LATEST IMPROVEMENTS IN VIDEO SUPER-RESOLUTION

USING GENERATIVE ADVERSARIAL NETWORKS

Oles Petriv

Bigger and Bigger

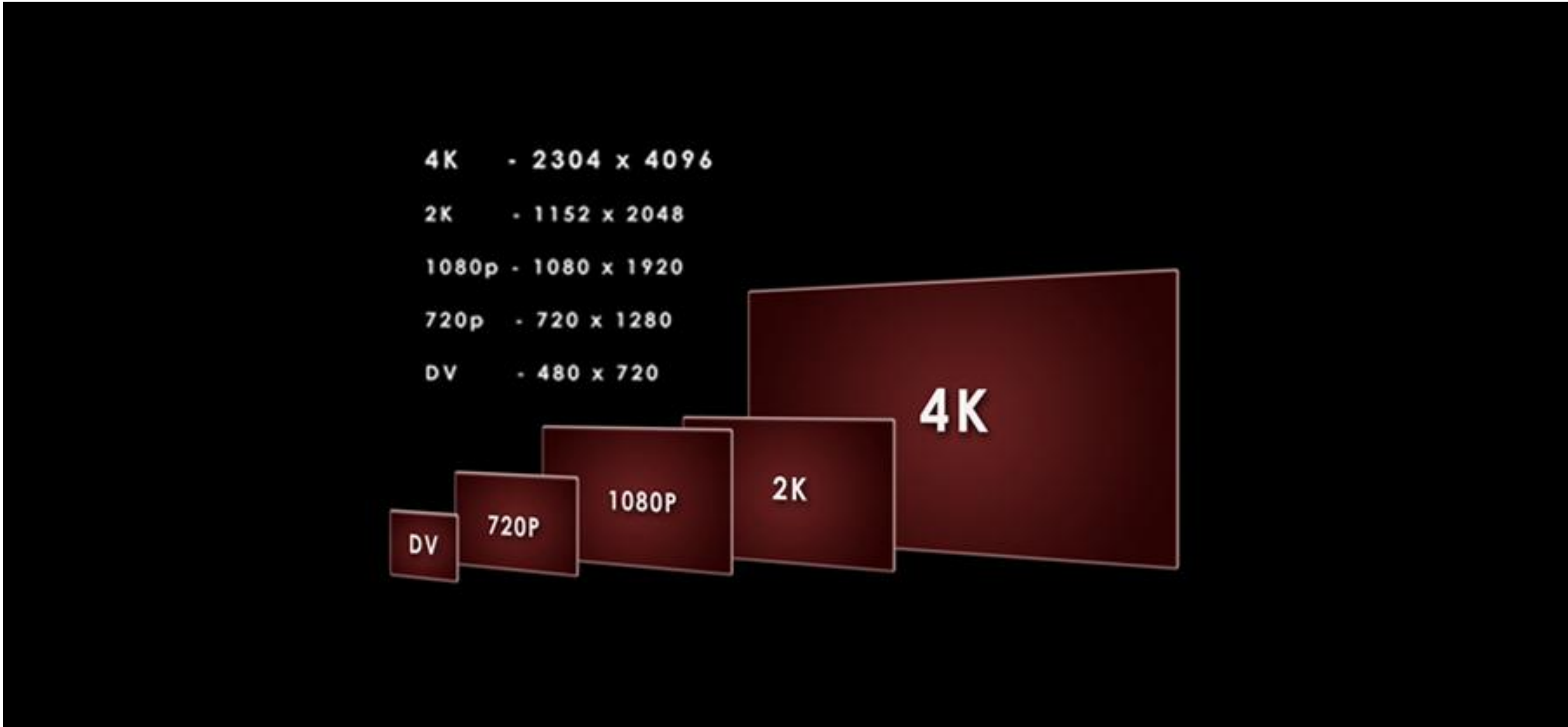


Image Interpolation

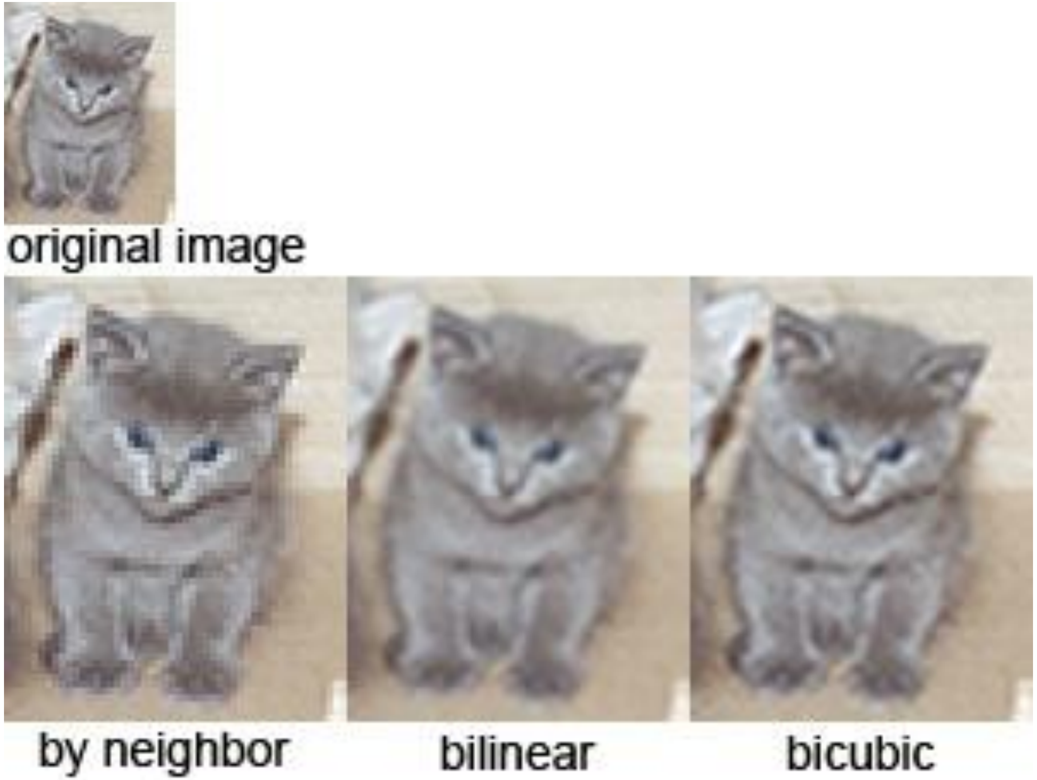


Image Interpolation

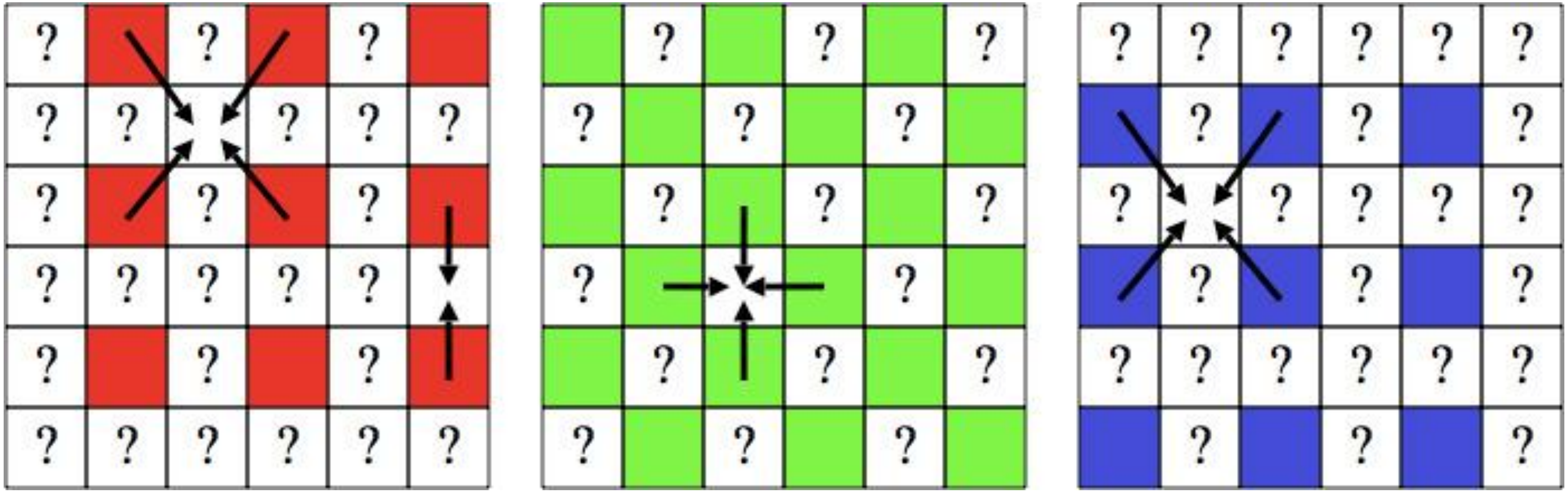
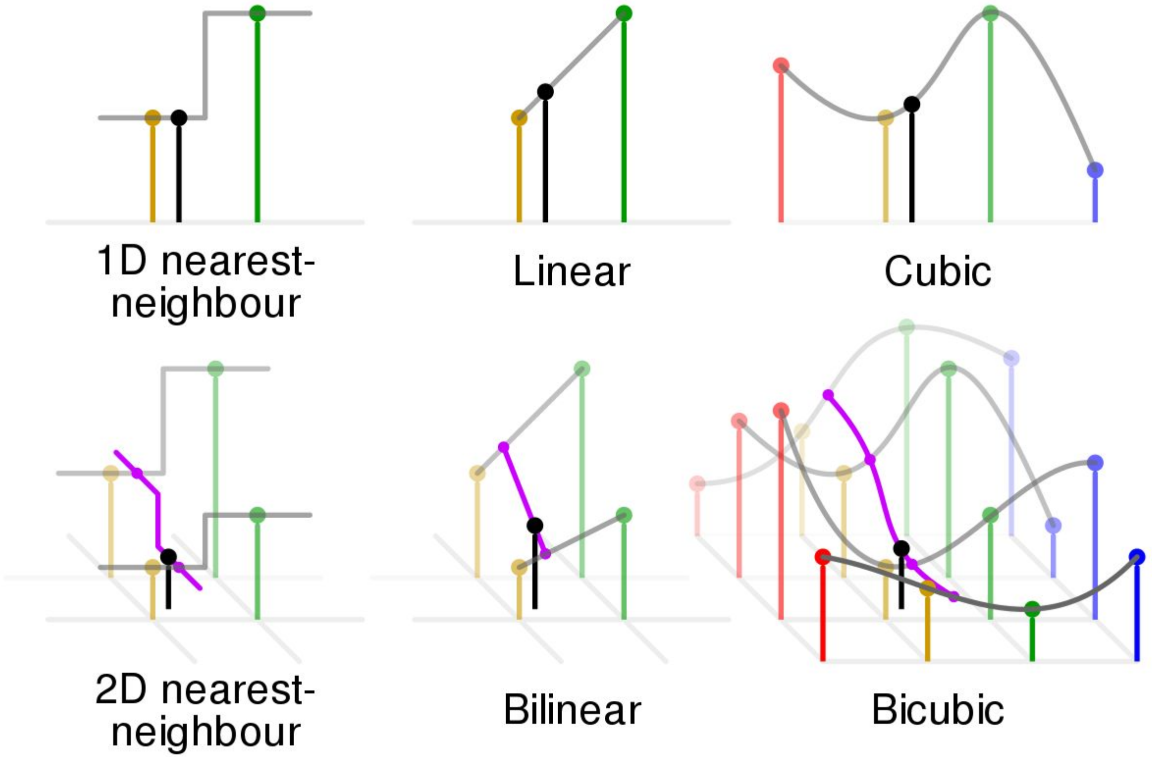
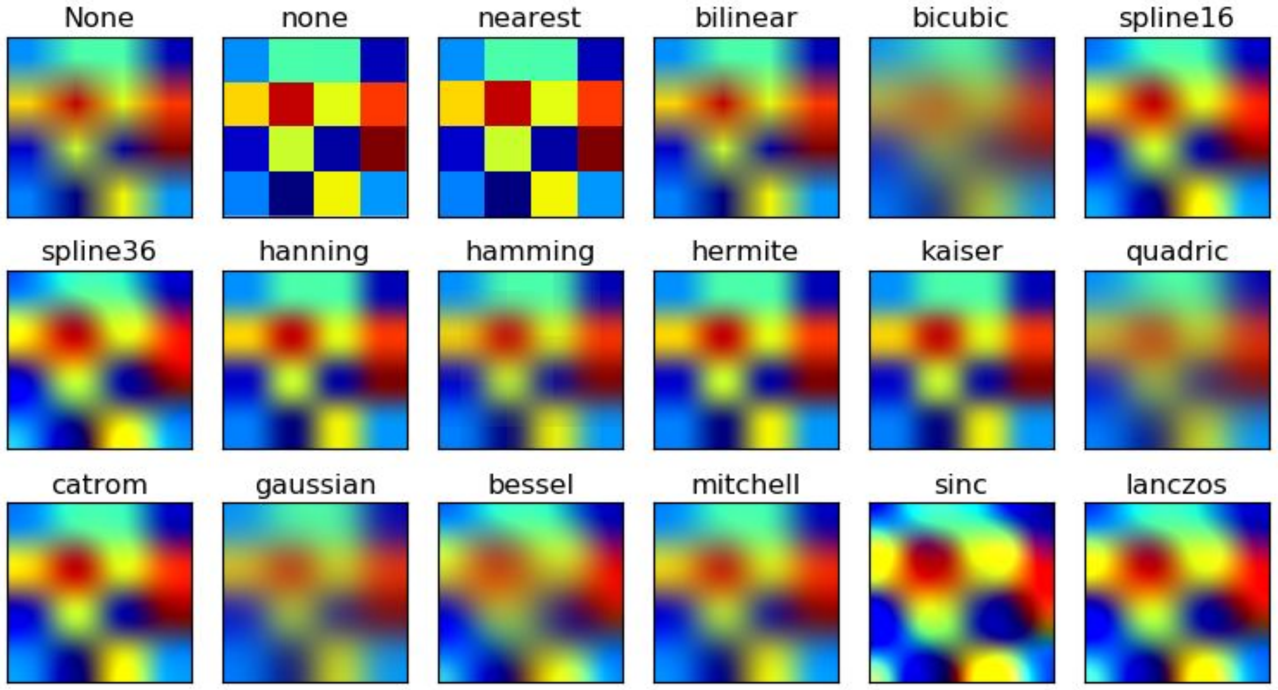


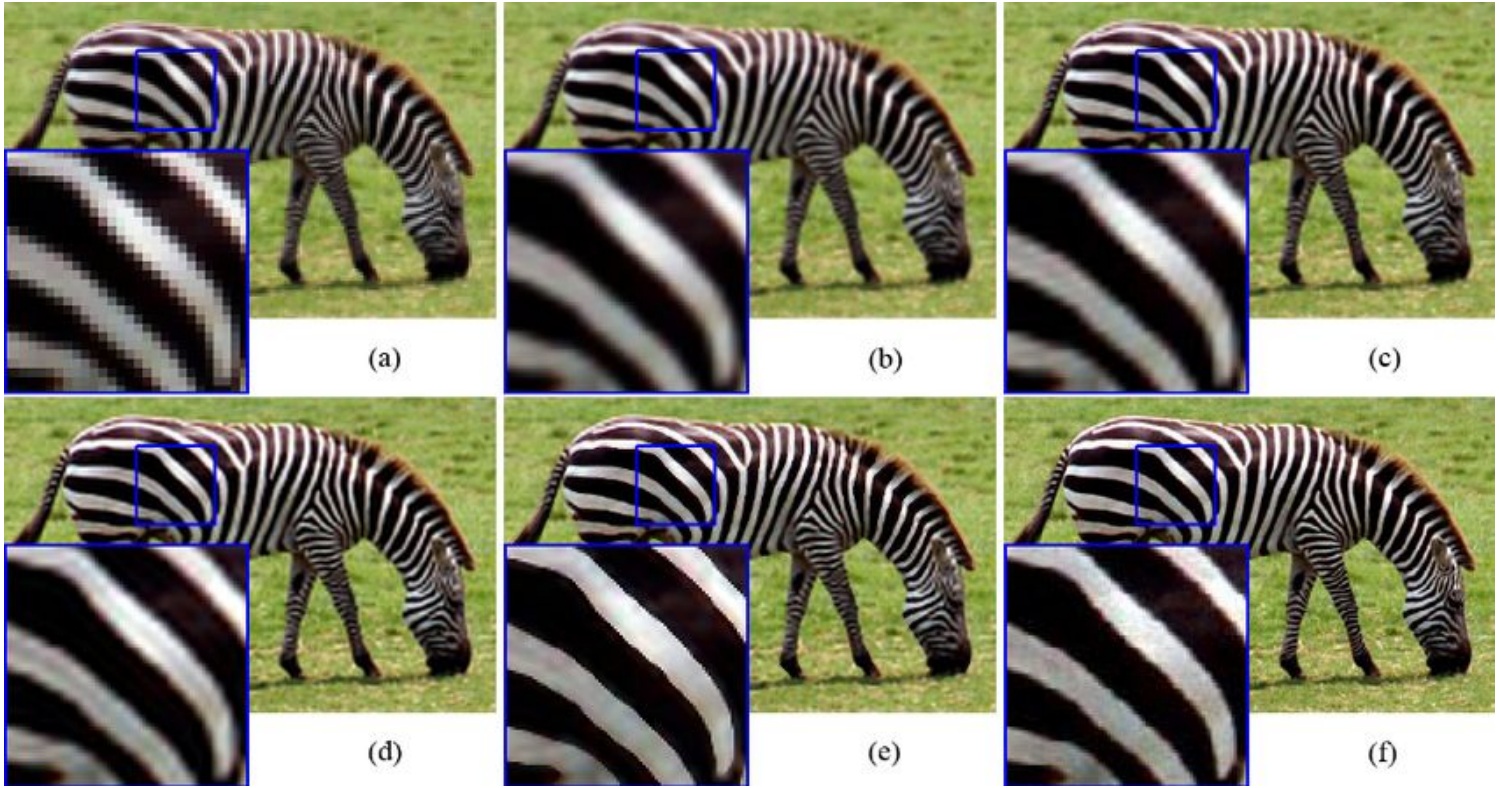
Image Interpolation



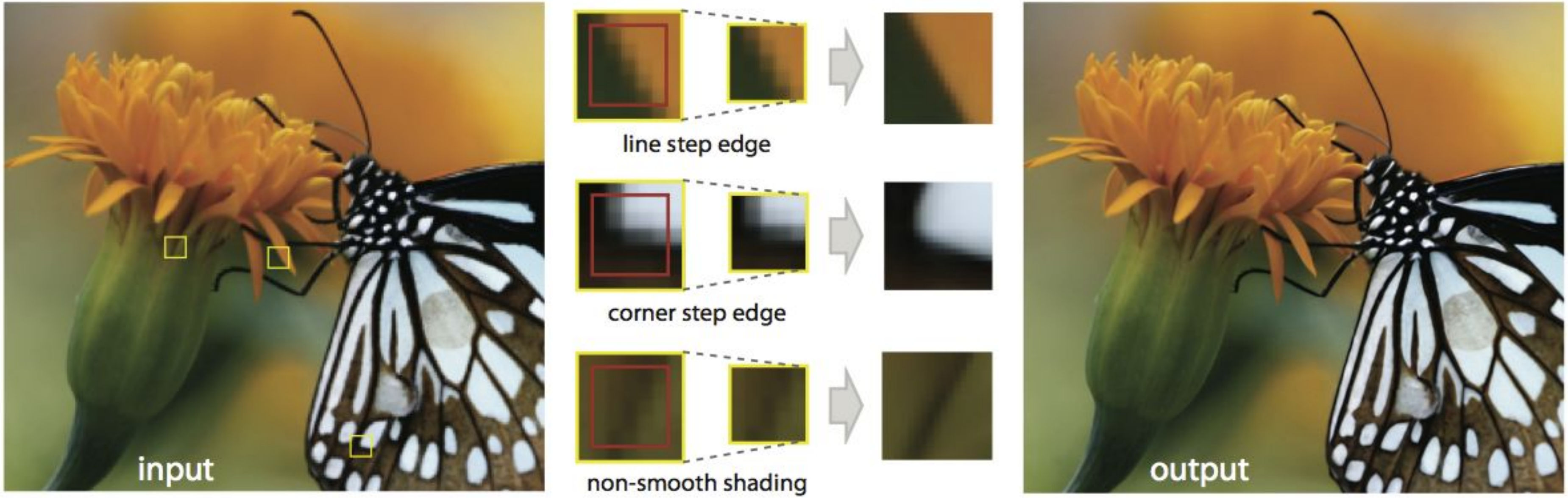
Interpolation artifacts



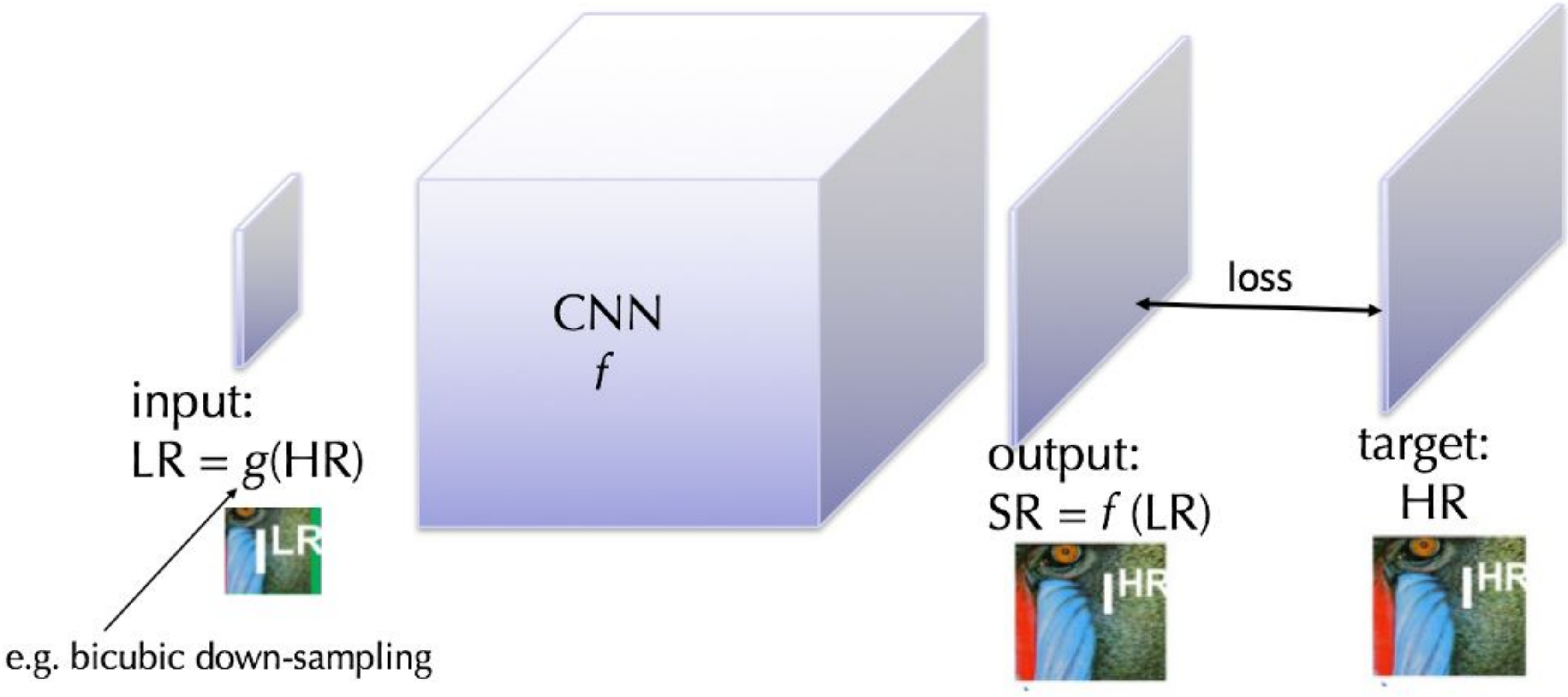
CNN methods:



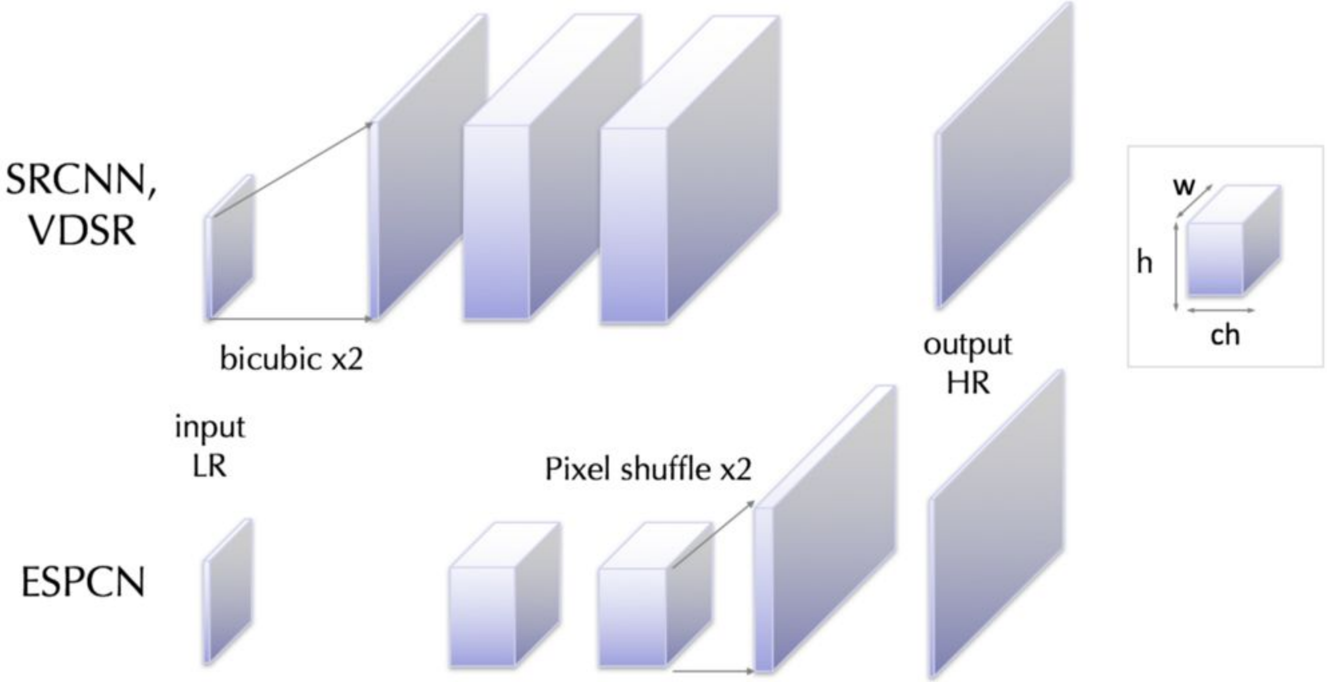
Local spatial pixel context:



Single Image SR:



Single Image SR:



SRCNN: http://personal.ie.cuhk.edu.hk/~ccloy/files/eccv_2014_deepresolution.pdf
ESPCN: https://arxiv.org/abs/1609.05158

Single Image SR:

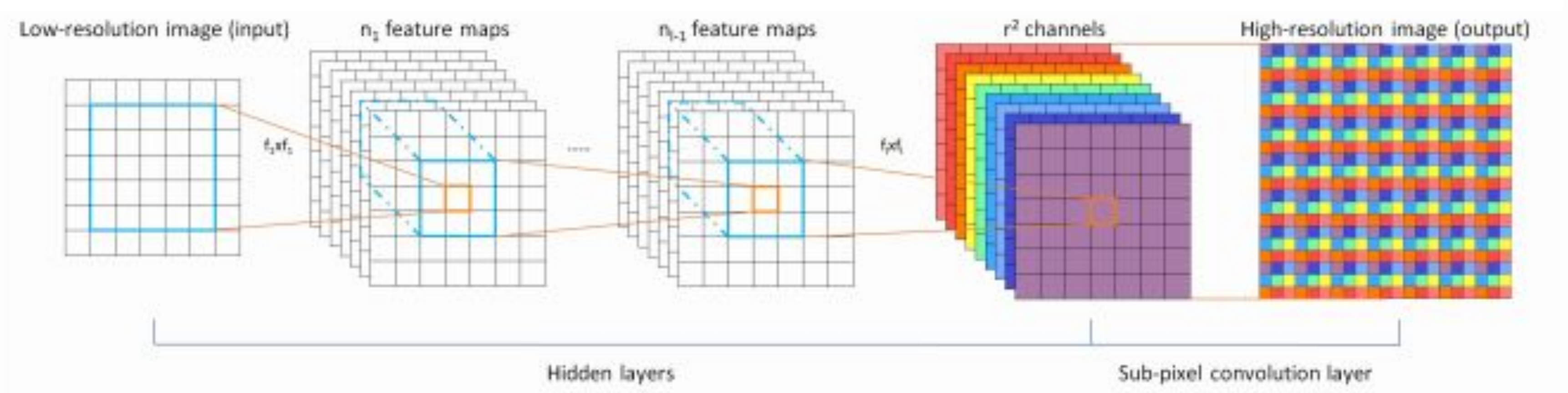
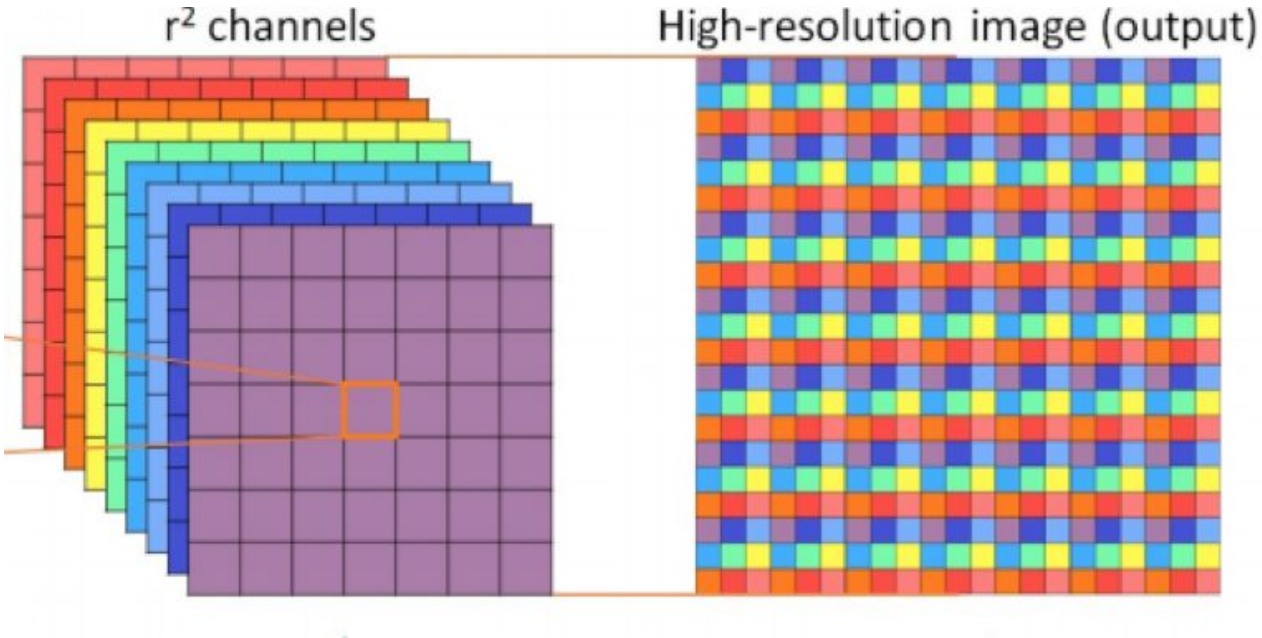


Figure 1. The proposed efficient sub-pixel convolutional neural network (ESPCN), with two convolution layers for feature maps extraction, and a sub-pixel convolution layer that aggregates the feature maps from LR space and builds the SR image in a single step.

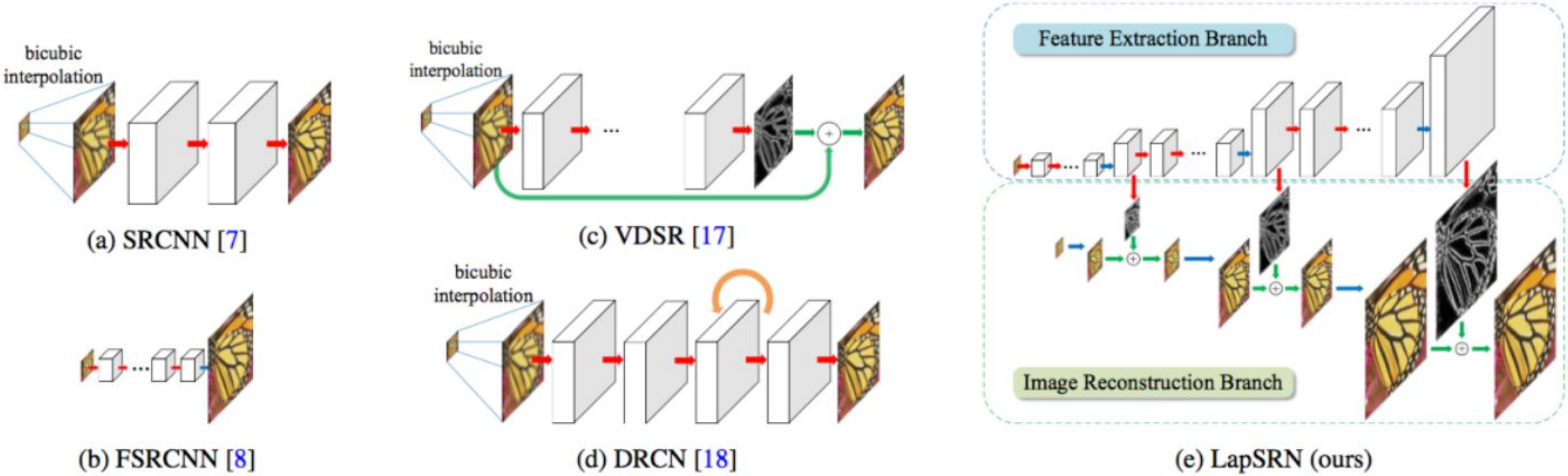
ESPCN: https://arxiv.org/abs/1609.05158

Single Image SR:



ESPCN: https://arxiv.org/abs/1609.05158

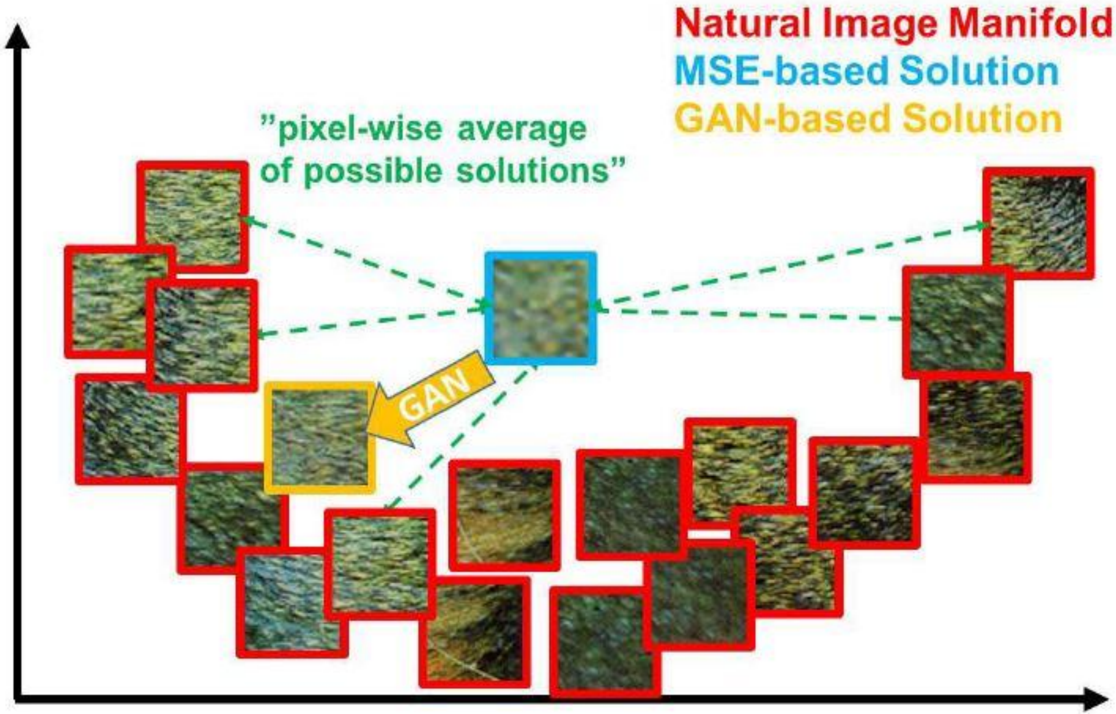
Single Image SR:



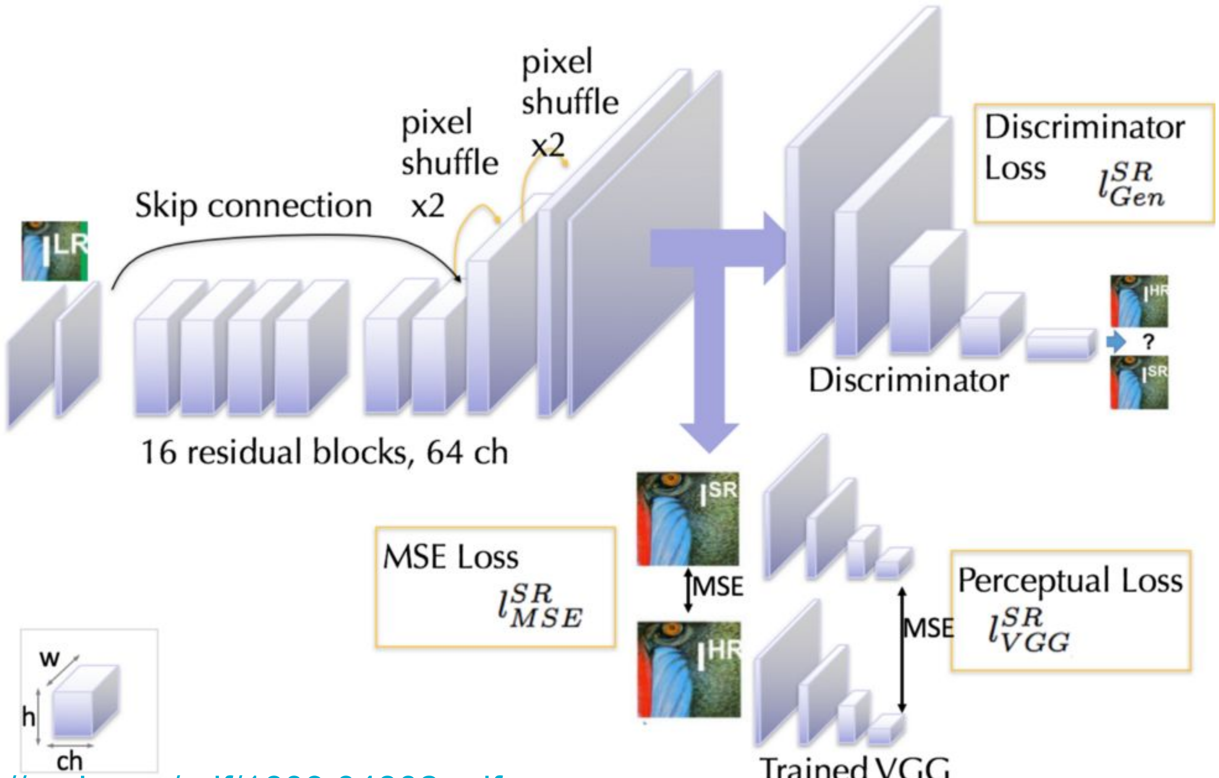
Various network architectures for solving SISR problem

Single Image SR:

One-to-many mapping:

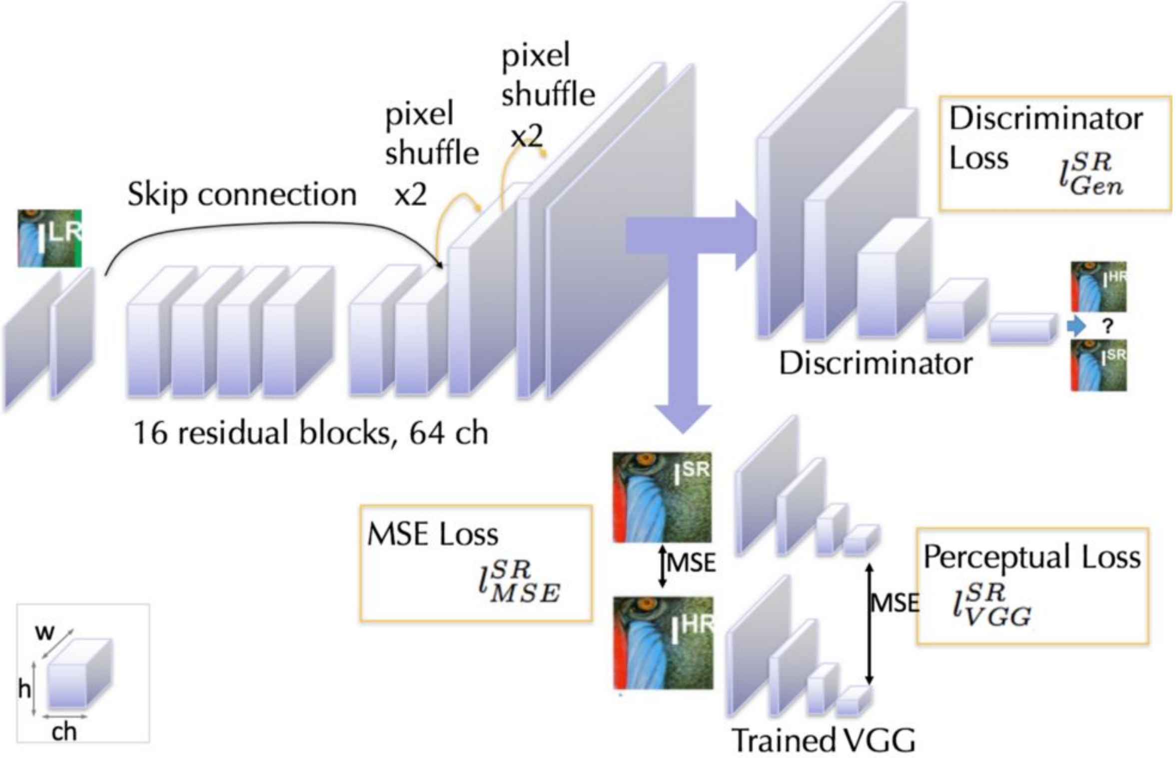


SRGAN: better perceptual quality



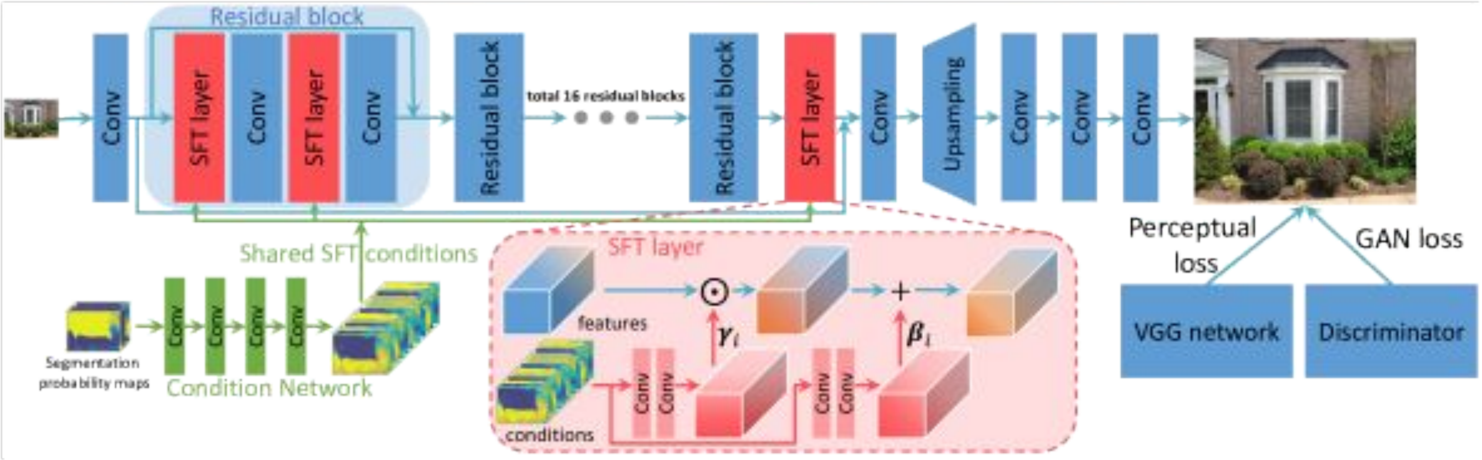
SRGAN: https://arxiv.org/pdf/1609.04802.pdf

SRGAN: better perceptual quality



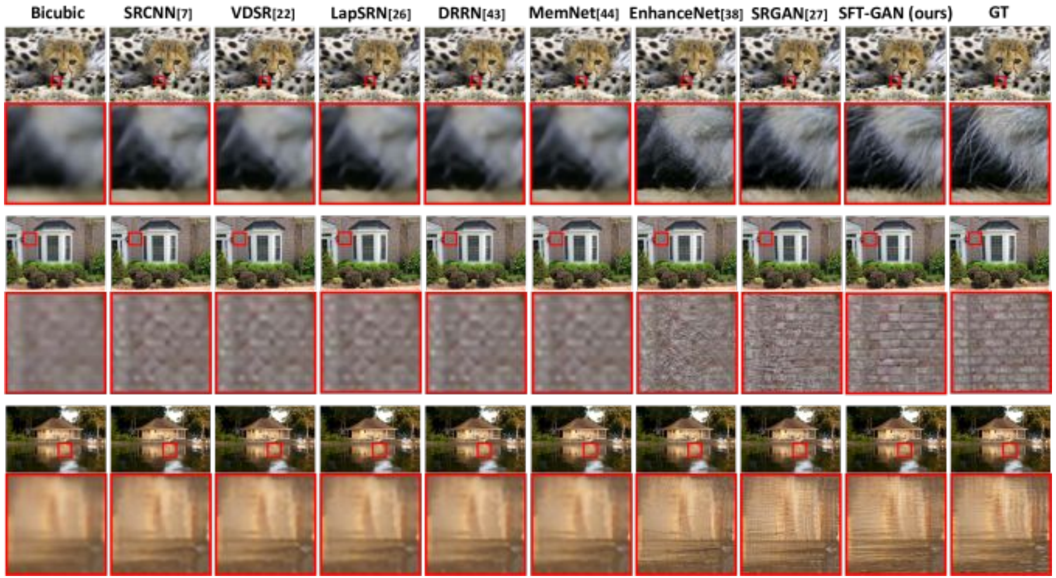
SRGAN: https://arxiv.org/pdf/1609.04802.pdf

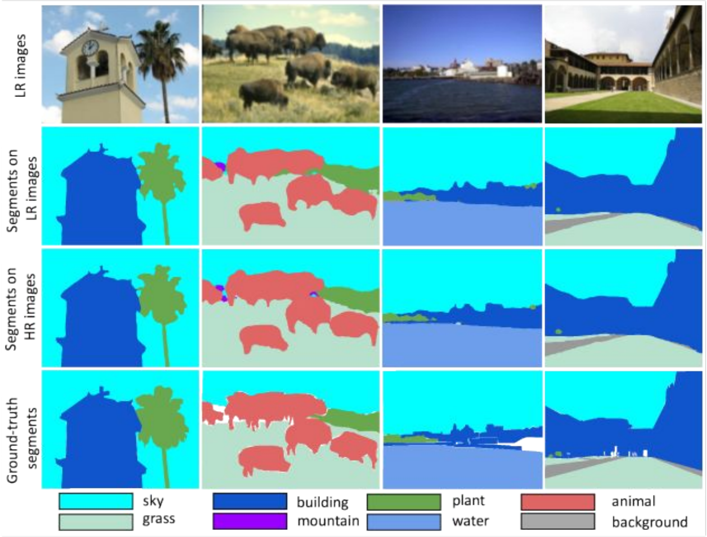
SFT-Net: better perceptual quality



SFTGAN https://github.com/xinntao/SFTGAN

SFT-Net: better perceptual quality





[SFTGAN](https://github.com/xinntao/SFTGAN) https://github.com/xinntao/SFTGAN

Our improvement: “soft” contextual pixel embeddings

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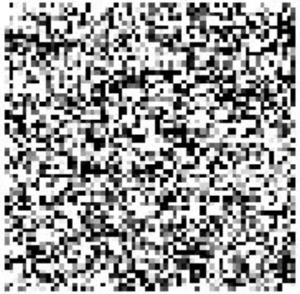
Quality Metrics: PSNR

PSNR = 40 dB

PSNR = 30 dB

PSNR = 20 dB

PSNR = 10 dB

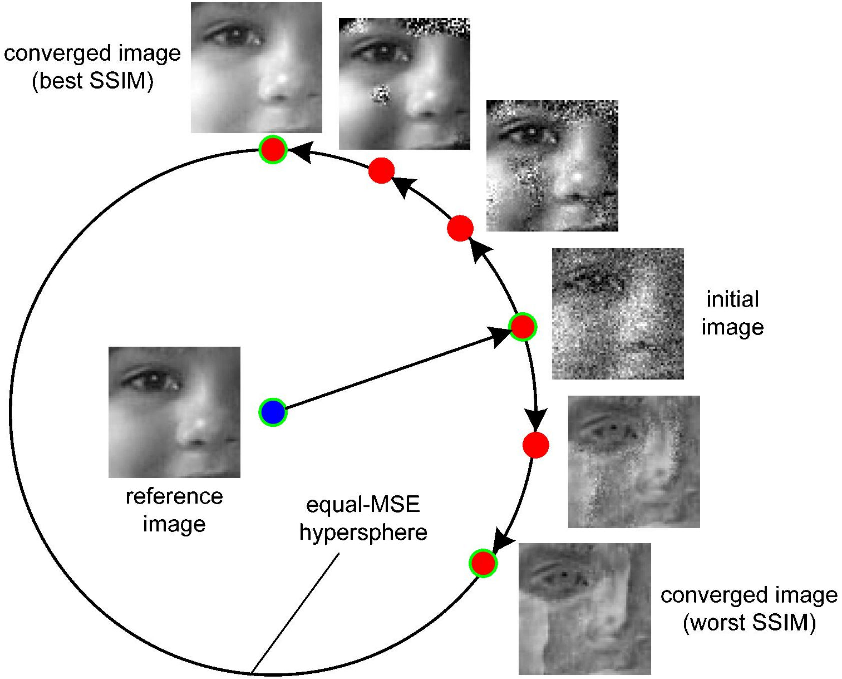


PSNR = 0 dB

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

Quality Metrics: SSIM

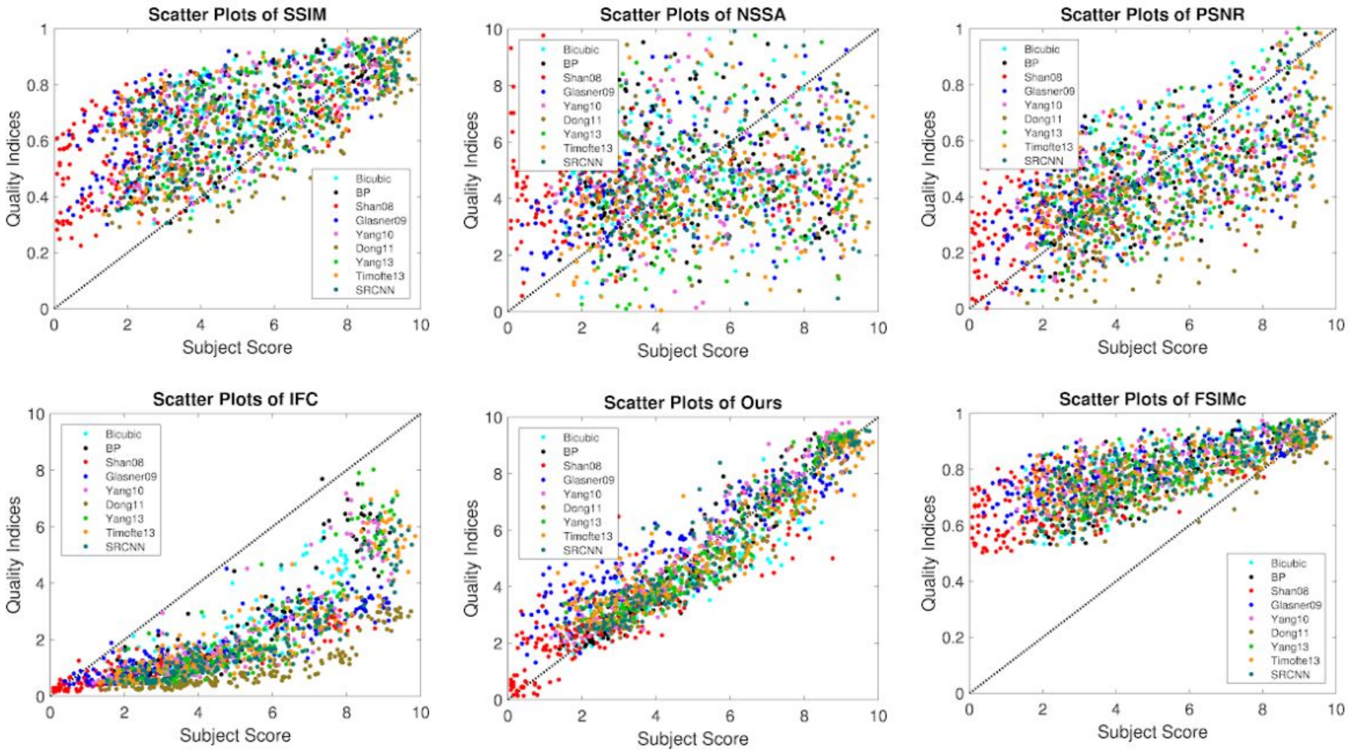


Quality Metrics: PIRM Perceptual index

PIRM2018

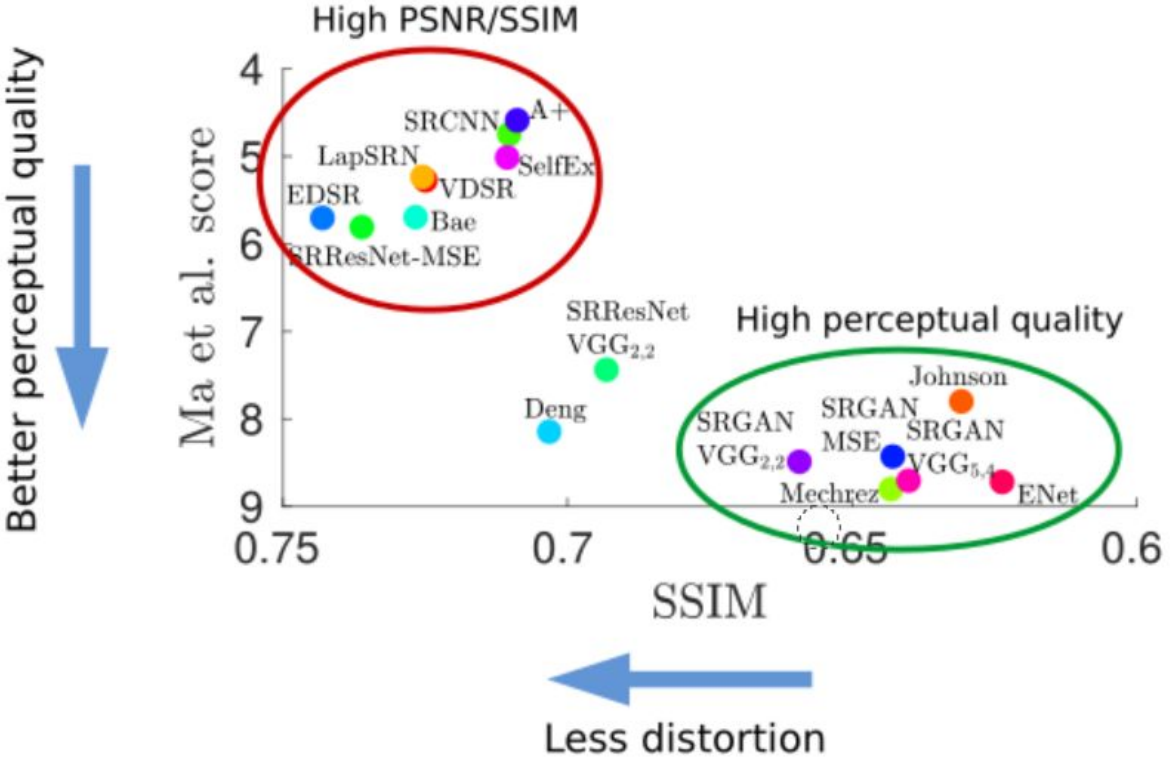
Ma et al. https://sites.google.com/site/chaoma99/sr-metric
PIRM https://www.pirm2018.org/PIRM-SR.html

Quality Metrics: PIRM Perceptual index

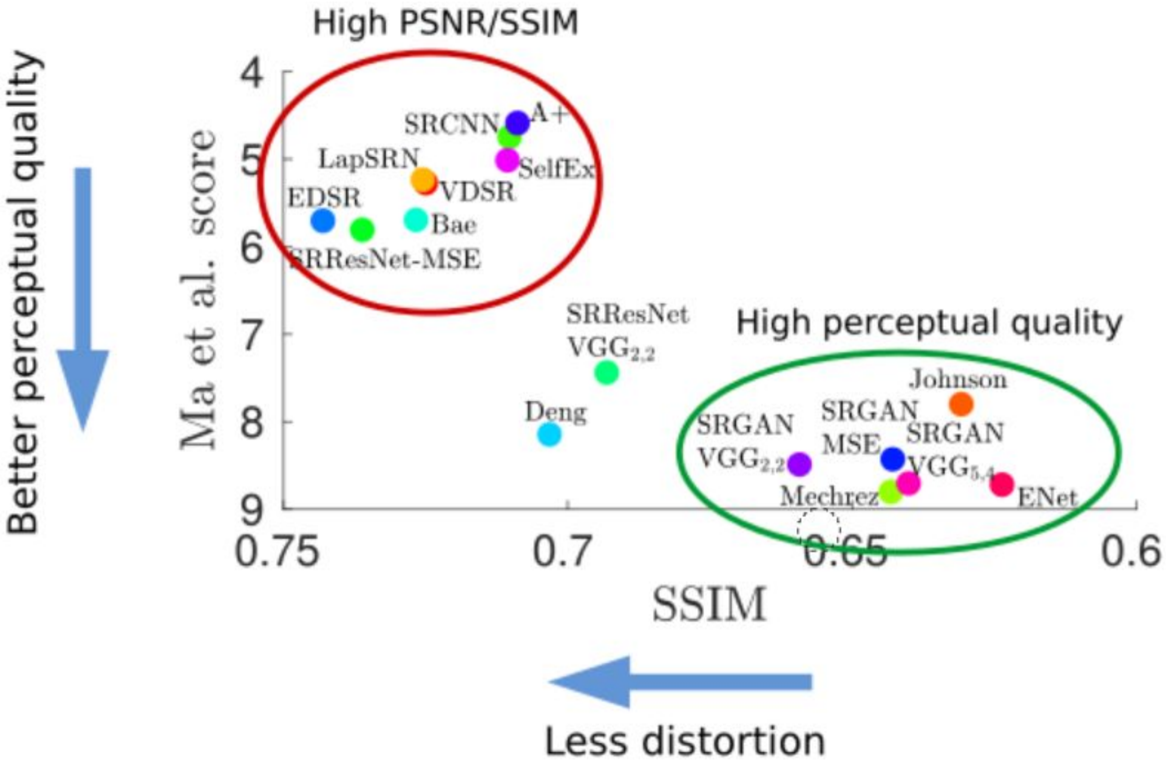


Ma et al. https://sites.google.com/site/chaoma99/sr-metric

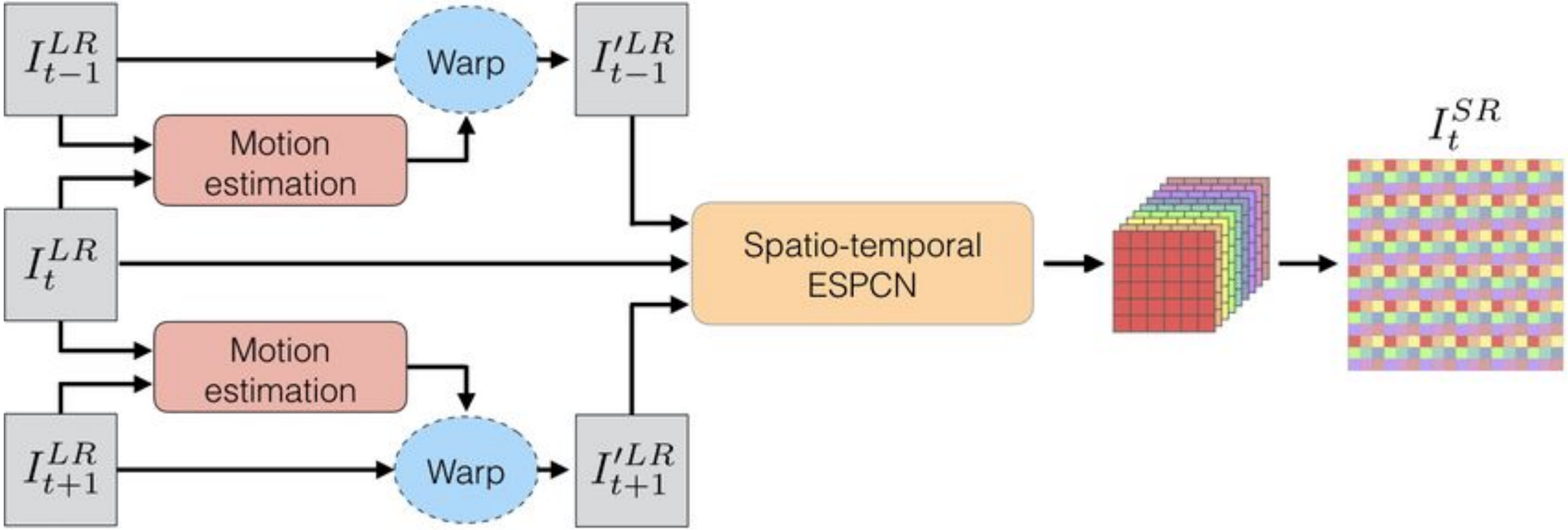
Quality Metrics: SISR model quality distribution



Quality Metrics: SISR model quality distribution

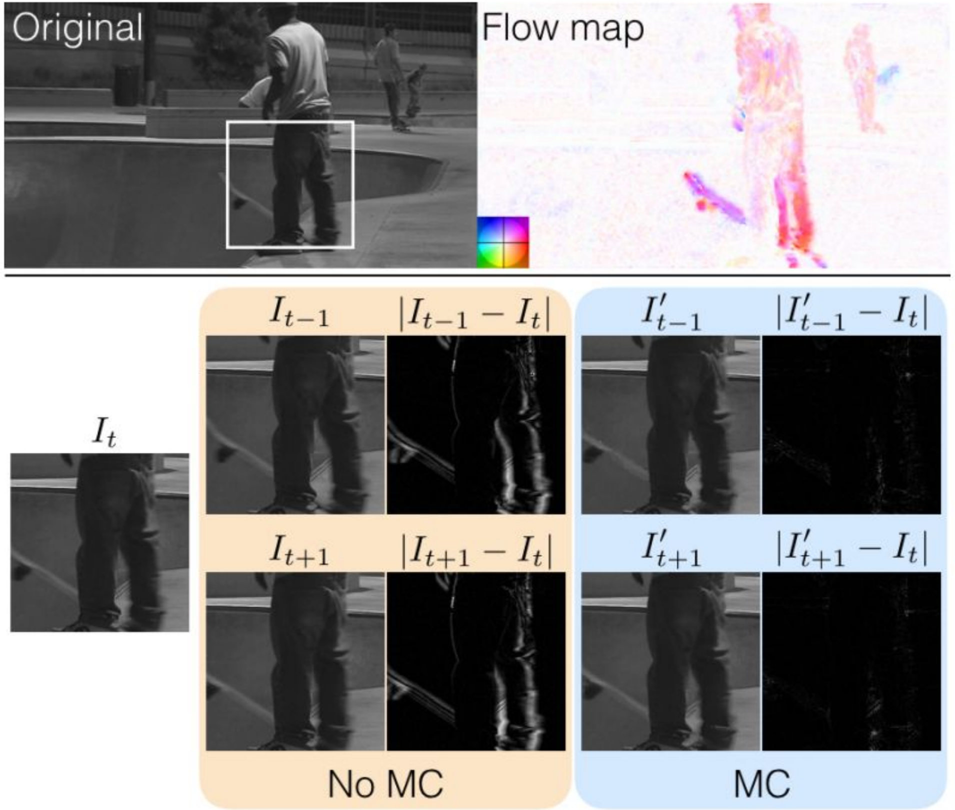


Video SR methods: **VESPCN**



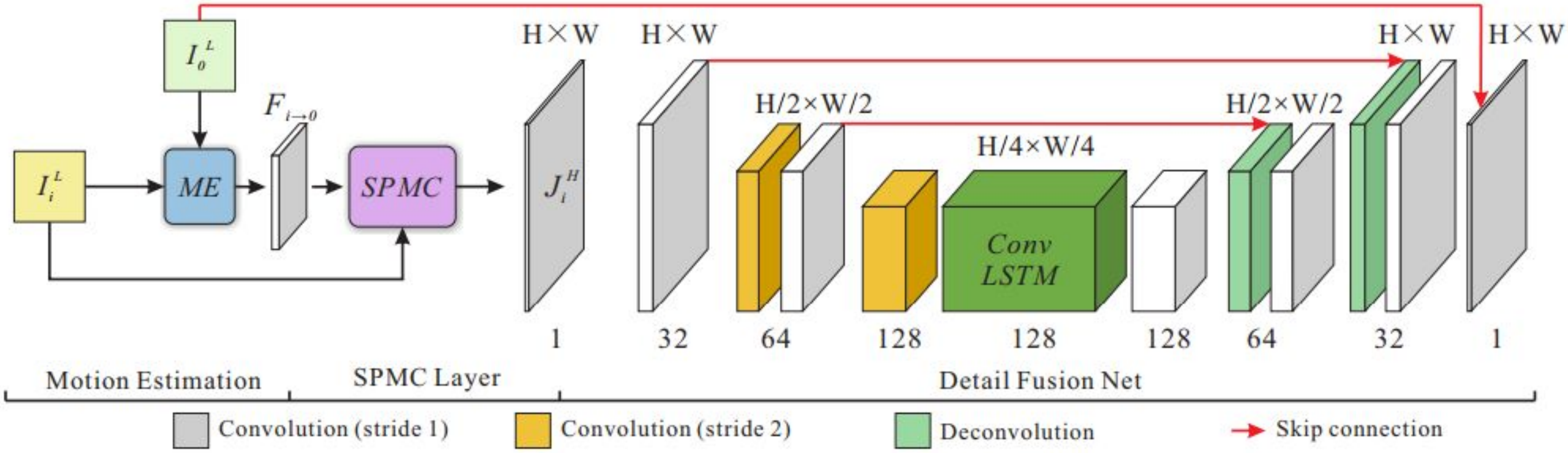
VESPCN https://arxiv.org/pdf/1611.05250.pdf

Video SR methods: **VESPCN**



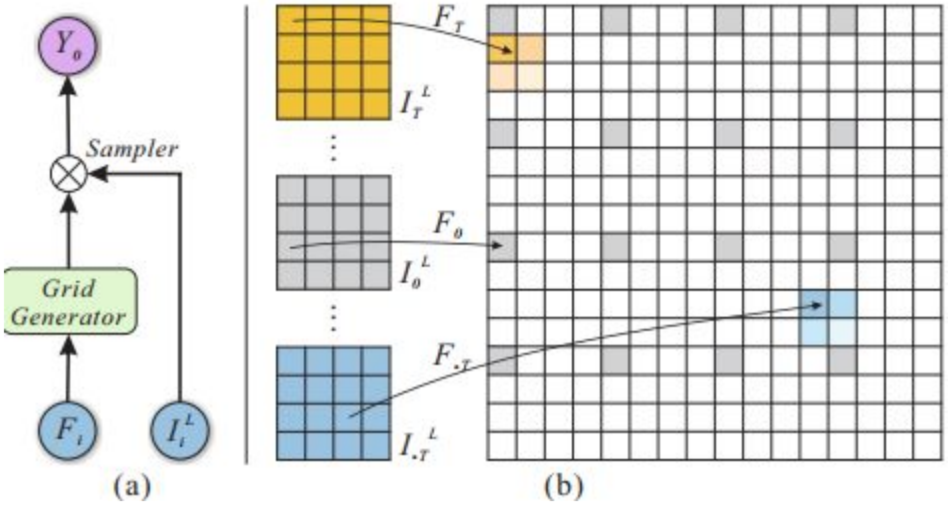
VESPCN https://arxiv.org/pdf/1611.05250.pdf

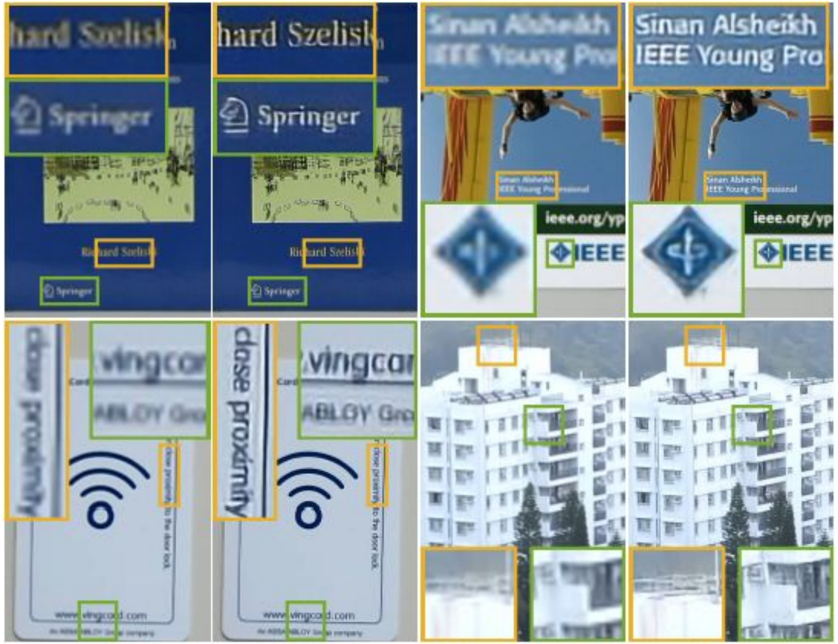
Video SR methods: Detail-revealing Deep Video Super-resolution



SPMC: https://arxiv.org/pdf/1704.02738.pdf

Video SR methods: Detail-revealing Deep Video Super-resolution

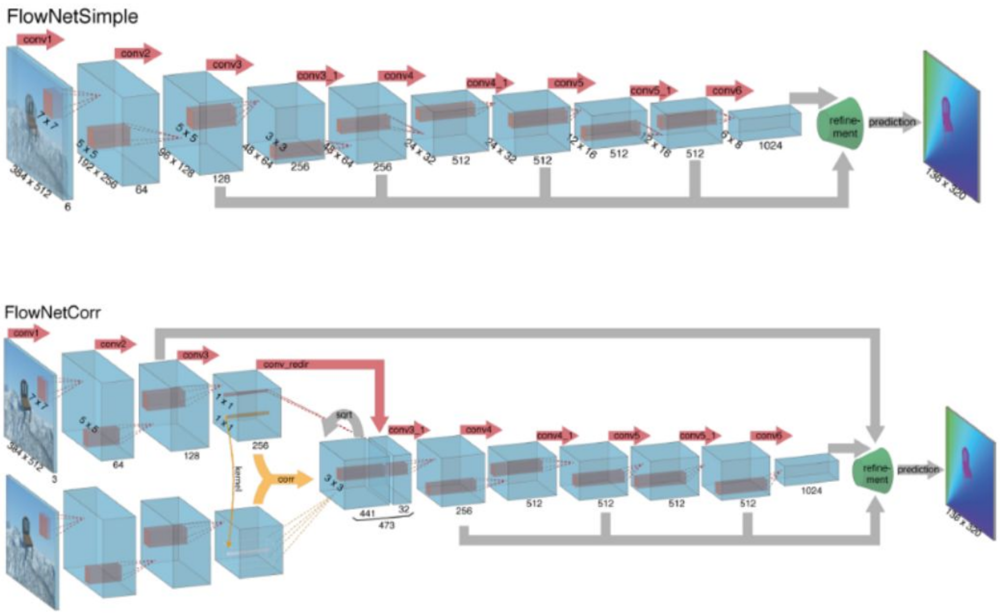


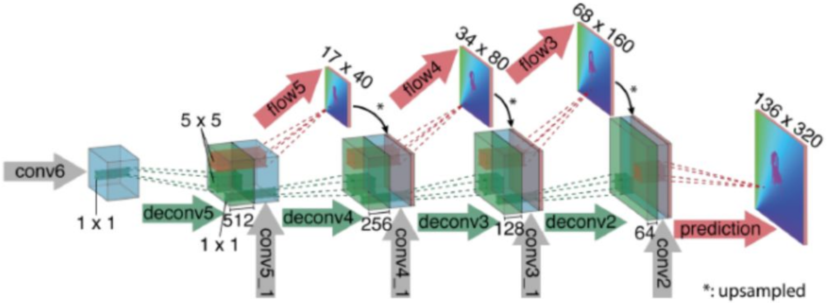


(a) Bicubic ×4 (b) Ours (c) Bicubic ×4 (d) Ours

SPMC: https://arxiv.org/pdf/1704.02738.pdf

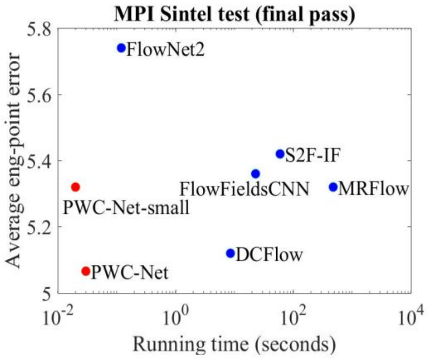
Optical flow: Flownet 2

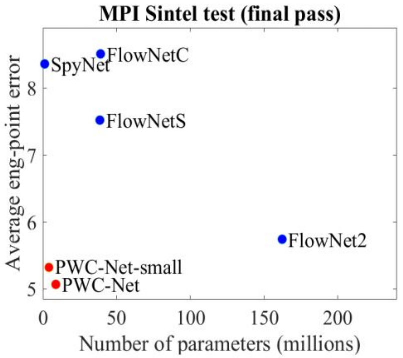




Flownet 2: https://arxiv.org/abs/1612.01925

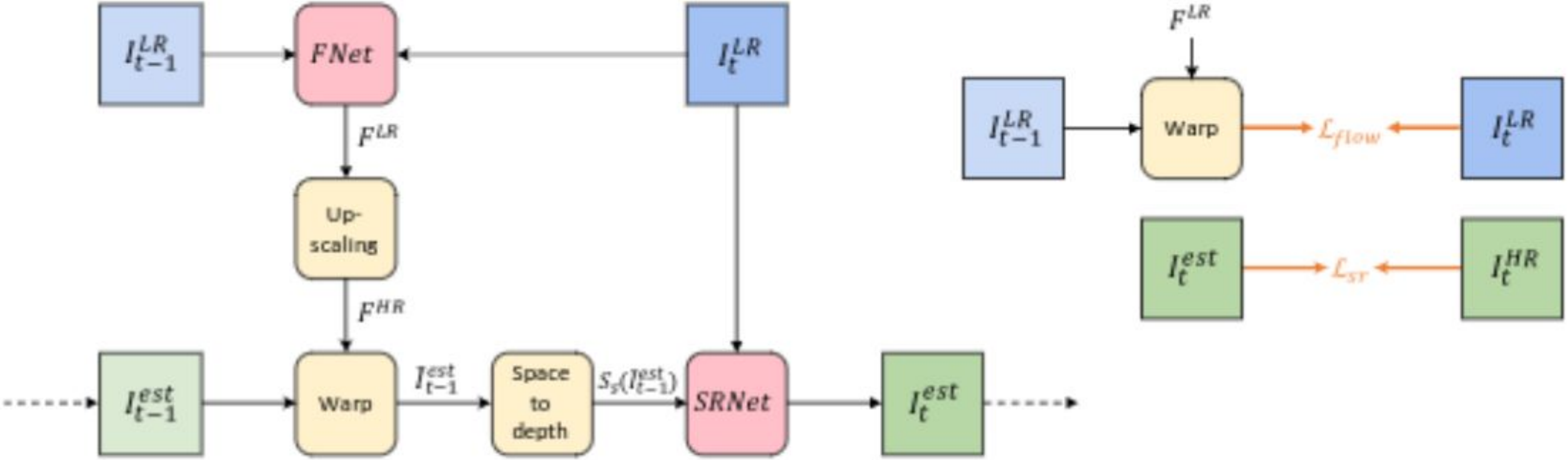
Optical flow: PWC-Net: CNNs for Optical Flow Using Pyramid, Warping, and Cost Volume





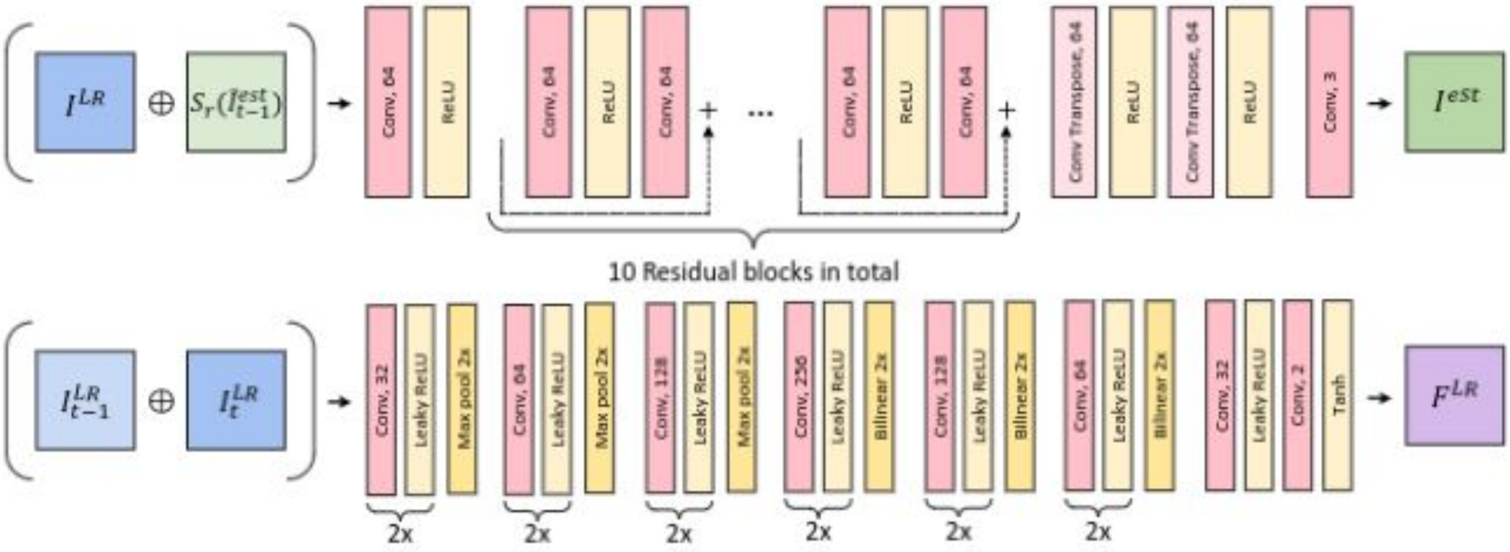
PWC-Net: https://arxiv.org/pdf/1709.02371.pdf

Video SR methods: Frame-Recurrent Video Super-Resolution



FRVSR: https://arxiv.org/abs/1801.04590

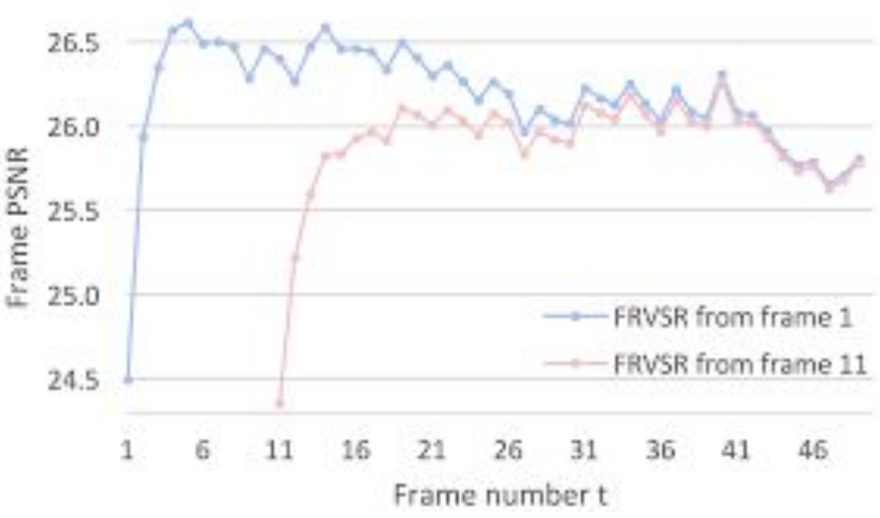
Video SR methods: Frame-Recurrent Video Super-Resolution

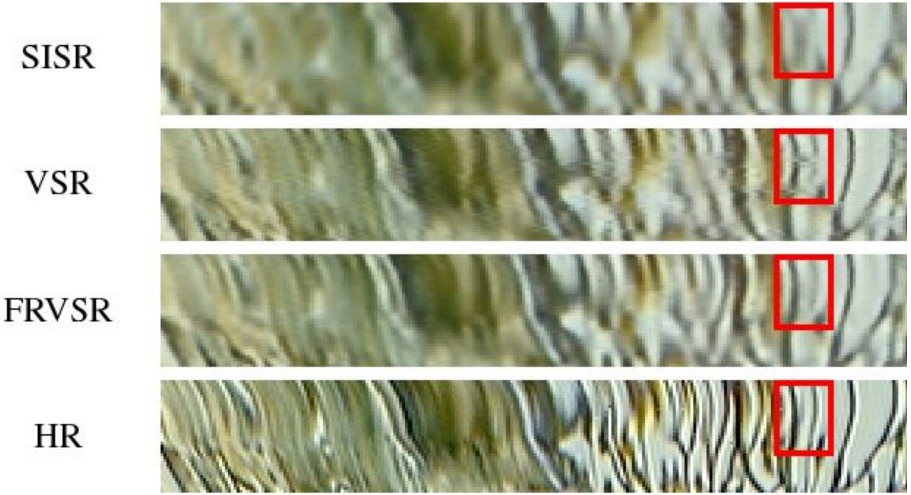


Architectures for super-resolution SRNet (top) and optical flow estimation FNet (bottom).

FRVSR: https://arxiv.org/abs/1801.04590

Video SR methods: Frame-Recurrent Video Super-Resolution





FRVSR: https://arxiv.org/abs/1801.04590

Video SR methods: Frame-Recurrent Video Super-Resolution

low-resolution input | our result | ground truth

FRVSR: https://arxiv.org/abs/1801.04590

Video SR methods: Dynamic Upsampling Filters Without Explicit Motion Compensation

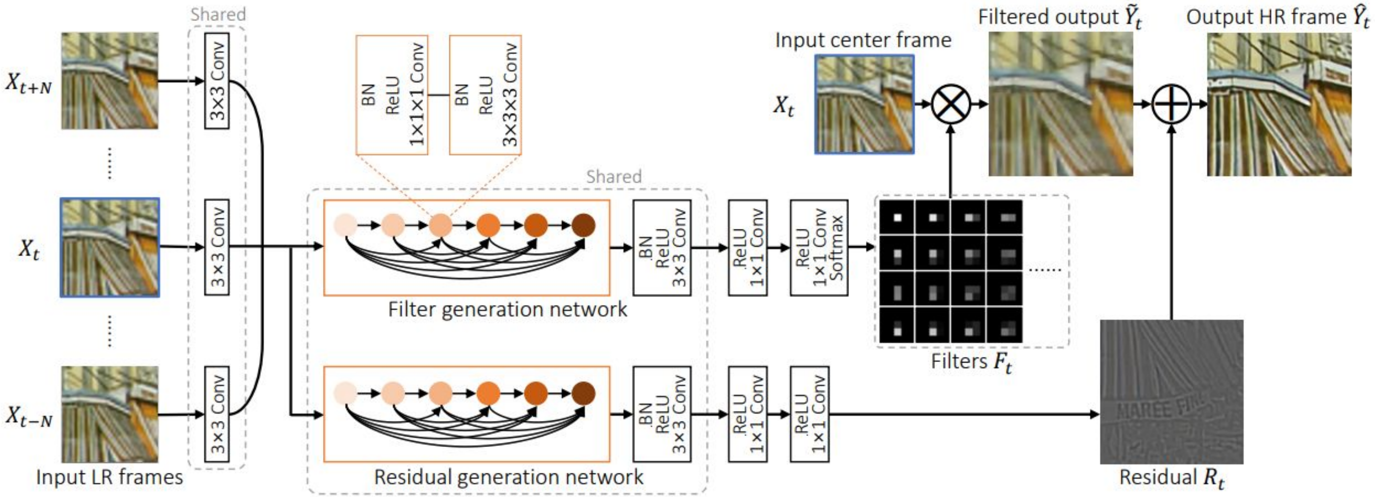


Figure 3. Network architecture. The weights of filter and residual generation networks are shared for efficiency. The dynamic upsampling filters F_t are generated adaptively to local motion, and residual R_t adds high-frequency details.

VSR-DUF: https://yhjo09.github.io/files/VSR-DUF_CVPR18.pdf

https://github.com/yhjo09/VSR-DUF

Video SR methods: Dynamic Upsampling Filters Without Explicit Motion Compensation

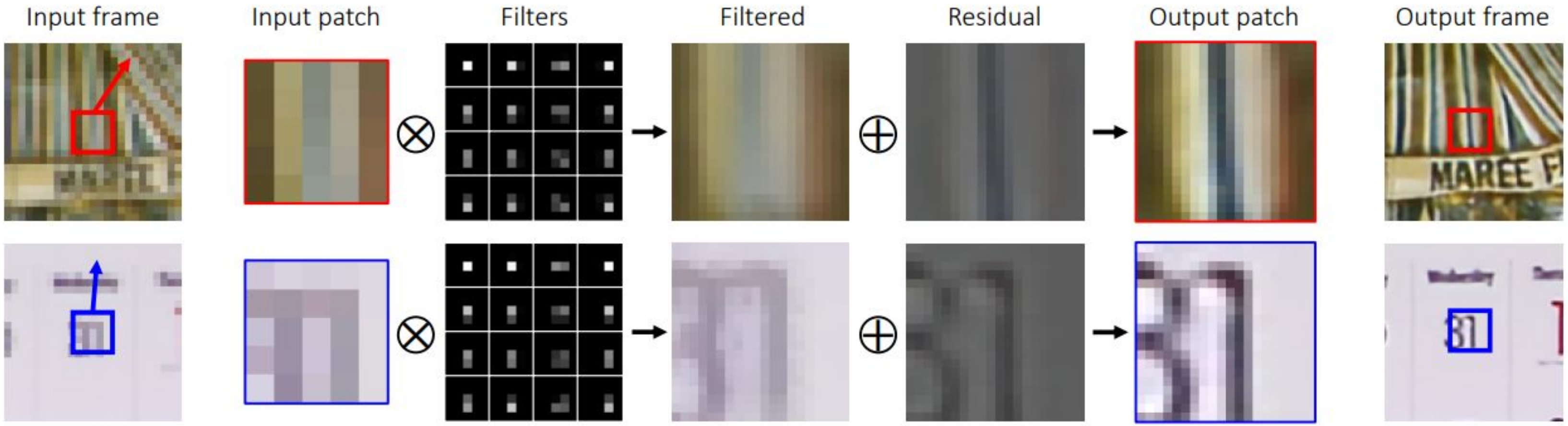
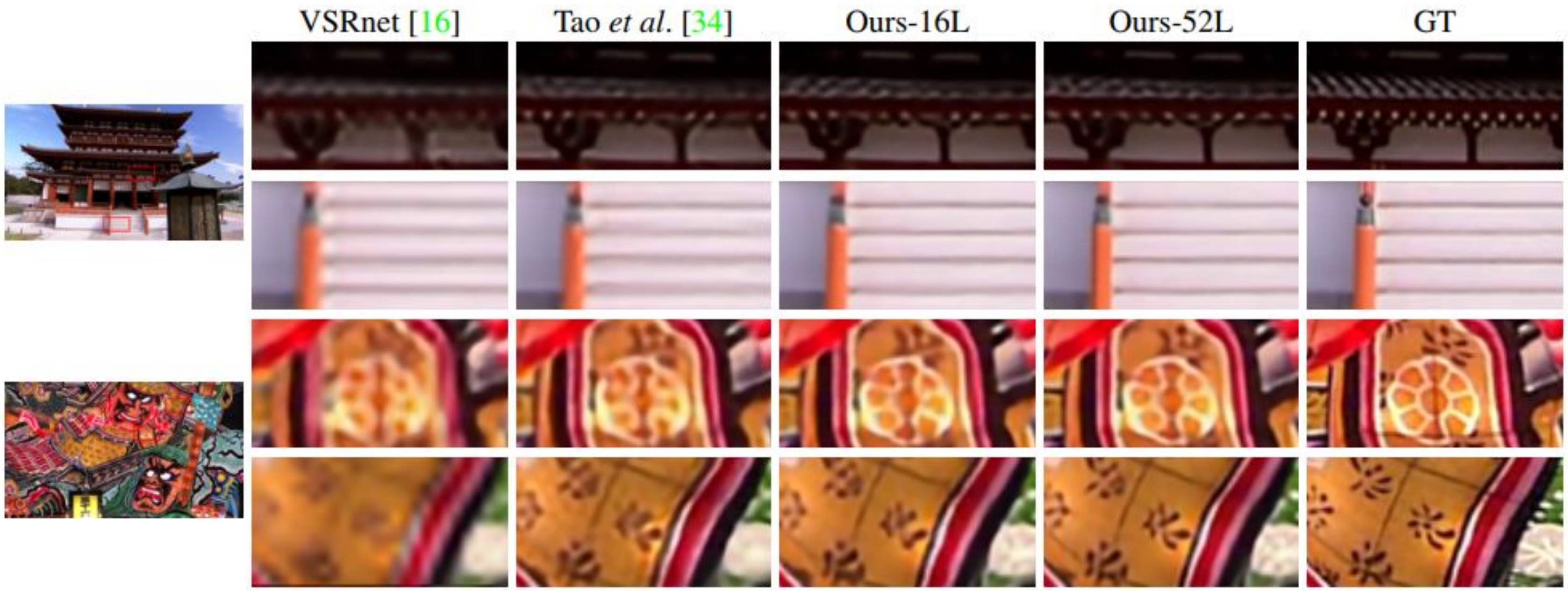


Figure 7. Examples of upsampling process in detail. The direction of the colored arrows indicates the direction of local motion. Two sets of 16 upsampling filters are for the center pixel of each input patch, and they are different since each input has different texture and local motion.

VSR-DUF: https://yhjo09.github.io/files/VSR-DUF_CVPR18.pdf
https://github.com/yhjo09/VSR-DUF

Video SR methods: Dynamic Upsampling Filters Without Explicit Motion Compensation



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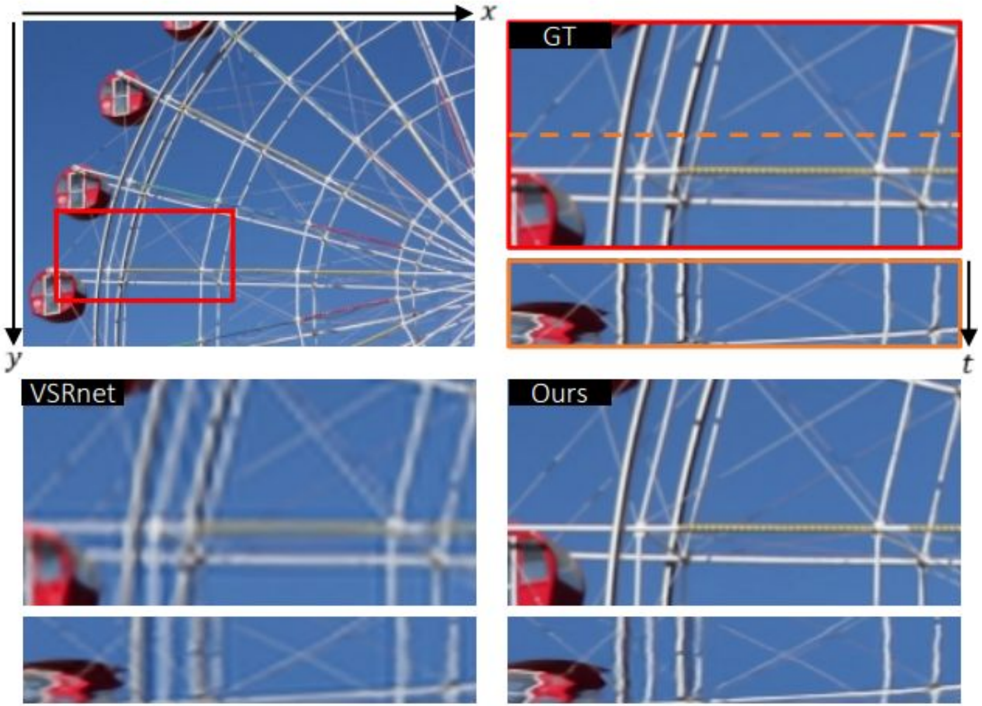

VSR-DUF: https://yhjo09.github.io/files/VSR-DUF_CVPR18.pdf
https://github.com/yhjo09/VSR-DUF

Soft texture embeddings + Dynamic upsampling filters:

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