

Chapter 05. 이미지 복원 (Image Reconstruction)

사실적으로 복원하는 기법

Photo-Realistic SISR single Image SR

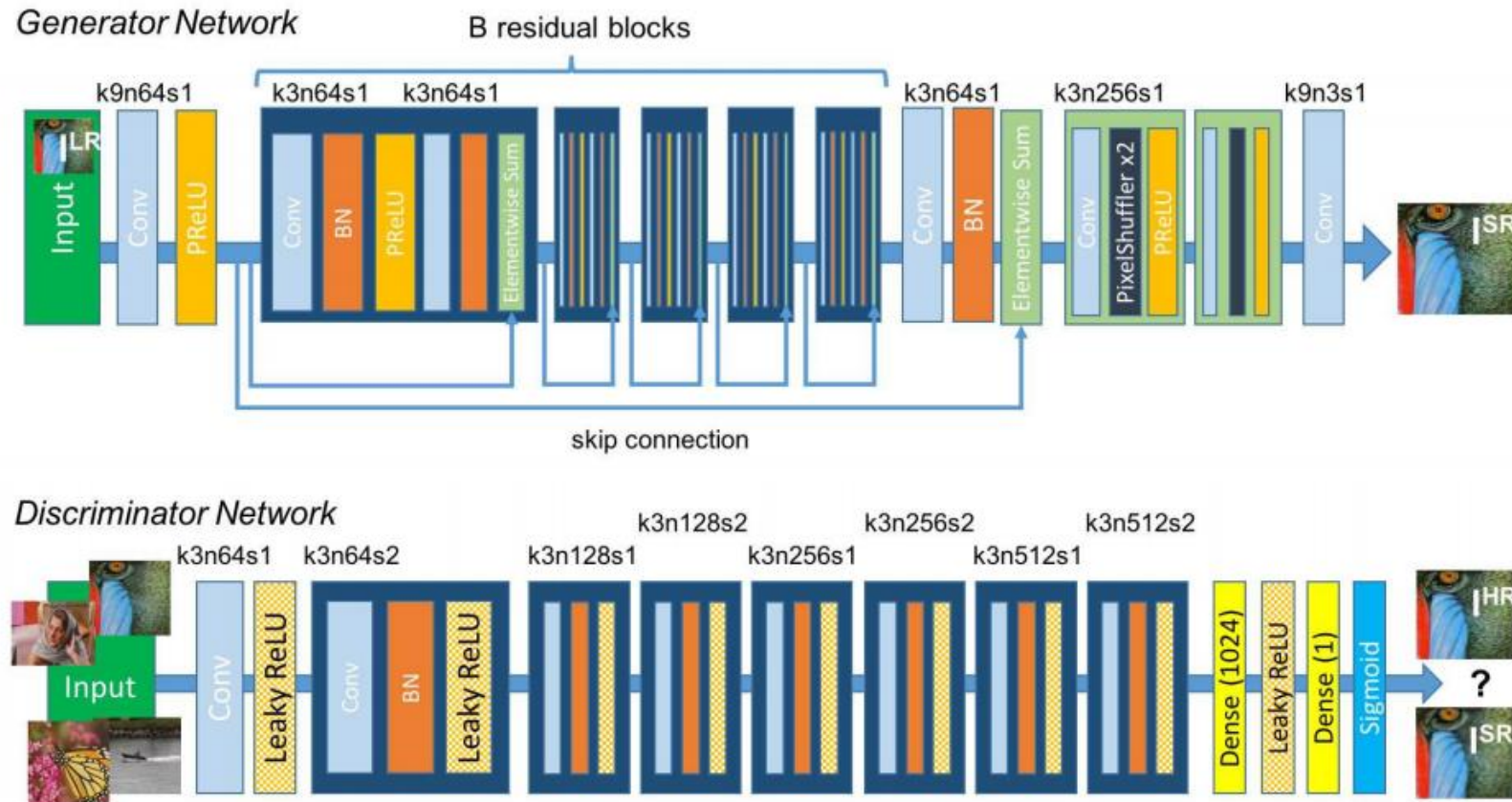


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]

SISR에 큰 활력을 불어넣은 연구로, Loss function의 중요성을 보여주었다.

<https://arxiv.org/abs/1609.04802>

Generative Adversarial Networks



GAN에 대해서는 다음 챕터에서 조금 더 자세히 다룬다.

Generator와 Discriminator를 경쟁시켜서 Generator를 향상시키는 기법.

GAN Loss의 당위성

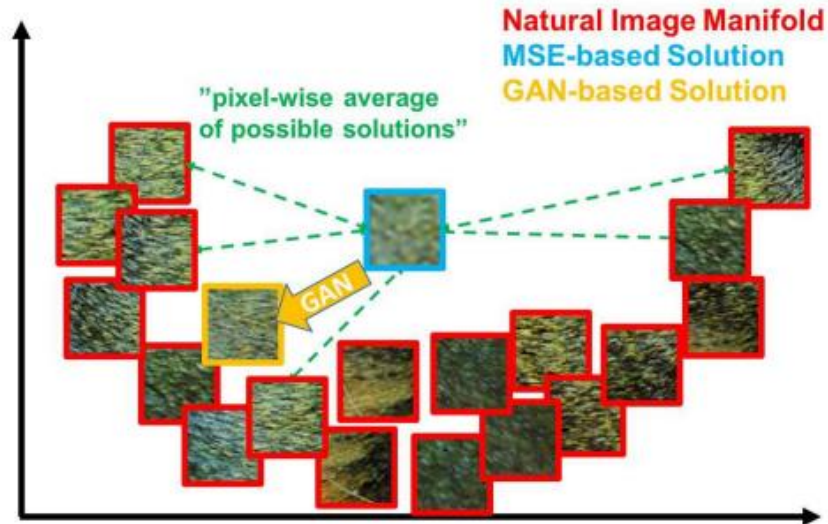


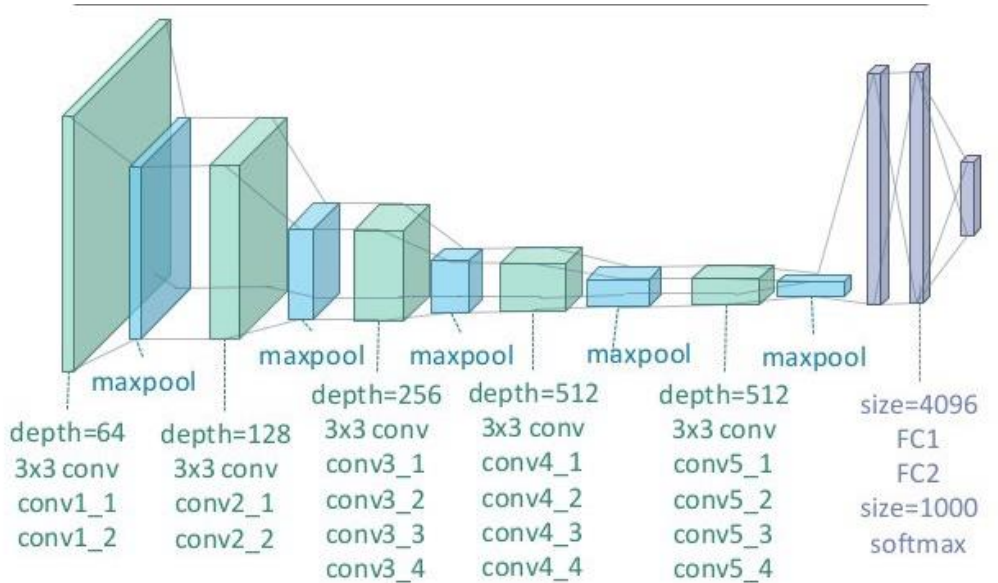
Figure 3: Illustration of patches from the natural image manifold (red) and super-resolved patches obtained with MSE (blue) and GAN (orange). The MSE-based solution appears overly smooth due to the pixel-wise average of possible solutions in the pixel space, while GAN drives the reconstruction towards the natural image manifold producing perceptually more convincing solutions.

MSE 기반의 솔루션은 ‘안전’하지만, 항상 무난하게 좋은 Blurry한 솔루션이다.

GAN 기반의 솔루션은 여러 가능성 중 더 ‘자연스러운’ 가능성을 선택한다.

VGG Loss

$$l_{VGG/i,j}^{SR} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y})^2 \quad (5)$$



LR과 HR을 직접 비교하지 않고, VGG19 feature를 추출하여 MSE로 비교한 것을 VGG loss라 한다.
화소 단위로 비교하지 않고, Perceptual한 단위로 비교하는 결과를 가져온다.

Loss Comparison

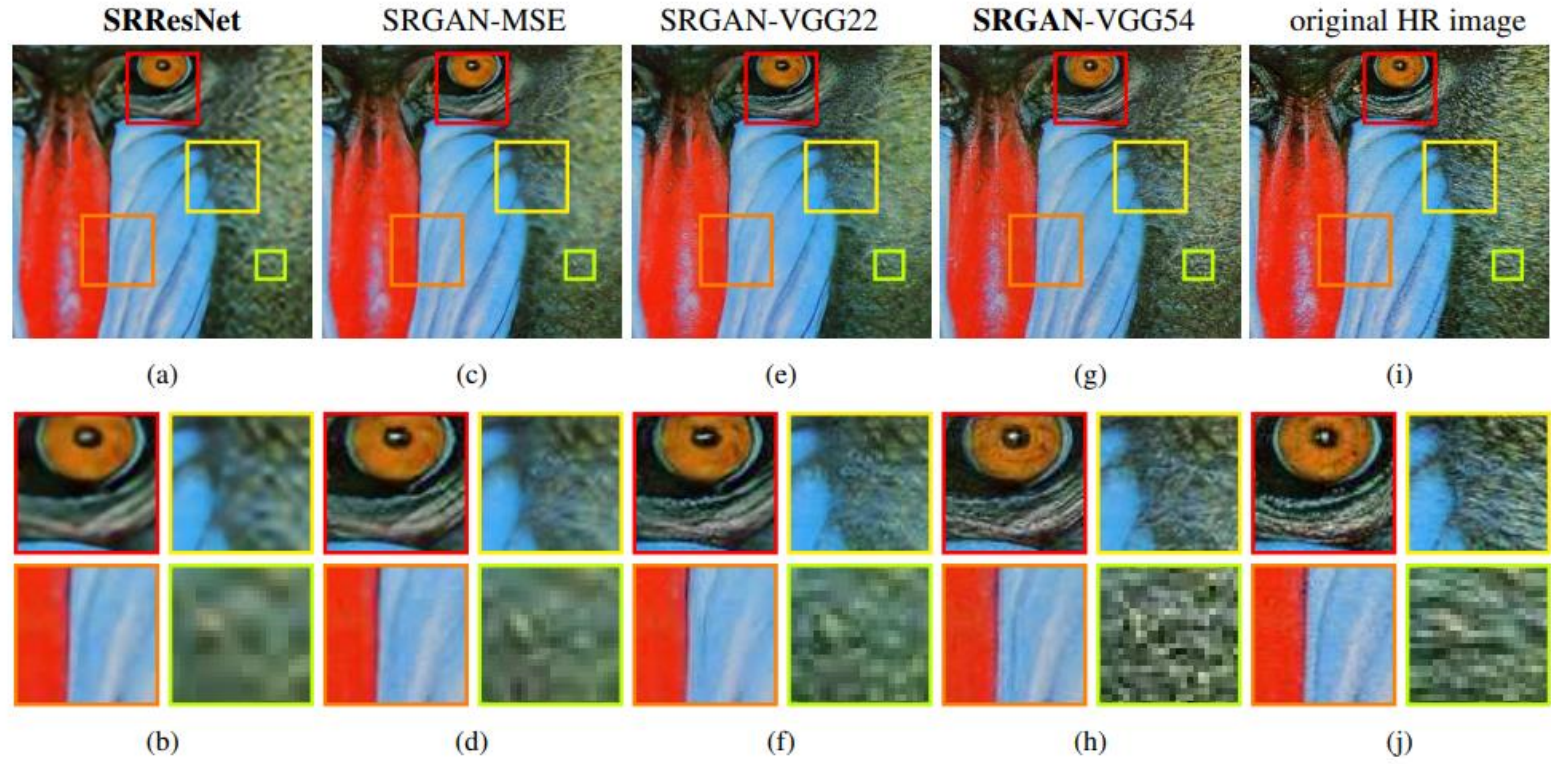


Figure 6: **SRResNet** (left: a,b), **SRGAN-MSE** (middle left: c,d), **SRGAN-VGG2.2** (middle: e,f) and **SRGAN-VGG54** (middle right: g,h) reconstruction results and corresponding reference HR image (right: i,j). [4× upscaling]

네트워크 구조만 개선한 SRResNet은 평탄한 영역에서는 성능이 좋으나, MSE의 한계가 나타난다.
SRGAN, VGG를 쓰면서 점차 개선되는 것이 보인다.

Insights

Table 1: Performance of different loss functions for SR-ResNet and the adversarial networks on Set5 and Set14 benchmark data. MOS score significantly higher ($p < 0.05$) than with other losses in that category*. [4× upscaling]

	SRResNet-		SRGAN-		
	MSE	VGG22	MSE	VGG22	VGG54
Set5					
PSNR	32.05	30.51	30.64	29.84	29.40
SSIM	0.9019	0.8803	0.8701	0.8468	0.8472
MOS	3.37	3.46	3.77	3.78	3.58
Set14					
PSNR	28.49	27.19	26.92	26.44	26.02
SSIM	0.8184	0.7807	0.7611	0.7518	0.7397
MOS	2.98	3.15*	3.43	3.57	3.72*

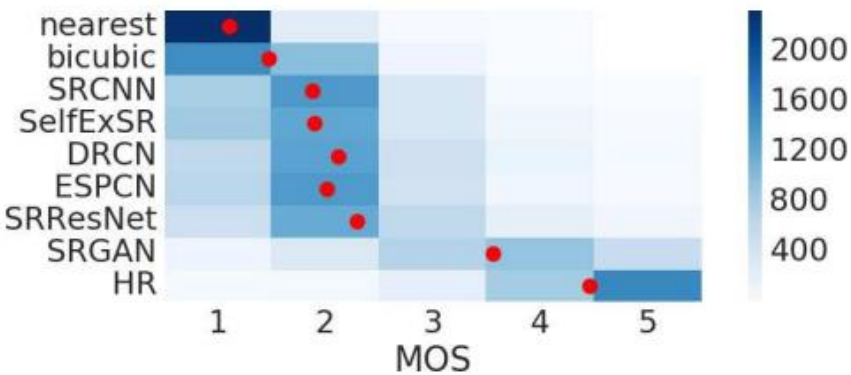


Figure 5: Color-coded distribution of MOS scores on **BSD100**. For each method 2600 samples (100 images × 26 raters) were assessed. Mean shown as red marker, where the bins are centered around value i . [4× upscaling]

MOS(Mean Opinion Score)를 도입하여 시각적으로 훌륭하다는 점을 강조하였다.
 학계에 새로운 시각을 던지려면, 그것을 수치적으로 잘 표현하는 것도 무척 중요하다.