Fine-Grained Dynamic Loss for Accurate Single-Image Super-Resolution

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Paper ID: 6873

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Introduction

Image super-resolution is a technique that utilizes low-resolution images or low-resolution image sequences to recover high-resolution images. The higher the resolution of an image, the sharper the image and the more information it can carry. However, due to the limitation of imaging equipment and the influence of external factors, it is not always possible to obtain high-resolution images, so the super-resolution reconstruction algorithm was born. It uses software to improve image resolution and is widely used in remote sensing and medical image processing. At present, the mainstream methods include interpolation-based , reconstruction based and learning-based methods.

In recent years, the convolutional neural networks (CNNs) based super-resolution methods have been extensively studied and have achieved tremendous improvement. As a pioneering work, Dong et al. proposed the super-resolution convolutional neural network (SRCNN) which only has three convolutional layers. Zhang et al. further uses residual connections and attention machanisms to increase the quality of SR images.

Many studies on SISR have been reported, they still face two challenges. First, though other algorithms such as attention mechanism can improve the performance of complex areas in image, there's still a gap to the ground truth (GT) one. Secondly, the number of parameters and computational cost of the network becomes higher to acquire better results. The presented SISR networks use loss functions that cover the full image grey value range, e.g. 0-255 for 8 bit images. It may increase the regression difficulty, in particular in textures image regions, because the image signals of different image regions do not obey the characteristics of fully dynamic range. This paper proposes a dynamic fine-grained loss for image super-resolution, and brings classification loss in SISR, the main contributions include:

(1)This paper innovatively proposes a dynamic fine-grained loss based on the classification loss, which improves the performance without extra computational cost.

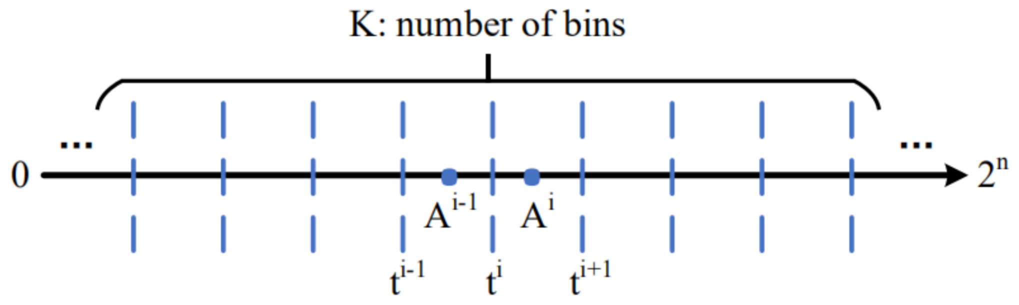
(2)Ablation experiments show that the method can greatly improve the reconstruction effect, especially in images with rich texture details.

(3)Extensive experiments conducted on benchmark SISR show that the proposed method is also applicable in other networks and can increase the quality of SR images.

Methods

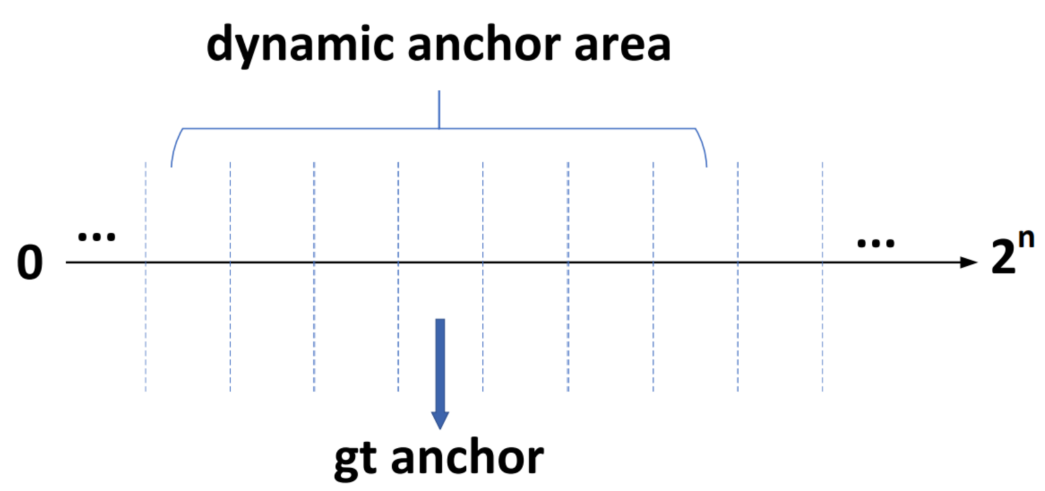
Different from the regression loss, as one can see in Figure 1 we choose a discretization method to generate several increasing scalar values of each pixel with threshold of 0 to 2n. Each scalar value represents an independent bin.

Figure 1



With the classification step above, the network can easily find the area near the gt anchor, the next step is how to generate the final precise pixel. However, particularly those images with rich texture detail, the classification result of bin is often several bins away from the gt anchor. For example, if the index of classified bin is 2 or more bins away from gt anchor, it is meaningless to regression in anchor area. Thus dynamic regression loss is necessary. As shown in Figure, dynamic anchor area is formed from numbers of bins on both sides of the predicted bin including the predicted bin itself. The number of bins was computed dynamically with a Class-Module, and then carries out small-scale regression within the range of dynamic anchor area。

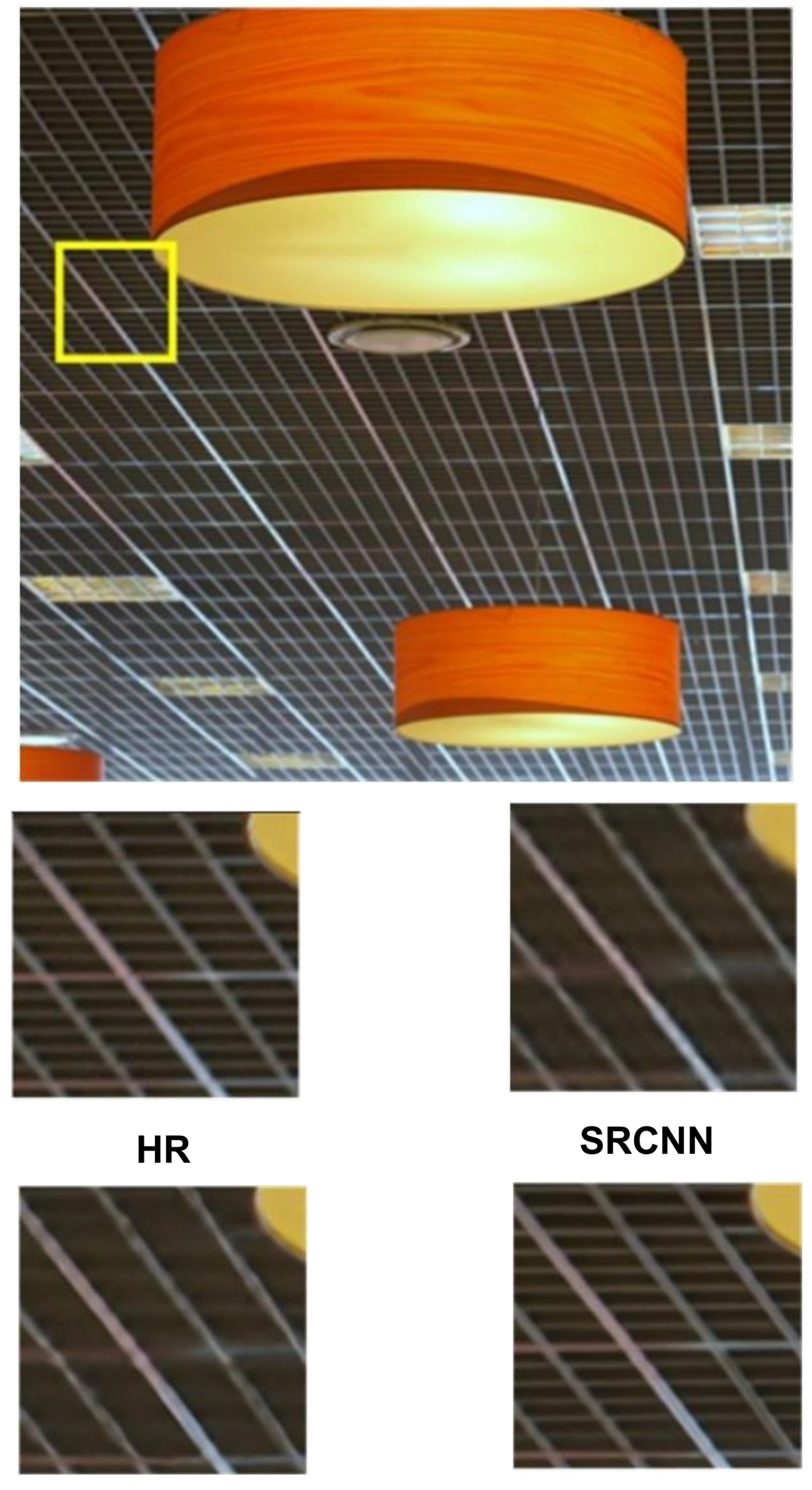
Figure 2



Results

Our method is evaluated on several classic benchmarks such as Set5, Set14, BSD100 and Urban100, and compared with the original baseline. Our method improves PSNR on LapSRN compared with baseline. This shows the advantages of the proposed method, especially in X4 SR, the proposed method is far more than baseline, and it also shows that our method can be transplanted to other networks. In addition to the quantitative results, we visualize the super resolution results in Figure 3, which including some common scenes. It can be observed that our method can reconstruct the texture consistent with HR while other methods fail to restore the texture and produce some irrelevant artifacts.

Figure 3



Conclusions

This paper proposes a dynamic classification regression loss, which first transforms the regression problem into a classification problem, then determines the anchor area, and then carries out small-scale regression within the range of dynamic anchor area, so as to reduce the learning difficulty of the network and improve the reconstruction performance. Compared with regression loss, our method has made a significant improvement in PSNR, especially for images with rich texture details. Moreover, a large number of experiments show that our method can be applied to more networks and improve the reconstruction performance.