CAIT-UTC-REG45

The Development of the Digital Twin Platform for Smart Mobility Systems with High-Resolution 3D Data

FINAL REPORT
December 2021

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In cooperation with

Rutgers, The State University of New Jersey
And
U.S. Department of Transportation
Federal Highway Administration

Disclaimer Statement

The Center for Advanced Infrastructure and Transportation (CAIT) is a Regional UTC Consortium led by Rutgers, The State University. Members of the consortium are Atlantic Cape Community College, Columbia University, Cornell University, New Jersey Institute of Technology, Polytechnic University of Puerto Rico, Princeton University, Rowan University, SUNY - Farmingdale State College, and SUNY - University at Buffalo. The Center is funded by the U.S. Department of Transportation.

1. Report No. CAIT-UTC-REG45	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle **The Development of the Digital Twin Platform for Smart Mobility Systems with High-Resolution 3D Data**		5. Report Date December 2021 6. Performing Organization Code CAIT/Rutgers University
7. Author(s) Peter J. Jin https://orcid.org/0000-0002-7688-3730,Yizhou Wang https://orcid.org/0000-0003-3234-4548, Tianya Zhang https://orcid.org/0000-0002-7606-9886,Yi Ge https://orcid.org/0000-0002-7186-9024, Jie Gong https://orcid.org/0000-0002-7915-7304, Anjiang Chen https://orcid.org/0000-0002-2645-9851, Noshin S. Ahmad https://orcid.org/0000-0002-4333-7653, Bowen Geng https://orcid.org/0000-0001-6143-0934		8. Performing Organization Report No. CAIT-UTC-REG45
9. Performing Organization Name and Address Rutgers, The State University of New Jersey 100 Brett Road, Piscataway, NJ 08854		10. Work Unit No. 11. Contract or Grant No. 69A3551847102
12. Sponsoring Agency Name and Address Center for Advanced Infrastructure and Transportation Rutgers, The State University of New Jersey 100 Brett Road Piscataway, NJ 08854		13. Type of Report and Period Covered Final Report 12/2020-11/2021 14. Sponsoring Agency Code
15. Supplementary Notes U.S. Department of Transportation/OST-R 1200 New Jersey Avenue, SE Washington, DC 20590-0001		
16. Abstract This project develops the main modules and algorithm models for the digital twin platform for a smart mobility testing ground currently under construction. LiDAR (Line Detection And Ranging)-sensor-based object detection and 3D infrastructure modeling modules are developed and tested in the project. The developed digital twin model is pilot tested to conduct near-miss analysis at the intersections of the DataCity Smart Mobility Testing Ground in New Brunswick, NJ.		
17. Key Words Digital Twin, Traffic Simulation, Traffic simulator, 3D Modeling	18. Distribution Statement	
19. Security Classification (of this report) Unclassified	20. Security Classification (of this page) Unclassified	21. No. of Pages 36 / 22. Price

Form DOT F 1700.7 (8-69)

Acknowledgment
The team would like to thank Middlesex County, New Jersey Department of Transportation, and the City of New Brunswick for assisting in the digital twin data collection and Connected and Automated Vehicle (CAV) application exploration in the project.

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DESCRIPTION OF THE PROBLEM

In the conventional model-centric paradigm, only coarse-grained data (e.g., traffic speed, flow, and density at some sensor locations or trajectories in probe vehicles) is used to validate and calibrate system models to support traffic operations, macroscopic or microscopic traffic control, and to develop new traffic mobility solutions. A data-centric paradigm is emerging, based on new fine-grained computer vision and (e.g., high-resolution LiDAR (Line Detection and Ranging) data. These high-dimensional, 3D data (HD-3D) need to be processed, analyzed, fused, visualized, generalized, and evaluated by models to eventually support real-time, highly customized Vehicle-to-Infrastructure(V2I), Vehicle-to-Vehicle (V2V), and Vehicle-to-Everything (V2X) applications.

Coarse-grained data used to be the only ground-truth dataset in practice. Most existing platforms are designed with specific underlying models that only focus on reproducing macroscopic accuracy. Such modeling schemes cannot reproduce or simulate the microscopic object dynamics captured by the new HD-3D data. Work developed based on the existing platforms cannot be directly deployed or tested in real-world systems without intensive, empirical field engineering. As a result, the gap in innovation, analytics, and system engineering capability between industrial R&D and academic research has widened.

In this project, we developed the key modules and models for building a digital twin for urban mobility, the Mobi-Twin platform. The platform focuses on developing critical sensing, computing, and simulation models to utilize the emerging self-driving grade high-resolution 3D data collected from the roadside. The proposed platform will use data from the New Brunswick Innovation Hub Smart Mobility Testing Ground to build a digital twin platform. The platform will be the foundation of a living lab to support academic and industrial research.

APPROACH

The proposed digital twin (Mobi-Twin) platform's developed modules in this project focus on enabling the microscopic accurate models and simulation of Urban Mobility System of Systems with the emerging self-driving grade high-resolution 3D data. The proposed digital twin platform will reproduce high-fidelity reality for modeling smart mobility objects (vehicles, pedestrians, and others) with seamless object-level integration among different systems. Key components of the Mobi-Twin platform include:

1. The 3D reconstruction and modeling platform will be developed to reconstruct the mobility objects and events in 3D with a virtual HD infrastructure background constructed from static LiDAR scanning.
2. A micro-accurate calibration module will be developed to achieve "microscopic-accurate" 3D simulation with a bi-level optimization process.
3. The desktop and web-based research interfaces will be enabled by developing pre-configured knobs and interfaces for that research.
4. The data-sharing interfaces will involve both the absolute perspective of system-wide dynamics and the relative perspective of individual agents.

LITERATURE REVIEW

Traffic Simulation and Simulator Models for Smart Mobility Research

The latest smart mobility research on the traffic flow theory and network control models for the upcoming mixed Manual, Electric, Connected, and Automated Vehicles (MECAVs) raise new data, computing, and modeling needs that are difficult to be addressed with existing data analytic and modeling platforms. To be considered are the transit systems, road and infrastructure systems, energy and environment systems, computing and communication systems, and social and community systems. In the existing literature, many papers on CAVs developed their customized add-ons of CAV simulation modules to be used in conjunction with existing traffic simulation and simulator models such as UrbanSIM, VISSIM, AIMSUN, Paramics, CARISM, and PreSCAN. Most authors identified the continuing need for field CAV data and multi-layer modeling platforms for traffic flow and CV communications. Most researchers attempting to study the characteristics of CAVs and MCAV mixed traffic had to rely on simulation data based on 2D vehicle data in- puts (speed, spacing, headway, flow, density). Very few used high-resolution datasets such as Naturalistic Driving Study (NDS) dashcam video to account for driver perceptions on vehicle control.

Due to the development of CAV technology, many algorithms and models need to be quickly tested and verified, so many digital twin models based on traffic simulation models and real-world testbeds emerge spontaneously for different purposes. To map the simulated CAV to the actual traffic flow, these digital twins can usually construct the micro-features of the actual traffic flow in a virtual traffic simulator environment. Wang et al. (2022) used the trajectory points from LiDAR sensors and imported them into a 3D map, and then the CAV driving logic can be improved by co-simulating with other vehicles. Kusari et al. (2022) simulated the driving behavior of CAV vehicles with Bayesian parameters based on some real-world car-following models and driver behavior data sets in the SUMO to validate and optimize the intelligent driver model in the digital twin virtual world. Tettamanti et al. (2018) used a real-time communication system that can directly broadcast the operation in the SUMO as the digital twin virtual world to the CAV that was tested in the real-world testbed. This 'Vehicle-In-the-Loop' method ensures that SUMO obtains the microscopic traffic flow characteristics centered on the experimental vehicle for simulation in real-time but also allows the experimental vehicle to run in the real world through the optimal solution given by the algorithm in the virtual world simulation.

Digital Twin Models in Other Industry

The digital twin is a concept to explore the communication, synergy, and coevolution between physical and digital replicates. The digital twin consists of three parts: physical product, virtual product, and the connection between physical and virtual parts. The digital twin is mainly used for fault diagnosis, predictive maintenance, and performance analysis.

- **Material Science**: Digital twin provides a solution to test the character of a specific piece of material without the need to prepare actual samples in the production environment. The material digital twin can be used in strength and stiffness analysis to model the fluid dynamics for optimization and simulation.
- **Manufacture and Industrial Products**: Digital twins enable efficient maintenance strategies and long-distance diagnosis and repair. General Electric (GE) builds digital twins of its critical engine components that process information collected from sensors to predict the

outcomes of business using artificial intelligence, physics-based models, and data analytics. These digital twins enable GE and its customers to maximize continued profitability and performance. (The Future for Industrial Services: The Digital Twin," Infosys Insights). Even minor improvements to quality and reliability lead to millions of dollars worth.

- **Life Science and Healthcare**: In the life and science and healthcare area, the digital twin is used to model the human body to investigate the behavior of the human body without performing invasive tests. The digital twin can facilitate remote support of complex equipment for predictive maintenance and optimized operations. The digital twin can also be used to model the workflows of staff and patients through the department to test different layout modifications and changes to the volume of demand.
- **Infrastructure and Urban Planning**: Infrastructure digital twins created as replicas of urban environments and transport networks are some of the most prominent digital twins. The digital twins are built to simplify the maintenance and operations of buildings, highways, and transportation hubs. IoT sensors will be used to collect data to monitor work conditions and progress. Then the infrastructure management plan will be executed to comply with local rules.
- **Energy Sector**: The energy sectors explore and adopt digital twins to improve safety and reliability while reducing costs. It has been applied in offshore oil and gas drilling systems, reducing the platform's workforce requirements and optimizing equipment maintenance. Big companies use the digital twin in the wind energy department to manage more giant turbines and meet aggressive reliability and cost-reduction targets.
- **Consumer, Retail, and E-commerce**: In the consumer and E-commerce area, digital twins are used to tracking product flows through supply chains. The digital twins are also used to build a virtual representation of a retail store to help consumers navigate the items they want to purchase and improve merchandise layouts.

The research of Digital Twin models started in 2003 to provide the foundations for product life-cycle management by creating a connection between physical products and virtual representation via data and metrology. The basic architecture is to collect measurements from physical entities using sensors, then realize them into virtual entities at some twinning rate. With the development in DT modeling, simulation, VV&A, data fusion, interaction, and collaboration, this technology has been realized and implemented widely in smart factories, industry 4.0, smart cities, etc., over the past decades. By introducing ADAS (Advanced Driver Assistance System), BIM (Building Information Modeling), GIS (Geographic Information System), etc., into the traditional Digital Twin concept, the smart city can be constructed for urban planning, traffic management, risk mitigation, pollution monitoring, etc. Here are the main modules of digital twin models.

3D Model Reconstruction: The first step to constructing a smart city with digital twin implementation is creating a map for the city landscape or roadway system. The most common technologies are the 6D BIM model, Finite Element Modeling, MATLAB/Simulink, SUMO, and Machine Learning, which have been applied broadly in railway health management, power supply maintenance, road network management, bridge monitoring, tunnel incident tracking, etc. For instance, with CAD and 3D-GIS software, the CGA model can be quickly established with limited errors. The next step is collecting data using cameras, LiDAR, and other sensors, transmitting data for calculation and prediction, and then making user advisory decisions. Moving objects' data can be stored and analyzed with video-related sensors such as CCTV and NVR (network video recorder). Besides video sensors, LiDAR point cloud ranging plays a crucial role in transportation and mobility digital twins construction. COSCO (Clustering of Symmetric Cross-sections of Objects) provides an even 10-time faster speed for symmetric object detection. At the micro level, an exemplary system installation proposed by El Marai et al. (2020) with high road user detection performance is depicted. A Digital Twin Box composed of a head-mounted 360º camera, GPS device, and other environmental measurement sensors was connected to an NVIDIA Jetson TX2 Single Onboard Computer. A live stream performed face and vehicle plate recognition in SOC. The data was also synced with the OpenStack platform via a 4G LTE network, so historical data would play an essential role in validation and calibration.

Transportation Applications: Most digital twin systems in the transportation and mobility domains work with ITS to provide better efficiency and safety for traffic management. Thus, the ITS can effectively optimize and coordinate traffic conditions by monitoring the flow of pedestrians, vehicles and roads, and traffic signals. The performance has been examined using RITM3, Trafficmap (AssetWise ALIM, Bentley), IRIS open source ATMS, Kimley-Horn Integrated Transport System, and SWARCO AG (Traffic Management Software, 2020). Wang et al.(2020) propose a digital twin framework combining ADAS (Advanced Driver Assistance System) and V2C (Vehicle To Cloud) communication by equipping vehicles with cellular hotspot (optional), GNSS (Global Navigation Satellite System), DVI (Digital Visual Interface) devices. The onboard devices communicate with cloud servers and provide driver advisory driving speed, indicating the performance leap via a case study conducted on cooperative ramp merging in Riverside, CA. Vehicle path planning can also be improved from the application of Digital Twin improves by dynamically making optimal decisions for users using the stochastic hidden Markov Model.

In some cases, MEC (Mobile Edge Computer) should also be introduced to achieve better network planning on larger scale projects, and an SDVN (Software-Digital-Vehicle-Network) with Digital Twin architecture proposed by Zhao et al. (2020). Controllers at different levels are set up to calculate routing requests acting on MEC. Data from MEC will be used to construct Digital Twin. By predicting vehicle trajectories based on historical and current data, the optimal routing strategies could be verified in a virtual network and sent back to road users in the physical network.

Driver Digital Twin (DDT) has also been studied for the transportation system and autonomous vehicles. Hu et al.(2022) proposed a theoretical construction of drive behavior-based digitalization using the information of drivers' personality, sensibility, capability, etc. collected from appearance-based, physiological-based, or driving-related sensors to form an H-CPS (Human-Cyber-Physical System). The Neural Network based method enabled the model to learn the fusion pattern in a data-driven way, increasing the robustness and accuracy.

Roadside LiDAR Data Analytics

Roadside LiDAR, a relatively newer technology in the infrastructure-based traffic sensing area, compared to a camera, has attracted tons of research interest in road user detection, classification, tracking, etc. To fulfill the large-scale high-resolution micro traffic data demand for the digital twin construction, point cloud data is needed from different places and merged, generating the need for the points to be registered to the same coordinate system. Tian et al.(2019) proposed using the matched reference points to calculate the transformation matrix for scale transformation, symmetry transformation, rotation transformation, miscut transformation, and translation transformation. The authors used least squares for the optimization to get the optimal matrix from multiple points. However, the authors could not provide a recommended number of reference points, and the vision comparison-based evaluation can be improved by providing a more quantitative analysis. Wu et al. (2019) proposed a point registration method with time synchronization, key points selection, triangle matching, which specifies three reference points, and ground surface adjustment to optimize the result. Their method has an advantage in processing efficiency, as their 0.02-second processing latency can easily handle the 10 Hz LiDAR data. Still, it relies on the building corners as reference points and is only semi-automatic. Yue et al. (2019) proposed the RGP (Registration with Ground and Points) method utilizing the reference points but also the 3D points of the road surface. They applied GA (global optimization) and HC (local optimization) methods to optimize the transformation. The RGP method does not require the GPS location of the LiDAR devices and provides the opportunity of integrating more than two LiDAR sensors.

With the points registered to the same coordinate system, the trajectories from different sensors can be merged for Digital Twin construction. The first thing for trajectory extraction is background filtering. Unlike on-vehicle LiDAR processing, the Roadside LiDAR has a relatively static background which eases the difficulty of background filtering. However, there are still potential improvements regarding automation and accuracy. The easiest way to constantly filter the static background at a low computational cost is to get a reference background frame for subtraction. The 3D-DSF (3D-density-statistic-filtering) method automated generating a background frame for static and dynamic background filtering considering the density distribution of LiDAR cloud points in the 3D space, which could filter up to 99.62% of the background points. Lv et al. (2019) applied RA (Raster-based Algorithm) to solve the problem that the background in each frame is not strictly identical to the prior frame. Still, their method requires manual selection for the initiative reference frame. However, these methods' accuracies are still imperfect due to the difficulty in excluding all background points while keeping all non-background points.

Roadside LiDAR-based vehicle/bicycle/pedestrian detection and tracking are performed on the cleaned points. Cui et al.(2019) proposed roadside LiDAR-enhanced connected infrastructures, of which 98% of the estimated speed had errors lower than two mph. The authors applied many LiDAR processing procedures, including 3D-DSF-based background filtering, density-based spatial clustering of applications with noise (DBSCAN)-based object clustering, artificial neural network (ANN)-based vehicle recognition, revised grid-based clustering (RGBC)-based lane identification, and global nearest neighbor (GNN)-based vehicle tracking, and evaluated the tracking performance by the speed difference from field-collected data. Wu performed and analyzed the speed estimation using the average point with the nearest point and concluded that the nearest point could better represent the vehicle in terms of speed estimation with a max error of 1.11876 mph. Zhang et al. (2022) proposed an ECE (Euclidean Cluster Extraction)-based clustering method. Instead of directly referencing the nearest point, the authors used the UKF (Unscented Kalman Filter) tracker with centroid as a reference and achieved an RMSE of 0.22m/s, which equals 0.492 mph. However, their tracking method only estimated the speed of the vehicles that are 5~15 meters away from the LiDAR, which significantly limits the applications. Zhao et al. (2019) applied a discrete Kalman filter tracking method to track vehicles and pedestrians. The classification results from a backpropagation artificial neural network (BP-ANN)-based classification model. Their tracking method achieved an accuracy of 95% within approximately 30 meters, with an average absolute speed difference of 1.43 mph. Most roadside LiDAR processing methods still use the experience to estimate the coverage but lack a comprehensive assessment of the adequate coverage that a LiDAR can cover.

METHODOLOGY

Digital Twin Input Data: LiDAR-based Data Segmentation Algorithms

LiDAR Data Structure for Processing

LiDAR is a modulated laser system that emits multiple laser beams. It compares the time of return (TOF) or frequency difference (Doppler frequency shift) of the signal and then detects the position, velocity, and other measurements of surrounding targets. According to how to deliver the laser beam, LiDAR can be categorized as non-scanning LiDAR or scanning LiDAR. Non-scanning LiDAR is called Flash LiDAR, which uses a solid-state component like a camera that picks up the TOF information of individual pixels. Non-scanning LiDAR is constrained by the size and density of detector arrays and leads to a limited detection range. Scanning LiDAR contains rotary parts, including non-mechanical scanning (Optical Phased Arrays (OPA) scanners) and mechanical scanning LiDAR. The mechanical rotary LiDAR is the most mature and standard type, which creates an FoV (field of view) with a fixed vertical resolution for each transmitter and receiver channel. Though this data rearrangement method is built on the mechanical rotary LiDAR scanner with view angle, it can also be generalized to other LiDAR devices such as the Micro-Electro-Mechanical Systems (MEMS) LiDAR with a specific horizontal and vertical scanning frequency. Despite the different manufacturing designs and principles, whether it is mechanic-based or mirror based, we can always interpret the LiDAR data based on horizontal and vertical angular, defined by the FoV and scanning frequency (see Figure LiDAR Sensor Coordinate System).

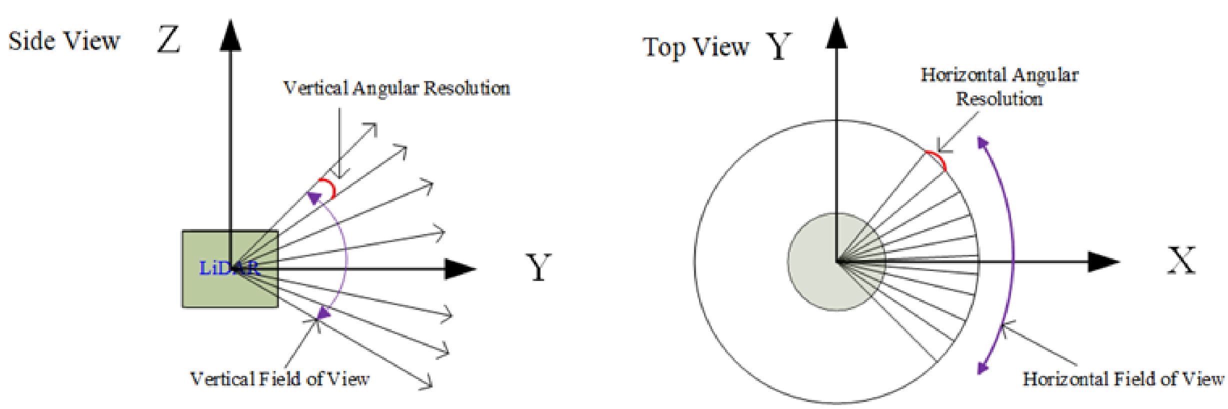


Figure 1. LiDAR Sensor Coordinate System

Here we defined a hash function to convert each LiDAR point from cartesian coordinates into spherical coordinates and store LiDAR points into a structured representation at different vertical and horizontal angles. For a given LiDAR point with spherical coordinates (α, β, Range), we use the following equation to map it onto the index of the elevation-azimuth grid (H(α), H(β)).

$$H(\alpha) = Round((FoV_h/2 + \alpha)/(Azimuth\ Resolution))$$

$$H(\beta) = Round((FoV_v/2 + \beta)/(Elevation\ Resolution))$$

Where $\alpha \in [-FoV_h/2, FoV_h/2]$, $\beta \in [-FoV_h/2, FoV_v/2]$. FoV_h is the horizontal field of view. FoV_v is the vertical field of view. If two points collide into the same grid, we preserve the point with a smaller range, as the static range of the background is often greater than the more informative foreground range.

For mechanical scanning LiDAR devices, the vertical angular is determined by the beam ID. Therefore, we only need to calculate the azimuth grid using horizontal angular value. Eventually, LiDAR points were stored in a high-dimensional tensor format with five channels to store X-Y-Z 3D measurement, range, and intensity for each LiDAR point. The final LiDAR data tensor has the size of (Azimuth Grids*Elevation Grids*Number of Variables) for each data frame. After the data transformation, the unstructured LiDAR point clouds are rearranged into a structured format.

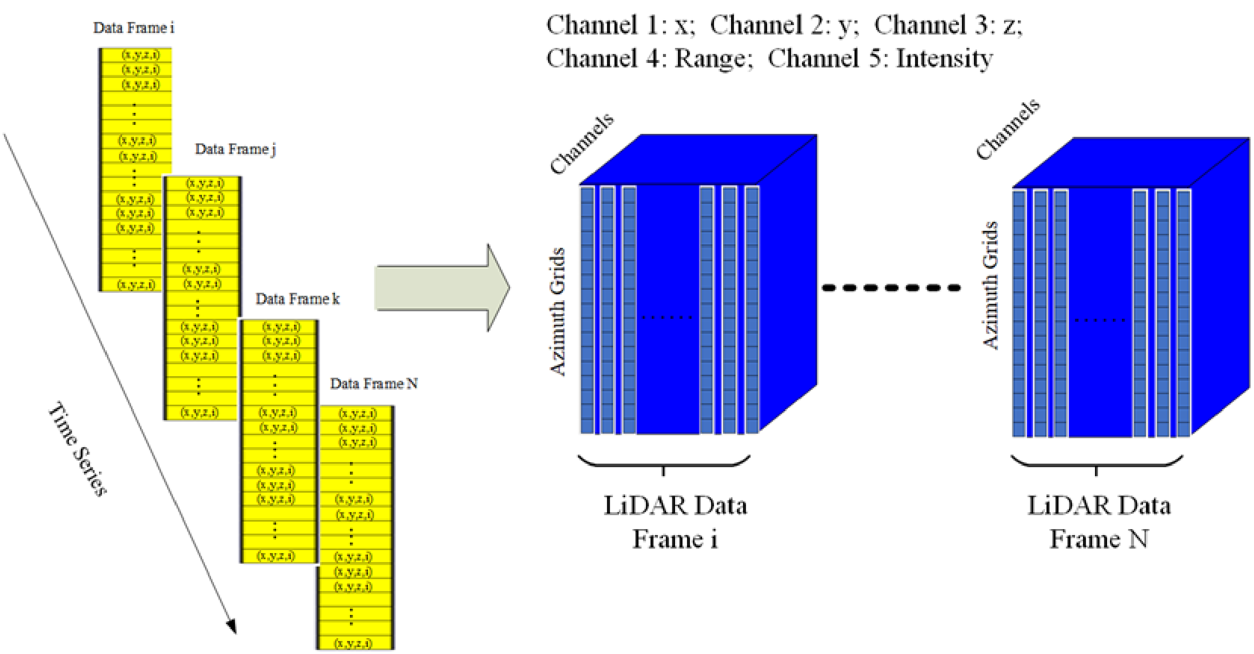


Figure 2. Data Transformation

Multimodal Gaussian Mixture Model

This section will fit the reorganized LiDAR data with Gaussian Mixture Models (GMM). The GMM models have been developed for decades and are still an active research topic, which is implemented with many skills and experience for satisfactory real-time performance. Fortunately, compared to the video data, the roadside LiDAR data does not experience illumination changes or shadows, camouflage (foregrounds have similar colors to the background), and challenges like that. The GMM method is excellent for handling dynamic LiDAR data backgrounds. The probabilistic GMM model that learns the background subcomponents is described as follows.

A recent data set of measurements $M_T = \{m_1, m_2, \ldots, m_T\}$ over a period T is captured by a mixture of K Gaussian distributions. For each elevation-azimuth unit at time t is estimated by:

$$P(m\_t) = \sum_{k=1}^{K} \omega_{(k,t)} * \eta(m_t, \mu_{(k,t)}, \Sigma_{(k,t)})$$

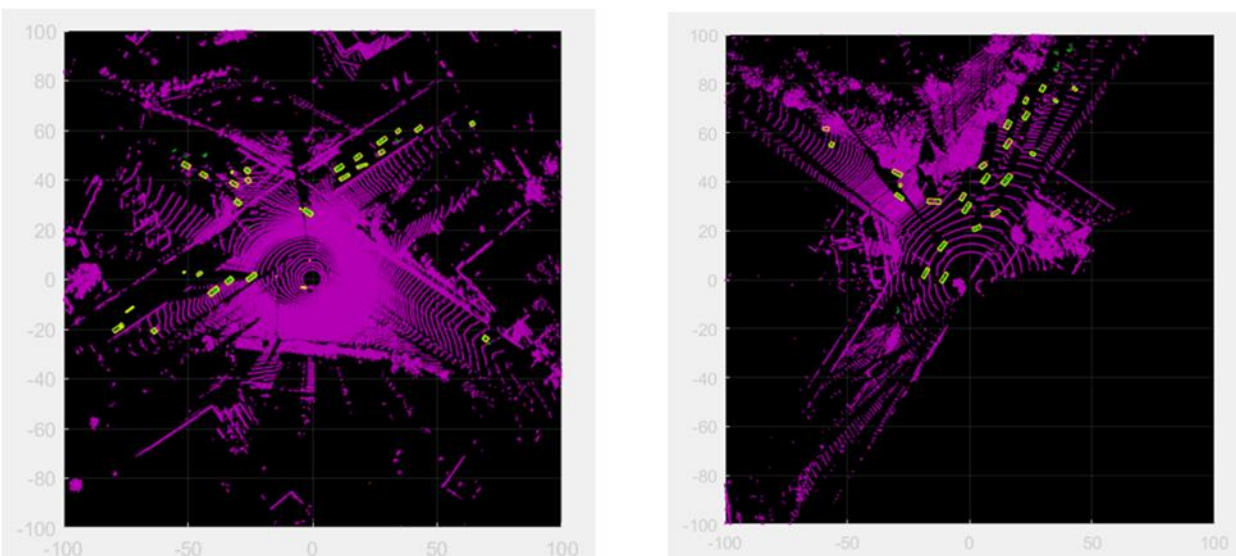
Where K is the number of Gaussian Distributions, which determines the multimodality of background. $\omega_{k,t}$ is the weight associated with the k^th Gaussian at the time t with mean and covariance matrix $\mu_{k,t}$,$\Sigma_{k,t}$. η(·) is the Gaussian Probability function given by:

$$\eta(m_t, \mu, \Sigma) = \frac{1}{(2\pi)^{(n/2)} \, |\Sigma|^{(1/2)}} \times exp(-\frac{1}{2} (m_t - \mu)^t \, \Sigma^{(-1)} (m_t - \mu))$$

Where n is the measurement dimension, in our model, we can use n=3 for the X-Y-Z three variables.

Roadside LiDAR Object Detection and Tracking

In this section, we aim to present the LiDAR background subtraction results using GMM methods. Figure 3 shows the vehicle/pedestrian detection results from the density-based bounding box estimator after foreground segmentation using the proposed adaptive GMM model. The main challenging issue is caused by perspective shadows, where targets were occluded by other vehicles. As the distance gets more significant, some distant objects could also be missing due to fewer laser rings.



US1 @ Bakers Basin

Albany @ George St

Figure 3. Roadside Adaptive Gaussian Mixture Model LiDAR Object Detection Results

We applied the JPDA-IMM-UKF algorithm for the multi-object tracking task to obtain path-level information for in-depth analysis. The IMM stands for Interacting Multiple Model (IMM) estimator (Mazor et al., 1998) that considers multiple models and filters to estimate the target state in heavy clutter. This JPDA-IMM-UKF algorithm is derived from the Unscented Kalman Filter (UKF) and resolves the data association issue by combing it with the Joint Probabilistic Data Association (JPDA). Figure x shows the O-D (Origin-Destination) analysis with tracked vehicle trajectories with roadside LiDAR vehicle detection outputs. After applying trajectory clustering techniques, with O-D information from all tracked vehicles at the intersection, we can acquire the movement counts that are often used to optimize signal timing.

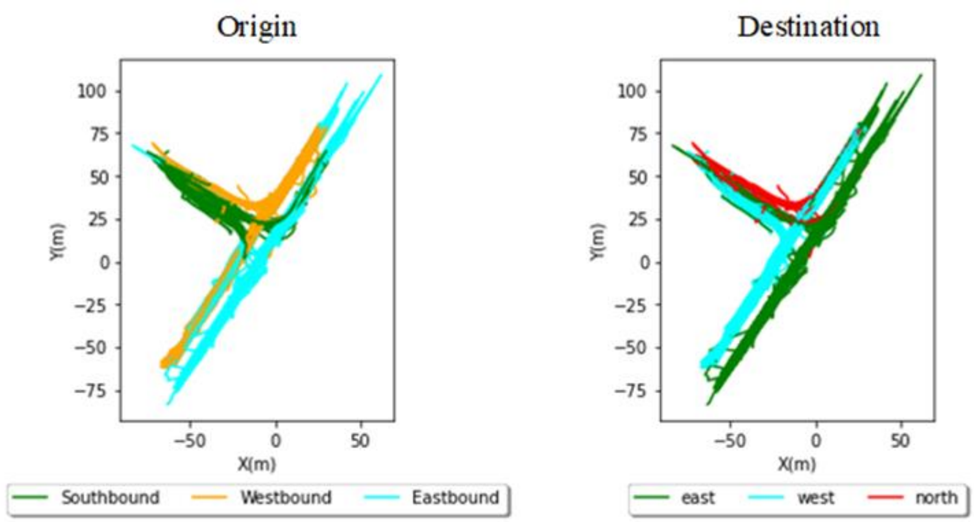
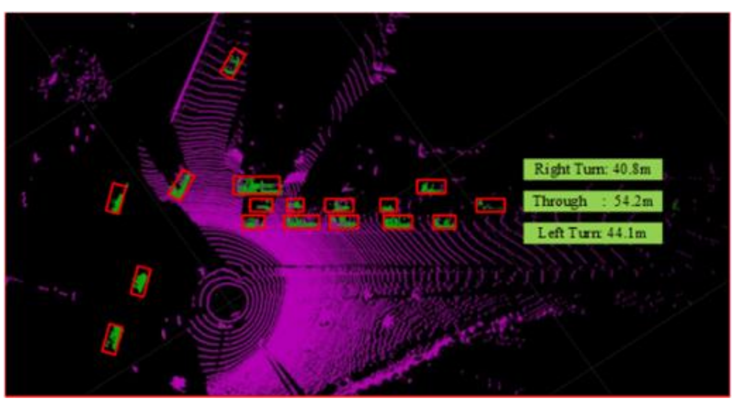


Figure 4. Roadside Lidar Vehicle Trajectory Clustering for Origin-Destination Analysis

Queue Length Estimation

In Error! Not a valid bookmark self-reference.5, the lane-by-lane queue length information could be effortlessly acquired using the object detection results with predefined lane area masks by the 3D measurement. The queue length measurements can be turned into input for adaptive traffic signal control and enable traffic managers to monitor systems in real time. As opposed to the conventional detector (e.g., Loop Detector, Radar) installed at fixed locations and only produces spot information, the LiDAR sensor generates much more extensive coverage as an ideal digital solution for smart infrastructure.



Error! Not a valid bookmark self-reference.**5. Lane by Lane Queue Length Measurement from Roadside LiDAR After Background Subtraction**

Signal Performance Measurements

LiDAR sensor is not only an add-on to current signalized intersection detectors but could also become an alternative to upgrade those legacy detection systems. Figure 6 shows that the LiDAR sensor replaces the traditional stopbar detectors (Video or Inductive loop) for lane-by-lane stopbar detections from all approaches. With the moving object trajectory and lane identification, we can adequately draw stopbar detection zones on a 2D bird-eye-view raster image and utilize LiDAR input as vehicle presence detection. Vehicle presence events can be detected based on the detection zone's density of foreground cloud points. The On-Off detector state, the corresponding detector ID, and timestamp for that event will be recorded.

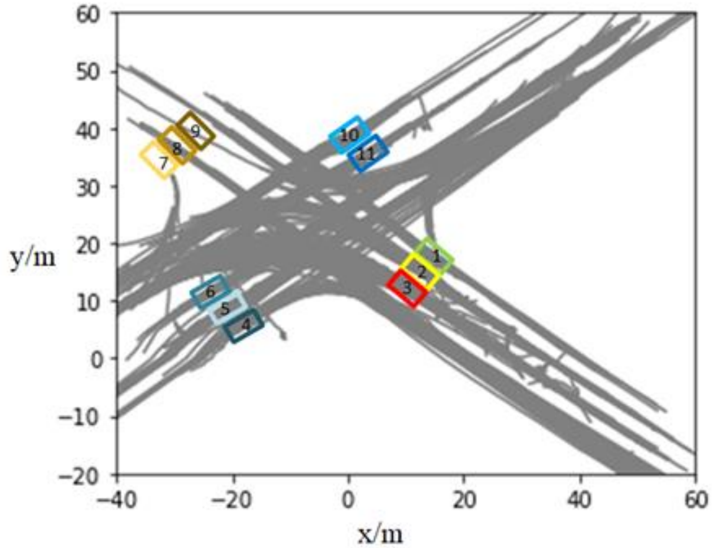


Figure 6. Using LiDAR as Stopbar Detectors for Signalized Intersection Signal Performance Metrics

In Figure 7, a novel signal performance metric named Rutgers Coordination Diagram (RCD) is created by combining Signal Phase and Timing (SPaT) data with stop bar detection from the LiDAR sensor (see Figure 9). The RCD diagram visualizes important signal performance metrics, such as vehicle departure headways, startup delay, phase duration, volume, occupancy, etc. From the new coordination diagram, the split failure issue can be quickly spotted and diagnosed using time headways. A significant time gap usually implies that the queuing vehicles were cleared. Therefore, vehicles arriving on green do not need to stop during that cycle. A split failure was considered if all gaps within one cycle were minimal and almost constant. Namely, the queuing vehicles for that approach cannot clear during the green interval. Another advantage of using LiDAR as a stopbar detector is that the LiDAR sensor has an accurate timestamp and doesn't have the latency issues found in the traditional stopbar detector. Compared to video image processing, there is no perspective distortion for the LiDAR sensor. The calibration process of the LiDAR-based stopbar detector is much easier than the video image detector.

Figure 7. Using LiDAR as Stopbar Detectors for Traffic Signal Performance Metrics (Phase 2: Northbound; Phase 6: Southbound; Phase 3: Westbound; Phase 4: Eastbound)

Surrogate Safety Measurement

Besides mobility applications, the roadside LiDAR sensor can also be used for safety-critical applications. For instance, LiDAR detection could identify near-miss situations at intersections and generate safety performances for signalized intersections.

Surrogate Safety Measures (SSMs) are one of the most used methods for identifying possible risks and assessing a hazardous condition. Each SSM is computed depending on the occurrence of road user conflicts. Conflict is defined as a visible point, line, or region where two or more road users intersect in time and space and have the potential to crash if their speed and direction stay unaltered. SSMs are considered the suitable safety evaluation approach for identifying near-miss conflict situations and recommending countermeasures by comparing the results to historical crash data. Several SSMs are utilized for assessment, including Time to Collision (TTC), Post Encroachment Time (PET), Maximum Speed, Speed Difference, and Deceleration Rate. As part of this study, PET was regarded as the SSMs for analyzing traffic conflicts at intersections between vehicles and pedestrians.

PET can be defined as "the time difference between the moment an "offending" vehicle passes out of the area of a potential collision and the moment of arrival at the potential collision point by the "conflicted" vehicle possessing the right-of-way" (Mahmud et al., 2017). No extrapolation of future locations or speed parameters is required for PET's computation. Instead, PET is computed based on the paired road users' trajectories. Figure 8 depicts a time-space diagram for calculating the PET for vehicle to-pedestrian conflicts.

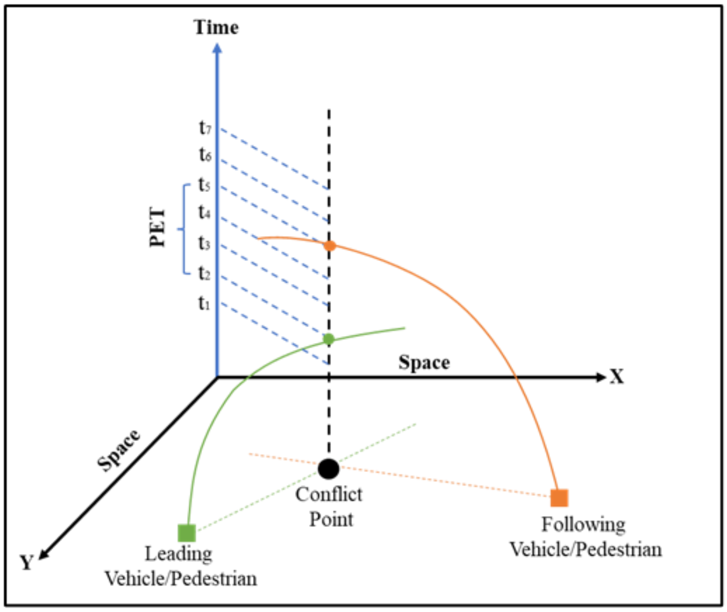


Figure 8. A time-space diagram to identify the PET

PET for paired road users at a conflict point is obtained as the following equation:

$$PET_t = t_{(F,t)} - t_{(L,t)}$$

Where:

$t_{(F,t)}$: the time when the following vehicle arrives at a conflict point
$t_{(L,t)}$: the times the leading vehicle leaves at a conflict point

As a part of this study, the extracted trajectory and object dimension data from LiDAR was considered. Similar to the previous studies, PETs with less than 5 seconds and less than 1.5 seconds were regarded as potential conflict and dangerous conflict, respectively (Gettman et al., 2008; Katrakazas et al., 2018). The study also considered 20 seconds as the arbitrary threshold for identifying all potential risks for vehicle-to-pedestrian collisions at the intersections.

The trajectories with conflicts of less than 20 seconds were considered to identify possible and dangerous conflicts using Equation 15. PET less than 1.5 seconds demonstrates a higher probability of a crash occurrence and a dangerous conflict. At the same time, a PET event between 1.5 and 5 seconds is a possible conflict. Table 1 depicts the analyzed PET results for an hour of LiDAR data, and Figure 9 shows the Spatial distributions of pedestrian-vehicle conflict points for Albany Street and George Street.

Table 1. PET Results for Albany Street and George Street

PET Threshold (Seconds)	*PET Events*	Description
PET Events < 20	25	Arbitrary Count
PET Events < 5	5	Possible Conflict
PET Events < 1.5	2	Dangerous Conflict

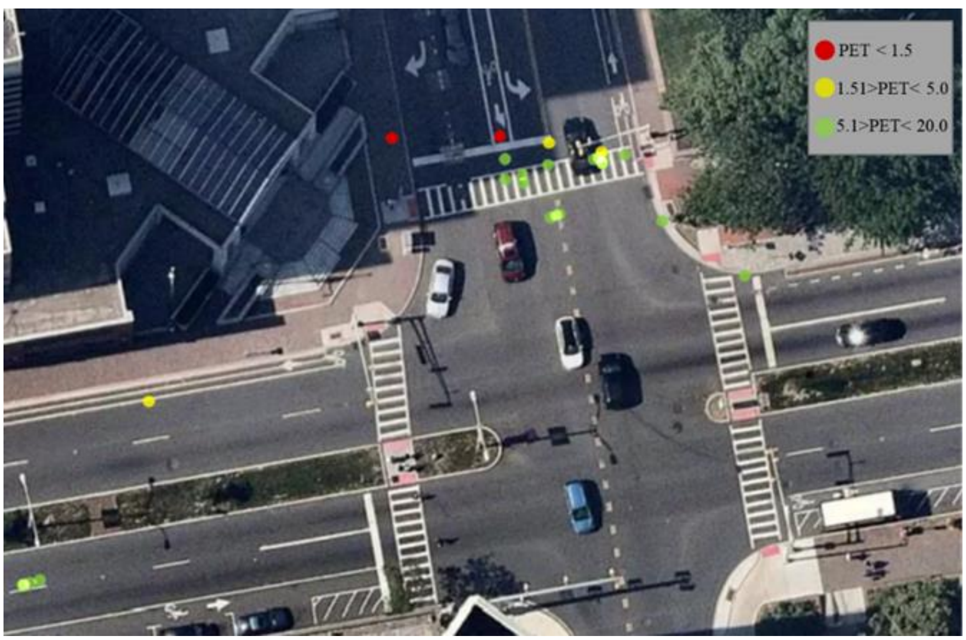


Figure 9. Spatial distributions of pedestrian-vehicle conflict points for the study Albany Street and George Street

Connected Vehicle Trajectory Generation

Connected vehicle technologies could save lives, improve personal mobility, enhance economic productivity, and transform public agency operations. Connected Vehicles technology allows vehicles to "see" all other road users' positions via V2I (Vehicle to Infrastructure) communication and critical exchange information—regardless of whether other travelers are in view, around a corner, or behind a building or cornfield. Acquiring road users' positions in real-time from roadside sensors offers a powerful 360-degree picture of threats and hazards along our roadways when LiDAR detected vehicle trajectory into V2X communications is integrated. Since the LiDAR sensor is installed at a fixed location, we can obtain its precise GPS location. Then, we applied point cloud registration to build the coordinate transformation between LiDAR's relative measurement with the world GPS coordinates in latitude and longitudinal. Figure 10 shows the projected trajectory with GPS locations feasible for connected vehicle applications. With the high-resolution real-time trajectory output, various connected vehicle applications can be deployed and prototyped, including 1. Blind Spot/Lane Change Warning (BSW/LCW); 2. Emergency Vehicle Preemption; 3. Freight Signal Priority (FSP); 4. Left Turn Assist (LTA); 5. Eco-Approach and Departure at Signalized Intersections; 6. Mobile Accessible Pedestrian Signal System (PED-SIG), etc.

Figure 10. LiDAR Trajectory for Connected Vehicle Applications

Digital-Twin-based CAV Application Testing Platform
CARLA (2017) simulator has been developed to support autonomous driving systems' development, training, and validation. CARLA provides open digital assets (urban layouts, buildings, vehicles). It supports flexible specification of sensor suites, environmental conditions, complete control of all static and dynamic actors, map generation, and much more. Therefore, CARLA can be used as the tool to build up the digital twin model for the New Brunswick Smart Mobility Testing Ground from various sensors fusion feed.

There are several main steps to realizing digital twin modeling with the CARLA simulator:
3D Reconstruction Modeling
The model retrieves captured movements or events of vehicles and pedestrians and reconstructs them into the digital world. The model is visualized in CARLA for its potential to be used in the Autonomous Vehicle simulation for supporting AV technology developments. CARLA has been developed from the ground up to support the development, training, and validation of autonomous driving systems. In addition to open-source code and protocols, CARLA provides open digital assets (urban layouts, buildings, vehicles) that were created for this purpose and can be used freely. The simulation platform supports flexible specifications of sensor suites, environmental conditions, complete control of all static and dynamic actors, map generation, and much more. The CARLA serves as a tool with the following valuable features: Scalability via a server multi-client architecture: multiple clients in the same or different nodes can control different actors.

- Flexible API: CARLA exposes a robust API that allows users to control all simulation aspects, including traffic generation, pedestrian behaviors, weather, sensors, and much more.
- Autonomous Driving sensor suite: users can configure diverse sensor suites, including LIDARs, multiple cameras, depth sensors, and GPS, among others.
- Fast simulation for planning and control: this mode disables rendering to offer a fast execution of traffic simulation and road behaviors for which graphics are not required.
- Maps generation: users can easily create maps following the OpenDrive standard via tools like RoadRunner.
- Traffic scenarios simulation: our engine ScenarioRunner allows users to define and execute different traffic situations based on modular behaviors.
- ROS integration: CARLA is provided with integration with ROS via our ROS-bridge
- Autonomous Driving baselines: we provide Autonomous Driving baselines as runnable agents in CARLA, including an AutoWare agent and a Conditional Imitation Learning agent.

CARLA Visualization: the reconstructed model will be visualized in the CARLA. As shown in Figure 11, buildings, traffic signs, lane markings, trees, and other objects can be shown in CARLA to establish a Digital Twin Model. Different sensor models and their corresponding simulations are also available for Autonomous Vehicle development.

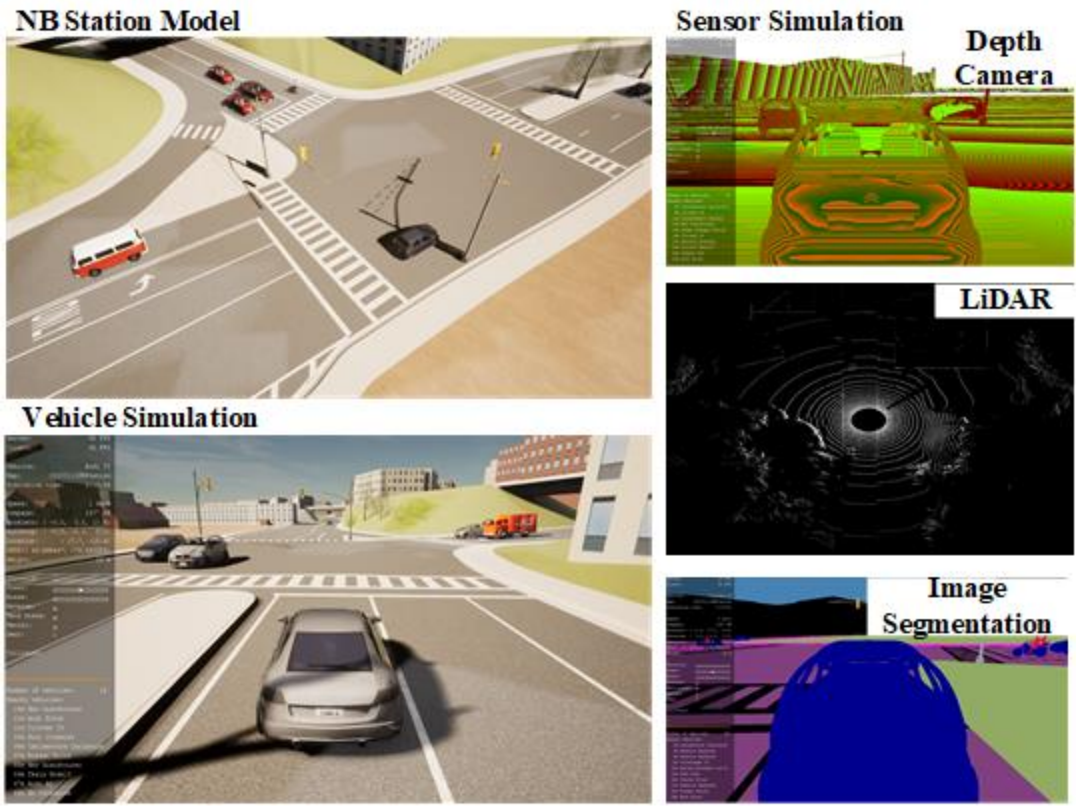


Figure 11. Digital Twin Models in CARLA

3D Urban Transportation Facility Modeling

This subtask of 3D urban transportation facility modeling for simulation includes the initial LiDAR or photogrammetry scanning to obtain the detailed environment of the surrounding infrastructure. Revit is then used to draw the 3D infrastructure model based on the scanned data. The 3D model can be imported into Unreal Engine or CARLA and add decorative objects and surfaces to the model. As shown in Figure 12, the digital twin model is created based on the LiDAR data and then imported into CARLA for later simulation use.

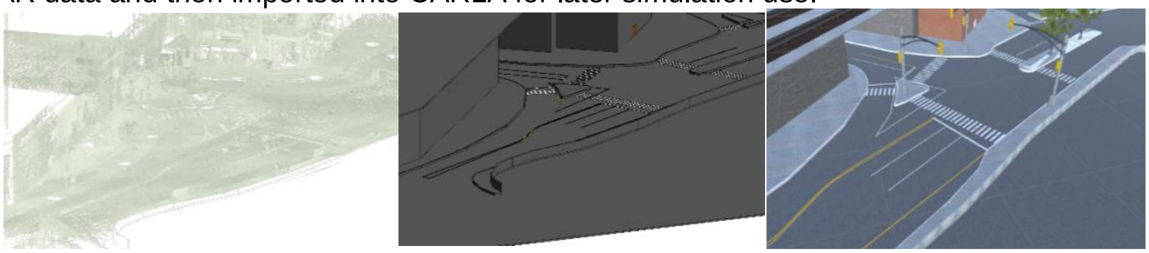


Figure 12. LiDAR Data (Left), Revit (Middle), and CARLA (Right) Model

Figure 13 shows the camera view following the Autonomous Vehicle in CARLA. The left panel provides helpful information such as speed, throttle, steer, and location of the vehicle, which provides an intuitive view of the vehicle's surroundings.

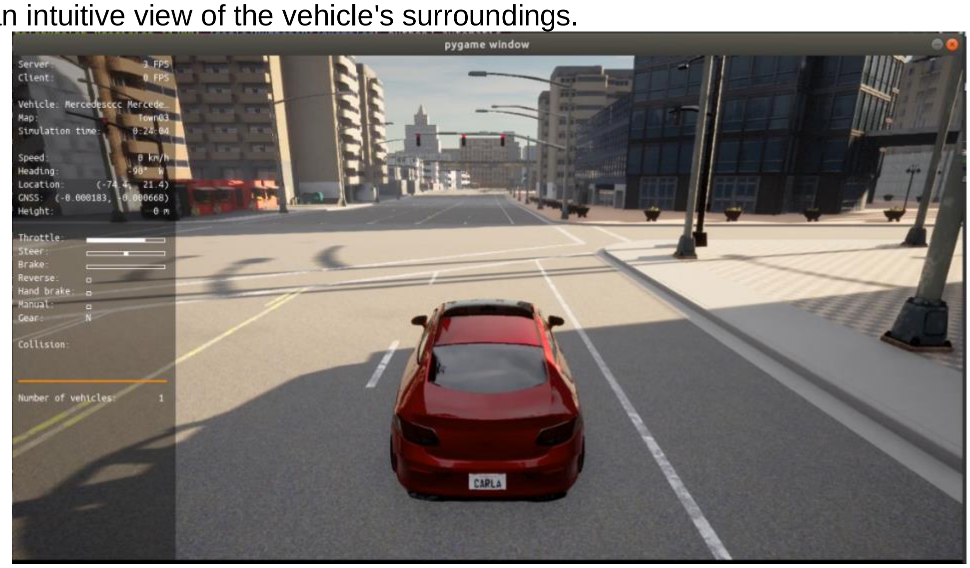


Figure 13. CARLA CAV Application Simulation Platform

In Figure 14, multiple vehicles run inside CARLA's digital twin mode. All the vehicles react to traffic signal changes and automatically interact with each other.

Figure 14. CARLA Traffic Simulation Scenario

SUMO Simulation Platform

SUMO (2018) (Simulation of Urban Mobility) is an open-source, highly portable, microscopic, and continuous multi-modal traffic simulation package designed to handle large networks. The SUMO includes road vehicles, public transport, and pedestrians. SUMO has a wealth of supporting tools that automate core tasks for creating, executing, and evaluating traffic simulations, such as network import, route calculations, visualization, and emission calculation. SUMO can be enhanced with custom models and provides various APIs to control the simulation remotely.

Solely based on CARLA, the simulation will lack realistic traffic simulation. CARLA has developed a co-simulation feature with SUMO to deal with this issue. It allows us to distribute the tasks and exploit the capabilities of each simulation in favor of the user. It is necessary to install SUMO to run the co-simulation. Building from source is recommended over a simple installation, as some new features and fixes will improve the co-simulation. Users can create sumo vehicle types, the equivalent to CARLA blueprints, based on the CARLA blueprint library. Figure 15 shows the procedure of creating a road network with RoadRunner and simulating the digital twin model with SUMO and CARLA to provide Autonomous Vehicle simulation on top of the professional traffic simulation.

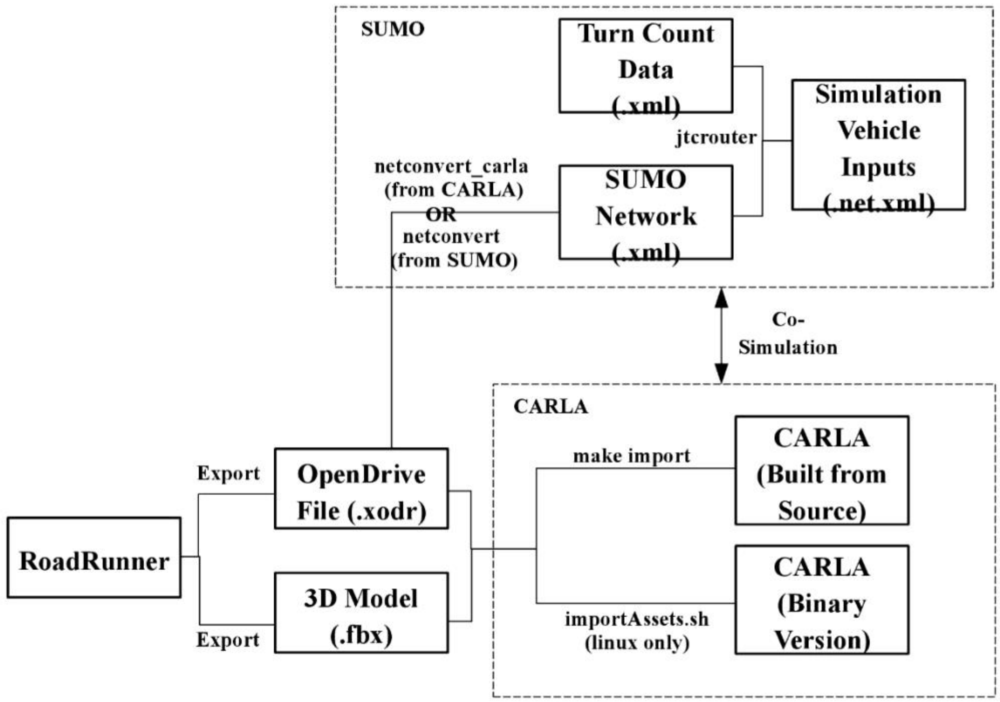


Figure 15. SUMO Traffic Simulation with CARLA

CARLA-SUMO Co-simulation Procedure

The following provides detailed steps to create a CARLA-SUMO co-simulation:

1. RoadRunner OpenDrive file -> SUMO Network:
 command line script: netconvert --opendrive 20200328NBStation.xodr -o test.net.xml

2. Manually edit the file "turnCntFake.xml" based on the vehicle counts from field data collection.
 “<edgeRelation from="125.0.00" to="59.0.00" count="3"/>” depicts that there are 3 vehicles moving from edge "125.0.00" to edge "59.0.00" during zero to 99 second.

```
<!-- need to make sure edges are connected-->
<interval id="generated" begin="0.0" end="99.0">
    <edgeRelation from="125.0.00" to="59.0.00" count="3"/>
    <edgeRelation from="125.0.00" to="128.0.00" count="20"/>
    <edgeRelation from="-128.0.00" to="-125.0.00" count="15"/>
    <!-- not connected due to roadrunner error
    <edgeRelation from="-128.0.00" to="182.0.00" count="8"/>
    -->
    <edgeRelation from="-182.0.00" to="-11.0.00" count="5"/>'
    <edgeRelation from="-59.0.00" to="128.0.00" count="5"/>
</interval>
```

Figure 16. Configuration of turnCntFake.xml

The edge id is viewable by right-clicking the lane in NETEDIT in SUMO, as shown below.

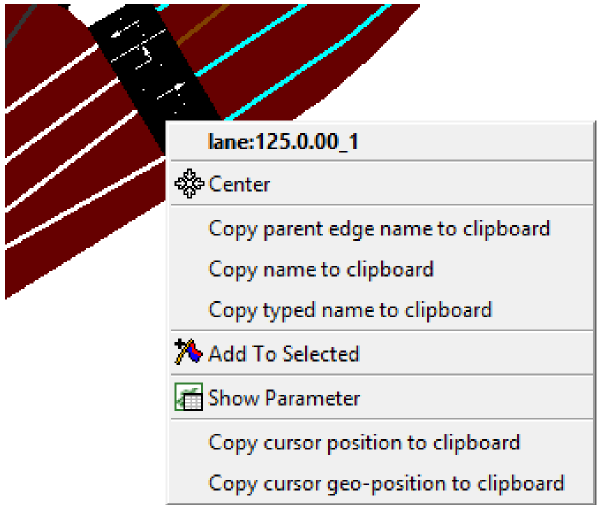


Figure 17. Edge ID

3. The JunctionTurnCountRouter (jtcrouter.py) generates vehicle routes from turn-count data. It converts the turn counts into flows and turn-ratio files suitable as jtcrouter input.

Command line script (change E:/devel/SUMO/tools/ to your SUMO path):

python E:/devel/SUMO/tools/jtcrouter.py -n test.net.xml -t turnCntFake.xml -o test.rou.xml -D

4. check the configure file "Configuration.sumo.cfg" and make sure the input file names are correct.

FINDINGS

Digital Twin-Based Safety Analysis

The current road safety practice of studying crashes at the aggregate level involves analyzing crash events for 3 to 5-year periods and often fails to capture the actual crash causalities and safety effects of time-dependent conditions at the operational level (Tarko et al., 2021). With increased comfort in driving and a perceived sense of safety, volatile driving becomes a leading cause of conflicts and crashes. The crash may have become a rarer event with the emerging intelligent vehicle technology and more advanced transportation infrastructure; however, collisions are more severe due to higher speeding tendencies by the drivers. Thus, real-time, high-resolution data have become essential in learning road user behavior and geometric defects of transportation infrastructure.

In light of this, a more proactive approach to safety improvement is now being widely adopted. Traffic safety is effectively estimated with a surrogate safety measure (SSM) - traffic conflicts, instead of actual crash events. A traffic conflict is "an observable event which would end in an accident unless one of the involved parties slows down, changes lanes, or accelerates to avoid collision" (Risser, 1985). Traffic conflicts should not be confused with crashes and can often be explained by evasive maneuvers of road users. Moreover, traffic conflicts can be utilized to estimate the probability of crashes. Observing traffic conflicts not only adequately measures safety-critical conditions but can also help to propose appropriate countermeasures. The proposed platform can evaluate the hazardousness of signalized intersections under heterogeneous traffic conditions. Various surrogate measures of near-miss conflict events include time to collision (TTC), Instantaneous Time To Collision (ITTC), Post Encroachment Time (PET), Maximum Speed, Speed Difference, and Deceleration Rate. This study uses LiDARs as stationary observers to detect conflicts between vehicles and road users. For instance, LiDAR detection could identify near-miss situations at intersections and generate safety performance measures for signalized intersections.

LiDAR is a modulated laser system that emits multiple laser beams and compares the time of return (TOF) or frequency difference (Doppler frequency shift) of the signal and then detects the position, velocity, and other measurements of surrounding targets. It can be used to extract high-resolution trajectories of moving pedestrians and vehicles. Several studies that used LiDAR to understand pedestrian-vehicle conflicts corroborate the applicability of this method (Wu et al., 2018; Lv et al., 2019; González-Gómez et al., 2021; Anisha, 2022). The LiDARs deployed at the intersection establish a digital 3D twin demonstration of the infrastructure and allow safety analysis for different scenarios. Besides, real-time traffic count data, road user classification, turning movement, and speed data are also accessible. Although LiDAR sensors are now only an add-on to current detectors of signalized intersections, these sensors can also become a suitable alternative for upgrading legacy detection systems.

Originated by Michael Grieves and his work with John Vickers of NASA in 2003, Digital Twin was introduced to provide the foundations for product life-cycle management by creating a connection between physical products and virtual representation via data and metrology. The basic architecture is to collect measurement, environment, and changes from physical entities using sensors, then realize them into virtual entities at some twinning rate. The process is bi-directional from a virtual entity to a physical entity by reversing "sensor-to-controller" and "controller-to-actuator" (Jones et al., 2020). According to Gao et al. (2021), Digital Twin technology has been applied in transportation infrastructure: railway (6D BIM model for health monitoring, MATLAB Simulink for power supply maintenance), highway (UML packages and PostgreSQL for road network management, MEC, SUMO and Python for roadway network construction), bridge (BIM model, Finite Element Model and Machine Learning for bridge preventive maintenance) and tunnel (BIM model, Finite Element Model and Machine Learning for noise prediction, cracks identification and incident tracking). In this study, the proposed digital twin aims to replicate the existing road infrastructure to facilitate improved estimation of safety and its analysis.

This study extensively studies PETs to understand the said conflicts at intersections. Post Encroachment Time (PET) is described as "the time difference between the moment an "offending" vehicle passes out of the area of a potential collision and the moment of arrival at the potential collision point by the "conflicted" vehicle possessing the right-of-way" (Mahmud et al., 2017). Qi et al. (2020) proposed a PET model to figure out lane-change characteristics and accurately forecast traffic safety in the merging area. This SSM is more suitable for understanding the right-angle traffic interactions and could be compared to the time gap between two consecutive vehicles in a car-following situation. PETs can only be directly measured from the trajectories of moving paired vehicles or road users.

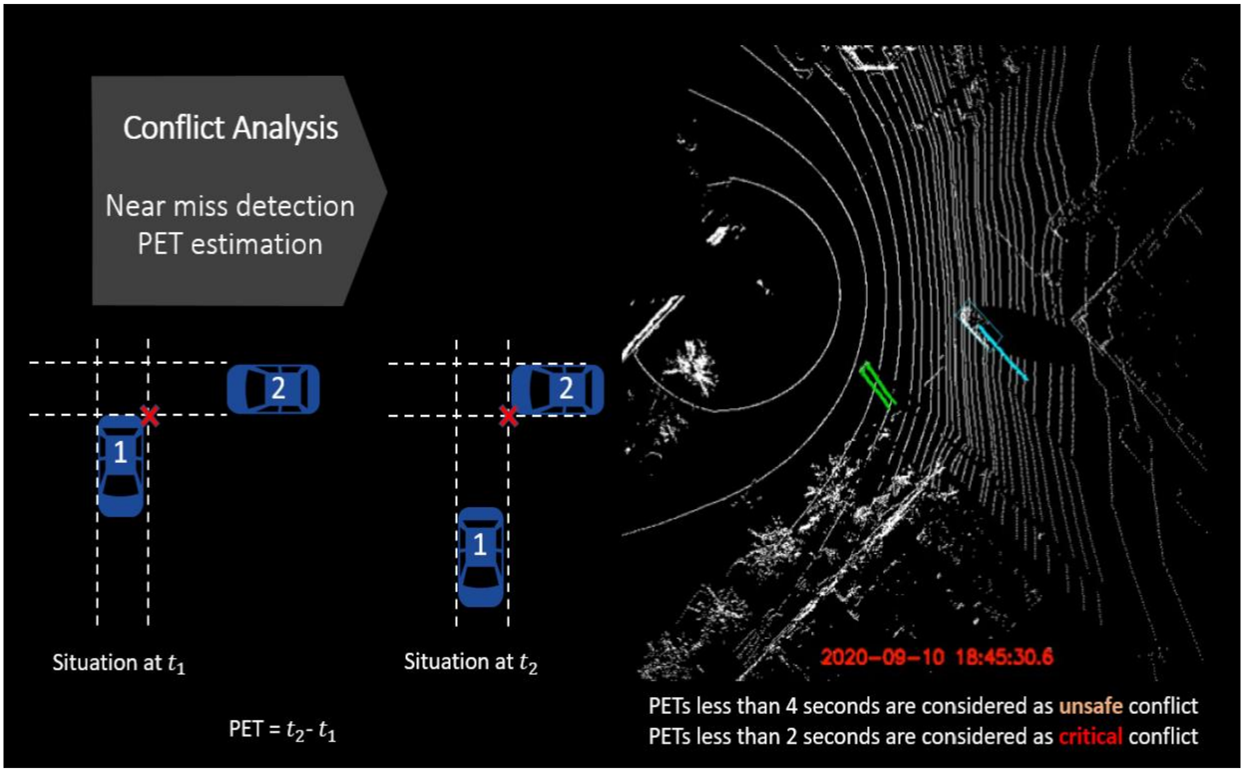


Figure 18. Estimating Post Encroachment Time (PET) for Near-Miss Detection

Figure 18 was produced from the extracted trajectory and object detection data from roadside LiDAR. Here, vehicle one is regarded as the leading vehicle, and vehicle 2 is the following vehicle. The potential conflict point at this intersection is depicted with a red cross. The time headway between these two vehicles (e.g., t2 – t1) is defined as the PET. Similar to existing literature, PETs of less than 4 seconds are considered an unsafe conflict, and PETs of less than 2 seconds are considered a critical or dangerous conflict. Critical conflicts demonstrate a higher probability of a crash occurrence and should be addressed accordingly.

The output from the LiDAR data was used to develop an interactive, user-friendly heatmap that can be modified to show the location of potential conflicts by selecting specific PETs and speed values of vehicles (see Figure 19). Moreover, details of conflicts can be retrieved by additional filtering of the type of road users (pedestrians, car, bus, bike, truck), turning movements, and time of conflicts.

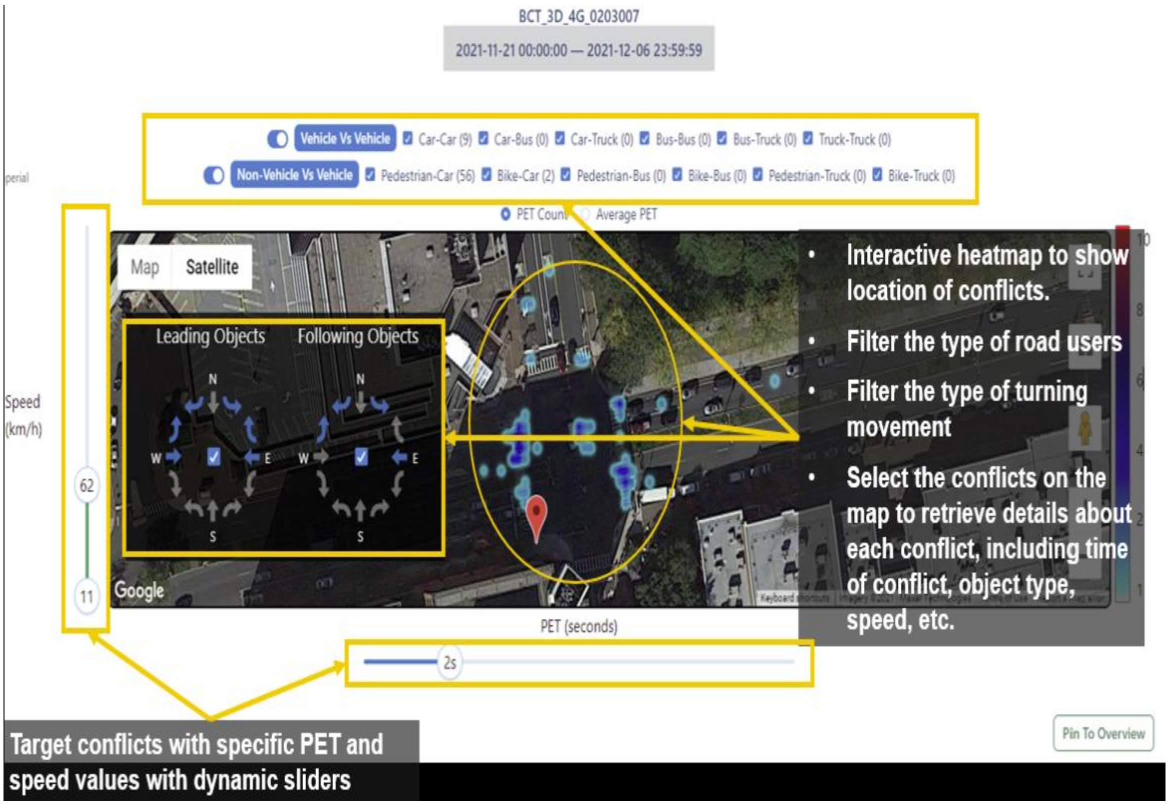


Figure 19. Interactive Heatmap for Potential Conflicts at Intersections

Adequately addressed traffic conflicts can reduce the severity and rates of road crashes. Some instances of near-miss crash events in pedestrian-vehicle interaction could be during a jaywalking or red-light running situation. Such conflict situations can provide important insights regarding the appropriateness of traffic signs and signal timing. Figure 20 displays the potential conflict locations and heatmap of jaywalking events by pedestrians at this intersection. The information is vital in enforcing pedestrian laws and proposing potential violation penalties.

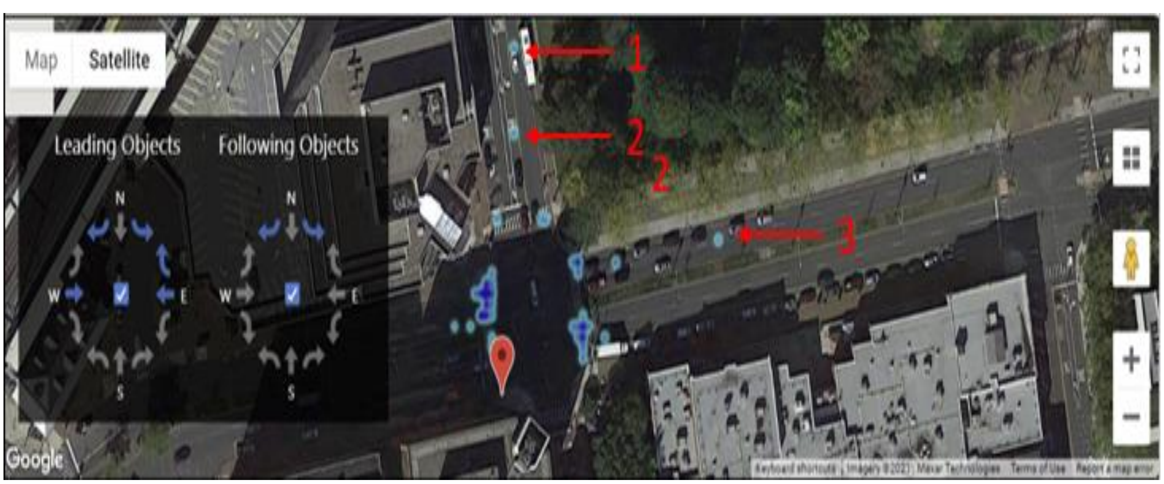


Figure 20. Location of Conflicts due to Jaywalking

Similarly, Figure 21 depicts the specific points at the intersection where a pedestrian is more likely to be hit by an oncoming vehicle due to a red-light violation. This information is critical in adjusting the speed regulations, signal timing, and mounting proper traffic signs. Obvious traffic signals warn drivers about the presence of intersections, allowing drivers to slow down their vehicles in time.

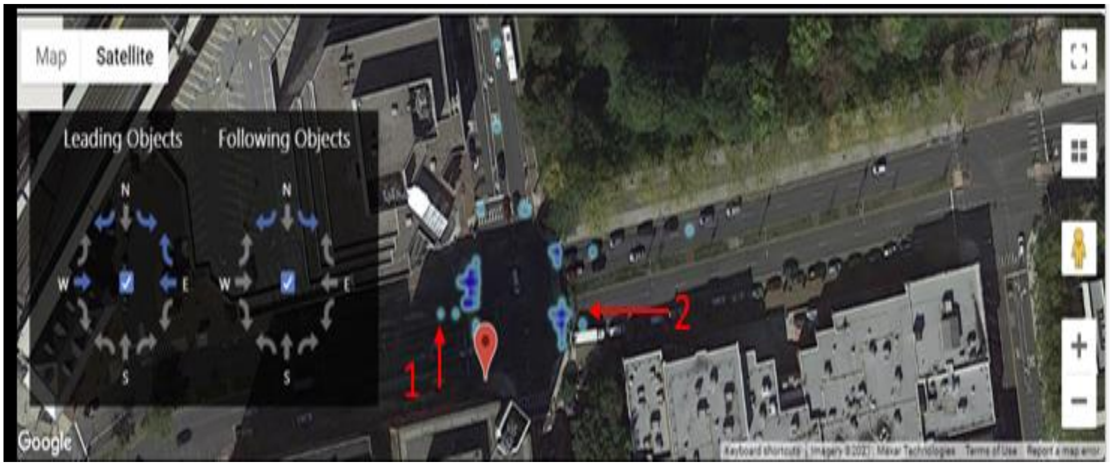


Figure 21. Location of Conflicts due to Redlight Running

Figure 22 depicts a general near-miss event during a pedestrian-vehicle interaction at a given intersection. The heatmap shows where the highly likely conflict points may be located. Any geometric or road signage changes can be considered based on the nature of these conflicts.

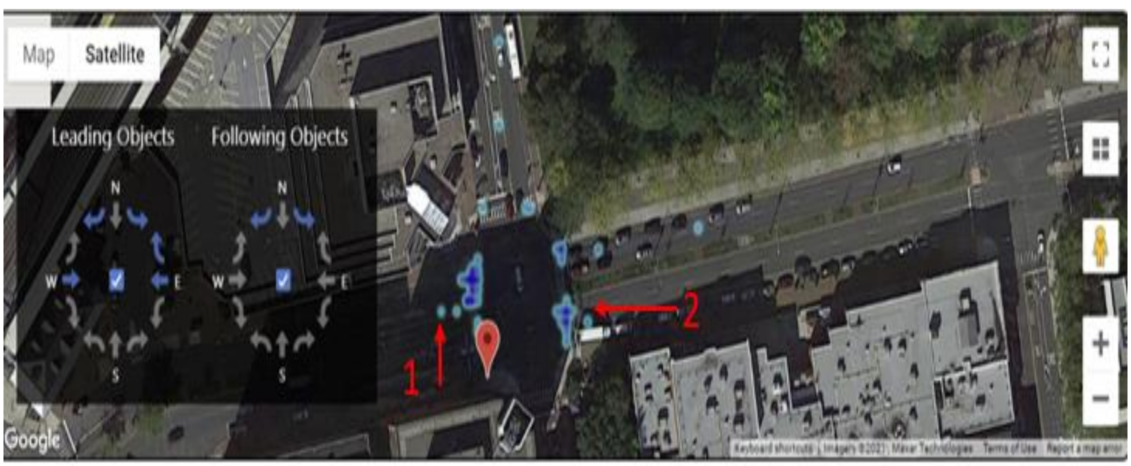


Figure 22. Pedestrian-Vehicle Near-Miss Points

Again, Figure 23 shows the heatmap for right-angle near-miss events between two crossing vehicles. The potential conflicting area can be further investigated, and adequate countermeasures can be implemented in light of this.

Figure 23. Vehicle-Vehicle Near-Miss Points

The complex relationship between human behavior and the road infrastructure, the erroneous documentation of crash reports, and difficulties in estimating both frequency and severity of crashes are why addressing safety issues becomes a challenge (Tarko, 2018). Yet, an accurate 3D replication of road infrastructure with real-time traffic data provides the promising capability to accurately pinpoint the underlying safety conditions.

CONCLUSIONS

This project develops several essential sensing, modeling, and application modules for the proposed digital twin platform.

- Digital Twin Model sensing: An integrated computer-vision- and LiDAR-based sensing module is developed to convert raw field video and point cloud data into vehicle trajectories.
- CARLA-based 3D Models based on LiDAR scanning data: Based on a pre-scanned 3D infrastructure model with ground LiDAR, the team developed procedures and algorithms to convert the infrastructure point cloud and vehicle trajectory data into a virtual digital twin mimicking the actual vehicle movement.
- Digital Twin vehicle trajectory-based Near-miss analytics application: The generated trajectories and infrastructure data were used in analyzing the intersection Near-miss conditions to identify safety issues and develop safety applications.

RECOMMENDATIONS

Based on the research outcome, the commended Mobi-Twin platform can include the following modules.

- **Digital Twin Sensing**: This module converts the field-collected roadside LiDAR and computer vision data into object shape, trajectory, and dynamic 3D road environment (360 images or 3D object maps). The developed sensing models from the project can be used to generate the high-resolution vehicle and pedestrian trajectories. Perspective transformation of the data may be needed to convert the data from the roadside view to the object view to accommodate CAV application testing.

- **Digital Twin Archiving**: This module directly archives individual object (vehicle/ped.) shape, trajectory, and dynamic projected 360-degree 3D surrounding data using the recommended LiDAR data structure and the LiDAR data reduction methods.
- **Digital Twin Modeling and Simulation**: This module calibrates the parameters of microscopic mobility models for each object to match their behavioral responses to 360 surroundings in HD-3D data. The microscopic simulation will be conducted at the object and the system level.
- **Digital Twin Visualization and Application Testing**: This module provide the interfaces to interact with analytics and control applications with 3D Objects reconstructed based on HD-3D data on 3D infrastructure Background. Playback capabilities have been demonstrated in this project's near-miss application testing study.

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