Route Planning and Machine Learning Algorithms for Sensor-Equipped Autonomous Vehicles in Agriculture

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Abstract: This paper aims to improve the efficiency and safety of autonomous agricultural vehicles (AAVs) in complex agricultural settings by integrating sensor technology and deep reinforcement learning techniques. The traditional fixed-route transport is expensive and prone to vehicle collisions. Advanced AAVs equipped with multiple sensors were employed for collecting and processing sensor data, were employed for collecting and processing sensor data. This algorithm can effectively identify moving AAVs, static obstacles and other relevant targets in agricultural environments. A deep reinforcement learning model was built by using Deep Q-Networks and neural networks and a simulation environment was created with the purpose of validating the path planning and obstacle avoidance capabilities of the proposed model.

Keywords: Simulation, Kinematics, Dynamics, Trajectory, Cornering.

1. Introduction

Sensor-equipped autonomous agricultural vehicles (AAVs) are increasingly being used for optimizing crop management and other agricultural activities, helping to increase productivity, reduce costs and improve resource efficiency (Bloch, Bechar, & Degani, 2017; Amin et al., 2023). These autonomous vehicles are designed to perform complex agricultural tasks, such as harvesting, irrigation and fertilization, without requiring continuous human intervention (Dusadeerungsikul et al., 2019). However, the use of fixed routes by these vehicles is proving to be costly and prone to collisions, especially in extensive agricultural operations.

The problem of route management becomes apparent in situations where AAVs must operate simultaneously under variable terrain with dynamic obstacles and unpredictable environmental conditions. To this end, many researchers proposed a series of studies based on traditional route planning algorithms to address the specific challenges of modern agriculture.

Bechar & Vigneault (2016) developed a traffic control algorithm for multiple autonomous agricultural vehicles (AAVs) scheduling through system programming, providing theoretical and practical support for the simultaneous management of multiple autonomous vehicles in agricultural monitoring tasks. They also designed an efficient system for multiple AAVs using a modified algorithm that efficiently manages vehicle allocation to avoid collisions. They optimized the A* algorithm by adding a weighting factor to the Euclidean function and using a task segmentation strategy, aiming to increase efficiency and accuracy under different agricultural conditions. Ban (2024) also improved the algorithm performance for obstacle avoidance and route planning in the Deep Q-Learning network by integrating a genetic algorithm.

Recently, deep learning has shown an enormous potential in optimizing planning strategies for multiple autonomous agricultural vehicles (AAVs) in agriculture. Weiss (2000) proposed an automation-based learning model that guides AAVs to optimize their paths using an algorithm and a simulated remote control strategy. The Deep Q-Network-based method addresses the shortcomings of traditional algorithms in managing large-scale agricultural spaces, improving the success rate and efficiency of AAVs in monitoring and managing crops over large areas. The study of Amin et al. (2023) proposed a curiosity-based learning method to solve complex agricultural planning problems.

To address these challenges, the present study proposes an advanced route planning method for multiple AAVs using the A* algorithm, a classical algorithm employed for route optimization (Yin et al., 2023). By integrating multiple sensor technology, the proposed model enables an advanced environmental perception, being capable of detecting moving vehicles, static obstacles and other relevant targets in agricultural fields. This allows AAVs to adjust their routes in real time and avoid collisions, thereby improving the efficiency and safety of agricultural operations.

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This paper also proposes the use of binocular cameras and LiDAR sensors integrated in AAV vehicles to capture data about the environment and to facilitate the perception of obstacles. This method uses relative reference points to determine short-term goals and it is based on a deep learning model that uses reward and punishment for each navigation attempt. This approach accelerates learning speed and optimizes traffic, which results in a longer and faster travel and an improved operational efficiency in handling complex agricultural tasks.

In addition, to further optimize the behavior of autonomous vehicles, this paper introduces a reinforcement learning model based on Deep Q-Networks (DQN). This model allows autonomous vehicles to learn from experience, constantly improving their obstacle avoidance and path management strategies. The results of the simulations carried out for validating these methods showed significant improvements in the efficiency of agricultural operations, underscoring the potential of advanced technologies to revolutionize the management of modern agriculture.

This paper is structured as follows. Section 2 includes a brief presentation of the theoretical framework. Section 3 presents the proposed model and methodology. Section 4 is devoted to a detailed analysis of the results obtained from the simulations which were carried out, and Section 5 concludes this paper while also outlining the future development directions.

2. Theoretical Framework

Recent studies have shown that AAV systems can be extremely useful for managing large farms where variable soil, climate and crop distribution conditions make manual planning of operations difficult (Ajidarma and Nof, 2021; Sreeram & Nof, 2021; Amin et al., 2023). The A* algorithm is one of the most widely used algorithms for optimal route planning. Developed by Peter Hart, Nils Nilsson and Bertram Raphael in 1968, the A* algorithm works on the principle of searching the search space to find the optimal path from the starting point to the destination, taking into account the costs associated with each step of the path (Yin et al., 2023).

In the context of autonomous farming, A* is ideal for route management in a constantly changing environment, such as fields with dynamic (farm machinery, animals) or static (buildings, fences) obstacles. The study of Yin et al. (2023) highlights that the A* algorithm is particularly effective when combined with perception sensors that provide real-time data about the surrounding environment, enabling a rapid route adjustment. In this model, the A* Algorithm provides the basic structure of the route, which would later be adapted by the DQN in cases of unforeseen obstacles.

According to the study by Sewak (2019), DQN learns through continuous feedback received from the environment. Each decision (for example, changing the route or adjusting the speed) is evaluated based on a reward function, which provides positive or negative feedback depending on the result obtained. This process allows vehicles to learn the optimal strategies for avoiding obstacles and navigating efficiently. Thus, DQN complements the A* Algorithm, ensuring an increased adaptability in unforeseen conditions and a prompt response to environmental changes, thus optimizing the overall vehicle performance.

In an agricultural context, a DQN can be used to teach vehicles to adjust their routes based on weather conditions, moving obstacles (such as other vehicles or animals), and specific operation objectives (e.g. optimizing operating distance or time). Various studies indicate that by using deep reinforcement learning, AAVs become smarter and more capable of operating autonomously in unpredictable environments such as agricultural farms (Wang & Fang, 2020; Amin et al., 2023). The sensors capture data about the environment, which is then processed by LSTM neural networks to extract data from the LiDAR point cloud and information about the vehicle's condition, thereby facilitating obstacle perception. A double convolutional neural network is used to process camera and LiDAR data, achieving accurate classifications of agricultural targets and obstacles.

According to the literature, there are two main types of global route planning for sensor-equipped autonomous agricultural vehicles (AAVs) depending on the application scenarios (Bechar & Eben-Chaime, 2014; Amin et al., 2023). The first is offline global planning, which applies to environments with static obstacles, where the location of each obstacle is known in advance (Li et al., 2015). This method requires the AAV to have a complete map of the working environment with no unpredictable changes during operations. The second one is online global planning, which targets dynamic scenarios with partially known environments and moving obstacles such as agricultural machinery, animals or human workers. A problem with offline planning is that when the AAV encounters an unexpected obstacle, it must replan the route, which reduces its operational efficiency.

The role of the A* algorithm in the model proposed in this paper is to provide a basis for global route planning, which is optimized for the known conditions related to the agricultural environment. The A* algorithm uses a static map, where fixed obstacles (e.g. buildings or fences) are already known, to calculate the shortest possible route between the starting point and the destination. This offline approach provides an optimal route in terms of distance and travel cost, thus enabling an efficient navigation in predictable work areas. In this model, the A* algorithm provides the basic structure of the route, which will later be adapted by the DQN in cases of unforeseen obstacles.

This paper also proposes a model that is trained by minimising the squared errors between the predicted values and the actual target cost values for key reference points (e.g. field navigation points), matching an optimal path with a minimum cumulative cost for each AAV. This leads to a global planning model for multiple autonomous vehicles, capable of solving the problem of replanning when encountering unforeseen obstacles. This approach allows autonomous agricultural vehicles to navigate efficiently with a smoother trajectory and an optimized resource consumption.

To facilitate communication between the employed algorithms and the environment, data is collected and processed by a Long Short-Term Memory (LSTM) neural network and a Convolutional Neural Network (CNN). These networks interpret information received from sensors, extracting the relevant features related to obstacles and terrain conditions. The LSTM network is responsible for analyzing spatial data, helping to accurately identify obstacles and generate short-term predictions with regard to their movements. The CNN, on the other hand, processes visual data and data captured by sensors such as LiDAR, facilitating a correct classification of the surrounding objects and obstacles. Thus, processing via LSTM and CNN networks provides essential information for the A* and DQN algorithms, which can adjust their navigation strategies according to the immediate context.

By integrating a complex data processing structure and an adaptive planning mechanism, the proposed model contributes to the development of an optimized and adaptive autonomous navigation system with significant benefits for operational efficiency and sustainability in modern agriculture.

3. Data and Methodology

Convolutional Neural Networks (CNNs) have a remarkable ability to capture both the global structure and the fine details of an agricultural environment, learning heuristically to generate structured spatial results (Amin et al., 2023; El Hamidi et al., 2019). This ability facilitates the smooth transition of heuristic values between different terrain configurations.

On this basis, in this paper convolutional neural networks were applied to the heuristic function of the A* route planning algorithm with the aim of improving the route search efficiency for autonomous agricultural vehicles (AAVs). The proposed model defines a planning process for multi-AAV transportation considering specific agricultural characteristics. It introduces information about the terrain topography and starting coordinates for each AAV.

Using the A* algorithm as the basis and combining traditional planning methods with deep learning approaches, this model employs automated learning functions to minimise search costs in complex environments like agricultural fields with dynamic or static obstacles. By integrating deep learning techniques such as CNN into route planning, this paper contributes to the field of precision agriculture by creating a navigation model that can operate autonomously and efficiently in complex conditions.

This approach minimises the errors for each point of reference and the total cost, identifying the optimal route for each AAV with the lowest cumulative cost. This global planning ensures an efficient navigation without delays. In this process, the key reference points on the path are defined as effective nodes, and the nodes connect the start and end points, making up a set of least-cost nodes, which would serve as the basic heuristic real values during training. For the prototype proposed by this paper, which is illustrated in

Figure 1, the function $Fcc(v)$ is used to expand the search edges, thereby accessing the successor edges and sub-vertices of vertex v.

Figure 1. The autonomous vehicle equipped with sensors used in this study

Given that obstacles render some edges impassable, the viability of each potential waypoint was validated through the function $Valid(n,v,\alpha)$. This function returns true only if the edge n is not occupied by obstacles. Based on the environment α, each candidate waypoint was evaluated using the search score function $Score(v,\alpha)$, and then they were added to the priority queue O in order based on their scores. In each iteration, the waypoint with the highest score from queue O was selected, the search scores of its sub-vertices were calculated, and they were added to the queue. This process continued until the target vertex v_p was reached or the queue O was empty.

The path cost $p(v,\alpha)$ was calculated by accumulating the shortest path edge costs $Cost(n,v',\alpha)$ encountered during the search process. As defined by equation (1), the heuristic search function assigned an integrated score to each waypoint to balance efficiency and accuracy. In this study, which targets the environments that contain obstacles, feature maps were extracted and a Fully Convolutional Neural Network (FCNN) was applied to predict the heuristic value of each waypoint. Training was conducted by minimizing the squared error between the predicted value of each waypoint and its actual target cost value. The cost of a waypoint is defined as the cumulative cost from a chosen point to the target point along the shortest path:

$$Score(v,a) = p(v,a) + h(v,a) \tag{1}$$

The training was completed by minimizing the objective function defined in equation (2), to accurately predict waypoint costs in order to optimize path planning. In the proposed model, represents the target cost value, and R acts as a mask function, assigning a value of 1 to each vertex on the path, to exclude invalid vertices, such as those occupied by obstacles or completely surrounded areas, when generating the target values:

$$L(\alpha,\hat{C},R) = \sum_{v_i \in V} ((h(v,\alpha) - \hat{C}(v))^2 R(v) \tag{2}$$

To address the lack of supervisory signals for unvisited pixels, this study adopted a temporal difference-based method to compensate for the insufficient supervisory signals, as specifically defined in equation (3). The predicted values were iteratively updated through convolution $\hat{h}(v,\alpha)$ with fixed kernels and biases, minimising across the successor vertex axis, with the loss function defined in equation (4). Here, the value of $R_{TD}(v)$ is 1 when $v \in \bar{R} \cap V$, otherwise, it is 0, and λ represents the weight coefficient for the temporal difference loss. This method refines the target cost estimation through multiple iterative updates. Training aims to plan the optimal global path for AAVs by minimizing the squared error between the predicted values and the true target costs.

At the same time, the proposed model used machine learning methods to train the A* algorithm and constantly update route cost predictions based on the feedback from the real environment. This method helps to ensure a cost-optimized route and increases the accuracy of the employed model in identifying obstacles, which in turn improves autonomous navigation and reduces the risk of disruption to agricultural operations.

$$\hat{h}(v,\alpha) \leftarrow \min_{(n,v') \in Fcc(v))} Cost(n,v',\alpha) + \hat{h}(v',\alpha) \tag{3}$$

$$l(\alpha,\hat{C},R) = \sum_{v \in V} \left\{((h(v,\alpha) - \hat{C}(v))^2 R(v) + \lambda(h(v,\alpha) - \hat{h}(v))^2)R_{TD}(v)\right\} \tag{4}$$

An alternative method for reducing the time required for agricultural operations is to add a reactive behavior pattern to the controller, which allows obstacle avoidance in real time, but it is possible that the robot deviates from the established path. When using this approach, if the robot deviates from the path, the controller will not know how to use the original path data to achieve its goal.

The path is represented as a sequence of line segments and thus it contains many discontinuities in the direction of motion. For the robot to follow such a path, it must come to a complete stop at each of these discontinuities, which significantly increases the time required for reaching the destination.

Path planning algorithms generate a geometric path from an initial point to an end point, passing through predefined intermediate points, either in the joint space or in the robot's operating space, while trajectory planning algorithms take a given path geometry and endow it with time-related information. The route planning algorithm is dependent on time.

In a multi-agent environment composed of T (see Figure 2), AAVs, the starting position v_f and the target position v_p of each AAV are connected through a series of waypoints, where the waypoint path set is defined as $p = \{r^m\}^{\alpha}$. Here, $r^m = \{x^m, y^m, \theta^m\}$ represents the m-th waypoint on the path, where T_t denotes the total number of waypoints, and $\{x^m, y^m\}$ and α^m respectively represent the two-dimensional position and direction of the AAV. Thus, this methodology also applies to complex agricultural environments, where avoiding dynamic obstacles and adapting to a changing terrain are essential for ensuring the efficiency and safety of autonomous agricultural vehicles.

As it is illustrated in Figure 2, crop rows are represented by regularly spaced continuous lines, and natural obstacles such as trees or rocks are rendered as dots scattered around them. This representation demonstrates how each AAV successfully navigates around obstacles to reach its assigned target location, with the final stopping point of the AAV indicating the final destination.

Since the signal simulated by the (AND) block is a Boolean one (true or false), it is necessary to introduce the double block into the motor control modeling scheme, which transforms the Boolean signal into a digital signal characterized by the values 0 (low) and 1 (high) (Figure 3).

4. Results

In modern agricultural automation systems, traditional AAVs typically follow predetermined routes or are guided by ground sensors to perform tasks such as crop handling or material transport. However, this dependence on well-maintained path planning not only significantly increases maintenance costs but also causes congestion among AAVs during task execution, leading to a decreased efficiency.

To overcome these challenges, this study proposed a comprehensive environmental perception model that integrates point cloud data generated by LiDAR, status information from the AAVs, and visual images captured by front-facing mounted cameras. This model utilizes deep reinforcement learning techniques to enhance the perception and path planning capabilities

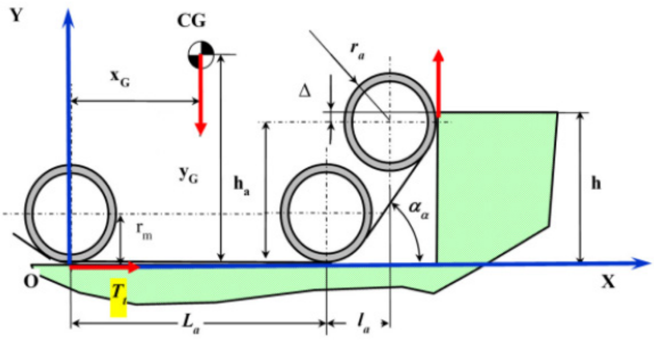
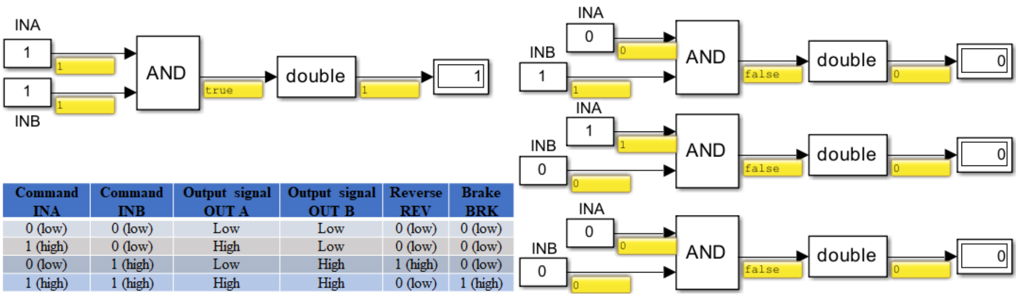


Figure 2. Simulated route planning based on possible obstacles



Command INA	Command INB	Output signal OUT A	Output signal OUT B	Reverse REV	Brake BRK
0 (low)	0 (low)	Low	Low	0 (low)	0 (low)
1 (high)	0 (low)	High	Low	0 (low)	0 (low)
0 (low)	1 (high)	Low	High	1 (high)	0 (low)
1 (high)	1 (high)	High	High	0 (low)	1 (high)

Figure 3. Motor control signal modeling

of multiple AAVs operating simultaneously in agricultural environments.

In this study, the AAV vehicle is equipped with LiDAR sensors and generates point cloud data. Due to the characteristic long sequence of point cloud data in time steps, long short-term memory networks (LSTMs) are used for processing, thereby extracting distance- and angle-related information about target points and obstacles, as it is shown in Figure 2. The LSTM network starts from an empty initial state, receiving the state information for the first step to generate the hidden state vector h_a. After that, the network generates a new hidden state h_n repeating this process until the AAV reaches its destination. In this study, the number of LSTM grid cell units was set at 530 to handle the 360-degree point cloud data output by LiDAR, with an update frequency set at 50 Hz and a detection range of [-90°, 90°]. As the AAV moves from the starting position to the destination, the environmental perception module can obtain and process the state information for the surrounding environment in real time, providing a real-time perception field of view for the AAV.

Moreover, in the block interface, the contact surface between the ground and the AAV wheels must be defined from the point of view of the frictional forces that appear between the wheels and the pathway. Both contact surfaces of these bodies are characterized at a microscopic level by non-homogeneities. Initially, when an external force induced by the DC motor acts on the wheels, the non-homogeneities of the two flat surfaces interact with each other, in the sense that they intertwine, generating a static frictional force that opposes the movement of the wheels and thus prevents movement between the two components in contact.

The modeling of the AAV operation is carried out taking into account the fact that its movement is rectilinear, being performed on a horizontal track and based on the assumption that the four wheels are driven by motors with the same torque and speed characteristics.

By carrying out experiments with 10 auto-guided vehicles for dynamic path planning, where the start and target points of each AAV are randomly generated, the efficiency and effectiveness of the proposed dynamic path planning algorithm can be deeply explored and validated.

The proposed simulation model analyzes the operation of the AAV in an accelerated motion regime, allowing the visualisation of its movement and of the power flow received from the DC motors and transmitted through the wheels to the AAV chassis, to set it in motion, and highlighting the energy consumption in each analysed case. The processing in the Matlab software editor of the signals resulting from the query of the general simulation model highlights the frictional forces that appear during the AAV movement between the wheels and the running path (Figure 4).

This simulation experiment not only verifies the obstacle avoidance capability of AAVs in complex dynamic environments, but it also reflects the potential of the proposed model to apply deep reinforcement learning algorithms for real-time decision making and path planning.

Through the real-time processing of visual information and decision-making, the AAVs can effectively deal with static obstacles that appear on their route, ensuring its safety and fluidity during task execution.

Conventional multi-agent planning algorithms often represent agents using basic shapes like rectangular boxes, and these algorithms are typically designed for static and fully known environments. By contrast, this study addressed the operational challenges faced by AAVs in agriculture, where both static obstacles and dynamic ones, such as other AAVs, must be accounted for. Additionally, the existing AAV path planning algorithms, commonly used in fields like warehouse logistics, are not well-suited for the dynamic and variable conditions found in agricultural settings, which highlights their limitations.

Both offline and online global planning assume that the environment is largely known. In agriculture, AAVs often operate in a partially known environment (such as already established vehicle paths or previously monitored sections of land). This paper proposes the use of the A* algorithm for global path planning, assuming that the locations of static obstacles in the environment are known. This algorithm was combined with deep learning methods that allow the vehicle to automatically learn heuristic functions in order to minimise search costs in complex agricultural environments.

From the perspective of this analysis, it can be seen that even in the complex scenarios where other Autonomous Guided Vehicles (AGVs) are considered as dynamic obstacles, the main AGV could effectively avoid these obstacles without

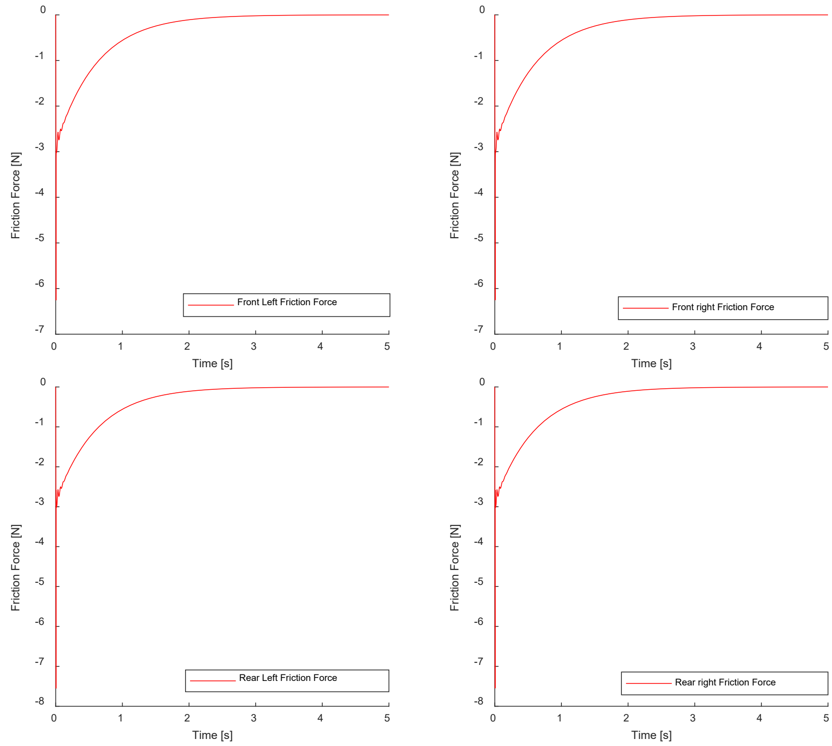


Figure 4. Variation of the frictional forces between the AAV wheels and the running path

any collision. The analytical results obtained from the simulations which were carried out not only validate the effectiveness of the proposed dynamic path planning algorithm, but also demonstrate the potential of the algorithm in handling complex dynamic environments in practical applications. These findings also provide valuable references and insights for future applications and research related to similar multi-AGV systems.

However, this reliance on a highly maintained route planning not only increases the significant maintenance costs, but also leads to queue congestion among AAVs during task execution, leading to a reduced efficiency. To address these issues, this paper proposed a comprehensive environment perception model that integrates point cloud data generated by LiDAR, state information related to AAVs, and visual images captured by front-facing mounted cameras. This model uses deep reinforcement learning techniques to provide extended perception capabilities for multi-AAV path planning.

The validation results confirmed that even in complex agricultural environments, the AAV system could successfully detect and avoid newly emerged static obstacles, which demonstrates its exceptional adaptability and obstacle avoidance efficiency. Through the experiments which were carried out, the algorithm presented in this study has proven its effectiveness and reliability in real-world agricultural scenarios, particularly in modern farming systems that demand high levels of automation and flexible responses to environmental changes. These achievements not only offer valuable insights for further research and development of AAV systems but also establish a solid foundation for technological innovation and practical applications in the agricultural sector.

5. Conclusion

This paper presented the design and implementation of a multi-sensor data processing framework with a two-branch structure characterised by input data sharing and multiple convolutional layers. This approach made it possible to distinguish between different types of obstacles and targets and integrated LiDAR sensors and camera features with the AAV's own information to form a comprehensive environmental perception model. The purpose of this design is to increase the processing efficiency of the proposed model and to achieve an efficient memory usage and a reduced inference time without compromising the prediction accuracy of the two branches. By integrating AAV-based environmental information and semantic scene segmentation, this framework achieved an accurate AAV localization and an efficient classification of the visual information obtained through the front-facing mounted camera.

The obtained experimental results confirmed that this paper successfully addressed the intricate requirements related to material handling in agricultural environments, making it possible to equip AGVs with advanced navigation and obstacle avoidance capabilities. The study also highlights the significant application potential of the proposed model in the context of agricultural logistics. Furthermore, the AGVs demonstrated a high reliability and safety during the agricultural operations, which underscores their strong potential for reducing manual labor costs, which proves their substantial economic value.

The main contributions of this research include a tailored waypoint fitting heuristic algorithm, adapted for the distinct characteristics of agricultural environments, built upon the A* algorithm, a multi-sensor feature fusion environmental perception algorithm, which combines data from AGVs' onboard cameras and LiDAR sensors, a reinforcement learning framework based on Deep Q-Networks (DQNs), which incorporates global guidance during the training phase to accelerate model convergence and a simulation-based testing environment which was developed to further explore the AGVs' path planning capabilities within complex agricultural landscapes.

Overall, this paper not only showcases the AGVs' ability to navigate through unpredictable obstacles in agricultural settings but it also offers a robust experimental support for implementing efficient material handling solutions in the agricultural sector.

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