Machine Learning Powered Roadside Asset Extraction using LiDAR

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ABSTRACT

Traditionally, road assets are monitored and inventory controlled getting direct access to each asset, which can be very time-consuming and requires numerous field recordings and trained personnel. With recent advancements in data collection technologies, vehicle-based data collection platforms can collect millions of data points from all spatial directions at highway speed per second. The big data incorporates LiDAR point clouds, 360^{o} degree imagery, and Laser Crack Measurement Sensor data. This paper presents the development of an innovative advanced machine learning algorithm capable of extracting roadside assets including traffic signs, guardrails, line painting, and rumble strips from the big database. The machine learning process starts with training steps in which hundreds of thousands of training datasets are used and then tested against the testing dataset. Once the testing database has passed at 99% or more, the trained program is ready to detect that asset. The techniques used to train machine learning algorithms to extract signs from the LiDAR database are developed using unsupervised clustering algorithm followed by autoclassification using machine learning classifiers with imagery. A similar approach has been taken to identify other assets such as guardrails, rumble strips, and line paintings. This process has been able to successfully identify and classify traffic signs from highways as well as urban and rural roads. The developed machine learning algorithm is programmed in parallel and performed at typical highway operation speed. Additional information about the geometry and retro-reflectivity properties are other important features that are also calculated and reported by this algorithm. The developed algorithm has been in production phase in the British Columbia Ministry of Transportations Asset Management project, in more than 13000 km of highways and has been able to pass all quality assurance mechanisms. This paper outlines the steps followed to develop a roadside asset extraction machine learning algorithm from the LiDAR and imagery database, as well as present a sample of the resultant roadway traffic sign asset database.

KEYWORDS: Traffic signs, LiDAR, machine learning, Line painting marker

1. INTRODUCTION

The roadway asset management is a crucial task for the Department of Transportation (DoT) to maintain the highest standard for road conditions and update them if necessary. The conventional methodology to update the asset inventory requires staff to have direct access to every single asset in person. This methodology is influenced by weather conditions and traffic flow, and requires traffic control to provide safety to the surveyors which might create traffic congestion (Kim et al., 2006).

(Gao, 2009) proposed to use satellite and aerial imagery and Light Detection and Ranging (LiDAR) data to provide the inventory of roadway assets. Although satellite imagery and LiDAR data are very useful for roadway designs, the resolution of the commercial satellite imagery is far lower than what is required to detect smaller assets such as traffic signs, curb and gutter, and guardrails (Singh & Garg, 2014). Nonetheless, aerial data collection is limited to the weather conditions and natural and man-made objects that might obstruct the aerial view of the roadway (e.g., trees, underpass, bridges).

With more recent advancement in camera and LiDAR sensor technologies, the more recent methodology could provide detailed inventory of roadway auxiliary assets using data collected with terrestrial mobile mapping technology. A typical mobile mapping vehicle collects imagery from a single or multiple camera, and LiDAR point cloud data from two LiDAR sensors. The LiDAR dense point cloud provides millions of geolocated informative points collected from environments as far as 200 m. To post-process imagery and point cloud information, we are using the combination of an Inertial Measurement Unit and the Global Navigation Satellite Systems (GNSS) (Tawk et al., 2014). The inertially assisted positioning system provides more accurate positioning capability and augments the GNSS accuracy in places with poor GPS satellite coverage (Bostanci, 2015).

Although mobile mapping has been in service for almost a decade, the asset identification from roadways, up until now, was done manually in an office environment. While this method is safer for the surveying crew and requires minimal traffic controls, asset identification is still very time-consuming and is influenced by human error (Lim et al., 2013).

The advances in machine learning algorithm in image recognition prompted Tetra Tech Canada Inc. (Tetra Tech) to automate the roadway asset extraction and recognition using in-house developed a neural network algorithm. The neural network algorithm was initially introduced in the 1960s (Widrow & Hoff, 1962); however, due to recent evolution in computational power, these algorithms are being implemented in various industries such as defense, agriculture, and transportation (Puig et al., 2015).

In this contribution, Tetra Tech has developed an algorithm that is able to automatically extract and recognize traffic signs from British Columbia's network of highways using augmented imagery and the LiDAR point cloud database. A semi-automated process is also introduced to detect and characterize other auxiliary assets such as line painting markers, curb and gutter, guardrails, cattle guards, and rumble strips.

2. METHODOLOGY

The methodology has been used by Tetra Tech to remotely inventory assets in near real-time with very high precision by incorporating it with integrated Pavement Surface Profiler (PSP) data. The PSP is a vehicle-based data collection platform that collects roadway corridor data and pavement condition data at normal driving speeds. The assets were extracted primarily from the LiDAR and panoramic imagery collected by the PSP as it was gathering pavement condition data on British Columbia's highway network (Figure 1-3). The use of LiDAR data collected in conjunction with the PSP's highly accurate GPS referencing system allows for the most accurate methodology available to pinpoint the positional location of an asset, except for in-situ land surveying.

Figure 1 Pavement Surface profiler platform comprises of (a) Inertial Laser Profiler (b) Distance Measurement Instrument (c) Right of the Way Camera (d) Panoramic Camera (e) two LiDAR 360^o Sensors (f) Laser Crack Measurement System (g) Inertial Movement Unit and GPS.

Tetra Tech's Trimble MX-8 and Reigl VUX LiDAR units incorporated into the PSP are some of the most accurate survey grade mobile LiDAR units available and can collect more than one million GPS referenced data points per second. The two 360^{o} sensors in a cross-plane orientation minimize LiDAR shadow and provide a high-density point cloud with full coverage of the roadway corridor. All of Tetra Tech's data is geo-referenced with an Applanix POS LV system ensuring that the location referencing of all images and LiDAR points used to confirm the inventory types is as accurate as possible. Based on inertially-aided GNSS or GPS technology, the POS LV provides robust continuous and accurate vehicle chassis position and orientation information even through areas of limited or poor GNSS coverage.

Figure 2, High resolution panoramic image collected from Tetra Tech PSP-7000 mobile mapping at highway speed. This panoramic image gives the user unique access to look around at all directions even at very low-light.

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Figure 3. LiDAR pointcloud data collected at highway speed displaying its optical intensity. Notice that the traffic signs are marked automatically using machine learning algorithm.

2.1 Traffic Sign Extraction and recognition

In this paper, Tetra Tech used an unsupervised clustering algorithm that can extract traffic signs using their geometrical properties (e.g., width, height, thickness) and the optical properties (e.g., intensity, reflectance, and amplitude). The clustering algorithm is then applied to the post-processed LiDAR point cloud and separates traffic signs from the background. The background is introduced to the algorithm by providing numerous training point cloud and minimalistic meaningful thresholds. The background in the road environment includes cars, pavements, trees, bridges, pedestrians, and advertising banners. The density based spatial clustering algorithm of application with noise was developed by (Ester et al., 1996), with its application in noise cancellations. However, Tetra Tech found a unique application for this algorithm to identify traffic signs from a dense point cloud database.

Figure 4, displays an example from TransCanada 1 Highway in Victoria Island, which illustrates imagery and point cloud information that are fed to the clustering algorithm to extract traffic signs. The extract information from traffic signs includes width, height, facing, distance to the road, vertical distance from pavement, and retro-reflectivity. This algorithm can measure the geometry and retro-reflectivity of traffic signs with great precision. The information about traffic signs is calculated in the office and on-the-fly using Tetra Tech's Canadian servers faster than real-time.

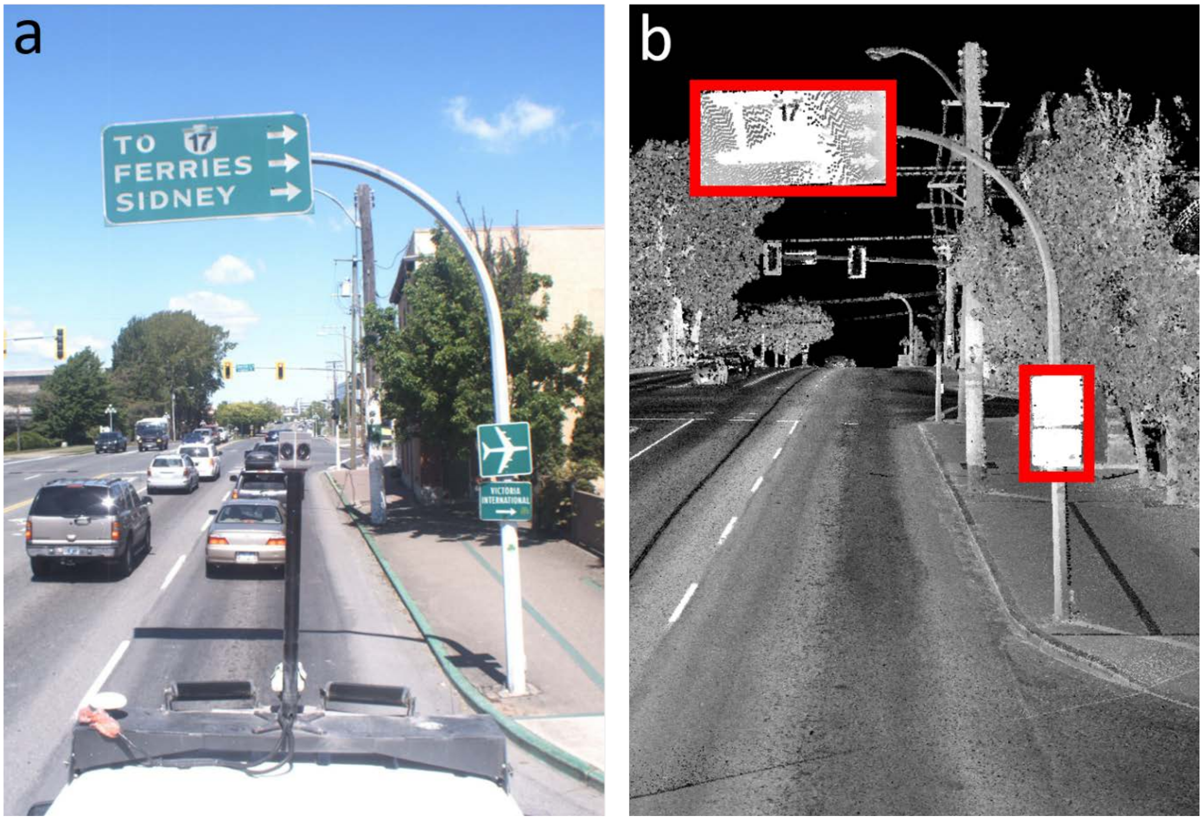

Figure 4. a) Front-center view from MX-8 acquisition system, b) Pointcloud representation of traffic signs automatically extracted using machine learning algorithm. The vortex color indicates the retro-reflectivity of the traffic signs shown inside red rectangles.

To recognize the category of each traffic sign we would need to be able to classify them based on their display properties (geometry, color, text). The North American Stop and Yield signs are the only ones with unique geometrical shape that we can detect and classify using solely LiDAR point cloud. However, for the rest of the traffic signs, it would be impossible to provide an automated classification solution. We can augment the point cloud database with additional imagery information and classify a wider range of traffic signs with the same shape, but with different text (e.g., speed limit sign with different posted speed limit).

2.2 Traffic Sign Classification

To understand the traffic sign classification, we extract the geometry (square, diamond, round, rectangle), color, and text from each traffic sign and create a training database for each traffic sign with images from various angles, lighting conditions, and distances. To create an inference from the training database for each traffic sign, we have developed a machine learning algorithm that is built on top of Google's Tensorflow machine learning infrastructure [NEED_SOURCE]. Figure 5 displays a portion of the training images that are used to recognize 100 km speed limit signs (code R-004--100km) that are collected by Tetra Tech from various cameras, angles, weather, and lighting conditions. The total amount, 576,000 of imagery information, was used to train the machine learning algorithm to classify more than 200 unique signs.

The training algorithm uses a convolutional neural network algorithm Inception model V3 (Szegedy et al., 2015) which takes in all images and true sign category labels and creates inference to categorize signs. This inference is then tested against a separate database labeled images that are not used in the training session. Upon successful classification of over 90% of the test database, the trained inference is used for classifying future traffic signs.

Figure 5 Illustrating portion of training images used for 100 km speed limit sign that are used to recognize speed limits with posted 100km (code R-004—100km). The training database comprises of labeled images from collected from various angles and lighting conditions by Tetra Tech mobile mapping vehicles.

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As part of quality control procedure, classified traffic signs are reviewed by a user that confirms automatic classifications as well rejecting mislabeling. The list of rejections is then pooled into the algorithm for a monthly update to the classifier and to avoid future mislabeling. This process is done through introducing negative sample images to the training database to let the algorithm learn from its mistakes. Having monthly updates to the machine learning algorithm, we could reduce the number of mistakes by the algorithm.

2.3 Linear Assets Detection

For linear assets, including guardrails, curb and gutters, and rumble strips, Tetra Tech developed a procedure to extract them from the LiDAR point cloud database. To extract them from the LiDAR point cloud database, we must transform the LiDAR point cloud from a geospatial domain to a domain we developed as 'Van domain'. In the Van domain, the surrounding environment is nearby the collection van, as observed in Figure 6.

Relative height with respect to the pavement plays an important role in detection and recognition of the linear assets. In the Van domain, the absolute height is replaced with relative height from pavement.

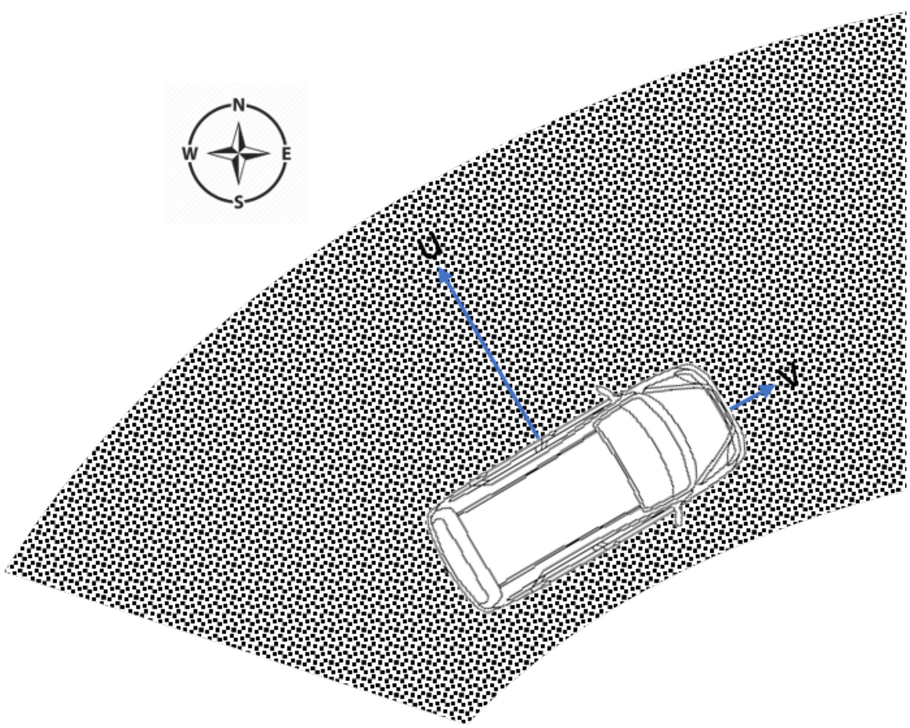

Figure 6 Illustrates the geospatial to van domain transformation required to extract linear assets on the road using LiDAR pointcloud

The transformation allows us to pick linear assets such as guardrails, and curbs and gutters with height filtering and tagging them accordingly. Figure 7 displays guardrail detection from the LiDAR point cloud transformed into the Van domain using a linear asset detection algorithm.

For other assets, we use recommended attributes that are more sensitive to the properties of the asset. Unlike guardrails and curbs and gutters that are visible in the relative height filter in the Van domain, LiDAR reflectance intensity is the attribute we found to be effective for line paint markings. The material properties of the pavement markers (e.g., glass bead coated paints) reflects most of the pulsed laser that it receives. We use this property to detect and classify line markers from the LiDAR point cloud in the Van domain. For extracting rumble strips, we propose a similar technique using the LiDAR point cloud inside the Van domain using spatial standard deviation attributes.

Once the linear assets are extracted from the LiDAR point cloud in the Van domain, the extracted information is transformed into the geo-referenced geospatial domain and compiled into a GIS layer for transferability.

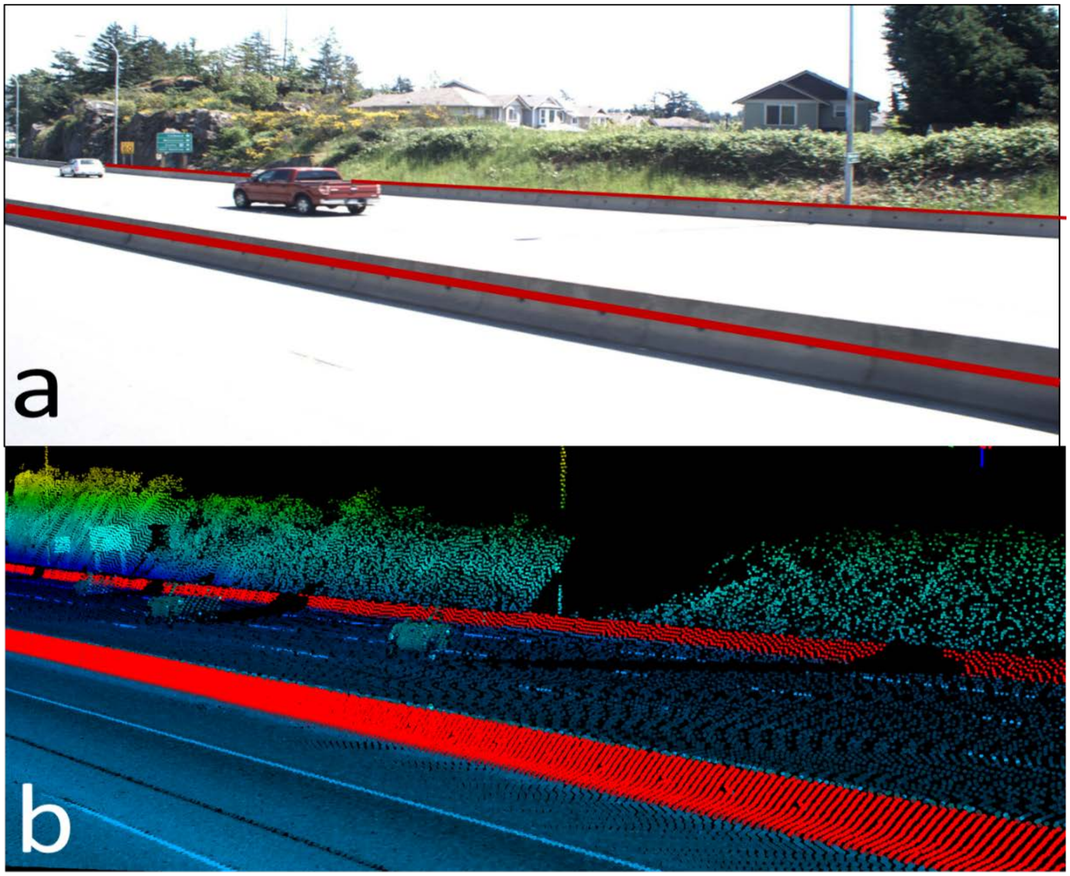

Figure 7 Guardrails detected from (a) imagery and (b) LiDAR pointcloud transformed into the Van domain collected by Tetra Tech PSP 7001 from TransCanada Highway 1 in Victoria.

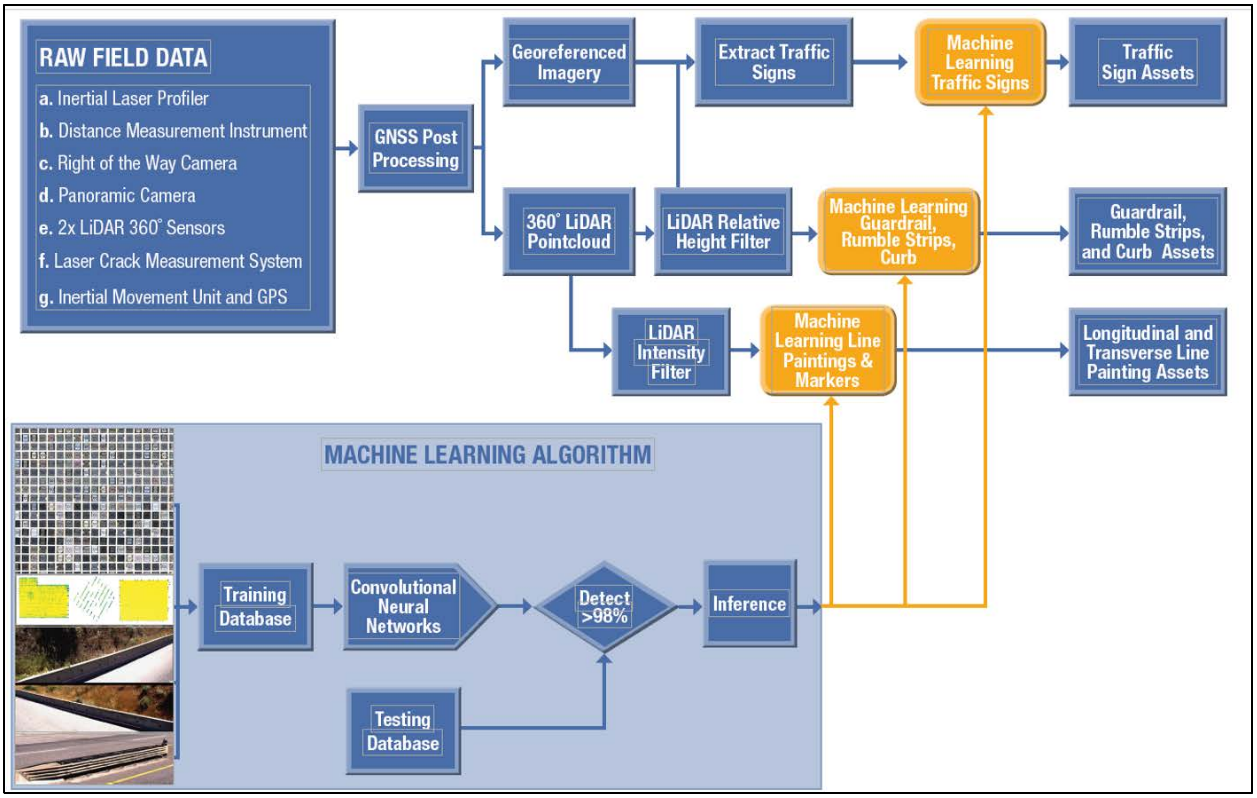

Figure 8. Designed flowchart to extract roadway assets from LiDAR pointcloud and imagery information.

3. APPLICATION OF ASSET EXTRACTION IN BC HIGHWAY NETWORK

The British Columbia Ministry of Transportation and Infrastructure has been updating their Corporate Highway & Resource Information System (CHRIS) asset inventory data in preparation for the maintenance contract renewal process for British Columbia's 28 Service Areas. The historical methodology for updating the asset data was monitored and inventoried manually by sending team members directly to access every single asset in person. This methodology is expensive and time-consuming. For this project, Tetra Tech continued its development on a robust automated and semi-automated asset extraction and classification methodology that would allow for the extraction and identification of the British Columbia Ministry of Transportation and Infrastructure's roadway assets from a combination of LiDAR and imagery data.

Tetra Tech used more than 13,000 km of LiDAR point clouds and panoramic imagery from British Columbia's highway network with machine learning algorithms capable of extracting the roadway corridor assets. Tetra Tech inventoried all traffic signs, guardrails, curbs, line paintings and markers, rumble strips, safety features, and roadside facilities with over 98% accuracy. The total assets for this project is approximately 65,000 traffic signs, 2,000 km of guardrails, 13,000 km of rumble strips, and 20,000 of other corridor assets.

4. CONCLUSION

In this paper we introduced a machine algorithm to extract roadway assets from terrestrial mobile mapping database comprising 360^{o} LiDAR and imagery. The roadway corridor asset inventory completed for this project using automated and semi-automated methodologies from the LiDAR data and panoramic imagery is less expensive and less time-consuming than the historical manual process. The data was collected by driving a single vehicle equipped with a mobile LiDAR unit and cameras along the highways at posted speeds. The machine learning process starts by training the high-performance computers (HPC) to detect assets from the background using millions of positive and negative datasets. The smaller testing dataset is available which are separated from a training session that is implemented to test the quality of the trained inference. Once the trained inference finds 99% of the assets from the testing datasets that are detected, the trained program is ready to detect that asset from field data. The training process required a large amount of computing power and CPU and GPU memory that are available at the Tetra Tech HPC servers. The techniques used to train machine learning algorithms to extract traffic signs from the LiDAR database are to use an unsupervised clustering algorithm and then classify using machine learning classifiers with imagery. A similar approach has been taken to identify other assets such as guardrails, rumble strips, and line paintings. This process has been able to successfully identify and classify traffic signs from highways as well as urban and rural roads.

REFRENCES

Bostanci, E. (2015). Motion model transitions in GPS-IMU sensor fusion for user tracking in augmented reality. *ArXiv*, (1). Retrieved from http://arxiv.org/abs/1512.02758

Ester, M., Xu, X., Kriegel, H.-P., & Sander, J. (1996). Density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings Of The International Conference On Knowledge Discovery And Data Mining* (Vol. pages, pp. 226–231). Retrieved from http://citeseerx.ist.psu.edu/viewdoc/similar?doi=10.1.1.121.9220&type=ab

Gao, J. (2009). *Digital Analysis of Remotely Sensed Imagery*. McGraw Hill. Retrieved from https://books.google.com/books?id=KHXSKc1bfusC&lpg=PA614&dq=mobile mapping&pg=PA614#v=onepage&q=mobile mapping&f=false

Kim, J. H., Jeong, D.-H., & Kim, B.-G. (2006). Photograph Database for Highway Facility Management in Mobile Mapping System (pp. 996–1002). Springer, Berlin, Heidelberg.

https://doi.org/10.1007/11751588_104

Lim, S., Thatcher, C. A., Brock, J. C., Kimbrow, D. R., Danielson, J. J., & Reynolds, B. J. (2013). Accuracy assessment of a mobile terrestrial lidar survey at Padre Island National Seashore. *International Journal of Remote Sensing*, *34*(18), 6355–6366. https://doi.org/10.1080/01431161.2013.800658

Puig, E., Gonzalez, F., Hamilton, G., & Grundy, P. (2015). Assessment of crop insect damage using unmanned aerial systems: A machine learning approach. *Australian Research Centre for Aerospace Automation; Institute for Future Environments; Science & Engineering Faculty*. Retrieved from http://eprints.qut.edu.au/95241/

Singh, P. P., & Garg, R. D. (2014). Road detection from remote sensing images using impervious surface characteristics: Review and Implication. *ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *1*(December), 955–959. https://doi.org/10.5194/isprsarchives-XL-8-955-2014

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2015). Rethinking the Inception Architecture for Computer Vision. Retrieved from http://arxiv.org/abs/1512.00567

Tawk, Y., Tomé, P., Botteron, C., Stebler, Y., & Farine, P.-A. (2014). Implementation and Performance of a GPS/INS Tightly Coupled Assisted PLL Architecture Using MEMS Inertial Sensors. *Sensors*, *14*(2), 3768–3796. https://doi.org/10.3390/s140203768

Widrow, B., & Hoff, M. E. (1962). Associative Storage and Retrieval of Digital Information in Networks of Adaptive `Neurons’. *Biological Prototypes and Synthetic Systems*, *1*(160).