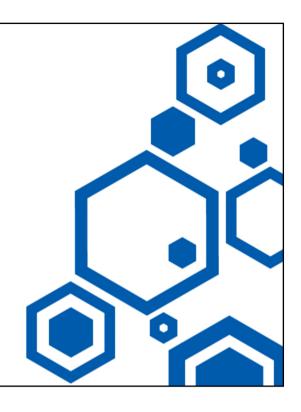


三维点云处理 第一节作业讲解

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纲要



▶第一部分: Kdtree & Octree

▶第二部分: benchmark

Kdtree & Octree



- ●黎老师github实现:https://github.com/lijx10/NN-Trees
- ●[作业1]Kdtree的构建&自适应切割维度

```
#自适应切割维度

def axis_round_robin_adaptive(db, point_indices):
    data = db[point_indices, :]
    var = np.max(data, axis=0) - np.min(data, axis=0)
    axis_var_max = max(var[0], var[1], var[2])
    if axis_var_max == var[0]:
    return 0

elif axis_var_max == var[1]:
    return 1

elif axis_var_max == var[2]:
    return 2
```

kdtree和octree的实现代码在黎老师的githup上都可以找到,作业代码跟里面的实现对比一下就可以了,建议大家至少看一遍实现逻辑,自适应切割维度这块是我单独实现了一个函数,求取当前数据的范围,取范围最大的一个维度作为下一轮的切分维度。

输入参数db是原始的数据,然后point_indices是递归步骤传入的索引,也就是point_indices_sorted[0:middle_right_idx] 和point indices sorted[middle right idx:]

Kdtree & Octree



●[作业4]Octree的构建

莫顿码对点的归属进行编码

或运算, &与运算

 $000,001 \rightarrow x$

 $000,010 \rightarrow y$

000, 100 \rightarrow z

从而确定点所对应的象限

```
# 作业
# 屏蔽开始
root.is_leaf = False
children_point_indices = [[] for i in range(8)]
for point_db = db[point_idx]
morton_code = 0
if point_db | > center[0]:
    morton_code = morton_code | 1
if point_db[] > center[1]:
    morton_code = morton_code | 2
if point_db[2] > center[2]:
    morton_code = morton_code | 4
    children_point_indices[morton_code].append(point_idx)
# create children
factor = [-0.5, 0.5]
for i in range(8):
    child_center_x = center[0] + factor[(i & 1) > 0] * extent
    child_center_x = center[2] + factor[(i & 4) > 0] * extent
    child_center_x = center[2] + factor[(i & 4) > 0] * extent
    child_center_x = center[0] + factor[(i & 4) > 0] * extent
    child_center_x = center[0] + factor[(i & 4) > 0] * extent
    child_center_x = center[0] + factor[(i & 4) > 0] * extent
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    child_center_x = center[0] + factor[(i & 4) > 0] * extent
    child_center_x = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[(i & 4) > 0] * extent
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    child_center_y = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[(i & 4) > 0] * extent
    child_center_y = center[0] + factor[0] +
```

Octree这块有一个莫顿编码的一个操作,它用来确定点属于哪这个立方体网格中所属哪个象限。或运算就是有一个数是1的话,他就取到1,如果没有1的话,就是0。然后与运算就是只有当两个数字都为1,然后它才可以取成1。比如这里就是跟X轴,就是跟001进行位运算。然后Y轴就是跟2也就是二进制010进行位运算。然后Z轴和4也就是100进行位运算

Kdtree & Octree



●[作业5]Octree fast radius search

如果当前节点被包含在worstDist当中

,就需要将每个点都压入result set.

如果该节点没有被完全包住,同时它 是叶子节点,就需要将该节点的点都 压入rseult_set.

```
Radius search normal:
Search takes 8587.214ms
```

Radius search fast: Search takes 5818.956ms

```
# 提示: 尽量利用上面的inside, overlaps, contains等函数
# 屏蔽开始
if contains(query, result_set.worstDist(), root):
# compare the contents of the octant
leaf_points = db[root.point_indices, :]
diff = np.linalg.norm(np.expand_dims(query, 0) - leaf_points, axis=1)
for i in range(diff.shape[0]):
    result_set.add_point(diff[i], root.point_indices[i])
# don't need to check any child
    return False

if root.is_leaf and len(root.point_indices) > 0:
# compare the contents of a leaf
leaf_points = db[root.point_indices, :]
diff = np.linalg.norm(np.expand_dims(query, 0) - leaf_points, axis=1)
for i in range(diff.shape[0]):
    result_set.add_point(diff[i], root.point_indices[i])
# check whether we can stop search now
    return inside(query, result_set.worstDist(), root)

# no need to go to most relevant child first, because anyway we will go through all children
for c, child in enumerate(root.children):
    if child is None:
        continue
    if False == overlaps(query, result_set.worstDist(), child):
        continue
    if false == overlaps(query, result_set.worstDist(), child):
        continue
    if octree_radius_search_fast(child, db, result_set, query):
        return True
```

在fast radius search里头就是做了一个提前剪枝操作。如果当前节点被完全包含在worstdist当中,就需要将它的每个点都压入这个result set。

如果这个节点没有被完全包住,然后它还是叶子节点的话,将该节点的点都压入 result set

benchmark



- ●数据范围
- ●调整min extent

```
def main():

# configuration
leaf_size = 32
min_extent = 1
k = 8
radius = 1

root_dir = '000000.bin' # 数据集路径
db_np = read_velodyne_bin(root_dir) # (124668, 3)
print(db_np.shape)
print(np.min(db_np,axis=0))
print(np.max(db_np,axis=0))

(124668, 3)
[-78.087395 -55.72341 -11.556541]
[77.96733 44.878613 2.8253412]
```

在这里我大概算了一下这个数据范围,它的是有12万多个点,然后它的最大和最小范围是以米来计算,大概x方向150m,y方向100m,z方向14m,因此我调整了一下octree的min extent值,不要太小

benchmark



●搜索时间为0?

修改query点的索引,0点可能会被直接找到。

```
print("kdtree -----")

construction_time_sum = 0

knn_time_sum = 0

radius_time_sum = 0

pradius_time_sum = 0

brute_time_sum = 0

# for i in range(iteration_num):

# filename = os.path.join(root_dir, cat[i])

# db_np = read_velodyne_bin(filename)

begin_t = time.time()

root = kdtree.kdtree_construction(db_np, leaf_size)

construction_time_sum += time.time() - begin_t

query = db_np[10000,:]
```

然后有些同学是有搜索时间为0的情况。在KDtree里头,第0个点有可能被一下子就找到这块,建议就是改一下这个query的索引值

benchmark



- ●运行结果
- Kdtree建树比Octree快
- 搜索速度与参数相关,Kdtree一般较快
- Kdtree和Octree的knn是暴力算法耗时的1/4以下即可

octree ------

Octree: build 5105.153, knn 1.996, radius 4.110, brute 10.108

kdtree -----

Kdtree: build 229.542, knn 0.997, radius 4.986, brute 11.095

这里就是一个运行结果的一个截图,一般结论就是Kdtree建树要比octree要快很多。然后搜索速的话,其实跟一些参数有关系,跟K,跟leaf size,还有radius半径,以及octree的extent都相关,但是他们一般都是比暴力搜索要快很多,基本是暴力搜索的4倍以上





