# SINGLE IMAGE SUPER-RESOLUTION WITH DILATED CONVOLUTION BASED MULTI-SCALE INFORMATION LEARNING INCEPTION MODULE

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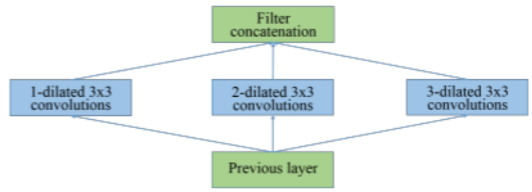
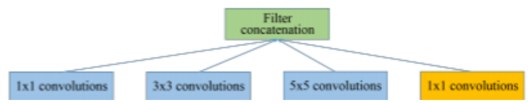
**ABSTRACT**

Traditional works have shown that patches in a natural image tend to redundantly recur many times inside the image, both within the same scale, as well as across different scales. Make full use of these multi-scale information can improve the image restoration performance. However, the current proposed deep learning based restoration methods do not take the multi-scale information into account. In this paper, we propose a dilated convolution based inception module to learn multi-scale information and design a deep network for single image super-resolution. Different dilated convolution learns different scale feature, then the inception module concate-




(a) Dilated convolution based inception module




### 4.3. Comparisons with State-of-the-Art Methods

We compare our method with five state-of-the-art learning based SR algorithms that rely on external databases, namely the A+ [20], SRF [21], SRCNN [5, 6], FSRCNN [8] and SCN [22]. A+ and SRF are two state-of-the-art traditional methods, while SRCNN, FSRCNN and SCN are three newest popular deep learning based single image super-resolution image methods. In Table 1, we provide a summary of quantitative evaluation on several datasets. The results of other five methods are the same as reported at FSRCNN. Our method outperforms all previous methods in these datasets. Compare with the newest FSRCNN, our method can improve roughly 0.33 dB, 0.22Db and 0.37 dB on average with respect to up-sample factor 2, 3 and 4 on Set5 dataset, respectively. Over the three dataset and three up-sample factor, our MSSRNet can improve roughly 2.33 dB, 0.6 dB, 0.46 dB, 0.74 dB, 0.32 dB and 0.25 dB on average, in comparison with Bicubic, A+, SRF, SRCNN, SCN and FSRCNN, respectively. To get better performance, we can increase the network depth (larger $m$), which is called deeper is better in the literature, and the network width with larger $n$. In our experiments, we have implemented the fatter network with $n = 16$ and $n = 32$, and the deeper network with $m = 10$ and $m = 15$. Both the deeper and the fatter networks show PSNR and SSIM gain. The reader can download our test code[1] to get more quantitative and qualitative results.

## 6. ACKNOWLEDGEMENTS

This work has been supported in part by the Major State Basic Research Development Program of China (973 Program 2015CB351804), the National Science Foundation of China under Grant No. 61572155.

[1] https://github.com/wzhshi/MSSRNet

**Table 1**. The results of average PSNR (dB) and SSIM on the Set5 [15], Set14 [16] and BSD200 [17] dataset

| Dataset | Scale | Bicubic | A+ | SRF | SRCNN | SCN | FSRCNN | MSSRNet |
|---|---|---|---|---|---|---|---|---|
| | | PSNR/SSIM | PSNR/SSIM | PSNR/SSIM | PSNR/SSIM | PSNR/SSIM | PSNR/SSIM | PSNR/SSIM |
| Set5 | ×2 | 33.66/0.9299 | 36.55/0.9544 | 36.87/0.9556 | 36.34/0.9521 | 36.76/0.9545 | 37.00/0.9558 | **37.33/0.9581** |
| | ×3 | 30.39/0.9299 | 32.59/0.9088 | 32.71/0.9098 | 32.39/0.9033 | 33.04/0.9136 | 33.16/0.9140 | **33.38/0.9178** |
| | ×4 | 28.42/0.8104 | 30.28/0.8603 | 30.35/0.8600 | 30.09/0.8503 | 30.82/0.8728 | 30.71/0.8657 | **31.10/0.8777** |
| Set14 | ×2 | 30.23/0.8687 | 32.28/0.9056 | 32.51/0.9074 | 32.18/0.9039 | 32.48/0.9067 | 32.63/0.9088 | **32.89/0.9117** |
| | ×3 | 27.54/0.7736 | 29.13/0.8188 | 29.23/0.8206 | 29.00/0.8145 | 29.37/0.8226 | 29.43/0.8242 | **29.57/0.8282** |
| | ×4 | 26.00/0.7019 | 27.32/0.7471 | 27.41/0.7497 | 27.20/0.7413 | 27.62/0.7571 | 27.59/0.7535 | **27.83/0.7631** |
| BSD200 | ×2 | 29.70/0.8625 | 31.44/0.9031 | 31.65/0.9053 | 31.38/0.9287 | 31.63/0.9048 | 31.80/0.9074 | **32.08/0.9118** |
| | ×3 | 27.26/0.7638 | 28.36/0.8078 | 28.45/0.8095 | 28.28/0.8038 | 28.54/0.8119 | 28.60/0.8137 | **28.78/0.8188** |
| | ×4 | 25.97/0.6949 | 26.83/0.7359 | 26.89/0.7368 | 26.73/0.7291 | 27.02/0.7434 | 26.98/0.7398 | **27.17/0.7489** |
| Avg. | | 28.80/0.8151 | 30.53/0.8491 | 30.67/0.8505 | 30.39/0.8474 | 30.81/0.8542 | 30.88/0.8537 | **31.13/0.8596** |

$$\text{Average} = \frac{37.33 + 33.38+31.10+32.89+29.57+27.83+32.08+28.78+27.17}{9} = 31.13$$

| | | |
|---|---|---|
| 0.32 dB SRCNN | = | 31.13 - 30.39 = 0.74 dB |
| 0.32 dB SCN | = | 31.13 - 30.81 = 0.32 dB |
| 0.25 dB FSRCNN | = | 31.13 - 30.88 = 0.25 dB |