INDOOR 3D POINT CLOUDS SEMANTIC SEGMENTATION BASES ON MODIFIED POINTNET NETWORK

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ABSTRACT:

Indoor 3D point clouds semantics segmentation is one of the key technologies of constructing 3D indoor models, which play an important role on domains like indoor navigation and positioning, intelligent city, intelligent robot etc. The deep-learning-based methods for point cloud segmentation take on higher degree of automation and intelligence. PointNet, the first deep neural network which manipulate point cloud directly, mainly extracts the global features but lacks of learning and extracting local features, which causes the poor ability of segmenting the local details of architecture and affects the precision of structural elements segmentation. Focusing on the problems above, this paper put forward an automatic end-to-end segmentation method base on the modified PointNet. According to the characteristic that the intensity of different indoor structural elements differ a lot, we input the point cloud information of 3D coordinate, color and intensity into the feature space of points. Also, a MaxPooling is added into the original PointNet network to improve the ability of attracting and learning local features. In addition, replace the 1×1 convolution kernel of original PointNet with 3×3 convolution kernel in the process of attracting features to improve the segmentation precision of indoor point cloud. The result shows that this method improves the automation and precision of indoor point cloud segmentation for the precision achieves over 80% to segment the structural elements like wall, door and so on, and the average segmentation precision of every structural elements achieves 66%.

1. INTRODUCTION

1.1 General Instructions

3D LiDAR technology has gradually became a important method of understanding the 3D indoor scene because of this advantages that it can acquire massive point cloud data with high speed, low cost and high precision. However, the semantic segmentation has become a hot spot of research fields like: 3D indoor modeling, indoor navigation, robot pattern etc. The traditional segmentation methods for point cloud has developed for a period of time. So there are amounts of classic segmentation algorithms, such as: segmentation methods base on edge (Himmelbach et al., 2009), segmentation methods base on surface (Li et al., 2011; Zhang et al., 2015; Hu et al., 2012) segmentation methods base on clustering (Chen et al., 2012; Sun et al., 2006; Lin et al., 2016), segmentation methods base on machine learning (Rusu et al., 2008; Rusu et al., 2009; Aldoma et al., 2011). With the improvement form lots of researchers, the traditional segmentation methods for point cloud has been enhanced constantly. However the traditional segmentation methods for point cloud require manually designed feature descriptors, which demand the designers possess empiric knowledge. There are lots of thresholds needed to be selected for traditional segmentation methods during the process of point cloud segmentation which is complicated, only suitable for specified tasks and poor in generalization. To enhance the automation and intelligence of point cloud segmentation, the segmentation methods for point cloud base on deep learning has became a latest research hot spot. Deep learning is a kind of novel technology that automatically extract the high level features of the input data by the structure of deep neural network. Currently, the segmentation methods base on deep learning are mainly divided into 3 types: (1) Convert point cloud into multi-view images then input the images into 2DCNN to realize the segmentation of 3D elements. (Su et al., 2015) put forward MVCNN network, which utilized 2DCNN network structure. However, converting point cloud to image will lose the spatial information of point cloud, which will affect the precision of segmentation; (2) The neural networks that use voxel as input. Daniel and Sebastian (2015) put forward VoxNet network model base on point cloud voxelization and supervised 3DCNN. This network preprocess the point cloud into voxel, then use 3D convolutional kernel to carry out convolution operation, which is the original 3DCNN network but along with the disadvantages, such as: additional computation,"dimension explosion" etc. (3) The deep neural network that directly use points as input. Qi et al. (2016), from Stanford, put forward PointNet network, which utilize multi-layer perception (MLP) to extract the global feature of point cloud and use maximum symmetric function to solve the problem of irregular format to achieve a good segmentation precision. However this network only pay attention to the global...
feature and ignore the local feature. So this network has poor
capacity of details segmentation.
This paper used the modified PointNet to segment the point
cloud of indoor structural elements. The main works are as
follow:
(1)Currently, there are few indoor point cloud dataset which
contain intensity information. So this paper constructed a indoor
point cloud data set contains 8 types of indoor structural
elements with intensity information for the experiment;
(2)Focusing on the indoor structural elements (door, wall,
window etc.) with different intensity information, this paper
input intensity information, coordinate information and color
information into the neural network as tensor to improve the
segmentation precision of PointNet to segment the indoor
structural elements.
(3)Focusing the problem that the original PointNet only pay
attention to extract the global features of point cloud but ignore
local features, this paper modified the structure of PointNet
network to let it has better ability to extract local features and
improve the segmentation precision of structural elements.

2. CONSTRUCTING THE INDOOR POINT CLOUD
DATA SET
Currently, there are only 2 public large-scale indoor 3D point
cloud data set which are showed in table 1. But these 2 public
data set contain no reflection intensity information. Hence, we
created a data set contains 4 areas, 8 semantic elements and
70,000,000 labeled points for better segmentation result of
indoor structural elements. The point cloud of this data set
contains not only spatial coordinate information \((X,Y,Z)\), color
information \((R,G,B)\), but also reflection intensity information.
We mainly utilized Faro Focus3D X130 scanner to acquire
point cloud and the technical index of it are showed in Table 2.
After acquiring the original point cloud, preprocessed the
original point cloud like: registering, denoising, getting sparse.
After preprocessing, labeled the point cloud manually and
divided the data set into training set and testing set which is
showed in Figure 1.

| Data Set       | Year | Format         | Feature of Point Cloud                       | Producer         |
|----------------|------|----------------|---------------------------------------------|------------------|
| S3DIS          | 2017 | Point Cloud    | \((X,Y,Z,R,G,B)\) Stanford                  | Faro Focus3D X130 |
| (Armeni et al., 2017) |      | RGB-D          |                                             |                  |
| Scannet        | 2017 | Point Cloud    | \((X,Y,Z,R,G,B)\) Stanford                  |                  |
| (Dai et al., 2017) |      | RGB-D          |                                             |                  |

Table 1. Current open large indoor point cloud datasets

3. METHOD

3.1 Structure of PointNet segmentation network
The structure of PointNet network is showed in Figure 2. It
utilized transformation network T-net for rigid transformation
and use maximum symmetric function to handle the problem of
disorder. The algorithm can be divided into 3 flowing steps:
(1)Utilize T-Net to learn a transformation matrix and then
multiply the matrix with point cloud to make sure that the rigid
transformation steadiness of point cloud.
(2)Utilize MLP to extract high dimensional feature from the
point cloud which has been transformed by T-Net and use
maximum symmetric to manipulate the disordered point cloud
to extract global feature.
(3)Fuse the global and local features and then utilize MLP to
downsample the features for the probability score to measure
what type the points might belong to.

3.2 Modify PointNet
We modified the original PointNet network. First, add reflection
intensity information of the point cloud into the feature space.
Then we add a layer to extract local feature and then fuse the
global feature and local feature. The modified network structure
is showed in Figure 3.

Table 2. Faro Focus 3D X130 scanner and main technical indicators

| Configuration | Producer | Faro Focus3D X130 |
|---------------|----------|-------------------|
| Ranging/m     |          | 0.5~130           |
| Distance      |          | 0.6mm/10m         |
| Accuracy Index|          | 360° × 120°       |
| Scanning View |          | 0.6mm/50m         |
| Speed         |          | 1,200,000 points/s|

Table 2. Faro Focus 3D X130 scanner and main technical indicators
3.2.1 The input Feature space

Because of the difference of distance between points and the sparse structure of point cloud, the point cloud need to be converted to the format that can be understand by neural network. The 3D coordinate \((X,Y,Z)\) represents the spatial information and the color \((R,G,B)\) represents the texture information. Also, the coordinates of original point cloud are normalized before input. The point cloud are divided according to the room they belongs to and then normalized base on the coordinate of the room. After acquiring the coordinate \((X',Y',Z')\), every room are divided into the area of 1m×1m. In addition, the reflection intensity information is added, because different structural elements contain different information of reflection intensity. Finally, every points in the point cloud are input as \([X,Y,Z,R,G,B, X', Y', Z']\), the feature space of 10 dimension, into the neural network.

3.2.2 Local feature extraction

During the process of optimizing the original PointNet network, we found that adding MLP with 4 layers on the original MLP helps to improve the precision of segmentation. Hence, we add 2 more layers of MLP behind the MLP-2 layer of the original network as the extracting layer for local features. Also, adding a MLP layer behind the original MLP-5 and parallel with the extracting layer for local features as the extracting layer for global features.

Compared with the original PointNet, our structure use more MLP layers to extracting the local feature, which have better ability to extract the correlation features between points. When optimizing the index of MLP layer network used to extract the high dimensional features, we found that the convolutional kernel in bigger size will get better segmentation precision during the semantic segmentation of indoor scene. So, we replace some of the 1×1 convolutional kernel of original PointNet network with 3×3 convolutional kernel to improve the segmentation precision of the network to segment the indoor structural elements. In addition, we add a MaxPooling layer behind the MLP-4 layer to extract the local feature for better ability to input the local feature of point cloud. Besides, let every point contain not only local feature but also global feature by fusing the local feature extracted by the first MaxPooling layer and the global feature extracted by the second MaxPooling layer. Utilizing the Concat operation of tensorflow framework to achieve the fusion of features. The algorithm of the Concat operation is showed in (1).

\[
\text{pool1 = tf.max_pool2d(conv4, [4, 4, 6, 1], padding = 'VALID')} \\
\text{pool2 = tf.max_pool2d(conv8, [4, 4, 6, 1], padding = 'VALID')} \\
\text{concat = tf.concat(axis = 3, values = [pool1, pool2])}
\]

4. RESULT ANALYSIS

After modifying the PointNet network, we utilized this network to segment the S3DIS data set and the indoor data set we created. We selected the Area1, Area2, Area3, Area4, Area6 as training set, and chose Area5 as testing set. Besides, we chose Area1, Area2, Area3 as training set and Area4 as testing set. To validate the effectiveness of the modified PointNet, we compared the segmentation result of using the modified network and original PointNet on S3DIS data set. We also compare the result of using the data set we constructed with reflection intensity and without reflection intensity. In addition, compare the result of using different kernel size of 3×3 and 1×1. We used Tensorflow deep learning framework, adam optimizer to train the network. The learning rate is 0.001, batch size is 16, epoch is 100 and the training consumed 21hours. The hardware and software we used to train the network are showed in Table 3 and Table 4.

| Hardware | CPU | GPU | RAM |
|----------|-----|-----|-----|
| i7-6700  | Nvidia GTX1060(6G) | 16G |

Table 3. Hardware of the experimental platform

| Operating system | Deep learning framework | GPU | Programme language |
|------------------|-------------------------|-----|--------------------|
| Ubuntu           | Tensorflow              | CUDA 8.0 | Python 3.5 |
| CUDA 8.0         |                          | 16.04 | 1.01               |

Table 4. Software of the experimental platform

4.1 Result

The segmentation results of using modified PointNet network to segment S3DIS data set are showed in Fig 4, and the results of segmenting the data set we constructed are showed in Figure 5. The upper half part of the result figure shows input data, and the lower half part shows the segmentation result. The data set we constructed consist with the part contains reflection intensity and the part without that and Figure 6.shows the comparing result. The upper half part shows the result of using the intensity information, and the lower half part shows the result without using intensity information. The objects in the red pane are important objects needed to be compared Figure 6. shows that the result of upper half part is better than the lower one.

4.2 Precision norms

The Intersection over (IoU), mean Intersection over Union (mIoU), overall accuracy (OA) are frequently-used norms in
Table 7. The Segmentation Accuracy of our Dataset

| Network                | mIoU (%) | ceiling (%) | floor (%) | window (%) | door (%) | board (%) | lamp (%) | Publicity cabinet (%) | others (%) |
|-----------------------|----------|-------------|-----------|------------|----------|-----------|----------|-----------------------|------------|
| PointNet (with I)     | 65.46    | 92.06       | 95.89     | 79.29      | 82.53    | 40.06     | 25.36    | 62.42                 | 50.09      |
| PointNet (without I)  | 64.97    | 91.27       | 94.76     | 77.21      | 81.39    | 38.52     | 24.79    | 61.63                 | 50.16      |
| Ours (with I)         | 68.24    | 92.93       | 96.23     | 80.68      | 85.37    | 42.63     | 26.43    | 63.56                 | 50.58      |
| Ours (without I)      | 66.78    | 92.13       | 95.53     | 78.36      | 83.12    | 41.73     | 25.63    | 62.26                 | 50.45      |

Table 5. IoU of Area5 in S3DIS Dataset

| Network          | PointNet (IoU) | Ours (IoU) |
|------------------|----------------|------------|
| mIoU             | 53.87          | 56.84      |
| ceiling          | 90.80          | 91.09      |
| floor            | 95.33          | 96.13      |
| wall             | 70.56          | 73.35      |
| beam             | 10.25          | 0.15       |
| column           | 13.92          | 26.51      |
| window           | 66.26          | 67.04      |
| door             | 78.62          | 80.36      |
| table            | 55.32          | 62.86      |
| chair            | 54.75          | 54.53      |
| sofa             | 15.32          | 29.26      |
| bookcase         | 50.76          | 51.14      |
| board            | 45.52          | 52.35      |
| clutter          | 52.86          | 54.17      |

Table 5. IoU of Area5 in S3DIS Dataset

| Size of convolutional kernel in PointNet | mIoU(%) | OA(%) |
|----------------------------------------|---------|-------|
| 1×1 (original PointNet)                | 54.12%  | 80.59 |
| 3×3                                    | 54.96%  | 81.03 |

Table 6. Segmentation Results of PointNet with Different Convolution Kernels on S3DIS

5. CONCLUSION

Focusing on the problem that PointNet network has poor ability to extract local feature of point cloud, this paper put forward a modified end-to-end deep neural network base on PointNet for semantic segmentation of indoor 3D LiDAR point cloud. Base on the structure of PointNet, we rea""
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**APPENDIX**

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