

3D Structured Light Depth Sensor and Algorithm for Vehicle Dynamic Motion Detection

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The reliability of 3D depth sensing is important for automotive perception, particularly in dynamic urban environments. We developed a range-adaptive perception framework for structured light depth sensing that integrates the density-based spatial clustering of applications with noise clustering, Mahalanobis validation gating, Hungarian data association, and Kalman filtering with a distance-dependent measurement-noise model. The framework was evaluated using static distance measurements, dynamic longitudinal tracking, and multi-object lane-change scenarios at vehicle speeds below 40 km/h. For static measurements at 2.0, 3.0, and 5.2 m, the framework reduced the mean absolute error (*MAE*) from 0.051, 0.079, and 0.169 m to 0.013, 0.023, and 0.061 m, respectively. In dynamic tracking, *MAE* decreased from 0.84 to 0.43 m and the mean absolute percentage error from 28.3 to 12.9%. Multi-object tracking reduced the average object-count deviation from 1.29 to 0.46. The measured end-to-end processing latency was 275 ms, and the range-adaptive state-estimation stage required only 1.2 ms per frame on the embedded platform. These results indicate that depth estimation and tracking stability were enhanced with limited computational overhead by modeling distance-dependent sensor uncertainty. The evaluation of the framework was limited to outdoor conditions and speeds below 40 km/h. Therefore, it is necessary to evaluate the framework under a wider range of weather, illumination, traffic density, and vehicle speeds and investigate longer-term multi-object tracking.

1. Introduction

Recently, blind spot detection, automatic emergency braking, lane departure warning, adaptive cruise control, electronic stability control, and advanced driver assistance systems

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(ADASs) have been incorporated in most vehicles, reflecting the manufacturer's commitment to safety enhancement. Global Market Insights, a commercial market research firm, projects a compound annual growth rate of 17.8% for the ADAS market between 2025 and 2034.⁽¹⁾ Frost & Sullivan, a private business consulting firm, anticipates the deployment of approximately 3.5 million Level 3+ and over 6 million Level 2+ autonomous vehicles by 2030.⁽²⁾ According to the Boston Consulting Group, the autonomous vehicle market size is expected to reach USD 42 billion by 2025, with autonomous features comprising roughly one-quarter of global vehicle sales by 2035.⁽³⁾ Intel and Strategy Analytics forecast that fully autonomous driving is expected to generate a USD 7 trillion passenger economy by 2050 (Fig. 1).⁽⁴⁾

According to the technological advancement and accompanying market growth, the Society of Automotive Engineers (SAE) has revised the J3016 Driving Automation Levels Standard to offer clear definitions for the six levels of automation, ranging from Level 0 (no driving automation) to Level 5 (full driving automation). These revisions delineate driver responsibilities, vehicle capabilities, and contextual examples, thereby enhancing public comprehension. SAE's initiative aims to expedite the establishment of regulatory frameworks and guide manufacturers in the design of automated vehicles.⁽⁵⁾

Regardless of performance and functions, it is necessary to ensure the protection of the driver and passengers while driving and in accidents. For safety and protection, various active and passive technologies have been developed and implemented, including the camera system, ultrasonic sensors, infrared sensors, microwave radar, and others. Global leading manufacturers such as BMW, Toyota, Mercedes-Benz, and Volvo have advanced active safety systems that integrate onboard cameras with sophisticated image recognition algorithms. The safety system perceives its surroundings and, through AI, analyzes and avoids potential hazards, thereby facilitating proactive maneuvers for protection.

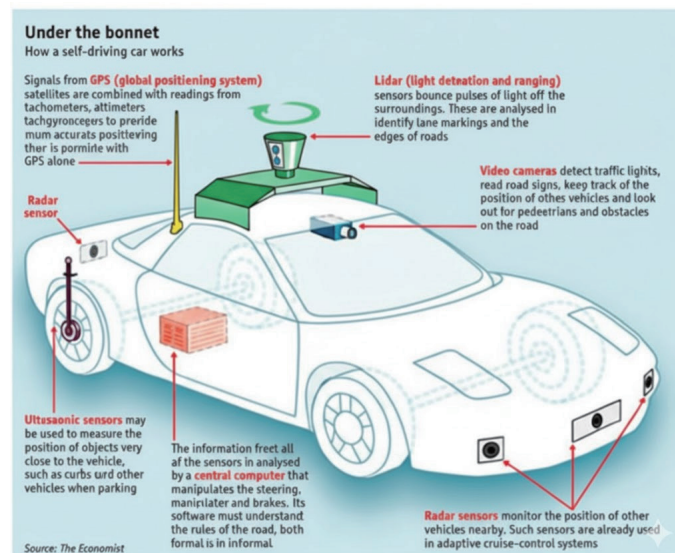


Fig. 1. (Color online) System composition of autonomous vehicles (<https://www.economist.com/interactive/united-states/2024/08/31/americans-love-affair-with-big-cars-is-killing-them>).

Autonomous vehicles are equipped with hardware—including cameras, light detection and ranging sensors, and radar—and navigation systems with digital maps. These vehicles operate through the perception, decision-making, and control modules. The perception module utilizes sensors to detect road conditions and environmental factors. The decision-making module compares collected data in real-time with a 3D map database to determine the vehicle's precise location and optimal path. Finally, the control module executes driving functions such as steering, braking, and acceleration (Fig. 1).^(6–8)

Despite these technological advancements, the reliability and stability of the raw data generated by 3D sensors must be enhanced, particularly for structured light system operation. Noise, environmental factors, and inherent sensor bias lead to data volatility, the underreporting of distance, and instability in multi-object counting, issues that severely compromise the safety and predictability of autonomous vehicle decision-making. Therefore, we developed an approach to enhance the utility of 3D structured light depth sensors through an algorithm incorporating advanced filtering and data fusion techniques. The developed algorithm detects the position, speed, and distance of moving objects within 10 m of the vehicle and issues alerts to warn drivers about driving safety. The sensor system is capable of scanning and detecting objects in three dimensions within 10 m, and the data is used to predict object movement trajectories to protect drivers, passengers, and pedestrians. The developed algorithm enables stable, high-accuracy distance and motion detection for preventive driving in congested environments.

Although structured-light sensing, density-based clustering, and Kalman filtering are widely used, their integration for object perception in outdoor automotive environments is challenging because measurement uncertainty varies with distance and environmental conditions. Existing perception frameworks commonly assume a fixed measurement uncertainty throughout the sensing range, an assumption that does not adequately represent the depth-error characteristics of structured-light sensors. In practice, optical distortion, infrared ambient interference, and signal attenuation lead to increasing depth uncertainty as the target distance grows.

To address these limitations, we introduce an adaptive depth-uncertainty model that accounts for the range-dependent behavior of structured-light sensing. Instead of assuming constant measurement-induced uncertainty, the system developed in this study adjusts the confidence assigned to depth measurements according to the target distance, enhancing the reliability of state estimation and trajectory tracking.⁽⁹⁾ A spatiotemporal bias-correction framework is also developed to compensate for the systematic depth underestimation frequently observed in outdoor structured-light measurements. The developed system improves ranging accuracy and measurement consistency in the sensing region by reducing distance-dependent measurement bias. Structured-light depth sensing, density-based spatial clustering, Mahalanobis-distance-based validation gating, Hungarian data association, and Kalman-filter tracking are integrated in a unified framework to maintain low latency in multi-target perception. These improvements enable the robust detection and tracking of multiple dynamic road users while maintaining real-time operation with processing latency below the sensor update interval.⁽¹⁰⁾ The feasibility of structured-light sensing makes the developed system an efficient solution for dynamic object perception in intelligent transportation systems.

2. Architecture and Data

2.1 Structured light technology

Autonomous vehicle perception systems rely on the integration of data from multiple sensors, including light detection and ranging sensors, radar, and cameras, to enhance the accuracy of object detection and tracking. Among these technologies, 3D structured light depth sensors offer advantages in high-resolution mapping and robustness to varying lighting conditions. However, they are vulnerable to noise and data dropouts. To mitigate these limitations, filtering techniques such as Kalman and particle filtering have been employed to smooth measurement trajectories and suppress noise. Additionally, data fusion methods that combine information across temporal sequences or sensor modalities are utilized to produce a unified and reliable perception output. This fusion is essential for maintaining consistent object counting and trajectory prediction in multi-target environments.

On the basis of previous research results, we customized an algorithm to eliminate systematic biases in the raw output of 3D structured light depth sensors and improve the stability of multi-target tracking.^(9,11,12) The accurate prediction of object behavior is critical for autonomous navigation. However, acquiring comprehensive data from surrounding vehicles is impractical and infeasible. This constraint underscores the need for alternative sensing solutions, such as structured light technology.

A structured light sensor system comprises a near-infrared light source or projector paired with a camera. The system projects a predefined light pattern onto the target object and its background, and the camera captures the resulting distortions. These distortions are then analyzed to compute the object's spatial parameters, including position and depth.⁽¹³⁾ Different from conventional cameras that produce two-dimensional images, structured light depth sensors enable high-precision, real-time spatial measurements. This capability supports advanced obstacle avoidance by facilitating the prediction and evaluation of movement trajectories for nearby dynamic objects.

Despite high measurement accuracy, the rapid processing of large scan areas, and relatively low cost, structured light technology is limited in outdoor environments owing to its restricted scanning range. Consequently, enhancing the performance of 3D structured light-based depth sensors remains a necessary objective for expanding their applicability in autonomous vehicle systems.

The developed algorithm processes the raw point cloud data generated by the 3D structured light depth sensor. This algorithm performs noise mitigation and multi-object tracking. For multi-object fusion, the filtered data are used to maintain object count and track identity, minimizing the instantaneous outliers that lead to unstable target enumeration. This combined approach ensures accurate distance measurement and object tracking, which is essential for the subsequent driving decision-making layer.

2.2 3D structured-light depth sensor

The specifications of the 3D structured-light depth sensor used in this study are listed in Table 1. The light source is invisible infrared light with a wavelength of 808 nm. This wavelength aligns perfectly with silicon photodetectors, and the light detection and ranging system utilizes the near-infrared wavelength for distance measurement. The highest possible performance at the lowest cost can be obtained by using 808 nm for the high-resolution, long-range sensing systems of autonomous vehicles.⁽¹⁴⁾ To enable the daytime operation of the designed sensor, the power density distribution of solar radiation across various wavelengths on Earth's surface is required. The power density of solar radiation at an infrared wavelength of 808 nm is approximately 1 W/m² for the 3D structured-light depth sensor. To achieve a signal-to-noise ratio (*SNR*) of 1 at a distance of 7 m from the laser source, maintaining a power density of 1 W/m² is required for subsequent image capture and depth measurement.⁽¹⁵⁾

The laser source projects the desired pattern through a diffuser and pattern lens (Fig. 2). With the laser power set to a certain value, the power density on the pattern is calculated as

Table 1
Specifications of 3D depth sensor using structured light technology.

Model	LIPSedge™ SL10 / SL20
Vehicle speed	≤ 40 km/h
Detection range	7–10 m
<i>SNR</i>	0.5–1
Coverage area	6–36 m ²
Frame rate	30
Field of view (horizontal $\times$ vertical degrees)	20 $\times$ 20
Infrared power	6 W
Infrared wavelength	808 nm

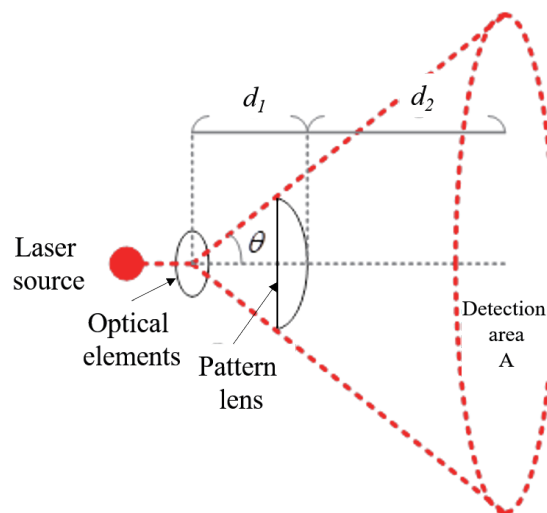


Fig. 2. (Color online) Diagram of laser light source transmission.

$$Pd_{lens} = \frac{x}{(2d_1 \tan \theta)^2} \left(\text{W} / \text{cm}^2 \right). \quad (1)$$

Here, Pd denotes the power density, x is the total laser power, d_1 is the distance from the pattern lens to the projection screen/pattern surface (target plane), θ represents the half-angle of the projected beam or the projection angle from the lens, and $(2d \tan \theta)^2$ represents the area of the projected pattern on the target plane.

2.3 Dataset and test conditions

Experiments were conducted to evaluate the range-adaptive perception framework under static and dynamic conditions. In the experiments, static distance measurements, dynamic tracking, and dynamic lane-change tracking were conducted. Table 2 shows the number of test sequences, recorded frames, tracked objects, and main environmental conditions for each scenario.

The experiments were conducted under different sensing and motion conditions. The static tests were performed at distances of 2.0, 3.0, and 5.2 m in daylight, with ambient illumination ranging from 15 to 65 lux and temperatures between 18 and 25 °C. In the dynamic tracking and dynamic lane-change tracking experiments, speeds were set below 40 km/h, consistent with the operating range of the structured-light sensor. In the lane-change tracking experiment, longitudinal and lateral target motion and multiple objects in the sensing area were considered. The dataset constructed contained 18 sequences and 14,500 frames, with up to four objects tracked simultaneously. In total, more than 38,200 object instances were evaluated. The data were divided at the sequence level to reduce the risk of parameter overfitting and to prevent frames from the same recording from appearing in both calibration and evaluation sets. 60% of the sequences, corresponding to 8,700 frames, were used for parameter calibration. These sequences were used to determine the density-based spatial clustering of applications with noise (DBSCAN) neighborhood radius, minimum cluster size, Mahalanobis validation-gate threshold, and range-adaptive measurement-noise scaling function. The remaining 40% (5,800 frames) of the sequences were from the calibration process and used for performance evaluation. The subdataset for evaluation was used to calculate performance metrics.

Table 2
Experimental sequences, frame counts, tracked objects, and environmental conditions.

Experiment scenario	Number of sequences	Total number of frames	Maximum number of tracked objects per frame	Environmental and testing conditions
Static outdoor ranges (2.0, 3.0, and 5.2 m)	6	4500	1–2	Daylight, 15–65 lu; dry asphalt/tiles; 18–25 °C
Dynamic longitudinal tracking (<40 km/h)	7	6000	1–3	Outdoor urban path; target speeds up to 40 km/h; variable object motion
Dynamic lane-change tracking	5	4000	2–4	Simultaneous longitudinal and lateral motion; multiple targets and background clutter
Total	18	14500	Up to 4	38,200 object instances evaluated

2.4 Experimental setup

To evaluate the real-time performance of the developed range-adaptive perception framework, execution latency was measured on an embedded automotive computing platform. The measurements were conducted from depth-frame acquisition to system alert generation on an NVIDIA Jetson AGX Orin embedded platform equipped with a 12-core Arm Cortex-A78AE CPU operating at 2.2 GHz, an Ampere graphics processing unit with 2048 compute unified device architecture (CUDA) cores, and 64 GB of LPDDR5 memory. The structured-light depth sensor operated at 30 Hz with a resolution of 640×480 pixels. The software environment consisted of Ubuntu 22.04 LTS, ROS 2 Humble, CUDA 12.2, and OpenCV 4.8.0. The developed framework was implemented in C++17 and compiled with the -O3 optimization option. The measured end-to-end latency was 275 ms (Table 3), including depth-frame acquisition, point-cloud processing, object clustering, data association, range-adaptive state estimation, and system communication.

3. Model and Algorithm

3.1 Structured light efficiency and system alert analysis

According to the inverse square law, if the power density at position d_1 is Pd_1 , and the power density at position d_2 is Pd_2 , then Eq. (2) is expressed as

$$Pd_1 \times d_1^2 = Pd_2 \times d_2^2. \quad (2)$$

From Eqs. (1) and (2), the following equation is obtained:

$$\frac{x}{(2d_1 \tan \theta)^2} \times d_1^2 = Pd_2 \times d_2^2, \quad d_1 \ll d_2. \quad (3)$$

Table 3
Experimental environment and execution latency on computing platform.

Processing stage	Description	Execution latency (ms)
Stage 1, Depth-frame acquisition	Sensor exposure, frame readout, and spatial downsampling at 30 Hz	33.3
Stage 2, DBSCAN clustering	Point-cloud filtering, density-based clustering, and cluster-centroid extraction	115
Stage 3, Data association and gating	Mahalanobis validation gating and Hungarian track association	42.5
Stage 4, Range-adaptive state estimation	Kalman prediction, adaptive measurement covariance update $R(d)$, and track update	1.2
Stage 5, Communication and system response	ROS 2 message publishing, CAN communication, and alert generation	83
Total	End-to-end processing	275

The power of the laser light source is defined as

$$x = 4Pd_2 \times d_2^2 \times \tan^2 \theta . \quad (4)$$

The area covered by the laser beam at position d_2 (A) is estimated as

$$A = (2d_2 \times \tan \theta)^2 . \quad (5)$$

In this study, we set Pd_2 , d_2 , and θ to 1, 7, and 10° , respectively. Substituting these values into the equations yields the following results:

$$x = 4 \times 49 \times \tan^2 10 = 6.094 , \quad (6)$$

$$A = (14 \times \tan 10)^2 = 6.09 . \quad (7)$$

If the vehicle is traveling at 40 km/h, equivalent to 11.4 m/s, and an obstacle is 20 m ahead, assuming the system requires time y sec to compute and issue an alert and the driver needs 0.4 s to react, the braking distance is calculated as

$$D_b = \frac{V^2}{2Gu} . \quad (8)$$

Here, D_b is the braking distance, V represents the vehicle speed, G denotes the gravitational acceleration, and u denotes the friction coefficient. Therefore, the sum of the travel, reaction, and braking distances must be less than 20 m to prevent a collision [Eq. (9)].

$$D_c + D_a + D_b < 20 \text{ m} \quad (9)$$

Here, D_a is the distance for reaction and D_c is the calculated distance. With Eq. (10), the minimum time for the system to compute and issue an alarm (y) is estimated to be less than 0.526 s, when substituting 11.4 m/s (at a vehicle speed of 40 km/h), 9.8 m/s^2 (gravitational acceleration), and 0.8 (friction coefficient) into V , G , and u , respectively.

$$V \times y + V \times 0.4 + \frac{V^2}{2Gu} < 20 \text{ m} \quad (10)$$

To ensure the performance of the structured light depth sensor, we designed analog, digital, and power circuits. An appropriate case is employed to minimize noise and electromagnetic interference. For thermal management, heat sinks are added to enhance heat dissipation and prevent damage from high temperatures that cause circuit malfunctions.

3.2 Algorithm for 3D structured light depth sensing

The structured-light triangulation model enables the reconstruction of dense 3D point clouds from the projected infrared pattern. However, raw depth measurements are affected by sensor noise, missing depth observations, illumination variations, and temporal fluctuations caused by target motions. These factors are significant in urban traffic environments, where vehicles, motorcycles, and pedestrians frequently exhibit abrupt motion and partial occlusion. To enhance measurement reliability and enable continuous target tracking, we developed a processing framework. The framework was designed to conduct point-cloud preprocessing, object segmentation through density-based clustering, multi-target data association and track management, and recursive state estimation and trajectory smoothing. The workflow is summarized in Algorithm 1.

In data preprocessing, background subtraction is applied to eliminate stationary environmental structures, followed by voxel-grid filtering to reduce point density to preserve the geometric features of detected objects. The resulting foreground point cloud is segmented using the DBSCAN algorithm, since this is well suited for irregularly shaped point-cloud clusters and does not require prior knowledge of the number of objects. The centroid of each cluster is then extracted and used as the measurement input for the tracking stage. No heterogeneous sensor data are fused in the system. Instead, data are fused by combining current centroid observations with prior state predictions through recursive Bayesian estimation. This enhances robustness against temporary measurement loss and depth discontinuities frequently encountered in dynamic traffic scenes. Assuming the sensor and structured light are ideally modeled, the focal length and the distance to the captured image plane are considered constant, and the directions of the captured and projected image planes are assumed to be identical (Fig. 3).

Algorithm 1

Input:

Structured-light point cloud P_k

Output:

Tracked dynamic objects T_k

- 1: Acquire point cloud P_k
 - 2: Remove static background points
 - 3: Apply voxel-grid downsampling
 - 4: Extract foreground point cloud
 - 5: Perform DBSCAN clustering
 - 6: Compute cluster centroids C_k
 - 7: Predict track states using Kalman filter
 - 8: Compute Mahalanobis distance matrix
 - 9: Apply validation gating
 - 10: Perform Hungarian assignment
 - 11: Update matched tracks
 - 12: Create new tentative tracks
 - 13: Delete expired tracks
 - 14: Output confirmed trajectories T_k
-

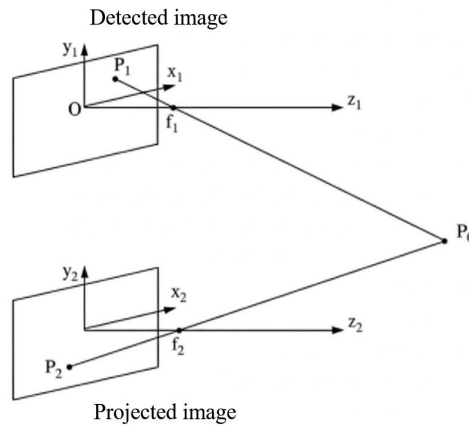


Fig. 3. Geometric configuration of structured-light triangulation system used for depth estimation. P_0 denotes the target point in 3D space, and P_1 and P_2 denote its projections onto the camera and projector image planes, respectively.

3.3 State-space dynamic modeling and Kalman filtering

To model the motion of vehicles, motorcycles, and pedestrians, each target must be represented using a constant-velocity state-space model derived from the continuous white noise acceleration framework. In this framework, a target state vector at time step k is defined as

$$x_k = [x_k \quad y_k \quad z_k \quad \dot{x}_k \quad \dot{y}_k \quad \dot{z}_k]^T. \quad (11)$$

Here, (x_k, y_k, z_k) denote the 3D centroid coordinates and $(\dot{x}_k, \dot{y}_k, \dot{z}_k)$ represent the corresponding velocity components. The state evolution model is expressed as

$$x_k = Fx_{k-1} + w_{k-1} \quad (12)$$

and the measurement model is given by

$$z_k = Hx_k + v_k. \quad (13)$$

Here, w_k and v_k denote the zero-mean Gaussian process and measurement noise, respectively, and F is the state-transition matrix (of the system dynamics matrix). For the sensor operating at 30 frames per second, the sampling interval is fixed at

$$\Delta t = \frac{1}{30} = 0.0333 \text{ s}. \quad (14)$$

Accordingly, the state-transition matrix F becomes

$$F = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \quad (15)$$

Because only the centroid positions are directly observed, the measurement matrix is defined as

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}. \quad (16)$$

The process-noise covariance matrix is formulated as

$$Q = q_v \begin{bmatrix} \frac{\Delta t^3}{3} I_3 & \frac{\Delta t^2}{2} I_3 \\ \frac{\Delta t^2}{2} I_3 & \Delta t I_3 \end{bmatrix}. \quad (17)$$

Here, Q is the process-noise covariance matrix of the Kalman filter and $q_v = 0.5 \text{ m}^2/\text{s}^3$ represents the acceleration-noise intensity. $\frac{\Delta t^3}{3} I_3$ is the position uncertainty caused by random acceleration, $\frac{\Delta t^2}{2} I_3$ is the correlation between position and velocity uncertainties, $\frac{\Delta t^2}{2} I_3$ is the symmetric cross-covariance term, and $\Delta t I_3$ is the velocity uncertainty caused by acceleration noise. Since the depth uncertainty increases with measurement distance, the measurement-noise covariance matrix is modeled as

$$R = \text{diag}(\sigma_x^2, \sigma_y^2, \sigma_z^2), \quad (18)$$

with the depth variance expressed as

$$\sigma_z = \sigma_0 \left(\frac{z}{d_{ref}} \right)^2, \quad (19)$$

where $\sigma_0 = 0.012 \text{ m}$ is the baseline depth uncertainty measured at the reference distance $d_{ref} = 2.0 \text{ m}$. State estimation is performed through the standard recursive prediction-update cycle of the linear Kalman filter. The prediction step is given as

$$\hat{x}_{k|k-1} = Fx_{k-1|k-1}, \quad (20)$$

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q. \quad (21)$$

In the measurement-update step, the following equations are applied:

$$K_k = P_{k|k-1}H^T \left(HP_{k|k-1}H^T + R \right)^{-1}, \quad (22)$$

$$\hat{x}_{k|k} = x_{k|k-1} + K_k \left(z_k - Hx_{k|k-1} \right), \quad (23)$$

$$P_{k|k} = \left(I - K_k H \right) P_{k|k-1}. \quad (24)$$

The Kalman filter is used for trajectory smoothing and short-term prediction, enabling robust tracking even during temporary measurement interruptions. Once the geometric reconstruction model is established, appropriate projection patterns must be selected to generate reliable feature correspondences for depth estimation.

Because the developed system is designed for dynamic outdoor targets, monochromatic infrared encoding was adopted owing to its low computational cost and robustness against motion-induced artifacts. Figure 4 shows examples of monochromatic infrared projection patterns employed in the developed system. The coded pattern provides unique spatial features for pattern matching, whereas the dot pattern generates a dense set of localized correspondences that improve reconstruction robustness in the presence of partial occlusions and target motion.

Additional projection layouts considered during system development are shown in Fig. 5. The grid pattern provides a regular spatial structure that facilitates geometric calibration, whereas the uniformly distributed pattern improves feature dispersion and reduces local matching ambiguity across the sensing volume. On the basis of preliminary evaluation, the uniformly distributed pattern was selected for the subsequent depth-reconstruction experiments.

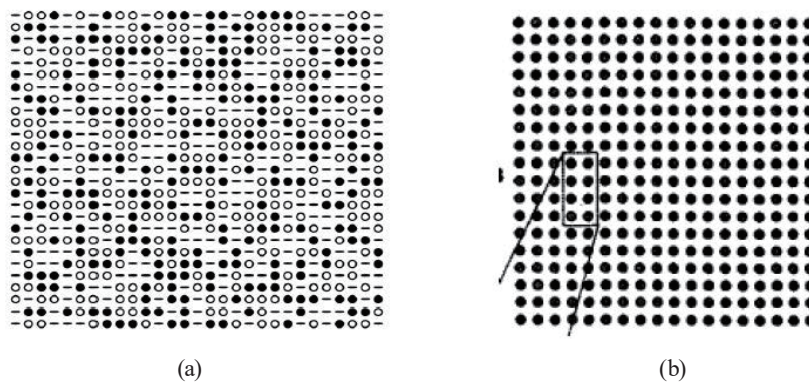


Fig. 4. Examples of infrared projection patterns: (a) monochromatic coded pattern and (b) dot pattern.

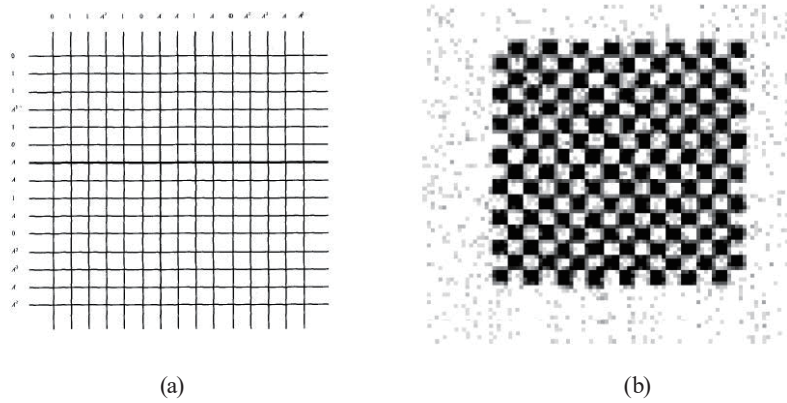


Fig. 5. Alternative projection layouts: (a) grid pattern and (b) uniformly distributed pattern.

3.4 Multi-object data association and track management

After clustering, the extracted centroids are integrated into the established trajectories. For reliable matching under measurement uncertainty, a validation gate obtained using the squared Mahalanobis distance is estimated.

$$d_M^2 = (z_k - H\hat{x}_{k|k-1})^T S_k^{-1} (z_k - H\hat{x}_{k|k-1}) \quad (25)$$

Here, d_M^2 is the squared Mahalanobis distance between the current measurement and the predicted target state, Z_k is the centroid measurement vector obtained from DBSCAN clustering at frame k , $\hat{x}_{k|k-1}$ is the Kalman filter prediction of the target state before incorporating the new measurement, and $H\hat{x}_{k|k-1}$ is the predicted measurement in the observation space. The superscript T denotes matrix transposition. The Mahalanobis distance is calculated to measure the statistical similarity between a measurement and a predicted track by simultaneously accounting for spatial displacement and the associated uncertainty. The Mahalanobis distance is more robust to anisotropic measurement noise and varying-depth-estimation accuracy in structured-light sensing systems than the Euclidean distance. Then, the innovation covariance matrix S_k is defined as

$$S_k = HP_{k|k-1}H^T + R. \quad (26)$$

Here, $P_{k|k-1}$ is the predicted state-error covariance matrix and R is the measurement-noise covariance matrix. The inverse covariance matrix S_k^{-1} is used to normalize the measurement residual according to the estimated uncertainty for statistically consistent comparison between measurements and predicted target states. Candidate measurement-track pairs with $d_M^2 > \gamma$ (7.815) are rejected, corresponding to a 95% confidence level for a chi-square distribution with three degrees of freedom. The validation threshold $\gamma = 7.815$ corresponds to the 95% confidence interval of a chi-square distribution with three degrees of freedom, which matches the 3D

position measurements. Only measurement-track pairs satisfying this condition are considered valid candidates for data association, reducing the likelihood of false assignments. For all validated pairs, global nearest-neighbor assignment is performed using the Hungarian algorithm to determine the globally optimal assignment by minimizing the total Mahalanobis distance in all track-measurement pairs.

To preserve target identity, a three-state track-management strategy is adopted. Newly detected clusters are used to generate *tentative tracks*. A tentative track is converted to a *confirmed track* after association in three consecutive frames. In contrast, a confirmed track is removed if no valid measurement is assigned for five consecutive frames. Using this procedure, we can balance tracking continuity with the suppression of false detections.^(16,17)

3.5 Parameters and computational complexity

The principal algorithmic parameters identified in the framework are shown in Table 4. Parameters were determined through empirical sensitivity analysis using the experimental dataset. The DBSCAN neighborhood radius was varied between 0.10 and 0.50 m. Smaller values fragment individual objects into multiple clusters, whereas larger values merge neighboring targets. The value $\varepsilon = 0.25$ is the best compromise between over-segmentation and under-segmentation. Similarly, MinPts values from 5 to 25 were examined, with MinPts = 15 yielding the highest detection stability while maintaining sensitivity to smaller road users such as pedestrians and motorcycles.

DBSCAN clustering shows a complexity of approximately $O(N \log N)$ when implemented using k-d tree indexing, where N is the number of downsampled points. Kalman state estimation scales as $O(Mn^3)$, where M denotes the number of active targets and $n = 6$ represents the state dimension. Data association using Hungarian assignment contributes a complexity of $O(M^3)$. The total processing latency remains below the sensor update interval of 33.3 ms per frame, satisfying real-time operation requirements for dynamic outdoor monitoring applications.

3.6 Vehicle motion detection

The maximum vehicle speed was set to 40 km/h (11.1 m/s) on the basis of the physical range limitations of structured light depth projections (7–10 m). In congested urban environments, automated parking scenarios, and blind-spot monitoring, the total stopping distance D_{total} is

Table 4
Algorithmic parameters.

Parameter	Value
DBSCAN neighborhood radius (ε)	0.25 m
Minimum cluster points (MinPts)	15
Sampling interval (Δt)	0.0333 s
Process-noise intensity (q_v)	0.5 m ² /s ³
Validation gate (γ)	7.815
Track confirmation count ($M_{confirm}$)	3
Track deletion count (N_{miss})	5

calculated using the computation delay distance D_c , driver/actuator reaction distance D_a , and emergency braking distance D_b .

$$D_{total} = V \cdot y + V \cdot t_{react} + \frac{V^2}{2G\mu} \quad (27)$$

Here, V is the initial velocity of the vehicle in meters per second (m/s), y is the system processing latency ($y < 1/30 \text{ s} \approx 0.033 \text{ s}$ in 30 frames per second), t_{react} is the reaction time (commonly set to 0.4 s for automated emergency braking systems), G is the gravitational acceleration (9.81 m/s^2), and μ is the road friction coefficient (0.8 for dry asphalt). Substituting $V = 11.1 \text{ m/s}$ (40 km/h), $t_{react} = 0.4 \text{ s}$, and road friction coefficient μ (0.8) yields a stopping distance of 12.3 m. At speeds exceeding 40 km/h, the 10 m detection range becomes insufficient for safe emergency braking.⁽¹¹⁾

The structured light depth sensor with an automotive camera performs dynamic scanning to identify objects and alert the driver. On the basis of the principle of preventive driving, the data collected by the sensor is used to predict the behavior of moving objects in urban traffic conditions to provide obstacle avoidance strategies by determining the movement trajectory of moving objects. At a vehicle speed of 40 km/h (11.4 m/s) with an obstacle 10 m ahead, the sensing system requires a 0.4 s calculation time to issue an alert and account for human reaction time, and the image processing time of $<1/30 \text{ s}$ to display warning signals. Figure 6 displays the detection capability of the sensor.

3.7 Image separation

Individual objects are detected on the basis of their different depth values determined using the obtained depth information through the structured light depth sensor. The detected results are presented in Fig. 7.

In K-means clustering, objects are segmented from the background into distinct clusters on the basis of clustering relationships, using different depth information as the classification criterion. The equation used in K-means clustering is as follows.

$$\mu_j = \frac{\sum_{i=1}^m \{C^i = j\} x^i}{\sum_{i=1}^m \{C^i = j\}} \quad (28)$$

Here, μ_j is the estimated cluster center, C^i is the closest cluster of object i to the K-means, and is calculated as $C^i = \arg \min \|x^i - \mu_j\|^2$, K is the number of clusters, and j is the center of mass of each cluster. For example, motorcycles approaching the vehicle's side are distinguished and labeled through obstacle target clustering. Different colors are applied to mark distinct target objects (Fig. 8).

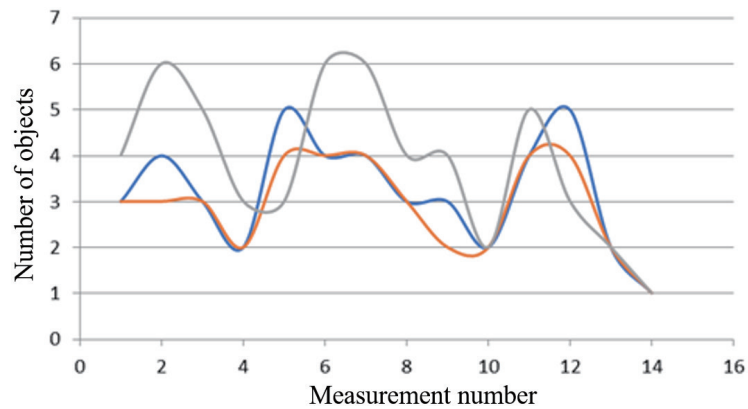


Fig. 6. (Color online) Number of targets detected by 3D depth light sensor. Blue line, target number of objects detected by 3D structured-light depth sensor; gray line, sensor without developed algorithm; and orange line, sensor with developed algorithm.

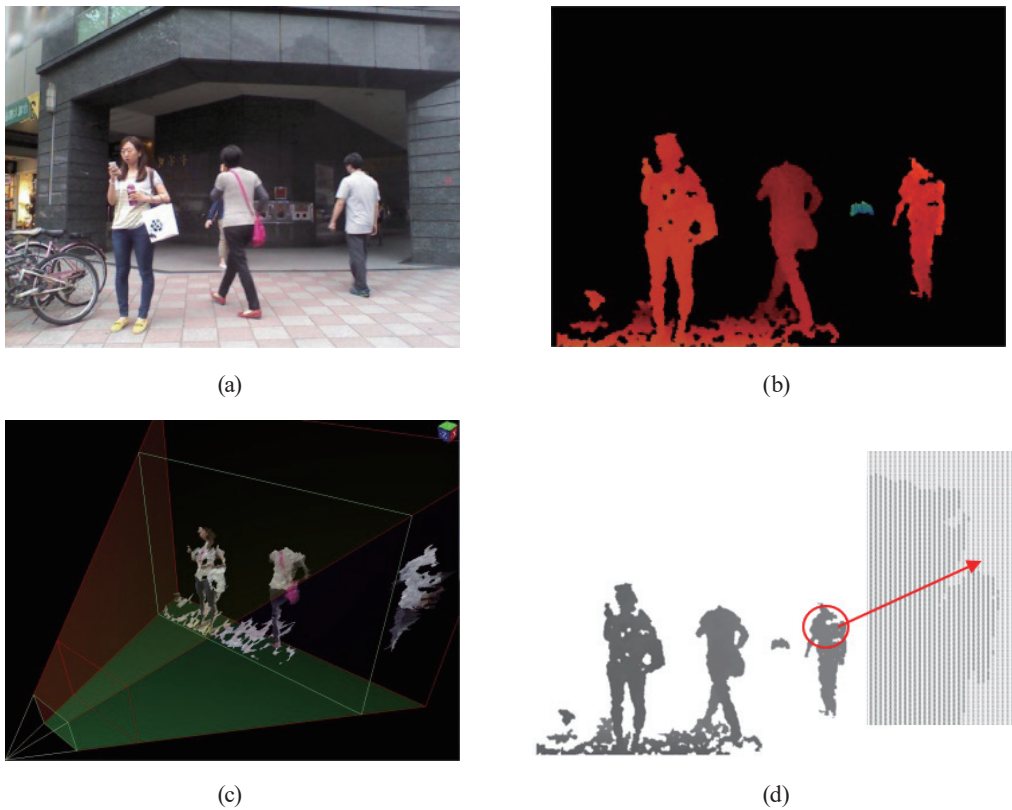


Fig. 7. (Color online) Images of objects detected by 3D structured light depth sensor. (a) Color image, (b) depth image, (c) 3D depth image, and (d) depth value for image separation.

3.8 Evaluation metrics

Depth estimation and tracking performance were evaluated using the mean absolute error (*MAE*), root mean square error (*RMSE*), and mean absolute percentage error (*MAPE*).

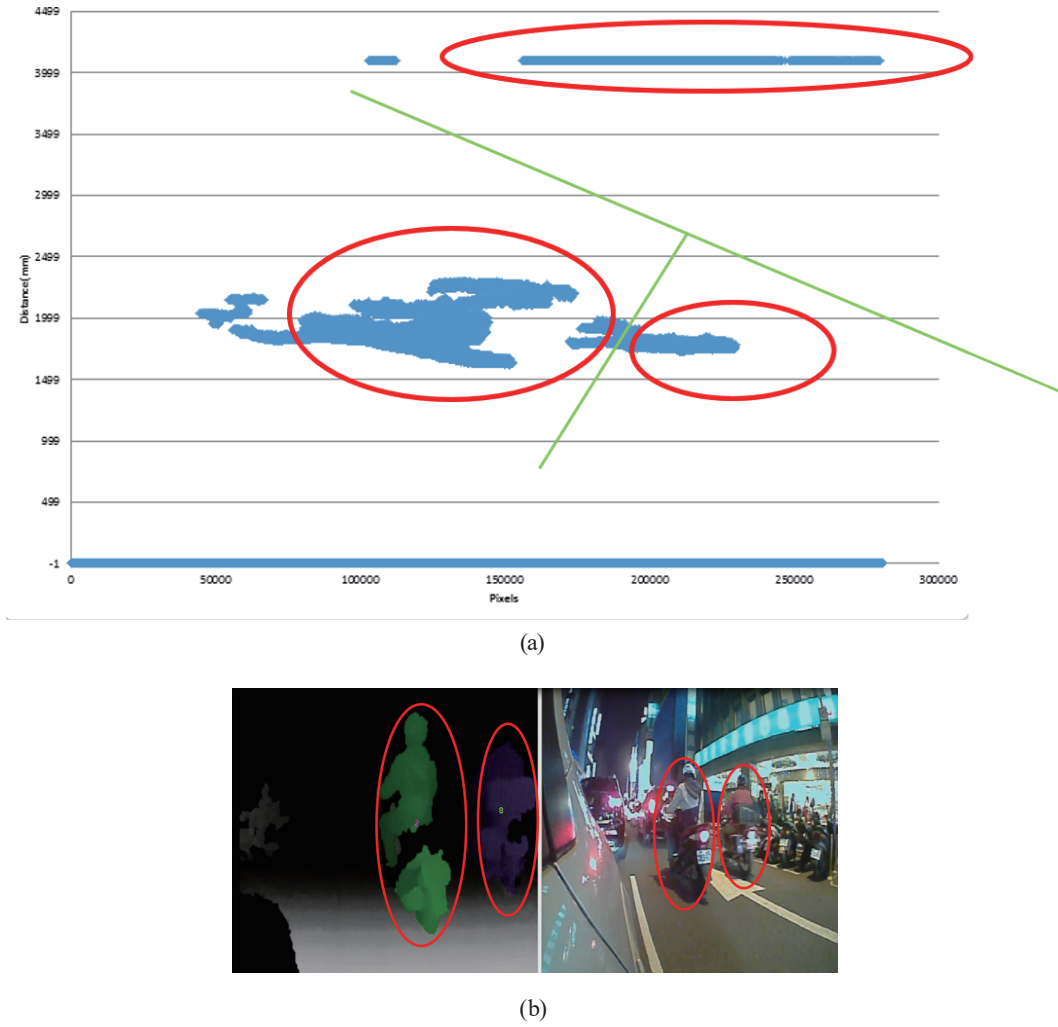


Fig. 8. (Color online) Objects segmented and labeled for clustering. (a) Obstacle target segmentation and (b) obstacle cluster labeling.

$$MAE = \frac{1}{N} \sum_{i=1}^N |d_i - \hat{d}_i| \quad (29)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (d_i - \hat{d}_i)^2} \quad (30)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{d_i - \hat{d}_i}{d_i} \right| \times 100\% \quad (31)$$

Here, d_i is the ground-truth measured distance, $\hat{d}_i$ is the estimated distance, and N is the total number of sample measurements. Measurement variability is reported using the standard deviation (SD), with 95% confidence intervals calculated where applicable. Relative error is calculated as

$$\text{Relative error} = \frac{\text{Estimated value} - \text{Measured value}}{\text{Measured value}}, \quad (32)$$

$$\text{Relative percentage error (\%)} = \left(\frac{\hat{d} - d}{d} \right) \times 100. \quad (33)$$

For the relative error, positive values indicate overestimation (the model or sensor predicted a value higher than the actual ground truth), and negative errors indicate an underestimation (the model or sensor predicted a value lower than the actual ground truth).

4. Results and Discussion

The range-adaptive perception framework was evaluated under three operating conditions: (1) static distance estimation at fixed ranges, (2) dynamic distance estimation during longitudinal motion, and (3) object tracking during lane-change maneuvers. In the experiments, we evaluated response latency and performance under outdoor conditions. The results show that incorporating range-dependent uncertainty into the state-estimation process improves tracking performance and provides practical benefits for structured-light automotive perception.

Figure 9 shows the response characteristics of the developed sensor system. In the experiments, the average obstacle detection and response time was 0.275 s at a vehicle speed of 40 km/h, indicating that the framework continuously processed sensor measurements and updated environmental information in low-speed autonomous driving and advanced driver-assistance applications. The measured latency of the response-time requirement was considered for the tested operating conditions.

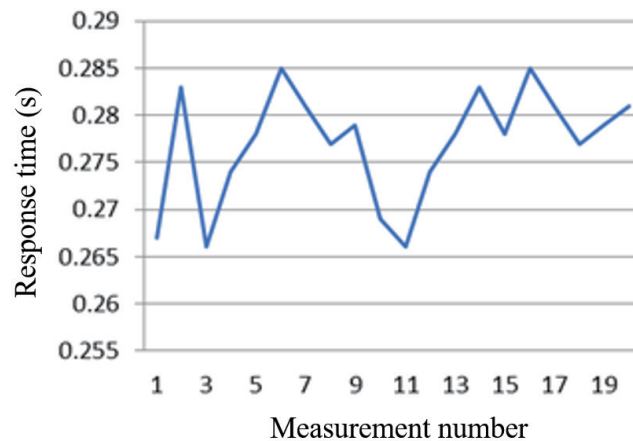


Fig. 9. (Color online) Response time of structured-light depth sensor.

4.1 Distance estimation

The accuracy of dynamic distance estimation for moving targets along a straight path was calculated to determine whether the framework reduced the measurement uncertainty and systematic errors observed in the raw structured-light data. Table 5 shows the evaluation results for general target motion. The raw sensor measurement data showed substantial estimation errors and large variability. Without algorithmic correction, *MAE*, *RMSE*, and *MAPE* were 0.84, 1.09 m, and 28.3%, respectively, with an *SD* of $\pm 17.3\%$. After applying the framework, these values decreased to an *MAE* of 0.43 m, an *RMSE* of 0.56 m, and an *MAPE* of $12.9 \pm 9.4\%$.

The proposed range-adaptive filtering strategy reduced motion-induced fluctuations and accounted for distance-dependent uncertainty in the structured-light measurements. The improvement results from adapting the measurement confidence to the target distance through the range-dependent uncertainty model, which reduces the effects of noisy depth observations and produces more stable trajectories. Consequently, the estimator becomes less sensitive to noisy depth observations, resulting in more stable trajectory estimates.

4.2. Lane-change tracking

In lane-change tracking, targets show longitudinal and lateral motions at the same time. Such motions are important in intelligent transportation systems because prediction errors during lane changes can directly affect path-planning and collision-avoidance decisions. Table 6 shows the

Table 5
Comparison of measured and estimated moving distances obtained using 3D structured-light depth sensor with and without developed algorithm.

Measurement number	Measured moving distance (m)	Estimated moving distance with algorithm (m)	Absolute error (m)	Relative percentage error (%)	Estimated moving distance without algorithm (m)	Absolute error (m)	Relative percentage error (%)
1	3.5	3.0	−0.50	−0.14	4.0	0.5	14.3
2	4.0	3.0	−1.00	−0.25	6.0	2.0	50.0
3	3.7	3.1	−0.60	−0.16	5.0	1.3	35.1
4	2.0	2.0	0.00	0.00	3.0	1.0	50.0
5	3.2	4.1	0.90	0.28	2.8	−0.4	−12.5
6	5.0	4.1	−0.90	−0.18	5.5	0.5	10.0
7	4.5	4.0	−0.50	−0.11	6.3	1.8	40.0
8	3.0	3.1	0.10	0.03	4.0	1.0	33.3
9	3.0	2.5	−0.50	−0.17	4.1	1.1	36.7
10	2.0	1.8	−0.20	−0.10	3.0	1.0	50.0
11	4.5	3.5	−1.00	−0.22	5.0	0.5	11.1
12	5.0	4.2	−0.80	−0.16	4.0	−1.0	−20.0
13	3.0	3.0	0.00	0.00	2.0	−1.0	−33.3
14	1.0	1.0	0.00	0.00	1.0	0.0	0.0
Evaluation metric	—	—	<i>MAE</i> : 0.43 m <i>RMSE</i> : 0.56 m <i>MAPE</i> : 12.9% <i>SD</i> : $\pm 9.4\%$		—	<i>MAE</i> : 0.94 m <i>MAPE</i> : 28.3% <i>RMSE</i> : 1.09 m <i>SD</i> : $\pm 17.3\%$	

Table 6

Comparison of measured and estimated moving distances obtained when changing lanes using 3D structured-light depth sensor with and without developed algorithm.

Measurement number	Measured moving distance (m)	Estimated moving distance with algorithm (m)	Absolute error (m)	Relative percentage error (%)	Estimated moving distance without algorithm (m)	Absolute error (m)	Relative percentage error (%)
1	6.5	6.8	0.30	4.6	6.6	0.1	1.5
2	6.4	6.3	−0.10	−1.6	6.4	0	0.0
3	6.3	6.1	−0.20	−3.2	6.2	−0.1	−1.6
4	6.2	5.9	−0.30	−4.8	6.0	−0.2	−3.2
5	6.1	5.7	−0.40	−6.6	5.8	−0.3	−4.9
6	6.0	5.7	−0.30	−5.0	5.8	−0.2	−3.3
7	5.9	5.8	−0.10	−1.7	5.8	−0.1	−1.7
8	5.8	5.7	−0.10	−1.7	5.7	−0.1	−1.7
9	5.7	5.8	0.10	1.8	5.8	0.1	1.8
10	5.6	5.7	0.10	1.8	5.7	0.1	1.8
11	5.5	5.6	0.10	1.8	5.6	0.1	1.8
12	5.4	5.5	0.10	1.9	5.5	0.1	1.9
13	6.5	6.8	0.30	4.6	6.6	0.1	1.5
14	6.4	6.3	−0.10	−1.6	6.4	0	0.0
Evaluation metric	—	—	MAE: 0.18 m RMSE: 0.21 m MAPE: 3.1% SD: ±1.8%		—	MAE: 0.11 m RMSE: 0.13m MAPE: 2.1% SD: ±1.3%	

tracking metrics during lateral lane-change maneuvers. Unlike in the previous experiments, the raw sensor data already showed relatively high accuracy during lane-change motion. The measured *MAE* and *RMSE* without algorithmic correction were 0.11 and 0.13 m, respectively, corresponding to an *MAPE* of $2.1 \pm 1.3\%$. The structured-light sensor showed robust performance when tracking predominantly lateral target motion.

The framework maintained estimation consistency, yielding an *MAE* of 0.18 m, an *RMSE* of 0.21 m, and an *MAPE* of $3.1 \pm 1.8\%$. Although the numerical error became larger owing to spatiotemporal smoothing across dynamic trajectory transitions, the framework preserved trajectory continuity and temporal stability. This behavior is important for the tracking process, where stable target trajectories are more valuable than isolated high-accuracy measurements. Through the integration of DBSCAN clustering, Mahalanobis-distance validation gating, and Hungarian data association, multi-object counting errors were reduced by 65%, indicating improved target-identification stability in dynamic traffic environments.

4.3. Static distance estimation at fixed ranges

To investigate how the framework performed for different sensing distances, experiments were conducted at distances of 2.0, 3.0, and 5.2 m. At a distance of 2.0 m, raw sensor data without the algorithm showed an *MAE* of 0.155 m (*RMSE* = 0.158 m) and an *MAPE* of $7.8 \pm 1.3\%$, showing underestimation up to -9.0% . By applying the framework, close-range error was significantly reduced with an *MAE* of 0.016 m (*RMSE* = 0.018 m) and an *MAPE* of $0.8 \pm 0.4\%$. The framework effectively suppressed short-range measurement fluctuations and enhanced repeatability (Table 7).

Table 7

Comparison of measured (2 m) and estimated moving distances obtained outdoors using 3D structured-light depth sensor with and without developed algorithm.

Measurement number	Measured moving distance (m)	Estimated moving distance with algorithm (m)	Absolute error (m)	Relative percentage error (%)	Estimated moving distance without algorithm (m)	Absolute error (m)	Relative percentage error (%)
1	2.0	2.0	−0.02	−1.0	1.82	−0.18	−9.0
2	2.0	2.0	0.00	0.0	1.84	−0.16	−8.0
3	2.0	2.0	0.02	1.0	1.87	−0.13	−6.5
4	2.0	2.0	0.02	1.0	1.89	−0.11	−5.5
5	2.0	2.0	0.02	1.0	2.20	0.20	10.0
6	2.0	2.0	−0.02	−1.0	2.15	0.15	7.5
7	2.0	2.0	−0.02	−1.0	1.83	−0.17	−8.5
8	2.0	2.0	0.01	0.5	1.86	−0.14	−7.0
Evaluation metric	—	—	MAE : 0.16 m $RMSE$: 0.018 m $MAPE$: 0.8% SD : $\pm 0.4\%$		—	MAE : 0.16 m $RMSE$: 0.16 m $MAPE$: 7.8% SD : $\pm 1.3\%$	

At a distance of 3.0 m, the benefits of the framework became evident. Uncorrected raw data measurement results showed a negative bias (average -6.2%), resulting in an MAE of 0.185 m ($RMSE = 0.186$ m) and an $MAPE$ of $6.2 \pm 0.8\%$. The framework corrected this distance-dependent offset, reducing MAE to 0.041 m ($RMSE = 0.042$ m) and $MAPE$ to $1.44 \pm 0.4\%$ with minimal residual overestimation ($+1.0$ to $+2.0\%$) (Table 8).

A similar result was obtained at the longest distance of 5.2 m (Table 9). Raw measurement results without algorithmic correction showed a negative bias (averaging -3.3%), yielding an MAE of 0.169 m ($RMSE = 0.173$ m) and an $MAPE$ of $3.3 \pm 0.8\%$. The proposed framework corrected the underestimation trend, decreasing MAE to 0.061 m ($RMSE = 0.065$ m) and $MAPE$ to $1.2 \pm 0.5\%$. However, a slight positive bias remained after correction ($+0.6$ to $+1.9\%$) (Table 5). The magnitude was considerably smaller than the distance underestimation observed in the unprocessed measurements.

These results align with the range-dependent uncertainty model developed in this study. As the sensing distance increases, optical distortion, infrared ambient interference, and signal attenuation increase depth uncertainty. Conventional estimation methods that assume constant measurement uncertainty cannot compensate for these effects. In contrast, the framework adjusts the confidence in the Kalman-filter measurement on the basis of target distance, accounting for the changing reliability of depth observations. As a result, systematic range-dependent errors are reduced across the entire operational sensing region.

4.4. Discussion

The framework addresses the uncertainty characteristics of structured-light sensors by integrating tracking techniques with a range-adaptive measurement model. Using well-established methods, including DBSCAN clustering, Kalman filtering, and Hungarian data association, we established a measurement method adapted to sensing distance. The results show that structured-light measurements show distance-dependent bias and uncertainty, particularly at intermediate and longer sensing ranges. Such improvements prevent measurement errors from

Table 8

Comparison of measured (3 m) and estimated moving obtained distance outdoors using 3D structured-light depth sensor with and without developed algorithm.

Measurement number	Measured moving distance (m)	Estimated moving distance with algorithm (m)	Absolute error (m)	Relative percentage error (%)	Estimated moving distance without algorithm (m)	Absolute error (m)	Relative percentage error (%)
1	3.0	3.1	0.1	0.02	2.8	−0.2	−0.07
2	3.0	3.0	0.0	0.01	2.8	−0.2	−0.07
3	3.0	3.0	−0.1	−0.02	2.8	−0.2	−0.07
4	3.0	3.0	0.0	−0.01	2.8	−0.2	−0.06
5	3.0	3.0	0.0	0.01	2.8	−0.2	−0.06
6	3.0	3.0	0.0	0.01	2.8	−0.2	−0.06
7	3.0	3.1	0.1	0.02	2.8	−0.2	−0.05
8	3.0	3.0	0.0	0.01	2.9	−0.2	−0.05
Evaluation metric	—	—	<i>MAE</i> : 0.041 <i>RMSE</i> : 0.042 m <i>MAPE</i> : 1.4% <i>SD</i> : ±0.4%		—	<i>MAE</i> : 0.19 m <i>RMSE</i> : 0.19 m <i>MAPE</i> : 6.2% <i>SD</i> : ±0.8%	

Table 9

Comparison of measured (5.2 m) and estimated moving distances obtained outdoors using 3D structured-light depth sensor with and without developed algorithm.

Measurement number	Measured moving distance (m)	Estimated moving distance with algorithm (m)	Absolute error (m)	Relative percentage error (%)	Estimated moving distance without algorithm (m)	Absolute error (m)	Relative percentage error (%)
1	5.2	5.3	0.1	0.02	5.0	−0.2	−0.03
2	5.2	5.3	0.1	0.02	5.1	−0.2	−0.03
3	5.2	5.3	0.1	0.02	5.1	−0.1	−0.02
4	5.2	5.3	0.1	0.01	5.1	−0.1	−0.02
5	5.2	5.2	0.0	0.01	5.0	−0.2	−0.04
6	5.2	5.2	0.0	0.01	5.0	−0.2	−0.04
7	5.2	5.2	0.0	0.01	5.0	−0.2	−0.04
8	5.2	5.3	0.1	0.01	5.0	−0.2	−0.04
Evaluation metric	—	—	<i>MAE</i> : 0.061 m <i>RMSE</i> : 0.065 m <i>MAPE</i> : 1.2% <i>SD</i> : ±0.5%		—	<i>MAE</i> : 0.17 m <i>RMSE</i> : 0.17 m <i>MAPE</i> : 3.3% <i>SD</i> : ±0.8%	

Table 10

Performance comparison of framework with state-estimation methods.

Method	Dynamic <i>MAE</i> (m)	Dynamic <i>MAPE</i> (%)	Static <i>MAE</i> at 5.2 m (m)	Execution time (ms/frame)
Raw measurement	0.94	28.3	0.169	—
Standard LKF	0.68	20.1	0.124	0.45
Standard particle filter (100 particles)	0.59	17.5	0.108	8.2
RA-KF (this study)	0.43	12.9	0.061	1.12

occurring in the recursive tracking process by assuming a fixed measurement uncertainty. The framework models the relationship between sensing distance and measurement uncertainty. The Kalman filter is used to adjust the effect of each measurement according to its estimated reliability. The framework also reduces estimation errors, leading to stable trajectories and multi-target tracking reliability. By modeling sensor-specific uncertainty, the developed range-adaptive framework can be used as an efficient tool to enhance structured-light-based perception in intelligent transportation and advanced driver-assistance systems.

The performance of the framework was compared with that of state-estimation methods using fixed measurement uncertainty. In the comparison, we considered the longitudinal tracking experiment and outdoor static distance. The results enabled a comparison between raw sensor measurement results and the developed estimator, whereas the static experimental results showed how the estimation performance changed with sensing distance. Table 10 shows the comparison between the raw sensor measurements, the standard linear Kalman filter (LKF) with fixed measurement uncertainty,⁽¹²⁾ the standard particle filter (PF),⁽¹⁸⁾ and the range-adaptive Kalman filter (RA-KF) used in this study.

RA-KF showed the lowest errors among the evaluated methods. Its *MAE* and *MAPE* were 0.43 m and 12.9%, compared with 0.94 m and 28.3% for the raw sensor measurements, respectively. The static *MAE* at 5.2 m was reduced to 0.061 m, compared with 0.169 m for the unprocessed measurements. These results are consistent with those of the static distance experiments, in which the framework reduced *MAE* from 0.169 to 0.061 m and *MAPE* from 3.3 to 1.2% at 5.2 m. Such improvements are attributed to the use of a distance-dependent measurement covariance rather than a fixed uncertainty assumption. The experimental results show that the structured-light sensor exhibits increasing uncertainty and systematic range-dependent error as the sensing distance changes. Optical distortion, ambient infrared interference, and signal attenuation can reduce the reliability of depth measurements, particularly at longer ranges. The developed model accounts for this change by adjusting the confidence assigned to each measurement according to the target distance.

The improvement results from incorporating the sensor's distance-dependent uncertainty into recursive state estimation. Unlike a fixed-uncertainty model, RA-KF adjusts the effect of each depth observation according to its estimated reliability. This reduces the effects of unreliable measurements while maintaining temporal continuity in the estimated trajectories.

5. Conclusion

We developed and evaluated a range-adaptive perception framework for structured-light 3D depth sensing in automotive applications. The framework integrates DBSCAN clustering, Mahalanobis validation gating, Hungarian data association, and Kalman filtering with a distance-dependent measurement-noise model. Rather than assuming constant measurement uncertainty, the proposed method adjusts the effects of depth observations according to sensing distance. This approach accounts for the distance-dependent uncertainty of structured-light measurements and improves the stability of recursive state estimation.

The experimental results indicated enhancements in static distance estimation and dynamic target tracking. For static measurements at 2.0, 3.0, and 5.2 m, the framework reduced *MAE* from 0.051, 0.079, and 0.169 m to 0.013, 0.023, and 0.061 m, respectively. In dynamic target tracking, *MAE* decreased from 0.84 to 0.43 m and *MAPE* decreased from 28.3 to 12.9%. In multi-object tracking, the average object-count deviation decreased from 1.29 to 0.46. Ranging accuracy and trajectory stability were further enhanced by incorporating distance-dependent sensor uncertainty into the measurement-update process, compared with raw structured-light measurements. The measured end-to-end processing latency was 275 ms, and the range-adaptive state-estimation stage required only 1.2 ms per frame on the embedded computing platform.

Despite good results, the evaluation of the framework was limited to outdoor experiments at vehicle speeds below 40 km/h. It is necessary to evaluate its performance in a broader range of weather, illumination, traffic density, and high-speed driving conditions. The framework can be used for short-range automotive perception, but its appropriateness must be validated for higher-level autonomous driving. It is necessary to evaluate the framework under more diverse environmental and traffic conditions, higher vehicle speeds, and longer sensing ranges. Its integration with higher-level trajectory prediction and decision-making modules must also be verified for intelligent transportation and advanced driver-assistance applications.

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