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Review

Applications of Autonomous Navigation Technologies for Unmanned Agricultural Tractors: A Review

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Abstract: The development of unmanned agricultural tractors (UAT) represents a significant step towards intelligent agricultural equipment. UAT technology is expected to lighten the workload of laborers and enhance the accuracy and efficiency of mechanized operations. Through the investigation of 123 relevant studies in the literature published in recent years, this article reviews three aspects of autonomous navigation technologies for UATs: perception, path planning and tracking, and motion control. The advantages and deficiencies of these technologies in the context of UATs are clarified by analyzing technical principles and the status of current research. We conduct summaries and analyses of existing unmanned navigation solutions for different application scenarios in order to identify current bottleneck issues. Based on the analysis of the applicability of autonomous navigation technologies in UATs, it can be seen that fruitful research progress has been achieved. The review also summarizes the common problems seen in current UAT technologies. The application of research to the sharing and integrating of multi-source data for autonomous navigation has so far been relatively weak. There is an urgent need for high-precision and high-stability sensing equipment. The universality of path planning methods and the efficiency and precision of path tracking need to be improved, and it is also necessary to develop highly reliable electrical control modules to enhance motion control performance. Overall, advanced sensors, high-performance intelligent algorithms, and reliable electrical control hardware are key factors in promoting the development of UAT technology.

Keywords: agricultural machines; agriculture automation; unmanned systems; autonomous operations; intelligent technologies; path navigation; motion control

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1. Introduction

Personnel loss in rural labor forces has increased in recent years, and labor costs are rising rapidly in China [1]. Promoting the development and popularization of unmanned agricultural tractors is crucial for improving land utilization efficiency and ensuring food security. The unmanned agricultural tractor (UAT) enables smart, standardized, and information-based operations [2]. It saves labor and avoids variable work quality caused by differences in operator skills. The autonomous navigation technologies used in UATs significantly enhance the quality and efficiency of field operations while reducing the driving difficulty and the operator's workload [3]. Therefore, it is imperative to study the autonomous navigation technologies used in UATs.

Recent years have witnessed rapid developments in UATs. Research on satellite-based global positioning systems (GPS) and BeiDou navigation satellite systems (BDS) for unmanned tractor navigation has been conducted, and practical applications have been implemented. These systems enable intelligent and precise operations, including plowing, land preparation, seeding, and harvesting. However, considerable room for improvement exists in the realm of autonomous navigation technologies for UATs, especially in terms of enhancing efficiency and reliability [4]. Agricultural environments are significantly more complex and diverse than the structured environment faced by autonomous cars, resulting in great difficulty in path planning and motion control [5]. The technologies involved in autonomous navigation of UATs include those related to sensing and perception, path planning, and motion control [6], as shown in Figure 1. Only through the comprehensive application of these technologies can autonomous navigation operations of UATs be achieved [7]. These aspects represent the challenges and crucial issues that must be addressed in the implementation of autonomous tractor technology. Numerous innovative studies in this area hold significant reference value for future research on autonomous driving of UATs. Understanding the characteristics of autonomous navigation technologies, identifying current bottlenecks, and studying the future development directions are important for the advancement of UATs [8].

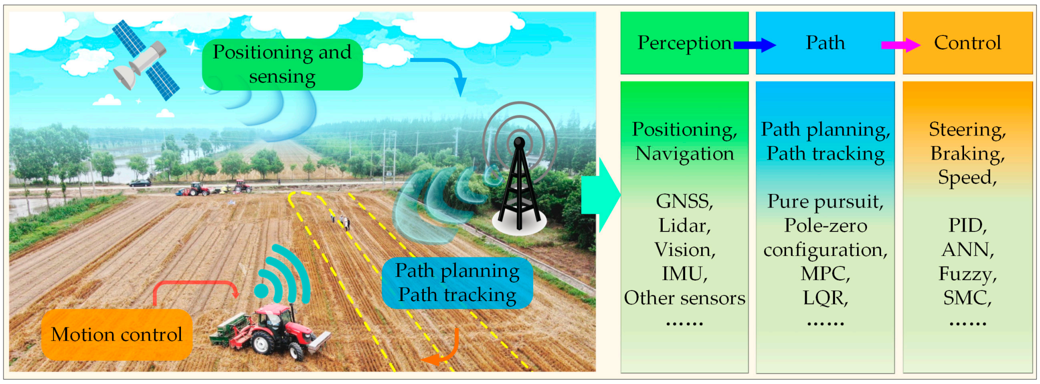


Figure 1. Sketch diagram of autonomous navigation technologies in UATs.

Based on the above considerations, this paper presents a comprehensive review of research progress surrounding the autonomous navigation technologies used in UATs. This review focuses on technical issues of perception, path planning and tracking, and motion control that are observed in UATs. It summarizes the advantages and limitations of existing technologies, analyzes the integration of autonomous navigation technologies in UATs, and provides several opinions on technology development.

The main contribution of this study lies in presenting the latest research developments in the field of UATs, which can provide scholars engaged in this field with a macroscopic technical overview. The prevalent challenges and trending topics discussed in this paper provide potential inspiration for future UAT studies.

The rest of the paper is organized as follows: Section 2 introduces the methodology of this study. Section 3 presents the perceptive techniques of UATs. Sections 4 and 5 investigate the path planning and the path tracking techniques, respectively. Section 6 presents motion control techniques. Applications of UATs in precision farming are reviewed in Section 7. Sections 8 and 9 present discussions, conclusions, and future work.

2. Methodology

To gather data for this study, relevant papers were sourced from the Web of Science, Elsevier Science, Wiley, CNKI, and PubMed databases, with a focus on title searches. The keywords used in the search were "unmanned tractor, agricultural unmanned systems, autonomous agricultural machinery navigation, agricultural navigation technologies, path planning, path tracking, and motion control", etc. The collected information was then organized, encompassing both journal articles and conference papers, and was tallied. The focus was on sources indexed in SCI and EI to align with research needs. Following the literature screening process, 125 articles were selected for review. The majority of the literature surveyed was from the past ten years, with specific details shown in Figure 2a.

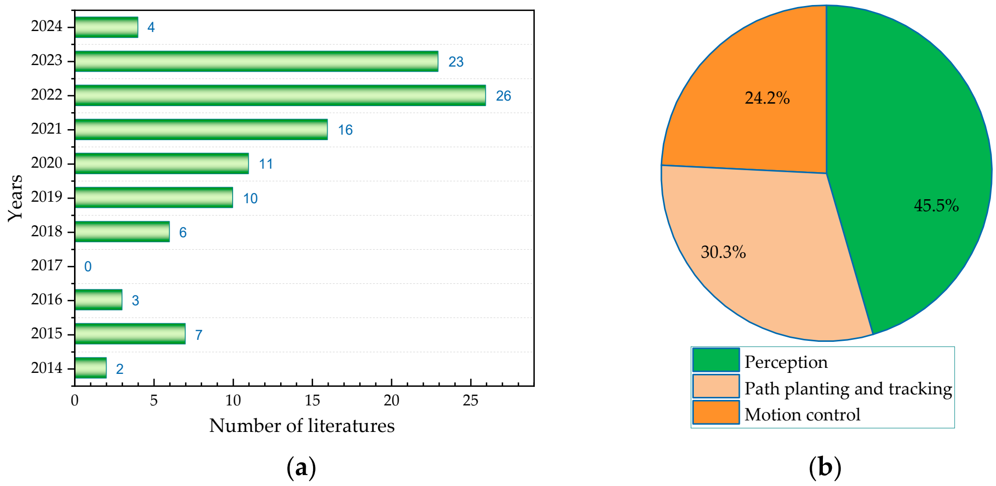


Figure 2. Literature survey analysis: (**a**) quantity per year; (**b**) literature ratio map of the three techniques.

Extensive research has been conducted on the application of UATs over the past five years, with a gradual increase in recent years. In this review, as shown in Figure 2b, there were 45 articles on the application of perceptive techniques, 30 articles on path planning and tracking techniques, and 24 articles on motion control techniques. Perceptive technique research studies were the most prevalent. The large volume of environmental perception data available, coupled with high algorithmic requirements and diverse methods, has led to extensive research in this field. Motion control technology has matured, and the research quantity relating to this area was relatively small. The most widely used applications for UATs include plowing, seeding, field management, and harvesting in large-field agricultural production processes. Application research on animal husbandry was the least common, as such an environment is not conducive to autonomous driving.

3. Perceptive Techniques of UATs

3.1. Positioning Technology

Positioning technology is critical for achieving autonomy and intelligence in UAT. Real-time positioning is a prerequisite for UAT to achieve path planning, path tracking, and motion control [9]. Satellite positioning enables the identification of farmland locations, work areas, operation deviation, and driving speed [10]. Positioning technologies include satellite positioning systems, laser radar systems, and onboard cameras. These technologies are used in conjunction with UATs to achieve precise and efficient operations [11].

The BDS and GPS are the two most widely used global navigation satellite systems (GNSSs) in agricultural engineering. Positioning data at the decimeter or centimeter level is required to achieve precise navigation in UATs. This is commonly achieved using differential GNSS technology, which enhances accuracy by transmitting corrected pseudo-range correction values or phase information measured at known reference stations to the mobile station. The diagram of differential positioning is shown in Figure 3. The principles of BDS and GPS are similar, involving the measurement and comparison of signals received by two or more receivers to eliminate signal errors.

For example, Jing et al. [12] designed an autonomous navigation control board consisting of a high-precision GNSS decoding module and an inertial measurement module. This system corrected data from the inertial navigation system (INS) and the high-precision positioning module. It was used to control parameters, such as the direction, speed, and heading angle of the tractors. Yang et al. [13] used the GNSS RTK receiver (Qianxun Positioning Network Co., Ltd., Shanghai, China) to record GNSS data continuously. Its positioning accuracy was ±2.5 cm. GNSS terminals, industrial computers, and mobile devices were used for data reception. Trimble successfully developed real-time kinematic (RTK) technology, enabling instant updates of GPS data while in motion. Trimble real-time extended (RTX) technology facilitates real-time accurate positioning with centimeter-level precision in a quick convergence period [14]. Nowadays, GNSS systems are inexpensive; the RTK-GNSS single-frequency receiver costs only USD800 in the USA [15]. Conversely, according to market investigations in China, a set of agricultural machinery based on the BDS navigation system is currently priced around USD1000 to USD3000.

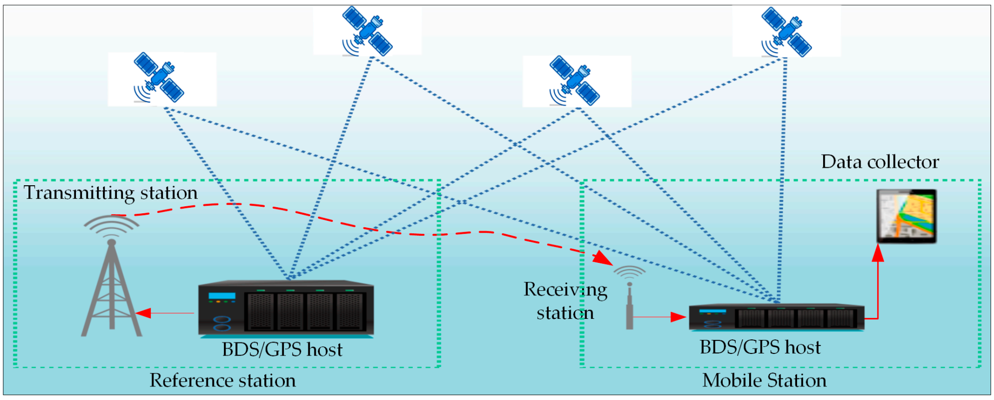


Figure 3. Diagram of the principle of differential positioning technology.

Due to the time delay and overload risk of differential positioning methods, Wang et al. [16] proposed edge computing to reduce the load on the data center and obtained satisfactory results. Wang and Noguchi [17] evaluated the centimeter-level enhancement service (CLAS) for controlling UAT using the quasi-zenith satellite system (QZSS). The QZSS transmits enhanced information through L6 signals to improve positioning accuracy in GNSS.

The deep integration of the BDS system with agricultural systems can provide precise and efficient support for agricultural modernization, promoting the development and enhancement of agricultural production in China. A typical BDS navigation system of UAT is composed as shown in Figure 4. Its application has been scaled in Xinjiang, Heilongjiang, and other regions [18]. For example, the DF2204 tractor, an autonomous navigation tractor with continuously variable transmission (CVT) and GNSS, was developed for unmanned operations [19]. An attitude heading reference system (AHRS) (MTI-30, Xsens company, Enschede, The Netherlands) sensor and an RTK-GPS positioning device were installed in a combine harvester for obtaining heading and position information [20]. Two sets of GNSS mobile receivers were developed for obtaining position information and ensuring the balance of the John Deere 5-904 tractor [21]. The BDS and MTI-300 INS were installed in the tractor and trailer, respectively, to obtain navigation information [22]. The DF2004-5A navigation driving system based on BDS was applied for a transplanter [23], and the GNSS AF300 navigation driving system based on BDS was developed for an AF300 tractor [24]. Alonso-Garcia et al. [25] assessed the application of inexpensive GPS receivers in a John Deere 6400 tractor with a maximum power of 73.5 kW. Their findings indicated that it is feasible to autonomously guide an agricultural tractor using a low-cost receiver as a positioning sensor, with a maximum speed of around 9 km/h.

The GNSS receiver can also provide heading information for UATs. Dual and single antennas have been used to measure heading information [26]. RTK-GPS and a four-antenna GPS system were used to provide heading information for tractor navigation in [27]. The dual antennas of the GNSS system are installed horizontally at the top of the tractor, enabling simultaneous measurements of position and heading information. GNSS can provide absolute position and heading information continuously in all weather conditions. However, the application of GNSS in complex field environments is limited by signal loss caused by extreme weather or blockages.

In 2016, the Galileo GNSS system emerged as the latest and most advanced development in satellite navigation. It is recognized for its superior tracking accuracy and speed compared to both GPS and GLONASS [28]. As of August 2021, there were 31 GPS satellites, 26 GLONASS satellites, 26 Galileo satellites, 15 BDS-2 satellites (which includes four experimental satellites), and 34 BDS-3 satellites orbiting the earth [29]. In China, the GLONASS GNSS system and the Galileo GNSS system have not been applied yet.

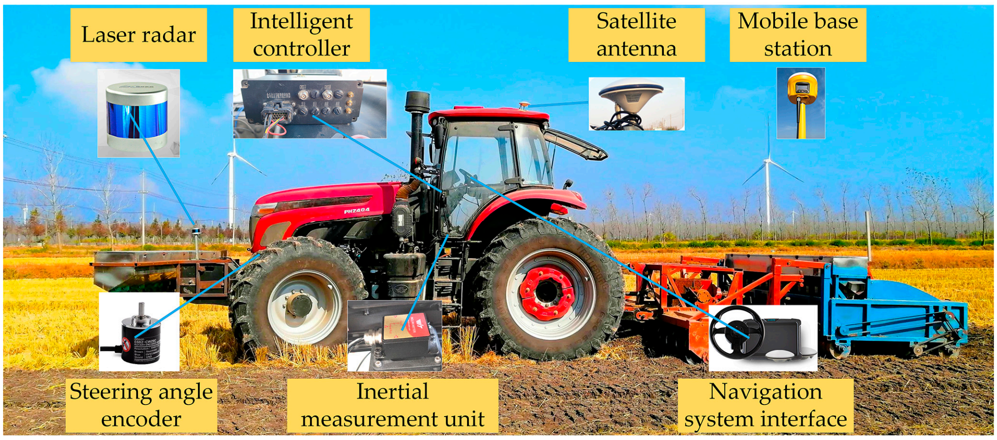


Figure 4. Typical BDS navigation system composition of UAT.

3.2. Sensing Technology

3.2.1. Field Environment Perception

The autonomous navigation of UATs requires environmental perception to perform tasks. The main objective of machine perception is to ensure that the UAT operates as expected and safely. Typical applications include obstacle detection, recognition of work area boundaries, and crop monitoring. Due to the challenging conditions faced by the sensors during agricultural operations, such as dust, rain, and extreme exposure to sunlight, sensor reliability has been a key challenge in environmental perception [30]. Currently, various sensors are used in UATs for field environment perception, including monocular vision, stereoscopic vision, lasers, radar, and ultrasonic sensors.

(1) Visual perception

Machine vision localization, perception, and measurement are typically used for UAT navigation at low speeds. Bakker et al. [31] proposed a row recognition method based on the Hough transform. A color camera was used to capture images of sugar beets in a greenhouse. The color images were converted to grayscale images in order to create sufficient contrast between the plant material and the soil background, substantially improving the image processing speed. To obtain real-time autonomous navigation information, Radcliffe et al. [32] integrated a multispectral camera-based machine vision device on a small agricultural vehicle. The root mean square errors (RMSEs) for automatic navigation were 2.35 cm and 2.13 cm in laboratory and field environments, respectively.

A navigation algorithm for machine vision was developed for a rice field weeding robot [33]. The results showed that the robot performed well at low weed density, with compensation accuracy of less than 2.5° and an average error from the target path of 4.59 cm. Mahboub and Mohammadi [34] proposed a combined positioning method that integrated BDS and visual navigation, providing accurate and real-time obstacle information in agricultural fields. The position deviation of the tractor was within ±0.1 m, resulting in high accuracy of autonomous navigation. Ma et al. [35] developed a visual module for an unmanned crawler tractor to obtain rice crop images in real time. The ExG(2G-R-B) algorithm and the Otsu and mask method were used for segmenting the binary images. In agricultural applications, Leica visual equipment can achieve high accuracy, and has potential in visual navigation. Some findings have indicated that the stereo viewing capability of the Leica ADS40-SH52 improves tree species classification performance, increasing overall accuracy by up to seven percentage points compared to nadir monoview data results [36].

Machine vision technology utilizes cameras as position measurement sensors. Image processing techniques are utilized to identify crop rows, determine a navigation reference line, and measure the relative position and heading information. The key advantages of machine vision technology are high speed, the ability to process a large amount of information, and versatile functionality. However, the commonly used Hough transform algorithm has disadvantages, such as difficulty in determining peak values, multiple repetitions of line segments, and high time and space complexity.

(2) Laser-based navigation

Thanpattranon et al. [37] designed a control method for a tractor-trailer with a single-sensor navigation system used in orchards. A control scheme for stopping the tractor-trailer using a laser range finder was designed for various tasks. The results demonstrated that the navigation of the tractor in orchards had high accuracy, and the trailer position was adjusted by a sliding hitch bar, enabling wide turns in the paths between the trees. The laser navigation method has many strengths, such as high frequency, high accuracy, and large range. This technology is particularly suitable for agricultural robots. However, there are high costs associated with it. In China, the market price of LiDAR used in the agricultural machinery industry ranges from USD800 to USD2000 per unit.

(3) Inertial measurement unit

An inertial measurement unit (IMU) is a measurement instrument based on the principles of inertial navigation, usually consisting of three accelerometers and three gyroscopes. The integration of the angular velocity and acceleration data enables the estimation of the object's velocity, displacement, and attitude information, achieving accurate navigation and positioning [38]. Gyroscopes and accelerometers are the most common components of IMUs. In UATs, gyroscopes are used for autonomous navigation, operation control, and attitude measurement to improve operational efficiency and precision [39]. An accelerometer consists of one or more acceleration sensors and is widely used in inertial measurement systems of UATs. They have good bias stability and are resistant to vibrations, shocks, and temperature changes.

(4) Multi-sensor data fusion and perception

An INS is a closed-loop navigation system that does not have real-time external information to correct errors during motion. Thus, a single inertial navigation system can only be used for short-term navigation. Long-term navigation systems of UATs need satellite navigation to correct errors periodically.

Currently, multi-sensor data fusion is the most widely used approach for UAT navigation. Figure 5 illustrates the combination of inertial and satellite navigation systems. Wang [40] proposed a navigation method consisting of satellite/inertial navigation systems. Experiments were conducted on denoising the data from the satellite/inertial navigation systems, resulting in a navigation accuracy improvement of 2 m. Xia et al. [41] combined information from an IMU and a GNSS. They used a robust regression approach to align the GNSS heading with the vehicle's longitudinal motion. They also proposed a slip angle estimation method based on the dynamic model. The results showed improved estimation accuracy of the slip angle.

The Kalman filtering algorithm is the main method for sensor data fusion. It can reduce cumulative errors in inertial navigation. Tian et al. [42] developed a field robot integrated IMU and GNSS navigation system. Kalman filtering was used to correct the errors in the inclination data. Liu et al. [43] proposed an integrated algorithm based on fuzzy reasoning and adaptive Kalman filtering for vehicle navigation and positioning using GPS and inertial navigation. The experimental results showed that the integrated algorithm had better positioning accuracy, precision, and stability than an RTK-GPS system.

Favorable results have been obtained from research and applications of machine vision, laser radar, inertial measurement unit, and multi-sensor data fusion. Field environment perception enables the efficient implementation of tasks [44]. However, there are still many challenges, such as data susceptibility to environmental interference, large data volumes, and insufficient real-time performance. Further efforts are needed to enhance the robustness of detection algorithms.

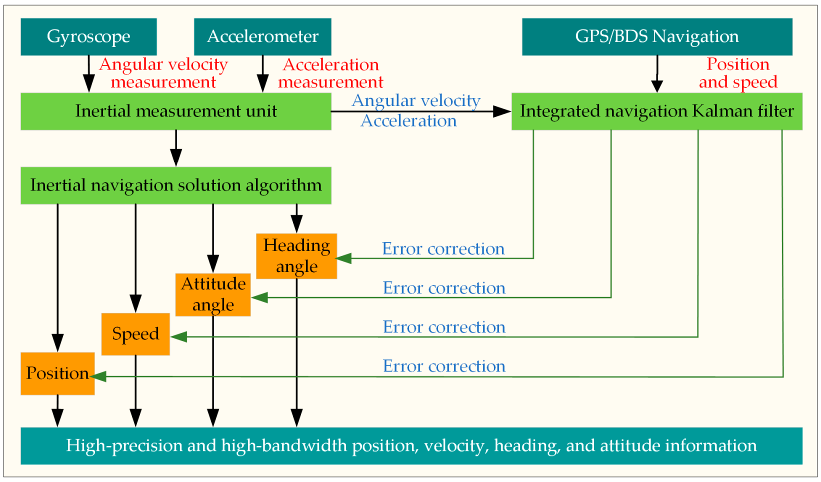


Figure 5. Combination of inertial and satellite navigation systems in UATs.

3.2.2. Operation State Perception

The perception of operational conditions of UATs primarily focuses on the engine, steering system, transmission system, vehicle body, and wheels. Key parameters include torque, rotational speed, emissions, attitude, vehicle speed, wheel speed, vibration, and strain [45]. The operational condition information includes the traction force of the suspension system, suspension lifting position, power take-off (PTO) torque, PTO speed, hydraulic flow rate, and pressure. Table 1 lists the perception methods for the operational states of UATs.

Table 1. Perception methods for the operational states of agricultural machinery.

Operation State	Perception Method	Advantages	Disadvantages
Vehicle Speed [46]	Radar speedometer, ground wheel, and GPS	Accurate ground wheel measurements at low speeds, accurate radar and GPS measurements at high speeds [47]	Inability to achieve high detection accuracy from low to high speeds
Tillage Depth [48]	Indirect detection using dual inclinometers, depth measurement using suspension angle sensors	Overcoming errors caused by field residue coverage and machinery vibration	Indirect calculation of tillage depth based on complex mathematical models with limited universality
Seeding Depth [49]	Combination of angle sensors and ultrasonic sensors	High stability and accuracy	Specific to the type of seed unit
Fertilizer Application [50]	Weighing by load cells with smart noise filtering	Simple structure, low cost, and high accuracy	Lack of long-term stability

A subsoiler equipped with flexible tines allows for obstacle avoidance while minimizing draft force. However, due to the substantial variation in soil resistance, tilling often results in depths that are considerably lower than the desired target value. To address this issue, researchers developed an electric-hydraulic system for a subsoiler [51]. Additionally, they introduced a novel method for detecting the tillage depth to overcome this challenge. The results showed that the control system improved the tillage quality of the subsoiler with flexible tines. Wang et al. [52] devised a precise perception system for corn fertilization planters. A capacitance sensor was designed to detect the amount of fertilizer online based on the different dielectric properties of fertilizer and air. The electrically driven seed metering system exhibited an impressive control accuracy of 98% for controlling grain spacing. Liu et al. [53] developed a sensor using a seed flow reconstruction technique to monitor seed flow rate. The technique converts continuous seed flow into distinct particles, reducing measurement errors from seed overlap. A particle counting method was proposed based on high-level sampling points. Real sowing results confirmed the sensor's effectiveness in detecting seed flow rates on grain drills. A new fertilizer volume detection system using single-line LiDAR was developed for the acquisition of fertilizer geometry data. The system employed escape value filtering and ordered point cloud set construction to reduce data noise, efficiently calculating fertilizer volume and mass. Field tests showed a maximum measurement error of 4.66% at fertilizer drain speeds between 20 and 70 revolutions per minute, providing innovative solutions for fertilizer discharge detection [54].

4. Path Planning Techniques of UATs

4.1. Path Planning Optimization

4.1.1. Factors of Path Planning

Path planning optimization of UAT requires the consideration of multiple factors, including operation time, turning way, quality, energy consumption, route length, and complexity [55]. The turning way at the end of the field affects the operational efficiency of UATs. Common turning methods include U-turns, semi-circular turns, light-bulb turns, and switch-back turns, as shown in Figure 6a. Each method has advantages for certain applications, and the method should be suitable for specific operation conditions. A study presented a novel dynamic headland turning path planning method utilizing an asymmetric switch-back turning strategy tailored for four-wheeled vehicles. The average trajectory length measured 11.84 m, with an average completion time of 28.4 s [56]. According to research, for the direct headland turning approach, the track length measured 3.96 $\pm$ 0.07 m, and the turning time was 21.15 $\pm$ 1.12 s. Comparatively, the direct headland turning method saved 46.3% of the time compared to bulb turning, 53.2% compared to fishtail turning, and 65.7% compared to the dynamic circle-back technique [57]. Different routes are used for different operational requirements. The patterns include S-shaped, T-shaped, square, and diagonal routes, as shown in Figure 6b. Additionally, a research study presented a path planning algorithm tailored for irregular field plots. This algorithm initially generated global static operational paths based on macroscopic mapping information of the working area. It also utilized radar sensors for real-time dynamic monitoring of the robot's local working environment to create local dynamic optimal paths, ensuring the smooth progress of irregular field operations [58].

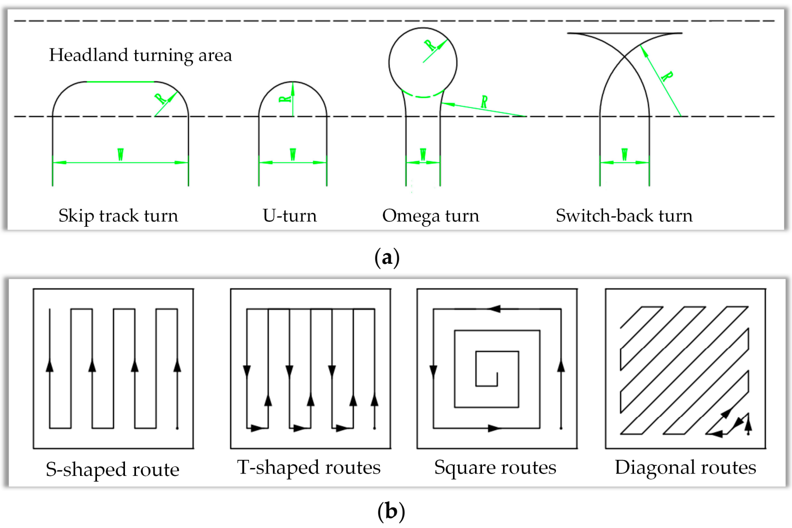


Figure 6. Path planning routes of UATs: (**a**) Turning methods; (**b**) Field routes.

4.1.2. Optimization Strategies

The navigation of UATs requires suitable operation paths, turning methods, and speeds. Therefore, field mapping is performed before implementing the automated control of UATs. The field boundaries and obstacles are identified to plan optimal paths for the tractor operations along predetermined routes. Path planning methods can be categorized into two types: global (macroscale) and local (microscale) [59], as shown in Figure 7. Each method includes various path-planning algorithms. Based on a pre-existing map, global path planning refers to the process of determining a route from the current location to a designated target position. Local path planning adjusts the motion in real time based on environmental sensing information.

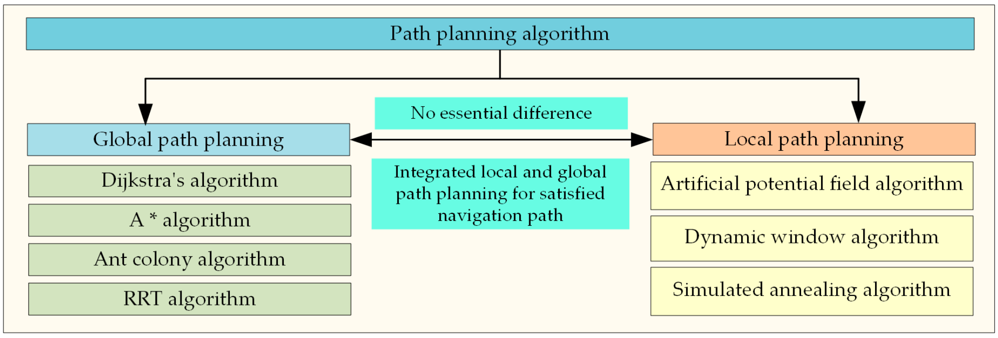


Figure 7. Classification of path planning algorithms.

4.2. Global Path Planning

In UAT driving systems, global path planning utilizes prior information about the terrain and road networks in the field to generate a global path. Real-time localization information is then used for path tracking, enabling the autonomous navigation of the tractor and improving operational efficiency and accuracy. Common global path planning algorithms include Dijkstra's, A*, ant colony, and rapid random tree (RRT) algorithms.

Many researchers have proposed improved path planning algorithms for UATs. Alshammrei et al. [60] modeled obstacle-free environments for mobile robots and used the Dijkstra algorithm offline to generate the shortest path, reducing the spatial complexity of the traditional Dijkstra algorithm. The improved algorithm achieved optimal path planning. Li et al. [61] optimized the heuristic function of the A* algorithm using the ant colony algorithm (ACA), resulting in an improved A* algorithm. Experimental results showed a significant reduction in the computation time with the improved A* algorithm.

A method based on real-time guided random tree expansion using sampled states was proposed for a UAT to avoid blind searching in the traditional RRT algorithm [62]. The improved algorithm achieved a search time of 1.208 s in the kiwifruit orchard environment, reducing search times by 74.31%, 46.28%, and 26.60% compared to RRT algorithm, goal-biased RRT algorithm, and RRT connect algorithm, respectively. The results (Figure 8a) showed that the improved algorithm exhibited better path planning efficiency and adaptability than the traditional RRT algorithm in a kiwi orchard. The task allocation of multiple machines was simulated using MATLAB and an improved ACA [63]. The experimental findings showcased the significant reduction in path costs achieved by the enhanced ACA. He and Fan [64] applied a local block optimization strategy to optimize the subregions separately, significantly improving the convergence speed and enhancing the optimization capability (Figure 8b). The improved algorithm reduced path lengths by 14.6% and cut turning points by 66.6% compared to the traditional ant colony algorithm. The traditional algorithm converged in 21 iterations, whereas the enhanced algorithm in this study converged in only 12 iterations. Wang et al. [65] developed an improved Dijkstra algorithm based on priority queues to prevent the omission of working areas and speed up path planning. To enhance the algorithm's effectiveness, it was integrated with various techniques, including the reciprocating method, nested method, and an integration of internal spiral path and nested approaches. The nested method was the main component. The proposed ant colony algorithm allocated tasks reasonably and effectively, reducing working path costs by 14–33%.

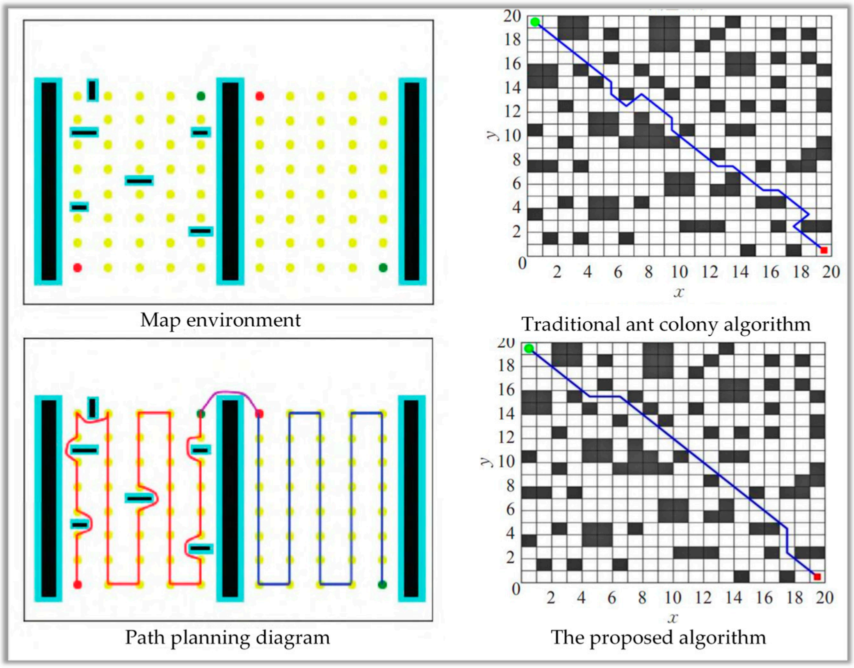


Figure 8. Schematic diagram of path planning based on different algorithms: (**a**) The improved RRT algorithm [62]; (**b**) Improved ant colony algorithm [64].

4.3. Local Path Planning

Local path planning refers to designing a short-term, localized path that guides the UATs based on real-time information on its current position and the surrounding environment. Local path planning enables UATs to make real-time adjustments to prevent collisions or getting stuck. Current local path planning algorithms include artificial potential field algorithms, simulated annealing algorithms, and dynamic window algorithms.

In response to the limitations of artificial potential field algorithms, İlhan [66] proposed an improved cross-operator simulated annealing algorithm called ISA-CO to enhance the convergence speed. Li et al. [67] employed a multi-neighborhood search approach to generate novel solutions, while simultaneously enhancing the temperature decay function. As a result, they achieved improved solution quality and accelerated convergence speed. Khan and Mahmood [68] combined two heuristic search algorithms, i.e., simulated annealing and ant colony algorithms, to improve the global search performance and time efficiency, demonstrating good practicality and robustness. Yin et al. [69] proposed a dynamic path planning method that integrated improved A* and dynamic window approach (DWA) algorithms. This achieved highly intricate and challenging robot path planning by avoiding obstacles, calculating optimal paths in real time, and maintaining high real-time performance and robustness.

A combination of global and local path planning techniques is often used for autonomous navigation of UATs in complex environments. Global path planning primarily focuses on route planning between the start and destination points, where motion speed is not a primary concern. On the other hand, local path planning emphasizes speed and direction to cope with complex and dynamic environmental changes. Global and local path planning work in conjunction to derive optimal paths. Table 2 lists the classification of path planning algorithms for the operational states of UATs.

Table 2. Classification of path planning algorithms.

Types	Algorithm	Advantages	Disadvantages
Global Path Planning	Dijkstra's algorithm	High accuracy, high success rate, good robustness	High complexity, low efficiency, time-consuming
	A* algorithm	Optimality, completeness, efficiency	Low efficiency, high complexity
	Ant colony algorithm	Positive feedback, strong robustness, strong adaptability	high complexity, prone to local convergence, low accuracy
	RRT algorithm	Simple algorithm, simple structure, strong applicability	High spatial complexity
Local Path Planning	Artificial potential field algorithm	Low complexity, small computational load, good real-time performance	Easily trapped in local minima
	Simulated annealing algorithm	Strong global optimization capability, easy implementation, high efficiency	Slow convergence, randomness involved
	Dynamic window algorithm	Low complexity, efficiency, good robustness	Speed and safety cannot be simultaneously optimized

5. Path Tracking Techniques of UATs

5.1. Motion Model for Path Tracking

Control algorithms are used for path tracking to ensure that UATs travel on the desired path at the required speed. In the navigation control system, the motion model regards the tractor as a rigid body, considering the tractor's physical properties and the forces acting on it. The linearized bicycle motion model is a simple and widely applicable approach. The UAT is abstracted as a two-wheeled vehicle in this motion model, using the X and Y coordinates of the rear wheel center of the tractor in the Cartesian coordinate system. The front wheel steering angle of the vehicle is controlled based on the position, attitude, and velocity of the tractor [70].

Fan et al. [71] developed an improved quantum genetic algorithm and weighting matrix optimization for weight selection of a UAT. The Ackermann steering principle was utilized to establish a kinematic model of the tractor. Subsequently, the model was discretized and linearized, as shown in Figure 9. A vehicle model was proposed for a four-wheeled steered robot used in agricultural applications. The robot was assumed to move without skidding in a two-dimensional planar environment [72]. The vehicle state and the input driving coordinates were obtained from steering encoders, and the information was translated into vehicle navigational commands.

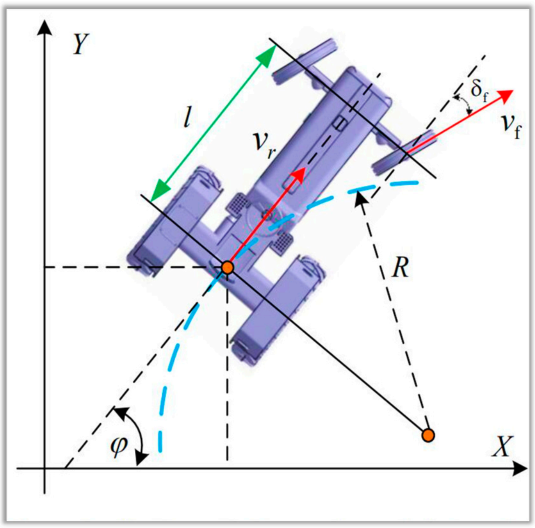


Figure 9. Single-track kinematic model of an UAT [71].

The planned navigation path represents the intended trajectory for UATs. It is crucial to research various aspects to track and control the path, including UAT motion models, navigation decision control, as well as steering and braking control. Furthermore, future efforts may focus on developing scientifically accurate motion models to enhance the efficiency and precision of path tracking.

5.2. Path Tracking Algorithms

5.2.1. Pure Pursuit Method

By employing the pure pursuit method, UATs can assess deviations in both position and orientation from the desired trajectory. This method effectively calculates distance and orientation errors to facilitate precise navigation. Control algorithms are then used to minimize the errors and achieve accurate path tracking. The pure pursuit method is computationally simpler to implement than other path tracking approaches. It also provides high path tracking accuracy in most scenarios. This method utilizes a lookahead point, as shown in Figure 10 [73]. The rear axle center of the UAT is the reference point, and a target point on the desired path is selected at an appropriate distance (lookahead distance). The front wheel steering angle is then calculated based on the real-time lateral and heading deviations. The UAT follows an arc toward the lookahead point to reach the desired target point at a certain velocity [74,75]. Yang et al. [76] proposed a path tracking algorithm of a UAT based on an optimal target location. This algorithm optimizes the lookahead distance adaptively by simulating the driver's lookahead behavior. It determines the lookahead region, establishes an evaluation model, and searches for the optimal target position based on the predicted model of the tractor's position. The proposed method exhibited a tracking error that was 20% lower in comparison to the pure pursuit algorithm.

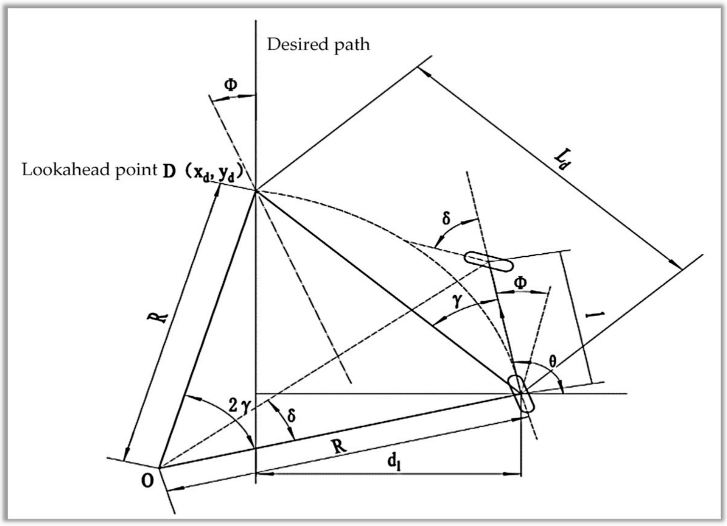


Figure 10. Pure pursuit control model [73].

5.2.2. Pole-Zero Configuration

Pole-zero configuration refers to selecting the positions of poles and zeros in a signal processing system. It is used to design filters or controllers to meet UAT system performance requirements. An appropriate pole-zero configuration ensures high stability, fast response, and minimum disturbances in a control system [77]. For example, adjusting the positions of the proportional–integral–derivative (PID) controller's poles and zeros can control the system's overshoot, response time, and steady-state error.

5.2.3. Model Predictive Control

Model predictive control (MPC) utilizes predictive models to select appropriate control actions based on the optimization objectives. It applies the control signal in the first-time step and applies updated control signals at subsequent sampling intervals. Kayacan et al. [78] proposed a robust trajectory-tracking error control method for UATs. They designed a linear model predictive controller based on the tracking error. This controller combines feedforward and robust control actions, significantly reducing tracking errors. Liu et al. [79] presented a path tracking MPC method for autonomous navigation vehicles. A comparison experiment was conducted with linear model predictive controllers. The proposed method resulted in fewer horizontal and longitudinal deviations from the track during circular path tracking. He et al. [80] developed a linear model, objective function, and constraint function using MPC for a paddy field tractor. They utilized the tractor's pose to establish a path tracking MPC method and proceeded to conduct field experiments. The results indicated that the pose-corrected MPC path tracking method prevented sudden lateral position errors caused by changes in relative position and attitude.

5.2.4. Linear Quadratic Regulator

A linear quadratic regulator (LQR) is a control system optimization method. It optimizes the control parameters of linear dynamic systems to achieve improved system performance [81,82]. Bevly et al. [83] designed an LQR path tracking approach based on a yaw dynamic model. The experimental results demonstrated that this model could control the tractor's lateral movement within 4 cm at speeds of up to 8 m/s, providing accurate high-speed navigation control of the tractor. The block diagram of the principle is shown in Figure 11.

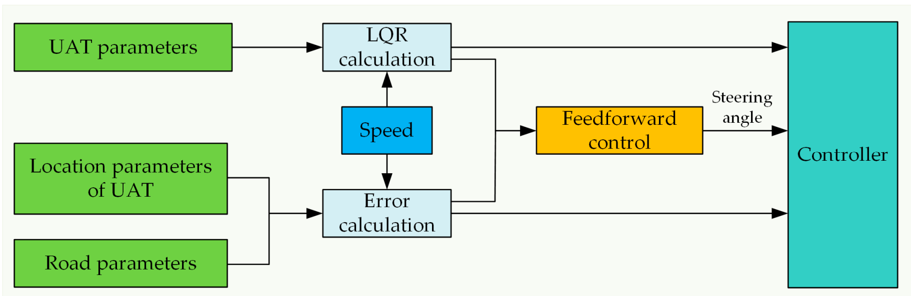


Figure 11. Diagram of the linear quadratic regulator (LQR) control principle.

5.2.5. Other Novel Approaches

In order to improve the adaptability of the full field path tracking algorithm, Cui et al. [84] proposed an improved fuzzy path tracking control method for a UAT and modified the Stanley model. It dynamically adjusts the gain coefficient. Field tests showed that the maximum path tracking error for straight and curved trajectories at the rated operating speed was less than 3 cm. Bodur et al. [85] developed an automatic path tracking system that used two lookahead reference points (2-LARP) to compensate for attenuated oscillations at curvature transitions. They found that the proposed algorithm reduced the peak lateral error to 20% of the error of the 1-LARP controller, significantly reducing lateral tracking deviation. Table 3 lists the classification of path tracking algorithms for the operational states of UATs.

Table 3. Classification of path tracking algorithms.

Algorithms	Advantages	Disadvantages
Pure pursuit method	Easy to calculate, easy to implement, strong robustness	Moderate accuracy and limited to low-speed scenarios
Pole-zero configuration	High stability, fast response	Not suitable for complex systems
Model predictive control	Suitable for large curvature conditions	Not suitable for high-speed conditions
Linear quadratic regulator	Easy to design and to implement	Strong dependence on model accuracy, not suitable for paths with large curvature

6. Motion Control Techniques of UATs

6.1. Control Methods for Automatic Navigation

The automatic navigation control of UATs primarily focuses on lateral position control. This ensures that the tractor remains on the planned operational path. It can also guarantee that any lateral position deviation from the path remains within a certain range. Therefore, motion control is required for the autonomous navigation of UATs [86].

6.1.1. PID Control

The most commonly used control method for unmanned vehicles is PID control [87,88]. He et al. [89] researched unmanned tracked peanut harvesters and improved the PID path tracking algorithm. They proposed a dual-PID path tracking control algorithm based on preview tracking and a virtual rotation angle. This method exhibits smooth control and small steady-state errors.

6.1.2. Neural Networks

Backpropagation (BP) neural networks possess strong adaptive capability to deal with uncertainties and low robustness of unmanned driving control. They have been used to optimize the parameters of navigation algorithms and improve the control accuracy and applicability [90]. Vargas-Meléndez et al. [91] proposed an integrated method of neural networks and Kalman filtering to estimate the vehicle's tilt angle. This method achieved better results than an estimator that used the suspension deflection to obtain pseudo-tilt angles.

6.1.3. Fuzzy Control

Unlike traditional control methods, fuzzy control does not require precise mathematical models and geometric relationships. Instead, it converts fuzzy linguistic descriptions into mathematical forms to describe imprecision and ambiguity. Meng et al. [92] proposed an improved particle swarm optimization-based adaptive fuzzy control method. This method quickly eliminates lateral errors in navigation operations of UAT and has a small overshoot and fast response. Xue et al. [93] designed a path tracking controller for agricultural robots using fuzzy control and machine vision methods with a variable field of view. This controller enabled the autonomous navigation of robots in cornfields, and field experiments demonstrated its effectiveness.

6.1.4. Sliding Mode Control

Sliding mode control (SMC) is utilized to address system uncertainties and disturbances by employing robust and adaptive controllers. It has high robustness, fast response times, and high control accuracy [94]. Li et al. [95] proposed a sliding mode variable structure method to design a path-following control algorithm for a UAT. The implemented control system allowed the tractor to efficiently carry out plant protection operations in maize rows during the late season. Jia et al. [96] proposed a radial basis function (RBF) network for the adaptive SMC of the tractor's steering angle. The method exhibited high fault detection capability, reliability, and accuracy. Additionally, the method reduced the failure rate of front-wheel steering angle measurement devices. He et al. [97] utilized the SMC method based on the exponential terminal sliding mode (TSM) surface to accelerate the system's response speed. They provided evidence that the SMC-active steering (AS) control method exhibited superior performance compared to the PID-AS control technique in terms of minimizing peak roll angles.

6.2. Motion Control of UATs

6.2.1. Steering Control

The structure of a typical control system for UATs is shown in Figure 12 [98]. The control of the execution unit is critical for achieving autonomous navigation. The steering actuator controls the steering motion of the UAT. It converts the control signals from the steering controller into steering torque to cause the wheels to turn. Mechanical and hydraulic steering actuators are commonly used. The mechanical type has an electric motor to power the steering axle of UAT. It is easy to install and widely adaptable.

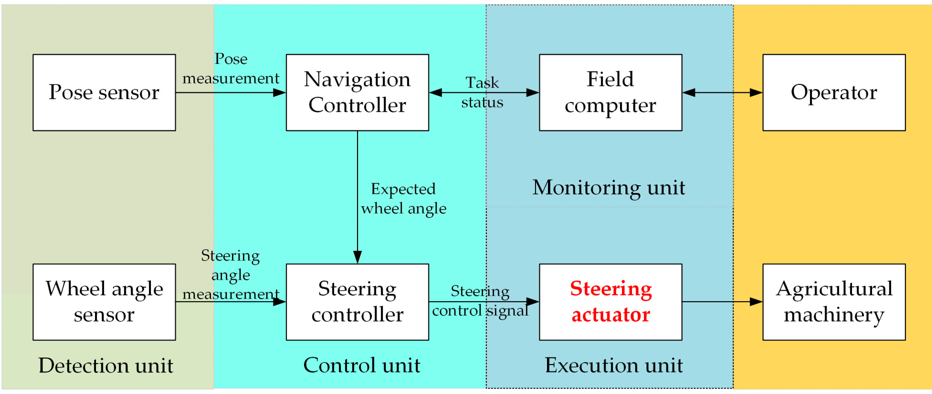
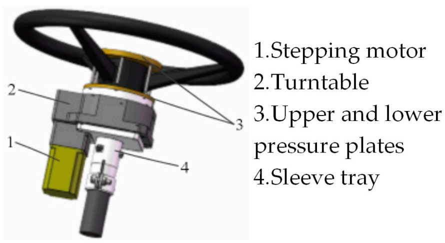
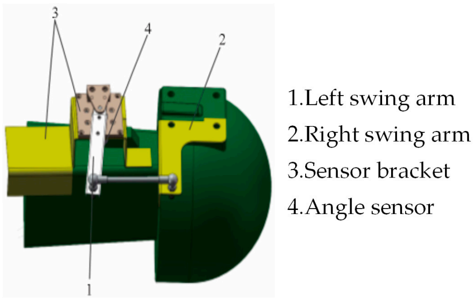


Figure 12. Structure of a typical control system for the autonomous navigation of UAT.

Mechanical and hydraulic steering systems have low accuracy, slow response times, and large error potential. They are unsuitable for high-precision operations of UATs. Electronic steering control is widely used. Electronic devices precisely control the motor's speed and steering angle. Zhang et al. [99] used a PLC (programmable logic controller) and a stepping motor to control the steering wheel's rotation (Figure 13) and achieve automatic navigation. Li et al. [100] proposed a PID control method for a four-wheel steering system. They designed a hydraulic multi-wheel steering system to improve the maneuverability and operational efficiency of a sprayer. The autonomous driving of UATs requires the control of basic functions like forward motion, stopping, and the ability to make quick turns. Therefore, steering control is crucial, and lateral torque control ensures rapid turning of the UAT [101]. Xu et al. [102] proposed a method to estimate a UAT's steering state and parameters. The controller analyzed the required steering torque and calculated the appropriate current to activate the steering motor, thereby facilitating the desired rotation of the motor.



(**a**)



(**b**)

Figure 13. Diagram of (**a**) the steering control module and (**b**) the steering angle detection module of a UAT [99].

6.2.2. Brake Control

The brake control module is a key component of the automatic control system. It controls the brakes to decelerate the vehicle. The objectives of brake control in UATs are to adjust the braking force, stop the vehicle, reduce the speed, and ensure that the moving object operates in a safe and stable manner. The design of the brake control module must consider multiple factors, such as control algorithms, brake types, dynamic adjustment, real-time control, and safety. It requires targeted design and implementation to achieve efficient, precise, and safe brake control.

6.2.3. Speed Control

Precise speed and turn control improve operational efficiency, enhances work quality, and ensures operational safety of UAT. Speed control autonomously adjusts the vehicle's velocity based on the required tasks or environmental changes. Automated speed control can adjust the speed with high precision based on the required tasks, work site, and terrain. Li et al. [103] designed an experimental platform based on a crawler tractor and an RTK-GPS control system. This system enabled the UAT to follow predetermined routes and achieve low tracking errors.

Common control techniques for turn control include steering wheel angle, differential, and dual-layer PID control methods. Turn control for autonomous driving systems requires multiple data sources, such as GPS position information, to improve control accuracy and vehicle safety. Zhou et al. [104] proposed a hybrid electro-hydraulic steering system with an improved method based on a competitive multi-objective particle swarm optimization algorithm. This system facilitated steering with an improved steering feel and reduced steering wheel backlash.

6.3. Controller Area Network Bus Technology for UATs

Advances in controller area network (CAN) bus technology have resulted in increased applications for UATs. Communication between electronic control units using CAN bus has been achieved in some developed countries [105]. The intelligence of smart agricultural machinery depends on the communication level, hardware structure, software architecture, and algorithms. Communication is required to ensure intelligent applications. Rohrer et al. [106] investigated the CAN bus technology for tractor data acquisition. The results showed that Leaf Light v2 (EAN: 73-30130-00685-0, Kvaser Inc., Mission Vieho, CA) and CanKing (v. 5.06.057, Kvaser Inc., Mission Vieho, CA, USA) software could provide raw logging data. CANcaseXL_log hardware combined with the CANalyzer software enabled the conversion of the raw logging data into a file to visualize the data. To examine variations in data acquisition and conversion, Marx et al. [107] utilized diverse data acquisition methods to collect CAN bus data from tractors. The results showed that using the waveform CAN bus data maintained the accuracy of digital data and reduced the processing time and memory requirements. Liu et al. [108] developed a CAN communication network system following the ISO 11783 [109] protocol specifically designed for a bifurcated power electric tractor. The results showed that the bus load rate of the proposed CAN bus network system was 12%, meeting the communication requirements. The research status of the use of CAN bus technology for the autonomous navigation of UATs reveals that this technology has been commercialized internationally, whereas China is in the research and experimental stage. Table 4 presents the characteristics of various control methods for the operational states of UATs.

Table 4. Comparison of characteristics for various control methods.

Control Method	Modeling	Applicable Systems	Advantages	Disadvantages
PID Control	No	Linear	Robustness, simple structure, easy implementation	Trade-off between overshoot and response time
Neural Networks	Yes	Nonlinear	Strong adaptability, robustness, high precision	Slow convergence, susceptibility to local optima
Fuzzy Control	No	Nonlinear	Robustness, adaptability, disturbance rejection, stability	Lower control precision, static error
Sliding Mode Control	No	Nonlinear	Robustness, fast response, simple implementation	Potential high-frequency oscillations

7. Application of UATs in Precision Farming

7.1. Applications in Plowing

The application of unmanned driving systems in plowing has already seen heavy implementation. A control method was developed for unmanned tractors to improve rotary tillage accuracy using model predictive control. Their method resulted in minimal yaw angle (0.06 rad) and lateral deviations (0.013 m) during rotary tillage. Cooperative control enhanced overall performance [110]. Crisnapati et al. [111] created a path planning system for autonomous tractors using Laravel and Google Maps. The algorithm generated paths based on user parameters, validated for rice field plowing missions with a maximum error of 2.61 m between waypoints and tractor position. This method allowed farmers to customize path distances based on puddler widths.

7.2. Applications in Field Management

Weed control, pesticide spraying, and orchard monitoring can be efficiently performed with UATs. An unmanned weeding machine for maize fields using navigation data from the seeding tractor was developed [112]. Based on this data, the intelligent autonomous weeder autonomously weeded the field, excluding the headlands. With a 50 cm hoe width and 75 cm row spacing, the study proved the feasibility of achieving precise weeding at the field level. Pan et al. [113] introduced a novel semantic mapping and navigation framework to enhance robot autonomy in orchards. This framework consisted of a semantic processing module and a navigation module. The developed visibility graph provided efficient global navigation guidance for autonomous vehicles in orchards, crucial for tasks like automated orchard harvesting and monitoring. By utilizing density, mean height, and angle features, the method significantly reduced processing time to just 0.1949 s.

7.3. Applications in Seeding

Using UATs for seeding can improve the standardization of planting. Hensh et al. [114] created an unmanned wetland paddy seeder that demonstrated precise seed metering and excellent maneuverability, achieving superior seeding quality compared to manual drum seeders. It enabled accurate remote seeding in wetlands with a tight turning radius of 0.8 m and minimal deviation from a straight path at 22.13 mm. Minn et al. [115] used RTK-GNSS positional sensors for real-time data collection of a multi-crop seed broadcaster on an autonomous seeding vehicle. The system performed optimally at a speed of 0.351 m/s, with seed distribution uniformity variations of 19% for green peas, 22% for cowpeas, and 25% for chickpeas.

7.4. Applications in Harvesting

There are also many applications for UATs in harvesting. Shang et al. [116] presented an obstacle detection algorithm using 2D lidar to prevent collisions between harvesters and obstacles in unmanned agricultural operations. They utilized a density-based clustering method to assess obstacle quantity and width. The algorithm achieved 95.06% accuracy in detecting multiple obstacles and 92.67% accuracy in stopping for hazardous obstacles.

7.5. Other Applications

In recent years, unmanned vehicles have gradually started to be applied in the breeding industry. Anzai and Sakurai [117] researched how cattle respond to herding by unmanned vehicles and its impact on grazing patterns. They used a small, unmanned ground vehicle to herd cows for seven days, strategically approaching them to influence their movement. The study suggested that robotic herding with unmanned vehicles can help control grazing distribution. To address low-light and low-stress environments in livestock and poultry houses, a method using "magnet-RFID" marks on the ground to detect navigation paths was proposed. This enables robots to automatically move between cages and be utilized as automatic disinfectant sprayers in livestock and poultry houses [118].

8. Discussions

The current trend shows a dwindling agricultural workforce, especially among the younger generation. Therefore, the urgent task for agricultural development is to invest in unmanned agricultural machinery to reduce dependency on manual labor. Consequently, numerous experts and scholars have initiated research on UAT technology. This article offers a comprehensive examination of advancements in perception, navigation, and control of UATs. Beyond these aspects, research on UAT technology also includes studies on mechanical structures like power shifting and CVT technologies [119], which are also essential for autonomous driving of tractors. This study focuses on the intelligent technology of UATs, leaving discussions on advancements in mechanical structures for future exploration.

Currently, UATs in China are still in the research and development stage and have not been fully commercialized. There are several companies working on them. For instance, in September 2023, China's YTO Group successfully rolled out 100 intelligent tractors [120], yet they have not undergone large-scale production. The John Deere company has also produced autonomous tractors [121], but their technology is only suitable for local use. Therefore, in actual production, semi-automated tractors with human-assisted driving are primarily used [122]. However, the development of UAT technology will inevitably have a potential impact on existing situations. UATs can save labor, increase operational standardization, and eliminate the inconsistencies of manual work. Once they are commercialized, the use of traditional tractors will decrease, promoting traditional manufacturers to transition into intelligent manufacturers [123].

UATs are mainly intended for medium to large-scale farms with highly standardized fields and sufficient economic capacity to purchase such equipment [124]. Traditional manually operated tractors, on the other hand, will primarily be used in small family farms and by individuals, as they are suitable for small and irregular fields. Of course, some manually operated tractors will still be used on large scale farms, such as tractors used for road transport [125], due to the complexity of agricultural roads, making autonomous driving both challenging and unnecessary.

9. Conclusions and Future Work

9.1. Conclusions

Extensive and comprehensive research has resulted in advances in the autonomous navigation of UAT. Critical intelligent technologies include GNSS, inertial navigation systems, fusion of positioning data and sensor information, integration of global and local path planning, and precise motion control. Based on a thorough summary and analysis of current research, the following conclusions can be drawn:

(1) The perceptive technique, including positioning, and internal and external sensing of tractors, are currently the two most widely studied technologies in the UAT field. GPS and BDS are widely used GNSS technologies for differential positioning. By using centimeter-level positioning data from GNSS satellite navigation systems, combined with inertial sensors, vision sensors, radar, etc., precise positioning and sensing of UATs can be achieved. Nevertheless, the utilization of GNSS technology for the autonomous navigation of UATs remains relatively limited due to extreme weather conditions and signal disruptions. Various sensors used in this field have both merits and drawbacks. Sensor fusion methods are commonly employed to increase positioning accuracy and reliability. Widely adopted information fusion approaches include Kalman filtering and particle filtering.

(2) Path planning and tracking are influenced by field conditions, types of machinery, and turning radius. The motion model precision significantly impacts the accuracy of UAT navigation, especially in complex field environments. Achieving effective and practical automatic boundary steering remains a challenging issue in autonomous navigation control, particularly for turns at field boundaries. Dividing the field into different types and then implementing full-coverage path planning for the target area is the main approach. Obstacle detection in the field can be accomplished using

machine vision methods or laser ranging. Stopping machinery is the simplest obstacle avoidance measure because a real-time path planning approach for obstacle avoidance is not yet available.

(3) Speed control and steering control form the foundation of motion control for UAT, while navigation tracking control constitutes its primary focus. The control of speed, and steering is crucial for ensuring the working precision and motion reliability of UAT. The combination of traditional and intelligent control algorithms, coupled with high-performance steering controllers, is essential for improving the navigation efficiency and precision of UAT. The key to whether a motion control method can adapt well to its environment lies in how control parameters are adjusted to enhance the speed and accuracy of the control system. The role of machine learning algorithms in motion state recognition and parameter optimization has become increasingly prominent in recent years.

9.2. Future Work

(1) In terms of perceptive techniques, high-precision maps of farmland with a priori knowledge will be a key focus of future research. It is necessary to conduct research on creating practical and efficient autonomous navigation scheduling systems tailored to China's conditions. It is crucial to design appropriate sensor combinations, select reliable and effective sensor fusion strategies, and leverage the advantages of sensors to ensure data redundancy or complementarity. Accelerating the usage of the Internet of Things and communication technology for environmental perception is also essential for the autonomous navigation of UAT. A big data cloud platform with 5G high-speed networks needs to be established for UATs to promote the remote monitoring technology.

(2) In terms of path planning and tracking techniques, full-coverage path planning algorithms suitable for irregular fields, multiple obstacles, and multiple constraints need be developed to achieve adaptive path planning for tractors and implements with different turning radii. It is required to develop advanced obstacle avoidance measures suitable for the operating environment of UAT. Real-time obstacle avoidance path planning should be implemented for the dynamic control of tractor and obstacle avoidance. Extensive research may be conducted to develop science-based mathematical models and algorithms for path planning and tracking to enhance efficiency and precision.

(3) In terms of motion control techniques, due to factors like varying loads, the methods based on kinematic models lack robustness and fail to account for changes in dynamic characteristics, making it difficult to achieve the desired results. The future trend should be to establish high-fidelity nonlinear dynamic models for autonomous driving agricultural equipment. Employing machine learning methods to create a tractor motion model can prevent inaccuracies in modeling. This can also help avoid significant changes in model parameters that might impact the efficiency of tractor motion control. This strategy is steadily emerging as a primary focus of research. Extensive research is required to be conducted in order to achieve high-precision and high-reliability motion control units.

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