Object Detection in Point Cloud: Poles

Geospatial Vision & Visualization

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Introduction

Object detection in Point Cloud is popular in HD Map and sensor-based autonomous driving.

There are basically four types of object you can obtain in daily scenario:
Road surface - painted lane marking and pavement area
Support facility - road boundary, road sign, **light pole**, etc.
Uncorrelated object - sidewalk, building, etc.
Moving objects - pedestrian, vehicle, bicycle, etc.

The goal of this project is to detect light poles.

Automatically detecting any of these is a very useful exercise.

Methodology

Python Open3D library could be used to create point cloud objects and implement segmentation/filtering.

Raw point cloud data files should be processed by converting latitude-longitude-altitude coordinates to X-Y-Z cartesian coordinates.

The data is then filtered so that only points that are likely to be in poles are remaining.

Sklearn.cluster is for segmenting light poles from overall background.

Algorithms

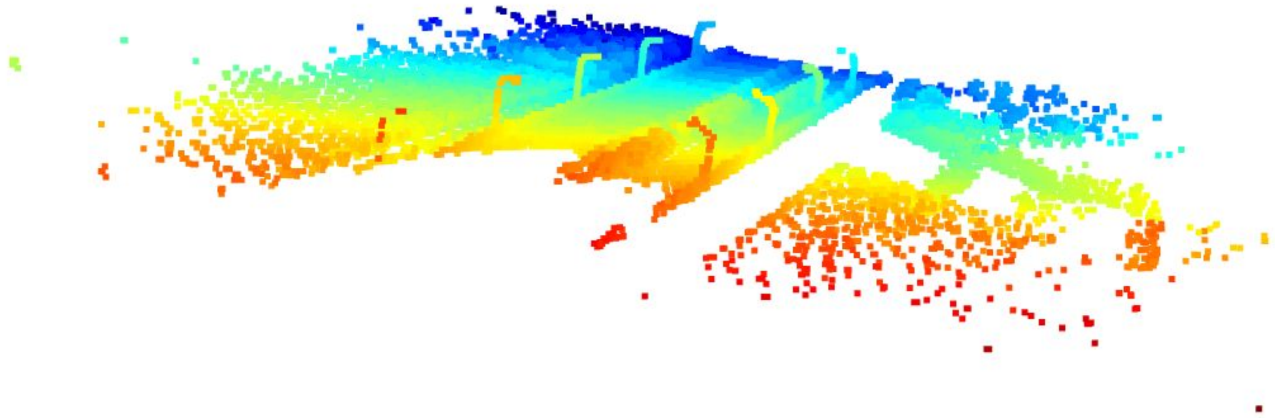
Preprocess Raw Data

The raw “point_cloud.fuse” file is in csv format containing latitude, longitude, altitude and intensity of each point cloud. The function takes the geographic coordinates and converts them into cartesian coordinates, as well as passing the intensity data. Then all XYZ points data are stored in file “All_data.obj”.

open3d.visualization.draw_geometries([point_cloud]) displays the 3D point cloud data.

Algorithms

Visualization



Algorithms

Downsample Point Cloud

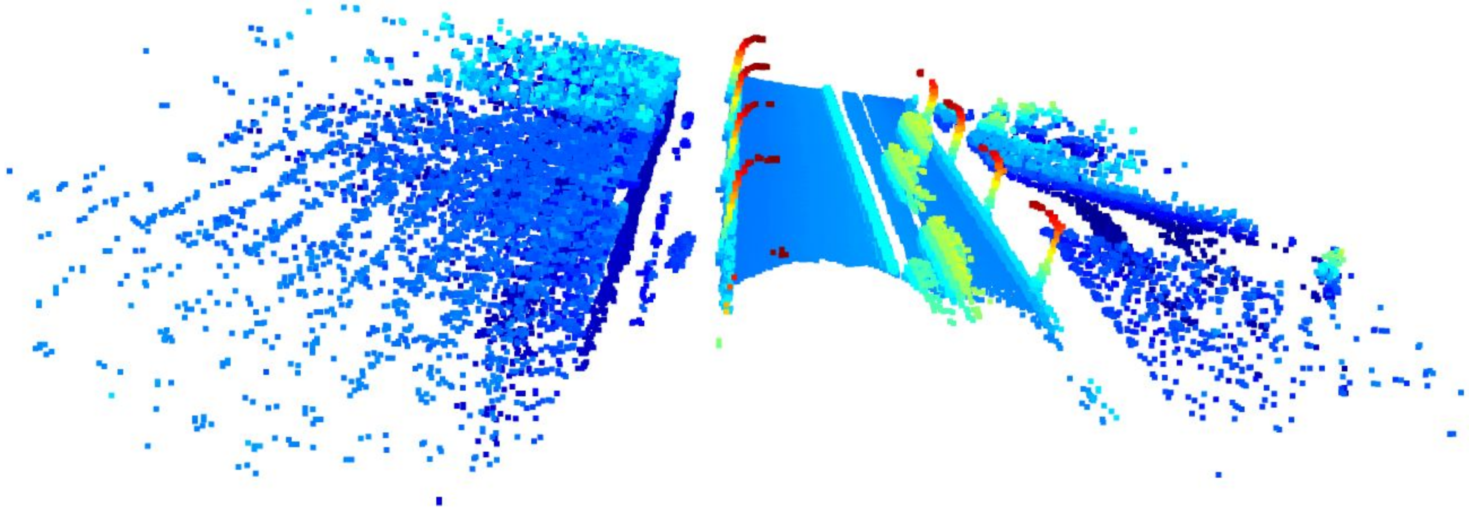
In order to reduce the number of points waiting for processing, we downsampled the input point cloud.

Set the voxel size as 0.8 and each occupied voxel generates exact one point by averaging all points inside.

Removed Statistical outliers. Took number of points from 1292208 to 39630.

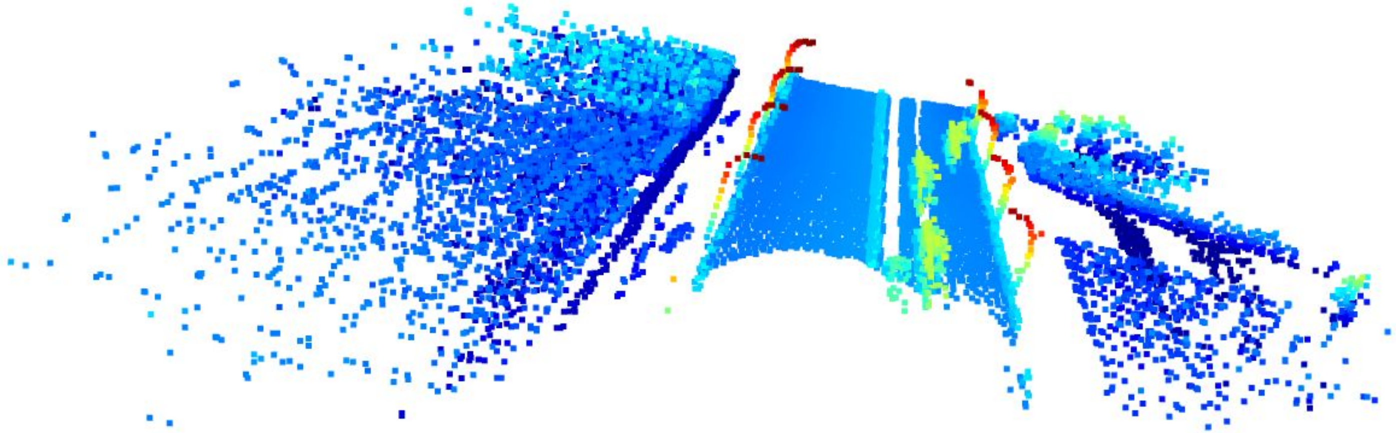
Algorithms

Before



Algorithms

After



Algorithms

Planar Filtering

This can be done by snapping points in the cloud to a grid. For each set of points that lie on a vertex of two dimensions, that variation in the third dimension could be used to filter data points.

For this project, we snapped points in X-Y plane and used the variation in Z axis to filter out data points that don’t have a large variation in Z (aka. Not high enough).

We also have commented code which does filtering in other planes in order to get rid of trees and buildings (which were not present in the given point cloud)

Algorithms

Clustering: Labelling each point in the cloud based on which pole is belongs to seemed helpful for fitting any kind of line to individual poles.
We considered using the geometry of the problem and splitting using the means of the point clouds in a hierarchical manner however this may not work if the arrangement of poles changes.

Therefore we next tried Kmeans clustering, the data if viewed from above looks exactly simple clusters that k means is good and separating.

Therefore we clustered based on x and y coordinates

Algorithms

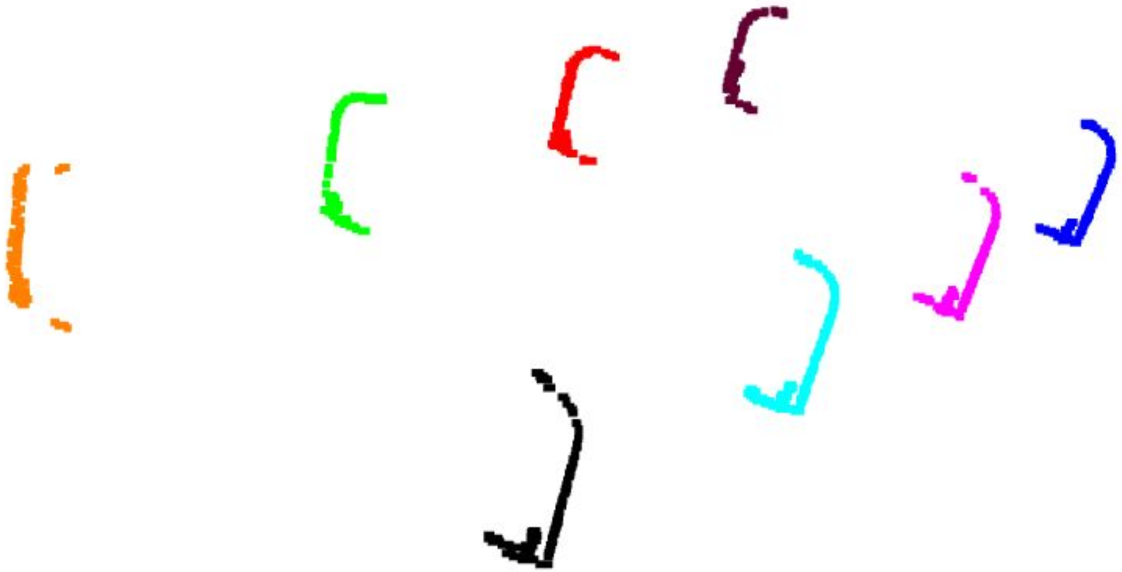
Automatically determining number of poles (with a pinch of salt)

A variation of the well known ‘elbow method’ is used with k means to determine the appropriate number of clusters (poles) in the cloud.

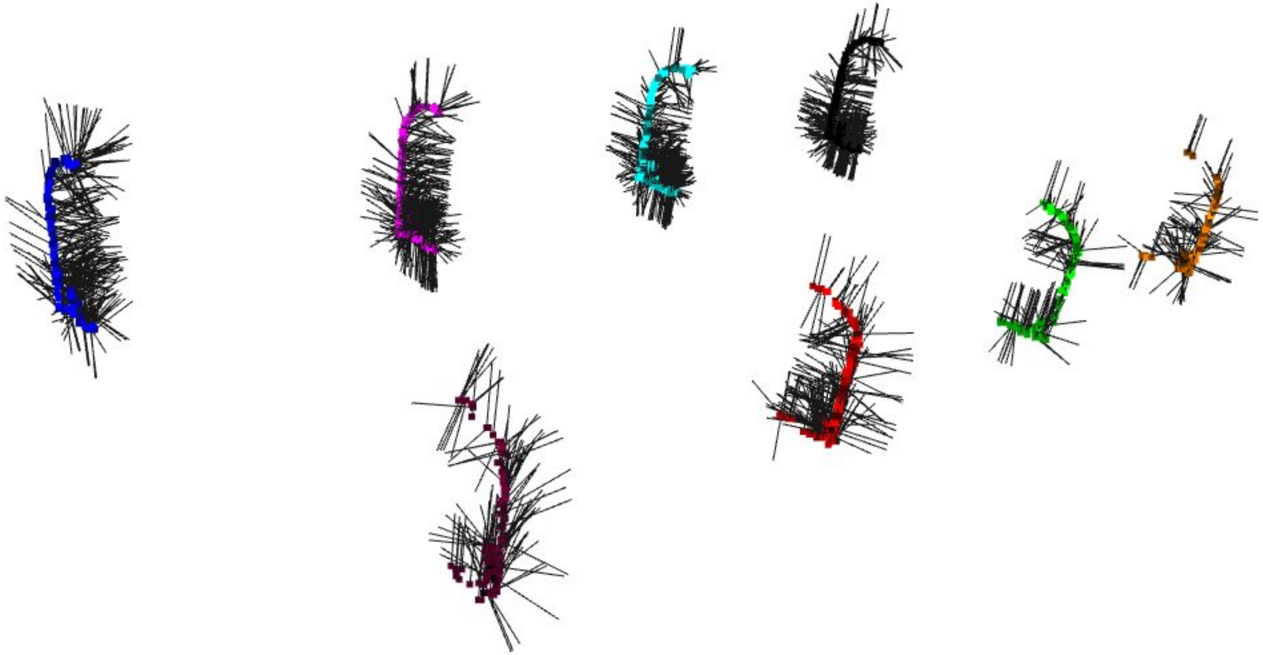
There is an assumption here that there are less than 15 poles in any given cloud but that number can be easily changed in our script without significant computation impedances.

The final clustering is done based on this

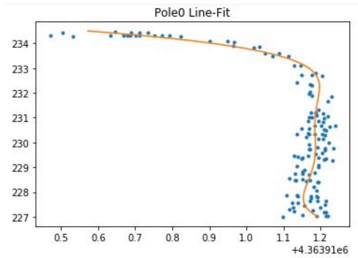
Result

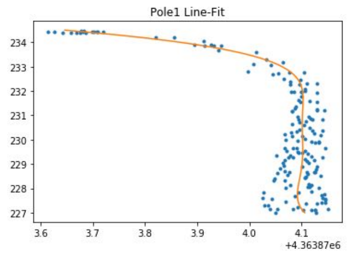


Result



Result


Pole0 Line-Fit
+4.36391e6


Pole1 Line-Fit
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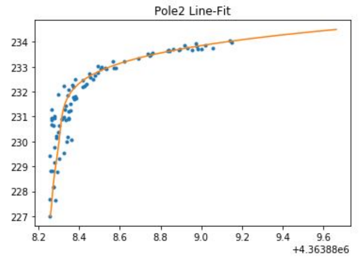
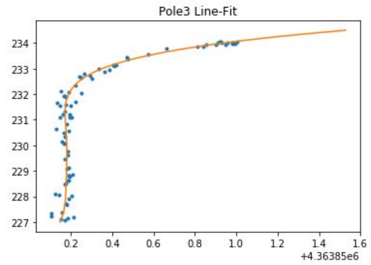
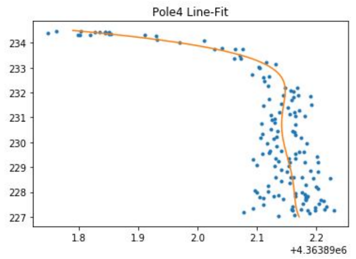
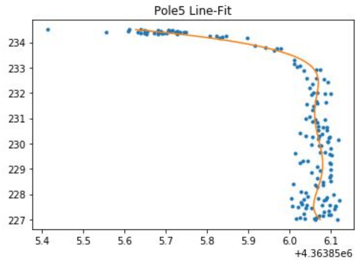
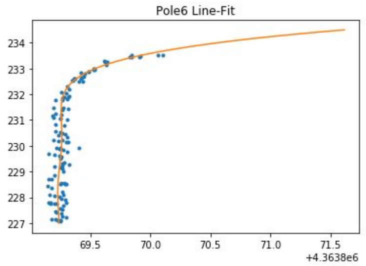
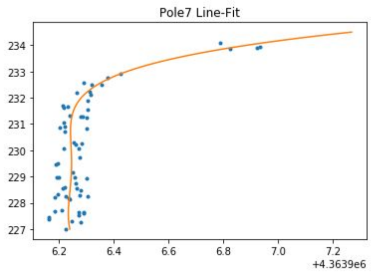

Pole2 Line-Fit
+4.36388e6


Pole3 Line-Fit
+4.36385e6


Pole4 Line-Fit
+4.36389e6


Pole5 Line-Fit
+4.36385e6


Pole6 Line-Fit
+4.3638e6


Pole7 Line-Fit
+4.3639e6

Conclusion

- Successful pole detection and visualization
- Used downsampling and clustering on preprocessed data to isolate poles
- Resulting pole data enables other useful calculations

Future Work

- The first next step to take would be to test our algorithm on more point clouds - to test robustness to similar shapes in the cloud such as trees and signposts.
- Inquest into more efficient way to find whole pole - currently the top curve of the pole has one or two points missing.
- Robust pole detection could further lead to classification of different pole types

References

- LLA to XYZ:
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- Elbow Method (Clustering):
  https://en.wikipedia.org/wiki/Elbow_method_(clustering)
- Point Cloud Lecture by David:
  https://www.youtube.com/watch?v=SJWJNbqynFY&feature=youtu.be
- Open3d Python-Api:
  http://www.open3d.org/docs/index.html