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THE ARTIFICIAL INTELLIGENCE DRIVEN AUTONOMOUS NAVIGATION OPERATION PATH PLANNING SYSTEM FOR AGRICULTURAL MACHINERY

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Abstract. This study aims to develop an artificial intelligence-based autonomous navigation job path planning system for agricultural machinery. The core algorithm of the system combines path planning, monocular vision, visual navigation map, area detection and color calibration, etc., to realize autonomous navigation and efficient operation of agricultural machinery in complex farmland environments. The system uses the visual navigation map and area detection algorithm to identify and plan the path of the target area. The color calibration module further improves the accuracy of image information and provides higher reliability for path planning. The simulation results show that the system can accurately detect the working area in the complex farmland environment, plan the optimal path, and ensure the stability and efficiency of the mechanical operation. Accurate data analysis shows that the path planning success rate of the system is more than 90% in various farmland scenarios, effectively improving the automation level of agricultural machinery operations. This study provides a new idea and practical basis for future intelligent development of agricultural machinery.

Key words: Artificial intelligence; Agricultural machinery; Autonomous navigation; Path planning; Visual image.

1. Introduction. With the development of modern agriculture, the intelligent demand for agricultural machinery is increasing daily. How to realize the autonomous navigation of agricultural machinery in complex farmland environments has become an important research direction. Against this background, the techniques of path planning, monocular vision, visual navigation map, area detection and color calibration have been widely used and studied. The combination of these technologies not only improves the efficiency of agricultural machinery but also lays the foundation for precision agriculture.

The traditional path planning method mainly relies on GPS and inertial navigation systems, but its accuracy and reliability have significant limitations in complex terrain and occlude environments. In literature [1], A path planning method based on the A* algorithm was proposed to solve the problem that traditional path planning is not flexible in path selection in farmland operations by introducing cost function and heuristic search. However, such methods still have the challenge of insufficient navigation accuracy in the face of an unstructured farmland environment. As a low-cost and high flexibility image acquisition method, monocular vision technology has a broad application prospect in agricultural machinery navigation. Document [2] uses a monocular camera to obtain farmland images and realizes farmland boundary identification through an image processing algorithm, effectively solving the problem of inaccurate farmland boundary detection. However, due to the complexity of the farmland environment, the robustness of monocular vision under different lighting conditions needs to be further improved. The generation and application of visual navigation maps are a vital link to realizing the autonomous navigation of agricultural machinery. Literature [3] proposes a farmland map construction method based on visual SLAM technology, which solves the problem of real-time map generation and updates in the farmland environment by matching continuous image frames and location estimation. This method is effective in structured environments, but the accuracy and stability of visual navigation maps in unstructured farmland still need further study. Area detection is a critical step in path planning. Literature [4] adopted a deep learning-based region detection algorithm to solve the problem of low target region recognition rate in

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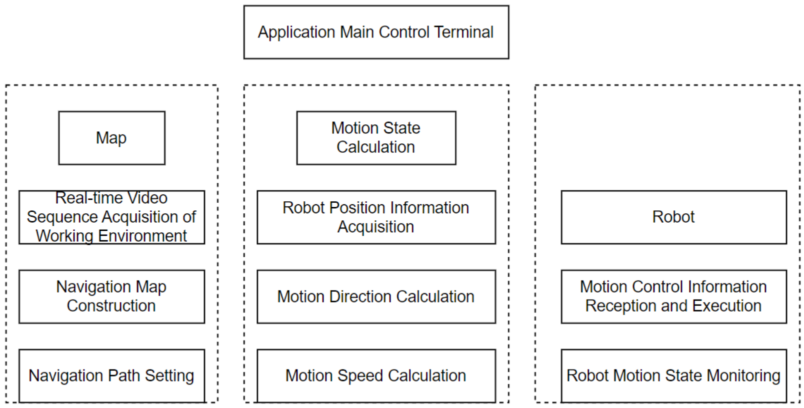

Fig. 2.1: Block diagram of the agricultural robot navigation system.

complex farmland scenes. However, due to the diversity of farmland scenes, this method lacks generalization ability. Current research focuses on improving the stability and accuracy of region detection algorithms in diverse scenarios. Color calibration plays a vital role in the visual navigation system, which can help the system maintain image recognition stability. Literature [5] proposed a calibration method based on color model conversion, which dynamically adjusts the image color space to solve the problem of image deviation caused by light changes in farmland operations. However, achieving accurate color calibration under complex lighting conditions is still a significant challenge in visual navigation systems.

In summary, the existing research has made remarkable progress in path planning, monocular vision, visual navigation maps, area detection and color calibration, but some shortcomings remain. This paper proposes an artificial intelligence-driven path planning system for agricultural machinery autonomous navigation [6]. The system combines path planning and monocular vision technology and realizes autonomous navigation in complex farmland environments through a visual navigation map and area detection algorithm. A color calibration module is also introduced to improve navigation accuracy under diverse lighting conditions. This paper will focus on the algorithm design, model simulation and experimental verification process of the system and analyze the simulation results in detail to provide a reference for the future development of intelligent agricultural machinery.

2. System structure design. The robot navigation system consists of two parts, including the main control terminal of the application system and the control terminal of the robot's lower computer. They are responsible for establishing navigation maps, planning paths, identifying robot positions, and updating the robot's motion status to ensure that the robot can follow the user's planned route [7]. The above application mainly uses the camera to collect the image of the working environment of agricultural machinery, and constructs its visual navigation diagram to locate it. Then, the data, such as the planned route and the starting point location, are used to analyze the following movement conditions. The control information of the moving condition is transmitted to the bottom controller of the robot through the network communication module [8]. Then, on the bottom controller, the robot moves according to the trajectory designed by the user. At the same time, the current working status of the slave controller is transmitted to the master controller of the application system as a data frame, which helps the master controller modify the robot arm's action in real time. The control process block diagram of the agricultural robot navigation system is shown in Figure 2.1.

3. Structural design of agricultural robot.

3.1. Agricultural robot motion model. The agricultural machine robot has a three-wheel all-round traveling mode. It is composed of three McNamm wheels, each at 120 degrees Angle, to form a walking mechanism, through the lateral speed and the corresponding relationship between the speed of the walking wheel, to realize the agricultural machinery robot [9]. It can follow the command issued by the navigation

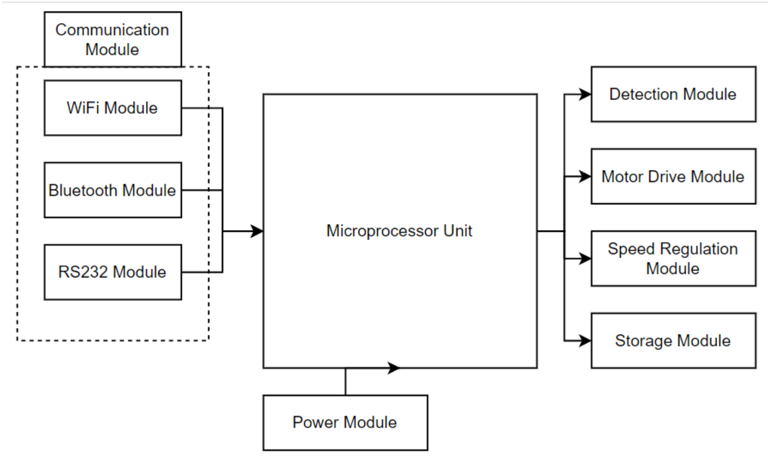

Fig. 3.1: Hardware structure block diagram.

control software and carry out the operation according to the route made by the user. The moving trajectory is a discrete point including starting and ending points. The accumulated error is reduced by updating the mobile node in real-time.

3.2. Hardware of the control terminal of the lower computer. In the control part of the slave machine, the acceptance of the control command of the host system, the guidance of the robot's motion trajectory, the adjustment of the motion difference and the detection of the state are completed [10]. It mainly includes a communication module, microprocessor module, power module, storage module, motor drive module and speed control module. The hardware configuration block diagram is shown in Figure 3.1.

The central controller of the navigation and positioning system transmits real-time positioning information, moving direction and speed calculation data to the subordinate microcontroller through the communication module [11]. Then, the speed adjustment module and the motor drive module are adjusted by the single-chip microcomputer to realize the adjustment of the motion state of the robot arm. With 32-bit STM32F103 as the slave chip, the system can receive and execute the instructions of the central controller of the application system and monitor the robot's movements. The DC motor on each moving wheel is driven by double pulse width modulation and pulse width modulation [12]. Then, the speed of each moving wheel is controlled. The power supply unit provides a continuous and stable operating voltage for the underlying controller of the robot.

4. Position and navigation of agricultural robots based on visual positioning. The system uses a single-eye camera to collect images of the job site, build a visual map of the job area, and carry out automatic navigation—real-time positioning and tracking of the robot's movement on the visual map [13]. At the same time, the user's customized route is combined to obtain the next moving direction and speed. This allows autonomous navigation from the starting point to the end.

4.1. Principle of Monocular Visual Positioning. The position accuracy is a necessary standard to measure the work efficiency when the robot moves autonomously. The 2D image of the working environment is drawn by transforming the Angle of view to achieve the transformation from world coordinates to image coordinates based on obtaining the working environment image of agricultural machinery using monocular vision [14]. In addition, the project uses the upper part as a reference plane to establish a navigation map based on vision.

4.2. Obstacle avoidance method of agricultural machinery arm in the process of moving. There are often mobile obstacles in the cooperative process of multiple agricultural machines. When encountering movement obstacles, achieving high precision, or avoiding the target is often impossible, failing multiple agricultural machinery equipment. However, the obstacle avoidance method designed by the potential field method can effectively avoid random obstacles in the movement and plan a feasible path [15]. The repulsive force between objects and the gravity between working targets overlap to make the manipulator move toward the predetermined working attitude under the push of external force. The mechanical arm is driven by the combined force of gravity F_a and repulsive force F_β to move in the direction of the purpose [16]. The role of the gravity potential field in the conventional artificial potential field method is:

$$V_a = \frac{1}{2}\lambda_b \left|R - R_{gaal}\right|^2 \tag{4.1}$$

F_α is the gravitational coefficient. Where R is the point coordinate vector required in the process of grasping the manipulator. R_{gool} is the object positioning vector.

$$F_a = -\operatorname{grad}(V_a) = \lambda_b \left|R - R_{gad}\right| \tag{4.2}$$

The repulsive force of the conventional artificial potential field method is:

$$V_\beta = \begin{cases} \frac{1}{2}\lambda_s\left(\frac{1}{\xi} - \frac{1}{\xi_0}\right)^1 & (\xi \leq \xi_0) \\ 0 & (\xi > \xi_0) \end{cases} \tag{4.3}$$

λ_s is the coefficient of repulsion. Where ξ is the distance from the central point of the obstacle to the harvesting arm. ξ_0 represents the range of action of the obstacle, which is usually a constant [17]. The negative slope of the resistance field is shown as follows:

$$F_\beta = -\operatorname{grad}(V_\beta) = \begin{cases} \lambda_s\left(\frac{1}{\xi} - \frac{1}{\xi_0}\right)^2 \frac{1}{\xi^2}\frac{\partial\xi}{\partial R} & (\xi \leq \xi_0) \\ 0 & (\xi > \xi_0) \end{cases} \tag{4.4}$$

The force acting on the robotic arm is

$$F_{\text{bowl}} = F_a + F_\beta \tag{4.5}$$

When the picking robot approaches the object, the resulting repelling effect causes the arm to deflect. Therefore, a potential method is proposed to ensure the trajectory of the acquisition manipulator [18]. In this method, the repulsion field is adjusted by changing the distance between objects to minimize the repulsion between objects. The modified function is

$$V_\beta = \begin{cases} \frac{1}{2}\lambda_s\left(\frac{1}{\xi} - \frac{1}{\xi_0}\right)2\left(R - R_{\text{goal}}\right)2 & (\xi \leq \xi_0) \\ 0 & (\xi > \xi_0) \end{cases} \tag{4.6}$$

Different from the general repulsion calculation method based on the artificial potential field, with the improved repulsion force, the suction force received by the robot when approaching the obstacle continues to increase, and the repulsion force will gradually decrease. As the picking robot gets closer, the repulsive force gets smaller, and gravity gets bigger. The repulsive force acting on the robotic arm is the resultant force. Its expression is as follows

$$F_\beta = F_{\beta 1} + F_{\beta 2} \tag{4.7}$$

When the object exerts $F_{\beta 1}$ repulsive force A on the robotic arm, there is also a gravitational force $F_{\beta 2}$ acting on the object.

4.3. Position and trajectory control of the agricultural mechanical arm. Agricultural machinery should avoid operation in various environments and ensure the optimal solution of the operation route. Suppose that the ant code of the agricultural robot is $\lambda(\lambda = 1, 2, \cdots, m)$, and all the nodes it passes through are marked as tabu $u_\lambda(\lambda = 1, 2, \cdots, m)$, and the forbidden search list is constructed. By optimizing the algorithm, the algorithm has the minimum search distance. Plan your following route. Suppose the interval $L_{i,j}(i, j =$

$0, 1, \cdots, n-1$) from node i to node j, then the pheromone density on the line between node ij and node j at time t is δ_{ij}. The probability of the colony moving from one place to another in each time is

$$f_{ij}^{\lambda} = \begin{cases} \frac{\delta_{ij}^{c}(t)\varphi_{ij}^{d}(t)}{\sum_{\lambda \in \text{ allowed }_{\lambda}} \delta_{ij}^{c}(t)\varphi_{ij}^{d}(t)} \\ j \in \text{ allowed }_{\lambda} \\ f_{ij}^{\lambda} = 0, \text{ other} \end{cases} \tag{4.8}$$

allowed $_{\lambda}$ provides every node that can be moved and selected. c is a motivator of information. d is the required revelatory factor. φ_{ij} is an illuminating function. At time $t+n$, information about the route (i, j) program can be adjusted to

$$\delta_{ij}(t+n) = (1-\xi) \times \delta_{ij}(t) + \Delta\delta_{ij}(t) \tag{4.9}$$

$$\Delta\delta_{ij}(t) = \sum_{i=1}^{m} \Delta\delta_{ij}^{\lambda}(t) \tag{4.10}$$

$\xi \in (0, 1)$ is the pheromone releasing factor. $\Delta\delta_{ij}^{2}(t)$ represents an increase in pheromones. The population density of ants can be divided into three categories: the ant week model, the ant number model, and the ant density model. The following formula can represent the ant cycle system pattern

$$\Delta\delta_{ij}^{2}(t) = \frac{W}{H_2} \tag{4.11}$$

The ant population model can be expressed as

$$\Delta\delta_{ij}^{2}(t) = \frac{W}{L_{ij}} \tag{4.12}$$

The ant density model can be expressed as

$$\Delta\delta_{ij}^{2}(t) = W \tag{4.13}$$

where H_2 is the sum between nodes. W is for pheromone. Combining the ant optimization and artificial potential field methods enables the agricultural robot arm to avoid arbitrary obstacles and achieve intelligent path planning. The flow of the position tracking algorithm is shown in Figure 4.1.

The rich and vast color space of RGB mode is used to better adapt to the color transformation requirements caused by environmental factors such as environment and lighting. Through the feedback adjustment of the path, the path planning is completed and determined as the shortest path, and then the path is output. Optimal processing can be performed when the minimum distance is not reached.

5. Experimental verification and analysis. A collision avoidance method based on a moving target is proposed. Its main objective is to prevent conflict between the agricultural machinery arm, the obstacle body, and the robot arm and enhance its obstacle avoidance ability. The operation scheme of multiple agricultural machines designed according to the law of moving obstacle avoidance is given. Many moving obstacle groups were established and simulated, and the following trajectory planning was obtained (Figure 5.1).

The effectiveness of this method is obtained through several experiments. Experimental results show this method can be used for trajectory planning under arbitrary obstacles. Finally, the ant colony algorithm, genetic algorithm, neural network, and fuzzy algorithm are compared, and the conclusions are shown in Table 5.1.

The simulation results show that the ant algorithm can achieve more success time, a more extensive average route and maximum operational efficiency.

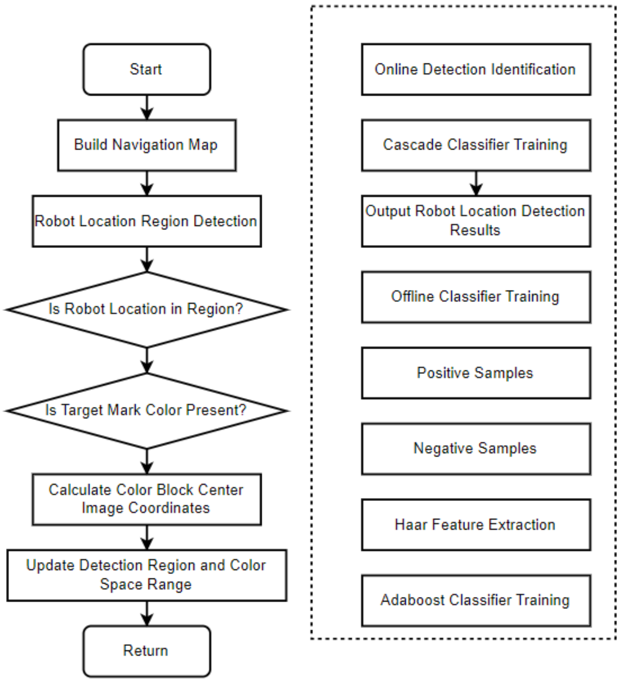

Fig. 4.1: Flow chart of the positioning tracking algorithm.

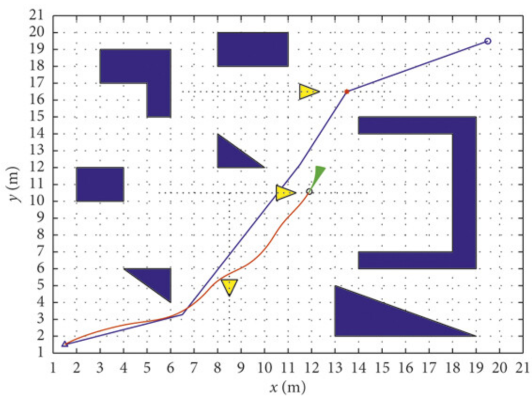

Fig. 5.1: Result of multiple dynamic path planning.

Table 5.1: Test result table for path planning.

Algorithm	Number of successes	Average path length /m	Average running time per cycle /s
Ant colony algorithm	49/50	4506	0.33
Genetic algorithm	47/50	5099	0.68
Neural network algorithm	46/50	5133	1.27
Fuzzy algorithm	45/50	4954	1.44

6. Conclusion. In this study, an artificial intelligence-based path planning system for agricultural machinery autonomous navigation was developed, which utilized monocular vision, visual navigation map, area detection and color calibration technology to achieve accurate navigation and operation in complex farmland environments. By designing a path planning algorithm, the system can effectively identify the working area, generate the optimal path to guide agricultural machinery operation and improve its automation level. The experimental and simulation results show that the system has a high degree of path planning accuracy and stability in various farmland scenarios, ensuring the continuity and efficiency of mechanical operation. By introducing a visual navigation map and color calibration module, the system can still stably detect regional boundaries under complex lighting conditions, reduce errors, and optimize navigation effects. Comprehensive evaluation shows that the path planning success rate of the system is more than 90%, which saves time and improves precision. The research results strongly support the development of intelligent agricultural machinery and provide a new idea and reference for the future intelligent path planning of agricultural machinery.

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