Automatic Detection of Roadside Safety Features

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Funded by NCDOT

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Volpe National Transportation Systems Center, US Department of Transportation

- Robert Rittmuller

Road safety challenges and opportunities for AI

- Severe injury crashes in NC are often dispersed across **48,673 miles** of two-lane rural roads
- Current process for assessing roadside hazards on NC rural roads is **tedious, time-consuming, and error-prone**, given the large network of rural roads
    - Site specific, performed by individual field investigation per location
- NCDOT collected **video log data for all secondary roads** including 76% of 2-lane rural roads in 2018 and 2019
    - **Three front-facing cameras**
    - **Every 26 feet**
- **Opportunity for using AI to automate safety analysis**

Pathfinder tool for manual inspection

Two related projects

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AI Tool with Active Learning for Detection of Rural Roadside Safety Features

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***Abstract*—Roadway safety, especially in rural areas, is one of the most critical components in transportation planning. In collaboration with North Carolina Department of Transportation (NCDOT), UNC Highway Safety Research Center (HSRC), and DOT Volpe National Transportation Systems Center, UNC Renaissance Computing Institute (RENCI) developed a roadside feature detection solution leveraging multiple convolutional neural networks. The solution used an iterative active learning (AL) computer vision model training pipeline integrated into an AI tool to detect safety features such as guardrails and utility poles in geographically distributed NC rural roads. We utilized transfer learning by adopting the Xception neural network architecture [1] as the feature extraction backbone which was then used in an iterative AL process supported by a web-based annotation tool. The annotation tool not only allowed for the collection of annotations through an iterative AL process for multiple safety features, it also enabled visual analysis and assessment of model prediction performance in the geospatial context. AL techniques were used to direct human annotators to label images that would most effectively improve the model aimed at minimizing the number of required training labels while maximizing the model's performance. The iterative AL process combined with a common feature extraction backbone allowed fast model inference on millions of images in the AL sampling space. This enabled a rapid transition between AL rounds while also reducing the computing requirements for each round. Model feature extraction weights were then fine-tuned in the last round of AL to obtain the best accuracy. Since only about 2.7% of 2.6 million unlabeled images in the AL sampling space contain guardrails, there is a significant class imbalance problem that must be addressed in our AL sampling strategies for the guardrail classification model. In this paper, we present our AI tool processing pipeline and methodology and discuss our AL results and future work. Our AI tool can be used to detect roadside safety features and be extended to also locate them for assessing roadside hazards.**

***Index Terms*—deep learning, convolutional neural networks, transfer learning, active learning, class imbalance**

I. Introduction

Roadside crashes account for a significant portion of traffic fatalities in the United States. In North Carolina, roadway departure crashes occur in predominately rural roads that are geographically dispersed across many miles with narrow lanes and unpaved shoulders despite the low traffic volume. The outcome of a roadway departure crash is a function of many factors including the characteristics of the roadside. Roadside features that affect the severity of a roadway departure crash include longitudinal features such as guardrails, narrow objects or point features such as utility poles, signs, and trees, side slope, and offset distance (from the edge of the roadway) to the roadside objects. Information on the roadside features can be used to derive a roadside hazard rating that ranges from 1 through 7 with 1 being the least hazardous roadside and 7 being the most hazardous roadside [2]. More recently, procedures have been developed to quantify the safety effect of roadside design elements on single-vehicle run off road departure crashes [3].

To identify and implement safety countermeasures to reduce the severity of crashes involving the roadside, state and local agencies need information on roadside features in their vast rural roadway network. Manual safety inspection and widespread data collections on these rural roads is labor intensive and potentially dangerous when conducted in the field. Many State

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RESEARCH

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Automated Roadside Object Detection and Geolocation by Leveraging Data Fusion of Airborne LiDAR and Videolog Images

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Abstract

Automated detection and geolocation of roadside objects are critical for effective roadway safety analysis and transportation planning, particularly in rural areas. This paper presents an approach for detecting and geolocating stationary roadside objects by fusing airborne LiDAR data with videolog images. While multi-modal sensor fusion has been widely studied and applied in autonomous navigation for enhanced spatial perception, to the best of our knowledge, existing methods all assume known sensor parameters and dense spatiotemporal resolution to facilitate spatiotemporal data alignment. However, in practice, datasets may have incomplete sensor metadata and sparse spatiotemporal resolution. We aim to enable automated detection and geolocation of roadside objects using videolog data comprising over 43 million images of North Carolina's rural roads. The videolog lacks camera intrinsic and pose parameters, and due to temporal downsampling of the initial video capture, consecutive images are spaced 26 feet apart, and GPS coordinates must be approximated. To address these limitations, we have integrated airborne LiDAR data with videolog images through a novel data registration and alignment approach, which estimates missing camera parameters through minimization of alignment errors between videolog road lane markings and projected LiDAR road edges, enabling more accurate computation of object bearings in our geolocation pipeline. Using utility poles as a case study, we demonstrate the effectiveness of our pipeline in detecting and geolocating roadside objects. This work contributes a practical and scalable solution to the often-overlooked challenge of sensor fusion with incomplete camera metadata.

Keywords Object geolocation · Data fusion · LiDAR · Road safety · Roadside objects

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Introduction

Crashes involving a roadway or lane departure are associated with a significant number of fatalities each year in the United States. These crashes include head-on collisions with vehicles from the opposing lane, collisions with roadside objects, and rollover crashes. The Federal Highway Administration estimates that more than 50% of traffic fatalities in the United States involve a roadway departure.[1] In North Carolina, more than 75% of serious injury and fatal lane departure crashes occur in rural areas, and more than 60% of these involve a fixed object.[2] To reduce the severity and frequency of these crashes, transportation agencies require timely and accurate information on roadside objects across extensive rural roadway networks. However, manual inspection and

1 https://highways.dot.gov/safety/RwD
2 https://connect.ncdot.gov/groups/echs/Documents/2024/2024%20NC%20SHSP.pdf

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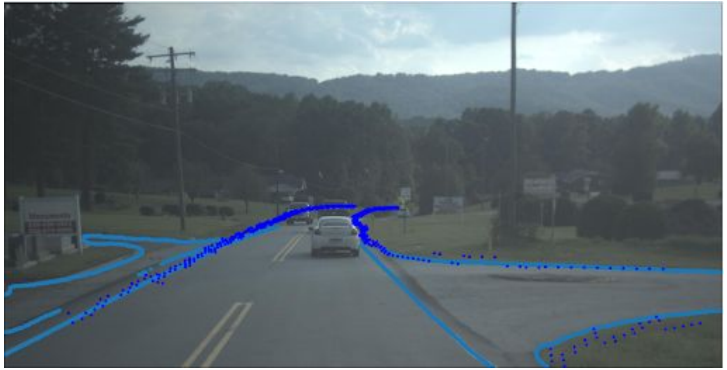
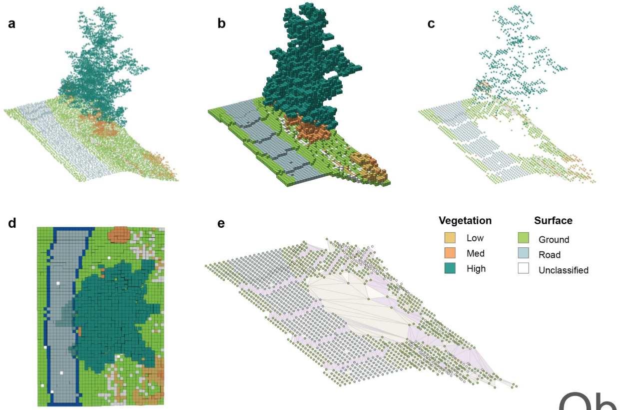
Object detection

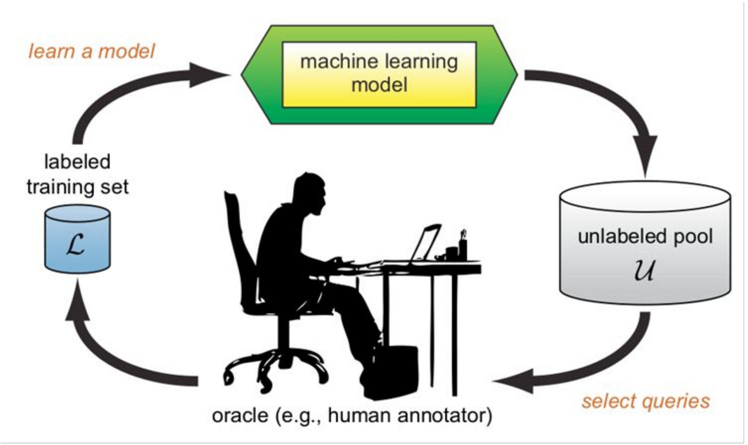




Object geolocation

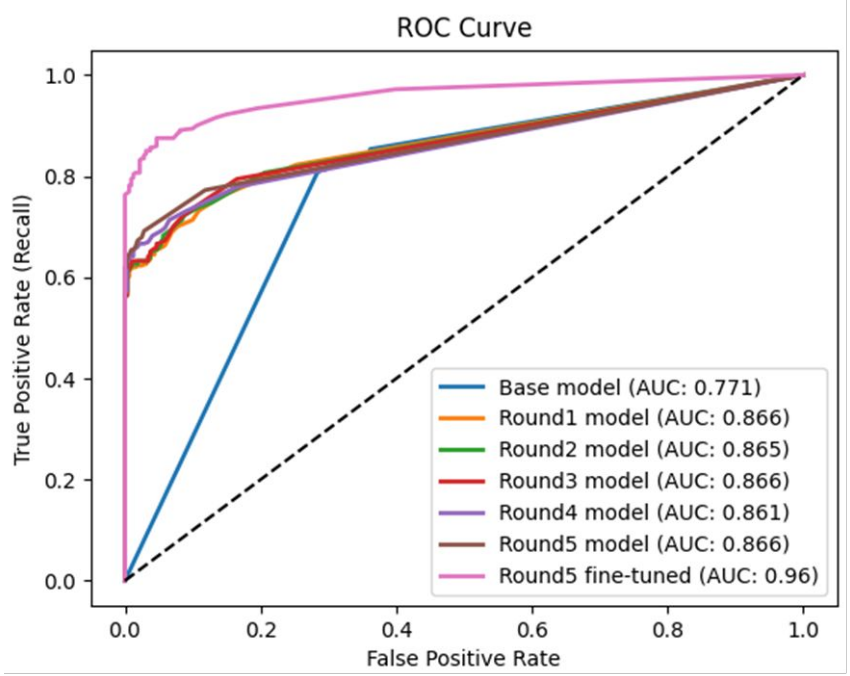
Object detection

- Guardrail and pole detection
  - Continuous and point objects
  - Detection, not segmentation
- Transfer learning
  - Xception NNA for feature extraction
- Active learning
  - Iterative training pipeline
  - Address significant class imbalance
    - 2.7% of 2.6M images have guardrails
- Web-based annotation tool
  - Efficient annotation and exploration

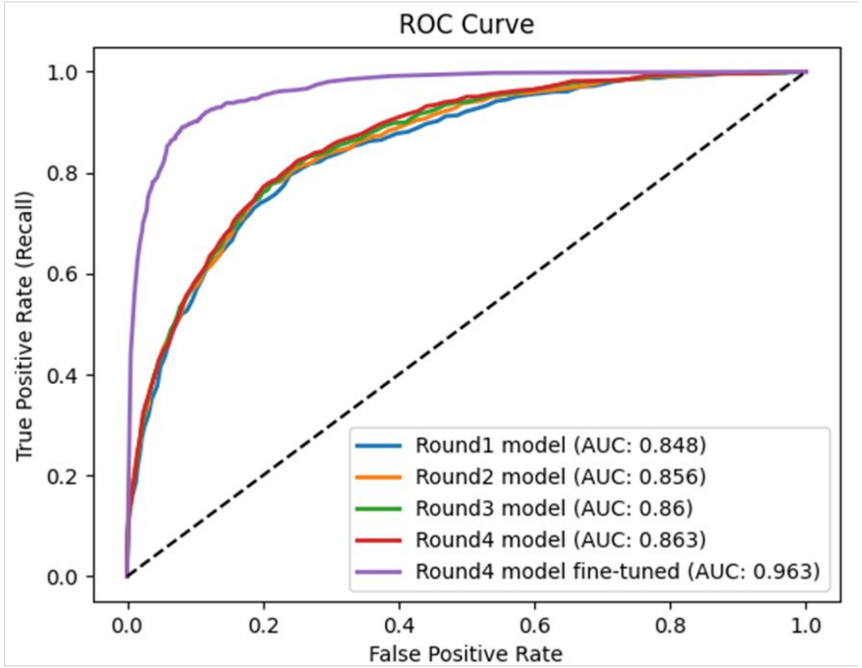


Active learning cycle (Source: active learning literature survey by Burr Settles)

Results



ROC curve of guardrail models through AL

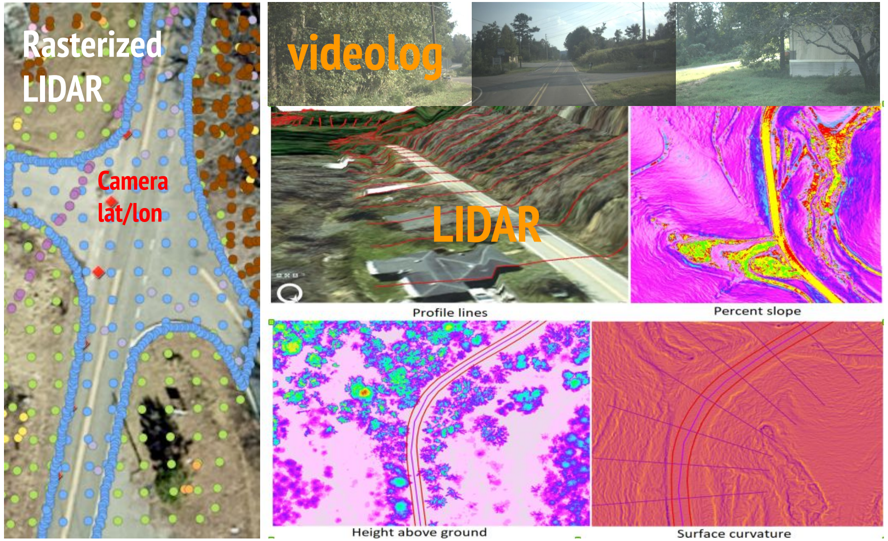


ROC curve of pole models through AL

How do we know whether an object is a hazard?

Object geolocation

- Data fusion of NCDOT videolog data and LiDAR data to extract and **geolocate** safety features, e.g., utility poles, guardrails, etc., for road safety initiatives
  - Pole distance from road
  - Relation to other objects
  - Relation to topological features
- Extract roadway geometry from LIDAR data after data fusion



Why data fusion is hard

- Unknown camera intrinsic (FOV) and extrinsic (location, orientation) parameters
- Images 26.4 feet apart
- Temporal downsampling of initial video capture → approximate GPS coordinates
- LIDAR point resolution (varying from 8 to 30 ppsm) may be insufficient
- Camera field of view is narrow (~20 degrees)
- Complicated road features (intersections, etc.)

Methodology

- **Object geolocation <==> data fusion between videolog and LIDAR data**
  - Use utility poles as the initial feature for geolocation to test and validate workflow pipeline
    - More difficult to geolocate than guardrail continuous features

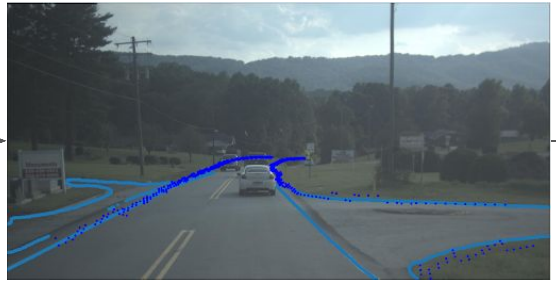
Image segmentation —utility poles→ Depth prediction → Object geolocation ↔ Data fusion

OneFormer pretrained model image segmentation result for an image in Cityscapes dataset

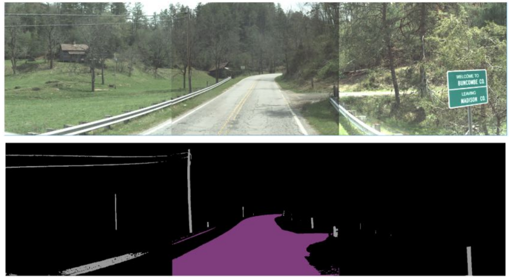
Approximate camera position
Approximate camera position

Methodology

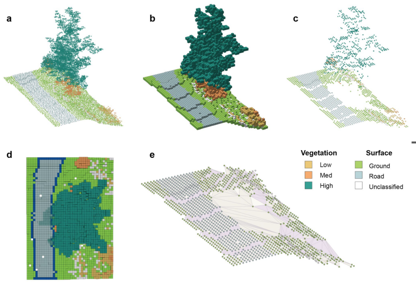
Camera parameter optimization



Aligned segmented road with LiDAR road - ***know where we are***



Segmented road and poles

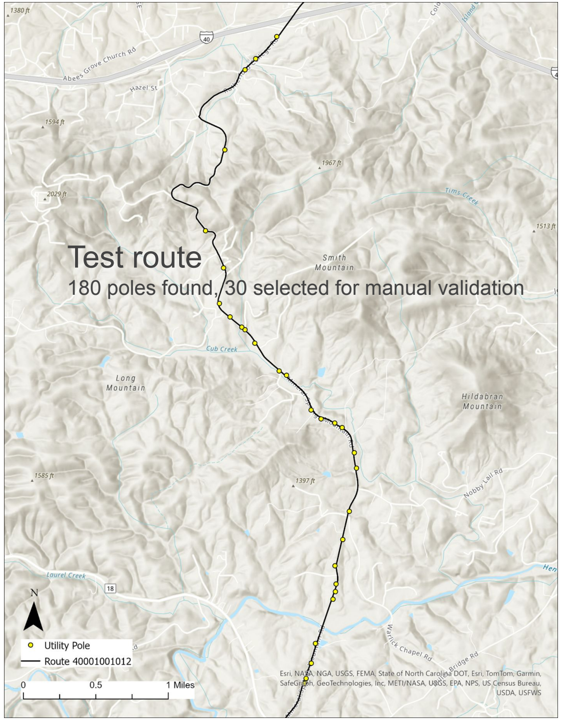


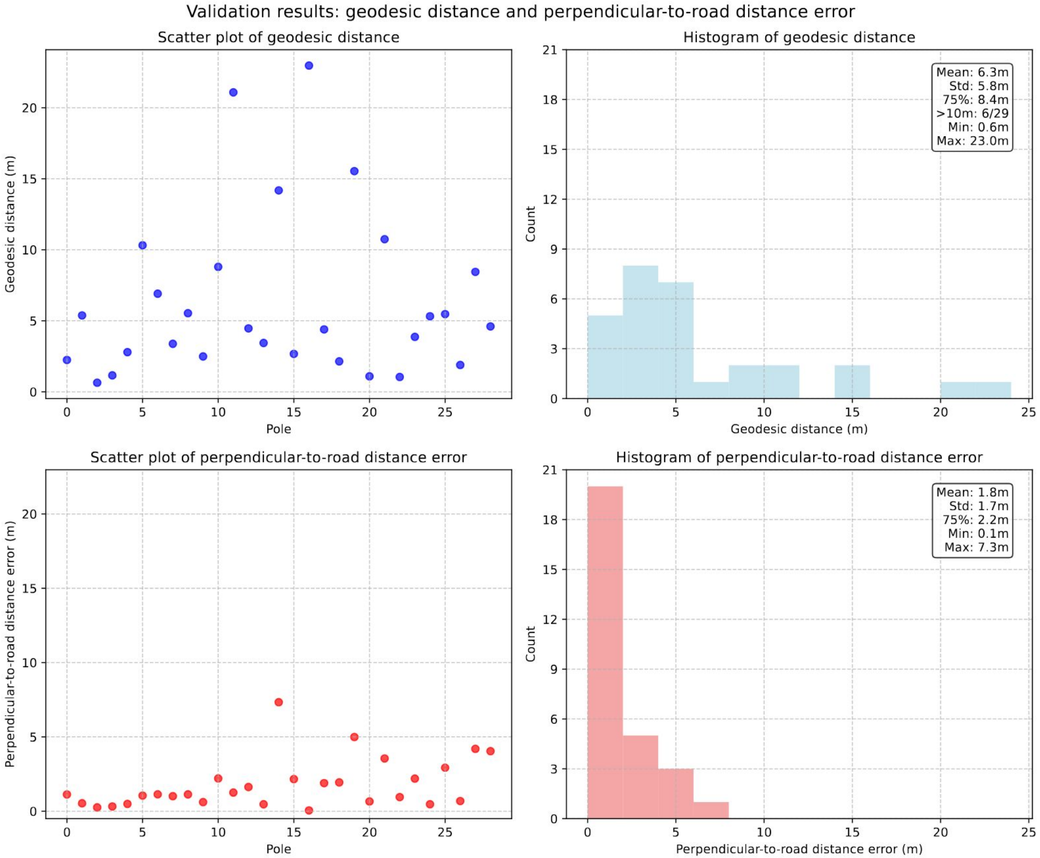
Rasterized and occlusion filtered LiDAR data

Object triangulation for geolocation - ***know where the object is***

Pole image location(s)

Results


Test route
180 poles found, 30 selected for manual validation
Utility Pole
Route 40001001012
0
0.5
1 Miles
N
Abees Grove Church Rd
Hazel St
Tims Creek
Smith Mountain
Cub Creek
Long Mountain
Hildabran Mountain
Laurel Creek
Nobby Lail Rd
Warlick Chapel Rd
1380 ft
1594 ft
1967 ft
2029 ft
1513 ft
1585 ft
1397 ft
Esri, NASA, NGA, USGS, FEMA, State of North Carolina DOT, Esri, TomTom, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, US Census Bureau, USDA, USFWS


Validation results: geodesic distance and perpendicular-to-road distance error
Scatter plot of geodesic distance
Geodesic distance (m)
Pole
Histogram of geodesic distance
Count
Geodesic distance (m)
Mean: 6.3m
Std: 5.8m
75%: 8.4m
>10m: 6/29
Min: 0.6m
Max: 23.0m
Scatter plot of perpendicular-to-road distance error
Perpendicular-to-road distance error (m)
Pole
Histogram of perpendicular-to-road distance error
Count
Perpendicular-to-road distance error (m)
Mean: 1.8m
Std: 1.7m
75%: 2.2m
Min: 0.1m
Max: 7.3m