University of Nevada, Reno

3-D Data Processing to Extract Vehicle Trajectories from Roadside LiDAR Data

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Civil and Environmental Engineering

By

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ABSTRACT

Accurate, high-resolution vehicle data including location, speed, and direction is essential to connected-vehicle applications, micro-level traffic performance evaluation, and adaptive traffic control. The connected-vehicle system provides longer detection distance for drivers (or autonomous vehicles) and pedestrians to "see" around corners or "through" other vehicles so that threats can be perceived earlier. The current connected-vehicle system highly relies on information broadcasted by each vehicle. The maximum safety benefits of current connected-vehicle deployment would need all vehicles to have connected-vehicle devices and broadcast their information in real time. However, the mixed traffic with connected-vehicles and unconnected-vehicles will exist for the next decades or even longer. Therefore, supplemental data to help the connected-vehicle deployment needs to be considered. The traditional traffic sensors only generate macro information like occupancy and estimated average speed. Hence the existed sensors would not be able to aid the research and application of connected vehicles with high accuracy vehicle data. Hence another innovative method which could yield high-resolution traffic data is desired.

This research developed a data processing procedure for detection and tracking of multi-lane multi-vehicle trajectories with a roadside Light Detection and Ranging (LiDAR) sensor. Different from existing perception methods for the autonomous vehicle system, this procedure was explicitly developed to extract trajectories from a roadside LiDAR sensor. This procedure includes six steps. They are preprocessing of the raw data, statistical outlier removal, least median of squares-based ground estimation method to accurately remove the ground points, vehicle data clouds clustering, principal component-based oriented bounding box method to estimate the location of the vehicles and geometrically based tracking algorithm.

The developed procedure has been tested against the intersection of Evans Street and Enterprise Road; a two way stops sign intersection; and Kietzke lane, an arterial road with 40 mph speed limit in Reno, Nevada. Then, the data extraction procedure has been validated by comparing tracking results and speeds logged from a testing vehicle through the onboard diagnostics interface (OBD-I), at a parking lot of University of Nevada, Reno. The validation results suggest that the tracking speed matches real driving speed accurately.

A case study was conducted to examine the accuracy of tracking multiple objects on the roads. 1000 data frames from the intersection of 15th Street and Virginia Street in Reno, Nevada, were used as source data frames. The proposed data processing framework successfully tracked 37 objects out of 38 objects on the road, which gives an accuracy of 97.4%. Then a support vector machine-based algorithm was developed to differentiate pedestrians/bicyclists and cars/buses. With the Radial Basis Function (RBF) kernel, this algorithm correctly classifies 35 objects among 38 objects, which gives an accuracy of 92.1%. The result of this case study indicates that the proposed data processing framework has a satisfactory tracking and clustering accuracy which could be used for

traffic micro information extraction.

This data processing procedure not only could be applied to extract high-resolution trajectories for connected-vehicle applications, but it could also be valuable to practices in traffic safety, traffic mobility, and fuel efficiency estimation. The ordinary Rectangular Rapid Flash Beacon (RRFB) could be upgraded to detect pedestrians automatically; this is especially important during night time. Adaptive traffic signal control which could adapt to special events or economic changes also becomes feasible from this research. Driving cycle development, which mainly relies on sampling vehicles, could become much more accurate because this research enables the possibilities to extract every vehicle's speed profile. In sum, this research provides a reliable way to extract high-resolution traffic data of all vehicles in the detection range of a roadside LiDAR, and it would benefit research in connected vehicles, traffic safety, traffic mobility and fuel consumption estimation.

Keywords: Roadside LiDAR, Vehicle Speed Tracking, Random Sample Consensus Method, Oriented Bounding Box, Support Vector Machine, Connected Vehicles, Traffic Safety, Traffic Mobility, Fuel Consumption Estimation.

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List of Abbreviation

ACC	Adaptive Cruise Control
CNN	Convolutional Neural Network
CVIC	Cooperative Vehicle Intersection Control
DEM	Digital Elevation Model
DSRC	Dedicated Short Range Communication
GPS	Global Positioning System
INS	Inertial Navigation System
KF	Kalman Filter
LiDAR	Light Detection and Ranging
LMEDS	Least Median of Squares
NDS	Naturalistic Driving Study
OBB	Oriented Bounding Box
OBD-I	On Board Diagnostics Interface
RBF	Radial Basis Function
ROI	Region of Interest
RRFB	Rectangular Rapid Flash Beacon
SVM	Support Vector Machine
USDOT	United States Departments of Transportation
VII	Vehicle Infrastructure Integration

1. Introduction

1.1 Statement of the Problem

Accurate, high-resolution vehicle data including location, speed, and direction is essential to connected-vehicle applications, micro-level traffic performance evaluation, and adaptive traffic control. Connected-vehicle technologies, applications and potential benefits have been studied since 2003 when United States Department of Transportation (USDOT) started the Vehicle Infrastructure Integration (VII) program (*1*). The connected-vehicle system provides longer detection distance for drivers (or autonomous vehicles) and pedestrians to “see” around corners or “through” other vehicles so that threats can be perceived earlier. There are a lot of application has been developed. But most of the applications are limited to present levels or prototype levels. These demonstration-oriented applications could not prove the effectiveness for road users. This problem was caused by the scope of proof-of-concept. The current connected-vehicle system is highly relying on information broadcasted by each vehicle. The maximum safety benefits of current connected-vehicle deployment would need all the vehicles to install connected-vehicle devices and to broadcast their information in real time. However, the mixed traffic with connected-vehicles and unconnected-vehicles will exist for the next decades or even longer. Therefore, supplemental data for the connected-vehicle deployment have to be considered.

A classical Light Detection and Ranging (LiDAR) sensor would transmit and receive light pulses with a relatively high frequency. By multiplying the time difference between emitting and receiving the pulse, the LiDAR is able to locate the objects. Recently, most autonomous vehicle LiDAR uses laser beams to detect objects rather than visible or infrared lights. LiDAR can scan a 360-degree horizontal range and able to detect the direction of arrival vehicles accurately, but it has a high cost comparing to other sensors. Thus its usage was limited. The popularity of the autonomous vehicles brought opportunities to the LiDAR sensors. The LiDAR sensor was widely adopted for object perception and recognition in the autonomous vehicle field. As an indispensable component for autonomous vehicles, the price of LiDAR sensor has decreased significantly in recent years. The LiDAR sensor used in this dissertation was Velodyne's VLP-16; it was $7,999 in 2017, with 100 meters of detection range radius, 360 degrees of horizontal sensing range, and weight 830grams. The 2017th LeddarTech Vu-8, which has 215 meters of detection range, 100 degrees of horizontal sensing range, and weight 107 grams was at the price of $750 by the time of this dissertation was completed. This trend enables traffic engineers to utilize cost-efficient LiDARs on roadsides to obtain high-resolution dataset including location, speed, and direction information which could be used for connected-vehicle applications, micro-level traffic performance evaluation, and adaptive traffic control.

The limitation of traditional sensors has restricted the use of high-resolution micro traffic data. Connected vehicles research, safety research and adaptive traffic signal control research are all limited by the resolution of data input. This research aims to provide a solution to this problem by developing a 3-D data processing procedure to extract high-resolution vehicle or pedestrian data from a VLP-16 LiDAR sensor.

1.2 Traditional Traffic Data Collector Sensors

Traffic sensor usually has three necessary modules: a transducer, a signal module and a data processing module (*2*). Some information is derived from the Traffic Detector Handbook (*3*).

Table 1 depicts widely used sensors in traffic engineering. Table 1 compares them to whether it is difficult to install and maintain, whether the detection accuracy is high and whether the performance would be affected by bad weather or inadequate illumination.

Table 1 Advantages and Disadvantages of Mainstream Traffic Sensors

Sensor	Strengths	Weaknesses
Loop Detector	• Well understand and widely used. • Provides macro traffic data such as average speed, headways, and volumes • Not easy to be affected by extreme weather conditions.	• Installation and maintenance require the stop of traffic. • Could not provide accurate speed tracking data.
Microwave Radar	• Not easy to be affected by extreme weather conditions. • Detection accuracy is great. • Installation and maintenance are easy.	• Traffic used Radar usually do not cover 360 degrees range. • Not every type of Radar could detect stopped vehicles or pedestrians.
Video Image Sensor	• The price is low comparing the rich data it collected. • Could collect data in multiple lanes and directions. • The data collected by several cameras for the same location could be reconstructed to provide a 3D view of that location.	• Installation and maintenance require regular cleaning; this is especially important in the windy area. • The performance would be seriously affected by bad weathers such as rain, snow or fog. The older types of cameras also require strong contrast to reach its maxim accuracy.

		• Some cameras are susceptible to shakes and vibrations caused by bad weather. • Confident nighttime detection requires excellent light enlightening.
LiDAR	• Able to accurately track the vehicle position, speed. Could also tell which type of vehicle has been detected. • Provide high-resolution data, extremely accurate. • Could cover a large area quickly with 360 degrees view. • Easy to install and maintain.	• The operation may be affected by colossal rain or snow. • The unit price is relatively high. Solid-state LiDAR, a new type of LiDAR system, claims to be cheaper but has no mature products on the market by the time this dissertation was written.

Additionally, Bluetooth sensors are also researched. The Bluetooth sensor uses MAC address to identify the road users. This is controversial because some users consider their privacy has been invaded. Besides, if the road users turn off their Bluetooth devices, the sensor just could not have any MAC addresses. In sum, the Bluetooth sensors have inherent weaknesses thus they are not considered the ideal candidate for this research.

1.3 LiDAR Products Information

LiDAR is short for light detection and ranging, and it is an innovative sensing technology for contactless sensing (*4*). The LiDAR system uses the time difference between emitting the light to the return of the light to calculate the location of the object. The pulse usually has a very high frequency. Hence the detection looks like “real-time” (*5*). There are three types of LiDAR in the market.

1.3.1 Airborne LiDAR

The airborne LiDAR means the LiDAR detection system would be installed in an aircraft. The high-frequency laser would be aimed to the ground to collect land surface information. Topographic airborne LiDAR would create surface models which are important for geography or archeology. Bathymetric airborne LiDAR would penetrate waters and collect the information along the river. It is claimed that it is as good as typical survey method as sonar and GPS, but cheaper and faster (*6*).

1.3.2 Terrestrial LiDAR

Terrestrial LiDAR constitutes two types: mobile LiDAR and static LiDAR. Mobile LiDAR is widely used in autonomous vehicles, used to perceive the objects, such as trees, buildings, traffic signs, pedestrians, and cyclists. Static LiDAR is usually mounted on a tripod and was majorly used to track the moving objects such as traffic. Both LiDARs in this category are generally cheaper and smaller than Airborne LiDARs.

Terrestrial LiDAR usually collect more dense information because the mounting position does not travel at high speed, this would help to create realistic 3D image or models for the surrounding objects. Hence recently this type of LiDAR is more popular than Airborne LiDAR systems.

1.3.3 Solid State LiDAR

Solid-state LiDAR is capable of aiming without scanning 360 degrees (*7*). Moreover, it cost less than currently scan-based LiDARs. Hence solid-state LiDAR is recognized as the next generation LiDAR products.

Solid State sensors would use micro-electromechanical systems with a static laser beam with a spinning mirror rather than the traditional sensor with scanning the laser beam. This improvement would greatly improve the robustness and reliability comparing to the current mainstream LiDAR system, while at the same time maintain the same detection range and accuracy. Moreover, such a system would be easier to mass produce hence have a much lower price. All those advantages lead the Automobile Tycoons, such as BMW, moving to focus on solid-state LiDAR (*8*).

The Quanenergy S3 is the only solid-state LiDAR on the market by the time this dissertation is written. The S3 solid state is small and ideal for integration on platforms required lightweight LiDAR. The S3 has no scanning parts, and the Quanenergy claims that it outperformed traditional LiDAR. The S3 LiDAR could generate more than 500,000 points per seconds. However, the S3 could only cover a 120-horizontal field of view.

1.3.4 LiDAR Applications

Forest Planning and Management

Figure 1 is from Terrestrial Laser Scanning International Interest Group meeting at Salford, UK. This figure suggests the application of forest management. LiDAR is widely used in planning and management of the forest industry *(9; 10)*. The idea is to use the LiDAR light to penetrate the dense canopy and measure the height of the canopy. Another example is LiDAR could measure some tree's root expansion.

Figure 1 Terrestrial LiDAR Image

Mapping and Archaeology

Figure 2 is from an article "Lasers in the Jungle" at Archaeology Magazine. This figure suggests the application of pyramid surface mapping (*11; 12*). By using LiDAR detection system, Digital Elevation Model (DEM) could be created. That DEM map could show a 3D view of the land surface. This is especially convenient if the airborne LiDAR system was deployed above some ancient buildings. The 3D views make it easier for researchers to visualize unclear roads, broken bridges or unnoticeable rivers if observed from the ground. Figure 3 is from Historical England Magazine. It is clear that LiDAR is a critical tool for some archeologist research the surface of the ground (*13; 14*).

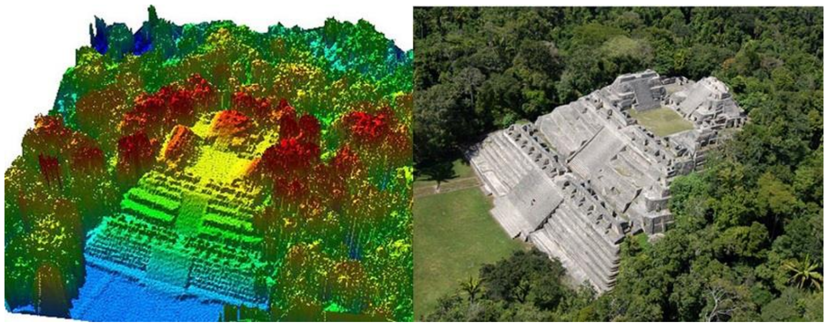

Figure 2 Mapping LiDAR Image

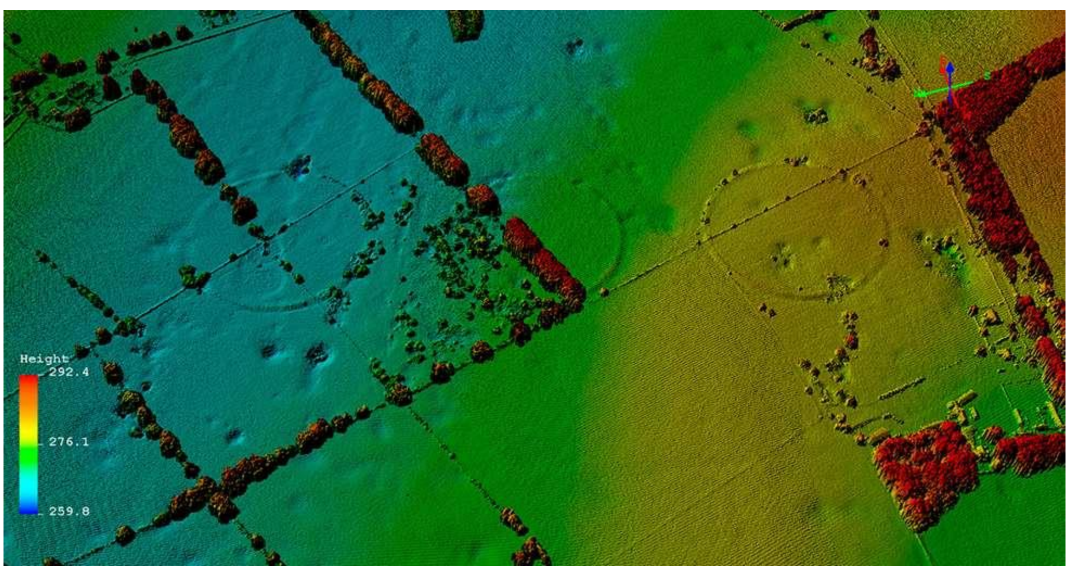

Figure 3 Archeology LiDAR Image

Highway Survey

Figure 3 is from an article "Consider the Benefits of Mobile LiDAR for Transportation Projects" at Informed Infrastructure Magazine. LiDAR data of highways helps engineers to measure the road network (*15*), such as LiDAR width, elevation, and length of road facilities.

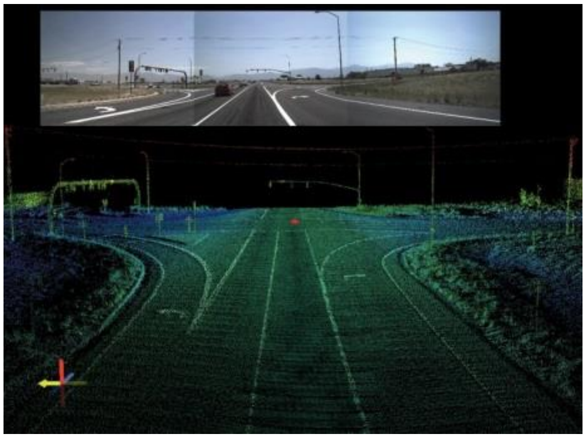

Figure 4 Transport Planning LiDAR Image

Solar Energy Planning

Figure 5 is from an article "Solar Energy" at Terraremote Website. Solar energy is getting popular for heating economically and environmentally friendly (*16; 17*). The solar panel is designed to consume and transfer the heat energy from the solar system. There are some unique findings that can only be identified with LiDAR data. For example, LiDAR helps to find out a solar panel, if not toward the south, which will have a significant impact on the solar conversion potential.

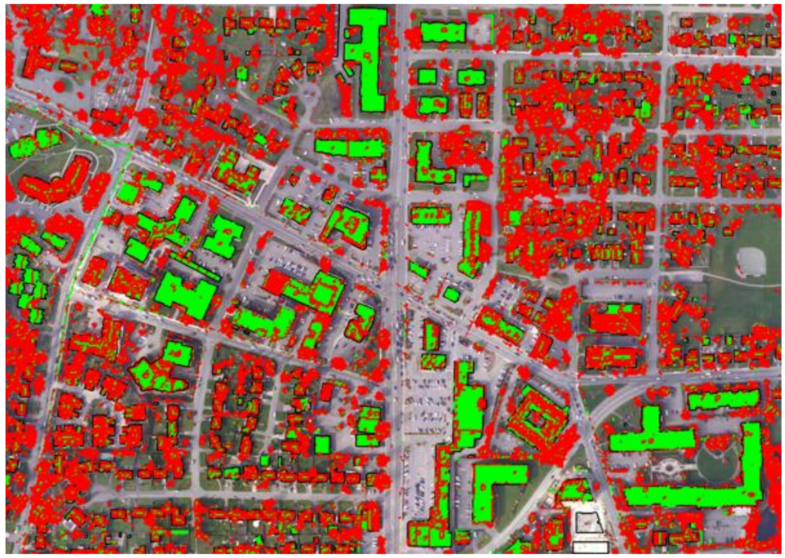

Figure 5 Solar Energy Planning LiDAR Image

Meteorology

Figure 6 is from an article “Terrain-induced Windshear & Turbulence over the Hong Kong International Airport” at Hong Kong Observatory website.

LiDAR has been used for the research and the study of the space and universe since the very beginning (*18; 19*). The LiDAR system could be deployed in the satellite, then the pulses are emitted from the satellite then hit the unvisitable particles in the space. That created image could help us to understand the climate change and the formulation of airflow.

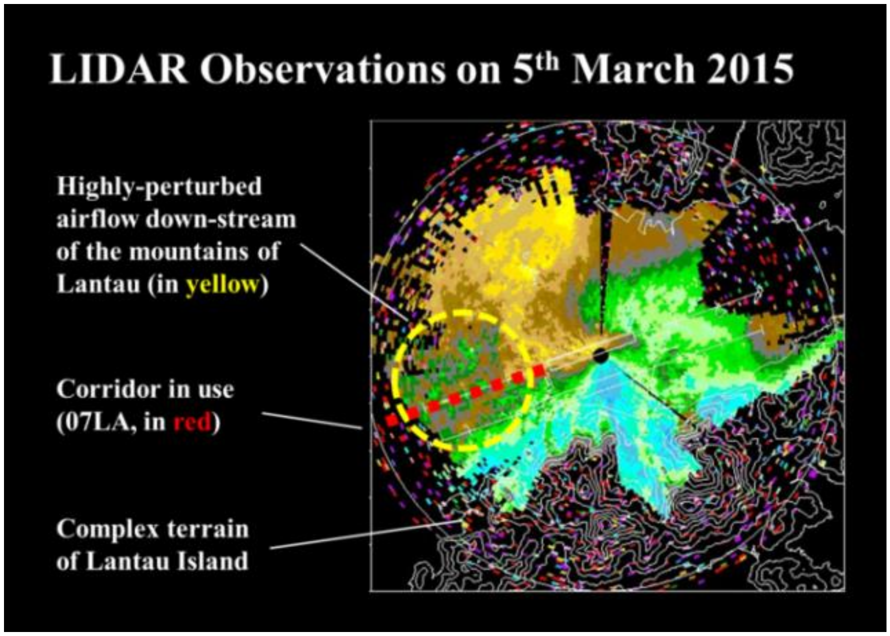

Figure 6 Meteorology LiDAR Image

Imaging

Figure 7 is from an article “UNAVCO Presents LiDAR Demonstration on Capitol Hill” on April 28th, 2010. This image gives the LiDAR scan results of three congressmen (*20*). LiDAR imaging technologies could help to create a 3D image of people or other objects. That would be useful for the 3D printing industry. Imagine you have some parts could not be easily manufactured in the traditional material forming way. A LiDAR system could be deployed and scanned the interested object, then 3D printing technology could be used to recreate the shape of this object. This would be important for some industries need to prototyping products within short time limits. LiDAR technology could also be used to track people in an indoor environment and improve the surveillance system detections.

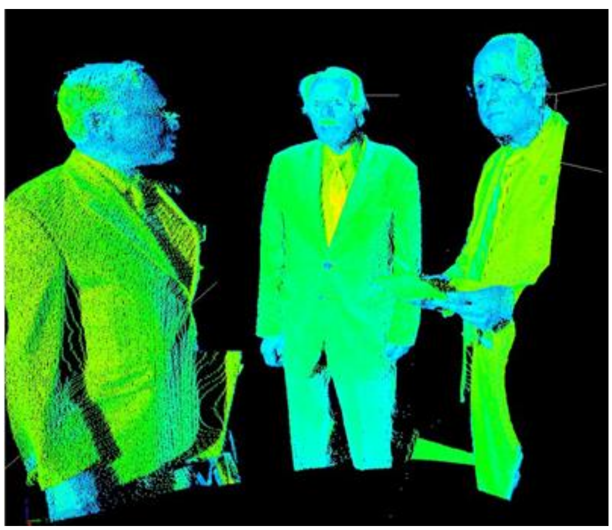

Figure 7 LiDAR Scan Showing 3D Image of Members of Congress

Vehicle Automation

Figure 8 is from an article “A “low-cost” LIDAR for the autonomous car of tomorrow” at Nov 12th, 2016. LiDAR is also widely used in autonomous vehicles (*21; 22*). LiDAR is used to perceive objects around autonomous vehicles. Vehicles, bicyclists, and pedestrians are all point could in LiDAR data to be perceived and identified. More information about LiDAR application for vehicle automation is elaborated in the following chapter.

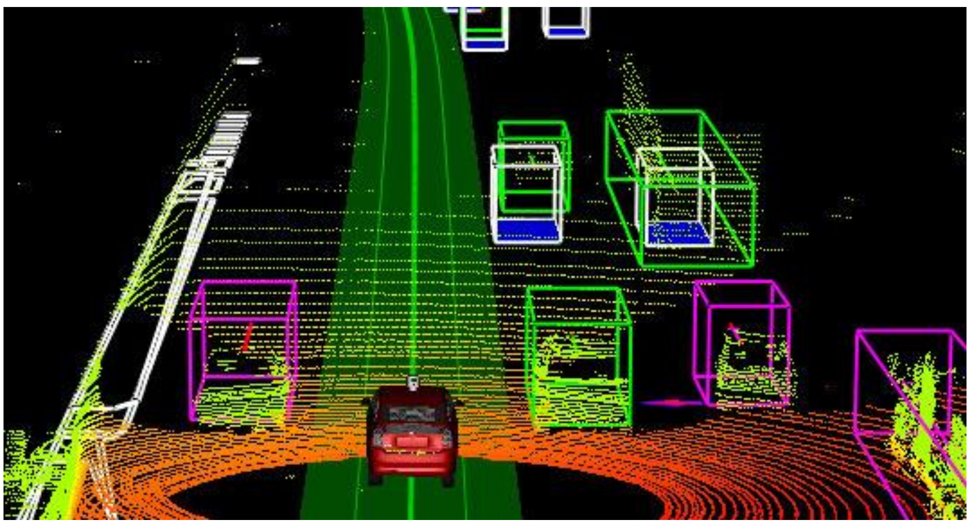

Figure 8 Vehicles Automation LiDAR Image

1.4 LiDAR Vendor Information

The LiDAR used in this research was purchased from Velodyne LiDAR Company. Velodyne LiDAR company was considered as one of the leading vendors in LiDAR market by researchers. Products in Velodyne LiDAR Company are displayed in the following table (*23*).

The VLP-16 sensor was the smallest, and cheapest products in this company by the time this dissertation was written. The research group considered the VLP-16 is the more cost-effective product than similarly sensors, this was especially important when a group of roadside LiDAR would be deployed along the road. Moreover, the VLP-16 retained the critical functions of Velodyne's LiDAR: real-time, round detection capability, long detection distance and relatively large points cloud. Hence this product was chosen for this research.

Mainstream LiDAR products in the current market are summarized in Table 3.

Table 2 Mainstream LiDARs and its Specifications

Key vendors	***Products***	***Channels***	***Range***	***Degrees***	***point per second***	***Price***
Velodyne LiDAR	HDL 64E	64	120	360	2.2 million	$75,000
	HDL 32E	32	80-100	360	0.7 million	$29,900
	VLP-16	16	100	360	0.3 million	$8000
	PUCK-Lite	16	100	360	0.3 million	$8000 - $10000
	Puck-High-Res	16	100	360	0.3 million	Unavailable

Quanenergy Systems	M8			360	0.42 million	Unavailable
	S3			120	0.5 million	Unavailable
	S3-Qi		100			Unavailable
	Q-guard		100			Unavailable
LeddarTech	Leddar Sensor Evaluation Kit	16	50	45		$299
	LeddarVu - STARTER KIT	8	215	100		$575
	LeddarVu - Multi-Element Sensor Module	8	215	100		$475
	LeddarOne - Single-STARTER KIT		40	3		$170
	LeddarOne - Single-Element Sensor Module		40	3		$115
	Leddar M16 - Multi-Element Sensor Module	16	100	95		$590
	Leddar IS16 - Multi-Element Industrial Sensor	16	50	45		$745
Riegl	VZ-2000 Long-Range High-Speed 3D Laser Scanners		2000	360	0.4 million	Unavailable

	VMX-1HA High-Performance Dual Scanner Mobile Mapping System		420	360	500 scan lines/sec	Unavailable

Other vendors such as Continental, Bosch, Delphi, Hella, Ibeo Automotive, Novariant, Phantom Intelligence, PulsedLight, Teledyne Optech, Trilumina, Valeo, and Innoviz have limited information. Those website links are summarized in Table 4.

Table 3 Other Vendors Information

Other vendors	**Website Information**
- Continental	http://continental-automated-driving.com/Navigation/Enablers/High-Resolution-Flash-LiDAR
- Bosch	http://safecarnews.com/bosch-invests-in-tetravue-for-3d-LiDAR-technology/
- Delphi	http://delphi.com/media-old/featurestories/lists/featured-stories/split-second-decisions-br-how-delphi-is-using-multiple-sensing-technologies-to-make-driving-even-safer
- Denso	http://www.eenewsanalog.com/news/denso-invests-laser-LiDAR-startup
- First Sensor AG	https://www.first-sensor.com/en/applications/industrial/length-measurement/laser-scanners-and-LiDAR-systems/
- Hella	http://wardsauto.com/news-analysis/LiDAR-drives-hella-s-acc-bid
- Ibeo Automotive Systems	https://www.ibeo-as.com/aboutibeo/LiDAR/
- Novariant	http://www.novariant.com/content/index.php/solutions-vision-sensors
- Phantom Intelligence	http://phantomintelligence.com/

- PulsedLight	https://www.sparkfun.com/products/14032?gclid=CjwKEAjw2qzHBRChloWxgoXDpyASJAB01Io04oL_kKdp3i5V8nlwzNVYkepLyznC8-jn7SLu5O_kDBoCGPDw_wcB
- Teledyne Optech	http://www.teledyneoptech.com/index.php/products/airborne-survey/LiDAR-systems/
- Trilumina	http://www.trilumina.com/product-sheets.aspx
- Valeo	http://clepa.eu/mediaroom/valeo-offer-new-low-cost-solid-state-LiDAR/
Innoviz	https://www.innoviz.tech/innovizone

1.5 Objective and Scope of the Research

The LiDAR sensor is widely adopted for object perception and recognition in the autonomous vehicle field. Scholars from Victoria Transport Policy Institute (*24*) have the confidence that well-tested autonomous vehicles would be for sale to the public and legally drive anywhere around the 2020s. They also suggest that the AVs would constitute half of the market at the 2040s. This statement suggests a tremendous increasing demand for autonomous vehicles in the upcoming decades. As an indispensable component for autonomous vehicles, the price of LiDAR sensor will inevitably be dragged down as the result of the massive production of autonomous vehicles. This trend enables the traffic engineers to utilize cheaper LiDARs to obtain high-resolution dataset including location, speed, and direction information which could be used for connected-vehicle applications, micro-level traffic performance evaluation, and adaptive traffic control.

However, the LiDAR application for transportation operation is different from a LiDAR application on its closest ally: autonomous vehicles. First, roadside sensing systems require LiDAR at fixed locations instead of a moving vehicle. The LiDAR will be installed at the roadside, or on the poles' top. Secondly, the system should be able to continually detect and track vehicles even without an ideal shape of the vehicle. This would demand the data processing algorithm to be scalable and robust to track the vehicle with a fewer channeled LiDAR sensor. Thirdly, the LiDAR sensor should be able to track the speed without the help of optical sensors. More sensors mean more maintenance labor and higher budgets, which would bring burden to the finance of city or state. In short, how LiDAR could help traffic engineers to gather critical micro information such as speed, volumes of traffic on the road, or conduct connected-vehicle applications, micro-level traffic performance evaluation, adaptive traffic control is remained to be questioned. Therefore, this dissertation aims to give a clear answer to this question.

2. Literature Review

2.1 Currently Connected Vehicle Research

The U.S. Department of Transportation's (USDOT's) Connected Vehicle (CV) Program collaborates with a lot of traffic agencies and entities and trying to develop technologies to link the traffic items on the road network, such as bus, truck, autonomous vehicles, pedestrians, and roadside devices *(25)*. In short, the USDOT aims to test and to develop the technologies to enable the seamless communication among the traffic objects and create a smart traffic system.

2.1.1 Communication

DSRC (Dedicated Short Range Communications) is a two-way short-to-medium-range wireless communications capability that permits very high data transmission critical in communications-based active safety applications (*26*).

The DSRC communication protocols constitute seven layers (from top to bottom): Safety Application Sublayer; Message Sublayer; Network and Transport Layer; LLC Sublayer; MAC Sublayer Extension; MAC Sublayer; Physical Layer (*27*). The Federal Communications Commission (FCC) allocates 75 MHz of spectrum in the 5.9 GHz band just for DSRC communication. The vehicle communications are expected to use these frequencies. The cross-modal program from ITS office at USDOT is aiming to test and use DSRC as major technology, other communication protocols as supplemental technology to enable the seamless communication among the traffic objects and create a smart traffic system (*28*).

Other communication technologies, such as 3G/4G, Bluetooth or Wi-Fi was not considered as effective and robust as DSRC communication. Comparing to these technologies, DSRC would have some un-comparing advantages. First of all, DSRC has its own bandwidth. This means the safe communication between vehicles or infrastructures was maximized. Other communication protocols won't have its own bandwidth; hence it is more susceptible to signal interference. DSRC also provide encrypted communication message protocols, which could further improve its safety. Secondly, safety information is given higher privilege comparing to other information. This is especially important because other communication protocols treat all messages equally. Traffic safety, without any doubt, should always be considered as a priority in the future intelligent transportation system. Lastly, DSRC is highly reliable even with high-speed moving objects or bad weather conditions. Other communication protocols, especially cellular networks, would periodically lose information packages with the harsh environment.

In short, DSRC could allow for the most trustworthy, robust and high-speed commination for V2V and V2I applications (*28*). DSRC could be the foundation for future safety and mobility communication systems in ITS.

2.1.2 Applications

Over the last five years, application prototyping and assessment have been a focus of federal connected vehicle research and development activity (*29*). Many application concepts have been developed and implemented. But most of these applications are limited to the presentation. This section would introduce some of the applications most related to this dissertation. By reading this section, the readers would better understand the significant contribution of this dissertation.

V2I Safety

- Stop Sign Gap Assist (SSGA)

  The roadside perception system would first perceive the objects and make the predictions of the position of those objects. Then that likely collision information is broadcasted for both parties at stop signs.

- Curve Speed Warning (CSW)

  The roadside perception system would first perceive the objects speed and make the predictions whether this object would pass the curve safely. Then those likely run out of the way warning information is broadcasted for speeding vehicles.

- Pedestrian in Signalized Crosswalk Warning (Transit)

  The roadside perception system would first perceive the pedestrian/bus speed and make the predictions whether the bus will collide with the pedestrian. Then those likely collision warning information is broadcasted for speeding vehicles.

V2V Safety

- Forward Collision Warning (FCW)

  The roadside perception system would perceive the leading/following speed and make the predictions whether the following vehicle has enough stop time. Those crash warning information would help the following vehicle driver gain more response time and take necessary actions to avoid a head-on crash.

- Intersection Movement Assist (IMA)

The roadside perception system would perceive all the objects on the road. If some huge commercial truck is blocking some driver's view of opposing or crossing traffic (vehicle or pedestrian), this system will broadcast those warning information to the drivers.

- Blind Spot/Lane Change Warning (BSW/LCW)

  The roadside perception system would perceive all the objects on the road. If some drivers would like to make the lane change but failed to notice the vehicle in his blind spot, the warning information would be broadcasted by roadside perception system. This would help the drivers to prevent crashes with dangerous lane changes.

Environment

- Connected Eco-Driving

  The roadside perception system would perceive all the objects on the road. The roadside system would further predict the optimum speed profile for each vehicle. Those recommended speed profile could be used as input for connected vehicles. By adopting those recommended driving speed profile, vehicles would save the fuels and drive more eco-friendly.

- Eco-Cooperative Adaptive Cruise Control

  The roadside perception system would perceive all the objects on the road. That collected information includes speed, acceleration, and location. These data could be analyzed and then feed into connected vehicles. If these data have been put into a vehicle's adaptive cruise control system, then the vehicle could seek the best adaptive cruise control strategy to reduce the fuel consumption and emissions.

Mobility

- Dynamic Speed Harmonization (SPD-HARM)

  The roadside perception system would perceive all the objects on the road. That collected information includes speed, acceleration, and location. These data are used to find the recommended target speed for all vehicles on the road. If there is a traffic jam, this system is expected to maximize throughput and reduce crashes.

- Queue Warning (Q-WARN)

  The roadside perception system would perceive all the objects on the road. It aims to give drivers the information about how many vehicles in the queues.

- Incident Scene Work Zone Alerts for Drivers and Workers (INC-ZONE)

  The roadside perception system would perceive all the objects on the road. It would predict the trajectories of incoming vehicles and gives the rank of risk based on the speed and trajectory. It would save on-scene worker's lives. Moreover, that information would be broadcasted to incoming vehicle drivers, to notify them the location of workers and aid the driver to make decisions such as stop, slow down or lane changes.

2.1.3 Others

Jackeline et al. (*30*) proposed an innovative idea about how to coordinate connected vehicles when they are merging into the highway. This was particularly interesting because the merging area was considered one of the most dangerous segments of the highway. This research formulated the problem to be a optimize problem, which had the objective as finding a secure and fuel-efficient strategy, such as what was the best speed profile for approaching the vehicle to choose and what is the optimal arrival time. He validated the effectiveness of algorithms based on simulation and claimed that this solution would tremendously decrease fuel consumption amount and travel time in merging areas, more importantly, those algorithms could help avoid any possible collisions.

Some researchers were studying how to defend connected vehicles against malware. Zhang et al. (*31*) claimed that the connected vehicles were becoming sensible for malware; because hackers and car hobbyist were all had more tools to compromise the security of the control units in connected vehicles. In this paper, he mentioned that Polymorphic malware, an artificial intelligence based malware that contained a malicious evolutionary code which could modify itself in every generation, was especially dangerous. The future connected vehicle users might download this type of malware into the system, and then put themselves lives in danger. He also claimed that the current malware detection methods all had limitations. In this research, a cloud-assisted vehicle malware defense framework was proposed to solve this problem. Cloud services were used to help connected vehicle users to identify malware, and to protect their safety and investment.

2.2 LiDAR Data-Processing Algorithms for Autonomous Vehicle Research

2.2.1 Introduction

Autonomous driving research launched at Carnegie Mellon University. They started their Navlab vehicles development project (*32*) in the 1980s. When EUREKA project was finished in 1994, the autonomous driving speed could reach up to130 km/h, with the ability to monitor both lane markings and surrounding vehicles (*33*). Today, CMU still leads many projects related to autonomous vehicles (*34*). Autonomous Driving Motion Planning project targets to create cost-effective, high-performance moving planning strategies for highways and local streets. Autonomous Vehicle Health Monitoring projects will absorb knowledge about the current state of their perception, activation, and computing capabilities into their jobs and route planning. Autonomous Vehicle Safety Verification Project explores all potential driving choice of an autonomous vehicle. This project is rooted in the fact that autonomous vehicle might not violate specified safety properties such as lane departures or vehicle collision. However, it might have deviate from the original designed path to avoid unplanned obstacles. This project detects any possible acceptable violation.

The autonomous vehicles usually equipped with sensors which could perceive the surroundings, a high-performance embedded computer, and some actuators to control the vehicle. Figure 9 shows the LiDARs adopted by some participated vehicles at the DARPA Urban Challenge. The LiDARs are usually installed at the top of the vehicles.

Figure 9 Testing Vehicles in DARPA Urban Challenge 2007, with Sensors on Top

Accurately and efficiently perceive the static or mobile objects around the AVs, was considered as most challenging task among all the necessary functions in AVs (*35*). Most of the current research combines the strength of LiDAR sensors and other sensors, such as cameras. The following chapters will illustrate and explain each step for LiDAR data processing in autonomous vehicles field.

2.2.2 Data Representation

Point cloud, feature-based cloud, and voxel-cloud are three most popular kinds of LiDAR data structures for autonomous vehicle environment representation (*36*). Point cloud generates an accurate representation, and easy to implement; nevertheless, it needs considerable computer resources such as large memory and computing resources, such as workstations. So, it is ideal for research purpose. Feature-based methods use local features, such as lines (*37*), surfaces (*38*) or superquadrics (*39*) to represent the sensor information. However, in practice, this method has many steps to implement thus are difficult for researchers new to this area. Voxel-cloud methods (Figure 10 suggested) voxelize the space into smaller grid particles, and each particle contains the summary information in that cell. Voxel-cloud method consumes less memory, could be easily implemented by researchers, hence considered as the most popular method for sensor data representation in autonomous vehicle research field.

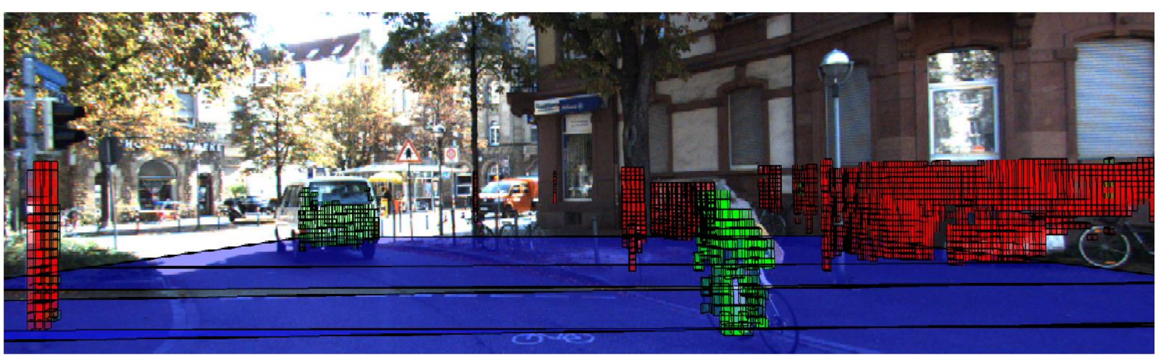

Figure 10 Grid-Based Data Representation Example

2.2.3 Ground Surface Perception

Correctly and accurately identify and segment the ground scanning plane is an essential step for the proposed data processing procedure. The Random Sample Consensus(RANSAC) (*40*) estimated the parameters from the assumed mathematical model. By iteration enough times, this method would consider the best-matched model as the candidate model for the dataset. This method was widely used in ground surface perception. The RANSAC iteration method contained four steps. First, a portion of the raw data was randomly chosen; this portion of data was called as hypothetical inliers. This predefined model was constructed by using these hypothetical inliers. Then all the rest of data were calculated against this predefined model; those points fitted this model well would be incorporated into this model. This larger estimation model was considered as a good model if there were enough points in this model. Finally, if the model was not good, another subset of the dataset was randomly selected and estimated. RANSAC can estimate the surface function parameters even with significant noises presented in the dataset, but it had no guarantee of delivering optimal solutions within limited iterations. This suggested that by computing a more significant number of iterations, the optimized solution was approximated. Other variants of RANSAC methods were also tested. RANSAC solved the selection problem as an optimization problem with a bounded loss function. The loss function was decided as a summation of geometric distance for every point to the estimated plane. When a point was within allowed distance, this point was considered belonging to the estimated plane hence the loss value for this point is set to zero. MSAC (M-estimator SAC) adopted a different loss value for points within allowed distance, while the MLESAC (Maximum Likelihood SAC) utilized different probability distribution at loss function for points within and outside allowed distance to evaluate the hypothesis. MLESAC modeled inlier points as unbiased Gaussian distribution and outlier points as uniform distribution. Partial evaluation methods, such as Randomized RANSAC (rRANSAC) and Randomized MSAC (rMSAC), first performed a preliminary test, and full estimation was only conducted when the hypothesis passes the test. This will decrease the necessary number of data for estimation, so would increase the speed. Guided sampling method, such as PROSAC (Progressive SAC), used prior knowledge such as a matching score, to generate candidate estimation from top-ranked data points. Guidance would reduce the necessary number of iteration than random sampling. However, it can make RANSAC slower due to additional computation burden. RANSAC needed to tune two variables concerning the given data: a threshold C for evaluating hypothesis (Here is the deviated angle) and an iteration number T for generating enough hypotheses. Least Median of Squares (LMedS) method did not need any tuning variable because it tried to minimize median squared error (9). Thus it was considered as a robust estimation. The robust here mean fast and insensitive to noises of the dataset.

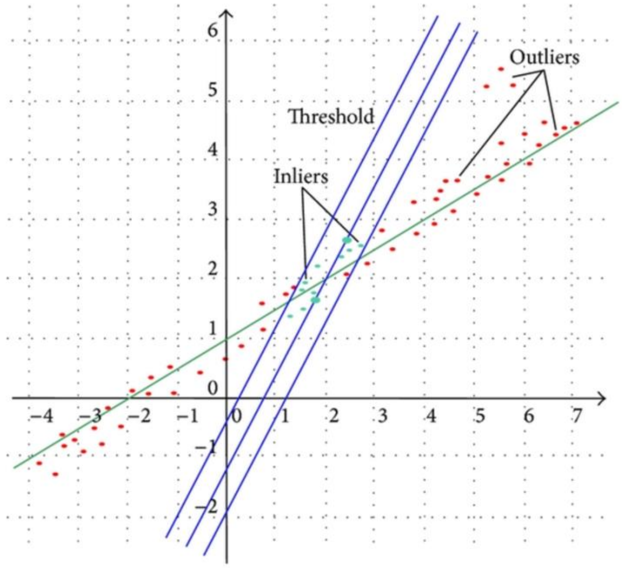

Figure 11 RANSAC Segmentation Example

Figure 11 suggests a step in classic RANSAC segmentation process. It should be noted that RANSAC would achieve its best performance when the detected ground is flat. When testing this method against intersection with large grades, the ground segmentation purpose is not satisfactory. The 'V-disparity' approach (*41*) uses stereo cameras to perceive the ground surface. Petrovskaya et al. (*42*) proposed an interesting method to detect ground using LiDAR data. If A, B, C are three scans on a flat surface. The slope in the middle of AB and BC should be near 0. This research proposed another geometric way to approximate the flat surface, unlike the mainstream RANSAC way.

Figure 12 is a raw LiDAR data frame, which contains concentric circles on the ground.

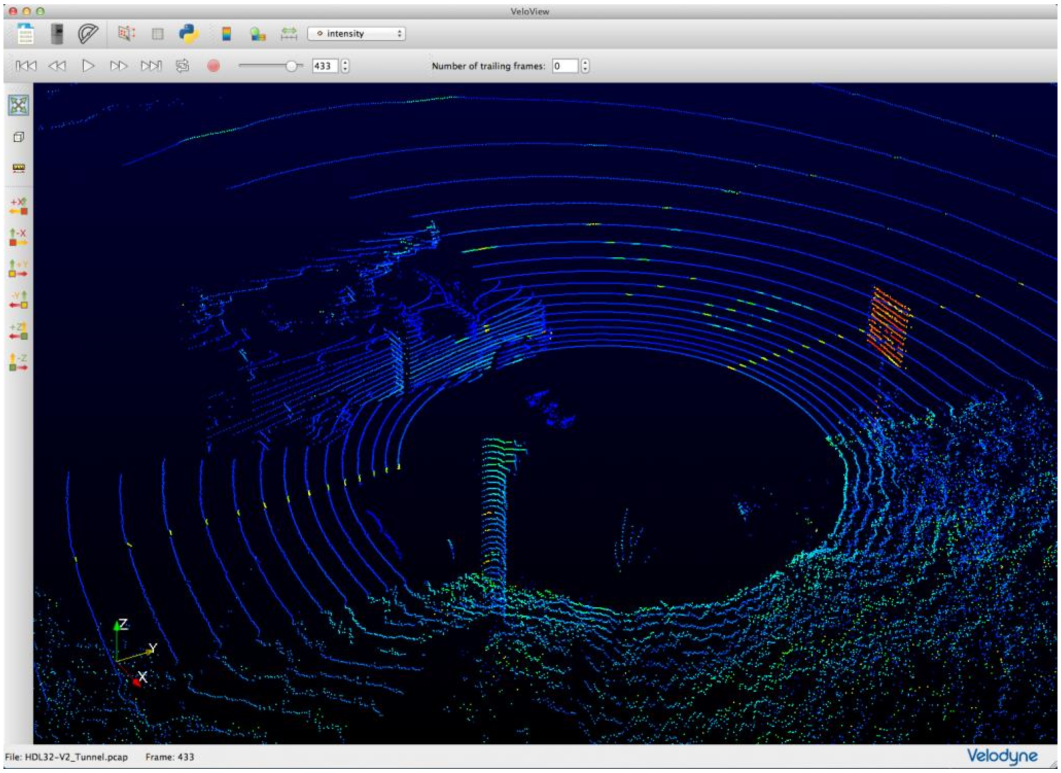

Figure 12 Raw LiDAR Data (Concentric Circles Indicate Ground Surface)

2.2.4 Pedestrians and Moving Vehicles Perception

How to perceive pedestrians and vehicles is considered as the most critical step. After ground surface perception and segmentation, the point clouds clusters are what left for recognized. These unidentified point clouds clusters are subjected to classify into passenger cars, bikes, and pedestrians. There is extensive research in this area.

Himmelsbach et al. (*43*) proposed a fast response 3D object perception procedure which could be applied to autonomous vehicles. In this paper, both object level features and Histograms of Point Level Features were removed. The object level features included Maximum object intensity, Mean object intensity variance, Object volume V. The Point level features included Lalonde features L1, L2 and L3, and Anguelov feature A1. An SVM classifier was adopted to classify objects. Two types of labels were identified: Vehicles or Non-vehicles. They claim that the accuracy could approach 96.7%. It is said that only 6 objects were assigned wrong labels from a total of 182 samples. Then a multiple model Kalman Filtering method was used to track the pedestrians or moving vehicles.

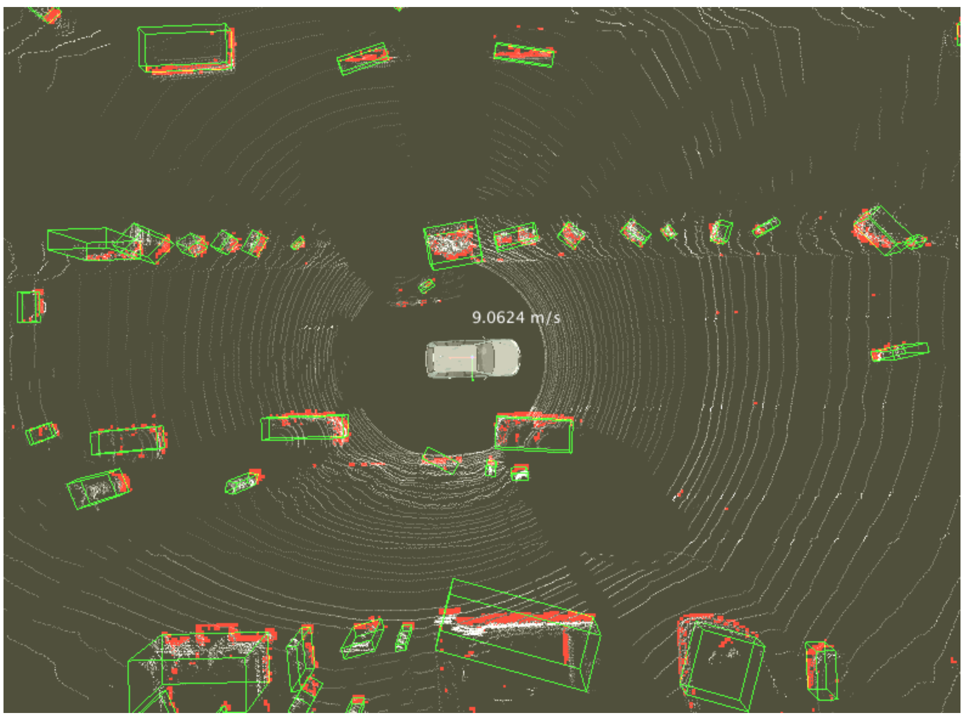

Figure 13 Objects Detected by a Fast Response Procedure

Figure 13 was from Himmelsbach's paper LiDAR-based 3D object perception (*43*).

Vatavu et al. (*44*) utilized 3D data extracted from dense stereo to construct the DEM map with clear connection among closed 3D geometrical locations. Then the particle filter tracking method was used to track the objects from the DEM map.

Asvadi et al. (*45*) utilized the 2.5D voxel spaces to separate input space. A 2.5D combination map was constructed by using input LiDAR data and localization data. This 2.5D motion grid was designed by comparing the current voxel space and updated static map. Then a Kalman Filter based tracking method was adopted for track moving objects.

Nashashibi et al. (*46*) addressed the problem of detection, tracking, and irrelevant object classification. The adopted some creative metrics such as the combination of geometrical information of the potential objects, the predicted occluded part information, and the length of tracking time. By experiment that method on lots of miles of driving data, this method was claimed to be effective, regardless what type of LiDAR sensor they deployed on the vehicle.

Using LiDAR alone could perceive the pedestrians and moving vehicles with high accuracy. However, most of the latest research utilized both LiDAR and optical sensors to gain more features in order to increase accuracy further. Cristiano et al. (*47*) proposed such a system. First of all, a linear Kalman Filter was adopted to segment space. The segments were then clustered. The feature vector contained five elements: segment centroid, normalized Cartesian dimension, internal standard deviation, Radius and mean average deviation from the median. The GMMC classifier was adopted as a LiDAR-based classifier. In the vision-based system, Haar-Like features were extracted, and the AdaBoost classifier was trained to conduct object detection. To effectively establish the link between LiDAR features and image features, a coordinate transformation system was constructed to find ROI in the image frame. A sum rule was then used to combine the output of each classifier based on posterior probability calculated by each classifier. The advantages of using a LiDAR associated with vision system were 1) the laser sensor was not very sensitive under extreme weather changes; 2) the distance/depth measurement was accurate; 3) vision system is cheap and contains differentiable features. In their later research (*48*), A 15-dimensional LiDAR-based feature vector, as well as classic HOG and COV features were extracted. Then naïve Bayes, GMMC, MCI-NN, FLDA, and RBF-SVM were deployed on the same dataset and compared. Two sensor fusion architectures, centralized and decentralized, was described and discussed. The result suggests that, combined with visual/color features, the proposed methodology would lead to a higher detection accuracy. Figure 15 depicts such a process (*47*).

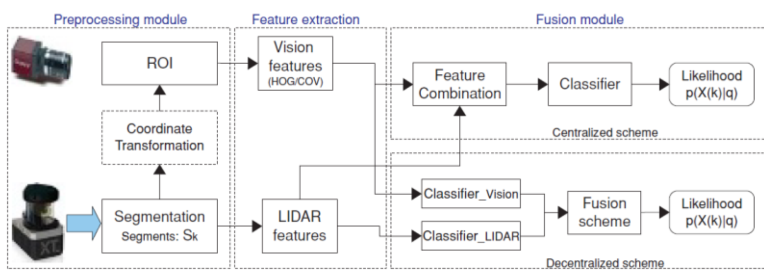

Figure 14 LiDAR and Image Feature Extraction and Fusion Example

Szarvas et al. (*49*) proposed a LiDAR and image integrated method and claimed accuracy of detection more than 90%. His method first used a LiDAR to locate the ROI (Region of Interest) fast, and then adopted a Convolutional neural network-based system to classify different objects.

2.2.5 Road Shape Estimation

Huang's thesis (*50*) described algorithms for feature detection and curve estimation, as well as an innovative curve representation that permitted quickly and efficient lane approximation. Road shape estimation could be very useful for lane change behavior detection, or lane change crash prediction. By the time of this dissertation was written, these applications have not been incorporated into the future research plan. Although road shape estimation is not indispensable for traffic engineers, this step is essential for autonomous vehicles to perceive the surrounding and to make decisions if in an unfamiliar environment.

2.2.6 Summary

Table 5 summarizes some of the most cited perception data processing procedure literature, especially in autonomous vehicle field (*44; 45; 51; 52*).

Table 4 Some Recent Work on 3D Perception System

Authors/Year	3D Sensor	Ego-motion estimation	Ground surface estimation	Representation of obstacle detection	Motion detection/clustering/segmentation	Tracking
Vatavu et al. 2015	Stereo camera	GNSS or GPS/IMU odometry	RANSAC, region-growing and least square fitting	2.5D digital elevation map	Object delimiters extracted from the projection of elevation grids	RaoBlackwellized particle filter
Asvadi et al. 2015	Velodyne LiDAR	GPS/IMU odometry	Cells contain points with low average and variance in height	2.5D elevation grid	A static local 2.5D map is built, and the last generated 2.5D grid is compared with the updated local map	Gating, nearest neighbor association, and Kalman filter
Azim et al. 2014	Velodyne LiDAR	GPS/IMU odometry matching	Assume planar ground	Octomap	Density-based spatial clustering	Global Nearest Neighborhood(GNN)

In sum, to efficiently utilize LiDAR sensor data, first, the ground plane needs to be identified and segmented. Then different objects, such as pedestrian and vehicles, are classified based on its different features. For most of the autonomous vehicles, both LiDAR and image features are adopted to improve the accuracy of identification and tracking result. However, The LiDAR application for roadside traffic surveillance is different with LiDAR application on autonomous vehicles. The LiDAR will be installed at the roadside, at the top of the signal pole, even at the top of the electrical pole. Secondly, the system should be able to continually detect and track vehicles even without an ideal shape of the vehicle. This would demand the data processing algorithm to be scalable and robust to track the vehicle with a fewer channeled LiDAR sensor. Thirdly, the LiDAR sensor should be able to track the speed without the help of optical sensors. More sensors mean more maintenance labor and higher budgets, which would bring burden to the finance of city or state. Fourthly, it is unclear whether multiple LiDAR data fusion is possible. Therefore, a data-processing procedure needed to be developed specifically for roadside LiDAR sensor data. This procedure needs to be able to track a vehicle without a good shape and function without the support of other optical sensors.

3. Procedure for Extracting High-Resolution Trajectories

The LiDAR sensor adopted in this dissertation is Velodyne VLP-16, which has the following specifications: 16 channels, 300,000 points per second, and has 360 degrees horizontal Field of View (FOV) as well as 15 degrees vertical FOV. Research group purchased this LiDAR sensor at a price of $8000 at 2015. Although there are other better LiDAR sensors, such as 32 channels HDL-32E or 64 channels HDL-64E, the VLP-16 was considered best for research for its affordable price.

The data processing procedure proposed in this research (*53; 54*) includes several modules such as preprocessing of the raw data, statistical outlier removal, a Least Median of Squares based ground estimation method to accurately remove the ground points, vehicle data clouds clustering, a Principle Component-based oriented bounding box method to estimate the location of vehicle, and a geometrical based tracking algorithm.

3.1 Raw Data Processing

The preprocessing algorithm first removes the 3D points of LiDAR sensor itself. The removing range usually could be set within one meter, which means all the data points in this one-meter radius range would be deleted. The reason for this step is the LiDAR sensor‘s data in this range has no valuable information. The region of interest (ROI) is then determined relied on the intersection’s geometry. First, the buildings, trees, traffic signs and other irrelevant objects would be filtered out from the original raw dataset. Filtering of the irrelevant object would decrease the data size for processing. So this will increase the efficiency of the follow-up algorithms by searching fewer points or spaces.

The background filtering will also reduce the influence of uninteresting objects in this step. Figure 15 shows the difference between a raw data frame and a preprocessed data frame.

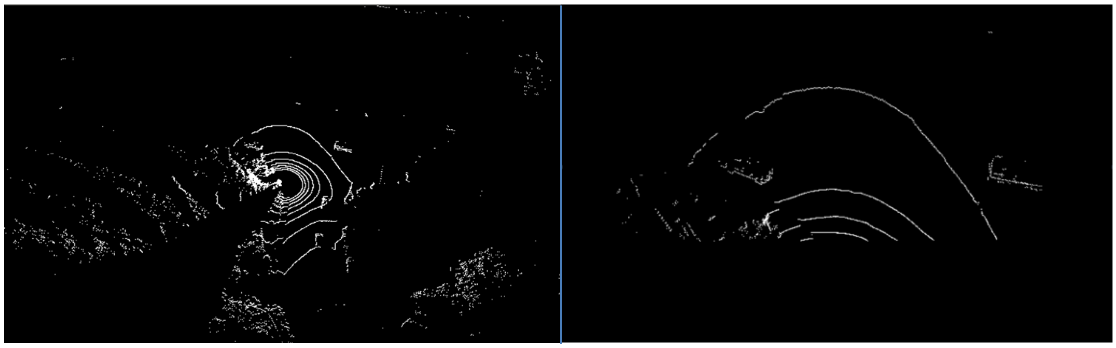

Figure 15 Raw Data Frame (Left) and Data Frame after Preprocessing (Right)

3.2 Statistical Outlier Removal

This step removes the noise data points near the targeting objects. These noises in each data frame would complicate the vehicle identification and tracking and could introduce errors of vehicle locations and speeds. A statistical outlier remover algorithm (*55*) was applied at this step. This sparse outlier removal algorithm is based on the computation of the distribution of its K neighbor's distances in the input data frame. For each point, the algorithm will compute the average distance to all the points close to it. It is assumed that all the points would follow a Gaussian distribution. Then by plotting all these points into the Gaussian distribution figure, any points outside of predefined standard deviation would be recognized as noise points and removed from the dataset. Figure 16 presents the comparison of before and after the outlier removal step.

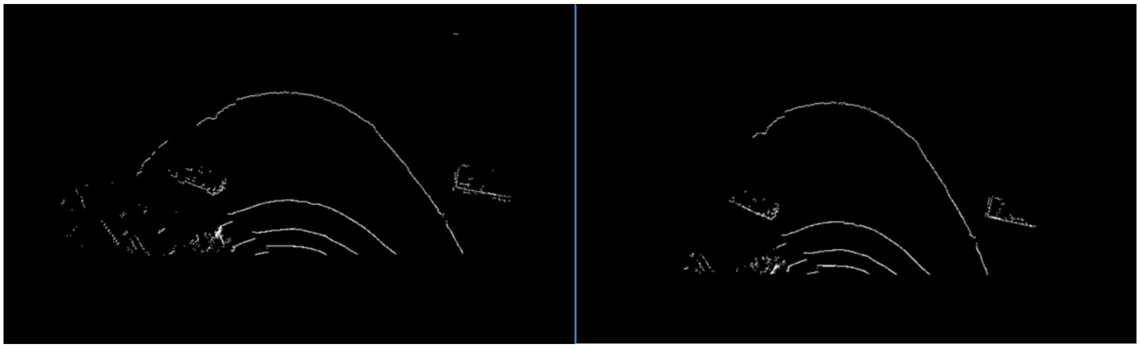

Figure 16 Data Frame Before Outlier Removal (Left) and After Outlier Removal (Right)

3.3 Ground Plane Identification and Segmentation

Ground plane identification and segmentation is an essential step for the proposed data processing procedure. The ground plane here is defined as a group of concentric circle points when LiDAR is scanning the ground. So, these sparse noises are subject to be identified and removed. The ground plane is recognized as the noise of the data frame, thus Random Sample Consensus(RANSAC) (*40*). The input of RANSAC method contains three parts: the data to be processed, a candidate mathematical model fit into the data frame outliers, and parameters related to the approximation of the model. Here a mathematical model was considered as a surface function which could represent the ground plane. There are two critical parameters. The first parameter is iteration times. The iteration limits were set to 200 times regarding efficiency and success rate. The second allowed error parameter is the allowed deviate angle. This deviate angle was set to 15 degrees, which means the direction of the estimated surface could not deviate 15 degrees away from the vertical vector (0, 0, 1). If the estimated surface has a degree more significant than this, it will automatically trigger failure segmentation. The RANSAC iteration method contains four steps. A random portion of the raw data was selected first. This portion of data was called as hypothetical inliers. Then all the rest of data were calculated against this predefined model; those points fitted this model well would be incorporated into this model. This larger estimation model was considered as a good model if there were enough points in this model. Finally, if the model is not good, another subset of data frame was randomly selected and estimated. RANSAC can estimate the surface function parameters even with significant noises presented in the data frame, but it has no guarantee of delivering optimal solutions within limited iterations. This suggests that by computing a more significant number of iterations, the optimized solution was approximated. Other variants of RANSAC methods (*56*) were also tested. RANSAC solves the selection problem as an optimization problem with a bounded loss function. The loss function is recognized as a summation of geometric distance for all the points to the estimated plane. When a point is within allowed distance, this point is considered belonged to the estimated plane hence the loss value for this point is set to zero. Least Median of Squares (LMedS) method does not need any tuning variable because it tries to minimize median squared error (*57*). Thus it is considered as a robust estimation. The robust here means fast and insensitive to noises of the data frame. Different modified RANSAC methods were tested against same data frames; the LMedS model was found to achieve high accuracy while only consume a limited computation time, as presented in Table 6. Therefore, it was adopted for ground plane segmentation method in this research. The accurate frame in the table was defined as a frame whose ground plane was perfectly removed and there is no scanning line on the ground left for this frame after ground plane segmentation.

Table 5 Ranking Table in Terms of Average Segmentation Time and Accuracy against Three Hundred Frames

Name	RANSAC	MSAC	MLESAC	rRANSAC	rMSAC	PROSAC	LMedS
Time	1us	1us	1us	2us	2us	2us	1us
Accurate Frame Numbers	231	242	25	187	158	236	291

It should be noted that none of the mentioned methods could guarantee a perfect segmentation for all tested data frames, thus in this research, a follow-up cleaning algorithm was designed. This algorithm removes a 0.2 meters thick cuboid by utilizing the plane model parameters, instead of just removing points in a plane. This follow-up algorithm deletes residual ground points around the plane while keeping the vehicle clouds points integrated and completed. Figure 17 indicates this effort.

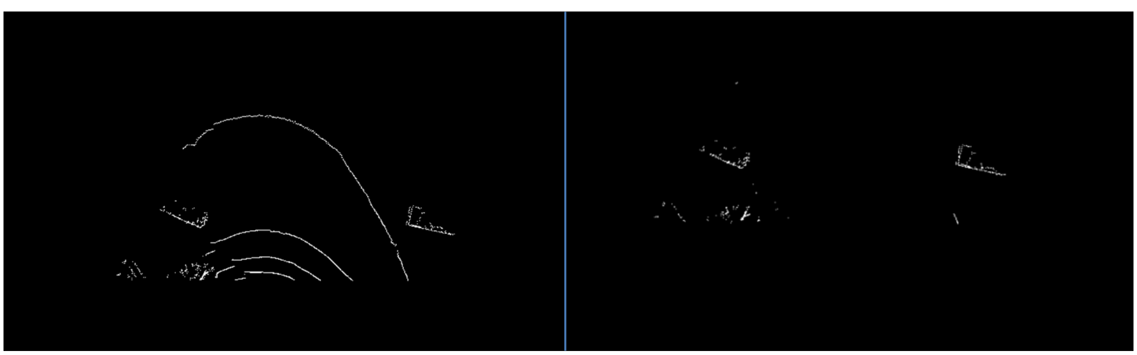

Figure 17 Data Frame After Outlier Removal (left) and Data Frame After Ground Plane Removal (right)

3.4 Vehicle Clustering

A clustering method is needed to cluster separate points to vehicles. The algorithm applied in this research was developed by Rusu et al. (*58*). This clustering algorithm was named Basic Clustering Techniques. The critical part is let the system understand what an object point cluster is, and what makes it different from one another. A threshold is required as the input to this algorithm, a minimal distance between two cloud sets needs to be estimated. He proposed to approximate nearest neighbors via the KD-tree structure (*59*). First, an empty list of clusters was set up, and an empty queue was set up. Then for a random point P in a LiDAR data frame, it is added to the current queue. The algorithm then searches points within a user-defined radius from point P. These neighbor points are marked as processed points, and won't be added to another queue. After the search for point P and adding all its neighbor points into the current queue, the corresponding queue will be saved then a new one is created. The next candidate point is randomly selected, and its neighbor points are searched in the same method. The algorithm terminates when all points are scanned and selected. After clustering, the points are grouped into individual objects and subject to extract the useful information. Figure 18 demonstrates clustered result.

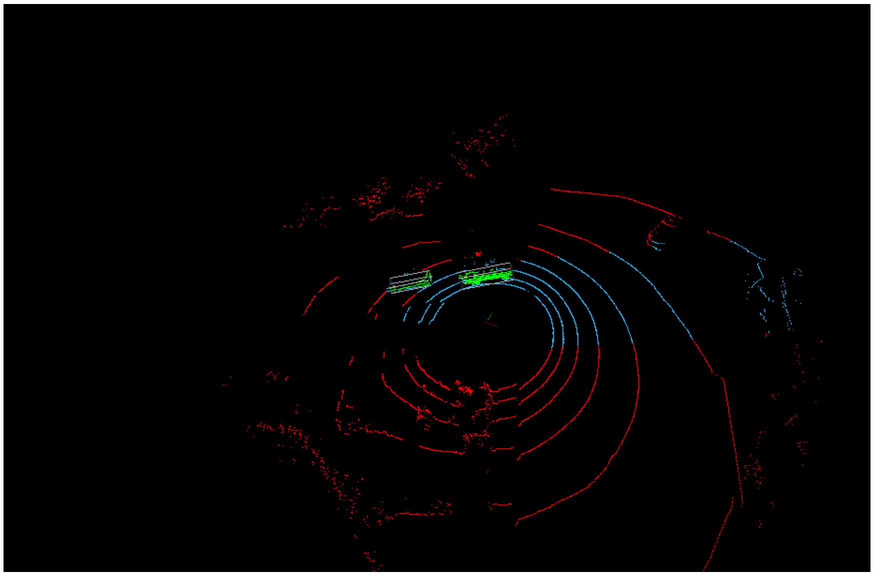

Figure 18 Clustered Results: The Blue Points Indicate Preprocessed Data; the **Green Points Indicate Clustered Interested Vehicles**

3.5 Vehicle Identification

Because the LiDAR sensor would penetrate the window of vehicles, or merely the scanning could not cover every corner of the vehicle, the vehicle identification step is to identify the location and shape of vehicles accurately. The space center of a cluster is first identified to represent the location of vehicles. However, the center of a vehicle shifts frames by frame due to the incomplete structure of objects. The LiDAR sensor only able to detects part of a vehicle body in a frame, so the detected part changes when the vehicle moves.

Thus, a reconstruction method is used to restore the shape of vehicles before identification the actual location of vehicles. It is a problem of finding the minimum-volume Oriented Bounding Box (OBB) by using the extracted object data points. There are several methods to identify the OBB for a group of points: O’Rourke’s Algorithm, Brute-Force Methods, PCA-Based Methods and some other method like (1+ε)-Approximation(*60*). In this research, a min-max PCA based OBB method was used to identify vehicle boundaries. This method first calculates the principle or eigenvectors, and then a reference coordinate system is constructed based on these eigenvectors. The original vehicle cluster is translated into this new reference coordinate system, and a bounding box is constructed for the vehicle. This bounding box is then translated back to the original coordinate system and used as the optimum bounding box for this vehicle. The front corner point and back corner point, which are closest to the sensor, are identified as a key data pair to represent the location of this vehicle. Figure 19 indicates the identified a vehicle boundary and the points used to track a vehicle.

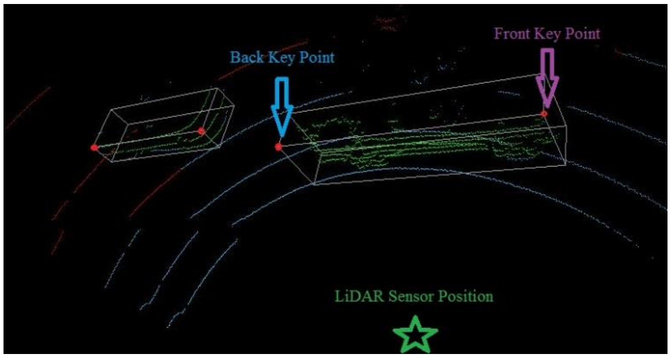

Figure 19 Identified Vehicle Boundary and Key Data Pair

3.6 Vehicle Tracking

Finally, an object tracking algorithm was developed to track vehicle trajectories. This tracking algorithm utilizes the geometric location information of vehicle key data pair to identify key points in different frames belonging to same vehicles. The algorithm tracks the front key point when the vehicle approaching the sensor and tracks the back corner key point when the vehicle is leaving the sensor.

Figure 20 describes the whole data processing procedure.

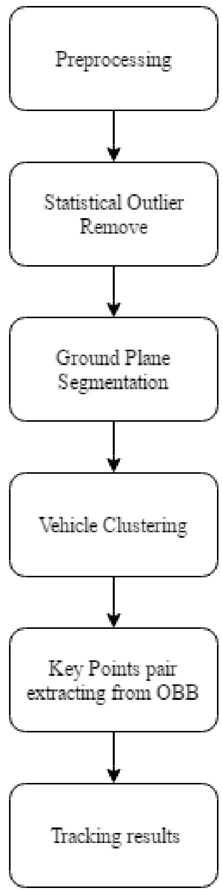

Figure 20 Flow Chart of Vehicle Speed Tracking with a Roadside LiDAR

3.7 Validation of Data Processing Procedure

The data processing procedures have been tested with data collected at three sites. These datasets are considered be able to represent real traffic scenarios.

To compare the tracking results and actual vehicle speeds, the authors installed a logging system in a testing vehicle. The logging system read and stored vehicle speeds from the onboard diagnostics (OBD) interface of the vehicle. This dataset was collected at the University of Nevada, Reno's northern parking lot. Figure 21 presents the comparison of the extracted speeds from LiDAR data and the logged speeds of the testing vehicle. The tracking results of both directions match the OBD speed very well, indicates that this data processing procedure is precise and able to track vehicles in both directions. The X-axis unit is frame index, Y-axis unit is Mph, blue points indicate tracking result, and the red line indicates OBD speed.

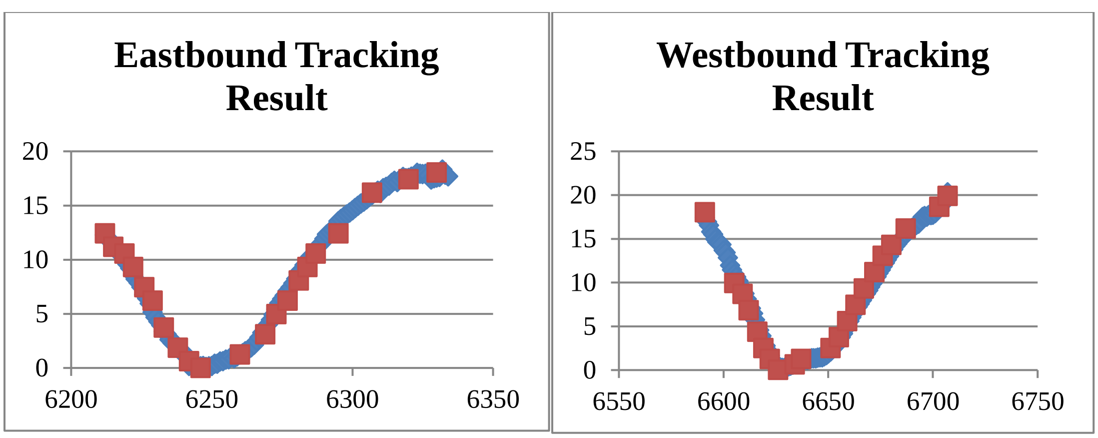

Figure 21 The Parking Lot Tracking Results

Another dataset was collected at the intersection of Evans Street and Enterprise Road in Reno, Nevada which is a two-way-stop-sign intersection with four legs. Trajectories of two vehicles are shown in Figure 22. The first vehicle stopped at the eastbound Enterprises Road, waited for a gap and then crossed the intersection. The follow-up vehicle decreased the speed and waited for the leading vehicle to pass the street, as the frame index 4000-4500 indicates. The follow-up vehicle then accelerated and approached to stop bar. When there was a gap, it accelerated sharply and crossed the intersection.

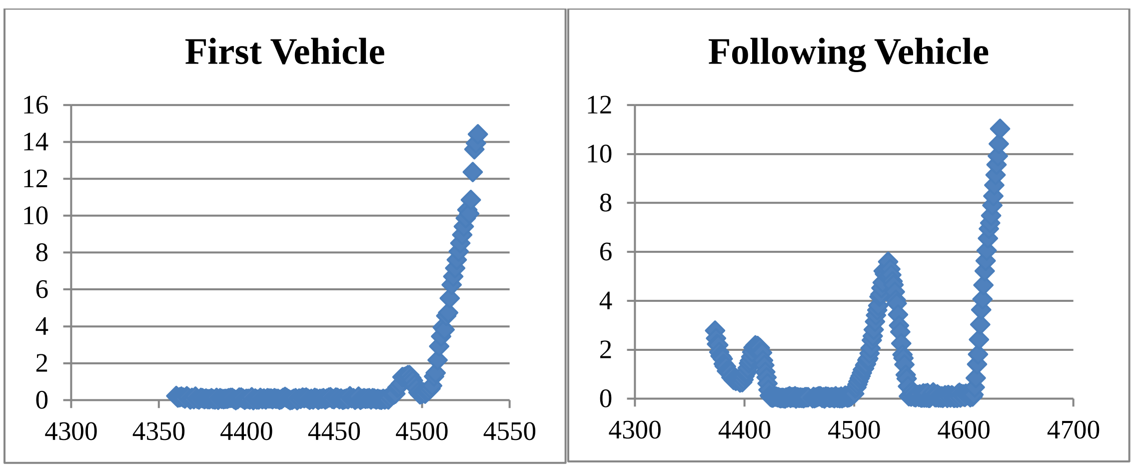

Figure 22 Evans and Enterprise Stop-Sign Two Vehicles Tracking Results

The data processing procedure was then applied to the data collected on Kietzke Lane. Kietzke Lane is an arterial road with the speed limit of 40 mph in Reno, Nevada. Figure 23 shows the tracking results. It should be noted that some vehicles slowed down when approaching the sensor, this is possibly the data collection attracted drivers’ attention and caused the speed reduction.

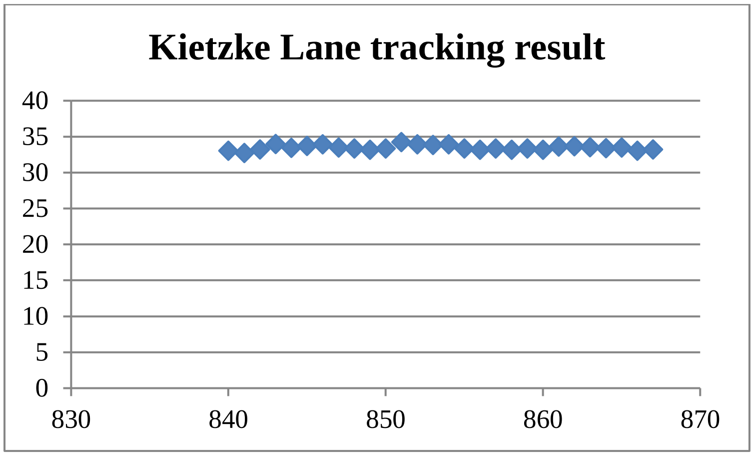

Figure 23 Kietzke Lane Tracking Results

Another finding from this research is that the tracking speed of the vehicle passing the sensor using this data processing procedure might suddenly drop or increase. The scanning shape of the vehicle may not be complete when the vehicle is close to the sensor, so when tracking the vehicles, the front key point would be cut short, this would cause the drop of the tracking speed. The sudden increase in speed is also possible because the sensor saves next frames vehicle data into current frame, which would cause a sudden extension of the front tracking point. Both situations are not likely to happen when there is a distance, preferably three meters, between the sensor and vehicles. Although these scenarios do not happen a lot, they should be identified, smoothed and reported before generating the actual tracking speed profiles in practice.

4. Object Recognition from a Roadside LiDAR Sensor

How to differentiate pedestrians/bicyclists and vehicle/bus is another crucial task in this research. In general, the object recognition contains three significant steps. First, feature extraction needs to be conducted. Secondly, appropriate classifier needs to be selected. Thirdly, the objects need to be classified accordingly.

4.1 Literature Review

Himmelsbach et al. (*43*) proposed using feature vectors to describe LiDAR scanned objects. The feature vectors contained object-level features and histograms of point level features. The object level features included the largest object intensity, average object intensity, object intensity variance and object volume. The point level features included Lalonde features which could describe the scatter-ness, linear-ness and surface-ness, and Anguelov feature which could capture the distribution of data clouds. A kD-tree was constructed to do a fast search. A support vector machine (SVM) was trained on a already labeled training data-set. The target of classification was to tell the difference between vehicle and non-vehicle. In the paper, there were 176 out of 182 objects correctly classified, yield 96.7% accuracy. This research used a Velodyne HDL- 64 LiDAR.

Teichman et al. (*61*) proposed using Holistic descriptors and Segment Descriptors to describe objects. Holistic descriptors included the highest speed, average speed, highest acceleration, average acceleration, highest angular velocity and some segment descriptors. The segment descriptors included oriented bounding box size, spin images, a histogram of oriented gradients. An augmented discrete Bayes filter classifier was developed to classify objects fast. In this paper, the researcher of Stanford University could achieve 98.5% accuracy on a 1.3 million labeled point clouds dataset. The task of classification was to classify between car, pedestrian, bicyclist, and background classes. This research used a Velodyne HDL-64E LiDAR sensor, which could generate about 1 million data points within one second.

Maturana et al. (*62*) proposed VoxNet, a new 3D convolutional neural network (CNN) for real-time object recognition. This system majorly addressed the problem of how to efficiently calculating along with huge amounts of point cloud data. The proposed system has two parts; one was a volumetric grid to represent the estimation of occupancy, the other one was a Convolutional Neural Network (CNN) would predict the class directly from the occupancy grid. The authors claimed that volumetric grid have more information than typical point clouds representation, and this representation would be very efficient. The authors argued that there were three motivations for them to choose CNN. The first reason was CNN could directly input volumetric grid information; this would make the classification task easier. The second reason was by stacking multiple layers this type of neural network could represent larger spaces. The third reason was that the commercial graphics hardware could easily support that. The proposed CNN consisted of Input Layer, Convolutional Layers, Pooling Layers, and Fully Connected Layer. The whole data processing framework was tested on Sydney Urban Objects Dataset, which contained labeled Velodyne HDL-64E LiDAR scans in 26 categories, for example 4WDs, cars, buses, trees, pedestrians, and buildings.

Lai et al.(*63*) proposed a way to using Google's 3D warehouse to train and classify objects. In this paper, they optimized a technique for shape feature-based recognition and introduced a probabilistic, exemplar-based classification method. They also displayed how to use Google's 3D warehouse to increase the performance of object recognition in another domain. In this research, they used a smaller set of spin image signature for each point as well as segment's minimum height as feature descriptors. A domain for exemplar-based learning approach was applied afterward. The results suggested that this domain adaption-based classifier outperformed LogitBosst and Multi-class SVM in accuracy and robustness.

4.2 Support Vector Machine

A support vector machine seeks to create a hyperplane in a very high dimensional space, and originally designed for the solving of two-class classification problems. To put it in another way, the SVM seeks the optimum hyperplane which would allow the maximum geometrical separation between two classes. The points on the hyperplane are called support vectors. Due to the nature of the dataset, sometimes it is impossible to achieve a perfect separation. Hence SVM could use slack variables to allow some of the points located in the opposite class. SVM seeks to optimize its primal problem to find the most significant margin in the dataset. Figure 25 depicts a two-class classification case using SVM.

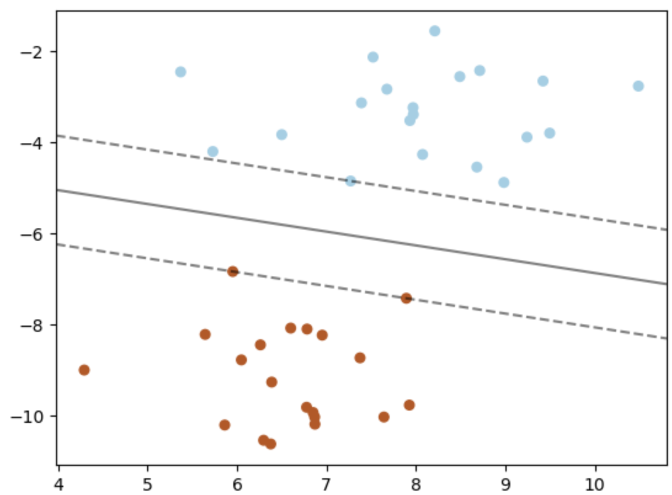

Figure 24 A SVM Classification Example

Given the training vectors Xi, I =1…,n, in two classes, and a vector y, SVM aims at solving the following primal problem (*64; 65*):

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$$
$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1, ..., n$$

The kernel is a way of mapping the vectors in another higher feature space. A kernel is a function kk that corresponds to this dot product,

i.e., k(x,y) = φ (x) Tφ(y) k(x,y) = φ(x) Tφ(y).

If some objects are not linearly separable in a lower feature space, mapping in higher feature space may allow it become linear separable.

4.3 Object Recognition Study

Selecting great features is the key for correctly identify objects. From the literature review, we could learn that the features fall into three types. Point features use a histogram to describe its features. Local features define a small area to describe the features. Global features adapt the whole data cloud geometric information. In this research, the shape of cloud points keeps changing, so it is very unstable to use local features or global features to describe the clouds. Three eigenvectors, as well as the cloud point's number, are used as features to achieve this discriminative task. Several different Support Vector Machine classifier (*66*) was then tested on those features to assign class labels.

Table 6 Part of Training Table, Identification Zero Indicate Pedestrian/Bicyclist, Identification One Indicate Cars/Buses

Identification	Eigenvector1	Eigenvector2	Eigenvector3	Point numbers
0	1.6086	1.37415	0.508575	80
0	1.6487	1.37721	0.377087	67
0	1.62817	1.38084	0.404202	60
0	1.61167	1.207	0.401193	62
0	1.61415	1.23093	0.457184	59
0	1.49094	1.23088	0.576513	61
0	1.39088	0.74139	0.373193	15
0	1.36448	0.583993	0.342423	14
0	1.39329	0.68799	0.651142	19
0	1.39027	0.767213	0.582005	19
0	1.37912	0.814165	0.649501	21
0	1.36489	0.687317	0.552423	18
0	1.34833	0.539579	0.476426	15
0	1.32924	0.695193	0.417093	18
1	3.70775	1.83262	1.24179	68
1	3.88347	1.84832	1.77437	102

1	3.94735	1.86505	1.71187	106
1	3.93755	1.91298	1.66293	109
1	3.91298	1.76556	1.59001	109
1	3.96283	1.77208	1.10843	109
1	4.0024	1.80707	1.3942	120
1	3.87637	1.88138	1.49816	148
1	11.0421	2.98472	2.28897	118
1	11.1075	2.99588	2.16623	114
1	11.1406	2.90252	2.22607	108
1	10.8162	3.04487	2.04528	192
1	10.9052	3.03547	2.12502	186
1	10.1597	4.61755	3.13038	323
1	10.3946	4.7539	3.11835	335

Different type of SVM classifier was tested using the same training dataset. Table 7 contained the test result.

Table 7 Different SVM Classifier Testing Result Table

SVM Type	Bus	Car	Pedestrians	Bicyclist	Accuracy
Linear Kernel	2 for 2	29 for 34	2 for 2	0 for 0	0.86842
RBF Kernel	2 for 2	31 for 34	2 for 2	0 for 0	0.92105
Poly Kernel	2 for 2	28 for 34	2 for 2	0 for 0	0.84211

5. Case Study

The proposed data processing procedure in this research could be used to identify how many vehicles and pedestrians are passing through an intersection. 1000 frames of LiDAR data at the intersection of 15th Street and Virginia Street near the University of Nevada; Reno was selected as the case study data source. The red five-pointed star in Figure 25 indicated the location of the LiDAR sensor. This intersection was selected for several reasons. First, the research objects, such as different type of vehicle, bicyclist, and pedestrians at this intersection were abundant. The Virginia Street was considered as one of the most important arterial roads in Reno, and 15th street provided direct access entering the campus. This intersection was usually busy and especially crowded at peak hours. Secondly, this intersection was a two way stop sign intersection. This type of intersection was not researched in the validation process; hence research on this intersection would provide more insight for two-way stop sign intersections. Thirdly, the LiDAR was mounted at a signal pole, rather than on a tripod at this intersection. It was believed that the LiDAR sensor would be mounted on a signal pole in practice for LiDAR safety concerns. Whether the data processing procedure still works well when the latitude of LiDAR was adjusted should be tested. In sum, this intersection was considered as the best location for a case study from the research group.

Figure 25 Google Map for Case Study Site

The datasets collected at this intersection contains hours of traffic data. A portion of this dataset was chosen to study the detailed tracking results. The criteria for choosing such a portion were followed:

1) This portion has abundant vehicle data, both buses and vehicles data should exist;
2) This portion has both stop-go and free flow traffic scenario, so both scenarios could be researched;
3) This portion has pedestrians crossing so the pedestrian tracking capabilities could be researched;
4) This portion has left turn vehicle, so the speed profile of left-turn vehicle would be researched.

Frame number 11000-12000 was considered meet the selection criteria defined above. A sample frame was presented in the Figure 26.

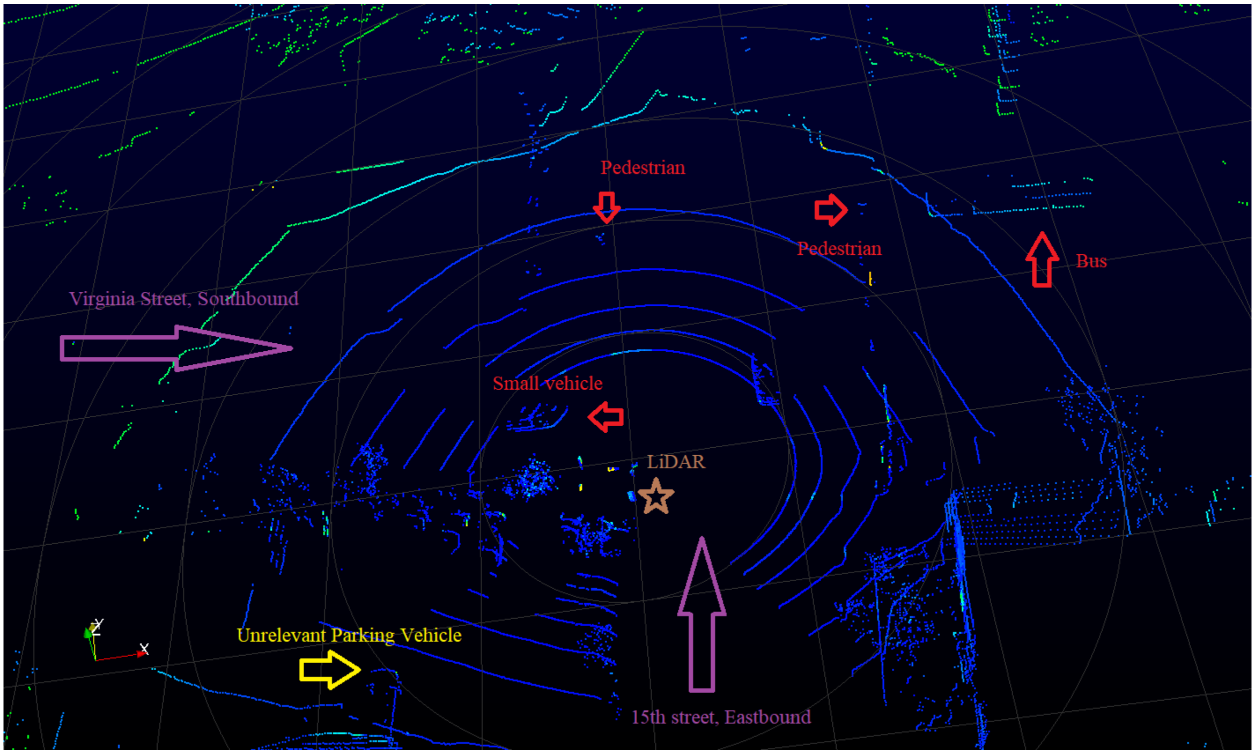

Figure 26 An Example Frame from Case Study Data Sources

1) Red symbols suggest target objects, such as pedestrians, buses or small vehicles;
2) Purple symbols suggest the moving directions;
3) Grey symbols suggest the LiDAR location;
4) Yellow symbols suggest irrelevant parking vehicles.

5.1 Tracking Results

Figure 27 is an example of bus tracking data. The tracking result suggests the data processing procedure stably track the bus with as many as 694 frames (69.4 seconds).

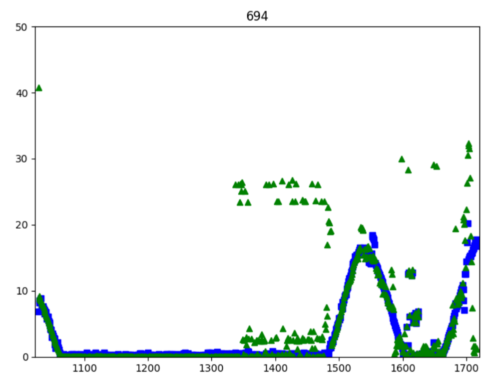

Figure 27 A Bus Tracking Example

Figure 28 is an example of small vehicle tracking data. This small vehicle tracking data made a full stop at the intersection. The tracking result suggests the data processing procedure stably track the vehicle with as many as 284 frames (28.4 seconds).

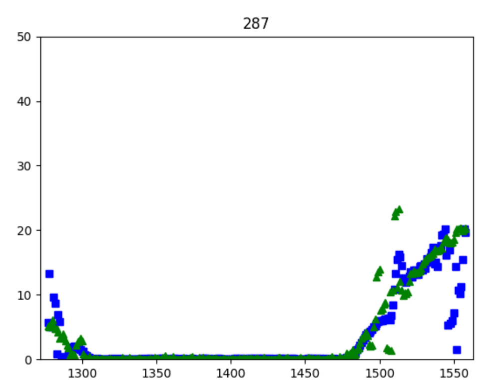

Figure 28 A Small Vehicle Tracking Example

Figure 29 is another example of small vehicle tracking data. This small vehicle tracking data did not make a full stop at the intersection. The tracking result suggests the data processing procedure stably track the vehicle with 98 frames (9.8 seconds).

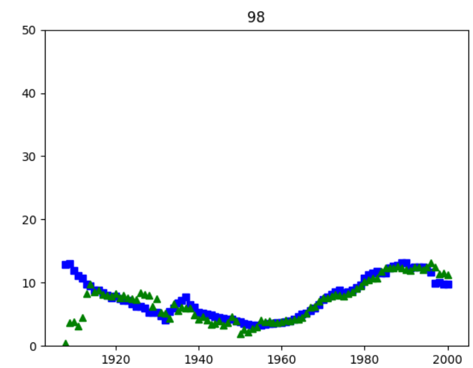

Figure 29 A Small Vehicle without Entirely Stop at Intersection

The Figure 30 suggest these small vehicles were passing the intersections with free flow traffic.

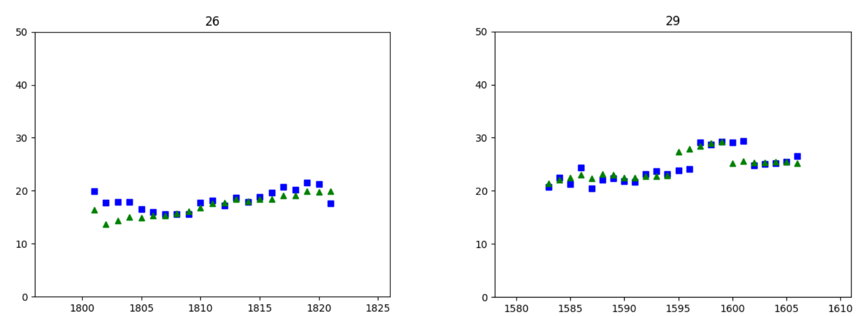

Figure 30 Small Vehicles with Free Flow Traffic

Figure 31 are examples of pedestrian tracking data. The tracking result suggests the data processing procedure stably track the pedestrian with 100 frames (10.0 seconds).

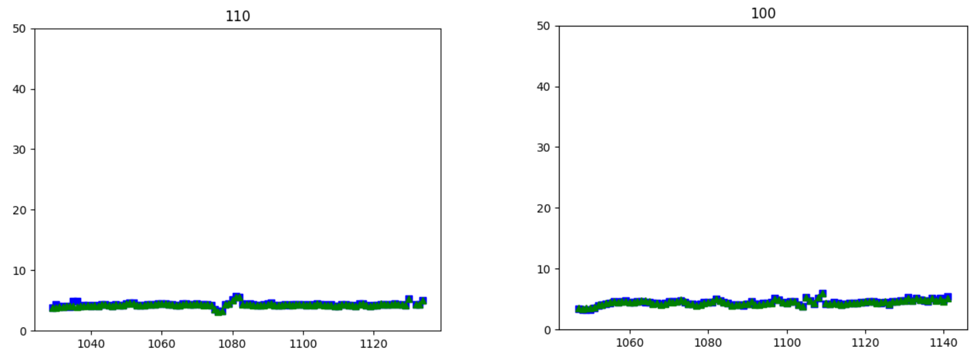

Figure 31 Pedestrians Tracking Data

Figure 32 is an example of left-turn vehicle tracking data. The tracking result suggests the data processing procedure stably track the left-turn vehicle with 177 frames (17.7 seconds).

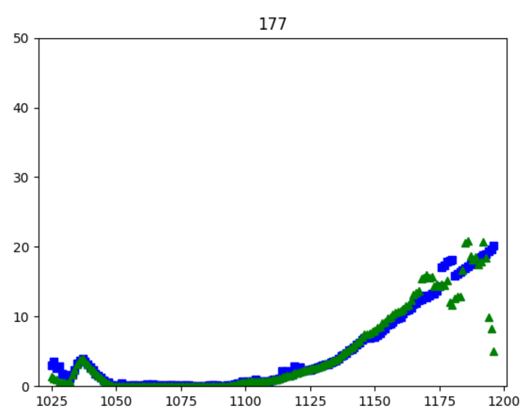

Figure 32 A Left Turn Vehicle Yield Pedestrians at Intersection

5.2 Curse of Blockage

From the manual counting, a total of 38 objects existed in this portion of the dataset. Among them, there are two pedestrians, five left turn vehicles (One of them is a bus), and three buses. Among 36 vehicles, 14 vehicles travel southbound at Virginia Street, 17 vehicles traveling northbound on Virginia Street, two Vehicles traveling eastbound on 15th street, and three vehicles traveling westbound on 15th street.

From the detection result, 39 tracking speed profiles were generated. Two southbound vehicles are counted twice; one northbound vehicle was not detected. The errors were majorly coming from blockage. There are two scenarios for miscounting errors.

First, the count of vehicles may increase because of blockage. The vehicles would stop in parallel behind the stop lines; the vehicle which is near to the sensor will block the vehicles far from the sensor, as the Figure 33 suggests. When the vehicle has been blocked is no longer blocked, this vehicle will show up again causing a double count. In this case study, two vehicles were counted twice because of this type of blockage.

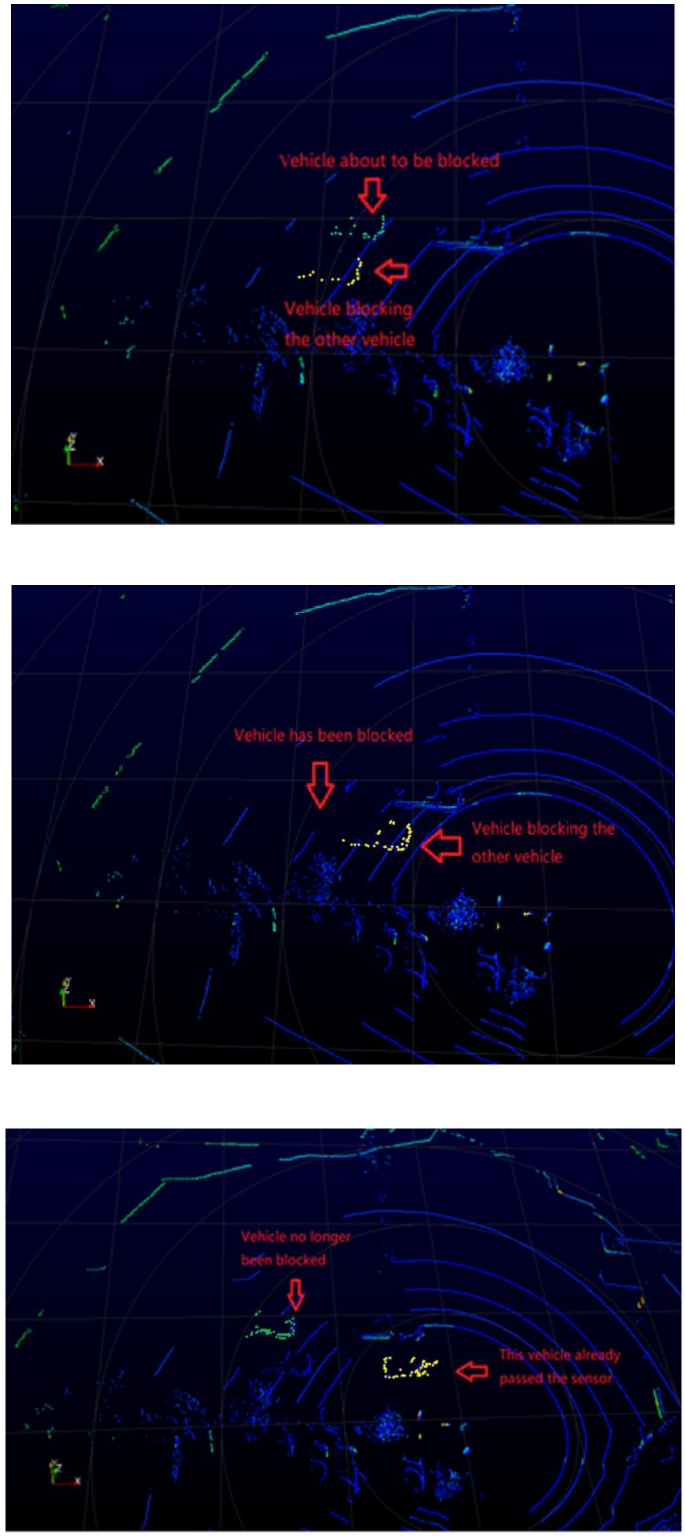

Figure 33 A Double-Count Example

Secondly, if the far-sensor vehicle was blocked by the near-sensor vehicles, the object points for the far-sensor vehicle would be much less than they should be. This would cause counting fewer vehicles in practice. In this case study, one vehicle in the lane far away from the sensor was lost by this type of blockage, as Figure 34 suggested.

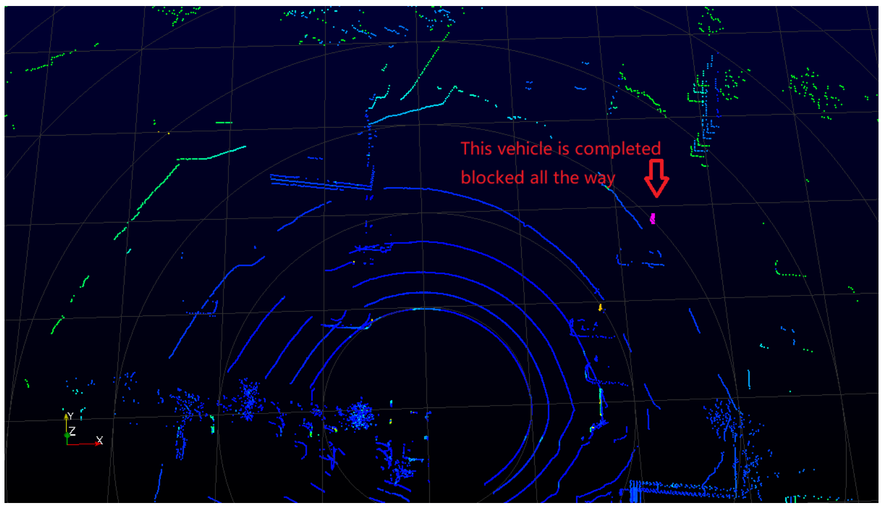

Figure 34 A Missing-Count Example

Additionally, even with potential blockage, two pedestrians are well tracked.

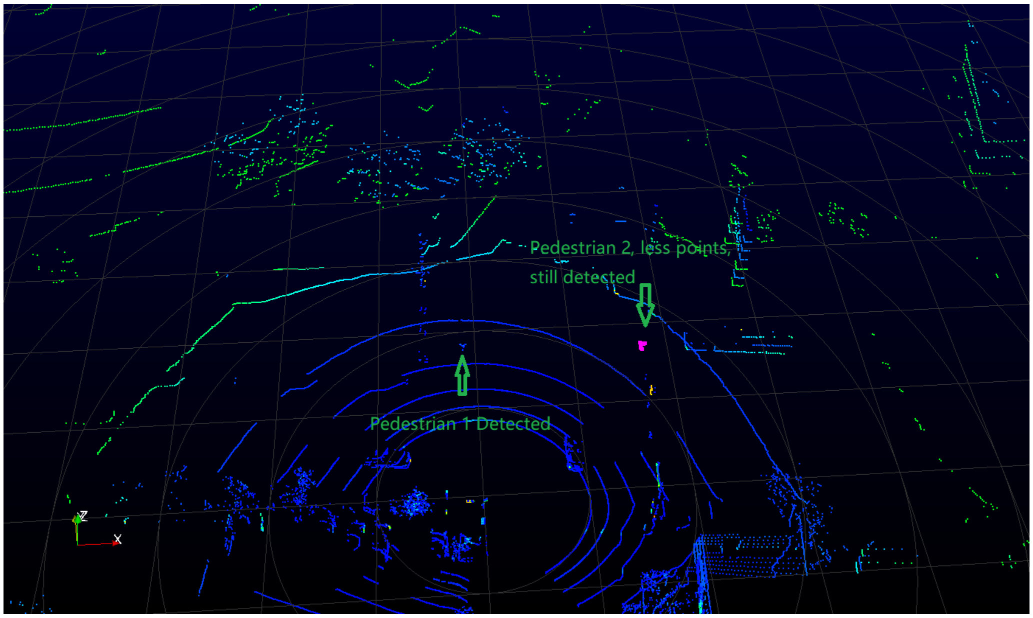

Figure 35 A Pedestrian Tracking Example

In sum, 37 objects were identified and tracked. Although two vehicles were counted twice, they are still correctly detected. This gives us an accuracy of tracking rate of 37/38 = 97.4% on objects on the roads for this case study.

5.3 The trade-off of Clustering Size

Another finding from this case study is the definition of clustering size is very critical. The minimum number of points belongs to a cloud point cluster has to be carefully chosen. If the clustering size is defined too small, a single vehicle would be identified as multiple objects. The scanned lines of the vehicle body are not always continuous. If the clustering size is defined too large, several vehicles would be aggregated into one giant object. In this case study, experimenting method was chosen to select an appropriate value. However, the threshold chosen by this way is still could not achieve a 100% accuracy. Figure 36 suggests an example scenario when two pedestrians are walking together or passing each other in a crosswalk. This would cause two pedestrians to be identified as single pedestrian and causing tracking errors by inappropriate clustering size.

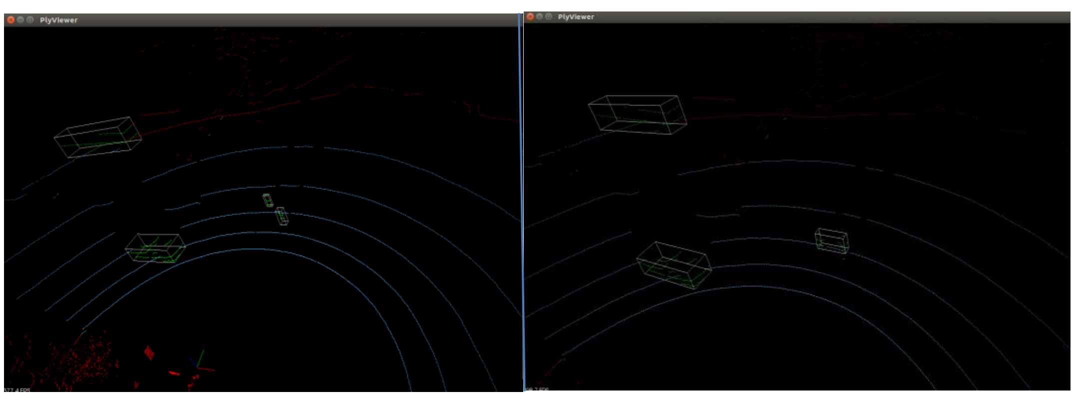

Figure 36 A Tracking Error Example

5.4 Object Recognition Results

Figure 37 contains the correctly identified small cars.

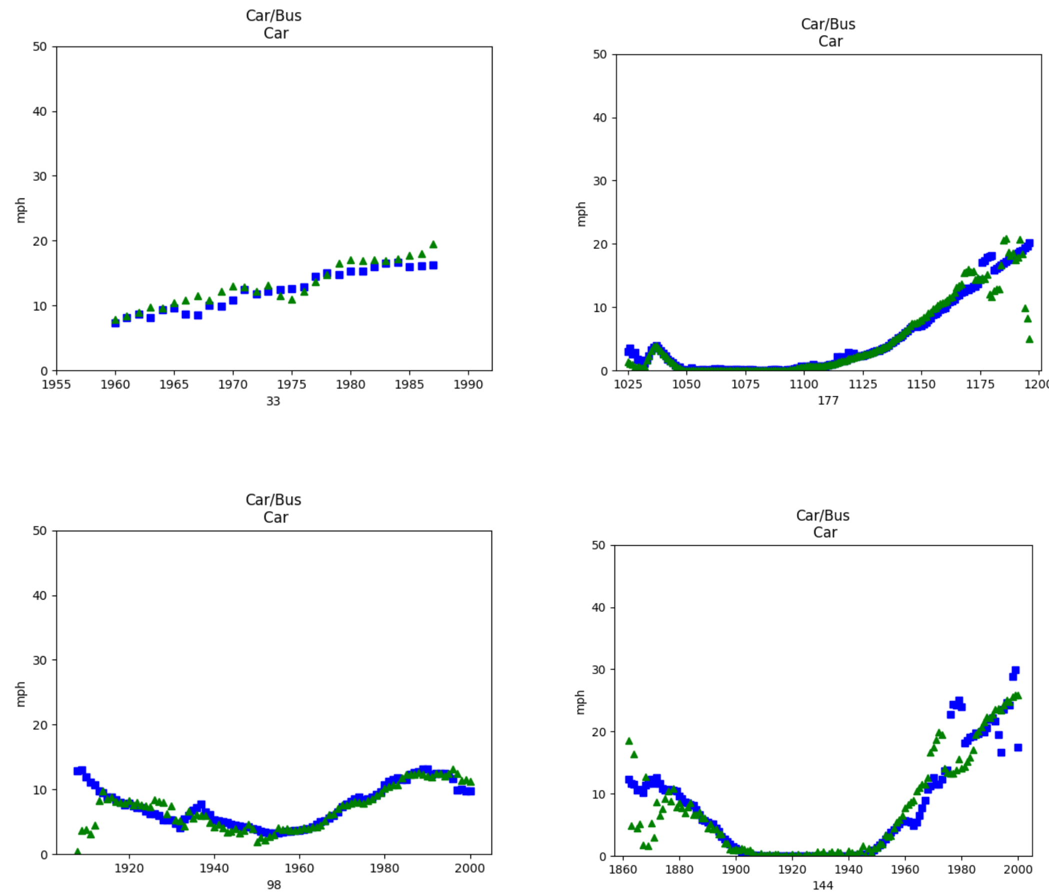

Figure 37 Some Correctly Identified Cars

Figure 38 contains the correctly identified pedestrians.

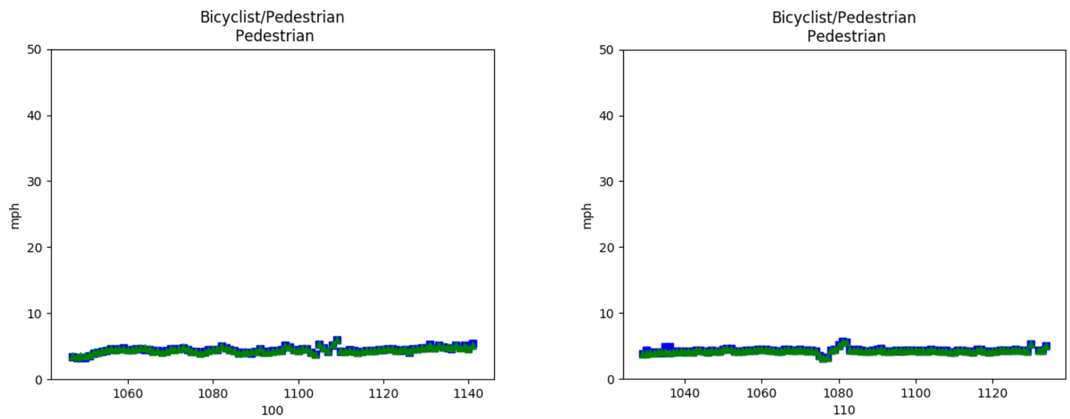

Figure 38 Both Pedestrians are Correctly Identified

Figure 39 contains the correctly identified buses.

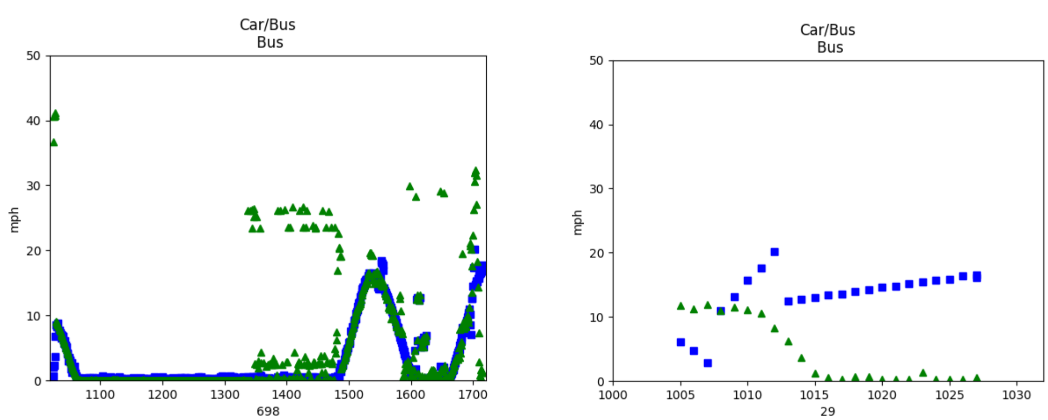

Figure 39 Both Buses are Correctly Identified

Among 38 objects, 35 objects were correctly classified. As the statistic suggests, the object recognition is not perfect. Figure 40 contains a group of wrong identified objects.

All these wrongly identification results are from the same scenario. The far-sensor vehicles are blocked by near-sensor vehicles; hence the shapes of these far-sensor vehicles are incomplete. Although these incomplete vehicles could still be tracked, the object recognition algorithm could not differentiate well when those incomplete vehicle's feature vectors are similar to bicyclist's feature vectors, as Figure 41 suggested. This problem could be solved by using additional features such as point features or local features in the future or just adding another LiDAR sensor to have a better shape of vehicles.

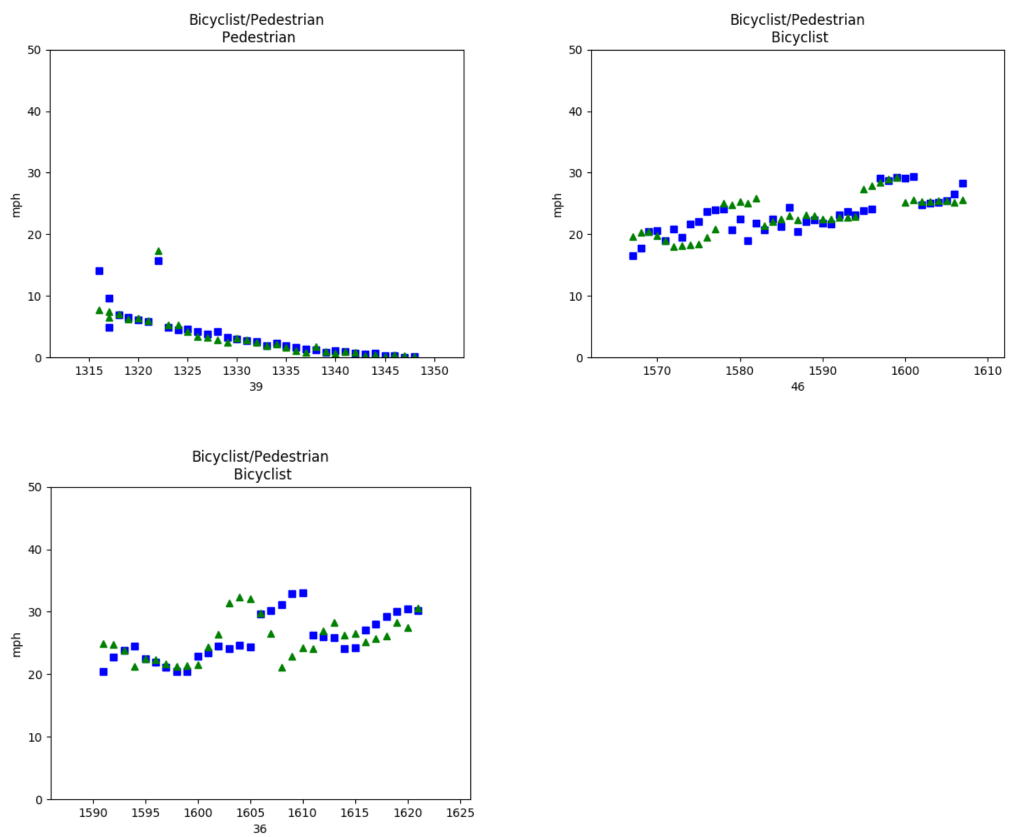

Figure 40 A Group of Wrongly Identified Vehicles

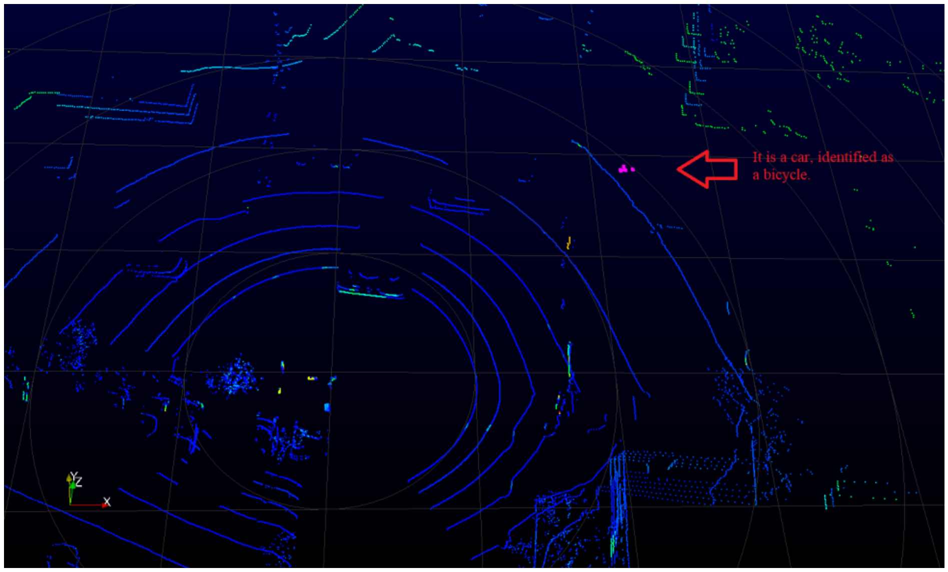

Figure 41 The Pink Vehicle Was Wrongly Identified as a Bicycle

In sum, in this research, with the global features and RBF kernel SVM classifier, the accuracy of identification is 35/38 = 92.1%. It should also be noted that using decision tree classifier would yield the same accuracy.

6. Possible Applications of Trajectory Data from a Roadside LiDAR

6.1 Connected Vehicles Research

The near future traffic would be mixed traffic between connected vehicles, and unconnected vehicles. The unconnected vehicles or pedestrians at the intersection can benefit from the high-frequency, real-time traffic data generated by this data processing framework directly. Figure 42 describes an example of this data processing framework. First, the roadside unit would detect the pedestrians. Then the detected location, speed, and direction would be sent to vehicles which might have a collision with the pedestrians. After the alert is received, the possible distracted driver would notice the pedestrians and pay attention to the pedestrians. Hence the pedestrians could be better protected. This communication procedure would not require every vehicle or pedestrian to be connected. Both unconnected vehicle and pedestrians could be perceived and protected.

Figure 42 Connected Vehicle Application Example

6.2 Traffic Safety

The Rectangular Rapid Flash Beacon (RRFB) is widely used in Reno, NV (Figure 43) to reduce crashes between vehicles. RRFB was designed to protect the pedestrians at un-signalized intersections or mid-block pedestrian crossings. These types of crossing are common in Reno, NV. The pedestrians need to push a button to activate the flash beacon, to notify the upcoming traffics their intention to cross the street. A report published by FHWA suggests that RRFB would increase the yield rate for drivers to pedestrians at St. Petersburg, Florida. However, some pedestrians are reluctant to push them when they are crossing the street. This behavior is especially dangerous at night time. The reason is that some drivers expect to see the flash beacon if pedestrians are crossing the street. If they do not see flash beacon, they will not slow down in middle block road segment. The RRFB could be upgraded to detect pedestrians if a LiDAR component was integrated automatically. The developed data processing procedure could also be applied here to improve traffic safety.

Figure 43 Currently Installed RRFB in Sutro Street, Reno, NV

The wildlife crossings signs could also be upgraded to a system similar to automatically RRFB. First LiDAR will detect the crossing wild animals; then the flashing beacon would notify the upcoming traffic (which is usually at high speed during rural highways), so the drivers would have more response time, and take necessary actions.

6.3 Mobility

In most cities, signal timing is revised every few years based on count data collected over two to three days. However, there are areas that traffic fluctuates tremendously because of concerts, sports games or growing communities. The fixed signal timing plan would not provide the ideal service for the intersections in those areas.

Traffic varies from month to month, week to week even within the same day of the week. A traffic plan that could make use of continuous detection vehicles would provide better performance. The data processing procedure developed in this research could be applied to this problem. The LiDAR could be installed at the intersection, and automatically perceive the vehicles on the road. The data processing procedure developed in this research has the capabilities to track how many vehicles turn left, how many vehicles go straight, how many vehicles turn right, and how many pedestrians crossing the street by days, hours, minutes even seconds. All of this real-time micro information could be adopted by traffic management agencies to provide a full picture of traffic management decisions.

6.4 Driving Cycle Development

Before conducting the LiDAR research, the author was involved in a driving cycle developed project based on Naturalistic Driving Study (NDS) data. Second-by-second speed data of different vehicles and different road conditions is required for driving cycle development. If a group of LiDAR sensors could be deployed along the road, the data processing procedure developed from this dissertation could directly retrieve speed profiles for every vehicle on the road. These speed profiles would significantly enhance the variety and accuracy of driving cycle development. By the time of this research was written, multiple LiDAR sensor deployments and data integration have already been tested. However, those LiDAR sensors are usually set up near the intersection, rather than along the road segment. It is possible that after integration of multiple roadside sensors data, we could generate more accurate driving cycles in particular road segment.

7. Summary and Future Research

The current connected-vehicle system relies on information broadcasted by each vehicle. However, not all the vehicles on the road will be connected. Therefore, supplemental data to help connected-vehicle to identify unconnected vehicles, pedestrians, bicyclists even skateboarders need to be considered and incorporated in such a system.

This research developed a data processing procedure for detection and tracking of multi-lane multi-vehicle speed trajectories with a roadside Light Detection and Ranging (LiDAR) sensor. Different from existing perception methods for the autonomous vehicle system, this procedure was explicitly developed to extract trajectories from a roadside LiDAR sensor. This procedure includes six steps. They are preprocessing of the raw data, statistical outlier removal, least median of squares-based ground estimation method to accurately remove the ground points, vehicle data clouds clustering, principal component-based oriented bounding box method to estimate the location of the vehicles and geometrically based tracking algorithm.

The developed procedure has been tested against the intersection of Evans Street and Enterprise Road; a two way stops sign intersection; and Kietzke lane, an arterial road with 40 mph speed limit at Reno, Nevada. Then, the data extraction procedure has been validated by comparing tracking results and speeds logged from a testing vehicle through the onboard diagnostics interface (OBD-I), at a parking lot of University of Nevada, Reno. The validation results suggest that the tracking speed matches real driving speed accurately.

A case study was conducted to examine the accuracy of tracking multiple objects on the roads. 1000 data frames from the intersection of 15th Street and Virginia Street at Reno, Nevada, was used as source data frames. The proposed data processing framework successfully tracked 37 objects out of 38 objects on the road, which gives an accuracy of 97.4%. Then a support vector machine based algorithm was developed to differentiate pedestrians/bicyclists and cars/buses. With Radial Basis Function (RBF) kernel, this algorithm correctly classifies 35 objects among 38 objects, which gives an accuracy of 92.1%. The result of this case study indicates that the proposed data processing framework has a satisfactory tracking and clustering accuracy which could be used for traffic micro information extraction.

This data processing procedure not only could be applied to extract high-resolution trajectories for connected-vehicle applications, but it could also be valuable to practices in traffic safety, traffic mobility, and fuel efficiency estimation. The ordinary Rectangular Rapid Flash Beacon (RRFB) could be upgraded to detect pedestrians automatically; this is especially important during night time. An adaptive traffic signal plan which could adapt to special events or economic changes also becomes feasible from this research. Driving cycle developments, which used to rely on sampling vehicles mainly, could become much more accurate because this research enables the possibilities to extract every vehicle’s speed profile. The driving cycle development procedures based on Naturalistic Driving Study (NDS) data is included as an essential reference for future driving cycle development based on NDS data. In sum, this research result provides a reliable way to extract high-resolution traffic data from a roadside LiDAR, and it would benefit research in connected vehicles, traffic safety, traffic mobility and fuel consumption estimation.

Future research first will investigate how to integrate multiple LiDAR sensors to extend the detection range. The extension of detection range requires additional algorithms to fuse multiple datasets into a single larger dataset. This larger dataset could provide tracking information in a large road segment. Another challenge is how to address rain or snow interference. The heavy rain or snow will introduce noises to the dataset. In extremely situation, it is even possible for them to make sensor detection range much smaller than pleasant weather. How to address this problem would be essential for deployment this system in areas regularly having these weather conditions. Finally, how to deliver the system output in real-time is also a key challenge. This is especially important if the future connected vehicles system requires limited response time.

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