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Review

Modelling and Control Methods in Path Tracking Control for Autonomous Agricultural Vehicles: A Review of State of the Art and Challenges

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Abstract: This paper provides a review of path-tracking strategies used in autonomous agricultural vehicles, mainly from two aspects: vehicle model construction and the development and improvement of path-tracking algorithms. Vehicle models are grouped into numerous types based on the structural characteristics and working conditions, including wheeled tractors, tracked tractors, rice transplanters, high clearance sprays, agricultural robots, agricultural tractor–trailers, etc. The application and improvement of path-tracking control methods are summarized based on the different working scenes and types of agricultural machinery. This study explores each of these methods in terms of accuracy, stability, robustness, and disadvantages/advantages. The main challenges in the field of agricultural vehicle path tracking control are defined, and future research directions are offered based on critical reviews. This review aims to provide a reference for determining which controllers to use in path-tracking control development for an autonomous agricultural vehicle.

Keywords: autonomous navigation; agricultural vehicle; path tracking; vehicle model; control method

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1. Introduction

According to a report by the Population Division of the United Nations Department of Economic and Social Affairs in 2019, it is expected that the total world population will reach 9.7 billion by the middle of this century, and the demand for food will grow rapidly [1]. For a long time, intensive and extensive agriculture has been a priority solution to the imbalance between population growth and food shortages, but this approach is costly and labor-intensive [2]. On the one hand, many countries' agricultural sectors are facing an aging agricultural workforce [3]. On the other hand, due to the development of urbanization, more and more young laborers are moving away from agricultural production activities and towards cities, which will lead to a difficult problem of food shortage in the future. To address food shortages and other issues in agriculture, agriculturally developed countries are researching autonomous agricultural vehicles, replacing the basic technique and labor force required by traditional farming with sensor technology and electro-hydraulic control technology [4]. The global population aging and labor shortage have promoted the demand for mechanization and automation in industries, agriculture, and other fields [5]. Benefiting from the development and improvement of satellite positioning technology, inertial navigation technology, and control theory, the agricultural vehicle automatic navigation technology is increasingly being applied in agricultural production activities such as plowing, sowing, fertilization, and harvesting, becoming a key technology for precision agriculture [6]. The agricultural vehicle automatic navigation technology enables vehicles to better adapt to the complex field, improves the accuracy and efficiency of agricultural machinery operations, and reduces repeated and missed operations. Not only that, but it can also reduce the prolonged fatigue and repetitive driving work of the driver, thereby obtaining sufficient time to monitor and control agricultural machinery [7].

The key technologies of agricultural machinery automatic navigation mainly include positioning and attitude measurement, path planning, and path tracking control [8]. Figure 1 shows the composition of the agricultural machinery's automatic navigation system. In order to achieve automatic navigation driving, it is necessary to install sensors on the vehicle that can provide a location, heading information, and environment information. The most frequently used positioning and attitude measurement technologies in the research of agricultural machinery automatic navigation driving include global navigation satellite system (GNSS), inertial navigation system (INS), machine vision (MV) navigation system, and light detection and ranging (LiDAR). The comparison of three commonly used positioning and attitude sensors is shown in Table 1. GNSS can provide accurate navigation information, such as location, orientation, and speed, in an unobstructed environment, and is widely used in vehicles' automatic driving. Alonso-García et al. [9] used low-cost GPS receivers as positioning sensors for agricultural tractors and evaluated the performance of tractor automatic navigation systems through tracking straight-line trajectory tests. The inertial navigation system (INS) collects acceleration and angular velocity information through the inertial measurement unit (IMU) and is not subject to external interference. However, as time goes by, the accumulation of sensor errors will lead to a decline in accuracy. LiDAR has the advantages of high precision, and strong anti-interference ability, and is widely used in orchard environment perception and navigation. Li et al. [10] used LiDAR to obtain the measurement data of the orchard tree, and finally fitted the straight line of the fruit tree, using the center of the tree row as the navigation path. A single sensor inevitably has certain limitations, which are not conducive to improving navigation and positioning accuracy and reliability. Therefore, positioning technology that combines the advantages of GNSS and INS is becoming increasingly popular in agricultural machinery automatic navigation driving. Yin et al. [11] developed autonomous rice transplanters using RTK-GNSS and IMU. The experimental results showed that the lateral error and heading error of linear path tracking were less than 10 cm and 5°, respectively.

Figure 1. Composition of agricultural machinery automatic navigation system.

Table 1. Comparison of advantages and disadvantages of three types of sensors.

Sensors	Advantages	Disadvantages
GNSS	Providing absolute position and heading information all-day	Affected by occlusion
INS	Providing high-precision and high-frequency attitude data	Inevitable drift by time and temperature
MV	Low cost, rich information, suitable for irregular land plots or signal-blocking environments	Affected by light and shadow
LiDAR	High precision, strong anti-interference ability	High cost, affected by dust

The path-tracking control technology is the key to achieving automatic navigation for agricultural machinery [12]. In the case of accurate agricultural machinery location and attitude information, the path tracking control model and method are important to improving the precision and robustness of agricultural machinery automatic navigation system. Many researchers have conducted extensive research on path-tracking control methods for agricultural vehicles. Common methods include PID control, fuzzy control, model predictive control, pure pursuit model control, Stanley model control, etc. The analysis and comparison of various control methods are shown in Table 2. PID has a simple structure and is widely used, but parameter tuning is difficult. Luo et al. [13] used the RTK-DGPS receiver to obtain positioning information, combined the tractor kinematic model with the hydraulic steering control model, and designed a PID-based straight-line tracking controller. When the forward speed is 0.8 m/s, the maximum tracking deviation is less than 15 cm, and the average tracking deviation is less than 3 cm. Although fuzzy control has the advantages of not relying on precise mathematical models and strong robustness, it requires the formulation of control rules based on expert experience. Liu et al. [14] and Meng et al. [15] used genetic algorithms and improved particle swarm optimization algorithms to optimize fuzzy logic controller parameters and improve controller performance, respectively. Model predictive control can compensate for system uncertainty and enhance stability, but it has the disadvantage of a large computational burden and is easy to fall into the minimum solution. Plessen et al. [16] improved the model predictive control algorithm and studied the trajectory planning and path tracking control methods of agricultural machinery under specific constraint conditions, and achieved high tracking accuracy. The pure pursuit model algorithm is a geometric control method, which has the advantages of fewer adjustment parameters and predictability of the algorithm, but the adaptive determination of look-ahead distance is relatively difficult. Huang et al. [17] proposed a method for agricultural machinery headland steering control, which utilizes the BP neural network to dynamically adjust the look-ahead distance and improve the traditional pure pursuit model.

From the past publications, there are no known reviews regarding the path tracking control methods for the different agricultural machinery in different working scenarios. Most previous research has focused on autonomous vehicles or robot path-planning algorithms, or path-tracking methods for a single type of vehicle. The differences between the recently published reviews of vehicle navigation technologies and this paper were compared and shown in Table 3. Therefore, it is necessary to review the path-tracking control methods of various autonomous agricultural vehicles in different working scenarios in order to gain an in-depth understanding related to this field.

Table 2. Comparison of advantages and disadvantages of different control methods.

Control Method	Advantage	Disadvantage
PID control	Simple structure, easy implementation, good robustness, and high accuracy	Parameter tuning is difficult, and there is a contradiction between overshoot and response time
Fuzzy control	It does not dependent on precise mathematical models and can be applied to nonlinear systems with good robustness and adaptability	The selection of rules is not systematic, the tracking error is large, and it is difficult to correct quickly
Pure pursuit control	Few control parameters and predictable	Poor robustness in selecting preview points and difficulty in adjusting the look-ahead distance
Optimum control	Performance indicators can be optimized	Poor adaptability to nonlinear systems and high requirements for model accuracy
Sliding mode control	Insensitivity to external disturbances, few adjustment parameters, and fast response speed	There is a chattering phenomenon
Model predictive control	It can compensate for the uncertainty of the system timely and enhance the stability of the system	High computational complexity and poor real-time performance
Neural network control	It has good adaptability to the nonlinear characteristics of agricultural machinery movement	The algorithm is complex, requires a large number of high-quality training samples, and has a weak generalization ability
Linear quadratic optimal control	It can obtain the optimal control strategy under a certain performance indicator	Poor performance on nonlinear models

The purpose of this paper is to summarize the application and development of path-tracking control methods in various agricultural vehicles in different working scenarios, including the construction of vehicle models and the application and improvement of control algorithms. This work can help researchers timely understand the current application status of path-tracking control methods in autonomous agricultural vehicles, and provide valuable guidance for the further development of intelligent agriculture and precision agriculture. The main work of this article is as follows. The first section summarizes the composition of the agricultural machinery automatic navigation system and the importance of path-tracking control technology and introduces and compares the path-tracking control methods that are frequently used in agricultural vehicles. Section 2 introduces different models of path-tracking control methods for automatic agricultural machinery navigation, including kinematic models and dynamic models. The next section focuses on the review and discussion of the application and improvement of agricultural vehicle path-tracking control methods in dry fields, paddy fields, orchards, agricultural robots, and facility agriculture, as well as articulated agricultural vehicles. Challenges and prospects of research on path-tracking control technology for agricultural vehicles' automatic navigation are discussed in Section 4. Finally, some conclusions of this paper are presented.

Table 3. Comparison of the current review paper with previous reviews.

Authors	Research Object	Research Topic	Sensor	Method or Algorithm	Application Scenario
Ren et al., 2023 [18]	Agricultural mobile platform	Autonomous mobility of the agricultural platform	Laser sensor, vision sensor, and IMU	Agricultural autonomous mobile platform navigation algorithm	Horticultural facility scene and field scene
Bai et al., 2023 [19]	Agricultural robots and autonomous vehicle	Vision-based navigation for agricultural autonomous vehicles and robots	Vision sensor	Vision-based data processing and computation method for navigation	-
Stano et al., 2023 [20]	Automated vehicle	Model predictive path tracking control for automated vehicles	-	Different MPC methods for path tracking control	-
Liu et al., 2023 [21]	Mobile robot	Path planning techniques for mobile robots	Laser radar sensor and vision sensor	Environment modeling method, path evaluation method, and path planning algorithm	-
Loganathan and Ahmad, 2023 [22]	Autonomous mobile robot	Path planning techniques for autonomous mobile robots	-	Classical path planning method and heuristic path planning method	-
Ruslan et al., 2023 [23]	Autonomous tracked vehicle	Modeling and control strategies in path tracking control for autonomous tracked vehicles	-	Geometric and kinematic controller, classical controller, adaptive and intelligent controller, model-based controller	-
Wang et al., 2022 [24]	Agricultural robot	Application of machine vision in agricultural robot navigation	Vision sensor	Image segmentation algorithm, object detection algorithm, and image matching algorithm	Dry fields, paddy fields, orchards, and greenhouses
Zhou and He, 2021 [25]	Agricultural machinery	Navigation path planning of agricultural machinery	-	Full coverage path planning method, global point-to-point path planning algorithm, obstacle avoidance path planning method, and local tracking path planning method	-
Roshanianfard et al., 2020 [26]	Autonomous agricultural vehicle	Review of autonomous agricultural vehicles	Positioning sensor, attitude sensor, and safety sensor	Controlling algorithm	-
Alberto-Rodriguez et al., 2020 [3]	Autonomous vehicles and self-guided tractor	Review of control on agricultural robot tractors	GNSS, IMU, MV, LiDAR sensor, and proximity sensor	Route planning algorithm and tracking algorithm	-
Zhang et al., 2020 [8]	Agricultural machinery	Agricultural machinery navigation technology	GNSS, INS, MV and LiDAR sensor	Fusion algorithm, path planning algorithm, navigation control method, etc.	-
Hu et al., 2015 [27]	Agricultural machinery	Automatic guidance of agricultural vehicles	GNSS, MV and INS	Path tracking control method	-
Mousazadeh, 2013 [28]	Agricultural autonomous off-road vehicle	Navigation systems of agricultural autonomous off-road vehicles	Vision sensor, RTK-GPS, Inertial sensor, LiDAR, etc.	Dead reckoning, image processing, statistical methods, fuzzy logic, genetic algorithm, etc.	-
Ours	Autonomous agricultural vehicle	Modeling and control methods in path tracking control for autonomous agricultural vehicle	GNSS, INS, MV and LiDAR	Path tracking control method	Dry field, paddy field, orchard, greenhouse, etc.

2. Vehicle Model Used in Agricultural Vehicle Path Tracking Control

The first step in designing the path-tracking control algorithm for autonomous agricultural vehicles is to establish a vehicle model. Many studies have confirmed that accurate vehicle models are an important precondition for designing path-tracking controllers. This paper introduces the application of the kinematic and dynamic models in different operation scenes and various agricultural vehicles. It focuses on the bicycle model, agricultural tracked vehicle model, and agricultural articulated vehicle model and summarizes the difficulties of the application of the kinematic model and dynamics model in agricultural vehicle path tracking.

2.1. Kinematic Vehicle Model

The path tracking of agricultural vehicles based on the kinematic model determines the front wheel rotating angle according to the position and heading parameters of the agricultural machinery, and then controls the vehicle to work along the predetermined path [29,30]. The existing research shows that a path-tracking controller based on a kinematic model can achieve better tracking accuracy for agricultural machinery under low-speed conditions. O'Connor [31,32] developed an automatic control system based on a simple kinematic model and tested it with a large agricultural tractor. The standard deviation of the lateral position in the linear tracking test is less than 2.5 cm, which proves that only the GPS controller can guide the tractor along a straight line very accurately. Bell [33] designed a path-tracking algorithm suitable for different curves using the kinematic model of agricultural machinery. Assuming that agricultural machinery operates on flat ground, without considering the sideslip, offset, pitching, etc., various four-wheel agricultural types of machinery, such as tractors, harvesters, and rice transplanters, can be simplified into bicycle model, which has the characteristics of simple structure and convenient parameter acquisition. As shown in Figure 2, a commonly used bicycle model in the automatic navigation of four-wheeled agricultural machinery is presented. The coordinates of the center point of the rear axle of the vehicle are (x_1, y_1), and (x_2, y_2) are the coordinates of the center point of the front axle of the vehicle. v_1 and v_2 represent centerline velocities of the rear and front axles, m/s, L is the wheelbase of the agricultural machinery, m, φ is the heading angle, rad, δ is the front wheel angle, rad. The bicycle model can be determined using Equation (1), where $\dot{x}$ denotes vehicle speed in the x-axis direction, m/s, $\dot{y}$ denotes vehicle speed in the y-axis direction, m/s, and $\dot{\theta}$ denotes heading angular velocity of the vehicle, rad/s.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\varphi \\ \sin\varphi \\ \frac{\tan\delta}{L} \end{bmatrix} v_1 \tag{1}$$

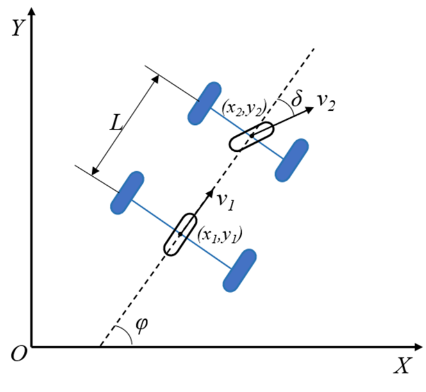

Figure 2. Bicycle kinematic model.

According to the motion characteristics of tracked walking mechanism, its kinematic model is a typical differential speed model, and the motion form depends on the speed of both sides of the tracks. Assuming that the centroid of the whole machine coincides with the geometric center and that the tracks on both sides do not slip and deflect, the kinematic model can be established. As shown in Figure 3, C represents the centroid of the whole machine, (x, y, θ) is the position and orientation coordinates of the tracked vehicle, W is the track gauge, m, v_L and v_R are the linear speeds of the left and right tracks, m/s. The agricultural tracked vehicle kinematic model can be determined using Equation (2)

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \frac{\cos\theta}{2} & \frac{\cos\theta}{2} \\ \frac{\sin\theta}{2} & \frac{\sin\theta}{2} \\ \frac{1}{w} & -\frac{1}{w} \end{bmatrix} \begin{bmatrix} v_R \\ v_L \end{bmatrix} \tag{2}$$

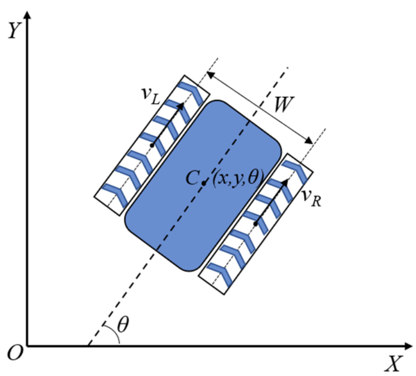

Figure 3. Agricultural tracked vehicle kinematic model.

The agricultural wheeled articulated vehicle is divided into two parts: the front and rear body. Different from the traditional front axle steering structure, it adds complexity to the path tracking control through the hinge point bending steering method. Based on the motion characteristics of articulated vehicles, the kinematic model is established, which is helpful in determining the path-tracking control variables of the agricultural wheeled articulated vehicle. Figure 4 shows the articulated vehicle kinematic model, O' is the instantaneous center, $P_1(x_1, y_1)$ and $P_2(x_2, y_2)$ are the midpoints of the front axle and rear axle, respectively, l_1 and l_2 are the distance between the front and rear axles and the hinge point, respectively, m, α, and β are the heading angles of the front and rear vehicle body, respectively, rad, γ is the articulated steering angle, rad, v is the front vehicle speed, m/s. The posture state of the articulated front axle can be determined using Equation (3).

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\alpha} \\ \dot{\gamma} \end{bmatrix} = \begin{bmatrix} \cos\alpha \\ \sin\alpha \\ \frac{\sin\gamma}{l_1\cos\gamma + l_2} \\ 0 \end{bmatrix} v + \begin{bmatrix} 0 \\ 0 \\ \frac{l_2}{l_1\cos\gamma + l_2} \\ 1 \end{bmatrix} \dot{\gamma} \tag{3}$$

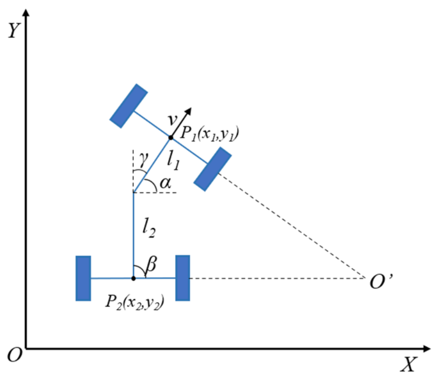

Figure 4. Agricultural articulated vehicle kinematic model.

2.2. Dynamic Vehicle Model

The agricultural vehicle dynamic model is usually based on Newton's second law for navigation controller design. The control system has good robustness to changes in external parameters because of considering the force during the movement of agricultural machinery. To improve automatic control performance under high speeds, Bevly et al. [34] proposed a yaw dynamics model, which was proved to be an improvement on the tractor controller based on the kinematic model. Eaton et al. [35] considered the influence of vehicle steering dynamics and developed a path-tracking controller using the backstepping algorithm. Compared with the kinematic model, the algorithm based on the influence of dynamic factors improves the controller performance. Based on the tractor two-wheel dynamics model, Wang et al. [36] proposed an improved Stanley controller (IMP-ST), and optimized controller parameters through multiple population genetic algorithm (MPGA) to achieve better tracking performance. In the research of a path-tracking control algorithm for caterpillar robots, Li et al. [37] established the dynamic model of the interaction between the caterpillar chassis and the soil by using multi-body dynamic simulation software. As shown in Figure 5, the simplified dynamic model of the caterpillar robot is presented. In Figure 5, O is the instantaneous center of rotation, O' is the geometric center, and R is the turning radius of the robot, mm.

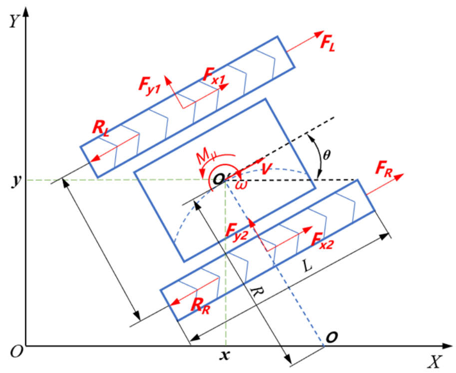

Figure 5. Tracked robot dynamic model.

2.3. Summary of Vehicle Models

Several vehicle models frequently used in path-tracking control of agricultural machinery have been introduced. The summary of agricultural vehicle models in path tracking control is shown in Table 4. The advantage of model control methods is that when accurate models can be obtained, the control performance is better; that is, the accuracy of the model is required to be higher. The method based on the kinematic model mainly adopts a small-angle linearization approximation model, and assumes that the agricultural machinery is low-speed and constant, but it will introduce linearization errors and increase the impact of speed changes on the performance of the controller. The control method based on the dynamic model can take into account the dynamic characteristics of agricultural machinery well, but the parameters are difficult to obtain online in real time. Moreover, the accurate establishment of the vehicle dynamic model becomes more difficult due to factors such as wind force, changes in the unit's own mass, and changes in the adhesion between the track and the ground. Existing studies have confirmed that when an agricultural vehicle with low speed, the path tracking control method based on a kinematic model can often achieve acceptable tracking accuracy and stability. Therefore, from a general point of view, the path-tracking control algorithm for agricultural vehicles based on the kinematic model is still worthy of further research and exploration.

Table 4. Summary of agricultural vehicle models in path tracking control.

Vehicle Models	Pros	Cons	Comments
Kinematic model	Easy to build, small computational burden	Neglecting vehicle dynamics parameters, introducing errors under assumed conditions, poorer robustness	Suitable for agricultural vehicles under low-speed conditions, four-wheel vehicles are often simplified as bicycle kinematic models, which are still popular in existing research.
Dynamic model	Analyzing the force during the vehicle movement process, good robustness to external parameter changing	Dynamic parameters are difficult to obtain online	The accuracy of the model is affected by many factors, and further research is needed.

3. Control Methods Used in Agricultural Vehicle Path Tracking Control

Path tracking control technology is to calculate and obtain vehicle motion parameters, such as vehicle speed, steering wheel angle, etc., based on vehicle kinematic or dynamic modeling according to the algorithm, so that the vehicle can reach and track the predefined work path. The basic principle is depicted in Figure 6. The operating accuracy of agricultural machinery in autonomous driving depends on the control algorithms so that high-precision algorithms can improve the quality and efficiency of agricultural machinery operations. The environmental conditions of different fields are different, and the types of agricultural machinery used are also different. This section introduces the application and improvement of path-tracking methods of different agricultural machinery in dry fields, paddy fields, orchards, agricultural robots and facility agriculture, and articulated agricultural vehicles.

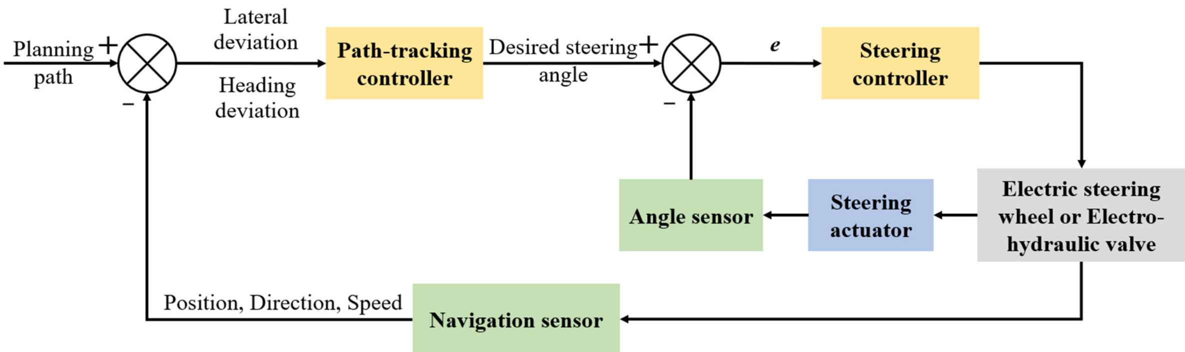

Figure 6. Block diagram of the path tracking control system.

3.1. Dry Field Agricultural Machinery

The essence of path tracking is that under the developed control algorithm, the target vehicle can track the planned path within a certain accuracy range so that the vehicle can work along the planned path. Tractors can form different operating units with other agricultural machinery to complete tasks such as plowing, sowing, fertilization, and cultivation. The operating environment of tractors is complex and changeable, and the driving skills of drivers vary from person to person, resulting in problems such as low efficiency, decreased operation quality, and waste of land resources in field operation. In order to address these issues, many experts have conducted research on the path-tracking control technology for autonomous tractors. Backman et al. [38] developed a 4 WS tractor path tracking algorithm, which uses the tractor's kinematic and dynamic model and the linear control law to control the steering of the tractor. Winter wheat sowing test results showed that the lateral tracking deviation of straight sowing is less than 0.05 m, and the heading angle tracking deviation is less than 1 degree. To improve the tractor's ability to track variable curvature paths, Wu et al. [12] designed a variable curvature path tracking method based on the front wheel angle feedforward compensation strategy, which comprehensively considers the driving speed and target path curvature to adjust the look-ahead distance dynamically.

The agricultural land surface usually fluctuates greatly, and tractors will be affected by interference, such as the interaction between the supporting agricultural machinery and the uncertain ground. When wheel slip occurs, the tracking error of tractors will increase and even affect subsequent agricultural production activities. Taghia et al. [39] developed a sliding mode controller with a nonlinear perturbation observer, and the new controller performed better when slip occurred compared with backstepping controllers and model predictive controllers. Ding et al. [40] constructed a second-order sliding mode (SOSM) controller for a tractor path tracking system, fully considering longitudinal and lateral wheel slips. Ji et al. [41] proposed a novel adaptive second-order sliding mode controller (ASOSM), which alleviates the chattering problem in traditional sliding mode control and improves the convergence speed and anti-interference ability of the system. Ge et al. [42] proposed a novel adaptive sliding mode control (ASMC) method for path tracking of unmanned agricultural vehicles. This method is robust in the presence of parameter uncertainty, disturbances, and changing road conditions. During the straight-line operation of the tractor, stable high-speed driving will improve its work efficiency, but when turning on the ground, the driving speed should be reduced to improve the stability of the steering and reduce the turning distance. However, influenced by complex environments and uncertain external disturbances, when the tractor speed increases, the defects such as nonlinearity, hysteresis, and instability of the tractor-field path system become more prominent, which will affect system performance. Combined with optimal control theory, Han et al. [43] designed a dual-parameter optimal control algorithm based on speed and steering angle. Zhang et al. [44] designed a dual objective joint sliding mode control algorithm to solve the influence of tractor speed on the performance of the navigation control system. The field test platform of the tractor's automatic navigation control system is shown in Figure 7. This algorithm achieves adaptive adjustment of speed while ensuring stable straight-line path tracking.

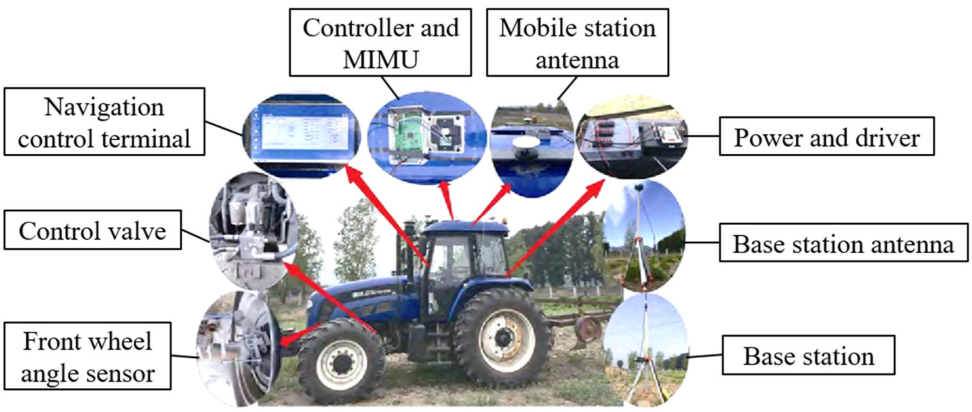

Figure 7. Tractor automatic navigation control system test platform.

The pure pursuit control method has the characteristics of simulating human driving behavior with few control parameters, but in agricultural scenes, the robustness of preview point selection is poor and cannot be adjusted adaptively. In the study of pure pursuit model look-ahead distance, dynamic look-ahead distance performs better in path tracking than fixed look-ahead distance, although better tracking accuracy can be obtained when the look-ahead distance is equal to the wheel distance. To address the problem of poor adaptability of traditional pure pursuit algorithms to speed changes, Jia [45] proposed an improved pure pursuit algorithm on the basis of a seeker optimization algorithm (SOA), which can calculate the look-ahead distance online using the fitness function. The improved pure pursuit model algorithm can effectively resist the influence of speed changes. Zhang et al. [46] used the Dongfanghong 1104-C tractor as the test platform to determine the look-ahead distance in the pure pursuit model in real-time through particle swarm optimization (PSO). Li et al. [47] and Zhang et al. [48] developed a path-tracking method for agricultural machinery on the basis of the fuzzy adaptive pure pursuit model, which realized online real-time adjustment of look-ahead distance. The developed navigation controller has the advantages of short rise time and small overshot. Zhang et al. [48] developed the automatic navigation operation system of a crawler-type rape seeder, as shown in Figure 8. Zhang et al. [49] used deep reinforcement learning (DRL) to improve the pure pursuit model algorithm and derive correction commands to reduce tracking errors due to the improper selection of preview points. Yang et al. [50] designed a path-tracking algorithm based on the optimal target point, which searched for the optimal target point in a forward-looking area using an evaluation function.

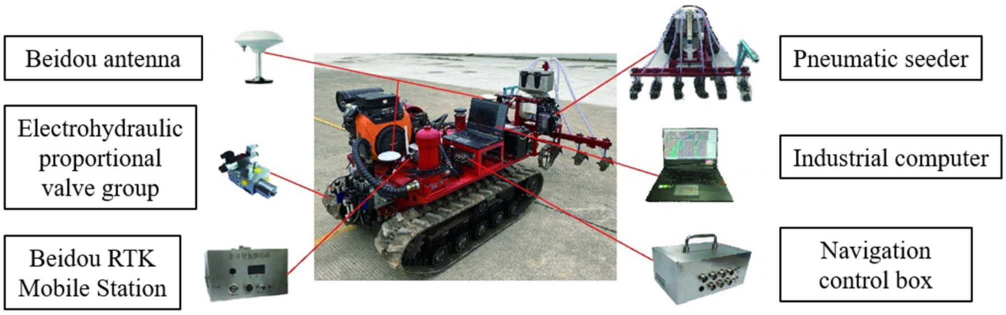

Figure 8. Automatic navigation system for crawler-type rape seeder.

The quality and efficiency of manual harvesting operations largely depend on the driver's driving skills. Applying automatic navigation technology to grain crop harvesting will help improve the quality, efficiency, and intelligence level of combined harvesters. To improve the quality of corn harvesting, Zhang et al. [51] developed an automatic tracking system for the corn harvester, which controlled the harvester by a pure pursuit model algorithm and dynamically adjusted the look-ahead distance by fuzzy logic. In response to the problem of missing cuts during the straight-line tracking harvesting operation of a combine harvester, Ding et al. [52] developed a single-neuron PID navigation controller for combine harvesters. Single-neuron PID can achieve rapid adjustment of control parameters through self-learning, which has the characteristics of small overshoot and fast entry into a steady state. The assisted driving system of a combined harvester with intermediate angle error can lead to path tracking deviation, which will limit the efficiency of the harvesting operation. Qiao et al. [53] proposed an improved path-tracking controller with mid-angle adaptive calibration. Hu et al. [54] developed a path-tracking PD controller for peanut harvesters. When the harvester operates automatically, the average absolute deviation and maximum deviation are 5.12 cm and 12.2 cm, respectively, which can ensure that the harvesting mechanism is aligned with the peanut row to realize digging and harvesting.

3.2. Paddy Field Agricultural Machinery

In the muddy and slippery rice field environment with uneven ground, compared with dry field agricultural machinery, paddy field machinery such as rice seeder and rice transplanter are more prone to sideslip, and even rolling and pitching, increasing the difficulty of automatic navigation of agricultural machinery. Most existing unmanned rice field agricultural machinery takes the front of the vehicle as the measurement and control object. There is a gap between the front machinery and rear implements, and the motion posture of the rear implements changes greatly relative to the front machinery, causing inconsistent travel trajectories between the front and the rear, leading to a decrease in straight-line operation accuracy and quality. In response to the above problems, He et al. [55] developed an unmanned path-tracking control method for agricultural rice machinery based on model predictive control based on the pose estimation of agricultural rice machinery. The experimental results indicate that this method can effectively suppress abrupt lateral position deviations caused by the relative position and attitude changes of the machine. Wei et al. [56] used GPS receivers and onboard sensors to gain the position and attitude information of rice transplanters and used the PID control method to construct a closed-loop steering control system, which achieved automatic navigation and headland steering of rice transplanters. In the research on the automatic driving of rice seeders, Zhang et al. [57] proposed a control strategy that uses fuzzy logic to adjust the PD controller parameter Kd adaptively. Compared with the PD controller with fixed parameters and the pure pursuit model control method, this method has a smaller overshoot, better robustness, and faster response speed. Tang et al. [58] and Shi et al. [59] established a fuzzy control model to adjust the look-ahead distance of the pure pursuit model in real-time. This method is adaptable to different vehicle speeds and can avoid oscillations when the rice transplanter operates at high speed, effectively improving the system's robustness. Wu et al. [60,61] designed a fast terminal sliding mode controller with a nonlinear disturbance observer, which can improve the anti-interference ability of rice seeders in paddy fields. The automatic driving control system of the rice seeding machine is shown in Figure 9. Chi et al. [62] linearized the kinematic model of the rice transplanter in Taylor series form and developed a path-tracking controller using a model prediction algorithm, which can track linear and curve paths.

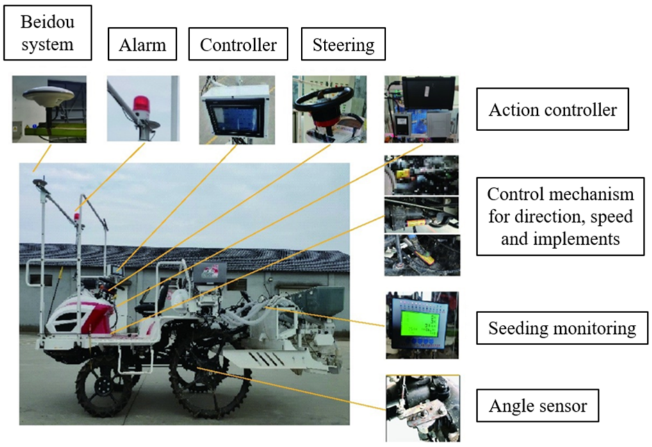

Figure 9. Automatic driving control system for rice seeding machine.

In the rice plant protection operation, the plant protection machinery needs to overcome the sliding interference caused by the muddy road surface of the paddy field and try to avoid rolling the rice seedlings, which increases the difficulty for the precise path tracking of rice field agricultural machinery. To solve the problems of driving wheel slipping and sinking in the paddy field, Wang et al. [63] constructed a layered path tracking strategy with model predictive control and fuzzy slip rate on the basis of the linear time-varying (LTV) kinematics model of the high clearance sprayer, which improves the tracking accuracy of the sprayer in muddy and slippery field. Liu et al. [64] developed a fuzzy adaptive predictive controller using model predictive theory, which can improve the robustness of the sprayer path-tracking. To improve the anti-interference ability and stability of the plant protection machinery, Lin et al. [65] proposed a path-tracking control method for rice field plant protection machines, which solved the chattering of the sliding mode control algorithm. Compared with wheeled tractors, tracked tractors have a large grounding area and are not easy to sink, making them widely suitable for paddy fields. However, the sliding phenomenon for tracked tractors in paddy fields is common. Most of the relevant research establishes control models under the assumption that tractors do not slip, which is difficult to achieve satisfactory accuracy. Jia et al. [66] studied the NF-752 tracked tractor mainly used for paddy field tillage, and comprehensively considered the effects of longitudinal speed and slip coefficient of both tracks. They proposed a path-tracking method based on a course control model, which to some extent, overcame the influence of slip-on control accuracy.

3.3. Orchard Agricultural Machinery

In the case of labor shortage and rising labor costs, the development of autonomous orchard agricultural machinery is helpful in reducing the labor intensity of orchard farmers and improving the efficiency and quality of orchard operations. Bayar et al. [67] proposed a model-based control method for orchard autonomous agricultural vehicles, which calculates the velocity and wheel angle based on the vehicle kinematics model, thereby improving the path tracking accuracy. Thanpattranon et al. [68] developed a navigation system suitable for curve path tracking in orchards, and the average deviation of path tracking during the experiment was 0.275 m. Based on RTK-BDS positioning technology, Xiong et al. [69] developed a straight-line path-tracking controller for the orchard sprayer. When the sprayer speed is 2 km/h, the maximum linear tracking deviation is 0.13 m, and the average tracking deviation is less than 0.03 m, which can effectively achieve accurate straight-line path tracking of the orchard. To ensure the high robustness and speed adaptability of the navigation controller, Xue et al. [70] developed an orchard tractor path-tracking controller. Simulation test results showed that the controller can track the straight line, and when the tractor turns, the average lateral errors at 2.5 m/s and 5 m/s are 7 cm and 13 cm, respectively. Opiyo et al. [71] designed a machine vision navigation system based on the central axis for autonomous orchard robots, and the fuzzy controller with heading and error as input can well track the medial axis.

In the study on path tracking of orchard tractors, Wu et al. [72] used the look-ahead distance fuzzy adaptive pure pursuit model to calculate the expected wheel angle. In addition, to cope with the soft road surface of the orchard and the vibration of the tractor itself, the feedforward control is added to the pure pursuit model control to minimize the sideslip. To achieve automatic driving of agricultural machinery in orchards, Zhang et al. [73] developed an autonomous orchard vehicle system using a two-dimensional laser, which utilizes fuzzy control to adjust the look-ahead distance of pure pursuit model dynamically. The structure of the orchard vehicle automatic platform is shown in Figure 10. Orchards have a high planting density, and low and narrow working passages, and small tracked tractors have the advantages of small size and strong terrain adaptability, which are widely used in orchards [74]. Liu et al. [75] designed a path-tracking algorithm using a virtual radar model for small, tracked tractors. The algorithm describes the relative position between vehicles and paths with a virtual radar map and generates driving instructions through a deep neural network to control the tractor. Compared with the fuzzy control algorithm, this algorithm has higher accuracy and driving stability and has better adaptability to orchard working paths.

Figure 10. Orchard vehicle automatic test platform.

3.4. Agricultural Robots and Facility Agricultural Machinery

Autonomous agricultural robots are widely used in pesticide spraying, weeding, planting, and field biological and environmental information collection. The ground conditions constantly change during the steering process, making it difficult to establish accurate mathematical models for controlled vehicles. In the research of agricultural wheeled robot path tracking, Li et al. [76] introduced a radial basis function (RBF) neural network to estimate the uncertainty disturbance in real-time and then designed an adaptive sliding mode control method, which can improve the system robustness while reducing chattering. Gökçe et al. [77] used a PID control strategy to control the agricultural robot and optimized the controller parameters through the PSO algorithm. In order to adapt to changes in speed and road, Sun et al. [78] proposed an improved path-tracking control algorithm based on the fuzzy Stanley model (FSM) and PSO. Cui et al. [79] proposed an improved Stanley model path-tracking algorithm based on the fuzzy algorithm, which adjusts the gain coefficient in real-time. In the above research on the improvement of the Stanley model algorithm, the fuzzy algorithm improves the tracking accuracy of the automatic turning, and the particle swarm optimization algorithm can further optimize the front wheel steering angle and decision-making. The agricultural tracked robot is a multi-input and multi-output system, having the characteristics of time-varying, nonlinearity, and uncertainty, which is easily affected by parameter disturbance, thereby causing negative impacts on the system [80]. Song et al. [81] designed a path-tracking strategy based on heuristic dynamic programming (HDP) for tracked agricultural robots, which can accurately track multiple complex straight-line paths. The sliding mode control method can adjust the uncertainties and parameter disturbances in the system and track the path in an exponentially convergent manner [82]. Li et al. [37] designed a tracked robot path-tracking system on the basis of a sliding mode variable structure algorithm.

The autonomous mobile operating platform in agricultural facilities can undertake tasks such as autonomous working and autonomous transportation of agricultural materials, which plays an important role in the development of facility agriculture. The space in agricultural facilities is small, and the mobile operating platform needs to change the driving direction frequently. Wang et al. [83] designed an automatic tracking platform for greenhouse fruit and vegetable picking and transportation based on Kinect sensing technology. The system uses the pure pursuit model method to track the expected path and uses the fuzzy algorithm to determine the look-ahead distance dynamically. In order to adapt to the rectangular path tracking working conditions, Yao et al. [84] used ultra-wideband (UWB) wireless positioning technology to obtain high-precision positioning information of the mobile platform and proposed a dynamic look-ahead distance determination method based on the deviation. The improved pure pursuit model algorithm can meet the demand for automatic navigation of mobile platforms in agricultural facilities. Chai et al. [85] improved the pure pursuit model by PSO and selected the optimal look-ahead distance according to the platform's real-time position. Based on the kinematic model of a 4WIS-4WID vehicle, as shown in Figure 11, Xu et al. [86] calculate the optimal look-ahead distance using a fuzzy algorithm.

The prominent problem faced by path-tracking technology based on the model predictive model is real-time performance. Linearization prediction models have better real-time performance than nonlinear prediction models, but linearization prediction models have the problem of weakening the controller's ability to respond to path curvature and heading changes. Oyelere et al. [87] solved the path-tracking problem of autonomous ground vehicles (AGV) using nonlinear model predictive control (NMPC) and linear model predictive control (LMPC) and proved through experiments that LMPC has better real-time performance than NMPC. Zhang et al. [88] proposed a path-tracking method on the basis of linear time-varying model predictive control (LTVMPC). The reference path of agricultural robots usually consists of straight lines and arcs, with significant curvature changes, so linearized prediction models are not suitable for optimizing real-time performance. Liu et al. [89] proposed a path-tracking method based on nonlinear model predictive control. Test results showed that the developed controller has a smaller deviation than the linear model predictive controller when tracking linear and circular paths. Aiming at the poor real-time performance of nonlinear model predictive control, Bai et al. [90] proposed to optimize by reducing the number of control steps or lowering the control frequency. Experimental results show that reducing the number of control steps is more suitable for agricultural robots with high flexibility.

Figure 11. Test prototype and test environment.

3.5. Agricultural Articulated Vehicle

Articulated vehicles mainly consist of two parts, the front, and the rear, connected by a rigid hinge body in the middle. The structural characteristics of the articulated vehicle not only reduce the turning radius, but also ensure the adhesion between the tire and the ground in rough terrain, making them suitable for transportation operations in non-structural rough terrain. Agricultural wheeled articulated vehicles experience severe vibrations when driving on rough terrain such as farmland. Compared with the traditional front-axle steering structure, the steering structure of the articulated vehicle allows both the front and the rear car body to move relative to the ground during the steering process, which increases the difficulty of path tracking. Zhao et al. [91] proposed a sliding mode variable structure path tracking controller for articulated agricultural vehicles. To suppress chattering, the symbolic function was replaced by a continuous function, and the Lyapunov function was used to prove its stability. Shao et al. [92] proposed an adaptive PID controller, which used the reinforcement learning algorithm to tune PID parameters adaptively. Reinforcement learning adaptive PID controllers have smaller overshot and vibrations than traditional ones so that the articulated vehicle can track the predetermined path more accurately. To improve the response speed of articulated agricultural vehicles, Meng et al. [93] proposed a linear quadratic regulator-genetic algorithm (LQR-GA) path-tracking method based on preview information. Preview information can improve the system response speed, and the genetic algorithm can optimize the control effect.

In order to keep the tractor and trailer on the same working trajectory, Backman et al. [38] designed a nonlinear model predictive path-tracking controller for the tractor-trailer system. During the straight-line path tracking, the lateral error of the trailer is much less than 10 cm. To improve the trajectory tracking performance of autonomous tractor-trailer systems, Kayacan et al. [94] combined fast-distributed nonlinear model predictive control with nonlinear movement level estimation for state and parameter estimation. The small agricultural tractor–trailer system is shown in Figure 12. The proposed method can improve the path-tracking accuracy of tractor-trailer systems and robustness to environmental disturbances. Apart from the development and improvement of control methods by the researchers mentioned above, commercial companies have proposed commercial solutions for autonomous tractor-trailer systems, such as John Deere's iGuide and iSteer and Trimble's TrueGuide. The difference between iGuide and iSteer, which is primarily used for straight-line path tracking, is that iGuide is a passive guidance solution where the implement does not have a steering system, while iSteer is an active guidance solution where both the tractor and the implement have a steering system.

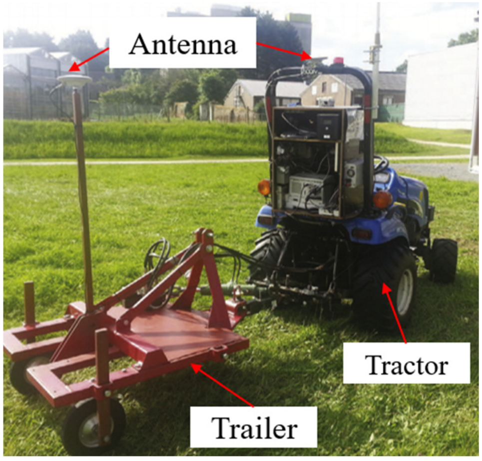

Figure 12. The tractor-trailer system.

3.6. Summary of Control Methods

The path-tracking control method directly affects the operation accuracy and efficiency of autonomous agricultural machinery. Path tracking control methods such as PID, fuzzy algorithm, pure pursuit model algorithm, and model predictive algorithm have been used in agricultural vehicles' automatic navigation. The summary of path-tracking control methods for agricultural vehicles in different operating scenarios is shown in Table 5. Different from structured scenes, the agricultural machinery operation environment is complex and subject to interference from many uncertain factors. The characteristics of different agricultural machinery working scenes are different, such as paddy field mud, easy obstruction in orchards, and limited space in the greenhouse. In such cases, the accuracy, stability, and robustness of agricultural vehicles' path tracking will be reduced.

Table 5. Summary of path tracking control methods for agricultural vehicles.

Working Scenario	Agricultural Vehicle	Control Method	Improvement of Control Methods	Practical Difficulties
Dry field	• Four-wheel tractor • Corn harvester • Peanut harvester • Rape Seeder	• Fuzzy control • Stanley model control • Sliding model control • Optimal control • Pure pursuit model control • PID control	• Optimizing Stanley controller parameters through GA • Developing a SOSM controller to suppress chattering • Adjusting the look-ahead distance by PSO, fuzzy algorithm, DRL, SOA • Adjusting the PID parameters by a single neuron	• Wheel slip • Path curvature change • Poor curve path tracking accuracy • Poor speed adaptability
Paddy field	• Rice transplanter • Rice seeder • Sprayer • Tracked tractor	• Pure pursuit model control • Model predictive control • Sliding model control	• Adjusting the look-ahead distance by the fuzzy algorithm • To improve anti-interference ability and suppress chattering by equipping disturbance observer • Improving robustness by combining fuzzy algorithm and MPC	• Paddy field machinery is easy to slip • Rear implements changes greatly relative to the front machinery

Table 5. *Cont.*

Working Scenario	Agricultural Vehicle	Control Method	Improvement of Control Methods	Practical Difficulties
Orchard	• Orchard tractor • Orchard sprayer • Orchard vehicle • Small, tracked tractor	• Pure pursuit model control • Fuzzy control • Model predictive control	• Adjusting the look-ahead distance by the fuzzy algorithm	• High plant density • Narrow walking channels • Signals are easily obstructed
Agricultural robot Facility agricultural vehicle	• Wheeled robots • Tracked robots • Facility mobile platform	• Sliding model control • PID control • Stanley model control • Heuristic dynamic programming control • Pure pursuit model control • Model predictive control	• Improving robustness and reducing chattering by combining RBF neural network and SMC • Optimizing PID parameters by PSO • Adjusting the look-ahead distance by the fuzzy algorithm and PSO • Improving the Stanley model using the fuzzy algorithm	• Agricultural facilities have limited space • Mobile platforms need to change direction frequently • Agricultural robots are susceptible to parameter disturbances
Tractor-trailer system	• Tractor-trailer	• Sliding model control • PID control • Nonlinear model predictive control	• Suppressing chattering by replacing the symbolic function with a continuous function • Tuning PID parameters adaptively using a reinforcement learning algorithm	• The steering structure of articulated vehicles increases the difficulty of path-tracking control

4. Research Challenges in Agricultural Vehicle Path Tracking Control

This paper reviews and summarizes the research status of vehicle model construction and control methods in path-tracking control of autonomous agricultural vehicles. In this section, challenges and opportunities in the field of path-tracking research for agricultural vehicles will be discussed, including vehicle modeling and controller development.

4.1. Vehicle Model

Most existing research develops path-tracking controllers on the basis of vehicle kinematic models because controllers designed based on kinematic models can meet most of the operating requirements under low-speed operating conditions. However, most kinematic models are constructed under certain approximate conditions, so ignoring these assumptions and directly applying kinematic models to agricultural machinery navigation control will bring greater uncertainty and influence on control accuracy. Compared with kinematic models, control methods based on dynamic models can fully consider the dynamic characteristics of agricultural machinery. However, the complexity of the contact between the agricultural machinery and the ground increases the difficulty of obtaining the model parameters accurately. On the other hand, there is a lack of further analysis of dynamic models, which makes it difficult to ensure the accuracy of the control results.

4.2. Controller Development

High-speed working of agricultural machinery is one of the future development trends, which is conducive to improving agricultural production efficiency. Therefore, further research should be conducted on automatic navigation path tracking methods for agricultural machinery under high-speed and variable-speed conditions. In the future development of agricultural machinery path-tracking controllers, the impact of speed on the system cannot be ignored. The slip of agricultural vehicle tires caused by uneven and slippery surfaces is still a key factor in reducing controller accuracy and stability. Although extensive research has been conducted on slip issues, most of them are based on linearized models, and the force analysis has not been fully carried out, resulting in limited accuracy in the model establishment. The pure pursuit model algorithm is applied to different types of agricultural machinery in different scenes, such as dry field tractors, rice transplanters, orchard tractors, and greenhouse agricultural robots. The look-ahead distance plays an important role in improving tracking accuracy. To achieve the adaptive adjustment of the look-ahead distance, existing research has combined the traditional pure pursuit model algorithm with fuzzy control, reinforcement learning algorithm, neural network algorithm, particle swarm optimization algorithm, etc. The determination of the look-ahead distance is affected by many factors, including vehicle speed, steering frequency, and path curvature while existing research has not fully considered the impact of speed and curvature variation on it. The Stanley model is a nonlinear feedback function based on the lateral tracking deviation, which generates steering angle commands using the relative geometric relationship between the vehicle and the predefined trajectory. Different from the pure pursuit model algorithm, the Stanley controller does not need to find the optimal look-ahead distance. The research of Stanley controller in agricultural machinery automatic navigation still needs further study. The traditional sliding mode control method has successfully solved the path-tracking problem of agricultural vehicles from interference suppression and convergence. However, the oscillation problem of sliding mode control also has a negative impact on the controller. Therefore, in path tracking control research of agricultural machinery, it still needs to be further studied to reduce the oscillation or find alternative solutions. In model predictive control research, the linearized predictive model has better real-time performance, but there is also a problem of weakening the controller's ability to respond to reference path curvature and heading changes, which needs to be studied and balanced in the future.

4.3. Overall Challenges in Path Tracking Control

Usually, the path-tracking control technology calculates vehicle motion parameters based on control algorithms, such as vehicle speed, steering angle, etc., so that the vehicle reaches and tracks the predetermined working path. The main challenges in the current path tracking control of agricultural vehicles include: (1) Although the existing kinematic model can achieve good results under low speed, there is a lack of further research on the dynamic vehicle model. (2) Most existing path-tracking control methods are based on linearized systems or independent of specific mathematical models without fully considering the influence of disturbances and uncertainties. (3) The existing research on path-tracking control methods mainly focuses on straight-line paths, but the tracking accuracy of curved paths, especially curved paths with variable curvature, needs to be improved to adapt to autonomous agricultural production. In the future, appropriate control algorithms should be developed and designed to realize the coordinated control of agricultural vehicles horizontally and vertically while coping with different complex working conditions.

5. Conclusions

Path tracking control is one of the hotspots in the research of agricultural vehicles' automatic navigation. Researchers use position and attitude sensors, vehicle kinematics models, and dynamics models to obtain position and heading errors and develop path-tracking controllers to control agricultural vehicles to work along reference paths. This paper reviews and summarizes the latest research status on path-tracking control of autonomous agricultural vehicles, including vehicle modeling and the development of path-tracking control methods. In terms of vehicle modeling, we reviewed and summarized the kinematic model and dynamic model of agricultural vehicles. The kinematic model includes the bicycle model (simplified four-wheel agricultural machinery kinematic model), the agricultural tracked vehicle kinematic model, and the agricultural articulated vehicle kinematic model. The kinematic model does not consider the dynamic parameters of the vehicle, so the calculation burden is small, and the structure is simple, but ideal assumptions often introduce errors. The kinematic model tends to achieve better tracking accuracy and effect under low-speed conditions. The dynamic model is beneficial for improving the robustness of control systems, but dynamic parameters are difficult to obtain online, and model accuracy is difficult to guarantee. Undoubtedly, establishing an accurate dynamic model is beneficial for improving the path-tracking accuracy of vehicles, and many researchers are currently working in this area.

In the aspect of controller development, most controllers are based on the vehicle kinematic model, and only a few controllers consider the dynamic characteristics of agricultural vehicles in the field. According to actual working conditions, researchers used GA, PSO, DRL algorithm, etc., to improve and optimize the traditional path tracking algorithm so as to improve the robustness and accuracy of the controller. Single neurons, PSO, and DRL algorithms are used to realize the tuning of PID control parameters. The look-ahead distance of the pure pursuit model has a significant impact on the path-tracking accuracy of vehicles. Existing research has adopted PSO, fuzzy algorithm, DRL, and SOA to improve the pure pursuit model to achieve dynamic adjustment of look-ahead distance. Sliding mode control has the characteristic of being insensitive to external disturbances, but there is a problem with chattering. Researchers have developed SOSMC and sliding mode controllers with disturbance observers to suppress chattering. The linear model predictive control has better performance than the nonlinear model predictive control, but the linear model predictive control has the problem of weakening the controller's ability to respond to reference path curvature and heading changes. The improvement of the model predictive control algorithm should be strengthened.

With the innovation of control theory and agricultural machinery development, intelligent controllers may provide better solutions for agricultural vehicle path tracking. In conclusion, it is hoped that this paper will provide sufficient background and understanding for path tracking control of autonomous agricultural vehicles.

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