RESEARCH

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4501 South 2700 West - P.O. Box 148410 - SLC,UT 84114-8410

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# UTILIZING LIDAR SENSORS TO DETECT PEDESTRIAN MOVEMENTS AT SIGNALIZED INTERSECTIONS

**Prepared For:**

Utah Department of Transportation
Research & Innovation Division

**Final Report**
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16. Abstract

National Highway Traffic Safety Administration (NHTSA) has reported that pedestrian fatalities increased by 44% from 2010 to 2019, and more than 20% of pedestrian fatalities occurred at intersections. To improve pedestrian safety, it would be necessary to first observe evolving pedestrian behaviors. To serve this purpose, in this research project, the investigators of the University of Utah and the University of Texas at Arlington jointly explored state-of-the-art LiDAR technology to detect and track vehicles and pedestrians in real time at signalized intersections. Compared with general LiDAR sensing technologies, the investigator has developed application-specific algorithms on top of generic perception algorithms to collect pedestrian behaviors. The developed algorithm can synchronize and fuse two types of real-time information: tracked pedestrians (by LiDAR) and real-time traffic signal status. In this context, three pedestrian behaviors were collected as a proof of concept: (1) Waiting time before they entered the intersection; (2) Effective perception-reaction time to the onset of WALK, and (3) crossing speed. Other than the proposed data collection, the research team also evaluated the scalability and potential training efforts for deployment at scale.

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|---|---|
| ATSPM | Automated Traffic Signal Performance Measures |
| B/C | Benefit/Cost Ratio |
| CMF | Crash Modification Factor |
| CMFC | Crash Modification Factors Clearinghouse |
| CRF | Crash Reduction Factor |
| DOT | Department of Transportation |
| FHWA | Federal Highway Administration |
| FYA | Flashing Yellow Arrow |
| HCM | Highway Capacity Manual |
| HSM | Highway Safety Manual |
| LiDAR | Light Detection And Ranging |
| MUTCD | Manual on Uniform Traffic Control Devices |
| NHTSA | National Highway Transportation Safety Administration |
| NI | No Injury |
| NLT | No Left Turn |
| NR | No Road |
| PRM | Permitted Left Turn |
| SI | Severe Injury |
| TAC | Technical Advisory Committee |
| UDOT | Utah Department of Transportation |

## EXECUTIVE SUMMARY

Pedestrian safety is critical to improving walkability in cities. Although walking trips have increased in the last decade, pedestrian safety remains a top concern. In 2018, 6,283 pedestrians were killed in traffic crashes representing the most deaths since 1990 (NHTSA, 2018). Approximately 20% of these occur at signalized intersections, where a variety of modes converge leading to the increased propensity for conflicts. Current signal timing and detection technologies are heavily biased toward vehicular traffic, often leading to higher delays and insufficient walk times for pedestrians, which could result in risky behaviors such as noncompliance. Current detection systems for pedestrians at signalized intersections consist primarily of pushbuttons. Limitations include the inability to provide feedback to the pedestrian that they have been detected especially with older devices and not being able to dynamically extend the walk times if the pedestrians fail to clear the crosswalk. Smart transportation systems play a vital role in enhancing mobility and safety and provide innovative techniques to connect pedestrians, vehicles, and infrastructure.

As an emerging sensing technology, LiDAR (Light Detection and Ranging) sensors are used to measure objects' movements and positions in three dimensions by emitting and receiving laser beams. They have become the core sensors for automated vehicles. LiDAR sensors have recently been used as novel roadside sensors in smart city applications. In this project, the investigators evaluated the LiDAR sensors' performance, including the hardware and software stabilities and accuracy. Another objective of this research is to evaluate exploratory applications of pedestrian behavioral data collection through synchronizing pedestrian tracking information and traffic signal status. The collected pedestrian data were then uploaded to a central system for visualization. The prototype LiDAR system for collecting pedestrian data was activated during the winter of 2021 and has been running steadily, without triggering cabinet flashings. The research findings will help UDOT's staff make better informed decisions when the LiDAR sensing solutions become one of the cost-effective options for vehicle detection in the near future.

# 1.0 INTRODUCTION

## 1.1 Problem Statement

This research aims to explore a state-of-the-art LIDAR technology to collect pedestrian behavioral data. According to the Motor Vehicle Traffic Fatalities Report published by the National Highway Traffic Safety Administration, pedestrian fatalities increased by 44% from 2010 to 2019, and more than 20% of pedestrian fatalities occurred at intersections. As such, the outcome of this project is anticipated to play a vital role in achieving the “Vision Zero” (traffic safety) goals through infrastructure technology innovations.

Compared with video-based or radar-based traffic detectors, LiDAR sensors have three major advantages in perceiving vehicles and pedestrians. First, the performance will not deteriorate in dark and foggy conditions because LiDAR sensing is based on active laser beam firing and reflection whereas video-based detectors are mostly based on comparing the objects and their backgrounds, becoming difficult in the above conditions. Second, LiDAR performance will not deteriorate in perceiving slow and still objects such as pedestrians or still vehicles while the radar-based traffic detectors are known for their poor performance in capturing slow or still objects; Third, the “ceiling” of LiDAR sensing accuracy is higher than the existing traffic detectors. The LiDAR sensing technology is being applied in autonomous vehicles to quickly perceive surrounding objects, requiring high adaptiveness and accuracy. As such, when LiDAR sensors are applied to highway applications, they are anticipated to be more effective for increasingly complicated traffic conditions. The unit price of LiDAR sensors has also dropped rapidly in recent years and is comparable to other video and radar detectors. This economical trend paves the way for large-scale deployment of LiDAR sensors by transportation agencies in the near future.

In general, there are three levels of algorithms for LiDAR-based applications:

(1) hardware algorithms to generate stable point clouds;

(2) point clouds clustering and object perception algorithms, and;

(3) application algorithms based on object perceptions in various domains.

The algorithm solutions at the first two levels are mature and commercially available while the algorithm development at the 3rd level for infrastructure applications has just started. In this research project, the investigators developed and evaluated an application algorithm to collect pedestrian behavioral data. By defining the situation-aware detection zones, the developed hardware and software package can be able to detect the presence of pedestrians in the zones, calculate their waiting time before crossing, and estimate the time they take to complete the crossing. Generic LIDAR sensors in the market only collect raw point cloud data. To apply the LIDAR sensors to traffic management, the needed research efforts can be divided into three steps. The first step is to collect the LIDAR data and adopt machine learning models to cluster the raw point clouds into objects and classify the objects into vehicles, pedestrians, or bicyclists. The second step is to further develop the perception software for the implementation of the machine learning models. The third step is to develop algorithms to retrieve the captured vehicles/pedestrians from the LIDAR sensors and adapt them to different applications. Notably, the perception software (the second step) for LIDAR sensors has not been commercially available until last year. Through real-world deployment in Texas, the investigators of this project concluded the selected LIDAR perception solution can detect and track pedestrians effectively and accurately. As such, it is important to conduct some proof-of-concept studies in Utah as it may offer a new solution to significantly improve both safety and mobility of pedestrians at signalized intersections.

As the proposed LIDAR hardware and software package can support real-time data processing and transmission, the obtained pedestrian information would include each pedestrian’s arrival time, waiting time, and street crossing time at intersections. Those valuable data can be sent back to the UDOT Traffic Operations Center for storage. Moreover, the data can be used to expand pedestrian-related metrics in ATSPM, where only pedestrian delay is provided at some intersections currently. The research would benefit Utah pedestrians because the installed LIDAR can effectively collect pedestrian data at intersections. Such information can be further used to understand pedestrian mobility/safety performances. For example, whether the programmed green duration is sufficient for pedestrians to complete the crossing.

## 1.2 Objectives

There are four research objectives in this project: (I) to better understand the potential of LiDAR sensing technologies in traffic management, including the performance under various traffic conditions (dark, snowy, foggy, etc.); (II) to estimate related learning curves and training efforts if the LiDAR solutions are deployed at scale; (III) to collect pedestrian behavioral data for analysis and visualization in the automated traffic signal performance management system (ATSPM); and, (IV) to evaluate the performance of turning movement counts based on the developed application algorithms on top of LiDAR sensors.[1]

## 1.3 Scope

The scope of this research is divided into several tasks described as follows:

### 1.3.1 Preliminary Investigation

The research team and the Technical Advisory Committee (TAC) members discussed and confirmed the proposed tasks during the first kick-off meeting, including the necessary resources for the project to succeed. These resources include (I) VPN accounts for access to the traffic control equipment behind UDOT's firewall; (II) A virtual machine (server) within UDOT's traffic control network to receive and archive data from LiDAR sensors and host the central software; (III) LiDAR deployment. The meeting attendees included the investigators from the University of Utah and the University of Texas at Arlington, the research project manager, and the TAC committee composed of staff from various UDOT divisions.

### 1.3.2 Literature Review

The second task of this project is to conduct a literature review of relevant studies on using novel sensors to detect multimodal traffic. The comparable technologies include video analytics, infrared sensors, radar sensors, and/or LiDAR sensors. The TAC committee is particularly interested in existing studies on the deployment of LiDAR sensors in the field for various purposes.

### 1.3.3 LiDAR Installation and Calibration

The third task of this project is to determine the working flow of deploying LiDAR sensing systems at intersections. This task is critical for the TAC committee to estimate the learning curves and needed training efforts if UDOT plans to deploy LiDAR sensors at scale in the future. During the sensor installations, lessons were learned, and the recommendations are described later.

[1] This task replaced an original task (coupling LiDAR with CAV infrastructure) in the proposal due to non-technical barriers.

#### 1.3.4 Pedestrian Data Collection

The fourth task is to collect pedestrian behavioral data at signalized intersections. It is based on LiDAR tracking information and synchronous traffic signal status. The information will be based on defined event zones.

#### 1.3.5 Central System and Database

In this task, the investigators set up a central system, referred to as UTA-in-Motion (UTAIM), to visualize the collected pedestrian information within the context of UDOT's ATSPM system.

#### 1.3.6 Turning Movement Counts with LiDAR Sensors

In this task, the investigators evaluate the accuracy of turning movement counts based on the traffic counting algorithm developed by the research team. The traffic counts are of high resolution. Each captured vehicle will be labeled by its movement (left-turn, through, right-turn, and u-turn on any approach) and its measured length.

#### 1.3.7 Recommendations and Conclusions

In this phase, the research team summarizes the key research findings and makes recommendations for a left-turn phasing design, based on the results of the above phases.

### 1.4 Outline of Report

This project report is organized with the following chapters:

- Introduction
- Literature review
- LiDAR sensor installation and fine-tuning
- Pedestrian data collection, analytics, and visualization
- Turning movement counts
- Conclusions

# 2.0 LITERATURE REVIEW

In most literature, pedestrians and bicyclists are often stated together, and detection is referred to as pedestrian and bicyclist detection (PBD). We will use pedestrian detection to describe the PBD technologies unless confusion is caused. Pedestrian detection becomes increasingly important in multimodal traffic operations. Such devices can not only detect their presence but also collect more information about behaviors like pedestrians' waiting time, walking speeds, etc. A rich body of literature on such sensing technologies is available as well, such as video processing, infrared cameras, radar, and LIDAR sensing technologies. The back-end algorithms of such sensing technologies are mostly based on clustering and machine-learning techniques. This literature review focus on two aspects: (i) pedestrian detection techniques; (ii) the application of these techniques.

## *Pedestrian Detection Using Cameras*

This technique subtracts moving objects (i.e., pedestrians) from the stationary background. Using video-based pedestrian detections, Kilambi et al. (Kilambi et al., 2008) adopted the Gaussian density method to estimate the number of people in a group. They used both heuristic learning methods and shape models to identify the variation of captured data. The basic assumption of the underlying model is that there is an average statistical distance maintained between the members of any crowd. The proposed projection method can find each blob area obtained from foreground segmentation in world coordinates using camera calibration information. Although the method can lower the issues generated due to the moving objects of different heights (i.e., vehicles) other than human height, it cannot give the crowd's motion trajectory information. Besides, the blob data cannot estimate the actual crowd size. Later on, Yoshinaga et al. used a blob descriptor to find the crowd size (Yoshinaga et al., 2010). They used background subtraction on the PETS2006 (PETS2006) dataset using the Parzen density estimation method to estimate pedestrian counts using a neural network. Although the pixel values in this model are observed in the massive frames, the developed neural network cannot always give the correct estimation.

Chan et al. developed a modified algorithm for surveillance video technology. The database used to prove the concept was a one-hour video recorded by a stationary digital camcorder (Chan et al., 2008). Chan and Vasconcelos further used Bayesian Poisson Regression for counting crowd size

(Chan and Vasconcelos, 2009). Bhuvaneshwar et al. proposed a systematic approach for counting and detecting pedestrians at an intersection using a video camera (Bhuvaneshwar and Mirchandani, 2004). In their study, median filtering and thresholding were applied to identify the difference between the moving objects at the intersection based on the height and area occupied by the object. They also proposed a shadow removal algorithm for detection and removal of the object from the image frames. The proposed system can report a general idea about the number and location of pedestrians at the intersection. Nonetheless, even though video-based pedestrian detection techniques can identify crowd size without the location information of pedestrians, the accuracy is highly sensitive to the position and installation angle of cameras, creating large errors. Because of these reported issues in practice, using video detection for large-scale pedestrians was limited (Li et al., 2012).

*Pedestrian Detection Using Thermal Cameras/Passive Infrared*

Pedestrians can also be detected using a thermal camera and passive infrared. Both thermal cameras and passive infrared (PIR) sensors use passive detection of infrared light. However, when thermal images are used for pedestrian detection, the actual size and color information cannot be accurately collected. Moreover, weather changes also impact the outcome since the thermal sensors also visualize temperature radiation from the objects in the images. John et al. (John et al., 2017) calibrated and analyzed the images from the thermal camera (FLIR far-infrared camera) and visible cameras (IDS visible camera) to perform pedestrian detection. In their approach, two types of cameras were initially calibrated using a heated calibration rig and further used the Particle swarm optimization (PSO) algorithm to estimate affine transformation. The algorithm works in three ways. Using the calibration information, primary grid points are first created. In the second and third approaches, objects and pedestrians are identified. For pedestrian tracking, the unclothed regions of the human body are captured using a thermal camera because of the human body's relatively high heat signature. Thus, the intensity and size-wise thresholds were used to identify the human face blob in the frame, and the centroid information is used to detect the pedestrian’s trajectory. At the same time, the trajectory is also identified by the visible camera using background subtraction. Two synchronous images are a pair only if it is available in both cameras. Baek et al. proposed a thermal position intensity histogram (TPIHOG) for pedestrian detection at night using a thermal camera (Baek et al., 2017). They used a combined TPIHOG and additive kernel support vector machine (AKSVM) to perform nighttime pedestrian detection. Kim developed a multi-stage cascade learning device for pedestrian detection at night time or in a location of lower light (Kim, 2019). In this approach, the author estimated the distance between the detected pedestrian area and the infrared camera location with the information on the position of the pedestrian who was detected in the real-world environment in the 2D thermal image.

*Pedestrian Detection Using Active Infrared*

Active infrared sensor is another method of pedestrian detection. Those sensors effuse an infrared light beam to the receiver located across a pedestrian path. If any pedestrian enters that path, the beam is blocked and thus one pedestrian count is added to the record. However, the limitation of active infrared detection is that it cannot identify pedestrians and bicyclists separately. Also, the range of detection locations is very small.  Because of its limitations, active infrared is generally used for pedestrian-only trails, where the pedestrian path is constrained and classification is not necessary, as summarized by Kothuri et al., (Kothuri et al., 2017).

*Detecting Using Radar Sensor*

Radio detection and ranging (RADAR) is an active sensor with a wide span of usable wavelengths (100m to 4mm). Because of the longer wavelength, it can cover more objects. However, longer wavelengths produce lower-resolution sensor data. Manston et al. used Radar advanced driver assistance system (ADAS) features in some of the aforementioned PUFFIN crossings to detect pedestrians moving in the crosswalk (Manston, 2011). When necessary, a dual antenna system can provide a curbside detection zone and a crosswalk detection zone. Limitations of radar include susceptibility to error from rainfall, though a 13 GHz radar has improved upon this limitation from earlier 24 GHz models. Radar can be used to detect pedestrians up to 30 meters away, though sensors for commercial applications generally specify a range of 18 meters.

*Pedestrian Detection Using LIDAR Sensor*

Light Detection and Ranging (LIDAR) sensor is an emerging sensing solution. In transportation, the LIDAR sensors were initially designed for autonomous vehicles to identify the surrounding objects. Although the application of LiDAR in transportation is mostly focused on autonomous vehicles, more and more LIDAR manufacturers have entered the area of infrastructure. With some natural physical advantages, LIDAR sensors are used to detect and trace pedestrians. Zhao et al. (Zhao and Shibasaki, 2005) proposed a pedestrian tracking approach using multiple single-row LiDAR sensors. In this approach, real-time pedestrian behavioral data from a wide area were collected through a 360-degree spinning LIDAR, then moving objects are extracted. They used the Kalman filter for developing a tracking algorithm to identify pedestrian trajectories. Later Zhao et al. applied a network of horizontal LiDAR sensors to monitor vehicle and pedestrian movement entering a large crowded intersection (Zhao et al., 2011). They used data clustering techniques in an integrated spatial and temporal data association framework to find the moving object and motion trajectory at the intersection. However, the clustering was conducted manually without considering the same object entered into the database from different sensors. Moreover, a few critical parameters were estimated based on experience, making the study lack generality and weak adaptability. Zhao et al. later presented a systematic approach for tracking and detecting pedestrians at an intersection using infrastructure-based LIDAR sensors (Zhao et al., 2019). The foremost step of the methodology is the background filtering of the collected data. After that, the objects are classified as pedestrians or vehicles. Object clustering and tracking are conducted according to the speeds and trajectory of each object identified from the sensor.

In a separate study, Zhao et al. used a deep autoencoder-artificial neural network (DA-ANN) for predicting the behavior of pedestrians along the sidewalk using roadside LIDAR sensors (Zhao et al., 2019). The developed model gathers pedestrian trajectory data from the roadside sensor and performs data extraction, partitioning, feature extraction, and model evaluation. Lv et al. developed a systematic approach to extract high-resolution traffic data from roadside LiDAR sensors to extract the trajectory information from the speed distance profile (SDP) of the road user to reduce vehicle-pedestrian conflicts (Lv et al., 2019). Wu et al. used high-resolution micro traffic data (HRMTD) from LiDAR sensors based on the spatial distribution of laser points, which filters both static and moving backgrounds efficiently (Wu et al., 2018). They used a background filtering method named 3D density-statistic-filtering (3D-DSF) for efficiently separating static and dynamic backgrounds. Combs et al. identified the range for pedestrian sensors (Combs et al., 2019). They estimated the maximum number of pedestrian fatalities that could be avoided if the system were converted into an automated vehicle environment. Grassi et al. developed a method based on data extraction and data fusion to detect pedestrians and classify them depending on their movement direction using both the LiDAR sensor and video camera (Grassi et al., 2011). They classified the data without tracking or movement analysis. Ansari et al. developed a hybrid pedestrian detection technology to identify both moving and static pedestrians by incorporating both 3D LiDAR data and vision sensors for data clustering (El Ansari et al., 2018). Visible image maps are generated from those that cluster for finding a common reason of interest. Furthermore, the pedestrians are identified using the Color-Based Histogram of Oriented Gradients (HOG) feature along with the Local Self-Similarity (LSS) feature provided in the Support Vector Machines (SVM) classifier. By using two-dimensional LIDAR data and monocular camera images, Bu et al. proposed end-to-end neural network architecture for pedestrian detection where an image-based orientation detection technology is used to get the actual orientation of the pedestrian from the 2D image (Bu et al., 2019). They also proposed a Regional Proposed Network (RPN) for the non-oriented pedestrian data and Predictor Net for predicting the oriented pedestrian. Soundrapandiyan et al. (Soundrapandiyan and Mouli, 2015) and Tang et al. (Tang et al., 2017) proposed an Offline Adaptive pedestrian detection method using a neural network and collecting data from the sensor and video detection database. Soundrapandiyan et al. performed background modeling of the image collected from the thermal camera, and pedestrian detection is conducted by local adaptive thresholding using the parameter from the input image; on the other side Tang et al. used controlled convolutional neural network (CCNN) architecture and modulating neural network (MNN) for detecting a pedestrian in a location. CCNN works on adaptively generating a priority classifier, which is later dynamically adjusted by MNN.

# 3.0 LIDAR SENSOR INSTALLATION

## 3.1 Preparation

Researchers had developed a series of software programs to transform general LiDAR sensors into a pedestrian behavioral data collecting system from a previous research project. Figure 3.1 demonstrates the system architecture. On top of generic LiDAR sensors, two programs were deployed: 1. LiDAR main program (main program hereafter); 2. Pedestrian information uploading and visualization in the central system. For this research, the research team applied virtual private network (VPN) accounts to access UDOT's traffic control intranet. In addition, UDOT also granted a virtual computer for the research team to remotely troubleshoot and monitor the health of the LiDAR system.

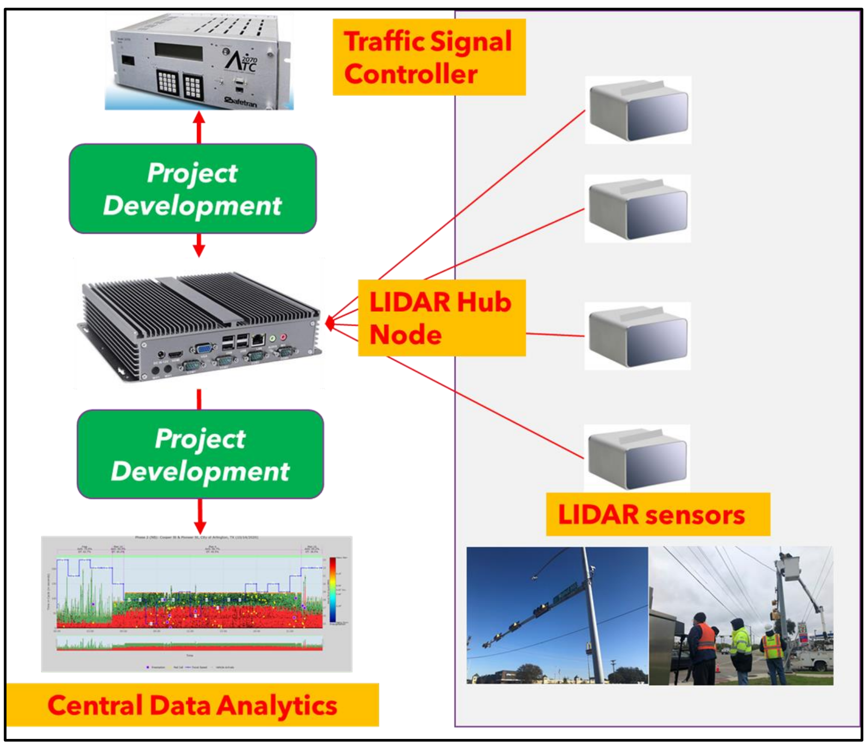


**Figure 3.1 System architecture of the LiDAR solution**

The selected intersection for this study is *600 N & N 300 W, Salt Lake City, UT 84103*. It is close to downtown Salt Lake City with uncongested or close-to-congestion traffic conditions during peak hours. The truck ratio (semi-truck or bigger) is very high. The daily number of crossing pedestrians (all four approaches) during weekdays ranges from 70 to 120.

Solid-state LiDAR sensors were selected for this study according to the intersection layout and physical characteristics of LiDAR sensors. Four LiDAR sensors were mounted on traffic signal poles 20 feet above the ground and their fields of view (FOV) were set up as shown in Figure 3.2.

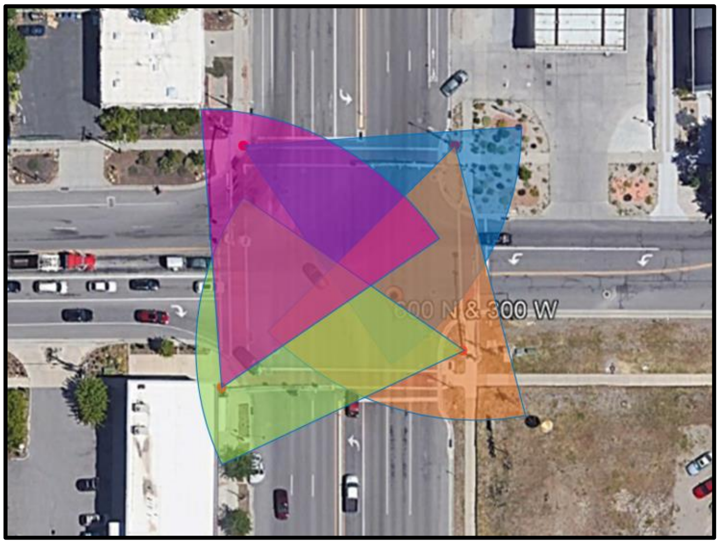


**Figure 3.2 LiDAR FOVs at 600 N & N 300 W, Salt Lake City (INT 7122), UT**

The researchers also installed the necessary software and database on the virtual machine for continuous pedestrian data storage, analytics and visualization.

## 3.2 Installation

The LiDARs were installed in February 2022. Before the planned date, a UDOT team had pre-installed the necessary wires and cables. Four LiDAR sensors were installed on top of the traffic light poles (20 to 25 feet high) at four corners of the intersection. It took about two hours to install the LiDAR sensors and the process was similar to installing other types of traffic sensors except that the height and angles needed to be fine-tuned carefully to make sure the intersection was fully covered. It took another 20 minutes to align those four sensors from LiDAR's edge computing node. Figure 3.3 and Figure 3.4 show the installation and sensor coverage


**Figure 3.3 Installing and calibrating LiDAR sensors in the field (Int 7122)**


**Figure 3.4 LiDAR coverage at the intersection**

### 3.3 Calibration and Alignment

LiDAR sensors can not only detect the presence of vehicles but also track objects within the scope. To track objects, all LiDAR sensors must be grounded and aligned to ensure the same tracked objects can be taken over from one LiDAR sensor to another to get the whole trajectory.

A few challenges were found during the sensors' calibration. Although this problem can only be identified with a directional multi-LiDAR configuration, both directional LiDAR and mechanical (360 degrees) LiDAR sensors have the so-called "Parallax-Error" issue as shown in Figure 3.5. To overcome this issue, the 4 LiDAR sensors were not aligned based on roadside still objects (e.g., buildings or poles). Instead, they were aligned according to captured vehicles and pedestrians.

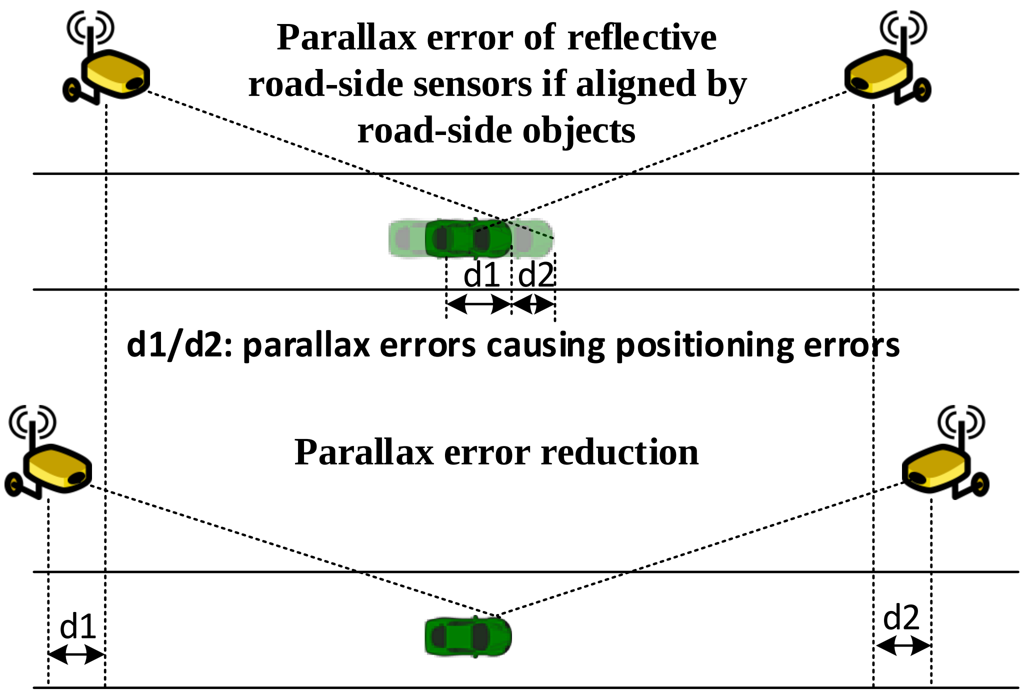


**Figure 3.5 Reduction of parallax error**

The researchers first aligned 4 LiDAR sensors for vehicles. Then, they sent students to walk across intersections while the researcher further calibrated the LiDAR sensors according to the pedestrian trajectories, as shown in Figure 3.6.


**Figure 3.6 LiDAR sensor alignment for vehicle and pedestrian perceptions**

# 4.0 PEDESTRIAN BEHAVIORAL DATA COLLECTION

## 4.1 Collecting Pedestrian Behavioral Data

Three types of pedestrian behavioral data were collected: (1) pedestrian waiting time before starting to cross on the initiation of the WALK phase; (2) effective perception-reaction (E-PR) time. This is the time between when a WALK is on and when a pedestrian enters the intersection. Note the effective perception-reaction time is different from the traditional perception-reaction time because EPR includes not only the perception-reaction time that waiting pedestrians recognize the onset of WALK and begin to move, but also the walking time until the pedestrians enter the intersection. Therefore, EPR is longer than the traditional perception-reaction time and EPR is more appropriate for determining the WALK duration; (3) crossing speed which is important to determine the pedestrian clearance setting in traffic signal timings.

The aforementioned parallax errors inevitably generate bias in measured pedestrian speeds and trajectories. To mitigate such bias, the research teams designed zone-based pedestrian-behavioral-data-collecting algorithms. They use static locations instead of dynamic speeds of objects. As shown in Figure 4.1, a pedestrian is timestamped and considered reaching an intersection when entering one of the waiting zones (1/1'). If there are person(s) dwelling in the waiting zones and the pedestrian calls are placed, then the pedestrian(s) are considered waiting for a cross. The algorithms also retrieve traffic signal status from the controller to understand the pedestrian(s)'s perception and reaction to traffic control operations. Whenever a WALK signal is on, those waiting pedestrians are tracked to check if they are crossing. If a tracked pedestrian enters the boundary zones (zones 2 and 3) during active WALK or early Pedestrian Clearance, then the pedestrian's effective perception-reaction (E-PR) time is recorded as the elapsing time from when the WALK is turned on to when the pedestrian enters the boundary zone. The same pedestrian will be further tracked until they reach the other end of the street (i.e., enter the other boundary zone). To accommodate those slow but legitimate crossing pedestrians, the algorithms offer an additional time window after the end of pedestrian clearance to ensure all the pedestrians reach the other side. In case a pedestrian deviates from the guided pedestrian crossing (e.g., "jaywalking") and therefore does not reach the boundary zone on the other side, this pedestrian's information is incomplete and therefore will be abandoned.

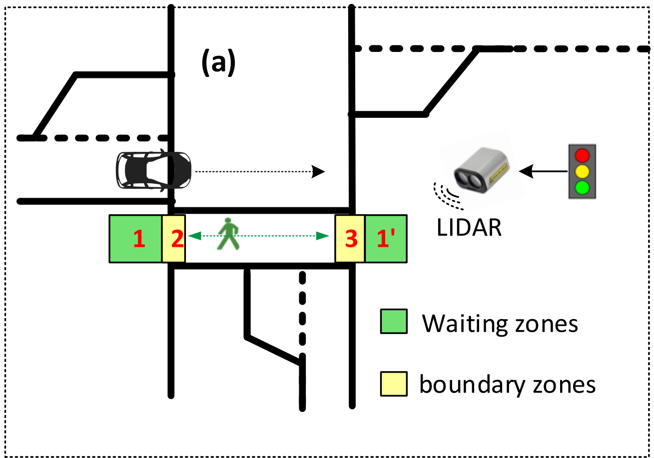


**Figure 4.1 Layout of pedestrian zones at signalized intersections**

Three types of data can be recorded:

(i) Individual pedestrian waiting time before crossing a signalized intersection (between the time when a pedestrian arrives at a waiting zone and when the corresponding WALK is activated later). The individual pedestrian waiting time offers a more accurate pedestrian delay estimation than the current pedestrian delay calculation (time from when a pedestrian call is placed to when the WALK is on). True pedestrian delays are critical to understanding pedestrians' decisions under different levels of delays.

(ii) Effective perception-reaction (E-PR) time: this is different from the traditional perception-reaction time because the E-PR is critical to determine the WALK's duration covering not only the perception-reaction (PR) time to WALK but also the time for a pedestrian walking from where he/she stands at the onset of WALK to the boundary zone. From the field observation, E-PR can be significantly longer than PR if the pedestrian waiting area is large and;

(iii) Crossing speed at which a pedestrian walks from one end to the other during WALK and Pedestrian Clearance. The crossing speed is critical to determine the duration of pedestrian clearance.

### 4.2 A Special Case at the Intersection

The above algorithms are designed for standard actuated pedestrian phasing configuration. As shown in Figure 4.2, they assume that WALK only lasts a short time (e.g., 5 sec) and the pedestrian clearance begins to count down. Only those pedestrians who enter the intersection before the onset of WALK and enter the intersection during WALK and the first few seconds of pedestrian clearance are legitimate and recorded. Although those assumptions are valid in general, the research team found a contradicting case at intersection 7122: the coordinated timing plan is set as max recalls with "WALK REST" on the mainline. Therefore, WALK will be automatically turned on and stay for a long time (e.g., over 30 seconds). The purpose of this configuration is to allow more pedestrians to enter and cross intersections during the mainline greens.

If a pedestrian reaches the intersection during the WALK REST and crosses the intersection immediately, then the time from when the WALK starts to when a new pedestrian enters the intersection is not necessarily the E-PR time. As a result, the research team found some E-PR values longer than 25 seconds between 7 AM to 7 PM during work days. To address this issue, the algorithms were modified to remove those misleading pedestrian records under WALK REST.

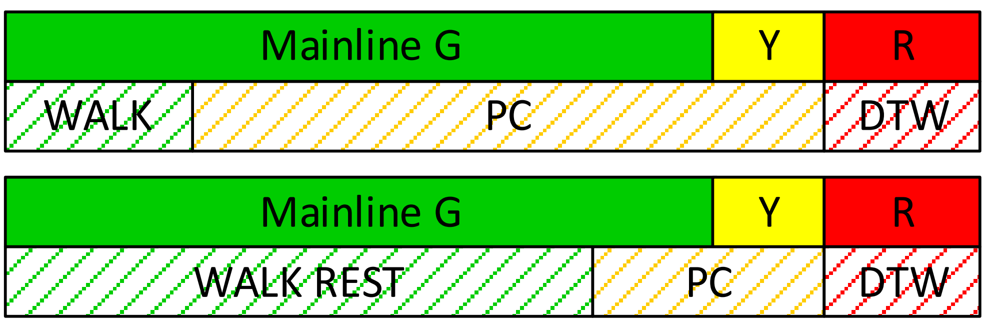


**Figure 4.2 Demonstration of actuated WALK and WALK REST**

### 4.3 Summary

In this chapter, we describe the LiDAR sensors' installation and calibration. We also explain the zone-based pedestrian behavioral data collection to mitigate the ubiquitous parallax errors in any reflective roadside sensors. Three critical pedestrian data items are collected at the signalized intersection based on synchronized LiDAR data and traffic signal control data:

pedestrians’ waiting time before they enter the intersection (pedestrian delays); pedestrians’ effective perception-reaction (E-PR) time (the basis to determine the duration of WALK) and; pedestrians’ crossing speed (the basis to determine the duration of pedestrian clearance).

## 5.0 PEDESTRIAN DATA PROCESSING AND VISUALIZATION

### 5.1 Description of Pedestrian Behavioral Data Collection at Signalized Intersections

A valid pedestrian record is stored in the database in Figure 5.1.

| Int_ID | Phase_No | Arrival_Time (Epoch) | Enter-Time (Epoch) | Leave-time (Epoch) | E-PR time (s) | Crossing time (s) |
|---|---|---|---|---|---|---|
| 7122 | 2 | 1668286993 | 1668287042 | 1668287056 | 1.3 | 14.3 |

**Figure 5.1 Pedestrian records in their raw form**

The fields are explained as follows:

- Int_ID: Intersection identification defined by agencies
- Phase_No: Pedestrian phase number
- Arrival_time(Epoch): When a pedestrian reached a waiting zone. “Epoch time” is a date and time representation widely used in computing. It measures time by the number of seconds that have elapsed since 00:00:00 UTC on 1 January 1970.
- Enter-time (Epoch): When a pedestrian walked into the pedestrian crossing after the WALK sign was activated
- Leave-time (Epoch): When the same pedestrian reached the other side of the pedestrian crossing during WALK and pedestrian clearance
- E-PR time(s): the effective perception-reaction time, the time elapsed from when the WALK was on to when the pedestrian entered the intersection
- Crossing time(s): The time for a pedestrian to walk from one side to the other

Note that E-PR time is different from the standard perception-reaction time defined in traffic engineering. It includes the perception-reaction time (to the onset of WALK) and walking time from the waiting zone to the crossing zone. The second term could be significant if the waiting area is large. The E-PR time is the foundation of the WALK time duration.

To calculate the E-PR time, it is assumed that most pedestrians have reached the waiting zones during red before the WALK is activated. The waiting pedestrians need to enter the intersection during WALK or the first few seconds of pedestrian clearance to be considered valid. The time window for a pedestrian to enter the intersection covers the WALK duration and the early seconds of pedestrian clearance. In other words, if a waiting pedestrian chose not to enter the intersection sometime after WALK is on, this pedestrian will be considered an outlier and ignored.

While the above assumption mostly holds under actuated pedestrian phases, the researchers found an issue at intersection 7122. The mainline phases (phases 2 and 6) are set to "MaxRecall + RestWalk" during weekdays, as shown in Fig. 4-2. As a result, the WALK durations become very long (30-40 seconds) with each cycle. The original algorithm considers all pedestrians entering the intersection during WALKs to be valid. Therefore, those pedestrians who arrived and entered the intersection during the REST WALK were all counted even though those pedestrians did not wait and respond to the onset of WALKs.

The researchers from UTA then adjusted the algorithm and ignore the E-PR time and pedestrian waiting time collection if the algorithm identifies that "REST WALK" is activated by reading the traffic signal controller's real-time status.

Also, note that a pedestrian record is considered valid and recorded only if the pedestrian strictly follows the indications of traffic lights. The rationale is that pedestrian facility design can only consider those observing and normal pedestrians. Pedestrians who chose to "jaywalk" or enter the intersections during yellow and red times are ignored in this context.

Each valid pedestrian record contains three measured timestamps: arriving time, entering (intersection) time, and leaving (intersection) time. Two more times are derived according to the three measured timestamps: effective perception-reaction time and crossing time.

## 5.2 The Pedestrian Data Uploading Process

New valid pedestrian records are not uploaded immediately. Instead, they are first added into a text file on the edge computer in the field. The text file is then uploaded to the central server via secure FTP protocol (SFTP) periodically (e.g., every 15 min). In the LiDAR computing node, the LiDAR main program continues to save new valid pedestrian data into a file. The other program will periodically take away the new data and upload it to the server.

### 5.3 Central System for Pedestrian Data Storage and Visualization

A virtual machine (Windows 10) was set up within UDOT's traffic control network to host the central system for this project, including: (1) an SFTP server to receive the uploaded pedestrian data from the intersection(s) and to dispatch the received files into the corresponding file folders; (2) Background data processor (BDP) to monitor each folder whenever a newly uploaded file was sent into that folder. The BDP will immediately parse and save into the pre-configured database (MySQL).

While it is a common practice for agencies to connect a general data analytics tool (e.g., PowerBI) to the database and visualize the results, the analytics are typically not associated with the context. To address this issue, the researchers from UTA have developed a stand-alone central solution, referred to as the *UTA-in-Motion* (UTAIM) to visualize and analyze pedestrian behaviors in the context of traffic signal control (see Figure 5.2). The overarching goal of UTAIM is to provide novel features for the Automated Traffic Signal Performance Metrics (ATSPM). UTAIM is notched to be either an independent, light ATSPM system or a futureproof add-on module for the existing ATSPM systems, such as UDOT's open-source ATSPM.

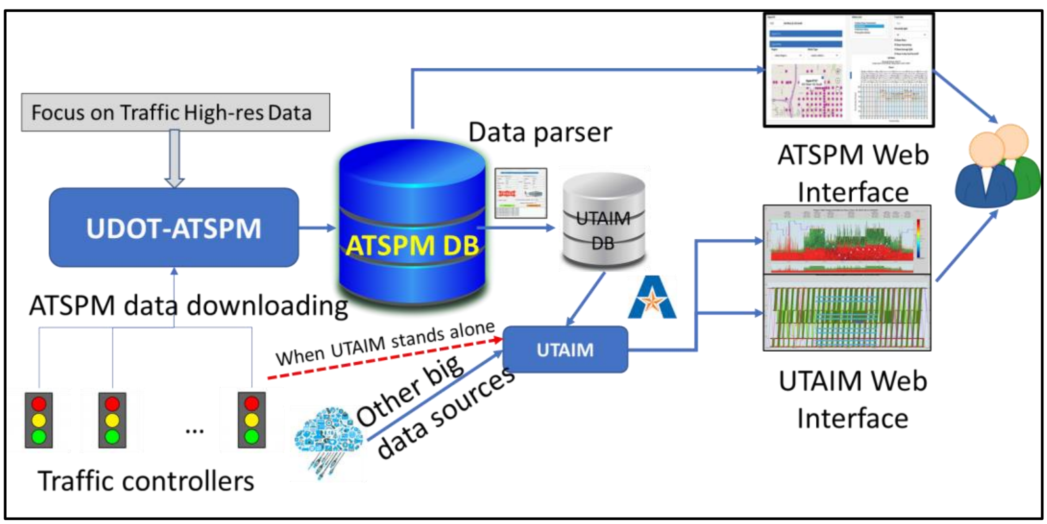


**Figure 5.2 Architecture of Central Solution for Pedestrian Behavioral Data Analytics**

One of the most popular ATSPM performance metrics is the PCD diagram to describe the percentage of vehicles arriving during greens. The UTAIM solution enhances the PCD diagram by introducing multimodal and big data into the existing data visualization. The new diagram is referred to as *Vehicle Arrival Diagram* (VAD). Figure 5.3 reveals the visualized information in basic VADs. It covers the basic information in PCDs as well as many other factors that affect the traffic signal performance including precipitation (source: Openweather); arterial level of service defined by the Highway Capacity Manual (data source: Google Map API or Waze API); traffic signal priority events, preemption events, and pedestrian call events (data source: High-res traffic signal logs). The VAD also summarizes the traffic signal performance according to time-of-day timing plans.

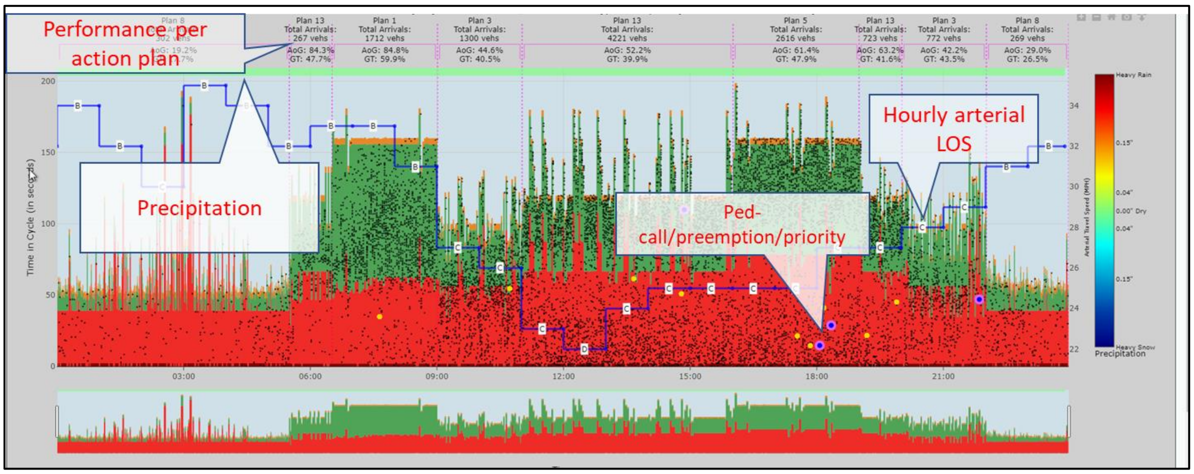


**Figure 5.3 Demonstration of basic vehicle arrival diagram**

In UTAIM, three behaviors of crossing pedestrians at signalized intersections are visualized and summarized on top of the VAD. Whenever an observing crossing pedestrian reached the destination side of the intersection, three timestamps will be recorded: the time when he/she arrives at the intersection (one of the waiting zones shown in Fig. 4-1): the time when he/she entered the boundary zone; and the time when he/she arrives at the other side of the street. As shown in Figure 5.4, a three-color code was adopted to describe the whole crossing behavior on top of VADs. The pedestrian information is summarized per phase by the hour, including the number of captured pedestrians, average waiting time, average E-PR time, and average crossing time. Such data can also be downloaded from the same page in a text file.

- Red bar: duration between arriving time and starting time to cross (i.e., waiting time);
- Yellow bar: the effective perception-reaction (E-PR) time: the time between the onset of WALK and when the pedestrian enters the intersection;

- Green bar: the crossing time between when the pedestrian enters the intersection and when the pedestrian leaves the intersection.

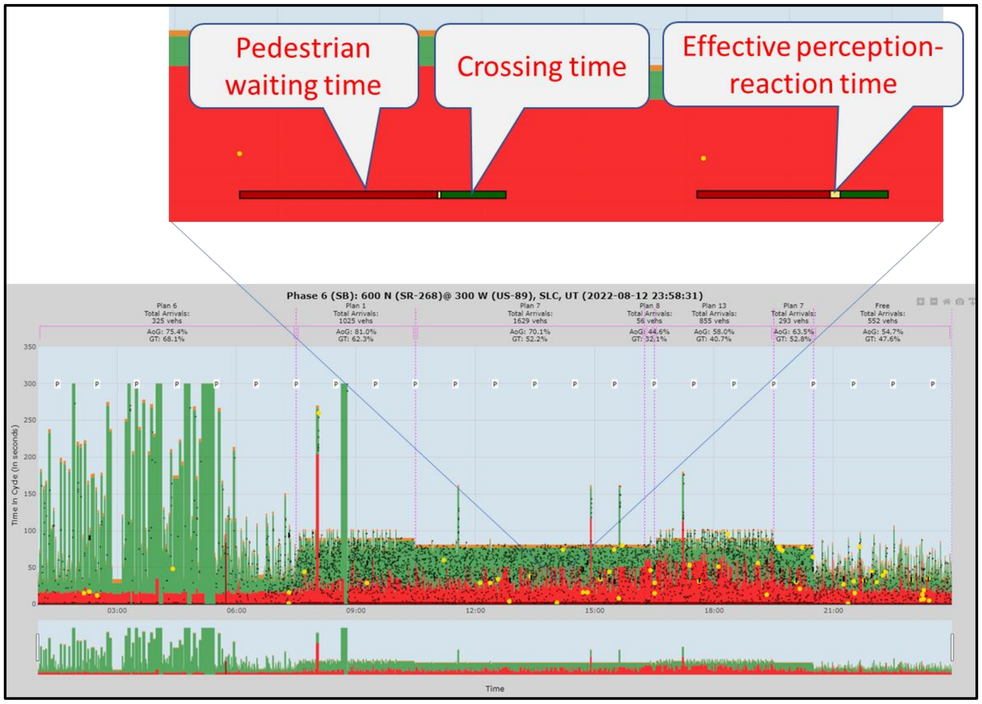


**Figure 5.4 VAD with pedestrian behavioral information**

### 5.4 Validation of Traffic Counts

Among several functions available for the field test, the TAC committee selected and requested the research team to evaluate the accuracy of vehicle counts and stop-bar vehicle detection. These two metrics are most critical in determining the performance of traffic sensing technologies.

The validation was "three-way": (1) a high-resolution PTZ camera was installed at the study intersection; (2) the perception algorithm UI; and (3) the traffic counting algorithm by the research team, based on LiDAR's perception software. Figure 5.5 is a snapshot of the video clip recorded for this experiment.

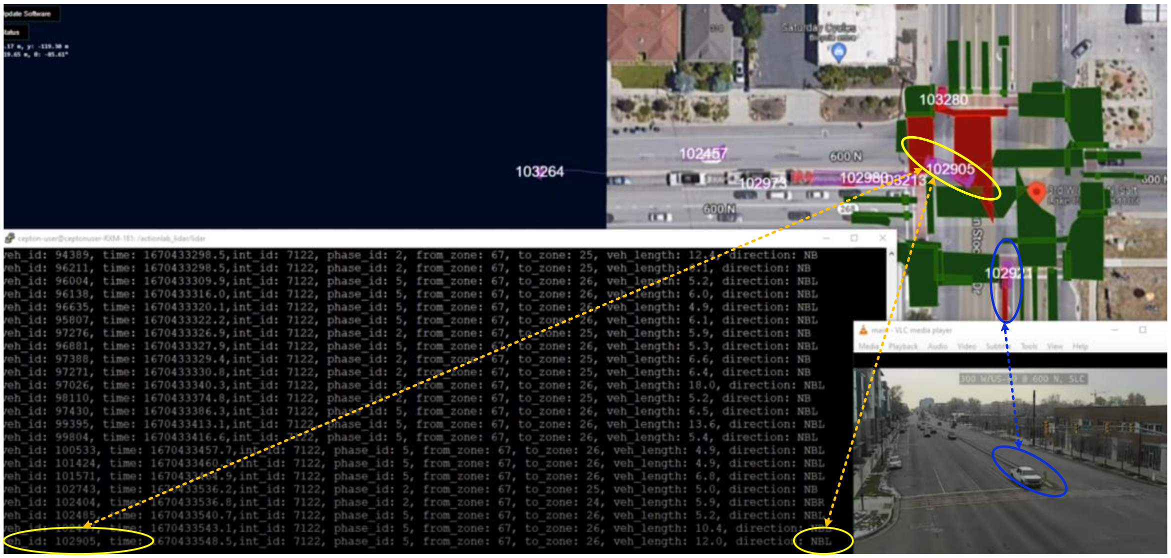


**Figure 5.5 A three-way validation for vehicle turning movement counts**

According to the characteristics of LiDAR-based perception, a tracked vehicle can hold a unique temporary ID until it leaves the intersection. The traffic counting function is based on two zones of a tracked vehicle path: (1) an origin zone (entrance zone) and (2) a destination zone (departure zone). If a tracked vehicle is identified to enter an origin zone and enter the departure zone later, then we can identify this vehicle's turning movement. Please see Figure 5.6, if a vehicle is captured in the origin zone first and captured in destination zone D1, then it must be a left-turn vehicle; if captured in the origin zone and destination zone D2, then it must be a through vehicle; and, if captured in the origin zone and destination zone D3, then it must be a right-turn vehicle.

This "two-zone" counting method can significantly reduce the double-counting issue using single zones before or after stop bars. For instance, one vehicle may occupy two counting detectors (while changing lanes) and then be double-counted by one detector while missed by another detector. In addition, the two-zone method can also be used to count vehicle movements on shared through-left or through-right lanes.

Note that the validation in this experiment is more rigorous than typical counting validations because every single vehicle was identified, tracked, and compared in three interfaces: camera, Web UI (perception), and the counting algorithm (application), rather than aggregated numbers.

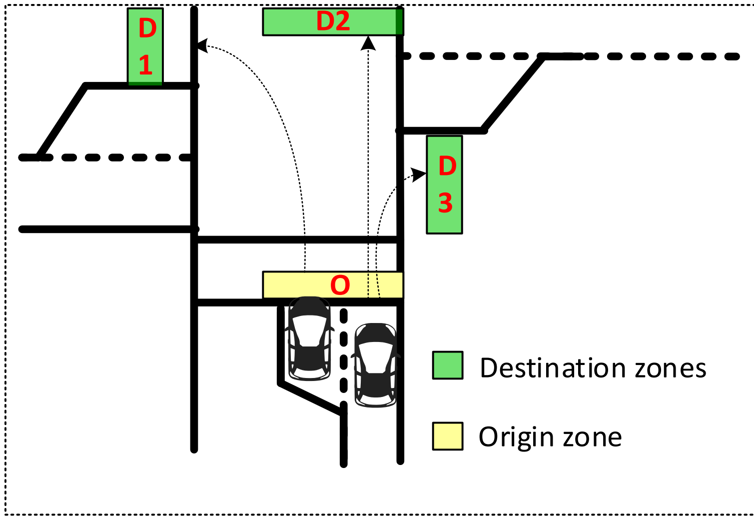


**Figure 5.6 Demonstration of the two-zone vehicle counting method**

### 5.5 Results Analysis

The experiment was conducted for one hour on the afternoon of December 5$^{th}$, 2022, and the northbound movements were validated including NB U-turn, NB left-turn, NB through, and NB right-turn. Tables 5.1 show the results, only one left-turn vehicle was missed. In addition, the lane-by-lane vehicle detection was accurate, too.

**Table 5.1 Traffic counts validation (NB) at INT 7122**

| NB | Left Turn | Right Turn | Thru | U-Turn |
|---|---|---|---|---|
| Camera (Ground truth) | 176 | 7 | 100 | 1 |
| LiDAR WEB-UI (Perception) | 176 | 7 | 100 | 1 |
| UTA LiDAR algorithm | 175 | 7 | 100 | 1 |

# 6.0 CONCLUSIONS

## 6.1 Summary of Research Findings

The objective of this project is to evaluate the potential of cutting-edge LiDAR sensing systems in traffic signal operations. In addition to the general LiDAR sensing solutions, the project team also demonstrated a novel LiDAR solution for traffic data collection. UDOT provided substantial assistance in equipment procurement, installation, and networking. During the project, the research team and TAC committee drew the following conclusions

1. The outdoor resolution for the LiDAR sensors to detect and track vehicles and pedestrians is at 10-15 Hz, meeting the requirements for traffic safety applications.
2. It would be necessary to provide enough training for the field team to understand the mechanism and objective of LiDAR sensing solutions. Once UDOT's field crews got familiar with the sensor, they could install the sensor correctly with ease. It typically required another 30 minutes to align the installed LiDAR sensors remotely (from the office or in the field).
3. There are pros and cons for two types of LiDAR sensors: 360-degree mechanical LiDAR and field-of-view solid-state LiDAR. Mechanical LiDAR cannot solve the issue of occlusion and is more tolerant of the parallax issue whereas multiple coupled solid-state LiDAR sensors can mitigate occlusion, but sensor alignment may face the challenge of parallax.
4. It is recommended to use up to four LiDAR sensors to cover typical intersections. Adding additional sensors should be carefully evaluated regardless of the financial consideration.
5. For any position of interest around stop bars or within intersections, it should be covered by at most two LiDAR sensors to avoid overcomplicating sensor alignment.
6. Grounding is critical for LiDAR perception
7. LiDAR sensor performance may deteriorate in rainstorms and snowstorms. Raindrops and snowflakes may reflect some point clouds and generate noise. During this project, the research team examined the performance a few times during rain and snow. They modified their algorithms according to the research findings.  The LiDAR sensors will still perform unless the rainstorms and snowstorms are exceptionally heavy.

### 6.2 Future Work

This project conducted a proof of concept. Based on the research findings, the project team will continue to work with UDOT and its TAC committee to conduct more transformative and extensive research based on the established testbed at intersection 7122 in Salt Lake City. More graphic user interface programs will be developed to facilitate the UDOT and TAC committee in testing and exercising the developed solutions and to help them make better-informed decisions on these emerging technologies.

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