# Research on Cascading Residual Network: Fast, Accurate, and Lightweight Super-Resolution

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Abstract

1. Introduction

As a computer vision task, super-resolution (SR) refers to the use of one or more low-resolution (LR) images to obtain high-resolution (HR) images. High resolution means that the pixel density in the image is high, which can provide more details, and these details are indispensable in many practical applications, such as shooting high-resolution medical and satellite images. The Cascading Residual Network (CARN) [1] solves the single-image super-resolution (SISR) problem, which uses a single LR image to restore HR. In recent years, methods based on convolutional neural network (CNN) have given outstanding performance in SISR tasks. The effect of the early simple neural network structure needs to be improved. Using a more complex network structure and a deeper convolutional layer can greatly improve the performance of the SISR task, but this is achieved at the expense of time and high computational complexity. Therefore, it is necessary to build a lightweight deep learning model to make it suitable for real-world applications, reduce the number of parameters and operations and increase the calculation speed.

In response to the above problems, the CARN family was proposed. First, the CARN model was proposed to improve performance, and then expanded to CARN-M model to optimize speed and number of operations. In short, CARN based on the cascading module neural network effectively improves performance on SR tasks, while the CARN-M algorithm combined with efficient residual block and recurrent networks is very effective on SR tasks. At the same time, these models only use A small number of operations and parameters.

2. Problem Statement

The SISR task is a computer vision task that restores the HR image through a single LR image. It is a many-to-one mapping, so it is usually difficult to implement. However, SISR is very useful because it is expected to break through the limitation of resolution, so it is a very active area. Recently CNN-based methods have performed well on SISR tasks. SRCNN is the first attempt of a deep learning (DL) method in the super-resolution problem. It has a simple structure, but the effect needs to be improved. Other CNN-based methods such as SRDenseNet [2], MDSR [3] and RDN [4] use more complex network structure and deeper convolutional layer, the effect is outstanding, but the cost is time and computational intensity, thus not suitable for real scenes.

To construct a fast, accurate, and lightweight super-resolution model and reduce required operations, the CARN family was 图示, 示意图

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Figure . (a) is the plain ResNet model, (b) is CARN model which the global cascading connection is indicated by the blue arrows.

3. Methodology

**3.1. Baseline Algorithms**

Inspired by FSRCNN [5], CARN takes LR images as input and outputs HR images restored by SR. As shown in Figure 1 [1], the design of the middle part of the CARN model is based on the ResNet [6], with the residual blocks in ResNet replaced by cascading blocks.

4. Experiments

**4.1 Dataset**

Following [1], we used DIV2K [7] dataset to train the model. It contains 800 training images, 100 validation images and 100 test images, the types of images are also rich. We also used Set5 [8], Set14 [9], B100 [10] and Urban100 [11] for testing and visualizing. Given that most of the pictures in the above data set are natural images, we also collected a dataset which contains only unnatural image to verify the performance of the model on unnatural images. The images in this dataset are from [Pixabay](https://pixabay.com/zh/) with Pixabay License.

**4.2. Evaluation**

Following [1], we used two commonly used metrics to quantify the results: peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [12]. At the same time, we also compare the results based on subjective judgments.

**4.3. Initial Results**

We trained the CARN model and CARN-M model for 150000 steps using DIV2K dataset. The patch size and batch size are both 64, and the loss function is L1 loss. (missing CARN-M)

We tested the trained model on datasets Set14, B100 and Urban100, and used the built-in method of scikit-image SciKit library to calculate PSNR and SSIM. The results are shown as Figure 2. We also tried the model provided by the author, whoever the result is different with ours. In our results, the overall PSNR and SSIM are lower, even for the original bicubic images. This may be because we used a different method to calculate the PSNR and SSIM. However, both PSNR and SSIM have been greatly improved.

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Figure 2. SR results with x4 scale.

5. Conclusion

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