

Abstract

Introduction

- The goal of **SR**(Super Resolution) is to enhance a **LR**(Low Resolution) image to a **HR**(High Resolution) image.
- The domain of SR research can be divided into 3 main areas: **SISR**(Single Image SR), **MISR**(Multi Image SR) and **VSR**(Video SR).
- Consider an LR video which consists of a sequence of frames: $LR_{t-n}, \dots, LR_t, \dots, LR_{t+n}$, where we super-resolve a target frame LR_t .
 - SISR: Only use LR_t , so obviously it fails to utilize temporal information.
 - MISR: Align all the neighboring frames and fuses them to utilize the missing details observed only in one or some of the frames.
 - VSR: Almost similar to **MISR**, but the alignment progress is done with concern for temporal smoothness, which is not concerned in **MISR**.
- **IQA**(Image Quality Assessment): **PSNR**(Peak Signal to Noise Ratio) and **SSIM**(Structural Similarity).

- PSNR:

$$MSE = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W (X(i, j) - Y(i, j))^2$$

$$PSNR = 10 \lg\left(\frac{(2^n - 1)^2}{MSE}\right)$$

- Larger is better, the unit is decible(db).
- n is number of bits per pixel.

- SSIM:

$$\mu_X = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X(i, j), \sigma_X^2 = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W (X(i, j) - \mu_X)^2$$

$$\sigma_{XY} = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W ((X(i, j) - \mu_X)(Y(i, j) - \mu_Y))$$

$$l(X, Y) = \frac{2\mu_X\mu_Y + C_1}{\mu_X^2 + \mu_Y^2 + C_1}, c(X, Y) = \frac{2\sigma_X\sigma_Y + C_2}{\sigma_X^2 + \sigma_Y^2 + C_2}, s(X, Y) = \frac{\sigma_{XY} + C_3}{\sigma_X\sigma_Y + C_3}$$

$$SSIM(X, Y) = l(X, Y) \cdot c(X, Y) \cdot s(X, Y)$$

- Larger is better.
- **L**ight, **C**ontrast and **S**tructure.
- To avoid the case where the denominator is 0, normally we use $C_1 = (K_1 \cdot L)^2, C_2 = (K_2 \cdot L)^2, C_3 = C_2/2$, and $K_1 = 0.01, K_2 = 0.03, L = 255$.

- In most cases, **CNNs** are well qualified for the job, but once the upscaling factors are large enough, **GAN** approach is nearly indispensable to render the "naturalness".
- Deep VSR can be divided into 5 types based on the approach to preserving temporal information.
 - Temporal Concatenation: **DUF**
 - Temporal Aggregation: **Robust Video Super-Resolution with Learned Temporal Dynamics**

- RNNs: Detail-revealing deep video super-resolution, Bidirectional recurrent convolutional networks for multi-frame super-resolution
 - many-to-one
 - many-to-many
- Optical Flow: Framerecurrent video super-resolution
 - warp
 - video super-resolution with convolutional neural networks
 - Total variation regularization of local-global optical flow
 - VESPCN: replace the optical flow model with a trainable motion compensation network.
- Pre-training then Fine-tuning
 - VESPCN
 - Detail-revealing deep video super-resolution
 - Robust Video Super-Resolution with Learned Temporal Dynamics
- 2D-conv & 3D-conv: <https://www.zhihu.com/question/266352189>
- Deep SR can be divided into 4 types of upsampling.
 - Predefined upsampling: SRCNN
 - LR-(interpolation)-MR-(CNNs)-HR
 - Single upsampling: FSRCNN, ESPCN, EDSR
 - Lengthy training time.
 - Progressive upsampling: LapSRN
 - Iterative up and downsampling: DBPN, RBPN

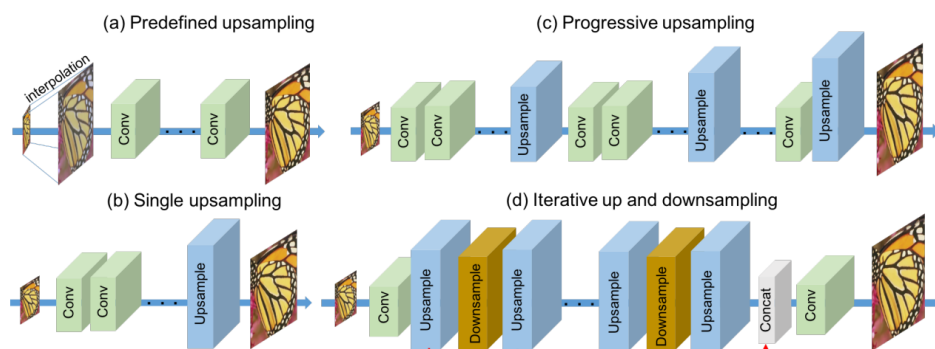


Figure 2. Comparisons of Deep Network SR. (a) Predefined upsampling (e.g., SRCNN [6], VDSR [22], DRRN [43]) commonly uses the conventional interpolation, such as Bicubic, to upscale LR input images before entering the network. (b) Single upsampling (e.g., FSRCNN [7], ESPCN [38]) propagates the LR features, then construct the SR image at the last step. (c) Progressive upsampling uses a Laplacian pyramid network which gradually predicts SR images [25]. (d) Iterative up and downsampling approach is proposed by our DBPN which exploit the mutually connected up- (blue box) and down-sampling (gold box) stages to obtain numerous HR features in different depths.

Related Work

timeline

- SRCNN[2014], VDSR[2016]
- DUF[2018], TDAN[2018], EDVR[2019]
- ESPCN(calc in Ir space)[2016], VESPCN(video espcn)[2017]
- DBPN[2018], RBPN[2019]
- SRGAN[2017]
- iSeeBetter(RBPN+SRGAN)[2020]

NTIRE

- 2017: EDSR
- 2018: RBPN

results

- SRCNN

Video Super-Resolution	Ultra Video Group HD - 4x upscaling	SRCNN	Average PSNR	37.52	# 2		Compare
Image Super-Resolution	Urban100 - 4x upscaling	SRCNN	PSNR	24.52	# 35		Compare
			SSIM	0.7221	# 31		Compare
Video Super-Resolution	Vid4 - 4x upscaling	SRCNN	PSNR	24.68	# 14		Compare
			SSIM	0.7158	# 13		Compare
			MOVIE	6.90	# 4		Compare
Video Super-Resolution	Xiph HD - 4x upscaling	SRCNN	Average PSNR	31.47	# 2		Compare

- EDVR

Results from the Paper


Edit

<div> Ranked #1 on Deblurring on REDS<div>→ Get a GitHub badge</div></div>							
TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	RESULT	BENCHMARK
Deblurring	REDS	EDVR_Deblur	Average PSNR	34.80	# 1		Compare
Video Super-Resolution	Vid4 - 4x upscaling	EDVR	PSNR	27.35	# 4		Compare
			SSIM	0.8264	# 3		Compare

- ESPCN

Video Super-Resolution	Ultra Video Group HD - 4x upscaling	ESPCN	Average PSNR	37.91	# 1		Compare
Video Super-Resolution	Ultra Video Group HD - 4x upscaling	bicubic	Average PSNR	36.20	# 3		Compare
Video Super-Resolution	Vid4 - 4x upscaling	ESPCN	PSNR	25.06	# 13		Compare
			SSIM	0.7394	# 11		Compare
			MOVIE	6.54	# 3		Compare
Video Super-Resolution	Xiph HD - 4x upscaling	bicubic	Average PSNR	30.30	# 3		Compare
Video Super-Resolution	Xiph HD - 4x upscaling	ESPCN	Average PSNR	31.67	# 1		Compare

- VESPCN



Ranked #10 on [Video Super-Resolution on Vid4 - 4x upscaling](#)
[→ Get a GitHub badge](#)


TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	RESULT	BENCHMARK
Video Super-Resolution	Vid4 - 4x upscaling	VESPCN	PSNR	25.35	# 12		Compare
			SSIM	0.7557	# 10		Compare
			MOVIE	5.82	# 2		Compare
Video Super-Resolution	Vid4 - 4x upscaling	bicubic	PSNR	23.82	# 16		Compare
			SSIM	0.6548	# 15		Compare
			MOVIE	9.31	# 5		Compare

- DBPN

TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	RESULT	BENCHMARK
Image Super-Resolution	BSD100 - 4x upscaling	D-DBPN	PSNR	27.72	# 11		Compare
			SSIM	0.740	# 18		Compare
Image Super-Resolution	Manga109 - 4x upscaling	D-DBPN	SSIM	0.914	# 14		Compare
Image Super-Resolution	Set14 - 4x upscaling	D-DBPN	PSNR	28.82	# 11		Compare
			SSIM	0.786	# 19		Compare
Image Super-Resolution	Set5 - 4x upscaling	D-DBPN	PSNR	32.47	# 12		Compare
			SSIM	0.898	# 16		Compare
Image Super-Resolution	Urban100 - 4x upscaling	D-DBPN	SSIM	0.795	# 15		Compare
Video Super-Resolution	Vid4 - 4x upscaling	DBPN	PSNR	25.37	# 11		Compare
			SSIM	0.737	# 12		Compare


- RBPN


Results from the Paper  Edit


Ranked #6 on [Video Super-Resolution on Vid4 - 4x upscaling](#)
[→ Get a GitHub badge](#)

TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	RESULT	BENCHMARK
Video Super-Resolution	Vid4 - 4x upscaling	RBPN/6-PF	PSNR	27.12	# 6		Compare
			SSIM	0.818	# 6		Compare

- iSeeBetter

Results from the Paper  Edit


Ranked #1 on [Video Super-Resolution on Vimeo90k](#)
[→ Get a GitHub badge](#)

TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	BENCHMARK
Video Super-Resolution	Vid4 - 4x upscaling	iSeeBetter	PSNR	27.43	# 3	Compare
			SSIM	0.835	# 1	Compare
Video Super-Resolution	Vimeo90k	iSeeBetter	PSNR	40.17	# 1	Compare

