Grand Challenge: Real-Time Object Recognition from Streaming LiDAR Point Cloud Data

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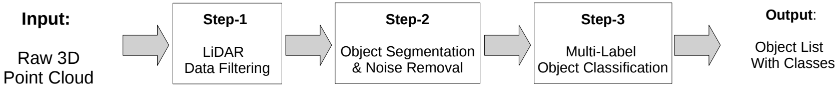
Data Processing Pipleline

Steps for data processing:

- **Step 1:** Data Filtering
- **Step 2:** Object Segmentation
- **Step 3:** Object Classification



Step 1: LiDAR Laser Line Data Filtering

- Filter out the LiDAR laser lines that build a cylinder 3D shape from the laser standing point ($x = 0, y = 0, z = 0$).
- Figure 1 visualizes the LiDAR data for a single scene with LiDAR laser lines and Figure 2 visualizes the data after filtering out the Laser lines.

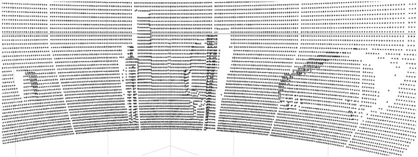


Figure 1: LiDAR Raw Point Cloud Data

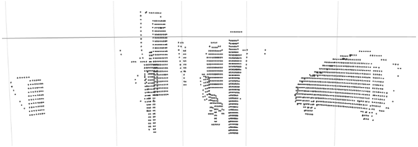


Figure 2: Data After Filtering the LiDAR Scan Lines

Step 2: Object Segmentation and Noise Removal

segment the point cloud to chunks of data

- **3D to 2D Projection:** projected the 3D data in 4 different ways to a 2D plane and reduced the data dimensionality

$$d = \text{Distance to a projection plane}$$

$$x' = x(\frac{d}{z}) \quad , \quad y' = y(\frac{d}{z}) \quad , \quad z' = z(\frac{d}{z}) = d$$

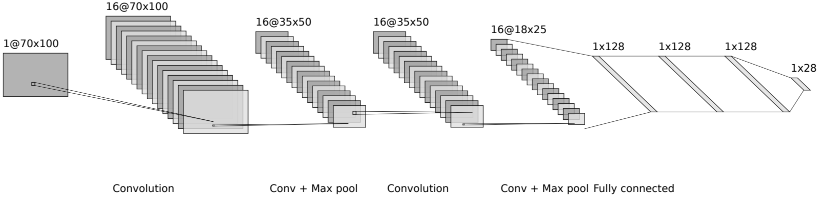
- **Object segmentation using Clustering:** different clustering methods to cluster the data
  1. **K-means and Mini Batch K-means** on the 3D and project 2D data.
  2. **Meanshift** on 3D and 2D data
  3. **DBSCAN** on 3D and 2D

Step 3: Multi-class Object Classification

Used for classification of point cloud data Convolutional Neural Network (CNN)

The convolutional layers:

- ▷ Max Pooling layer
- ▷ Dropout Layer
- ▷ Fully Connected Layer



Evaluation

Experiment Setups

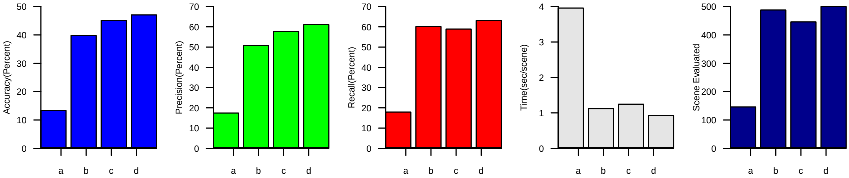
We evaluated our implementation [1] using the 4 different experiment setups:

- 2-Layer CNN on projected data to 2D (Single View) and Object Segmentation with 3D DBSCAN
- 2-Layer CNN on projected data to 2D (Using perspective projection) and Object Segmentation with 3D DBSCAN
- 4-Layer CNN on projected data to 2D (Single View) and Object Segmentation with 3D DBSCAN
- 4-Layer CNN on projected data to 2D (Using perspective projection) and Object Segmentation with 3D DBSCAN

[1] Github Repository of our Implementation `https://github.com/kiat/debs2019`

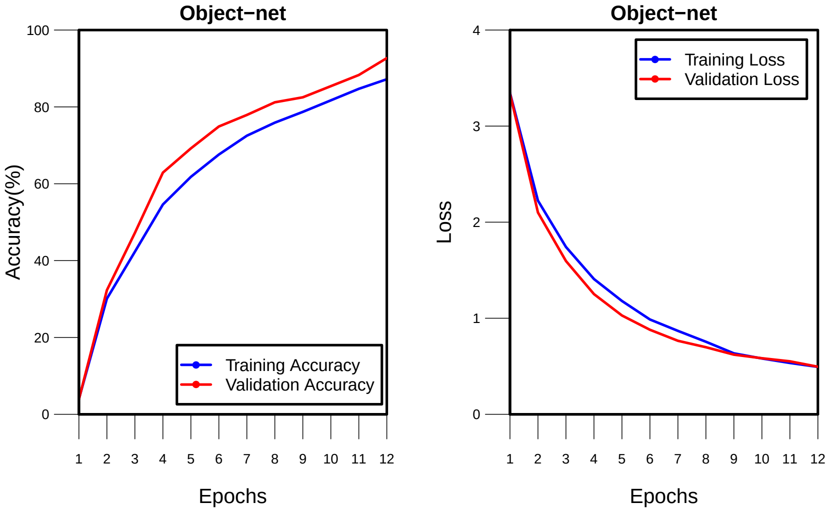
Evaluation: Experiment Settings on DEBS2019

Precision, Recall, Accuracy and Processing Time of 4 different our Experiment Variation



- a= 2−Layer CNN on projected data to 2D (Single View) and Object Segmentation with 3D DBSCAN
- b= 2−Layer CNN on projected data to 2D (Using perspective projection) and Object Segmentation with 3D DBSCAN
- c= 4−Layer CNN on projected data to 2D (Single View) and Object Segmentation with 3D DBSCAN
- d= 4−Layer CNN on projected data to 2D (Using perspective projection) and Object Segmentation with 3D DBSCAN

Training and Validation Accuracy and Loss



Related Work

In this brief section, we review some of the most related publications regarding LiDAR point cloud object recognition problem.

- [Yavartanoo et al., 2018] introduces multi-view stereographic projection; it first transforms a 3D input volume into a 2D planar image using stereographic projection.
- [Zhou and Tuzel, 2018] is the best-ranked model on KITTI [Geiger et al., 2012] for 3D and birds-eye view detections using LiDAR data only
- [Wu et al., 2018] present SqueezeSeg which projects point cloud to the front view with cells gridded by LiDAR rotation
- [Riegler et al., 2017] design more efficient 3D CNN or neural network architectures that exploit sparsity in the point cloud
- [Huang and You, 2016] take a point cloud and parse it through a dense voxel grid, generating a set of occupancy voxels which are used as input to a 3D CNN to produce one label per voxel
- [Maturana and Scherer, 2015] used deep learning models is to first convert raw point cloud data into a volumetric representation, namely a 3D grid

Conclusion

Conclusion

Lessons learned from our implementation are:

- Classification of LiDAR point cloud can achieve high accuracy and real-time processing time by projecting the 3D data into 2D view.
- Classification using CNN on point cloud does not need a large number of hidden layers to achieve high accuracy.
- CNN may fail to classify if the scene includes tiny objects or objects have variable density like “Tree Objects”.
- If multiple objects are in a scene and they are hiding each other (completely or partially) then object segmentation using DBSCAN or other traditional clustering methods may fail to separate objects.

Thank you!

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