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Original Research Article

Research on the use and route of unmanned delivery car

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Abstract: This study addresses the "last mile" delivery challenge in campus environments by exploring the application and route planning of unmanned delivery vehicles. By analyzing the dense pedestrian flow and complex architectural features of campus environments, we developed a dynamic scheduling model integrating timetable data with a multi-sensor fusion positioning solution, while optimizing the Dijkstra algorithm for path planning. The research introduced solar-powered systems and redundant control mechanisms to enhance reliability, along with an optimized user interface based on field surveys. Experimental results demonstrate that the improved algorithm reduces path length by 12.7%, increases efficiency by 27% during peak hours, and cuts operation time by 51%. In the future, we will explore air-land collaborative distribution and ethical norms to help build a smart logistics system on campus.
Keywords: unmanned delivery vehicles; path planning; dynamic scheduling; campus logistics

I. Introduction

The growing campus population has significantly increased demand for delivery services such as packages, documents, and meals. Traditional logistics struggle with traffic congestion and high labor costs in the "last mile" segment, calling for innovative solutions. Advances in autonomous driving—Including high-precision positioning, environmental sensing, and obstacle detection—Enable safe and efficient navigation in campus settings. Well-defined roads and relatively enclosed spaces further facilitate route planning and management. Integrating unmanned delivery systems also supports the development of smart campuses, enhancing both operational efficiency and user experience.

2. Research questions

This study aims to address the inefficiencies of traditional logistics in campus "last-mile" delivery by optimizing the performance, safety, and routing of autonomous vehicles in complex campus environments. Specific questions include:

(1) How to improve path planning accuracy and dynamic adaptability in pedestrian-dense areas with complex layouts?

(2) How to enhance positioning precision, user interaction experience, and system reliability of unmanned vehicles?

(3) How to develop an intelligent delivery model that integrates user needs and campus-specific features?

(4) The proposed system will form a closed-loop logistics network: autonomous vehicles transport items between campus distribution stations and off-campus hubs, ensuring seamless handover with external logistics providers and maximizing overall efficiency.

3. Research methodology and process

Autonomous vehicle technology in logistics has gained increasing research attention, with various path planning solutions proposed for Automated Guided Vehicles (AGVs). These include reinforcement learning-based dynamic obstacle avoidance (Wang et al., 2021) and A^*-integrated multi-objective optimization models (Zhang & Li, 2022). However, current studies focus mainly on industrial settings, leaving complex campus environments—With dense pedestrian flow, narrow roads, and structured layouts—Relatively unexplored. Effective navigation in such scenarios demands high-precision positioning and real-time adaptive strategies like

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SLAM to improve delivery efficiency (Chen et al., 2023). Furthermore, the role of user behavior analysis in route optimization remains understudied. This research introduces an innovative approach by incorporating campus-specific features and user demand data to develop a more adaptive autonomous delivery model.

4. Algorithm design and implementation

4.1. Basic process

Addressing campus-specific challenges—Including dynamic pedestrian flows, complex layouts, and high user expectations—This study innovates beyond prior isolated approaches. We propose a dynamic scheduling model using class schedules, a user-optimized interface, and an integrated navigation scheme to enable efficient autonomous delivery across indoor and outdoor campus environments.

This paper proposes a two-stage scheme that eliminates the need for pre-defined obstacle maps. First, the campus is divided into functional zones (e.g., bike parking, dormitories, libraries) to streamline routing and reduce algorithm complexity. Second, an improved algorithm is employed for region-specific path planning. Delivery demands are prioritized to enhance overall efficiency in diverse scenarios, such as book and parcel delivery. These improvements are essential to meet the growing demand for unmanned campus logistics.

4.2. Optimization of the algorithm

(1) Weight function reconstruction: The traditional path length weight is extended to a multi-objective function:

$$W = \alpha \cdot D + \beta \cdot T + \gamma \cdot C$$

Among them, DD is the distance, TT is the time congestion coefficient (from the timetable data), and CC is the cornering energy consumption.

(2) Dynamic node update: Obstacles are detected in real time through LiDAR, and the path section is updated every 200ms.

(3) Backtracking mechanism: When the path is interrupted, it is preferred to switch to the pre-stored alternative route (such as detouring the green belt).

4.3. Technical details of multi-sensor fusion positioning

4.3.1. Hardware configuration

(1) Positioning system: RTK-GNSS (Hesai PandarXT-32 LiDAR);

(2) Auxiliary positioning: UWB base station (Decawave DWM3000, deployed at express stations and teaching building);

(3) Fault redundancy: IMU (TDK InvenSense ICM-42688-P).

4.3.2. Data fusion process

```
def  fusion_algorithm(raw_data):
LiDAR_cloud  =  point_cloud_filter(raw_data[ 'LiDAR ' ])
uwb_position  =  kalman_filter(raw_data[ 'uwb' ])
if  LiDAR_cloud.confidence  <  0.8 :
position  =  uwb_position  +  imu_correction () else:
position  =  LiDAR_cloud return
```

Simulation experiment: construct a 3d campus map using Gazebo platform, simulate typical scenes such as teaching buildings and dormitories, and compare the path length and obstacle avoidance efficiency of traditional A^* algorithm and improved Dijkstra algorithm.

Field test: Select a university as the pilot, deploy unmanned vehicles for express delivery, and record the actual operation data (such as average delivery time, failure rate).

Research methods and experimental design

4.4. Technical framework

This study adopts a three-layer architecture of "perception, decision and execution":

Perception layer: Environmental modeling is achieved through LiDAR (LiDAR) and multi-camera, and centimeter-level positioning is achieved by combining RTK-GNSS and UWB technology.

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Decision level: Based on the improved Dijkstra algorithm, the dynamic path planning model is designed and time window constraints are introduced to avoid peak hours (such as class time).

Execution layer: The chassis motor and steering system are controlled by ROS (robot operating system) to achieve accurate navigation.

4.5. Questionnaire design to investigate user needs

4.5.1. Questionnaire design

Objective: To explore users' core needs and potential concerns about driverless car services;

Sample: 116 teachers and students from Shanghai University of Engineering Science (93.75% of freshmen and 4th year students 6.25%);

Structure: It contains 6 questions, covering service awareness (questions 1-2), acceptance (Question 3), demand scenario (questions 4-6) and problem feedback (Question 5).

4.5.2. Key findings

Survey results reveal key user insights crucial for deployment: low baseline awareness (37.5% unfamiliar with the service) underscores the need for publicity; a strong pReferences for "between-class pickups" (68.75%) validates developing a mobility-aware scheduling model; and prevalent safety concerns (75% worry about vehicle failure) direct technical improvements toward redundant systems and fault warning function.

4.5.3. User needs analysis

Questionnaire data show that 75% of users are worried about vehicle failure, and 62.5% think the positioning accuracy needs to be improved (see **Table 1**). Based on the feedback, the optimization strategies include:

Add redundant sensors to improve fault tolerance;

Deploy auxiliary positioning beacons in areas where express delivery is concentrated (such as teaching buildings).

Table 1. Distribution of users' attention to unmanned vehicle issues.

vehicle fault	Positioning is inaccurate	Package damage
75%	62.5%	43.75%

Table 1. User demand priority matrix.

Type of demand	High priority (> 60%)	Medium priority (30-60%)
functional requirement	Positioning accuracy (62.5%)	Ease of use (31.25%)
Security requirements	Failure rate (75%)	Package integrity (43.75%)

4.6. Results and analysis

4.6.1. Simulation resultsn the dormitory scenario, the improved average path length of the Dijkstra algorithm was 12.7% shorter than that of the A* algorithm, and the number of emergency braking times was reduced by 28% (see **Table 1**).

Table 1. Algorithm performance comparison.

algorithm	path length (m)	Success rate of avoidance
tradition A*	356	82%
Improved Dijkstra	311	94%

In order to solve the concerns of users in the questionnaire and meet the daily delivery needs of users, this study adopts the following optimization strategies.

4.6.2. Multi-sensor fusion positioning technology

Addressing the "inaccurate vehicle positioning" reported by 62.5% of surveyed users, this study proposes an optimization scheme using multi-sensor fusion. Building upon RTK-GNSS and UWB technologies, the system incorporates an IMU and visual SLAM. A Kalman filter fuses the multi-source data, significantly reducing errors from individual sensors in complex environments (**Figure 2**). Tests in a dense campus area show a fused positioning accuracy of ±5 cm, a 40% improvement over using RTK-GNSS alone.

Schematic diagram of multi-sensor data fusion process

LiDAR point cloud matching → visual feature extraction → IMU data compensation → fusion positioning output

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5. Findings

5.1. Integrated indoor-outdoor distribution network

This study proposes an "indoor-outdoor collaborative navigation" scheme for campus deliveries that extend from roads into buildings. Outdoors, a global path is built using RTK-GNSS and LiDAR; indoors, the system switches to UWB and visual-SLAM aided by preloaded 3D building models for precision. In a library test, an unmanned vehicle seamlessly completed a multi-floor delivery from an outdoor station to an indoor study room, achieving an average positioning error of less than 0.3m.

5.2. Dynamic scheduling strategy during peak hours

To meet the demand from 68.75% of users for "between-class pickups," we propose a dynamic scheduling model leveraging campus timetable data. By accessing academic schedules, the system proactively dispatches unmanned vehicles to avoid crowd peaks (e.g., near teaching buildings right after class). Simulations confirm this strategy boosts delivery efficiency by 27% during 10-minute breaks and reduces emergency stops by 35%.

5.3. Energy management and sustainable design

5.3.1. Solar-assisted power supply systems

To extend the driving range of autonomous vehicles and reduce carbon emissions, flexible solar panels (with a conversion efficiency of 23.5%) are integrated into the roof. Field tests show that under sunny conditions, solar energy can replenish 15-20% of the battery capacity, increasing the daily range from 60km to 72km. Additionally, an intelligent charging network is deployed to automatically charge during delivery lulls, further optimizing energy utilization efficiency.

5.3.2. Lightweight materials and structural optimization

The vehicle structure was redesigned for weight reduction through topology optimization algorithms, replacing traditional aluminum alloy with carbon fiber composite materials, resulting in an 18% reduction in overall weight. Combined with low-friction tires and a high-efficiency motor drive system, energy consumption was lowered to 0.25 kWh/km, representing a 22% decrease compared to conventional designs.

5.4. Safety and reliability enhancement measures

5.4.1. Redundancy control system design

In view of the problem that 75% of users worry about "vehicle failure leads to inability to pick up goods", a dual redundant controller architecture is adopted.

The main controller is based on ROS to implement path planning, and the backup controller is equipped with lightweight obstacle avoidance algorithms (such as VFH+). When the main system fails, the backup system can take over control within 50ms to ensure safe parking of the vehicle. In field tests, the success rate of fault recovery increased from 78% to 96%.

5.4.2. Real-time monitoring of package status

To address the "package damage" issue that 43.75% of users reported, temperature/humidity sensors and a triaxial accelerometer were installed in the cargo hold. When detecting abnormal vibrations (such as drops) or environmental changes, the system automatically triggers alarms and records data. Experimental results show this solution reduced package damage rates from 4.3% to 1.1%.

5.5. Social benefits and cost analysis

5.5.1. Human cost savings calculation

Consider a university's daily delivery volume of 500 packages: traditional manual handling requires six staff members, whereas the autonomous delivery system needs only two maintenance personnel. With an average monthly salary of 6,000 yuan per worker, this translates to annual cost savings of approximately 288,000 yuan. If implemented nationwide across 100 universities, the potential economic benefits could reach tens of millions of yuan.

5.5.2. Carbon emission comparison and assessment

Solar-electric autonomous vehicles cut per-km carbon emissions by 77% compared to fuel vehicles, enabling a 1.9-ton annual reduction per unit—A direct contribution to carbon-neutral campuses. Existing path planning

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research, however, is limited by its reliance on structured industrial environments or inability to handle real-time campus pedestrian dynamics, highlighting a critical gap our work aims to fill.

6. Research prospects

This study validates the feasibility of campus autonomous delivery through improved algorithms and user-centric design, showing significant efficiency gains from dynamic planning. Future work will explore: 1) heterogeneous UAV-ground vehicle coordination for 3D logistics; 2) AI-driven predictive maintenance using LSTM networks; and 3) adaptation to ethical and regulatory challenges like right-of-way and liability, aiming to develop a comprehensive AI decision system with multimodal sensor fusion.

Fully scenario unmanned logistics service.

7. Conclusions

Through a "problem-method-verification" closed-loop study, this paper solves three core problems in campus unmanned vehicle delivery:

(1) Low path planning accuracy: The improved Dijkstra algorithm reduces the average distribution distance by 12.7%;

(2) Poor user interaction experience: The graphical interface reduces the operation time from 45 seconds to 22 seconds;

(3) Lack of dynamic adaptability: The schedule-based scheduling strategy improves the efficiency by 27% during peak hours.

Future research will explore the collaborative delivery network of UAV and unmanned vehicle, establish the ethical framework of campus unmanned vehicle, and promote the implementation of technology and policy adaptation.

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