes sense to apply only to a specific class of tasks; this method is unlikely to be appropriate for a CS operating in real-time mode.

In RCS, there is a trade-off between the accuracy, speed and reliability of the calculation. An increase in the number of information bases increases accuracy, but reduces productivity and vice versa. RCS is configurable, it can be dynamically changed for optimization for different types of tasks and algorithms, ensuring flexibility and efficiency of its application. That is, RCS has a high degree of adaptability, which allows you to adjust its parameters to solve a wide range of problems, from those requiring high accuracy to problems with limited computing resources.

The methods for organizing exchange operations in BPNS, such as variable scaling, lack the flexibility and universality of those employed in RCS. This makes it possible to approach the solution of different types of problems more flexibly and selectively, which is inherent in the cognitive system.

The results of recent studies [28] have shown that further progress on the way to increase the productivity, fault tolerance and reliability of RCS objects of critical application is connected with the development of the theory and practice of NC, as the main component of artificial intelligence systems. The basis for the creation of NC is ANN, which, in turn, is based on the principles of functioning of biological neural networks (BNN) of the human brain. The use of ANN, when presenting information in the NMB in the RCS, allows you to effectively use information processing tools with massive parallelism in the implementation of arithmetic operations. In addition, the use of ANN when processing information allows you to quickly carry out exchange operations between the accuracy of the calculation of the algorithm, the speed of its implementation and reliability in the dynamics of the computing process, i.e. in real time, which is inherent in the human brain.

Of particular interest is the problem of creating NC based on ANN by using non-positional code structures in RCS. The main goal of creating and using NC is to increase the user and system performance of neuroprocessing based on the use of neural network technology. It was found that ANN models, as well as cluster systems, are suitable for organizing a highly parallel computing process and have high throughput in real time. ANN, which are the foundation for the creation of NK, must have the following basic properties: the computational function of each NK node must be simple and constant; the data transmission communication network must have a large bandwidth; high parallelism of data transfer between computing nodes [31].

The features of BNN are, first of all, the high speed of information processing, which is achieved due to the parallel work of neurons and synapses. Each neuron performs slow analog processing of information, however, the greater absolute connectivity of the neural network between neurons through synapses provides real-time parallel processing of large arrays of data. Secondly, the BNN does not have specific local places (areas) in which information is stored. Memorization and storage of information occurs in a distributed manner throughout the network structure, by modifying the weights and thresholds of perceptrons. In this case, BNN are considered insensitive to the loss of part of the network, which ensures high reliability of the functioning of the human brain. It is obvious that the listed features of the BNN are holographic signs of human brain activity [19]. Thus, the task of creating NC is to create and improve ANN models of adequate BNN. As it was shown above, these models should be based on holographic features of information processing, which will ensure ultra-high productivity and fault tolerance (reliability) of information processing. It is shown in the literature that RCS provides deep (at the level of microoperations) parallelism of processing large arrays of information. In this case, RCS codes are a natural, natural mathematical basis for creating ANN. In this aspect, this circumstance determines the importance and relevance of research devoted to the search for methods of increasing productivity, fault tolerance, reliability, survivability, and reliability of special-purpose CS based on the use of NC operating in RCS [32]. At the beginning, we will show that RCS is a natural mathematical basis for creating artificial modular neural networks (AMNN) of a finite ring, i.e. we will show the adequacy of mathematical models of NC in RCS and BNN. The existing AMNN of the final ring, created on the basis of the principles and methods of functioning of the BNN, are the basis for the creation of NC in RCS.

When creating a NC in the RCS, it is necessary to take into account, first of all, such properties of the BNN as: independence of the functioning of each of the neurons; simplicity (low bit rate) of performing the operation with one neuron; equal functioning of each individual neuron in the BNN; the complexity and large number of neuron connections in the BNN. The listed main properties of the BNN make it possible to implement the holographic principles of functioning and information storage in the human brain. Thus, the creation of NC is the creation of ANN, implementing holographic principles and methods of information processing and storage, similar to those laid down in BNN. The structural and methodological scheme of NC is presented in Fig. 1.

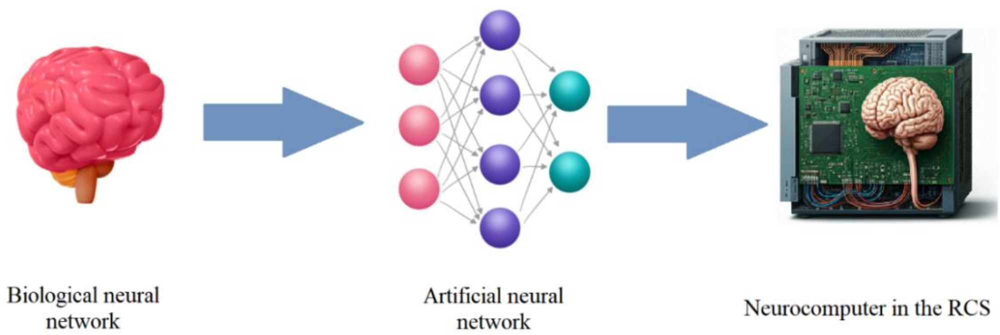

Fig. 1. Structural and methodological diagram of a neurocomputer

Creation of ANN, realizing holographic principles and methods of information processing and storage, similar to those inherent in BNN, requires, first of all, determination and application of the existing or development of a new mathematical apparatus. This mathematical apparatus should bring holographic features of information processing and storage to NC. As noted above, the encoding of numbers in RCS allows to construct a computing device in which the processing of all digits of a number (residues n_t) in RCS is performed independently of each other and in parallel in time. In this case, the structural scheme of the calculator in RCS is the simplest ANN – a set of separate elementary calculators functioning independently of each other and in parallel in time.

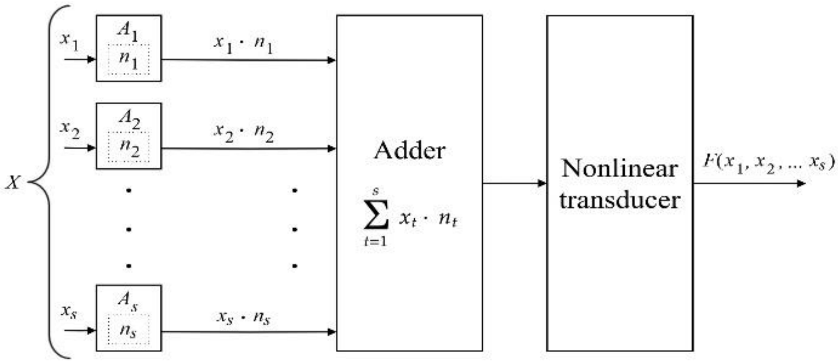

Fig. 2. Scheme of a formal neuron

The known scheme of technical realization of a biological neuron, i.e. the scheme of an artificial (formal) neuron, is presented in Fig. 2.

This circuit consists of a set $\{A_t\}$ of amplifiers with gain coefficients n_t (corresponding to the synaptic strength of the biological neuron), who's inputs receive a set of X, where $\{x_t\}$ $(t = 1, 2, 3, ..., s)$, quantitative values of environmental signs (outputs of other neurons). The signals $\{x_t\}$ correspond to signals arriving from other neurons at the synapses of a given biological neuron. Each signal $\{x_t\}$ is multiplied by an appropriate weight $\{n_t\}$ and fed to an adder corresponding to the cell body of the biological neuron. The gain coefficients n_t can be tuned during the learning process of the artificial neuron. At the outputs of the amplifiers A_t there are signals corresponding to the values of $x_t \cdot n_t$, which are input to the inputs of the adaptive adder, where they are algebraically summed. The sum signal $\sum_{t=1}^{s}(x_t \cdot n_t)$ enters the nonlinear converter, where the process of recognizing the image (situation) F given by a set of attributes is carried out according to its value $\{x_t\}$.

As can be seen from the scheme of construction and functioning of a perseptron or the scheme of a simple neural model (formal neuron) of the BNN (Fig. 2), the main basic operation of neurocomputing is the operation of summation of pairwise products of the form $\sum_{t=1}^{s}(x_t \cdot n_t)$. This circumstance to a greater extent determines the possibility of effective utilization of RCS for creation of super-performance NC. Thus, in this operation, multiplication in RCS, using the tabular principle of arithmetic operations realization, is performed for only two machine cycles of NC operation, which is unattainable for BPNS.

According to the existing ANN theory, a single neuron is capable of performing only the simplest recognition procedure (the simplest computation).

However, the efficiency of neural networks is based on the simultaneous joint use of multiple neurons, i.e. neural networks.

Formal neurons (FN) are combined into layers.

An ANN layer is a set of formal neurons (see Fig. 2) with a single input. A simplified scheme of one ANN layer is presented in Fig. 3.

The analytical relation defining the dependence of the output A_r on the FN input x_t in one layer of ANN is defined as follows:

$$F_r = f_r\left(\sum_{t=1}^{s} x_t \cdot n_{rt} + u_r\right), \quad (4)$$

where F_r – output signal of the r- th neuron; f_r – activation function of the r-th neuron; x_t – input signal; n_{rt} – gain (attenuation) x_t; u_r – bias constant.

If the ANN consists of L layers, the outputs F_r of the neural network will be defined through its inputs $\{x_t\}$ as follows:

$$H_r^{(j)} = f_{r_j}^{(j)}\left(\sum_{t_j=1}^{T_j} x_{r_j t_j}^{(j)} \cdot n_{r_j r_j}^{(j)} + u_{r_j}^{(j)}\right), \quad (5)$$

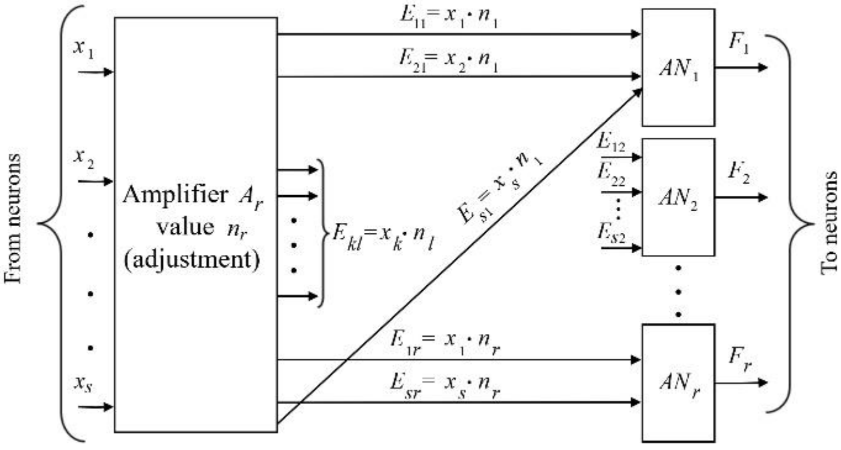

Fig. 3. Scheme of the ANN layer (where AN – artificial neuron)

where $r_j = 1, 2, ..., R$; R – is the number of neurons of the considered ANN; $j = 1, 2, ..., L$; L – the number of layers of the ANN.

On the other hand, the form of representation of numbers N in RCS is based on the use of the expression:

$$N = \sum_{t=1}^{s} n_t \cdot O_t (\mathrm{mod}\, B) = \sum_{t=1}^{s} n_t \cdot O_t - y_N \cdot B, \qquad (6)$$

where $B = \prod_{t=1}^{s} b_t$ – the volume of the range of represented numbers in RCS; s – the number of bases of RCS; O_t – orthogonal bases of RCS; y_N – rank of number N.

Formal (semantic) similarity of mathematical models (4), (5) and (6), as well as analytical similarity of ANN with the basic formulas of data processing represented in RCS makes it possible to effectively implement the NC model. The basis for this is the consistency of the principles of RCS functioning with modern concepts of cognitive processes.

As a result, the use of RCS allows us to create superperforming, reliable and highly fault-tolerant NC functioning in real-time data processing.

Conclusions

The creation of AI capable of imitating the human mind is hampered by the limited capabilities of modern computing systems and the lack of a full-fledged theoretical model describing cognitive processes at the level necessary for their artificial realization.

The development of AI systems involves a wide range of issues and technical aspects. Due to the limited scope of this study, the main attention was focused on the consideration of the hypothesis of a possible model of information processing in NC that is as close as possible to the human cognitive system.

This paper is devoted to the consideration of one of the potential variants of NC realization on the basis of non-positional structure of data representation and processing in RCS. NC utilize parallel information processing, distributed data storage and the ability to learn by example, which can be provided by NPCRS in RCS. Since traditional positional numbering systems cannot effectively process large volumes of unstructured data and identify complex relationships in parallel. It is shown that it is possible to create modern NC by implementing NMB on the basis of RCS, which allows more naturally modeling the hierarchical structure of neural networks. This approach is justified by the following factors:

1. The impossibility of providing the requirements for modern NC (the need to improve performance, reliability, survivability and fault tolerance) in BPNS. Traditional computers are based on sequential data processing and have a bottleneck in data transfer between the processor and memory, which limits performance when processing large amounts of data typical for AI tasks. This is especially important for complex tasks that require real-time processing of large amounts of data.

2. Due to the application of the main three principles of data processing in RCS, the considered AI model based on the proposed NC structure has increased reliability and fault tolerance. Mechanisms of self-diagnostics and automatic recovery based on the principles of redundancy and modularity ensure the continuity of the system functioning even in case of hardware or software failures. In other words, RCS has properties that correspond to the modern ideas about the mechanisms of information processing in the human brain.

3. The principles and methods used in RCS show consistency with modern concepts of information processing in BNN, which can provide a number of benefits for AI.

4. An important prerequisite for the creation of NC in RCS is the consistency, identity of mathematical models of ANN (formal neuron, perseptron, single-layer and multilayer artificial neural network, etc.) and mathematical relations of data processing in NMB RCS.

It is shown that the use of RCS allows to create a NC with improved performance characteristics, which is especially important for matrix operations, widely used in NN. RCS allows to parallelize the calculation of matrix elements, which leads to a significant acceleration of matrix multiplication.

The proposed model demonstrates high fault tolerance due to the application of redundancy and self-recovery methods of RCS. The architecture of the AI system based on the proposed NC functioning in the RCS is designed taking into account the requirements of high reliability. The implementation of a modular structure with a clear division of functions and the use of distributed computing allows minimizing the impact of failures of individual components on the overall performance of the system.

Due to these properties, the AI system acquires increased resistance to failures and ability to adapt to changing conditions. Application of RCS allows to reduce power consumption due to simplified hardware realization of arithmetic devices and absence of transfers between digits, and as a result contributes to the reduction of the cost of neurocomputer systems.

This paper is a foundation for further development of neurocomputers, and AI models in general, based on alternative numbering systems, which is an actual direction of research that can lead to the creation of faster, energy-efficient and fault-tolerant AI systems.

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Нейрокомп'ютер, що функціонує в системі залишкових класів

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Анотація. Мета. Мета полягає в обґрунтуванні можливості створення нейрокомп'ютера (НК) обробки даних на основі використання одного з видів непозиційної машинної арифметики системи залишкових класів (СЗК). **Методологія**. В основу досліджень проблеми створення НК покладено методологію, засновану на використанні методів синтезу непозиційних структур подання коду (НСПК), а також реалізації методів обробки даних у СЗК. Сукупність даних методів реалізується на основі використання трьох основних принципів обробки даних у СЗК: незалежності обробки чисельних значень вмісту залишків; рівноправності функціонування каналів обробки даних; мало розрядність даних у числовому поданні вмісту залишків. **Результати.** Результати проведеного дослідження підтверджують можливість створення НК, які використовують СЗК як основу для обробки інформації. Доведено формальну (семантичну) схожість математичних моделей, а також аналітичну схожість уявлення штучних нейронних систем з основними формулами обробки даних, представлених у СЗК. Встановлено відповідність операції виваженого підсумовування в нейроні з операціє додавання за модулями СЗК. Показано, що функція активації нейрона може бути ефективно апроксимована з використанням операцій множення за модулями СЗК. Аналітично показано, що представлення ваги синапсів в елементах НСПК дозволяє реалізувати паралельні обчислення, аналогічні паралельній обробці інформації в людському мозку. **Наукова новизна.** Вперше проведено комплексне дослідження впливу СЗК на такі ключові характеристики нейрокомп'ютерів НК, як швидкодія при обробці великих обсягів даних, надійність зберігання та передачі інформації, а також загальна стійкість до відмови. Запропоновано новий підхід до побудови НК, що ґрунтується на використанні нейромережевого математичного базису, що базується на непозиційних кодах СЗК. Впровадження даного математичного апарату у структуру нейронних мереж забезпечує можливість досягнення вищої точності та природності при моделюванні ієрархічної організації, властивої біологічним нейронним мережам когнітивної системи людини. **Практичне значення.** Перспективами подальших досліджень є розробка конкретної апаратної реалізації надпродуктивних та високовідмовостійких НК на основі СЗК, а також вивчення можливості застосування даного підходу для вирішення конкретних завдань штучного інтелекту, таких як розпізнавання образів та обробка природної мови.

Ключові слова: обробка даних; штучний інтелект; штучний нейрон; система класів залишків; когнітивна система людини; нейрокомп'ютер; нейронна мережа; математична основа нейронної мережі.