Application of Artificial Intelligence on UAV Path Planning

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Abstract. With the rapid development of artificial intelligence, its application effect in the field of UAV path planning is becoming more and more significant. It plays a great role in path search optimization, environment perception modelling, dynamic environment adaptation, and multi-UAV collaboration. Reinforcement learning algorithms train UAVs to fly stably in complex environments by minimizing the reward function as well as obstacle avoidance. LSTM (Long Short Term Memory Network) makes use of processing dynamic changes and being more adapt to complex environment. Machine-to-machine collisions are also avoided by realizing multi-machine collaboration through multi-intelligent body reinforcement learning. However, due to the limitations of the current technology, there are still many challenges, such as high algorithm complexity and limited computational resources. This paper introduces the development of AI and describes the application and effect of AI in UAV path planning. In the future, with the continuous improvement of arithmetic power and algorithmic innovation, UAV path planning based on AI will be more autonomous in complex environments, improve the endurance time, and realize the overall task in the state of multi-machine cooperation. Optimal completion of the overall mission under the state of multi-aircraft cooperation.

Keywords: Drone Path Planning, Reinforcement Learning, Neural Network, Artificial Intelligence

1 Introduction

The UAV is a vehicle that can be remotely controlled. UAVs have widespread applications in military and civil use due to their low cost, compactness, flexibility, and ease of operation. Among them, path planning has a major impact on safely performing the flight mission safely, avoiding obstacles, and being able to calculate an effective route from the initial position to the target position. With the rapid development of artificial intelligence (AI), the role of AI in UAV path planning is becoming more and more obvious. Researchers have improved the intelligence and adaptability of path planning through various technical solutions.

AI-based UAV path planning is currently a key research direction in the field of UAVs, which aims to enable UAVs to autonomously plan a safe and efficient optimal

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path in complex environments. Reinforcement learning optimizes the flight path by allowing trial-and-error learning in the environment, with the goal of maximizing cumulative rewards. During flight, the UAV takes different actions (e.g., changing flight direction, altitude, etc.) according to the current environmental state and its own flight state, and adjusts its strategy according to the reward signals feedback from the environment to gradually find the optimal path planning. Intelligent algorithms simulate the behaviour of biological groups in nature, such as Particle Swarm Optimization, Ant Colony Optimization, etc., to work out the UAV path planning issue. Taking Particle Swarm Optimization as an example, Drone path is thought og as location of particles in the search space. Through the information sharing and collaboration between the particles, the speed and position of the particles are constantly updated to find the optimal path. Deep Learning Algorithms such as Convolutional Neural Networks, the UAV can learn and analyze a large amount of environmental image data to identify different terrain, obstacles, and target features. For example, with a trained model, the UAV can quickly recognize obstacles such as trees in the forest and buildings in the city, providing accurate environmental information for path planning.

Path planning first needs environmental sense. With the help of various sensors equipped by drones, such as cameras and radar, etc, information about the surrounding environment is obtained in real time. The data obtained by sensors provides basic input for path planning. Secondly, map construction, according to the data obtained from the sensors, the environmental map where the UAV is placed is constructed by using Simultaneous Localization and Map Construction (SLAM) technology. An intuitive model of the environment is provided for the path planning algorithm. This is followed by path search: based on the building of a good map, the artificial intelligence algorithm is used to search for the optimal path from the initial point to the target point. During the search process, the algorithm considers multiple factors, such as path distance, flight safety, collision avoidance needs, etc., and finds the optimal flight path that meets the requirements through continuous optimization and adjustment. Finally, path optimization and adjustment. As the environment may be dynamically changing, such as the appearance of new obstacles or changes in the target location, the UAV needs to optimize and adjust the planned path in real time. Meanwhile, considering the flight performance limitations of the UAV, such as the maximum flight speed, radius of turning circle, etc., the path also needs to be further optimized to ensure the safety of drones and stably fly along the planned path.

Uav path planning based on artificial intelligence is wedely used. For example, in the logistics field, drones can utilize AI path planning technology to quickly and accurately transport goods from warehouses to designated locations. In agricultural production, drones can autonomously plan flight paths according to the topography and other terrain of the farmland, and carry out accurate pesticide spraying, fertilization and other operations. By perceiving and learning from the farmland environment, the drone can avoid omission or repeated spraying, improve the operation effect, reduce the use of pesticides and fertilizers, and reduce the pollution of the environment.

In the future, AI-based drone path planning will be deeply integrated with more technologies, such as the Internet of Things. It allows UAVs to interact and collaborate with other intelligent devices to further expand their application scenarios. With the continuous AI technology development, drone path planning algorithms will better adapt to complex and changeable environments. For instance, in inclement weather conditions, drones can adjust their flight paths through real-time analysis of meteorological data and model prediction. Future drones will have stronger autonomous decision-making capabilities and can flexibly adjust path planning strategies according to different mission requirements and environmental changes.

Many AI-based path planning algorithms have been proposed in published researches. The purpose of this review is to summarize the path planning algorithms for UAVs to calculate optimal or near-optimal paths and propose major constraints and the work needed to be done to overcome these limitations. In the age of digitalization, artificial intelligence is at the heart of technological innovation, which has led to new innovations and breakthroughs in drone path planning. From the recent research review, this text identifies the critical factors that need to be considered in the research to indicate the direction that needs to be broken in later research projects.

The structure of this article is as follows: for Section 2, AI development is reviewed. Section 3 describes the traditional path planning algorithms and the current drone limitations. Section 4 sketches drone path planning issues. Section 5 outlines some recent UAV path planning solutions in thepublished researches. In Section 6, an analysis is conducted to uncover future advancements. Finally, Section 7 contains the summary of findings and conclusions.

2 Development of artificial intelligence (AI)

Artificial Intelligence is the central force guiding mankind into the age of intelligence. In the context of the apparent significance of AI technology, different fields have achieved innovation by combining artificial intelligence according to their own development characteristics. For example, Deep learning-based big data AI technology holds promising prospects for modern technological innovation, enabling its application across various fields to gradually establish a universal and systematic design decision model [1]. Meanwhile, Deep learning algorithms are progressively overcoming the constraints of conventional AI design modules during revolutionary development in big data-driven AI technology.

Machine learning plays a vital role in UAV-related research and has a positive impact on path planning. By leveraging meta-learning methods to improve the capacity for emotion recognition, this technology can be utilized for the human-machine interaction scenarios of unmanned aerial vehicles (UAVs), enabling them to better understand the emotional states of operators and thus execute task instructions more accurately and optimize flight paths. In addition, there is the method of automatic machine learning to build face recognition model, which can be applied to the identification task of UAV. In the execution of search, monitoring and other tasks, the target is identified quickly and accurately, provide decision-making basis for path planning, and ensure that the efficiency with which the UAV completes the task is remarkable.

In the application of multiple fields to expand the rich path planning scenarios, artificial intelligence is widely used in the field of UAVs, which brings more possibilities for path planning. In terms of spatial target observation, the research results of ISAR image quality level assessment of space targets based on feature fusion help

UAVs to assess the quality of the collected images when performing space observation tasks, and adjust the flight paths according to the assessment results to obtain better quality image data [1].

By improving the algorithms and models, the performance of UAVs is significantly improved, which in turn optimizes the path planning. Rough set theory is used to optimize computer network routing, enhance the efficient use of network resources, and reduce data transmission delay and packet loss, which is important for UAVs to achieve stable and efficient communication and path planning in the network environment. The improved probabilistic routing algorithm increaseds the the message transmission success rate and decreases the average latency by considering the movement direction of nodes, enabling UAVs to transmit data more reliably and plan better flight paths in delay tolerant networks [1].

The integration of artificial intelligence with other fields brings new development opportunities for UAV path planning. In the area of Internet of Things, Combining the fog computing system with the Internet of Things improves the data retrieval efficiency and privacy protection capability. When performing tasks in the Internet of Things environment, drones can use this technology to obtain the required data more quickly and optimize the flight path [1]. The outcomes of the research into indoor loop detection relying on semantic topology matching can be applied to positioning and navigation for UAVs within the indoor setting. Through the construction of semantic topology map, more accurate loop detection can be realized to help the UAV to plan a more accurate flight path in the indoor complex environment [1].

Artificial intelligence algorithms such as machine learning are widely used in the research sphere of how to plan UAV paths. Reinforcement learning is used to propose a path-planning algorithm designed for energy conservation to solve the turbulent disturbance and find the most efficient path planning [2]. Machine learning is utilized for optimizing the coverage path planning of UAV, which cuts down the energy consumption during the UAV flight, improves the execution efficiency, and adapts to the tasks in complex areas [3]. Meanwhile, AI is also integrated with big data and IoT technologies to achieve UAV-to-UAV interconnectivity and obtain more environmental information for path normalization [4].

3 Path planning algorithms for UAVs based on artificial intelligence

In this section, path planning algorithms proposed in the literature will be reviewed, based on the artificial intelligence direction broadly categorized into two directions: neural networks, and reinforcement learning.

3.1 Neural network based path planning

In many studies, neural networks are utilized in the path planning of bio - inspired UAVs: a mechanism to simulate the neural activity of position cells in the mammalian hippocampus, combined with the STDP learning rule, to generate dynamic synaptic vector fields to guide UAVs to plan paths within intricate surroundings in [5]. The working process is presented in Figure 1. The dynamic properties of the membrane potential corresponding to the position cells are first simulated using the Leaky Integrate-and-Fires neuron model. Each position cell has a three-dimensional region corresponding to it, and its activation enhances as the UAV approaches the three-dimensional region. The cognitive map of three-dimensional space, established by place cells, is defined by synaptic connection weights that reflect the topological characteristics of the environment. In simpler terms, the spatial structure of the environment is converted into a parameterized form within the neural network, leveraging a weight optimization process to facilitate intelligent decision-making. The prominent weight is dynamically adjusted through STDP rules: STDP strengthens the prominent connection in the target direction, weakens the connection in the obstacle direction, and gradually forms the prominent weight distribution of the optimal path. The synaptic vector field of each position cell is generated by weighted averaging the weights of neighbouring neurons, which guides the UAV towards moving towards the direction of the target. The UAV position is iteratively updated based on the current velocity prediction as well as the vector field adjustment to ensure continuity of path planning and to realize the obstacle avoidance function. Finally, the results are simulated using Python and AirSim, and the results show that the planned paths are smoother and more suitable for the constraints of UAV dynamics than the traditional methods.

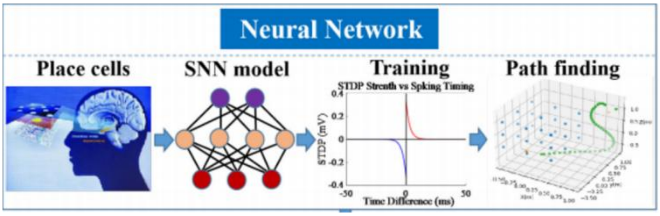

Fig. 1. Diagram of the neural network process [5]

In addition to simulating the neural activity mechanisms of position cells in the mammalian hippocampus, there is also making use of an enhanced bat algorithm to optimize migration learning convolutional neural networks (CNNs) and a bio-inspired optical flow balancing algorithm for obstacle avoidance [6].

The other is the UAV path planning combining neural network and reinforcement learning: The RPP-LSTM method: using the LSTM network as the Q-value network of deep Q-network (DQN), introducing the LSTM into the DQN framework, utilizing the memory capability of LSTM to deal with the multistep decision-making problem, and designing the hierarchical Reward-Punishment function in [7]. The experiments verify that in static environments combining the memory properties of recurrent neural networks and deep reinforcement learning algorithms: the paths are shorter and smoother under the RPP-LSTM method, and can successfully track the dynamic target points, and the heading adjustment is more flexible. In unfamiliar environments, RPP-LSTM can still plan safe paths with significantly improved robustness. However, the training complexity of the LSTM network is high, the computational overhead is relatively large, and the experimental scenarios are limited to simulation environments, which makes the lightweight LSTM structure a new idea for research and improvement.

3.2 Reinforcement-based learning path planning

Reinforcement learning is a branch of machine learning that allows agents to learn optimal strategies in their interaction with the environment. As shown in Figure 2, The agent performs actions in the environment and receives rewards (or feedback) based on the results of the action. These reward signals guide the agent to adjust its strategy to maximize the long-term cumulative reward.

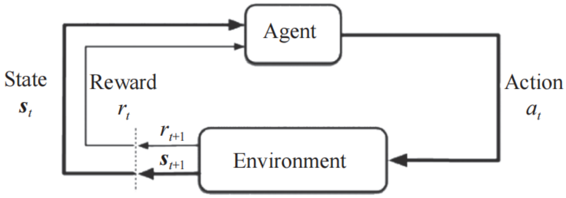

Fig. 2. Classical diagram of reinforcement learning [7]

While reinforcement learning is applied to UAV path planning, then it can help UAVs to efficiently reach the target location through trial and error and learning how to avoid obstacles while avoiding obstacles in [8]. The performance of some learning algorithms such as DDPG, TD3, SAC, SoftQ and other algorithms in path planning is evaluated by simulating the simulation environment in combination with sensors. In the performance comparison, DDPG achieves the highest reward and the fastest execution speed in training; TD3 has the best performance in obstacle avoidance and generalization among 2-6 obstacles. However, all algorithms fail at greater than or equal to 7 obstacles, this indicates that the current method has a limited generalization ability for high-density obstacles. Strong Exploration Capability Reinforcement learning is the core of autonomous decision making for UAVs, which enables UAVs to autonomously plan paths for dynamic obstacle avoidance in complex and unknown environments, and significantly improves efficiency and real-time performance through algorithmic improvements. But the algorithm performs poorly in dense obstacles.

In many researches in order to make the UAV find the optimal path from the starting point to the midpoint in the complex environment, the IQ-FAT algorithm i.e. the combination of the pollen algorithm and the table method is proposed in [9]. The initial population is generated by FPA, the path coordinates and target coordinates are calculated, the optimal individuals are filtered to initialize the Q-table, after which the Q-table is used to record the environmental information to adjust the Q-value of the state around the new obstacle downward through the gradient. IQ-FAT was compared with other traditional algorithms such as Q-learning and APF in the test environment of high-density regular obstacles, irregular geometric obstacles, and indoor long bar obstacles. The results show that IQ-FAT has 45%-60% less convergence time and smoother curves in complex environments. And compared to algorithms such as GA and SSA, the path length and smoothness are better, and the path can still be planned in dense obstacles; compared to APF and ACA, the response time is also shorter.IQ-

FAT significantly improves the convergence speed of Q-learning, and provides a solution for efficient path planning for UAVs in complex environments. Deep Q-learning combined with neural networks is utilized to deal with more complex state spaces, such as extracting information from deep images, which can avoid obstacles in real time in [10]. In multi-UAV path planning, reinforcement learning in many studies can address both dynamic multi-obstacle path assignment as well as goal assignment. The combination of a goal assignment network and Twin-Delayed DDPG algorithms work in tandem to improve the goal completion rate in [11]. Combining the SAC algorithm and a sampling-based path planning algorithm to generate pathways. Reinforcement learning allows the drone to dynamically adjust strategies to optimize path planning and following [12]. In addition, an experience sharing mechanism is mentioned in the multi-intelligence framework, which further suggests that reinforcement learning is used to coordinate the behavior of multiple UAVs and accelerate strategy convergence.

4 Challenges and future trends

In the development process of combining artificial intelligence and UAV path planning, despite the many achievements, there is some room for development and improvement in adapting to complex environments and algorithm performance. In this section will be divided into algorithm performance bottlenecks as well as complexity and energy consumption efficiency optimization to be discussed in three aspects.

4.1 Algorithm performance bottlenecks and complexity

For situations with dynamic obstacles and dynamic targets, UAVs are required to respond quickly. However, in high-dimensional complex environments or the UAV flight range increases, the computation grows exponentially, and the path generation time becomes longer, which makes it difficult to achieve the expected rapid response and unable to respond to changes in the dynamic environment in real time [5]. In dynamic environments, to realize fast response and real-time update of path information, the computational efficiency of the algorithm is required to be highly efficient, but the complexity of the computation is inversely proportional to the computational efficiency and the implementation of the actual experiments is limited by the processing capacity of the hardware. In the future, hardware optimization, dynamic perception fusion and algorithm lightweight are needed to improve the practicability.

Some storage like neural network parameters or Q-table storage can be very large in high dimensional complex environments [7,9]. In addition, like reinforcement learning algorithms require a lot of iterative training, convergence is slow thus affecting the real-time performance of the algorithm. In the complex environment, although the convergence rate of IQ-FAT algorithm improves, the proportion of the convergence time will decrease as the increasing complexity of the map increases [9]. In complex environments, although the convergence speed of the IQ-FAT algorithm is improved, the percentage improvement in its convergence time decreases as the complexity of the map continues to increase. When facing complex scenarios such as indoor obstacles of a specific length, the algorithm's difficulty in planning a path increases, and although the path can still be found, the convergence time is lengthened compared to simple scenarios. When dealing with dynamic obstacles in dynamic environments, although it can respond, its response ability may be deficient when facing more complex dynamic scenes with multiple fast-moving obstacles with complex trajectories. Although the RPP-LSTM algorithm solves the single-step decision-making problem to a certain extent and improves the accuracy and robustness of path planning, the LSTM network may not be able to adequately capture all the environmental information when facing extremely complex environments with frequent dynamic changes, leading to decision-making errors. Training LSTM networks requires a large amount of sample data and computational resources, and the training time is long. In practical applications, it may not be possible to obtain enough training data in time to adapt to new environmental changes, affecting the real-time and adaptability of the algorithm.

4.2 Multi-UAV Collaborative Path Planning

Multi-UAV collaboration needs to satisfy multiple constraints such as avoiding hazardous areas to achieve the efficiency and safety of the collaborative task [10]. And in dynamic environments, coordinated UAV obstacle avoidance, multi-objective optimization, and UAV-to-UAV communication interference or disruption greatly increase the complexity of path planning [11]. How to accurately assess the contribution of each UAV in the whole to avoid certain UAVs over-optimizing their own objectives and affecting the overall mission [12].

All of the above are problems that need to be thought about and researched to be solved. Multi-UAV path planning is still facing many problems, such as algorithms, environment perception, communication and other aspects. In terms of algorithm, different scenarios have different requirements for algorithms so it is difficult for one algorithm to adapt to multiple scenarios, which limits the practical application of multi-UAV path planning in different environments. Accurately modeling complex environments in terms of environmental perception is very difficult. Because the environment can be dynamic, irregular, the complex and changeable shapes and layout make it difficult to model accurately. Reinforcement learning can be usedto continuously interact with the environment and adjust the strategy based on reward signals to learn how to avoid obstacles and reach the destination efficiently [12]. In terms of communication, if the number of UAVs gradually increases, the limited communication broadband cannot support the large amount of data transmission will lead to the transmission of incomplete information or data, thus affecting the effectiveness of path planning collaboration. In terms of task allocation collaboration, the reasonableness of task allocation directly affects the overall performance of the system, and if the allocation is unreasonable it will lead to uneven task allocation.

4.3 Energy consumption efficiency optimization

One of the main challenges of UAVs in flight missions is the limited airborne energy storage capacity, which limits the flight time and range of action. The use of hybrid genetic algorithms and Q-learning is mentioned to overcome these limitations [13]. The genetic algorithm generates candidate paths through global search, while Q-learning adjusts the paths in real time through reinforcement learning, considering the speed of the UAV and the distance to obstacles. Although this approach shows high energy efficiency in simulations, there may be unresolved blocking issues in practical applications.

At the algorithm level of UAV energy consumption efficiency optimization, there is a collaborative problem in the fusion of traditional optimization algorithm and modern artificial intelligence algorithm [14]. Although the genetic algorithm can perform global search and generate diverse candidate paths, it is not capable of precise adjustment of local paths and real-time decision-making. The learning algorithm can learn and make decisions based on environmental feedback, but in large-scale complex environments, it has a slow convergence speed and is susceptible to the influence of initial values. When integrating the two, it is difficult to find the best balance point, resulting in limited overall optimization effect. In different scenarios, it is difficult to determine the optimal fusion ratio and parameter settings of the GA and Q learning algorithms, which affects the full performance of the algorithms. The complex and changing environment poses a great challenge to the efficiency of UAV energy consumption. The distribution of obstacles in the actual flight environment is complex, and dynamic obstacles and irregular terrain increase the difficulty of path planning. UAVs need to frequently adjust their flight paths and speeds when avoiding these obstacles, which can lead to additional energy consumption. Meteorological conditions in the environment, such as strong winds and rainfall, change the UAV's flight resistance and energy consumption, increasing the complexity of energy management.

Current algorithms have difficulty in accurately predicting and adapting to these complex environmental factors, leading to the difficult optimal energy consumption efficiency. The hardware equipment of UAVs has bottlenecks in the optimization of energy consumption efficiency. On the one hand, the development of battery technology for UAVs is relatively lagging, and the energy density is limited, which can't meet the demand of long-time and high-load flight. This makes UAVs must consider energy reserves when performing missions, limiting their flight range and mission execution time. On the other hand, the computational power of the hardware also affects energy efficiency. To reduce energy consumption, it may not be possible to run complex algorithms, thus affecting the accuracy of path planning and optimization of energy efficiency. In UAV path planning, energy consumption efficiency is not the only optimization objective, but also needs to consider multiple objectives such as mission completion time and flight safety. In practical applications, there are often conflicts between these objectives. To reduce energy consumption, a longer but more energy-efficient path may be chosen, which will increase the mission completion time while the pursuit of fast mission completion may lead to excessive flight speed, increasing the risk of collision with obstacles and reducing flight safety. How to balance these conflicting goals is a big problem for energy consumption efficiency optimization. The current research is difficult to consider these factors comprehensively, resulting in the inability to achieve overall optimal path planning in practical applications.

The literature reviewed above is basically based on the intelligence of artificial to solve the problem of UAV path planning in complex dynamic environments, in which the future trend is summarized [15]. Algorithms based on Voronoi diagram and Q-learning are combined with other intelligent algorithms (e.g., Genetic Algorithms, Particle Swarm Optimization Algorithms) to take advantage of their respective strengths and to improve the efficiency and quality of path planning. A multi-algorithm approach is integrated to solve the UAV path planning problem, using the advantages of each algorithm to achieve algorithm optimization. By improving the network structure, adjusting the reward function and exploring more effective training methods, the learning efficiency, convergence speed and decision accuracy of the algorithm are improved, and the training time and resource consumption are reduced, so that it can better adapt to the dynamic environment changes. Study the multi-UAV collaboration path planning strategy to solve the problem of multi-aircraft coordination and collision avoidance [13]. The idea of multi-intelligence body reinforcement learning optimizes task allocation and path planning to improve the overall effectiveness and synergy of multi-UAV systems in complex tasks. Construct a more realistic and complex environment model, simulate various factors in the real scene, and consider more terrain and landforms, building distribution, etc., to improve the adaptability of the algorithm in the complex environment [16]. For example, a 3D stochastic complex simulation environment was constructed in [17]. Algorithm validation and optimization are carried out on the actual UAV hardware platform, considering the actual factors such as sensor errors, communication delays, hardware performance limitations, and so on. Through actual flight tests, the algorithm is continuously improved to enhance its feasibility and effectiveness in real scenarios, and to promote the UAV path planning algorithm from theoretical research to practical application.

5 Conclusion

In the era of rapid development of artificial intelligence, UAVs are gradually evolving from simple remote-controlled flights to intelligent bodies with autonomous decision-making. Using AI to solve UAV path planning is an innovation: breaking through the limitations of traditional algorithms; it is also a challenge: energy limitations, computational resource limitations, and so on. Currently, AI is widely used in the field of UAV path planning, such as path search optimization, environment-aware modelling, dynamic environment adaptation, and multi-UAV collaboration.

In this paper, various AI-based UAV path planning algorithms in the literature published in web of science from 2023 to 2025 are explored, and AI-based UAV path planning is divided into two aspects to be explored, on the one hand, neural networks, by simulating the computational model constructed by the structure and function of the biological nervous system, are able to learn from the data to realize complex pattern recognition, function approximation and prediction tasks. On the other hand, reinforcement learning algorithms train UAVs to fly stably in complex environments, reward function design minimization as well as obstacle avoidance. Although most of the reviewed studies validated their algorithms using simulation experimental simulations, future research should implement and test their algorithms in real-world environments to improve real-time performance. Due to the limitations of the current technology, many problems still need to be solved by researchers, such as high algorithm complexity and limited computational resources; complex AI algorithms make energy consumption faster and shorten the UAV's endurance, which makes this paper give future research directions. Advances in artificial intelligence have made drone path planning systems smarter, which has led to a gradual increase in the efficiency of social operations, providing a powerful tool for both exploration and discovery as well as for life.

References

1. Mei, G.'Research on Big Data Artificial Intelligence Technology Based on Deep Learning'.2023. In: Kountchev, R., Nakamatsu, K., Wang, W., Kountcheva, R. (eds) Proceedings of the World Conference on Intelligent and 3-D Technologies (WCI3DT 2022). Smart Innovation, Systems and Technologies, vol 323. Springer, Singapore.
2. Chen, S., Mo, Y., Wu, X., Xiao, J., & Liu, Q. 'Reinforcement learning-based energy-saving path planning for UAVs in turbulent wind'. 2024. Electronics, 13(16), 3190.
3. B. Jia et al., 'Coverage Path Planning for IoUAVs With Tiny Machine Learning in Complex Areas Based on Convex Decomposition,' in IEEE Internet of Things Journal, vol. 11, no. 12, pp. 21103-21111, 15 June15, 2024.
4. Y. Miao, K. Hwang, D. Wu, Y. Hao and M. Chen, 'Drone Swarm Path Planning for Mobile Edge Computing in Industrial Internet of Things,' in IEEE Transactions on Industrial Informatics, vol. 19, no. 5, pp. 6836-6848, May 2023.
5. Chao, Y., Augenstein, P., Roennau, A., Dillmann, R., & Xiong, Z. 'Brain inspired path planning algorithms for drones'.2023. Frontiers in Neurorobotics.
6. Z. Zhang, S. Wang, J. Chen and Y. Han, 'A Bionic Dynamic Path Planning Algorithm of the Micro UAV Based on the Fusion of Deep Neural Network Optimization/Filtering and Hawk-Eye Vision,' in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 53, no. 6, pp. 3728-3740, June 2023.
7. J. Zhang, Y. Guo, L. Zheng, Q. Yang, G. Shi and Y. Wu, 'Real-Time UAV Path Planning Based on LSTM Network,' in Journal of Systems Engineering and Electronics, vol. 35, no. 2, pp. 374-385, April 2024.
8. S. Garg, H. Masnavi, B. Fidan, F. Janabi-Sharifi and I. Mantegh, 'Benchmarking Off-Policy Deep Reinforcement Learning Algorithms for UAV Path Planning,' 2024 International Conference on Unmanned Aircraft Systems (ICUAS), Chania - Crete, Greece, 2024, pp. 317-323.
9. L. Bo et al., 'Improved Q-Learning Algorithm Based on Flower Pollination Algorithm and Tabulation Method for Unmanned Aerial Vehicle Path Planning,' in IEEE Access, vol. 12, pp. 104429-104444, 2024.
10. Fu, Y., Yang, S., Liu, B., Xia, E., & Huang, D. 'Multi-UAV cooperative trajectory planning based on the modified cheetah optimization algorithm'. 2023. Entropy, 25(9), 1277.
11. Kong, X., Zhou, Y., Li, Z., & Wang, S. 'Multi-UAV simultaneous target assignment and path planning based on deep reinforcement learning in dynamic multiple obstacles environments'. 2024. Frontiers in Neurorobotics.
12. Zhao, X., Yang, R., Zhong, L., & Hou, Z.'Multi-UAV path planning and following based on multi-agent reinforcement learning. Drones', 2024. 8(1), 18.
13. S. Kumari, E. Sodhi, D. Gupta and A. Pratap, 'AoI-Aware Deep Reinforcement Learning Based UAV Path Planning for Defence Applications,' 2024 IEEE Space, Aerospace and Defence Conference (SPACE), Bangalore, India, 2024, pp. 230-234.
14. R. A. Saeed, E. S. Ali, M. Abdelhaq, R. Alsaqour, F. R. A. Ahmed and A. M. E. Saad, 'Energy Efficient Path Planning Scheme for Unmanned Aerial Vehicle Using Hybrid

Generic Algorithm-Based Q-Learning Optimization,' in IEEE Access, vol. 12, pp. 13400-13417, 2024.
15. Su, W., Gao, M., Gao, X., & Xuan, Z. 'Enhanced multi-UAV path planning in complex environments with voronoi-based obstacle modelling and Q-learning'. International Journal of Aerospace Engineering, 2024.
16. Zhao, X., Yang, R., Zhong, L., & Hou, Z. 'Multi-UAV path planning and following based on multi-agent reinforcement learning'. 2024.Drones, 8(1), 18.
17. Guan-Ting Tu, & Jih-Gau Juang. 'UAV path planning and obstacle avoidance based on reinforcement learning in 3D environments'.2023. Actuators, 12(2), 57.