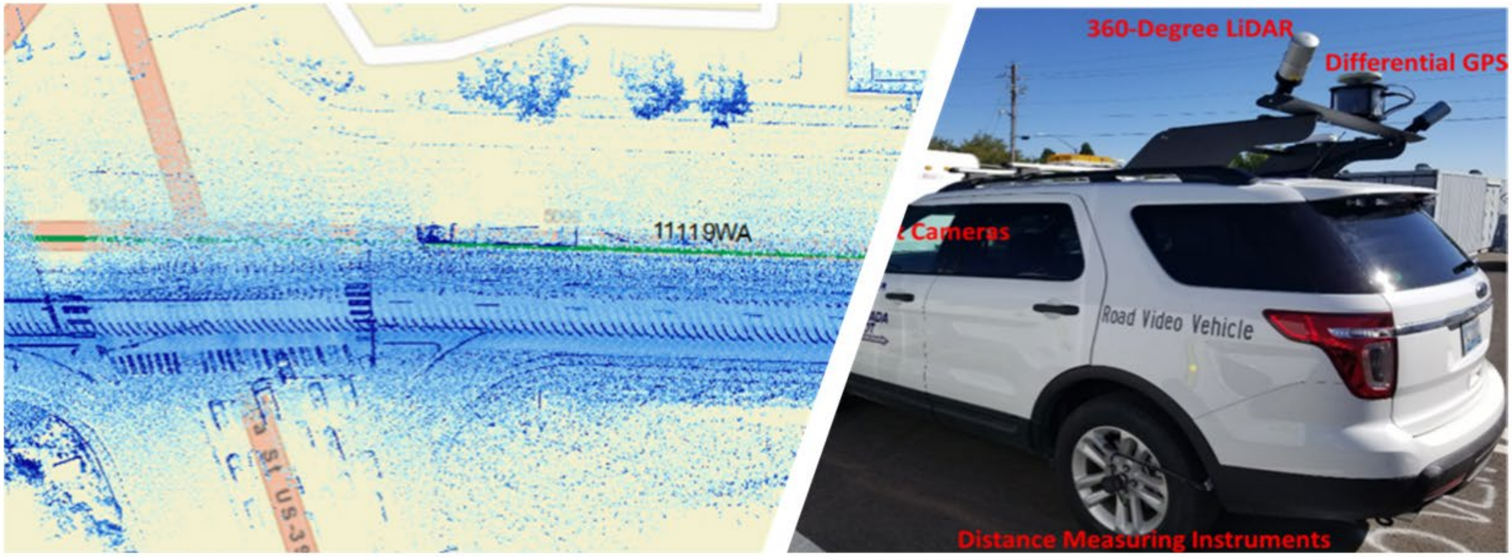

Automatic Road Feature Extraction from State-Owned Mobile LiDAR Data for Traffic Safety Analysis and Evaluation

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16. Abstract

The mobile LiDAR data is a promising solution to the existing road feature data gap based on its high accuracy and extended road network coverage. However, because of the lack of an automatic measuring tool, road features are currently read by data operators and measured manually in the cloud points. This project developed an ArcGIS toolbox—Automatic Road Feature Extraction from LiDAR (ARFEL)—that automatically extracts highly accurate road geometric features from mobile LiDAR data collected on roads. The tool integrated an intuitive user interface and a LiDAR-data processing engine as a toolbox of ArcGIS (the GIS software adopted by most traffic agencies). ARFEL takes the geolocated mobile LiDAR data as input, extracts road features required for safety analysis, and creates GIS data layers of road features. The performance of the tool was evaluated with different road types, and influencing factors were reported in this study.

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1. PROBLEM STATEMENT AND RESEARCH QUESTIONS

Nationwide, 38,680 people were killed in traffic crashes in 2020, and there is growing sentiment that coordination across municipal agencies and areas of expertise is required to mitigate the priority issue of traffic deaths and injuries. This is also a significant problem in the rapidly growing metropolitan statistical area of Reno-Sparks, Nevada (pop. 470,000), which has seen a recent influx of high-tech companies and an associated population growth of 11% since 2010 (U.S. Census Bureau, 2019). With the increase in road users on the city's strained transportation infrastructure, safety has been an increasing concern. It has been recognized as an urgent need to address traffic safety as a community-based priority and through a data-driven approach.

Like many other regional traffic agencies, the Regional Transportation Commission (RTC) of Washoe County, Nevada needs accurate, up-to-date road feature data to perform data-driven traffic safety analysis, select countermeasures, and evaluate projects with the models recommended by the Highway Safety Manual and related safety analysis tools, such as the Interactive Highway Safety Design Model. These data-driven tools and models require accurate, complete datasets of historical crashes and road features to deliver accurate results. RTC Washoe's major roadway data sources are from the Nevada Department of Transportation (NDOT), including the statewide linear-referencing GIS network, the state Highway Performance Monitoring System (HPMS) data, and other data manually extracted from aerial satellite maps or street views, such as Google Earth and Bing Maps. The primary concern with data from these sources is that they either do not include all required data elements, do not provide required accuracy, or do not cover all public roads.

NDOT collects mobile LiDAR data of all its routes and functionally-classified roads in the cardinal direction (Northbound or Eastbound). The data is post-processed using GPS corrections and precise ephemeris files. The NDOT mobile LiDAR data is a promising solution to the existing road feature data gap based on its high accuracy and extended road network coverage. However, because of the lack of an automatic measuring tool, road features are currently read by data operators and measured manually in the cloud points. Manually extracting data from LiDAR data requires significant time and labor, especially considering repeat work for recurring LiDAR data collection along roads: LiDAR data on a road segment is re-collected approximately every three years, and road feature data always needs to be updated.

The major research questions answered in this project are:

1) What are deep learning algorithms recommended for segmenting, classifying, and measuring road features?
2) What LiDAR data properties need to be considered for road feature identification and classification? (Selecting critical data properties for classification algorithms is also called *feature engineering*.)
3) How should the sample dataset be prepared to train deep learning algorithms efficiently?
4) How can the accuracy of road features extracted from mobile LiDAR data be evaluated?
5) How can we sustainably maintain the data extraction tool for added road features to support and apply the tool in other regions?

2. PREVIOUS KNOWLEDGE GAPS

RTC and NDOT use the traditional methods to collect road data, primarily field survey and measurement through Google Earth (Pro), Bing Maps, or other aerial or mobile imaging resources, but these traditional methods have huge labor and time costs. Satellite images also have problems: they are out-of-date and low-resolution in some regions. These issues have been major obstacles in recent traffic safety data collection and analysis projects. Ground-based imaging, often referred to as a mobile mapping system, is a specially instrumented vehicle installed with high-definition cameras for image capture. Because of the lack of accurate spatial measurements or depth information with images, it is challenging to locate road features automatically and accurately from ground-based images.

Some transportation agencies have traditionally employed backpack-based data collection as a manual data collection method. Backpack-based data collection uses lightweight, mobile equipment. Descriptive data for the objects of interest are recorded using image-capturing devices or electronic devices using hand-held, laptop, or pen-based computers. Field survey is highly time- and labor-intensive and can thus only be applied for a limited portion of the road network.

Aerial imaging systems with LiDAR, also called airborne laser mapping, can collect data at high altitudes and thus can cover even remote locations relatively quickly. Coverage is adversely affected by data resolution, tree cover, overpasses, and other canopy effects. The United States Geological Survey (USGS) maintains and provides national elevation datasets from airborne LiDAR data. While these datasets provide national elevation information, the resolution is not high enough to identify boundaries of roads, lanes, shoulders, sidewalks, and foreground slopes.

To provide high-resolution airborne LiDAR cloud points, agencies also use drones to collect data in targeted areas or road segments. Drones collect survey data much more efficiently than traditional human methods, but they are limited by weather, battery endurance, and air space management. While drones are especially useful and capable for collecting survey data in areas that are difficult for engineers/surveyors/vehicles to access, mobile LiDAR data collection systems on vehicles, Figure 1, are more flexible and easily cover public roads and surrounding environments (about 400 ft from the data collection vehicle). When weighing data collection methods and resources for the entire public road network, mobile LiDAR data is the superior option among today's available data sources.

Recognizing the importance of mobile LiDAR data for road feature databases—especially geometry-design related features—several states, such as Nevada, have been collecting mobile LiDAR data for years. While these data collection efforts are mainly conducted and sponsored by state DOTs, the data can benefit all traffic agencies. To extract road features from the mobile LiDAR data, agencies and their vendors invest significant effort in manual data extraction using LiDAR data operation software for review and measurement. By taking advantage of recent data mining and deep learning methodologies, researchers have proven that automatic methods of extracting road features from LiDAR data are feasible. Most traffic safety engineers and planners do not have expertise in programming deep learning algorithms introduced in research papers. **Thus, most states that own mobile LiDAR data still do not fully benefit from their available datasets.**

Figure 1. NDOT road video vehicle equipped with differential sensors.

3. HOW THE ARFEL GIS TOOLBOX ADDRESSES THE KNOWLEDGE GAPS

RTC Washoe and the technical team from the University of Nevada, Reno (UNR) and Texas Tech University (TTU) developed an ArcGIS toolbox—Automatic Road Feature Extraction from LiDAR (ARFEL)—that automatically extracts highly accurate road geometric features from mobile light-detection-and-ranging (LiDAR) data collected on roads. To address the need to generate high-quality road feature data from state-owned mobile LiDAR datasets, the project team reviewed, trained, evaluated, selected, and implemented LiDAR data processing technologies into the ARFEL tool. The tool integrated an intuitive user interface and a LiDAR-data processing engine as a toolbox of ArcGIS (the GIS software adopted by most traffic agencies). ARFEL takes the geolocated mobile LiDAR data as input, extracts road features required for safety analysis, and creates GIS data layers of road features. The generated road feature data allows further query, analysis, and visualization in ArcGIS or any other GIS software or platform.

Input: The input component loads existing regional GIS road networks and geolocated mobile LiDAR data in the LAS format. It also manages the loaded cloud points and road maps in computer memory for the following data processing.

LiDAR data processing: LiDAR data processing converts large LAS data (high-density 3D cloud points) into two-channel high-resolution raster files with elevation and intensity as channel values (like grey-level or GRB values of pictures) for the data labeling and extraction that follows.

Road feature extraction: This applies selected deep learning models to complete road feature extraction from the two-channel raster files. This is the core component of the LiDAR processing engine.

Output: This component writes the extracted road features into GIS data layers. The current version of the toolbox can automatically identify and extract the following road features from the mobile LiDAR data:

- Guardrail existence of road segments
- Number of lanes and lane widths of road segments
- Curb existence of road segments
- Sidewalk existence of road segments

RTC planners and other agencies with access to mobile LiDAR data can use the tool to extract road feature data for data-driven safety analysis, evaluation, and prediction. NDOT and other state or region agencies can also use the tool to prepare road feature data for traffic safety improvement. The current technology is at level 7: prototype demonstrated in an operational environment with the technology readiness levels defined in the FHWA's Technology Readiness Level Guidebook.

4. DATA USED AND METHODOLOGICAL APPROACH

Data

NDOT collects mobile LiDAR data of all its routes and functionally-classified roads in the cardinal direction (Northbound or Eastbound). The data is post-processed using GPS corrections and precise ephemeris files. The begin/end frame numbers are corrected to make the route start and end where it should. The GPS corrections are then applied to adjust the mileage of linear referencing with the most accurate length and position. The corrected routes in the proper project folders are uploaded to the NDOT data server for access. A sample of NDOT's mobile LiDAR data is shown in Figure 2.

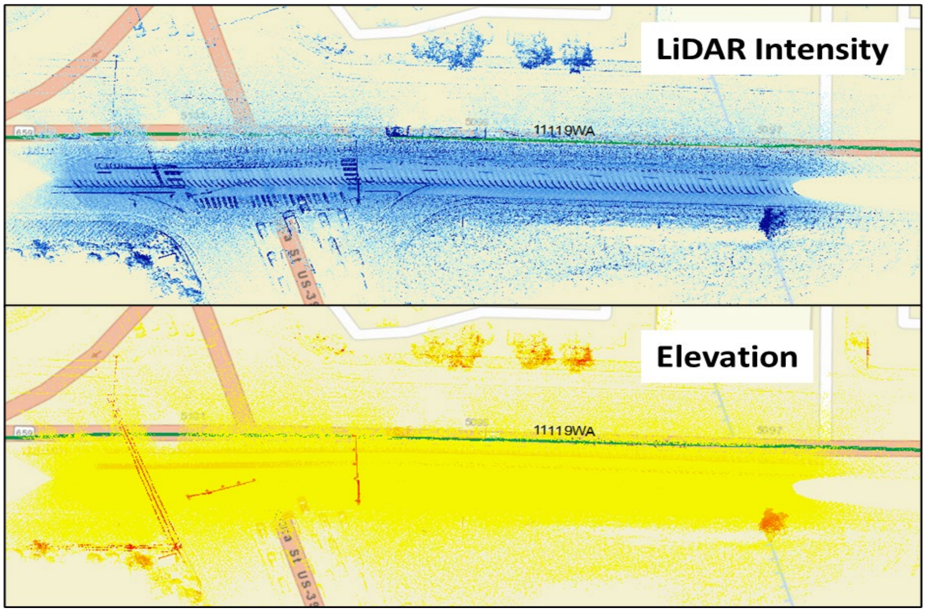

Figure 2. Sample of NDOT mobile LiDAR data.

The mobile LiDAR data contains high-quality 3D cloud points of traveled ways and roadsides; these cloud points have been geolocated to the WGS_1984_UTM_Zone_11N GIS coordinates. Roadway and roadside surfaces are represented with high-accuracy (4 centimeters), high-density 3D points that contain depth, laser reflection intensity, and geolocation information. NDOT's LiDAR data is stored in LAS format, which contains all cloud points projected in a geographic coordinate. There are more than 5 million points for a 300-ft segment of the rural two-lane-two-way road (about 250M file size). NDOT has collected mobile LiDAR data on a total of 10,854 miles of road, including 1,236 miles of Interstate Routes, 3,981 miles of U.S. Routes, 5,427 miles of State Routes and an additional 210 miles of Frontage Roads, State-Owned, and Access Roads. The collection for this cycle was from 2017to 2019. NDOT shares its mobile LiDAR data with RTC and other traffic agencies in Nevada.

This project used mobile LiDAR data collected on ten roadway segments of various functional classes and with a total length of 43 miles.

Table 1 Information of road segments for mobile LiDAR data used in this project

ROUTE ID	STREET NAME	FROM	TO	FUNC CLASS	LENGTH (Mile)
140WA	PRATER WAY / 4TH ST	MCCARRAN BLVD	FRWA05	4	3.220
141WA	2ND ST / GLENDALE AVE	KIETZKE LN	MCCARRAN BLVD	3	2.651
144WA	PLUMB LN	KIETZKE LN	TERMINAL WY	3	0.588
149WA	KIETZKE LN	S VIRGINIA ST	GALLETTI WY	4	3.844
150WA	ROCK BLVD	HYMER AVE	VICTORIAN AVE	4	0.315
1119WA	MCCARRAN BLVD	S VIRGINIA	S VIRGINIA ST	3	23.031

		ST			
190584 WA	KILEY PKWY	SR445	HENRY ORR PKWY	4	0.539
140481 WA	WINGFIELD SPRINGS RD	WINGFIELD PKWY	CALLE DE ORO PKWY	6	2.165
106785 WA	CAUGHLIN PKWY	SR659	SR659	6	3.334
134316 WA	SOMERSETT PKWY	DEL WEBB PKWY	MAE ANNE AVE	4	4.074

Methodology

The project study showed that segmentation and classification with all 3D cloud points are unnecessary to extract road features. Converting LAS LiDAR data into the GIS raster format significantly improves data processing efficiency and operation. The raster conversion compresses LAS data into high-resolution grids and only keeps each grid's elevation and laser reflection intensity information. Each geolocated LAS file is converted to two geolocated raster layers: one is a raster of elevation, and the other is a raster of reflection intensity, also called a two-channel image, illuminated in Figure 2.

With the converted grid data and selected algorithms, the following steps are performed to extract road features:

1) Split centerline GIS into short segments (e.g., 100 ft).

2) For each centerline segment, apply segmentation technology to the related two-channel LiDAR image to differentiate road surface objects. Then, use classification methods to recognize the classification of each object.

3) Identify the existence of road features and calculate the corresponding values such as lane width.

4) Integrate road features identified for each centerline segment and create separated GIS layers for each extracted road feature.

The ARFEL tool was developed with the Python programing language, which is supported by the ArcGIS ArcPy library (API for GIS operation) and several existing deep learning/data mining Python libraries, such as the Keras deep learning framework (https://keras.io).

Segmentation and clustering aim to find regions of objects or meaningful parts of objects. It is necessary to divide an image into object regions before object classification. We use image segmentation to look for objects that either have some measure of homogeneity within themselves or have some measure of contrast with the objects on their border. We trained and tested edge/line detection algorithms, such as gradient operators, compass masks, and advanced edge detectors, for line road feature extraction (lane boundaries and curbs), together with segmentation methods, such as area road features (sidewalks and ramps) region growing and shrinking, clustering, boundary detection, and combined approaches. Table 2 lists the clustering and segmentation algorithms tested in this project.

Table 2 Clustering and segmentation algorithms tested in this project

Image Clustering	Image Segmentation
K-Means	Felzenszwalb's method
2D DBSCAN	Quickshift
MeanShift2DClustering	Compact watershed
Canny Edge detection	Random walker
Canny+Hough Transform	SLIC-K-Means
Hough Transform (line shape detecting algorithms)	OPTICS
Jenks Natural Breaks	
Histogram 1D Clustering	
KernelDesnity1DClustering	
NaturalBreaksOptimization1DClustering	

Feature Engineering - for supervised classification tasks, feature selection is a critical step in training classifiers. Good features should be able to distinguish different classes effectively and can be easily obtained from datasets. We extracted the following cluster/segment features to assist classification:

- Count of points
- Distribution direction
- Average elevation-change
- Deviation of elevation-change
- Average intensity
- Deviation of intensity

Classification - The deep learning algorithms were used for road feature classification. The project reviewed and applied the basic convolutional neural network (CNN), advanced region-based convolution neural network (RCNN), Fast RCNN, Faster RCNN, and Mask RCNN. The project team also applied other classification algorithms such as k-nearest neighbor, Random Forest, low-layer neural network, and learning vector quantization. These non-CNN methods can also provide accurate classification results with good feature engineering (developers select the significant data properties for classification models). The final selected algorithms are Random Undersampling Boost (RUSBoost) and Adaptive Boosting for Multiclass Classification (AdaBoostM2).

Training Dataset and Validation

LiDAR data of PRATER WAY / 4TH S.T. (Functional Class 4, two-way-two-lane suburban road) and 2ND ST / GLENDALE AVE (Functional Class 3, multilane no-access-control urban street) was used as the training dataset to calibrate the clustering and classification parameters for the features of guardrail, lane, curb, and sidewalk. Data of the other road segments were used as the test dataset. The project used Google Street View to validate the feature extraction accuracy. The guardrail information extraction showed high accuracy along with the test road segments but reported private land fences as guardrails on a few segments of functional class 6 roads. The material and quality of pavements influenced curb and sidewalk extraction. Parameters calibrated by the training data did not provide good accuracy on some test roads with different roadway pavement materials, curb shapes, sidewalk surface qualities, and surface situations beyond the sidewalk. Separated parameter calibration is needed to extract lane information on various routes. The tool identified 85%-90% of lane markings based on observation with Google Street View. The accuracy or road feature extraction was mainly influenced by the performance of data clustering rather than feature classification. LiDAR data occlusion (caused by vehicles and roadside objects), dataset noises, and indistinguishable intensity/elevation values from surrounding cloud points are the challenges of clustering. This project did not evaluate the clustering accuracy and classification accuracy separately. However, calibration with sample data from the same road segment can lead to accuracy higher than 95%. Using the tool to extract road features requires calibration for each regional route type.

5. OUTLINE, INSIGHTS, AND UTILITY OF THE TOOL

The Moving Ahead for Progress in the 21st Century (MAP-21) reauthorization legislation identifies the need for improved, more robust safety data for better safety analysis to support the development of states' Strategic Highway Safety Plans and their Highway Safety Improvement Programs (HSIPs). The Federal Highway Administration (FHWA) 's HSIP is a data-driven program that relies on the crash, roadway, and traffic data to identify and evaluate problems. While all states and regions have maintained good crash record datasets, data about required road features are often missing or are poor-quality. Integrating high-quality road data with crash and traffic data helps agencies make better decisions and more effective use of limited funds to improve safety.

The current lack of comprehensive roadway safety data, including information on the roadway and roadside features, is a major gap that prevents RTC Washoe and other agencies from performing serious safety analysis with the Highway Safety Manual and other data-driven safety analysis tools. The developed ARFEL tool bridges the available NDOT mobile LiDAR data and the road data required for traffic safety analysis. Although the algorithms were trained with road LiDAR data from Nevada, the trained models can be used and further trained for other regions if local mobile LiDAR data is available. The tool can be extended to extract additional road features—this only requires creating a new training dataset for the new features and training the data segmentation and classification models.

Note that state DOTs, such as NDOT, collect mobile LiDAR data on road segments every few years. The automatic methods of the ARFEL tool will significantly reduce the high labor and time costs of these repeated measurements by humans. Unlike existing published research or research for a specific agency, the proposed tool will be available for any owners/users of mobile LiDAR data with ArcGIS software.

RTC can apply this tool to prepare road data that is essential to:

- Analyze relationships between crashes and road factors.
- Identify locations and characteristics of crashes using network screening.
- Select appropriate countermeasures and strategies.
- Evaluate safety improvement projects.

6. LESSONS LEARNED, CHALLENGES, AND OPPORTUNITIES

- GIS road centerline network and mobile LiDAR data with linear referencing (LAS format) are the required input for the tool.

- ArcGIS is needed as the toolbox platform.

- The road surface elevation (z value) and laser reflection intensity are the two significant LiDAR data pro ArcGIS support LAS cloud points data, but efficiency is low.

- Redundant data with hundreds and thousands of points in each square foot in the LAS data

- The raster data format (pixels of images) is more efficient for ArcGIS and A.I. algorithms and avoids redundant information for geometric feature extraction.

- Low-LiDAR-density zones may exist because of laser occlusion during the data collection; Roadside infrastructure, like streetlight poles, and other vehicles

- The key information in roadway data extraction from LiDAR is line features, such as the lane markings, curbs, guard rails; The tested 2D segmentation and clustering algorithms provide area clusters rather than the expected features. 1D clustering algorithms to process elevation difference and intensity separately provide better clustering accuracy. Revised 2-D DBSCAN to accommodate pixel locations and elevation differences for clustering road feature objects. Perform better clustering accuracy and generate usable clustering object results.

- All the data processing steps and GIS functions are implemented in Python. The Python code is packaged as an ArcMap plugin toolbox.

- The developed ArcGIS toolbox supports the desktop version of ArcGIS and can be mitigated to ArcGIS pro. However, the requirement of ArcGIS licensing for running some of the Python codes limited its deployment on Linux/Unix-based cloud high-performance computation.

- The accuracy or road feature extraction was mainly influenced by the performance of data clustering rather than feature classification. LiDAR data occlusion (caused by vehicles and roadside objects), dataset noises, and indistinguishable intensity/elevation values from surrounding cloud points are the challenges of clustering.

- Guardrails are easier to identify and locate, while curbs are more difficult to identify correctly than other features; curb shapes, curb materials, and road surface pavement materials can impact the clustering results when training data from different routes calibrate parameters.

- The limited training dataset determined the current clustering and classification approach. The project team will apply the tool for actual road feature extraction of different route types, although it will require the effort of calibration. Along with the road feature extraction, a good amount of accurate road features will be aggregated and meet the requirements of training deep neural networks. An extensive training dataset and application of deep neural networks are expected to enhance the accuracy and robustness of the tool.

7. WEB LINK TO THE SUPPORTING DOCUMENTATION AND THE END PRODUCTS

https://nevada.app.box.com/v/USDOT-SDI-ARFEL