3D STREET POLE-LIKE OBJECT DETECTION AND RECOGNITION FOR SELF-DRIVE CAR LOCALIZATION

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ABSTRACT

Unprecedented resources have been devoted for autonomous driving worldwide, and Taiwan is no exception. Self-drive bus trials are undergoing among major cities including Taipei, Taoyuan, Taichung and Kaoshiung. One of the most important tasks for self-drive bus navigation is to localize itself based on landmarks of pre-built 3D semantic maps. This paper investigates street pole-like object detection and recognition from the 3D point cloud data. Both traditional covariance and new AI-based deep learning techniques are used to evaluate the results.

INTRODUCTION

Due to the advance of laser technology, there has been increasing studies on 3D reconstruction and object recognition based on point cloud data. The applications include: 3D mapping, terrain surveying and visualizing**,** robotic navigation, and autonomous driving. This paper focus on street object detection and recognition for localization purpose.

Generic point cloud localization has been investigated in [1] based on cell like grid and probability distribution. Serafin et al. [2] explored the online 3D object detection based on line and planar features. Qi et al. [3] studied the detection and classification of 3D objects using covariance features and supporting vector machine.

The raw data was scanned at the site of Taichung Sui-Nan Economic Park with the road length about 2.5 km. The equipment used was RIEGL VMQ-1HA 360 line scan LiDAR, scanning frequency is 500Hz, with aids of IMU and RTK. The final precision is under 3-5 cm.

THE ALGORITHMS

The task of this project is to identify various street pole-like objects (ref. Fig.1) from point cloud data. The developed algorithm consists of two stages: first, a binary classification method has been proposed to distinguish between road and non-road points. Second, another classification scheme was created to classify different types of pole-like objects in the non-road point set.

For each point p in the input point-cloud dataset P, an associated local unit G_p has been defined as a set of points $q \in P$ such that distance between p and q is less than a specified threshold. Then, principal components analysis (PCA) was performed to each local unit G_p for each $p \in P$. Let λ_i and u_i denote the associated eigenvalues and eigenvectors, where $i = 1, 2, 3, \ldots, d$, where d is the dimension of the data.

For the binary classification, we used random forests [4] classifier. Four discriminating features used in the classification process (similar to [5]) are as follows.

- The linearity l characterizes the elongation factor of the neighborhood points.

$$l = \frac{\lambda_1 - \lambda_2}{\lambda_1}$$

- The planarity n describes how well the set of points can be fitted by a plane.

$$n = \frac{\lambda_2 - \lambda_3}{\lambda_1}$$

- The scatteredness s represents the distribution status of the local points. For instance, a large value of s corresponds to an isotropic and spherical distribution.

$$s = \frac{\lambda_3}{\lambda_1}$$

- The verticality v reflects weather the neighboring points are perpendicularly aligned to the ground plane.

$$v = -\left(\frac{u_{3_3}}{\sum_{i=1}^{3} u_{3_i}} - 1\right)$$

All these feature values are in the range [0, 1] and the binary classifier was performed on each G_p to separate road and non-road points.

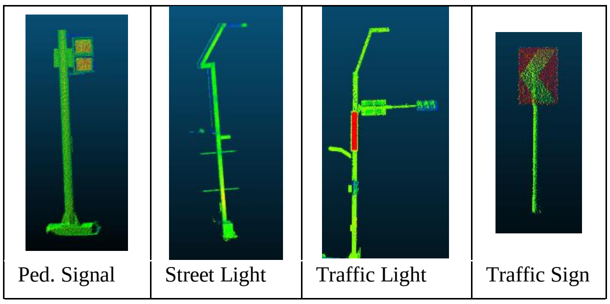

Fig.1 Examples of 3D street pole-like objects.

In the second stage, the non-road point cloud was voxelized in order to extract pole-like object regions before passing them to the classification model. By analyzing the connectivity of the isolated voxels among different horizontal slices of the voxel grid, the points belonging to a pole-like object can be detected and segmented. Let O_i denote a set of points in P belonging to a particular segment.

We employed the random forests technique again to discriminate between types of pole-like objects (see examples in Fig.1). Three of the aforementioned features (linearity, planarity, and scatteredness) plus a newly defined height value were fed into the classification model this time.

- The height h specifies the vertical length (i.e., along z-axis) of the segmented point cloud.

$$h = maxZ(p) - min\,Z(p)\,, \forall p \in O_i$$

Each O_i would be classified into one of the four categories: pedestrian signal, street light, traffic light, and traffic sign.

EXPERIMENTAL RESULTS

A comparative experiment with the results obtained by PointNet [3] and by our approach was conducted to evaluate the accuracy of the proposed recognition method. Table 1 shows the dataset size of each category for the experiment.

Due to the permutation invariant property (i.e., the symmetric function concept) of the PointNet, we must resample each point cloud O_i, ensuring that it contains exactly 1024 uniformly distributed points. Then, we normalized it into a unit sphere. The PointNet classification network applies input and feature transformations, and aggregates point features by max pooling. A four-fold cross validation strategy was adopted and the classification results are shown in Table 2 and summaries in Table 3.

Table 1 Dataset sizes for our experiment.

Categories	Pedestrian Signal	Street Light	Traffic Light	Traffic Sign
Sizes	103	282	167	35

Table 2 Classification results.

Categories Results		Pedestrian Signal	Street Light	Traffic Light	Traffic Sign
Set 1	RF Precision	70%	95%	97%	25%
	Recall	92%	90%	71%	44%
	PN Precision	81%	90%	94%	43%
	Recall	68%	95%	100%	38%
Set 2	RF Precision	78%	93%	95%	86%
	Recall	81%	96%	93%	67%
	PN Precision	100%	10%	97%	100%
	Recall	100%	98%	100%	100%
Set 3	RF Precision	67%	84%	93%	67%
	Recall	62%	90%	100%	22%
	PN Precision	83%	95%	100%	43%
	Recall	91%	91%	92%	100%
Set 4	RF Precision	80%	88%	87%	50%
	Recall	62%	93%	95%	38%
	PN Precision	100%	97%	89%	33%
	Recall	76%	98%	97%	50%

Note: RF for Random Forest and PN for PointNet

Table 3 Summary of the experimental results.

Method	Proposed Method (Random Forest)	PointNet
Overall accuracy	85.25%	92.50%
Average accuracy	78.50%	84.00%
Average recall	74.75%	87.13%

CONCLUSION

In this paper, we proposed a pole-like object detection and classification algorithm using shape features such as linearity, planarity and scatterdness. At first, the road point cloud data is removed, and voxelization is used to reduce the computation. The pole-like objects are then extracted from the non-road data. Finally, the random forest classifier is applied for labeling. Results are compared with PointNet, a deep learning classifier. Although PointNet has a performance margin over the proposed method, the massive computation can be a hindrance to large scale applications. Future works includes integrating random forest and deep learning for more efficient computation. Lidar reflectivity can also be considered to increase the classifier discriminative power.

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