Multiple-image Super Resolution Using Both Reconstruction Optimization and Deep Neural network

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Which one do you prefer? Image Resolution



High – Resolution (HR):

Pixel density within an image is large, therefore offering more details.





Low – Resolution (LR):

Pixel density within an image is small, therefore offering less details.

How can we achieve high Resolution?

Increase the number of sensor elements per unit area

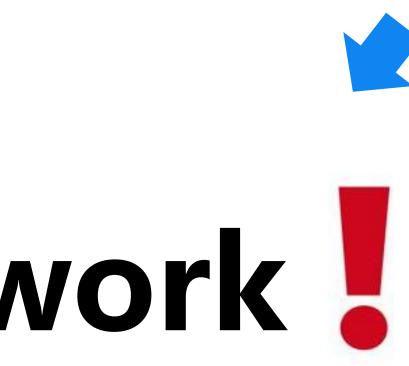
Increase the sensor density by **reducing** the sensor size



Do not work



Increase the hardware cost



Is there another way to achieve high resolution ?

Another way to address this problem is to accept the image degradations and use signal processing **technique** to process the captured images, to trade off **computational cost** with the **hardware cost**.

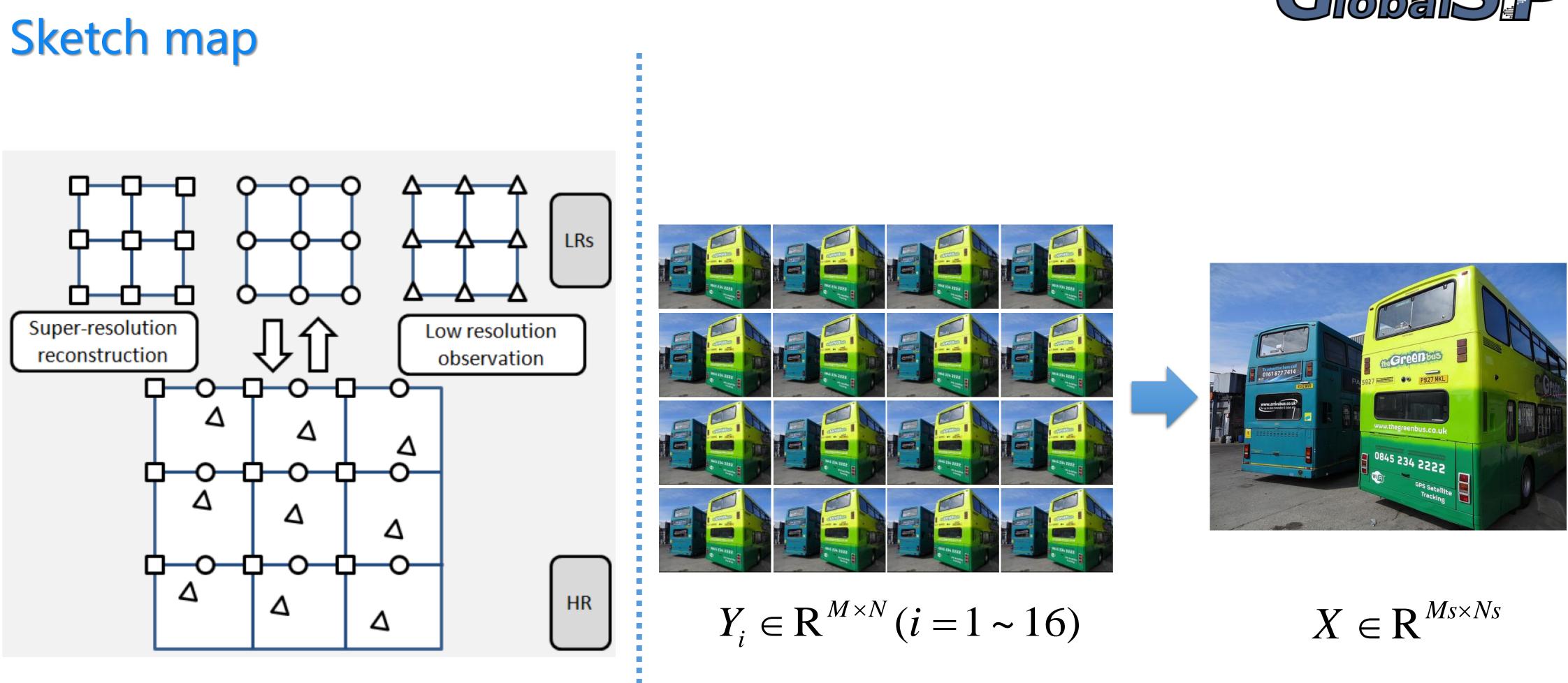
These techniques are specifically referred to as the **Super Resolution (SR) reconstruction.**



What is Super Resolution?

Generate a high-resolution (HR) image from a single or a set of low-resolution (LR) images.





★ schematic diagram ★





Development history

1990 - 2000

- [1] H. Stark, P. Oskoui, POCS
- [2] M. Irani, S. Peleg, IBP
- [3] B. C. Tom, A. K. Katsaggelos, ML
- [4] R. R. Schulz, R. L. Stevenson, MAP
- [5] M. Elad, A. Feuer, Adaptive Filtering

1964 - 1990

J.L.H arris and J.W.G oodman

proposed a single frame image spectrum extrapolation is the earliest superresolution image processing method. Subsequently, Tsai and Huang presented multiple frames super-resolution reconstruction method, and provided the reconstruction method based on frequency domain.

2008 - 2010Jianchao Yang. Sparse coding. [1] Image Super-Resolution via Sparse Representation, TIP 2010 [2] Image Super-Resolution as Sparse Representation of Raw Image Patches, CVPR

2008



Xiaoou Tang. Deep learning for SR

[1] Learning a Deep Convolutional Network for Image Super-Resolution, ECCV 2014

[2] Image Super-Resolution Using Deep Convolutional Networks, PAMI 2015

[3] Compression Artifacts Reduction by a Deep Convolutional Network, **ICCV 2015**

Li Xu. Change filter size.

[1] "Handling Motion Blur in Multi-Frame Super-Resolution" IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015. [2] "Deep Convolutional Neural Network for Image Deconvolution" Advances in Neural Information Processing Systems (NIPS), 2014.

2014 – now

Jianchao Yang. sparse-coding.

[1] Deep Networks for Image Super-Resolution With Sparse Prior. (ICCV), 2015 Li Fei-Fei. Real Time.

[1] Perceptual Losses for Real-Time Style Transfer and Super-Resolution. ECCV 2016 [2] Photo-Realistic Single Image Super-**Resolution Using a Generative Adversarial** Network. (CVPR), 2017

Classification

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Reconstruction-based

- Adding prior information.
- Register and reconstruct.
- Larger magnification factor or insufficient input images will bring a dramatically degradation of reconstruction performance.

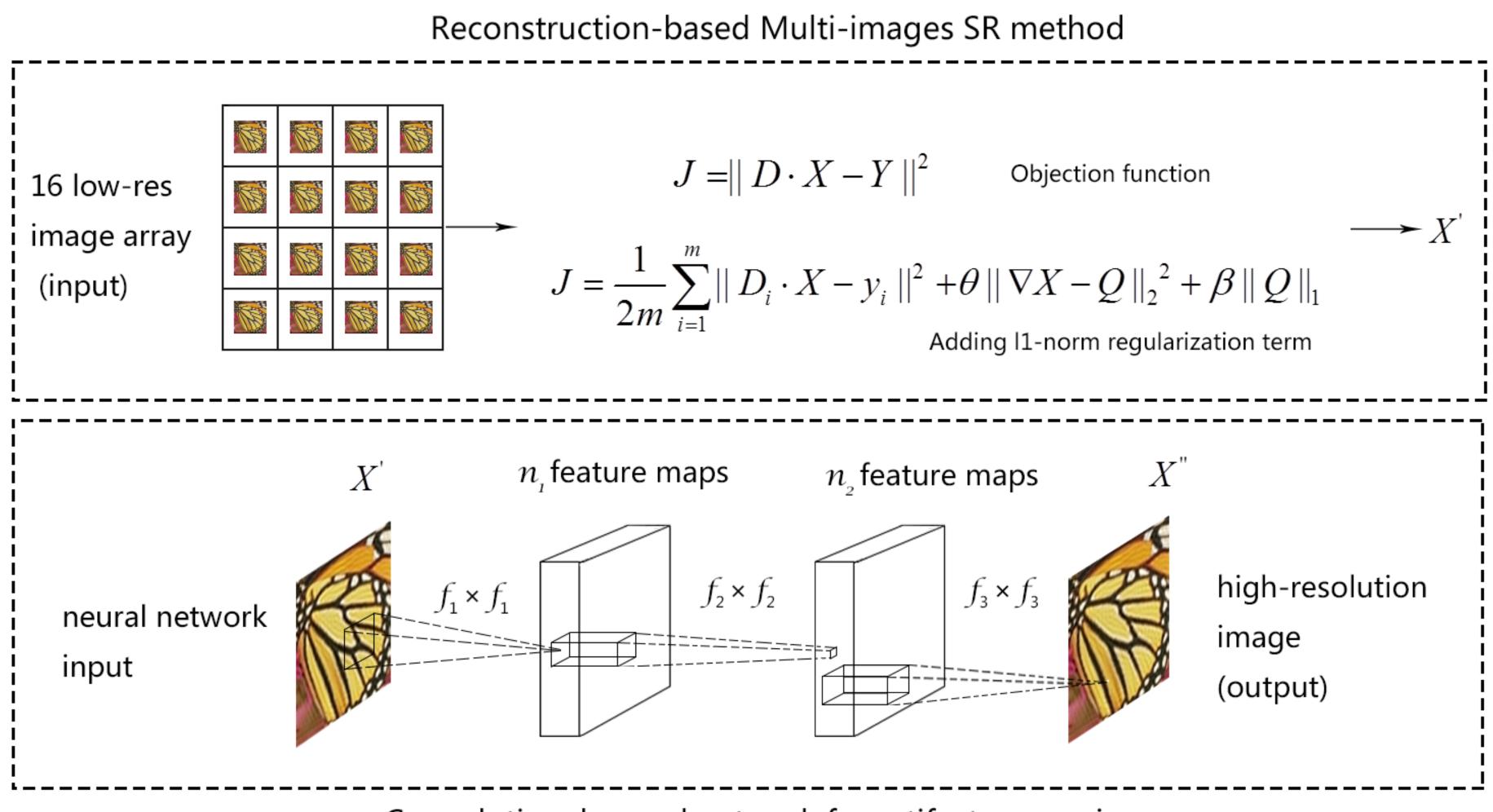


Example-based

- Sparse Coding
- Deep Neural Network.
- Need enormous databases of millions of high-resolution and low-resolution patch pairs, and are therefore computationally intensive.



Multiple-image Super Resolution



Convolutional neural network for artifacts removing





- High-resolution image. (ground truth image)
- Low-resolution images. (input images)
- Down sampling matrix
- Reconstructed high-resolution image. (output image of the reconstructionbased method)
- Reconstructed high-resolution image. (output image of the CNN)



$$X \in \mathbf{R}^{Ms \times Ns}$$

$$Y_i \in \mathbb{R}^{M \times N} (i = 1 \sim 16)$$

$$D_i \in \mathbb{R}^{MN \times MNs^2} (i = 1 \sim 16)$$

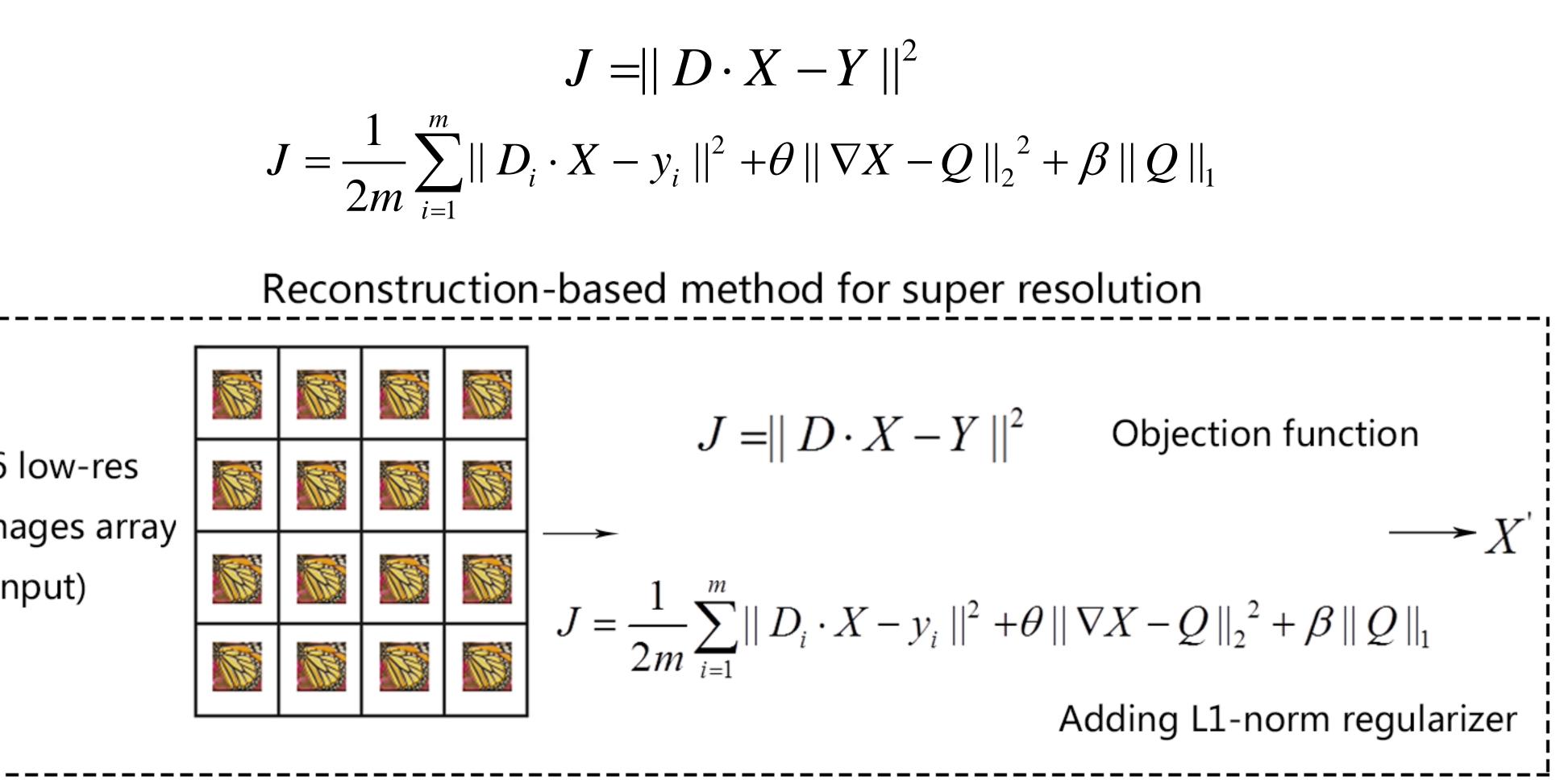
$$X' \in \mathbb{R}^{Ms \times Ns}$$

$$X'' \in \mathbf{R}^{Ms \times Ns}$$

Cost function

 $Y = D \cdot X$

$$J = || D \cdot U = \frac{1}{2m} \sum_{i=1}^{m} || D_i \cdot X - y_i ||^2$$



16 low-res images array (Input)



Output image



★ Groundtruth image

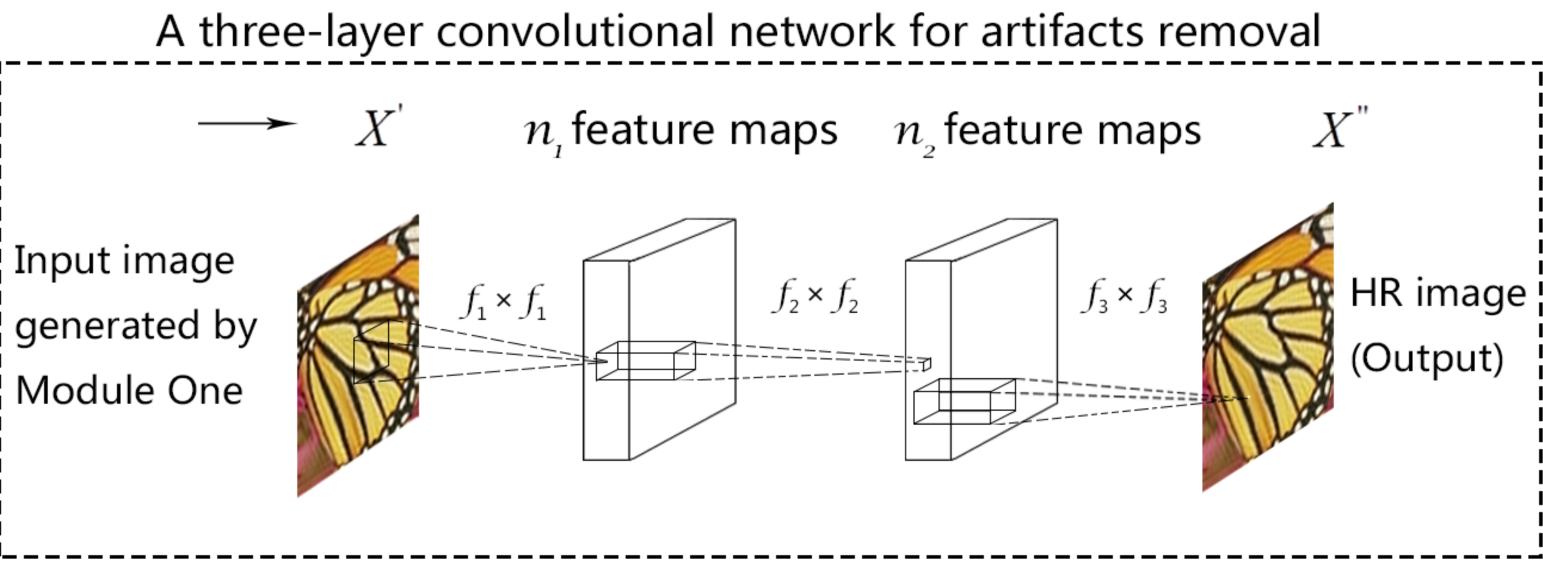
★ Bicubic image



★Reconstruction-based image

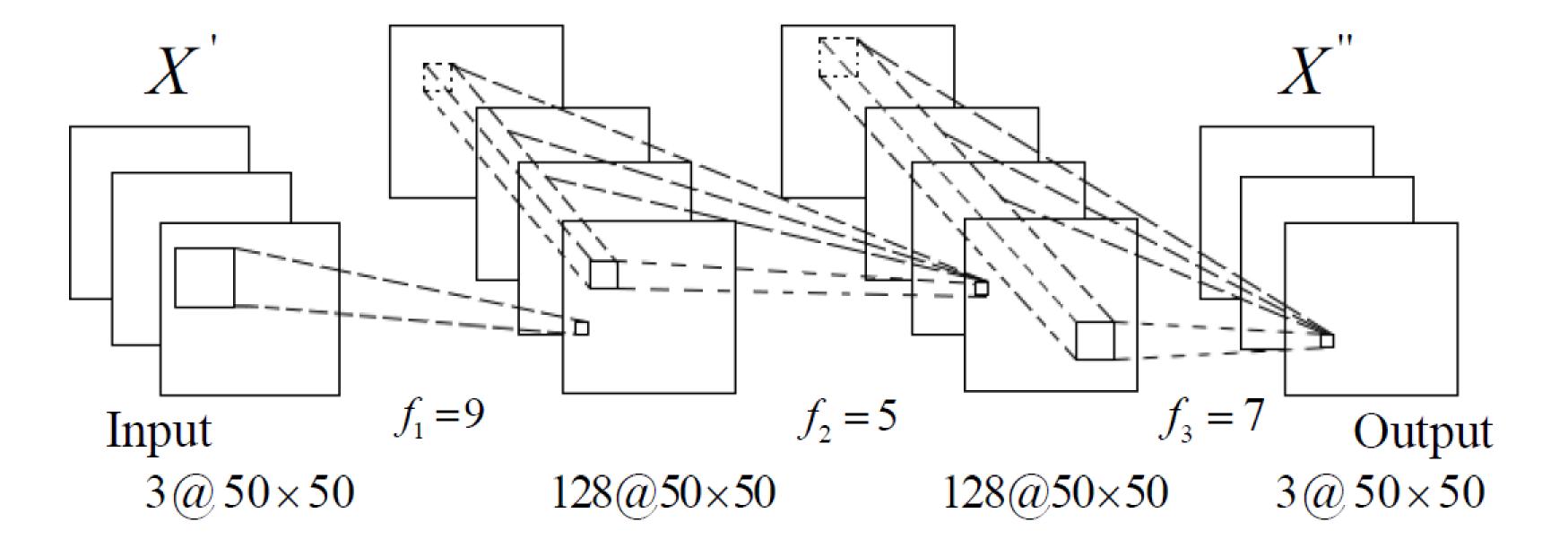
Remove artifacts







Artifacts removal



\star A three-layer Artifacts removal neural network \star



Output image

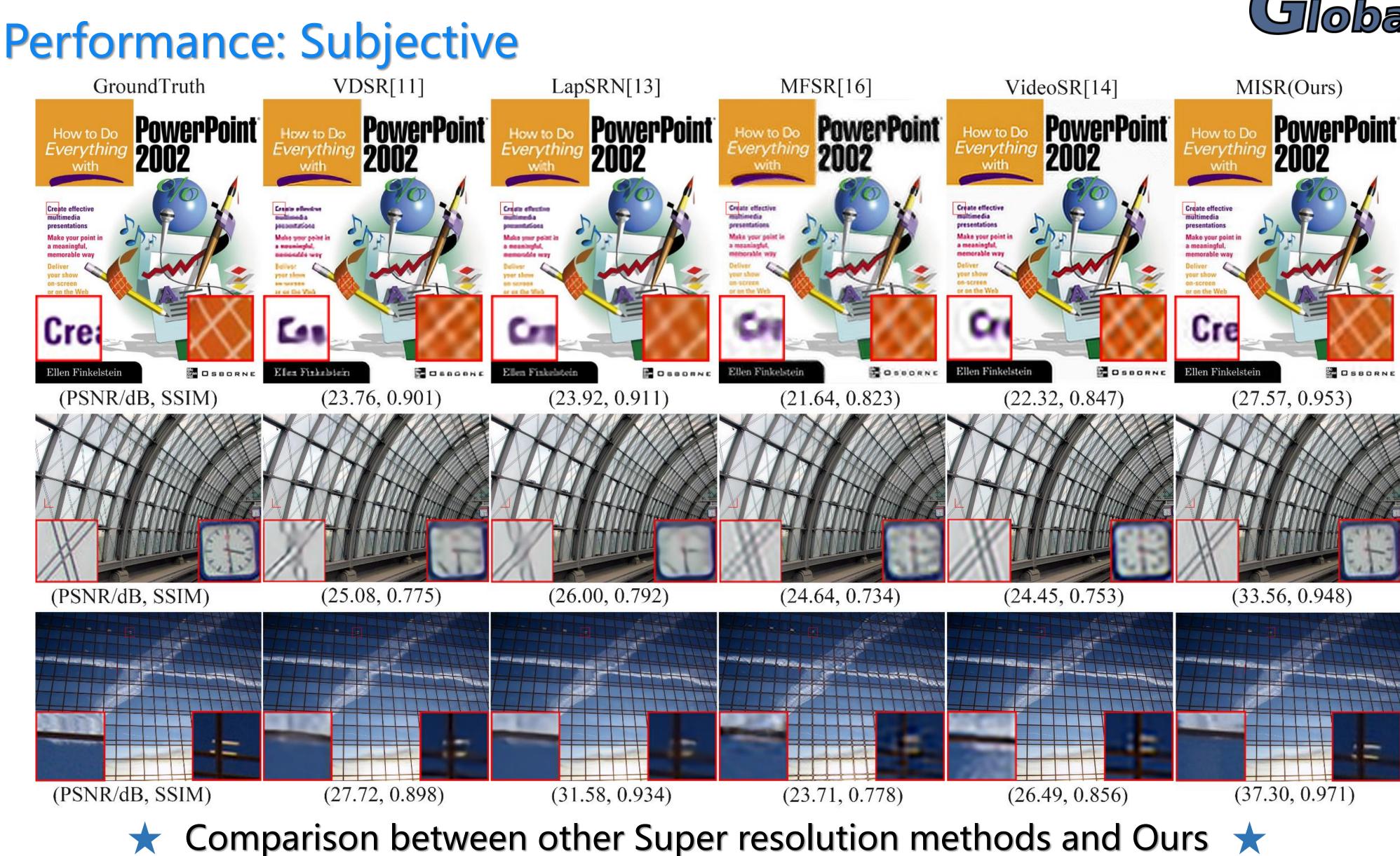


★ Groundtruth image

★ Reconstrue image

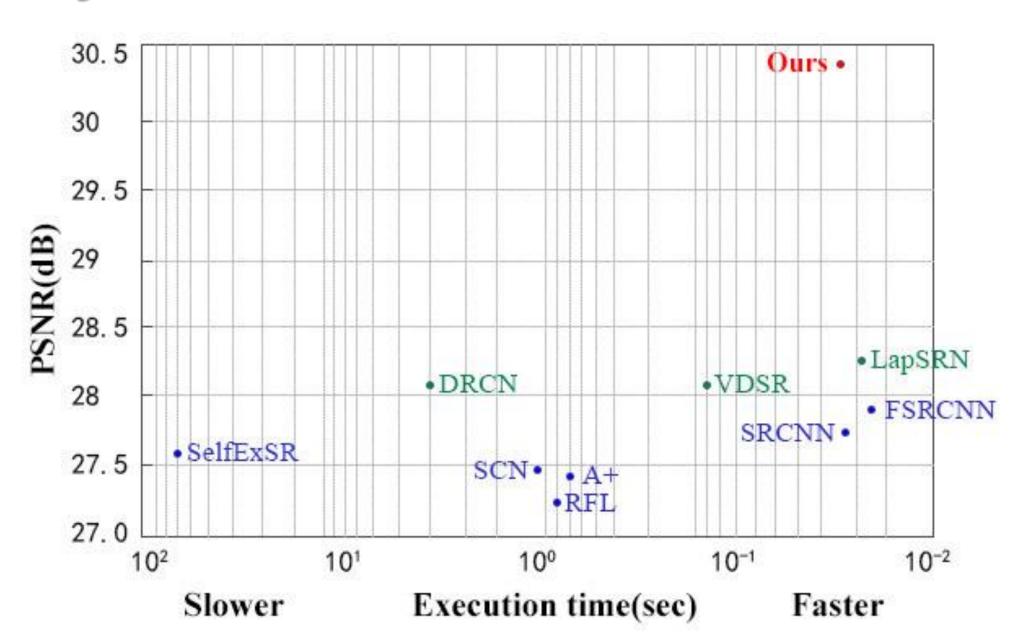


\star Reconstruction-based \star Re + SR image





Performance: Objective

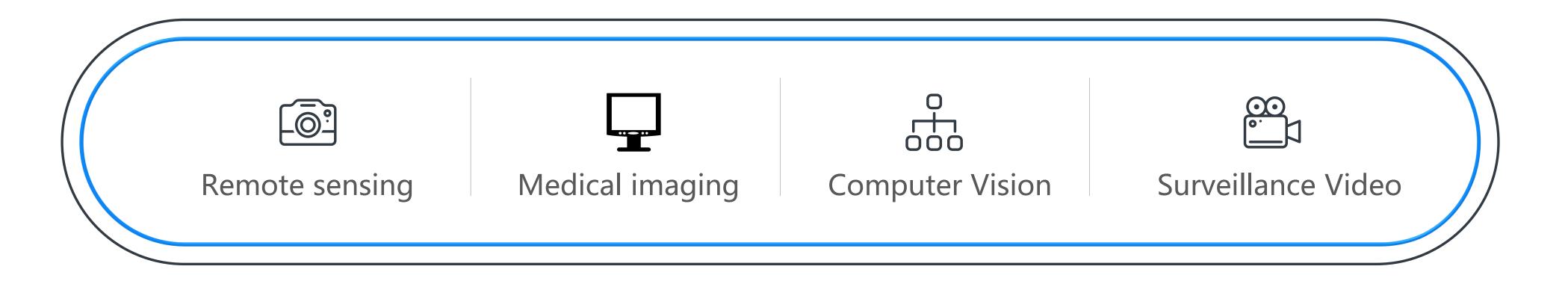


Dataset	Bicubic	VDSR[11]	LapSRN[13]	MFSR[16]	VideoSR[14]	MISR(Ours)
	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
Set5	28.423/0.810	30.289/0.871	31.522/0.885	27.627/0.811	28.450/0.845	38.200 /0.96 3
Set14	26.101/0.704	27.166/0.763	27.168/0.744	25.617/0.740	26.121/0.774	32.808 /0.910
Urban100	23.152/0.659	24.178/0.736	25.201/0.755	23.171/0.704	21.605/0.659	32.073 /0.939

Table 1. Average PSNR/SSIM for $4 \times$ scale factor on datasets Set5 [1], Set14 [22] and Urban100 [9]. The bold indicates the best performance. The proposed method outperforms the state-of-the-arts by a large margin.







- Medical imaging (e.g. CT, MRI (magnetic resonance imaging), etc..)
- Satellite imaging
- Video surveillance
- Converting NTSC (National Television Standards Committee) video content to high-definition television







THANKS

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