Intelligent Control Technology for Unmanned Vehicles

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Abstract. Unmanned driving has attracted much attention due to its high efficiency, environmental protection, safety and other attributes, and has become a strategic hotspot at home and abroad. However, its intelligent control technology still faces two difficulties: on the one hand, there is a lack of a systematic review of the evolution of relevant intelligent control technologies in this field; on the other hand, existing research has significant contradictions in terms of model complexity and environmental generalization capabilities. This paper divides intelligent control technology into data-driven control and hybrid control through the construction of a motion model. Through the analysis of existing research, it is pointed out that there are three major limitations of current unmanned driving intelligent technology: algorithm dependence; poor environmental generalization ability; poor interpretability of decision-making and control. This paper aims to fill this research gap, point out the limitations of the current field, and provide a reference for relevant researchers.

Keywords: Unmanned ground vehicles, coupled control, intelligent control.

1 Introduction

The origin of driverless technology can be traced back to the radio-controlled unmanned reconnaissance vehicles used by the military to perform dangerous tasks during World War II [1]. In the 1970s and 1980s, the United States, Japan, Germany and other countries began further research. It was not until 2004 that the Advanced Research Projects Agency (DARPA) of the United States Department of Defense held a series of autonomous driving challenges, which aroused enthusiasm for civilian expansion, and driverless vehicles gradually shifted from military to civilian use [2]. From computer vision, sensing, and control technology to today's artificial intelligence, every wave of driverless vehicle technology is accompanied by technological breakthroughs. Constantly injecting new impetus into this new technology. Thanks to the social needs of green, safe, and intelligent, as well as the continuous improvement of sensor performance accuracy, chip computing power algorithms, and related disciplines and theories. Driverless cars have come from military camps and are constantly moving forward on the road of intelligent cities, becoming an important part of the development strategies of various countries [3].

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The intelligent control technology of unmanned vehicles is the core of the autonomous driving system. The system can be roughly divided into three parts. First, the external environment is perceived and recognized through the on-board sensors, then the vehicle path is planned through intelligent algorithms, and finally the path is matched by controlling the position and speed of the vehicle's throttle and steering to achieve the purpose of intelligent driving. According to the J3016 standard of the Society of Automotive Engineers (SAE), the degree of automobile automation can be divided into six levels from L0 to L5. However, the cars currently produced by car companies are still at L2, which is still a long way from true intelligent driving [4].

In addition, thanks to the improvement of computing power and the application of artificial intelligence. With the help of cutting-edge technologies such as 5G communications, high-precision maps, and deep learning, more complex and advanced model algorithms can be implemented on unmanned vehicles. Algorithms for intelligent control technology of unmanned vehicles are emerging in an endless stream, from traditional PID control, model predictive control, to the rise of the deep learning revolution and end-to-end control, to the various hybrid algorithms and multimodal fusion models derived today. There are many types of algorithms, but there are few systematic reviews of them. Therefore, this article aims to fill this research gap by studying emerging algorithms in recent years and analyzing the limitations of the current field.

2 Methodology

When it comes to the motion planning and control of driverless vehicles, it is often necessary to control the vehicle's kinematics and dynamics system. Because the dynamic control of the vehicle requires accurate kinematics and dynamics parameters of the vehicle, the study of the vehicle model is indispensable. The appropriate control variables are selected through the specific driving cycle of the unmanned vehicle, and the mathematical model is used to equivalent the actual vehicle system. The vehicle model is usually divided into kinematic model and dynamic model. According to the speed and complexity of the vehicle, the appropriate model is selected or even combined for hybrid modeling. For example, more degrees of freedom are introduced to achieve more accurate fitting to the actual situation. This paper will give a simple vehicle model based on plane motion in a Cartesian coordinate system.

2.1 Vehicle kinematic model

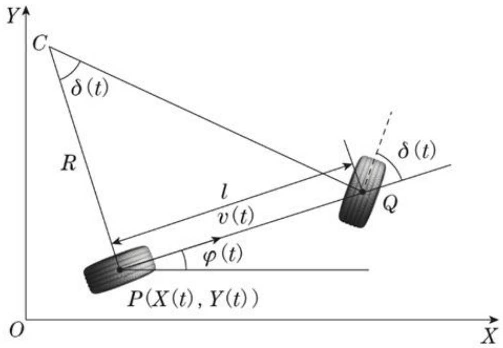

Fig. 1. Vehicle kinematic model [5].

The kinematic model of the vehicle is completely based on the geometric relationship of the control system, which is used to accurately describe the constraints of the vehicle motion relationship and to study the motion law of the vehicle body and its position in space. It is usually expressed by vector decomposition, trigonometric function formula and other methods. It does not consider the forces that affect the motion, so it is more suitable for low-speed driving conditions and low-precision scenarios such as path planning.

In kinematic modeling, the following assumptions are usually given: the vehicle is in plane motion; The steering angles of the left and right front wheels and the rear wheels are approximately equal; Ignore the measured force on the tire; Ignore the side slip angle of the wheel; No wheel slip movement [6].

In the Cartesian coordinate system XOY. C is the instantaneous steering center of the vehicle; Q. P is the center of the front axle and the center of the rear axle of the vehicle respectively, and the only C point is determined by the direction perpendicular to the two wheels; $R = cp$ is the instantaneous turning radius of point p; L is the vehicle wheelbase, $\delta\ (t)$ is the front wheel steering angle of the vehicle; $v\ (t)$ is the central speed of the rear axle of the vehicle; $\varphi\ (t)$ is the heading angle of the vehicle, which is defined as the angle between the speed $v\ (t)$ and the positive direction of the X axis; $(x\ (t), y\ (t))$ are the coordinates of point P.

Therefore, according to the circular motion formula, the Vehicle kinematics model can be obtained.

$$\begin{cases} \dot{X}(t) = v(t)\cos\left(\varphi(t)\right) \\ \dot{Y}(t) = sin\left(\varphi(t)\right) \\ \dot{\varphi}(t) = \dfrac{v(t)}{l} tan\left(\delta(t)\right) \end{cases} \tag{1}$$

Three state variables, global coordinate position $x\ (t)$, $y\ (t)$ and heading angle $\varphi\ (t)$, are used to describe the plane motion of the vehicle through the two control variables of front wheel steering angle $\delta\ (t)$ and vehicle rear axle center speed $v\ (t)$.

2.2 Vehicle dynamic model

However, when the vehicle is running at high speed, the assumption that the front and rear wheel side slip angles are approximately zero will no longer be applicable, so the simple kinematic model is no longer reliable. At this time, it is necessary to study the dynamic model for vehicle lateral motion analysis to replace the kinematic model. Further analysis is made on the transverse and longitudinal forces of tires. The vehicle kinematics model is as shown in figure 2.

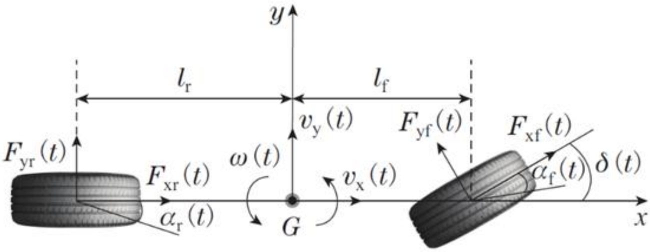

Fig. 2. Vehicle kinematic model [5].

For the dynamic model of the vehicle, the vehicle is usually moving in the plane; It is assumed that the vehicle is controlled by front wheel steering.

When XGY is the body coordinate system, G is the vehicle centroid. $v_x\ (t)$ and $v_y\ (t)$ are the longitudinal and lateral speeds of the vehicle, respectively. The corresponding $\alpha_f\ (t)$ and $\alpha_r\ (t)$ are the front and rear wheel side slip angles, respectively. $F_{xf}\ (t)$ and $F_{xr}\ (t)$ are the longitudinal forces on the front and rear wheels in the tire plane, $F_{yf}\ (t)$, $F_{yr}\ (t)$ is the value of the front and rear wheels in the tire plane. Under lateral force, L_f and L_r are the front and rear wheelbase respectively, $\omega\ (t)$ is the vehicle angular velocity. Therefore, the dynamic model of the vehicle can be obtained based on Newton's second law.

$$\begin{cases} m\ddot{x}(t) = F_{xf}(t)cos\delta(t) + F_{xr}(t) + mv_y(t)\omega(t), \\ m\ddot{y}(t) = F_{yf}(t)cos\delta(t) + F_{yr}(t) - mv_x(t)\omega(t), \\ \quad l_z\ddot{\varphi}(t) = F_{yf}(t)cos\delta(t)l_f - F_{yr}(t)lr, \end{cases} \tag{2}$$

Where m is the mass of the vehicle. I_z is the vertical rotational inertia of the vehicle. The tire longitudinal force and the tire slip ratio $s\ (t)$ have the following relationship:

$$\begin{cases} F_x(t) = f_x\big(s(t)\big) \\ s(t) = \dfrac{v_x(t) - n(t)r}{n(t)r} \end{cases} \tag{3}$$

Where $F_x\ (t)$ is the longitudinal force of the tire; $f_x\ (\cdot)$ represents the longitudinal force function; $n\ (t)$ is the tire rotation speed; R is the tire radius. The tire lateral force is related to the tire sideslip angle, which is assumed at small angles. The following expression is

$$\begin{cases} F_{yf}(t) = 2C_f\left(\delta(t) - \dfrac{\left(v_y(t) + \omega(t)l_f\right)}{v_x(t)}\right), \\ F_{yr}(t) = 2C_r\left(\dfrac{\left(-v_y(t) + \omega(t)l_r\right)}{v_x(t)}\right), \end{cases} \tag{4}$$

Where C_f, C_r is the lateral stiffness of the front and rear wheels respectively.

3 Control Algorithm

With the continuous improvement of the computing power of vehicle chips in recent years, the emergence of various large-scale data sets such as Kitti and nuScenes makes the implementation of more advanced control algorithm theories and more complex deep learning control algorithms on real vehicles no longer far away [7, 8]. These intelligent control technologies can be roughly divided into data-driven control and hybrid control based on the combination of traditional control and intelligent control. The following will mainly take advanced control algorithms such as improved fuzzy proportional integral differential control, reinforcement learning and end-to-end as examples to discuss the development trend and achievements of advanced algorithms in driverless control technology.

3.1 Data-driven control

The rudiments of data-driven control technology can be traced back to the beginning of the 21st century. In the second driverless challenge held by the Advanced Research Projects Agency (DARPA) of the US Department of Defense in 2005, Stanford Stanley vehicles combined vision and rule control for the first time. The human driving data is used to guide the controller to dynamically speed limit and optimize the threshold and Markov model parameters of obstacle detection. The near-field drivable area provided by lidar is used as the training sample to dynamically update the Gaussian mixture model to adapt to different environments. In order to reduce the dependence on the map, the strategy is dynamically adjusted through real-time data to adapt to the complex desert environment [6].

Based on deep Q-network, Jin et al. [9] proposed a method of combining dual deep Q-network (DDQN) with ant colony optimization algorithm (ACO): using DDQN to solve 3D environment path planning, generate the optimal path cost matrix between tasks, and then combine ACO to assign tasks. To solve the multi-UGV path planning and task assignment (MUPPA) problem in multi-UGV collaborative inspection. By clarifying the Markov decision process model and the setting of reward function, the total cost of the system is significantly reduced, and the collaborative work performance of multiple UGVs is effectively improved. But at the same time, the data dependence of DDQN requires additional large amounts of training when facing new and complex environments. When the number of UGVs is too large, the poor scalability of ACO will significantly increase the delay of task assignment.

Li et al. [10] used DQN as the core algorithm and achieved dynamic obstacle avoidance by retraining from the initial training on UGV to the cross-domain of unmanned surface vehicles (USV), and combined neural network model predictive control (NN-MPC) to improve robustness. It is obvious that this method reduces the training time by 28% through the migration of pre-trained models, which to a certain extent solves the problem of high acquisition costs and also demonstrates the versatility of DQN in complex dynamic environments. This also means a higher algorithm versatility and the correlation between the cross-domain combination of the two makes it also highly transferable in vehicle dynamic obstacle avoidance. However, this method is very dependent on simulation and still needs further adjustment when migrating. In addition, the computing power required for deployment is high. The parallelization of DQN and NN-MPC requires GPU acceleration, which makes it more difficult to deploy on the edge.

Although DQN has shown extraordinary effects in dynamic obstacle avoidance and multi-vehicle coordination, its reliance on manually defined state space and reward functions has led researchers to move towards a more thorough end-to-end control paradigm of perception-decision-execution full-stack optimization that generates continuous control instructions directly from raw sensor input.

Xiao et al. [11] proposed an end-to-end vision-lidar-inertial odometry framework. By using CNN+RNN to automatically extract multimodal features and using the attention mechanism to achieve feature fusion, the direct mapping from raw sensor data (grayscale image/3D point cloud/IMU) to 6-DoF pose estimation was fully realized to solve the odometer problem of UGV, reducing the positioning error and the relative error of the odometer. End-to-end processing is performed from the perception layer. Li et al. [12] started from the end-to-end application of the decision-making control layer and constructed a complete path from the first-person perspective visual input to the motion control command by realizing the joint representation learning of visual-motion information based on the reinforcement learning framework and the BSE encoder, which significantly improved the accuracy and robustness of the formation control.

Both of them reveal some advantages of end-to-end: high environmental adaptability; good cross-task generalization. But at the same time, the difficulty of end-to-end training and adjustment is very high, and its particularity will lead to the black box of its training process. Inadequate handling and response when facing some rare extreme situations.

3.2 Fusion control

Unmanned vehicles are always a complex problem in practical applications. On the one hand, when using traditional control methods such as PID, MPC, etc., there is often a strong model dependence, and there are limitations in nonlinearity and environmental interaction. On the other hand, when using some advanced intelligent control algorithms, there are often safety concerns caused by the black box problem of the training process, and it seems that there is no omnipotent algorithm that can do it. Therefore, researchers have cast their attention on hybrid control, through the complementary advantages of each model, or the adoption of a hierarchical control strategy. Through the selection and organic combination of different algorithm models in different scenarios, it has become a new paradigm that takes into account both adaptability and robustness.

In the basic control field, Dong et al. [13] proposed a weeding system based on machine vision that combines fuzzy adaptive PID with a pulse width modulation controller (PWM). That is, the PID parameters (kp, ki, kd) are dynamically adjusted by real-time image recognition of weed density through fuzzy logic, and then the valve switching frequency is controlled by PWM to accurately match the flow rate. While revealing the initial form of fuzzy control, it also improves the response speed of the system compared to traditional PID, making it more energy-efficient and more robust. However, it is worth pointing out that when facing new crops, fuzzy rules still need to be manually defined, and the system still needs to be improved in terms of dense occlusion scenes and scalability.

As the complexity of the task increases further, the hybrid architecture evolves toward hierarchy. Zhang et al. [14] proposed a hierarchical strategy to cope with the requirement of rapid adjustment of the driving direction of UGV when driving in the wild. The upper layer of this system uses a combination of sliding film control and PID to estimate the yaw moment, realizing the transformation of structural/non-structural parameter uncertainty modeling as lumped disturbances. The lower layer uses an adaptive weighted particle swarm optimization (PSO) algorithm to adjust the tire's side slip angle and distribute the torque through the vertical load. In this way, the influence of structural parameter uncertainty is eliminated. This system combines the excellent robustness of synovial control with the global optimization capability of PSO, successfully handles parameter uncertainty, simplifies complexity and improves response speed. However, this system is limited to heading control and does not involve the avoidance of dynamic obstacles. In addition, this system relies on an accurate dynamic model and may be affected by unmodeled disturbances in practical applications.

Finally, focusing on the dynamic obstacle avoidance work of Li et al. [9], UGV deep learning control breaks through the limitations of a single platform and is a new direction for hybrid control to expand across domains. The DDQN-ACO framework adopted by this system decouples offline learning from online optimization: DDQN pre-training captures common environmental features, and ACO adapts to dynamic task requirements in real-time, supporting multi-UGV expansion while reducing computing latency. Achieve a common transformation from data-rich fields to training data-scarce fields. While reducing training costs, it also puts higher requirements on computing hardware.

4 Limitations and Key Technologies

Based on the analysis of the current research status in the field of intelligent control technology for unmanned vehicles, we can see that there are currently the following challenges:

The first is the limitation of hardware computing power. With the further development of autonomous driving technology, models are gradually becoming multimodal and complex, which puts forward higher specifications for the computing power of vehicle-mounted chips. However, vehicle-mounted chips are often limited by power consumption and safety requirements, and their computing power is far behind other platforms. All of these put forward requirements for the deployment of higher-precision, larger and more complete models.

Besides, the environmental adaptability of driverless vehicles also needs further innovation. In the current driverless field, driverless cars are limited in their ability to handle some complex situations. For example, the performance of sensors will be greatly limited in extreme weather such as heavy rain and fog. It is difficult to predict sudden situations such as pedestrians and vehicles changing lanes and other violations. Misjudgments and other problems may occur in complex terrains such as construction sections. Even the huge driving training library of the end-to-end driving network can hardly cover all rare situations, and focus on additional training is needed.

In addition, driverless technology often falls into the dilemma of explainability of decision control. In particular, decision systems based on deep learning often have invisible processes due to the black-box nature of their training process. This has raised questions about its safety and ethics, especially when it comes to determining responsibility for accidents. How to trace the decision-making and how to define responsibility have become obstacles to further breakthroughs in driverless safety certification.

In order to solve the above important problems, this article believes that the following technologies will receive special attention.

1) Deploy large models on the edge. Edge deployment can significantly improve the response speed of the system, reduce local computing requirements, and solve the problem of high cloud computing latency.

2) Develop a multimodal deep fusion perception model and a cross-modal feature alignment algorithm. Integrate more information resources to build a more comprehensive perception system, and make up for the shortcomings of each other through intelligent calls and information integration in different situations.

3) Decentralized group intelligence, share multi-vehicle data knowledge for collaborative training while ensuring privacy. Through multi-agent collaboration, the optimization of intelligent transportation systems in the near future and the coordinated operation of vehicle groups can be achieved, and the operating efficiency of unmanned vehicles can be improved.

4) Digital twin adversarial simulation experiments and safety verification, through the construction of high-fidelity virtual test fields combined with extreme edge cases generated by adversarial generative networks for simulation verification, reduce training costs. At the same time, seek proof of the control algorithm at the theoretical level, impose underlying security logic restrictions on the algorithm to help breakthroughs at the security level and accelerate further implementation.

5 Conclusion

This paper systematically combs the development path of intelligent control technology for unmanned vehicles, revealing the three major limitations of the current field:

dependence on computing power, insufficient environmental generalization ability, and black-box decision-making. It fills the research gap in the current field. Although the current control technology shows a composite trend of multi-algorithm fusion and multi-architecture development under the support of learning methods such as deep reinforcement learning, it shows extraordinary potential for handling complex road conditions. However, it still needs to be improved in extreme sudden dynamic situations, safety certification and decision explanation, and computing power bottlenecks. Future research needs to focus on edge deployment, multi-modal model fusion, and the establishment of simulation simulation confrontation and theoretical verification to promote the safety certification of unmanned driving technology. Further promote its safety and accelerate its further implementation.

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