Spatially-Variant Degradation Model for Dataset-free Super-resolution

Supplementary Material

A Visual Representation of Membership Function

The visual representation of the proposed membership function $\{\mu_i\}_{i=1}^{N_{\mathcal{D}}}$ with varying values of σ_g and $N_{\mathcal{D}}$ in Eq.(5) is shown in Fig. 1. It is evident that as the number of membership functions $N_{\mathcal{D}}$ increases, the mean difference between different membership functions diminishes. This implies that the texture information from distinct areas is extracted more finely. Additionally, as σ_g increases, the overlapping regions under the membership functions expand, indicating that the structural information utilized by different membership functions becomes more similar.

B Hyper-parameter Analysis of Membership Function

We empirically analyze the impact of σ_g on SVDSR. The PSNR and SSIM performance of SVDSR under different σ_g are shown in Tab. 1, and the corresponding visualization results of fuzzy coefficient matrices and atom blur kernels are shown in Fig. 2.

It can be seen that when σ_g is 0.5, the texture information of different intensities in the image can be effectively extracted. When σ_g takes other different values, the captured texture information will be missing at certain frequencies. The learned atom degradation kernel of the central atom exhibits a clear shape resembling an anisotropic Gaussian kernel, which is very different from the shapes of other kernels. The leftmost atom degradation kernel approximates an isotropic Gaussian blur kernel because the pixels extracted by corresponding membership function in the textureless area cannot provide sufficient degradation information for learning the atom degradation kernel. Since the high-frequency region contains a small number of pixels and a lot of noise, it is difficult for the rightmost atom degradation kernel to learn a clear shape. Taking into account the quantitative results and the visual results of the learned atom degradation kernels and fuzzy coefficient matrices, σ_g is empirically set to 0.5.

C Network Architecture

The generator G is based on an encoder-decoder backbone structure. A skip connection structure is imposed to focus on capturing more global shallow-level information, implemented in the frequency domain using FFT/IFFT. Instance normalization layers are incorporated to alleviate overfitting in the absence of a dataset. The detailed network architecture is shown in Fig. 3.

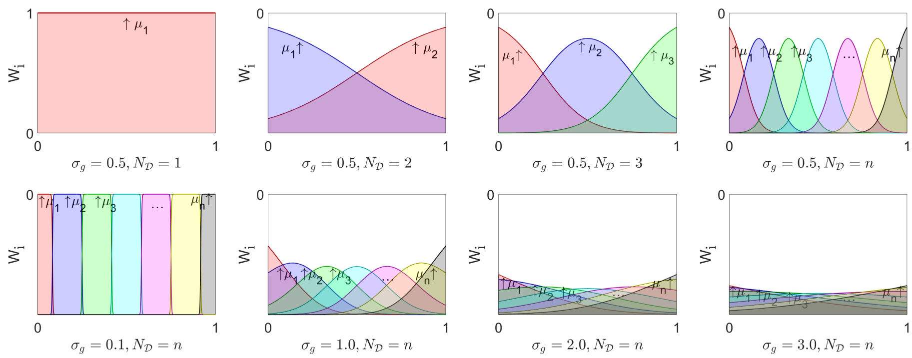

Fig. 1: Visualization of the membership function with different $N_{\mathcal{D}}$ (1st row) and σ_g (2nd row).

Table 1: The impact of the σ_g on Set5 with the scale factor of 2..

	σ_g= 0.1	σ_g= 0.5	σ_g= 1.0	σ_g= 2.0	σ_g= 3.0
PSNR	33.14	33.51	33.45	33.30	33.17
SSIM	0.90	0.92	0.92	0.91	0.91

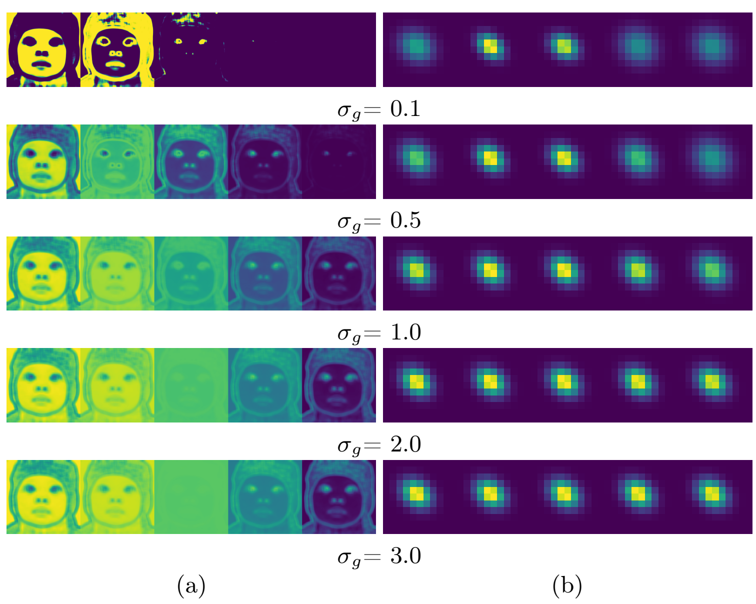

Fig. 2: (a)Visualization of the fuzzy coefficient matrices under the different σ_g. (b)Visualization of the learned atom degradation kernels under the different σ_g. The atom degradation kernel in (b) correspond to the fuzzy coefficient matrices in (a) that are similar in position to the respective atom degradation kernel.

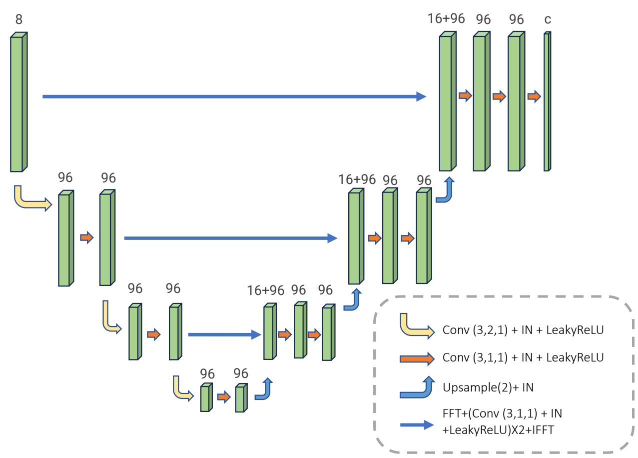

Fig. 3: The detailed network architecture of the generator G. "Conv (k,p,s)" represents the 2-D convolution operator with kernel size k, stride s and reflection padding size p, and "Upsampling (s)" represents the bilinear interpolation operator with scale factor s. IN represents the instance normalization layers.