Electronics and Information Technologies, 2025, 32, 19–38
http://publications.lnu.edu.ua/collections/index.php/electronics/index

UDC: 004.032.26

INFORMATION TECHNOLOGY OF AUTONOMOUS NEUROFUZZY MOTION CONTROL OF THE GROUND MOBILE ROBOTICS PLATFORM

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Tsmots, I., Teslyuk, V., Opotyak, Yu., Rabyk, V. & Oliinyk, O. (2025). Information Technology of Autonomous Neurofuzzy Motion Control of the Ground Mobile Robotics Platform. *Electronics and Information Technologies*, 32, 19–38. https://doi.org/10.30970/eli.32.2

ABSTRACT

Background. The development of ground-based mobile robotic platform (GBMRP) motion control systems requires ensuring autonomy, adaptability to dynamic environmental changes, and consideration of limitations on computing resources, mass, dimensional parameters, and energy consumption. Traditional methods of GBMRP motion control, based on accurate mathematical models, are ineffective in real dynamic conditions, where it is impossible to accurately describe the state of the GBMRP and its environment. Therefore, for GBMRP motion control in such situations, the development of an appropriate information technology based on fuzzy logic and neural networks is proposed.

Materials and Methods. Information technology for autonomous neurofuzzy control of the GBMRP movement is developed based on integrated, hybrid, and problem-oriented approaches using component-oriented technology. Fuzzy logic methods will ensure the flexibility and stability of the control system in the presence of noise, measurement errors, and unpredictable environmental changes, and enable integration with neural networks to increase accuracy and speed. Neural network methods offer enhanced accuracy in navigation measurements, data recovery, and the construction of a neural-like defuzzifier, resulting in improved control signal formation.

Results and Discussion. An information technology for autonomous neurofuzzy control of the GBMRP movement has been developed, which, through the use of methods and means of collecting, storing and processing navigation data under conditions of interference and incomplete information, a combination of fuzzy logic and neuro-like structures based on the Sequential Geometric Transformations Model, has ensured adaptability and decision-making under conditions of uncertainty, and the accuracy of the formation of control signals. A fuzzy logic rule base has been developed, providing an adequate representation of expert knowledge in the control system.

Conclusion. In this work, an information technology for autonomous neurofuzzy control of the GBMRP in dynamically changing situations has been developed, based on integrated, hybrid, and problem-oriented approaches using component-oriented technology, while considering limitations on computing resources and energy consumption.

Keywords: information technology, fuzzy logic, neural network, ground mobile robotics platform, platform motion control, defuzzification

INTRODUCTION

The current stage of robotics development is characterized by an increase in requirements for autonomy, adaptability, and intellectuality of information technology tools for controlling ground-based mobile robotic platforms (GBMRP). Such means should provide autonomous control of the movement of the GBMRP under conditions of uncertainty, minimal predictability of the environment, the impact of external disturbances, and limitations on computing resources, mass-dimensional parameters, energy consumption, and cost. Therefore, a pressing issue is the development of information technology for autonomous traffic control of the GBMRP, which will meet the listed requirements.

To date, numerous studies and publications have been conducted on the development of information technology components for autonomous neurofuzzy movement control of GBMRP [1,2]. The primary objective of these studies is to develop effective components for the information technology of autonomous neurofuzzy motion control of the GBMRP, aiming to synthesize a real-time movement control system for the GBMRP that meets constraints on dimensions, power consumption, and cost.

The analysis of the work [3,4] showed that the uncertainty of the external environment in which the GBMRPs operate necessitates the inclusion of a set of intelligent sensors and neural network data processing tools in their composition, which should enable autonomous and safe control of the platform's movement.

One of the most important areas of research is the development of neural network algorithms for the GBMRP motion control system [5,6]. In these works, the authors propose a system of neural network control of the movement of the GBMRP, which provides movement in conditions of uncertainty and minimal predictability of the environment. The articles [7,8] consider the use of deep learning methods for developing neural network control systems for the GBMRP.

The development of mobile platform control systems is the combination of fuzzy logic with the adaptive capabilities of artificial neural networks [9,10]. The paper [11] shows that Takagi–Sugeno controllers with neural adaptation can effectively implement real-time navigation and obstacle avoidance strategies. Such control systems combine the ability to learn from experience with logical interpretation of rules, which makes them suitable for mobile platforms with uncertain or partially known environmental models.

In further research, adaptive neuro-fuzzy inference systems (ANFIS) were proposed, which have become the standard in tasks involving local navigation and stabilization of robot movement. In particular, [12, 13] demonstrated the effectiveness of ANFIS controllers for reactive navigation and obstacle avoidance based on sensor data (laser, ultrasound, GPS). Such approaches ensure smooth trajectories and noise resistance of sensors through a combination of fuzzification, fuzzy rules (such as TSK, proposed by Takagi, Sugeno, and Kang), and training of membership function parameters.

The current direction in the development of neurofuzzy systems is to create hybrid architectures that combine fuzzy logic with deep learning and reinforcement learning methods. Papers [14, 15] demonstrate the feasibility of learning fuzzy rules in environments with variable dynamics using deep reinforcement learning (DRL+ANFIS). This approach enables you to optimize not only instantaneous reactions but also long-term performance criteria, including trajectory time, power consumption, and resistance to dynamic interference.

Of particular interest is the SGTM, which is being developed in Ukrainian scientific schools and considers the process of information processing in neurolike structures as a sequence of geometric transformations in the feature space [16, 17]. This approach is related to modern ideas in geometric deep learning, as it enables the formation of transformation-invariant data representations. The use of SGTM in the motion control systems of a mobile robotic platform enables the development of non-iterative learning algorithms and achieves zero methodological error during defuzzification, which is particularly important for real-time implementation on hardware platforms (FPGA, SoC, SBC) [18, 19].

The practical implementation of neurofuzzy controllers necessitates consideration of the limitations imposed by real-time and hardware resources. As noted in [20], for mobile robots based on microcontrollers or single-board computers, a balance between accuracy, speed, and energy efficiency is important. Hardware implementations on FPGAs enable the implementation of cascades of fuzzy rules in pipeline mode, resulting in minimal delays in processsing touch data [21, 22]. The articles [23, 24] demonstrate that the use of the tabular-algorithmic method for implementing basic operations in neurofuzzy motion control of a mobile platform results in improved performance and reduced computing resource requirements.

Therefore, an urgent task is to develop the components of the information technology for autonomous neurofuzzy movement control of the GBMRP, which is based on fuzzy logic and SGTM-based neural networks, and to synthesize systems of neurofuzzy control for the movement of the GBMRP on this basis.

MATERIALS AND METHODS

Traditional methods of classical control of the movement of the GBMRP, which are based on accurate mathematical models, are ineffective in real dynamic conditions, where it is impossible to accurately describe the state of the GBMRP and the environment. To control the movement of the GBMRP in such conditions, on the basis of fuzzy logic and neural network methods, a control system is created, which must be able to build a route and control the parameters of movement (set the speed of movement and angles of rotation).

Fuzzy logic provides formalization of expert knowledge in the form of linguistic if-then rules and decision-making based on incomplete or inaccurate sensory data. The use of fuzzy logic in the GBMRP control system will ensure the flexibility and resilience of the control system to noise, measurement errors and unpredictable changes in the environment; provide effective management without the need to create an accurate mathematical model of the object and environment; high adaptability to dynamic changes and uncertainty; smooth adjustment and absence of sharp fluctuations in control signals; ease of implementation of the rule base and the possibility of its further configuration or training; the ability to integrate with neural networks to improve the accuracy and speed of the system.

One of the ways to achieve high technical and operational characteristics of the means of information technology for controlling the movement of GBMRP is the use of neural networks based on the paradigm of the Successive Geometric Transformations Model (SGTM) for evaluating data from sensors in conditions of interference and incomplete information, building a neural defuzzifier with increased accuracy of generating signals for controlling the drive of the GBMRP. A feature of SGTM-based neural networks is the fundamental possibility of non-iterative calculation of the weights of synaptic connections between neural elements, as well as the use of a tabular algorithmic method for their implementation.

It is advisable to develop an information technology for autonomous neurofuzzy control of the movement of GBMRP based on integrated, hybrid, and problem-oriented approaches using component-oriented technology. Therefore, the development of information technology for autonomous neurofuzzy motion control of the GBMRP is a pressing scientific and practical task aimed at enhancing the level of intelligence, reliability, and technical and operational characteristics of the GBMRP movement control system.

The object of research is the processes of collecting, storing, and processing navigational data, as well as the neurofuzzy control of the movement of GBMRP. The subject of the study is the models, methods, algorithms, and structures of information technology tools for autonomous neurofuzzy control of the movement of the GBMRP in real-time.

The purpose of this work is to develop an information technology for autonomous neurofuzzy control of the movement of GBMRP, which operates under conditions of uncertainty, minimal predictability of the environment, and the influence of external disturbances, while also considering limitations on computing resources, mass-dimensional parameters, and energy consumption.

To achieve this goal, the following main objectives of the study are defined:

- development of the structure of information technology for autonomous neurofuzzy control of the movement of the GBMRP;
- means of collecting and storing navigational data on the state of the GBMRP environment;
- methods and tools for processing navigation data;
- methods and means of route planning for GBMRP;
- models and means of collision avoidance;
- methods and means of fuzzification of navigation data;
- a base of rules of fuzzy logic for controlling the movement of GBMRP;
- methods and means of forming fuzzy conclusions;
- methods and means of neuroid defuzzification;
- tabular and algorithmic method of increasing the speed of the means of neurofuzzy control of the GBMRP;
- kinematic model of GBMRP.

RESULTS AND DISCUSSION

Development of the information technology structure for autonomous neurofuzzy movement control of GBMRP

The development of information technology for autonomous neurofuzzy control of the movement of GBMRP in conditions with a dynamic change in the situation is proposed to be carried out based on an integrated approach, which includes:

- methods and means of collecting navigational data on the dynamic state of the GBMRP environment;
- methods and means of storing navigation data on the dynamic state of the environment of the GBMRP;
- methods and means of processing and evaluating navigation data from sensors in conditions of interference and incompleteness of information;
- methods and means of planning the route of the GBMRP;
- methods and means of fuzzy control of the movement of the GBMRP;
- bases of rules for unclear control of the movement of the GBMRP;
- methods and means of training and functioning of the neural network in the process of defuzzification;
- tabular and algorithmic method of increasing the speed of the GBMRP motion control means;
- modern element base (microcontrollers, systems on a chip, programmable logic integrated circuits such as FPGAs, etc.);
- means of computer-aided design of software and hardware.

The development of information technology tools for autonomous neurofuzzy control of the movement of GBMRP is proposed to be carried out using component-oriented technologies. The essence of component-oriented development technology is to divide the means into independent, interconnected functional components (modules), which can be developed, tested, and improved separately, and then integrated into a single system through standardized interfaces.

An approach based on this technology provides modularity and scalability of the architecture, reuse of software and hardware solutions, reduction of development time and implementation costs, and the ability to flexibly adapt the system to new conditions or update the technological base.

The component-oriented design technology is based on the following principles: functionality encapsulation, where each component implements its own logic independently of the others; use of standardized interfaces; component interchangeability, where updating or replacing a separate module does not require a complete redesign of the system; hierarchy of architecture, in which components can be combined into subsystems (navigational, analytical, executive, etc.); support for reuse, in which finished components can be integrated into other robotics platforms; hardware-software coordination, which ensures correspondence between software components and physical modules of the equipment.

According to component-oriented development technology, the GBMRP motion control system comprises several functional components, each of which performs well-defined tasks and has a standardized interface for interaction with other subsystems. For the synthesis of the GBMRP motion control system, the following components can be used: sensory data collection, neural network accuracy improvement, data processing, and fuzzy logical decision-making.

The structure of the information technology for neurofuzzy control of the GBMRP movement in dynamic situations is shown on **Fig. 1**.

To control the movement of GBMRP, we will use a hybrid approach that integrates: fuzzy logic for decision-making in conditions of uncertainty and the formation of adaptive control actions; neuro-like structures for the implementation of fast computing; and hardware and software for adaptive motion control in real time.

The use of fuzzy logic will ensure decision-making in the face of fuzzy or contradictory data, as well as the smoothness and continuity of control actions. With neurofuzzy control of the GBMRP, along with fuzzy logic, neuro-like structures utilizing the SGTM paradigm are employed, which provide speed, repeatability, and the ability to operate with large volumes of data. The SGTM paradigm is based on a non-iterative approach to training neuro-like structures, which involves the direct calculation of weights during a gradual decrease in the dimensionality of the space of input multidimensional data on neurons of the hidden layer.

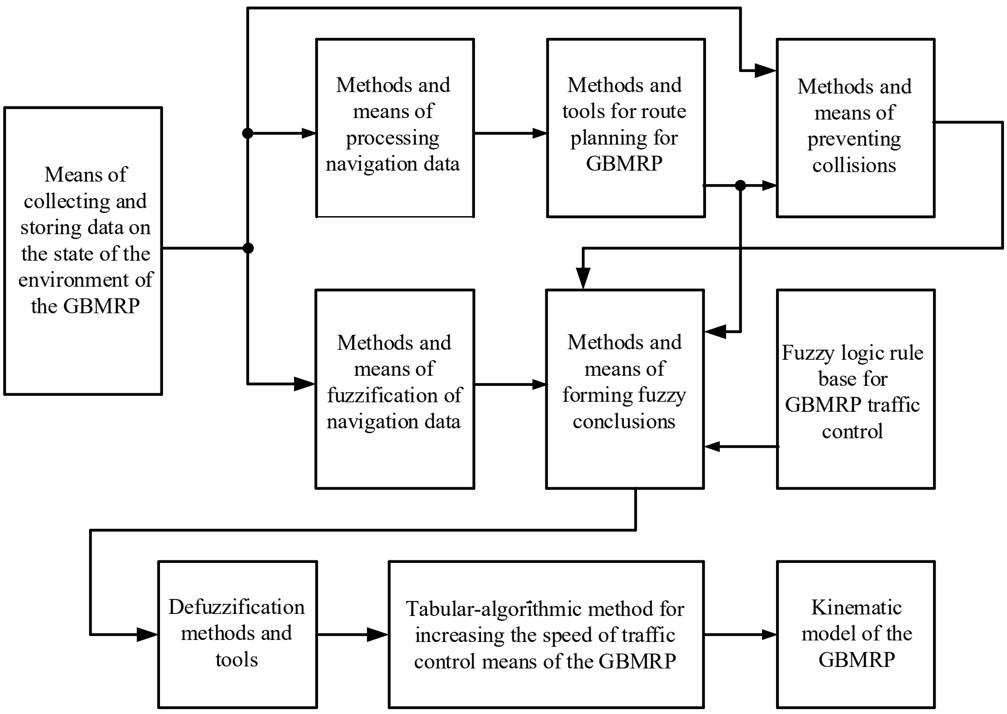

Fig. 1. Structure of information technology for autonomous neurofuzzy motion control of GBMRP.

The implementation of information technology for neurofuzzy control of the movement of GBMRP is proposed to be carried out based on a problem-oriented approach, which involves a combination of software and specialized hardware. The process of interpenetration of software (universal) and hardware (specialized) ensures their implementation with high technical and operational characteristics.

The development of means of information technology for controlling the movement of the GBMRP is proposed to be carried out according to the following principles: variability of the equipment composition, which provides for the presence of a processor core and replaceable specialized means, with the help of which the core is adapted to the requirements of a specific application; modularity; pipeline and spatial parallelism of data processing; openness of software; specialization and adaptation of hardware to the structure of data processing algorithms.

The main stages of the implementation of the information technology of neurofuzzy control of the movement of GBMRP are:

- means of collecting and storing data on the state of the environment of the GBMRP;
- methods and tools for processing navigation data;
- methods and means of route planning for GBMRP;
- methods and means of fuzzification of navigation data;
- a base of rules of fuzzy logic for controlling the movement of GBMRP;
- methods and means of forming fuzzy conclusions;
- methods and means of defuzzification;
- tabular and algorithmic method of increasing the speed of the means of neurofuzzy control of the GBMRP;
- kinematic model of GBMRP.

Means of collecting and storing navigational data on the state of the environment of the GBMRP.

With neurofuzzy control of GBMRP movement, it is necessary to continuously monitor the navigation state of the environment, measure distances to obstacles, determine coordinates, and control the direction and speed of the GBMRP movement.

To collect and store navigation data on the state of the GBMRP environment, the following tools may be used: Raspberry Pi microcomputer, ESP32-C3 microcontroller, MPU-6050 gyroscope, QMC5883L digital compass, YDLidar X4 lidar, GPS module, and a set of sensors for collecting climatic parameters. Each sensor must have dedicated computing resources for processing the received data. Their implementation is possible using modern microcontrollers that have the appropriate sets of interfaces (SPI, I^2C, Serial) and are equipped with sufficient computing resources to ensure interaction with the sensors and implement the necessary data pre-processing in real-time. The collection and storage of navigation data on the state of the environment of the GBMRP is controlled by the Raspberry Pi microcomputer, the information from which is transmitted to the control system.

The navigation data used to control the movement of the GBMRP is stored in a database implemented on a single-board Raspberry Pi computer. The type of database affects both the performance and scalability of the hardware and software solution, as well as its ability to efficiently analyze, process, and manage data. Traditional relational databases, such as PostgreSQL, MySQL, or SQL Server, are robust and have extensive functionality, but they require more system resources and are not optimized for operations that are common in IoT and GBMRP. These databases are optimized for processing complex queries and providing transactional sequences, but they are not efficient when working with large amounts of data received from navigation sensors that arrive at high intensity. The advantages, for example, of the InfluxDB database are its ability to efficiently process large amounts of timestamped data. Working with data in the form of time series is used to prepare datasets for machine learning models when predicting future states based on historical data.

Methods and tools for processing navigation data.

Methods and tools for processing navigation data in GBMRP are a key component of ensuring the autonomy, accuracy, and safety of mobile platform movement in complex environments. The main methods of processing navigation data in the GBMRP are:

- localization methods that are designed to determine the position and orientation of the GBMRP in space;
- route planning methods that are designed to find the optimal path of the GBMRP, taking into account the map and obstacles;
- methods of avoiding obstacles in real time, which are designed for dynamic adaptation of the movement of the GBMRP to new circumstances;
- sensor integration techniques that combine data from different sensors to improve accuracy and reliability;
- artificial intelligence techniques that enable environmental perception, decision-making, route planning, and adaptation to changes in the environment.
- methods and means of processing navigation data in the GBMRP with autonomous navigation, which operate in conditions with dynamic change of situations, interference, and incompleteness of information, should provide the following requirements:
  – autonomous navigation of the GBMRP, which will provide independent route planning, obstacle avoidance, and recovery from failures;
  – high accuracy of positioning of the GBMRP;
  – reliability of navigation data, i.e., the ability to work in conditions of noise, signal loss, and temporary sensor failures;
  – integration of navigation data from various sources;
  – adaptability to changes in the environment of the GBMRP;
  – processing navigation data and real-time management decision-making;
  – building environmental maps;
  – orientation of intelligent algorithms to built-in problem-oriented systems with limited computing resources;
  – reduction of energy consumption, dimensions, and weight.

Neural-like means of recovering lost navigation data. To recover the lost navigation data, we will use a neural network based on the SGTM paradigm. Since the data for recovery from a typical sensor is overwhelmingly presented in the form of a time series, we can use the time window method to process it. In this case, the number of neural network inputs equals the selected time window size.

As a result of neural network processing, forecasting (reproducing lost) data for the next countdown is performed. The quality of reproduction in this case depends on the number of neurons in the hidden layer; however, a compromise between the accuracy of training and the accuracy of prediction (reproduction of lost data) should be considered in this context. The optimal values of this parameter are determined by the dataset data, their number, and structure.

A significant advantage of SGTM-based neural networks over others is their ability to learn quickly and non-iteratively. Additionally, these neural networks effectively replicate the lost data for the reference group.

Means of intelligent processing of navigation data. Means of intelligent processing of navigation data should provide an increase in the accuracy of measuring motion parameters, predicting geographical coordinates, and facilitating effective interaction with the environment despite interference.

The means of intelligent processing of navigation data in the GBMRP consist of the following modules: wireless communication and data protection; processing, analysis and recovery of lost data; neural network improvement of the accuracy of measuring movement parameters; neural network improvement of the accuracy of determining geographic coordinates; neural network forecasting of geographical coordinates and route of movement of the GBMRP; data collection and storage; determination of geographical coordinates and control of the movement of the GBMRP.

Methods and means of intelligently improving the accuracy of the measurement of navigation parameters. The task of increasing the accuracy of data obtained from various navigation sensors in the conditions of interference and incomplete information is important for the GBMRP. The complexity of solving such problems lies in the fact that the accuracy at the output of the sensors is a consequence of the influence of many factors, each of which has a different degree of influence on the result.

The task is especially challenging when it is impossible to clearly distinguish the factors influencing the system and when the magnitude of their influence on the resulting parameter is unknown. Navigation sensors, which are widely used in many systems, are particularly indispensable for GBMRP.

The measurement accuracy of such sensors is affected by noises that are caused by both their design and the external environment. It is proposed to utilize neural network singular spectral analysis (SSA) to enhance the accuracy of navigation sensor measurements, which enables the detection and removal of noise from the output signal. Using the neural network SSA, an information technology has been developed to improve the accuracy of measuring the parameters of movement and spatial orientation of the GBMRP. The main stages of such information technology are:

- collection and storage of data from navigation sensors;
- pre-processing of navigation data;
- determination of neural network parameters based on SGTM for singular spectral analysis;
- development of a neural network based on SGTM for SSA;
- detection and removal of noise in the measuring output signal;
- development of a neural network structure based on SGTM for measuring the navigation parameter with increased accuracy;
- setting up a neural network based on SGTM and calculating weighting factors;
- calculation of tables of macropartial products for tabular and algorithmic implementation of neuroelements;
- problem-oriented implementation of a neural network based on SGTM to measure the navigation parameter with increased accuracy.

For the implementation of neural network SSA, neural networks based on the SGTM paradigm with projective and ordered lateral connections were selected, which are fast, non-iterative, do not accumulate errors, and do not have limitations on measurability. The use of such neural networks for implementing neural network SSA will ensure real-time operation and achieve high technical and operational characteristics.

Forecasting the movement of GBMRP. There are various algorithms for predicting the route and movement of the GBMRP. The choice of a specific algorithm is carried out taking into account various conditions. In particular, the GBMRP operates under deterministic or non-deterministic, static or dynamic conditions.

If the GBMRP operates in static conditions, then the forecasting of motion is reduced to finding a sequence of points in the trajectory of the possible movement of the GBMRP, with the possibility of conflict-free obstacle avoidance. If dynamic changes in the external environment are possible during the movement of the GBMRP, then, in addition to finding trajectory points, it is necessary to regulate the speed of movement on specific sections of the route.

Algorithms for global planning of the movement of GBMRP in deterministic conditions contain information about the external environment. Therefore, it is possible to identify specific areas where the movement of the GBMRP is feasible and then select the optimal path. A problem in predicting the movement of the GBMRP can be solved using both accurate and heuristic algorithms.

The main disadvantage of accurate algorithms is the high computational complexity, and heuristic algorithms do not guarantee the completeness of the search for the optimal path. The advantages of heuristic algorithms include reducing computational complexity and sensitivity to data errors. Some of these algorithms focus on finding the optimal path. At the same time, they read the data from the map of the external environment and consistently try to find the best way for the movement of the GBMRP, avoiding obstacles. Such algorithms are effective even when there are a large number of various obstacles in the way of GBMRP.

Despite this, in real-world conditions, the GBMRP operates in uncertain environments, and the solution to the motion forecasting problem cannot be carried out by either accurate or heuristic algorithms. Therefore, in this case, the best option is to use artificial intelligence tools. Currently, the most common methods for predicting the movement of GBMRP are neural network algorithms.

In general, the following requirements are set for neural network algorithms for predicting the movement of GBMRP:

- minimizing the passage time;
- minimizing the length of the path;
- minimization of deviations from a given trajectory;
- reliability (absence of algorithm failures);
- ensuring the impossibility of collisions with obstacles and other GBMRPs.

Under conditions of uncertainty, the movement of the GBMRP can be predicted with the help of artificial neural networks. When implementing motion forecasting algorithms, it is essential to consider the dimensions of the GBMRP.

The advantage of using a neural network approach for implementing GBMRP motion prediction is the possibility of parallel signal processing. This is achieved by combining a large number of neurons into layers and connecting neurons across different layers in a specific manner. Also, artificial neural networks provide the ability to learn.

The solution of the problem of GBMRP forecasting based on the neural network approach is reduced to the following stages:

- formalization of the planning task;
- network topology selection;
- displaying the interaction of network neurons in the form of a neural map (surface);
- calculation of the full trajectory in the form of some procedure of "ascent" to the top of the surface (target).

The conditions for applying this approach are determined by the formalization of the motion forecasting problem. The input data consists of environmental data collected from sensors hosted on the GBMRP. Based on the information obtained, the configuration of the given space and the location of obstacles are determined. Determining the exact configuration of the workspace largely depends on the technical capabilities of the sensor system, so it is necessary to use high-quality sensors to obtain the necessary information.

The main advantages of using neural network algorithms for predicting the movement of GBMRP include the possibility of their hardware implementation in the form of neuro-accelerators. Since neural networks can quickly adapt to changes, they can be used to predict the movement of GBMRP in dynamic, non-stationary environments.

Methods and tools for route planning for GBMRP

Planning of GBMRP routes is a multifactorial task that should take into account groups of the following factors:

- environment – static, dynamic obstacles and road conditions;
- technical limitations of the GBMRP – battery reserve, maximum carrying capacity, movement speed, ability to overcome obstacles, type of movement;
- sensors and navigation systems – lidar, video camera, angular velocity meter, digital compass, and GPS;
- route restrictions – minimizing distance, avoiding dangerous areas, minimizing the time to complete the task, and taking into account priorities.

Geometric methods can be used to plan the route of the GBMRP, which are grouped on a mathematical model of the environment using geometric calculations to find the optimal route. Such methods include the graph method of GBMRP route planning, which involves using graphs to model space and finding the optimal path between given points. Building a navigation graph for planning the route of the GBMRP involves the following stages:

- modeling space as a set of nodes and edges, where nodes are points at which the GBMRP can stop or change direction, and edges are the paths along which the GBMRP can move;
- assigning each edge a weight that characterizes the costs necessary for its passage (length, time, energy consumption, etc.);
- optimization of the graph by eliminating unnecessary nodes and clarifying weights, taking into account dynamic conditions (moving obstacles).

To plan the route of the GBMRP in complex environments, we will utilize the Navigation Stack package, which is specifically designed to integrate with navigation systems within the ROS 2 (Robot Operating System) framework. The main components of the Navigation Stack package are:

- Global Planner, which provides a path from the start to the end point based on a global map using the A* or Dijkstra algorithm;
- Local Planner, which provides real-time obstacle avoidance and trajectory correction based on sensor data using the DWA (Dynamic Window Approach) or TEB (Timed Elastic Band) algorithm.

Planning the route of the GBMRP using the Navigation Stack package involves setting the coordinates of the start and end point (target) for the ride. Global Planner used a map for optimal path planning to the target. The Local Planner takes into account dynamic obstacles and adjusts the route in real-time.

Collision Avoidance Models and Tools.

An important element of the GBMRP traffic control system is the collision avoidance subsystem, which utilizes safety zones and Petri nets. The safety zone for GBMRP defines the area around the platform where collisions are avoided, ensuring a safe distance between the platform and other objects in the environment.

The main factors that affect the size of the safety zone are: the size of the GBMRP itself and the cargo it carries; the speed of movement of the GBMRP; the response time of the sensors, which is required to detect an obstacle; the braking distance, which depends on the mass of the GBMRP with a load and the power of the brake system. The diameter of the safety zone D for the GBMRP is calculated according to the formula:

$$D = vt_r + \frac{v^2}{2a} + M, \tag{1}$$

where v is the speed of movement of the GBMRP (m/s), t_r is the sum of the reaction time of sensors and data processing (s), a is the acceleration of braking (m/s²), and M is the additional margin.

Simulation models using safety zones to avoid collisions during the movement of GBMRPs are based on the principle of creating virtual constraints that define a safe space around the platform. By utilizing safety zones, GBMRPs can make informed decisions about their routes and actions in real-time, thereby avoiding collisions with both static and dynamic obstacles.

To prevent collisions of GBMRP with obstacles, it is proposed to use a model based on the theory of Petri nets. In mathematical form, the collision avoidance model based on the theory of simple Petri nets can be written as follows:

$$Mod\_CA =< P, T, M_0 >, \tag{2}$$

where Mod_CA is the collision avoidance model based on the theory of simple Petri nets, P is the set of positions, T is the set of transitions, and M_0 is the initial marking.

The development of such a model involves the use of priorities and safety zones defined by the GBMRP, the size of which is determined by formula (1). In such a model, when a dynamic obstacle (such as vehicles and people) violates the safety zone of the GBMRP, a priority mechanism is proposed to resolve the conflict situation. When moving the GBMRP to ensure effective coordination of their movement, avoiding collisions, and achieving a common goal, the urgent task is to assign priorities to vehicles, people, and the GBMRP.

The following parameters can be used to determine the priority of the GBMRP: distances to obstacles, type of obstacle (static or dynamic), features of the dynamic obstacle (such as vehicles or people), and occupancy of traffic sectors. When controlling traffic on the GBMRP using the priority mechanism and safety zone, it is assumed that vehicles and people within the safety zone have a higher priority than those on the GBMRP.

Therefore, the GBMRP must slow down and give way to vehicles and people who have higher priority. In the event of the signal indicating a violation of the security zone disappearing, the platform continues to perform the previously assigned task.

A collision avoidance model considering the priority mechanism and safety zone based on colored Petri nets is written as follows:

$$Mod\_col\_CA =< P, T, F_{in}, F_{out}, M_0, TypeP, TypeM >, \tag{3}$$

where Mod_col_CA is a collision avoidance model taking into account the priority mechanism and the safety zone based on colored Petri nets, P is a set of positions, T is a set of transitions, F_{in} is a set of input arcs, F_{out} is a set of output arcs, M_0 is the initial marking, $TypeP$ is the types (colors) of markers that may be present in a particular position, $TypeM$ is the types of markers.

In the model, we have two types of markers $TypeM\_A$ and $TypeM\_B$. The presence of a $TypeM\_B$ marker in the position signals that the GBMRP resolves the conflict situation.

Methods and means of fuzzification of navigation data

Fuzzification of data from navigation sensors (GPS, gyroscopes, accelerometers, digital compasses, LiDAR) involves converting this data into fuzzy sets or linguistic variables that are understandable to humans. The peculiarity of such a transformation is the formation of belonging functions and the determination of the number of terms of the linguistic variable.

The choice of the membership function depends on the following characteristics of the navigation data: noise, data dynamics, and value distribution. When developing a motion control system for the GBMRP, the following belonging functions are most often used: triangular, trapezoidal, Gaussian, sigmoidal, and parabolic. For real-time navigation data fuzzification, it is advisable to choose a triangular function that is easy to implement. The main methods used for the fuzzification of navigation data are: the method of equal degrees, discrete fuzzification, continuous fuzzification, the method of splitting by parameters, and the combined method. Of the listed methods for fuzzification in fuzzy motion control systems of the GBMRP, it is most expedient to use the method of continuous fuzzification and the combined method. The continuous fuzzification method provides a smooth transition between different levels of fuzzy affiliations. This method works with fuzzy sets, which allow elements to belong to a set with a certain degree of belonging (values from 0 to 1). Continuous fuzzification reduces the impact of sudden changes in the system's inputs, making it more resistant to noise.

After the fuzzification is completed, specific values of belonging functions for each of the linguistic terms used in the database of production rules of the fuzzy inference system should be determined for all input variables. In the process of fuzzy control of the movement of the GBMRP, both input and output linguistic variables are used. The input linguistic variables represent the data that enters the fuzzy logic system for analysis. Instead of exact numerical values, these variables can be represented by fuzzy concepts, i.e., terms. Fuzzification tools for converting input navigation data (distance d, target orientation angle φ) into linguistic variables are implemented by a microcontroller that performs data collection.

Fuzzy logic rule base for GBMRP traffic control

The formation of a base of fuzzy logic rules for managing the movement of GBMRP is a complex and multifaceted process that involves creating clear logic for real-time decision-making. The primary purpose of such management is to ensure the reliability, safety, and efficiency of the platform's movement in conditions with dynamic changes in the situation.

After detailing the functions of the input and output linguistic variables, it is necessary to develop rule bases for the two output variables, V_R, and V_L. The base of fuzzy logic rules for the output V_R variable is given in **Table 1**.

The input linguistic variable d (distance from the GBMRP to the target) is divided into five terms over the measurement interval: VSD – very small distance, SD – small distance, AD – average distance, BD – big distance, VBD – very big distance. The input linguistic variable φ (the angle of orientation to the target) is divided into seven terms in the range [−180°..+180°]: NBA – negative big angle, NAA – negative big angle, NSA – negative small angle, ZA – zero angle, PSA – positive small angle, PAA – positive average angle, PBA – positive big angle.

The base of fuzzy logic rules for the output variable V_L is given in **Table 2**.

Each fuzzy logic rule base for the output variables V_R (**Table 1**) and V_L (**Table 2**) includes 35 rules of the form *IF-THEN*. The output linguistic variables of the controller (speed of the right V_R and left wheels V_L) of the GBMRP are divided into five terms: VLS – very low speed, LS – low speed, AS – average speed, BS – big speed, VBS – very big speed.

Table 1. **Fuzzy logic rule base for the output variable V_{R}**

Distance, d	Angle, φ						
	NBA	NAA	NSA	ZA	PSA	PAA	PBA
VSD	BS	AS	LS	LS	VLS	VLS	VLS
SD	VBS	BS	AS	LS	VLS	VLS	VLS
AD	VBS	VBS	BS	AS	VLS	VLS	VLS
BD	VBS	VBS	VBS	BS	VLS	VLS	VLS
VBD	VBS	VBS	VBS	VBS	VLS	VLS	VLS

Table 2. **Fuzzy logic rule base for the output variable V_L**

Distance, *d*	Angle, φ						
	NBA	NAA	NSA	ZA	PSA	PAA	PBA
VSD	VLS	VLS	VLS	LS	LS	LS	AS
SD	VLS	VLS	VLS	LS	AS	BS	VBS
AD	VLS	VLS	VLS	AS	BS	VBS	VBS
BD	VLS	VLS	VLS	BS	VBS	VBS	VBS
VBD	VLS	VLS	VLS	VBS	VBS	VBS	VBS

Methods and means of forming fuzzy conclusions

The means of forming fuzzy conclusions are an important part of the system of fuzzy control of the movement of the GBMRP. The formation of a fuzzy output provides control over the movement of the GBMRP in conditions with dynamic changes in the environment's situation. The process of forming fuzzy inference is based on the rules of fuzzy logic by performing the following stages: aggregation, activation, and accumulation.

At the aggregation stage, fuzzy sets are combined that correspond to the bases of fuzzy logic rules. For each rule, the degree of execution is determined, which depends on fuzzy input values and their comparison with the conditions of the rules. Methods such as minimum (AND) and maximum (OR) functions, or other functions, are commonly used to determine the results.

At the activation stage, the degree of truth of the original variable for each rule is determined. This is achieved by applying an activation function, for example, by limiting the value of the degree of truth (truncation). The result of each rule is represented as a truncated or modified fuzzy set.

The final stage of fuzzy inference is accumulation, which involves determining the membership function for each of the original linguistic variables in the set. At this stage, the initial values of all fuzzy rules are combined into a single fuzzy multiple value, representing the system's resulting output. The following accumulation methods are used to combine fuzzy sets: Maximum, Summation, Probabilistic Sum, Average, Weighted Average, Fuzzy Integral, and Minimum. When using the maximization method, the maximum value of the belonging function is selected from all results. This method is used when it is necessary to find the most significant answer from the rules.

Methods and means of neural-like defuzzification

For defuzzification, we will utilize a neural network based on the SGTM paradigm, which assigns a numerical value to each of the initial linguistic variables.

Such neural-like defuzzification provides a reduction in computational complexity and an increase in the accuracy of receiving the GBMRP control signal.

The schemes of interaction of the fuzzy inference former with the neural network of defuzzification are shown in **Fig. 2**, where $x_1,\ldots x_n$ – input control variables; $F_{y1},\ldots F_{yn}$ is the output parameter of the fuzzy inference former, the number of which corresponds to the number of terms of the original linguistic variable; y *is* the resulting value of the control signal.

The architecture of a neural-like defuzzifier based on the SGTM paradigm, which determines the numerical value of the original variable δ, is illustrated in **Fig. 3**.

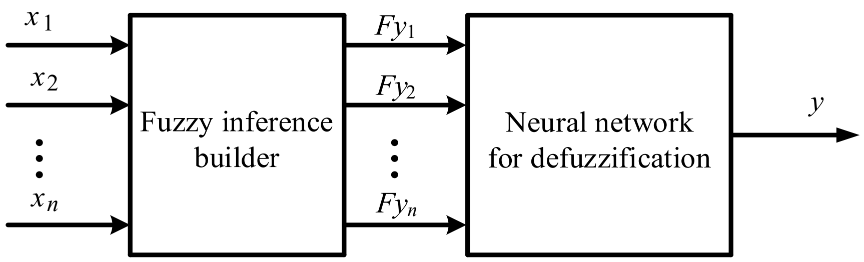

Fig. 2. Schemes of interaction of the fuzzy inference generator with a neural network for defuzzification/

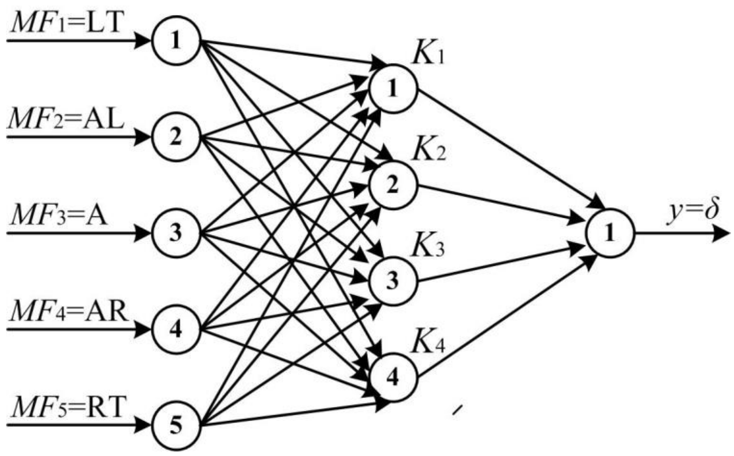

Fig. 3. Architecture of a neural-like defuzzifier for finding the numerical value of the output variable δ.

A neural defuzzifier is used in the fuzzy logic controller to control the movement of the GBMRP based on fuzzy logic. The following input and output linguistic variables are used for such control:

- Distance (D) is the distance from the GBMRP to the object (input variable);
- Angle (θ) is the angle between the object and the input variable.
- Deviation (δ) is the deviation of GBMRP relative to the input data *D* and *θ* (output variable).

The affiliation function $MF_\delta(x)$ for the output variable (δ) is given by a triangular affiliation function with the following five terms: T(δ)={LT, AL, A, AR, AT}.

The form of the membership function $MF_\delta(x)$ for the original variable (δ) is shown in **Fig. 4**.

The ownership function $MF_\delta(x)$ of the original variable (δ) is determined by the parameters a, b, c. These parameters are determined based on experimental or expert data. Its value at point *x* is calculated by the expression:

$$MF_\delta(x) = \begin{cases} 1 - \dfrac{b-x}{b-a}; & a \le x \le b \\ 1 - \dfrac{x-b}{c-b}; & b \le x \le c \\ 0; & x \notin (a,c) \end{cases} \qquad (4)$$

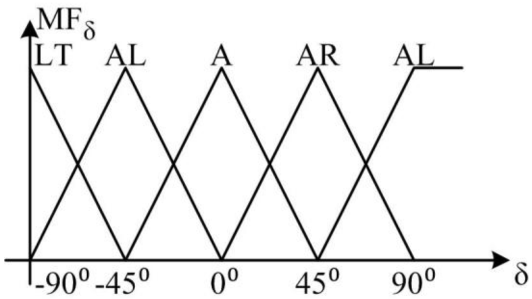

Fig. 4. Appearance of the membership function of the output variable δ.

For the output *of* $y = \delta$ of the neuro-like defuzzifier, a table of training vectors was formed based on the belonging function (**Table 3**).

Table 3. **Table of training vectors for output $y = \delta$**

Number	MF1	MF2	MF3	MF4	MF5	δ (deg)
1	0.533	0.467	0	0	0	-69
2	0.578	0.422	0	0	0	-71
3	0.378	0.622	0	0	0	-62
4	0	0.333	0.667	0	0	-15
5	0	0.289	0.711	0	0	-13
6	0	0	0.756	0.244	0	11
7	0	0	0.800	0.200	0	9
8	0	0	0.156	0.844	0	38
9	0	0	0	0.889	0.111	50
10	0	0	0	0.933	0.067	48
11	0	0	0	0.044	0.956	88
12	0	0	0	0	1.0	90

The stage of neural defuzzification based on fuzzy logic provides the receipt of a signal $y = \delta$ to control the movement of the GBMRP. In the process of learning, vectors are calculated: $M_j^{(m)}$, $\alpha_j^{(m)}$ and β_j, where $j = 0,\ldots,n$; $m = 1,\ldots,n-1$, n is the number of neurons of the input layer of the network. The results obtained are recorded in files and used in the operation of the neural defuzzifier in the mode of operation.

Tabular-algorithmic method of increasing the speed of means of neurofuzzy control of the GBMRP

When implementing the means of neurofuzzy control by the GBMRP, the problem of providing a real-time mode, reducing weight, dimensions, power consumption, and cost arise. One way to ensure such high technical and economic characteristics is the use of the tabular-algorithmic method for implementing the basic operations of algorithms for neurofuzzy control within the GBMRP. Most of the basic operations of the algorithms for neurofuzzy control of the GBMRP are reduced to calculating the scalar product. When implementing the operation of calculating the scalar product, it is advisable to use a multi-operand approach, in which the process of calculating the scalar product is considered as the execution of a single operation based on elementary arithmetic operations. The basis of this approach is multiplication algorithms with the direct formation of partial products starting from the lowest digits of the factors.

The calculation of the scalar product in floating-point format is written as follows:

$$Z = \sum_{s=1}^{k} W_s X_s = \sum_{s=1}^{k} w_s 2^{m_{W_s}} x_s 2^{m_{xs}}, \tag{5}$$

where w_s and m_{W_s} – respectively the mantissa and the order of the multiplied W_s; x_s and m_{xs} – respectively the mantissa and the order of the input given (multiplier) X_s; k is the number of pairs of products, $s = 1, .., k$. To calculate the scalar product with the previously known multiplication of W_s , we will use the tabular-algorithmic method, which involves the preliminary calculation of tables of macropartial products of mantissa p_{Mi} and the determination of the maximum value of the order of macropartial products $max\, m_{P_{M_i}}$, where n is the bit depth of the mantissa of factors x_s, $i = 0,...,n$.

Kinematic model of GBMRP

Based on the geometric and mechanical properties of the GBMRP, a differentially controlled kinematic model is developed. For example, the GBMRP may use one passive and two independent active wheels for movement, which are driven by DC motors. The passive wheel of the GBMRP is used to maintain the balance of the platform. Such a wheel does not generate a traction force, but rather follows the movement of the platform. The active wheels are positioned symmetrically relative to the central axis of the platform and are independently controlled by motors, ensuring the rotation of the wheels at specified speeds. A key feature of such a kinematic model is that the passive wheel does not directly affect the model; instead, it ensures the speeds of the active wheels entirely determine the stability of the GBMRP and the movement of the platform. A kinematic model of the GBMRP is used to plan trajectories, control, and simulate the movement of the differential drive platform.

Discussion of research results

The developed information technology for autonomous neurofuzzy control of the GBMRP movement is effective in ensuring the autonomy, adaptability, and stability of the system in response to dynamic environmental changes and external interference. The conducted experiments and simulations confirmed that the combination of fuzzy logic and neuro-like structures, based on the Sequential Geometric Transformation Model paradigm, provides an increase in the accuracy of movement without the need to create an accurate mathematical model of the GBMRP and its environment. Compared to classical control methods [25, 26], which require precise mathematical models and do not adapt well to uncertainty, the proposed neurofuzzy technology demonstrates:

- greater resistance to noise and incompleteness of sensor data;
- high adaptability to dynamic changes in the environment;
- smoothness and safety of GBMRP maneuvers;
- the ability to implement on hardware and software with limited resources.

The results obtained indicate that the proposed information technology for autonomous neurofuzzy movement control of GBMRP is effective, reliable, and suitable for practical implementation. The combination of fuzzy logic, neural-like structures, and a component-oriented approach provides the system with high technical and operational characteristics, confirming the relevance and expediency of using this technology for the autonomous control of robotic platform movement in complex, changeable, and variable conditions. Therefore, based on the results of the work performed, it is possible to formulate the following scientific novelty and practical significance of the research results. The scientific novelty of the obtained research results is the development of an information technology for neurofuzzy control of the movement of the GBMRP, which, due to the use of methods and means of collecting, storing and processing navigation data from sensors in the conditions of interference and incompleteness of information, a combination of fuzzy logic and neuro-like structures, triangular membership functions for fuzzification of input navigation data, a database of fuzzy logic rules, neural defuzzification based on SGTM provided adaptability and decision-making under uncertainty, high speed and high accuracy of real-time control signal generation.

The practical significance of the research results lies in the creation and implementation of the neurofuzzy information technology for GBMRP control, which enhances the speed, accuracy, and stability of functioning in uncertain and dynamic environmental conditions. The use of the developed methods, models and components of the information technology of neurofuzzy motion control of the GBMRP provides: adaptability of the control system to changes in traffic parameters and road environment; collision avoidance thanks to the integration of intelligent navigation algorithms and sensor data; real-time management through the use of tabular-algorithmic methods for the implementation of basic operations of neural defuzzification and navigation data processing.

CONCLUSION

It is proposed to develop an information technology for autonomous neurofuzzy control of the movement of the GBMRP in conditions with a dynamic change of the situation based on an integrated approach, which includes methods and means of collecting, storing, and processing navigation data, planning the route of the GBMRP, fuzzy logic, neural-like SGTM-based networks, a tabular-algorithmic method for calculating basic operations, and a modern element base. It is proposed to implement information technology means for neurofuzzy control of the GBMRP movement based on a problem-oriented approach, which involves a combination of software and specialized hardware. The following principles have been chosen for the implementation of the means of information technology for controlling the movement of the GBMRP: variability of the equipment composition, which provides the presence of a processor core and replaceable specialized tools; modularity; pipeline and spatial parallelism of data processing; openness of software; specialization and adaptation of hardware to the structure of data processing algorithms. An information technology for neurofuzzy control of the movement of the GBMRP has been developed, which, due to the use of methods and means of collecting, storing and processing navigation data from sensors under the influence of interference and incompleteness of information, a combination of fuzzy logic and neural structures, neural defuzzification based on SGTM provided adaptability and decision-making in conditions of uncertainty, high speed and high accuracy of real-time control signal generation. It is demonstrated that the combination of fuzzy logic and a neural-like network based on the SGTM offers adaptability and decision-making capabilities under uncertainty, as well as neuro-like defuzzification with high speed and accuracy.

It is shown that the use of triangular affiliation functions for fuzzification of input navigation data (distance to target d and angle of orientation to target φ) provided a smooth transition between levels of fuzzy sets, reduced the impact of noise and sudden changes in sensor signals, which is confirmed by the stable operation of the controller in various traffic scenarios. A set of rules for fuzzy logic has been developed, which provides an adequate representation of expert knowledge in the control system, as evidenced by the correct adaptation of wheel speeds when changing the distance and angle of orientation of the platform. The effectiveness of the rule base is confirmed by the smoothness of the

GBMRP's maneuvers, as well as the absence of sudden accelerations and braking, even in unpredictable environmental changes.

ACKNOWLEDGMENTS AND FUNDING SOURCES

This work was performed within the R&D "Methods and means of intelligent measurement of movement parameters and determination of spatial orientation of ground mobile robotic platforms" [0124U000822] carried out by Lviv Polytechnic National University and funded from the state budget of the Ministry of Education and Science of Ukraine for 2024-2026.

COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that the research was conducted in the absence of any conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, [I.Ts., V.T.]; methodology, [I.Ts., V.T.]; investigation, [Yu.O., V.R.]; writing – original draft preparation, [I.Ts., V.T.]; writing – review and editing, [Yu.O.]; visualization, [O.O.].

All authors have read and agreed to the published version of the manuscript.

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ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ АВТОНОМНОГО НЕЙРОНЕЧІТКОГО УПРАВЛІННЯ РУХОМ НАЗЕМНОЇ МОБІЛЬНОЇ РОБОТОТЕХНІЧНОЇ ПЛАТФОРМИ

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АНОТАЦІЯ

Вступ. Сучасний етап розвитку наземних мобільних роботизованих платформ (НМРП) характеризується зростанням вимог до системи управління рухом щодо автономності, адаптивності до динамічних змін у оточуючому середовищі при врахуванні обмежень на обчислювальні ресурси, масо-габаритні параметри і енергоспоживання. Традиційні методи управління рухом НМРП, які ґрунтуються на точних математичних моделях, є неефективними в реальних динамічних умовах, де неможливо точно описати стан НМРП і середовища. Тому для управління рухом НМРП у таких умовах пропонується розроблення відповідної інформаційної технології на основі нечіткої логіки та нейромереж.

Матеріали та методи. Інформаційна технологія автономного нейронечіткого управління рухом НМРП розробляється на базі інтегрованого, гібридного та проблемно-орієнтованого підходів з використанням компонентно-орієнтованої технології. Методи нечіткої логіки забезпечать гнучкість і стійкість системи управління до шумів, похибок вимірювань, непередбачуваних змін у навколишньому середовищі, уможливлюють інтеграцію з нейронними мережами для підвищення точності та швидкодії. Нейромережеві методи забезпечують підвищення точності навігаційних вимірювань, відновлення втрачених даних та побудову нейроподібного дефазифікатора з підвищеною точністю формування сигналів управління.

Результати. Розроблено інформаційну технологію автономного нейронечіткого управління рухом НМРП, яка за рахунок використання методів та засобів збору, збереження та опрацювання навігаційних даних в умовах дії завад і неповноти інформації, поєднання нечіткої логіки та нейроподібних структур на основі моделі послідовних геометричних перетворень, забезпечила адаптивність та прийняття рішень в умовах невизначеності, точність формування сигналів керування. Розроблено базу правил нечіткої логіки, яка забезпечила адекватне відображення експертних знань у системі управління.

Висновки. У роботі на базі інтегрованого, гібридного та проблемно-орієнтованого підходів з використанням компонентно-орієнтованої технології розроблено інформаційну технологію автономного нейронечіткого управління рухом НМРП в умовах динамічної зміни ситуації, що враховує обмеження щодо обчислювальних ресурсів та енергоспоживання.

Ключові слова: інформаційна технологія, нечітка логіка, нейроподібна мережа, наземна мобільна робототехнічна платформа, управління рухом платформи, дефазифікація

Received / Одержано	Revised / Доопрацьовано	Accepted / Прийнято	Published / Опубліковано
14 November, 2025	01 December, 2025	01 December, 2025	25 December, 2025