

Research on methods for controlling a group of mobile robots under uncertainty

Maksym Moisieiev¹ Vladyslav Yevsieiv²

1. CITAR Department, Kharkiv National University of Radio Electronics, UKRAINE, Kharkiv, Nauki Ave. 14., e-mail: maksym.moisieiev@nure.ua
2. CITAR Department, Kharkiv National University of Radio Electronics, UKRAINE, Kharkiv, Nauki Ave. 14., e-mail: vladyslav.yevsieiv@nure.ua

Abstract: The article considers modern methods for controlling a group of mobile robots in environments with a high level of uncertainty, which is a relevant task in the context of the development of the Industry 5.0 concept. The main attention is paid to the analysis of centralized and decentralized approaches, probabilistic models, fuzzy logic, collective intelligence methods, and reinforcement learning algorithms. The conducted research demonstrates their features, advantages, and limitations when applied in production and service scenarios. It is shown that decentralized and bioinspired methods provide high stability and scalability, while probabilistic models and fuzzy logic allow you to work effectively with incomplete information. Machine learning methods provide the ability to adapt and self-learning, but require significant computing resources. The results obtained indicate the feasibility of integrating different approaches into hybrid systems, which allows you to increase the efficiency and reliability of group control of robots in complex environments.

Keywords: mobile robots, group management, uncertainty, decentralized methods, fuzzy logic, POMDP, collective intelligence, reinforcement learning.

I. INTRODUCTION

In the current conditions of the development of Industry 5.0 and intelligent production systems, the problem of effective control of groups of mobile robots that work in a common space with humans and other technical agents is of particular importance. The growing complexity of production and service processes requires robotic systems to have the ability to adapt, make quick decisions, and coordinate interaction even in situations where the external environment is characterized by a high level of uncertainty. Such uncertainty can be caused by incomplete sensor data, delays in communication channels, and dynamic changes in the environment, which complicate trajectory planning and coordination of actions. Research into control methods in these conditions is important for ensuring the stability, safety, and reliability of multi-component robotic systems. In addition, the use of adaptive approaches, such as fuzzy logic, probabilistic models, or multi-level control strategies, allows you to create algorithms that can take unpredictability into account and reduce the risks of collisions. The relevance of the research is also determined by the need to increase the autonomy of mobile robots, their ability to collaborate and flexibly distribute tasks in a team, which directly affects the efficiency of production processes, logistics and service. Thus, the study and development of new methods for controlling a group of mobile robots in environments with a high level of uncertainty is a strategic direction of modern

robotics, which opens up opportunities for creating more intelligent and sustainable systems in real scenarios.

II. MATHEMATICAL DESCRIPTION OF METHODS FOR CONTROLLING A GROUP OF MOBILE ROBOTS

Methods for controlling a group of mobile robots under uncertainty are one of the key problems of modern robotics, as they provide the possibility of effective functioning of multi-component systems in complex and dynamic environments. One of the most common approaches is centralized control, which is based on the creation of a single coordination center for decision-making. This method allows achieving a high level of coherence of actions, but its disadvantage is vulnerability to communication failures and limited scalability in large groups.

$$\min J = \sum_{i=1}^N \sum_{t=1}^T C(x_{i,t}, u_{i,t}) \quad (1)$$

Where: N - number of robots; T - number of time steps; $x_{i,t}$ - state of the i -th robot at time instant t ; $u_{i,t}$ - control signal for i -th robot at time instant t ; $C(x_{i,t}, u_{i,t})$ - cost function that takes into account energy consumption, time, or distance.

In contrast, decentralized control is used, where each agent makes decisions based on local information, which increases the system's resilience to failures and reduces dependence on the central node. In the context of Industry 5.0, decentralized control models are of particular relevance, as they provide greater flexibility and autonomy when interacting with a person in a production environment.

$$u_i(t) = f(x_i(t), \mathcal{N}_i(t)) \quad (2)$$

Where: $x_i(t)$ - local state of the i -th robot; $\mathcal{N}_i(t)$ - information from neighbors in the interaction zone; $f(\cdot)$ - function of the local control law.

Probabilistic methods are of great importance, among which models based on Markov processes and partially observable Markov processes (POMDP) stand out. They allow us to formalize uncertainty about the states of the environment and choose optimal actions taking into account incomplete sensor data. The use of POMDP in mobile robotics ensures decision-making in situations where only partial information about obstacles, object motion dynamics, or the behavior of other agents is available.

$$P(s_{t+1}|s_t, a_t), O(o_t|s_t, a_t), R(s_t, a_t) \quad (3)$$

Where: s_t - state of the system at a point in time t ; a_t - robot action; $P(s_{t+1}|s_t, a_t)$ - probability of transition to a new state; $O(o_t|s_t, a_t)$ - probability of receiving an observation o_t ; $R(s_t, a_t)$ - a reward function that describes the goal (for example, minimizing time or avoiding collisions).

In turn, fuzzy logic provides the ability to process uncertain and imprecise data, which is typical in working with real sensory systems. It allows you to build decision-making rules based on linguistic variables and ensures the adaptation of robot behavior to complex environmental conditions. Such approaches are especially effective in systems where human interaction is required, since they bring the control process closer to natural decision-making principles.

$$u = \sum_{k=1}^M \mu_k(x) \cdot w_k \quad (4)$$

Where: x - input data (e.g. distance to obstacle, speed); $\mu_k(x)$ - membership function for the k -th rule; w_k - weighting factor or control value; u - control output signal.

An equally important direction is the use of collective intelligence methods based on bioinspired models, in particular swarm or ant colony algorithms. Their feature lies in the ability of a group of robots to collectively achieve a global goal through simple local interaction rules. Such algorithms are resistant to failures of individual agents, provide adaptation to changes in the environment and allow for effective solutions to search, exploration or route optimization problems. In the context of Industry 5.0, these methods become the basis for the formation of collaborative robotic systems capable of self-learning and interaction with humans as equal participants in the process.

- for the swarm:

$$u_i(t+1) = wv_i(t) + c_1r_1(p_i - x_i(t)) + c_2r_2(g - x_i(t)) \quad (5)$$

Where: $x_i(t)$ - position of the i -th robot; $v_i(t)$ - speed of the i -th robot; p_i - the best solution found by the robot; g - the best global solution; w_1, c_1, c_2 - inertia and learning coefficients; r_1, r_2 - random variables.

- for the ant algorithm:

$$P_{ij}(t) = \frac{\tau_{ij}(t)^\alpha \cdot \eta_{ij}(t)^\beta}{\sum_k \tau_{ik}(t)^\alpha \cdot \eta_{ik}(t)^\beta} \quad (6)$$

Where: $\tau_{ij}(t)$ - amount of pheromone on the edge $i \rightarrow j$; $\eta_{ij}(t)$ - heuristic information (e.g. 1/distance); α, β - pheromone and heuristic influence coefficients.

Modern research also focuses on machine learning and deep reinforcement learning, which allow robots to learn new behavioral strategies through experience and interaction with the environment. Such methods are aimed at creating adaptive systems that can adapt to unpredictable changes and improve the efficiency of decision-making in real time. Their application opens up new opportunities for creating

intelligent robotic teams that can work effectively in the uncertain conditions of modern production.

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{\hat{a}} Q(\hat{s}, \hat{a}) - Q(s, a)] \quad (7)$$

Where: $Q(s, a)$ - function of the value of the state and action; α - learning coefficient; γ - discounting coefficient of future rewards; r - reward for action a in state s ; \hat{s} - next state.

Thus, the study and integration of existing methods for controlling a group of mobile robots in environments with a high level of uncertainty is a significant contribution to the development of the concept of Industry 5.0 and the formation of new generations of adaptive and sustainable robotic systems.

III. COMPARATIVE ANALYSIS OF METHODS FOR CONTROLLING A GROUP OF MOBILE ROBOTS

The study of methods for controlling a group of mobile robots under uncertainty shows that each of the approaches has its own application features, advantages and limitations. Centralized control is most often used in production lines or logistics systems, where there is a single coordination center that can quickly distribute tasks between all agents. An example is automated warehouses, where robots move according to a single plan to reduce the time for delivering goods. The main advantage of this method is high efficiency in small systems, but the disadvantage is its dependence on the reliability of the communication channel and the difficulty of scaling with a large number of robots. Decentralized control, on the other hand, has demonstrated its effectiveness in cases where communication between all robots is not always possible. It is actively used in search and rescue systems, where robots must make decisions independently in conditions of loss of communication. The advantage of the method is its resistance to failures and high autonomy, but the difficulty lies in ensuring global consistency of the actions of the entire group.

Probabilistic methods, in particular POMDP, have shown high efficiency in navigation among dynamic obstacles. For example, when transporting parts in production shops, where people and other robots can change their movement trajectories unpredictably, the use of POMDP allows robots to adapt their decisions to incomplete or inaccurate information. The advantage of this approach is the ability to work with uncertain data, but the main disadvantage is the computational complexity, which increases with the number of agents. Fuzzy logic is often used in collision avoidance and smooth speed control problems. It allows for real-time decision-making based on fuzzy rules, which is well suited to the nature of sensor data, which always contains errors. An example is the control of a group of robots in service environments, where they must work next to a person, ensuring safe interaction. The strength of fuzzy logic is adaptability, and the weakness is the dependence on the correctness of the formalization of rules and membership functions.

Collective intelligence methods are practically applied in large groups of mobile robots to perform search or monitoring tasks. For example, swarm algorithms are effective for exploring areas after disasters, when each robot

performs local tasks, but together they provide a global result. They have the advantage of high scalability and fault tolerance, but demonstrate limited effectiveness in tasks where precise coordination and synchronization of actions are required. In turn, ant algorithms are well suited for optimizing routes in logistics systems, but suffer from slow convergence, which can be critical in fast-paced production processes. Machine learning and reinforcement learning methods have opened up new opportunities in managing mobile teams. An example is delivery robots that learn to optimize routes in a constantly changing urban environment. The main advantage of this approach is the ability to self-learn and accumulate experience, which significantly increases efficiency in the long term. However, the weakness remains the need for large computational resources and training samples, which limits their application in real-time modes for systems with limited resources. Thus, the study demonstrates that each method has its niche in controlling groups of mobile robots in environments with a high level of uncertainty, and a promising direction is their integration into hybrid systems that can combine the advantages of different approaches and compensate for their shortcomings.

IV. CONCLUSION

The study showed that the problem of controlling a group of mobile robots under uncertainty is of strategic importance for the development of intelligent systems of Industry 5.0. Analysis of existing methods showed that centralized control is effective in small systems, but its limitations are manifested in scaling and loss of resilience to failures. Decentralized approaches, on the contrary, provide high autonomy and flexibility, allowing robots to make decisions based on local information. Probabilistic methods, such as POMDP, have proven their effectiveness in situations with partial observation and dynamic environmental changes. The use of fuzzy logic has proven its feasibility in decision-making tasks based on inaccurate data, which is typical for sensor systems. Collective intelligence methods have demonstrated the ability to scale the system and maintain operability even when individual agents fail. Machine learning and reinforcement learning algorithms have shown promise in creating adaptive control strategies, but require significant computing resources. Comparative analysis shows that each method has its own niche of use depending on the type of environment and the requirements for speed and accuracy of decision-making. In real scenarios, special attention is required to combine methods, which allows to compensate for their shortcomings and enhance their advantages. An important direction of further research is the development of hybrid models that integrate elements of probabilistic, fuzzy and bioinspired approaches. This opens up new opportunities for creating robotic systems that are resistant to uncertainty. The conclusions of the work confirm the relevance of multi-level strategies for coordinating a group of robots. Their practical implementation will contribute to increasing the efficiency of production, logistics and service processes in dynamic environments. Thus, the proposed approach defines a promising vector for the development of robotics in conditions of rapid change and growing requirements for autonomy and safety.

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