A Novel Method for Semantic Segmentation on Lidar Point Clouds

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Abstract. Autonomous driving relies on multiple sensors, such as lidar and cameras, to perceive the surrounding environment and the vehicle's own position. Among them, lidar point cloud segmentation is a crucial and challenging task for 3D scene understanding. In this paper, we propose a novel deep learning method RPNet for lidar point cloud segmentation that combines range image-based segmentation and point based segmentation. Our method extracts point cloud features from range images and predicts 3D point cloud labels from point clouds. The segmentation results of both branches are fused to improve accuracy. We evaluate our method on the Semantic KITTI dataset and show that it outperforms other fusion algorithms in terms of effectiveness and robustness.

Keywords: Semantic Segmentation · Lidar Point Clouds · Deep Learning

1 Introduction

Lidar is a remote sensing system that uses a pulsed laser beam to measure the position, velocity, and other characteristics of target objects. It can sense the surrounding environment and infer high-precision three-dimensional information [1], LiDAR has become

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one of the indispensable sensing sensors for autonomous driving systems [2]. The perception module of autonomous driving relies on various sensors, such as cameras, lidar, positioning devices, etc., to collect information about the surrounding environment and the vehicle's own position. The perception module then processes and analyzes the collected information with perception algorithms [3]. The decision making and control of the autonomous driving system depend on the information provided by the perception module, so it is very important to perform accurate perception in all aspects. Lidar has the advantages of being independent of light conditions, fast frequency, high accuracy, and rich information collection [4]. By scanning the surrounding environment, it can provide the sensing system with point cloud data that contain high-precision environmental information.

The processing of lidar point clouds involves many tasks, such as filtering, segmentation, and object recognition. Among these tasks, point cloud segmentation is a key step, aiming at segmenting the point cloud into different semantic parts and delivering this information to the autonomous driving system to help the system realize real-time, robust and accurate perception of the surrounding environment. Exploring the semantic segmentation technology of point cloud and realizing the real-time accurate segmentation of point cloud using deep learning methods is a challenging and realistic task, which is of great significance for the development of autonomous driving technology and intelligent transportation as well as the promotion of its application in other large-scale point cloud semantic segmentation tasks.

Lidar point cloud segmentation requires accurate allegorical segmentation of the scene, which increases the difficulty of point cloud semantic segmentation due to the complex characteristics of the point cloud itself, such as sparsity, large volume, and high noise, and the limitation of the equipment's computational capability. Traditional segmentation methods, such as geometric feature-based point cloud segmentation, use geometric models to fit point cloud images, which are difficult to meet the real-time and generalization requirements of complex scenes. Deep learning has been gradually applied to 3D point cloud data processing and become a mainstream research method due to its advantages such as automatic feature extraction. Although large-scale semantic segmentation systems require multi-sensors, working together and assisting each other, in this paper, we hope to take the point cloud as an independent information source, and further improve the accuracy of point cloud segmentation under the deep learning method by researching the segmentation model, fusion method and other parts.

In this paper, we propose a novel lidar point cloud segmentation method based on deep learning. Our method uses range image-based point cloud segmentation, which takes a 3D point cloud, projects it to obtain a 2D range image, and performs a convolutional segmentation of the image, which is based on Darknet's network architecture and aims to capture both local and global features of the point cloud. To complement the features of the point cloud, point-based branches are also added to directly project the 3D point cloud data point by point, and the segmentation results of the two branches are fused to make the segmentation results more accurate. In order to address the efficiency of fusion and the fusion effectiveness based on both considerations, we also investigate novel fusion methods. We evaluate our method on a publicly available lidar point cloud dataset, Semantic Kitti, and demonstrate that it is more effective and robust compared to other fusion algorithms. The contributions of this paper are as follows:

1. For the large-scale point cloud segmentation problem, we designed an end-to-end dual-branching model, which directly extracts the point cloud data branches to obtain the semantic information of each specific point, and at the same time, uses the point cloud projected as a branch of the range image to obtain the local semantic information, which solves the problem of achieving a better trade-off between the running speed and the segmentation performance in the point cloud semantic segmentation algorithm.
2. An attention-based inter-branch fusion approach is adopted, and a post-processing algorithm is used to further enhance the semantic segmentation results of the full point cloud as the range image segmented by the 2D semantic segmentation method produces a fuzzy output.
3. we conducted semantic segmentation experiments on Semantic KITTI dataset and proved the effectiveness of this method, the miou achieved by this method is 72.1%, which is 52% higher than the basic pointnet method, 19.6% higher than the basic range image based segmentation method and higher than other fusion method.

The rest of this paper is organized as follows. Section 2 reviews the related work on lidar point cloud segmentation, including both traditional and deep learning-based approaches. Section 3 describes the proposed method in detail, including the network structure, loss function, and training strategy. Section 4 describes the experimental setup and presents the experimental results. Section 5 concludes the paper and discusses future work.

2 Related Work

2.1 Point Cloud Segmentation Method

The point cloud obtained from laser scanning contains most of the ground points, and this high redundancy can cause problems for subsequent processing such as detection and classification of the target point cloud, so traditional point cloud semantic segmentation methods generally include multiple stages: first, the ground points need to be segmented off, then the remaining point clouds are individually formed into blocks, and then operations such as classification are performed based on the features extracted from each point cloud block [5].

Semantic segmentation of point clouds based on traditional methods can be divided into two categories: methods based on purely mathematical models and geometric inference techniques and methods based on machine learning. For example, the methods based on triangular mesh surface for region growth and the model fitting methods based on RANSAC [6] proposed in the literature, etc. These methods can achieve point cloud segmentation faster by fitting linear and nonlinear models to point cloud data using the basic features and geometry of point clouds. Machine learning-based methods use typical supervised learning algorithms including support vector machines (SVMs) [7, 8], random forests [9], etc., and have achieved more successful results in some tasks such as 3D model detection and segmentation. However, such methods usually rely on a set of manual features called feature descriptors or descriptors. These features are coupled to the point cloud density [10] and it is time consuming to find these relevant features from a large number of point clouds due to the presence of noise and inhomogeneous density. Although some acceleration algorithms have made improvements to the extraction time, they are changes on small-scale data scenarios, which are difficult to generalize to large-scale complex scenarios. Moreover, the multi-stage processing may bring the accumulation of errors. Most importantly, the time consumed by manual feature extraction is unacceptable for real-time applications, while autonomous driving requires more and more real-time and robustness of algorithms, and traditional methods are not adapted to such scenarios.

In addition to traditional methods for point cloud segmentation, there is also deep learning-based semantic segmentation of point clouds. Deep learning [11] has the unique advantage of being able to automatically extract data features using convolutional networks and enables end-to-end training. According to the different data representations of point cloud input networks, there are three main categories of voxel-based and 3D convolutional methods, disordered point cloud-based methods, and point cloud 2D processing-based methods for semantic segmentation.

Deep learning methods based on disordered point clouds. This category of methods is to input the point cloud directly into the deep network for processing. When processing point cloud data, this class of methods has to solve the problem of disorderly input of point clouds as well as to ensure that the spatial transformation of point clouds remains invariant. Pointnet proposed by Qi et al. [12] pioneered the method of using deep learning network processing directly on point cloud data, but Pointnet focuses more on global features and does not learn enough local features of point clouds, which causes it to lose the ability to capture The ability to capture spatial relationships between features is lost, which limits its applicability to complex scenarios. The learning of local features is crucial to the segmentation task, and many research methods have made improvements to address this problem. For example, the PointCNN framework proposed by U et al. [13] designs an X-Conv algorithm to learn local region features. It not only improves the accuracy but also reduces the network complexity than Pointnet.

In 2018, SqueezeSeg [14] developed by Wu et al. used spherical projection for point clouds to support the use of 2D convolution and proposed a real-time fully convolutional semantic segmentation method. The point cloud 2Dization method, although it loses dimensional information and is not a leader in terms of accuracy, it relies on the maturity of 2D deep learning algorithms and is cost-effective in terms of real-time and spatial complexity, and can be used in many small or specific scenarios such as road scenes [15]. The earliest deep voxel network is the VoxNet network architecture proposed by Maturana and Scherer [16], which is used for point cloud target detection and classification tasks. With the application and development of fully convolutional neural networks in images, Tchapmi et al. [17] were inspired to propose a three-dimensional fully convolutional network architecture, SEGCloud.

2.2 Fusion Segmentation Methods

Since single views are more or less problematic, some recent approaches try to fuse two or more different views. For example, the approach in [18] performs early fusion by combining point information from bird's-eye and distance maps, which are then fed into a subsequent network. AMVNet [19] designs a late fusion method by computing the uncertainty of the outputs of different views and using an additional network to refine the results. FusionNet [20] proposes a point-voxel interaction MLP that aggregates features between adjacent voxels and corresponding points, reduces the time required for adjacency search, and achieves acceptable accuracy for large point clouds. In particular, PVCNN [21] proposed an efficient point-voxel fusion method. In this method, voxels provide coarse-grained local features, while points provide fine-grained geometric features by performing simple MLPs on each point.

3 Method

3.1 Network Architecture

Aiming at the problems such as semantic loss caused by lidar point cloud segmentation projecting 3D point cloud into 2D range image, inspired by the method of rangenet++, we design a two-branch segmentation model, which takes RANGE-BASE and POINT as inputs, and through the feature fusion method based on the mechanism of self-attention, fuses the information of different modalities and supplements the information lost due to the change of dimensionality, so as to obtain a more accurate segmentation output (Fig. 1).

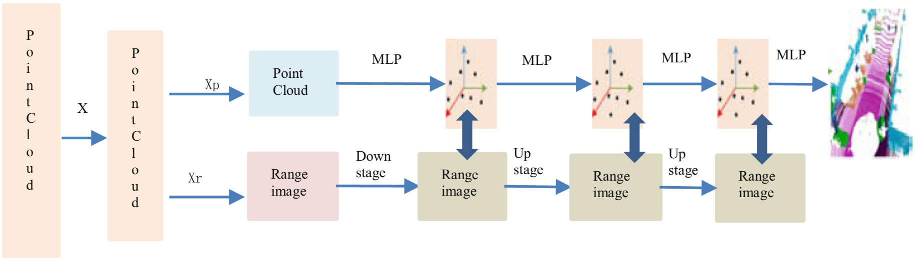

Fig. 1. Shows the network architecture of the method in this paper.

The method we proposed, named RPNET, contains two branches, the R branch and the P branch. First we preprocess the point cloud data X to obtain the R branch input X_r and the input X_p of the P branch. The R branch transforms the points in the three-dimensional space by the spherical coordinate to the point represented by the range image representation in 2D space, uses darknet as baseline for semantic segmentation, maps the fused features to the semantic label space using the fully connected layer, and outputs the semantic labels of each point to obtain the feature F_a. The P branch contains multiple MLP structures, and directly performs point-by-point feature extraction on the 3D point cloud to obtain the feature F_b. Attention mechanism is utilized to dynamically adjust the weight of the features obtained from the two branches in order to improve the fusion effect. The fused features are centralized in the P branch, and through the MLP structure, the point cloud reconstruction is performed to regenerate the point cloud after semantic segmentation.

3.2 Point-Based Point Cloud Segmentation Network Structure Design

The 3D coordinates of each point and other arbitrary feature vectors are used as input, where the feature vectors include information such as RGB values, normal vectors and curvature. A shared two-layer fully connected layer is used to process the feature vectors of each point, and a maximum pooling layer is used to aggregate the feature vectors of each point. Finally, a fully-connected layer is used to map the aggregated feature vectors to different semantic classes.

3.3 Range Image-Based Point Cloud Segmentation Network Structure Design

Using the projection function $P : R^{N\times(3+C)} \rightarrow R^{(M\times D)}$, the points in 3D are projected into the 2d plane to obtain a representation of the points of the point cloud on the 2D image. A hash map from the point cloud form to the 2D form is created using the build hash function, and the features are passed from the 2D image onto the point-based branches using a bilinear interpolation method with the following equations and partial derivatives:

$$F_p(i) = \Phi(\delta(j), F_R) = \sum_{u\in\delta(j)} \phi(u, j)F_R(u)$$

$$\phi(u, j) = (1 - \lfloor j_x - u_x \rfloor)\big(1 - \lfloor j_y - u_y \rfloor\big)$$

An encoder-decoder hourglass type architecture is used, inspired by the Darknet53 backbone. The encoder allows to encode contextual information and the decoder up-samples features extracted by the convolutional backbone encoder to the original image resolution. A total of three times of point cloud feature propagation and feature fusion are performed in downsampling and upsampling to complement each other's feature information.

3.4 Attention-Based Feature Fusion Method

The attention mechanism can weight the different local features of the point cloud data, which makes the features of each point more accurately represented. In contrast, other fusion methods such as voting fusion or averaging fusion simply count the results and do not reflect the local features of the point cloud data well. Also for the phenomenon of data category imbalance, i.e., some categories have more or less data than others. Using the attention mechanism can weight the data of different categories according to their characteristics, so as to better deal with the unbalanced data. Therefore, the attention-based fusion approach is chosen in this paper to better integrate the feature vectors extracted from the two branches.

The self-attention mechanism is selected to calculate the attention weight of each point by the following equation:

$$\boldsymbol{w}_i = \frac{1}{Z}\mathrm{softmax}(\boldsymbol{a}(\boldsymbol{f}_i))$$

$$\boldsymbol{f}_{\text{out}} = \sum_{\text{i}=1}^{N} \boldsymbol{w}_i \boldsymbol{f}_i$$

where, $\boldsymbol{f}_i$ denotes the feature vector of the ith point, $\boldsymbol{a}$ denotes a fully connected layer, softmax denotes a softmax function, Z is a normalization constant, $\boldsymbol{w}_i$ denotes the attention weight of the ith point, and $\boldsymbol{f}_{\text{out}}$ denotes the weighted feature vector.

After calculating the attention weights of each point, they are applied to the semantic labels. The attention weights of each point are multiplied by its corresponding semantic label to get the weighted semantic label, and then the weighted semantic labels of all points are summed to get the final semantic label. The weighted semantic labels are calculated by the following equation:

$$\boldsymbol{y}_{\text{out}} = \sum_{i=1}^{N} \boldsymbol{w}_i \boldsymbol{y}_i$$

where, $\boldsymbol{y}_i$ denotes the semantic label of the ith point, and $\boldsymbol{y}_{\text{out}}$ denotes the weighted semantic label.

3.5 Training Pipeline

In this paper, we use the Adam optimization algorithm and cross-entropy loss function to optimize the model. The core idea of the Adam algorithm is to maintain the first-order moment estimates and second-order moment estimates for each parameter and use these estimates to update the parameters. The update of the Adam algorithm The formula is as follows.

In each batch of training, the difference between the output of the model and the true label, i.e., the loss function, needs to be calculated. In this paper we use the cross-entropy loss function to calculate the loss.

$$L(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log \hat{y}_i$$

where y is the true label, $\hat{y}$ is the prediction result of the model, and N is the number of categories. The smaller the value of the cross-entropy loss function, the closer the prediction result of the model is to the true label.

After calculating the loss function, the back propagation algorithm is used to calculate the gradient of each parameter and the Adam optimizer is used to update the value of each parameter. The dataset is divided into a training set and a validation set, and the validation set is used to evaluate the performance of the model during the training process.

4 Experiment

4.1 Dataset and Implementation

To implement the deep learning experiments, a GPU-equipped computer with PyTorch framework is required. Dataset preparation: an appropriate point cloud data is selected, here the Semantic KITTI dataset is selected. The Semantic KITTI dataset is an open dataset for semantic segmentation of point clouds, which contains point cloud data collected by LiDAR sensors The Semantic KITTI dataset is an open dataset for point cloud semantic segmentation, which contains point cloud data collected by LiDAR sensors, and semantic labels labeled by human. The Semantic KITTI dataset is divided into a training set and a validation set, where the training set contains 21 sequences and the validation set contains 1 sequence.

We trained 150 epochs on the training set and evaluated the model performance using the validation set. During training, we used learning rate decay to reduce the learning rate to avoid overfitting. A higher learning rate of 10^{-3} is used early in training (first 10 epochs) to converge quickly, and then the learning rate is gradually reduced to enhance model stability. The last few epochs use a smaller learning rate to fine-tune the model and improve accuracy. We also used the early stop method to terminate the training process early to avoid overfitting. Finally, the model that performs best on the validation set is selected for testing.

4.2 Comparison with Other Methods

The experimental results are shown in the following table, while the classical point-based segmentation algorithm, range image-based segmentation algorithm, and with some fusion algorithms are also listed in the table. We mainly choose data from seven main categories of objects to show the result. It can be seen that the proposed method in this paper has improved the value of miou as well as the value of iou for small targets, compared with other methods (Table 1).

Table 1. Experimental results compared to other algorithms

method	car	bicycle	motorcycle	truck	persons	bicyclist	road	Mean IoU	mean accuracy
Pointnet++	53.7	1.9	0.2	0.9	0.9	1.0	72.0	20.1	--
Rangenet++	91.4	25.7	34.4	25.7	38.3	38.8	91.8	52.5	89.0
FusionNet	95.3	47.5	37.7	41.8	59.5	56.8	91.8	61.3	--
SPVNAS	97.2	50.6	50.4	56.6	67.4	67.1	90.2	67.0	--
RPNet	93.5	46.1	48.0	40.9	63.9	54.3	92.7	62.7	91.7
RPNet + self-attention	92.6	52.5	50.7	56.5	62.6	55.7	93.3	72.1	92.2

The experimental results show that our fusion segmentation module can effectively perform the point cloud semantic segmentation task on Semantic KITTI dataset and achieve a good performance. The fusion model has high performance and the final mio value can reach 72.1%.

4.3 Ablation Studies

We used the additive fusion method and the attention-based fusion method, respectively, and through the experimental results, we can see that the miou of the additive method reaches 62.7%, and after using the attention-based fusion method, the effectiveness of the feature fusion is greatly improved, and the miou reaches 72.1% (Table 2).

Table 2. Ablation studies on the use of self-attention mechanisms

	Mean IoU	Mean Accuracy
RPNet	62.7	91.7
RPNet + self-attention	72.1	92.2

5 Conclusion

In this paper, by surveying the current practice and literature on point cloud segmentation techniques, we discuss the current research progress related to point cloud segmentation and propose a novel deep learning based lidar point cloud segmentation method. Our method uses range image-based point cloud segmentation to extract the features of point clouds. We also add a point-based branch to directly predict the 3D point cloud data point by point, and make the segmentation results more accurate by fusing the segmentation results of the two branches, which complement each other's features. We evaluate our method on a publicly available lidar point cloud dataset, Semantic KITTI, and demonstrate that it is more effective and robust compared to other fusion algorithms. In future work, we will investigate more accurate segmentation methods by addressing data imbalance in the dataset, optimizing the capability of the algorithm while improving the generalization capability of the model to provide a more accurate reconstruction basis for map reconstruction and other tasks. In addition, we will design lightweight lidar point cloud segmentation method, and facilitate the application of the algorithms in edge computation [22–24].

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