深蓝学院
shenlanxueyuan.com

三维点云处理第三期

——第四章作业讲评

主讲人 郝爽

题目

Homework

Object detection pipeline for lidar

- Use KITTI 3D object detection dataset, select 3 point clouds, do the followings.
- Step 1. Remove the ground from the lidar points. Visualize ground as blue.
  - Any method you want – LSQ, Hough, RANSAC
- Step 2. Clustering over the remaining points. Visualize the clusters with random colors.
  - Any method you want
- Step 3. Classification over the clusters
  - Homework of Lecture 5
- Step 4. Report the detection precision-recall for three categories: vehicle, pedestrian, cyclist
  - Homework of Lecture 5

解题思路

- 数据分析：kitti地面点不是严格的平面，高度差最大可能超过0.5m，拟合完平面后需要结合策略去做精细分割。一帧点云大概有12万个点，处理时间可能很长。kitti数据包含大量噪点。

- 思路分析：首先是地面点的提取，地面点提取的好坏决定了后面聚类的结果好坏。地面提取遗漏的小部分地面点对聚类影响很大。

- 预处理：Voxel Grid降采样

- 地面点分割：LSQ、Hough Transform、RANSAC

解题思路： 地面提取

- If we know the inlier points
  - Least Square
- What if there is small amount of outliers?
  - Robust Least Square, e.g., robust loss function
  - Hough Transform
  - RANSAC
- What if there are lots of outliers / more than one models in data?
  - Hough Transform
  - RANSAC

解题思路： 地面提取

Hough Transform – Summary

Advantage

- Robust to noise
- Robust to missing points of the shape
- Can be extended to lots of models

Disadvantage

- Doesn’t scale well with complicated models
    - Usually works for models with less than 3 unknown parameters

RANSAC - Summary

Advantages

- Simple and general
- Usually works well in practice, even with low inlier ratio like 10%

Disadvantages

- Need to determine the inlier threshold τ
- Need large number of samples when inlier ratio is low

RANSAC最适合点云地面提取

解题思路：地面提取

RANSAC平面拟合

1 确定迭代次数N、inlier ratio r和阈值tau

2 对每一次迭代

  2.1 随机选取三个点，构建平面模型

  2.2 遍历所有点，计算点到平面距离

    2.2.1 距离小于阈值tau为内点

    2.2.2 距离大于阈值tau为外点

  2.3 内点比例达到r停止迭代，否则返回2继续迭代

3 确定使得内点数量最多的模型

解题思路：地面提取

Attention

1 随机取三个点，共线判断

非满秩，两两组成的向量共线

2 平面模型

PCA，叉乘，解一元三次方程组

3 根据高度滤波

根据kitti的lidar安装高度，将地面范围内的所有点先提取出来，排除非地面点的干扰

4 平面法向量和竖直方向的夹角

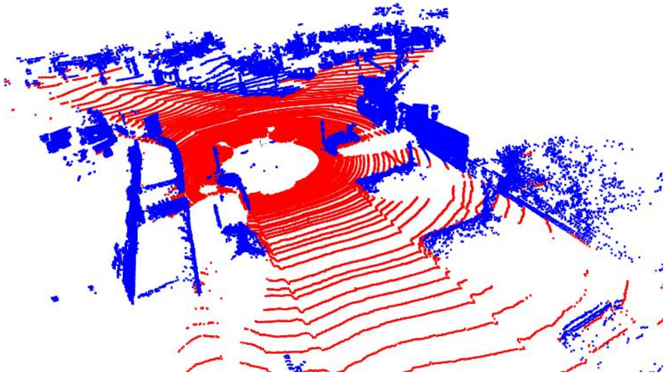
三个点确定的法向量与竖直方向的夹角比较小

解题思路： 地面提取

Tricks：RANSAC不能保证地面提取的很彻底

按照xyz分治，按照距离，八叉树

```
#分区
x_filter_1 = voxel_filtered_pc[:,0] >= 0.0
y_filter_1 = voxel_filtered_pc[:,1] >= 0.0
x_filter_2 = voxel_filtered_pc[:,0] < 0.0
y_filter_2 = voxel_filtered_pc[:,1] < 0.0
filter_1 = np.logical_and(x_filter_1,y_filter_1)
filter_2 = np.logical_and(x_filter_1,y_filter_2)
filter_3 = np.logical_and(x_filter_2,y_filter_2)
filter_4 = np.logical_and(x_filter_2,y_filter_1)
#分区做ransac
segmented_points_1 = ground_segmentation(data=voxel_filtered_pc[filter_1,:])
segmented_points_2 = ground_segmentation(data=voxel_filtered_pc[filter_2,:])
segmented_points_3 = ground_segmentation(data=voxel_filtered_pc[filter_3,:])
segmented_points_4 = ground_segmentation(data=voxel_filtered_pc[filter_4,:])
#合并
segmented_points = np.vstack((segmented_points_1,segmented_points_2,\
    segmented_points_3,segmented_points_4))
```



By zhp曾

解题思路： 目标聚类

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方法比较

	K-Means	GMM	Spectral	Mean Shift	DBSCAN
Metric	Euclidean	Euclidean	Similarity	Density /Euclidean	Density /Euclidean
# of clusters	Pre-defined	Pre-defined	Heuristic	Automatic	Automatic
Robustness to outlier	Bad	Medium	Good	Good	Good
High dimension data	Medium	Medium	Good	Bad	Bad
Complexity	$O(t \cdot k \cdot n \cdot d)$ t: iteration k: # of clusters n: # of data d: dimension	$O(t \cdot k \cdot n \cdot d)$ t: iteration k: # of clusters n: # of data d: dimension	$O(n^3)$ n: # of data	$O(Tnlog(n))$ n: # of data T: # of centers	$O(n \cdot \log(n))$ n: # of data

解题思路： 目标聚类DBSCAN

1. 将所有的点都标记为未被访问
2. 构造Kd-Tree，确定radius和min_samples两个参数
3. 从未访问点集合中随机取一个点p，标记p为被访问，radius-NN查找所有邻居
   3.1 若邻居数小于min_samples，标记p为噪点；
   3.2 若邻居数大于等于min_samples，则p为core point，创建新簇C，转步骤4
4. 遍历p的所有邻居n，若n未被访问，将n的类别标记为C，若邻居n也为core point，重复步骤4
5. 重复步骤3和4，直到所有点都被访问

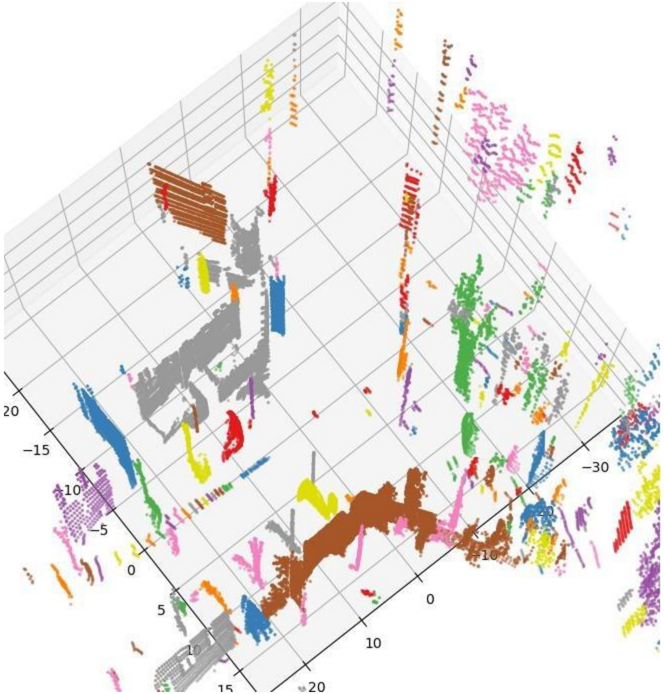
解题思路： 目标聚类

1 radius和min_samples的取值，

可以通过分析kitti点云来决定

2 一般的同学radius设置为0.5到1.0，

min_samples设置为4到10左右



By zhp曾

解题思路： 目标聚类

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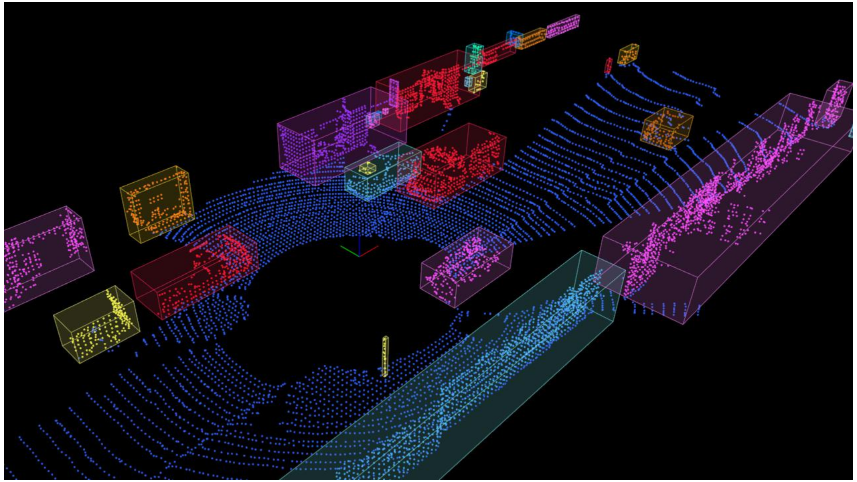

```
## Process Pipeline

1. Read the raw Lidar point-cloud from the KITTI dataset
2. Crop the main Region of Interest (ROI) for further processing
   (Centre as the Origin, L = 60 m, W = 20 m, H = 3m)
3. Down-sample the cropped point-cloud using Voxel Grid Down-sampling method,
   with leaf size = 0.2 m
4. Segment the ground plane using the RANSAC, with a max number of iterations of
   100 and a threshold of 0.2 m
5. Cluster the foreground points into a series of small clusters and assign them
   an unique ID & a random color
6. Draw a Bounding Box for each of the clusters
**Additional: Track the same object across frame and keep its color consistent**
7. Use a simple Hungarian method with Bounding Box IOU as a gauge to associate
   objects between two adjacent time frames (e.g. t = k, t = k+1)
8. For the new objects clustered by **Step 6 **at t = k+1, if it has a
   corresponding object at t = k, it will be assigned with that ID and painted
   with the same color as its counterpart
```

By SS47816

在线问答

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Q&A

感谢各位聆听！

Thanks for Listening