ДОДАТОК А

Код програми моделювання

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim

# ------------------------------
# Параметри
# ------------------------------
num_robots = 3
num_steps = 100
dt = 0.1
hidden_dim = 64
input_dim = 10
output_dim = 2
epsilon = 1e-2
goal_threshold = 0.5  # Порогова відстань до цілі

# ------------------------------
# Нейронна мережа
# ------------------------------
class PolicyNetwork(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim):
        super(PolicyNetwork, self).__init__()
        self.fc1 = nn.Linear(input_dim, hidden_dim)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_dim, hidden_dim)
```

```
        self.fc3 = nn.Linear(hidden_dim, output_dim)

    def forward(self, x):
        x = self.relu(self.fc1(x))
        x = self.relu(self.fc2(x))
        return self.fc3(x)

# ------------------------------
# Функції втрат
# ------------------------------
def loss_goal(x_j, y_j, x_g, y_g):
    return (x_j - x_g) ** 2 + (y_j - y_g) ** 2

def loss_collision(d_m):
    return torch.sum(1 / (d_m + epsilon))

def loss_smooth(a_v, a_w, a_v_prev, a_w_prev):
    return (a_v - a_v_prev) ** 2 + (a_w - a_w_prev) ** 2

# ------------------------------
# Оновлення стану робота
# ------------------------------
def update_state(x, y, theta, v, w, a_v, a_w, dt):
    v_new = v + a_v * dt
    w_new = w + a_w * dt
    theta_new = theta + w_new * dt
    x_new = x + v_new * torch.cos(theta_new) * dt
    y_new = y + v_new * torch.sin(theta_new) * dt
    return x_new, y_new, theta_new, v_new, w_new

# ------------------------------
```

```
# Ініціалізація
# ------------------------------
robots_states = []
start_positions = []

# Єдина ціль
goal_x = torch.tensor(np.random.uniform(5, 10), dtype=torch.float32)
goal_y = torch.tensor(np.random.uniform(5, 10), dtype=torch.float32)

for i in range(num_robots):
    x0 = torch.tensor(np.random.uniform(-5, 5), dtype=torch.float32)
    y0 = torch.tensor(np.random.uniform(-5, 5), dtype=torch.float32)
    theta0 = torch.tensor(np.random.uniform(-np.pi, np.pi), dtype=torch.float32)
    v0 = torch.tensor(0.0, dtype=torch.float32)
    w0 = torch.tensor(0.0, dtype=torch.float32)
    robots_states.append([x0, y0, theta0, v0, w0])
    start_positions.append([x0.item(), y0.item()])

policy_net = PolicyNetwork(input_dim, hidden_dim, output_dim)
optimizer = optim.Adam(policy_net.parameters(), lr=0.01)

all_trajectories = [[] for _ in range(num_robots)]
a_v_prev = torch.zeros(num_robots)
a_w_prev = torch.zeros(num_robots)
times_to_goal = [None for _ in range(num_robots)]

# ------------------------------
# Основний цикл моделювання
# ------------------------------
for t in range(num_steps):
    optimizer.zero_grad()
```

```
losses = []

for j in range(num_robots):
    x_j, y_j, theta_j, v_j, w_j = robots_states[j]

    d_m = torch.tensor(np.random.uniform(0.5, 2.0, 3), dtype=torch.float32)

    input_vec = torch.cat([
        x_j.view(1), y_j.view(1), theta_j.view(1), v_j.view(1),
        torch.norm(torch.stack([x_j - goal_x, y_j - goal_y])).view(1),
        d_m,
        goal_x.view(1), goal_y.view(1)
    ])

    action = policy_net(input_vec)
    a_v = action[0]
    a_w = action[1]

    x_j_new, y_j_new, theta_j_new, v_j_new, w_j_new = update_state(
        x_j, y_j, theta_j, v_j, w_j, a_v, a_w, dt
    )

    l_goal = loss_goal(x_j_new, y_j_new, goal_x, goal_y)
    l_col = loss_collision(d_m)
    l_smooth = loss_smooth(a_v, a_w, a_v_prev[j], a_w_prev[j])

    loss = l_goal + 0.1 * l_col + 0.05 * l_smooth
    losses.append(loss)

    a_v_prev[j] = a_v.detach()
    a_w_prev[j] = a_w.detach()
```

```
            robots_states[j] = [x_j_new.detach(), y_j_new.detach(), theta_j_new.detach(), v_j_new.detach(), w_j_new.detach()]
            all_trajectories[j].append([x_j_new.item(), y_j_new.item()])

            # Розрахунок часу досягнення цілі
            if times_to_goal[j] is None:
                dist_to_goal = torch.sqrt((x_j_new - goal_x) ** 2 + (y_j_new - goal_y) ** 2)
                if dist_to_goal.item() <= goal_threshold:
                    times_to_goal[j] = t * dt

        total_loss = torch.stack(losses).sum()
        total_loss.backward()
        optimizer.step()

    # -------------------------------
    # Візуалізація
    # -------------------------------
    colors = ['blue', 'green', 'orange']

    plt.figure(figsize=(10, 10))
    for i, (traj, start) in enumerate(zip(all_trajectories, start_positions)):
        traj_arr = np.array(traj)
        plt.plot(traj_arr[:, 0], traj_arr[:, 1], color=colors[i % len(colors)], linewidth=3, label=f'Robot {i+1}')
        plt.scatter(start[0], start[1], marker='o', color=colors[i % len(colors)], s=80)
        plt.scatter(goal_x.item(), goal_y.item(), marker='*', color='red', s=150)

    plt.xlabel('X')
    plt.ylabel('Y')
    plt.title('Trajectories of Robots to Common Goal')
```

```
plt.legend()
plt.grid()
plt.show()

# -------------------------------
# Виведення часу досягнення цілі
# -------------------------------
for i, t_goal in enumerate(times_to_goal):
    if t_goal is not None:
        print(f"Робот {i+1} досяг цілі за {t_goal:.2f} сек.")
    else:
        print(f"Робот {i+1} не досяг цілі протягом {num_steps * dt:.2f} сек.")
```

ДОДАТОК Б

Апробація результатів кваліфікаційної роботи

Міністерство освіти і науки України

Харківський національний університет радіоелектроніки

Кафедра комп'ютерно-інтегрованих технологій, автоматизації та робототехніки

IX Міжнародна Конференція
ВИРОБНИЦТВО
&
МЕХАТРОННІ СИСТЕМИ 2025

IX International Conference
MANUFACTURING
&
MECHATRONIC SYSTEMS 2025

M&MS
2025
IX International Conference
25-26 October
Kharkiv

УДК: 005:004.896:62-65:338.3

Виробництво & Мехатронні Системи 2025: матеріали IX-ої Міжнародної конференції, Харків, 25-26 жовтня 2025 р.: тези доповідей / [редкол. І.Ш. Невлюдов (відповідальний редактор)].-Харків: [електронний друк], 2025. – 115 с.

У збірник включені тези доповідей, які присвячені сучасним тенденціям розвитку технологій та засобів виробництва та мехатронних систем, передовому досвіду та впровадженню їх в галузях систем промислової автоматизації та керування виробництвом; системній інженерії; CAD/CAM/CAE системах; мехатроніці (електро-механічних системах, електронних інструментах систем керування, механічних CAD системах); робототехніці та засобахм інтелектуалізації; MEMS (сучасних матеріалів та технологіях виготовлення MEMS) та компонентах і технологіях автоматизації видобутку, переробки та транспортування нафти та газу.

Manufacturing & Mechatronic Systems 2025: Proceedings of IX st International Conference, Kharkiv, October 25-26, 2025: Thesises of Reports / [Ed. I.Sh. Nevlyudov (chief editor).] .- Kharkiv .: [electronic version], 2025. - 115 p.

The collection includes the thesises of reports on modern trends in the development of technologies and means of production and mechatronic systems, top experience and implementation of them in fields of: industrial automation and production management systems; systems engineering; CAD/CAM/CAE systems; mechatronics (electrical and mechanical systems, electronic control tools, mechanical CAD systems); robotics and intellectual toolls; MEMS (modern materials and manufacturing technologies MEMS) and components and technologies for the automation of oil, gas and oil extraction, processing and transportation.

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Варшавський університет сільського господарства (WULS - SGGW)
Азербайджанський державний університет нафти і промисловості
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МАТЕРІАЛИ

IX-ої Міжнародної Конференції

ВИРОБНИЦТВО
&
МЕХАТРОННІ СИСТЕМИ 2025

(25-26 жовтня 2023)
Харків, Україна

ЗМІСТ

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

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***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.

$$minJ = \sum_{i=1}^{N}\sum_{t=1}^{T} C(x_{i,t}, u_{i,t}) \qquad (1)$$

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.

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

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.

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

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.

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

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:

$$u_i(t+1) = wv_i(t) + c_1 r_1(p_i - x_i(t)) + c_2 r_2(g - x_i(t)) \qquad (5)$$

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:

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

Where: $\tau_{ij}(t)$ - amount of pheromone on the edge $i \to j$; $\eta_{ij}(t)$ - 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.

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

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; $\acute{s}$ - 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.

References

[1] Zia, A., & Haleem, M. (2025). Bridging research gaps in industry 5.0: Synergizing federated learning, collaborative robotics, and autonomous systems for enhanced operational efficiency and sustainability. IEEE Access.

[2] Dobrzańska, M., & Dobrzański, P. (2025). Simulation Model as an Element of Sustainable Autonomous Mobile Robot Fleet Management. Energies, 18(8), 1894.

[3] Chen, Z., Wang, W., Liu, W., Liu, Y., & Xi, J. (2025). The Effects of Communication Delay on Human Performance and Neurocognitive Responses in Mobile Robot Teleoperation. arXiv preprint arXiv:2508.18074.

[4] Gupta, S., Mamodiya, U., Hossain, A. Z., & Al-Gburi, A. J. (2025). A Framework for Bluetooth-Based Real-Time Audio Data Acquisition in Mobile Robotics. Signals, 6(3), 31.

[5] Delgado Asencio, C., Segura Manzano, F., & Andújar Márquez, J. M. (2025). Hygrobot: Hydrogen-Powered Mobile Robotic Platform for Rough Terrain: Electro-Mechanical Design, Physical Implementation, and Experimental Testing. Applied Sciences, 15(9), 5028.

[6] Pastrana Triana, M. A., Santana, M. S., Mendoza Peñaloza, J. A., Nunes de Oliveira, L. H., & Muñoz Arboleda, D. M. (2025). Comparison of gmdh and perceptron controllers for mobile robot obstacle following/avoidance with hardware-in-the-loop validation. Journal of Intelligent & Robotic Systems, 111(1), 1-23.

[7] Sarkar, C., Das, A., & Jain, R. K. (2025). Development of CoAP protocol for communication in mobile robotic systems using IoT technique. Scientific Reports, 15(1), 9269.

[8] Zhao, Y., Mantha, B. R., Knijnenburg, B. P., & Li, D. (2025). Exploring the feasibility of mobile robots for post-occupancy evaluations. Building Research & Information, 53(1-2), 165-182.

[9] Ness, S. (2025). Integrating AI Models for Voltage and Current Monitoring in Autonomous Mobile Robots to Prevent Power System Blackouts. IEEE Access.

[10] Li, J., Chu, J., Zhao, F., Li, S., Li, W., & Chen, D. (2025). Constrained Optimal Planning to Minimize Battery Degradation of Autonomous Mobile Robots. arXiv preprint arXiv:2506.13019.

[11] Pérez-Juárez, J. G., García-Martínez, J. R., Medina Santiago, A., Cruz-Miguel, E. E., Olmedo-García, L. F., Barra-Vázquez, O. A., & Rojas-Hernández, M. A. (2025). Kinematic Fuzzy Logic-Based Controller for Trajectory Tracking of Wheeled Mobile Robots in Virtual Environments. Symmetry, 17(2), 301.

[12] Zhang, Z., Yang, H., Bai, X., Zhang, S., & Xu, C. (2025). The path planning of mobile robots based on an improved genetic algorithm. Applied Sciences, 15(7), 3700.

[13] Eirale, A., Martini, M., & Chiaberge, M. (2025). Human following and guidance by autonomous mobile robots: A comprehensive review. IEEE Access.

[14] Damjanović, D., Biočić, P., Prakljačić, S., Činčurak, D., & Balen, J. (2025). A comprehensive survey on SLAM and machine learning approaches for indoor autonomous navigation of mobile robots. Machine vision and applications, 36(3), 55.

[15] Attar, H., Abu-Jassar, A. T., Yevsieiev, V., Lyashenko, V., Nevliudov, I., & Luhach, A. K. (2022). Zoomorphic mobile robot development for vertical movement based on the geometrical family caterpillar. Computational intelligence and neuroscience, 2022(1), 3046116.

[16] Nevliudov, I., Yevsieiev, V., Baker, J. H., Ahmad, M. A., & Lyashenko, V. (2020). Development of a cyber design modeling declarative Language for cyber physical production systems. J. Math. Comput. Sci., 11(1), 520-542.

[17] Nevliudov, I., & et al.. (2020). Method of Algorithms for CyberPhysical Production Systems Functioning Synthesis. International Journal of Emerging Trends in Engineering Research, 8(10), 7465-7473.

[18] Lyashenko, V., Abu-Jassar, A. T., Yevsieiev, V., & Maksymova, S. (2023). Automated Monitoring and Visualization System in Production. International Research Journal of Multidisciplinary Technovation, 5(6), 9-18.

[19] Mustafa, S. K., Yevsieiev, V., Nevliudov, I., & Lyashenko, V. (2022). HMI Development Automation with GUI Elements for Object-Oriented Programming Languages Implementation. SSRG International Journal of Engineering Trends and Technology, 70(1), 139-145.

[20] Nevliudov, I., Yevsieiev, V., Lyashenko, V., & Ahmad, M. A. (2021). GUI Elements and Windows Form Formalization Parameters and Events Method to Automate the Process of Additive Cyber-Design CPPS Development. Advances in Dynamical Systems and Applications, 16(2), 441-455.

[21] Kragic, D., Gustafson, J., Karaoguz, H., Jensfelt, P., & Krug, R. (2018, July). Interactive, Collaborative Robots: Challenges and Opportunities. In IJCAI (pp. 18-25).

[22] Nevliudov, I., Yevsieiev, V., Maksymova, S., Gopejenko, V., & Kosenko, V. (2025). Development of mathematical support for adaptive control for the intelligent gripper of the collaborative robot manipulator. Advanced Information Systems, 9(3), 57-65.

[23] Maksymova, S., Yevsieiev, V., Chala, O., & Ababneh, J. (2025). DECISION-MAKING MODEL FOR CONTROLLING A COLLABORATIVE ROBOT-MANIPULATOR BASED ON THE SENSOR FUSION METHOD AND THE RULES OF RULE-BASED SYSTEMS. Multidisciplinary Journal of Science and Technology, 5(6), 526-538.

[24] Невлюдов, І. Ш., Євсєєв, В. В., & Гурін, Д. В. (2025). Model development of dynamic representation a model description parameters for the environment of a collaborative robot manipulator within the industry 5.0 framework. Системи управління, навігації та зв'язку. Збірник наукових праць, 1(79), 42-48.

[25] Yevsieiev, V., Abu-Jassar, A., Maksymova, S., & Demska, N. (2025). Development of a model for recognizing various objects and tools in a collaborative robot workspace. ACUMEN: International journal of multidisciplinary research, 2(1), 224-239.

[26] Yevsieiev V. Mobile Robots and Autonomous Vehicles in the Mobility as a Service (MAAS) Concept / V. Yevsieiev // Sustainable smart cities and communities: business and innovation solutions 2025 : Thesises of Reports of I st I International Conference, April 21, 2025. - Kharkiv, 2025. - P.7-8.

[27] Yevsieiev V. Using Multi-Agent Systems in the Management of Collaborative Robots / V. Yevsieiev // Computer-integrated technologies, automation and robotics 2025 : Thesises of Reports of II st All-Ukrainian Conference, May 16-17, 2025. - Kharkiv, 2025. - P. 13-17

[28] Yevsieiev, V., Maksymova, S., Gurin, D., & Alkhalaileh, A. (2024). HR data visualization of the distance to the object in the collaborative robot workspace based on hc-sr04 sensor. ACUMEN: International journal of multidisciplinary research, 1(4), 388-401.

[29] Yevsieiev, V., Maksymova, S., Abu-Jassar, A., & Ababneh, J. (2025). MATHEMATICAL MODEL OF LOCAL DECISION-MAKING FOR COLLABORATIVE ROBOTS USING EDGE COMPUTING. Multidisciplinary Journal of Science and Technology, 5(6), 34-46.

[30] Yevsieiev, V. Comparative Analysis of the Characteristics of Mobile Robots and Collaboration Robots Within INDUSTRY 5.0. / V. Yevsieiev, D. Gurin // Sectoral research XXI : characteristics and features : collection of scientific papers "SCIENTIA" with proceedings of the VI International Scientific and Theoretical Conference, September 8, 2023. - Chicago : European Scientific Platform, 2023. - P. 92-94.

[31] Gurin, D., Yevsieiev, V., Maksymova, S., & Abu-Jassar, A. (2024). Effect of Frame Processing Frequency on Object Identification Using MobileNetV2 Neural Network for a Mobile Robot. Multidisciplinary Journal of Science and Technology, 4(8), 36-44.

[32] Gurin, D., Yevsieiev, V., Maksymova, S., & Alkhalaileh, A. (2024). MobileNetv2 Neural Network Model for Human Recognition and Identification in the Working Area of a Collaborative Robot. Multidisciplinary Journal of Science and Technology, 4(8), 5-12.

[33] Yevsieiv, V. Using the Triangulation Method to Measure the Distance to Objects in the Working Area of a Collaborative Manipulator Robot / V. Yevsieiv, S. Starikova // Manufacturing & Mechatronic Systems 2024 : Proceedings of VIII st International Conference, October 25-26, 2024. - Kharkiv, 2024. - P.107-109.

[34] Yevsieiev V. Simulation of the operation of the sensor system of a mobile robot in the Autodesk tinkercad environment / V. Yevsieiev, S. Starikova // Комп'ютерні ігри і мультимедіа як інноваційний підхід до комунікації-2023 : матеріали III Всеукр. наук.-техн. конф. молодих вчених, аспірантів і студентів, Одеса, 28-29 жовтня 2023 р. - Одеса : ОНТУ, 2023 . – С. 21-23.

[35] Yevsieiev, V., Ababneh, J., Maksymova, S., & Abu-Jassar, A. (2025). DEVELOPMENT OF A MATHEMATICAL MODEL FOR SIMULATING A DECENTRALIZED CONTROL SYSTEM FOR COLLABORATIVE ROBOT NETWORKS. Multidisciplinary Journal of Science and Technology, 5(5), 1187-1202.

ДОДАТОК В

Демонстраційний матеріал

Формат	Позиція	ПОЗНАЧЕННЯ	НАЙМЕНУВАННЯ	Кількість	Примітки
			Текстові документи		
А4	1	ГЮИК. 442351.020 ПЗ	Пояснювальна записка	84	с.
			Інші документи		
	2		Додаток А	6	с.
			Код програми		
			моделювання		
	3		Додаток Б	2	с.
			Апробація		
			результатів		
			кваліфікаційної		
			роботи		
	4		Додаток В	14	с.
			Демонстраційний		
			матеріал		

ГЮИК. 442351.020 ПЗ

Змін	Арк.	№ документу	Підпис	Дата
Розробив		Моісєєв М.С.		
Перевірив		Євсєєв В.В.		
Норм. контроль		Теслюк С.І.		
Затвердив		Невлюдов І.Ш.		

Розроблення системи керування групою мобільних роботів у умовах невизначеності	Літера	Аркуш	Аркуш
	Н	1	1
	Кафедра КІТАР ХНУРЕ		