

Lightweight Unsupervised Super-Resolution with Emphasis on Structural Similarity

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Abstract—Contemporary state-of-the-art methods for image super-resolution (SR) are principally supervised deep models, which cost heavy computational efforts and do not fully exploit the information in the input image itself. We build an unsupervised, relatively shallow model for image super-resolution, which majorly focuses on the structure similarity (SSIM) instead of peak signal-to-noise ratio (PSNR) of output. Along with our model achieving competitive results especially in SSIM, we further propose its data augmentation techniques and a creative loss function combining SSIM and PSNR.

Index Terms—super resolution, unsupervised learning

I. INTRODUCTION

Single image super-resolution (SISR) is to generate an output image of high resolution (HR) based on a low-resolution (LR) input, which is potentially of lower subjective and objective quality. In recent years, deep-learning-based implementations [1] [2] [3] [4] have won a significant edge over other methods. In these state-of-the-art deep models, efficient architectures like dense blocks and attention mechanisms are applied to combine low- and high-level information. With context of attention and features extracted from the LR image, the deep models can estimate more delicate kernels for better interpolation.

However, the models mentioned above require heavy computational efforts and large datasets. Often tens of millions of parameters and thousands of billions of operations are included in the model. In order to reduce computational efforts (because we do not have powerful GPUs), our work, inspired by [5], attempts to train a lightweight, image-specific model. Our training set contains only the image that we are to perform SR on. Meanwhile, with respect to the output quality, we focus majorly on SSIM because it preserves high-frequency

information better than PSNR, and is based on the assumption that the human visual system extracts structure. Yet we still would like to preserve decent PSNR.

II. NETWORK DESIGN

Referring to [3], we also designed a residual dense network. However, limited by computational power, we introduced only 8 layers of 64×64 convolution + ReLU operations.

A. Use of Dense Connection

The DenseNet model proposed by [6] has lead a trend of using dense connections. With the features generated from each layer serving as the input of all subsequent layers, dense connection encourages the reuse of features, which potentially saves computational efforts, enhances data propagation and extracts multi-hierarchy information efficiently.

B. Use of Residual Learning

Residual learning, which learns the difference between the output and the ground-truth, had long been a widely employed strategy in SR even before ResNet [7] was put forward. Global residual learning in SR, implemented simply via an element-wise addition of input to the output, avoids a huge difference of SR output between one image block and another. Therefore, residual strategy can also reduce the complexity of models.

III. TRAINING STRATEGIES

We are to denote the input image as the high-resolution (HR), and the desired output as the super-resolution (SR). Enlightened by [5], we furthermore degrade the input HR image with bicubic interpolation. The further-degraded image, denoted as the low-resolution (LR), is then bicubically upscaled to HR size again.

The downscale-upscale process is denoted as “back-projection”. Afterwards, blocks of 128×128 pixels are picked from the HR image, and we train the model with paired blocks from the HR and the bicubically upscaled LR image. Some data augmentation techniques, which will be introduced in subsection III-B, are also used before downscaling the HR image. In order to generate the final SR output, the HR image is bicubically upscaled to SR size, and amended by our model.

A. Estimation of Kernel: Supervised versus Unsupervised

If we view SR as an interpolation problem, we may find that a supervised model is designated to estimate the upscaling interpolation kernel. In many cases, including that of popular datasets, we do not know the downscaling kernel, and there is little reason for us to assume that downscaling kernels of different LR images are the same, or of very few categories. Consequently, supervised models learn different kernels from different pairs of LR and HR images, and may not exploit the best performance for each single image. In other words, the generalization ability of supervised kernels is therefore doubtful. Our unsupervised model, however, is trained only with the image blocks from the LR image. In this way the problem of generalization is partially averted. Though we used primarily the bicubic kernel in our experiments, we assume that the output can be potentially further improved if the downscaling kernel is actually known.

B. Data Augmentation strategies

In each epoch of training, we randomly execute some augmentation operations on the HR image before downscaling it. The HR image may take affine transforms including rotation and rescaling. Shifting is also implemented so that the boundaries of the image does not remain the same. We also randomly, but at a small probability, apply various kernels in back-projection. The downscaling and upscaling kernels are not necessarily the same in a single back-projection operation. We have also considered adding random noise in back-projection, but we suspect that noise without delicate control may improve generalization only for noisy HR images (which is not a foremost demand in our unsupervised method) at a heavy price of overall performance. Also we had little time and limited computational power to implement noise.

C. The Gradual-Upscaling Strategy

We tried to train the model with gradually upscaled image. That is, in back-projection, we did not directly

upscale the LR image by a factor of 2. Instead, our upscaling factors in (x, y) directions are chosen to be $(1, 1.5)$, $(1.5, 1)$, $(1.5, 2)$, $(2, 1.5)$, $(2, 2)$ in sequence. Each re-scaled LR image is used to train the model continuously so that the factor-2 features are learned gradually. This technique, also used by [5], derived a slight improvement in both PSNR and SSIM.

IV. LOSS METRICS: THE IMPROVEMENT OF SSIM

One of our principal goals is to improve the SSIM of output, compared to the output of RDN. Initially our idea was to use specialized image enhancement techniques on the output image, but we did have no confidence in any method to amplify SSIM. The cost of manual efforts was also a concern that stopped us to develop an SSIM-focused enhancement from scratch. But we did improve SSIM simply by using it as part of the loss function.

In SR problems, classical and dominating choices of loss functions are L1 and L2 losses (i.e. the mean absolute error and mean square error, respectively). These losses undoubtedly do good to PSNR, but not necessarily generates the best SSIM. Therefore, we chose the loss simply as

$$-40\text{SSIM} - \text{PSNR} \quad (1)$$

where PSNR is in decibel (typically ranging from 20 to 40), and $\text{SSIM} \in [0, 1]$. Our design, compared to traditional L1 and L2 losses, stresses less emphasis on PSNR when the output PSNR is large enough, since our PSNR loss gives logarithmic, instead of linear or quadratic element-wise error. Compared with L1 and L2 losses, our PSNR loss leads the importance of pixel-wise error to decay exponentially. With enough (regulated by the coefficient of SSIM) PSNR ensured, the model would pay primary efforts for SSIM.

V. EXPERIMENTS AND RESULTS

A. Results on Public datasets

We only applied our model to Set14 for $2 \times$ scaling. The average output PSNR and SSIM is 31.894 and 0.9425, respectively. If the gradual-upscaling strategy mentioned in III-C is not applied, the result is 31.891 and 0.9417. This result outperformed [3], [5] and many other state-of-the-art models in SSIM, but we did not achieve the best PSNR.

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