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VA-GCN: A point cloud analysis network used to mine local aggregation information

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ABSTRACT

In recent years, point cloud analysis models have made breakthroughs due to the development of local aggregation operators. In this article, we propose a new point cloud analysis network, Vector Attention Graph Convolution Network (VA-GCN) based on Vector Attention Convolution (VAConv) modules. VA-GCN can be easily embedded into other complex point cloud analysis models, which can promote the development and application of point cloud models in the field of artificial intelligence. In addition, we designed an open-source software for point cloud classification based on VA-GCN. Its ease of use and efficiency will allow non-professionals to quickly get started.

Code metadata

Current Code version	*V1.0*
Permanent link to code / repository used of this code version	https://github.com/SoftwareImpacts/SIMPAC-2021-96
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/2940276/tree/v1
Legal Code License	*MIT*
Code Versioning system used	*git*
Software Code Language used	*Python, Pytorch*
Compilation requirements, Operating environments & dependencies	*Microsoft Windows*
If available Link to developer documentation / manual	https://github.com/hht1996ok/VA-GCN/blob/VA-GCN/README.md
Support email for questions	hht1996ok@zju.edu.cn

1. Introduction

During recent years, researchers in the field of computer vision have made major breakthroughs in 3D point cloud processing, greatly improving the performance of current point cloud models in 3D shape classification [1–4], 3D part segmentation [1,2,4–7], 3D semantic segmentation [1,2,4,7,8], 3D object detection [9,10] and other tasks. With the vigorous development of 3D vision in areas such as autonomous vehicles and robots, 3D point clouds have become an important research topic.

However, due to the disorder, sparsity and irregularity of the point cloud, how to efficiently use the information of the point cloud has drawn the most interest. To address this problem, we propose a new point cloud analysis model, Vector Attention Graph Convolution Network (VA-GCN), which can efficiently process point cloud data and conduct classification and segmentation tasks.

In this article, we will introduce a VA-GCN based software designed for point cloud classification and segmentation. Due to the robustness of VA-GCN, the software is also applicable for poor quality data sets, such as the situation where the number of points in point cloud is small or the point cloud position is acquired under severe jitter. By adjusting the number of input point clouds and model parameters, the software we developed can strike a balance between computational cost and accuracy so as to flexibly adapt to various scenarios. Our software is implemented in Python and can be easily integrated into modules written in other programming languages. Users can also easily expand functions according to their requirement. In order to meet the needs of high-precision inference, we have added the Multi-Sample Inference

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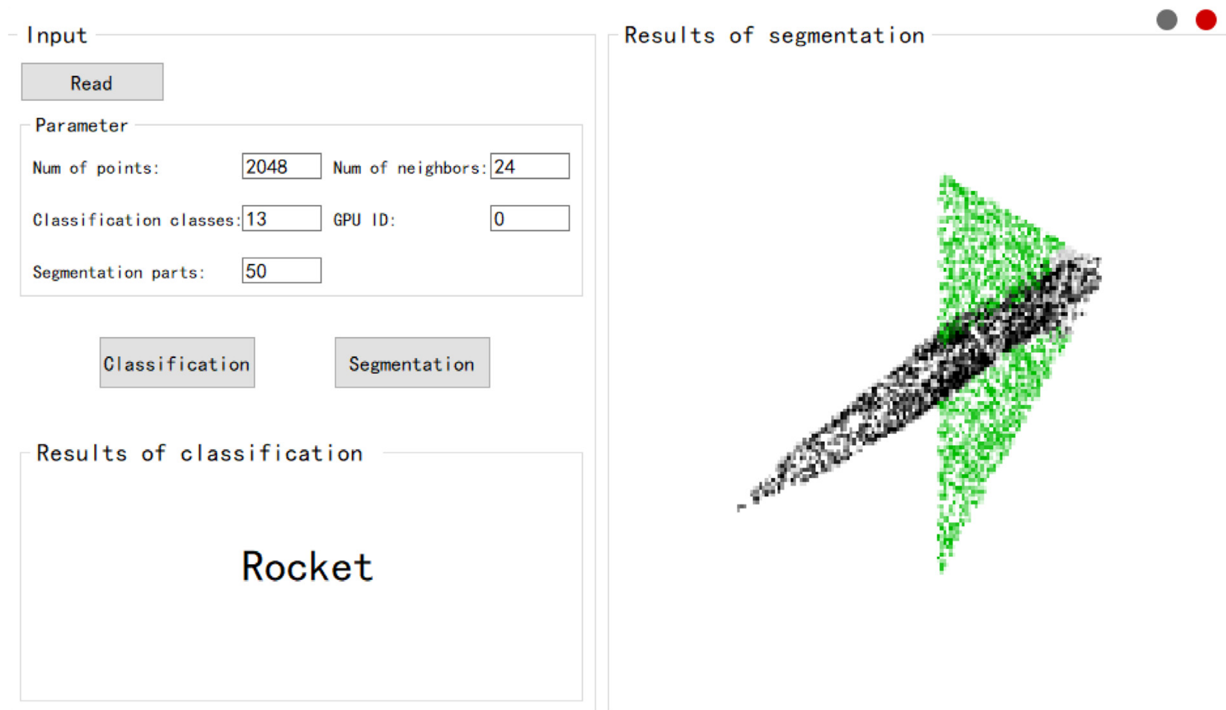

Fig. 1. Interface of VA-GCN software under inference. Num of points is the number of input points. Num of neighbors is the number of neighborhood points selected for each point in the point cloud. Classification classes is the number of classification or segmentation categories. GPU ID represents the index of used GPU (for example: 0 means the software is using the GPU with the index of 0). These four items must be filled in. Segmentation parts must be filled in when performing 3D segmentation tasks.

(MSI) function to the software, but it is worth noting that using MSI will increase the inference time.

2. Usage and evaluation

The software we designed can realize 3D classification, 3D part segmentation and 3D semantic segmentation. The user interface (UI) of the software is shown in Fig. 1. First, click "Read" to read the point cloud file to be analyzed; then fill in the relevant parameters; finally click the "Classification" or "Segmentation" button to perform point cloud classification or segmentation task.

If you need to retrain or finetune VA-GCN models on other data sets, the following command could be executed:

≫ python train_classification.py –model VAGCN_cls –log_dir VAGCN_cls

If you want to perform batch testing on a certain data set, you can run the following command line:

≫ python test_classification.py –log_dir VAGCN_cls

If users need to configure network parameters to meet the needs of different scenarios, they can directly modify the parameters of the parse_args function in the source code. Adjustable parameters include the GPU index, batch size, number of classes, learning rate, number of input points, number of iterations, optimizer, whether to use normal vector information, as well as weight and training file saving path.

As shown in Fig. 2, we evaluated the robustness of VA-GCN to the number of input points and random perturbation. In the extreme case where the number of input points is 64 and the random perturbation range is set to [-0.3, 0.3], the classification accuracy of VA-GCN can still maintain between 87.7% and 93.4%, which proves that VA-GCN has strong robustness to the changes of these two factors. Even if the point cloud data is acquired under severe jitter, our model can still guarantee high classification accuracy, which is significant for the practical usage in the real-world case for commercial applications.

Fig. 3 is a comparison of the point cloud segmentation results of VA-GCN and PointNet++. It can be seen that VA-GCN accurately segmented the tiny parts that are easier to be ignored or misclassified, while the segmentation results of PointNet++ are much rougher. Compared to the ground truth, VA-GCN has higher segmentation accuracy. This shows that VA-GCN can provide users with efficient and accurate point cloud segmentation results by focusing more on the details, in contrast to PointNet++.

3. Impact overview

VA-GCN can find broad applications in the field of point cloud data analysis, and it can be applied to a variety of tasks including 3D classification, 3D part segmentation, and 3D semantic segmentation. At the same time, our VA-GCN has the universal data preprocessing and training module, which greatly improves the efficiency of its reuse. The software we made provides a simple and efficient solution to point cloud analysis. In the software, we provide an inference method by sampling point clouds multiple times. Although it will increase the inference time, it can get more accurate classification results. To be more specific, our software can help the researchers in the field of point cloud analysis from the following perspectives:

1. This software is easy to operate and flexible. Users only need to input their own data set and adjust the network parameters for training. Our software will automatically perform data preprocessing and set up model architecture as well as training pipelines. At the same time, our software can also perform distributed training according to the number of GPUs set by the user, which will satisfy the need to require large memory in some scenarios.

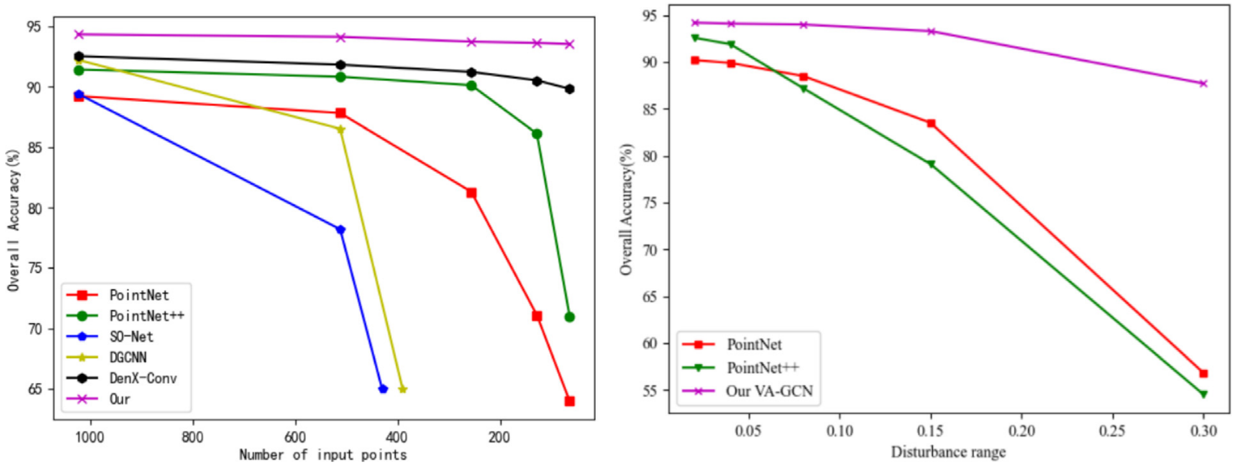

Fig. 2. Robustness experiment of VA-GCN in terms of the number of input points and the input random disturbance.

Fig. 3. Segmentation results of PointNet++ and VA-GCN compared with the ground truth.

2. Our software still has excellent performance on sparse or noisy point cloud data, making it a robust choice. In extreme cases, VA-GCN maintains high-precision predictions, which can help users solve difficult point cloud analysis problems.
3. Researchers can further explore the point cloud analysis model on the basis of VA-GCN. Because our software provides complete data preprocessing and network training functions, researchers only need to focus on the study of model structure and parameters without rewriting the basic functions, which will save them a lot of time.

4. Conclusions

We have developed a point cloud analysis software called VA-GCN. Owing to the flexibility and versatility of VA-GCN, users can develop new point cloud analysis models based on our software or integrate it with other existing modules. Their own data sets for training and testing can be deployed conveniently and quickly, without repeating tedious tasks such as network construction and data preprocessing. The UI we designed is easy to operate and user-friendly to non-professionals.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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