Abstract

Directly learning features from the point cloud has become an active research direction in 3D understanding. Existing learning-based methods usually construct local regions from the point cloud and extract the corresponding features using shared Multi-Layer Perceptron (MLP) and max pooling. However, most of these processes do not adequately take the spatial distribution of the point cloud into account, limiting the ability to perceive fine-grained patterns. We design a novel Local Spatial Attention (LSA) module to adaptively generate attention maps according to the spatial distribution of local regions. The feature learning process which integrates with these attention maps can effectively capture the local geometric structure. We further propose the Spatial Feature Extractor (SFE), which constructs a branch architecture, to aggregate the spatial information with associated features in each layer of the network better. The experiments show that our network, named LSANet, can achieve on par or better performance than the state-of-the-art methods when evaluating on the challenging benchmark datasets. The source code is available at https://github.com/LinZhuoChen/LSANet.

1 Introduction

With the rapid growth of various 3D sensors, how to effectively understand the 3D point cloud data captured from those 3D sensors is becoming a fundamental requirement. In the 2D image processing domain, deep convolutional neural network (CNN) based methods have achieved great success in almost all computer vision tasks. Unfortunately, it is still tricky to directly migrate these CNN based techniques to 3D point sets oriented research. Point sets have their unique property of invariance to permutations and cannot be accurately represented by regular lattices, making those successful methods in 2D image domain unsuitable to be applied in 3D cases. The most common direction is transforming 3D data to voxel grids [Maturana and Scherer, 2015; Riegler et al., 2017; Wang et al., 2017; Engelcke et al., 2017; Graham et al., 2018] or multiple views of 2D images [Su et al., 2015] to take advantage of existing operations used in 2D images. However, it would lead to some negative issues such as quantization artifacts and inefficient computation [Qi et al., 2017a; Li et al., 2018a].

Recently, some seminal researches attempted to process point cloud data directly by developing specific deep learning methods, e.g. PointNet [Qi et al., 2017a] and PointNet++ [Qi et al., 2017b]. As a pioneering work, PointNet introduces a simple yet efficient network-based architecture, while its feature extraction is point-wise and thus cannot exploit the local region information. PointNet++ [Qi et al., 2017b] gets the local regions by using farthest point sampling (FPS) and ball query algorithms, then extracts the features of each local region, achieving excellent results on different 3D datasets. However, the feature extraction operations in PointNet++, which are shared Multi-Layer Perceptron (MLP) and max-pooling, are independent with spatial structure in the local region and can not capture the geometric pattern explicitly as shown in Fig. 1 (a). To overcome this difficulty, SpiderCNN proposes a complicated family of parametrized non-linear functions, where the parameters of convolution are determined according to the spatial coordinates in the local re-
In summary, our contributions are as follows:

- The Local Spatial Attention (LSA) module is proposed, which can generate the attention map for each local region according to its spatial distribution. Combining these attention maps with feature extraction processes can make these operations effectively take the spatial relations in local regions into account.

- We integrate the LSA module with the feature learning process of PointNet++ [Qi et al., 2017b], including the shared MLP and max pooling, to perceive fine-grained shape patterns and get convincing results. An additional branch architecture with SFE is also proposed to combine the spatial coordinates with associated features in each stage of the network progressively.

Our modules are light and flexible. Extensive experiments show that the performance of our LSANet is comparable to or better than state-of-the-art methods. We further explain the details of the proposed LSA module and the branch architecture with our SFE explicitly in Sec. 3. Our results on multiple challenging datasets and ablation study are shown in Sec. 4.

2 Related Work

**Volumetric and Multi-view approach:** Volumetric approach converts the point sets to a regular 3D grid where the 3D convolution can be applied [Maturana and Scherer, 2015; Qi et al., 2016]. However, the 3D convolution usually introduces high computation cost, and the volumetric representations are often inefficient due to the sparse property of the point sets. Some existing works [Riegler et al., 2017; Wang et al., 2017; Engelcke et al., 2017; Graham et al., 2018; Klokov and Lempitsky, 2017] aim at improving computational performance. For instance, some representations for deep learning with sparse 3D data are proposed such as Octree [Wang et al., 2017], Kd-Tree [Klokov and Lempitsky, 2017]. In [Engelcke et al., 2017], the authors use a feature-centric voting scheme to implement a fast 3D convolution. While in [Graham et al., 2018], a new sparse convolutional operation is introduced to perform efficient 3D convolution on sparse data. Multi-view approaches convert the 3D point sets to a collection of 2D views so that the popular 2D convolutional operations can be applied on the converted data [Su et al., 2015; Kalogerakis et al., 2017]. As an example, the multi-view CNN [Su et al., 2015] constructs the CNN for each view, and a view pooling procedure is used to aggregate the extracted features of each view.

**Point-based approach:** PointNet [Qi et al., 2017a] is the...
milestone work for directly processing point sets using the deep neural network. It extracts each point’s feature with a shared MLP and aggregates them with a symmetric function, such as max pooling, which is independent of input order. However, PointNet [Qi et al., 2017a] cannot combine the information of neighbor points. To address this issue, PointNet++ [Qi et al., 2017b] uses FPS and neighborhood query algorithms to sample centroids and their neighbor points and then extracts their features using a shared MLP and max pooling. The feature extraction operations mentioned above still do not take the local spatial distribution into account as shown in Fig. 1 (a). That is, in existing methods, the operations on points at different spatial locations use the same weighting factors. On the contrary, by combining the attention maps generated by LSA module with subsequent operations, we can make such process spatially variable.

There are some other concurrent point-based approaches to process point sets using deep learning, such as [Li et al., 2018a; Huang et al., 2018; Shen et al., 2018; Li et al., 2018b; Su et al., 2018]. Especially, SO-Net [Li et al., 2018a] applies the self-organizing network on the point sets processing. RSNet [Huang et al., 2018] uses Recurrent Neural Network (RNN) to process point sets. KCNet [Shen et al., 2018] introduces the kernel correlation to combine the information of the neighborhood, and PointCNN [Li et al., 2018b] learns a $\chi$ transform from the point sets to permute them in canonical order. In [Su et al., 2018], they project the point features into regular domains, so that the typical CNNs can be applied. The sparse data can also be represented as meshes [Monti et al., 2017] or graphs [Defferrard et al., 2016; Yi et al., 2017], and there are some works that aim at learning feature from these representations. We refer the reader to [Masci et al., 2016] for a more comprehensive survey.

3 Our Method

Firstly, we introduce the method of extracting spatial distribution feature of the local region; then the generation of attention maps, which based on the spatial distribution feature, is described in depth. We elaborate on the integration of attention map with other operations and introduce our LSANet finally.

3.1 Extract spatial distribution feature

Let the relative coordinate of each point in a local region is $\{P_i | P_i \in \mathbb{R}^3, i = 1, ..., K\}$, where $K$ is the number of points in a local region. The spatial distribution feature consists of two parts, one is the spatial feature of the point itself, and the other is the spatial feature of the local region where the point is located.

The spatial feature of the point can be expressed as:

$$S^p_i = \mathbf{W}_0 P_i,$$

where $\mathbf{W}_0 \in \mathbb{R}^{64 \times 3}$, and $S^p_i \in \mathbb{R}^{64}$, which is the spatial feature of the point itself.

We use the following formula to encode the spatial distribution of the whole local region:

$$S^g = \frac{1}{K} \sum_{i=1}^{K} \mathbf{W}_1 P_i,$$

where $\mathbf{W}_1 \in \mathbb{R}^{64 \times 3}$. As shown above, $S^g$ encode spatial information of all points in the local region. To preserve permutation invariance, we apply the same weight $\mathbf{W}_1$ to all points in the local region.

We combine the spatial feature of each point with the spatial distribution of the region and get the final spatial distribution feature:

$$S_i = [S^p_i, S^g],$$

where $\{,\}$ denotes the concatenation operation, $S_i \in \mathbb{R}^{128}$ is the spatial distribution feature of each point, which is generated by the above formula and associated with not only spatial location itself but also all points of the local region, encoding the spatial information explicitly. Different points in the same local region share the same $S^g$. We will utilize each point’s spatial distribution feature to generate attention maps next.

3.2 Generation of Attention maps

Suppose the feature of a local region in the $l$-th layer is $\{X_i | X_i \in \mathbb{R}^{F_l}, i = 1, ..., K\}$, where $F_l$ denotes the channel of $X_i$ in the $l$-th layer, $K$ is the number of points in the local region, and $l$ is the index of layers in the LSA module.

We use the LSA module to generate attention maps for their subsequent feature extraction operations. The LSA module takes spatial distribution feature of local region as input, expressed in $\{S_i | i = 1, ..., K\}$, where $S_i \in \mathbb{R}^{128}$, $i$ is the index
of the neighboring points. Note that $S_l$ is related to the spatial structure of $X_l^i$ and its local region. In order to generate the first attention map for the corresponding operation, we define the attention coefficient as $e_l^i = f_\theta(S_l)$, where $f_\theta$ is a non-linear function which is determined by the learnable parameters $\theta$. In this work, we use a fully connected network as $f_\theta$ to get the attention coefficient $e_l^i$, which can be expressed as:

$$e_l^i = \sigma(W_s^1(S_l)),$$

where $\sigma(\cdot)$ denotes the sigmoid function, $W_s^1 \in R^{F_l \times 128}$, and $s$ means that the $W_s$ belongs to our LSA module. For the output $e_l^i \in R^{F_l}$, it has the same dimension as the point feature $X_l^i$. We can use the following formulation to generate new attention map for the further feature learning process:

$$e_l^i = \sigma(W_s^{l-1}(e_l^{i-1})),$$

where $W_s^{l-1} \in R^{F_l \times F_{l-1}}$. Note that $e_l^i \in R^{F_l}$ shares the same dimension as $X_l^i$. We use the ReLU$^l$ activation function after each $W$ to introduce nonlinearity. Therefore, the formula mentioned above generates the expected attention maps which are related to the spatial distribution in each local region. Note that the process mentioned above can be easily extended with multiple local regions. Fig. 3 (b) shows the whole processes.

3.3 Combine attention maps with other operations

Next, we show how our attention maps participate in other feature extraction operations, which allows the feature extraction processes to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account. For example, combining the attention map with the feature extraction operations, which allows the feature extraction operations to take the local spatial distribution into account.

$$X_l^i = W_m^{l-1}(X_l^{i-1} \otimes e_l^{i-1}) = W_m^{l-1}X_l^{i-1},$$

where $\otimes$ denotes element-wise multiplication, $W_m^{l-1} \in R^{F_l \times F_{l-1}}$, the parameter $m$ means that the weight belongs to the shared MLP operation which is shown in Eq. (3a). $e_l^{i-1} \in R^{F_l}$, and $X_l^{i-1} \in R^{F_l}$. As shown in Eq. (6), the value of $W_m^{l-1}$ is independent with the spatial coordinate of $X_l^{i-1}$ and shared across different points in the local region. After combined with the attention map $e_l^{i-1}$, the value of the updated weight $W_m^{l-1}$ is related to the spatial distribution. For each point $X_l^{i-1}$ in the local region, $W_m^{l-1}$ can adaptively learn to assign different weights according to its spatial distribution, with which the local shape pattern can be captured better. The entire process is shown in Fig. 3.

The max pooling operation selects the point with the strongest response in each channel regardless of spatial relationship in the local region. However, by combining the attention map, the pooling operation can be guided to select the optimal point based on its spatial distribution, which can be formulated as:

$$Y = \max_{i \in \{1, \ldots, K\}} (X_l^i \otimes e_l^i),$$

where $Y \in R^{F_l}$, $X_l^i \in R^{F_l}$, and $e_l^i \in R^{F_l}$. We will further investigate it by experiments to show that the combination of the attention map with the feature extraction operations can lead to better results, which is shown in Tab. 3.

In our work, the proposed LSA module is embedded into the feature learning process of PointNet++ [Qi et al., 2017b] as shown in Fig. 3.

3.4 Network Architecture

To combine spatial coordinates with the features in each layer better, we propose an additional branch architecture, in which Spatial Feature Extractor (SFE) is mounted to get high-dimension spatial representation as shown in Fig. 2. The input of SFE are the raw coordinates of local regions or the spatial feature from the previous SFE. To improve the dimensions of the coordinates, we send the spatial coordinates information of input to shared MLP. Then we combine the output of the shared MLPs with the input and use it as the spatial information that flows into the backbone network for abstraction representation. Finally, we use shared MLP to enhance the representation of spatial information further and inflow it into the next SFE. In this way, we can lift the dimension of raw coordinates and get more abstract representation layer by layer.

The architecture of LSANet is shown in Fig. 2. Note that we combine our LSA module with the feature learning process of PointNet++ [Qi et al., 2017b], and add the additional branch to enhance the spatial feature representation using the SFE. We use farthest point sampling (FPS) and ball query algorithms to sample and group, which are the same as PointNet++. The output features of the last LSA layer are aggregated by a fully connected network for classification. The segmentation model extends the classification model using the FP module in PointNet++ [Qi et al., 2017b] to upsample the reduced points and outputs per-point scores for semantic labels.

4 Experiments

We evaluate the performance of the proposed LSA module and additional branch architecture with extensive experiments. First, the experimental results of our LSANet and other state-of-the-art point-based approaches on the ModelNet40 [Wu et al., 2015], ShapeNet [Yi et al., 2016], ScanNet [Dai et al., 2017], and S3DIS [Armeni et al., 2016] are shown in Sec. 4.1. Second, we perform the ablation study to validate our LSANet design, and then visualize what our LSA module learns in Sec. 4.2. At last, we analyze the space and time complexity in Sec. 4.3.

4.1 Classification and Segmentation Tasks

Dataset: We apply our LSANet on the following datasets:

- ModelNet40 [Wu et al., 2015]: This dataset includes 12,311 CAD models from the 40 categories, and we use the official split with 9,843 for training and 2,468 for testing. To get the 3D points, we sample 1,024 points uniformly from the mesh model.
- ShapeNet [Yi et al., 2016]: 6,880 models from 16 shape categories and 50 different parts consist in the ShapeNet [Yi et al., 2016], and each shape is annotated with 2 to 6 parts. Following [Qi et al., 2017b], we use
14,006 models for training and 2,874 for testing. 2,048 points are sampled uniformly from each CAD models, and each point is associated with a part label. These points with their surface normals are used as input, assuming that the category labels are known.

- ScanNet [Dai et al., 2017]: The ScanNet [Dai et al., 2017] is a large-scale semantic segmentation dataset containing 2.5M views in 1513 scenes. Since ScanNet is constructed from real-world 3D scans of indoor scenes, it is more challenging than the synthesized 3D datasets. In our experiment, we follow the configuration in [Qi et al., 2017a] and use 1201 scenes for training, 312 scenes for testing with 8192 points as our inputs. We remove the RGB information in this experiments and only use the spatial coordinates as input.

- S3DIS [Armeni et al., 2016]: The S3DIS dataset contains 3D scans in 6 areas including 271 rooms. Each point is annotated with the label from 13 categories. We follow the way in [Qi et al., 2017a] to prepare training data and split the training and testing set with k-fold strategy. 8192 points are sampled in each block randomly for training. We use XYZ, RGB and normalized location on each point as input.

**Network Configuration:** The configuration of LSANet is shown in Tab. 2. The architecture of LSANet is the same as corresponding PointNet++ network except for the SFE and LSA module. Since PointNet++ did not experiment on S3DIS datasets, we use the same architecture as ScanNet.

We use Adam optimizer, and the initial learning rate is 0.002 which is applied with exponential decay. The decay ratio is 0.7 applied every 40 epochs. We use the ReLU activation function, and the batch size of data is 32. We train the LSANet for 250 epochs on two NVIDIA GTX 1080Ti GPUs.

**Results:** Tab. 1 compares our results with state-of-the-art works on the datasets mentioned above. For the task of Classification, we divide the settings into the pre-aligned and the unaligned according to whether they rotate randomly during the training or testing phase, due to a large portion of the 3D models from ModelNet40 are pre-aligned. To compare fairly, we report our LSANet’s performance in both settings. We use the overall accuracy as the evaluation metric. For the input of 1024 points without surface normal, in terms of the overall accuracy and Unaligned setting, our method achieves 1.6% higher than the multi-scale grouping (MSG) network of PointNet++ even though we do not use multi-scale grouping (MSG) in the SA module. Our LSANet also outperforms the PointNet++’s MSG architecture which uses both 5000 points and surface normal as input. These results show the effectiveness of our module, and in general, we realize better accuracy than other methods in both settings. In the segmentation task, we evaluate our LSANet on the ShapeNet, ScanNet, and S3DIS. We note that our method outperforms all the compared methods, such as PointNet++ which does not have our LSA module and additional branch. Our LSANet also outperforms the approaches based on [Qi et al., 2017a] such as SpecGCN [Wang et al., 2018] and SpiderCNN [Xu et al., 2018].
et al., 2018]. The visualizations of segmentation results on ShapeNets is shown in Fig. 4.

4.2 Analysis and Visualization

We now validate our proposed LSANet design by control experiments with classification task on the ModelNet40 [Wu et al., 2015] dataset under unaligned settings, and then we visualize the attention maps generated by our LSA module.

**Module validation:** We demonstrate the positive effects of our LSA module and SFE by ablation experiment. We also remove the integration of attention maps from max pooling and the region spatial encoder part of LSA module in Fig. 3 to verify their effectiveness. The detailed results are shown in Tab. 3.

As shown in these experiments, the LSA module and SFE bring 1.1% and 1.2% accuracy improvement respectively, illustrating the effectiveness of our modules. We also observe that the region spatial encoder of LSA module improves the results, which shows the validity of the whole region information. The results also show that the max pooling combined with attention map can select the optimal point based on its spatial distribution and achieve better effects.

**Visualization of the Local Spatial Attention map:** In Fig. 5, we randomly pick 512 representative points with their neighboring ones of an object in the test set of ModelNet40 [Wu et al., 2015] dataset, and visualize the response of LSA module to these local regions before MLP in each channel (as discussed in Sec. 3.3). It is obvious to see that our LSA module obtains different preferences for directions in each channel. This module guarantees that our LSANet can effectively perceive fine-grained patterns by learning attention maps.

### 4.3 Complexity Analysis

We further compare both space and time complexities with other methods, in which the classification network is used. Tab. 4 shows that our LSANet has proper parameters with fast inference time. In addition, our segmentation network involves fewer parameters than our classification network (see Tab. 5).

Table 3: Ablation study on ModelNet40 classification task under unaligned settings.

| Method Configuration                      | OA   |
|------------------------------------------|------|
| PointNet++ [Qi et al., 2017b (SSG)]      | 90.1%|
| PointNet++ + SFE                         | 91.3%|
| PointNet++ + LSA (w/o region spatial encoder) | 91.5%|
| PointNet++ + LSA (w/o max-pooling)       | 91.4%|
| PointNet++ + LSA                         | 91.7%|
| PointNet++ + LSA + SFE (ours)            | 92.3%|

Table 4: Comparison of different methods on the number of parameters and inference time.

| Method                        | Parameters | Inference time |
|-------------------------------|------------|----------------|
| PointNet++ (SSG) [Qi et al., 2017b] | 1.48M      | 0.027s         |
| SpecGCN [Wang et al., 2018]    | 2.05M      | 11.254s        |
| SpiderCNN [Xu et al., 2018]    | 5.84M      | 0.085s         |
| LSANet (ours)                  | 2.30M      | 0.060s         |

Table 5: The number of our LSANet’s parameters on four datasets.

5 Conclusion

In this work, we propose a novel LSA module and a branch architecture with our SFE. Based on such new design, our LSANet has more powerful spatial information extraction capabilities and provides on par or better results than state-of-the-art approaches on standard benchmarks for different 3D recognition tasks including object classification, part segmentation, and semantic segmentation. We also provide ablation experiments and visualizations to illustrate the effectiveness of our LSANet design.
cnn for 3d shape segmentation. In *CVPR*, pages 6584--6592, 2017.