AN IMPROVED SUPER-RESOLUTION GENERATIVE ADVERSARIAL NETWORK

Long Jie, Shao Lijun, Liu Guoqing

Inner Mongolia University of Science and Technology, China

Supervisor RenYan

An improved SRGAN image generation model proposed to address the increasing demand for high-resolution images and the problem of model gradient disappearance due to the excessive amount of parameters and deeper convolution layers in SRGAN for reconstructing high-resolution images. First, used a null convolution residual block model in the SRGAN discriminator to alleviate the gradient disappearance; second, the CBAM attention module adds to the discriminator as a way to extract image features further; finally, adaptive averaging pooling is added to the discriminator to reduce the number of model parameters. The experimental results show that the improved SRGAN reconstructed images are evaluated in the standard datasets AID and RSOD, reaching 29.58 and 27.37 in peak signal-to-noise ratio (PSNR), respectively, and 0.86 and 0.84 in structural similarity (SSIM), respectively.

Keywords: remote sensing, SRGAN, gradient vanishing, high resolution.

I. Purpose of the Study

The overall structure of the SRGAN discriminator is shown in Fig. 1, where the low-resolution images are passed through the generator to generate super-resolution images. The discriminator uses the null residual structure as the primary network structure and combines CBAM and other activation functions, pooling, and other operations to discriminate the results, resulting in better-quality super-resolution images.

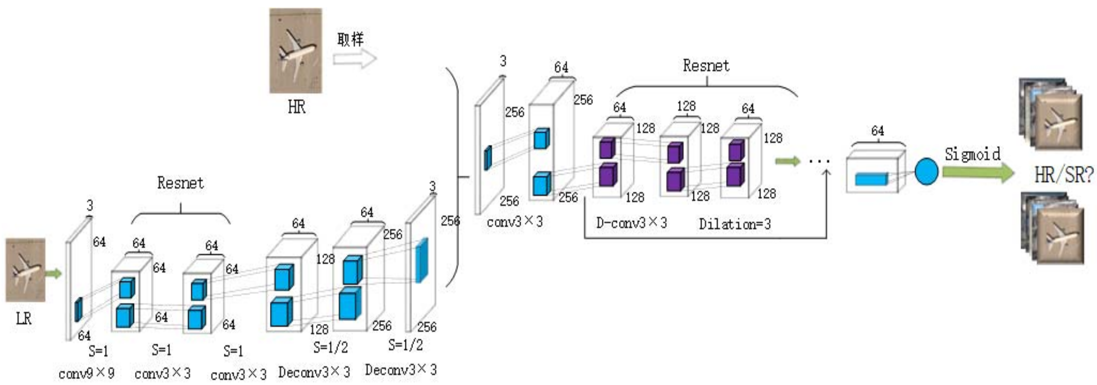


Fig. 1. Overall structure of SRGAN

A. Suppressing gradient disappearance and enhancing feature extraction

1. Problem Analysis

The original SRGAN discriminator uses a standard CNN network, and the deepening of CNN network layers will cause gradient disappearance/gradient explosion. The gradient weakening phenomenon leads to a network information transfer error, and the network information is not well updated. Secondly, the images generated by SRGAN have some distortion in details, and the image target should be given more attention to texture details to generate more realistic and realistic high-resolution images.

2. Improvement strategy

Residual structure can solve the network degradation problem in deeper networks [1]. Null convolution increases the perceptual field without reducing resolution [2]. CBAM allows important information to be assigned higher weights [3].

Where the null convolution replaces the CNN, and the residual structure is formed; second, the Leaky-ReLU activation function is replaced by PReLU in the residual block. It is causing Faster convergence and lower error. Each residual operation is integrated with an attention mechanism to optimize the result.

B. Reducing the number of participants

1. Problem Analysis

The number of parameters will increase as the number of layers of the network deepens. In this paper, we found that SRGAN overfitting occurs with the increase of training batches.

2. Improvement strategy

Adaptive averaging pooling can compress the spatial dimension and take out the mean value of the corresponding dimension, and fewer network parameters can suppress overfitting[0], which can suppress some useless features to a certain extent. In this paper, we propose to introduce adaptive averaging pooling before the fully connected layer to reduce the data dimensionality and overfitting. The structure diagram of SRGAN discriminator is shown in Fig. 2.

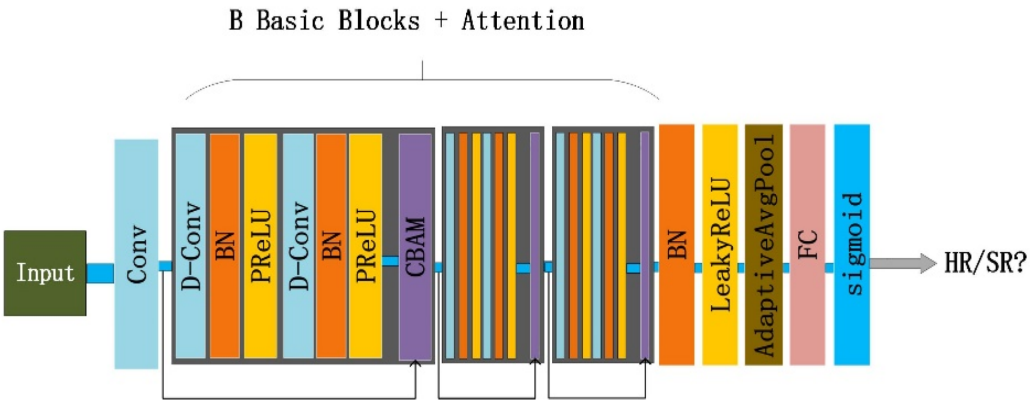


Fig. 2. Structure of SRGAN discriminator

II. Experimental Methods

The standard dataset AID dataset and RSOD dataset were used for testing and validation. The peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) are used as the evaluation indexes for the quality of reconstructed images generated by SRGAN before and after the improvement; the changes of model parameters before and after the improvement are also compared using parametric quantities (Params) to verify the superiority of the improved algorithm in this paper(Unit: 10000). The evaluation indexes such as recall and accuracy are also used to classify and validate the data enhancement effect before and after the improved SRGAN algorithm in MobnetNetV2 network.

Table 1

Image reconstruction comparison

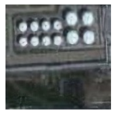
	original	**SRGAN**	**Improve SRGAN**
AID			
PSNR/SSIM	∞/1	27.18/0.79	29.58/0.86
RSOD			
PSNR/SSIM	∞/1	27.58/0.78	29.32/0.85
Params		521.5425	207.2879

Table 1 compares the original SRGAN and improved SRGAN reconstruction on RSOD and AID datasets. The improved algorithm has improved in PSNR and SSIM compared with the improvement, and the reconstructed images are softer. At the same time, the number of parameters (Params) is significantly reduced, and the number of parameters is reduced by about 60 %, effectively alleviating the parameter complexity.

The number of samples in the original data is expanded by 5 % using the improved SRGAN algorithm before and after the dataset AID and RSOD, where I denote the original dataset method without data enhancement. The classification was validated using MobileNetV2. The image classification results are shown in Table 2. In this subsection, taking the AID dataset as an example, the improved SRGAN effect is 11.02 % and 2.22 % higher in accuracy than the unenhanced and SRGAN methods, respectively.

Table 2

Comparison of multi-algorithm classification results

Dataset	**Method**	**Top-1**	**Accuracy**	**Recall**	**F1 Score**
AID	I	85.38	83.76	83.83	83.14
	SRGAN	93.04	92.56	92.8	92.63
	Improve SRGAN	**95.25**	**94.78**	**94.64**	**94.6**
RSOD	I	94.96	95.05	94.83	94.91
	SRGAN	98.45	98.53	98.47	98.49
	Improve SRGAN	**100**	**100**	**100**	**100**

III. Summary

To address the problem of gradient disappearance in the training of SRGAN models, an improved SRGAN model is proposed. The experiments show that the improved SRGAN improves the peak signal-to-noise ratio and structural similarity compared with the pre-improvement algorithm and also improves image classification results.

References

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AN ALGORITHM OF DYNAMIC HETEROGENEOUS NETWORKS LINK PREDICTION

Wu Hao, Ni Xiang-ming

Inner Mongolia University of Science and Technology, China

Supervisor Zhao Yu-hong

By considering the evolution of networks over time and the rich semantic and structural characteristics of heterogeneous networks, DyMDGCN model is proposed in this paper. The model uses multi-channel partition to deal with heterogeneous networks, and then combines RNN and time attention capture evolution mode to obtain the final node embedding vector from and apply it to link prediction. In order to verify the effectiveness of this method, this paper selects two real dynamic heterogeneous network data sets of Twitter and EComm for experiments, and compares the AUC index with the traditional algorithm. The results show that this method can deal with heterogeneous network information and capture the dynamic evolution information of the network, and has a certain improvement in accuracy compared with the traditional algorithm.

Keywords: dynamic network, heterogeneous network, link prediction, dyMDGCN, time attention, AUC.

1. Introduction

A dynamic heterogeneous network link prediction method based on network representation learning is proposed in this paper, which is roughly shown as follows:

1. In order to deal with the heterogeneous network while being able to obtain deep relationships, this paper selects the MDGCN method, which divides the heterogeneous network by using the multi-channel division method, using meta-paths as channels and processing each channel by graph convolution to obtain the node feature relationships, and to obtain the deep relationships, the method also uses the Graph Inception model to construct a hierarchy from simple To obtain deep relationships, the method also uses the Graph Inception model to construct a hierarchical structure from simple to complex, so by combining the two, a more accurate and comprehensive node-relationship feature vector can be derived.

2. In order to obtain the evolutionary patterns of the network considering the dynamics of the network, this paper combines the RNN with the attention mechanism. Firstly, RNN learns the evolutionary patterns of the network snapshots, and the most generalized LSTM and GRU methods are selected in this paper; then, unlike the traditional methods, this paper does not choose to stitch all the vectors but instead, the temporal self-attentive model is used to The final node vector of the last snapshot is used for the downstream task.

2. DyMDGCN model

2.1. Basic ideas of the DyMDGCN model

The main task of dynamic heterogeneous network embedding is how to capture both heterogeneous information and temporal evolution patterns on a dynamic network. In this paper, we propose a new approach for dynamic heterogeneous network embedding, which