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

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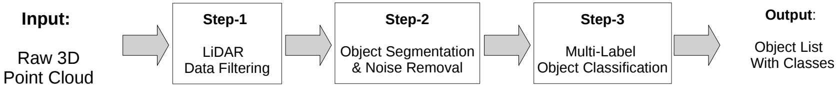
Data Processing Pipleline

Architecture

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.

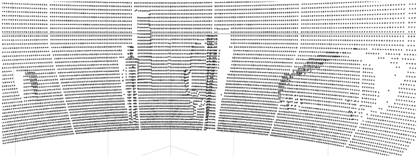


Figure 1: LiDAR Raw Point Cloud Data

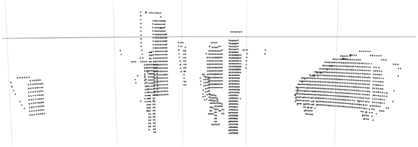


Figure 2: Data After Filtering the LiDAR Scan Lines

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

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

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

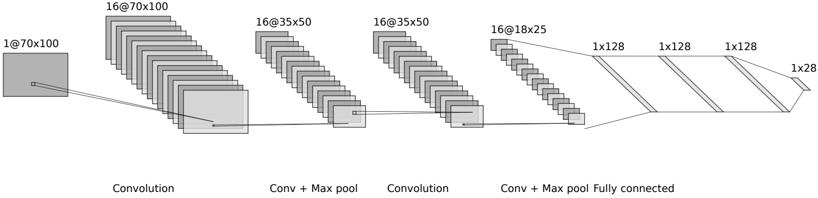
- **Object segmentation using Clustering:** different clustering methods to cluster the data
  1. **K-means and Mini Batch K-means** on the 3D and project 2D data.
  2. **Meanshift** on 3D and 2D data
  3. **DBSCAN** on 3D and 2D

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



Real-time Data Stream Processing

How to achieve real-time stream processing?

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

Fast algorithm and efficient implementation.

- Choose appropiate alogirthm
- Be caution about implementation details, e.g. which PL? (C++)

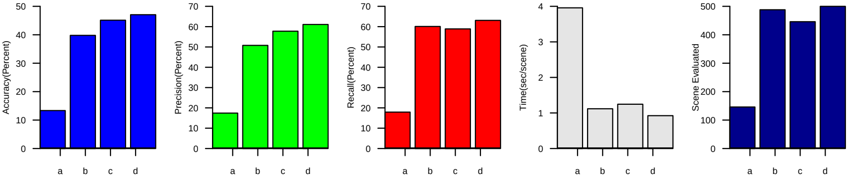
Evaluation

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`

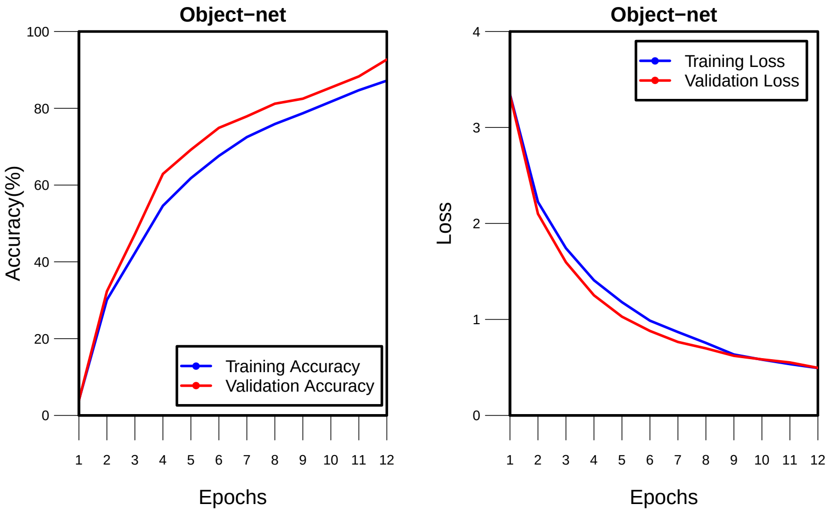
Precision, Recall, Accuracy and Processing Time of 4 different our Experiment Variation



- 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

Evaluation: Accuracy and Loss

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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