The Sensor Dilemma in Intelligent Transportation Systems: Evaluating Radar, Lidar and Camera

Preprint

Faizan Mir, Rimple Sandhu, Stanley Young, and Qichao Wang

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The Sensor Dilemma in Intelligent Transportation Systems: Evaluating Radar, Lidar, and Camera

Faizan Mir,[1] Rimple Sandhu,[2] Stanley Young, P.E., M.ASCE,[1] Qichao Wang, M.ASCE,[2] and Todd Osborn[1]

[1]Center for Integrated Mobility Sciences, National Renewable Energy Laboratory, Golden, CO 80401
[2]Computational Science Center, National Renewable Energy Laboratory, Golden, CO 80401
Corresponding email: faizan.mir@nrel.gov

ABSTRACT

Intelligent transportation systems (ITS) are at the forefront in advancing the way we interact with and perceive the transportation network. This revolution is fueled by the significant advancement in sensor perception technologies such as radar, lidar, and video imaging, which are the most popular modalities for ITS. Real-time perception data from these sensors allow intelligent infrastructure-side decision-making to improve the energy, efficiency, and safety at traffic intersections. As traffic departments across the United States transition from traditional loop detectors and emulators and embrace newer technologies, they are often left with a dilemma in choosing a sensor technology for infrastructure-based perception that is reliable, inexpensive, and easy to set up and that has robust performance in varying weather conditions. However, choosing a sensor that checks all these boxes is not straightforward, as every sensor type has unique benefits and drawbacks. Radar is excellent at detecting long-range vehicles and weather resistance but lacks high resolution. Lidar is expensive and weather-sensitive, while cameras provide rich visual data at a low cost but are constrained by lighting and visibility. This study examines radar, lidar, and camera sensor capabilities to ascertain whether any of these qualifies as the "best" sensor for ITS perception. While no single sensor can meet all the demands of ITS, a hybrid approach combining multiple sensor modalities like radar, lidar, and cameras offers the most robust solution for enhancing the safety and efficiency of ITS. Through this evaluation, we hope to draw attention to the necessity of the National Renewable Energy Laboratory's infrastructure perception and control framework, which presents a multisensor track data fusion engine to assimilate multiple data streams in order to provide robust and reliable perception.

KEYWORDS: Digital twin, intelligent transportation system, perception, radar, lidar, camera

INTRODUCTION

One of the main challenges in smart cities is providing smart transportation services to different stakeholders, which is essential for sustainable development and improving people's quality of life. Traffic congestion has been a recurring problem as urban populations continue to grow, and

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as economic and social activity expands throughout the urbanization process. Two emerging technologies have lately caused a major revolution in the transportation industry and are presently driving the wave of innovation: (1) connected vehicles and (2) autonomous vehicles. Interest toward adopting advanced sensing technologies in the realm of transportation to enhance traffic management has increased due to the increasing trend toward automation and connectivity. The use of advanced information, communication, automated control, and other intelligent technologies in transportation services is at the core of intelligent transportation systems (ITS).

The loop detector, a large coil of electrically charged wire buried beneath the pavement surface, has been one of the most commonly used tools for determining traffic flows for almost 50 years. The electrical inductance of the coil varies as a big metal item passes overhead, altering the flow of electricity across it and setting off the detector. As traffic departments across the United States transition from traditional loop detectors due to high installation and maintenance costs and their inability to distinguish between vehicle types, and inability to detect vulnerable road users. Hence while choosing newer technologies that offer superior sensing capabilities, they are often left with a dilemma in choosing a sensor technology that is reliable, inexpensive, and easy to set up and that has robust performance in varying weather conditions. Radar, lidar, and video cameras are promising technologies that have evolved to enable infrastructure-based perception.

This paper evaluates the performance of roadside radar, lidar, and camera for infrastructure-based perception by deploying these sensing technologies on the Infrastructure Perception and Control (IPC) mobile laboratory at a four-way traffic intersection in the city of Colorado Springs, Colorado. In addition to outlining the sensing performance, this study also starts to address important challenges involved with the setup and long-term reliability of using these sensors for infrastructure-based perception. This study provides necessary practical learning for the cooperative driving automation and traffic engineering communities to consider while choosing the right sensing technologies for deployment at traffic intersections, in addition to documenting findings for ongoing research and development efforts in other areas.

LITERATURE REVIEW

Intersections are responsible for almost half of all traffic injuries, and according to the Federal Highway Administration, more than 2.8 million intersection-related crashes occur each year in the United States (Rich et al. 2004). For this reason, the Federal Highway Administration has made the traffic intersection a focus area and a national, state, and local traffic safety priority. In recent years, many of the inductive loop detectors at traffic intersections have been replaced by video cameras and other technologies, which are low cost and easy to maintain and provide robust performance. Most of these video cameras are programmed to detect an object in a certain zone of the intersection and send the equivalent binary on/off signal to the traffic controller, similar to older inductive loop technology. Due to improvements in object detection algorithms, especially using deep-learning approaches, these video detection methods are beginning to be

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used to detect and track moving objects on the road (Boukerche and Hou 2022; Chapel and Bouwmans 2020) beyond simple inductive loop emulation. Tao et al. (2017) proposed an "Optimized You Only Look Once" (OYOLO) method with the new convolution neural network based on the "You Only Look Once" (YOLO) algorithm for traffic scene detection. Zhou et al. (2020) presented CenterTrack, a simultaneous detection and tracking algorithm that applies an object detection model and predicts the association within previous frames. Yu et al. (2023) proposed a trajectory recovery framework that identifies vehicle trajectories across multiple traffic cameras and reconstructs their path. Even with all the advancement in video detection technologies, there remain some challenges and disadvantages of the new technology such as low viewing angles (Yang et al. 2010), poor long-range detection capability, and poor detection ability in varying lighting and adverse weather conditions (Bansal et al. 2014; Hassaballah et al. 2021; Yang and Pun-Cheng 2018).

To overcome the challenges of video detection, several other sensors such as lidar and radar have been presented as an alternative for detecting and tracking vehicles at traffic intersections. Yin et al. (2021), Zhang et al. (2020), and Zhao et al. (2019) present algorithms to use roadside lidars for detecting and tracking cars and pedestrians at traffic intersections. Although roadside lidar provides high-resolution 3D information of objects within the intersection, it lacks the ability to provide long-range detection. Installing multi-lidar units can resolve the issue of providing sufficient coverage to cover the vehicle within and approaching the intersection. Having a multi-lidar setup presents another significant challenge related to calibration, as the point clouds from each lidar need to be aligned together to prevent aliasing and duplicate detection. Chang et al. (2023) and Ren et al. (2023) proposed autocalibration algorithms to calibrate multiple overlapping lidar sensors; however, the approach relies on accurate detection, tracking, and density of the moving objects within the overlapping field of view of the sensor. Additionally, lidar performance degrades significantly due to light scattering and occlusions in adverse weather conditions like fog, snow, and rain, posing a question regarding the robustness of the sensors for critical applications such as traffic signal control (Dreissig et al. 2023; Filgueira et al. 2017; Kutila et al. 2018; Zang et al. 2019).

4D multiple-input multiple-output (MIMO) radars are gaining popularity for infrastructure-based perception due to their advanced capabilities in capturing precise and comprehensive object data as compared to traditional Doppler radar systems (Felguera-Martin et al. 2012; Gong et al. 2024). Including elevation as the "fourth dimension" provides significant improvement over traditional radars, which lack vertical angle resolution. Schrader et al. (2024) and Tan and Yang (2022) deployed roadside radars to generate vehicle trajectories across highway corridors. The new generation of roadside radars provides superior detection range but lacks the high-resolution detection capability as compared to camera and lidar.

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METHODS

The state-of-the-art IPC mobile laboratory has the ability to deploy the latest generation of perception sensors and technologies at traffic intersections and capture real-time traffic data. In this study, the IPC mobile laboratory was deployed at a four-way traffic intersection in the city of Colorado Springs, Colorado (Figure 1). Two Econolite EVO radars were deployed on the extendable mast of the IPC lab, and two additional EVO radars were mounted on diagonally opposite traffic poles. These pole-mounted radars were aligned to capture data in the south-west and north-east directions (Figure 1). The data from the radar sensors mounted on the IPC lab and traffic poles were sent to individual hubs mounted within the IPC lab and traffic control cabinet, respectively, for processing, and the data from all four radars were recorded using a NUC computer located in the IPC mobile lab at a resolution of 10 Hz. In addition to radar, an Ouster OS1 lidar and Cepton X90 lidar were also mounted on the extendable mast to capture traffic data within the intersection at a frequency of 10 Hz. An Axis P3255-LVE dome camera with a built-in object detection capability, as well as the capability to generate object tracks, was also mounted on one of the extendable masts to capture traffic data at a frequency of 10 Hz. This setup containing multiple modes of sensors—with radar providing long-range detection, lidar providing 3D information within the intersection, and camera providing additional details—provides a robust image of the intersection that will be used to evaluate the sensor performance for infrastructure-based perception systems.

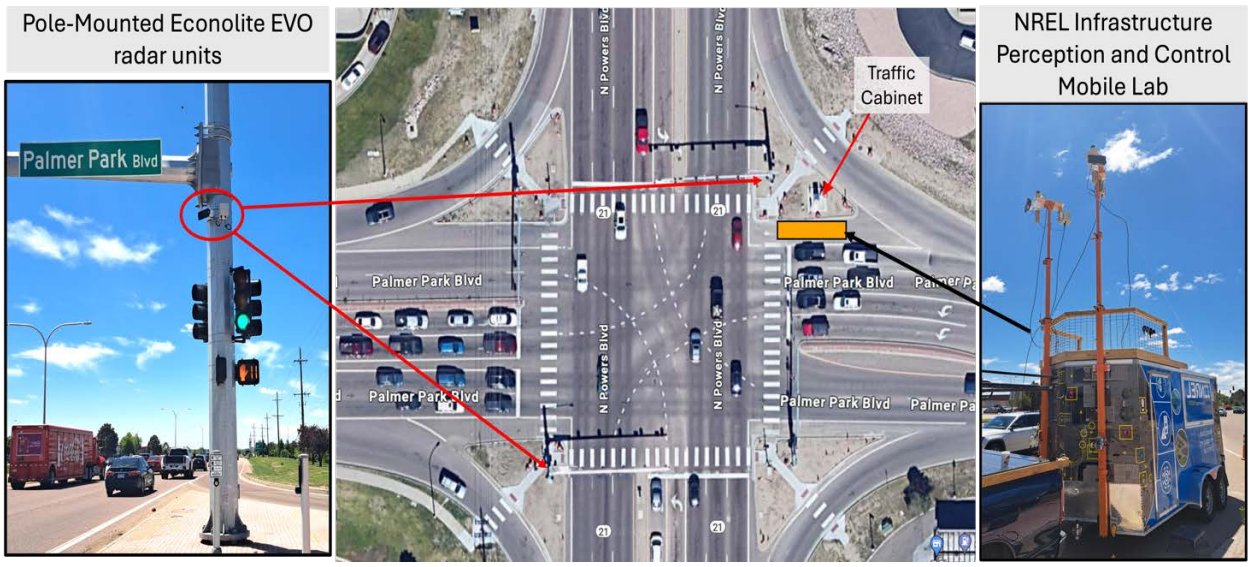

Figure 1. Test site with location of pole-mounted sensors and IPC mobile lab within the intersection.

The detailed specifications of the sensors used in this study are given in Table 1. The extendable mast was raised to a height of about 6 m, and the radars on the IPC lab were set to an elevation angle of 7°–8°, while those on traffic poles were set to 3°–4°. Both the Cepton and Ouster lidars were tilted toward the intersection to get a high-density point cloud for tracking

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vehicles within the intersection. The camera was also tilted toward the ground to get better ground plane projection of the objects within the traffic intersection.

Table 1. Specification of the various perception sensors deployed within the traffic intersection

Properties	Radar	Lidar		Camera
Model	Econolite EVO	Ouster OS1	Cepton X90	Axis P3255-LVE
Range (m)	275	100	90	70–80
Field of view, horizontal (degrees)	110°	360°	90°	
Sampling rate (Hz)	10	10	10	10
Classification	Vehicles, nonmotorized, small trucks, big trucks	Cars, trucks, pedestrians, two-wheelers	Vehicles, pedestrians	Vehicles, pedestrians
Perception software	InnoSenT (ISYS-5220) API	Outsight Shift	Helius	Axis Analytics

A test vehicle equipped with a high-accuracy Emlid post-processing kinematic global navigation satellite system (GNSS) receiver was used to simulate connected vehicles within the intersection and collect ground truth data to calibrate the system. A GNSS receiver mounted on top of the vehicle collected the trace data from the roving vehicle. Differential correction was obtained by setting up an Emlid Reach RS3+ base unit at the test site, which sent corrections to the rover using long range radio communication. The differential correction data were used to improve the accuracy of the GNSS location of the roving vehicle. The vehicle tracks from the roving GNSS-instrumented vehicle provided the essential ground truth data required for sensor calibration and monitoring. Figure 2 shows the GNSS tracks of the test vehicle as it drove through the intersection.

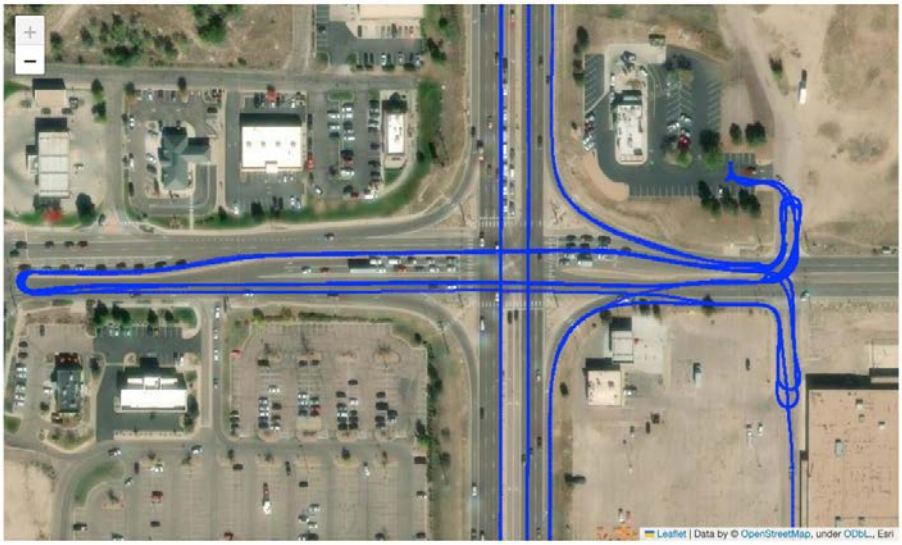

Figure 2. Tracks of the test vehicle equipped with GNSS receiver.

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RESULTS AND DISCUSSION

The sensor captures and sends the raw data to an edge device located inside the IPC lab, where they are classified and stored as an object track file after classification. The object track data from each sensor are in their local coordinate frame (Figure 3) and need to be transformed into a uniform coordinate frame. Domhof et al. (2021), Mir et al. (2024a), and Heidbrink et al. (2024) present a calibration methodology to transform data from multiple radars, lidars, and cameras into a common coordinate frame.

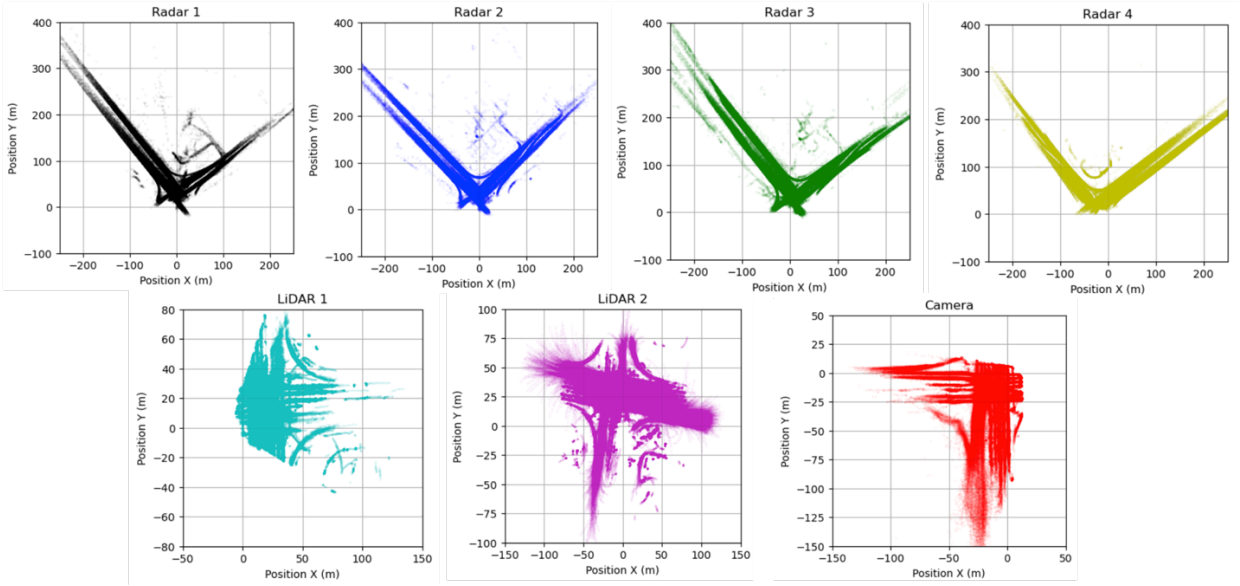

Figure 3. Object track data from individual sensors captured in a local coordinate frame.

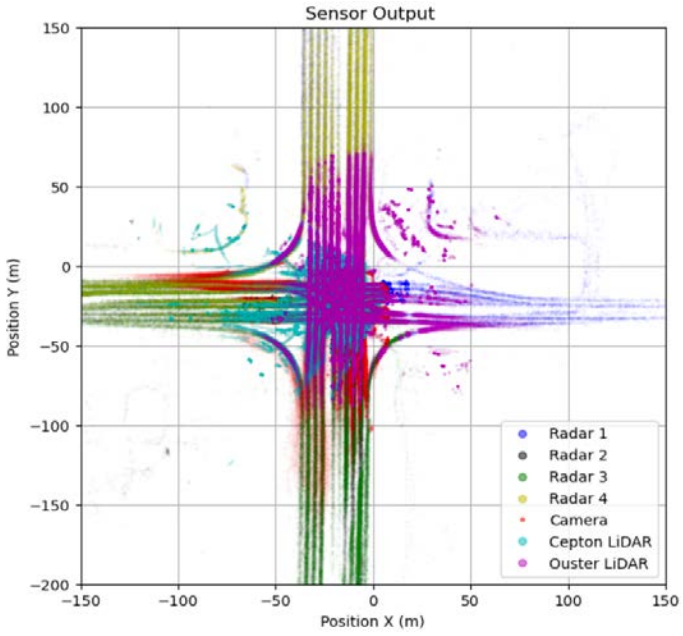

Figure 4. Radar, lidar, and camera object track data after transformation into a global frame of reference.

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The sensor data were transformed by solving the 2D translation and rotation (Figure 4). In this section we analyze the sensors based on detection range, object classification, vulnerable road user (VRU) detection, and object counts.

Prediction Algorithms

Both radar and lidar sensors employ prediction algorithms that help them maintain a unique object ID for a detection as it gets occluded and reemerges into the field of view. These algorithms are important for these sensors to keep track of a single object and avoid duplicate counts of the same detected object. The object track data of the EVO radar provide a variable "Prediction_Count" that specifies if the specific detection is actual or predicted by the algorithm. For the Ouster OS1 lidar, a similar variable "Seen_Last_Scan" generated from the Outsight Shift perception software gives information for whether the object data point was an actual detection in the lidar scan. Figure 5(a) shows the spatial plot of the actual detections from the Ouster lidar, and Figure 5(b) shows the spatial plot of the actual detections and predictions made by the Outsight Shift perception software. Although these predictions help the lidar maintain a consistent object ID, they provide poor track predictions of the spatial coordinates of the object as it moves out of the sensor's field of view. This prediction cannot be used for perception and needs to be filtered from the data frame, as it would generate incorrect vehicle tracks. The Cepton lidar data frame did not provide any information regarding the prediction of the data.

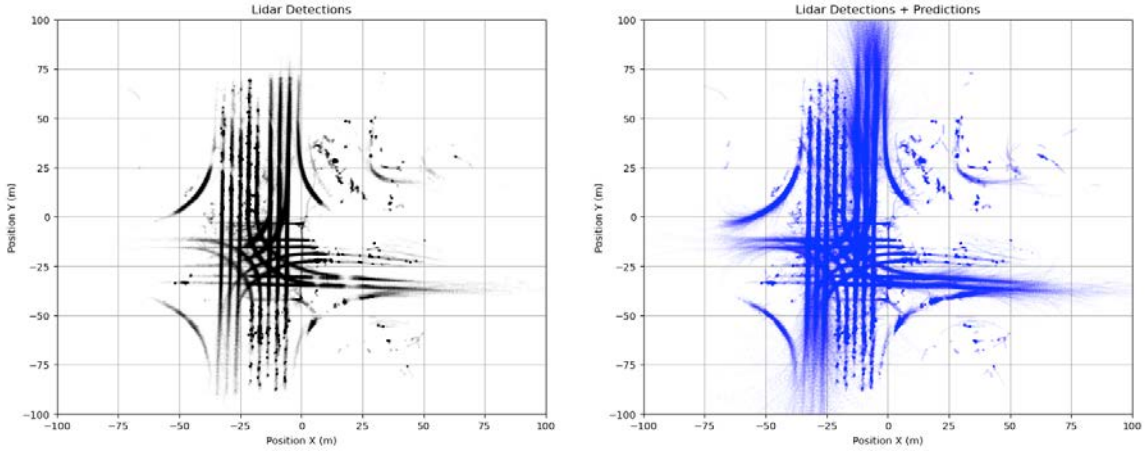

Figure 5. (a) Spatial plot of actual detections from the Ouster lidar and (b) spatial plot of actual detections and predictions from the Outsight Shift perception software.

In this study, we only considered actual detection from the EVO radar and Ouster sensors to evaluate the range, classification, and VRU detection presented below.

Detection Range

The location of the sensor in 3D space can be given by the coordinates (x_s, y_s, z_s), and the center of each detected object is given by the coordinate $(x_{p,i}, y_{p,i}, z_{p,i})$, where $i \in [1,2, \ldots . n]$. The distance (d_i) of each detected point from the sensor can be defined as:

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$$d_i = \sqrt{\left(x_{p,i} - x_s\right)^2 + \left(y_{p,i} - y_s\right)^2 + \left(z_{p,i} - z_s\right)^2}$$

Calculating the Euclidian distance of each detected point from the sensor using this equation, we can analyze the detection range of different sensors. Figure 6 illustrates the detection range of radar and lidar sensors deployed in this study. Radar sensors demonstrate a superior range, with vehicle detections extending up to 400 meters from the intersection, while the maximum detection range for nonmotorized users (bikes and pedestrians) is approximately 100 meters. In comparison, the Cepton Vista X90 (Lidar 1) achieved a maximum detection range of about 120 meters, and the Ouster OS1 (Lidar 2) reached a range of 100 meters. Camera detections were not assessed for range, as their performance depends on multiple factors, including mounting height and the detection algorithms employed. Furthermore, objects appearing smaller in the image plane introduce greater spatial error, which stems from reliance on precise camera extrinsic calibration parameters. These results offer valuable insights into the detection capabilities of different sensors, emphasizing the importance of sensor range as a key factor when selecting a perception system for traffic intersections.

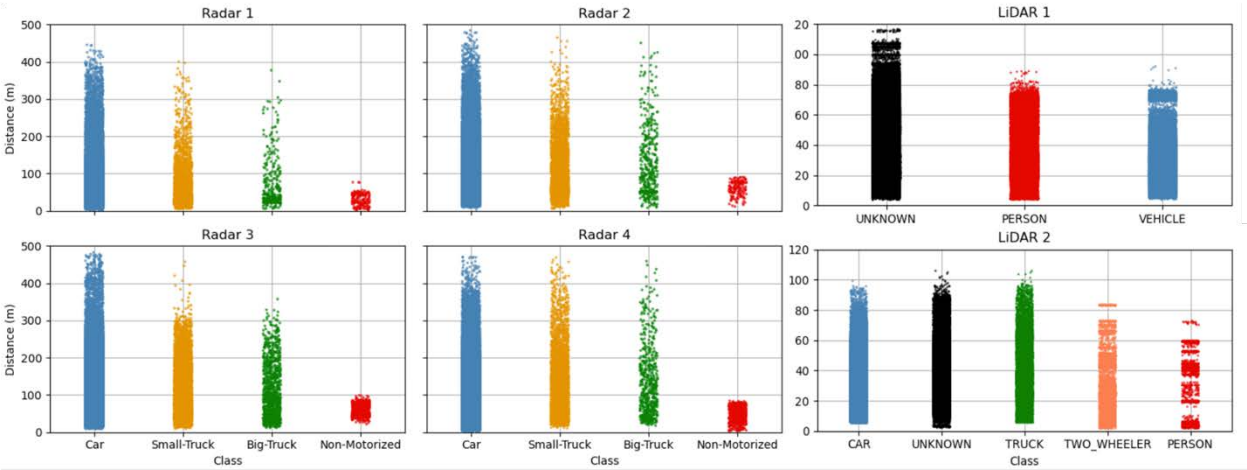

Figure 6. Detection range of various sensors with respect to detection class.

VRU Detection

Detecting and monitoring VRUs, including pedestrians and cyclists, are critical components of a robust infrastructure-based perception system. Traffic intersections are the key areas of interaction between vehicles and VRUs; accurate detection systems can significantly reduce the likelihood of accidents by providing real-time information to traffic management systems and connected vehicles. Figure 7(a) illustrates the movement of nonmotorized (bike and pedestrian) detections from the EVO radar, with the sensor locations marked by stars. Analysis of the radar data reveals significant misclassification, with numerous vehicles in the left-turning lane incorrectly identified as pedestrians. This highlights the radar's limitations in accurately detecting VRUs due to a significantly smaller radar cross-section (RCS) meaning they reflect less energy back to the sensor making it harder for a Radar sensor to detect pedestrians and other VRUs. Furthermore, the number of pedestrian detections vary significantly between sensors

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mounted on the IPC mobile lab (Radar 3 and Radar 4) and those installed on traffic poles (Radar 1 and Radar 2). This discrepancy can be attributed to the lower elevation angle of the IPC radar units, which offers a closer perspective for nearby objects. Figure 7(b) illustrates the pedestrian detection results from two lidar units and a camera. The Ouster lidar and the camera demonstrated superior VRU detection performance compared to other sensors. However, the Cepton lidar incorrectly classified vehicles within the intersection as pedestrians, likely due to calibration errors during setup. This highlights the importance of precise sensor alignment and calibration requirement for camera and lidar sensors.

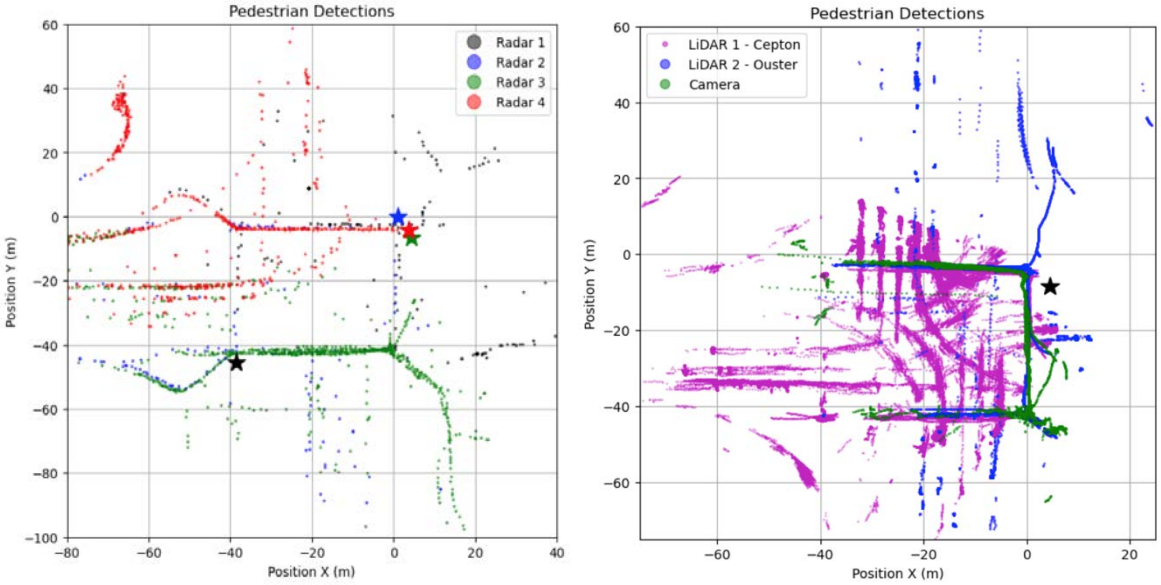

Figure 7. (a) Pedestrian detections from (a) radar and (b) lidar and camera.

The results in this study, which analyzed real-world traffic data at a traffic intersection, highlight the strengths and limitations of various sensor technologies. The results underscore that no single sensor is sufficient to provide a robust perception system for detecting both vehicles and VRUs at intersections. Radar provides excellent long-range detection, making it effective at tracking vehicles at a distance. However, its limitations in detecting VRUs pose a significant challenge for creating safer, smarter urban environments. Conversely, cameras and lidar offer superior detection of VRUs and vehicles within intersections, delivering high-resolution data crucial for short-range safety applications. However, these sensors have their own drawbacks with regard to limited range and difficult calibration procedures. While cameras have been in the perception domain for a long time, lidar is a relatively newer technology, and questions regarding its long-term reliability need to be addressed. These findings emphasize the importance of a multisensor fusion framework to overcome the limitations of individual sensors. By combining data from multiple sensor types, we can create a robust and comprehensive perception system capable of delivering reliable, real-time detection at intersections (Liu et al. 2024). The National Renewable Energy Laboratory's IPC framework serves as a prime example of this approach. This open-source framework fuses sensor data from multiple perception sensors and connected vehicles to create a real-time digital twin driving multiple downstream application

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to increase the efficiency and safety at intersections (Mir et al. 2024b; Young et al. 2022). As technology advances, the continued development of reliable, accurate, and robust perception systems for multisensor data fusion will play a vital role in improving safety, efficiency and fostering sustainable, equitable transportation networks.

CONCLUSIONS

This paper reports the results derived from the field deployment of the IPC mobile lab equipped with multiple radar, lidar, and camera sensors at a traffic intersection in the city of Colorado Springs, Colorado. Capturing traffic data using these sensors, we evaluate individual sensors based on detection range, classification, and VRU detections. The results indicate the superior long-range detection performance of roadside radar sensors and limited VRU detection. Camera and lidar sensors provide a viable alternative to radar sensors, providing highly detailed information about the VRUs and vehicles; however, they have limited range and a difficult calibration process. The National Renewable Energy Laboratory's IPC fusion engine provides a key solution to this problem by integrating multiple sensors technologies and removing the reliance on one single sensor to create a robust sensing system.

Future work is planned to evaluate the performance of the IPC fusion engine and compare it with individual sensor outputs. Testing the various sensors' perceptions in varying environmental conditions and generating vehicle counts for traffic estimation is also planned as future work.

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