Security of Infocommunication Systems and Internet of Things
2024 Vol 2, No 2
https://doi.org/10.31861/sisiot2024.2.02009

Received 13 December 2024; revised 25 December 2024; accepted 28 December 2024; published 30 December 2024

Analysis of Machine Learning Methods in Navigation and Trajectory Planning for Autonomous Control of Unmanned Systems

Roman Trembovetskyi*, Inna Rozlomii and Vira Babenko

Information Security and Computer Engineering Department, Cherkasy State Technological University, Cherkasy, Ukraine

*Corresponding author (E-mail: r.s.trembovetskyi.asp24@chdtu.edu.ua)

ABSTRACT This article investigates the use of machine learning methods in navigation and trajectory planning for the autonomous control of unmanned systems. The main approaches, such as deep learning and reinforcement learning, are considered, offering innovative solutions to challenges arising in dynamic and complex environments. An overview of machine learning methods is conducted, highlighting their advantages over traditional algorithms due to flexibility, adaptability, and the ability to operate under uncertainty. The application of machine learning in trajectory planning is analyzed, including the use of autoencoders, generative models, and graph neural networks for predicting and optimizing routes. Existing problems and challenges are discussed, particularly ensuring safety and reliability, the need for large volumes of high-quality data, issues of model interpretability, and regulatory aspects. Prospects for development are identified, including the development of more efficient algorithms, enhancing model transparency, and establishing standards for the responsible deployment of autonomous systems. In conclusion, it is emphasized that machine learning is a transformative force in the field of autonomous navigation and trajectory planning. Overcoming current challenges and continuing innovation will unlock the full potential of unmanned systems, bringing significant benefits to society and the economy through widespread application across various sectors.

KEYWORDS machine learning, autonomous navigation, trajectory planning, unmanned systems, deep learning.

I. INTRODUCTION

The development of unmanned systems has become one of the most significant directions in modern engineering and technology. Autonomous drones, driverless cars, and maritime vessels are already actively used in various sectors – from military and industrial applications to agriculture and logistics. With the increasing complexity of tasks performed by these systems, there arises a need for more efficient and adaptive methods of navigation and trajectory planning.

Traditional navigation algorithms often have limitations in complex and dynamic environments. Machine Learning (ML), particularly its subfields such as Deep Learning and Reinforcement Learning, offers new approaches to addressing these challenges. The utilization of ML enables unmanned systems to learn from experience, adapt to new conditions, and make more optimal decisions in real time.

This article explores contemporary machine learning methods applied in navigation and trajectory planning for autonomous control of unmanned systems. Special attention is given to practical implementations and the analysis of the effectiveness of these methods in various applications.

The objective of this paper is to investigate and synthesize current approaches to using machine learning methods in the navigation and trajectory planning of unmanned systems, and to identify prospects and directions for future research in this field.

II. AUTONOMOUS CONTROL OF UNMANNED SYSTEMS

Autonomous control of unmanned systems enables vehicles and robots to operate independently using advanced sensors, control algorithms, and real-time data processing. These systems rely on precise navigation, perception, and decision-making mechanisms to execute tasks in dynamic environments without human intervention.

Autonomous control of unmanned systems relies on several key components [1] to ensure precise operation and decision-making. They are shown in Figure 1.

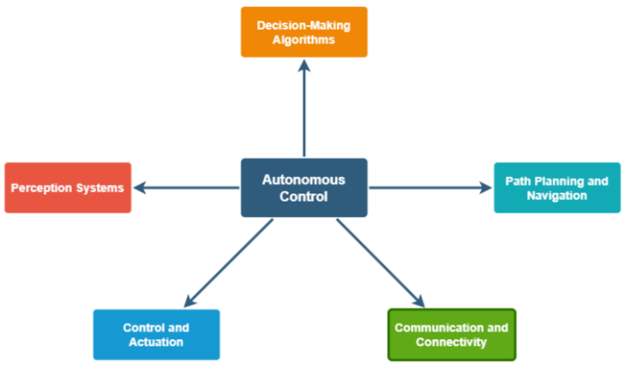

FIG. 1. Key components of autonomous control.

Perception systems, including LiDAR, radar, cameras, and inertial sensors, provide real-time environmental awareness. **Navigation and trajectory planning** utilize algorithms to determine optimal routes while avoiding obstacles. **Control systems**, such as proportional-integralderivative (PID) controllers and adaptive control methods, regulate movement and stability. **Communication networks**, including satellite links and vehicle-to-vehicle (V2V) communication, enable data exchange and coordination. Finally, **decision-making** algorithms, based on rule-based logic and sensor fusion, allow autonomous systems to react dynamically to changing conditions, ensuring safe and efficient operation.

Among all components, navigation and trajectory planning plays a crucial role in ensuring safe and efficient movement in dynamic environments. The use of machine learning significantly enhances these processes by improving environmental perception, enabling rapid adaptation to unforeseen changes, and optimizing routes in real time.

III. OVERVIEW OF MACHINE LEARNING METHODS IN AUTONOMOUS NAVIGATION

Machine learning has become a cornerstone in the advancement of autonomous navigation systems for unmanned vehicles, including drones, self-driving cars, and maritime vessels. By leveraging machine learning, these systems can learn from experience, adapt to changing environmental conditions, and make optimal decisions in real time [2]. This capability is crucial for navigating complex and unpredictable environments where traditional rule-based systems may fall short. The machine learning model types are shown in Figure 2.

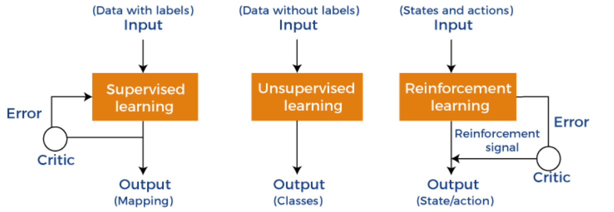

FIG. 2. Machine learning model types [3].

One of the foundational methods is supervised learning, where models are trained on labeled datasets. In the context of autonomous navigation, supervised learning is extensively used for object detection and recognition tasks. For instance, convolutional neural networks (CNNs) are employed to process visual inputs from cameras to identify and classify objects such as traffic signs, pedestrians, other vehicles, and obstacles [4].

CNNs effectively extract hierarchical features from images and videos, enabling the system to make informed decisions based on visual cues.

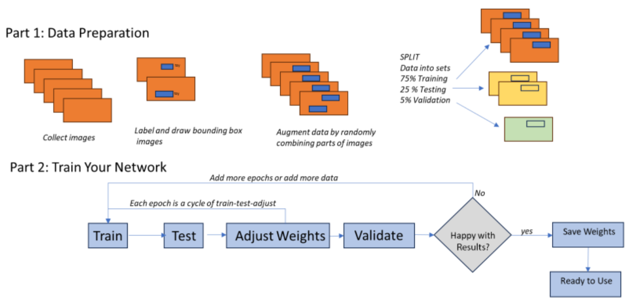

FIG. 3. CNN process [4].

Unsupervised learning methods are utilized to discover hidden patterns and structures in data without prior labeling [5]. In autonomous navigation, unsupervised learning is valuable for processing sensory information and constructing environmental maps. This approach allows unmanned vehicles to independently identify significant features of their surroundings.

Techniques like clustering and dimensionality reduction help in organizing sensory data from LiDAR, radar, and ultrasonic sensors, facilitating tasks such as simultaneous localization and mapping (SLAM) without the need for pre-existing maps [6].

Particular attention is drawn to reinforcement learning (RL), where an agent learns optimal behaviors through interactions with the environment and receives rewards for certain actions (Figure 4). This method enables systems to learn complex policies for decision-making tasks, such as avoiding obstacles, navigating dynamic environments, and planning efficient trajectories [7].

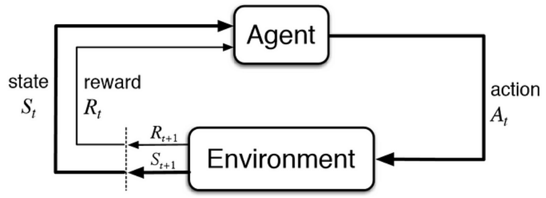

FIG. 4. Reinforcement learning concept [8].

The integration of deep neural networks with reinforcement learning, known as Deep Reinforcement Learning (DRL), allows for solving high-dimensional and continuous control problems [9]. DRL algorithms like Deep Q-Networks (DQNs) [10] and Proximal Policy Optimization (PPO) [11] enable agents to learn directly from raw sensory inputs, making them suitable for real-world navigation challenges.

Traditional navigation algorithms, such as shortest path search algorithms (e.g., Dijkstra's algorithm or A* algorithm) [12-14], have limitations in conditions of unpredictable changes and incomplete information. They often require accurate environmental models and cannot adapt to new situations without recalculation. These algorithms may struggle with dynamic obstacles or changes in terrain, leading to inefficiencies or failures in navigation. In contrast, machine learning methods provide greater flexibility and robustness, enabling systems to handle uncertainty and operate effectively in partially known or rapidly changing environments [15].

However, the use of machine learning in navigation is accompanied by certain challenges. The necessity for large volumes of high-quality data for training can be problematic, especially in specific or rare scenarios such as extreme weather conditions or unusual terrains. Collecting and annotating this data can be time-consuming and costly. Additionally, there are concerns regarding the safety and reliability of such systems, as navigation errors can have serious consequences, including accidents or mission failures [16]. The complexity of deep neural networks also complicates the interpretation of their decisions, which can be critical in the context of accountability and trust in unmanned systems. This "black box" nature of deep learning models raises issues in debugging and verifying the system's behavior under different conditions.

Moreover, machine learning models can be vulnerable to adversarial attacks or unexpected inputs that were not represented in the training data, leading to unpredictable behavior. Ensuring the robustness and security of these systems is an ongoing area of research. There is also a need for standardization and regulatory frameworks to govern the deployment of machine learning-based navigation systems, ensuring they meet safety standards and ethical considerations.

Despite these challenges, progress in the field of machine learning opens new possibilities for improving autonomous navigation. Advances in computational power, such as the use of GPUs and specialized AI hardware, facilitate the training and deployment of more complex models. Techniques like transfer learning and data augmentation help mitigate the data scarcity problem by leveraging existing models and expanding available datasets. Research into explainable AI (XAI) aims to make machine learning models more interpretable, enhancing trust and transparency [17].

The continuous development of algorithms and methodologies contributes to the creation of smarter and more adaptive unmanned systems. Hybrid approaches that combine machine learning with traditional algorithms can capitalize on the strengths of both, leading to more reliable and efficient navigation solutions [18]. As a result, autonomous systems are becoming increasingly capable of effectively performing complex tasks in diverse real-world environments, from urban settings with dense traffic to remote areas with challenging terrains.

The future of autonomous navigation lies in the synergy between advanced machine learning techniques and robust system design. By addressing current limitations and continuing to innovate, we move closer to realizing fully autonomous unmanned systems that are safe, efficient, and trustworthy, with wide-ranging applications across industries.

IV. TRAJECTORY PLANNING USING MACHINE LEARNING

Trajectory planning is a crucial component in ensuring the autonomy of unmanned systems. It involves determining the optimal path from a starting point to a destination while considering environmental constraints and the characteristics of the vehicle. Traditional planning methods often rely on static algorithms and known environmental models, which may be insufficient in dynamic or unknown conditions [19]. The application of machine learning methods addresses these issues by providing flexibility and adaptability in trajectory planning.

Deep learning is utilized to process large volumes of data and detect complex patterns, which is essential when planning in complex environments. For instance, autoencoders and generative models are used to learn representations of the environment and predict possible paths, allowing unmanned systems to evaluate various scenarios and choose the optimal route [20]. Graph Neural Networks (GNNs) enable modeling the environment as a graph, where nodes represent positions and edges represent possible transitions, thus learning optimal paths in complex topologies [21]. The GNN model blueprint is shown in Figure 5.

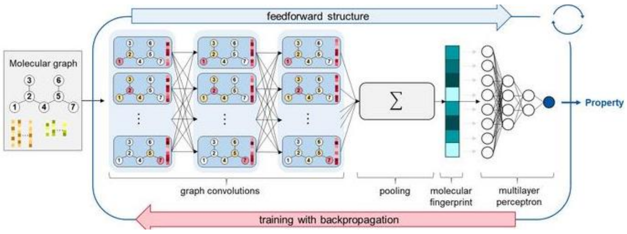

FIG. 5. GNN model [22].

Deep Reinforcement Learning is an effective approach for action planning in dynamic and unknown environments. It allows agents to learn trajectory planning policies based on experience, processing high-dimensional input data such as images or three-dimensional maps. Policy and value-based algorithms like A3C (Asynchronous Advantage Actor-Critic) [23] and DDPG (Deep Deterministic Policy Gradient) [24] are used to learn continuous actions in real-time.

Route optimization involves not only avoiding obstacles but also considering other factors such as energy consumption, time, and safety. ML models can consider multiple objective functions simultaneously, balancing different criteria through multi-objective optimization [25].

Examples of implementing these methods in unmanned systems include autonomous vehicles that use ML for trajectory planning by considering road conditions, traffic, and traffic regulations. Companies like Tesla and Waymo are actively integrating deep learning into their autopilot systems [26]. Drones apply ML for navigation in complex environments such as urban areas or forests, where they need to avoid obstacles and optimize routes to conserve energy [27].

Future research is focused on developing more efficient and interpretable models, as well as integrating ML methods with traditional planning algorithms to achieve better performance and reliability.

V. ANALYSIS OF EXISTING METHODS AND THEIR LIMITATIONS

Modern machine learning methods for autonomous navigation and trajectory planning demonstrate significant progress, yet their practical implementation faces systemic limitations. Based on the literature review, we outline key advantages, drawbacks, and research gaps.

A. Deep Learning. Deep learning models, such as convolutional neural networks and transformers, excel in processing multimodal sensor data (e.g., LiDAR, cameras) for obstacle detection and environmental mapping [3, 18]. Their hierarchical feature extraction enables robust performance in complex scenarios, such as urban navigation. However, these models are highly dependent on the quality and diversity of training data. For instance, systems trained in simulated environments like CARLA often underperform in real-world conditions due to domain gaps, such as lighting variations or sensor noise [28]. Computational demands further limit their deployment on resource-constrained platforms, necessitating optimization techniques like network pruning and quantization [29, 30]. Autonomous vehicles, such as those developed by Tesla, demonstrate high accuracy in structured environments but struggle in extreme weather or unstructured terrains, highlighting the fragility of purely data-driven approaches [15].

B. Reinforcement Learning: Adaptability vs. Safety. Reinforcement learning, particularly deep RL, offers adaptability in dynamic environments by learning policies through reward mechanisms. Algorithms like Deep Deterministic Policy Gradient and Proximal Policy Optimization enable agents to navigate without explicit environment models [9, 19]. Despite these advantages, DRL requires extensive training iterations, making real-time deployment challenging. Safety concerns also arise, as agents may exploit reward function flaws – for example, circumventing obstacles indefinitely to maximize rewards [27]. A case study on drone navigation revealed that DRL agents successfully avoided static obstacles but failed to adapt to sudden wind gusts due to insufficient training data diversity [26].

C. Unresolved Challenges and Recommendations. Three major gaps hinder the widespread adoption of ML in autonomous systems. First, the lack of standardized testing frameworks complicates cross-method comparisons, as most experiments rely on custom simulations [18]. Second, the "black-box" nature of ML models, especially DRL, undermines trust in safety-critical applications. While explainable AI tools like LIME and SHAP provide partial insights, they fail to fully decode complex decision-making processes [29]. Third, ethical and regulatory frameworks for ML-driven failures remain underdeveloped, raising accountability concerns [15].

To address these challenges, we propose three strategies. First, integrating DRL with online planners like RRT* could enhance responsiveness to dynamic obstacles [12]. Second, deploying quantized neural networks and transfer learning would reduce computational overhead for embedded systems [30, 31]. Third, hybrid architectures that activate traditional algorithms during ML failures could improve safety [14]. Advancing XAI tools and establishing ethical guidelines are equally critical to fostering trust and reliability.

VI. CONCLUSION

The integration of machine learning methods into navigation and trajectory planning has significantly advanced the capabilities of autonomous unmanned systems. Throughout this article, the exploration of how machine learning, particularly deep learning and reinforcement learning, offers innovative solutions to the challenges faced in dynamic and complex environments has been conducted.

In the overview of machine learning methods in autonomous navigation, it is highlighted how supervised learning aids in object detection and recognition, unsupervised learning helps in environmental mapping, and reinforcement learning enables systems to make optimal decisions through interactions with their surroundings. These methods surpass traditional algorithms by providing greater flexibility, adaptability, and the ability to handle uncertainty.

Trajectory planning using machine learning has been shown to enhance the autonomy of unmanned systems. By employing deep learning models such as autoencoders, generative models, and graph neural networks, systems can predict and optimize paths in intricate environments. Reinforcement learning further allows for real-time adaptation to changes and obstacle avoidance, improving efficiency and safety.

Practical applications across various industries demonstrate the tangible benefits of these advancements. Autonomous vehicles now navigate urban environments with increased safety and efficiency, drones perform complex tasks in challenging terrains, and robots optimize operations in industrial settings. These successes underscore the potential of machine learning to revolutionize navigation and trajectory planning.

However, challenges remain in ensuring safety, reliability, and ethical compliance. The need for large amounts of high-quality data, model interpretability, computational constraints, and regulatory considerations are significant hurdles that must be addressed. Ongoing research and development aim to create more efficient algorithms, improve model transparency, and establish standards for the responsible deployment of autonomous systems.

Machine learning has emerged as a transformative force in the field of autonomous navigation and trajectory planning. By overcoming current challenges and continuing to innovate, the full potential of unmanned systems can be unlocked. This progress promises not only to enhance operational efficiency and safety but also to bring substantial benefits to society and the economy through widespread adoption in various sectors.

AUTHOR CONTRIBUTIONS

R.T., I.R. – formal analysis; I.R., V.B. – conceptualization, methodology; I.R. – investigation; R.T. – writing original draft preparation and editing; V.B. – supervision, validation.

COMPETING INTERESTS

The authors declare no conflict of interest.

REFERENCES

[1] K. Nonami, M. Kartidjo, K.-J. Yoon, and A. Budiyono, *Autonomous Control Systems and Vehicles*, Springer Science & Business Media, 2013.

[2] M. X. Evangeline and Karthik, *Modeling, Simulation, and Control of AI Robotics and Autonomous Systems*, IGI Global, 2024.

[3] (n.d.). [Online]. Available: https://images.javatpoint.com/tutorial/machine-learning/images/machine-learning-models2.png. [Accessed: Dec. 12, 2024].

[4] F. X. Govers III, *Artificial Intelligence for Robotics: Build intelligent robots using ROS 2, Python, OpenCV, and AI/ML techniques for real-world tasks*, 2nd ed., Packt Publishing, Birmingham, 2024.

[5] G. Bonaccorso, *Hands-On Unsupervised Learning with Python: Implement Machine Learning and Deep Learning Models Using Scikit-Learn, TensorFlow, and More*, Packt Publishing, 2019.

[6] S. Arshad and G.-W. Kim, "Role of Deep Learning in Loop Closure Detection for Visual and Lidar SLAM: A Survey," *Sensors*, vol. 21, no. 4, p. 1243, 2021. doi: 10.3390/s21041243.

[7] A. M. Roth, D. Manocha, R. D. Sriram, and E. Tabassi,

Explainable and Interpretable Reinforcement Learning for Robotics, Springer International Publishing, Cham, 2024. doi: 10.1007/978-3-031-47518-4.
[8] (n.d.). [Online]. Available: https://miro.medium.com/v2/1*7cuAqjQ97x1H_sBIeAVVZg.png. [Accessed: Dec. 12, 2024].
[9] Z. Fan, "An exploration of reinforcement learning and deep reinforcement learning," *Appl. Comput. Eng.*, vol. 73, no. 1, pp. 154-159, 2024. doi: 10.54254/2755-2721/73/20240386.
[10] Y. Huang, "Deep Q-Networks," in *Deep Reinforcement Learning: Fundamentals, Research and Applications*, H. Dong, Z. Ding, and S. Zhang, Eds., Springer Singapore, 2020, pp. 135-160. doi: 10.1007/978-981-15-4095-0_4.
[11] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv preprint* arXiv:1707.06347, 2017.
[12] E. Dhulkefl, A. Durdu, and H. Terzioğlu, "Dijkstra algorithm using UAV path planning," *Konya J. Eng. Sci.*, vol. 8, pp. 92-105, 2020.
[13] J. Ding, Y. Zhou, X. Huang, K. Song, S. Lu, L. Wang, "An Improved RRT∗ Algorithm for Robot Path Planning Based on Path Expansion Heuristic Sampling," *J. Comput. Sci.*, vol. 2023, 101937, 2023. doi: 10.1016/j.jocs.2022.101937.
[14] A. Marashian and A. Razminia, "Mobile robot's path-planning and path-tracking in static and dynamic environments: Dynamic programming approach," *Robot. Auton. Syst.*, vol. 172, p. 104592, 2024. doi: 10.1016/j.robot.2023.104592.
[15] D. Arce, J. Solano, and C. Beltrán, "A Comparison Study between Traditional and Deep-Reinforcement-Learning-Based Algorithms for Indoor Autonomous Navigation in Dynamic Scenarios," *Sensors*, vol. 23, no. 24, p. 9672, 2023. doi: 10.3390/s23249672.
[16] A. Tampuu, T. Matiisen, M. Semikin, D. Fishman, N. Muhammad, "A Survey of End-to-End Driving: Architectures and Training Methods," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, pp. 1-21, 2020. doi: 10.1109/tnnls.2020.3043505.
[17] R. Dwivedi et al., "Explainable AI (XAI): Core Ideas, Techniques and Solutions," *ACM Comput. Surv.*, vol. 54, no. 3, p. 1-42, 2022. doi: 10.1145/3561048.
[18] B. Y. Suprapto et al., "Designing an Autonomous Vehicle Using Sensor Fusion Based on Path Planning and Deep Learning Algorithms," *SAIEE Afr. Res. J.*, vol. 115, no. 3, pp. 86-98, 2024. doi: 10.23919/saiee.2024.10551314.
[19] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, "A survey of deep learning techniques for autonomous driving," *J. Field Robot.*, vol. 37, no. 3, pp. 362-386, 2020. doi: 10.1002/rob.21918.
[20] B. R. Kiran et al., "Deep Reinforcement Learning for Autonomous Driving: A Survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 1, pp. 1-18, 2021. doi: 10.1109/tits.2021.3054625.
[21] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A Comprehensive Survey on Graph Neural Networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 1, pp. 4-24, 2021. doi: 10.1109/tnnls.2020.2978386.
[22] (n.d.). [Online]. Available: https://www.pi-research.org/project/gnn/featured_hu7d801bb7c748537ad832916140f12452_219604_720x0_resize_q75_lanczos.jpg. [Accessed: Dec. 12, 2024].
[23] V. Mnih, "Asynchronous Methods for Deep Reinforcement Learning," *arXiv Prepr.* arXiv:1602.01783, 2016.
[24] H. Tan, "Reinforcement learning with deep deterministic policy gradient," in *2021 International Conference on Artificial Intelligence, Big Data and Algorithms (CAIBDA)*, IEEE, 2021, pp. 82-85.
[25] H. Wang, Z. Wang, and X. Cui, "Multi-objective Optimization Based Deep Reinforcement Learning for Autonomous Driving Policy," *J. Phys.*, vol. 1861, no. 1, p. 012097, 2021. doi: 10.1088/1742-6596/1861/1/012097.
[26] M. Bansal, A. Krizhevsky, and A. Ogale, "ChauffeurNet: Learning to Drive by Imitating the Best and Synthesizing the Worst," 2018. [Online]. Available: https://arxiv.org/abs/1812.03079.
[27] M. Kim, J. Kim, M. Jung, and H. Oh, "Towards monocular vision-based autonomous flight through deep reinforcement learning," *Expert Syst. With Appl.*, vol. 198, p. 116742, 2022. doi: 10.1016/j.eswa.2022.116742.
[28] M. Zeller, "Safety Assurance of Autonomous Systems using Machine Learning: An Industrial Case Study and Lessons Learnt," *INCOSE Int. Symp.*, vol. 33, no. 1, pp. 320-333, 2023. doi: 10.1002/iis2.13024.
[29] P. Sun et al., "Scalability in Perception for Autonomous Driving: Waymo Open Dataset," 2020. [Online]. Available: https://arxiv.org/abs/1912.04838.
[30] R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, and D. Pedreschi, "A Survey of Methods for Explaining Black Box Models," *ACM Comput. Surv.*, vol. 51, no. 5, p. 1-42, 2019. doi: 10.1145/3236009.
[31] Y. Cheng, D. Wang, P. Zhou, and T. Zhang, "Model Compression and Acceleration for Deep Neural Networks: The Principles, Progress, and Challenges," *IEEE Signal Process. Mag.*, vol. 35, no. 1, pp. 126-136, 2018. doi: 10.1109/msp.2017.2765695.

Roman Trembovetskyi

PhD student Information Security and Computer Engineering Department in Cherkasy State Technological University. Research interests: machine learning, unmanned mobile systems, drones engineering, Internet of Things.

ORCID ID: 0009-0001-2697-0879

Inna Rozlomii

PhD, Associate Professor Information Security and Computer Engineering Department in Cherkasy State Technological University. Research interests: information security, methods of cryptographic information transformation, Internet of Things, databases.

ORCID ID: 0000-0001-5065-9004

Vira Babenko

Doctor of Technical Sciences, Professor, Information Security and Computer Engineering Department in Cherkasy State Technological University. Research interests: information protection in computer systems, security of information and communication systems, methodology for synthesizing cryptographic transformation operations, development of cryptographic primitives.

ORCID ID: 0000-0003-2039-2841

Аналіз методів машинного навчання у навігації та плануванні траєкторій для автономного керування безпілотними системами

Роман Трембовецький*, Інна Розломій, Віра Бабенко

Кафедра інформаційної безпеки та комп'ютерної інженерії, Черкаський державний технологічний університет, м. Черкаси, Україна

*Автор-кореспондент (Електронна адреса: r.s.trembovetskyi.asp24@chdtu.edu.ua)

АНОТАЦІЯ У цій статті досліджується застосування методів машинного навчання у навігації та плануванні траєкторій для автономного керування безпілотними системами. Розглядаються основні підходи, такі як глибинне навчання та навчання з підкріпленням, які пропонують інноваційні рішення для викликів, що виникають у динамічних та складних середовищах. Проведено огляд методів машинного навчання, підкреслюючи їхні переваги над традиційними алгоритмами завдяки гнучкості, адаптивності та здатності працювати в умовах невизначеності. Проаналізовано застосування машинного навчання у плануванні траєкторій, включаючи використання автоенкодерів, генеративних моделей та графових нейронних мереж для прогнозування та оптимізації маршрутів. Обговорюються наявні проблеми та виклики, зокрема забезпечення безпеки та надійності, необхідність у великих обсягах високоякісних даних, питання інтерпретованості моделей та регуляторні аспекти. Визначено перспективи розвитку, такі як розробка ефективніших алгоритмів, підвищення прозорості моделей та встановлення стандартів для відповідального впровадження автономних систем. У підсумку наголошується, що машинне навчання є рушійною силою змін у сфері автономної навігації та планування траєкторій. Подолання поточних викликів і подальші інновації розкриють повний потенціал безпілотних систем, приносячи значні переваги суспільству та економіці через їх широке застосування в різних галузях.

КЛЮЧОВІ СЛОВА машинне навчання, автономна навігація, планування траєкторій, безпілотні системи, глибинне навчання.