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EVALUATION AND APPLICATION ALGORITHM OF ARTIFICIAL INTELLIGENCE UNMANNED VEHICLE CONTROL DEVICE BASED ON IOT INTELLIGENT TRANSPORTATION

Min Zeng

School of Mechanical and Vehicular Engineering
Nanchang Institute of Science and Technology
Nanchang 330108, China
&
Faculty of Mechanical Engineering Technology, Universiti Malaysia Perlis
02600, Arau, Perlis, Malaysia
e-mail: zm13767456525@163.com

Wenlong Sun*, Zhiqiang Wang, Hui Chen

School of Mechanical and Vehicular Engineering
Nanchang Institute of Science and Technology
Nanchang 330108, China
e-mail: sunwenlong1000@126.com, zqwang89@163.com, xueshu627@163.com

Mohd Sani Mohamad Hashim

Faculty of Mechanical Engineering Technology, Universiti Malaysia Perlis
02600, Arau, Perlis, Malaysia
e-mail: sanihashim@unimap.edu.my

Abstract. With the rapid development of technology, unmanned vehicles have become a hot research topic in the field of intelligent transportation. Unmanned

* Corresponding author

vehicles have many advantages, such as improving traffic efficiency, reducing traffic accidents, and reducing energy consumption. However, the controllability and safety of unmanned vehicles have always been a key issue in research. The Internet of Things can achieve information exchange and data sharing between vehicles, transportation facilities, traffic management centers, etc., providing real-time traffic and road condition information, and providing accurate data support for intelligent decision-making and path planning of unmanned vehicles. Therefore, the artificial intelligence unmanned vehicle control device based on IoT intelligent transportation has become an important research direction. This paper used deep reinforcement learning as the decision-making control algorithm, and designed a set of unmanned vehicle control system based on the DDPG (Deep Deterministic Policy Grad) algorithm, supplemented by meta DDPG algorithm, which is the knowledge of meta learning. Through the test of the simulation platform, it was concluded that the control system has good generalization. This study combined the Internet of Things and artificial intelligence algorithms, which has certain guiding significance for the development and application of unmanned vehicles in the future.

Keywords: Internet of Things, intelligent transportation, unmanned vehicles, meta-DDPG algorithm, simulation platform

1 INTRODUCTION

In recent years, due to the rise of artificial intelligence, more intelligent products have entered people's lives, and the most significant impact on people's lives is undoubtedly autonomous cars. Unmanned vehicle is an intelligent vehicle product that integrates computer, communication, control and other technologies. As is an artificial intelligence product that has been applied in the field of artificial intelligence. By utilizing modern sensing and information processing technologies, real-time monitoring of the surrounding environment of the vehicle, the vehicle's state, and the driver's state is achieved. In case of dangerous situations, the driver is promptly notified to take certain actions. The research on intelligent vehicles has two important meanings. One is to improve traffic efficiency, and the other is to ensure the safety of drivers. It also plays an irreplaceable role in high-end technologies such as deep sea exploration and space exploration, which shows how important the research of unmanned vehicles is as one of the hottest AI (artificial intelligence) research projects.

With the rapid development of the social economy, people's living standards have been greatly improved, and cars have become basic household goods. At the same time, the incidence of road traffic accidents is also rising. At present, some regions still need to strengthen their understanding of road traffic safety, pay insufficient attention to road traffic safety work, and progress is slow. At the same time, the proportion of road transportation accidents in production safety accidents is still high, and serious traffic violations and accidents still occur. In some regions, accident prevention has not been effectively controlled, and the number of accident deaths is still on the rise. In recent years, in order to ensure the safety of passengers in cars, the automotive industry has introduced various safety technologies, but they still cannot completely avoid the dangers caused by some people. Therefore, researchers have shifted their attention to high-tech, and autonomous driving technology has emerged as a result. Unmanned cars can reduce driving under the influence, malicious driving and other behaviors, reduce traffic accidents and casualties, effectively improve the safety of road traffic, and ease the pressure of traffic congestion. In recent years, due to Alpha Go's victory over the world's top professional Go players, deep learning and reinforcement learning have become a hot topic in academic research. They have achieved excellent results in image recognition and robot control. Later, people put forward a new idea, which combines the deep learning with the ability of perceiving abstract features and the reinforcement learning with the ability of adaptive decision-making, and is very suitable for solving the unmanned driving decision-making research that needs continuous action output. However, due to the blindness of early training in deep learning, it not only delays the training progress, but also poses potential risks, making it difficult to ensure the safety of unmanned driving. To solve this problem, this paper studies the intelligent decision-making method of intelligent transportation system based on deep reinforcement learning, and uses the meta deep learning algorithm to achieve efficient control and management of unmanned vehicles and improve the safety, and intelligence and dynamic response ability of unmanned vehicles.

In this paper, we try to propose a new control algorithm to improve the performance and stability of the control device of unmanned vehicles. This algorithm can be combined with techniques such as deep learning, reinforcement learning, or evolutionary algorithms to enable more efficient path planning, dynamic traffic decisions, and optimal control. In addition to traditional sensor data, driverless cars can also rely on data collected by IoT devices and other data sources to make decisions. In this paper, we propose a decision method which combines sensor data with traffic state and meteorological data to improve the decision accuracy and robustness of the control device.

This paper mainly evaluates and researches the control device of artificial intelligence unmanned vehicles based on the intelligent transportation of the Internet of Things. First of all, the background and purpose of the thesis are studied, the background of the Internet of Things, intelligent transportation and artificial intelligence and their importance in modern society are expounded, and the research topics are clearly proposed. Then, a literature review was conducted, which was divided into the basic concepts and development status of intelligent transportation of the Internet of Things and the application of artificial intelligence in the field of driverless vehicles. Secondly, it is the design and implementation of artificial intelligence unmanned vehicle control devices based on intelligent transportation of the Internet of Things. It mainly focuses on the overall system architecture and components, unmanned vehicle perception and data collection, and algorithm design and optimization. Algorithm design and optimization are the main content, and the design, optimization, real-time scheduling and path planning of decision-making control algorithms are also studied. Then the experimental verification was carried out, the experimental environment was designed first, and the driving strategy test effect of DDPG and the generalization effect of strategy based on meta-learning were studied. Finally, the application scenarios of unmanned vehicles in intelligent transportation of the Internet of Things are prospected.

The research contribution of artificial intelligence unmanned vehicle control device evaluation and application algorithm based on Internet of Things intelligent transportation is mainly manifested in the following aspects:

Improve traffic efficiency: The combination of Internet of Things technology and artificial intelligence enables unmanned vehicles to obtain road information, the status of traffic lights, the location and speed of other vehicles in real time, etc., by optimizing path planning and decision-making, effectively alleviate traffic congestion and improve road efficiency.

Reduce the risk of accidents: through high-precision sensors and advanced algorithms, unmanned vehicles can more accurately judge the surrounding environment and avoid potential hazards. At the same time, accidents caused by human factors of drivers can be reduced, thereby improving road safety.

Reduce environmental pollution: Unmanned vehicles that optimize driving strategies can control the throttle and brakes more rationally, reduce unnecessary fuel consumption and emissions, and thereby reduce environmental pollution.

Improve the convenience of travel: The autonomous driving characteristics of unmanned vehicles allow people to carry out other activities in the car, improving the convenience of travel.

2 LITERATURE REVIEW

2.1 Basic Concepts and Development Status of IoT Smart Transportation

Intelligent transportation of the Internet of Things refers to the interconnection of various devices, sensors, vehicles and infrastructure in the transportation system through the Internet of Things technology to realize the perception, transmission, processing and application of information, so as to improve the efficiency, security and environmental friendliness of the transportation system. Batty conducted an analysis of some smart cities around the world and also presented in detail the concept of artificial intelligence, as well as governance under the sustained support of the population. Through various methods, they attempted to meet the needs of communities in various fields such as economy, mobility, and living environment [1].

The Internet of Things smart transportation requires the construction of intelligent transportation facilities, such as intelligent traffic signal lights, intelligent parking lots, intelligent street lights, etc., to achieve information collection and transmission. Zhu et al. believed that intelligent transportation system (ITS) driven by sections has great potential and capability to make the transportation system efficient, safe, intelligent, reliable and sustainable. IoT (Internet of Things) provides the way and driving force for seamless integration of virtual transportation systems from the physical world to the network world. They proposed the vision and work of combining the artificial intelligent transportation system with the real intelligent transportation system to create and enhance the "intelligence" of loT enabled ITS. With the increasing popularity of intelligent transportation systems and the enhancement of depth perception ability, people can quickly create an artificial transportation system equivalent to a physical transportation system in the computer, so as to have a parallel intelligent transportation system, that is, the real intelligent transportation system and artificial intelligent transportation system. The evolution process of transportation systems was studied from the perspective of parallel worlds [2]. The intelligent transportation of the Internet of Things collects traffic data through sensors and monitoring equipment, such as traffic flow, speed, road status, etc., and then processes and analyzes the data through cloud computing, big data analysis and other technologies. Zhu et al. believed that the intelligent transportation system could generate a large amount of data, and introduced the application cases of big data analysis in the intelligent transportation system, including road traffic accident analysis, road traffic flow prediction, public transportation service planning, personal travel route planning, rail transit control, asset maintenance, etc. [3]. Data analysis based on IoT smart transportation can achieve intelligent and optimized traffic management, such as traffic signal optimization, traffic congestion prediction, and route planning. Nallaperuma et al. proposed a Simple Transportation Management Protocol (STMP) based on unsupervised online incremental machine learning, deep learning and deep reinforcement learning to address these limitations. STMP integrated heterogeneous big data streams such as traffic networks, intelligent sensors, social media, etc., and realized functions such as concept drift detection, frequent and non frequent traffic incident differentiation, impact propagation, traffic flow prediction, commuter sentiment analysis, and optimization of traffic control decisions [4]. These scholars' research on IoT intelligent transportation can provide a certain theoretical basis for this article's research. However, due to their lack of focus on the role of IoT intelligent transportation in unmanned vehicle control devices, there is no effective viewpoint for the evaluation of unmanned vehicle control devices. This leads to significant problems in the evaluation of unmanned vehicle control devices, which is not conducive to the better application of IoT in unmanned vehicles. The intelligent transportation of the Internet of Things is currently in a rapid development stage. With the continuous maturity of IoT technology and the gradual improvement of intelligent transportation system, IoT intelligent transportation has been widely used worldwide. Many cities have begun to deploy intelligent transportation facilities, such as intelligent traffic lights, intelligent parking systems, and intelligent traffic management platforms. At the same time, the development of big data analysis and artificial intelligence algorithms has also provided strong support for intelligent transportation of the Internet of Things, making traffic management and optimization more intelligent and accurate. However, IoT smart transportation still faces some challenges, such as privacy protection, security, and standardization. With the continuous progress of technology and the accumulation of application experience, the intelligent transportation of the Internet of Things is expected to achieve a more intelligent, efficient and sustainable transportation system in the future.

2.2 Application of Artificial Intelligence in the Field of Unmanned Vehicles

The application of artificial intelligence in the field of unmanned vehicles is one of the key technologies for achieving autonomous driving. Unmanned vehicles obtain data from the surrounding environment through sensors such as LiDAR and cameras, and then use artificial intelligence algorithms for image recognition, object detection, and scene understanding to achieve perception and recognition of roads, vehicles, and pedestrians. Chiaroni et al. proposed perception of the self vehicle environment. On the one hand, traditional analysis methods often rely on manual design and features, and on the other hand, learning methods aim to design their own appropriate representations of the observed scene [5]. Based on perceived environmental information, unmanned vehicles need to make corresponding decisions and plan their travel paths. Artificial intelligence algorithm can analyze and predict different traffic conditions through deep learning, reinforcement learning and other methods to make optimal decisions. Grigorescu et al. proposed an automated driving architecture based on artificial intelligence, convolutional and recurrent neural network, and deep reinforcement learning paradigm. They also studied the modular perception planning action pipeline, where each module was constructed using deep learning methods and an End2End system that directly maps sensory information to turn commands [6]. In the actual driving process, the unmanned vehicle needs to control the acceleration, braking, steering and other actions of the vehicle. Artificial intelligence algorithms can achieve precise control and execution of vehicles through control systems and feedback mechanisms. Fu et al. believed that it is a key issue to realize automatic braking to reduce accidents through accurate decision-making and control of vehicles, especially in the early diffusion stage of the development of autonomous vehicle. Therefore, an automatic braking decision-making strategy based on deep reinforcement learning in emergency was proposed. This strategy fully considered and met the three key influencing factors of efficiency, accuracy, and passenger comfort. Firstly, a detailed analysis was conducted on the lane changing process and braking process of the vehicle, including key factors in the design of autonomous braking strategies. Secondly, the DRL (deep reinforcement learning) process was used to determine the optimal strategy for automatic braking [7].

Through the research of scholars, it can be seen that the continuous development and innovation of artificial intelligence in the field of unmanned vehicles have provided important support for achieving safe, efficient, and intelligent unmanned driving. However, there are still many problems in the research of unmanned vehicle control evaluation, and there is still room for exploration on how to improve the privacy protection, security, and standardization of unmanned vehicle data.

It is reasonable to position this article as a theme of the special issue. With the rapid development of the Internet of Things and artificial intelligence, as an important part of intelligent transportation, the evaluation of its control device and the research of its application algorithm have important academic and application value. The topic involves the combination of several cutting-edge technology fields such as the Internet of Things, intelligent transportation and artificial intelligence. The evaluation and application algorithm for the control device of unmanned vehicles is proposed to meet the needs of unmanned vehicles in the intelligent transportation system of the Internet of Things, which is novel and cutting-edge. The topic involves the intersection of multiple fields such as the Internet of Things, intelligent transportation, artificial intelligence, and control theory. The special issue can attract scholars and experts from different fields to discuss the evaluation and application algorithms of autonomous vehicle control devices.

3 DESIGN AND IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE UNMANNED VEHICLE CONTROL DEVICE BASED ON IOT INTELLIGENT TRANSPORTATION

3.1 Overall System Architecture and Components

The unmanned vehicle control system based on the Internet of Things utilizes sensors and IoT technology to perceive the surrounding environment of the vehicle, make intelligent decisions based on the obtained data, and interact in real time with other IoT devices and entities. The system includes perception module, decision module, execution module, interaction module, and application module. These modules work together to enable autonomous driving and obstacle avoidance in various environments and conditions, thereby improving driving safety and convenience. The perception module obtains environmental information; the decision-making module makes decisions based on data and objectives; the execution module is responsible for executing decisions; the interaction module achieves communication with other devices; the application module customizes specific scene functions. Through the integration of the Internet of Things, this system provides safer, more efficient, and intelligent solutions for autonomous vehicle driving [8, 9]. The overall framework structure of the system is shown in Figure 1.

1. **Perception module.** The perception module utilizes various sensors and devices in the Internet of Things to obtain information about the vehicle's surrounding environment. These sensors can include cameras, radars, LiDAR, ultrasonic sensors, etc. Through the Internet of Things, perception modules can achieve data sharing and collaborative work between sensors to obtain more

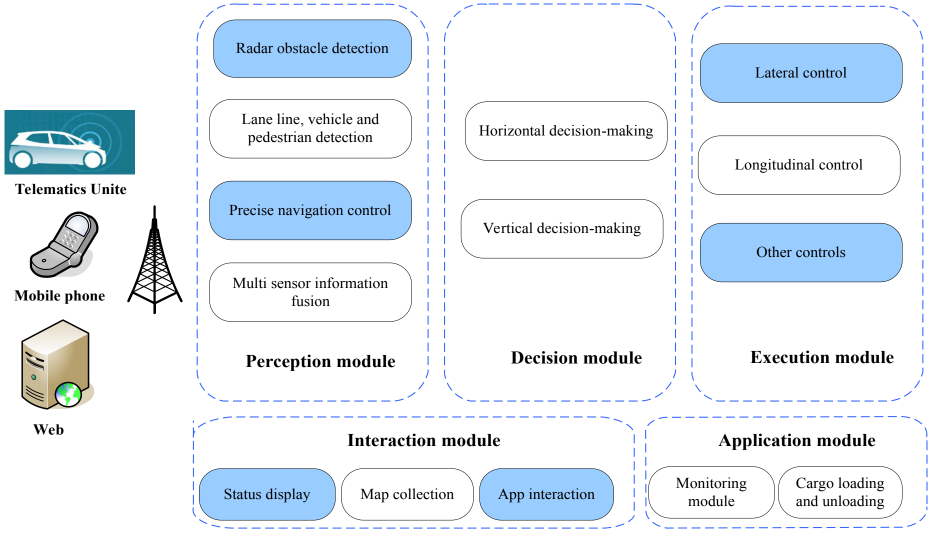


Figure 1. IoT unmanned vehicle control system framework

comprehensive and accurate environmental information. In addition, the perception module can communicate with other IoT devices, such as traffic lights and road monitoring systems, to obtain real-time traffic and road condition information.

2. **Decision module.** The decision-making module based on the Internet of Things communicates with cloud servers or central control systems connected to the Internet of Things to obtain more data and information to support decision-making. These data can include traffic flow, weather conditions, roadworks information, traffic control instructions, etc. By comprehensively analyzing and processing these data, the decision-making module can more accurately formulate driving strategies and flexibly make decision adjustments.
3. **Execution module.** The execution module based on the Internet of Things enables unmanned vehicles to communicate and collaborate in real time with other devices in the Internet of Things. The execution module can communicate with traffic lights, pedestrian sensors, vehicle recognition systems, etc., to obtain real-time traffic information and dynamic information of other vehicles or pedestrians. In this way, the execution module can adjust the vehicle's driving speed, direction, and braking timing based on this to ensure safe driving and collaboration with other participants.
4. **Interaction module.** The IoT-based interaction module allows unmanned vehicles to intelligently interact with other IoT devices and entities. By communicating with internet connected devices in the Internet of Things, unmanned vehicles can obtain real-time navigation information, road condition information,

service requests, and more. At the same time, the unmanned vehicle can also send commands and requests to other IoT devices, such as controlling parking spaces and service stations near the vehicle through smart home.

5. **Application module.** Application modules based on the Internet of Things can be customized and developed for specific application scenarios. For example, unmanned taxi applications can include connections to passenger phones, integration of payment systems, and more. Logistics distribution vehicle applications can include real-time interaction with warehouse management system, goods tracking, etc. By integrating with the Internet of Things, application modules can provide more intelligent, convenient, and efficient services and functions.

The integration and collaborative work of these modules enables IoT-based unmanned vehicle control systems to obtain more comprehensive and accurate environmental information, make smarter decisions, and interact in real time with other IoT devices and entities, providing users with a safer and more efficient unmanned vehicle driving experience. Figure 2 is the main page of the system platform. The IoT unmanned vehicle control platform is a comprehensive solution that utilizes IoT technology and unmanned vehicle control modules to achieve comprehensive monitoring, management, and control of unmanned vehicles. It can provide a one-stop solution, including various core control technologies, sensor information collection technologies, remote monitoring and diagnosis technologies, and can connect to various mainstream manufacturers' devices, providing a unified platform for management. This comprehensive solution plays an important role in ensuring the stable operation and safety of unmanned vehicles.

This platform obtains real-time information such as the position, status, and sensor data of unmanned vehicles through wireless connection and data transmission, providing comprehensive data analysis and decision support. Users can remotely monitor and manage the operation status of unmanned vehicles, schedule tasks, optimize path planning, and achieve collaborative task execution through connections with other IoT devices and systems. The platform also has risk management and safety warning functions, which can timely identify and respond to potential risks and safety issues, ensuring the safe operation of unmanned vehicles. The user interface is friendly, providing convenient interaction methods, and allowing users to easily access and control unmanned vehicles. Through the IoT unmanned vehicle control platform, users can achieve intelligent and efficient management of unmanned vehicles, improve operational efficiency and safety, and promote the further development of unmanned vehicle technology.

The IoT autonomous vehicle control platform is a complex system whose system model and problem definition can vary according to specific application scenarios and needs. Here is an example of a possible system model and problem definition:

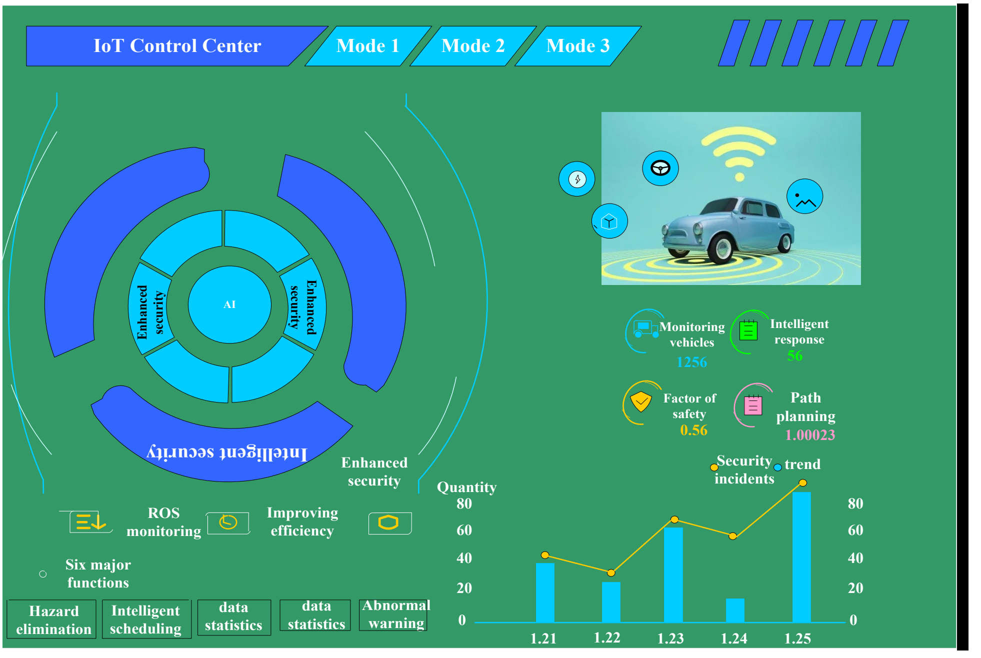


Figure 2. IoT unmanned vehicle control platform

System model:

- **Sensors:** Unmanned vehicles are equipped with a variety of sensors, such as cameras, LiDAR, ultrasonic sensors, etc., for sensing the surrounding environment. Cameras are primarily used to gather visual data, which includes information about barriers, traffic signals, and road conditions. They are also used to recognize other vehicles, pedestrians, and road signs. LiDAR uses a laser beam to measure the time it takes for an item to reflect back, giving precise information on the object's shape, speed, distance, and position in the surrounding environment. By generating an ultrasonic wave and timing when it reflects back, an ultrasonic sensor can determine how far away an obstacle is. In order to achieve autonomous driving, this sensor data can assist autonomous cars in carrying out tasks including obstacle avoidance, target recognition, path planning, and environment perception.
- **Data transmission:** The data acquired by the sensor is transmitted to the control platform via wireless communication or wired connection.
- **Control platform:** Composed of software and hardware, it is responsible for receiving and processing sensor data, making decisions and controlling the unmanned vehicle.

Decision algorithms: Based on sensor data and prior knowledge, the control platform uses decision algorithms to analyze the environment, plan a path, and formulate a course of action.

Execution mechanism: The control platform converts the decision results into instructions, and controls the acceleration, braking, steering and other actions of the unmanned vehicle through the execution mechanism.

Feedback mechanism: The unmanned vehicle continuously collects feedback information, including sensor data and executive feedback, for real-time adjustment of the control strategy.

Problem definition:

Path planning: How to determine the best driving path for an unmanned vehicle, taking into account road conditions, traffic rules, environmental obstacles and other factors?

Obstacle avoidance strategy: How to avoid collisions with other vehicles, pedestrians or obstacles based on sensor data?

Real-time decision making: How to make real-time decisions based on sensor data and prior knowledge to ensure safety and efficiency in a dynamically changing traffic environment?

Communication and data security: How to ensure the secure transmission of sensor data and control instructions to prevent hacking attacks and data breaches?

Energy management: How to optimize the energy efficiency of unmanned vehicles, extend the driving range, and improve the overall system sustainability?

User interface and interaction: How to design an intuitive and user-friendly user interface that enables operators to monitor and intervene in the operation of unmanned vehicles?

This is only part of the definition of the problem, which should be planned and defined in more detail according to actual needs. The design and development of the IoT autonomous vehicle control platform needs to take into account various technical, security, management and user experience issues.

The Internet of Things' unmanned vehicle control platform offers several benefits, which are primarily evident in the following areas:

1. Automation and intelligence: Unmanned vehicles can be controlled intelligently and automatically thanks to Internet of Things technologies. Unmanned vehicles are equipped with sensors, controllers, and other devices that allow them to perceive their surroundings, plan their route automatically, perform autonomous navigation, and intelligently avoid obstacles. This can lower the amount of manual intervention and labor expenditures while also increasing the operational efficiency and safety of autonomous vehicles.

2. Remote management and monitoring: Internet of Things-based unmanned vehicles have the ability to upload data and information instantly, enabling remote management and monitoring. Administrators can monitor the unmanned vehicle's position and status at all times via the cloud platform or mobile application. They may also remotely operate the vehicle, including halting, starting, and changing its course. This makes managing and operating unmanned vehicles much more convenient.
3. Effective data processing and analysis: With the use of Internet of Things technologies, massive volumes of data can be collected and processed. The data produced during the operation of unmanned vehicles may be mined and analyzed using cloud computing and big data analysis technologies, and useful information can be collected to maximize the effectiveness and performance of unmanned vehicles. Additionally, by using this data, the quality of services and product designs can be enhanced.
4. Adaptable customization and growth: The Internet of Things-based unmanned vehicle control platform offers good customization and growth. Unmanned vehicles can have their configuration and design altered to best suit the requirements of diverse application situations and maximize a range of features and performance. Simultaneously, the platform may be readily expanded and modified to satisfy new market demands and technical requirements due to the ongoing advancements in technology and changes in application requirements.

3.2 Unmanned Vehicle Perception and Data Collection

The project intends to take the existing driverless vehicle as the research object, adopt ARMCotex-M3 (Advanced RISC Machines Cortex-M3) series microprocessor as the processing core, JDK (Java Development Kit) as the research and development platform, and camera, smoke, temperature and humidity, and motion target detection sensors as the system sensing device, WIFI (WIreless FIdelity) as the communication substrate, and wireless network as the communication substrate, to complete the communication between mobile phone and driverless vehicle [10, 11].

Drones have three modes of perception operation, namely sleep mode, safe mode, and autonomous mode. Sleep mode is mainly used for long-term storage or transportation of unmanned vehicles, safety mode is mainly used for maintenance or testing of unmanned vehicles to ensure their operation within a safe range, and autonomous mode is mainly used for normal operation and driving of unmanned vehicles. These three perception modes each have their own characteristics, and combined use can more comprehensively ensure the safety, stability, and efficient operation of unmanned vehicles.

Sleep mode: the unmanned vehicle only activates smoke sensors, temperature and humidity sensors, and moving object detection sensors. The camera and WIFI module are in a passive start state in this mode. When any of these three types of sensors feedback to the processor, it could automatically trigger a response from the camera and WIFI module, causing it to enter security mode, and also send an alarm signal to the mobile client.

Security mode: environmental information could be collected along a fixed inspection route. During driving, unmanned vehicles could continuously collect surrounding environmental information. If normal, after one inspection, everything could be told to the mobile client. If there are any abnormalities, an alarm could be immediately sent to the mobile client during the inspection. After a patrol, the drone could fall into a deep sleep.

Automatic control mode: users can use their mobile phones to control the driving mode, driving status, and status of various modules of unmanned vehicles, thereby achieving the goal of self-control.

As shown in Figure 3, after logging in, users can achieve remote connection between unmanned vehicles and mobile phones, and can also choose the working mode of unmanned vehicles to determine their operating status. If sleep mode is selected, only the smoke sensor, temperature and humidity sensor, and moving object detection sensor could be activated, while the camera and WIFI module could be placed in sleep, thereby increasing the standby time of unmanned vehicles. No one has the opportunity to turn on the camera and the wireless network interface controller and immediately notify the mobile phone when abnormal conditions are detected outside. If automatic security mode is selected, the unmanned vehicle could follow its operating route, find a safe road on its own, and conduct safety inspections on it. During the inspection process, if any abnormalities are found, its data could be immediately sent to the terminal, and an alarm could be issued immediately. Subsequently, a security inspection could continue. After reaching the destination, it could automatically turn around, return to the starting point, and be set to sleep. If self-control mode is selected, all modules of the unmanned vehicle are controlled by the mobile end, and can be used for manual security patrols.

Intelligent security technology based on the Internet of Things is currently a major trend in the development of artificial intelligence technology, which could greatly improve human living standards. The system uses the Internet of Things as the carrier and ARM-Cortex-M3 as the core processor to achieve remote human-machine interaction, but many details still need to be improved and adjusted in the future. On this basis, this study proposes the following improvement ideas: first, in the indoor environment, the combination of automatic monitoring and tracking monitoring is used to overcome the limitations of single tracking monitoring. Secondly, it is capable of automatic charging to achieve continuous operation. The third is to add a steering gear, expand the camera's field of view, and integrate it with moving object recognition to achieve automatic capture of moving objects. Further exploration is needed to determine whether the above points are feasible.

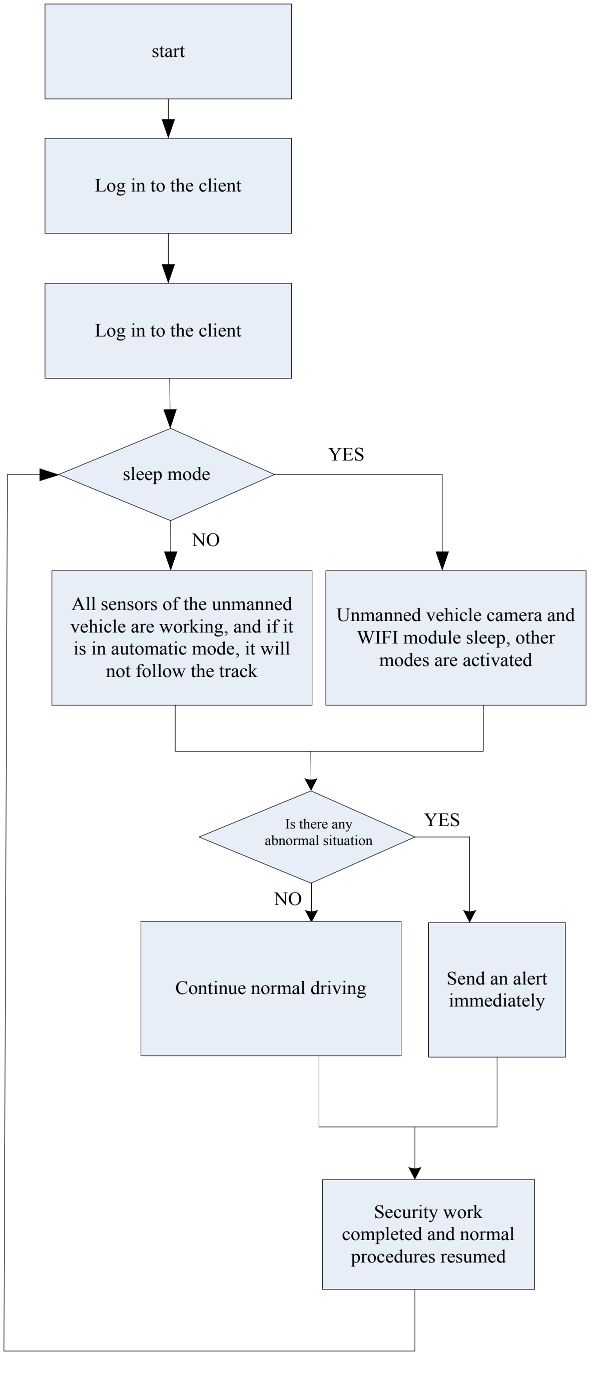


Figure 3. Implementation process flow diagram

3.3 Algorithm Design and Optimization

3.3.1 Algorithm Design

Deep reinforcement learning is used as the decision-making control algorithm. The algorithm based on DDPG, supplemented by the knowledge improvement algorithm of meta learning, is modeled to find the optimal control method [12]. Decision control algorithms are an important component of modern control theory, widely used in fields such as autonomous driving, industrial production, aerospace, communication networks, etc., providing more efficient, precise, and intelligent solutions. With the continuous development of technology, it is believed that decision control algorithms will have broader application prospects in the future.

The decision-making control algorithm uses deep reinforcement learning in the evaluation and application algorithm of artificial intelligence unmanned vehicle control device based on intelligent transportation of the Internet of Things. This is primarily accomplished by training a deep neural network to simulate the decision-making control process of unmanned vehicles. Unmanned vehicles employ sensors to gather data about their surroundings, such as traffic patterns, barriers, and road conditions. This data is transformed into a format, such pictures or LiDAR data, that the algorithm can handle. The perceived environmental data is represented as a state vector that includes environmental impediments and traffic signals in addition to the position, speed, and direction of the autonomous vehicle. To build a deep reinforcement learning model for predicting future rewards and probability distributions based on the current state, as well as an optimizer for updating the neural network's parameters based on historical data, one must first define the behavior space of unmanned vehicles, or all possible behaviors or actions. Additionally, the autonomous vehicle chooses the best course of action to follow during training by taking into account its surroundings and the results of the reinforcement learning model. Simultaneously, the reinforcement learning model is updated by using the environment's feedback outcomes as reward signals. The reinforcement learning model gradually discovers the best decision-making control technique through a process of continuous iteration. Multiple sensor fusion technology, multi-target tracking algorithms, and collaborative control strategies are examples of supplementary technical means that can be taken into consideration in practical applications to enhance the decision-making control performance and resilience of unmanned vehicles. Simultaneously, the algorithm's scalable and real-time nature must be taken into account in order to accommodate unmanned vehicle systems of varying sizes and complexity.

Among them, x represents the position of the vehicle on the road, surrounding obstacles, and other state information. The state set can be referred to as the state space X. a_t represents the acceleration, steering, and braking information of the vehicle, and the action set can be referred to as the action space A. In actual unmanned driving, it is necessary to design appropriate reward functions based on the requirements of environmental scenarios. The rewards and punishments obtained by unmanned vehicles after the action occurs could be determined by the reward function. The following are several important functions in the algorithm.

1. **Reward function [13].** It is assumed that x_t and a_t represent the environmental state observed and actions taken by the agent at time t; the timely reward obtained is set to $q(x_t, a_t)$; Q_t represents the cumulative reward value that the agent can receive after time t:

$$Q_t = q(x_t, a_t) + \gamma q(x_{t+1}, a_{t+1}) + \cdots = \sum_{k=0}^{\infty} \gamma^k q(x_{t+k+1}, a_{t+k+1}). \tag{1}$$

   Among them, γ is the discount coefficient that represents the proportion of future rewards in the current situation, and γ is 0 indicating that only current rewards are considered. If the γ value tends towards 1, it indicates a greater bias towards future interests. $\gamma^k q(x_t, a_t)$ refers to the value displayed by the reward obtained at time $k+1$ at time t.

2. **Value function [14].** This method adopts two types of methods to evaluate the advantages and disadvantages of strategies: one is the state value function $S(x)$, and the other is the behavioral value function $B(x, a)$. The state value function $S(x)$ refers to the expected cumulative returns obtained from strategy π starting from state x. Under the same circumstances, this value function could change with the change of strategy π.

$$S^{\pi}(x) = E_{\pi}[Q_t | x_t]. \tag{2}$$

The behavioral value function $B(x, a)$, also known as the B function, refers to the expected cumulative benefits obtained by an agent based on strategy π, starting from state x and adopting strategy a.

$$B(x) = E_{\pi}[Q_t | (x_t, a_t)]. \tag{3}$$

In each unmanned case, the task T_i has a starting state distribution $p(T_i)$, and the loss function LT_i of each task corresponds to the reward function Q mode f_θ is a strategy, dividing the state x_t with the operation a_t. A strategy corresponding to it. The loss formula for the task T_i and the model f_θ is:

$$L_{T_i}(f_\theta) = -E_{x_t a_t \ f\theta, qT_i} \left[\sum_{t=1}^{H} Q_i(x_t, a_t) \right]. \tag{4}$$

On this basis, a deep learning method based on meta learning is proposed, which can quickly obtain new experimental strategies using less experimental data. This new experimental work may be aimed at training a new type of unmanned vehicle under new driving conditions, or enabling it to successfully achieve the goal of maintaining safe driving in the lane under such conditions. For example, in meta learning training, a virtual unmanned vehicle may have learned to walk on a highway, and in the new traffic simulation environment, it can adjust based on limited road information to reach its destination faster. At the same time, this method can also be applied to deep reinforcement learning, overcoming the inefficiency of traditional DDPG methods and improving the accuracy and directionality of the model [15].

3.3.2 Algorithm Optimization

Based on the above, the reward function is optimally designed. In the autonomous driving decision system of DDPG algorithm, from the performance demonstrated by the model, although it can already achieve autonomous driving of vehicle and operate safely, it is still possible. However, in the process of autonomous driving, there are still some inevitable problems, such as excessive lateral sway during straight driving, delayed braking during turns, and steering deviation from the centerline of the lane. In order to minimize the lateral oscillation of unmanned vehicles during their journey and ensure that the direction of travel is consistent with the direction of the road, brakes can be applied in advance and decelerated when turning to ensure their safe turning. Based on the above required requirements, this section has made the following improvements to the original reward function:

$$Q_t = \begin{cases} n_1 v - n_2 v_e - n_3 d_m - n_4 \varphi_i^2, \\ -D, \text{Driving out of the lane.} \end{cases} \tag{5}$$

Among them, v represents the longitudinal effective speed of the vehicle; v_e represents the lateral error velocity; d_m represents the distance between the vehicle and the centerline of the lane; n_1, n_2, n_3, and n_4 are penalty coefficients respectively, and the newly added $n_4\varphi_i^2$ items represent the penalty amount for lane direction deviation.

3.4 Real-Time Scheduling and Path Planning

Forward looking mechanism refers to the mechanism that the vehicle selects a point in the path in front of the vehicle as the target point, and controls the vehicle to approach the point continuously. Firstly, it is necessary to determine a predicted aiming distance L that is proportional to the direction of the vehicle's travel. In the direction of the vehicle's travel, the higher the speed, the farther the preview. When the speed is smaller, the preview becomes closer. Then, in the path, the mechanism could use the path point closest to the preview distance from the center of the rear axle to each path point as the preview point. However, during the search process, there may also be situations as shown in Figure 4: when searching for a path ahead, there are multiple points that match the preview distance. Therefore, the first point encountered during the search process that is larger than the preview distance could be used as the preview point, that is, point a.

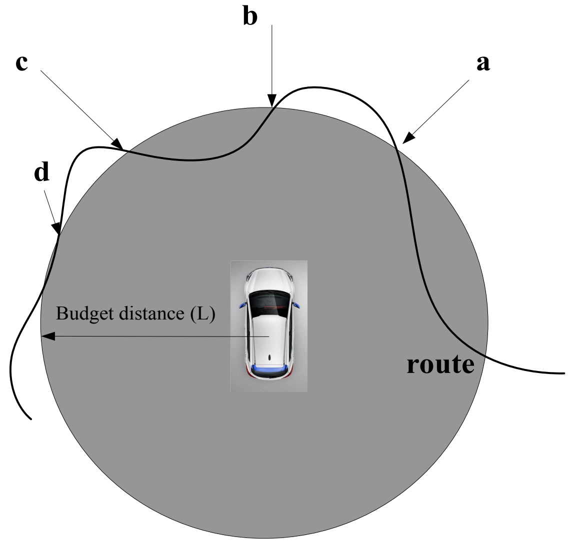
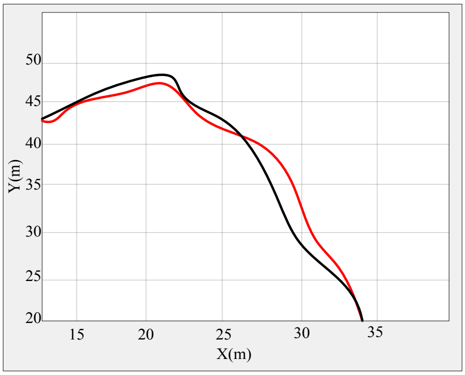


Figure 4. Multiple preview points in the path that meet the budget distance

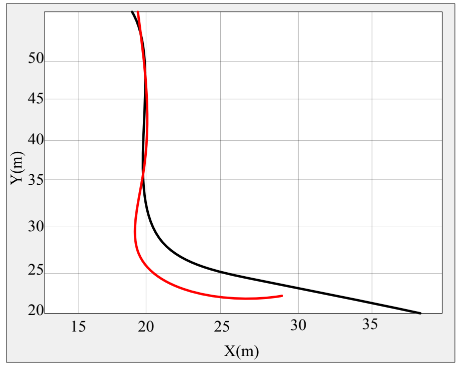
The basic theory and steps of the path tracking planning algorithm are as follows [16]:

- The first step is that after initialization, the algorithm obtains information such as speed, gear, four-wheel mileage and steering wheel angle from the body, and obtains the positional coordinates of the body as well as the current heading angle of the vehicle through the positioning algorithm.
- The second step is to determine whether the vehicle's body control unit has received the local trajectory of the vehicle.
- The third step is to find the point on the local path that is most closely related to the vehicle's location. This step is to find a predetermined starting point for the next step. Usually, in the process of finding the nearest point, the route point closest to the vehicle at the previous moment is used as the starting point, and a search is conducted within a certain area (when the route is just generated, the first point in the route is used as the starting point), thereby avoiding the overall search of the route and accelerating the calculation speed of the algorithm.
- The fourth step is to set the line of sight of the target and find the target that matches the line of sight, which is the target point to be tracked.

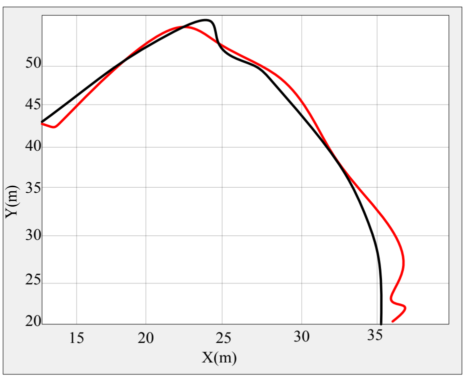
Firstly, based on the control of steering wheel angle, as well as the control of different pre aiming distances and steering wheel angles, this article selected four sets of steering trajectory data to study. During the tracking of the steering trajectory, the vehicle's speed was always maintained at 4 kilometers per hour. The tracking results are shown in Figure 5.



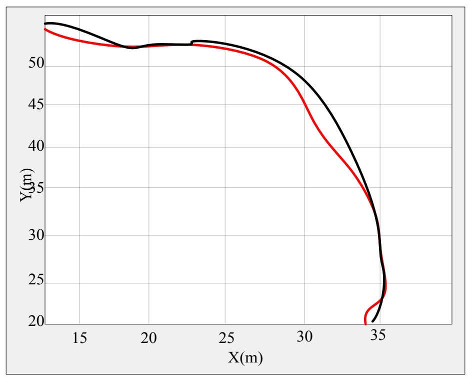
a) the preview distance is 7 m, and the gain is 16 times



b) the preview distance is 7 m, and the gain is 24 times



c) the preview distance is 5 m, and the gain is 16 times



d) the preview distance is 5 m and the gain is 24 times

Figure 5. Tracking effect diagram

Among them, the red line segment represents the path planning route; the black line segment represents the actual positioning trajectory of the vehicle body; the X and Y axes are the world coordinate system coordinate axes, in meters.

As shown in Figures 5 a) and 5 b), when the expected aiming distance was 7 meters, the steering wheel could advance, which could lead to "oversteer" between the actual turning track and the planned route. However, under the magnification of 24 times, the steering wheel could be overloaded. As shown in Figure 5 c), if the forward looking distance was reduced, it can eliminate the orbit inscribed, thereby reducing the orbit tracking error. As can be seen from Figure 5 d), when the gain coefficient was increased, a significant inscribed phenomenon occurred again.

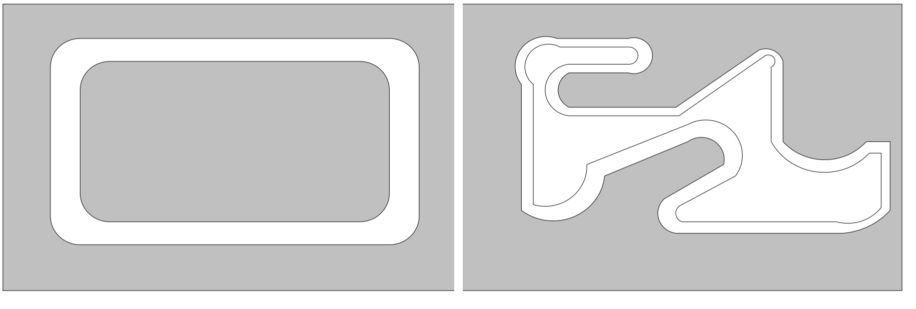
From the above vehicle turning and straight path tracking experiments, it can be seen that in different road environments, selecting the same control parameters may have opposite effects on the tracking effect. People need to weigh and select the most suitable control parameters for path tracking through experiments, testing, and algorithm optimization.

4 EMPIRICAL RESEARCH AND RESULT EVALUATION

4.1 Experimental Design

Developing autonomous driving technology on real roads requires not only accurate detection and tracking of targets, but also path planning, and there are too many uncertain and dangerous factors on real roads. To solve the above problems, this question could build an intelligent transportation management system based on intelligent transportation system, and verify the decision-making algorithm of driverless vehicles in different scenarios through the virtual simulation platform.

The meta depth deterministic strategy algorithm mentioned earlier in this article needs to be updated in a multitasking environment at the beginning of training, so there should be diversification in the selection of driving environments on virtual simulation platforms. Regarding the selection of the track, this paper has made the following considerations: firstly, the length of the track should not be too short, otherwise the trained unmanned driving algorithm may be accidental even if it can safely run a turn. Secondly, it is necessary to cover various possible curves in real life, so that this method has strong sensitivity to different types of curve information, and it can make quick decisions when encountering new problems. Thirdly, the selected virtual driving environment should be representative and have a targeted training effect for the algorithm in both straight and curved roads. Therefore, in Meta-DDPG, two different competition venues were selected for simulation experiments.



a) Speedway-1 b) Mixed-1

Figure 6. Meta-DDPG training track map

From Figure 6, it can be seen that the complexity of the track showed an increasing trend. The Speedway-1 track was the simplest, and the Mixed-1 track was also the most complex. A small turn was considered normal if the turning angle was below 180°, and a large turn was considered if the turning angle exceeded 180°. Therefore, it can be seen that on the speedway track, there were 4 long straight tracks and 4 right angle curves; there were 10 short straight tracks, 6 normal curves, and 3 U-shaped curves in the Mixed track. On this basis, the same exploration strategy could be used to train two different sports modes on the same track, in order to compare the performance of the two sports modes under different sports modes. The comparison was focused on two aspects: the performance of strategy training effectiveness and the generalization effect of strategies.

4.2 Experimental Results and Data Evaluation

1. The driving strategy testing effect of Meta-DDPG

   In order to fully validate the algorithm's lane keeping decisions, deceleration before turning, and other driving strategies, the Mixed track was selected as the test track. The following figure shows the driving effect of Meta-DDPG algorithm on simulated tracks.

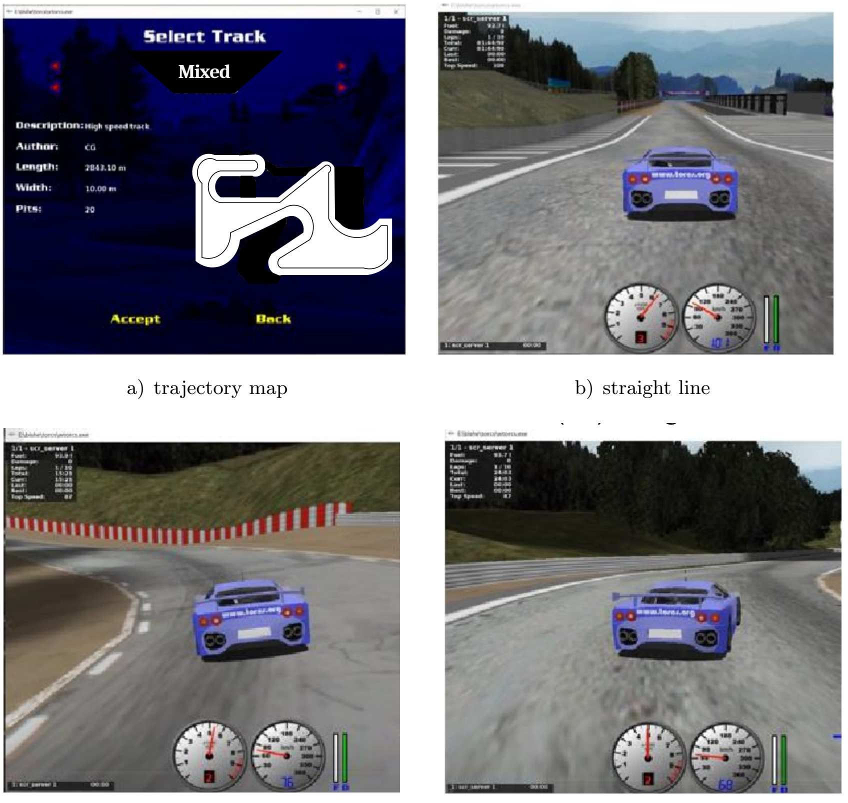
   From Figure 7, it can be seen that during the straight driving phase, the vehicle can maintain the stability of the body well and drive straight along the central axis of the road. When entering U-shaped and obtuse corners, the turning situation can also be predicted in advance and the steering wheel can be adjusted to maintain the inclination of the body and safely turn. The specific numerical parameterization effect can be seen in Figure 8.

   In order to better demonstrate the decisions made by unmanned vehicles based on the surrounding situation, in this article, only screenshots of the running effect of 1 000 steps were taken. As the values and units of control actions such as the steering wheel, throttle, and brake were different, the data was normalized. -0.6 represents full left turn of the steering wheel; 0.6 represents full right turn of the steering wheel; 0 represents both throttle and brake in suspension. On the contrary, 0.6 represents stepping fully.

   As shown in Figure 8, during the first 400 runs, when the vehicle entered the S-turn, the change in turning angle was significant. At this point, corresponding braking and deceleration should be applied. During the driving process between 350 to 550 and 650 to 850, the car maintained a straight running mode, allowing for moderate acceleration, with steering and braking data tending towards zero. During this process, there may be occasional slight adjustments in steering, acceleration, and braking information.

2. Strategy generalization effect based on meta learning [17]

   In this project, it is expected to incorporate meta learning methods into deep learning methods, which can effectively overcome overfitting problems in the deep learning process. However, due to the inability to demonstrate its impact



a) trajectory map

b) straight line

c) U-shaped curve

d) regular bends

Figure 7. The driving effect of Meta-DDPG algorithm on Mixed tracks

on training results through a simple track, an additional track could be added for the experiment, namely Speedway-1, Track-2, and Mixed-1.

The characteristics of these tracks are shown in Figure 9.

Track	Accumulated Return Value	Whether to Complete the Track
Speedway-1	305 628.65	Yes
Track-2	456 215.11	Yes
Mixed-1	502 365.25	Yes

Table 1. Meta-DDPG generalization cumulative return results

According to the test data shown in Table 1, the Meta-DDPG algorithm can not only drive smoothly over Speedway-1 tracks, but also safely on Track-1 and Mixed-1

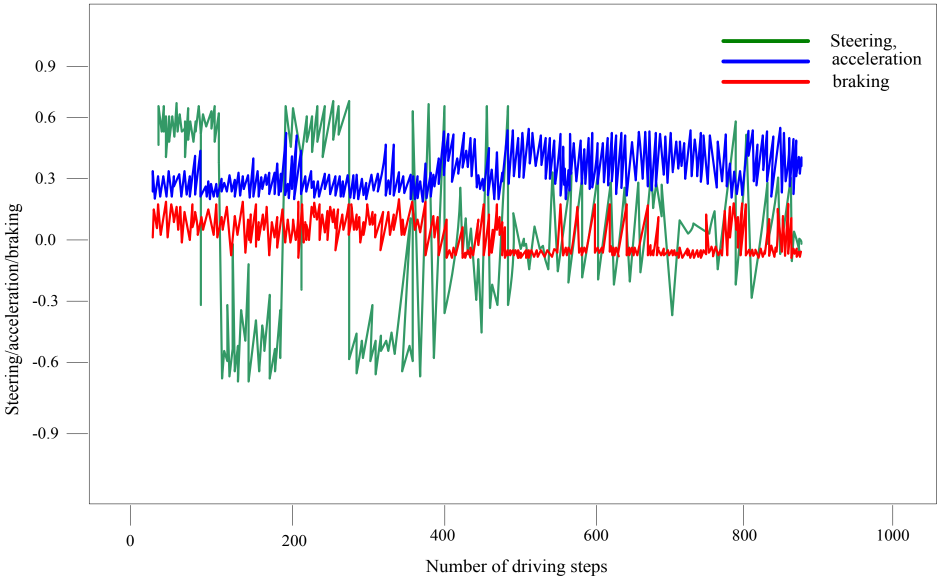


Figure 8. Unmanned driving behavior decision data based on Meta-DDPG

tracks. However, due to differences in the length of the track, there were certain differences in the number of steps taken, resulting in differences in the cumulative rewards obtained. The Mixed-1 track had a higher complexity and a longer total track length, so its cumulative reward value was higher than the other two tracks. However, from the experimental results, it can be seen that this algorithm can be used in multiple tasks, with significant advantages in generalization performance [18].

5 UNMANNED VEHICLE APPLICATION SCENARIOS IN IOT SMART TRANSPORTATION

Unmanned vehicles are an important application in the field of intelligent transportation in the Internet of Things. By combining advanced technologies such as artificial intelligence, sensors, and communication technology, they achieve autonomous vehicles [19]. The emergence of unmanned vehicles could bring revolutionary changes to the transportation field, not only improving traffic safety and efficiency, but also reducing energy consumption and environmental pollution. Currently, autonomous vehicles can obtain and analyze real-time traffic data, optimize driving routes and speeds, and reduce traffic congestion through intelligent perception and decision-making systems. Meanwhile, due to the fact that the driving decisions of autonomous vehicles are based on real-time perception and precise calculations, traffic accidents caused by driver negligence or errors can be reduced. In addition, unmanned security patrol vehicles can patrol the community 24 hours

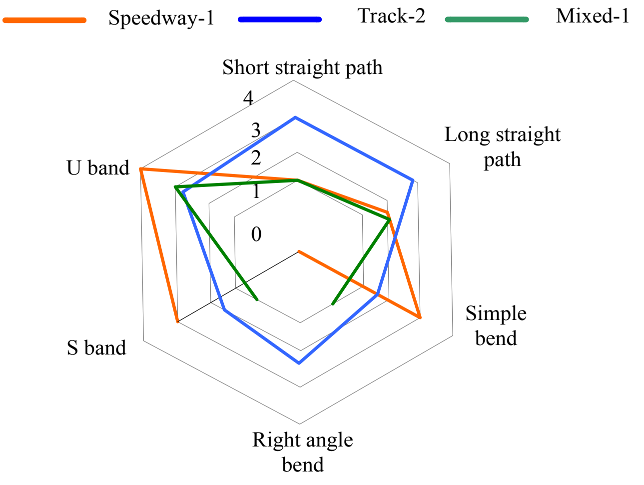
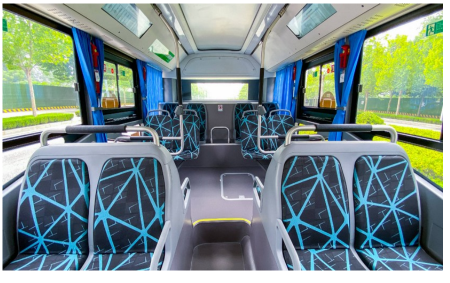
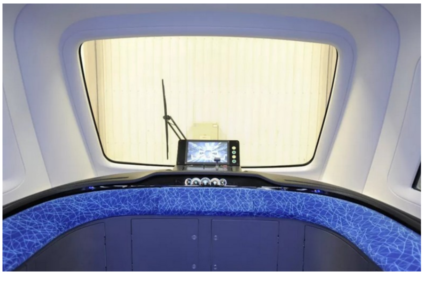


Figure 9. Comparison of Speedway-1, Track-2, and Mixed-1 test tracks



a) Unmanned bus



b) Unmanned subway

c) Unmanned logistics vehicle

d) Unmanned ridesharing company

Figure 10. Unmanned vehicle application scenarios in IoT intelligent transportation

a day, monitor abnormal situations in real time, and coordinate with the police to ensure the safety of residents' lives. In the intelligent transportation system, unmanned vehicles have a wide range of application scenarios. The following are some typical application scenarios, as shown in Figure 10.

1. **Public transport:** Unmanned vehicles can be used in urban public transport systems, replacing traditional buses and subways. Through unmanned vehicles with autonomous navigation and intelligent scheduling capabilities, passengers can choose their destination as needed, achieving more flexible and personalized travel. At the same time, unmanned vehicles can improve the operational efficiency of public transportation, reduce congestion, and optimize route planning based on passenger demand through real-time data analysis and intelligent scheduling algorithms, minimizing waste of time and resources [20, 21].
2. **Freight logistics:** Unmanned vehicles in IoT smart transportation can also be applied in the field of freight logistics. Unmanned vehicles can automate the transportation and distribution of goods, not only reducing manpower and operating costs, but also improving transportation efficiency and safety [22]. Through network connectivity and real-time data exchange, unmanned vehicles can achieve intelligent collaboration with logistics systems, monitor the location and transportation status of goods in real time, and provide accurate logistics information to users. In addition, unmanned vehicles can also flexibly adapt to different environments and road conditions, choose the optimal route and speed, and achieve the best cargo delivery effect.
3. **Travel service:** Unmanned vehicles can provide users with a brand new travel experience and personalized services. Users can book unmanned vehicle services through mobile applications, and unmanned vehicles could plan routes and schedule vehicles based on their needs and preferences. During the journey, unmanned vehicles can provide a highly automated driving experience, bringing passengers a safer, more comfortable, and convenient way of travel. At the same time, unmanned vehicles can also provide various information and entertainment services through intelligent terminals, such as navigation, music, video, etc., providing passengers with a more diverse and colorful travel experience.

Unmanned vehicles, as an important component of intelligent transportation in the Internet of Things, have broad application prospects. With the continuous progress and maturity of technology, unmanned vehicles could gradually integrate into people's daily lives, bringing people safer, more efficient and convenient modes of transportation [23]. However, while unmanned vehicles are widely used, they also face some challenges, such as technical safety, laws and regulations, road planning, etc., which require joint efforts from all parties to solve. It is believed that in the near future, unmanned vehicles could become an important symbol of intelligent transportation in the Internet of Things, bringing new development opportunities to urban transportation.

This article discusses research methodologies integrating deep reinforcement learning and DDPG algorithms, and focuses mostly on the significance of Internet of Things-based control for unmanned vehicles. First, you might include facts, charts, and case studies in the article to present the research findings in a more understandable way. Persuasion can be strengthened by providing a more detailed explanation of the application effect of IoT control in driverless cars using particular data and graphics. It is primarily validated by giving information on the success rate, driving distance, and time of unmanned vehicles driven by the Internet of Things, and contrasting it with conventional control techniques. Second, carry out a more thorough examination and conversation regarding the implications of driverless cars in the future. Driverless cars are predicted to become more common in public transportation, agriculture, logistics and distribution, and other application scenarios as Internet of Things technology advances. It is possible to underline even more the benefits and significance of IoT control in driverless cars by going over these application scenarios. Lastly, to strengthen the article's authority and trustworthiness, citations to professional viewpoints and findings from related research can be included. It is possible to more clearly convey the importance and utility of IoT control in driverless cars and to spark additional research and conversations by referencing the opinions and findings of credible sources. In conclusion, this piece can be made more persuasive and influential by combining data, case studies, graphics, and future prospects. Better advancements in this subject can be made by delving deeper into the application and impact of IoT control in driverless vehicles.

6 CONCLUSIONS

In conclusion, based on the intelligent transportation and artificial intelligence algorithm of the Internet of Things, this research designed a set of unmanned vehicle control system based on deep reinforcement learning and meta learning, and verified its good generalization performance through the test of the simulation platform. Through the deep reinforcement learning algorithm, people can enable the unmanned vehicle to learn the optimal decision-making strategy in the continuous interaction, so as to achieve autonomous navigation and path planning. The introduction of meta learning knowledge, namely Meta-DDPG algorithm, further improved the learning and generalization capabilities of the system, enabling unmanned vehicles to quickly adapt and learn in new environments and tasks. Through testing on a simulation platform, this paper has verified that the designed unmanned vehicle control system has good generalization performance. The system can exhibit stable and efficient behavior in different scenarios and tasks, demonstrating its potential and feasibility in practical applications.

However, there are still some shortcomings in this study. Firstly, due to time and resource constraints, this paper only conducted tests on simulation platforms and did not conduct experiments in real environments. Although simulation platforms can provide a highly controllable environment, the noise and uncertainty in the real environment may have an impact on the performance of the system. Therefore, further field experiments could be necessary.

Secondly, this study only focused on the control system of unmanned vehicles, without considering other factors such as safety, laws and regulations. In practical applications, unmanned vehicles also need to face complex road traffic environments and human-machine interaction issues. Therefore, future research can further explore these aspects and comprehensively consider multiple factors to achieve more comprehensive and reliable unmanned vehicle systems.

Future research can further optimize the deep reinforcement learning algorithm and meta learning algorithm to improve the learning ability and generalization ability of the system. At the same time, other advanced AI technologies, such as deep learning, reinforcement learning and transfer learning, can be considered to further improve the performance and reliability of unmanned vehicles.

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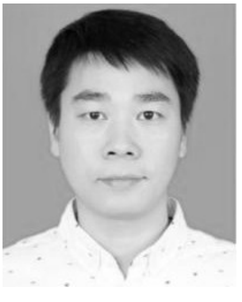
Min Zeng received his Master's degree from the Wuhan University of Technology, P.R. China. Now, he is studying for Ph.D. in the School of Mechanical Engineering and Technology, Universiti Malaysia Perlis, Malaysia. Also, he works in the College of Mechanical and Vehicle Engineering, Nanchang Institute of Science and Technology. His research interest include robot technology and autonomous vehicles.

Wenlong Sun received his Master's degree from the Central South University of Forestry and Technology, P.R. China. He is currently working in the School of Mechanical and Vehicle Engineering of Nanchang Institute of Science and Technology. He studies agricultural mechanization, automobile electrical appliances and automobile structure design.

Zhiqiang Wang graduated from the North University of China, with a primary research focus on machine learning and thermal management of power batteries. Currently employed at the Nanchang Institute of Science and Technology.



Hui Chen received his Master's degree from the Wuhan University of Science and Technology, P.R. China. Now, he works in the College of Mechanical and Vehicle Engineering, Nanchang Institute of Science and Technology. His research interest include mechanical manufacturing technology and robot technology.

Mohd Sani Mohamad Hashim is currently Senior Lecturer at the Faculty of Mechanical Engineering Technology, Universiti Malaysia Perlis, with a primary research focus on autonomous vehicles, mobile robotics, finite element analysis and green technology.