Collective Sensing as an Enabler for Cyber-Resilient Connected Corridor

MIT Mobility Initiative Research Project Summary

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Executive Summary

Recent advances in sensing and communication technologies have paved the way for collective sensing in traffic management, enabling real-time data sharing among multiple entities. This facilitates the detection and tracking of traffic participants and the assessment of current traffic conditions. Our project addresses the critical need to evaluate transportation sensing technologies that aggregate data from both vehicles on the road and roadside sensors, each of whom face unique challenges.

Infrastructure-assisted collective sensing, which involves the real-time sharing and merging of data from various roadside sensors for object detection, requires addressing challenges related to sensor placement strategies. Relocating roadside sensors after their initial fixed installations incurs significant costs. Many current deployment strategies rely on engineering heuristics and are constrained by budget limitations that limit post-deployment adjustments. This project introduces polynomial-time heuristic algorithms and a simulation tool for the ex-ante evaluation of infrastructure sensor deployment. By modeling this as an integer programming problem, we guide decisions on sensor locations, heights, and configurations to balance cost, installation constraints, and coverage. Our simulation engine, integrated with open-source urban driving simulators, evaluates the effectiveness of each sensor deployment solution through the lens of object detection. A case study with infrastructure light detection and ranging (LiDAR) revealed that integrating additional low-resolution LiDAR could provide greater incremental benefits than incorporating more high-resolution ones. These results underscore the necessity of investigating cost-performance trade-offs prior to deployment.

On the other hand, merging data collected by on-board sensors from multiple vehicles faces distinct challenges arising from cyber threats posed by inside adversaries—those with legitimate and stolen credentials for vehicular communication. These adversaries can spoof legitimate vehicle identities, compromising the integrity of sensing data crucial for decision-making in traffic management. For instance, future traffic signal control systems could rely on shared vehicle positions and speeds to adjust green and red-light durations dynamically, enhancing intersection throughput. However, if vehicle-shared data is compromised, the performance of these "smart" traffic signals could be worse than fixed timing systems. This project explores the use of multi-factor authentication (MFA), an increasingly popular security engineering technique commonly used in internet and mobile computing, to safeguard interconnected roadside infrastructure from adversaries who might inject manipulated sensing data, thus preventing erroneous traffic management decisions.

Methodology

Simulation-based evaluation of infrastructure-assisted collective sensing

Advances in sensing and communication technologies have made possible the real-time sharing and merging of data collected by multiple traffic entities for collective perception. When a vehicle or infrastructure sensor detects an anomaly or obstacle in its vicinity, it disseminates this information to other entities in real time. This enables vehicles or infrastructure that may not have direct line-of-sight or sensory access to the obstacle to become cognizant of its presence. Therefore, this approach helps individual traffic participants form a bird's eye view of the target region and prevents occlusion risks in urban areas with high traffic volume. While the vehicle-based collective perception has been well explored, the infrastructure-based collective perception, which requires the deployment of multiple roadside sensors, has been hindered by the lack of guidance for roadside sensor placement and the potentially high costs for ex-post evaluation. For sensors with high procurement and installation costs, such as LiDAR, there is an urgent need for effective ways of ex-ante design and evaluation, as shown in Fig.1 (left). Decisions on infrastructure-sensor deployment strategies are often made based on engineering heuristics. These decisions require balancing factors such as sensor resolution, range, number, cost, locations, and placement height. Optimizing the configurations and placements of infrastructure sensors is crucial to minimize occlusion risks. However, for projects constrained by budget, it might not be feasible to make ex-post adjustments to deployment strategies.

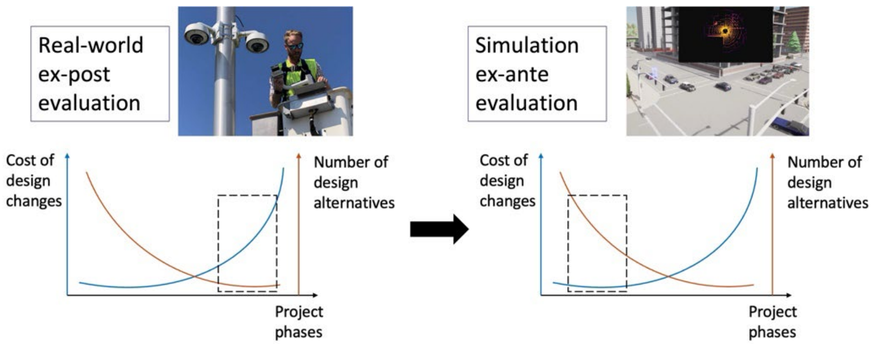


Figure 1: Cost reduction by ex-ante evaluation for infra-sensor deployment [1]

This paper presents algorithms and a simulation-based framework to support the ex-ante assessment of infrastructure sensor deployment for collective perception applications, as shown in Fig.1 (right). The infrastructure-sensor deployment is formulated as an integer programming problem. It can be solved with polynomial time heuristics to derive sensor locations, installation heights, and configurations. The goal is to balance procurement cost, physical constraints for installation, and sensing coverage (i.e., to what extent a target region is monitored by the sensors installed). Additionally, we implement the proposed integer programming algorithms in a sensor-deployment engine to support the evaluation process, as shown in Fig. 2. In addition to interacting with open-source urban driving simulators for essential sensor deployment data, the engine can extract and merge synthetic data from various infrastructure sensors synchronously.

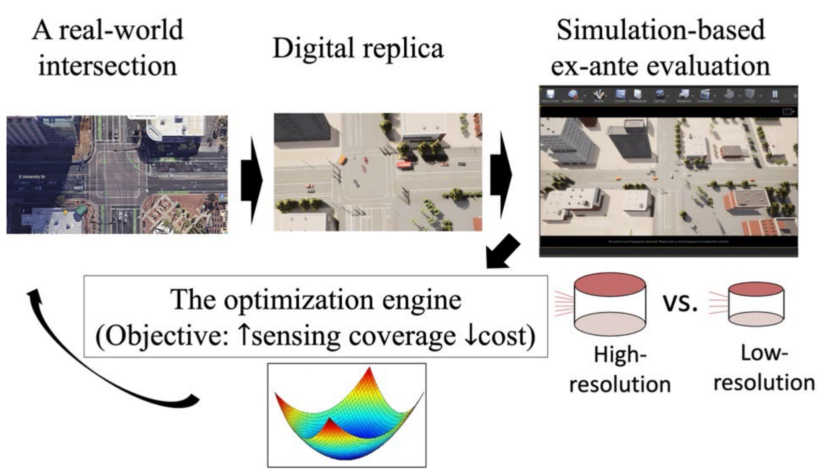


Figure 2: Ex-ante evaluation of infrastructure sensor deployment [2]

A multi-factor approach for vehicle-assisted collective sensing

Many connected vehicle applications depend on securely merging data streams shared by multiple vehicles by a surrounding roadside infrastructure in a given region, i.e., vehicle-to-infrastructure (V2I) data exchanges. One example is signal preemption, where transit buses or emergency vehicles request traffic signal priority to navigate intersections. However, a roadside adversary may exploit the mechanism by pretending to be an authorized vehicle to gain control of signal priority. Current V2I security schemes rely on cryptographic techniques that could be insufficient to eliminate such threats. The non-line-of-sight (NLOS) nature of the radio frequency channels used for V2I communication makes it challenging for infrastructure to differentiate between a moving vehicle and roadside adversaries who can hold valid credentials.

In this project, we explore the use of multi-factor authentication (MFA) scheme that leverages both NLOS and line-of-sight (LOS) visual communication to enhance V2I security, as shown in Fig. 3. Central to the MFA scheme is a challenge-response process, where the infrastructure transmits encoded messages via the NLOS channel and requires the vehicle to respond through the LOS (visual) channel using its LED headlights, assuming the vehicle is equipped with them. The visual confirmation provides a physical presence check to guarantee the existence of a real moving vehicle. To facilitate the visual confirmation, we implemented a 3D Convolutional Neural Network (CNN) to automatically decode visual messages contained in the response, as shown in Fig. 4.

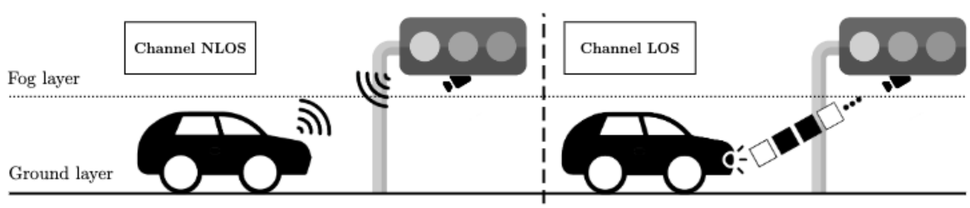


Figure 3: Two-channels (NLOS and LOS) authentication process [3]

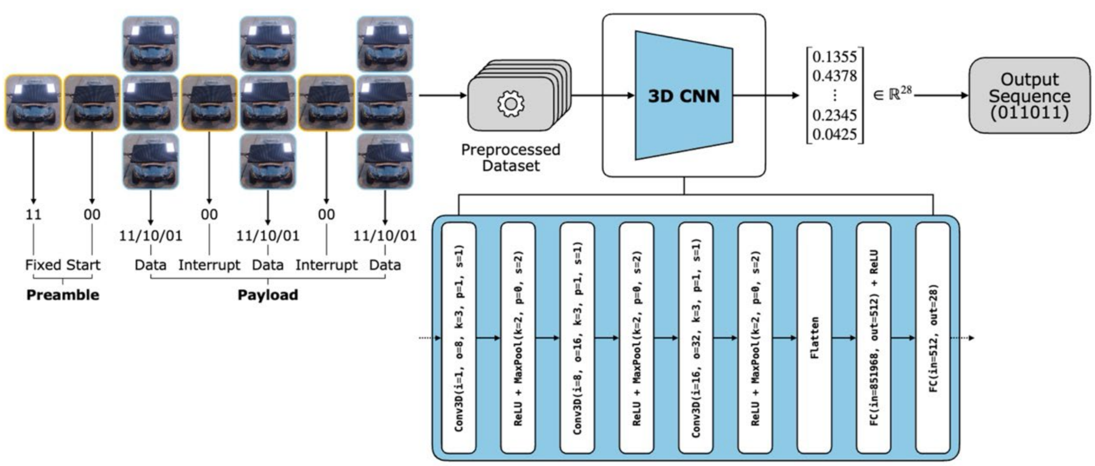


Figure 4: The proposed visual encoding scheme and 3D CNN for LOS channel authentication [3]

Key results and findings

Infrastructure-assisted collective sensing

Although merging data from multiple infrastructure LiDARs might improve detection accuracy, we also need to consider the cost incurred by adding more sensors. The results from our tests on synthetic datasets suggest that sensor deployment strategies that adopt multiple high-end LiDARs is not necessarily favorable to projects with budget constraints. In particular, adding more low-resolution LiDARs can result in substantially higher performance gains than adding high-resolution ones, as shown in Fig. 5. For example, for Type 1 low-resolution sensors, an approximately 20% improvement in object detection accuracy is obtained by increasing the number of LiDAR from one to two, while only a seven percent difference is observed between two and four LiDAR settings, as given in Fig. 5. For Type 3 high-resolution LiDARs, only around 3% improvement is achieved by adding three more LiDARs to the single-sensor solution.

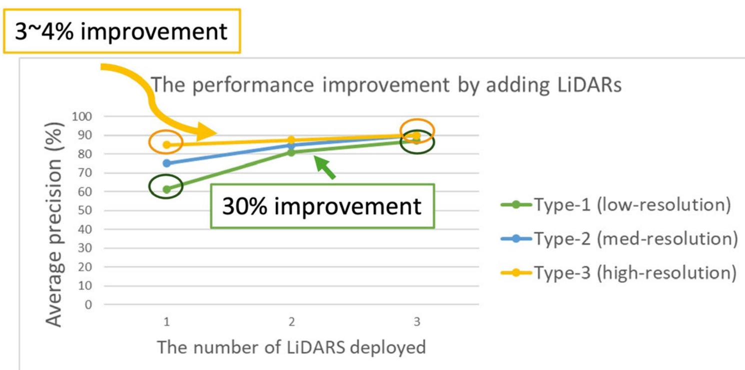
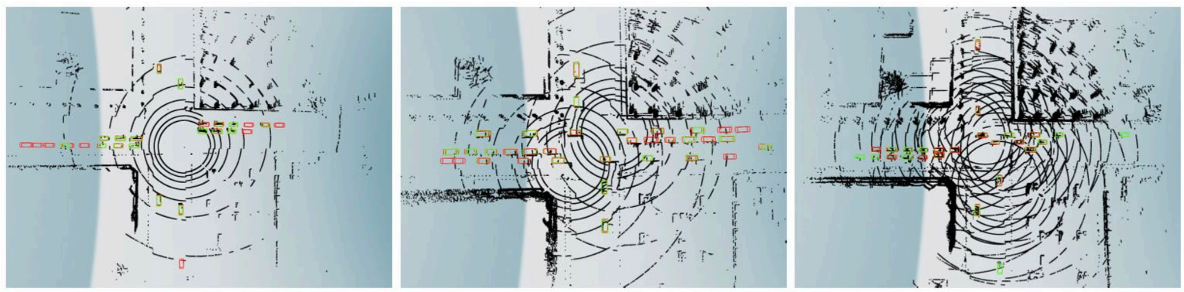


Figure 5: Performance improvement by adding more LiDARs [2]

Another interesting finding involves the difference in error mode in detecting vehicles between low and high-resolution LiDARs. Since adding more low-resolution (i.e., Type-1) LiDARs leads to the largest increase in detection performance, it will be beneficial for us to understand the possible reasons behind the improvement. For Type-1 LiDARs, the deployment solution with a small sensing budget results in more false positives than the solution with a large sensing budget. For example, the object detection algorithm that uses a single or two LiDARs predicts more vehicles (red boxes) that do not exist in the ground truth (green boxes) than using four LiDARs, as shown in Fig. 6a, 6b, and 6c. When only one sensor is used, we can observe from Fig. 6a and 6b that error predictions mainly occur at the boundary regions where the point cloud is sparse.

Our interpretation is that the deep learning model (PointPillar) we used for compressing 3D point clouds sometimes makes mistakes due to sparse data points. This happens because the model has to create uniform 3D grids from unevenly distributed points, which can result in noise being mistakenly identified as important data. Detailed error analysis can be found in [2]. The results also imply that the nominal detection range of LiDARs, which are originally designed for vehicle perception, is not necessarily a good indication of its actual performance when it comes to roadside sensing.



(a) The number of LiDARs=1 (b) The number of LiDARs=2 (c) The number of LiDARs=4

Figure 6: The visualization of the detection errors by Type-1 (low-resolution) LiDARs

Vehicle-assisted collective sensing

The project team previously explored using QR code-like designs to spatially encode secret messages for authenticating moving vehicles, as illustrated on the right side of Fig. 7 [4]. Although feasible in a laboratory setting, this approach requires the addition of an extra module to vehicles' LED headlights. Moreover, the operational time for decoding the pattern is prolonged due to the multiple steps involved, including vehicle detection, cropping the LED headlight, and spatial decoding, as depicted in Fig. 8.

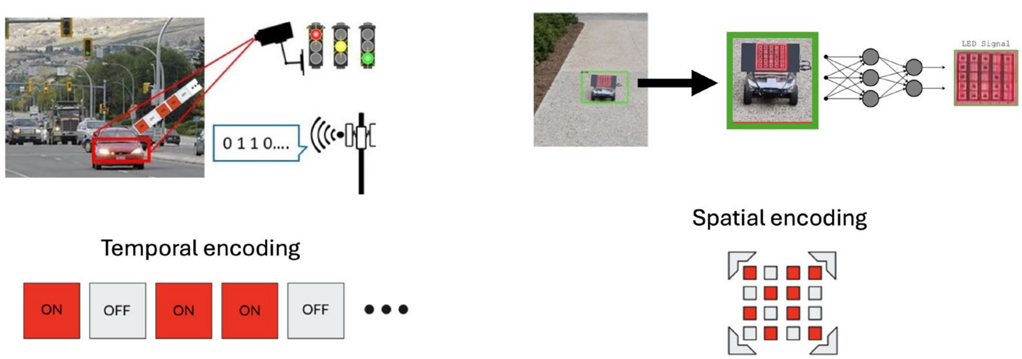


Figure 7: Two visual channel designs using LED flashlights to encode messages for authentication

In contrast, the newly proposed temporal encoding scheme, shown on the left side of Fig. 7, leverages the existing LED headlights to encode on-and-off patterns for vehicle authentication. Experimental results indicate that this new scheme, built on 3D convolutional neural networks, can identify temporal correlations within a video sequence of frames, allowing for single-step message decoding. This approach meets the timing constraints imposed by moving vehicles and the coverage area of infrastructure sensors. In the context of transportation applications built on V2I communication, such as signal preemption, the proposed scheme satisfies the latency requirements, considering the speed of vehicles passing through intersections.

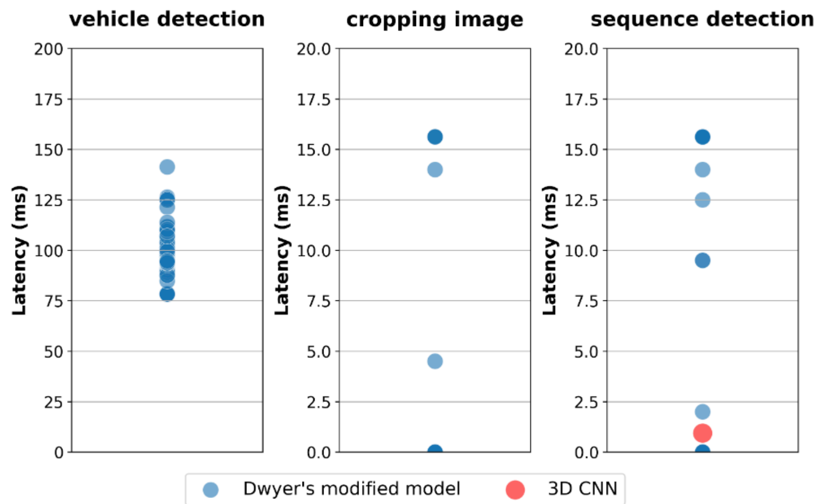


Figure 8: Comparison of authentication latencies between previous work [4] and the proposed scheme

Significance and Impact

The project advances the development of a secure, safe, clean, and inclusive mobility system through the following contributions.

- **Cyber-Resilient Connected Corridors:** The project aims to bolster the security of Vehicle-to-Infrastructure (V2I) communication through innovative multi-factor authentication (MFA) techniques that combine non-line-of-sight (NLOS) and line-of-sight (LOS) channels. By ensuring the integrity of data exchanged between vehicles and roadside infrastructure, this approach mitigates the risk of cyber threats, which can compromise traffic management systems. This directly contributes to reducing the likelihood of accidents caused by compromised traffic signals and unauthorized vehicular access to sensitive areas like intersections.
- **Addressing Diverse Safety and Mobility Needs:** The project's ability to detect and accurately identify different types of road users, including vulnerable populations such as pedestrians, cyclists, and those with disabilities, is crucial for creating an inclusive transportation system. The enhanced detection capabilities ensure that traffic management systems can adapt to the presence of slower or less mobile individuals, preventing potential accidents and ensuring that everyone can navigate urban spaces safely.
- **Cost-Efficient Sensor Deployment:** The project's emphasis on cost-effective sensor deployment strategies—such as the use of multiple low-resolution LiDARs instead of fewer high-resolution ones—significantly reduces the environmental footprint associated with sensor manufacturing, transportation, and installation. By optimizing sensor placement and configuration ex-ante, the project minimizes the need for ex-post adjustments, which would otherwise result in additional resource consumption and waste.
- **Enhanced Traffic Flow Management:** The secure and reliable data provided by the collective sensing framework allows for more efficient traffic signal control, reducing unnecessary idling, and optimizing vehicle flow through intersections. This reduction in traffic congestion leads to lower vehicle emissions, contributing to cleaner urban environments.

Real-world Realization – Chandler, AZ as a City Testbed

The results from the ex-ante evaluation, particularly its implications for the high-low resolution tradeoff during the first stage of the project, have motivated the project team to test the effectiveness of the collective sensing solutions in real-world scenarios. In collaboration with the Maricopa County Department of Transportation (DOT) in Arizona, the ASU team has converted an intersection in the Riggs corridor in Chandler, AZ into a real-world testbed for evaluating the proposed mechanisms for detecting both motorized vehicles and vulnerable road users to enhance traffic safety and efficiency, as illustrated in Fig. 8. The project team aims to address several research questions through the development of this real-world testbed.

Previous results from simulated environments suggest the potential of using multiple low-resolution sensors, which are lower in cost, to achieve detection performance comparable to that of single high-resolution sensors. However, addressing questions related to the high-low resolution tradeoff in real-world scenarios requires additional effort to ensure the method's broad applicability. For instance, the current sensor deployment algorithm primarily focuses on LiDAR. The algorithm for optimizing sensor deployment locations needs to be adapted to accommodate multimodal sensors, each with its unique working principles and coverage areas. Additionally, algorithms for detecting and tracking traffic participants must be capable of merging data streams from heterogeneous sensors, each of which may generate unique data reflecting different physical properties of the objects being detected. Furthermore, the marginal gains from adding multiple low-resolution sensors appear to apply primarily to vehicles, with less consideration given to vulnerable road users.

Moreover, algorithms for optimizing sensor locations and merging sensing data streams must account for uncertainties arising from deployment and operation processes. Actual sensor deployment may not precisely follow the recommended installation locations and angles due to physical constraints or installation inaccuracies by construction workers. During operation, the quality of data streams collected by the roadside sensing system may degrade under adverse weather conditions, with each sensor exhibiting unique failure modes. The ex-ante evaluation supported by simulation must consider these uncertainty factors to generate robust deployment plans.

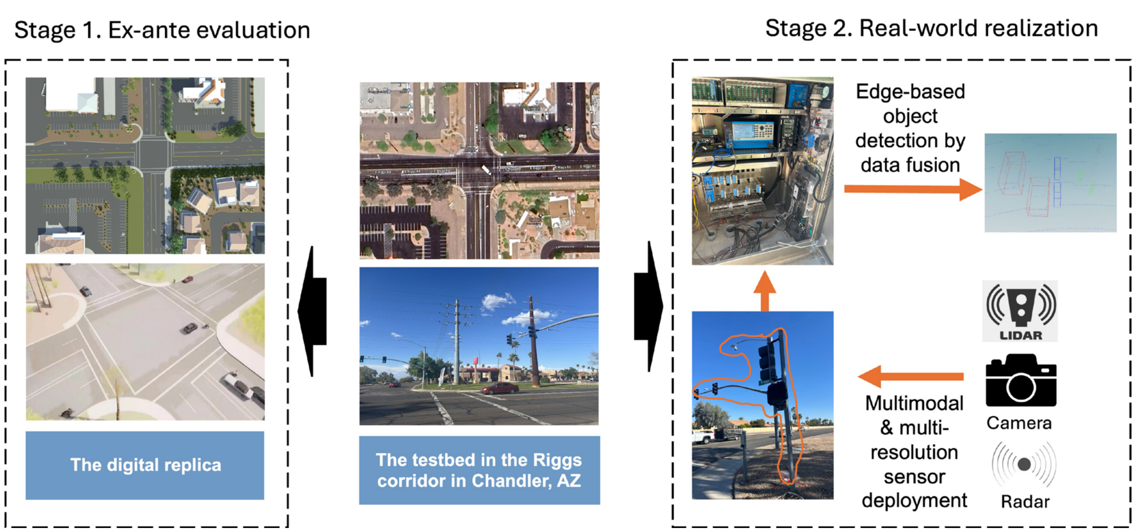


Figure 8: Evaluating collective sensing mechanisms in the city of Chandler, AZ [5]

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