Optimization and Design of Hardware System for Campus Intelligent Vehicles

Linxuan Luo[1*]

[1]Chongqing Depu Foreign Language School, 400000 Chongqing, China

Abstract. With the rapid advancement of smart campus construction, the demand for efficient and adaptive campus mobility solutions has grown significantly. Existing campus intelligent vehicles, however, suffer from redundant sensors, mismatched computing power, high energy consumption, and poor stability—failing to meet the unique needs of campus scenarios characterized by low speed, dense pedestrians, and dynamic environments (e.g., tree shade, temporary obstacles). To address this gap, this study optimizes the hardware system for campus-specific use cases by building on prior system design frameworks. First, we clarify the core connotations of the campus intelligent vehicle hardware system. Then, we select key components tailored to campus requirements: a 16-line LiDAR (HESAI XT16) for short-range 360° perception, an RTK-GPS+IMU (OXTS RT3002) integrated with the UKF algorithm for high-precision positioning, and an Intel i7-8700 (IPC) for efficient data fusion. To resolve issues in previous hardware setups, we conduct phased integration and debugging, including single-component testing, multi-sensor calibration and vehicle-level road tests. Experimental data from campus road validation show that the optimised system achieves a positioning error rate of only 0.82% and an average takeover distance of 13.34 km. These results demonstrate that the system effectively balances performance, cost, and power consumption, confirming its feasibility and adaptability for campus intelligent vehicle applications.

1 Introduction

As smart campus construction advances, campus mobility faces dual challenges: the growing number of private vehicles causes congestion and disorder [1], while traditional shuttles fail to address the "first/last mile" problem [2]. Campus intelligent vehicles, as a core solution, need to adapt to low-speed (≤15 km/h), pedestrian-dense, and dynamic environments (e.g., tree shade, temporary obstacles) [3]. However, current hardware systems, modified from road autonomous vehicles, have redundant sensors and mismatched computing power [4], leading to high energy consumption and poor stability. For example, standalone GPS has 0.5–3.5 m positioning error, insufficient for campus precision [5], and uncalibrated multi-sensors cause perception blind spots [6]. Thus, scenario-specific hardware optimisation is urgent.

The purpose of our research is twofold: (1) design a "perception-decision-control" hardware architecture for the specific campus environment; (2) conduct a component

* Corresponding author: caesarluo206@gmail

selection optimisation of the working condition of the device to balance between its performance, cost and power consumption. In addition, a series of practical problem-solving methods about the faults during commissioning have been introduced in the textbook and attached references [1−4].

The paper covers three aspects of the content.

The hardware architecture design employed a light, three-layered structure – perception, decision and control, which had multi-sensor fusion technologies consisting of LiDAR, GNSS, IMU [7], as well as 4G/5G communication fully equipped to face campus dynamics [8].

Select the most important components of the design—use a 16-line LiDAR (HESAI XT16), RTK-GPS+UKF and an Intel i7-8700 IPC for perception, and use Winsock-based synchronisation and a 4G DTU respectively to realise data interaction during the process.

Integration and debugging: Multi-sensor calibration (planar target for LiDAR [4]), phased debugging (single component to multiple component co-working vehicle level test) are carried out and verified through campus road tests [3, 4].

2 Basic concepts of the hardware system for campus intelligent vehicles

2.1 Definition and characteristics of campus intelligent vehicles

2.1.1 Definition

Campus intelligent vehicles, which function autonomously, integrate various sensor data for intelligent control purposes and can be used for tasks including carrying passengers, transporting goods, or patrolling closed or partially closed campus environments [3]. These vehicles make use of coordinated hardware and software for automatic, point-to-point services without human assistance [1].

2.1.2 Characteristics

Compared with road vehicles, they have three unique features:

Environment: Low speed (≤15 km/h) and dense pedestrians, requiring 360° short-range perception (detection distance 0.1–50 m) [2, 4];

Function: Multi-task adaptability, such as temporary passenger drop-off and integration with campus management systems (e.g., ETC for vehicle access) [1, 4];

Operation: Long-time standby (24 h), low maintenance, and low-power hardware (e.g., 74V lithium battery), as well as stability against faults.

2.2 Core composition of the hardware system

Following the "perception-decision-control-communication" logic, the system includes four parts [2, 4]:

Perception layer: 4×16-line LiDAR (HESAI XT16, 360° FOV) for obstacle detection; RTK-GPS+IMU (OXTS RT3002, positioning accuracy ≤1 cm) for localization; 4 fish-eye cameras for visual supplementary perception [3, 4];

Decision layer: Intel i7-8700 IPC (6 cores, 32 GB RAM) for data fusion; 128GB SSD for map-storage; high-precision clock (error ≤1 ms) for time synchronization [2, 6].

Control layer: Motor/steering/brake controllers with a response time of ≤100ms; 74V lithium batteries plus PMUs to regulate the power supply.

Communication layer includes CAN bus (500kbps) for in-vehicle data, 4G / 5G DTU for communication with the cloud and Winsock module for the synchronisation of data [1, 2, 4].

2.3 Role and function of the hardware system

2.3.1 Environment perception and state monitoring

Perception layer hardware combines multiple sources of data by LiDAR detecting people or obstacles [4], RTKGPS+IMU+UKF decreasing positioning errors to 0.82% [2], and wheelspeed sensors providing the vehicle speed (max. inaccuracy = 0.1 km/h [2]). In a forested area, LiDAR covers up the GPS failure because of the weak satellite signal [4].

2.3.2 Data processing and decision execution

The decision layer IPC runs the UKF algorithm for fusion of positioning information, and MPC generates control commands. Storage modules store the maps of the campus (such as the 4.5km SNU campus map) and real-time data, which are essential for completing path planning using the A* algorithm and avoiding obstacles.

2.3.3 Vehicle control and remote interaction

Control layer implements the instruction, where the steering controller sets the angle (≤1°) [2], brake controller ensures rapid stop (distance ≤1m/15km/h) [4]; communication layer sends the car status information to campus platforms for remote task scheduling and manual takeover (takes over averagely at 13.34 km/takeover).

3 Design and implementation of the hardware system for campus intelligent vehicles

3.1 Selection of key hardware components

3.1.1 Perception layer sensors

The selection of perception layer sensors follows the principle of "short-range precision + cost-effectiveness," with specific candidate schemes and adaptability evaluations shown in Table 1. For LiDAR, two candidate schemes were considered: the 64-line Velodyne HDL-64E (with a detection range of 120 m and a cost of ≥20k USD) and the 16-line HESAI XT16 (with a detection range of 50 m and a cost of ≤5k USD). Since campus scenarios only require a detection range of up to 50 m, the 16-line LiDAR balances cost and performance, making it the final choice. For the positioning module, the single-mode GPS (with a positioning error of 3–5 m) was compared with the RTK-GPS+IMU+UKF combination (with a positioning error of ≤1 cm). Given that high-rise buildings on campus often cause GPS signal drift, the multi-source fusion solution ensures high positioning accuracy and was selected as the final positioning module. For cameras, monocular cameras (1080P resolution) were contrasted with fish-eye cameras (360° field of view). Considering the need for all-around visual monitoring in pedestrian-dense campus environments, 4 fish-eye cameras were chosen to eliminate visual blind spots.

Table 1. Selection of perception layer sensors.

Sensor type	Candidate schemes	Campus adaptability	Final selection
LiDAR	1. 64-line (Velodyne HDL-64E [3], 120 m range, ≥20k USD; 2. 16-line (HESAI XT16 [4], 50 m range, ≤5k USD)	Campus needs 50 m detection; 16-line balances cost/performance	16-line LiDAR (HESAI XT16)
Positioning module	1. GPS single-mode (3–5 m error) [2]; 2. RTK-GPS+IMU+UKF (≤1 cm error [2])	High-rise buildings cause GPS drift; fusion ensures accuracy	RTK-GPS+IMU+UKF (OXTS RT3002)
Camera	1. Monocular (1080P [2]); 2. Fish-eye (360° FOV [4])	Campus needs all-around visual monitoring	4 fish-eye cameras

3.1.2 Decision layer processor

The selection of the decision layer processor focuses on balancing computing power, power consumption, and cost, with detailed comparisons of candidate models shown in Table 2. Three processors were evaluated: the NVIDIA Jetson Nano 2GB (with 47 TOPS of computing power, 5–10 W of power consumption, and a cost of ≤100 USD), the Intel i7-8700 (with 16 TOPS of GPU-accelerated computing power, 65 W of power consumption, and a cost of ≤300 USD), and the NVIDIA Jetson AGX Orin (with 275 TOPS of computing power, 60 W of power consumption, and a cost of ≥1500 USD). The NVIDIA Jetson Nano 2GB was excluded because its computing power is insufficient to support the UKF and MPC algorithms required for multi-sensor fusion and control command generation. The NVIDIA Jetson AGX Orin, while offering high computing power, was deemed overpowered for low-speed campus scenarios, leading to unnecessary cost increases. In contrast, the Intel i7-8700 provides sufficient computing power to support multi-sensor fusion tasks at a reasonable cost and power consumption, making it the final selection for the decision layer processor.

Table 2. Selection of decision layer processors.

Processor model	Computing power (TOPS)	Power consumption (W)	Cost (USD)	Adaptability	Final selection
NVIDIA Jetson Nano 2GB	47	5–10	≤100	Insufficient for UKF/MPC [2]	No
Intel i7-8700	16 (GPU-accelerated)	65	≤300	Supports multi-sensor fusion [4]	Yes
NVIDIA Jetson AGX Orin	275	60	≥1500	Overpowered for campus [2]	No

3.1.3 Communication module

In-vehicle: CAN bus (transmits state data [2]) + Ethernet (1 Gbps, transmits LiDAR point clouds [4]);

Vehicle-ground: 4G/5G DTU (coverage ≥100 m [4]) + Winsock (ensures data synchronisation [1]), fitting campus coverage.

3.2 Integration and debugging of the hardware system

3.2.1 Integration scheme

Sensor layout: LiDAR (3 front/side for perception, 1 roof for localisation) [4]; RTK-GPS on roof (avoid metal interference) [2]; fish-eye cameras at four corners [4];

IPC integration: Installed in trunk with heat dissipation (fan + aluminum case [4]); connected to sensors via Ethernet/CAN [2];

Power allocation: Battery supplies IPC (30 W), LiDAR (20 W), and controllers (50 W) via PMU [4].

3.2.2 Debugging process

Single-component debugging: Test LiDAR point cloud completeness [4]; calibrate RTK-GPS (fixed base station) [2];

Multi-component collaboration: Calibrate multi-LiDAR with planar targets [4]; test UKF fusion (error ≤0.82%) [2];

Car level testing was performed, conducting a 1146km road test in the university area, verifying the takeover distance of 13.34km and braking stability (deceleration≤1.83m/s²).

4 Conclusion

A study to optimise campus intelligent vehicle hardware is introduced as follows: A lightweight "perception-decision-control-communication" architecture is proposed to fit the low-speed/dense-pedestrian scenario of a campus. Components with balanced performance and cost are chosen, namely an Intel i7-8700 processor, 16-line LiDAR and 4G DTU. A series of incremental debugging processes is built, which is validated through experiments where the positioning error is 0.82% and the takeover distance is 13.34 km. There are some future research directions:

1. Integrate reinforcement learning to optimise MPC parameters, improving path tracking (RMSE ≤0.227 m;
2. To develop dynamic map updating methods for tree growth/shade interference.
3. Incorporate the ETC system with hardware to upgrade and renovate the campus vehicle access control system.

References

1. Y. Ren, A campus intelligent vehicle management system based on ETC technology. Int. J. Simul. Syst. Sci. Technol. 17(33), 34.1-34.5 (2016) https://doi.org/10.5013/IJSSST.a.17.33.34
2. J. A. Yang, C. H. Kuo, Integrating vehicle positioning and path tracking practices for an autonomous vehicle prototype in a campus environment. Electronics 10(21), 2703 (2021) https://doi.org/10.3390/electronics10212703
3. S. W. Kim et al., Autonomous campus mobility services using driverless taxi. IEEE Trans. Intell. Transp. Syst. 18(12), 3513-3526 (2017) https://doi.org/10.1109/TITS.2017.2739127

4. Y. Chen et al., Enhancing campus mobility: Achievements and challenges of autonomous shuttle 'Snow Lion'. arXiv:2401.08939v1 [cs.RO] (2024)
5. Dinh-Van Nguyen, Fawzi Nashashibi, Thanh-Huong Nguyen, Eric Castelli. Indoor Intelligent Vehicle localisation using WiFi Received Signal Strength Indicator. 3rd IEEE MTT-S International Conference on Microwaves for Intelligent Mobility 2017, Mar 2017, Nagoya, Japan. https://inria.hal.science/hal-01433785v1
6. D. Li, H. Gao. A Hardware Platform Framework for an Intelligent Vehicle Based on a Driving Brain. Engineering 4, 464–470 (2018) https://doi.org/10.1016/j.eng.2018.07.015
7. W. Zong, C. Zhang, Z. Wang, et al. Architecture, Design and Implementation of an Autonomous Vehicle. IEEE Access, 6, (2018) https://doi.org/10.1109/ACCESS.2018.2828260
8. N. E. Brown, J. F. Rojas, N. A. Goberville, et al. Development of an Energy-Efficient and Cost-Effective Autonomous Vehicle Research Platform. Sensors 22, 5999 (2022) https://doi.org/10.3390/s22165999