IEEE Robotics and Automation Letters (RA-L) paper, presented at ICRA 2026, Vienna, Austria. Cite as RA-L paper.

Optical LiDAR Communication: Repurposing Existing LiDAR Sensors for Infrastructure-to-Vehicle Communication

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***Abstract*—As autonomous mobile robots increasingly operate in real-world environments, safety has emerged as a critical challenge, particularly regarding obstacle and pedestrian detection in building blind spots and reliable traffic signal recognition. While traditional Vehicle-to-Infrastructure (V2I) systems adopt high-capacity communication through 5G networks or via Optical Wireless Communication (OWC), these approaches require dedicated communication hardware that proves impractical for small, low-cost robots. Additionally, the communication bandwidth required for robot-oriented V2I, such as blind spot object detection and traffic signal states, is relatively limited; the high-capacity communication of 5G is often unnecessary.**

To address these challenges, we propose a novel optical communication system named Optical LiDAR Communication (OLC), which repurposes existing LiDAR sensors as communication devices. By integrating LiDAR Injection with 2D Code technology, OLC achieves cost-effectiveness through V2I communication without requiring additional hardware on robots. Real-world experiments confirmed that the proposed method achieves a communication success rate of over 76% at distances up to 30 meters. Furthermore, as a proof-of-concept, we develop two key V2I systems utilizing OLC: traffic signal information transmission and blind-spot obstacle detection, and real-time communication performance was demonstrated. These results indicate that the proposed method has potential as a V2I platform for next-generation robotics infrastructure.

I. Introduction

In modern robotics, LiDAR sensors serve as essential components, providing critical 3D pointcloud information of the surrounding environment for self-localization and object detection. This capability is particularly crucial in shared human-robot environments, such as warehouse logistics robots or autonomous delivery systems navigating urban landscapes, where accurate detection directly impacts safety. However, all sensors, including LiDAR, have physical limitations in their field of view and cannot detect blind spots behind buildings or equipment. Additionally, in urban navigation, traffic signal information, which is critical for safe driving, may be misrecognized or obstructed by other vehicles or pedestrians and thus overlooked. These limitations of sensors pose a significant risk not only to robots but also to surrounding pedestrians and workers, making them a critical challenge for the social implementation of robots.

Manuscript received: April, 9, 2025; Revised July, 28, 2025; Accepted September, 28, 2025.

This paper was recommended for publication by Editor Hyungpil Moon upon evaluation of the Associate Editor and Reviewers' comments.

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This research was supported in part by JST CREST JPMJCR23M4, JST PRESTO JPMJPR22PA and JSPS KAKENHI 24K02940.

See this project's supplementary at https://sites.google.com/keio.jp/keio-csg/projects/optical-lidar-communication

Digital Object Identifier (DOI): see top of this page.

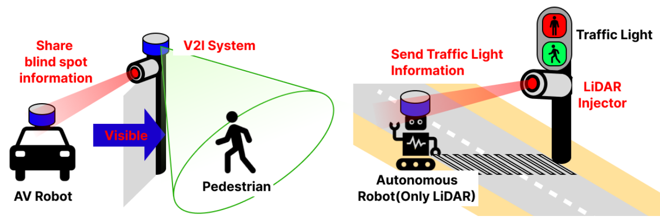

Fig. 1: Conceptual diagram of the proposed OLC-based V2I system: (left) V2I system for blind spot detection, (right) V2I system for traffic light detection.

As a solution to these challenges, Vehicle-to-Infrastructure (V2I) systems, which transmit information from infrastructure to robots, have gained significant attention. In autonomous vehicles, the use of wireless communication technologies such as 5G has been proposed [1], [2], enabling low-latency and high-capacity transmission of blind spot information to vehicles within a range of several hundred meters. However, these systems have two fundamental issues. First, they require expensive communication equipment and dedicated infrastructure, making it difficult to implement in low-cost robotic platforms. Second, the information needed for V2I in robotics (such as pedestrian positions, vehicle positions, and traffic signal states) is limited, meaning that the high-capacity communication of 5G may be excessive.

As an alternative V2I solution, optical communication technologies such as Visible Light Communication (VLC) and Optical Camera Communication (OCC) have garnered increasing interest [3]–[6]. These methods transmit data through visible light patterns, offering directional communication resistant to interference and jamming. However, they still require dedicated hardware components, significantly increasing implementation costs for existing robotic systems. Additionally, while mobile robots need stable communication over distances of several tens of meters, OCC and VLC perform poorly in outdoor environments due to interference from ambient light sources like sunlight [7], [8]. Table.I provides a comparative analysis of existing communication methods alongside our proposal. The required communication distance for outdoor

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TABLE I: Comparison with existing methods: The table defines the sufficient conditions for a V2I system

	Outdoor Communication Distance	Cost	Information Volume
OLC	30m	✓	11.3 kbps
OCC [7]	≤10m	✓	1Mbps≤, ≤10Gbps
VLC [8]	20m	✗	100 Mbps
FSO [10]	≤800m	✗	1 Gbps
V2I requirement †	20m	low	≤500bps

When transmitting only obstacle coordinates.

environments is calculated based on the stopping distance of a vehicle traveling at 60 km/h on dry road surfaces, while the information volume requirements are derived from [9].

Given these challenges, we propose a novel optical communication system named Optical LiDAR Communication (OLC) that repurposes existing LiDAR sensors for V2I applications. While previous research has identified LiDAR's vulnerability to laser interference attacks (LiDAR Injection) [11]–[13], our approach transforms this vulnerability into an opportunity and pioneers the first communication method based on LiDAR Injection. Specifically, we convert transmission information into a 2D code and inject this code pattern directly into the robot' s LiDAR as a pointcloud through LiDAR Injection, thereby establishing a new optical communication channel. This method has the following features:

- **Low-cost implementation:** Eliminates the need for dedicated communication devices and utilizes existing LiDAR sensors as communication devices.
- **Security:** Enhances security with authentication through Time-based One-Time Password (T-OTP) protocols.
- **Performance:** High directivity of laser light and utilization of redundancy of 2D codes achieves success rate of over 76% at distances up to 30m.

The contributions of this paper are as follows:

1) Design and implementation of a new optical communication system, OLC, demonstrating the feasibility of communication using existing LiDAR sensors.
2) Quantitative evaluation in real environments to clarify performance indicators such as communication distance, success rate, and error rate, demonstrating the practicality of the proposed method.
3) Development of a low-cost and reliable V2I system based on OLC, with practical implementations of blind spot detection and traffic signal information transmission.

The remainder is organized as follows: §II reviews related work, §III introduces our OLC system based on LiDAR Injection, §IV describes our V2I implementation, §V presents experimental results, §VI details case studies of traffic signal applications, §VII addresses limitations, and §VIII concludes.

II. Related Works

A. V2I System

Vehicle-to-Infrastructure (V2I) systems have been extensively researched as communication frameworks that deliver environmental data from infrastructure to vehicles and robots. Existing research falls into three applications: (1) traffic signal information transmission [2], [14], (2) traffic flow optimization [15], and (3) blind spot obstacle detection [16], [17]. In particular, for blind spot detection, existing V2I systems integrate pointcloud data from LiDAR installed in Road Side Units (RSU) and vehicle-mounted LiDAR via wireless communication to estimate the position of obstacles in blind spots.

A significant limitation of existing V2I systems is the cost of deploying communication infrastructure. For autonomous vehicles, implementing 5G communication systems requires expensive base stations and specialized communication equipment, creating a considerable financial barrier.

B. Optical Wireless Communication

Optical communication technology has evolved in two main directions: wired (fiber optics) and wireless. In the field of optical wireless communication (OWC), four primary methods have been studied: Free Space Optics (FSO) [18], Li-Fi [19], Visible Light Communication (VLC) [3], and Optical Camera Communication (OCC) [5]. These methods can be broadly classified into two categories: FSO, which uses direct laser irradiation, and Li-Fi/VLC/OCC, which use modulated diffused light from LEDs or other sources.

However, these technologies have significant limitations. As shown in Table.I, methods that utilize diffused light are affected by environmental interference such as sunlight, limiting outdoor communication distances to just a few meters. Additionally, FSO and VLC require dedicated transmitters and receivers, resulting in high system implementation costs.

In contrast, our proposed Optical LiDAR Communication (OLC) system utilizes LiDAR sensor effectively addressing these challenges. The inherent ranging capabilities of LiDAR enable long-distance outdoor communication and eliminates additional hardware on the robot side.

C. LiDAR Injection Technology

LiDAR Injection was initially studied as an attack method against LiDAR sensors. Cao et al. [12] demonstrated that arbitrary pointclouds could be generated by irradiating controlled pulsed lasers to the LiDAR sensors. Sato et al. [20] further advanced this technique, achieving more accurate artificial pointcloud data injection like Figure.3(c).

Our research repurposes this ”vulnerability” into an opportunity, proposing OLC, which transforms LiDAR into a communication device. Specifically, we leverage laser-based pointcloud injection as a communication channel and conduct comprehensive analysis of its error characteristics to develop a reliable communication system.

III. Optical LiDAR Communication

A. System Overview

Our proposed Optical LiDAR Communication (OLC) system repurposes existing LiDAR sensors as communication receivers without additional hardware modifications. As shown in Figure.2, OLC comprises three main steps:

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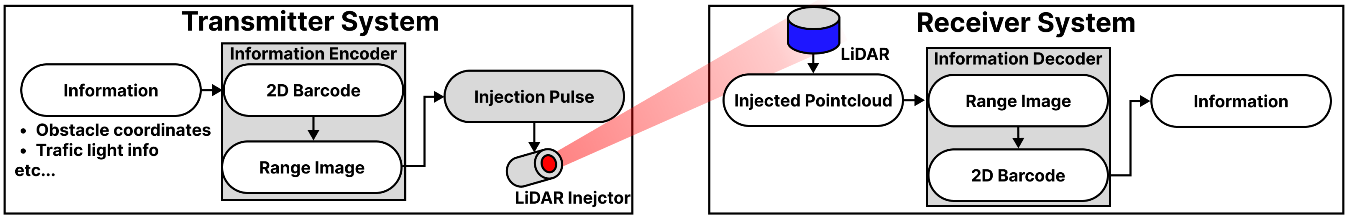
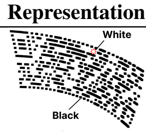
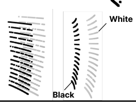
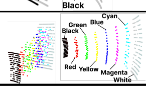


Fig. 2: OLC (Optical LiDAR Communication) architecture: The transmitter encodes data into laser pulse patterns; the infrared tracking system targets and injects these patterns into a remote LiDAR sensor; finally, the receiver reconstructs the original data from the injected pointcloud patterns.

TABLE II: Classification of OLC methods by code type and pointcloud representation. Single-Presence OLC uses presence/absence encoding, Dual-Distance OLC employs two distance levels, and Multi-Distance OLC utilizes eight color-coded distances to triple data capacity.

Image Code	Pointcloud Representation	Method	Data Rate (bps)	Advantages	Limitations
 2D Code		Single-Presence OLC	3.76k	- Simple implementation	- High noise sensitivity - Not practical for real-world applications
		Dual-Distance OLC	3.76k	- Low noise sensitivity	- Low transmission capacity
 3D Code		Multi-Distance OLC	11.3k	- High transmission capacity - Low noise sensitivity	- Complex implementation

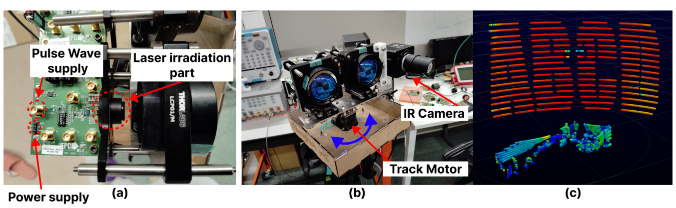


Fig. 3: LiDAR Injection system used in this work [21]: (a) Laser system configuration emitting precisely timed pulse bursts controlled by a Function Generator(FG); (b) Tracking system with IR camera detection and precision motor targeting; (c) Example showing fine-grained character-level injection capability.

1) **Transmitter Processing:** Information is encoded into a 2D code like Rectangular Micro QR Code (RMQR-Code) and Data-Matrix, which is converted to a binary image that decides the laser irradiation pattern.
2) **LiDAR Injection:** The infrastructure emits synchronized laser pulses toward the target LiDAR following the irradiation pattern. An infrared camera tracks the LiDAR's position while motors maintain targeting precision [21].
3) **Receiver Processing:** The target LiDAR processes injected signals as pointcloud data, reconstructs the original 2D code, and decodes the information.

1) Principle of LiDAR Injection: LiDAR sensors operate by emitting infrared laser pulses and measuring the time-of-flight (ToF) of the reflected light to accurately determine object distances. Building on this fundamental principle, pioneering work by Shin and Cao [11], [12] demonstrated that external pseudo-laser pulses can be strategically projected to inject arbitrary pointcloud patterns into a LiDAR's perception system. As illustrated in Figure.3 (c), Sato et al. [20] established that synchronizing the LiDAR's scanning cycle with the injection device enables precise spatial positioning of injected pointcloud data, which we extend and build upon in this work.

2) Transmitter Processing in OLC: Our study proposes an optical communication system that leverages LiDAR Injection technology. The transmitter processes data through the following methodology: First, the information to be transmitted is encoded into a 2D Code (such as a QR code) and represented as a binary image. This binary image then serves as the template for pointcloud pattern injection into the target LiDAR. Following [20], we implement selective laser pulse emission where pulses are precisely emitted at positions corresponding to black pixels in the image, while no laser is emitted for white pixels. By synchronizing the laser pulse pattern with the LiDAR' s rotational scanning, the binary image' s structure is accurately reconstructed in the pointcloud received by the target LiDAR. This approach creates a spatial encoding where each pixel from the original binary image is represented in the LiDAR's spatial domain by either the presence or absence of points at specific (x, y) coordinates.

3) Laser Targeting for Moving LiDAR: To facilitate communication with moving LiDAR sensors, we implement the dynamic LiDAR targeting technique developed by Sato et al. [21]. The system employs an infrared camera that detects the LiDAR's laser emissions in real-time, while a servo motor adjusts the laser aiming position with high precision, as depicted in Figure.3 (b). This integrated approach enables accurate pointcloud injection even when targeting robots in motion.

4) Receiver Data Processing: The receiver analyzes the injected pointcloud and converts it to a binary image, where point presence or absence represents pixel values. When successful, this reconstructed image matches the transmitter's original pattern. The system then decodes the 2D code to recover the transmitted information.

B. Classification of OLC Communication Methods

OLC can be classified along two axes: "Type of Code Used" and "Pointcloud Manipulation Method," each with trade-offs in implementation complexity, noise robustness, and data transmission capacity.

Under "Type of Code Used," we distinguish between:

- 2D Code formats (such as RMQR-Code and Data-Matrix), detailed in §III-F
- 3D Code, which encodes information using eight colors by overlaying multiple binary images [22]

For "Pointcloud Manipulation Method" we distinguish:

- Binary control (presence/absence of pointclouds)
- Distance modulation of injected pointclouds

By combining these approaches, we categorize OLC into three distinct types, as summarized in Table.II:

1) Single-Presence OLC: Uses 2D Code with binary pointcloud presence control. Simple implementation but susceptible to noise.
2) Dual-Distance OLC: Uses 2D Code with two-level distance control (near/far), providing enhanced robustness against noise.
3) Multi-Distance OLC: Employs 8-level distance modulation to encode three 2D Codes simultaneously. Provides triple data capacity in the same spatial region, though with higher implementation complexity.

C. Single-Presence OLC

Single-Presence OLC is a communication method that controls only the presence or absence of pointclouds. As shown in Table.II (a), black pixels indicate the presence of pointclouds, while white pixels indicate their absence, thus representing binary information. The primary advantage of this method is its straightforward implementation, enabling basic communication capabilities. However, as discussed in the following section, this approach faces significant challenges that make practical communication difficult due to LiDAR systems' built-in noise filtering mechanisms.

D. Dual-Distance OLC

Dual-Distance OLC controls the distance of pointclouds in two levels to enable communication. As shown in Table.II (b), black pixels correspond to short-distance pointclouds, while white pixels correspond to long-distance pointclouds. The critical advantage of this approach lies in its maintenance of continuous pointcloud structures even when transitioning between near and far distance encodings in the horizontal direction, effectively circumventing LiDAR's built-in noise filtering mechanisms that typically eliminate isolated returns.

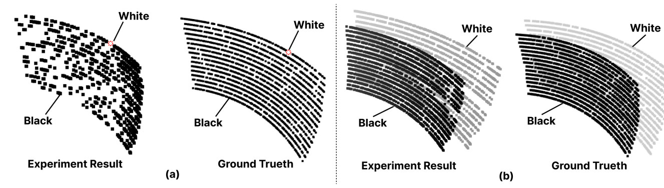


Fig. 4: Comparison of injected pointclouds using a 2D mosaic image and the Ground Truth. **(a)** Single-Presence OLC: A large portion of the injected pointclouds disappears, resulting in a sparse distribution. **(b)** Dual-Distance OLC: Injected pointclouds closely match the Ground Truth.

In VLP-16 LiDAR, isolated points in the horizontal direction are classified as noise and automatically removed when neighboring points are absent. This built-in noise filtering algorithm explains why Single-Presence OLC suffers from severe point loss, whereas Dual-Distance OLC remains largely unaffected. To verify this effect, we conducted a comparative experiment using a 2D mosaic image with a 50% black-to-white ratio. As shown in Figure.4, Single-Presence OLC experiences significant point loss due to noise filtering, whereas Dual-Distance OLC retains almost all pointcloud information. This confirms that Dual-Distance OLC is better suited for practical OLC applications, and therefore our real-world experiments were conducted using the Dual-Distance OLC method.

E. Multi-Distance OLC

Although LiDAR Injection theoretically allows for extremely high resolution in the distance domain, there is a limitation: only one point can be injected per vertical/horizontal scan angle. This restriction limits the ability to overlay multiple 2D codes simultaneously. To overcome this, Multi-Distance OLC applies color QR code techniques [22] to enable distance-based multiplexing.

The proposed Multi-Distance OLC encodes 8-color pointclouds into an RGB image, where each channel (Red, Green, Blue) corresponds to a separate 2D Code. When overlapping occurs, mixed colors (e.g., Red + Green = Yellow) are used. The resulting encoding scheme allows for three times the information density within the same spatial region, significantly improving communication efficiency compared to conventional 2D Code-based methods.

a) Transmitter Processing: The transmitter follows these steps:

1) **Generation of 2D Codes:** The transmission data is divided into three segments, each of which is encoded as a separate 2D Code.
2) **Compression into a Color QR Code:** Each binary 2D Code is assigned to one of the RGB channels (Red, Green, Blue). This creates an RGB image where each pixel is represented using one of eight colors: black, red, green, yellow, blue, cyan, magenta, and white.

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TABLE III: Comparison of Features between RMQR-Code and Data-Matrix [24]

	RMQR-Code	Data-Matrix
Detection Difficulty	Easy	Difficult
Error Correction Capability	30%	18%≤, ≤33%
Information Density (binary/pixel)	2.71	6.12

3) **Generation of a Range Image:** The color QR Code is mapped to a range image, where each color is assigned a specific distance level for LiDAR Injection.

The transformation from the RGB image to the Range Image is expressed by:

$$I_{range} = \left[\sum_{c=0}^{2} I_{rgb}(i,j,c) \cdot 2^{c} \right]_{i'=0,j'=0}^{i'=h_{rgb},j'=w_{rgb}} \tag{1}$$

Each distance level corresponds to a specific color:

$$I_{\text{range}}[i,j] = \begin{cases} 7 \leftrightarrow \text{Longest Point (White)} \\ 6 \leftrightarrow \text{2nd Distance Point (Cyan)} \\ 5 \leftrightarrow \text{3rd Distance Point (Magenta)} \\ 4 \leftrightarrow \text{4th Distance Point (Blue)} \\ 3 \leftrightarrow \text{5th Distance Point (Yellow)} \\ 2 \leftrightarrow \text{6th Distance Point (Green)} \\ 1 \leftrightarrow \text{7th Distance Point (Red)} \\ 0 \leftrightarrow \text{Shortest Point (Black)} \end{cases} \tag{2}$$

F. 2D Code Methods Used in OLC

The specific 2D Code formats implemented in this study are RMQR-Code [23] and Data-Matrix [24]. These codes are widely used, with many open-source implementations available, making them suitable for this research prototype.

RMQR-Code and Data-Matrix each have unique characteristics. RMQR-Code is known for its high detection accuracy due to its finding patterns, whereas Data-Matrix features alignment patterns and supports higher data capacity (approximately three times that of RMQR-Code). Table.III compares these two codes. Their error correction capabilities play a crucial role in mitigating communication errors during LiDAR Injection. A performance comparison of these codes in the proposed LiDAR communication system is detailed in §V-B. df

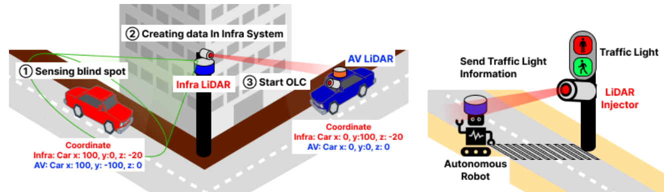
IV. V2I SYSTEM WITH OPTICAL LIDAR COMMUNICATION

In this paper, we propose two novel V2I systems for autonomous robots utilizing OLC: the Traffic Light V2I System and the Blind Spot Detection V2I System. These systems aim to establish low-cost infrastructure communication to support safe robotic navigation.

A. Overview of the V2I System

The proposed V2I systems differ in terms of information characteristics and processing requirements:

Traffic Light V2I System transmits traffic light states to vehicles via LiDAR. Unlike camera-based recognition, this approach enables simplified sensor configuration but stable traffic recognition. Traffic light states require only 2 bits of data, making them easily transmittable within OLC's bandwidth constraints.



(a) (b)

Fig. 5: Novel V2I systems for autonomous robots utilizing OLC as shown in Figure.2: (a) Blind Spot Detection V2I System: A V2I system designed to transmit obstacle information (red car) located in the blind spot of an autonomous robot (blue car) to the robot itself. (b) Traffic Light Detection V2I System: A V2I system that transmits traffic light information to an autonomous robot via the onboard LiDAR sensor.

Blind Spot Detection V2I System transmits obstacle information from infrastructure LiDAR to vehicles. This system detects obstacles in blind spots, transforms coordinates to the vehicle's reference frame, and transmits this data via OLC.

Both systems implement three key processes: (1) Time-based One-Time Password (T-OTP) generation for secure authentication, (2) coordinate transformation for the Blind Spot system, and (3) communication protocol generation combining authentication with transmitted data.

B. Proposed OLC Communication Protocol

Our protocol ensures security and efficiency through an authentication key generated via Time-based One-Time Password (T-OTP) combined with V2I-specific data.

1) T-OTP Authentication Mechanism: T-OTP generates time-limited authentication passwords [25] that distinguish legitimate OLC transmissions from malicious injections. Both the V2I system and vehicle synchronize time (via GNSS) and share a secret key to generate passwords following RFC 6238 [26].With this mechanism, an attacker who does not know the valid authentication key can't impersonate legitimate OLC transmissions, ensuring secure V2I communication.

2) Data Structure for Communication: Each V2I protocol includes the T-OTP authentication key in the header with system-specific payloads:

- **Traffic Light V2I System**: Traffic light state information (red/green, etc., 1-8 bits).
- **Blind Spot Detection V2I System**: Transformed obstacle coordinates $\boldsymbol{T} \cdot \boldsymbol{O}_{\boldsymbol{i}}^{\boldsymbol{T}}$, the angle θ required for rotation calculation, and the autonomous robot' s coordinates.

With 16-bit encoding for numerical values, a single obstacle requires 112 bits. OLC's capacity (376 bits/frame for Dual-Distance OLC, 1128 bits/frame for Multi-Distance OLC) allows transmission of 3-10 obstacle points per frame.

C. Coordinate Transformation for Blind Spot Detection

A critical requirement of the OLC Blind Spot Detection System is transforming infrastructure LiDAR-detected obstacle coordinates into the vehicle's reference frame.

The key challenge is determining the rotation angle θ between coordinate systems. Our method leverages the injected pointcloud's starting position and the vehicle's coordinates to compute this transformation. Since this position connects infrastructure and vehicle coordinates, we can derive the rotation matrix from the relative positions of all components.

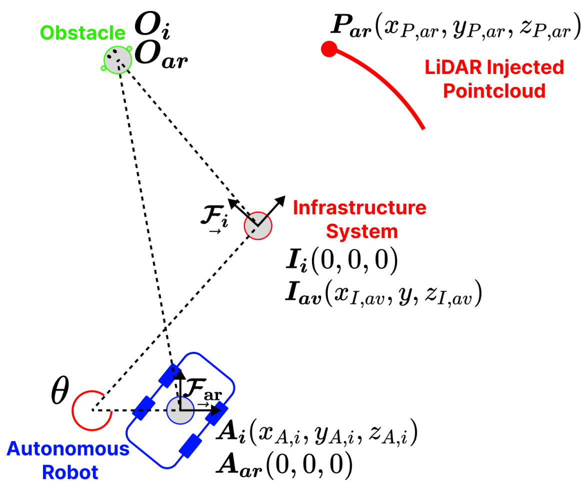


Fig. 6: Coordinate systems: Infrastructure LiDAR ($\vec{\mathcal{F}}_i$) and autonomous vehicle LiDAR ($\vec{\mathcal{F}}_{ar}$) with obstacle (O_i), vehicle position (A_i), infrastructure origin (I_i), and injected pointcloud start position (P_{ar}).

1) Coordinate Transformation Algorithm: Let the Infra LiDAR coordinate system be $\vec{\mathcal{F}}_i$, and the autonomous vehicle LiDAR system be $\vec{\mathcal{F}}_{ar}$. An obstacle in the blind spot is denoted O_i (in $\vec{\mathcal{F}}_i$), and the autonomous vehicle' s coordinate is $A_i(x_{A,i}, y_{A,i}, z_{A,i})$. The Infra LiDAR origin is $I_i = (0,0,0)$ (all in $\vec{\mathcal{F}}_{ar}$). In $\vec{\mathcal{F}}_{ar}$, let the injected pointcloud's leftmost point be $P_{ar}(x_{ar}, y_{ar}, z_{ar})$, the obstacle's transformed coordinate be O_{ar}, the vehicle origin be $A_{ar} = (0,0,0)$, and the Infra LiDAR origin be $I_{ar} = (x_{I,ar}, y_{I,ar}, z_{I,ar})$.

To transform O_i into $\vec{\mathcal{F}}_{ar}$, apply rotation $R(\theta)$ and translation T. Using the direction from A_i and P_{ar}, θ is:

$$\theta = \arctan\left(\frac{x_{A,i}y_{P,ar} - y_{A,i}x_{P,ar}}{-x_{A,i}x_{P,ar} - y_{A,i}y_{P,ar}}\right) \tag{3}$$

The rotation and translation matrices are:

$$R(\theta) = \begin{pmatrix} \cos\theta & -\sin\theta & 0 & 0 \\ \sin\theta & \cos\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad T = \begin{pmatrix} 1 & 0 & 0 & -x_r \\ 0 & 1 & 0 & -y_r \\ 0 & 0 & 1 & -z_r \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{4}$$

where (x_r, y_r, z_r) is the rotated position of A_{ar} in $\vec{\mathcal{F}}_i$. Finally, the obstacle' s coordinate in $\vec{\mathcal{F}}_{ar}$ is:

$$O_{ar}^T = T \cdot R(\theta) \cdot O_i^T \tag{5}$$

TABLE IV: Comparison of communication accuracy in Single-Presence OLC using RMQR-Code and in Dual-Distance OLC using RMQR-Code and Data-Matrix as source data (RMQR-Code: 15x59, Data-Matrix: 16x48)

	RMQR-Code (Presence)	RMQR-Code (BW)	Data-Matrix (BW)
avg. Error Pixel Rate (%)	9.19	0.532	1.19
avg. Success Rate (%)	44.5	100	100

V. OLC Experiment Results

A. Experimental Conditions

In this experiment, the Velodyne VLP-16 LiDAR was used as the receiving device on the vehicle side, and the LiDAR Injector following previous studies [20], [21] were utilized. All experiments were conducted indoors for convenience and controlled conditions, with the exception of the long-distance experiment detailed in §V-B2.

The hardware configuration used in [21] totals approximately \$2.3k, plus the cost of the FG: \$6.7k for the Agilent model or \$3.2k for the Tektronix model. As discussed in [21], this cost can be significantly reduced by replacing the FG with FPGAs.

For evaluation, we conducted communication experiments using 200 frames for Single-Presence OLC, 200 frames for Dual-Distance OLC, and 500 frames for the Multi-Distance OLC in §V-B1, and 1000 consecutive frames in §V-B2. Each experiment was performed once, and only the frames that were synchronized with the LiDAR scanning cycle—excluding those where synchronization failed—were considered for analysis to calculate the statistical properties using the below metrics.

- **Error Pixel Rate**: The ratio of differing pixels between the recovered and original images.
- **Success Rate**: The probability of accurately recovering the 2D code information through communication.

B. Evaluation of OLC Communication Performance

In this experiment, RMQR-Code and Data-Matrix were implemented and evaluated in Dual-Distance and Multi-Distance OLC modes. The study focused on (1) the impact of different 2D code types, (2) performance differences between OLC methods, and (3) the effect of communication distance.

1) Indoor Experiment: Table.IV, Table.V presents results from indoor tests. Regardless of whether RMQR-Code or Data-Matrix was used, both Dual-Distance and Multi-Distance OLC methods achieved a 100% Success Rate with an Error Pixel Rate below 2%. This confirms that the choice of 2D code doesn't impact communication performance and that both OLC methods are equally effective in maintaining low error.

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TABLE V: Communication accuracy in Multi-Distance OLC using RGB-combined RMQR-Code and Data-Matrix as source data (RMQR-Code: 15x59, Data-Matrix: 16x48)

	RMQR-Code (RGB)	Data-Matrix (RGB)
Red Channel Error Pixel Rate (%)	0.478	0.0784
Green Channel Error Pixel Rate (%)	0.246	0.0819
Blue Channel Error Pixel Rate (%)	0.246	0.0227
avg. Success Rate (%)	100	100

TABLE VI: Long-distance communication results using Dual-Distance OLC (RMQR-Code: 15x59, Data-Matrix: 16x48)

	5m	10m	15m	20m	25m	30m
avg. Success Rate (%)	99.5	100	100	100	82.8	75.7

2) Long-Distance Experiment: To assess long-distance OLC performance, we conducted tests by varying the distance between the LiDAR Injector and the receiving LiDAR from 5m to 30m in 5m increments, using the Dual-Distance OLC method. As shown in Table.VI, communication maintained a 100% success rate up to 20m, after which it gradually declined. Notably, even at the maximum tested distance of 30m, the system still achieved a 75.7% success rate. These results confirm that the proposed method successfully meets the requirement for Vehicle-to-Infrastructure (V2I) communication at distances exceeding 20m. These findings demonstrate that OLC is capable of achieving long-range communication while maintaining high accuracy and reliability.

VI. Case Study

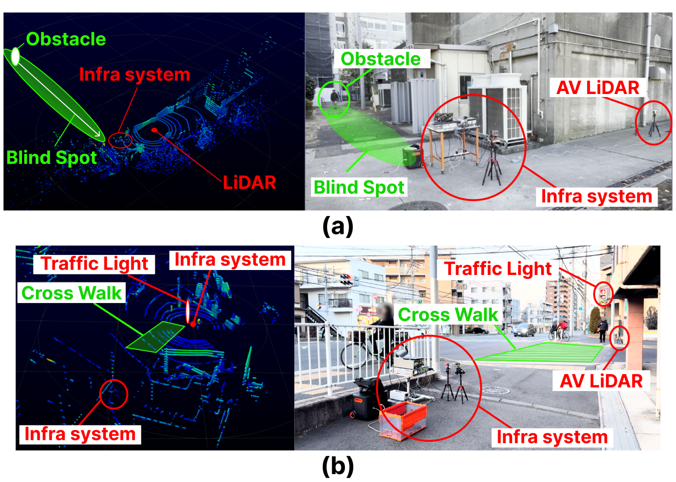

Fig. 7: Case Study of V2I System Using OLC: (a) Blind Spot Detection System: Assumes that an infrastructure system detects pedestrians in blind spots in real time and transmits their positions to the AV LiDAR using Single-Presence OLC. (b) Traffic Light Detection System: Assumes that the infrastructure system obtains real-time traffic light status and sends it to the AV LiDAR via Single-Presence OLC.

To evaluate the practicality of OLC, we conducted case study experiments on the two V2I systems proposed in §IV. Each system was tested once using the Single-Presence OLC method due to hardware limitations; our function generator lacks sufficient memory (>7.1 MB) required for the dynamic waveform control necessary for Dual-Distance and Multi-Distance OLC. As detailed in § III-C, Single-Presence OLC exhibits significantly lower noise filtering capabilities compared to more robust OLC variants, resulting in reduced communication success rates.

A. Traffic Light Detection V2I System

This system requires real-time communication of dynamically changing traffic light states (red/yellow/green). This case study verifies whether OLC can accurately transmit such dynamic information. As shown in Figure. 7(b), we positioned an AV LiDAR and an infrastructure system on opposite sides of a crosswalk. We assume that the infrastructure system can obtain traffic light information in real time and transmit it to the AV LiDAR through the OLC channel.

Experimental results confirmed that the traffic light state transmitted via OLC updated synchronously with actual changes from green to red. The communication success rate was 5.08%, primarily due to frequent occlusions by pedestrians and vehicles caused by the 1m ground-level installation. This demonstrates that the system can effectively communicate dynamic traffic information when line-of-sight is maintained.

B. Blind Spot Detection V2I System

This system focuses on two critical capabilities: (1) Real-time transmission of dynamic obstacle positions in blind spots, and (2) Accurate coordinate transformation through the use of OLC injection coordinate information.

As in Figure. 7(a), we positioned the AV LiDAR on the right side of the scene. A pedestrian moved toward the camera, deliberately entering the AV LiDAR's blind spot. We assume that the infrastructure system, equipped with a LiDAR Injector, can detect the pedestrian's position in real time and transmit the coordinate data to the AV LiDAR via OLC. This experiment specifically focused on verifying the coordinate transformation accuracy described in §IV.

Results confirmed that the pedestrian's position in the blind spot was successfully shared in real time at approximately 1.5 second intervals and the communication success rate was 19.0%. Using these conditions and the transformation methods described earlier, the Euclidean error between the calculated and actual positions in the AV LiDAR coordinate system was found to be 10cm to 50cm, depending on the angular error θ, which varied from 0.1 to 10 degrees. This error range is sufficiently small for practical V2I applications, enabling the autonomous vehicle to recognize obstacles that its own LiDAR could not detect.

VII. Discussions

A. Multi-Vehicle Communication Constraints

The number of vehicles that can be supported simultaneously is limited to 1 in the current design, which stems from the directional nature of laser-based communication systems. OLC faces the same challenge, and the technology to inject into multiple LiDARs simultaneously has not yet been established. One approach to achieve this would be to switch between different LiDARs using time-division multiplexing; however, this would create time lags due to motor movements when aiming at different LiDARs, preventing continuous communication. Another solution would be to equip the infrastructure side with multiple injectors. While this approach would eliminate time lags, it represents a trade-off with increased infrastructure costs.

B. Environmental Robustness

Atmospheric scattering from rain, fog, and snow reduces laser transmission and communication reliability [27]. Additionally, rain exposure to the housing can cause equipment failure, requiring protective covers and maintenance mechanisms for practical deployment.

VIII. Conclusion

We proposed *Optical LiDAR Communication (OLC)*, a novel optical communication system that repurposes existing LiDAR sensors on autonomous vehicles as communication receivers. Unlike traditional V2I systems that rely on high-capacity 5G networks or dedicated OWC hardware, OLC achieves cost-effectiveness by eliminating the need for additional communication hardware. Our experimental evaluation showed a 100% success rate at 20m and over 76% at 30m. Both RMQR-Code and Data-Matrix achieved error rates below 2% for transmitting the moderate bandwidth requirements typical of robot-oriented V2I applications. To validate practical applications, we implemented two V2I systems addressing critical safety challenges: traffic signal information transmission and blind-spot obstacle detection. Both systems achieved effective real-time communication, demonstrating OLC's potential as a V2I platform for next-generation robotics infrastructure.

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