Research on Logistics Avoidance Strategy of Campus Unmanned Distribution Based on Markov Decision Process

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Abstract: In the campus environment, the tools currently used for distribution include a considerable number of unmanned logistics vehicles. These unmanned logistics vehicles are prone to walking difficulties in the process of walking on campus because of the flow of people on campus. It is very complex, and various road conditions will invalidate unmanned logistics vehicles' avoidance strategy. Based on the above situation, this paper uses the Markov decision-making process to improve the algorithm for the traditional campus unmanned logistics and the avoidance strategy of the delivery vehicle. The distribution logistics route is fitted so that the unmanned logistics distribution vehicle is more intelligent and the structure is more effective.

1. Introduction

Currently, campus logistics and distribution are in high demand, and couriers arrive on campus in large numbers daily. Implementing this system will be very challenging if these couriers are all delivered manually. Therefore, there are currently unmanned logistics vehicles on campus. Following the logistics information contained in the campus express delivery, the logistics vehicle can automatically distribute the corresponding express, greatly improving the campus delivery process and enhancing its efficiency. Over the years, campus delivery unmanned vehicles have become increasingly popular. Due to the complex road conditions on campus, unmanned logistics vehicles are often unable to determine the road conditions when driving on campus [1]. A complex crowd flow environment can lead to algorithm overload, which can lead to the stagnation of unmanned delivery vehicles on campus, posing a significant risk to their efficient and safe operation. Thus, it is necessary to identify and optimize the application scenarios for unmanned delivery vehicles. As a result, the algorithm has been improved. This paper aims to examine the strategy algorithm of unmanned vehicles for campus logistics distribution to avoid people flow and identify any deficiencies. This algorithm has been optimized, and the process has been improved to make the vehicle more adaptable to the complex road conditions found on campus. The purpose of this paper is to enhance the local path optimization process for the above algorithm so that it can better adapt to the environment of unmanned distribution on campus and become more efficient.

2. Research Status of Campus Unmanned Distribution Logistics

In their warehouse management systems, major enterprises use unmanned logistics distribution vehicles. There are several scenarios in which these unmanned logistics vehicles can perform corresponding navigation tasks. The first unmanned logistics and distribution vehicles were only used for a few simple cargo handling tasks when they were developed, and such cargo handling tasks generally did not involve identifying complex road conditions or traffic signs, so they were used in warehouses. Additionally, the algorithm used is a relatively simple path recognition algorithm [2]. Afterward, unmanned logistics distribution vehicles began to drive on the road, transporting freight between companies, so it became necessary to identify the traffic conditions. Corresponding algorithms identify vehicles and pedestrians, and their running process is very fast

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and light. As a result, this algorithm can only identify relatively neat road conditions during the running process, and its ability to identify chaotic road conditions is still somewhat limited. In the early Chaoyang unmanned logistics distribution vehicle, this type of algorithm was also applied, resulting in low distribution efficiency. Unmanned delivery vehicles will have difficulty driving during the peak period of students commuting to and from classes. This seriously impacts the efficiency of unmanned logistics distribution vehicles throughout the day [3]. Because of the complex road conditions on campus, it is necessary to improve the application of unmanned logistics distribution vehicles.

3. Construction of a Logistics Simulation Model for Unmanned Distribution on Campus

The construction block diagram of the campus unmanned logistics vehicle distribution simulation model is shown in Figure 1 below.

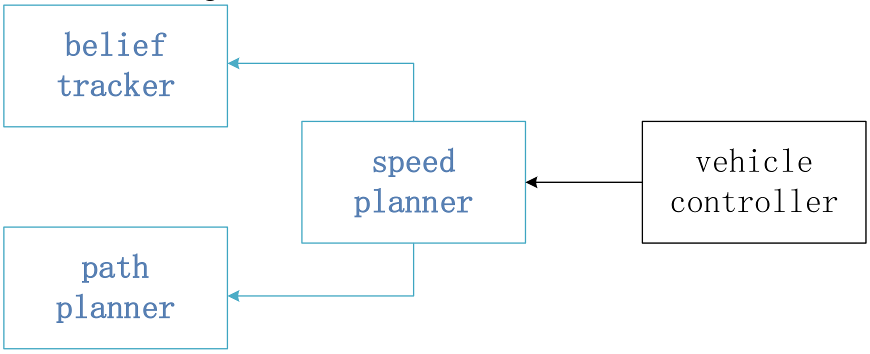

Figure 1 Simulation model of campus unmanned logistics vehicle distribution

The vehicle's original path planning algorithm is enhanced with navigation measures corresponding to the crowd's automatic driving algorithm to ensure the calculation's accuracy. Layered structural calculations are performed during cross-traffic to enhance the vehicle's performance. The accelerometer and gyroscope are two of the most important devices for detecting road conditions on campus. As a general guideline, the following principles should be considered. Based on input and detection information, this accelerometer measures the acceleration of the system, transmits common application information to multiple sensors, and determines the speed and acceleration of the unmanned distribution vehicle.

4. Development of Campus Unmanned Distribution Logistics Avoidance Strategy Based on Markov Decision Process

4.1 Research on Unmanned Markov Decision Process of Campus

In the study of unmanned Markov decision processes on campus, the critical gap plays an important role in determining whether pedestrians cross the road. This formula is expressed as formula (1).

$$\text{Critical Gap} = \frac{l}{v} + \mathrm{F} \tag{1}$$

Among them, l represents the width of the main road of campus traffic, v represents the average speed of campus students crossing the street, and F represents the safety margin of campus students crossing the street (unit: seconds).

As shown in formula (2), the safety margin time for student access is calculated as follows.

$$PSMT = \mathrm{T_V} - \mathrm{T_P} \tag{2}$$

The above formula is the difference between the time $\mathrm{T_V}$ when the campus unmanned logistics distribution vehicle passes through the conflict area and the time $\mathrm{T_P}$ when the students pass through the conflict area during the peak period of campus traffic, the larger the value, the smaller the advantage of unmanned logistics distribution vehicles on campus [4].

The campus unmanned Markov decision model is shown in Figure 2 below.

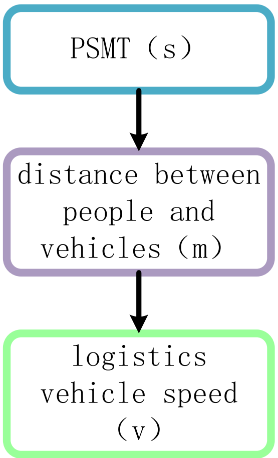

Figure 2 Campus unmanned Markov decision model

Campus logistics unmanned vehicles display road condition information based on a static complex road condition set to display concentrated objects of complex road conditions. A one-dimensional vector of different eigenvalues represents the specific meaning of all complex road condition samples in the complex road condition set. A complex road condition association method is used in the campus logistics unmanned vehicle to associate the features of the complex road conditions with their corresponding eigenvectors. The associated process can be incorporated into the complex road condition analysis portrait, which allows it to be combined with the above-mentioned complex road condition analysis scoring theory [5].

4.2 Research on the Analysis Algorithm of Unmanned Distribution Logistics Routes in Campus Based on Markov Decision Process

The construction of the Markov decision process road condition model of campus unmanned distribution logistics is shown below in formula (3) (4).

$$\vec{e}_{\mathrm{G}} = \frac{\vec{\mathrm{g}} - \vec{\mathrm{p}}}{\|\vec{\mathrm{g}} - \vec{\mathrm{p}}\|} \tag{3}$$

$$\vec{F}_{\mathrm{G}} = \mathrm{A}_{\mathrm{G}}\left(v_{\mathrm{P}}^{0}\vec{e}_{\mathrm{G}} - \vec{v}_{\mathrm{P}}\right) \tag{4}$$

Where $\vec{e}_{\mathrm{G}}$ is the unit vector of the student's position pointing to the target point during the peak period of campus traffic, $\vec{\mathrm{g}}$ is the target point position, A_{G} is the weight coefficient, which is the reciprocal of the relaxation time τ of students during the peak period of campus traffic, $\vec{\mathrm{p}}$ is the location of students during peak traffic hours on campus, v_{P}^{0} is the expected speed of students during peak traffic hours on campus, $\vec{v}_{\mathrm{P}}$ is the current speeds for students during rush hour on campus.

The Markov decision-making repulsive force model of campus unmanned distribution logistics based on the above model is constructed as follows in formula (5) (6).

$$\vec{e}_{ij} = \frac{\vec{p}_i - \vec{p}_{\mathrm{j}}}{\left\|\vec{p}_{\mathrm{i}} - \vec{p}_{\mathrm{j}}\right\|} \tag{5}$$

$$\vec{F}_P = A_{ij} \sum_{j=1}^{n} \varphi_{ij} \cdot \vec{e}_{ij} \tag{6}$$

Among them, A_{ij} is the weight coefficient, $\vec{p}_j$ is the position of other campus traffic peak students within the interaction radius of the campus traffic peak period, $\vec{e}_{ij}$ is the unit vector pointing from the campus traffic peak period student j to the student i, and φ_{ij} is a function describing the strength of interaction.

4.3 Environment Construction of Markov Decision Process of Campus Unmanned Distribution Logistics

The environment construction of the Markov decision-making process of campus unmanned distribution logistics is shown in Figure 3 below. In the conflict zone, the expected trajectories of students and unmanned distribution logistics vehicles on campus during the peak period of campus traffic will intersect at some point in the future. At this time, one of the unmanned logistics vehicles on campus or the students during the peak period of campus traffic needs to take action to avoid the other [6].

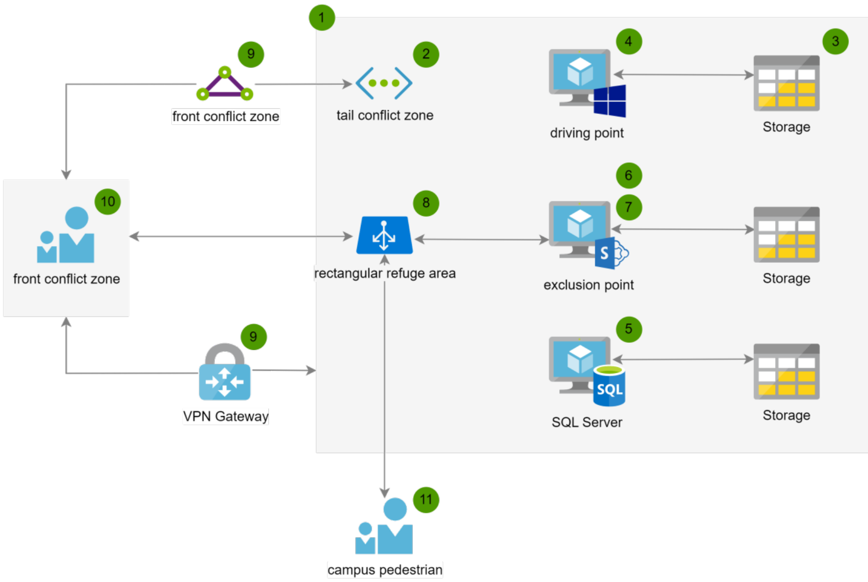

Figure 3 The environment of Markov decision-making process for unmanned campus distribution logistics

An exploratory research algorithm for analyzing road conditions is the Markov decision process of campus unmanned distribution logistics. This algorithm is primarily used to classify complex road conditions according to their attributes. It is an algorithm for unsupervised learning. Regarding road condition analysis, the Markov decision-making process of campus unmanned distribution logistics effectively divides complex road conditions into different road condition clusters by measuring the similarity and intimacy, as well as the alienation of complex road conditions. Differences in distance and similarity coefficients are used to distinguish clusters. As a part of the Markov decision-making process used in this paper, large-scale screening of complex road condition points is conducted first to determine the center of the road condition analysis [7]. As much as possible, this conflict point should reflect the characteristics of the complex road condition point. Through this process, the other values in complex road conditions are brought closer to the driving point of the unmanned logistics vehicle. Therefore, classification characteristics are formed, and the distance is then recalculated based on the above content. In this way, it is possible to ensure that the conflict point of complex road conditions is more accurate so that the final search of the conflict point of complex road conditions may be accomplished.

4.4 Research on Markov Decision Local Path Algorithm

Due to the proliferation of Internet big logistics road condition information, Markov decision-making local path algorithm optimization has received extensive attention as a frontier branch of road condition identification. Presently, the research direction of Markov decision local path algorithm optimization technology is primarily aimed at combining Markov decision local path algorithm optimization with complex road condition judgment and control logistics road condition information iteration in order to manage complex road condition information effectively and prevent information loss. A number of technologies are employed in this process, including logistics road condition information iteration, road condition recognition technology, and complex road condition judgment management. A major focus of research in this field is the combination of logistics road condition information and complex road condition judgment and control of logistics road condition information iteration. Therefore, the objective of this paper is to examine the application of Markov decision local path algorithm optimization to complex road condition judgments and the control of logistics road condition information iteration as part of the development of a technology combining Markov decision local path algorithm optimization with logistics road condition information analysis [8].

As a protection complex road condition judgment control system, the intrusion detection complex road condition judgment control system is commonly used as a complex road condition judgment and control logistics road condition information iteration method, which can identify and intercept the effects of complex road conditions both internally and externally. Thereby, the complex road condition judgment control system can be protected in real-time. In this way, the relevant logistics road condition information in the iterative process of judging and controlling the logistics road condition information by collecting and counting complex road conditions can be found, and the abnormal behavior of the complex road condition judging control system can be found, so as to detect the complex road conditions, judge and control the logistics road condition information iteration and complex road conditions. Determine the situation that the control system is affected by complex road conditions. A complex road condition judgment control system for intrusion detection typically formulates an abnormal activity logistics road condition information table based on the established normal server and the relevant logistics road condition information between the users, so that it can predict complex road conditions in a timely and effective manner.Therefore, it can timely and effectively judge the situation that the complex road condition judgment control system is affected by the complex road conditions [9].

5. Experiment Design for Verification of Campus Unmanned Distribution Logistics Avoidance Strategy Based on Markov Decision Process

In Figure 4, we illustrate the experimental design flow for verifying the logistics avoidance strategy of unmanned campus distribution based on the Markov decision process. While interacting with the crowd at the intersection, the driver of the campus unmanned distribution logistics vehicle frequently uses the brake pedal and accelerator pedal. The steering wheel is rarely used for avoidance behaviors. It is possible to better interact with students on campus during peak traffic hours by simply using acceleration and deceleration actions. In order to design the decision algorithm for the campus logistics distribution vehicle, this paper applies the horizontal and vertical decoupling method .

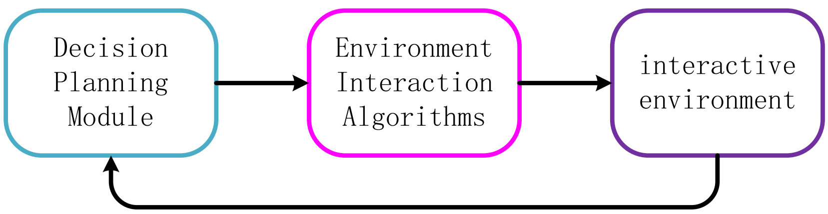

Figure 4 The experimental design diagram of the verification of the campus unmanned distribution logistics avoidance strategy based on the Markov decision process

6. Conclusion

In this paper, the corresponding algorithm optimization is made based on the road condition identification problem encountered by traditional campus logistics distribution vehicles during peak periods. The algorithm is applied to a campus distribution logistics vehicle avoidance strategy to evaluate the effectiveness of the algorithm. It optimized and improved the Markov decision-making process and the avoidance strategy of campus logistics distribution vehicles. A multi-discriminant basis and corresponding discriminant loop are added to the traditional algorithm for road condition recognition. In addition, the iterative process of the algorithm is improved in order to optimize the path taken by the unmanned vehicle to avoid the peak flow of people.

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