



**PROTOTYPING AUTOMATED  
FRAMEWORK FOR ASSET  
EXTRACTION AND  
CHARACTERIZATION FROM MOBILE  
LIDAR DATA**

**Final Report**

**SPR 866**



Oregon Department of Transportation





# **PROTOTYPING AUTOMATED FRAMEWORK FOR ASSET EXTRACTION AND CHARACTERIZATION FROM MOBILE LIDAR DATA**

## **Final Report**

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by

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| 16. Abstract: To be able to handle the statewide mobile lidar data ODOT collects efficiently, there is a need for a robust workflow with significant automation that can extract many types of features by effectively leveraging various feature extraction tools and algorithms to support applications. In particular, road characterization has been identified as a key application for information extraction from mobile lidar data. In this literature review, the team first provides a brief overview of the model inventory of roadway elements (MIRE 2.0) to help identify the attributes that are of interest as well as feasible to extract from mobile lidar data. Next, a review of the existing commercial software summarizes the common challenges in using these solutions for feature extraction and characterization tasks. Lastly, the existing work related to road characterization is reviewed covering the topics of ground filtering and road extraction, cross slopes and grades, and horizontal curve, followed by a summary of the benefits of using mobile lidar data as well as the challenges of the existing studies. |                                                            |                                                                                                                                                                   |           |
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| Physical Quantity            | Symbol  | When You Know              | Multiply By              | To Find                     | Symbol      |
|------------------------------|---------|----------------------------|--------------------------|-----------------------------|-------------|
| Length                       | n       | inches                     | 25.4                     | millimeters                 | mm          |
| Length                       | ft      | feet                       | 0.305                    | meters                      | m           |
| Length                       | yd      | yards                      | 0.914                    | meters                      | m           |
| Length                       | mi      | miles                      | 1.61                     | kilometers                  | km          |
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| Area                         | ft2     | square feet                | 0.093                    | square meters               | m2          |
| Area                         | yd2     | square yard                | 0.836                    | square meters               | m2          |
| Area                         | ac      | acres                      | 0.405                    | hectares                    | ha          |
| Area                         | mi2     | square miles               | 2.59                     | square kilometers           | km2         |
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| Volume                       | gal     | gallons                    | 3.785                    | liters **                   | L           |
| Volume                       | ft3     | cubic feet                 | 0.028                    | cubic meters                | m3          |
| Volume                       | yd3     | cubic yards                | 0.765                    | cubic meters                | m3          |
| Mass                         | oz      | ounces                     | 28.35                    | grams                       | g           |
| Mass                         | lb      | pounds                     | 0.454                    | kilograms                   | kg          |
| Mass                         | T       | short tons (2000 lb)       | 0.907                    | megagrams (or "metric ton") | Mg (or "t") |
| Temperature (exact degrees)  | oF      | Fahrenheit                 | 5 (F-32)/9 or (F-32)/1.8 | Celsius                     | oC          |
| Illumination                 | fc      | foot-candles               | 10.76                    | lux                         | lx          |
| Illumination                 | fl      | foot-Lamberts              | 3.426                    | candela/m2                  | cd/m2       |
| Force and Pressure or Stress | lbf     | poundforce                 | 4.45                     | newtons                     | N           |
| Force and Pressure or Stress | lbf/in2 | poundforce per square inch | 6.89                     | kilopascals                 | kPa         |

\*SI is the symbol for the International System of Measurement

\*\* Volumes greater than 1000 L shall be shown in m<sup>3</sup>

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|------------------------------|-------------------|-----------------------------|-------------|----------------------------|---------------------|
| Length                       | mm                | millimeters                 | 0.039       | inches                     | in                  |
| Length                       | m                 | meters                      | 3.28        | feet                       | ft                  |
| Length                       | m                 | meters                      | 1.09        | yards                      | yd                  |
| Length                       | km                | kilometers                  | 0.621       | miles                      | mi                  |
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| Volume                       | m <sup>3</sup>    | cubic meters                | 35.314      | cubic feet                 | ft <sup>3</sup>     |
| Volume                       | m <sup>3</sup>    | cubic meters                | 1.307       | cubic yards                | yd <sup>3</sup>     |
| Mass                         | g                 | grams                       | 0.035       | ounces                     | oz                  |
| Mass                         | kg                | kilograms                   | 2.202       | pounds                     | lb                  |
| Mass                         | Mg (or "t")       | megagrams (or "metric ton") | 1.103       | short tons (2000 lb)       | T                   |
| Temperature (exact degrees)  | oC                | Celsius                     | 1.8C+32     | Fahrenheit                 | oF                  |
| Illumination                 | lx                | lux                         | 0.0929      | foot-candles               | fc                  |
| Illumination                 | cd/m <sup>2</sup> | candela/m <sup>2</sup>      | 0.2919      | foot-Lamberts              | fl                  |
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For More Information see: <https://www.fhwa.dot.gov/publications/convtabl.cfm>



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Dr. Che has financial interests in EZDataMD LLC, a company which commercializes point cloud analysis technology related to this research. The conduct, outcomes, or reporting of this research could benefit EZDataMD LLC and could potentially benefit Dr. Che.





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# **1.0 INTRODUCTION**

## **1.1 PROBLEM STATEMENT**

ODOT Geometronics operates a survey-grade mobile lidar system to regularly collect point cloud data on roadways statewide. Detailed point-cloud data are captured along with video enabling ODOT to not only see a video of the road similar to Google Street View but also obtain very precise measurements of surrounding features of interest. ODOT's investment in mobile lidar has provided a substantial return on investment (Martin et al., 2020). The lidar data supports a wide number of projects and applications, including asset management, sight distance evaluations, pavement and marking evaluations, landslide monitoring, and accident reconstruction. The entire state highway system is typically scanned on a two-year interval, but Geometronics also supports special-purpose projects with the mobile lidar as needed. For asset management and infrastructure monitoring, mobile lidar data provides rich information (e.g., position, orientation, geometry, condition, etc.) of road features, such as road surfaces, road markings, lamp poles, buildings, curbs, sidewalks, driveways, and so forth. While the data collection process is highly efficient and streamlined, manual extraction of features from the data to support ODOT's needs is generally time consuming, subjective, and error prone, especially when analysts lack proper training on the wide range of processing techniques and software.

Although some tools exist for semi-automated extraction of a specific feature (e.g., road markings) from lidar data and have been implemented on a project-by-project basis, they can sometimes require training. Depending on the features and data quality, the performance can rely on user input and fine-tuning. As a result, many tools are not feasible to apply to in statewide asset management programs and do not necessarily provide the desired attributes. Moreover, such tools are usually developed specifically for a certain object (or limited number of objects). Currently, there are no well-defined workflows for data processing and information extraction that can integrate multiple tools together. Simply stacking the tools in the workflow can result in a tremendous amount of duplicated effort and reduces its scalability. To be able to handle the statewide mobile lidar data ODOT collects efficiently, there is a need for a robust workflow with significant automation that can extract many types of features by effectively leveraging various feature extraction tools and algorithms to support applications. In particular, road characterization has been identified as a key application for information extraction from mobile lidar data.

## **1.2 BACKGROUND AND SIGNIFICANCE OF WORK**

The geomatics research team from Oregon State University (OSU) has completed several research projects with ODOT and other funding agencies (e.g., PacTrans, National Science Foundation) focused on leveraging mobile lidar data in a variety of applications including road marking evaluation (SPR799), sight distance analysis, curb ramp assessment (SPR844), rockslope stability analysis (SPR809), road roughness assessment (SPR744), and an in-progress project to extract bike lane and crosswalk inventory (SPR850). During these projects, the team

comprehensively reviewed and documented the state of the art of object recognition, segmentation, and classification of mobile lidar data (Che et al., 2019b) as well as developed a series of automated tools (e.g., Che et al., 2019a, Jung et al., 2019, Che et al., 2024) to support mobile lidar data processing. Although these tools are highly functional and versatile, in their current state, these standalone research tools need to be adapted to support a broader range of applications and expanded to provide additional information to support ODOT's analysis needs. To overcome this challenge, an efficient framework that efficiently and effectively implements a feature extraction and characterization algorithms or methods for a variety of transportation assets is required.

### **1.3 OBJECTIVES OF THE STUDY**

Given the large volume of mobile lidar data and the complexity of the scenes, manual processing is tedious, time-consuming, and requires expertise in lidar technology, particularly given that most software is limited in automated feature extraction. Such cost in resources and time results in missed opportunities and limits the full potential of the data collected. Because accurate asset information is fundamental to maintaining safe roadways, any process which eases the burden of manual data collection, design work, and analysis is all required to support improved safety and operations of ODOT's highway network.

To overcome such challenges, an efficient data processing framework including some specific feature extraction and supporting analysis algorithms need to be developed. This research developed a prototype mobile lidar data processing framework that can be seamlessly integrated into ODOT's current workflows. The framework includes the following components:

- General data processing procedures, such as ground filtering that separates the ground and non-ground points, and road detection, were implemented and tested by the research team to automatically classify the mobile lidar point cloud data.
- A detailed characterization of the road surface (e.g., horizontal and vertical curve parameters, cross section parameters, etc.) can be computed from the mobile lidar trajectory data as well as the roadway detection results in the point cloud. Some characteristics include curve type, curve center and radius, curve start and end points, slope of cross sections and so on.
- Integration of existing feature extraction approaches (e.g., ROME road marking extraction, VROOM road surface detection, curb extraction) developed by the research team in previous projects into this framework to enhance performance by taking advantage of the information extracted from each step of the process. For instance, the road marking extraction tool can benefit from the data that has gone through ground filtering and road detection processes to improve its robustness and accuracy.
- For other features (e.g., lamp posts, guardrails), the team also explored automated solutions leveraging machine learning approaches for feature extraction. The impact of the training datasets was also discussed in the context of real-world applications.

The proposed framework is designed in such a way that the result of road extraction and characterization of each type of feature can be stored in the point cloud for future use as well as feature objects in a GIS database that can be incorporated into ODOT's TransGIS platform to support inventory assessment, advanced spatial analysis, and performance reporting. Ultimately, this framework will enable the rich, up-to-date information to be readily available across ODOT and its partners. It is worth noting that ODOT operated a Leica Pegasus: Two for the data collection when the project started. Later it was replaced with a Riegl VMX-2HA which is an enhancement of the data acquisition capability in terms of efficiency, accuracy, and resolution. While the methods and tools were primarily developed for the Leica mobile lidar system, they will work for the Riegl system as well. To achieve the same or higher performance, additional fine-tuning and minor modification might be needed.



## **2.0 LITERATURE REVIEW**

### **2.1 OVERVIEW**

This literature review is organized as follows. First, a brief overview of the model inventory of roadway elements (MIRE 2.0) is provided to help identify the attributes that are of interest as well as feasible to extract from mobile lidar data. Next, a review of the existing commercial software summarizes the common challenges in using these solutions for feature extraction and characterization tasks. Lastly, the existing work related to road characterization is reviewed covering the topics of ground filtering and road extraction, cross slopes and grades, and horizontal curve, followed by a summary of the benefits of using mobile lidar data as well as the challenges of the existing studies.

### **2.2 MODEL INVENTORY OF ROADWAY ELEMENTS (MIRE 2.0)**

The Model Inventory of Roadway Elements (MIRE 2.0, FHWA 2017) is a guideline developed by the FHWA of data elements to support a comprehensive roadway and traffic data inventory primarily focused on data-driven safety management applications. The importance of geospatial location information to integrate the many elements is stressed. In particular, this information is important to meet requirements outlined in the All Road Network of Linear Referenced Data (ARNOLD) memorandum by the FHWA in 2012. MIRE identifies several elements as Fundamental Data Elements (FDEs) which have been legislated in the MAP-21 and FAST Acts. In the MIRE data dictionary, elements are categorized into six data types: Segment, Intersection, Intersection Leg, Interchange/Ramp, Horizontal Curve, and Vertical Grade.

Mobile lidar can provide information to support the development and updating of these databases. Table 2.1 summarizes the MIRE data elements associated with the segment data type, and Table 2.2 provides the descriptions of complexity rating to extract the attributes associated with the elements. Each element information attribute has been categorized into an element information category by the research team for clarity. The table also identifies which elements fall within the scope of research projects SPR850 and SPR866 and potential methods to obtain this information from mobile lidar. Complexity ratings to describe the likely level of automation or difficulty in extracting the metric from mobile lidar data are provided. These ratings are defined in Table 2.3. Lastly, potential issues are identified. For the Intersection, Intersection Leg, and Interchange/Ramp Element Data Types (II-IV), many of the element attributes were outside the scope of SPR866 or not readily obtained with mobile lidar data.

**Table 2.1: MIRE data elements associated with the Horizontal Curve and Vertical Grade data types.**

| <b>MIRE 2.0 Data Type</b> | <b>Element Information Category</b> | <b>Element Information Attribute</b>             | <b>Potential Method(s) to obtain information</b>                                      | <b>Complexity Rating</b> | <b>Potential Issues</b>                                                                                              |
|---------------------------|-------------------------------------|--------------------------------------------------|---------------------------------------------------------------------------------------|--------------------------|----------------------------------------------------------------------------------------------------------------------|
| V. Horizontal Curve       | Geometry                            | 193. Curve Identifiers                           | Obtained through a GIS analysis based on milepost layers                              | 1                        |                                                                                                                      |
| V. Horizontal Curve       | Geometry                            | 194. Curve Feature Type                          | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        |                                                                                                                      |
| V. Horizontal Curve       | Geometry                            | 195. Horizontal Curve Degree or Radius           | Can be extracted from basic mathematical function fitting to extracted lane markings. |                          |                                                                                                                      |
| V. Horizontal Curve       | Geometry                            | 196. Horizontal Curve Length                     | Can be extracted from basic mathematical function fitting to extracted lane markings. |                          |                                                                                                                      |
| V. Horizontal Curve       | Geometry                            | 197. Curve Superelevation                        | Extract from cross sections.                                                          | 0                        |                                                                                                                      |
| V. Horizontal Curve       | Geometry                            | 198. Horizontal Transition/Spiral Curve Presence | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Spiral curves, especially the starting point, may be difficult to detect given subtle changes in curvature at start. |

| <b>MIRE 2.0 Data Type</b> | <b>Element Information Category</b> | <b>Element Information Attribute</b>                | <b>Potential Method(s) to obtain information</b>                                      | <b>Complexity Rating</b> | <b>Potential Issues</b>                                                                                              |
|---------------------------|-------------------------------------|-----------------------------------------------------|---------------------------------------------------------------------------------------|--------------------------|----------------------------------------------------------------------------------------------------------------------|
| V. Horizontal Curve       | Geometry                            | 199. Horizontal Curve Intersection/Deflection Angle | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Spiral curves, especially the starting point, may be difficult to detect given subtle changes in curvature at start. |
| V. Horizontal Curve       | Geometry                            | 200. Horizontal Curve Direction                     | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Spiral curves, especially the starting point, may be difficult to detect given subtle changes in curvature at start. |
| VI. Vertical Grade        | Geometry                            | 201. Grade Identifiers and Linkage Elements         | Obtained through a GIS analysis based on milepost layers                              | 1                        |                                                                                                                      |
| VI. Vertical Grade        | Geometry                            | 202. Vertical Alignment Feature Type                | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Vertical angle points may be difficult to detect (assuming the change in grade is very small)                        |
| VI. Vertical Grade        | Geometry                            | 203. Percent of Gradient                            | Can be extracted from basic mathematical function fitting to                          | 0                        | Vertical angle points may be difficult to detect                                                                     |

| <b>MIRE 2.0 Data Type</b> | <b>Element Information Category</b> | <b>Element Information Attribute</b> | <b>Potential Method(s) to obtain information</b>                                      | <b>Complexity Rating</b> | <b>Potential Issues</b>                                                                       |
|---------------------------|-------------------------------------|--------------------------------------|---------------------------------------------------------------------------------------|--------------------------|-----------------------------------------------------------------------------------------------|
|                           |                                     |                                      | extracted lane markings.                                                              |                          | (assuming the change in grade is very small)                                                  |
| VI. Vertical Grade        | Geometry                            | 204. Grade Length                    | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Vertical angle points may be difficult to detect (assuming the change in grade is very small) |
| VI. Vertical Grade        | Geometry                            | 205. Vertical Curve Length           | Can be extracted from basic mathematical function fitting to extracted lane markings. | 0                        | Vertical angle points may be difficult to detect (assuming the change in grade is very small) |



**Table 2.2: Complexity Rating Descriptions**

| <b>Complexity Rating</b> | <b>Description</b>                                                                       |
|--------------------------|------------------------------------------------------------------------------------------|
| 0                        | Basic metric to extract once data are labeled/classified directly from mobile lidar data |
| 1                        | Basic metric to obtain in a GIS analysis once object is extracted                        |
| 2                        | Potentially could be extracted with advanced algorithm, may require supplemental data    |
| 3                        | Likely will require a semi/automated or manual approach to extract                       |

## 2.3 EXISTING SOFTWARE

The emerging market for road feature extraction with lidar data continues to grow as more industries and government organizations seek ways to use point clouds for efficient road maintenance. There have been many efforts to develop solutions within the industry for automated and efficient road feature extraction. In this section, the research team provides a brief overview of existing commercial solutions for roadway feature extraction (Table 2.3). It is worth noting that given the scope of this project, the review mostly focuses on a few technical aspects including the input data, supported features, extraction methods, platforms, and result formats. Additionally, the information acquired in this review is only based on publicly available information.

While some software solely uses image data (e.g., *Blynscy-Payver* with dashcam footage as input), many solutions take mobile lidar data as a primary input with image data as a secondary source. For example, some solutions such as *PILLAR* and *TopoDOT*, use both MLS and image data for feature extraction. *Voxelmap* uses lidar and image data obtained from various platforms, such as satellites, manned aerial and unmanned platforms, mobile sensors, and wearable devices.

The common features that these software solutions support include lane markings, curbs, signs, and road surfaces. In addition, *Voxelmaps*, *Outsight*, and *Leica* are able to detect moving objects from the scene such as vehicles. Some solutions such as *Blynscy* features approaches that can assess the pavement condition by detecting and evaluating cracking, striping, and potholes. Additionally, software such as *PILLAR* provides tools that can perform more quantitative measurements and evaluations such as calculating areas, volumes, and so on.

As to the extraction methods, machine learning has become a common choice within industry solutions. Particularly, the use of deep learning is continuing to grow in road feature extraction (*Blynscy* and *Voxelmaps*), as it enables training of a much more complex model than ordinary learning models to tackle complicated tasks. Meanwhile, some solutions (*TopoDOT* and *Trimble*) provide semi-automated methods. For example, Trimble Business Center provides a tool that allows the user to pick and trace solid lane markings from point cloud data. *Outsight Augmented Lidar Box* provides a real-time, learning-less classification for the point cloud data.

While some software packages offer standalone applications, more solutions serve as a plugin to a larger and broader platform to fit into the working climate. For example, *TopoDOT* is often run

as a plugin on *Bentley's MicroStation* while Trimble's line feature extraction tool is available in *Trimble Business Center*. On the other hand, *Blynco* provides a cloud-service platform, named *Payver*, enabling easy access to the solution.

The processed results are provided in various formats. *Voxelmap* provides options to export outputs in various file formats, including Shapefile, NDS, GeoJSON, and XML. *PILLAR* exports outputs in standard GIS formats, such as Shapefiles and geodatabases. It also provides data visualizations using colorized point clouds, JPG, and video file formats. *Outsight* provides a point-wise classification of point cloud data in real-time. *TopoDOT* enables users to extract and save features in GIS/CAD formats.

CalTrans also conducted a preliminary investigation into the automated lidar feature extraction software recently in 2021 (Yen, 2021) including a more detailed breakdown of different types of features (e.g., line features, point features). The research covered software including *Atlas Survey Control Centre (SCC) Point Cloud Module*, *Bentley Descartes*, *Certainty 3D TopoDOT*, *Esri ArcGIS desktop and ArcGIS Pro*, *EZDataMD LidarTools*, *InnovMetric PolyWorks Surveyor*, *Leica Cyclone Suite*, *Rapidlasso LASTools*, *Terrasolid Suite*, *Trimble Business Center (TBC) Point Cloud Module*, as well other open-source software including *CloudCompare* and *Point Data Abstraction Library (PDAL)*. Additionally, the study also conducted interviews with 19 DOTs and 6 consultants via a survey questionnaire. The study highlighted the importance of having a workflow in place to handle the data compatibility with minimal information loss when adopting new software as well as the cost associated with it (e.g., training, licensing, maintenance, data storage, data transferring, etc.). In particular, the report pointed out

*“Extraction is largely a manual process undertaken by our internal survey teams with little support or provision from GID, as they confirm they do not have the current skill base or capacity to support processing of these mass datasets. We are looking for that step up in automation to help speed up our extraction processes whilst maintaining the level of quality and completeness our clients expect in terms of topographical outputs.”*

Having reviewed the recent commercial solutions, the research team found there are few technologies that have proved fully functional models through robust and reliable validations. Though deep learning is powerful, generalization is still one of the fundamental unsolved problems, and it has not been fully addressed in commercial solutions. Considering varying road conditions from location to location, commercial solutions may need to be retrained each time new data becomes available. On the other hand, although some solutions offer functionalities to process different types of data (e.g., images or point cloud), the extraction analyses are usually not combined, and it is unclear how the resulting features are integrated and registered in a final product. Lastly, many approaches have not proven their flexibility, and therefore, they may not integrate effectively into ODOT's workflow for a state-wide task.

**Table 2.3 Summary of the commercial products for automated (or semi-automated) roadway feature extraction**

| Company         | Link                                                                                                                                                                                                              | Data                         | Features                                                                                           | Method                             | Notes                                                                     |
|-----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------|----------------------------------------------------------------------------------------------------|------------------------------------|---------------------------------------------------------------------------|
| Blynscy         | <a href="https://blynscy.com/payver/">https://blynscy.com/payver/</a>                                                                                                                                             | Image (Dash cam footage)     | Signs, curb, crack, stripe conditions, potholes, cones, etc. (about 50 features)                   | Machine learning (deep learning)   | Cloud-service                                                             |
| Voxelmaps       | <a href="https://www.voxelmaps.com/products/voxelmaps-insight-platform">https://www.voxelmaps.com/products/voxelmaps-insight-platform</a>                                                                         | Lidar (TLS, ALS, MLS), image | Moving objects, road assets                                                                        | Machine learning (deep learning)   | Add-on to Voxelmaps Insight Platform Export shape, NDS, GeoJSON, and XML. |
| PILLAR          | <a href="https://www.pillaroma.com/collection/#auto">https://www.pillaroma.com/collection/#auto</a>                                                                                                               | MLS, image                   | Signs, guardrails, trees, bridge clearances, mowing acreage, striping, ditches, overhead utilities | Machine learning                   | Export GIS formats, Shapefiles, geodatabases                              |
| Orbit / Bentley | <a href="https://orbitgt.com/products/3dm-feature-extraction/">https://orbitgt.com/products/3dm-feature-extraction/</a>                                                                                           | MLS                          | Points, polylines, catenary curves, areas, volumes, circles<br><br>Poles, traffic signs, shapes    | Fully automated<br>Semi-automated, | Desktop application                                                       |
| Outsight        | <a href="https://www.outsight.ai/features">https://www.outsight.ai/features</a>                                                                                                                                   | MLS                          | Ground, road surface, road markings, vegetation, vehicles                                          | learning-less classification       | Point-wise classification, real-time                                      |
| Leica           | <a href="https://leica-geosystems.com/en-us/products/mobile-mapping-systems/software/leica-pegasus-manager">https://leica-geosystems.com/en-us/products/mobile-mapping-systems/software/leica-pegasus-manager</a> | MLS                          | Roads, pavements, buildings, low and high vegetation, street furniture, and moving objects         | Machine learning                   | Add-on (road:factory) to Leica Pegasus:Manager desktop application        |
| TopoDOT         | <a href="https://new.certainty3d.com/workflow/extract">https://new.certainty3d.com/workflow/extract</a>                                                                                                           | MLS + image                  | break-line elements such as pavement edges, ditches,                                               | Semi-automated                     | Add-on to Bentley's MicroStation                                          |

| Company | Link                                                                                                                                                                                                                    | Data | Features                                                                                | Method             | Notes                                                     |
|---------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------|-----------------------------------------------------------------------------------------|--------------------|-----------------------------------------------------------|
|         | /processSection                                                                                                                                                                                                         |      | curbs, bridges,<br>drain inlets<br>road surface,<br>ground, signs,<br>poles, guard rail |                    | Export CAD<br>outputs                                     |
| Trimble | <a href="https://community.trimble.com/blogs/hannah-poon/2022/01/05/solid-double-lane-line-feature-extraction">https://community.trimble.com/blogs/hannah-poon/2022/01/05/solid-double-lane-line-feature-extraction</a> | MLS  | solid single, solid<br>double, and/or<br>dashed lane<br>markings                        | Semi-<br>automated | Trimble<br>Business<br>Center –<br>desktop<br>application |

## 2.4 ODOT PROCEDURE

In the past, ODOT heavily relied on manual data processing for most of the feature extraction jobs, posing a substantial barrier to the scope and scale of the use of mobile lidar data. Fortunately, recently Geometronics has become the first group in ODOT to adopt *TopoDOT* and other software which support extraction for a wide variety of transportation assets with a semi-automated workflow.

Taking the road surface as an example, features, such as road edges/curbs, gutters, and so on, can be extracted and stored as the breaklines that can be presented in the data products (e.g., TIN digital terrain models). Then other features, such as the guardrails and striping, can be added as line features while arrow markings, traffic signs, lampposts can be stored as point features where different attributes can be attached to the vertices in a table. The software serves as a plugin in Bentley Microstation platform, which can streamline the data delivery to maximize the compatibility for the other groups that use the same platform for design and analysis.

The overall pipeline of the software is designed to extract individual types of objects and result in vectorized features (e.g., vertices, linework, etc.) under users' supervision. Thus, the algorithms and approaches vary on different objects resulting in different levels of required manual involvement and performance. For instance, for striping extraction, the data can be filtered by intensity value to highlight the road markings. Then the users will provide manual input to guide the algorithm to track the road markings and generate line features. For other features, template matching and parametric processing are usually involved as well, and users usually have the flexibility to adapt the parameter settings and/or intervene in the extraction tasks. Regarding the road characterizations, there are related functions in the software, but such tasks are usually performed by the design team in other software plugins such as OpenRoads Designer.

Although software such as *TopoDOT* significantly improves ODOT's efficiency and productivity in utilizing mobile lidar data, there are still a few challenges:

While the workflow reduces the data to linework, vertices, and TIN models, information loss is inevitable because these data products are not inherently mapped to their source point cloud data.

Such workflow is only suitable for a local project. There is a limit for how much data can be handled at once, which makes it challenging for tackling statewide data/projects. Part of it is due to the limitation of the *Microstation* platform.

The performance of the automatic approaches can be heavily impacted by point density and noise/undesired points. Such issues can be addressed by user interventions, but for artifacts occurring throughout the data, an extensive manual process is needed.

The workflow is designed to get around point cloud classification, which has its strength and advantages. Nevertheless, importing a pre-classified point cloud can potentially reduce the data volume and improve efficiency. The classification of the mobile lidar point cloud data can also benefit the data re-use by reducing duplicate data processing.

## **2.5 EXISTING RESEARCH**

### **2.5.1 Ground filtering and road extraction**

Ground filtering is a common stage for processing mobile lidar data which separates the ground and non-ground points. Such a process would make the following classification and feature extraction for other transportation assets such as road extraction and lamp posts because (1) the ground filtering adds semantic information to the dataset which can be leveraged to classify other objects; (2) the data volume can be substantially reduced for the following process. There are a number of papers over the years that have provided literature reviews and discussions on feature extraction from mobile lidar data (Puente et al., 2013, Williams et al., 2013, Guan et al., 2016, Gargoum et al., 2017, Wang et al., 2018, Ma et al., 2018). The research team also published a literature review that covers the state-of-the-art in object recognition, segmentation, and classification of mobile lidar point clouds (Che et al., 2019). Since then, in the most recently completed ODOT SPR-850 project, the research team has also reported a detailed literature review on ground filtering and road extraction including the prior research conducted by the team. Thus, the following section only covers the more recent studies.

Xu et al. (2022) projected the 3D point cloud data into rasters and tested a number of image clustering/segmentation algorithms as well as deep learning in road feature classification in ArcGIS in an effort supported by the Nevada Department of Transportation. They reported that the occlusion, low-density areas, and low contrast of intensity can be challenging for adopting those 2D image processing techniques. Additionally, Fernández-Arango et al. (2022) proposed a workflow to create terrain models for the ground surface to support pedestrian analysis. In their workflow, the mobile lidar point cloud is first filtered based on the scan angle rank and the number of returns and outliers. Then the ground filtering takes place to extract the ground surface points by filtering the data progressively based on elevation and normal vector. To cope with the low-density area, the Inverse distance weighted (IDW) is implemented to interpolate the DTM generated from the ground points. More broadly, Chen et al. (2022) conducted a survey for road extraction in remote sensing data including a variety of data sources such as aerial and satellite images, SAR images, and lidar point clouds. Regarding mobile lidar data, some methods have succeeded in taking advantage of the camera images from the mobile mapping system while an increasing number of studies are focusing on applying deep learning framework in extracting road surface.

### **2.5.2 Horizontal Curve**

Horizontal curves are critical components of the roadway in their role as a transition between straight segments. Determining the precise characteristics of curves including location, length, and radius can be crucial to mitigating the potential safety hazard to motorists (Hans et al., 2009; Rasdorf et al., 2012). To achieve this objective, a number of studies have been reported focusing on measuring these characteristics via various techniques and equipment such as field survey, GNSS, inertial system, GIS roadway maps, satellite imagery, mobile mapping/lidar systems, and airborne lidar systems, and so on. Findley et al., (2013) conducted a review to compare different techniques for collecting horizontal curve data.

Although a conventional field survey with survey equipment such as total station and GNSS receivers can provide very accurate data that can be used to calculate the curve characteristics, it can be labor-intensive and time consuming and more importantly, having the survey crews work on the road or roadside pose safety concerns. Fortunately, mounting GNSS receivers on a moving platform such as a vehicle and collecting the data in a relatively high frequency (typically 1 Hz or higher) makes the data acquisition much more efficient where the geolocations of the measurements on the road can be directly translated to GIS platforms to create or update the asset inventory (Breyer, 2000; Cheng et al., 2008; Souleyrette, 2011; Li et al., 2012; de Frutos and Castro, 2014). Then the characteristics of the curve can be computed in the same way as in conventional survey methods except that the errors in the GNSS measurements need to be taken into account (Imran et al., 2006; Karamanou et al., 2009; Jiménez et al., 2009). Such a process can also be automated to a large degree (Li et al., 2012).

To further improve the accuracy of the GNSS measurements (typically a few centimeters), additional sensors can be integrated into the mobile mapping system such as inertial measurement unit (IMU) and distance measuring instrument (DMI). Moreover, other remote sensing sensors (e.g., lidar scanners, cameras) can also be added to the system to be able to collect more information that can all be georeferenced. Nevertheless, it is worth noting that the GNSS-based positioning still heavily relies on sky visibility. As a result, such systems can suffer from long tunnels or tree canopies that block the satellite signals. As discussed in the previous section on measuring cross slopes and grades, the trajectory data from the system by combining GNSS, IMU, and DMI measurements can be a good source for obtaining the horizontal alignment of the road surface (Yun and Sung, 2005; Ai and Tsai, 2015; Luo and Li, 2018).

Another way of extracting the horizontal alignment of the curve is to take advantage of point cloud data acquired by the mobile lidar systems. The concept is the same as the one discussed in extracting cross sections and longitudinal profiles where the road markings can serve as the reference to help determine the roadway's alignment. The trajectory data can provide an initial estimation of the orientation of the road to help filter out the transverse stripes. For example, Holgado-Barco et al. (2015) presented a semiautomatic algorithm to extract the road horizontal alignment from mobile lidar point cloud data. In addition, Martín-Jiménez et al. (2018) proposed a workflow to utilize road markings to automatically extract the circular arcs, straight lines, and clothoids for risk assessment. More recently, Zhang et al. (2019) proposed a method to optimize the curve fitting from the road marking extraction result by adopting a hull detection process to reconstruct the curve to address the potential errors in using the points on the stripes due to the variant point density and wear of the markings.

There are some other studies taking advantage of the video logs or images collected by the mobile mapping system to recognize the road surface, road markings, and other features using image processing techniques (e.g., Marinelli et al., 2017). Nonetheless, the image quality can vary drastically based on various factors such as lighting conditions, calibration accuracy, occlusions, and so on. It is also worth noting that there are some studies using airborne lidar data to extract the road surface and its characteristics (e.g., Zhang et al., 2003; Zhou et al., 2021). However, the relatively low accuracy and resolution of the airborne lidar data can be challenging because (1) it can be difficult to recognize the features to define the road alignment; (2) the measurement might not be sufficiently precise to derive accurate characteristics.

Because the horizontal alignment of the roadway does not require vertical measurement or elevation information, other approaches utilizing high-resolution satellite imagery can also be effective in characterizing the horizontal curves. To recognize the roadway from the images, a wide variety of computer vision and image processing algorithms have been developed to support the following extraction of the road horizontal alignment (Easa et al., 2007; Tarel et al., 2007; Dong et al., 2007). The extraction result is often directly imported into GIS database for calculation and inventory (Martinelli et al., 2009; Li et al., 2012). Rasdorf et al. (2012) evaluated different GIS-based methods and tools for curve analysis including Curvature Extension, Curve Calculator, and Curve Finder, available in ArcGIS and developed by some state DOTs (Florida DOT, New Hampshire DOT), respectively. One limitation of using high-resolution satellite imagery is that it can be difficult to obtain accurate results in urban areas due to a lot of occlusions caused by bridges and buildings.

### **2.5.3 Cross slopes and grades**

Longitudinal slopes along the road are known as grades which are considered a significant factor influencing vehicle performance such as real-world emissions of light duty vehicles (Bae et al., 2001, Zhang et al., 2006). Cross slopes which are known as superelevation on horizontal curves usually are designed to improve roads and drivers' safety by accelerating the drainage of water on highways and preventing hydroplaning; likewise, these slopes can control lateral vehicle wandering by counteracting centrifugal forces (Gargoum et al., 2018, Tsai et al., 2013, Shams et al., 2018). Nonetheless, cross slopes that are too steep can cause vehicles to drift, skid laterally when braking, and become unstable. Thus, there is a need for transportation agencies to identify roadway sections that do not meet minimum criteria, which requires accurate slope measurements (Shams et al., 2018). Because the characteristics of the road surface can be different from the roadway design due to construction quality, wear, damage, or other events, it is necessary to capture the as-built data periodically to update the road inventory. A variety of techniques can be used for acquiring these characteristics of the roadway including conventional surveying, remote sensing data such as USGS digital elevation models (DEMs), a mobile inertial system, photogrammetry with high-resolution stereo images, GNSS measurements, lidar systems such as aerial, mobile, and terrestrial laser scanning (Souleyrette et al., 2003, Baffour and Robert, 2002). Factors such as accuracy, safety, cost, and efficiency play important roles in the selection of one method over another (Baffour and Robert, 2002).

#### **2.5.3.1 *Conventional surveying***

Conventional surveying methods provide very accurate results in measuring grades and cross slopes of the road. Direct measurements of these slope characteristics could be achieved using a digital level and rod, total station and prism, slope meter, or digital inclinometer (e.g., smart level). However, these approaches can be very time-consuming (especially for short intervals or large areas) and pose safety risks to personnel due to the close proximity to traffic (Souleyrette et al., 2003). That being said, the conventional surveying data can still serve as reference data to verify and evaluate the performance of the emerging technologies in characterizing the roadways given their high accuracy and precision.



#### **2.5.3.2     *Photogrammetry***

Compared to conventional surveying, photogrammetry as a remote sensing technique, is able to capture the geometry of the road surface in high resolution and accuracy from an aerial platform (e.g., airplane, UAV) with minimal traffic control and crews working on the road. For example, a DEM can be generated to determine the elevations and grade of the roadways alongside the orthophoto providing more texture information (Zhang et al., 2006). Burgett et al. (2021) investigated whether the use of commercially available UAVs and software could create surveys to be used for preconstruction surveys. Although the authors argued that state departments of transportation could potentially use UAVs in the creation of preconstruction surveys, collecting high-resolution aerial imagery and ground controls can be expensive and time consuming to produce reasonable cross-slope accuracy, especially when a large area needs to be covered on a regular basis (Souleyrette et al., 2003). Cassule et al. (n.d.) proposed a semi-automated workflow for measuring cross slope and the study result shows that mobile lidar and UAV photogrammetry provides more accurate results than UAV-lidar systems. In the data processing, the pavement edges, lane lines, and centerlines are identified and used to extract the road surface. Then the cross section can be defined with a given buffer (e.g., 4 inches) and used to calculate the cross slope. It is also worth noting that the lighting condition and texture of the pavement can significantly affect the data quality (Simpson, 2018).

#### **2.5.3.3     *GNSS***

Baffour and Robert (2002) discussed the use of multi-antenna configurations that are synchronized with a single global positioning system (GPS) receiver to determine the 3D orientation of the moving vehicle. Furthermore, the GPS data need to be post-processed against a base station (a process known as post-processing kinematic, PPK) and filtered to remove outliers (Zhang et al., 2006). Di Mascio et al. (2012) presented a procedure to determine the geometry of horizontal and vertical road alignment using GNSS receivers where the center line was estimated for determining the cross slopes with least squares optimization. Bae et al. (2001) tested and compared two methods for estimating the road grade using a GPS system mounted on a vehicle. Similarly, Lakakis et al. (2013) developed a low-cost mobile system that integrated two GNSS receivers aligned perpendicular to the driving direction that could obtain the horizontal and vertical alignment of a road at the same time.

#### **2.5.3.4     *Lidar***

Lidar technology has also been widely used in extracting cross slopes and grades. Although it is possible to measure such characteristics from some lidar systems such as terrestrial lidar (Chin and Olsen, 2015) and airborne lidar (Souleyrette et al., 2003; Ural et al., 2015; Shams et al., 2022), mobile lidar offers substantial benefits to map the road network across a larger area due to its resolution, accuracy, and mobility (Shams et al., 2018).

Because a mobile lidar system is usually equipped with an IMU and operated along the roadway, the trajectory data including the position and orientation of the system at any given moment can be directly used in obtaining slope information. For example, Luo et al. (2016) and Luo and Li (2018) calculated the cross slopes and grades using the pitch and roll angles from the trajectory. To cope with the fact that the vehicle is not necessarily leveled against the pavement surface and the vibration of the vehicle during data collection, the slope measurements need to be calibrated using the two lidar sensors (mounted on both sides of the vehicle) integrated into the system.

More studies take advantage of the trajectory to derive cross sections from the point cloud data which provides more detailed and accurate geometric information of the road surface. For instance, some lidar systems are configured to let the scan lines or profiles perpendicular to the travel direction. As a result, each scan line represents a cross section of the roadway where the cross slopes can be easily derived as well as the grades (Tsai et al., 2013; Ai and Tsai, 2016). Some other methods extract the cross sections from the trajectory assuming the cross section should be perpendicular to the moving direction where the sampling interval and the width of the cross sections need to be given by the users (Holgado-Barco et al., 2014). Similarly, other data sources such as a GIS layer of the road alignment can be potentially used for determining the directions of the cross slopes and grades as well (Zhang et al., 2006).

Another strategy for extracting the road alignment for estimating the direction of the cross slopes and grades is to take advantage of the road markings. Such methods may require the use of trajectory data, which is not always available for the data users and sometimes. Moreover, road markings can be further utilized to define the road boundaries and individual lanes, and other attributes of the road. For example, Holgado-Barco et al. (2017) proposed an approach that recognizes road markings from MLS point cloud data and provided a geometric inventory of cross-sections such as superelevation. Another challenge in estimating the road alignment with mobile lidar trajectory is that the vehicle is not necessarily kept in the same lane throughout the survey. Even when the system is operated in the same lane, the exact moving direction can still vary which needs additional considerations. Thus, some studies still take advantage of the trajectory data, but use it as a constraint in the longitudinal stripe extraction which will then be used in slope measurements (e.g., Gargoum et al., 2018). Similar to the idea of exploiting the road markings to obtain the road horizontal alignment, some other features can potentially serve as reference data to achieve the same objectives. For instance, in the case of scanning through a tunnel, Puente et al. (2016) defined points along the tunnel's axis and created cross sections perpendicular to it with the markings being used to define the road boundaries.

The studies utilizing mobile lidar data for slope measurements are summarized in Table 2.4.

**Table 2.4 Summary table of the existing studies using mobile lidar data and their approaches to extract road alignment for slope measurements.**

| References                                                       | Approach for extracting road alignment                                       |
|------------------------------------------------------------------|------------------------------------------------------------------------------|
| Luo et al., 2016; Luo and Li, 2018                               | Direct slope measurement from the trajectory data                            |
| Tsai et al., 2013; Holgado-Barco et al., 2014; Ai and Tsai, 2016 | Extracting profiles using the trajectory data                                |
| Zhang et al., 2006                                               | GIS-derived road alignment estimates.                                        |
| Holgado-Barco et al., 2017                                       | Road marking extraction                                                      |
| Gargoum et al., 2018                                             | Road marking extraction with additional constraints from the trajectory data |
| Puente et al., 2016                                              | Utilizing constraints from the environment (e.g., tunnel)                    |

## 2.5.4 Machine learning models for classification

In addition to the ground features, mobile lidar systems can also capture streetside transportation assets in great details, which can be leveraged in asset inventory and management (Yadav et al., 2016). Given the complexity of automating such classification process in the point cloud data, a growing number of studies attempted to leverage machine learning (ML) and deep learning (DL) for classifying street-side assets (Fukano & Masuda, 2015; Che et al., 2019). Given the distinguished attributes of various pole-like objects, even the classic ML models such as random forest (RF) and neural networks (NNs) can potentially achieve accurate and efficient feature detection and classification. More ML and DL models and categories are summarized in Table 2.5. It is worth noting that the actual efficacy of ML methodologies depends on rigorous model training and the nature of the datasets used, enabling the classification of pole-like objects in various urban to rural settings (Lehtomaki et al., 2016).

**Table 2.5. Summary of ML and DL models for point cloud data classification.**

| Categories                                                                   | Models                                                                                                     |
|------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|
| 3D point-based models                                                        | PointNet (Qi, Su, et al., 2017).<br>PointNet++ (Qi, Yi, et al., 2017).                                     |
| Voxel-based models                                                           | VoxelNet (Zhou & Tuzel, 2017).                                                                             |
| Graph-based models                                                           | Dynamic Graph CNN (DGCNN) (Wang, Sun, et al., 2019).                                                       |
| Deep learning architectures                                                  | 3D Convolutional Neural Networks (3D-CNNs) (Maturana & Scherer, 2015).<br>PointConv (Wu et al., 2020)      |
| Recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) | Sequential Models (Huang & You, 2016).                                                                     |
| Ensemble learning methods                                                    | Random Forests (Breiman, 2001).                                                                            |
| Classical machine learning algorithms                                        | Support Vector Machines (SVMs) (Cortes & Vapnik, 1995).<br>K-Nearest Neighbors (KNN) (Cover & Hart, 1967). |
| Clustering algorithms                                                        | DBSCAN (Density-Based Spatial Clustering of Applications with Noise) (Ester et al., 1996).                 |
| Hybrid approaches                                                            | Combining Models (Landrieu & Simonovsky, 2018).                                                            |

Han et al. (2021) pioneered an end-to-end deep learning network tailored for semantic segmentation within urban scenes utilizing mobile lidar data. Their network architecture encompassed a feature abstraction module crucial for encoding local features, enhancing the model's ability to discern semantic elements. The challenges inherent in large-scale outdoor point cloud segmentation for urban scene comprehension were underscored in their work. This emphasized the imperative of integrating essential metrics and methodologies to bolster the development of ML models tailored for transportation asset management. The diversity of road scenes, properties of the pole-like objects of interest and their environments directly influences the characteristics of point cloud data captured by mobile lidar. Rural roads, for instance, may exhibit distinct traffic devices and environmental features not commonly found in urban settings, and vice versa (Yao et al., 2017; Han et al., 2021). Consequently, ML models trained specifically on either rural or urban scenes may exhibit varying levels of performance when tested across different road environment scenarios (Yao et al., 2017). Moreover, mobile lidar data itself presents a set of challenges, including noise or artifacts, incomplete point data for the pole-like objects of interest, varying point density, and potential obstructions from irrelevant features (Olsen, 2013; Luo et al., 2016).

These complexities underscore the importance of conducting experiments across diverse settings with various data complexities. Such experiments are crucial for understanding how these factors impact the training of ML models, thereby optimizing their performance for effective pole-like object classification across various settings and data complexities (Lytkin et al., 2023). It is worth noting that the many ML approaches developed for autonomous driving (e.g., Lytkin et al., 2023) are usually not applicable to survey-grade mobile lidar datasets due to the significant difference in data quality and level of details. Similarly, the data collected using different systems and in different areas could result in substantial differences in the performance of the

models. Therefore, it is not adequate to simply use the reported accuracy trained and tested on a benchmark or synthetic dataset to assess the model's performance.

### 2.5.5 Summary

To extract the road characteristics such as cross slopes, grades, horizontal curves, mobile lidar data is advantageous compared to other methods and techniques for the following reasons:

- The mobile lidar system usually integrates various sensors including GNSS receivers, IMU, and DMI that can be combined to generate a precise trajectory.
- The camera and lidar sensors in the mobile lidar system collect high quality 3D point cloud data and video logs which can provide rich information and context of the roadway.
- The mobile lidar system can cover a large area very efficiently with one or multiple passes through the project area at normal driving speed.
- The geo-referenced mobile lidar data ensure all the derivative data product or analysis results can be projected to their geolocation to create or update a geodatabase which enables more asset management and other applications.

However, there are a number of challenges that need to be overcome while using mobile lidar data to characterize the roadway:

- The performance and robustness of each step (e.g., ground filtering, road extraction, road marking detection, etc.) in the point cloud processing including feature extraction can affect the final results of road characterization.
- Most of the existing studies designed and developed the methods for the specific mobile lidar system. Unfortunately, those algorithms can be sensitive to the data from different mobile lidar systems, or at the very least, require extensive parameter fine-tuning.
- Updating state-wide road network inventory requires automatic methods for processing mobile lidar data to have a decent efficiency, robustness, and scalability to be able to tackle a large volume of data collected in a wide variety of scenarios without having to constantly change settings.

Regarding the street-side transportation asset feature extraction, although various ML models have the potential to automate this process, their performance can be significantly impacted by the quality of their training dataset annotation and selection. Despite the importance of this issue, there has been limited research on how the practical challenges in annotating training datasets impact model accuracy. As a result, this research also established a data processing framework and assessed different ML and DL models as well as various strategies of compiling the training datasets to mimic a real-world scenario.

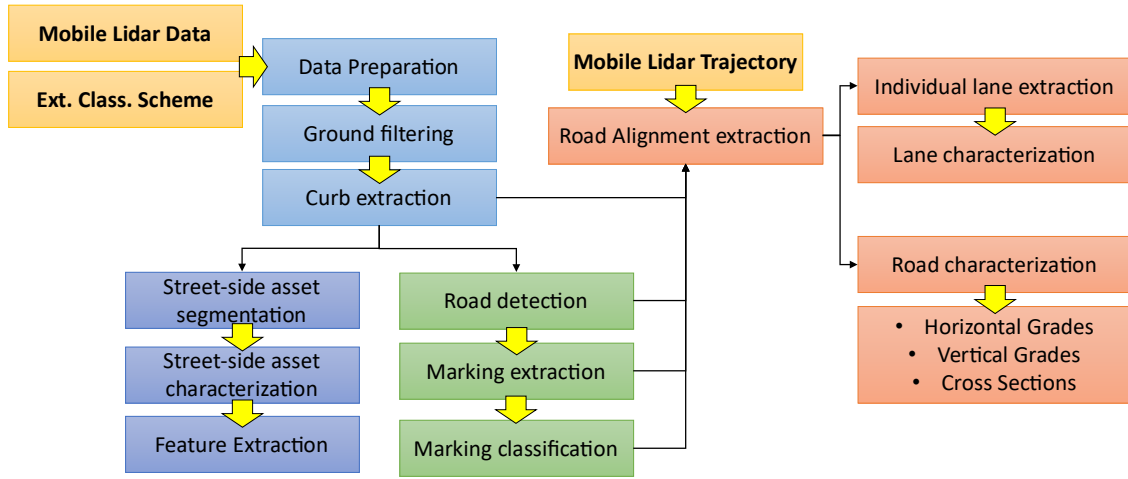


## 3.0 PROCESSING FRAMEWORK AND BENCHMARK DATA

### 3.1 DATA PROCESSING FRAMEWORK OVERVIEW

The proposed framework (Figure 3.1) consists of the following components:

- Inputs mobile lidar data files including the trajectory, point cloud, and image data as input for the corridor of interest. Basic procedures such as data partition and quality check are needed for data preparation to make sure the input files are in line with the target file sizes and resolutions for certain features of interest.
- The proposed extended classification scheme presented in this report can provide additional flexibility in annotating the dataset to overcome the challenges of the limited pre-defined classification labels available in the current ASPRS LAS specification. This classification scheme follows a hierarchical format such that a point can be labeled both as ground (generically) and road. It also maps to the simple ASPRS las specification classification for compatibility.
- Then the transportation features and assets can be divided into two categories, ground features and streetside assets.
  - For the ground features, a hierarchical approach can be implemented to extract ground, curbs, road surface, and road markings in order. The sequence of the processing ensures robustness and efficiency when coping with data covering a wide variety of scene types.
  - The street-side transportation assets can be separated and extracted after the non-ground points are identified after ground filtering and curb detection. Object segmentation approaches such as Vo-Norvana are leveraged in this process to simplify the data. The classification of objects can be achieved by machine learning models using the extracted segments.
- Once the mobile lidar data is processed and assigned with semantic information, it can be leveraged for a wide variety of transportation applications. Taking road characterization as an example, an estimate of the road alignment can be reliably obtained from the trajectory data (precise path of the mobile lidar system during data collection). Thus, by pairing the point cloud and trajectory data, horizontal and vertical curves, and cross sections can be identified, extracted, and characterized, which can support a wide range of analysis that produces different attributes of the statewide highway systems.



**Figure 3.1 Overview of the key steps in the proposed mobile lidar data processing framework.**

## 3.2 BENCHMARK DATA DEVELOPMENT

The mobile lidar datasets that ODOT collects and archives are usually organized in a basic folder structure. The point cloud data is stored in ASPRS LAS format and divided into relatively small chunks/files based on the timestamps. For the Leica Pegasus: Two system, each chunk usually contains about 20 million points. For the data collected by the dual-profiler system, point clouds from both profilers can be saved into the same file. Under the LAS specification, data from different profilers should be distinguished with the field of Source ID. Unfortunately, this is not always the case for the data ODOT is collecting. Some of the software writes this information in the classification field.

Regarding data storage, the LASzip format (usually known as LAZ) was primarily used in the project while all the data at ODOT is currently stored in LAZ format. LASzip is a lossless compression of the LAS format and compatible with most of the existing tools and software. For a typical LAS file storing mobile lidar data, converting it to LAZ format can save over 70% of the storage space. This file size reduction is important, especially considering the data volume that ODOT is collecting on regular basis and the fact that multiple copies will be created in the proposed framework to record the intermediate results. There are many tools that are able to achieve the conversion efficiently (e.g., LASTOOLS, CloudCompare, EZPC-EZLAS, etc.). Note that the interim files at interval stages of processing would not need to be archived - just the final point cloud after the classification procedures are complete.

### 3.2.1 Testing Datasets

The research team leveraged the testing datasets that were organized and labeled in a previous project (SPR850) including existing mobile lidar datasets covering 5 distinct sites. These datasets were identified by the research team in conjunction with the TAC of SPR850, and they cover a variety of scenes (e.g., urban, suburban, rural, scenic) throughout the state where the presence,



style, and complexity of assets will vary. While the focus of SPR850 was on road markings including cross walk and bike lanes, the research team, in this project, expanded the types of classified features annotated within this database to develop a more comprehensive training and validation dataset via manual annotation. These data will also be beneficial for future research in identifying more types of transportation assets. It is worth noting that although some open-source datasets are available to the research community, they are not necessarily captured with the survey-grade mobile lidar system and the annotation is not geared towards transportation applications. During labeling, the team utilized the proposed extended classification scheme, which will be discussed in detail in the following section. The manual labeling also leveraged ground filtering and other tools to improve the efficiency of such procedures.

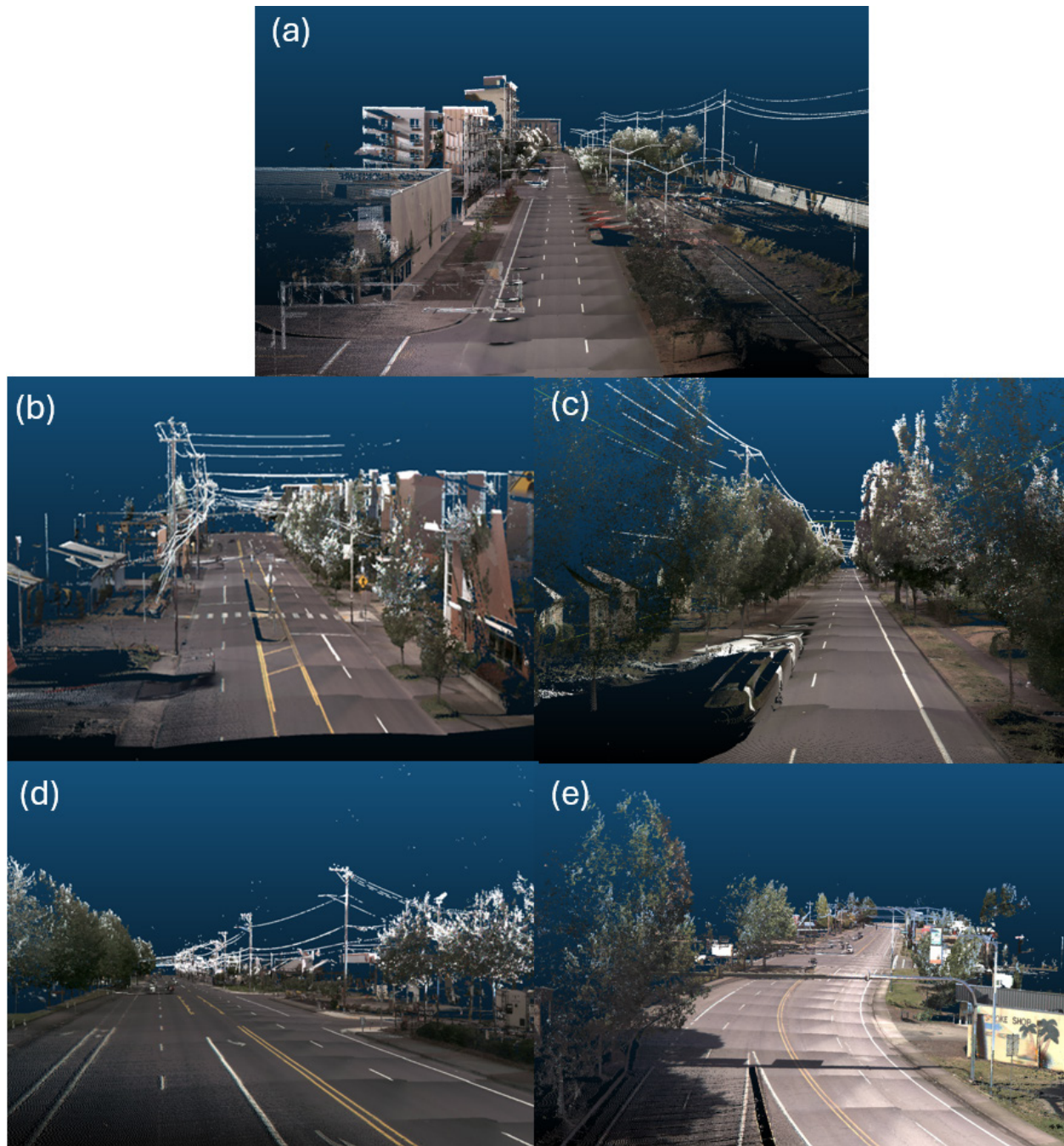
The MLS point cloud dataset used for this case study was collected with a Leica Pegasus: Two mobile lidar system, provided by ODOT. The dataset was sampled from 33 road scenes (Table 3.1) in 5 distinct sites (Table 3.2) across the state. Table 3.2 summarizes the number of pole-like (poles, traffic signs, traffic lights, streetlamps), classified objects as labeled by annotation, and unclassified (unlabeled) objects. This sampling strategy ensured that sufficient instances were included for the study while covering different environmental settings, thereby providing robust support for model training and testing. It is worth noting that it is important to take environmental settings (e.g., urban, suburbs, coastal, rural) into account such that the methods can be developed and validated to be applied to data covering the entire state highway system. Additionally, at this stage only a general assessment was made based on where the MLS data was collected rather than rigorous or detailed evaluation for each data scene.

**Table 3.1. Summary of scene datasets**

| <b>Scene ID</b> | <b>Approximate Length (m)</b> | <b>Point Count (ground points excluded)</b> | <b>No. of Pole-like Objects</b> | <b>No. of Labeled/ Classified Objects</b> | <b>No. of Unlabeled/ Unclassified Objects</b> |
|-----------------|-------------------------------|---------------------------------------------|---------------------------------|-------------------------------------------|-----------------------------------------------|
| 1               | 228                           | 5,623,733                                   | 34                              | 183                                       | 528                                           |
| 2               | 487                           | 4,466,825                                   | 84                              | 533                                       | 1,377                                         |
| 3               | 555                           | 4,536,305                                   | 57                              | 525                                       | 1,266                                         |
| 4               | 430                           | 5,201,415                                   | 36                              | 879                                       | 517                                           |
| 5               | 457                           | 6,699,430                                   | 46                              | 395                                       | 1,155                                         |
| 6               | 458                           | 7,370,642                                   | 21                              | 643                                       | 1,087                                         |
| 7               | 525                           | 5,431,188                                   | 32                              | 513                                       | 1,131                                         |
| 8               | 806                           | 3,490,529                                   | 51                              | 578                                       | 1,065                                         |
| 9               | 337                           | 5,239,370                                   | 37                              | 603                                       | 609                                           |
| 10              | 522                           | 4,443,629                                   | 25                              | 956                                       | 1,010                                         |
| 11              | 577                           | 3,255,549                                   | 35                              | 202                                       | 753                                           |
| 12              | 219                           | 1,933,835                                   | 39                              | 159                                       | 528                                           |
| 13              | 649                           | 5,622,309                                   | 38                              | 1,261                                     | 1,415                                         |
| 14              | 718                           | 2,958,133                                   | 79                              | 441                                       | 1,488                                         |
| 15              | 434                           | 4,337,766                                   | 75                              | 358                                       | 1,091                                         |
| 16              | 499                           | 4,052,692                                   | 52                              | 523                                       | 1,163                                         |
| 17              | 519                           | 4,915,034                                   | 65                              | 242                                       | 1,155                                         |
| 18              | 287                           | 4,875,621                                   | 39                              | 364                                       | 1,014                                         |
| 19              | 510                           | 5,323,498                                   | 71                              | 288                                       | 1,164                                         |
| 20              | 421                           | 4,355,204                                   | 39                              | 631                                       | 820                                           |
| 21              | 456                           | 4,030,879                                   | 55                              | 1,419                                     | 903                                           |
| 22              | 461                           | 4,058,106                                   | 72                              | 794                                       | 916                                           |
| 23              | 370                           | 3,607,550                                   | 42                              | 1,023                                     | 526                                           |
| 24              | 468                           | 5,232,642                                   | 27                              | 617                                       | 715                                           |
| 25              | 650                           | 4,279,398                                   | 39                              | 703                                       | 1,033                                         |
| 26              | 384                           | 4,916,775                                   | 20                              | 708                                       | 718                                           |
| 27              | 292                           | 3,295,701                                   | 37                              | 168                                       | 759                                           |
| 28              | 945                           | 3,059,385                                   | 61                              | 1,098                                     | 1,541                                         |
| 29              | 289                           | 4,435,735                                   | 30                              | 338                                       | 610                                           |
| 30              | 602                           | 4,441,965                                   | 51                              | 854                                       | 1,092                                         |
| 31              | 504                           | 3,625,834                                   | 48                              | 485                                       | 1,009                                         |
| 32              | 518                           | 4,669,326                                   | 38                              | 1,026                                     | 1,321                                         |
| 33              | 670                           | 3,783,501                                   | 65                              | 344                                       | 1,257                                         |

**Table 3.2. Summary of site categories of datasets modified from Olsen et al. (In Press).**

| <b>Site ID</b> | <b>Location in Oregon</b> | <b>Environmental Setting</b>             | <b>Highways (mileposts)</b>           | <b>No. of Scenes</b> | <b>Scenes</b>                         | <b>Approximate Length (km)</b> | <b>Point Count</b> | <b>No. of Pole-like Objects</b> | <b>No. of Labeled/Classified Objects</b> | <b>No. of Unlabeled/Unclassified Objects</b> |
|----------------|---------------------------|------------------------------------------|---------------------------------------|----------------------|---------------------------------------|--------------------------------|--------------------|---------------------------------|------------------------------------------|----------------------------------------------|
| <b>1</b>       | Downtown Salem            | Urban                                    | HWY 221 (MP16–21), HWY 99EB (MP0–8.5) | 10                   | 4, 5, 6, 7, 8, 13, 24, 25, 26, and 27 | 5.1                            | 103,080,058        | 698                             | 12930                                    | 19,190                                       |
| <b>2</b>       | Tigard and King City      | Busy Suburban                            | HWY 99W (MP8–13) HWY 141 (MP2–7)      | 7                    | 20, 21, 22, 23, 28, 29, and 30        | 3.5                            | 27,988,824         | 350                             | 6,157                                    | 6,408                                        |
| <b>3</b>       | Hillsborough              | Less dense suburban with some near rural | HWY 029 (MP 0–18) HWY 102 (MP 88–91)  | 6                    | 9, 10, 11, 12, 14, and 15             | 2.8                            | 22,168,282         | 290                             | 2,719                                    | 5,479                                        |
| <b>4</b>       | Albany                    | Moderate size city                       | HWY 99E (MP0–8)                       | 3                    | 31, 32, and 33                        | 1.7                            | 12,078,661         | 151                             | 1,855                                    | 3,587                                        |
| <b>5</b>       | Portland                  | Small, rural city                        | HWY 213 (82 <sup>nd</sup> Ave)        | 7                    | 1, 2, 3, 16, 17, 18, and 19           | 3.1                            | 33,793,708         | 402                             | 2,658                                    | 7,666                                        |



**Figure 3.2. Examples of MLS datasets collected in different environment settings used in this research (a) Urban, (b) Busy suburban, (c) Less dense suburban with some near rural, (d) Moderate size city, and (e) Small rural city**

### **3.2.2 Extended Classification Scheme in LAS/LAZ**

Data standards help data owners and users to interpret the data in the same way. For classification in particular, most of the data formats/standards organize the classification field in a numeric system, which can be arbitrary in some instances. ASPRS LAS is a widely-used

format to store point cloud data given its minimal data size and compatibility with a variety of software. Even ASPRS LAS specifies certain classes of objects, it does not necessarily cover the streetside and other transportation assets.

According to the latest ASPRS LAS specifications, the pre-defined classification includes common objects such as ground, vegetation, building, road surface, and so on. However, the classification system is mostly designed for airborne lidar data and thus limited to what objects an airborne lidar system can typically capture. To take advantage of what has been standardized in ASPRS LAS specifications while being able to distinguish various transportation assets in the same LAS/LAZ file, the team proposes a classification scheme including both the LAS standard classification and a custom classification field, namely extended classification, designed for mobile lidar data and transportation asset feature extraction.

Table 3.3 and Table 3.4 provides a list of common object classes with their classification including both LAS Class ID and extended Class ID. It is worth noting that although LAS specification provides custom class field, because the maximum classification ID is 255, the user definable classes are only available with a classification ID between 64 and 255. Additionally, the user-definable classes are not necessarily recognizable by software which will limit some of the applications of the data. For example, the ground points can be classified between road surface and ground class in a LAS file, which can be directly taken for generating terrain models. However, if the road markings in the data are labeled as a separate ID in the user definable range (64 – 255), a new class of ground points will have to be built into the software or program, which may not be very straightforward.

Since the Extended Class ID will be stored as an extra-bytes field associated with each individual data record, it can go in parallel with LAS class ID. The Extra Bytes variable length record (VLR) can be set up as shown in Table 3.5. Then to further provide the information about the proposed classification scheme, the research team also proposes to add another VLR that serves as a classification lookup table. It should be noted that this is different from the native classification lookup in LAS specification where it covers class ID from 0 to 255. The extended classification lookup will indicate the extended classification ID and the description. For every class recorded in the extended classification lookup, the extended class ID and class description occupies 4 bytes and 32 bytes, respectively (Table 3.6). As a result, a total of 36 bytes multiplied by the number of classes will be recorded in the LAS/LAZ file as a VLR (Table 3.7).

**Table 3.3 Extended Classification Field for LAS files (LAS Class ID: 0 – 14). (Gray rows highlight the extended classes sharing the same LAS class ID)**

| <b>Extended Class ID</b> | <b>Extended Class Meaning</b> | <b>LAS Class ID</b> | <b>LAS Class Meaning</b>  |
|--------------------------|-------------------------------|---------------------|---------------------------|
| <b>000000</b>            | Created, Never Classified     | 0                   | Created, Never Classified |
| <b>100000</b>            | Unknown/unclassified          | 1                   | Unclassified              |
| <b>200000</b>            | Unspecified ground            | 2                   | Ground                    |
| <b>200100</b>            | Sidewalk                      | 2                   | Ground                    |
| <b>200200</b>            | Curb ramp                     | 2                   | Ground                    |
| <b>300000</b>            | Low Vegetation                | 3                   | Low Vegetation            |
| <b>300100</b>            | Grass                         | 3                   | Low Vegetation            |
| <b>400000</b>            | Medium Vegetation             | 4                   | Medium Vegetation         |
| <b>400100</b>            | Bush                          | 4                   | Medium Vegetation         |
| <b>500000</b>            | High Vegetation               | 5                   | High Vegetation           |
| <b>500100</b>            | Tree                          | 5                   | High Vegetation           |
| <b>600000</b>            | Building                      | 6                   | Building                  |
| <b>700000</b>            | Low Point (Noise)             | 7                   | Low Point (Noise)         |
| <b>800000</b>            | LAS Reserved                  | 8                   | Reserved                  |
| <b>900000</b>            | Water                         | 9                   | Water                     |
| <b>100000</b>            | Rail                          | 10                  | Rail                      |
| <b>110000</b>            | Road surface                  | 11                  | Road Surface              |
| <b>110100</b>            | Road marking                  | 11                  | Road Surface              |
| <b>110110</b>            | Lane marking                  | 11                  | Road Surface              |
| <b>110120 – 119999</b>   | Other markings                | 11                  | Road Surface              |
| <b>120000</b>            | LAS Reserved                  | 12                  | Reserved                  |
| <b>130000</b>            | Wire – Guard (Shield)         | 13                  | Wire – Guard (Shield)     |
| <b>140000</b>            | Wire – Conductor (Phase)      | 14                  | Wire – Conductor (Phase)  |
| <b>140100</b>            | Powerline                     | 14                  | Wire – Conductor (Phase)  |
| <b>140200</b>            | Telephone/TV cable            | 14                  | Wire – Conductor (Phase)  |

**Table 3.4 Extended Classification Field for LAS files (LAS Class ID: 15 – 65). (Gray rows highlight the extended classes sharing the same LAS class ID)**

| Extended Class ID | Extended Class Meaning   | LAS Class ID | LAS Class Meaning        |
|-------------------|--------------------------|--------------|--------------------------|
| 150000            | Transmission Tower       | 15           | Transmission Tower       |
| 160000            | Wire-Structure Connector | 16           | Wire-Structure Connector |
| 170000            | Bridge Deck              | 17           | Bridge Deck              |
| 180000            | High Noise               | 18           | High Noise               |
| 190000            | Overhead Structure       | 19           | Overhead Structure       |
| 190100            | Traffic sign             | 19           | Overhead Structure       |
| 190200            | Traffic light            | 19           | Overhead Structure       |
| 190300            | Street lamp              | 19           | Overhead Structure       |
| 190400            | Highway Gantry           | 19           | Overhead Structure       |
| 190500            | Tunnel                   | 19           | Overhead Structure       |
| 190600            | Bridge girder            | 19           | Overhead Structure       |
| 200200            | Ignored Ground           | 20           | Ignored Ground           |
| 210000            | Snow                     | 21           | Snow                     |
| 220000            | Temporal Exclusion       | 22           | Temporal Exclusion       |
| 230000 – 639999   | LAS Reserved             | 23-63        | Reserved                 |
| 640000            | Road barrier             | 64           | User Definable           |
| 640100            | Curb                     | 64           | User Definable           |
| 640200            | Guard rail               | 64           | User Definable           |
| 640300            | Cable barrier            | 64           | User Definable           |
| 640400            | Jersey barrier           | 64           | User Definable           |
| 650000            | Pole-like object         | 65           | User Definable           |
| 650100            | Traffic sign             | 65           | User Definable           |
| 650200            | Traffic light            | 65           | User Definable           |
| 650300            | Street lamp              | 65           | User Definable           |

**Table 3.5 Extra bytes specification for the extended classification field.**

| Key items in Extra Bytes structure | Value                    |
|------------------------------------|--------------------------|
| Data_type                          | 6 (long, 4 bytes)        |
| Options: no_data_bit               | Not set (not applicable) |
| Options: min_bit                   | Not set (not applicable) |
| Options: max_bit                   | Not set (not applicable) |
| Options: scale_bit                 | Not set (not applicable) |
| Options: offset_bit                | Not set (not applicable) |
| Name                               | Ext_Class                |
| Description                        | Extended classification  |

**Table 3.6 VLR record data specification for the extended classification lookup table.**

| Index | Extended Class ID (4 bytes) | Class Description (32 bytes) |
|-------|-----------------------------|------------------------------|
| 0     | 000000                      | Created, Never Classified    |
| 1     | 100000                      | Unknown/unclassified         |
| 2     | 200000                      | Unspecified ground           |
| 3     | 200100                      | Sidewalk                     |
| 4     | 200200                      | Curb ramp                    |
| 5     | 300100                      | Grass                        |
| 6     | 400100                      | Bush                         |
| 7     | 500100                      | Tree                         |
| 8     | 600000                      | Building                     |
| 9     | 700000                      | Low Point (Noise)            |
| ...   | ...                         | ...                          |

**Table 3.7 VLR record header specification for the extended classification lookup table.**

| VLR field                  | Value                                     |
|----------------------------|-------------------------------------------|
| User ID                    | LASF_MLS                                  |
| Record ID                  | 0                                         |
| Record Length After Header | 36 bytes per class ID × number of classes |
| Description                | MLS Classification Lookup                 |

### 3.2.3 Data Annotation

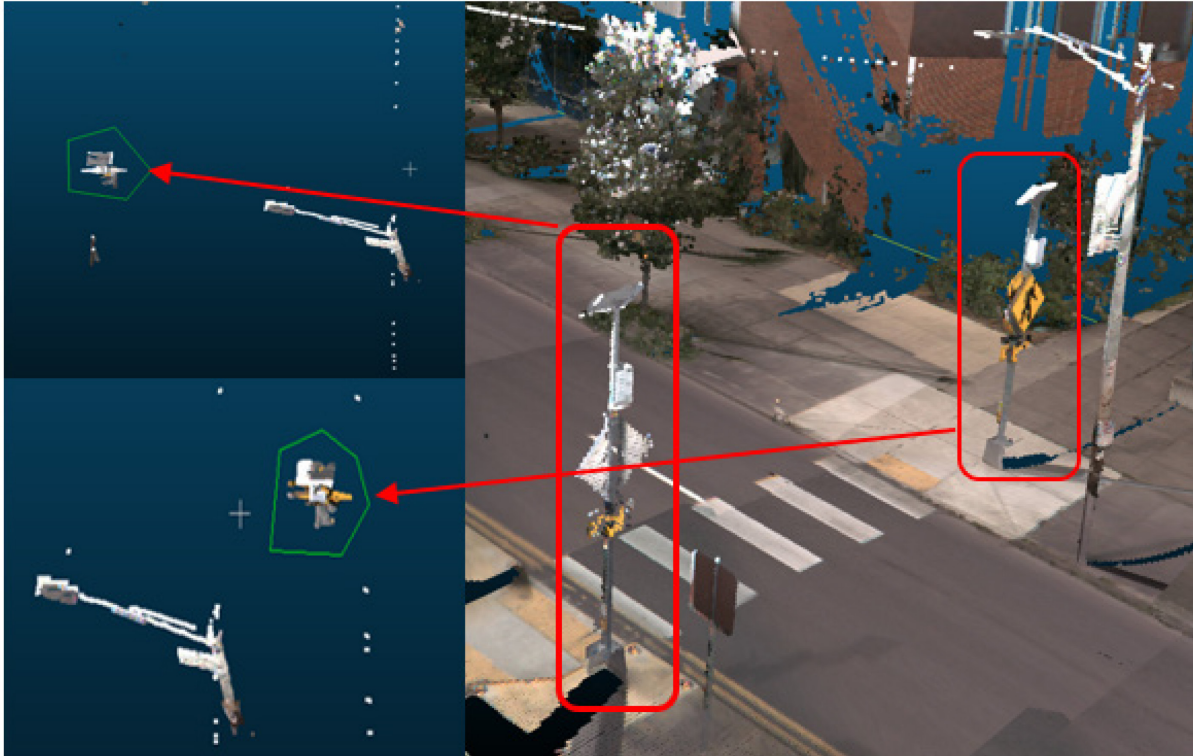
To facilitate efficient annotation and labeling of features within the MLS dataset, a comprehensive labeling scheme was proposed (Table 3.8). Such a scheme simplifies the inherent complexity of the pole-like objects and the associate streetside features by assigning each element a specific extended classification ID (“Ext Class”). The extended classification ID is stored as extra bytes with the point cloud data in ASPRS LAS/LAZ format. The root extended classification ID ("Root Ext Class") corresponding to each extended classification is designed to be directly mapped to the ASPRS LAS specification standard, which will provide additional compatibility of the proposed approach across various software packages and tools. The proposed scheme also supports the potential addition of new labels within the extended classification ID.



**Table 3.8. Classification scheme in the proposed approach**

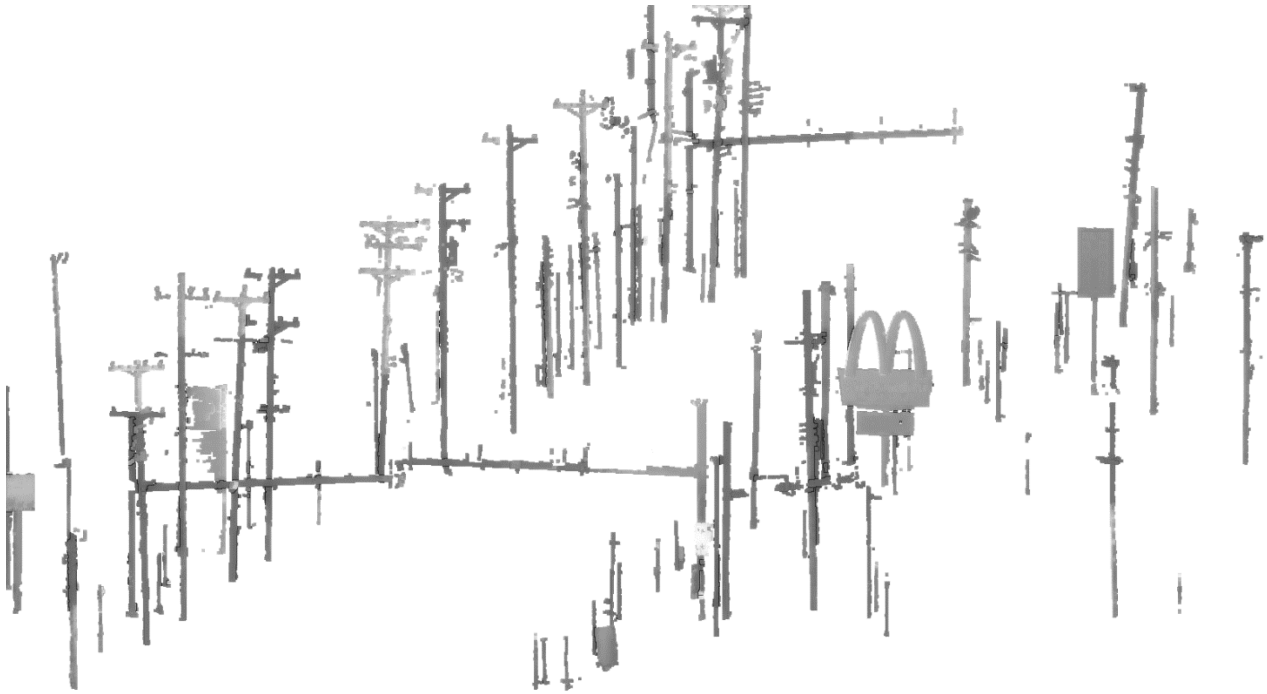
| <b>Ext. Class</b> | <b>Label</b>             | <b>Root Ext. Class</b> | <b>Root Ext. Class Label</b> | <b>In Class Priority</b> |
|-------------------|--------------------------|------------------------|------------------------------|--------------------------|
| <b>010000</b>     | Unclassified             | 010000                 | Unclassified                 | 99                       |
| <b>140100</b>     | Powerline                | 140000                 | Wire – Conductor (Phase)     | 1                        |
| <b>140200</b>     | Telephone/TV cable       | 140000                 | Wire – Conductor (Phase)     | 2                        |
| <b>140000</b>     | Wire – Conductor (Phase) | 140000                 | Wire – Conductor (Phase)     | 99                       |
| <b>190100</b>     | Traffic sign             | 190000                 | Overhead Structure           | 1                        |
| <b>190200</b>     | Traffic light            | 190000                 | Overhead Structure           | 2                        |
| <b>190300</b>     | Streetlamp               | 190000                 | Overhead Structure           | 3                        |
| <b>190400</b>     | Highway Gantry           | 190000                 | Overhead Structure           | 4                        |
| <b>190000</b>     | Overhead Structure       | 190000                 | Overhead Structure           | 99                       |
| <b>050000</b>     | High Vegetation          | 050000                 | High Vegetation              | 99                       |
| <b>050100</b>     | Trees                    | 050000                 | High Vegetation              | 1                        |
| <b>650100</b>     | Traffic sign             | 650000                 | Pole-like object             | 1                        |
| <b>650200</b>     | Traffic light            | 650000                 | Pole-like object             | 2                        |
| <b>650300</b>     | Streetlamp               | 650000                 | Pole-like object             | 3                        |
| <b>650000</b>     | Pole-like object         | 650000                 | Pole-like object             | 99                       |

The in-class priority (“In Class Priority”) is provided to cope with the cases where the segmented features can be categorized into multiple extended classes under the same root extended class. This is quite common for streetside assets where a single feature can serve for multiple functions. For example, a single utility pole can carry streetlamps, multiple traffic signs, powerlines/cables, and others, which can easily cause confusion for annotation process. With the proposed scheme, one can prioritize one class over another for a certain application when developing the training dataset for machine learning models. Depending on specific applications and experimentation needs, the proposed scheme for objects of interest may require re-mapping of the classification ID and label. To address this, the team developed a tool (Appendix C) that offers additional flexibility in the labeling scheme, which will also benefit future research requiring customized schemes.



**Figure 3.3. Annotating and labeling pole-like objects (Pedestrian Crossing Traffic Sign with its pole)**

In this case, the team focused particularly on pole-like objects and defined pole-like objects as vertical, single-legged features with continuous upward extension, including traffic sign poles, traffic light poles, streetlamp poles, and utility poles (Figure 3.4). Clustered structures with multiple legs, like poles supporting an advertisement sign, were also considered. Mounted elements on these poles include traffic signs, traffic lights, and streetlamps.



**Figure 3.4. Extraction of pole-like objects of the MLS dataset**

Then the team extracted traffic signs from the data during the manual data annotation process considering the following attributes:

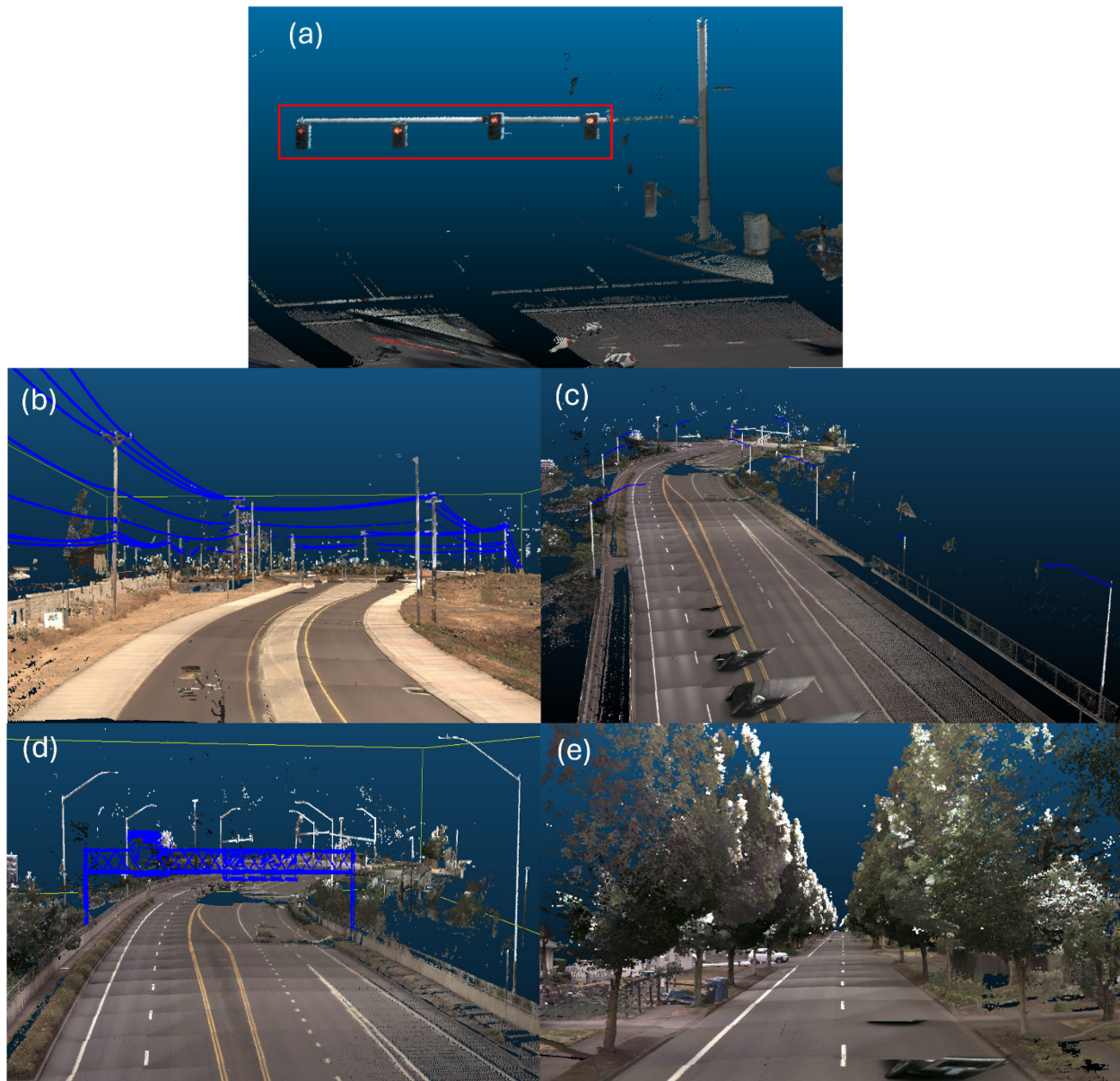
- Location: placed in close proximity of roadways, sidewalks, and medians, particularly at intersections, crosswalks, and curves (Figure 3.5.a and b).
- Shape: specific shapes like inverted triangles for yield signs, octagons for stop signs, and diamonds for warning signs (Figure 3.5.b and c).
- Height: Typically mounted at least 7 feet above the road, ensuring visibility.
- Reflectivity: traffic signs are made from reflective materials for nighttime visibility, showing higher intensity in MLS data (Figure 3.5.d).



**Figure 3.5. Considerations in annotating traffic signs (a) Close proximity to the road ways (b) Close proximity to the crosswalks (c) Different signage shapes (d) High reflectance/intensity of traffic signs.**

Traffic lights were positioned on pole-like structures at intersections, with general traffic lights mounted on horizontal arms (Figure 3.6.a) and pedestrian lights on vertical arms for easy identification. Streetlamps (Figure 3.6.c) varied in height and were placed along roadways and walkways. Overhead structures such as tunnels, bridges, and gantries (Figure 3.6.d) spanned roadways, supporting traffic signs and lights to ensure visibility and safety. Vegetation, including both low and high vegetation like trees, was distinguishable by its greenery, trunks, branches, and leaves in the point cloud (Figure 3.6.e). Powerlines (Figure 3.6.b), identifiable by their metallic, whitish appearance, stretched horizontally between utility poles at higher heights.





**Figure 3.6. Other object considerations (a) Traffic lights at intersections (b) Powerlines connecting utility poles (c) Streetlamps attached to poles at higher heights (d) Highway overhead gantry mounted with traffic signs (e) Trees aligned off curbs**

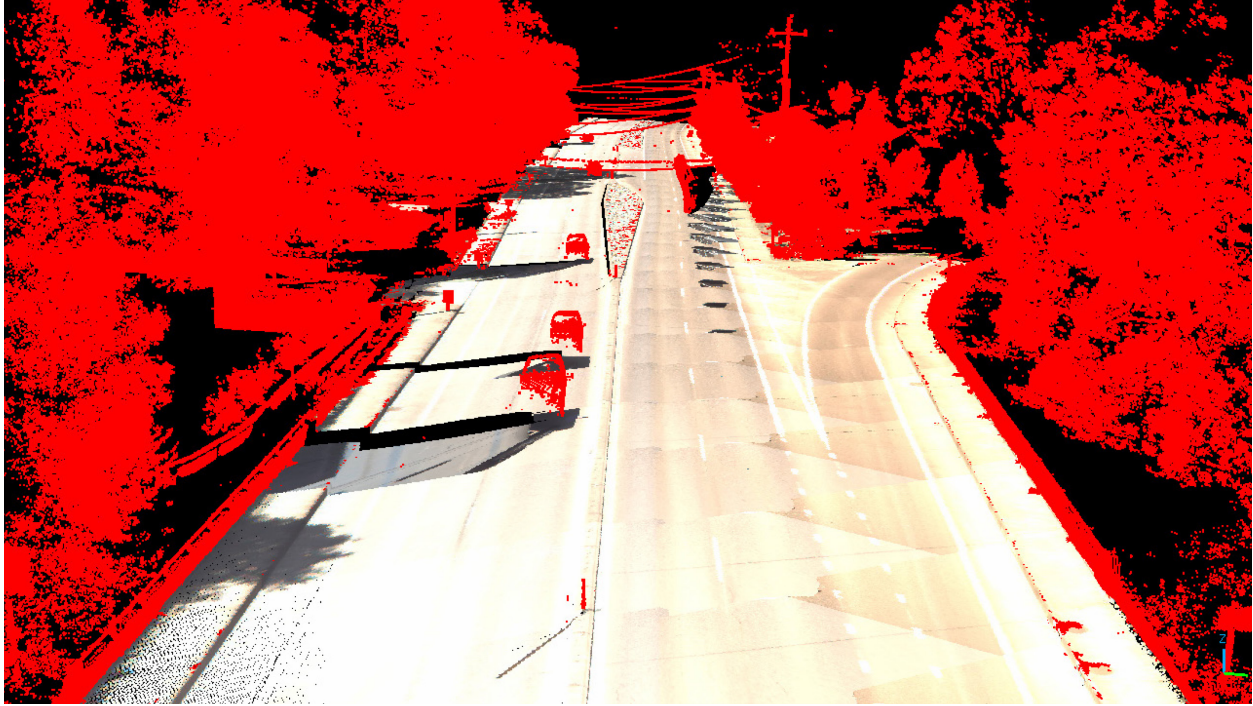


## 4.0 FEATURE EXTRACTION

### 4.1 GROUND FILTERING

Ground filtering is a process to separate the ground and non-ground points. It is an important step to extract some basic semantic information to support the additional classification of features. For example, once the ground and non-ground are classified in the mobile lidar data, the objects such as sign posts can be extracted from the non-ground points. Such a strategy substantially reduces computational complexity because the ground points often constitute the majority of the data points. Additionally, several objects are connected via the ground surface; hence, removing the ground points would break these connections to improve the robustness and consistency of the object segmentation. Furthermore, the ground points can be used to generate terrain models for topographic mapping, road design, and other applications.

A number of ground filtering algorithms have been proposed by the research team in previous work with different emphasis and use-case scenarios. For example, for a structured terrestrial laser scan, the variation in point density can be calculated and used to detect ground points (Che & Olsen, 2017). Mobile lidar data can be organized in a similar structure (Che & Olsen, 2019) for processing. However, compared with terrestrial laser scan data with inherent structure, structuring of mobile lidar data can be heavily reliant on the trajectory reconstruction, which can be sensitive to the parameters such as scanning angular resolution and IMU rate (the actual values can be different from the specification of the systems). Recently, the research team proposed a versatile and efficient ground filtering algorithm, namely Vo-SmoG (Che et al., 2021). It does not require any pre-processing or cleaning since it includes several basic filters such as the isolated voxel filter directly built into the workflow. Moreover, the algorithm is relatively forgiving to the parameters given by the users as demonstrated in Section 4.5. The basic concept of Vo-Smog is to track large smooth surfaces with lower elevation in a subset of the data as ground points with capacity to handle noise and artifacts. In the proposed prototype developed in this research, Vo-SmoG was selected as the primary algorithm to tackle the ground filtering process. An example of ground filtering result of Vo-SmoG on a mobile lidar data is shown in Figure 4.1.

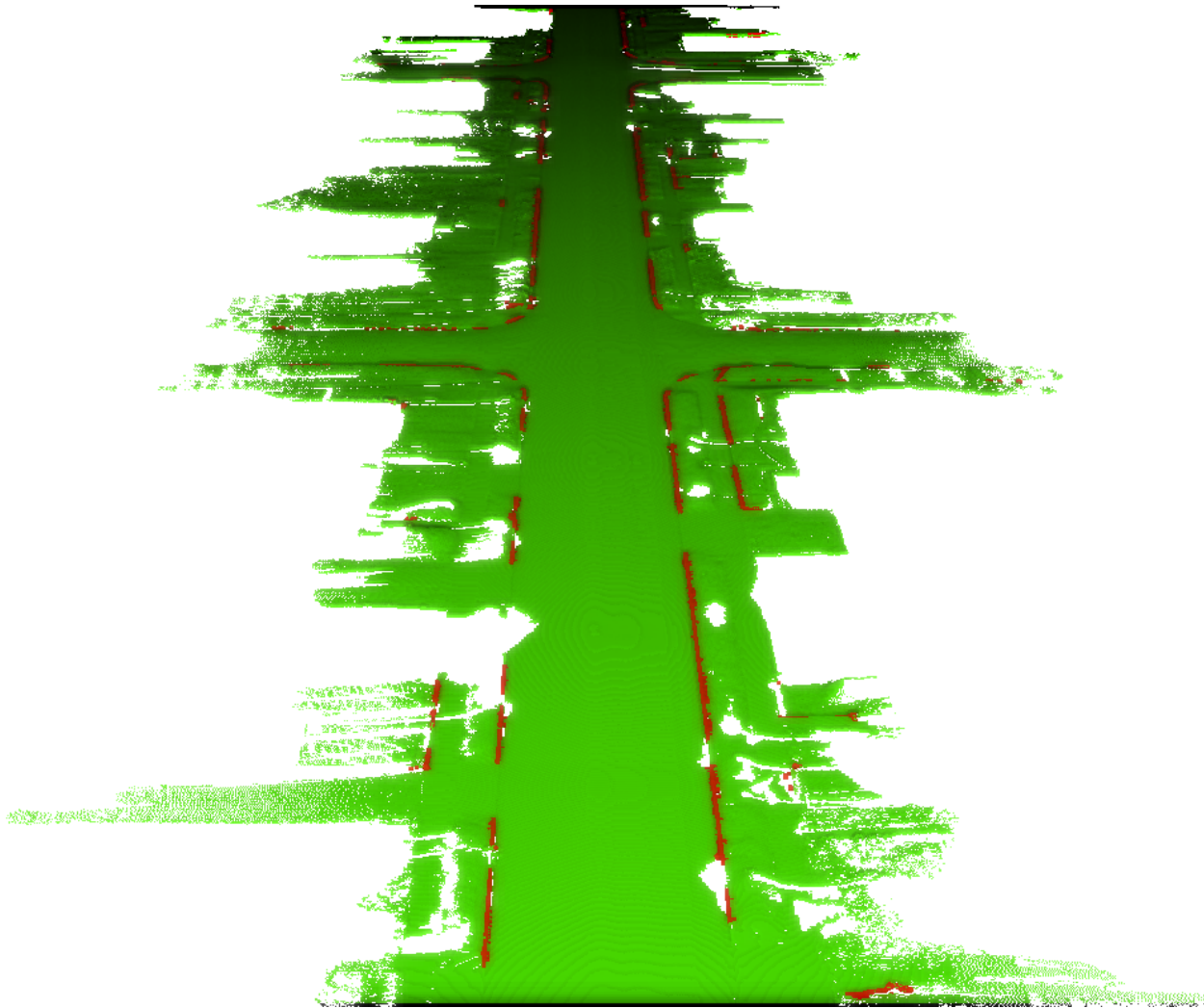


**Figure 4.1 Example Vo-SmoG ground filtering results where red points indicate non-ground objects.**

## **4.2 CURB EXTRACTION**

Curbs are usually built between the roadway and sidewalk or median and features a sudden elevation change, which can cause some ambiguity in the ground filtering process. Using Vo-SmoG ground filtering as an example, the curb face can be included in the ground points if the elevation deviation tolerance is sufficient to cover the elevation change at the curb. But when the evaluation deviation tolerance and proximity filtering are given relatively tight thresholds, the curb face can be partially identified as ground. Fortunately, the research team has developed a preliminary solution to address this issue in their prior effort for extracting curbs and curb ramps from mobile lidar data (Che et al., 2024). The basic concept is to first look at the ground points and identify the area with a sudden elevation change within a given range. Then using the same range, the ground and non-ground points between the maximum and minimum elevations in those areas will be re-classified as curb candidates. The curb extraction result can be further refined based on the linearity of the curb lines and the size of the clusters detected along the curb candidates (Figure 4.2). Leveraging the curb extraction as a refinement of ground filtering, the following process taking place within either ground or non-ground points can result in a more consistent outcome. Additional tools to handle the curb extraction results have been developed by the research team in ODOT research project (SPR850), where curbs are used to identify the bike lanes and raised median. Further enhancements such as ability to interpolate between data gaps and reduction of false positives were made through SPR866 to improve the robustness.





**Figure 4.2 Example of curb extraction based on the ground filtering results where green and red points represent ground and curbs, respectively**

### **4.3 ROAD DETECTION**

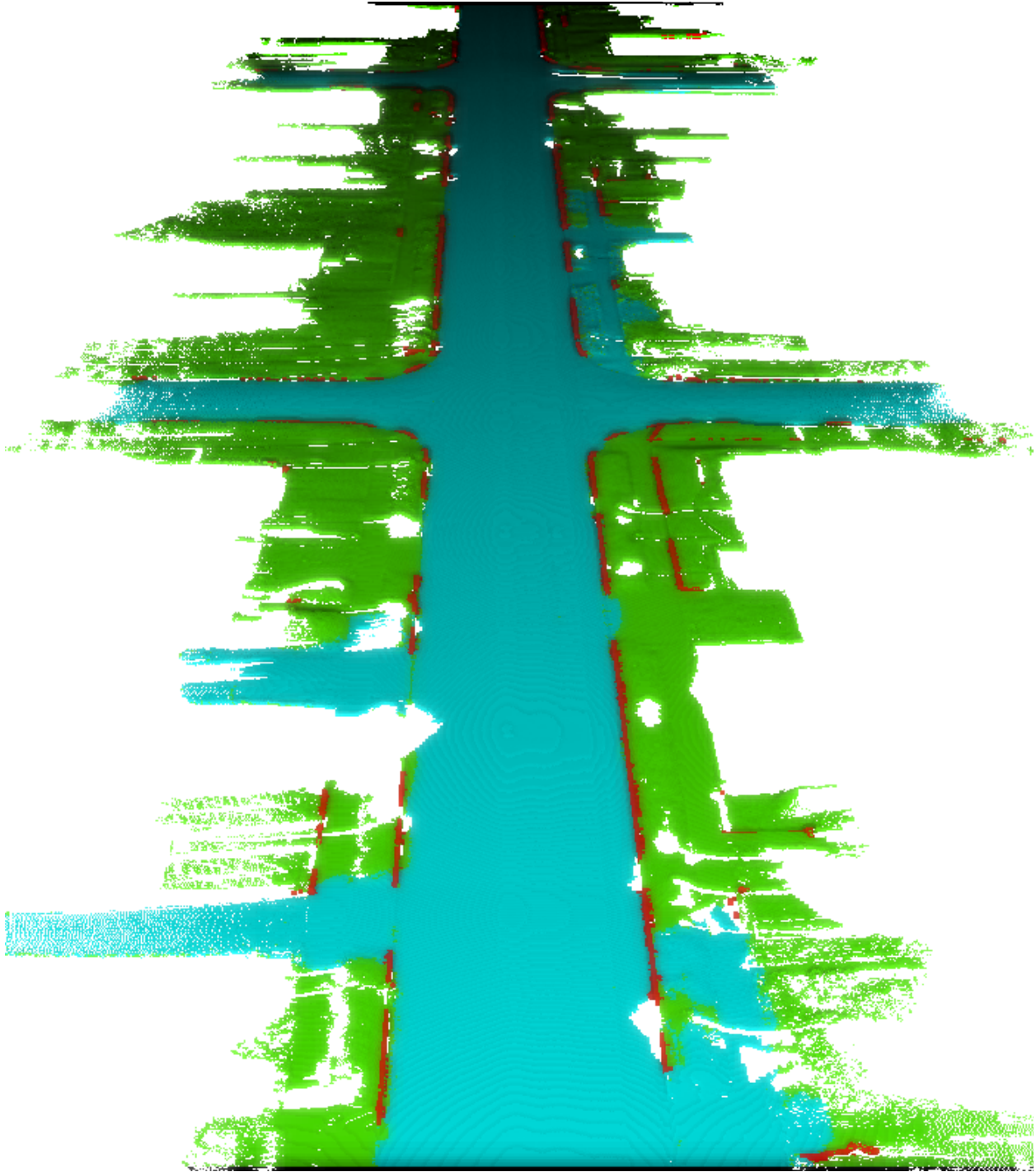
Road detection is an important preprocessing step before road marking extraction. Ground filtered lidar data generated in Section 3.4 serves as input for road detection. By limiting the search area for road markings to the detected road surface, the computational cost of the road marking extraction process can be significantly reduced while improving accuracy and reliability of road marking extraction. Throughout past projects, the research team has developed several ways to detect roads from lidar data.

- In SPR799 (Olsen et al. 2018), the team implemented a RANSAC-based road surface extraction method. RANSAC (RANDOM SAMPLE Consensus) is an iterative algorithm to estimate the parameters of a mathematical model from a set of observed data points that may contain outliers. To apply RANSAC algorithm for road detection, the ground filtered point cloud is divided into smaller sections with constant intervals.

2nd order polynomial fitting is performed for each section to approximate the cross section of road surface data. This RANSAC segmentation approach is advantageous because it enables the road surface to be extracted, even in the absence of curbs. However, it may not be suitable for some flat road surfaces in rural areas.

- In a Pactrans project (Jung et al. 2020), the team developed another method that uses region growing for road detection. In this approach, the ground points are rasterized into a 2D elevation image using the z-coordinates and then converted into a slope image using a Sobel operator. A region growing method is applied to the slope image to segment the road surface from non-road objects based on the abrupt slope changes between them. A limitation to this method is that region growing can be computationally expensive.
- In SPR850 project, the research team developed a new method using Otsu method on the rasterized slope data. Otsu's method (Otsu, 1979), or Otsu's thresholding, is an image segmentation technique that finds an optimal threshold value to separate an image into two classes, such as foreground and background, based on pixel intensity distribution. It is particularly effective for images with bimodal intensity histograms. Otsu's method is applied to the slope image to segment the smooth road surface. The primary advantage of using Otsu's method for road detection is the reduced processing time compared to region growing.

The team decided to adopt the EZFeat road detection algorithm, which was inspired and modified from the VROOM algorithm developed by the research team (Che & Olsen, 2018). This algorithm shared similar data structuring and processing workflow as Vo-SmoG and curb detection approaches. As a result, the results can be more consistent, and the leverage of such previous procedures is more streamlined. For example, in addition to the classified point cloud data, the EZFeat curb detection algorithm also produces a simplified feature layer named EZFT (explained further in Appendix A). These layers can be read by the program along with the input files to assist the feature extraction process which significantly improves the robustness and accuracy of the results. Figure 4.3 shows an example of the extracted road surface from mobile lidar data.

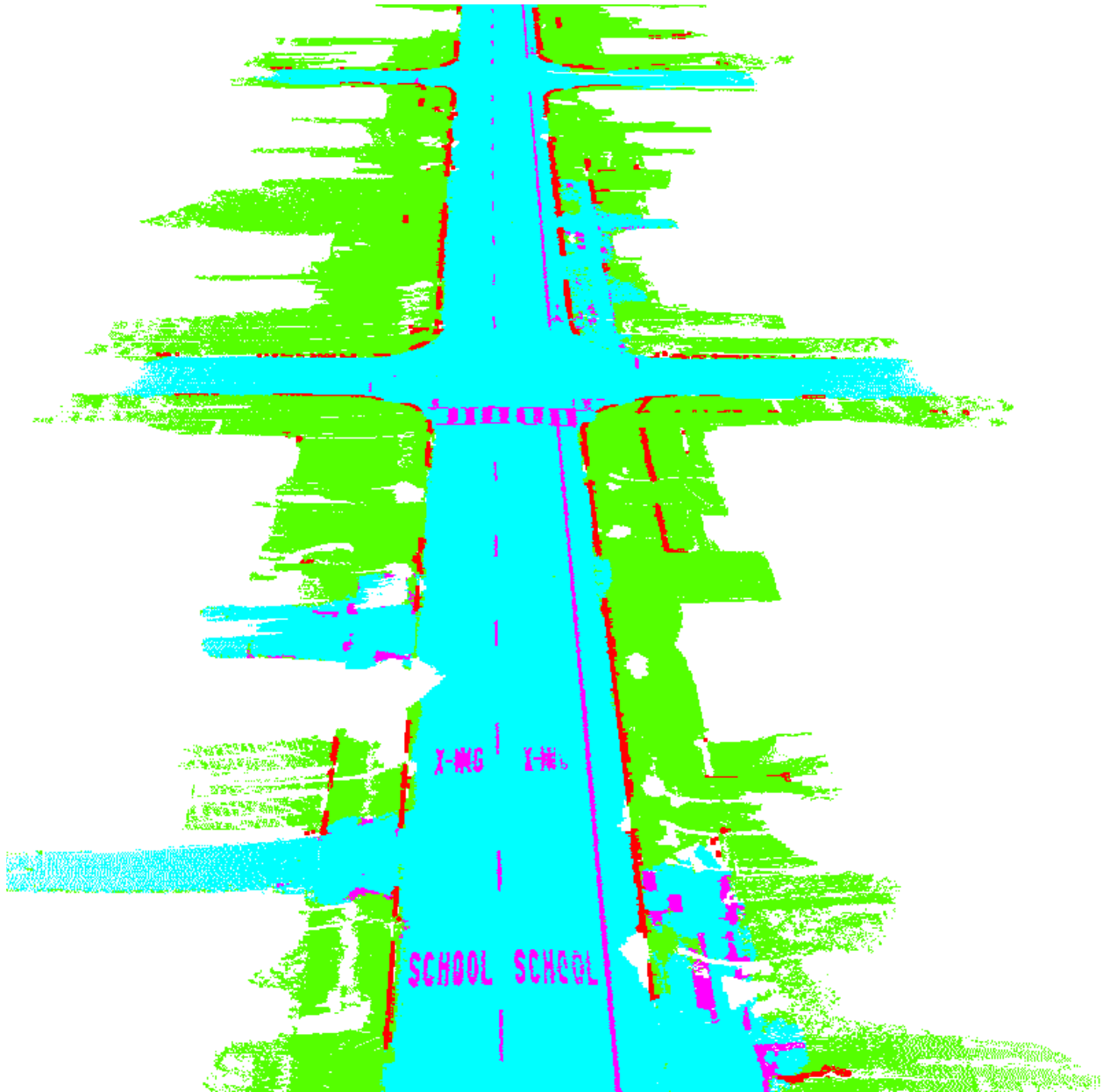


**Figure 4.3 Example road surface extraction result where cyan points represent the road surface, red represents curb points, and green represents generic ground points**

#### **4.4 MARKING EXTRACTION/CLASSIFICATION**

Once the road surface is segmented from the point cloud data, it enables a much more efficient process for road marking extraction given that the search area is substantially reduced in size.

For the same reason mentioned above, the team utilized EZFeat road marking extraction to implement the road marking extraction process. The implementation leveraged the ROME algorithm developed by the research team in previous effort (e.g., ODOT SPR799, SPR850) and fits within the same framework with curb and road extraction algorithms. Within the points classified as road, the approach primarily utilizes the intensity values to separate the pavement and road markings. Next, several noise filtering procedures refine the extraction results. Figure 4.4 shows an example of the extracted road markings from mobile lidar data. Note that, in this case, the markings are not further classified into different types. The grouping/segmentation is conducted using a simple connected component process.



**Figure 4.4 Example of road marking extraction where magenta points represent the road markings, blue represents the road surface, red indicates curbs, and green indicates general ground points.**

## **4.5 GROUND FEATURE EXTRACTION PRAMETER ANALYSIS**

Extensive testing was performed in order to identify stable, default parameters for use in the Vo-Smog ground filtering, EZFeat road extraction, and EZFeat curb extraction tools developed by both OSU and EZDataMD LLC. The algorithms were evaluated on several different datasets from a variety of scene types to ensure that the algorithms and the recommended parameters were robust so they would perform well with a wide range of datasets. Challenging situations were noted in this process. The testing was completed in two primary phases:

Identify the most influential parameters. In this step, a single parameter was varied at a time through a range of realistic values. Other values were kept constant based on the initial default values. The results were then qualitatively compared when altering the parameter. The comparison focused on evaluating several aspects including the complete capture of ground, curbs or road (true positives/false negatives) as well as locations with erroneous extraction of slope toes, road edges, or other features (false positives/true negatives). In the first phase, only a small subset of the datasets were tested.

Evaluate the impact of the most influential parameters in more detail. This second phase extended the testing to many more datasets; however, only the most influential parameters from phase 1 were included in the testing. The parameters were again varied within the ranges to evaluate their impact on the results; however, in some cases they were tested with finer increments when greater sensitivity was observed.

Note that the intent of this exercise is to identify default values that work well in most situations. During actual implementation, these parameters may need to be adjusted based on the particularities of the data collected, the site characteristics, and the mobile lidar system used. Nevertheless, they should provide a reasonable starting point from which the operator can fine-tune.

#### **4.5.1 Vo-Smog Ground Filtering**

For the Vo-Smog ground filtering process (Che et al., 2021), the parameters `scale_grnd`, `max_disp`, `scale_noise`, and `max_gap` were identified to be the most influential. Reasonable results were obtained for all datasets tested and were relatively consistent across the parameter ranges tested. Table 4.1 provides a brief description of each key parameters being tested. Table 4.2 summarizes the testing parameters and recommended values for processing general datasets. Figure 4.5 provides an example of increasing the `max_gap` that helps capture additional ground points off of the road surface.

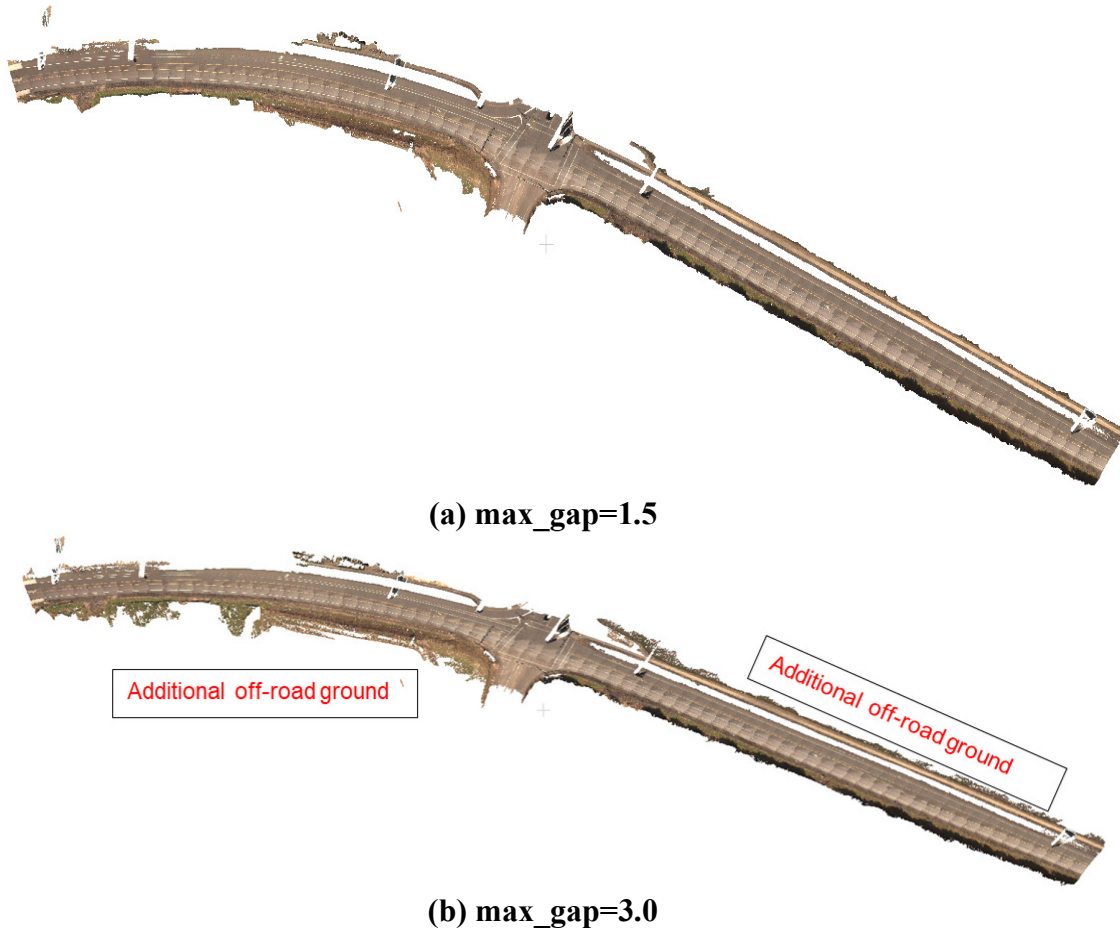
**Table 4.1: Description of general parameters for Vo-Smog ground filtering.**

| <b>Parameter</b> | <b>Parameter Description</b>                                                                                               |
|------------------|----------------------------------------------------------------------------------------------------------------------------|
| scale_noise      | Voxel size for noise filtering.                                                                                            |
| scale_grnd       | Voxel size for detecting ground candidates                                                                                 |
| scale_norm       | Voxel size for normal estimation                                                                                           |
| scale_seed       | Window size for detecting ground seeds to start the region grow process                                                    |
| scale_prox       | Voxel size for proximity filtering to refine the classification of individual points                                       |
| max_dnorm        | Maximum normal gradient for smooth ground surface detection                                                                |
| max_disp         | Maximum surface displacement for smooth ground surface detection                                                           |
| max_gap          | Maximum gap between ground points during region grow process and preliminary modeling                                      |
| min_ncore        | Minimum size of a ground segment to help filter out small segments of noise misclassified as ground                        |
| prox_disp        | Maximum displacement for proximity filtering to help refine the classification of individual points from the original data |
| max_niter        | Maximum number of iterations                                                                                               |

**Table 4.2: General parameters determined in the testing for Vo-Smog ground filtering.**

| Parameter   | Units | Recommended Value | Tested Range    | Datasets (Phase 1) | Test Values (Phase 1) | Datasets (Phase 2) | Test Values (Phase 2)              | Sensitivity | Challenging Dataset |
|-------------|-------|-------------------|-----------------|--------------------|-----------------------|--------------------|------------------------------------|-------------|---------------------|
| scale_noise | -     | 5<br>5            | 2-5             | 01, 04             | 2,3,4,5               | 01-10              | 2,3,4,5                            | Moderate    | -                   |
| scale_grnd  | m     | 0.15              | 0.1-0.2<br>m    | 01, 08             | 0.10, 0.15,<br>0.20   | 01-33              | 0.10, 0.15,<br>0.20                | Very High   | -                   |
| scale_norm  | m     | 0.15              | 0.1-0.2<br>m    | 01                 | 0.10, 0.15,<br>0.20   | N/A                | N/A                                | Minimal     | -                   |
| scale_seed  | m     | 30                | 20-50<br>m      | 01, 08             | 20, 30, 50            | 01-33              | 20,30, 50                          | Minimal     | -                   |
| scale_prox  | m     | 0.05              | 0.025-<br>0.1 m | 01                 | 0.025, 0.05,<br>0.1   | N/A                | N/A                                | Minimal     | -                   |
| max_dnorm   | deg   | 15                | 10-20<br>deg    | 01                 | 10,15,20              | N/A                | N/A                                | Minimal     | -                   |
| max_disp    | m     | 0.05              | 0.01-<br>0.05 m | 01, 08             | 0.01,0.03,0.0<br>5    | 01-10              | 0.01, 0.02,<br>0.03, 0.04,<br>0.05 | High        | -                   |
| max_gap     | m     | 3.0               | 1.0-3.0<br>m    | 01, 04             | 1.0, 1.5, 3.0         | 01-33              | 1.0, 1.5,<br>2.0, 2.5, 3.0         | High        | -                   |
| min_ncore   | -     | 30                | 20-50           | 01, 04             | 20, 30, 50            | N/A                | N/A                                | Minimal     | -                   |
| prox_disp   | m     | 0.02              | 0.01-<br>0.05 m | 01                 | 0.01, 0.02,<br>0.05   | N/A                | N/A                                | Minimal     | -                   |
| max_niter   | -     | 3                 | 3-5             | 01                 | 3, 5                  | N/A                | N/A                                | Minimal     | -                   |





**Figure 4.5.** Example difference in results based on varying the maximum gap from 1.5 (a) to 3.0 m (b) for dataset 11. At 3.0 more off road topographic points were preserved in the data.

### 4.5.2 Curb Extraction

Table 4.3 provides brief descriptions of the parameters being tested. Table 4.4 summarizes the value ranges of the parameters tested as well as the datasets tested for curb extraction. Overall, most parameters were found to be stable. The min\_len parameter did show some influence on the level of detail observed in the results. A smaller value helped preserve some of the curb; however, it also resulted in more false positives. Similarly max\_gap, scale\_xy, max\_dnorm and max\_error showed some slight variances in the results when tested within the ranges tested.

In Dataset 11, there were several aspects that made it challenging to extract the curbs (Figure 4.6). First, a substantial portion of the dataset did not have curbs present as it was a rural segment of highway. Second, the toes of adjacent hillslopes were sometimes confused as curbs. Additionally, there was a large data gap parallel to the road that was very close to the curb that prevented extraction of the curb. Increasing the min\_dz to 0.10 reduced the false positives substantially, but also resulted in a significant portion of the curb being missed in the extraction.

Dataset 23 is a rural setting similar to Dataset 11 but with a less pronounced hill. Only a small portion contained curbs at an intersection with a gas station (Figure 4.7). In this location, several false curbs were detected below the guardrail, along the sidewalk, or near the edge of the road. Increasing `min_dz` to 0.10 m reduced false positives substantially.

Dataset 13 is a typical example of most datasets where curbs were generally extracted well; however, some false positives remained (Figure 4.8). A slight increase in `scale_XY` to 0.15 m helped reduce some of those false positives.

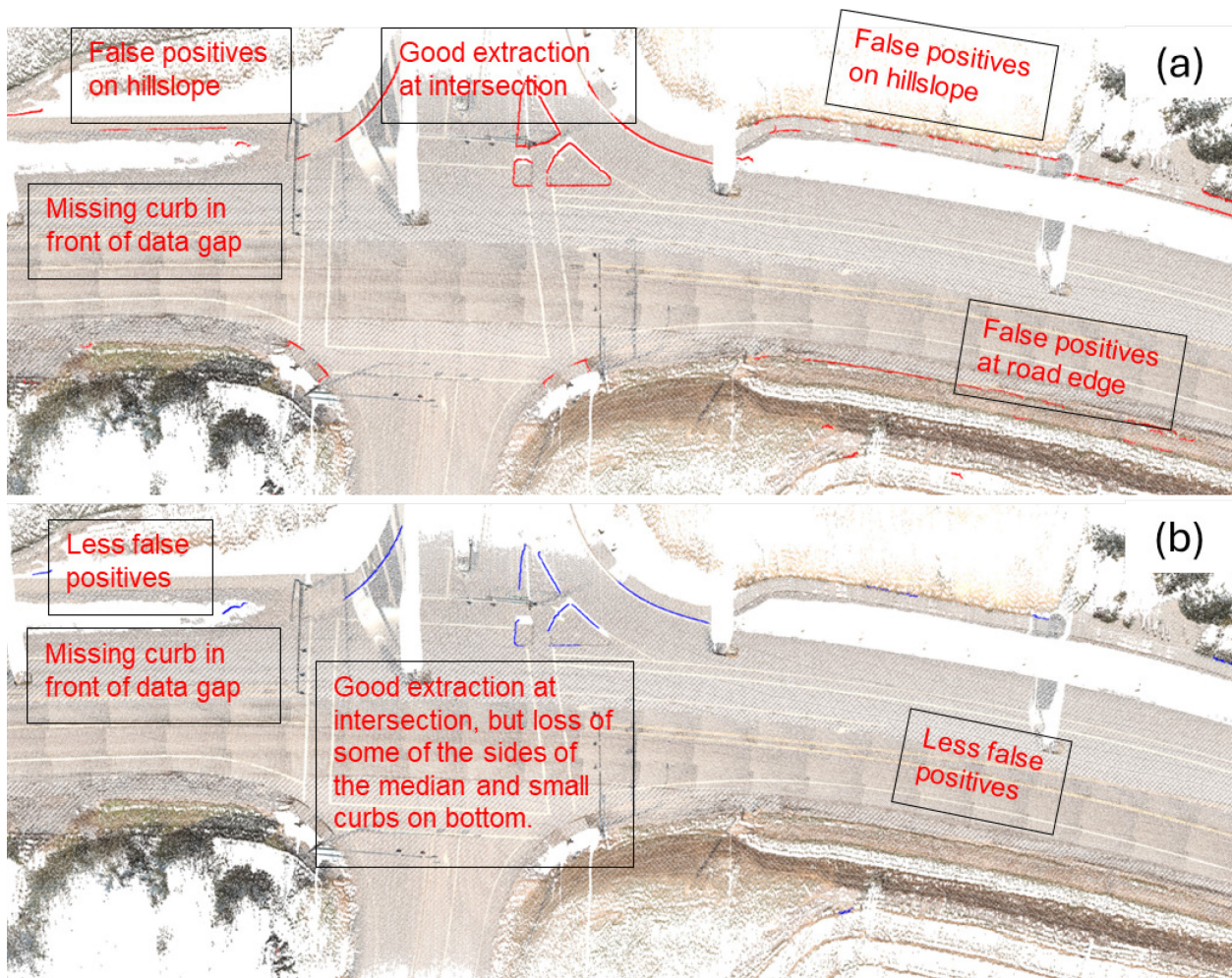
Dataset 29 had a curb present on one side of the highway but not the other (Figure 4.9). It is also in a rural location similar to Dataset 23. The extraction generally performed well, especially when increasing `min_dz` to 0.10 m to reduce false positives. However, a trade off is that some of the curbs are lost on the side streets with minimal coverage from the mobile lidar driven on the main street.

**Table 4.3: Parameter description for EZFeat Curb Extraction.**

| Parameter                  | Parameter Description                                             |
|----------------------------|-------------------------------------------------------------------|
| <code>max_gap</code>       | Maximum gaps for tracking a curb line                             |
| <code>scale_xy</code>      | Voxel size for analysis                                           |
| <code>min_dz</code>        | Minimum elevation change to qualify as part of a curb             |
| <code>max_dz</code>        | Maximum elevation change to qualify as part of a curb             |
| <code>max_dnorm</code>     | Maximum normal gradient for the curb face                         |
| <code>max_error</code>     | Maximum positioning errors for each individual point for analysis |
| <code>min_len</code>       | Minimum length of a curb segment                                  |
| <code>range_pca</code>     | The radius used for running Principal Component Analysis          |
| <code>min_linearity</code> | Minimum linearity for a curb segment                              |

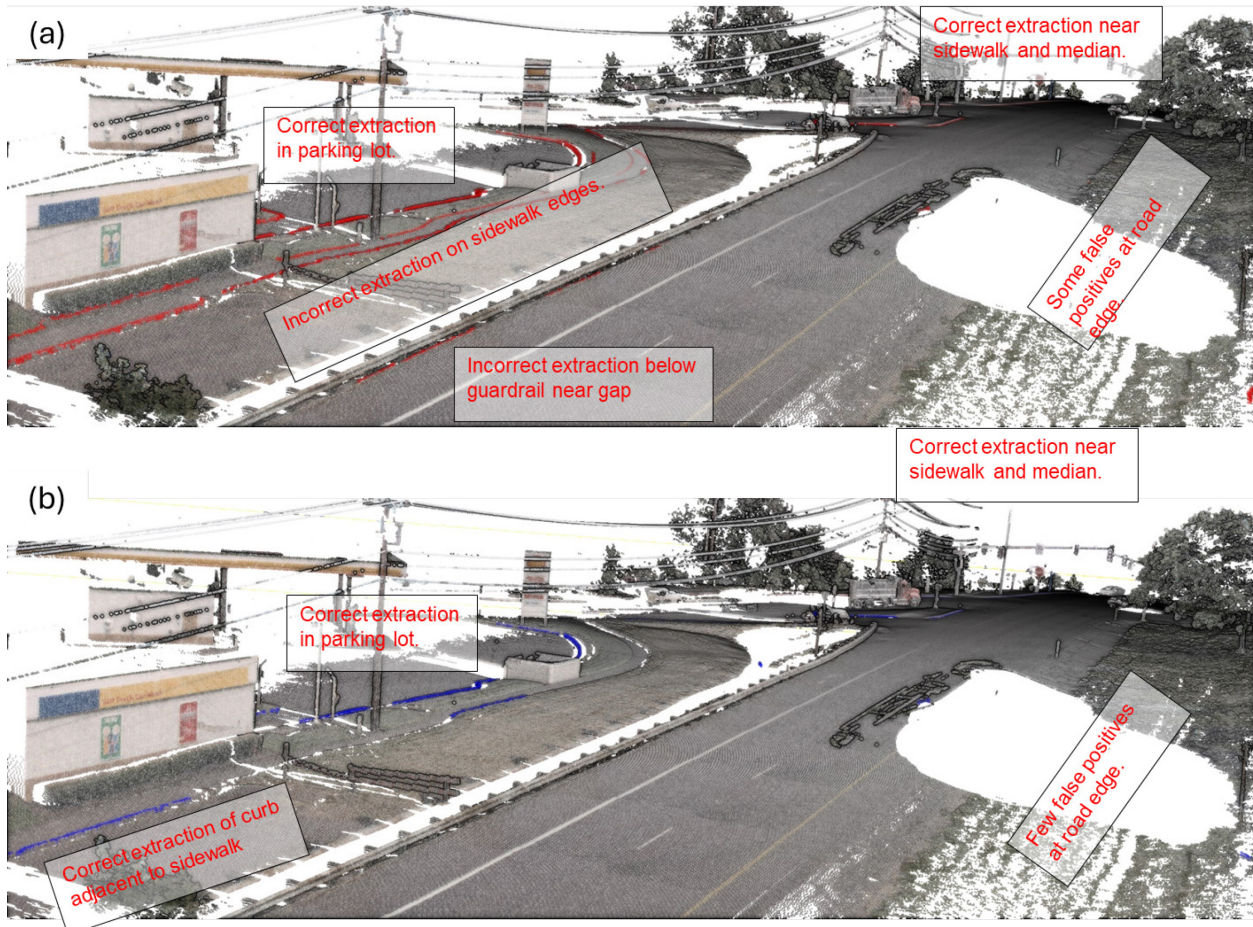
**Table 4.4: Optimal parameters determined in the testing for EZFeat Curb Extraction.**

| Parameter            | Units | Recommended Value            | Tested Range | Datasets (Phase 1) | Test Values (Phase 1) | Datasets (Phase 2)                                                             | Test Values (Phase 2)    | Sensitivity | Problematic Datasets    |
|----------------------|-------|------------------------------|--------------|--------------------|-----------------------|--------------------------------------------------------------------------------|--------------------------|-------------|-------------------------|
| <b>max_gap</b>       | m     | 2.0                          | 1.0-2.0      | 03, 04, 05, 06, 07 | 1.0, 1.5, 2.0         | 01-33                                                                          | 1.0, 1.5, 2.0            | Moderate    | 11                      |
| <b>scale_xy</b>      | m     | 0.15                         | 0.075-0.15   | 03, 04             | 0.075, 0.1, 0.15      | 01-33                                                                          | 0.075, 0.10, 0.125, 0.15 | Moderate    | 11                      |
| <b>min_dz</b>        | m     | 0.05 (urban)<br>0.10 (rural) | 0.05-0.10    | 03                 | 0.05, 0.10            | N/A                                                                            | N/A                      | Very High   | -                       |
| <b>max_dz</b>        | m     | 0.25                         | 0.20-0.35    | 03                 | 0.20, 0.35            | N/A                                                                            | N/A                      | Very High   | -                       |
| <b>max_dnorm</b>     | deg   | 5.0                          | 2.0-5.0      | 03, 04             | 2.0, 3.0, 4.0, 5.0    | 01, 03, 05, 07, 09, 11, 15, 21, 29                                             | 2.0, 3.0, 4.0, 5.0       | Moderate    | 09 (slight), 11, 23, 29 |
| <b>max_error</b>     | m     | 0.01                         | 0.005-0.02   | 03, 04, 05, 06     | 0.005, 0.01, 0.02     | 01, 03, 05, 07, 09, 11, 15, 21, 23, 29 31, 33                                  | 0.005, 0.01, 0.015, 0.02 | Moderate    | 11, 23, 29              |
| <b>min_len</b>       | m     | 3.0                          | 2.0- 5.0     | 03, 04             | 2.0, 3.0, 5.0         | 01-33 for 2.0, 01, 03, 05, 07, 09, 11, 15, 21, 22, 29, 31, 33 for other values | 2.0, 3.0, 4.0, 5.0       | Very High   | -                       |
| <b>range_pca</b>     | m     | 0.5                          | 0.4- 0.6     | 03, 04             | 0.04, 0.05, 0.06      | N/A                                                                            | N/A                      | Minimal     | -                       |
| <b>min_linearity</b> | -     | 0.80                         | 0.6-0.95     | 03, 04, 05, 06     | 0.6, 0.8, 0.95        | N/A                                                                            | N/A                      | Minimal     | -                       |

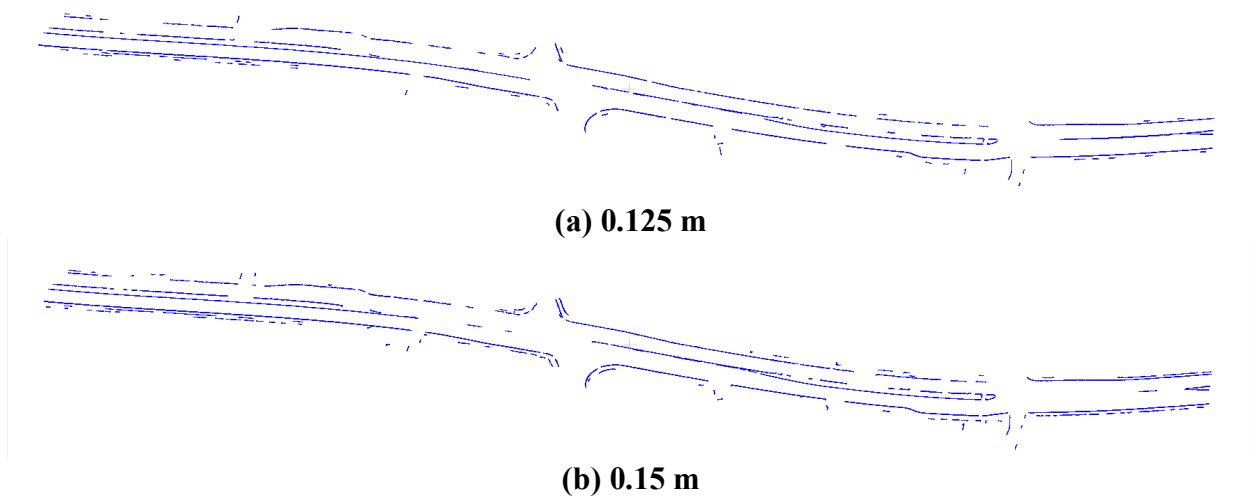


**Figure 4.6. Example of extracted curb ramps from Dataset 11 using (a) recommended parameter values and (b) using  $\text{min\_dz} = 0.10$  to reduce the false positives, but at the loss of some of the curb near the median**

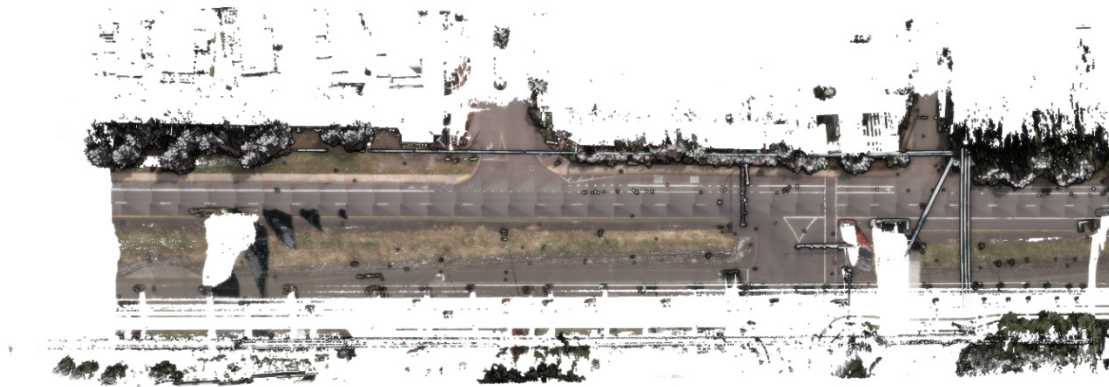




**Figure 4.7. Example curb extraction from DS23 using (a) recommended values and (b)  $\text{min\_dz} = 0.10$  to reduce the false positives**

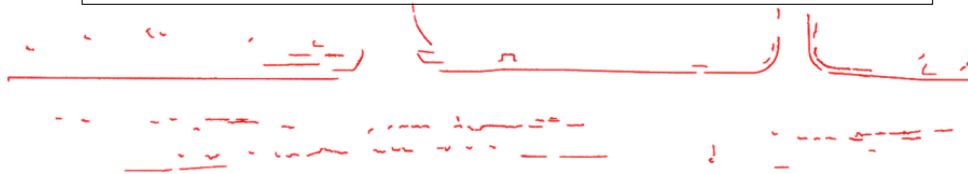


**Figure 4.8. Comparison of scale  $XY = 0.125$  m (a) and  $0.15$  m (b) on Dataset #13. In this case lowering from the recommended value reduced some noise in the curb extraction**



(a)

Correct extraction of curbs adjacent to sidewalk. Some false positives.



False positives adjacent to grassy areas.

(b)

Correct extraction of curbs adjacent to sidewalk. Reduced false positives.

Loss of a portion of the curb on side street.



Substantially reduced false positives adjacent to grassy areas.

(c)

**Figure 4.9. Example curb extraction from DS29 using (a) recommended default parameter values and (b)  $\text{min\_dz} = 0.10$  to reduce the false positives present in the scene. A small portion of the curb is lost from the side street.**

### 4.5.3 Road Detection

Lastly, the EZFeat Road Detection Algorithm was tested, which is an update from the VROOM algorithm in Che and Olsen (2018). Generally, the road detection results were not sensitive to the parameter adjustments. Table 4.5 provides a brief description of each parameter being tested. Table 4.6 summarizes the parameters and datasets tested. Some parameters such as `scale_xy`, `max_gap`, `max_dnorm` and `min_width` had moderate influence on the extraction results within the ranges tested.

Dataset 12 was one that had some challenges with the road extraction (Figure 4.10) near a roundabout. A portion of the road in the lane opposite of where the mobile lidar was driven was not extracted given a median barrier blocking the path. Remarkably, the algorithm performed well in the roundabout where the mobile lidar travels at slower speeds.

Dataset 26 was another example of extraction issues where a raised median in the middle and two occlusions from vehicles that spanned that entire side of the road prevented the region growing from occurring (Figure 4.11). Overall, this represents a small portion of the area and could be corrected with basic GIS tools when the results of the feature extraction are aggregated.

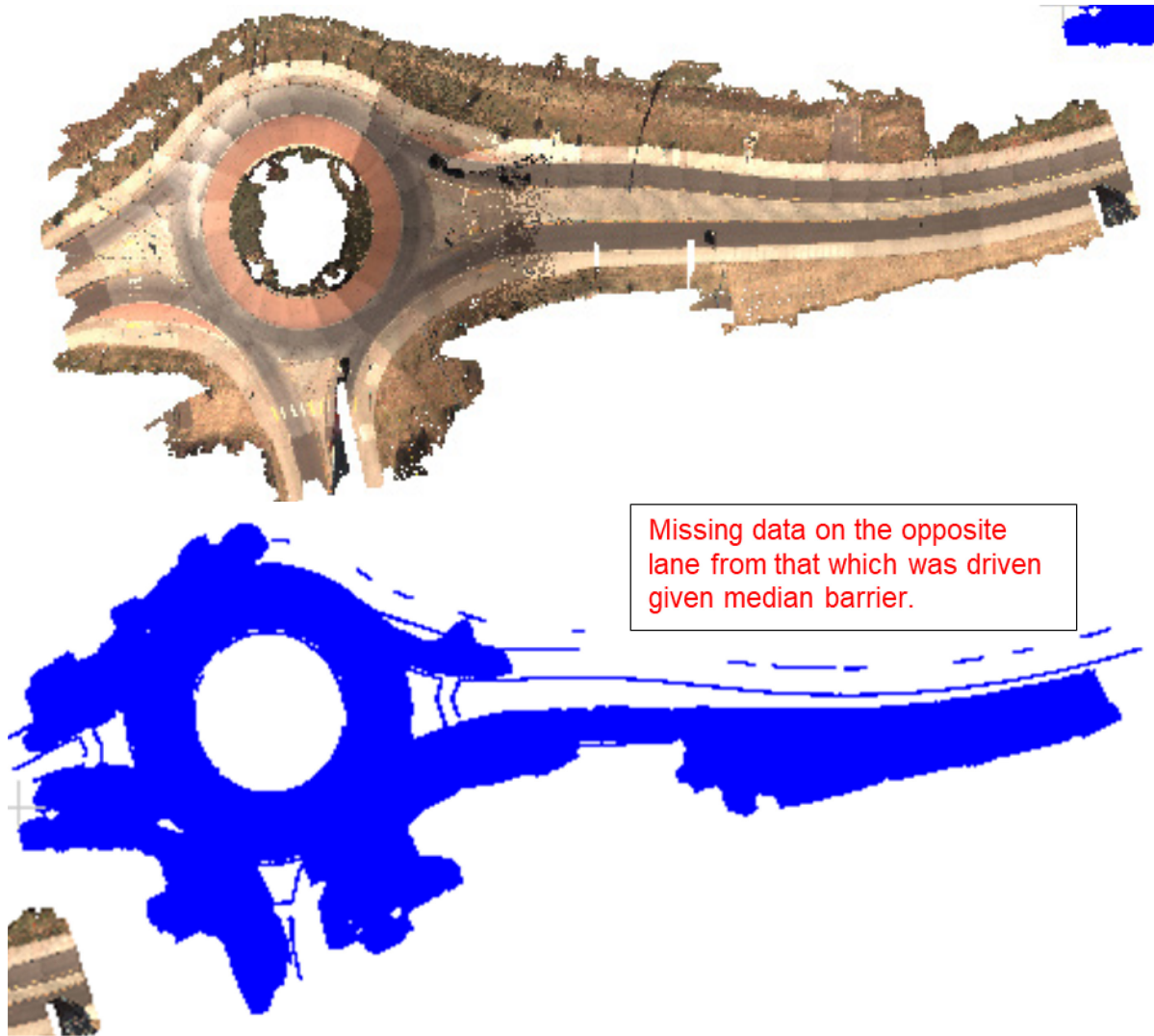
**Table 4.5: Description of parameters for EZFeat Road Extraction.**

| Parameter              | Parameter Description                                                                   |
|------------------------|-----------------------------------------------------------------------------------------|
| <code>scale_xy</code>  | Voxel size for analysis                                                                 |
| <code>max_gap</code>   | Largest gap to fill during modeling process                                             |
| <code>max_error</code> | Maximum positioning error for individual points                                         |
| <code>max_dnorm</code> | Maximum normal gradient for the road surface                                            |
| <code>min_width</code> | Minimum width of the road surface detected                                              |
| <code>max_width</code> | Maximum width of the road surface detected                                              |
| <code>min_ncore</code> | Minimum of the size of a road segment                                                   |
| <code>prox_disp</code> | Displacement for the proximity filtering for refining the point classification results. |

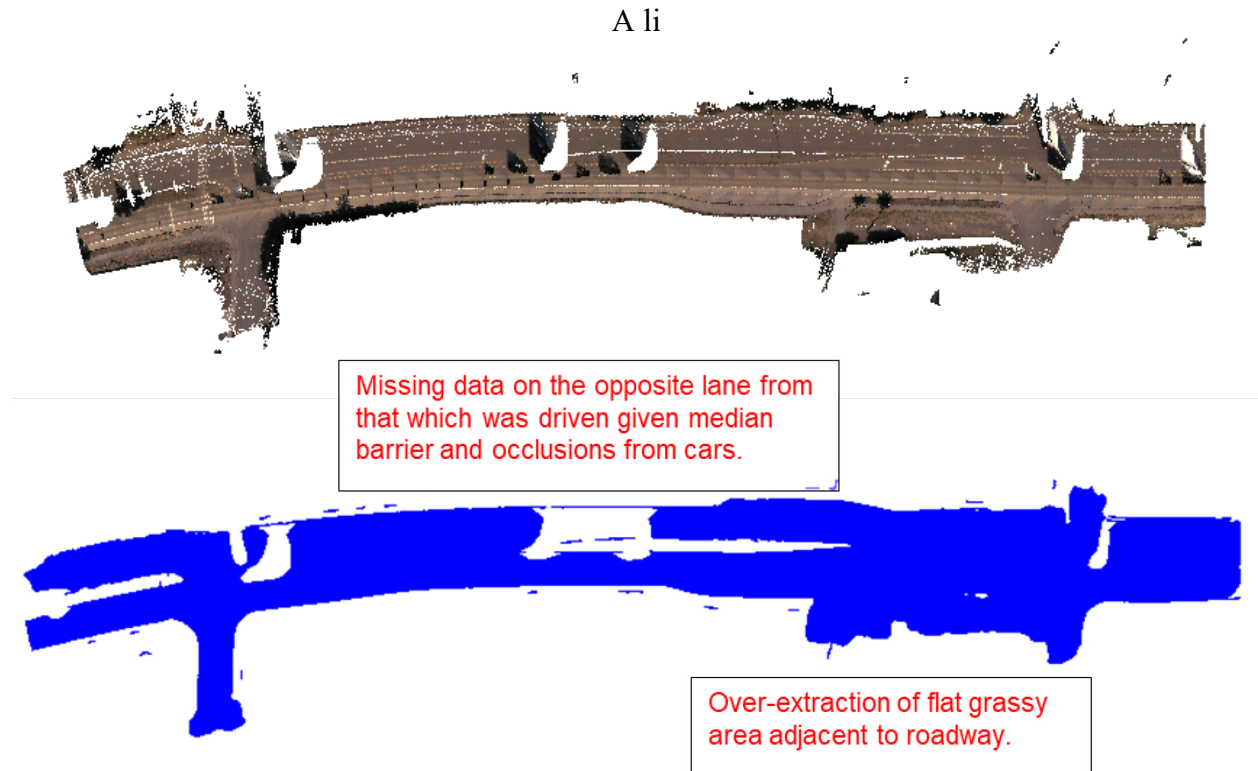
**Table 4.6: General parameters determined in the testing for EZFeat Road Extraction.**

| Parameter | Units | Recom-<br>mended<br>Value | Tested<br>Range | Datasets<br>(Phase 1) | Test Values<br>(Phase 1) | Datasets<br>(Phase 2) | Test<br>Values<br>(Phase 2)       | Sensitivity | Challenging<br>Datasets            |
|-----------|-------|---------------------------|-----------------|-----------------------|--------------------------|-----------------------|-----------------------------------|-------------|------------------------------------|
| scale_xy  | m     | 0.30                      | 0.1-0.5         | 14, 33                | 0.1, 0.3, 0.5            | 01-33                 | 0.1, 0.2,<br>0.3 ,0.4,<br>0.5     | Moderate    | 12, 26 (slight)                    |
| max_gap   | m     | 2.0                       | 1.0-2.0         | 14, 33                | 1.0, 1.5, 2.0            | 01-33                 | 1.0, 1.5,<br>2.0                  | Moderate    | 12                                 |
| max_error | m     | 0.01                      | 0.005-<br>0.02  | 14, 33                | 0.005, 0.01,<br>0.02     | 01-33                 | 0.005,<br>0.01,<br>0.015,<br>0.02 | Minimal     | 12                                 |
| max_dnorm | deg   | 3.0                       | 2.0-5.0         | 14, 33                | 2.0, 3.0, 4.0,<br>5.0    | 01-33                 | 2.0, 3.0,<br>4.0, 5.0             | Moderate    | 12, 15<br>(slight), 26<br>(slight) |
| min_width | m     | 3.0                       | 3.0-5.0         | 14, 33                | 3.0, 4.0, 5.0            | 01-33                 | 3.0, 4.0,<br>5.0                  | Moderate    | -                                  |
| max_width | m     | 0.0                       | N/A             | N/A                   | N/A                      | N/A                   | N/A                               | Minimal     | -                                  |
| min_ncore | #     | 10000                     | 5000-<br>20000  | 14, 33                | 5000, 10000,<br>20000    | N/A                   | N/A                               | Minimal     | -                                  |
| prox_disp | m     | 0.01                      | 0.01-<br>0.02   | 14, 33                | 0.01-0.02                | N/A                   | N/A                               | Minimal     | -                                  |





**Figure 4.10. Example extraction of the road surface at a roundabout in dataset 12.  
(scale\_xy=0.3)**



**Figure 4.11. Example road extraction from DS26 with some data gaps in the opposite lane resulting from a combination of barriers and medians. (scale\_xy = 0.3)**

#### 4.5.4 Summary

Table 4.7 summarizes the recommended general parameters for Vo-Smog ground filtering, EZFeat curb extraction and EZFeat road detection for mobile lidar systems. Note that when applied to a different mobile lidar system from the Leica Pegasus 2 (e.g., ODOT's new Riegl mobile lidar system), the parameters should be tested as system noise and point density may be different.

**Table 4.7: Summary of recommended parameters for general use of Vo-Smog ground filtering, curb extraction and road detection for mobile lidar systems.**

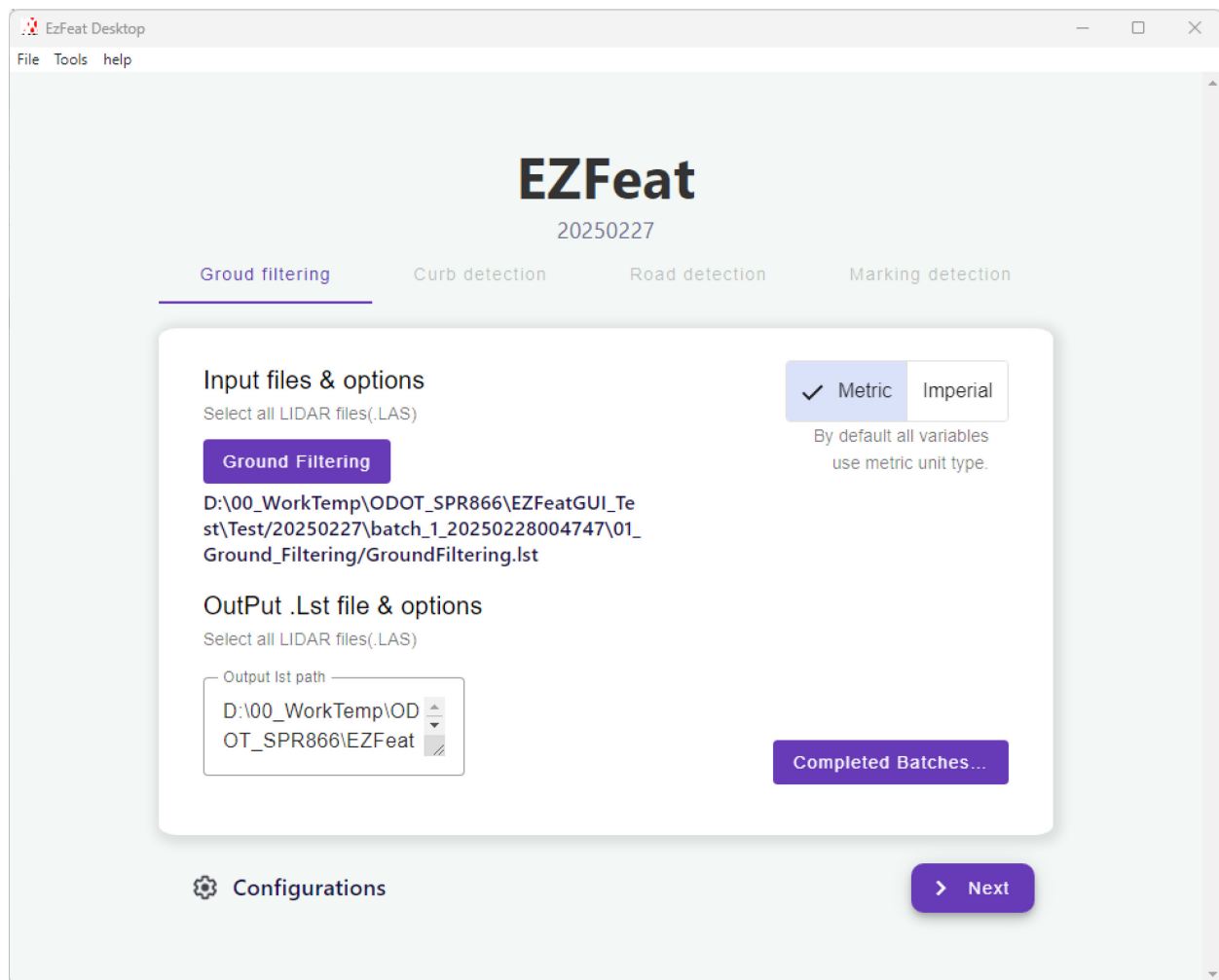
| <b>Parameter Group</b>       | <b>Vo-Smog</b>                                                                                                               | <b>Curb Extraction</b>                                             | <b>Road Detection</b>                            |
|------------------------------|------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------|--------------------------------------------------|
| <b>Scale</b>                 | scale_noise: 5 5<br>scale_grnd: 0.15 m 0.15 m<br>scale_norm: 0.15 m 0.15 m<br>scale_seed: 30 m<br>scale_prox: 0.05 m, 0.01 m | scale_xy: 0.15 m                                                   | scale_xy 0.3 m                                   |
| <b>Normal Variation</b>      | max_dnorm: 15 deg                                                                                                            | max_dnorm: 5.0 deg                                                 | max_dnorm 3.0 deg                                |
| <b>Error</b>                 | N/A                                                                                                                          | max_error: 0.01 m                                                  | max_error 0.01 m                                 |
| <b>Displacements\Offsets</b> | max_disp: 0.05 m<br>prox_disp: 0.02 m                                                                                        | min_dz: 0.05 m (urban)<br>min_dz: 0.10 m (rural)<br>max_dz: 0.25 m | prox_disp 0.01 m                                 |
| <b>Geometry</b>              | N/A                                                                                                                          | min_len: 3.0 m<br>range_pca: 0.5<br>min_linearity :0.80            | min_width 3.0 m<br>max_width 0.0 m<br>(infinite) |
| <b>Gaps</b>                  | max_gap: 3.0 m                                                                                                               | max_gap: 2.0 m                                                     | max_gap 2.0 m                                    |
| <b>Number of Points</b>      | min_ncore (min cell size): 30                                                                                                | N/A                                                                | min_ncore 10000                                  |
| <b>Iterations</b>            | max_niter: 3                                                                                                                 | N/A                                                                | N/A                                              |

## 4.6 SOFTWARE PROTOTYPE FOR GROUND FEATURE EXTRACTION

The utilization of several distinct, single-type feature extraction tools described in the previous sections make the data processing framework modular. These tools all support batch processing, and any tool or module can be run and evaluated separately. They can also be replaced as long as the same data standards are followed. Another benefit is that the workflow can be easily customized by changing orders of specific feature extraction steps, skipping certain steps in the workflow, running a specific step with different settings, and so on.

Nevertheless, such flexibility and versatility also come with tradeoffs. For example, although each step of the workflow is automated, it could require the users to operate and run the programs. In SPR850, the team delivered a script to streamline the process involving multiple tools and steps via command lines. Nonetheless, the arguments and parameters may not be intuitive to average users. Moreover, certain configurations (e.g., paths to the executables, data folders, etc.) that are machine-specific need to be set up carefully in the script. Given the nature of the use of an ASCII format in the command line scripts, they can also be vulnerable to unintended edits. Therefore, a user-friendly GUI can facilitate the implementation of the framework across multiple programs and personnel who do not necessarily have the insights and understanding of all the algorithms with their settings in the tools mentioned in the previous sections.

To this end, the OSU team partnered with EZDATAMD LLC to develop a software prototype for ground feature extraction (Figure 4.12). This prototype incorporated the Vo-SmoG ground filtering, EZFeat curb detection, road detection, and road marking extraction into a streamlined workflow. A intuitive GUI built in the software prototype helps users create workspace to manage the projects and tasks. For most tasks, the program defaults to fine-tuned parameters that can cover the majority of the use cases; however, power users have the ability to further adjust the settings for each step. This prototype also stores the intermediate results which enables iterative refinement where users can skip the steps that have provided satisfactory results. Appendix A provides a user guide with more details of the installation, setup, functions, and components of a project.



**Figure 4.12. Screenshot of the EZFeat ground feature extraction software prototype**

## 5.0 ROAD CHARACTERIZATION

The accurate characterization and representation of roadway geometry is essential for transportation planning, design, maintenance, analysis, and other applications. However, traditional surveying methods to measure such attributes can be labor-intensive, time-consuming, and often pose safety risks to surveyors working in active roadway environments even with necessary traffic control. Fortunately, a survey-grade mobile lidar system, equipped with high-quality lidar sensor, IMU, and GNSS, is able to capture the 3D geometry of the roadway at a very high resolution and accuracy by simply traveling through the area of interest at a normal driving speed in a much more efficient and safer manner. In this study, the team developed methods and tools to extract and characterize features including horizontal curves, vertical curves, and cross sections. It is worth noting that these tools were designed with a strong emphasis in handling statewide highway systems.

### 5.1 ROAD ALIGNMENT EXTRACTION

#### 5.1.1 Road Marking-based Road Alignment

The detected road markings can be utilized to determine the road alignment. The team developed a method extracting the center line of each lane based on the road marking extraction and classification results (Figure 5.1). The longitudinal stripes including both solid and broken/dash lines can be identified in the ROME tool (Jung et al., 2024). To get the preliminary lane alignment, the dash lines need to be connected. Next, several cross sections can be extracted at a user-defined interval. The center point at each cross section between every two adjacent longitudinal stripes along the cross section can be obtained. Finally, these center points can be connected and turned into polylines defining the center line of each lane.

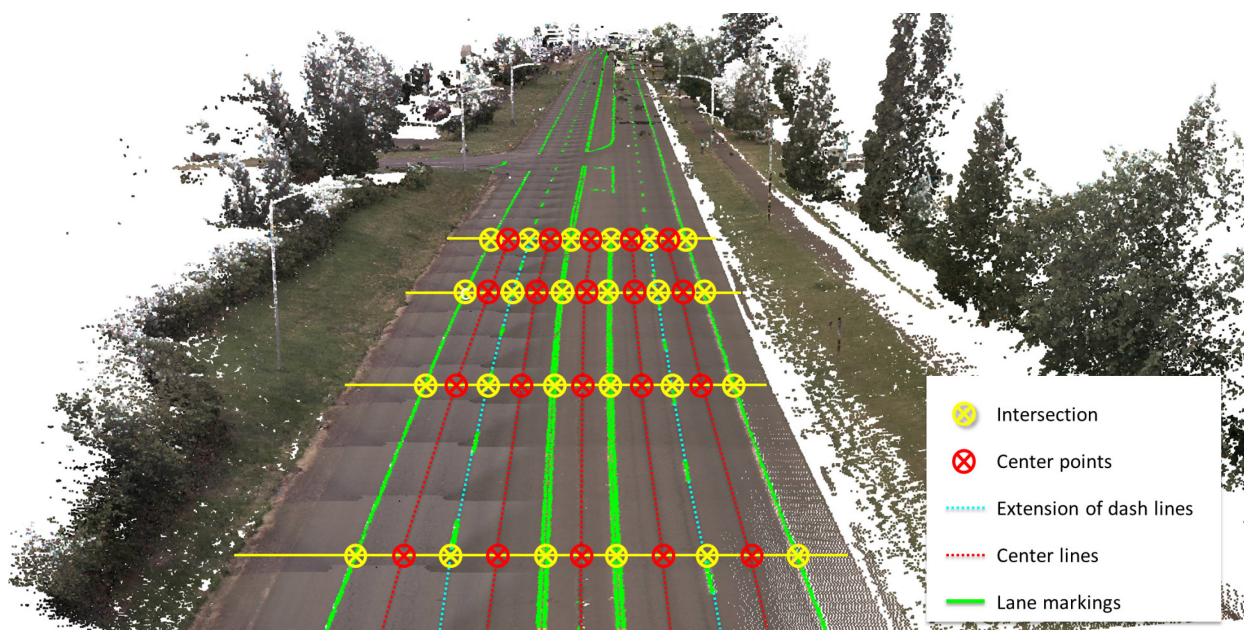
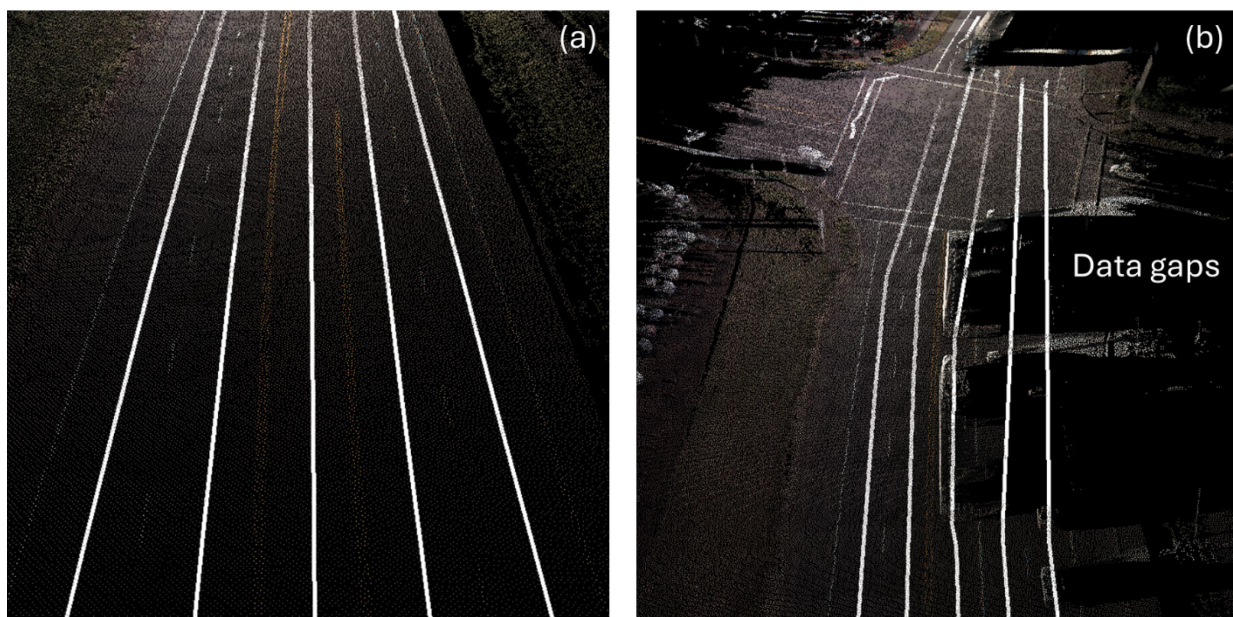


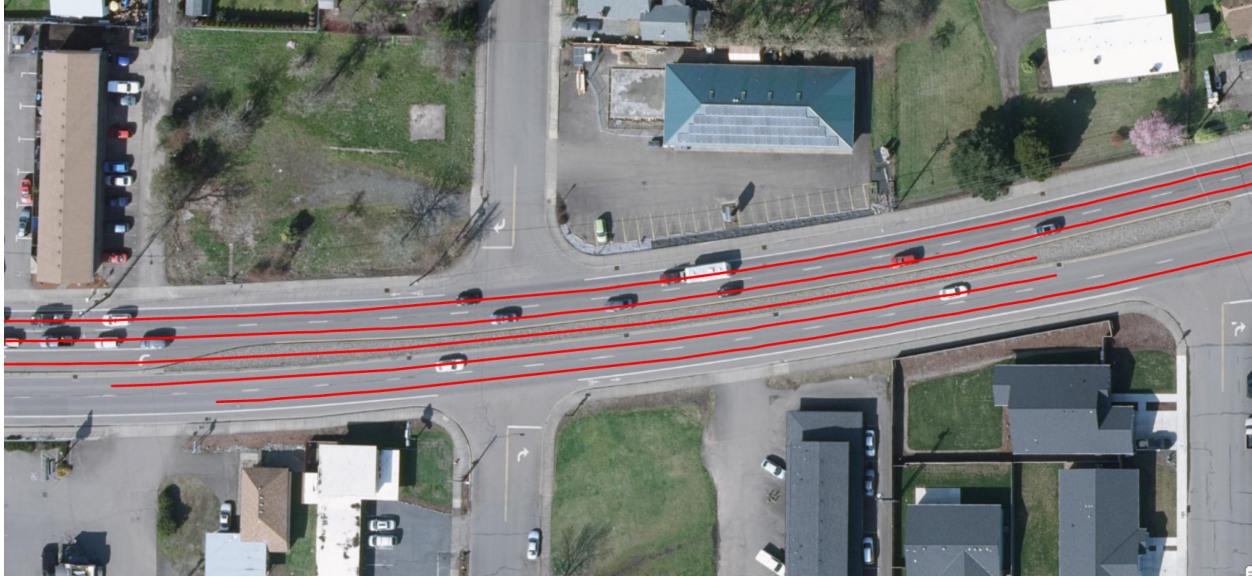
Figure 5.1 Conceptual image for identifying individual lanes from extracted road markings



During the testing and evaluation, the proposed approach provided promising results where the center lines can be extracted (Figure 5.2). However, the quality of the marking detection results can depend on several factors such as degradation of the existing markings, occlusions caused by other vehicles or objects, and other situations when there is a large gap between sections of the longitudinal stripes or non-linear traffic patterns (e.g., shifted lane). In the example in Figure 5.2, for a straight section of the highway with road markings in good condition, the proposed approach is shown to be very effective and cover all lanes including the two-way left-turn median. On the other hand, in the case of an intersection, it can be seen that the left turn lanes from both directions were incorrectly connected as one lane. In some other cases, if the numbers of lanes from both legs of the intersection are different, the lane tracing can become error-prone in attempting to resolve the discrepancy. Figure 5.3 provides another example with the road alignment results visualized in ArcGIS Pro software where some of the lanes are only partially extracted mostly because the data quality can vary when covering multiple lanes, which renders the road marking extraction more challenging. In the context of road characterization, another limitation of the road marking-based road alignment extraction is the loss of geometric information as shown in the examples. The large interval set to draw cross sections for extracting center lines can result in inaccurate measurements of characteristics (e.g., curvature) of the road, especially for horizontal curves. Although the cross-section interval can be reduced to preserve more geometric details, it will significantly increase the computational complexity and be a lot more sensitive to noise and errors in marking extraction, which can then cause invalid results. Therefore, from this initial testing the team concluded that such approach is not feasible to be used in road characterization for statewide asset management purposes. That being said, for some specific projects and geometric configurations, this proposed approach still has the potential to provide information of individual lanes including the boundary and center lines.



**Figure 5.2 Example of road alignment extraction results from road markings at: (a) straight sections; (b) an intersection**



**Figure 5.3 Example of road alignment extraction results (red) from road markings displayed in ArcGIS Pro**

### 5.1.2 Trajectory-based Road Alignment

The trajectory data provides precise position and orientation of the mobile lidar system at a given moment. While its primary purpose is to precisely track the path of the vehicle in order to generate the 3D geometry from the lidar systems, in this study, it is leveraged as a core input to perform robust curve extraction and characterization. It also serves as the base for generating cross sections. During the mobile lidar data collection, the system is usually operated on one lane and does not frequently change lanes. Hence, the trajectory data can be considered as a proxy of the road alignment. Compared to the road marking-based approach described in the previous section, the trajectory is considered continuous (with a typical data rate at 200 Hz) and mostly follows the traffic pattern so that there is no ambiguity for the intersection or areas with data gaps.

While the trajectory can be directly used to obtain the road alignment, there are other considerations of the data that can be tackled to achieve a better performance in the following analysis. The spatial density of the trajectory points is a function of the data rate (200 Hz) and vehicle speed (typically at the speed limit). The vehicle speed can change due to the traffic and other circumstances causing variant point density. For example, when the vehicle is taking a sharp turn or going through a more complex traffic pattern such as a roundabout, it is usually expected to slow down resulting in denser trajectory data than a straight section of the highway. If this data is directly used in the following road characterization process, it can cause inconsistency in identifying and characterizing the curves given the variant resolution. When the vehicle stops or moves at a very low speed, in addition to the very dense trajectory points being recorded, some drifting errors can occur resulting in lower relative accuracy in positioning.

To mitigate the issues of large data volume, variant resolution, and drifting at low speed, the trajectory data was down-sampled by setting criteria in both temporal and spatial resolutions. A



user-defined minimum separation of the time stamps and 3D locations was applied to the trajectory data for the down-sampling process. The default values for the time and space separations are 2.5 s and 100 ft, respectively. As shown in Figure 5.4, the down-sampled trajectory data is smoother and spaced more consistently which enhances the effectiveness and efficiency of the following analysis. All of the analysis described in the following sections for horizontal curves, vertical curves, and cross sections input the down-sampled trajectory data.



**Figure 5.4 Example of variant point spacing and down-sampling results of the mobile lidar trajectory data**

## 5.2 CURVE IDENTIFICATION AND CHARACTERIZATION

With the down-sampled trajectory data as the primary input, the horizontal and vertical curves can be identified, classified, and characterized (Figure 5.5). The proposed approach first segments the road into a number of road segments based on the curvature and slope gradient for horizontal and vertical curves, respectively. Then the results can be refined by further analysis based on the road segments to identify the horizontal and vertical curves. Because different types of curves follow different mathematical models, it is necessary to distinguish the curve types and analyze each type of curve feature accordingly (Figure 5.6).



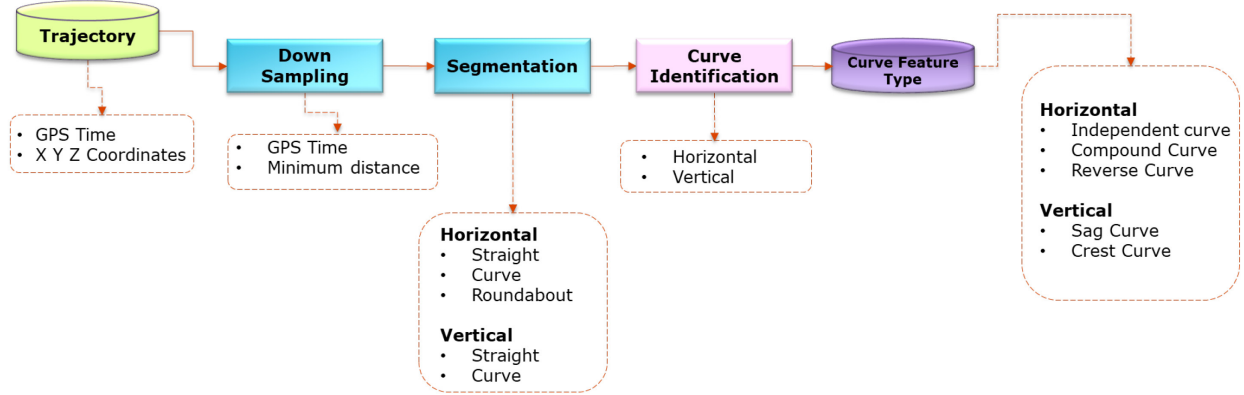


Figure 5.5 Workflow for curve segmentation and identification.

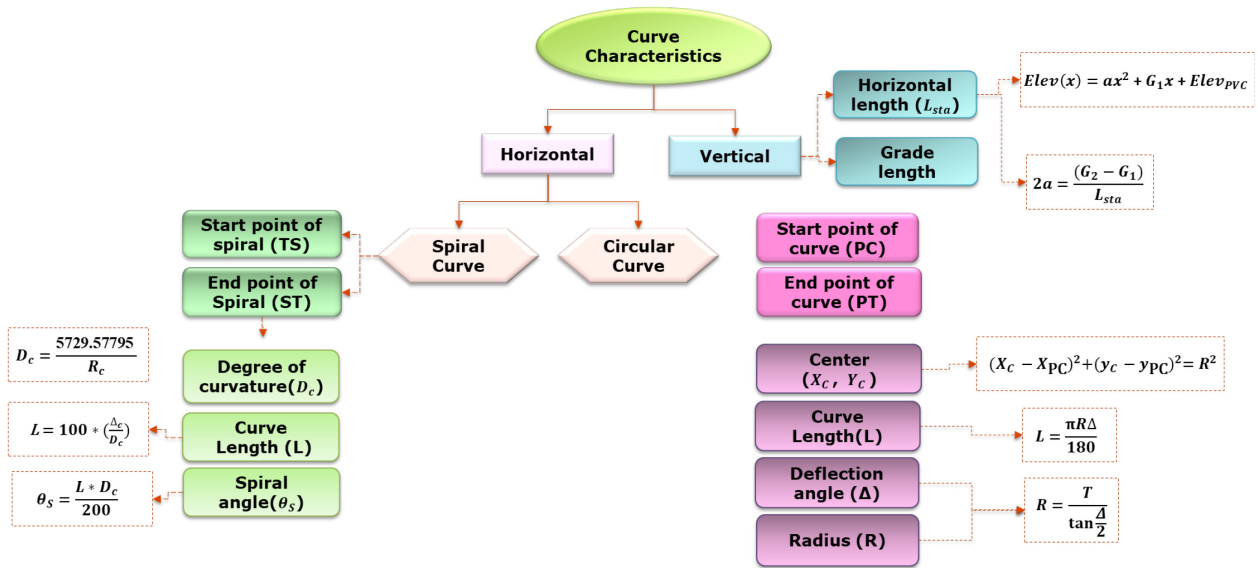


Figure 5.6 Overview of characterization for horizontal and vertical curves

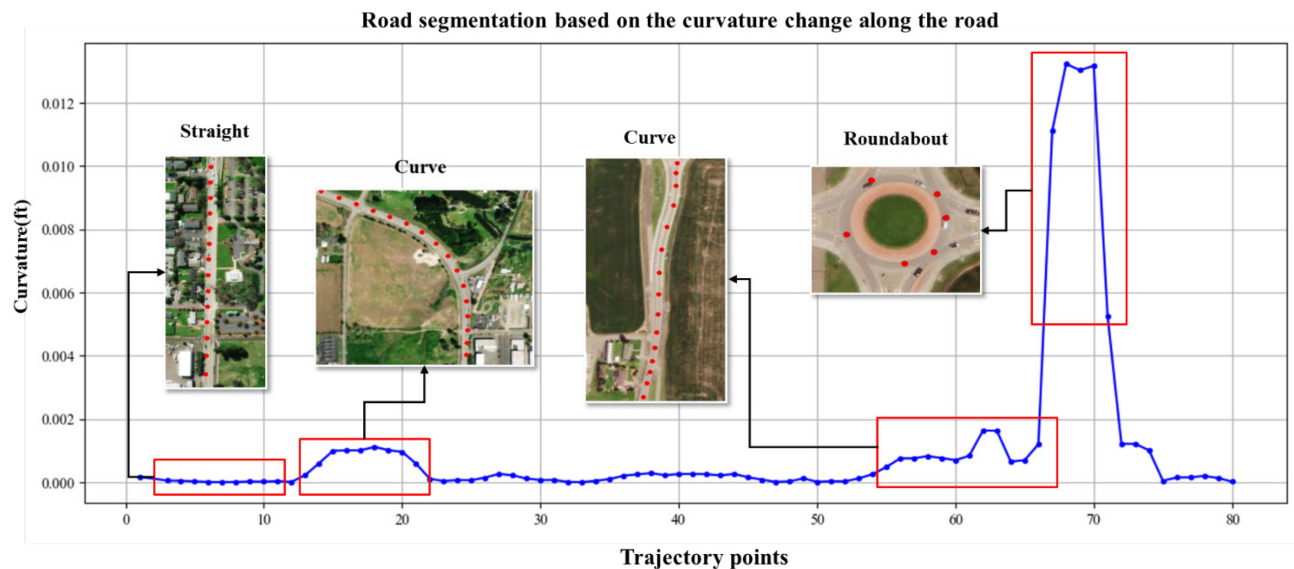
### 5.2.1 Horizontal Curves

To characterize the horizontal features of the highway from the down-sampled trajectory points, curvature can be calculated at each trajectory point with its adjacent two neighboring records using their X-Y coordinates. A circle passing all three points can be determined and the inverse of its radius  $R$  is defined as the curvature at the trajectory point under analysis following the following equation:

$$\text{Curvature} = \frac{1}{R} \quad (5-1)$$

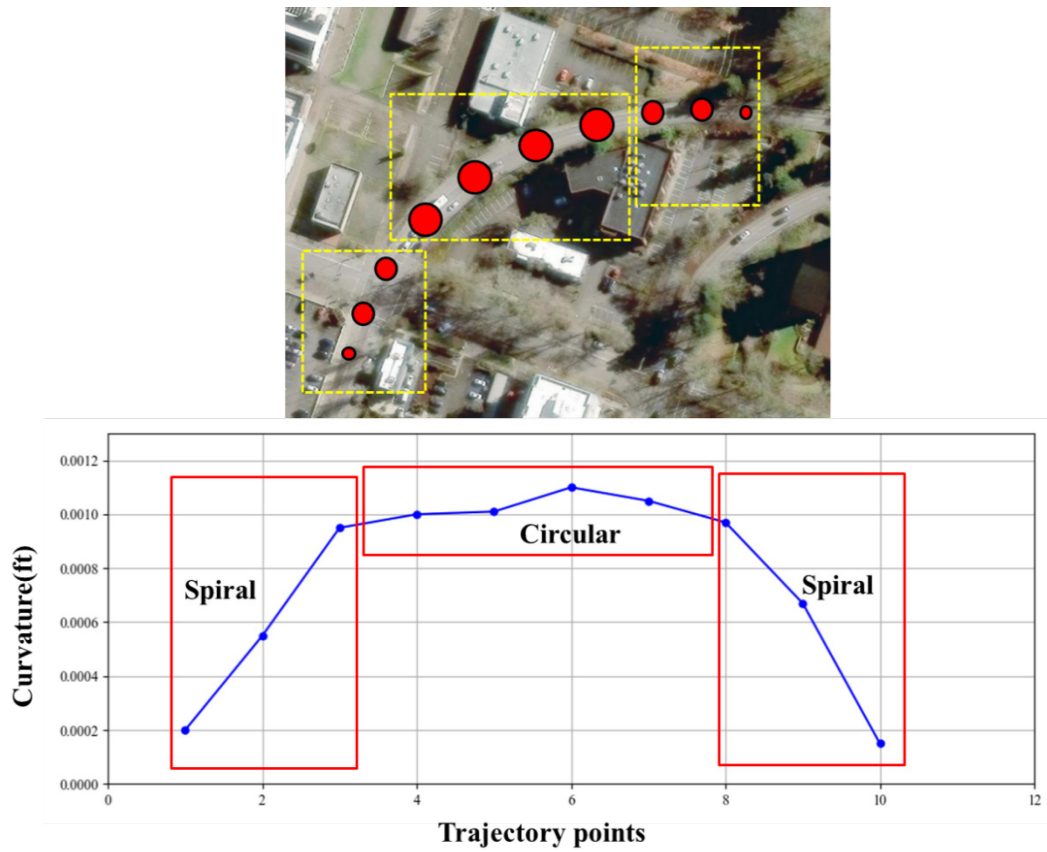
It is worth noting that in the case of three consecutive trajectory points being colinear, the curvature will be assigned with value of 0 as the radius of a straight line is infinite.

Once the curvature is computed at each trajectory point, two thresholds can be given to categorize them into straight, curved, and turning (e.g., roundabout) points (Figure 5.7). It is worth clarifying that the approach is developed using the arc definition for curves rather than chord definition.

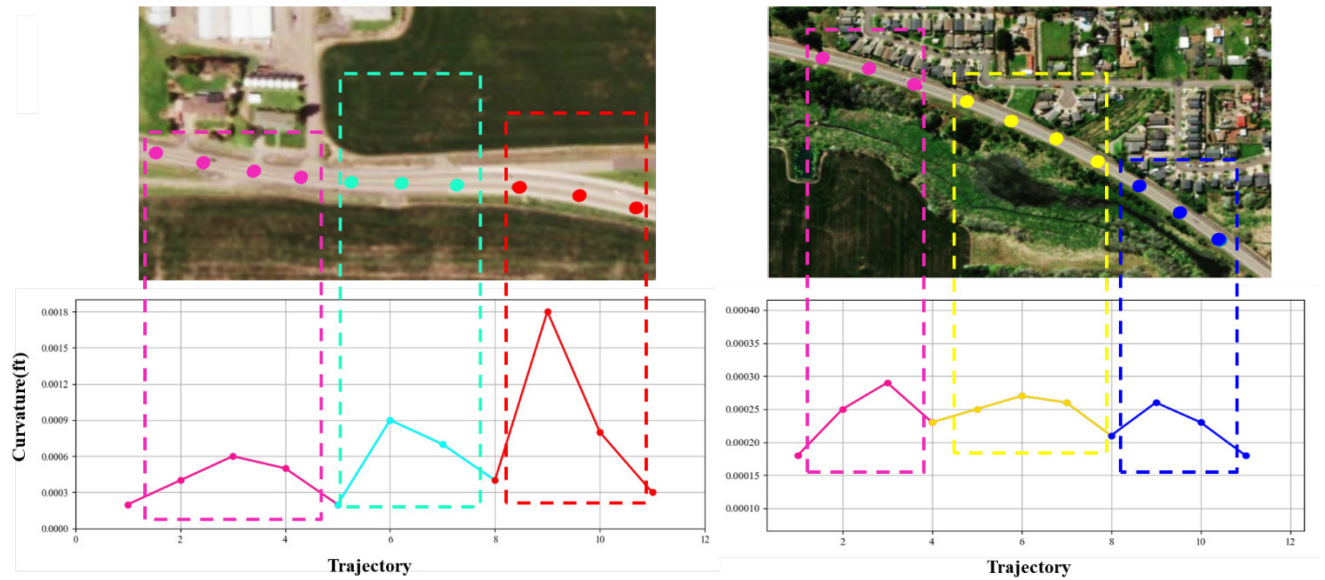


**Figure 5.7 Curvature derived from trajectory data which can be used to segment the highway into different categories**

The trajectory sections identified as curves can be further analyzed and categorized into three types: independent, compound, and reverse. Independent curves are defined as simple curves with consistent curvature (Figure 5.8). Compound curves come with multiple peaks or valleys in the curvature profiles, indicating the transitions from one radius to another, which is the basis to divide a compound curve into multiple simple curves (Figure 5.9). Reverse curves are similar to compound curves in terms of the curvature profiles where multiple peaks or valleys can be detected. The difference is that the centers of the two consecutive arcs with opposite curvatures lie on opposite sides of the baseline (Figure 5.9). Spiral curves, in contrast, are characterized by a gradual and continuous change in curvature, typically used to provide a smooth transition between straight and curved segments. Rather than having abrupt changes in radius, spiral curves progressively increase or decrease in curvature, helping to improve ride comfort and safety by easing vehicles into or out of a circular path.



**Figure 5.8** The change in curvature for different portion of an independent horizontal curve



**Figure 5.9** Decomposing reverse and compound curves into individual simple curves

After identifying distinct curves and organizing compound and reverse curves into simpler components, their geometric characteristics can be calculated by fitting circles with least-squares optimization. Specifically, the center of a curve ( $X_c, Y_c$ ), the radius of the curve ( $R$ ), the deflection angle ( $\theta$ ), and the length of the curve ( $L$ ) can be first determined. Given a set of trajectory points ( $x_i, y_i$ ), its distance ( $d_i$ ) to the center of the best-fitting circle ( $X_c, Y_c$ ) can be determined with the following equation:

$$d_i = \sqrt{(x_i - X_c)^2 + (y_i - Y_c)^2} \quad (5-2)$$

In the case of a perfect fit, the distance  $d_i$  should be the same as the radius  $R$ . Thus, the loss function can be designed accordingly as follows:

$$\text{Loss Function} = \sum_{i=1}^n \left[ \sqrt{(x_i - X_c)^2 + (y_i - Y_c)^2} - R \right]^2 \quad (5-3)$$

The center  $X_c, Y_c$  is found by solving parameters that minimize the sum of squared residuals (i.e., the loss function). Radius ( $R$ ) is computed as part of the least-squares optimization process, and the optimal solution of it can be determined as the average distance between all points on the curve and the curve center:

$$R = \frac{1}{n} \sum_{i=1}^n \sqrt{(x_i - X_c)^2 + (y_i - Y_c)^2} \quad (5-4)$$

where  $n$  is the total number of points on the curve.

Given the fact that such optimization will converge iteratively, an initial estimate of the center and radius is needed. The centroid of the data is used as the initial center and then used to compute the initial radius estimate:

$$X_c^{initial} = \frac{1}{n} \sum_{i=1}^n x_i, \quad Y_c^{initial} = \frac{1}{n} \sum_{i=1}^n y_i \quad (5-5)$$

$$R^{initial} = \frac{1}{n} \sum_{i=1}^n \sqrt{(x_i - X_c^{initial})^2 + (y_i - Y_c^{initial})^2} \quad (5-6)$$

where  $x_i, y_i$  are the coordinates of the  $i$ -th point, and  $n$  is the total number of points in the curve segment.

The deflection angle ( $\Delta$ ) of each curve is calculated using the starting point, end point, and center point along a curve. Two vectors,  $v_1$  and  $v_2$ , can be established between center point and start/end point on a curve. The law of the cosines can be used to compute the interior angle  $\theta$  and consequently deflection angle, as follows:

$$\cos(\theta) = \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|} \quad \Delta = 180 - \theta \quad (5-7)$$

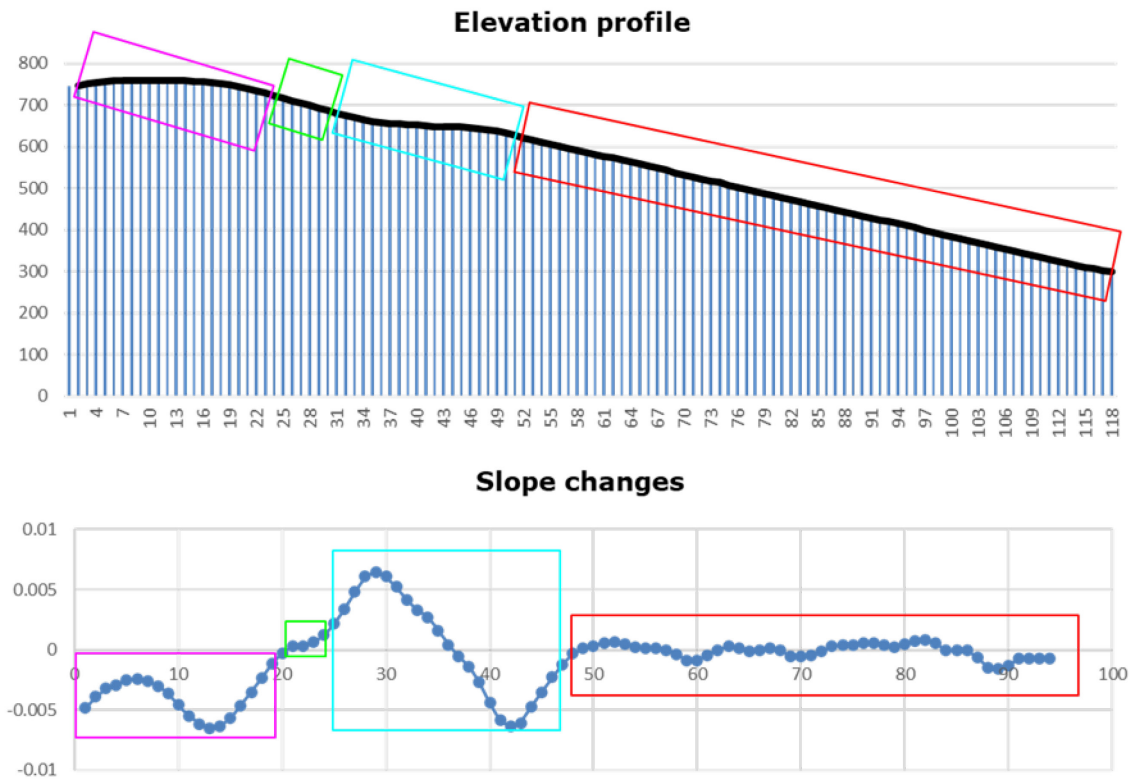
then the length of the curve  $L$  is determined with the deflection angle  $\theta$  in radians and radius  $R$  by:

$$L = R \cdot \Delta \cdot \frac{\pi}{180} \quad (5-8)$$

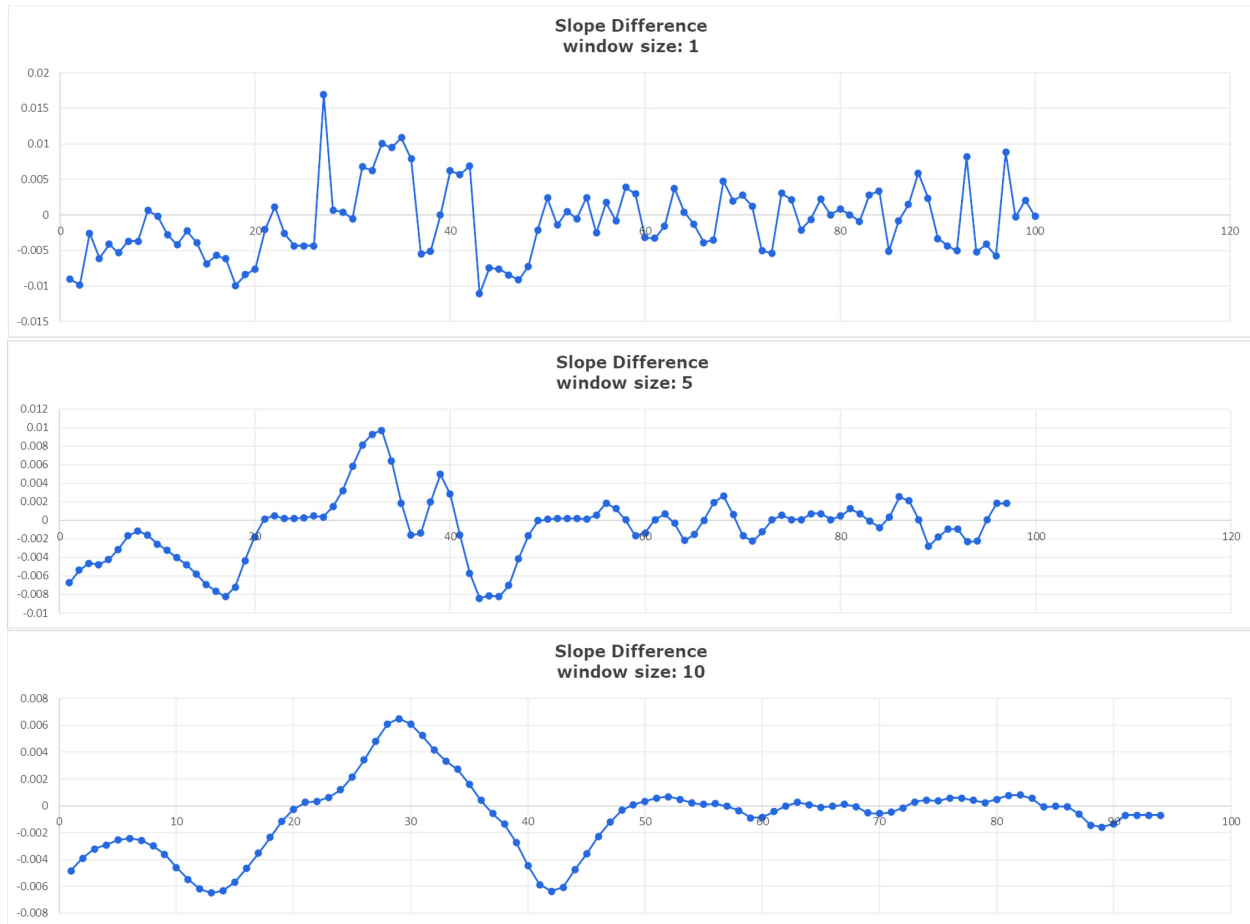
This formula provided a precise estimation of the arc length based on the circle's geometry.

## 5.2.2 Vertical curves

Vertical curves are tackled following the same pipeline of segmentation, identification, classification, and characterization but using different techniques. In this project, the research team focused more on the vertical curve at a larger scale which is better suited for statewide management. Given the noise level of the local slope measurements, the team implemented a moving window approach to first fit a straight line using linear regression within each moving window of the elevation profile. The slope can be derived from the linear regression result and the gradient of the slope can serve as the metrics to determine whether a section of the road is part of a curve or not (Figure 5.10). It is worth noting that to make the analysis more robust and tolerant to high-frequency noise, the team compared the slope change results using different moving window sizes (Figure 5.11). While slope gradients provide a preliminary estimate of transitions, a curvature analysis similar to the horizontal curve identification and characterization can be carried out to further verify the presence of a vertical curve. After vertical curves are identified, their length can be calculated from the horizontal distance between start and end point of the curves.



**Figure 5.10 Identifying and segmenting vertical curves from elevation profile derived from mobile lidar trajectory**



**Figure 5.11 Impact of the window size for slope measurements**

### 5.3 CROSS SECTION EXTRACTION AND CHARACTERIZATION

Once the estimated road alignment can be reliably derived from the mobile lidar trajectory data, cross sections that are perpendicular to the travel direction can be easily generated at a given interval along the road alignment. Then a number of points can be sampled along the cross lines with a given sampling spacing. The elevations at these sample points can be extracted from a digital terrain model (DTM) generated from the ground points captured by the mobile lidar system. It is worth noting that in addition to the elevation, the DTM also includes other fields including GPS time and classification where all the average values are taken for populating each cell. As the DTM of the road is generated with both road and curb classes, the classification information can help better define the road boundary. The team recommends setting the sampling spacing at least twice as large as the cellsize of the DTM to avoid artefacts due to mismatched resolution and data gaps. Additional analyses to evaluate the parameter sensitivity of the proposed approach will be discussed in detail in the following sections.

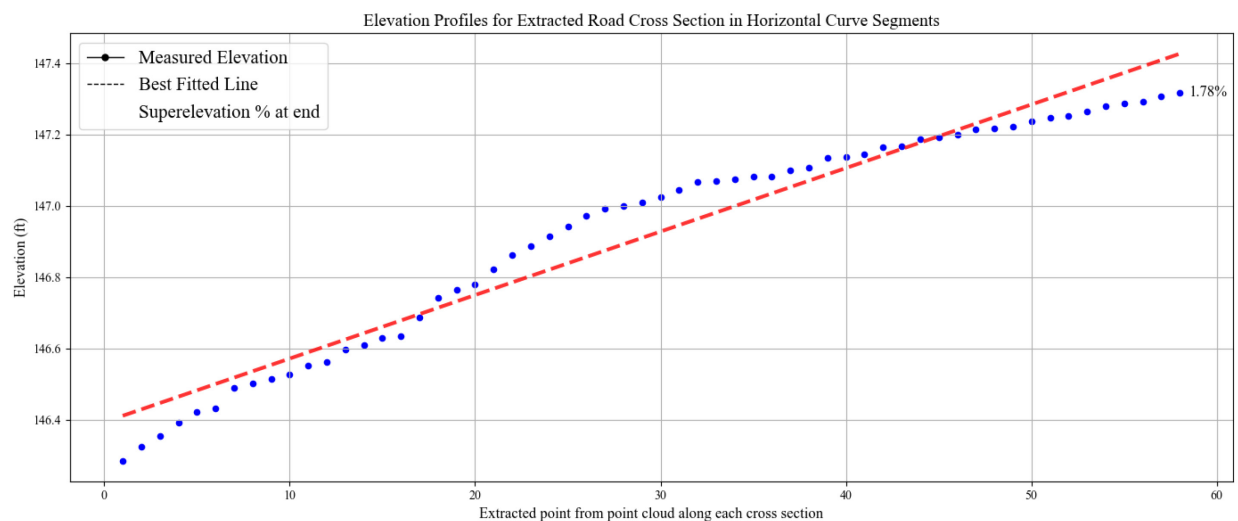
Depending on the width and slope variation on a cross section, the cross lines are also categorized into different types including wide, narrow, bumpy, and normal. Each type of cross line is described as follows and more visual examples can be found in the following sections:

**Wide and Narrow Cross-Section Lines** are identified based on a threshold applied to the cross-section length. Wide cross-section lines typically indicate intersections, parking lots, or exits, while narrow cross-section lines generally represent gaps in the point cloud.

**Bumpy Cross-Section Lines** are detected by computing slopes between consecutive points along the cross-section and applying a threshold to the rate of change in slope values. These cross-section lines typically appear in areas where the road surface has cracks or asphalt defects, making them unreliable for cross-slope calculations.

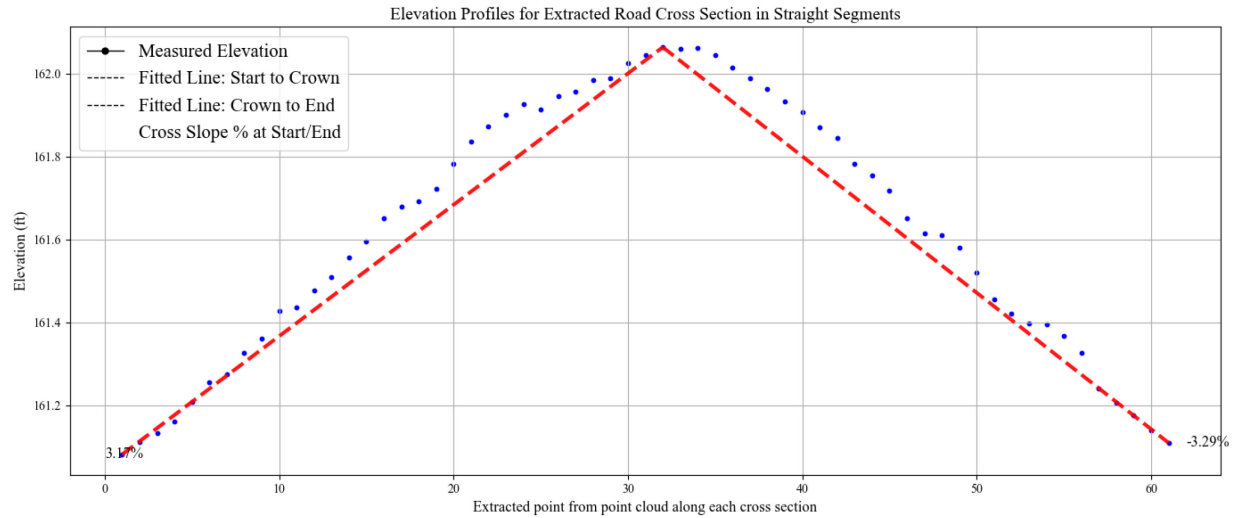
**Normal Cross-Section Lines.** The remaining cross-section lines, which do not fall into the above categories, are classified as Normal. These lines are used for cross-slope, super elevation and lane-width calculations.

To further characterize the cross sections, two cases need to be distinguished and analyzed separately (Figure 5.12 and Figure 5.13). A super-elevated cross section can typically be found at a horizontal curve where the elevation on the outside edge is higher than the center and the inside edge. In this case, there is only one cross slope that needs to be accounted for. At a straight section, on the other hand, the cross section usually can be defined as normal crown where the elevation is higher at the center and lower on the side. In the proposed approach, the sample point with the highest elevation is used as the initial estimation of the crown point. A least squares fitting can be performed to each side of the crown followed by updating the crown point to the intersection of the two best fitting lines. Such a process can be repeated to achieve a more precise result until it converges (Figure 5.14). In addition to the cross slope, the total width of the road can be estimated as the length of cross lines, which can also be an indicator of the number of lanes.

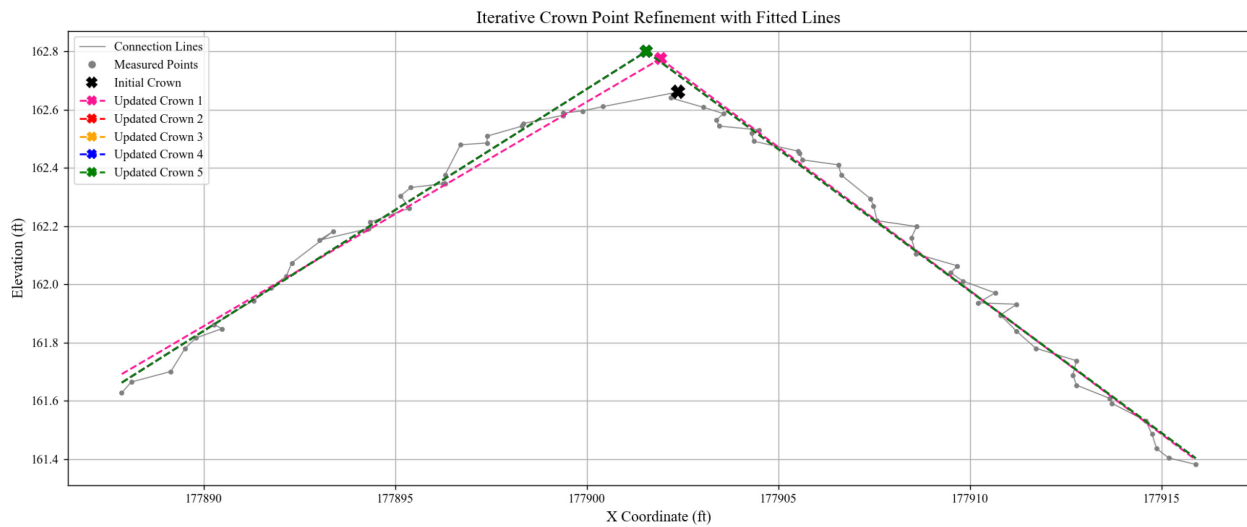


**Figure 5.12** The best fitting lines to 10 different Normal cross section points on horizontal curve part of the road. The slope of fitted line is equal to Superelevation on that cross section





**Figure 5.13 The best fitting lines to 5 different Normal cross section points on straight part of the road, after finding the updated crown point in each cross section. The slope of fitted line is equal to Cross Slope on that cross section**



**Figure 5.14 Updating the crown points using linear regression**

## 5.4 EVALUATION AND DISCUSSION

To demonstrate the effectiveness of the proposed approaches, the team conducted rigorous evaluation for the key step and output of the workflows. Since the workflow for each feature can be generally divided into identification/classification and characterization, the evaluation was performed in the same way.

### 5.4.1 Horizontal and Vertical Curves

To evaluate the accuracy of horizontal and vertical curve identification, the reference data was created manually by extracting different types of curves from the mobile lidar point cloud data. The experiment was performed using the GIS tools that the team developed, and the processing time and key parameters are also provided in Table 5.1. The following evaluation metrics were defined to quantify the performance of the proposed approach:

- **True Positive (TP):** Horizontal and vertical curves that were correctly identified as curves.
- **False Negative (FN):** Horizontal and vertical curves that were not identified despite being present in the dataset.
- **False Positive (FP):** Segments incorrectly identified as horizontal and vertical curves, which are not actual curves.

The research team further computed correctness, completeness, and quality (sometime known as precision, recall, and F1-score), defined as follows, to summarize the results for each dataset and each type of curves (Table 5.2, Table 5.3, Table 5.4, Table 5.5, Table 5.6)

$$Correctness = \frac{TP}{TP + FP} \quad (5-9)$$

$$Completeness = \frac{TP}{TP + FN} \quad (5-10)$$

$$Quality = 2 \times \frac{Correctness * Completeness}{Completeness + Correctness} \quad (5-11)$$

**Table 5.1 Running time and key parameters for horizontal curve identification and characterization.**

| <b>Data</b>          | <b>Running Time<br/>(second)</b> | <b>Minimum Distance<br/>(foot)</b> | <b>Time Spacing<br/>(second)</b> | <b>Lower Curvature Threshold<br/>(foot<sup>-1</sup>)</b> | <b>Upper Curvature Threshold<br/>(foot<sup>-1</sup>)</b> |
|----------------------|----------------------------------|------------------------------------|----------------------------------|----------------------------------------------------------|----------------------------------------------------------|
| <b>RIEGL Mission</b> | 18                               | 30                                 | 2.5                              | 0.5                                                      | 6                                                        |
| <b>T01_HWY068</b>    | 14                               | 100                                | 2.5                              | 0.15                                                     | 3.5                                                      |
| <b>T01_HWY072</b>    | 12                               | 100                                | 2.5                              | 0.15                                                     | 4.5                                                      |
| <b>T01_HWY102</b>    | 13                               | 100                                | 2.5                              | 0.15                                                     | 4.5                                                      |
| <b>T01_HWY150</b>    | 13                               | 100                                | 2.5                              | 0.1                                                      | 3                                                        |
| <b>T03_HWY029</b>    | 14                               | 100                                | 2.5                              | 0.13                                                     | 3                                                        |
| <b>T03_HWY141</b>    | 18                               | 50                                 | 2                                | 0.25                                                     | 5                                                        |
| <b>T06_HWY091</b>    | 12                               | 100                                | 2.5                              | 0.15                                                     | 5                                                        |

**Table 5.2 Performance of horizontal curve identification and characterization for independent curves on each testing dataset.**

| <b>Data</b>          | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|----------------------|-----------|-----------|-----------|
| <b>RIEGL Mission</b> | 39        | 3         | 0         |
| <b>T01_HWY068</b>    | 1         | 0         | 0         |
| <b>T01_HWY072</b>    | 13        | 2         | 0         |
| <b>T01_HWY102</b>    | 8         | 0         | 2         |
| <b>T01_HWY150</b>    | 10        | 1         | 0         |
| <b>T03_HWY029</b>    | 10        | 2         | 0         |
| <b>T03_HWY141</b>    | 14        | 1         | 0         |
| <b>T06_HWY091</b>    | 14        | 3         | 0         |

**Table 5.3 Performance of horizontal curve identification and characterization for compound curves on each testing dataset.**

| <b>Data</b>          | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|----------------------|-----------|-----------|-----------|
| <b>RIEGL Mission</b> | <b>39</b> | <b>0</b>  | <b>0</b>  |
| <b>T01_HWY068</b>    | <b>0</b>  | <b>0</b>  | <b>0</b>  |
| <b>T01_HWY072</b>    | <b>3</b>  | <b>0</b>  | <b>0</b>  |
| <b>T01_HWY102</b>    | <b>1</b>  | <b>0</b>  | <b>1</b>  |
| <b>T01_HWY150</b>    | <b>3</b>  | <b>0</b>  | <b>1</b>  |
| <b>T03_HWY029</b>    | <b>8</b>  | <b>0</b>  | <b>1</b>  |
| <b>T03_HWY141</b>    | <b>0</b>  | <b>0</b>  | <b>0</b>  |
| <b>T06_HWY091</b>    | <b>10</b> | <b>1</b>  | <b>1</b>  |

**Table 5.4 Performance of horizontal curve identification and characterization for reverse curves on each testing dataset.**

| <b>Data</b>          | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|----------------------|-----------|-----------|-----------|
| <b>RIEGL Mission</b> | 3         | 0         | 2         |
| <b>T01_HWY068</b>    | 1         | 0         | 0         |
| <b>T01_HWY072</b>    | 2         | 0         | 0         |
| <b>T01_HWY102</b>    | 0         | 2         | 1         |
| <b>T01_HWY150</b>    | 1         | 0         | 0         |
| <b>T03_HWY029</b>    | 0         | 1         | 0         |
| <b>T03_HWY141</b>    | 2         | 1         | 0         |
| <b>T06_HWY091</b>    | 1         | 1         | 0         |

**Table 5.5 Performance of horizontal curve identification and characterization for turns/roundabouts on each testing dataset.**

| <b>Data</b>          | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|----------------------|-----------|-----------|-----------|
| <b>RIEGL Mission</b> | 0         | 2         | 0         |
| <b>T01_HWY068</b>    | 0         | 0         | 0         |
| <b>T01_HWY072</b>    | 1         | 0         | 0         |
| <b>T01_HWY102</b>    | 2         | 0         | 0         |
| <b>T01_HWY150</b>    | 1         | 0         | 0         |
| <b>T03_HWY029</b>    | 2         | 0         | 0         |
| <b>T03_HWY141</b>    | 4         | 0         | 0         |
| <b>T06_HWY091</b>    | 0         | 0         | 0         |

**Table 5.6 Performance of vertical curve identification and characterization on each testing dataset.**

| <b>Data</b>                 | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|-----------------------------|-----------|-----------|-----------|
| <b>RIEGL Export_Mission</b> | 25        | 2         | 0         |
| <b>T01_HWY068</b>           | 17        | 0         | 1         |
| <b>T01_HWY072</b>           | 19        | 0         | 0         |
| <b>T01_HWY102</b>           | 13        | 1         | 0         |
| <b>T01_HWY150</b>           | 7         | 1         | 0         |
| <b>T03_HWY029</b>           | 11        | 0         | 0         |
| <b>T03_HWY141</b>           | 8         | 0         | 1         |
| <b>T06_HWY091</b>           | 18        | 0         | 0         |

### 5.4.2 Cross Sections

In this evaluation, cross-section lines were automatically generated along the testing roadways with an interval of 10 m. For each cross section, the sampling spacing was set to be 0.5 m. Regarding the classification of the cross section, the metrics are defined as follows:

- **True Positive (TP):** Cross-sections that were correctly classified.
- **False Negative (FN):** Cross-sections that were not identified despite being present in the dataset.
- **False Positive (FP):** Cross-sections that were incorrectly classified into a category to which they do not actually belong.

Some examples of correctly and incorrectly identified cross sections are provided below (Figure 5.15, Figure 5.16, and Figure 5.17) and the quantitative summary is shown in Table 5.7. The wide cross section is usually tagged when an intersection, ramps, or driveway is present. This can be helpful for further spatial analysis when the cross-section information needs to be aggregated as these wide/narrow/bumpy cross sections should be treated as exceptions given the fact that they do not necessarily follow the assumptions about a cross section such as normal crowns.

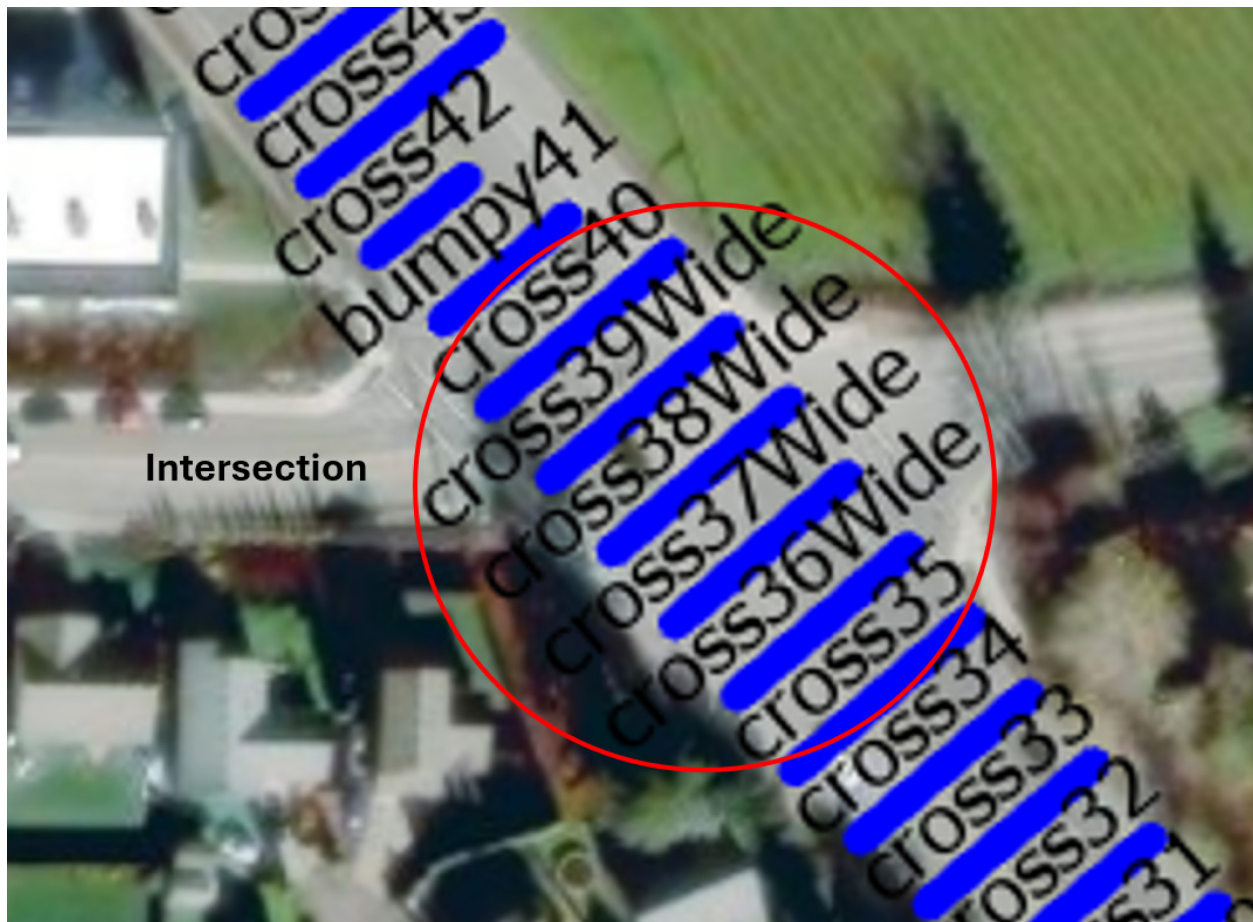


Figure 5.15 Example of correctly detected wide cross sections at an intersection

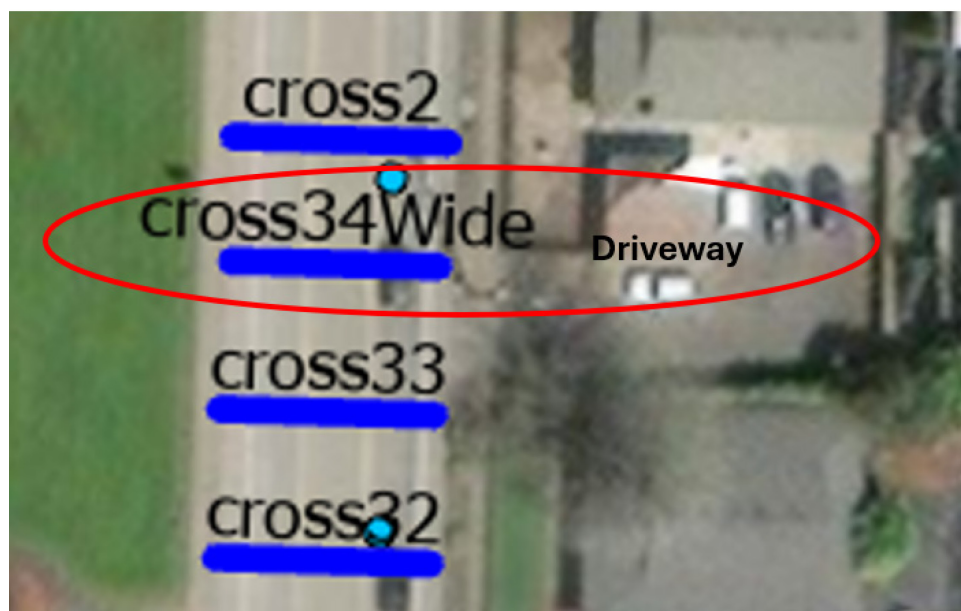


Figure 5.16 Example of correctly detected wide cross sections at a driveway to the parking lot



**Figure 5.17 Example of incorrectly detected cross sections near an intersection with raised median presence**

**Table 5.7 Evaluation for cross section identification/classification in each testing dataset.**

| <b>Data</b>       | <b>TP</b> | <b>FP</b> | <b>FN</b> |
|-------------------|-----------|-----------|-----------|
| <b>T01_HWY068</b> | 43        | 2         | 2         |
| <b>T01_HWY102</b> | 32        | 1         | 3         |
| <b>T01_HWY150</b> | 64        | 2         | 2         |
| <b>T03_HWY029</b> | 69        | 4         | 5         |
| <b>T03_HWY141</b> | 33        | 2         | 2         |

To conduct the sensitivity analysis, the Cross Section toolbox developed by the research team was run multiple times, considering different cell sizes for generating the DEM from the down sampled point cloud, as well as varying the spacing between points on the cross lines. As shown in Table 1, the analysis considered cell sizes of 0.15, 0.25, 0.5, and 0.75 meters, with the spacing set to twice the cell size. The minimum cell size was set at 0.15 meters because, after down sampling, the point cloud has a 0.1meter gap between points, meaning that a DEM with a smaller cell size will not have additional interpolated data at a finer resolution.

As discussed in the previous sections, the sensitivity to the key parameters is more relevant for the development of the GIS tools. The research team picked the dataset T03\_HWY068\_NB for this test where the cell size for the DTM creation along with the sampling spacing along a cross line were varied and tested (Table 5.8). The team also calculated the difference between the cross slopes to both sides as an indicator of the consistency. For each slope observation with different cell size, the result with cell size of 0.15 m served as the reference and others were compared against it to compute the difference of the absolute slope. The average difference is plotted and shows a clear trend where the slope will be underestimated when the cell size increases (Figure 5.18). The reason for this is that there is a higher chance for a point along the cross line to be sampled closer to the crown.

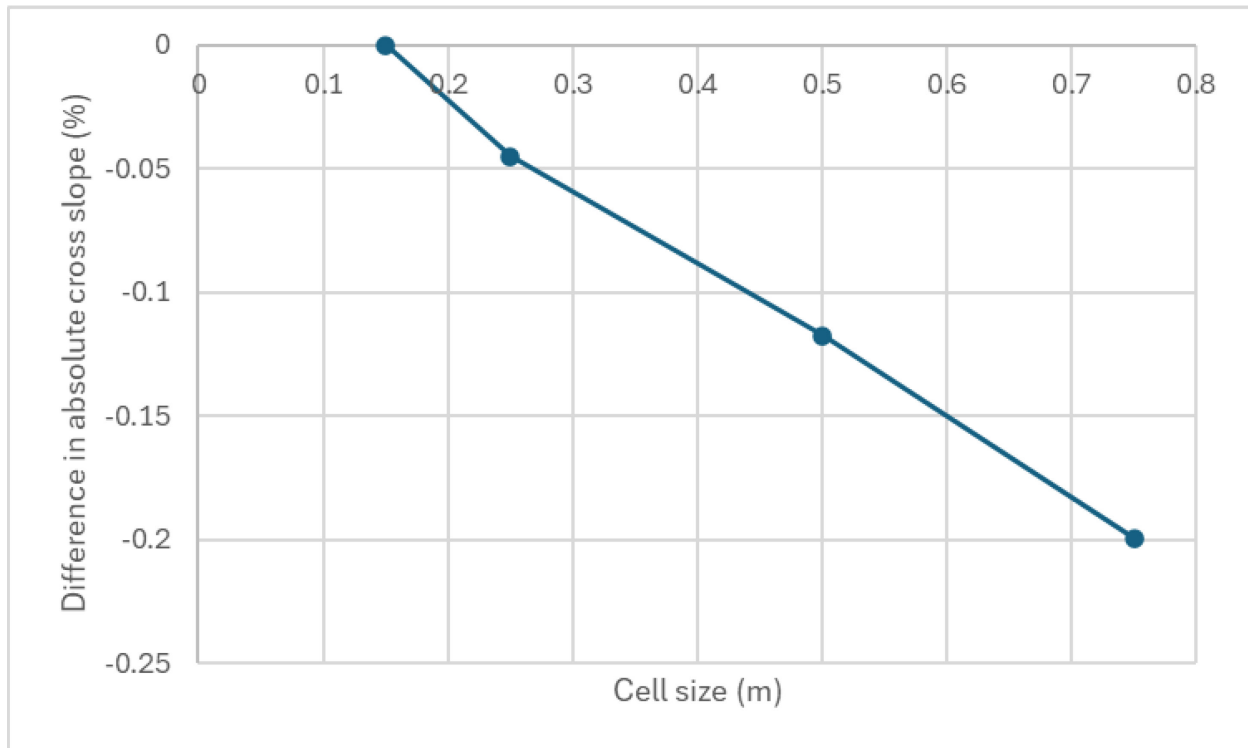
The team also recorded the processing time with different cell sizes as the smaller cell size could result in larger data volumes and computational complexity. Fortunately, it was found that the processing time was typically around 1 minute 20 seconds for most cases.



**Table 5.8 Cross slope measurements with different cell size and sampling spacing setting.**

| <b>Cross Sections</b> | <b>Cell Size (m)</b> | <b>Spacing (m)</b> | <b>Slope 1 (%)</b> | <b>Slope 2 (%)</b> | <b>Difference between Slope1 and Slope 2</b> |
|-----------------------|----------------------|--------------------|--------------------|--------------------|----------------------------------------------|
| Cross 1               | 0.15                 | 0.3                | -2.754             | 2.665              | 0.089                                        |
| Cross 1               | 0.25                 | 0.5                | -2.743             | 2.770              | 0.027                                        |
| Cross 1               | 0.5                  | 1.0                | -2.884             | 2.377              | 0.507                                        |
| Cross 1               | 0.75                 | 1.5                | -2.596             | 2.840              | 0.244                                        |
| Cross 2               | 0.15                 | 0.3                | -3.165             | 3.143              | 0.022                                        |
| Cross 2               | 0.25                 | 0.5                | -3.192             | 3.060              | 0.132                                        |
| Cross 2               | 0.50                 | 1.0                | -2.852             | 3.260              | 0.408                                        |
| Cross 2               | 0.75                 | 1.5                | -2.937             | 2.893              | 0.044                                        |
| Cross 3               | 0.15                 | 0.3                | -3.005             | 3.213              | 0.208                                        |
| Cross 3               | 0.25                 | 0.5                | -2.797             | 3.290              | 0.493                                        |
| Cross 3               | 0.50                 | 1.0                | -2.894             | 3.043              | 0.149                                        |
| Cross3                | 0.75                 | 1.5                | -2.925             | 2.749              | 0.176                                        |
| Cross 4               | 0.15                 | 0.3                | -3.063             | 3.279              | 0.216                                        |
| Cross 4               | 0.25                 | 0.5                | -2.957             | 3.420              | 0.463                                        |
| Cross 4               | 0.50                 | 1.0                | -3.166             | 3.159              | 0.007                                        |
| Cross 4               | 0.75                 | 1.5                | -3.184             | 2.669              | 0.515                                        |
| Cross 5               | 0.15                 | 0.3                | -2.477             | 2.984              | 0.507                                        |
| Cross 5               | 0.25                 | 0.5                | -2.499             | 2.907              | 0.408                                        |
| Cross 5               | 0.5                  | 1.0                | -2.551             | 2.878              | 0.327                                        |
| Cross 5               | 0.75                 | 1.5                | -2.324             | 2.854              | 0.530                                        |
| Cross 6               | 0.15                 | 0.3                | -2.249             | 3.274              | 1.025                                        |
| Cross 6               | 0.25                 | 0.5                | -2.076             | 2.860              | 0.784                                        |
| Cross 6               | 0.5                  | 1.0                | -2.076             | 2.860              | 0.784                                        |
| Cross 6               | 0.75                 | 1.5                | -2.084             | 2.901              | 0.817                                        |
| Cross 7               | 0.15                 | 0.3                | -2.493             | 3.064              | 0.571                                        |
| Cross 7               | 0.25                 | 0.5                | -2.573             | 2.974              | 0.401                                        |
| Cross 7               | 0.5                  | 1.0                | -2.621             | 2.737              | 0.116                                        |
| Cross 7               | 0.75                 | 1.5                | -2.368             | 2.848              | 0.480                                        |
| Cross 8               | 0.15                 | 0.3                | -3.348             | 3.003              | 0.345                                        |
| Cross 8               | 0.25                 | 0.5                | -3.309             | 2.913              | 0.396                                        |
| Cross 8               | 0.5                  | 1.0                | -3.302             | 2.924              | 0.378                                        |
| Cross 8               | 0.75                 | 1.5                | -2.946             | 2.928              | 0.018                                        |
| Cross 9               | 0.15                 | 0.3                | -3.199             | 2.840              | 0.359                                        |
| Cross 9               | 0.25                 | 0.5                | -3.257             | 2.817              | 0.440                                        |
| Cross 9               | 0.5                  | 1.0                | -3.289             | 2.776              | 0.513                                        |
| Cross 9               | 0.75                 | 1.5                | -2.902             | 2.822              | 0.080                                        |
| Cross 10              | 0.15                 | 0.3                | -2.551             | 2.671              | 0.120                                        |
| Cross 10              | 0.25                 | 0.5                | -2.619             | 2.657              | 0.038                                        |
| Cross 10              | 0.5                  | 1.0                | -2.235             | 2.730              | 0.495                                        |
| Cross 10              | 0.75                 | 1.5                | -2.353             | 2.678              | 0.325                                        |
| Cross 11              | 0.15                 | 0.3                | -2.612             | 2.329              | 0.283                                        |

| Cross Sections | Cell Size (m) | Spacing (m) | Slope 1 (%) | Slope 2 (%) | Difference between Slope 1 and Slope 2 |
|----------------|---------------|-------------|-------------|-------------|----------------------------------------|
| Cross 11       | 0.25          | 0.5         | -2.535      | 2.302       | 0.233                                  |
| Cross 11       | 0.5           | 1.0         | -2.478      | 1.959       | 0.519                                  |
| Cross 11       | 0.75          | 1.5         | -2.151      | 2.396       | 0.245                                  |
| Cross 12       | 0.15          | 0.3         | -2.89       | 3.248       | 0.358                                  |
| Cross 12       | 0.25          | 0.5         | -2.71       | 3.313       | 0.603                                  |
| Cross 12       | 0.5           | 1.0         | -2.725      | 3.094       | 0.369                                  |
| Cross 12       | 0.75          | 1.5         | -2.381      | 3.111       | 0.730                                  |
| Cross 13       | 0.15          | 0.3         | -3.212      | 2.865       | 0.347                                  |
| Cross 13       | 0.25          | 0.5         | -3.331      | 2.684       | 0.647                                  |
| Cross 13       | 0.5           | 1.0         | -3.31       | 2.711       | 0.599                                  |
| Cross 13       | 0.75          | 1.5         | -3.492      | 2.522       | 0.970                                  |
| Cross 14       | 0.15          | 0.3         | -3.743      | 3.700       | 0.043                                  |
| Cross 14       | 0.25          | 0.5         | -3.739      | 3.468       | 0.271                                  |
| Cross 14       | 0.5           | 1.0         | -3.415      | 3.440       | 0.025                                  |
| Cross 14       | 0.75          | 1.5         | -3.19       | 3.406       | 0.216                                  |



**Figure 5.18 Trend of the cross-slope measurements with different cell size for creating the DTM**

### 5.4.3 Summary

Table 5.9 shows the summary of the identification/classification performance for horizontal curves, vertical curves, and cross sections, respectively. The detailed breakdown will be covered in the following sections. The reference data to compare against in this case was manually developed by the research team.

**Table 5.9 Summary of identification/classification performance of the proposed methods.**

|                   | <b>Correctness</b> | <b>Completeness</b> | <b>Quality</b> |
|-------------------|--------------------|---------------------|----------------|
| Horizontal Curves | 90.61%             | 95.54%              | 93.01%         |
| Vertical Curves   | 96.72%             | 98.33%              | 97.52%         |
| Cross Sections    | 95.63%             | 94.50%              | 95.06%         |

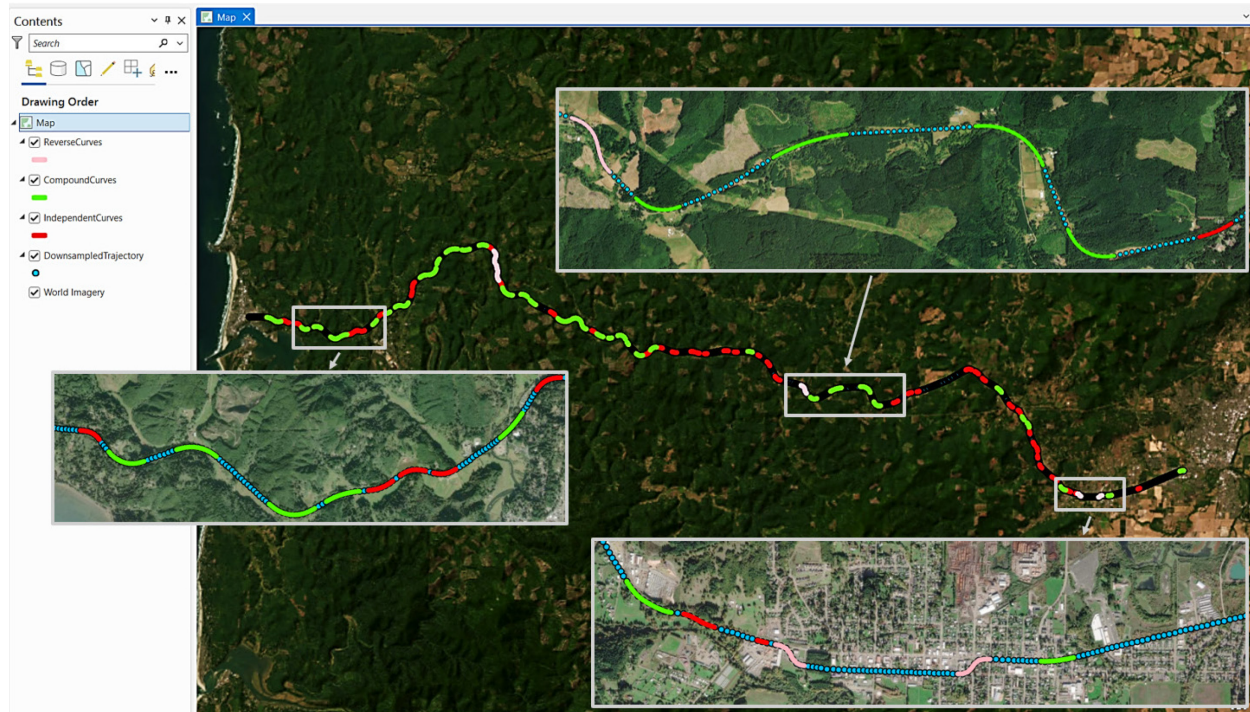
The accuracy of the road characterization, however, is challenging given lack of field survey data for validation. These data used for comparison purposes should also be collected at a similar time as the mobile lidar data collection covering the same area, which makes it even more challenging. Moreover, in some cases, the determination of the road characterization can be subjective as the centerline of the road is sometimes loosely defined for the field measurement. To this end, instead of assessing the absolute accuracy of the road characterization, the research team focuses more on the sensitivity analysis for cross section characterization which can be more dependent on the parameter settings.

## 5.5 GIS TOOL IMPLEMENTATION

The research implemented the methods described in this chapter into a set of prototype ArcGIS Pro Toolboxes focusing on horizontal curve identification and characterization, vertical curve identification and characterization, cross section extraction and characterization, as well as a separate visualization tool to help users display the analysis results support. The GIS tools have a user-friendly interface with minimal input from users as some of the key parameters have been populated with default values. The intermediate and final results are stored into a geodatabase as a number of csv files, which will be easy to read, edit, and re-purpose for other applications.

The results can be visualized in ArcGIS via the visualization tool. The primary reason for adding an option to separate the visualization of the results from the data processing and analysis is to reduce the computation time in ArcGIS just for visualization. The research team found that the visualization process leveraging ArcGIS functions can be time-consuming, especially when multiple datasets need to be processed. Thus, it is recommended to run the tools without enabling the visualization options when performing batch processing to large number of datasets.

An example of the curve identification can be found in Figure 5.19. More details about installation, operations, example results, and parameter fine-tuning are included in Appendix B.



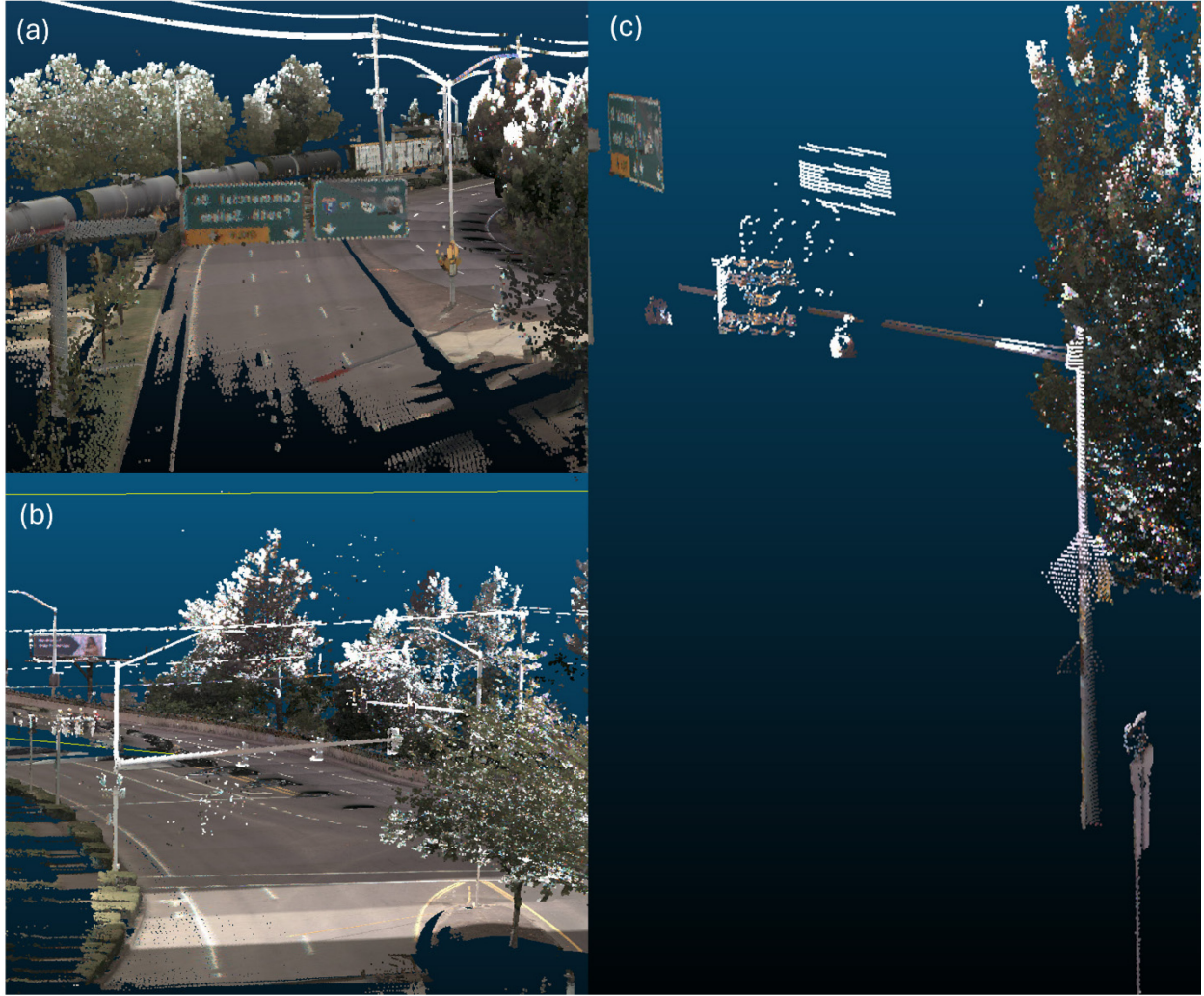
**Figure 5.19 Example result from the horizontal curve identification from the ArcGIS toolbox developed in this project**

## 6.0 STREETSIDE ASSET EXTRACTION LEVERAGING MACHINE LEARNING METHODS

### 6.1 DATASETS AND PRE-PROCESSING

The datasets used for training and testing an ML or DL model for transportation asset inventory are typically generated from either real-world or synthetic data. Real-world datasets (**Figure 6.1**) are point cloud scans derived from MLS surveying of the transportation environment of interest. Such datasets may present the following challenges:

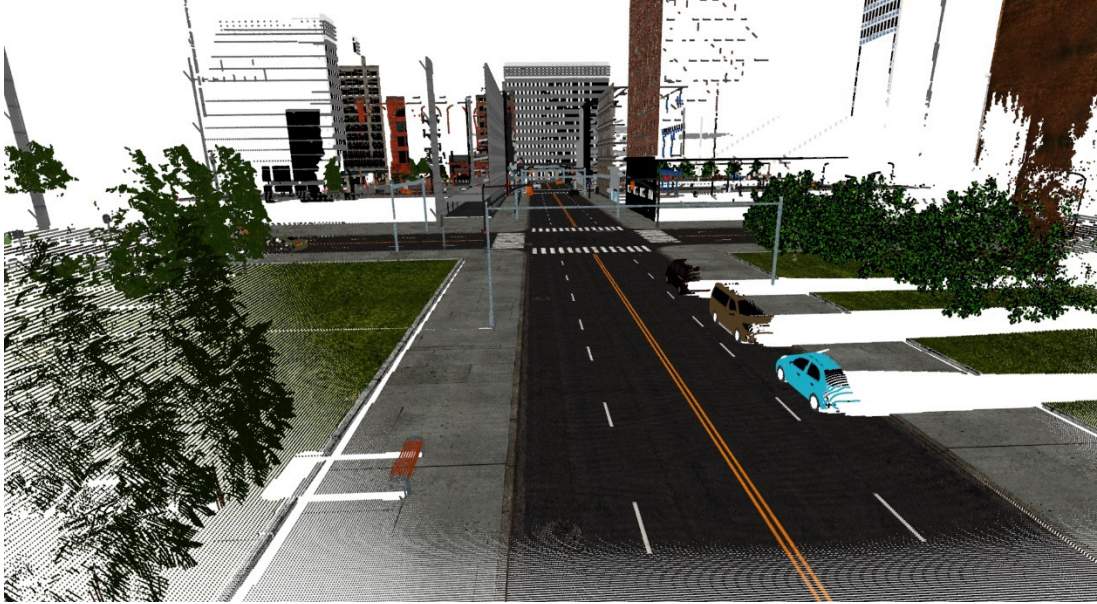
- Data gaps: Features of interest may not be fully captured due to the limited line of sight or occlusions (**Figure 6.1b**).
- Varying density: The point density is a function of the range and angle of incidence between the scanning system and the objects.
- Range walk: Large errors in ranging measurement can occur on highly reflective objects due to the saturation of intensity values. (**Figure 6.1b and 1.2c**).
- Incomplete annotations: It is very common that the datasets are only annotated to address certain objects, which do not cover the entire scene and result in substantial unclassified points.
- Labeling errors: Labeling such datasets can sometimes be subjective and the manual annotation can be inconsistent and error-prone in some cases (**Figure 6.1a**).



**Figure 6.1. Samples of real-world datasets: (a) A detached information sign might cause misclassification, and a streetlamp with traffic sign could create categorization ambiguity; (b) Point scattering off trees onto the pole-like object (traffic light with streetlamp) (c) Traffic sign point offset artifact due to intensity saturation effects**

Capturing real-world datasets may be costly and usually requires a significant amount of manual effort in preparing the dataset for training ML models. To overcome this challenge, several studies used synthetic datasets (**Figure 6.2**) (Lytkin et al., 2023; Griffiths & Boehm, 2019; Deschaud et al., 2021; Pan et al., 2020a; Behley et al., 2019; Hu et al., 2021). Synthetic datasets are primarily designed to replicate the perception of outdoor environments and hence may be unrealistic since it is challenging to mimic all the noise, artifacts and random occlusions. Hence, in this case study, only real-world MLS datasets were considered.





**Figure 6.2.** Sample of the scene of SynthCity synthetic dataset (Source: SynthCity, n.d.)

Creating ground truths within the MLS dataset for classification tasks necessitates a robust labeling scheme to accurately annotate features of interest (Zhu et al., 2020). Sometimes it can involve integrating a user-defined classification field with numerical encoding into the storage structure of the MLS point cloud. For example, a common data standard scheme specified by ASPRS LAS specification (Table 6.1) includes classifications for certain objects, but often excludes the streetside assets (Ryan, 2013). It is important to note that most studies and publicly available datasets do not provide detailed specifics and logic regarding the user-defined labeling schemes which are also not expected to be modified for different applications.

Data annotation and labeling are important for deploying machine learning models, and it is typically achieved by manual process. Even with software tools, it can still be very labor-intensive and time-consuming, especially for large datasets needed for training ML models. Some studies have been conducted to develop an alternative approach for annotation. For instance, Pan et al. (2020) and Song et al. (2022) segment point clouds into range images, track them across frames, and use a pre-annotation program with predefined rules. Objects are then annotated using a pre-trained Mask R-CNN. This method, while effective for nearby segments, still requires human correction and is more suited for autonomous driving than survey-grade transportation asset management. Some others achieved automatic annotation using synthetic or semi-synthetic datasets, which can lack the complexity of real-world data as discussed earlier (Lytkin et al., 2023).

**Table 6.1. ASPRS LAS Specification 1.4: Standard Point Classification**

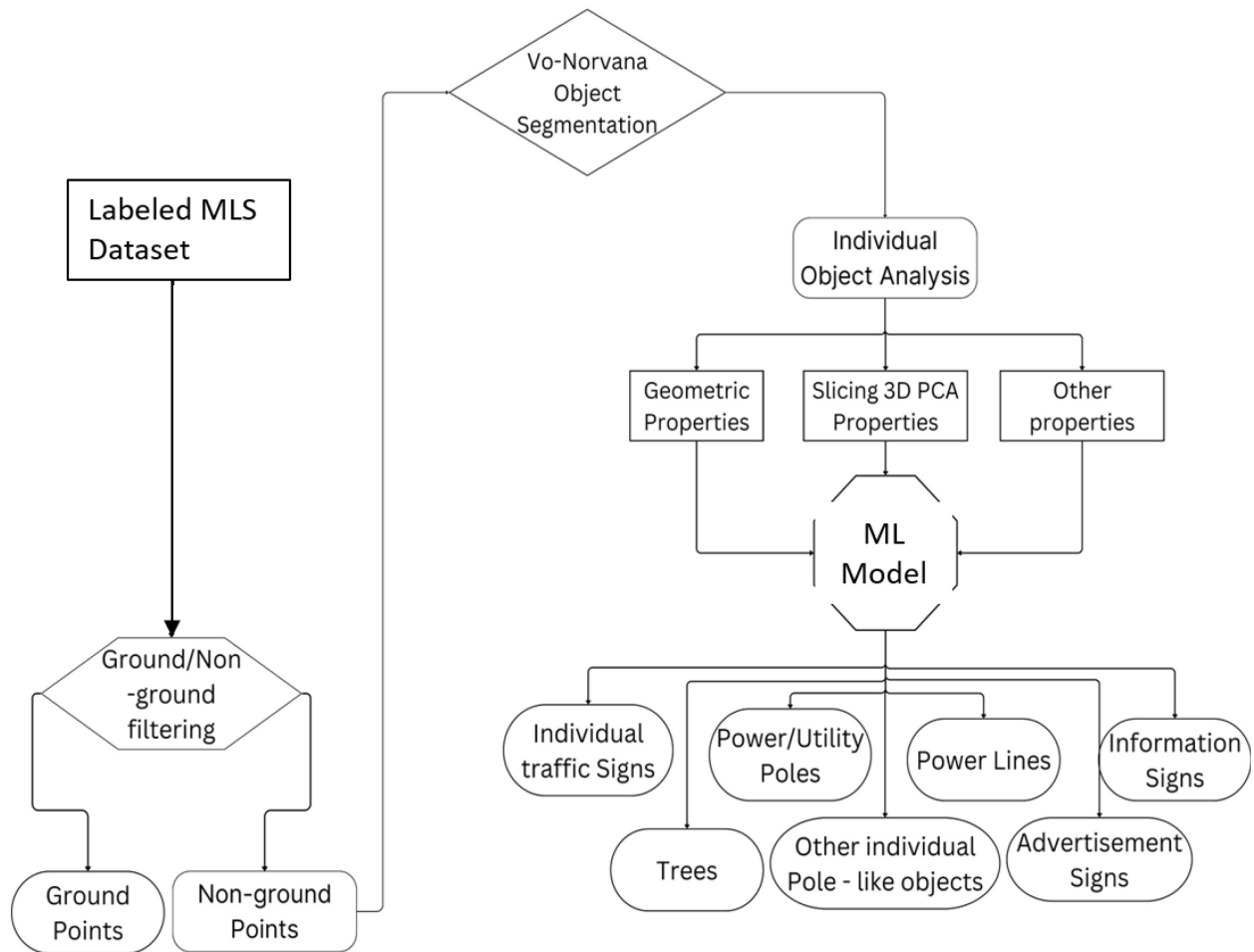
| <b>Classification value</b> | <b>Meaning</b>                            |
|-----------------------------|-------------------------------------------|
| 0                           | Created, never classified                 |
| 1                           | Unclassified                              |
| 2                           | Ground                                    |
| 3                           | Low vegetation                            |
| 4                           | Medium Vegetation                         |
| 5                           | High vegetation                           |
| 6                           | Building                                  |
| 7                           | Low point (noise)                         |
| 8                           | Reserved                                  |
| 9                           | Water                                     |
| 10                          | Rail                                      |
| 11                          | Road Surface                              |
| 12                          | Reserved                                  |
| 13                          | Wire - Guard (Shield)                     |
| 14                          | Wire -Conductor (Phase)                   |
| 15                          | Transmission Tower                        |
| 16                          | Wire-structure Connector (e.g. insulator) |
| 17                          | Bridge Deck                               |
| 18                          | high Noise                                |
| 19 - 63                     | Reserved                                  |
| 64 -255                     | User definable                            |

## 6.2 METHODOLOGY

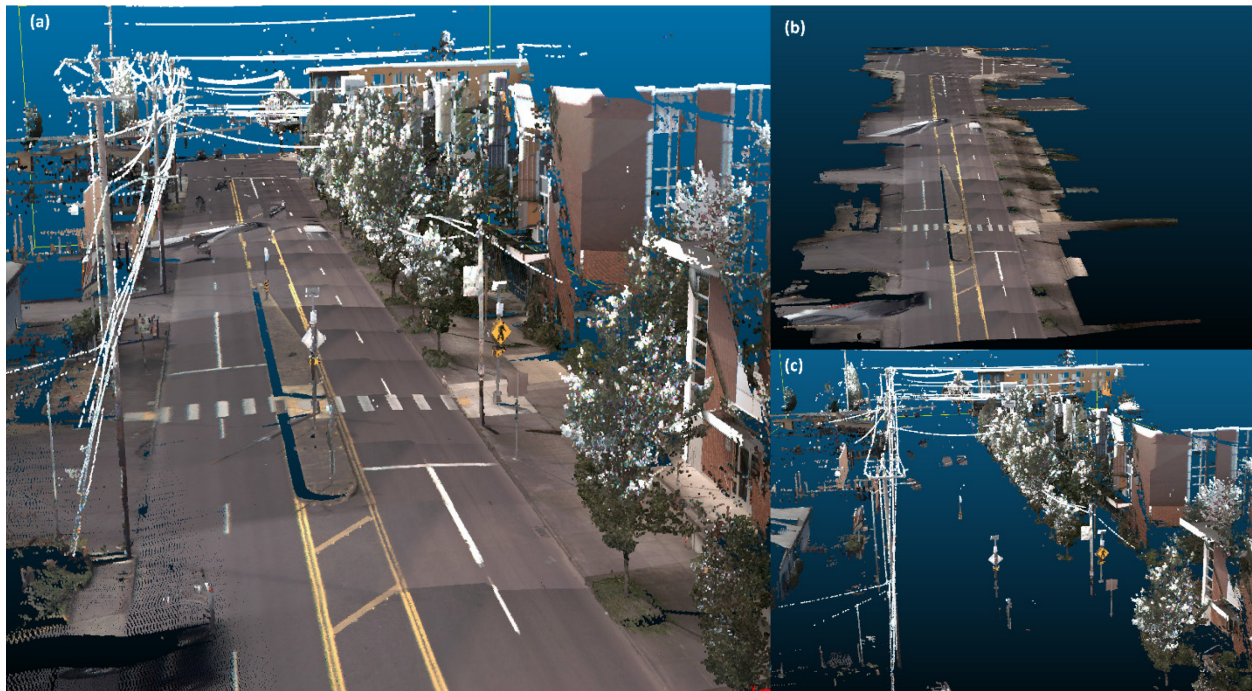
### 6.2.1 Feature Analysis

Because plugging the point cloud directly to an ML model can easily result in failure of the models without extensive fine-tuning as well as increase the computational complexity and time, a series of pre-processing was performed to simplify the data for both training and testing (Figure 6.3). The proposed workflow started with ground filtering using Vo-SmoG (Che et al., 2021) to separate ground and non-ground points (Figure 6.4), followed by Vo-Norvana (Che & Olsen, 2023) segmentation to group the off-ground points into individual objects (Figure 6.5). Once individual objects including both with and without valid classification (i.e., classified and unclassified objects) are obtained via Vo-Norvana, a more detailed and accurate analysis can be carried out for each object segment. Various properties of individual object segments were extracted (Table 6.2), with their corresponding labels serving as the input data for the machine learning models, which will ensure that the models could learn from a diverse and representative set of features, ultimately leading to more robust and accurate extraction and classification results. The following sections will describe and discuss the attributes extracted from the point cloud of each individual object in detail.

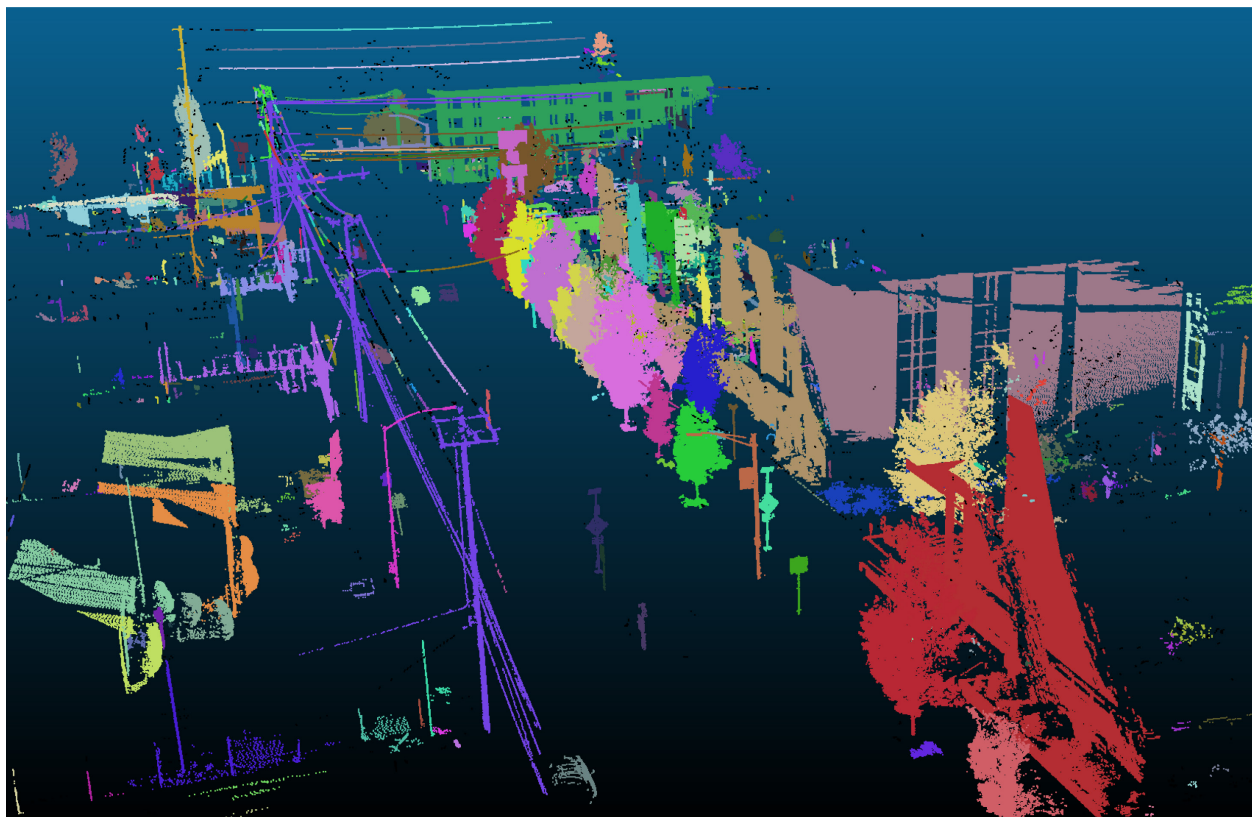




**Figure 6.3. Feature analysis and automation methodology**



**Figure 6.4. Filtering of ground & off-ground points using Vo-SmoG (a) Original MLS point cloud; (b) ground points (c) off-ground points**



**Figure 6.5. Segmentation of objects using the Vo-Norvana (Che & Olsen, 2023) approach where each object is assigned a random color**

**Table 6.2. Individual object properties for analysis and classification**

| <b>Key</b>                                                 | <b>Description</b>                                                                                     | <b>Purpose</b>                                                                                                                               | <b>Category</b>                            |
|------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------|
| Extended Class Label (names)                               | Contains the class names of which objects belong                                                       | Provides type of object                                                                                                                      | Classification                             |
| Extended Class Percentage                                  | This shows the percentage to which most points in a particular object belongs to a particular class    | Indicates level of Certainty an object belongs to a class and serves as a confidence score to validate the integrity of the training dataset | Classification                             |
| Extended Class ID                                          | Contains the Extended Class values from the label scheme                                               | Provide knowledge of the type of object for validation                                                                                       | Classification                             |
| XYZ bounding box dimensions                                | Shows the XYZ dimensions in length of the individual object bounding box                               | Provides the XYZ dimensional extremities of the object                                                                                       | Basic Geometry                             |
| PCA 2D_XYZ dimensions                                      | Contains the 2D-XY dimensions in length from the 2D PCA                                                | Provides PCA 2D characteristics of the object                                                                                                | PCA Geometry                               |
| Number of points in five slices along the Z-axis           | Each object is sliced into 5 slices along the Z-axis, this shows the number of points in each slice    | Provides the physical nature of the object as a histogram at various heights along the object                                                | Horizontal cross sections                  |
| XY dimensions of each slice                                | This shows the XY-dimension (length and width) for each of the 5 slices                                | Provides the length/width of the object in the XY direction at various heights along the object                                              | Basic Geometry + Horizontal cross sections |
| Diagonals of each slice                                    | This shows the diagonal length for each of the 5 slices                                                | Provides the expansion character along various heights of the object                                                                         | Basic Geometry + Horizontal cross sections |
| Area of each slice                                         | This shows the area covered for each of the 5 slices                                                   | Provides the surface area at various heights along the objects                                                                               | Basic Geometry + Horizontal cross sections |
| PCA XYZ-Dimensions, PCA Diagonal, PCA Areas for each slice | This performs a PCA analysis for XYZ-bounding dimensions, diagonals and areas for each of the 5 slices | PCA provides more precise and localized properties for each slice along the entire object structure                                          | PCA Geometry + Horizontal cross sections   |

A simple bounding box of the object provides insights into the size and shape of the space covered by the points. This information can be used to separate objects with significant differences in spatial extent. To further characterize the object's structure at different heights,

which will provide more details of the variations and features at multiple levels, each point cloud object was sliced along its vertical axis, creating a series of 2D slices. The number of points in each slice along the vertical axis were obtained to generate a histogram, which can represent the shape of an object by summarizing the density and distribution of points at different heights. It is worth noting that using the original point cloud in this process can take the scan pattern (e.g., range, angle of incidence, line of sight, etc.) into account as well. Additionally, the normalization inherently that comes with a histogram can support ML models better than a metric with an unspecified range.

The axis-aligned bounding box is effective in general but does not work so well with objects placed in different orientations. PCA is a technique that could be used to align objects with their major axis (eigen vectors). Such an approach can enable a more consistent description of an object, especially for those which have distinguished geometric shapes. For example, the point cloud on a traffic sign can be aligned with the orientation of the sign sheet. The dimension and other information extracted from such adaptive bounding box can be leveraged by ML models to separate it from other objects with a similar axis-aligned bounding box such as a small tree. Then similar local attributes such as slice dimensions, diagonals, and areas can be computed to facilitate the following ML model training.

## **6.2.2 Machine Learning**

### ***6.2.2.1 Training and Testing Data Preparation***

Prior to training the ML models, the team structured the training and testing datasets to allow comprehensive cross-training and testing to gain more insights of the impact of training dataset selection. The labeled MLS datasets were organized into four groups:

- **Scene-to-Scene Cross-Matrix:** This group consists of 33 road scene datasets (Table 3.1, which were cross-examined by being trained and tested against each other. This approach allows for a detailed comparison of each scene's performance.
- **Site-to-Site Cross-Matrix:** The 33 road scene datasets were merged based on their corresponding sites (Table 3.2), resulting in 5 datasets. These combined site datasets were cross-examined by being trained and tested against each other. This test was designed to assess the impact of a site selection to the effectiveness of ML model.
- **All-Combined Datasets:** All the datasets were combined into a single comprehensive dataset unit for cross-matrix training and testing using percentage split methodology. The combined dataset was divided into 80% training and 20% testing. Training data was incrementally introduced at 20% intervals (i.e., 20%, 40%, 60%, and 80%), while the testing samples remained constant throughout the experiment. This approach provides an overview of the overall accuracies of the ML models, as well as an assessment of class imbalance effects and the impact of varying training data volume.

- **All-Combined Target Features:** In this group, all unclassified and/or unlabeled (unidentifiable) objects within the MLS datasets were removed, leaving only the labeled (identifiable) objects (which are the target feature of interest only) for the ML models. This serves as a control mechanism to validate the results of all combined dataset, resulting in more robust overall accuracy. This dataset was further organized and processed in the same manner of percentage split as done in the All-Combined Datasets.

In this task, accuracy score was computed to evaluate model performance. The accuracy score provides the ratio of correct predictions (true positives and true negatives) to the total number of samples (i.e., objects), providing an intuitive indication of the probability of the model making the correct predictions. In other words, the accuracy score used in this study focuses solely on the overall correctness of predictions. This computation is illustrated in the following equation.

$$\text{Accuracy} = \frac{\text{Number of correct crediction}}{\text{Total number of predictions}} = \frac{\text{True positives} + \text{True negatives}}{\text{Total number of samples}} \quad (6-1)$$

From accuracy equation, true positives and true negatives are the number of positive and negative samples correctly predicted as positive and negative respectively, and the total number of samples are the total number of instances in the dataset, which includes true positives, true negatives, false positives, and false negatives.

#### 6.2.2.2 *ML Models*

There were three ML models tested in this study: RF, NN, and PointNet++. These ML models were configured consistently in the training and testing process to minimize the bias that might be introduced via the set up. The optimized range of parameters for each model was determined through several generalized runs of model training and testing. To ensure reproducibility of the experiment results, the ML models were constrained with a constant seed state to ensure that same dataset manipulations are executed even when random process was involved. The same class weights (Table 6.3) were also applied across all data groups and models during both training and testing to ensure consistency while prioritizing the features of interest.

RF, an ensemble learning method, constructs multiple decision trees during training and combines their outputs to enhance predictive accuracy and mitigate overfitting. Each tree in the forest is trained on a random subset of the object property analysis metric data, making the model robust against noise and reducing the risk of overfitting compared to a single decision tree. This approach is effective for handling this datasets with a large variety of objects, achieving higher accuracies (Breiman, 2001; Shaik & Srinivasan, 2019). In contrast, neural networks (NNs) are computational models inspired by the human brain, consisting of layers of interconnected neurons that process and transmit information. These models learn patterns, from simple to complex, in the object property analysis metric data by iteratively adjusting the weights of the connections based on

prediction errors during training. As a result, the outcomes can be quite variable, influenced by error minimization processes and data sampling (Zhang, 2000; Rocha et al., 2007). For both RF and NN, a stratified k-fold cross validation was used as the object sampling technique to ensure all objects are well represented across all samples and subsets.

**Table 6.3. Class label weight prioritization**

| <b>Label</b>               | <b>Weight</b> | <b>Name</b>                 |
|----------------------------|---------------|-----------------------------|
| <b>10000</b>               | 2             | Unclassified                |
| <b>50000</b>               | 3             | High Vegetation             |
| <b>50100</b>               | 3             | Trees                       |
| <b>110112 -<br/>110160</b> | 1             | Road Making Label           |
| <b>140000</b>              | 5             | Wire – Conductor<br>(Phase) |
| <b>140100</b>              | 7             | Powerline                   |
| <b>140200</b>              | 6             | Telephone/TV cable          |
| <b>190100</b>              | 8             | Traffic sign                |
| <b>190400</b>              | 4             | Highway Gantry              |
| <b>400100</b>              | 3             | Bush                        |
| <b>650000</b>              | 9             | Pole-like object            |
| <b>650100</b>              | 10            | Traffic sign                |
| <b>650200</b>              | 10            | Traffic light               |
| <b>650300</b>              | 10            | Streetlamp                  |

PointNet++ is a deep learning architecture specifically for processing 3D point cloud data. Building on the original PointNet model, PointNet++ captures local structures at multiple scales through hierarchical grouping of points, allowing it to learn both global and local features from unstructured point clouds. This model was implemented on the XYZ coordinates of the individually segmented objects. PointNet++ is particularly well-suited for tasks such as 3D shape classification and segmentation, where understanding the geometric details of the data is crucial (Qi, Yi, et al., 2017).

Each model was configured as follows:

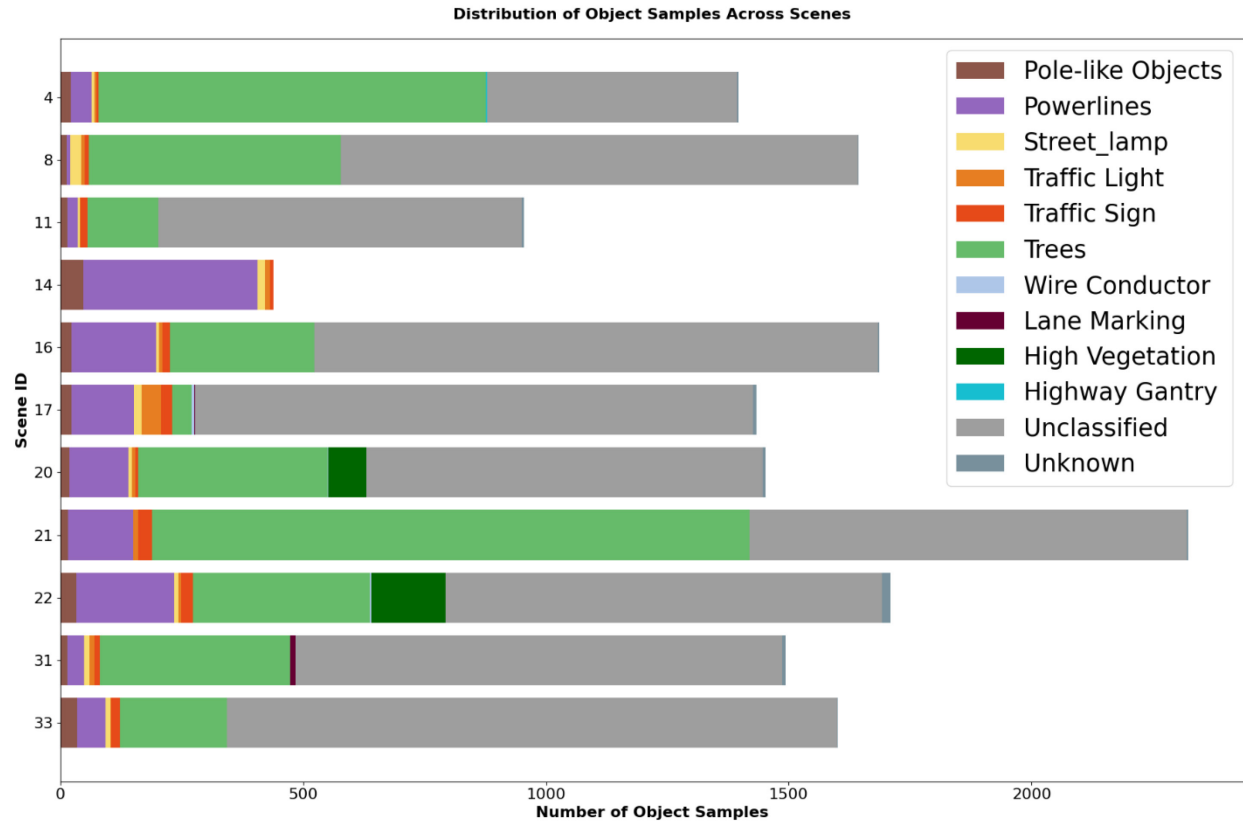
- **Random Forest:** The RF model was configured to automatically find the best classifier within a predefined range of parameters. The number of estimators varied from 50 to 500, and the maximum depth ranged from 1 to 20. These parameters were maintained consistently across all training and testing data groups. A specific random seed value was used for the random state to ensure reproducibility and consistency in the results.

- **Neural Network:** The NN was established with two hidden layers and automatically optimized using Optuna to determine the best-performing model within a specified range of parameters. The parameters included 50 to 100 neurons in the first layer, 20 to 100 neurons in the second layer, a learning rate ranging from 0.001 to 0.1, and activation functions of ReLU, sigmoid, and tanh, with a fixed softmax activation function for the output. The number of epochs ranged from 100 to 1000, and a fixed Stochastic Gradient Descent (SGD) optimizer was used. The same seed value as used for RF was applied to NN to ensure consistency in reproducibility within itself and that of the RF.
- **PointNet++:** This primarily relied on the 3D (XYZ) coordinates of the segmented objects to perform hierarchical point set feature learning. The process was enhanced by incorporating the normal vectors of the object point set, which enriches the geometric information. The normal vectors were estimated by identifying a point's neighbors through a radius or k-nearest neighbors search, fitting a plane using PCA, and deriving the normal as the eigenvector associated with the smallest eigenvalue where consistent orientation of normals is ensured for coherence.

## 6.3 RESULTS AND DISCUSSION

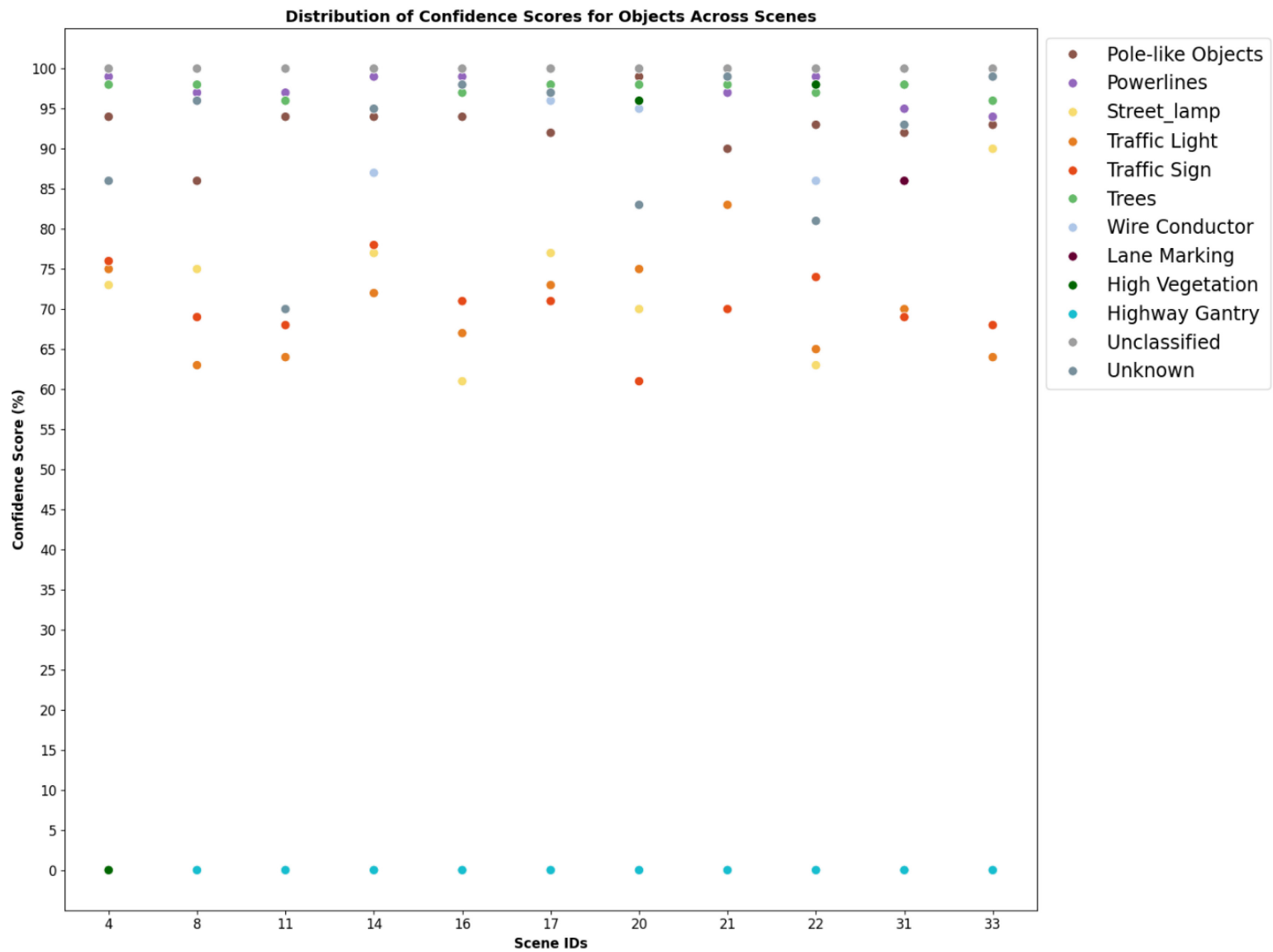
### 6.3.1 Training Data Analysis

The training data analysis focused on a selected subset of the scenes in the dataset and examined the distribution and number of object samples (Figure 6.6) with associated confidence scores (Figure 6.7) as defined in Table 6.2. Additionally, the point cloud of the training scenes 4, 11, 14, and 21 were visually examined (Figure 6.8) with the classified objects for scenes 4 and 14 (Figure 6.9 and Figure 6.10) and will be further discussed with the testing results in the following sections.

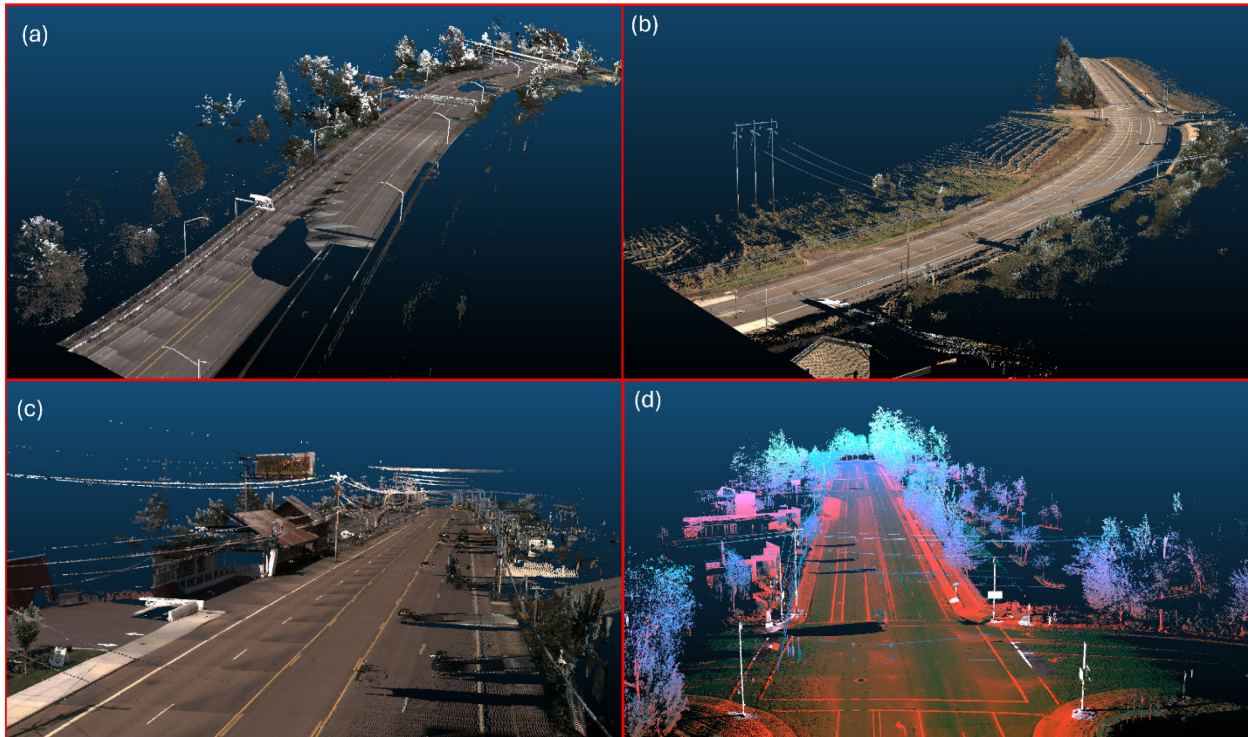


**Figure 6.6. Analysis of objects across training scenes**

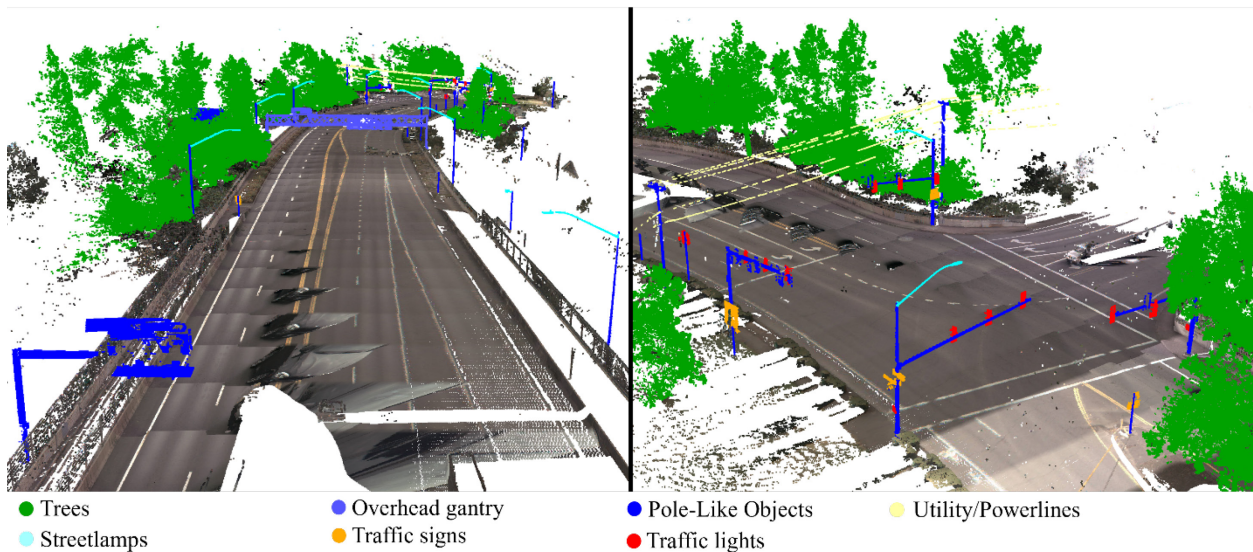




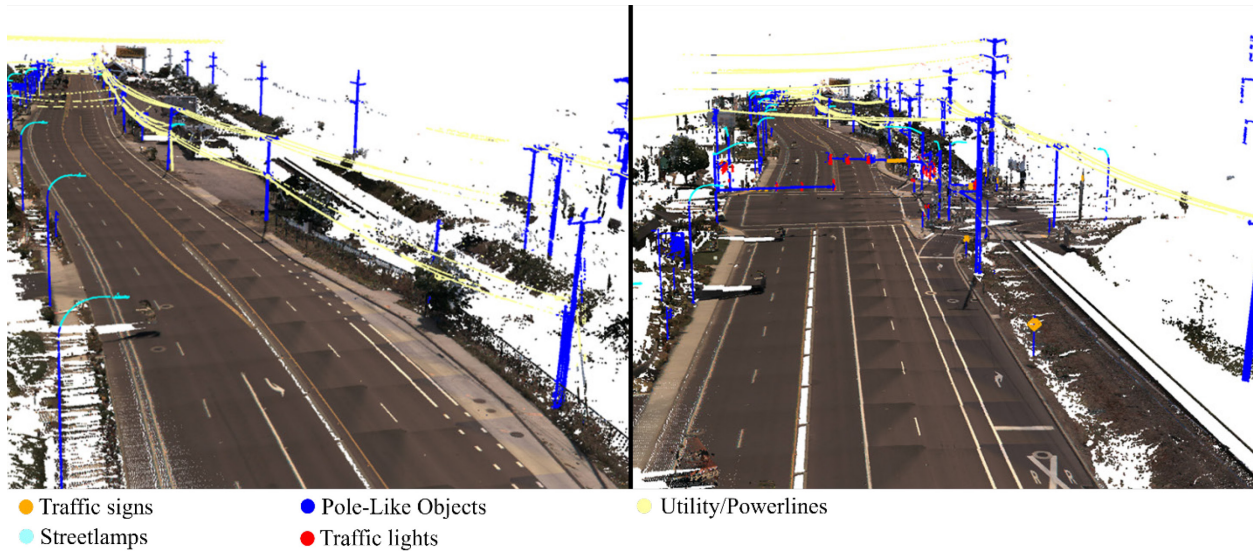
**Figure 6.7. Confidence scores for segmented objects across training scenes**



**Figure 6.8. MLS dataset (a) Scene 4 including a fairly balanced number of trees and other pole-like objects (b) Scene 11 with few pole-like objects (c) Scene 14 including fewer trees but more other pole-like objects (d) Scene 21 (RGB color not available, colored by blending intensity and elevation) including a lot more trees than other types of objects**



**Figure 6.9. Classified objects of Scene 4**



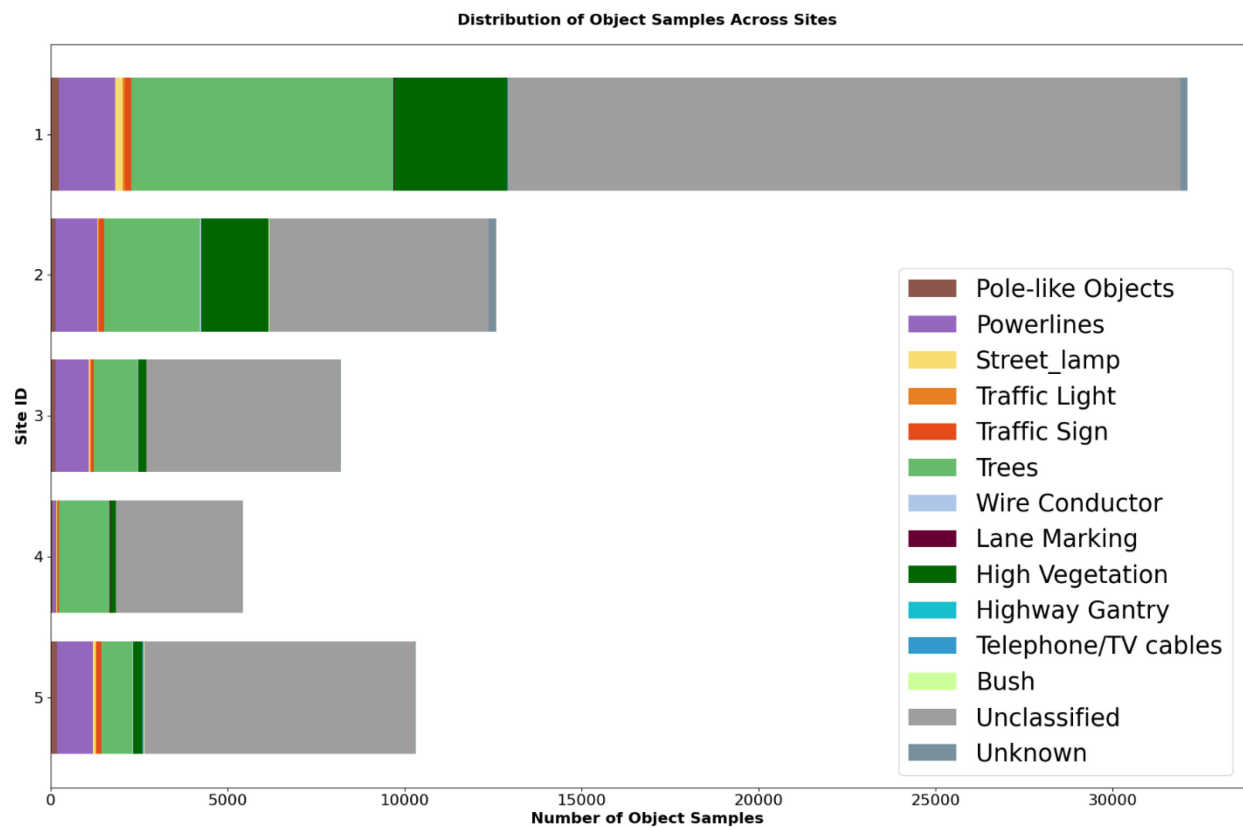
**Figure 6.10. Classified objects of Scene 14**

Scene 21 contains the largest number of object samples, over 2,000, primarily consisting of trees (at 98% confidence) and unclassified features (at 100% confidence). Powerlines are the third-largest category with 97% confidence. Other features, such as streetlamps (at 0%), traffic lights (at 83%), traffic signs (at 70% confidence), and pole-like objects (at 90% confidence), are underrepresented with lower confidence levels. Also, it is important to note that the lack of RGB color information in this scene makes identifying and labeling objects like trees and powerlines easier, resulting in more identifiable object samples of these features than other pole-like objects. Scene 4 shows a similar trend to scene 21 but with fewer samples and higher confidence levels, dominated by trees (at 98% confidence) and unclassified features (at 100% confidence). The main features of interest are minimally represented with confidence levels ranging from 0% to 94%.

Scene 14 stands out with minimal unclassified and irrelevant features, where powerlines (at 97% confidence) occupy most of the objects identified. This scene, however, still has the largest number of pole-like objects (at 94% confidence) among others. Other features are moderately represented with confidence levels from 72% to 94%.

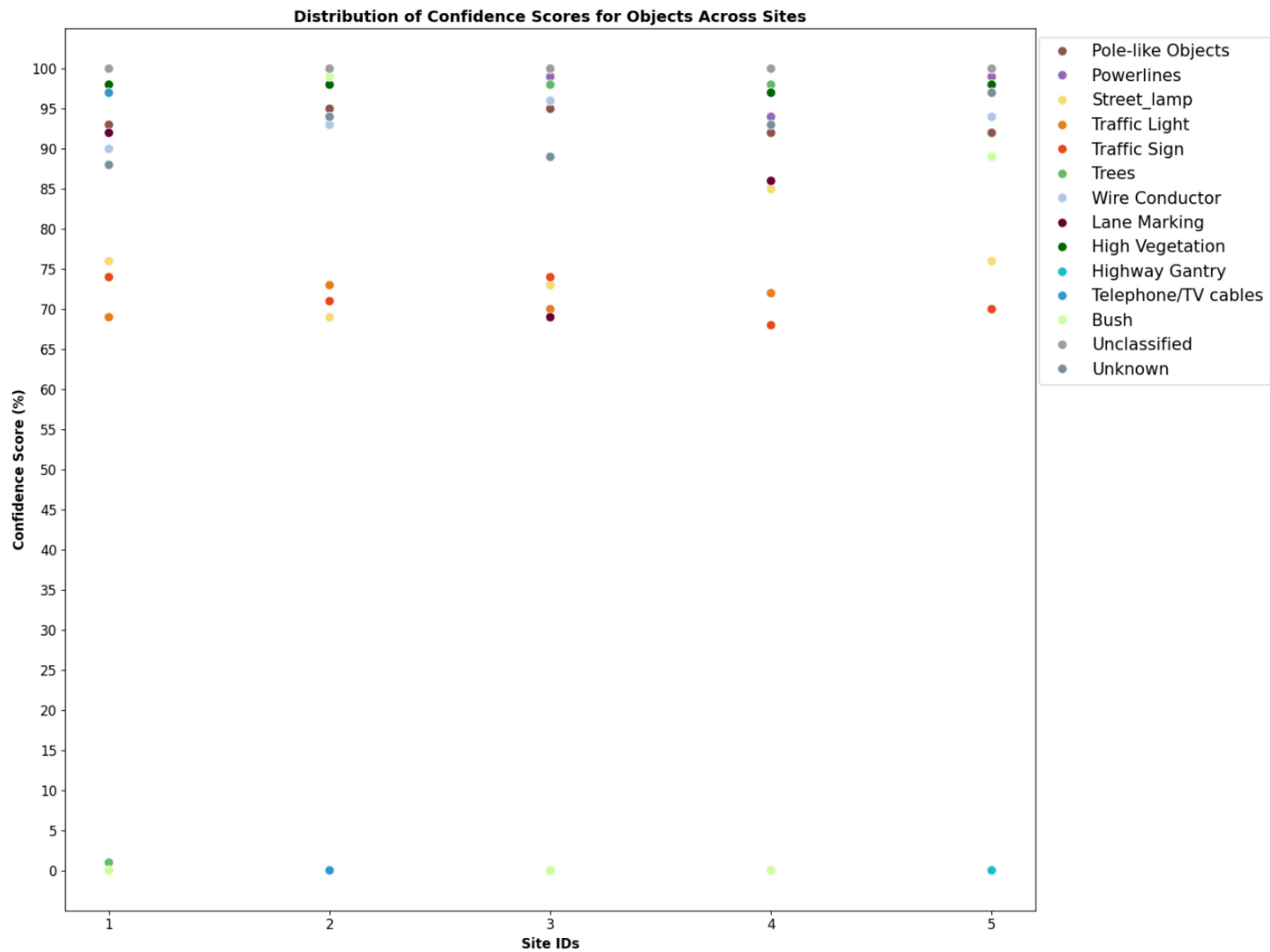
Compared to Scene 21 and 4, Scene 11 has moderate sample counts and feature representation, but is still dominated by trees and unclassified objects. Similar cases can be found in Scene 8, 16, 17, 31, and 33. Notably Scene 11, with the second smallest number of samples, is dominated by unclassified features (at 100% confidence), with few trees (at 97% confidence) and minimal pole-like objects (ranging from 64% to 94% confidence). In this study, overhead highway gantries happened to be the least represented across the board with 0% confidence, while unclassified objects are highly represented at the highest confidence levels (100%). This highlights real-world challenges, such as the difficulty of effectively labelling all objects within a given MLS dataset before developing a robust ML model. It also underscores scenarios where certain objects may be absent or under-represented in the training datasets.

Similar analysis was conducted by grouping the training datasets by site (Figure 6.11 and Figure 6.12). The distribution shows that Site 1 has the highest number of total object samples, predominantly consisting of unclassified features, followed by trees and high vegetation, with confidence levels ranging from 69% to 100%. Notably, telephone/TV cables are present only in Sites 1 and 2, with confidence scores of 97% and 0%, respectively. This underscores the challenge of accurately segmenting all labeled objects for training ML models. Sites 1 and 2 also have a relatively similar number of unknown objects, contributing to their unclassified category (Table 2.2). Other features in these sites are minimally to moderately represented compared to those in other sites. Although Site 3, 4, and 5 also contain unclassified objects, their quantities are less significant compared to site 1.



**Figure 6.11. Analysis of objects across training sites**





**Figure 6.12. Confidence scores for segmented objects across training sites**

### 6.3.2 Scene-to-Scene Analysis

The RF model and NN models were both trained and evaluated across various dataset configurations, including scene-to-scene, site-to-site, and all-combined datasets. This evaluation encompassed scene-to-scene cross-examination visualized through an accuracy matrix (Figure 6.13), followed by a statistical summary Table 6.4 and Table 6.5 for RF and NN respectively.

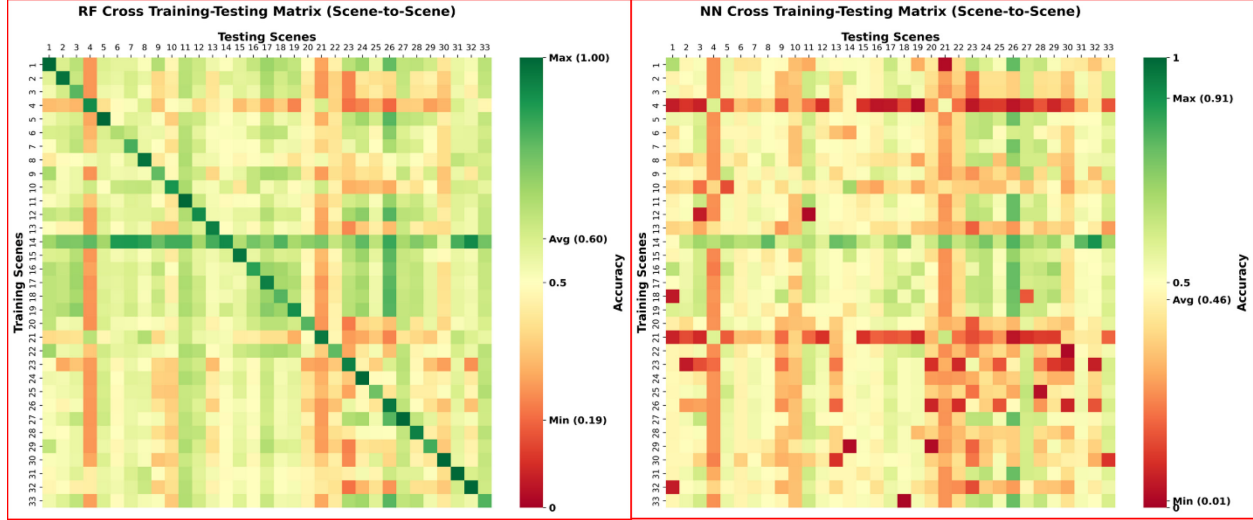


Figure 6.13. RF and NN scene-to-scene accuracy matrix

Table 6.4. Statistical summary of scene-to-scene analysis for RF.

| Statistic          | Overall Accuracy | Internal Accuracy (Diagonal Only) | External Accuracy (Diagonal Excluded) |
|--------------------|------------------|-----------------------------------|---------------------------------------|
| Mean               | 0.54             | 0.91                              | 0.53                                  |
| Standard Deviation | 0.14             | 0.08                              | 0.12                                  |
| Minimum            | 0.19             | 0.68                              | 0.19                                  |
| Maximum            | 1.00             | 1.00                              | 0.93                                  |

Table 6.5. Statistical summary of scene-to-scene analysis for NN.

| Statistic          | Overall Accuracy | Internal Accuracy (Diagonal Only) | External Accuracy (Diagonal Excluded) |
|--------------------|------------------|-----------------------------------|---------------------------------------|
| Mean               | 0.45             | 0.52                              | 0.45                                  |
| Standard Deviation | 0.15             | 0.09                              | 0.15                                  |
| Minimum            | 0.01             | 0.33                              | 0.01                                  |
| Maximum            | 0.91             | 0.76                              | 0.91                                  |

For the Random Forest (RF) model, significantly higher accuracies are consistently observed along the diagonal, which represents training and testing on the same dataset. This diagonal accuracy, averaging 0.91, reflects the internal accuracy of the model, quantifying the effectiveness of the training process. In contrast, all other results represent external accuracy, with an average of 0.53, offering a more realistic metric closer to practical applications where ground truth labels are not available for all the datasets.

Notably, some road scenes, such as Scene 4 and 21 as shown as examples in the prior section, consistently exhibit poor performance. The average external accuracy for Scene 4 as a training dataset is 0.39, and 0.34 as a testing dataset, while for Scene 21, it is 0.47 as a training dataset and 0.35 as a testing dataset. Despite this, their internal accuracies remain high, at 0.92 for Scene 4 and 0.96 for Scene 21. On the other hand, Scene 14 stands out for its highest performance as a training dataset, with an average external accuracy of 0.77, though it does not perform as well when used as a testing dataset. This analysis demonstrates that while RF models trained from a single scene generally provide decent and consistent performance, there are exceptions with some scenes leading to potential overfitting issues.

Unlike the results of RF models, in the Neural Network (NN) model's scene-to-scene analysis, the highest accuracies are not necessarily along the diagonals. While the diagonal accuracy for the NN model averages 0.52, the independent testing average is slightly lower at 0.45. Consistent with the RF analysis, Scene 4 and 21 lead to poor performance as well. When these scenes are used as training datasets, their average external accuracies are 0.19 and 0.23, respectively, and as testing datasets, both achieve an average external accuracy of 0.29. Despite their poor external accuracy, the internal accuracies are moderate, with Scene 4 at 0.59 and Scene 21 at 0.63. Scene 14, similar to the RF models, performs exceptionally well as a training dataset in the NN model, with an average external accuracy of 0.68.

In general, the performance trends observed in the scene-to-scene Analysis for both RF and NN models can be attributed to the composition and representation of features within each scene as discussed in previous sections. Scene 21, dominated by a large number of object samples primarily consisting of trees and unclassified features, exhibits lower confidence levels for key features like streetlamps and traffic signs. Such errors result in poor external accuracy for both models and could be exacerbated by lower quality of the data labeling process due to lack of RGB color. Scene 4, with a similar object composition to Scene 21 but with fewer samples, follows the same performance pattern, reflecting challenges in accurately representing underrepresented objects. In contrast, Scene 14 has minimal unclassified features and a strong representation of pole-like objects and powerlines, and thus performs exceptionally well as a training dataset as a result. The better representation with higher confidence in key features likely contribute to Scene 14's superior external accuracy in both RF and NN models, underscoring the impact of object composition and confidence levels on model performance across different scenes.

### **6.3.3 Site-to-Site Analysis**

The results of the RF and NN model were further evaluated with site-to-site cross-examination (Figure 6.14) followed by statistical summary (Table 6.6 and Table 6.7).

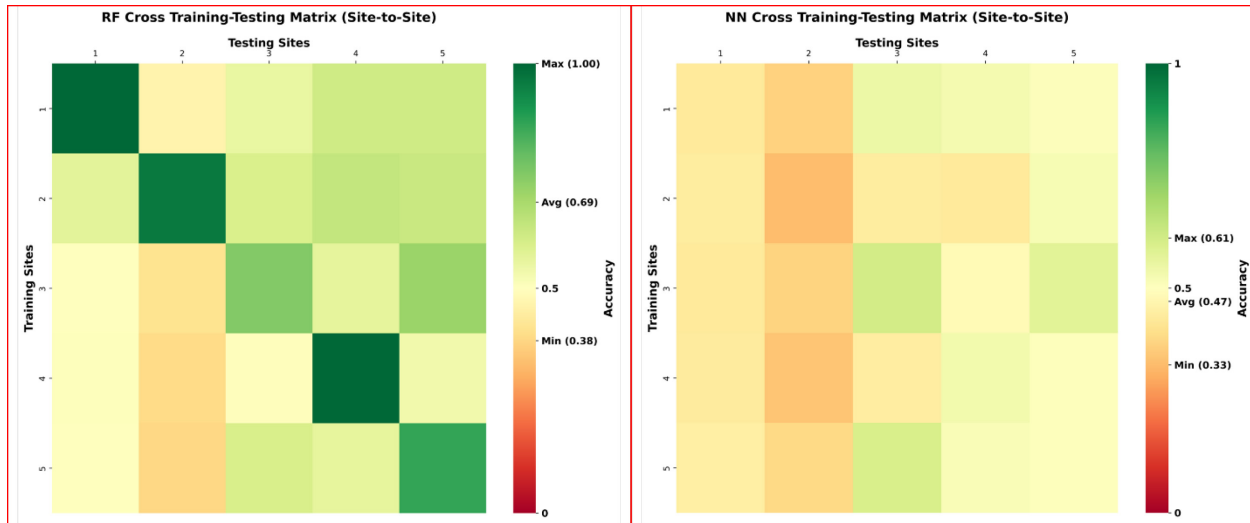


Figure 6.14. RF site-to-site accuracy matrix

Table 6.6. Statistical summary of site-to-site analysis for RF.

| Statistic          | Overall Accuracy | Internal Accuracy (Diagonal Only) | External Accuracy (Diagonal Excluded) |
|--------------------|------------------|-----------------------------------|---------------------------------------|
| Mean               | 0.62             | 0.92                              | 0.54                                  |
| Standard Deviation | 0.17             | 0.09                              | 0.09                                  |
| Minimum            | 0.38             | 0.75                              | 0.38                                  |
| Maximum            | 1.00             | 1.00                              | 0.72                                  |

Table 6.7. Statistical summary of site-to-site analysis for NN.

| Statistic          | Overall Accuracy | Internal Accuracy (Diagonal Only) | External Accuracy (Diagonal Excluded) |
|--------------------|------------------|-----------------------------------|---------------------------------------|
| Mean               | 0.47             | 0.48                              | 0.47                                  |
| Standard Deviation | 0.07             | 0.10                              | 0.07                                  |
| Minimum            | 0.33             | 0.33                              | 0.35                                  |
| Maximum            | 0.61             | 0.61                              | 0.60                                  |

For the Random Forest (RF) model, the site-to-site analysis reveals similar diagonal trends to those observed in the scene-to-scene analysis, where internal and external accuracies are 0.92 and 0.54, respectively. The detailed breakdown shows that Site 1 and 2 underperformed when used as testing datasets, with external accuracies of 0.41 and 0.52, respectively. However, when these sites were used as training datasets, the external accuracies improved to 0.57 for Site 1 and 0.61 for Site 2. This discrepancy may be explained by the fact that these two sites contain more road scenes than others. Notably, both sites also include Scene 4 and 21 (Table 3.2), which were previously identified to associate with poor performance.



In contrast, the Neural Network (NN) model's site-to-site analysis does not fully exhibit the diagonal performance trend seen in the RF model, particularly at Site 1 and 2. These sites have similar internal (diagonal) and external accuracies (0.48 and 0.47, respectively). Site 2 performed poorly as a testing dataset, achieving an external accuracy of 0.37, followed by Site 1 with 0.44, mirroring the trend observed in the RF model. However, Site 1 outperformed Site 2 as a training dataset, with an external accuracy of 0.49 compared to 0.46 for site 2, deviating slightly from the RF model's trend. Moderate to high performance can be observed for all the individual sites as training datasets when tested against Site 3 through 5, which are consistent as discussed for RF. In general, Site 1 and 2, which were collected from urban and suburban environments, perform better as training datasets due to their large object count and diverse distribution, as discussed in previous sections. However, their performance is notably poorer when used as testing datasets, likely for the same reason of having features that are under-represented in the training datasets (i.e., Site 3 through 5).

### 6.3.4 All-Combined Datasets and Target Features Only

In this analysis, the team combined all 33 road scenes and randomly sampled the training and testing datasets with given percentages. To ensure the consistency of the comparison, the same 20% of the test samples were reserved for testing while varying the volume of the training data from 20% to 80% of the entire samples. Because the labeled data also includes the unclassified features, the performance for all features as well as the accuracy within the target features (with unclassified objects excluded) was summarized for RF and NN models (Table 6.8).

**Table 6.8. Summary of RF and NN model performance under different sampling ratio.**

|                 | RF Model     | RF Model             | NN Model     | NN Model             |
|-----------------|--------------|----------------------|--------------|----------------------|
|                 | All Features | Target Features Only | All Features | Target Features Only |
|                 | Test20 %     | Test20 %             | Test20 %     | Test20 %             |
| <b>Train20%</b> | 0.584        | 0.731                | 0.468        | 0.587                |
| <b>Train40%</b> | 0.605        | 0.738                | 0.487        | 0.601                |
| <b>Train60%</b> | 0.616        | 0.741                | 0.522        | 0.638                |
| <b>Train80%</b> | 0.622        | 0.747                | 0.522        | 0.646                |

For both the Random Forest (RF) and Neural Network (NN) models, the accuracy is moderate overall and tends to improve as the volume of training datasets increases. This observation supports the notion that expanding the training samples generally enhances the model performance thanks to the greater variability of features. Specifically, the accuracy for target features is significantly higher than that for all-feature combined datasets. This trend is particularly relevant in real-world applications where training datasets with unclassified features are common, as only a subset of features may be of interest and hence annotated.

The presence of unclassified features can confuse models, as this class lacks homogeneity, leading to decreased performance. This challenge has unfortunately been less addressed or discussed by most existing studies and methods that have been tested on fully classified datasets. However, in practice, producing thorough and manual annotations for all objects is often infeasible due to the time-consuming and labor-intensive nature of the task. The consistent difference in accuracy between all features and target features serves as a quantitative metric to assess the impact of partially annotated datasets.

The NN model, when applied to all-combined and target feature-only configurations, shows results consistent with those of the RF model. The accuracy trends indicate that the target feature-only datasets slightly outperform the all-combined datasets, reinforcing the idea that focusing solely on target features can enhance model performance. This observation aligns with the findings discussed in the RF model's analysis. However, NN generally underperforms in terms of accuracy compared to RF by about 0.1 across all configurations. One possible reason for this is that the attributes extracted from individual objects are more suited to weak learners such as decision trees in RF. Additionally, a larger discrepancy can be observed in the internal accuracy between RF and NN in both scene-to-scene and site-to-site analyses, where RF significantly outperforms NN.

On the other hand, the differences between internal and external accuracy are much smaller for NN compared to RF. The average difference between internal and external accuracy is 0.07 for NN in scene-to-scene analysis and just 0.01 in site-to-site analysis. This suggests that with a limited amount of manually annotated data, NN may provide a more accurate estimate of the accuracy from the training dataset than RF. This can be an important consideration in practical applications where annotated data is limited, as NN's smaller discrepancy between training and testing performance might indicate a more reliable generalization capability under these conditions.

### **6.3.5 PointNet++**

The team further tested PointNet++, a hierarchical deep learning model designed for processing 3D point clouds directly, with the same real-world MLS datasets. Given the complexity of the model, the team decided to skip the scene-to-scene analysis and directly ran it with the site-to-site configuration to provide the model with a larger training dataset. Unfortunately, the team were not able to produce meaningful results using this approach (Qi et al., 2017). It is possible to obtain valid results with extensive fine-tuning of the parameters. However, in this experiment, PointNet++ appeared to be a lot more computationally expensive and time-consuming during training and testing. Additionally, it is worth acknowledging that the way PointNet++ was deployed within the data processing framework did not necessarily align with the ideal situation that the model was originally designed for. But as this study primarily focused on the practical value of these techniques, it is an indicator showing the challenges of incorporating such DL models into an existing data processing framework where the architecture of the model is not inherently compatible with how the data is pre-processed and organized.

## 6.4 FINDINGS & RECOMMENDATION

### 6.4.1 Key Findings

This study evaluated how training data selection impacts ML & DL models for pole-like object classification using Random Forest (RF) and Neural Networks (NN). The feasibility of incorporating DL approaches such as PointNet++ to an existing data processing workflow was also assessed and discussed. The analysis of training datasets for pole-like object classification in mobile laser scanning (MLS) data emphasizes the impact of object representation and confidence levels. Specifically, the scenes with less representations of object of interest (e.g., streetlamps and traffic signs) and more unclassified/unlabeled objects can result in poor ML model performances. The lack of supporting information such as RGB color can also affect the quality of the training data development. Additionally, demonstrated in the site-to-site analysis, both the variety and counts of the target objects can be important for the training the machine learning models. This underscores the importance of expanding training datasets to include a broad range of object samples and improving target feature representation to enhance model performance, while noting that the presence of unclassified features poses a significant challenge in practical scenarios where comprehensive object labeling is often not feasible.

Key findings for the ML and DL models can be summarized as follows:

- Random Forest (RF) consistently exhibited higher accuracies in segment-to-segment and site-to-site analyses compared to NN. The effectiveness of RF can be attributed to its ability to handle diverse data characteristics with numerous simple decision trees.
- While Neural Networks (NN) did not achieve the same internal accuracy compared against RF, it still showed consistent trends and moderate performance. More interestingly, the internal accuracy of NN models was on par with their external accuracies, which could provide a more realistic estimate of their real-world performance.
- PointNet++ performed poorly compared to RF and NN in this study, likely due to the fact that it was deployed within the same data pre-processing framework (e.g., ground filtering and segmentation). PointNet++ struggled to accurately predict the varied and nuanced features in these datasets, which are not present in synthetic datasets like ModelNet40. Weighting the target features as well as the complexity of the data including noise and incomplete coverage has become a major challenge for the model.

### 6.4.2 Recommendations

Based on the results and discussions from the study, several recommendations can be made to enhance the performance and applicability of ML and DL models for pole-like object classification in transportation systems as follows:

- While Random Forest (RF) performed well, testing other models such as Gradient Boosting Machines (GBM) or Support Vector Machines (SVM) could offer additional improvements, particularly with feature-targeting strategies.
- Incorporating deep learning models such as Convolutional Neural Networks (CNNs) for image data can be beneficial. DL models excel in image segmentation and classification, so leveraging image data in conjunction with point cloud data could enhance overall performance.
- Automated and efficient data labeling techniques can greatly reduce manual labor. Techniques such as semi-supervised learning, active learning, and transfer learning can help increase labeled data consistency, quality and quantity.
- Compatibility between data processing workflows and model architecture is an important consideration, especially for those DL models developed with complex architecture. Solving the compatibility is not trivial as simply deploying a model could result in invalid results or require extensive fine-tuning.

## 7.0 CONCLUSION

In this project, to conclude, the research team has achieved the following significant accomplishments and contributions:

- Developed a data processing framework covering extraction of various transportation assets and features (e.g., road surface, pavement markings, utility poles)
- Expanded the mobile lidar benchmark datasets being developed in SPR850 to include more streetside transportation assets with the enhancement of extended classification scheme proposed by the research team as well as a tool for changing class labels.
- Evaluated the effectiveness of each step in the feature extraction workflow, including ground filtering, curb extraction, road detection, marking extraction) and tested their sensitivity to key parameters.
- Designed and created a user-friendly prototype software package implementing the automatic ground feature extraction workflow.
- Developed a data processing workflow for streetside asset classification in mobile lidar point cloud data.
- Investigated the performance of common machine learning and deep learning approaches (e.g., random forest, neural network, pointnet++) in a real-world case scenario and how it can be impacted by the training and testing datasets.
- Developed an efficient methodology for road characterization including horizontal and vertical curves, as well as cross sections using the mobile lidar data leveraging the feature extraction results and the mobile lidar trajectory.
- Assessed the accuracy of the curve identification in the proposed methodology as well as the parameter sensitivity for the road characterization results.
- Created an ArcGIS toolbox that implemented the proposed methodology to identify, analyze, and visualize curves and cross sections from mobile lidar data.

The following findings and recommendations are listed to help with the adoption and implementation of the research outcome from this project:

- Mobile lidar data can serve as a reliable source for asset management as it captures transportation assets in detail with very high accuracy and efficiency.
- The mobile lidar data can be preemptively processed through the proposed framework with default settings to reduce duplication of processes and improve the efficiency of data management.

- During the project, ODOT switched from the Leica mobile lidar system to a Riegl mobile lidar system which can achieve better data quality in terms of accuracy and resolution. The research team tested datasets from both systems and the proposed methodology was demonstrated to be effective. Some parameter fine-tuning may need to be done for different sensors.
- While the data processing framework is mostly automatic, it still requires some manual work especially for QA/QC purposes.
- Machine learning and deep learning approaches show some promise in classification and feature extraction. However, it can be significantly impacted by how the training datasets are established in terms of scene types, presence of objects, data structures, and so on.
- It can be challenging for some deep learning algorithms to be directly adopted depending on their requirements of structuring the data in a certain way and completeness of labeling.
- Sometimes data annotation can be subjective and ambiguous as the algorithms mostly assume one-to-one match between the data (e.g., data points, segments, objects) and classification labels.
- Mobile lidar trajectory is demonstrated to be a reliable source for estimating horizontal and vertical road alignment. Road markings captured in the point cloud can help achieve the same goal, but it can struggle for areas where markings are absent or not accurately extracted.
- For statewide asset management purposes, the use of GIS platforms with the tools developed by the research team is shown to be effective and efficient. The visualization of the results sometimes can be time-consuming and become a hurdle for batch processing. The research team made the visualization module optional and as a standalone tool to mitigate it.

These advancements provide Oregon DOT with more efficient tools for transportation asset management, leading to better decision-making, planning, and maintenance efforts to enhance safety and mobility. It is recommended that ODOT continue to build upon these tools to achieve even higher ROI with their mobile lidar system to support a wide range of applications.

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