Road Sign Retro-Intensity LiDAR Identification & Analysis

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Chapter 1: Introduction

"According to the National Safety Council even though only a quarter of all travel occurs at night, about half of traffic fatalities occur during nighttime hours[1]. A percentage of these nighttime fatalities can be attributed to intoxication and fatigue, but these factors are not controlled by agencies. In order to address the limited visual cues, present during nighttime driving, FHWA established the minimum maintained retroreflectivity levels which would ensure adequate levels retroreflectivity on signs throughout the nation's roadways. Enhancing the retroreflectivity of traffic signs is beneficial to all motorists, it is particularly important to older drivers. The vision of a motorist declines as they age. Starting at age 20, the amount of light needed by a motorist to see doubles every 13 years. By the year 2020, one-fifth of the population in the United States will be over the age of 65. Increasing the visibility of traffic signs not only improves safety for all motorists, but it allows elderly motorists to retain their mobility and independence."[2]

To maintain the condition of traffic signs, state departments of transportation evaluate signs to identify which ones need to be replaced. The US Department of Transportation published in 2007 their aim to check on regulatory, warning, and guide signs every 7 years and street name and overhead guide signs approximately every 10 years. Our goal is to automate the process of identifying road signs and their condition levels so that evaluation can happen at quicker frequencies efficiently to account for the differing rates of deterioration depending on the many variable factors around a sign that can cause visibility to decrease. Currently, the two manual methods used are nighttime visual inspection and retroreflectometer assessment.

[1] Department of Transportation; Federal Highway Administration. How Retroreflectivity Makes Our Roads Safer. 2001. http://www.ttap.mtu.edu/ library/nightlights.pdf

[2] Boggs, Wesley Bill. "An analysis of traffic sign performance for the establishment of a maintenance plan." (2012).

However, these methods are slow and time-consuming. Many agencies across the nation have voiced concern about meeting the new retroreflectivity mandates, due to current budget constraints and an already stretched labor force. Georgia Department of Transportation (GDOT) expects approximately 3.5 million highway signs on state highway, and so the manual methods to identify the condition of sign are practically prohibitive for network level inventory. LiDAR could be a very effective method that saves a significant amount of time and resources. This approach has been validated by past semesters of Georgia Tech's Smart City Infrastructure research subteam called LiDAR Road Sign Retro-Intensity which found LiDAR results are an improved approach compared to reflectometer gun used formerly. The LiDAR data collection can be done very quickly as no stopping is required and full scan of the sign is taken rather than just four corner points of the sign. Each sign typically has hundreds of data points associated with it. With LiDAR, it is possible to combine the objectivity of the retroreflectometer with the comprehensiveness of human evaluation for traffic sign condition assessment. This semester our goal is to optimize accuracy, efficiency, and memory of the LiDAR algorithm that detects signs and outputs their condition.

Objectives:

To improve and optimize the methodology to accurately extract all the traffic signs from LiDAR point cloud in order to give an effective deterioration analysis and lifetime prediction.

Data:

I-285 and I-75 north of Atlanta

Tasks:

- Locate and identify signs in LiDAR point cloud data.
- Export sign data for multiple years in order to do deterioration analysis.
- Identification of false positives in the LiDAR sign extraction methodology – classify the cases of false positives (guard rails, trucks, slope stability walls, etc.)
- Quantify the characteristics of false positives and refine the code for more accurate extraction of signs from point cloud.
- Identification of missing signs in the LiDAR point cloud. Determine the reasons for missing signs (such as no lidar present on the signs, not enough points on the signs, incomplete sign capture, etc.)

Chapter 2: Literature review

There are 9 sheeting types and 5 backing classes for signs depending on retro-reflectance, color, and durability. The two main sheeting types are engineering grade and prismatic. Engineering grade sheeting types include tiny glass beads and is prone to melting and fading faster. The prismatic sheeting type is more reflective and degrades slower due to being composed of microprisms. Sign manufacturers give an approximate life expectancy of their signs which has become a standard for transportation departments to know when to replace signs. These life expectancies are too general to be reliable and, depending on the manufacturer, may be intentionally low to increase sales. Knowing the factors that impact sign deterioration would be an important step in knowing when signs need to be replaced.

When asked what factors affect sign deterioration, intuitive answers like sign orientation, climate, and age are often suggested. A study performed by Black, Bykentl et al.[3] in 1997 suggested that age, precipitation, ground elevation, temperature, and sheeting type were all significant variables in sign deterioration. However a 2011 study performed by Ré and Carson [4]state that the 1997 study's significant variables aren't reliable. Ré and Carson also concluded that sign orientation and offset distance from the road were not significant. This trend of finding contradictory and differing significant variables is common in the research done on sign deterioration. It's almost as if there aren't any significant variables to rely on. Ré and Carson also agree that the current state of research on the long-term deterioration of traffic signs is that there haven't been any significant variables identified besides age. Paul Carson, a research engineer at the Texas Transportation Institute, succinctly stated that "No service life projection or model is absolute or always appropriate"[5]. As we can see from the state of the research on the subject, Carson's quote is true. There is no magic formula that we can apply to all the signs in the state and know exactly when to replace them. This is why obtaining individualized information on each sign is important, and necessary, to accurately portray the life expectancy of each sign.

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[3] BLACK, BYKENTL et al. "Deterioration of Retroreflective Traffic Signs —. _ Deterioration Variables." (1997).
[4] Ré, Jonathan & Miles, Jeffrey & Carlson, Paul. (2011). Analysis of In-Service Traffic Sign Retroreflectivity and Deterioration Rates in Texas. Transportation Research Record: Journal of the Transportation Research Board. 2258. 88-94. 10.3141/2258-11.
[5] Brimley and Carlson, (2013) The current state of research on the long-term deterioration of traffic signs Transportation Research Board 92nd Annual Meeting, Washington DC, 2013 (2013)

Chapter 3: Methodology

Researchers here at Georgia Tech have been collecting LiDAR data (paired with videos) for several years of routes on major interstates around Atlanta, GA. Our task was to sift through this data and find the points corresponding to signs and look at the retroreflectivity values over the years to determine the current status and projected life expectancy of the signs. A couple of programs were developed before we realized that there are many different types of algorithms that could be implemented with varying results. It took a lot of resources to write a whole program around a different implementation and then have different validation methods specific to that implementation. In an effort to streamline the research around which algorithms are the most effective, we created a testbed to standardize code and provide an equal way to test different algorithms. In short, all the algorithms have the same inputs and outputs and performance is measured with the same tools in order to give a fair comparison. The idea is to identify the highest performing algorithms and then create a final, optimized program revolving around those high performers. Details of the code and the algorithms can be viewed in our GitHub repository, though a rough explanation of the flow of the testbed is explained below.

The overarching steps in the testbed are:

1. Read in data
2. Filter
3. Cluster
4. Classify
5. Export

LiDAR data is stored in a .csv file in XYZ format with corresponding metadata. The following picture shows the format of the data.

	A	B	C	D	E	F	G	H
1	Id	X	Y	Z	Angle	Distance	Retro	UTC
2	2000000	-84.4529	33.88139	278.7242	-0.61897	4.322	0.224	69034
3	2000001	-84.4529	33.88139	278.7216	-0.6292	4.27	0.349	69034.01
4	2000002	-84.4529	33.88139	278.7308	-0.63941	4.201	0.333	69034.01
5	2000003	-84.4529	33.88138	278.7178	-0.64965	4.169	0.345	69034.01
6	2000004	-84.4529	33.88138	278.7411	-0.65984	4.082	0.357	69034.01
7	2000005	-84.4523	33.88181	284.9044	0.08881	71.696	0.118	69034.02
8	2000006	-84.4524	33.88179	284.0415	0.07852	68.482	0.212	69034.02
9	2000007	-84.4524	33.88172	283.0219	0.06822	57.533	0.224	69034.02
10	2000008	-84.4525	33.88165	282.2211	0.05792	46.243	0.255	69034.02
11	2000009	-84.4526	33.88163	281.7152	0.04763	42.578	0.267	69034.02

We read in the data and store it in a pandas dataframe. We then filter out data that we deem insignificant (low Ra values, large distances, etc). Next we try to cluster the points, or group them together to represent objects in the real world. We are using a centroid based clustering algorithm for this. Finally we try to determine if each cluster is a sign. We use an elementary point counting algorithm for this that provides a hard threshold to determine if a cluster is a sign. If a cluster has more than x points, then it is a sign. We end with assigning a picture label to each sign to let us know what picture to go look at to see the sign in real life.

Chapter 4: Analysis & Conclusions

A large part of this semester ended up trying to understanding past semester's work due to minimal documentation as well as finding the best visualization software that satisfies our goals. This included having free non-license access, exportation capabilities that enable efficient group selection of points, and retention of original metadata with exported points. The best software that we ended up using was CloudCompare. The various 3D point cloud visualization softwares are documented for future knowledge and can be found in our Github repository. Through CloudCompare we were able to “grade” our algorithms. In our testing data that included about 50 road signs, our algorithms had 4 false negatives and 3 false positives. Some of the reasons behind the false negatives are stacked signs, small signs, vegetation that blocks signs, and low Ra values (below our filtering threshold). Some false positives were caused by reflective material on non-sign objects. There are some important takeaways from analyzing our results through CloudCompare. First, filtering by Ra values can be dangerous as we can potentially set the threshold above the Ra values for bad signs, which beats the whole purpose of the program. We have to get the points of all the signs, even if they are low. Retroreflective material on non-sign objects are a pain and we need a way to identify them. These and other observations indicate that our clustering and classification algorithms need to be more robust. Some ideas include clustering with a neural network and classifying with algorithms like RANSAC that will check to see if a cluster is a plane. This highlights the value of a test bed. There are many different combinations of algorithms that we can pair with one another. The testbed will allow us to swap them out quickly and have a standardized way to validate the results.

Overall, we concluded after this semester that the goal is not 100% automation but rather being able to get groupings for signs like ‘satisfactory’, ‘needs replacing’, and ‘unknown’ to ultimately bring a huge helping hand to Georgia Department of Transportation.

Chapter 4: Future Recommendations

For next semester, we plan to keep diving into false positive and false negative analysis. This is proposed to be done by continuing to tweak and create new filters, clustering and classifying algorithms, and comparing these adjustments to identify the best algorithm potentially via an autograder system with established benchmarks to meet. Enabling an autograder system means we will need to establish a ground truth for a certain set of data and compare algorithm results. This may become a tedious process as one will have to go through each sign and obtain its outputted sign points and correlated images to assess the algorithm output. We also only want to be analyzing signs on the immediate shoulder of the van driving. Therefore, we intend to implement a transverse distance filter that will also narrow down our evaluation and minimize false positives and negatives. Inherently, adjustments to what retro-intensity value that points are filtered out needs to occur to include some wide-open signs that were missed entirely. We are also intending to move away from making objects of points and clusters as this will be incredibly inefficient considering we are trying to scan in miles upon miles of data. Currently, we are only analyzing a mile and a half of highway LiDAR data. Additionally, seeing that CloudCompare is open-source, we could implement a feature to retain point metadata, which would save a significant amount of time for future analysis.

References:

- https://drive.google.com/drive/folders/154elg1w_9Mz0YV3UhWQpMSyDrKuz5Mu3?usp=sharing
    - Google Drive folder provides access to all literature referenced and collected