

A new method for detecting aerosols: combining atmospheric detection LiDAR technology with intelligent driving technology

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Abstract The existing aerosol mobile detection system has problems such as over-reliance on labor power and difficulty in conducting continuous operations in toxic and polluted environments. This paper presents a new method for detecting aerosols. The method combines atmospheric detection LiDAR technology and intelligent driving technology. Through modular design (including control module, aerosol detection module, environment sensing and positioning module, and wire control chassis module), an intelligent cruise detection system for aerosols was built. For path planning, Gaussian pseudo-spectrum method was used. The obstacle avoidance constraints and physical constraints during cruise detection movement was fully considered. Experiments were also conducted for three different application scenarios of continuous vertical detection, scanning detection and unmanned intelligent cruise detection. The experimental results show that the system can effectively and continuously acquire the vertical and spatial distribution of aerosol pollutants. It can achieve three-dimensional scanning and positioning tracking of atmospheric aerosols. The system features unmanned intelligent cruising and detection capabilities, enabling it to provide data on the vertical distribution and dynamic variation of aerosols for regional pollution prevention and control. More detection experiments will be conducted in different environments in the future. We will continue to explore the application of this technology in intelligent cruise control, detection, and pollution prevention, providing new ideas for regional pollution monitoring.

Keywords: aerosol detection system; intelligent driving technology; LiDAR; regional pollution monitoring.

1. Introduction

Aerosols not only affect air quality (Monks et al., 2009), causing reduced visibility and leading to a high incidence of traffic accidents(Gao et al., 2019), but also have an impact on climate(Kok et al., 2023).**Some pathogens and viruses can be transmitted via airborne atmospheric aerosols, which may trigger human diseases. (Rylander et al., 2020).** This poses a serious threat to public health and daily life.(Oh et al., 2020; Pope Iii, 2002).

Remote sensing techniques are widely applied for atmospheric aerosol monitoring, and can be categorized into two primary types: active remote sensing and passive remote sensing. While ground-based in-situ monitoring features high accuracy, it only yields single-point results and cannot resolve the continuous spatiotemporal distribution of aerosols, particularly their vertical structure.(Garrido et al., 2021). As an active remote sensing technique, LiDAR offers inherent advantages over passive detection methods, including ultra-high detection sensitivity, high spatiotemporal resolution, and the capability for three-dimensional target profiling(Eitel et al., 2016). It provides all-weather monitoring of clouds, aerosols, and atmospheric constituents(Cairo et al., 2024), making it widely used for atmospheric environment detection. According to different platforms, it is divided into Space-borne LiDAR, airborne LiDAR and ground-based LiDAR. Large scale and multi latitude atmospheric data can be obtained through space-borne LiDAR, which can provide data for areas that are difficult to observe on the ground.(Chen et al., 2023; Sun et al., 2024). Numerous studies have utilized aerosol products derived from spaceborne Light Detection and Ranging (LiDAR) to characterize the surface physicochemical properties and vertical profiles of aerosols, and to investigate their long-range transport processes(Donovan et al., 2024; Sato et al., 2025; Song et al., 2024; Yang et al., 2025). **Compared with extensive ground-based LiDAR networks, the number of operational space-borne LiDARs is scarce. Despite continuous performance upgrades of satellite payloads in recent years, the low signal-to-noise ratio caused by orbital overpasses and long slant ranges severely restricts high-frequency, fine-scale continuous monitoring of regional aerosols.** Airborne LiDAR is a LiDAR system mounted on aircraft or drones, capable of providing large-area coverage and highly mobile detection scanning. Airborne LiDAR has been widely utilized in atmospheric aerosol research, with applications including investigating the surface properties of desert aerosols, characterizing marine aerosol concentration distributions and the vertical structure of urban pollution,(Eckert et al., 2024; Li et al., 2022; Zhou et al., 2022), and measuring the optical properties of atmospheric particulate matter.(Girdwood, 2023). Furthermore, multiple studies have leveraged airborne LiDAR-derived aerosol remote sensing products to achieve high-accuracy vertical retrieval of aerosol properties(Burton et al., 2013; Dmitrovic et al., 2024; Müller et al., 2014; Tesche et al., 2009). However, the high cost and airspace limitations have hindered the continued use of airborne LiDAR. **Ground-based LiDAR is widely used to detect aerosol pollution.(Baars et al., 2026).** It can achieve

continuous fixed-point detection and effectively monitor the vertical airspace over a specific area(Yang et al., 2024). LiDAR fixed on a building for continuous fixed-point vertical detection(Kuang et al., 2023), it can capture of aerosol transport processes(Yang et al., 2021a). Zhang et al. used a ground-based lidar network to analyze a dust aerosol transport over northern China in 21 years(Zhang et al., 2024). LiDAR paired with a gimbal can carry out scanning detection. Horizontal scanning effectively captures contaminants within the detection distance. It enables pollutants to be effectively tracked and potential sources of contamination to be identified(Kuang et al., 2023). The cone scanning can detect the pollutants in the scanning area by stereoscopic scanning and provide strong data support(Xie et al., 2015). Vertical detection and scanning detection can only achieve fixed-point detection within a specific area, resulting in limited detection coverage. **When ground-based LiDAR is mounted on mobile platforms (e.g., vehicle-mounted platforms, shipborne platforms, etc.), navigation-integrated mobile detection can be realized. (Sanchez Barrero et al., 2024a).** This configuration boasts the inherent advantages of long detection range and wide spatial coverage, enabling the implementation of large-scale mobile sounding of atmospheric aerosols(Wang et al., 2024; Zhang et al., 2020). It is even possible to observe the optical characterization of pollutants in a geographic area on a continuously moving basis and to detect sources of pollution(Lv et al., 2017; Wang et al., 2009). **Existing studies have established an active-passive synergistic aerosol observation system for marine and terrestrial mobile platform scenarios.(Sanchez-Barrero et al., 2026a).** On one hand, they have utilized aerosol products derived from shipborne LiDAR to reveal the vertical distribution of open-ocean aerosols and the transoceanic transport law of continental aerosols(Duflot et al., 2011; Floutsi et al., 2023; Sanchez-Barrero et al., 2026b; Yin et al., 2019). However, shipborne LiDAR is restricted to operation within coastal and open-ocean waters, and is inherently unable to cover key regions for aerosol pollution prevention and control, including inland urban areas, industrial parks, and inland rivers and lakes, nor can it conduct land-based tracking observation of the long-range trans-regional transport of dust aerosols. On the other hand, researchers have developed a vehicle-mounted mobile observation platform equipped with Hyperspectral Resolution LiDAR (HSRL) and passive sensors, achieving high-precision mobile quantitative characterization of the vertical profiles and microphysical properties of clouds and aerosols in the near-surface atmosphere(Chazette and Totems, 2023; Dieudonné et al., 2015; Popovici et al., 2018, 2021; Sanchez Barrero et al., 2024b).

However, the need for uninterrupted cruise detection during regional pollution prevention and control actions, can lead to a significant loss of operator energy. This has resulted in a significant increase in labor costs for existing manned cruise detection systems. In addition, being in an environment with high concentrations of toxic pollutant emissions can cause irreversible damage to the bodies of researchers. In order to address the above issues, this paper presents a new method for

detecting aerosols. The method combines atmospheric detection LiDAR technology and intelligent driving technology. The system can carry out unmanned cruise detection for long periods of time. Atmospheric LiDAR can be coupled with an autonomous driving platform to enable synergistic mobile observation of atmospheric aerosols. Compared to other platforms, it offers multiple advantages in technical (longer endurance time, simpler system implementation), regulatory (no airspace restrictions), and safety (higher safety) aspects. This work is designed to provide a new approach for regional atmospheric pollutant monitoring. The second part introduces the system and research method. The third part analyzes the results of different experiments. The fourth part is summary and prospect.

2. Systems and research method

2.1 System Principles and Models

Intelligent cruise detection system for aerosols is shown in Fig. 1. The system comprises a control module, an aerosol detection module, an environment sensing and positioning module, and a wire control chassis module, and is integrated into a small electric unmanned vehicle. The control module is composed of industrial controller, computing platform, vehicle controller and gateway. The selected computing platform hosts the Baidu Apollo autonomous driving system. The environment sensing and positioning module includes vehicle LiDAR, binocular camera, and an integrated navigation system (including GPS antenna and inertial navigation). The vehicle LiDAR is a 16-line laser LiDAR, which integrates 16 laser emission channels. It has a maximum detection range exceeding 150 meters, a ranging accuracy of ± 2 cm, a point cloud output rate of up to 320,000 points per second, and features a 360° horizontal field of view and a 30° vertical field of view. The binocular camera selected is the "Changjiang-5" binocular stereo camera. In the experimental process of this system, binocular camera serves as an auxiliary sensing method with a relatively low frequency of use and does not act as the primary source of perception information. The wire control chassis module consists of brake module, drive module and steering module.

The aerosol detection module and the unmanned vehicle system each have their own control units. As the "brain" of the whole system, the control module controls the operation of the whole system. The computing platform receives the localization data and environmental data detected by the environment awareness and localization module through the processing gateway. Based on this input, it's dynamically computing the required gear ratio, velocity parameters, and braking force for the unmanned vehicle and transmits these values via the vehicle controller to the wire control chassis module. The wire control chassis module feeds back the state of the moving vehicle parameters (speed, acceleration, rotational speed and braking, etc.) to the computing platform. The environment sensing

and positioning module communicates with the computing platform via the Internet, while the Drive-by-Wire Chassis Module communicates with it via the CAN bus. The aerosol detection module installed on top of the unmanned vehicle employs a compact, portable Mie-scattering LiDAR. The overall dimensions of the Mie-scattering LiDAR are controlled within $200\text{mm} \times 200\text{mm} \times 420\text{mm}$, with a total weight of 13.5kg and a power consumption of less than 100W(Kuang et al., 2023). **The LiDAR system comprises a transmitting optical path, a receiving optical path and a dual-channel detection unit. The 1064 nm laser beam is expanded and emitted into the atmosphere. Backscattered light from aerosols and atmospheric molecules is collected by the receiving telescope, then split into two polarization channels by a polarization prism. The beams are focused onto avalanche photodiodes for photoelectric conversion, followed by multi-pulse integration in the data acquisition card. An embedded control board with dedicated Mie-scattering LiDAR software manages system timing, laser triggering, and data acquisition, storage and transmission.**

An Nd:YAG solid-state laser emitting 1064 nm eye-safe infrared radiation with a pulse repetition frequency of 10 kHz and a single-pulse energy of 15 μJ is employed in the transmitter. An avalanche photodiode (APD) is used as the photodetector, and a GCC-402053 polarization prism is integrated in the optical path for aerosol depolarization measurement. The lidar has a range resolution of 7.5 m and 1800 acquisition channels, with a theoretical maximum detection altitude of 13.5 km. Limited by laser energy attenuation during long-term observation, its practical effective vertical detection altitude stably exceeds 2.5 km, meeting the requirement for vertical pollutant detection in industrial parks. The Mie-scattering LiDAR is equipped with a 1064 nm light source and an APD detector. Developed for aerosol monitoring, it is designed for high-precision detection of the vertical fine structure of aerosols and clouds. Its backscattered lidar signals include Mie scattering from aerosol particles and Rayleigh scattering from atmospheric molecules, with Rayleigh scattering generally weaker in the atmospheric boundary layer, where Mie scattering dominates under high aerosol loading(Freudenthaler et al., 2018; López-Cayuela et al., 2022).The LiDAR system and the industrial controller form an integrated system. All modules within the LiDAR system communicate with the industrial controller via TCP/IP protocols over Ethernet/Wi-Fi networks. The inverter provides a stable 220V power supply to the LiDAR and computing platform. Fig.1b is the module distribution of the detection system. The relevant technical parameters of the system can be seen in Table1.

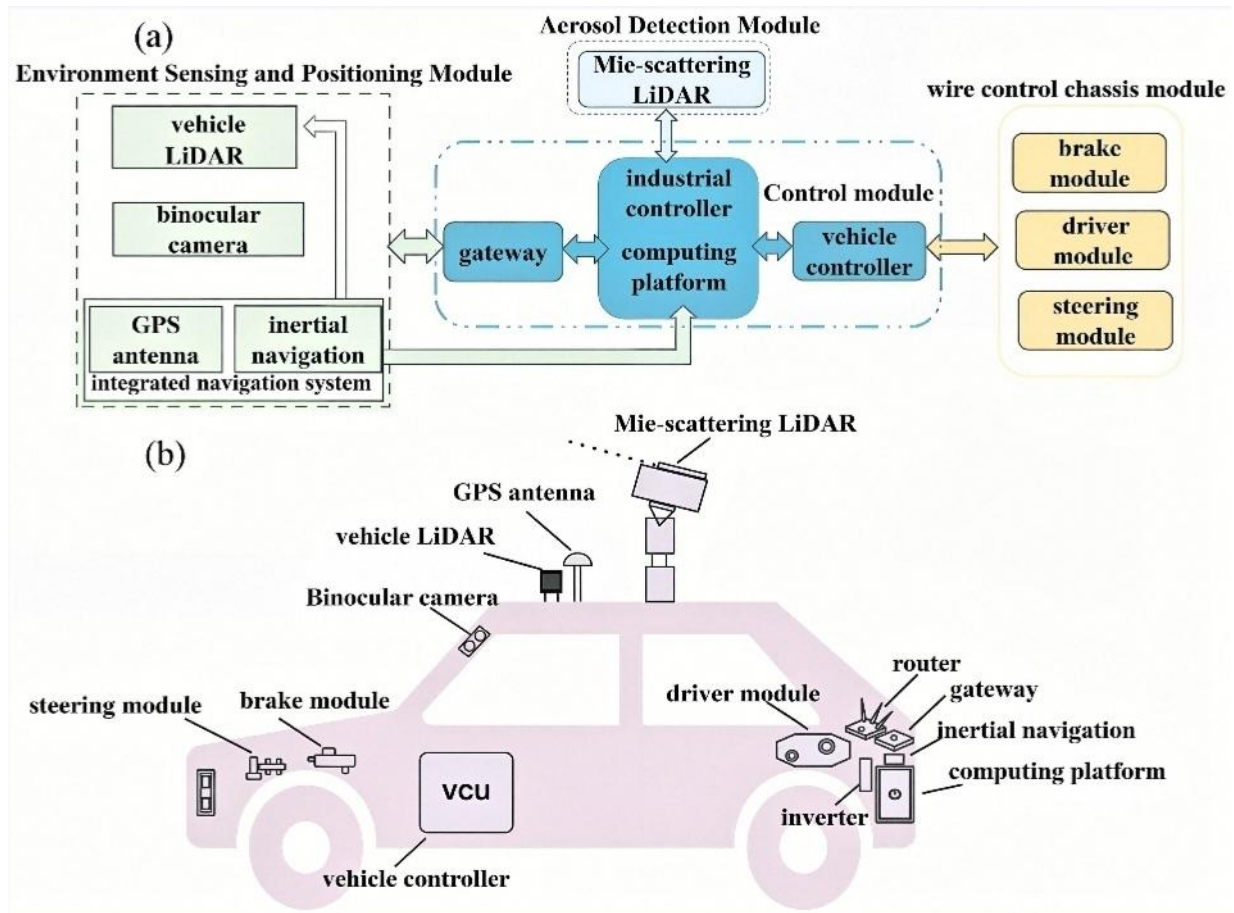


Fig. 1 Intelligent cruise detection system for aerosols: (a)The system schematic; (b) The module distribution of the detection system (this figure is an original creation by the authors).

Table 1 Relevant technical parameters of Intelligent cruise detection system for aerosols

Name	Parameters	Numerical Value
Mie-scattering LiDAR Technical Parameters	Laser Wavelength	1064nm
	Pulse energy	15μJ
	Pulse Repetition Frequency	10kHz
	Acquisition Channel	1800
	Distance Resolution	7.5m
Unmanned Vehicle Technical Parameters	Wheelbases(L)	2.56m
	Vehicle Front Overhang(f)	0.902m
	Vehicle Rear Overhang(r)	0.883m

2.2 Aerosol detection methods

Laser pulses are emitted into the atmosphere by the Mie-scattering LiDAR, and energy attenuation of the laser occurs along its propagation path as a result of the atmospheric extinction effect. A portion of these laser pulses are backscattered by aerosol particles and air molecules and returned along the original propagation path, with extinction attenuation undergone once again during the return propagation (Megie, 1985). **The telescope of the LiDAR ultimately captures the returning light, and the acquired backscattered lidar signals are substituted into the lidar equation. (Yang et al., 2021b):**

$$P(z) = \frac{C[\beta_m(z) + \beta_a(z)] \cdot e^{\{-2 \int_0^z [\alpha_m(z') + \alpha_a(z')] dz'\}}}{z^2} \quad (1)$$

In the formula (1), $P(z)$ is the received backscattered lidar signals of height z , C is the LiDAR constant. β_m and β_a are the backscattering coefficients of atmospheric molecules and aerosols respectively. α_m and α_a are the extinction coefficients of atmospheric molecules and aerosol molecules, respectively. z is the height of aerosol LiDAR detection.

In this study, the original backscattered lidar signals are mainly processed by range-squared correction to obtain the Range-Corrected Signal (RCS), which is used to qualitatively reflect the trends in aerosol concentration and vertical distribution characteristics. The equation of Range-corrected signal is :

$$X(z) = P(z) \cdot z^2 \quad (2)$$

2.3 Kinematic Model of Unmanned Vehicle and Obstacle Avoidance Constraints

Considering experimental safety, the speed is maintained at a low level, all wheels are in a rolling state, and the influence of lateral force is ignored; vehicle dynamics are ignored, so only the vehicle kinematic model is considered.

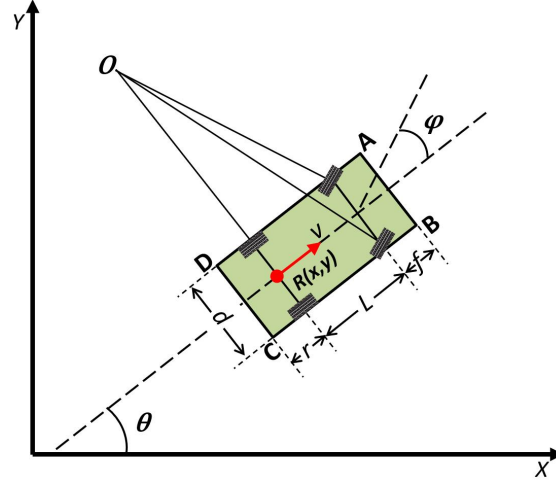


Fig. 2 The kinematic model of the vehicle.

In Fig. 2. L , f , r and d are the wheelbase, front overhang, rear overhang and width of the vehicle respectively; point $R(x, y)$ is the center of the rear axle of the vehicle; v is the velocity of point R along the longitudinal axis of the vehicle; O is the instantaneous steering center of the vehicle; φ is the equivalent swing angle of the front wheel; θ is the heading angle of the vehicle; A , B , C and D are the four contour vertices of the vehicle body respectively.

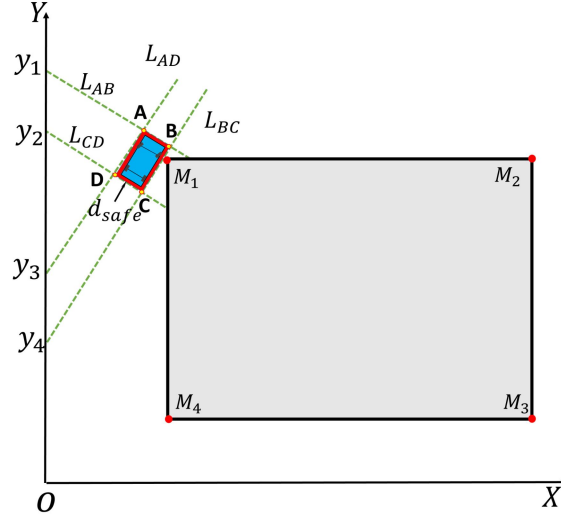
During the vehicle movement process, the state variables of point $R(x, y)$ in the ground coordinate system include: lateral displacement x , longitudinal displacement y , velocity of the rear axle center point v , vehicle acceleration a , vehicle heading angle θ , and equivalent swing angle of the front wheel φ ; The control variables include the vehicle acceleration rate j and the angular velocity of the front wheel's equivalent swing angle ω . Thus, the kinematic differential equations of the vehicle can be obtained as follows:

$$\frac{d}{dt} \begin{bmatrix} x(t) \\ y(t) \\ v(t) \\ a(t) \\ \theta(t) \\ \varphi(t) \end{bmatrix} = \begin{bmatrix} v(t) \cdot \cos \theta(t) \\ v(t) \cdot \sin \theta(t) \\ a(t) \\ j(t) \\ v(t) \cdot \tan \varphi(t) / L \\ \omega(t) \end{bmatrix}, t \in [t_0, t_f] \quad (3)$$

In the formula (3): t_0 and t_f are the initial and termination moments respectively of the unmanned vehicle respectively.

Vehicle collision avoidance constraints are important when solving trajectory planning problems. The actual top-view projection shape of the vehicle is close to a rectangle. Here the vehicle contour is

210 depicted with an enlarged rectangle. d_{safe} is the safety threshold to ensure that the vehicle is collision
 211 free.



212
 213 **Fig. 3** Schematic diagram of obstacle avoidance constraints.

214 As shown in Fig. 3. The red area around the vehicle is the safety threshold to ensure a collision-free
 215 vehicle. If the vehicle does not collide with point M while traveling, the point M coordinates are always
 216 outside the rectangular $ABCD$ region. Remember that the four sides of the rectangle are the lines L_{AB} ,
 217 L_{BC} , L_{CD} , and L_{AD} , and their linear equations are as follows:

$$\begin{cases} L_{AB} = k_1 \cdot x + y_1 \\ L_{CD} = k_1 \cdot x + y_2 \\ L_{AD} = k_2 \cdot x + y_3 \\ L_{BC} = k_2 \cdot x + y_4 \end{cases} \quad (4)$$

219 k_1 is the slope of the lines L_{AB} , and L_{CD} , k_2 is the slope of the lines L_{AD} , and L_{BC} . If the line L_{AB} is
 220 parallel or perpendicular to the X-axis so that the point M is outside the rectangle $ABCD$, then the
 221 coordinates of the point M must satisfy the following conditions:

$$\begin{cases} M_{ix} < D_x(t) \text{ or } M_{ix} > A_x(t) \text{ or } M_{iy} < C_y(t) \text{ or } M_{iy} > A_y(t), \theta = 0^\circ \\ M_{ix} < D_x(t) \text{ or } M_{ix} > C_x(t) \text{ or } M_{iy} < D_y(t) \text{ or } M_{iy} > A_y(t), \theta = 90^\circ \\ M_{ix} < A_x(t) \text{ or } M_{ix} > D_x(t) \text{ or } M_{iy} < D_y(t) \text{ or } M_{iy} > C_y(t), \theta = 180^\circ \\ M_{ix} < D_x(t) \text{ or } M_{ix} > C_x(t) \text{ or } M_{iy} < A_y(t) \text{ or } M_{iy} > D_y(t), \theta = 270^\circ \end{cases} \quad (5)$$

223 In the formula (5), ($i = 1, 2, 3, 4$ represent the four vertices of the rectangle). For a line L_{AB} that is
 224 neither parallel nor perpendicular to the X-axis, if point M lies outside the quadrilateral $ABCD$, the
 225 following conditions must hold:

$$\begin{cases} (M_{iy} - k_1 \bullet M_{ix}) < y_2 \text{ or } (M_{iy} - k_1 \bullet M_{ix}) > y_1 \\ (M_{iy} - k_2 \bullet M_{ix}) < y_4 \text{ or } (M_{iy} - k_2 \bullet M_{ix}) > y_3 \end{cases} \quad (6)$$

2.4 Unmanned Mobile Detection Path Planning Algorithm

The motion of a vehicle is fundamentally a problem of solving a dynamic system. Incorporating constraints and an objective function then forms an optimal control problem. This paper employs the segmented Gaussian pseudo-spectral method to solve the optimal control problem. The method constructs Lagrange interpolation polynomials to approximate the state and control variables after discretizing the continuous optimization problem at the Legendre-Gauss (LG) collocation point. And replace the differential equation constraints with algebraic constraints, thus transforming the optimal control problem into a Nonlinear Programming (NLP) problem to be solved. Qiu et al. proposed a hierarchical trajectory planning and tracking control algorithm for unmanned vehicles combining Model Predictive Control (MPC) and Gaussian Pseudo-spectral Method (GPM). (Qiu et al., 2021).

An optimal control problem typically comprises: the system dynamics differential equations, physical constraints, obstacle avoidance constraints, boundary constraints, and a performance index function. The optimal control parameters are obtained by minimizing the performance index function while satisfying all constraints. The Bolza problem in nonlinear optimization is one of the main problems in classical calculus of variations that deals with the conditions for extreme points under certain constraints (Wang et al., 2021). This problem has a special feature of the mixed nature of the functional represented as the sum of an integral functional and a function on the boundary. It not only emphasizes the system state at the terminal moment, but also stresses the requirements for the control system process. Without loss of generality, the Bolza problem for nonlinear optimal control can be described as:

$$\min \psi = \phi(\xi(t_0), t_0, \xi(t_f), t_f) + \int_{t_0}^{t_f} g(\xi(t), \mu(t), t) dt \quad (7)$$

In the formula (7): $\xi(t)$ and $\mu(t)$ are the state and control variables of the system, respectively. The state variables $\xi(t)$ encompass the vehicle's longitudinal displacement x , lateral displacement y , velocity v , acceleration a , heading angle θ , and wheel steering angle φ . The control variables include the wheel angular velocity ω and jerk. $\xi(t) \in R^n$ and $\mu(t) \in R^m$ satisfy.

$$s.t. \begin{cases} \dot{\xi}(t) = f(\xi(t), \mu(t), t) \\ M(\xi(t), \mu(t), t) \leq 0 \quad t \in [t_0, t_f] \\ N(\xi(t_0), t_0, \xi(t_f), t_f) = 0 \end{cases} \quad (8)$$

In the formula (8): In the first line, describes the differential equation of state of the system. In the second line, $M(\xi(t), \mu(t), t) \leq 0$ represents the inequality constraints in the vehicle's path planning,

including collision avoidance constraints and the physical limitations of the vehicle system (such as maximum speed, maximum steering angle, acceleration limits, etc.). In the third line, $N(\xi(t_0), t_0, \xi(t_f), t_f) = 0$ represents the equality constraints in the vehicle's path planning, including the condition that the vehicle is stationary at both the initial and final times, as well as the continuity constraints in multi-stage planning (i.e., the terminal state of the previous stage must equal the initial state of the subsequent stage).

Based on the above context, the nonlinear optimal control problem for vehicle trajectory planning can be described as follows: the objective is to minimize t_f , that is $\min t_f$. Meanwhile, within the time interval $t \in [t_0, t_f]$, the vehicle system must satisfy the state differential equations, physical system constraints, obstacle avoidance constraints, and boundary condition constraints. The detailed solution procedure of the optimal control problem via the Gaussian pseudospectral method can be found in the Appendix.

Kinematic equation (3) defines the feasible motion capability of the vehicle. This equation characterizes the relationship between control inputs (jerk and front-wheel angular velocity) and the evolution of the vehicle states. The obstacle locations provided by the perception module are incorporated as path constraints in the trajectory planning problem, such that all obstacles must remain outside the vehicle's safety envelope throughout the planned path, thereby restricting the feasible state space. The optimal control algorithm searches within this constrained space to solve for the optimal control inputs, ensuring that the generated trajectory avoids obstacles while also adhering to the vehicle's kinematic constraints.

3 Experimental results and analysis

3.1 Vertical Detection

We conducted continuous fixed-point outdoor detection in Hefei (31.8593° N, 117.2160° E) on February 24, 2025. Fig. 4a shows the Range-corrected signal data of that day. In Fig. 4a, the temporal evolution of the vertical distribution of the near-surface aerosol layer is illustrated. The height of the aerosol layer was maintained at about 1.5 km for a long period of time. The Range-corrected signal intensity of aerosol exhibits relatively high values below 1 km. The signal intensity shows pronounced temporal variability, gradually decreasing from 1 $\text{W} \cdot \text{km}^2$ to 0.2~0.3 $\text{W} \cdot \text{km}^2$ between 06:00 and 17:00. After 17:00, the signal intensity recovers and stabilizes at approximately 0.5 $\text{W} \cdot \text{km}^2$. Clouds were also detected at 2km to 2.5km.

Many previous studies have correlated multi-source data with LiDAR data to investigate variations in aerosol concentration (Tu et al., 2022; Xiao et al., 2023). In order to verify the accuracy of the system's

detection, we also selected the hourly particulate matter concentration observed at the ground station in Hefei City on February 24th. Fig. 4b shows the variation curve of particulate matter concentration on the 24th (daily average concentration thresholds of $150\mu\text{g}/\text{m}^3$ and $75\mu\text{g}/\text{m}^3$ for PM_{10} and $\text{PM}_{2.5}$, respectively). When the $\text{PM}_{2.5}/\text{PM}_{10}$ ratio is below 0.5, it means large particle pollutants account for the main part of the air. When the ratio is 0.5 or above, it indicates that air pollution is dominated by fine particle pollutants. $\text{PM}_{2.5}$ and PM_{10} concentrations were higher than $100\mu\text{g}/\text{m}^3$ from 0:00 to 5:00. $\text{PM}_{2.5}/\text{PM}_{10}$ values were around 0.8, indicating that the pollution in this phase is local fine particulate matter. Then, the three curves dropped rapidly reaching a minimum at 10:00 ($56\mu\text{g}/\text{m}^3$ for PM_{10} ; $23\mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$ and 0.41 for $\text{PM}_{2.5}/\text{PM}_{10}$). At 16:00, the subsequent concentrations all rebounded, and the $\text{PM}_{2.5}/\text{PM}_{10}$ value stabilized between 0.5 and 0.6. The variation trend of the particulate matter concentration data is consistent with the detection results of the LiDAR.

To verify the physical rationality of the observation results, the vertical aerosol distribution from this cruise detection is compared with contemporaneous MERRA-2 reanalysis data. As a large-scale product, MERRA-2 reflects the regional aerosol spatiotemporal variation and transport background, while the lidar captures fine local vertical structures, showing complementary spatial scales. Given the limited single-day samples and result contingency, MERRA-2 serves only as a large-scale atmospheric reference to confirm the consistency of lidar results with regional background characteristics and exclude instrument anomalies and inversion deviations. By retrieving the MERRA-2 reanalysis data (Fig.5 and Fig.6). Fig.5 shows that Hefei experienced a distinct aerosol pollution episode from the 22nd to the 24th. Fig. 6 shows the hourly averaged data on the 23rd. Fig (a)–(c) illustrate the northwest-to-southeast transport of the pollution plume from 11:30 to 14:30 UTC, with the Hefei area impacted by the pollution process. However, constrained by its relatively coarse spatial resolution, MERRA-2 struggles to capture the details of local, short-term, and vertical variations in aerosols. Through vertical detections and comparative analysis, we can obtain a more refined vertical distribution of aerosols from the LiDAR results. **The comparison shows consistency in the main aerosol layer height and signal intensity variation trend, preliminarily verifying the physical rationality of the system observations. Restricted by the test period and site constraints, this study concentrates on the system integration and detection feasibility verification of the unmanned vehicle-borne aerosol lidar, and continuous observations under diverse conditions and over multiple periods are not performed in the current work. Future work will expand samples covering different pollution levels and meteorological conditions, and conduct systematic cross-validation and quantitative accuracy evaluation combining MERRA-2 data, ground monitoring data and synchronous fixed-point lidar observations.**

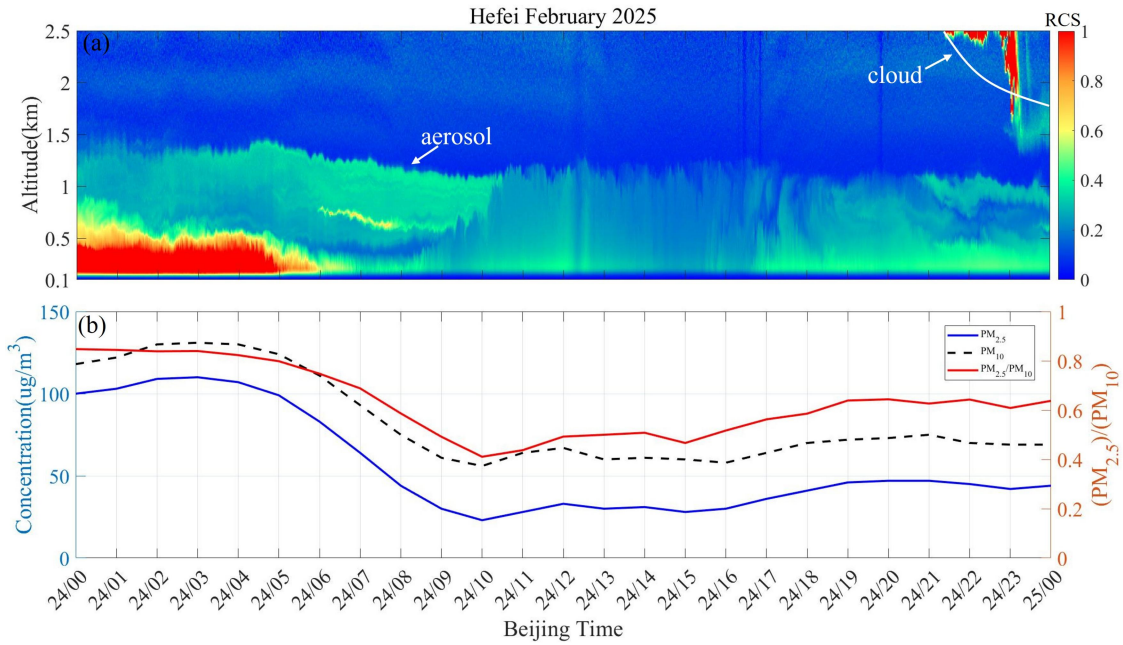


Fig. 4 Temporal variations in pollutant on 24 February: (a) The Range-corrected signal ($\text{W} \cdot \text{km}^2$) from Mie-scattering LiDAR; (b) The concentration of particulate matter at the ground station (the blue line indicates $\text{PM}_{2.5}$, the black line segment indicates PM_{10} , and the red line indicates $\text{PM}_{2.5}/\text{PM}_{10}$).

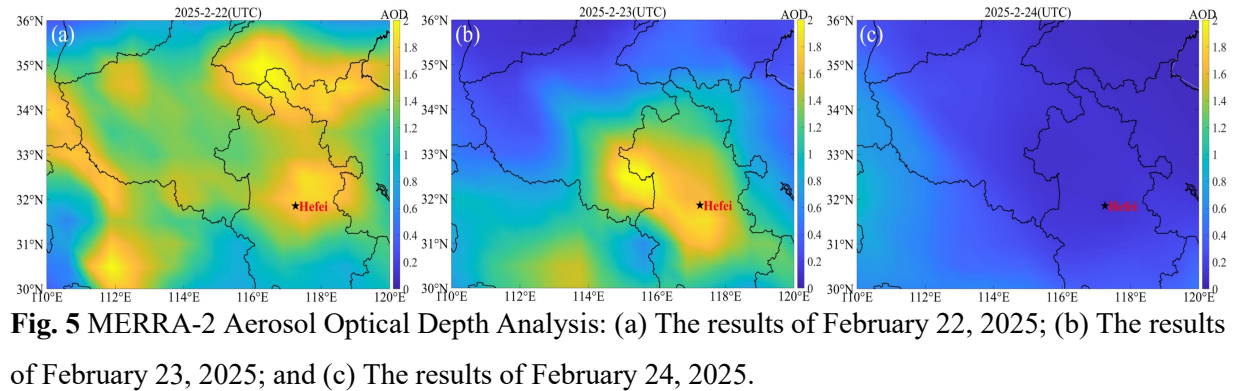


Fig. 5 MERRA-2 Aerosol Optical Depth Analysis: (a) The results of February 22, 2025; (b) The results of February 23, 2025; and (c) The results of February 24, 2025.

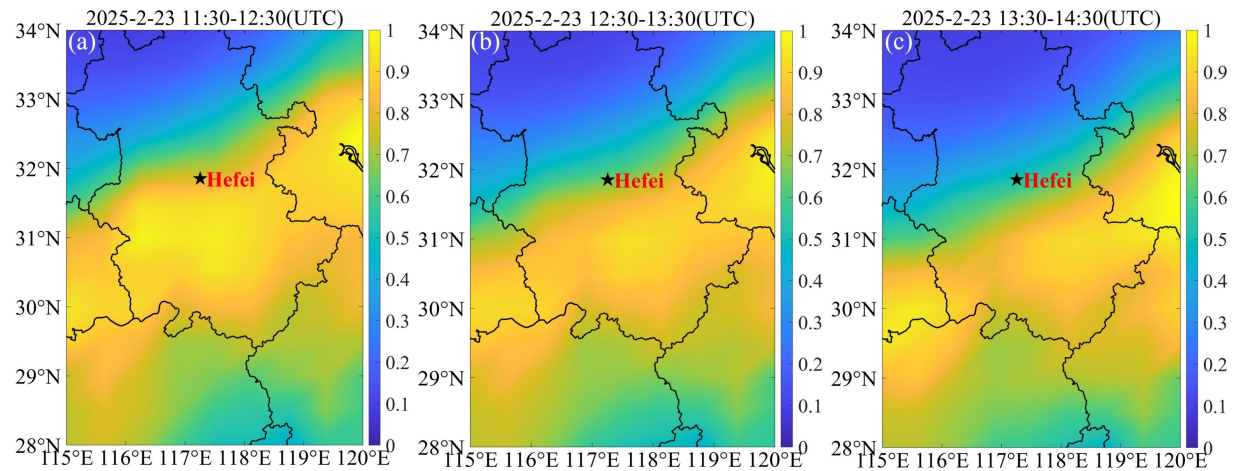


Fig. 6 MERRA-2 Total Aerosol Extinction AOT: (a) 2025-2-23 11:30-12:30(UTC); (b) 2025-2-23 12:30-14:30(UTC) and (c) 2025-2-23 13:30-14:30(UTC); UTC = CST – 8 h

3.2 Cone-Scanning Detection

Cone-scanning detection relies on the synchronous rotation of the LiDAR gimbal in both elevation and azimuth to realize three-dimensional spatial sampling. With a fixed elevation angle, the LiDAR rotates uniformly over the full 0° – 360° azimuth range to conduct stereoscopic tomographic sampling of the atmosphere within a 2.5 km detection radius. This mode can simultaneously capture the spatial distribution of aerosol and cloud masses at different azimuths and altitudes, compensating for the limitation of fixed-point vertical detection, which only provides single vertical profiles and lacks horizontal spatial coverage.

Owing to constraints imposed by the experimental environment, horizontal scanning is not feasible. We conducted cone-scanning detection experiments in Hefei (31.8593° N, 117.2160° E) on February 28, March 5, and March 6, 2025, respectively. To ensure reliable retrieval results, backscattering LiDAR signals from a sufficient number of independent laser pulses are accumulated at each azimuth angle. The parameters are set as follows: the 0° direction corresponds to due west, the elevation angle is 75° , the step angle is 1° , and the full scan takes approximately one hour. The Range-corrected data were optioned for a range of 2.5 km. Fig. 7. shows the Range-corrected signal of cloudy days (February 28), polluted days (March 5) and clean days (March 6). **Cloudy condition on 28 February (Figure 7a):** Continuous cloud echoes are observed at 2 km altitude in the 0° – 100° southeast azimuth, with only sparse aerosol plumes at 2.1–2.3 km, indicating low overall aerosol loading; **Polluted condition on 5 March (Figure 7b):** Thin clouds are widely distributed at 0.85–1.5 km near the ground. Aerosol plumes spread along the scanning circumference with a much larger coverage, and high near-ground backscattered lidar signals reflect elevated regional aerosol concentrations; **Clean condition on 6 March (Figure 7c):** No concentrated cloud or aerosol signals are observed across the entire detection radius. The values of range-corrected signals stay at extremely low levels throughout the field of view, demonstrating clean atmospheric conditions. The system can achieve three-dimensional scanning and positioning tracking of atmospheric aerosols.

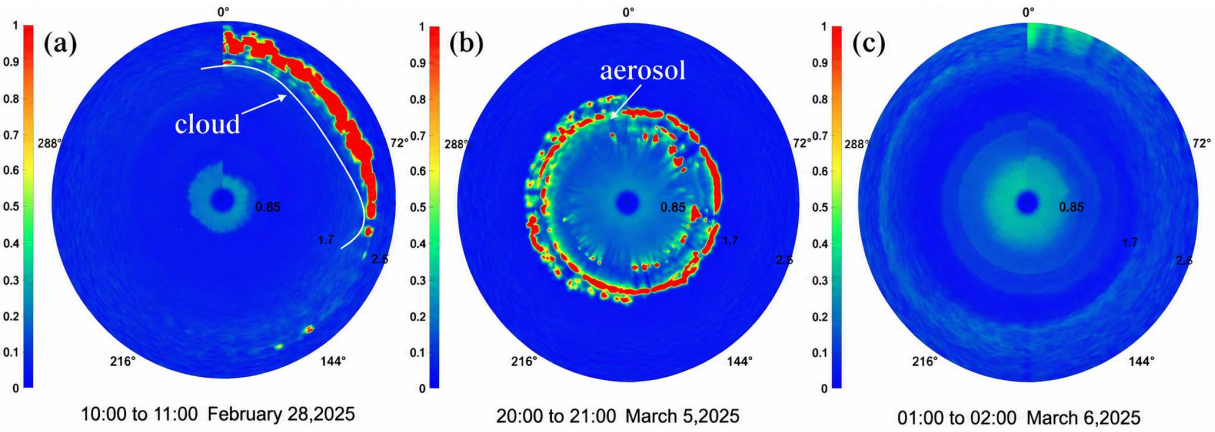


Fig. 7 Range-corrected signal($\text{W}\cdot\text{km}^2$) from cone-scanning detection:(a) The results of February 28, 2025; (b) The results of March 5, 2025; and (c) The results of March 6, 2025.

3.3 Unmanned Intelligent Cruise Detection

We did an unmanned intelligent cruise detection experiment in Hefei (31.8593°N , 117.2160°E) on February 26th. The location of the experiment was chosen near a laboratory building within the school. See Table 1 for unmanned vehicle parameters. The physical constraints are shown in Table 2. Fig. 8 shows the validation and simulation analysis of the trajectory planning algorithm based on the Gaussian pseudo-spectral method. Through simulation and emulation, we can achieve obstacle avoidance during the cruising detection process, and ensure safe and normal cruising according to the planned path.

Before the experiment, enter the Mie-scattering LiDAR system to configure the relevant detection parameters. This is followed by turning on the wire control chassis module of the unmanned vehicle and the modules related to the environment sensing and positioning module. Finally, the planned path is selected and the vehicle switches to autopilot.

Fig. 9 shows a plot of the Range-corrected signal from one unmanned cruise detection. We first clarify the background air pollution conditions on the test day: the air quality index (AQI) of Hefei reached 115, with synchronous ground monitoring values of $\text{PM}_{2.5}$ was $80\mu\text{g}/\text{m}^3$, and PM_{10} was $100\mu\text{g}/\text{m}^3$ (Data from China Environmental Monitoring Station; <http://106.37.208.233:20035>). It can be seen from Fig. 9a that the near-surface pollution layer was confined within the altitude range of 0–0.3 km throughout the observation period. The range-corrected signal gradually decreased from $0.8\text{ W}\cdot\text{km}^2$ to $0.2\text{ W}\cdot\text{km}^2$ as the vehicle cruised forward, indicating a continuous reduction of aerosol concentration along the traveling path. In the later stage of the experiment, the aerosol layer rose to 0.5 km, which corresponds to the gradual uplifting of the local atmospheric boundary layer and the increased vertical diffusion height of aerosols over time.

This cruise measurement demonstrates the unique advantages of the vehicle-borne detection system over fixed-point lidar. Conventional fixed-site lidar can only acquire time-resolved vertical aerosol profiles at a single location. In contrast, this unmanned cruising observation system enables the acquisition of three-dimensional spatial aerosol distributions with geolocation and altitude information.

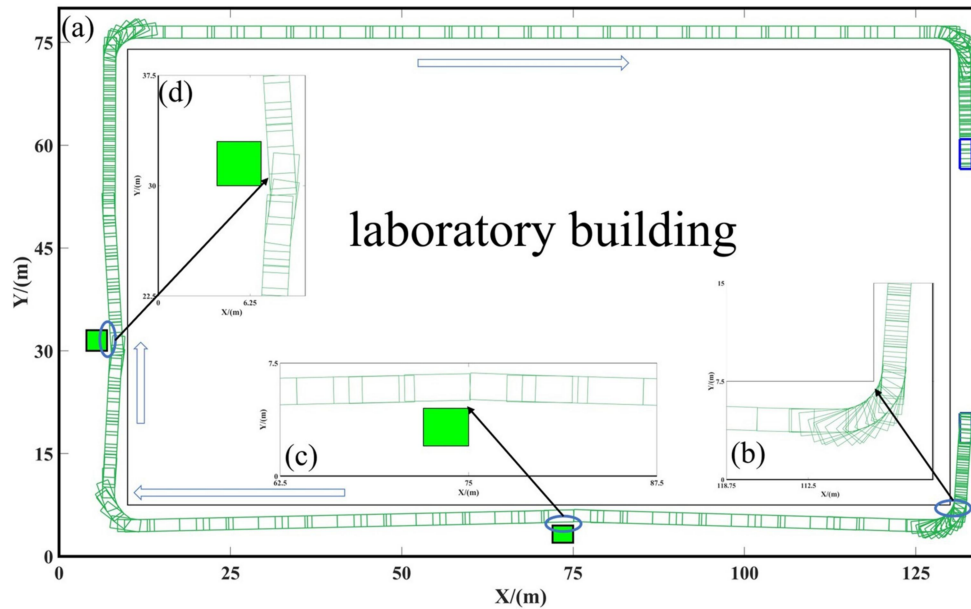


Fig. 8 Simulation of Cruise Detection Path Planning:(a) Navigation mobile route map; (b), (c) and (d) The simulation of obstacle avoidance for cornering, obstacle 1 and obstacle 2, respectively.

Table 2 Physical constraints for unmanned vehicles

Physical Constraints for Unmanned Vehicles					
parameters	$v_{\max}$	$a_{\max}$	$j_{\max}$	$\varphi_{\max}$	$\omega_{\max}$
numerical value	1.0m/s	0.1m/s ²	0.5m/s ³	0.56rad	0.56rad/s

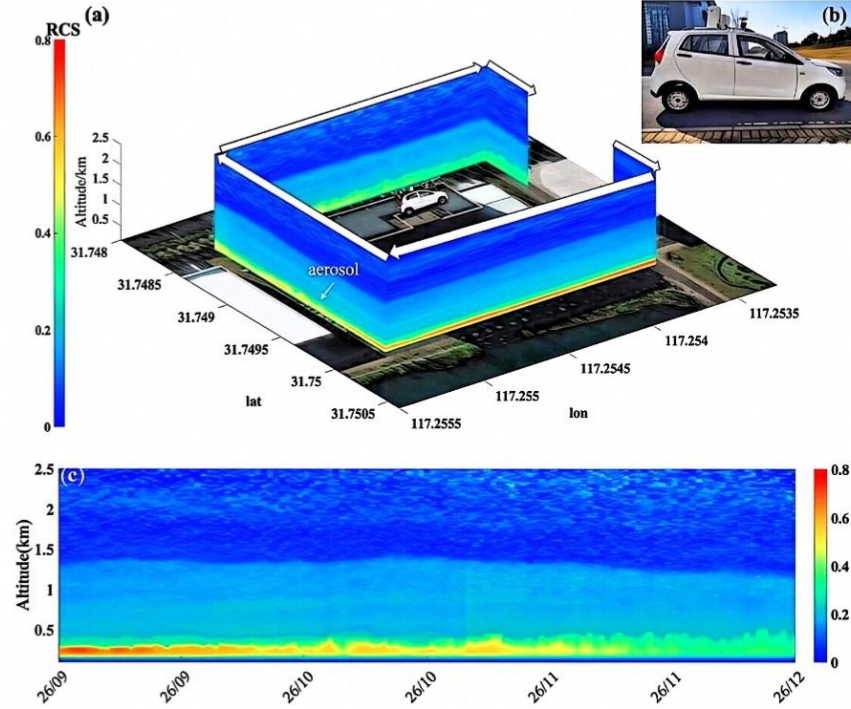


Fig. 9 Range-corrected signal ($\text{W} \cdot \text{km}^2$) superimposed on the map:(a) A map of Range-corrected signal for unmanned move detection (arrows are in the direction of vehicle travel); (b) An unmanned vehicle undergoing an unmanned walking experiment;(c) An unmanned Intelligent Cruise Detection : the temporal variation of Range-corrected signal ($\text{W} \cdot \text{km}^2$). (The map is a simple block map, ©2025Baidu-GS (2023)3206.)

4 Discussion

We have developed an aerosol detection system based on an unmanned driving platform and conducted initial tests. In the future, we will expand the detection scenarios and duration, and conduct diverse detection experiments for various pollution scenarios. In subsequent long-term experiments, the intelligent cruising detection system for complex scenarios will be further optimized. Currently, based on our summarized experience from earlier stages, the following scenarios may arise where our method could fail or degrade in performance. Firstly, when hardware such as LiDAR ages—for instance, laser energy attenuation leads to a decline in detection accuracy. Secondly, the existing path planning algorithm fails to adapt to complex traffic conditions. Since we have not conducted extensive road testing, further research on dynamic obstacle avoidance will be pursued in subsequent work.

Additionally, we are capable of detecting haze and other polluted weather conditions. As shown in Figure 8, our long-term continuous observations of polluted weather clearly reveal the detailed vertical structure of aerosols. However, our method will also fail when encountering harsh weather

conditions such as rain and snow. Raindrops and snowflakes cause intense Mie scattering and absorption of the laser pulses, leading to severe attenuation of the effective backscattered signal and introducing significant background noise. This results in a reduction of the raw signal-to-noise ratio (SNR), thereby affecting the accuracy of aerosol optical parameter retrieval and shortening the effective detection range.

In the initial design phase of the system, we prioritized the implementation of the system's core functionalities, high level of system integration, and overall platform mobility. Therefore, the entire system has indeed not yet undergone rigorous water and dust resistance rating certification tests. Operation under continuous precipitation conditions entails certain operational risks. Vibrations occurring during unmanned intelligent cruise experiments may affect the stability of the lidar system. Such vibrations can cause slight misalignment between the transmitting and receiving optical paths, thereby inducing non-aerosol fluctuations in the Range-Corrected Signal (RCS), and may even lead to detection blind zones or a sharp drop in the signal-to-noise ratio. Therefore, to eliminate the influence of vibration, the moving speed was controlled within 1.0 m/s in the experiments of this study. In future work, an active vibration damping platform will be installed to improve the data reliability of mobile measurements.

5 Conclusions

We propose a new approach to aerosol detection that combines atmospheric detection LiDAR technology and smart driving technology. The intelligent cruise detection system for aerosols was built through a modularized design. The system includes: a control module, an aerosol detection module, an environment sensing and positioning module, and a wire control chassis module. Firstly, continuous vertical detection experiments show that the system can continuously observe the vertical distribution of aerosols for a long time (24 hours). And it can provide the fine structure of clouds and aerosols from 0-2.5km. Through analysis, the variation of aerosol pollution in the detection area can be obtained. In addition, through scanning detection, the system has long-term 0-360° scanning detection capability. The system is capable of effective detection of different weather conditions (clean, polluted and cloudy days). Finally, an unmanned intelligent cruise detection experiment is conducted. The results of the experiment showed that the aerosol height increased from 0.3km to 0.5km on the day of the experiment and the pollution concentration gradually decreased from 0.8 $W \cdot km^2$ to about 0.2 $W \cdot km^2$. It shows that the system is capable of stable unmanned cruise detection and has ability to monitor the concentration and spatial distribution of pollutants. Experimentally demonstrated in three different ways: the system can obtain the vertical and spatial distribute on of aerosol pollutants effectively and continuously; it can achieve three-dimensional scanning and positioning tracking of atmospheric aerosols; The system features unmanned intelligent cruising and detection capabilities, enabling it to provide data on the

vertical distribution and dynamic variation of aerosols for regional pollution prevention and control.

Our team realized multi-sensor fusion. The safety and effectiveness of this method are verified by the experiments of three application scenarios in the park. In the future, we will continue to explore the application of relevant technologies in intelligent cruise, detection and pollution prevention, and provide new ideas for regional pollution monitoring.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

The LiDAR data presented in this study are available from the corresponding author upon request(yh9599@mail.ustc.edu.cn). Particulate matter concentration data from China Environmental Monitoring Station for providing the particulate matter data(<http://106.37.208.233:20035>). MERRA-2 provides Total Aerosol Extinction AOT data and Aerosol Optical Depth Analysis data (<https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/>).

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Author Contributions

Supervision, HY; designed the study, XMZ; Methodology, XMZ; Software, HY and ZQK, DYQ, ZYF; XMZ and XYL; Writing–original draft, XMZ; Writing–review & editing, YLH, ZYF, XMZ, XYL, DY Q and HY.

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Appendix

The detailed formulation for solving the optimal control problem using the Gaussian pseudospectral method is provided below.

- (1) time-domain transformations: The initial-final time domain $t \in [t_0, t_f]$ is partitioned into U subintervals. In the GPM algorithm, the intervals of time-variable discrete points are $\tau \in [-1, 1]$, so the subinterval moments need to be transformed in the time domain. For any arbitrary time instant $t \in [t_{v-1}, t_v]$ within the v -th subinterval, conversion by expression to $\tau \in [-1, 1]$.

$$\tau = \frac{2 \cdot t - (t_{v-1} + t_v)}{t_v - t_{v-1}}$$

After time-domain transformation, the optimal control problem within subinterval x can be formally stated as follows:

$$\min \psi^{(v)} = \phi^{(v)}(\xi^{(v)}(\tau_0), t_{v-1}, \xi^{(v)}(\tau_f), t_v) + \frac{t_v - t_{v-1}}{2} \int_{\tau_0}^{\tau_f} g(\xi^{(v)}(\tau), \mu^{(v)}(\tau), \tau : t_{v-1}, t_v) d\tau \quad s.t. \begin{cases} \dot{\xi}^{(v)}(\tau) = \frac{t_v - t_{v-1}}{2} f(\xi^{(v)}(\tau), \mu^{(v)}(\tau), \tau : t_{v-1}, t_v) \\ M(\xi^{(v)}(\tau), \mu^{(v)}(\tau), \tau : t_{v-1}, t_v) \\ N(\xi^{(v)}(\tau_0), \tau_0, \xi^{(v)}(\tau_f), \tau_f) \end{cases}$$

In the formula, $\xi^{(v)}(\tau)$ and $\mu^{(v)}(\tau)$ represent the state variable and control variable, respectively, after time-domain transformation at time t in the v-th subinterval $[t_{v-1}, t_v]$.

(2) variable discretization: Discretize the state and control variables at Legendre-Gauss (LG) collocation points and construct Lagrange polynomial approximations to represent the states ξ and controls μ during the maneuvering process. Legendre polynomials of order N on the interval $[\tau_0, \tau_f]$ are:

$$P_N(\tau) = \frac{1}{2^N \cdot N!} \times \frac{d^N}{d\tau^N} [(\tau^2 - 1)^N]$$

With the zeros $(\tau_1, \tau_2, \tau_3, \dots, \tau_N)$ and the initial point τ_0 forming the constellation of N+1 collocation points, the state and control variables at each collocation point are defined as:

$$\begin{cases} \xi(\tau_0), \xi(\tau_1), \dots, \xi(\tau_N) \\ \mu(\tau_0), \mu(\tau_1), \dots, \mu(\tau_N) \end{cases}$$

At N + 1 collocation points, construct a Lagrange interpolating polynomial using the following basis functions.

$$\begin{cases} L_i(\tau) = \prod_{j=0, j \neq i}^N \frac{\tau - \tau_j}{\tau_i - \tau_j} \\ \tilde{L}_i(\tau) = \prod_{j=0, j \neq i}^N \frac{\tau - \tau_j}{\tau_i - \tau_j} \end{cases}$$

The approximate polynomials for the state variables, control variables, are expressed as follows:

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$$\begin{cases} \xi^{(v)}(\tau) \approx \sum_{i=0}^N L_i^{(\mu)}(\tau) \bullet \zeta^{(v)}(\tau_i) \\ \mu^{(v)}(\tau) \approx \sum_{i=0}^N \tilde{L}_i^{(\mu)}(\tau) \bullet U^{(v)}(\tau_i) \end{cases}$$

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By differentiating the aforementioned expression, the derivative of the state variable can be approximated using the derivative of the interpolation polynomial. For example, the derivative of the state variable at a time point can be expressed as:

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$$\dot{\xi}^{(u)}(\tau_k) \approx \sum_{i=0}^N L_i^{(u)}(\tau_k) \bullet \zeta^{(v)}(\tau_i)$$

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Transformation of kinematic differential equation constraints into algebraic equality constraints:

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$$\dot{\xi}^{(u)}(\tau_k) - \frac{t_v - t_{v-1}}{2} f(\zeta(\tau_k), U(\tau_k), \tau_k) = 0$$

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(3) Under discretization, the equality and inequality constraints for system variables are formulated respectively as:

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$$\begin{cases} M(\zeta^{(v)}(\tau_k), U^{(v)}(\tau_k), \tau_k : t_{v-1}, t_v) \leq 0 \\ N(\zeta^{(v)}(\tau_0), \tau_0, \zeta^{(v)}(\tau_f), \tau_f) = 0 \end{cases}$$

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Through the discretization, the optimal control problem of vehicle trajectory planning can be transformed into a nonlinear programming problem. Performance metrics can be obtained for discrete conditions:

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$$\min \psi^{(v)} = \phi^{(v)}(\xi^{(v)}(\tau_0), t_{v-1}, \xi^{(v)}(\tau_f), t_v) + \frac{t_v - t_{v-1}}{2} \sum_{k=0}^N \rho_k \bullet g(\zeta(\tau_k), U(\tau_k), \tau_k)$$

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In summary, through discretization at the collocation points, the Bolza optimal control problem is transformed into a standard nonlinear programming (NLP) problem.