Super-resolution

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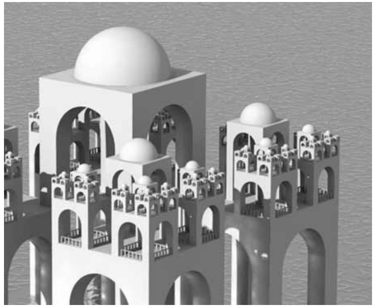
Image super-resolution

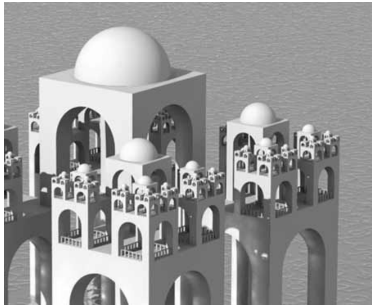
n 

m

*Slide courtesy, Super Resolution From a Single Image, iccv 2009, Glasner

Image super-resolution

n



m

αn

αm

α - scale factor

*Slide courtesy, Super Resolution From a Single Image, iccv 2009, Glasner

Degradation model

I_{HR}

αn

αm

Degradation model

I_{HR}

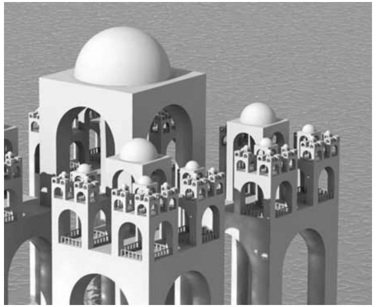
αn

αm

$$\mathrm{f}_\alpha : \mathbb{R}^{\alpha m \times \alpha n} \longrightarrow \mathbb{R}^{m \times n}$$

$$I_{\mathrm{LR}} = \mathrm{f}_\alpha(I_{\mathrm{HR}})$$

n



m

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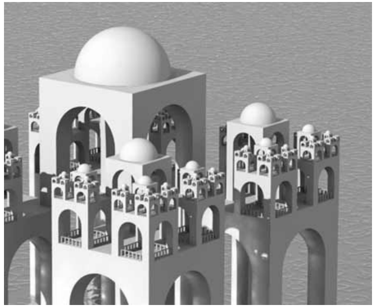

m

f_α - can be a combination of decimation, noise, and blur

Single image super-resolution (Hallucination)

$$\mathrm{g}_\alpha : \mathbb{R}^{m \times n} \longrightarrow \mathbb{R}^{\alpha m \times \alpha n}$$

*Slide courtesy, Single image super-resolution, Cs129 Computational Photography James Hays, Brown, fall 2012; Slides of Libin “Geoffrey” Sun and James Hays

Single image super-resolution (Hallucination)

$$g_\alpha : \mathbb{R}^{m \times n} \longrightarrow \mathbb{R}^{\alpha m \times \alpha n}$$

Main goals

- Be faithful to the low resolution input image $I_{\mathrm{HR}}^{est} = g_\alpha(I_{\mathrm{LR}})$

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- Produce a detailed, realistic output image

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Single Image SR via Deep Learning

- SRCNN (Super-Resolution Convolutional Neural Networks) : ECCV 2014, PAMI 2016 : 3 layer CNN, MSE loss, input - bicubic interpolated image

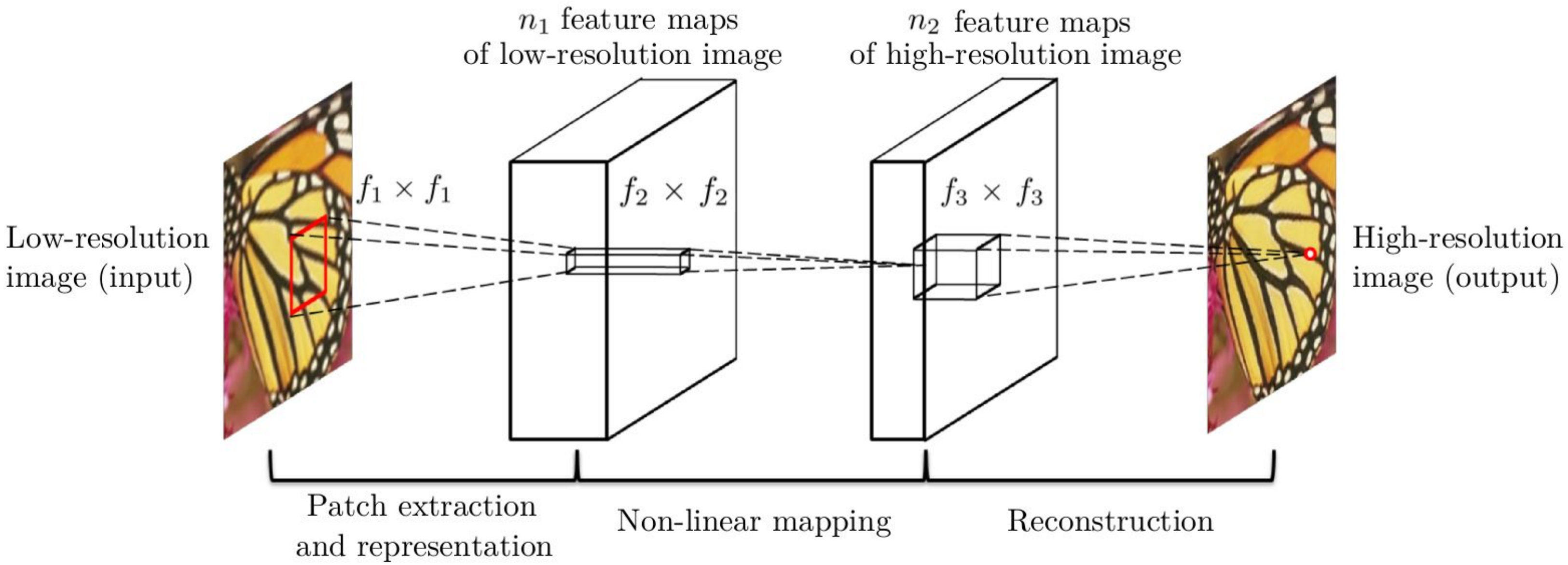
- Follow up works => focused on improvement in run-time, accuracy, perceptual quality, and extensions to videos

- Some of the key findings

    - larger context, training tricks, architectural modifications=> better performance
    - feature extraction in LR dimension => improvement in speed
    - VGG Loss and GAN loss => better perceptual quality
    - Recurrent networks => for videos

*ECCV - European Conference on Computer Vision, PAMI - IEEE Transactions on Pattern Analysis and Machine Intelligence

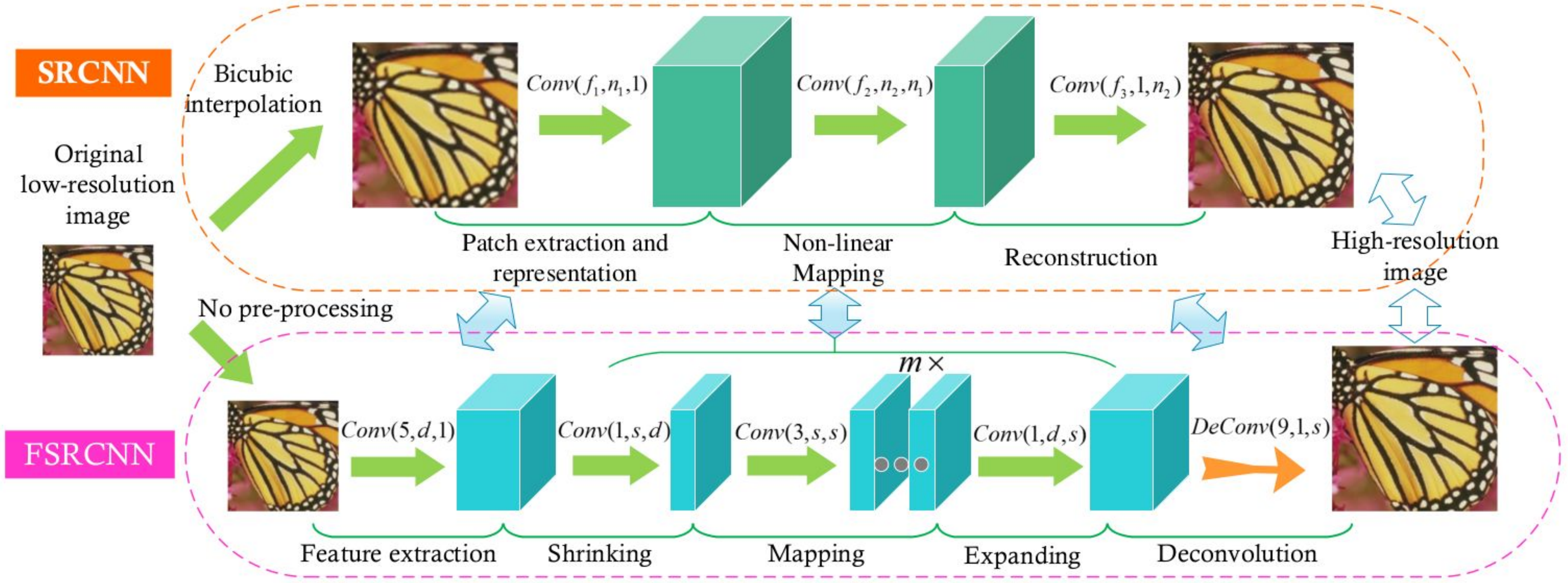
SRCNN (ECCV 2014, PAMI 2016) - net arch



SRCNN details

- Loss function $L(\Theta) = \frac{1}{n}\sum_{i=1}^{n} ||F(\mathbf{Y}_i;\Theta) - \mathbf{X}_i||^2$
- input is the bicubic interpolated form of LR image
- number of filters : n1 = 64, and n2 = 32
- filter size (f1 - f2 - f3) : 9-1-5, 9-3-5, and 9-5-5
- 9-5-5 performs best => utilizing neighborhood information in the mapping stage is beneficial
- experiments with more layers didn’t succeed => “the deeper the better” doesn’t hold true with this deep model for super-resolution

FSRCNN (Fast Super-Resolution Convolutional Neural Network : ECCV 2016) net arch



FSRCNN details

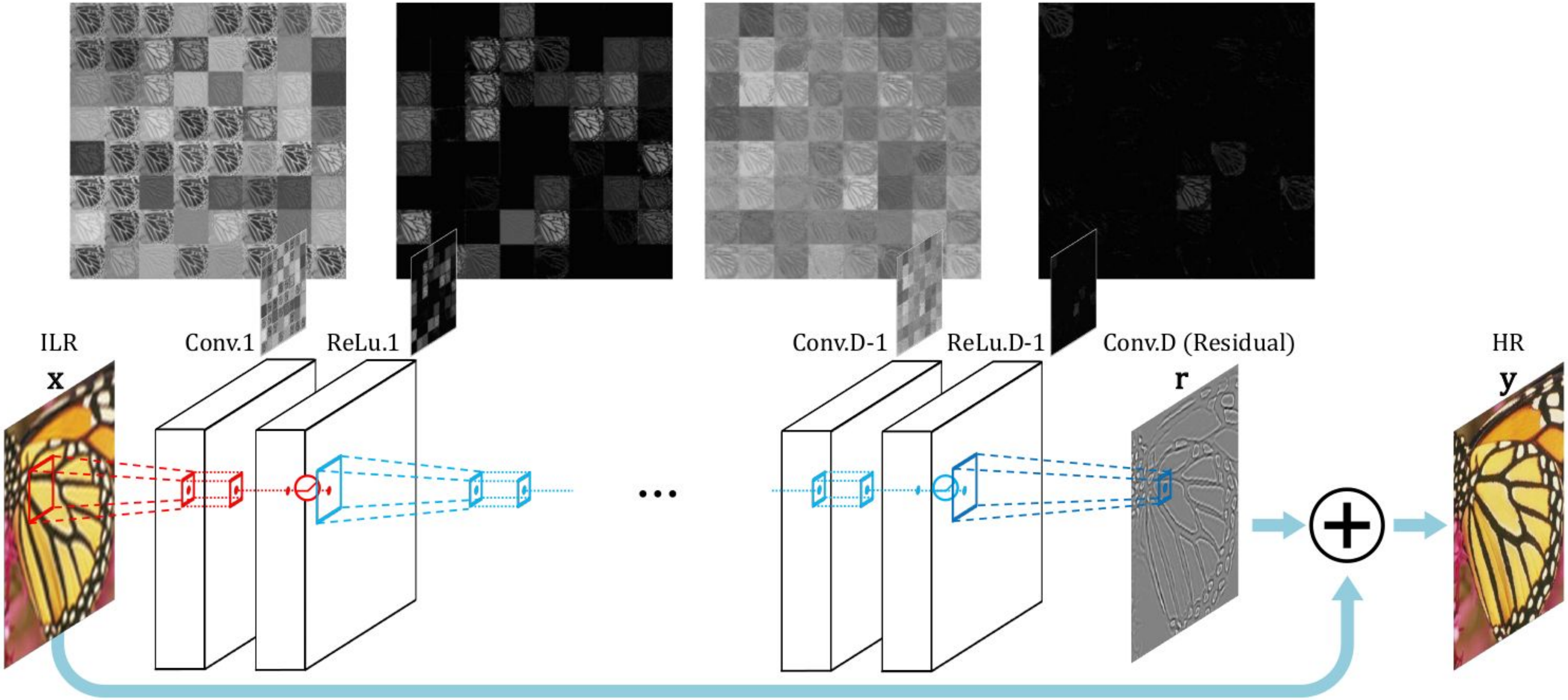
- Faster + better performance as compared to SRCNN

- 8 layer CNN, MSE loss, input - original LR image

- Tricks for speed up - All layers except last works on LR dimension, last layer performs upsampling using a deconv layer, middle layer filters are of size 3 x 3, and contain lesser number of filters

- total number of parameters reduced by 4 and speedup of 40 x as compared to SRCNN

VDSR (Accurate Image Super-Resolution Using Very Deep Convolutional Networks : CVPR 2016) net arch

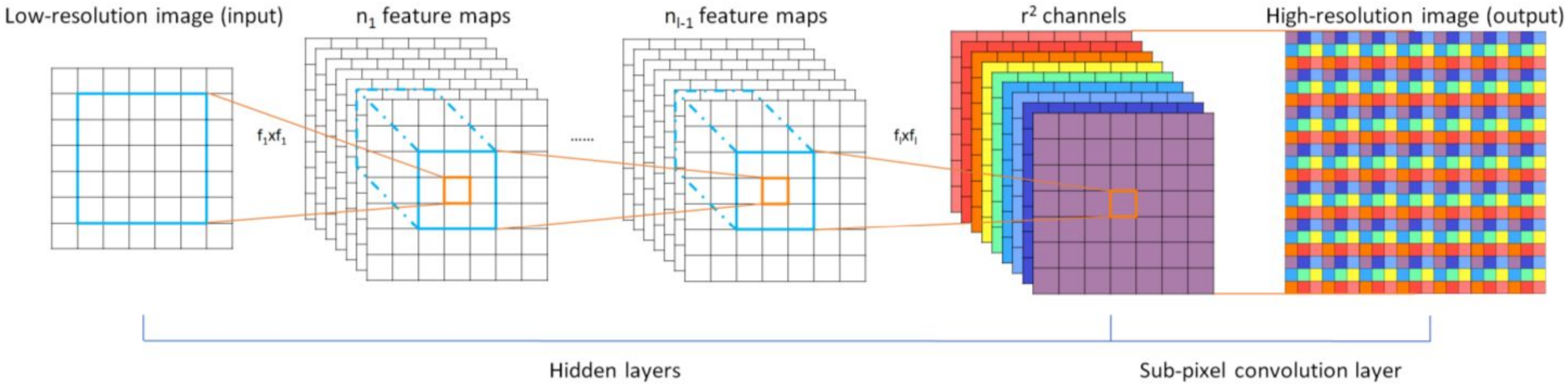


*CVPR - IEEE Conference on Computer Vision and Pattern Recognition

VDSR details

- very deep CNN, 20 layers
- to improve convergence they train for residual + use higher learning rate and adjustable gradient clipping
- input - bicubic interpolated form of LR image; LOSS - MSE between residual and network output
- context : utilize contextual information spread over very large image regions

ESPCN (Efficient Sub-Pixel Convolutional Neural Network : CVPR 2016) net arch



ESPCN details

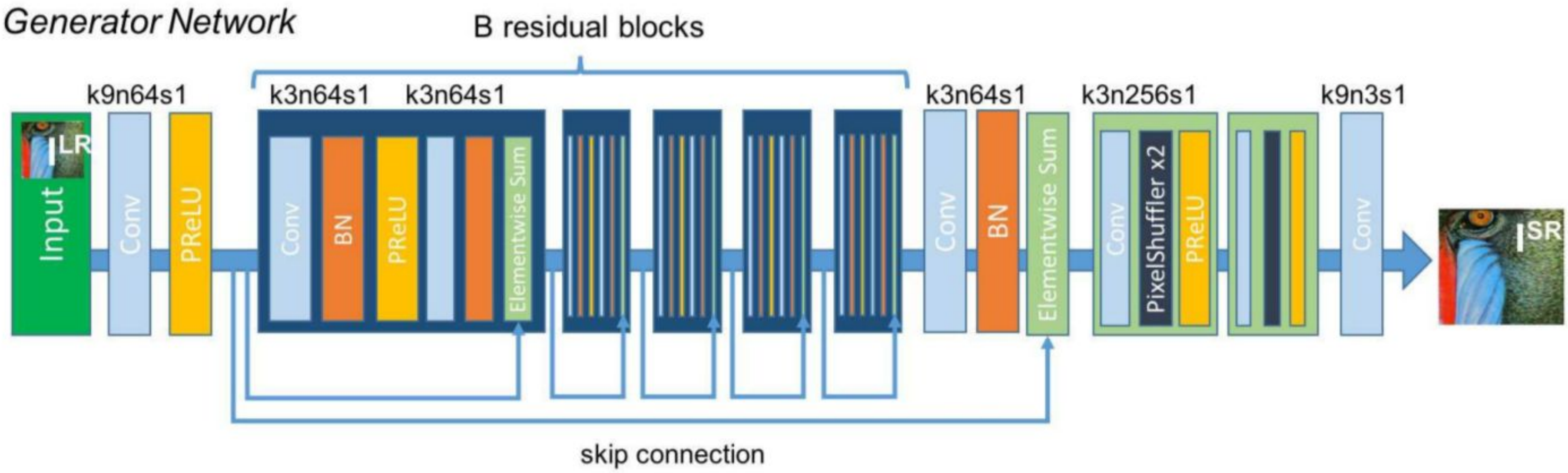
- Faster + better performance as compared to SRCNN

- 3 layer CNN (similar to SRCNN), MSE loss, input - original LR image

- Tricks for speed up - All layers except last works on LR dimension, last layer performs upsampling using an efficient sub-pixel convolution layer

- They perform video SR by applying single image SR in a frame by frame fashion. Speed up achieved by ESPCN allowed them to perform real-time SR of 1080p videos

SRResNet (super resolution residual network : CVPR 2017) net arch (photo-realistic SR)



SRResNet details

- deep CNN, with 16 residual blocks
- Modified form of ResNet is used to build network architecture
- Used as the generator network for the photo-realistic SR work by Ledig et al (CVPR 2017)
- input - LR image; LOSS - MSE
- Significant improvement in performance as compared to SRCNN, ESPCN, DRCN

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network : SRGAN (CVPR 2017) net arch

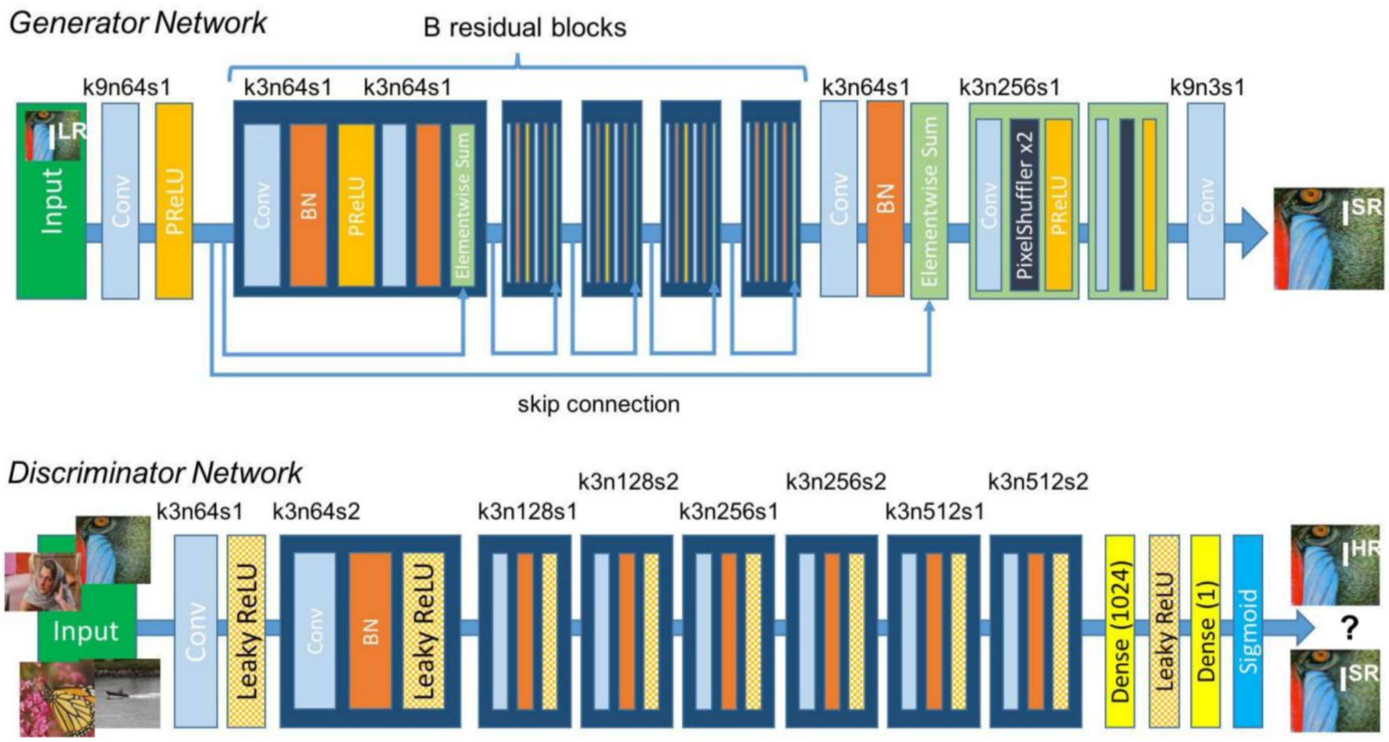


Figure 4: Architecture of Generator and Discriminator Network with corresponding kernel size (k), number of feature maps (n) and stride (s) indicated for each convolutional layer.

SRGAN details

- SRResNet as generator
- Loss = combinations of (MSE, VGG loss, Adversarial loss)
- Input - LR image; efficient sub-pixel convolution layer for upsampling
- Better MOS (Mean Opinion Score) as compared to existing works

The Perception-Distortion Tradeoff (CVPR 2018)

- distortion and perceptual quality are at odds with each other

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- distortion metrics - PSNR, SSIM, IFC

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- distortion metrics - PSNR, SSIM, IFC

- perceptual quality metrics - mean opinion score (MOS), no-reference quality measures such as NIQE

The Perception-Distortion Tradeoff (CVPR 2018)

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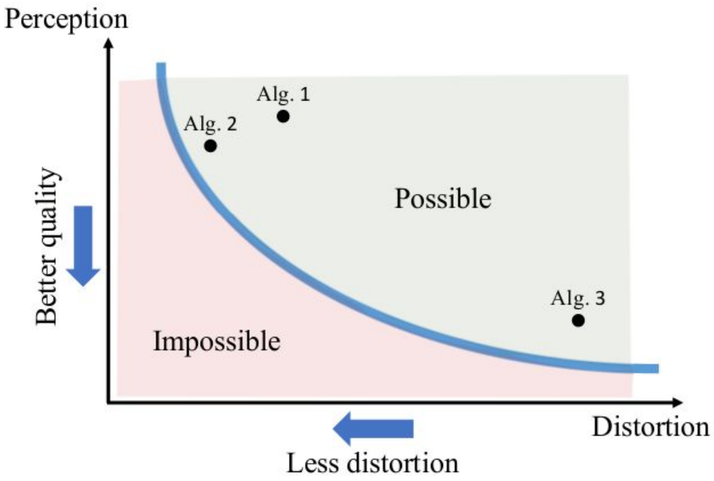

The Perception-Distortion Tradeoff (CVPR 2018)

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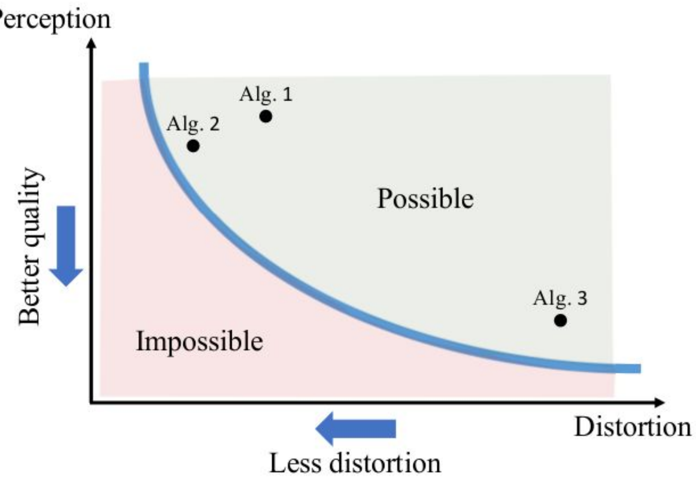


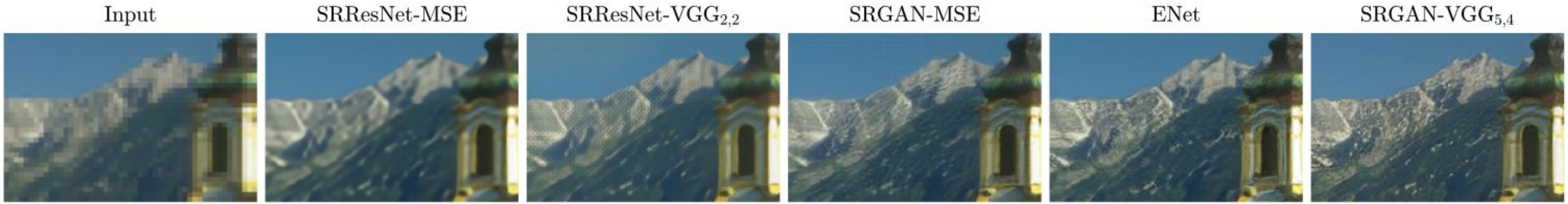
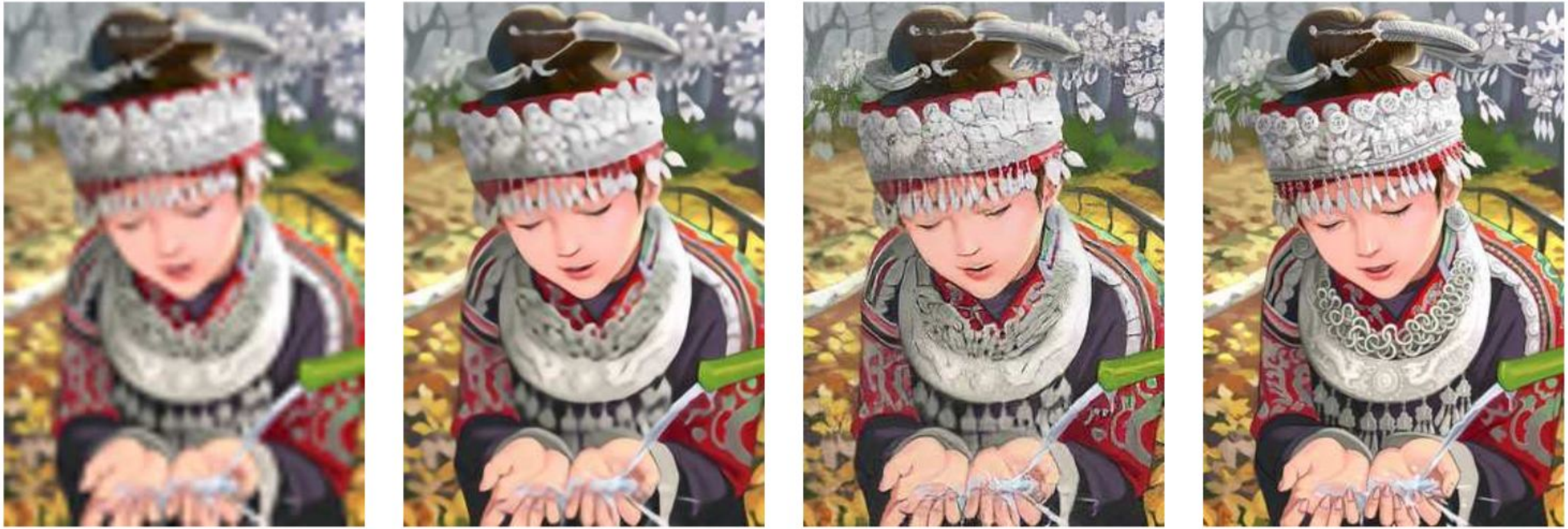


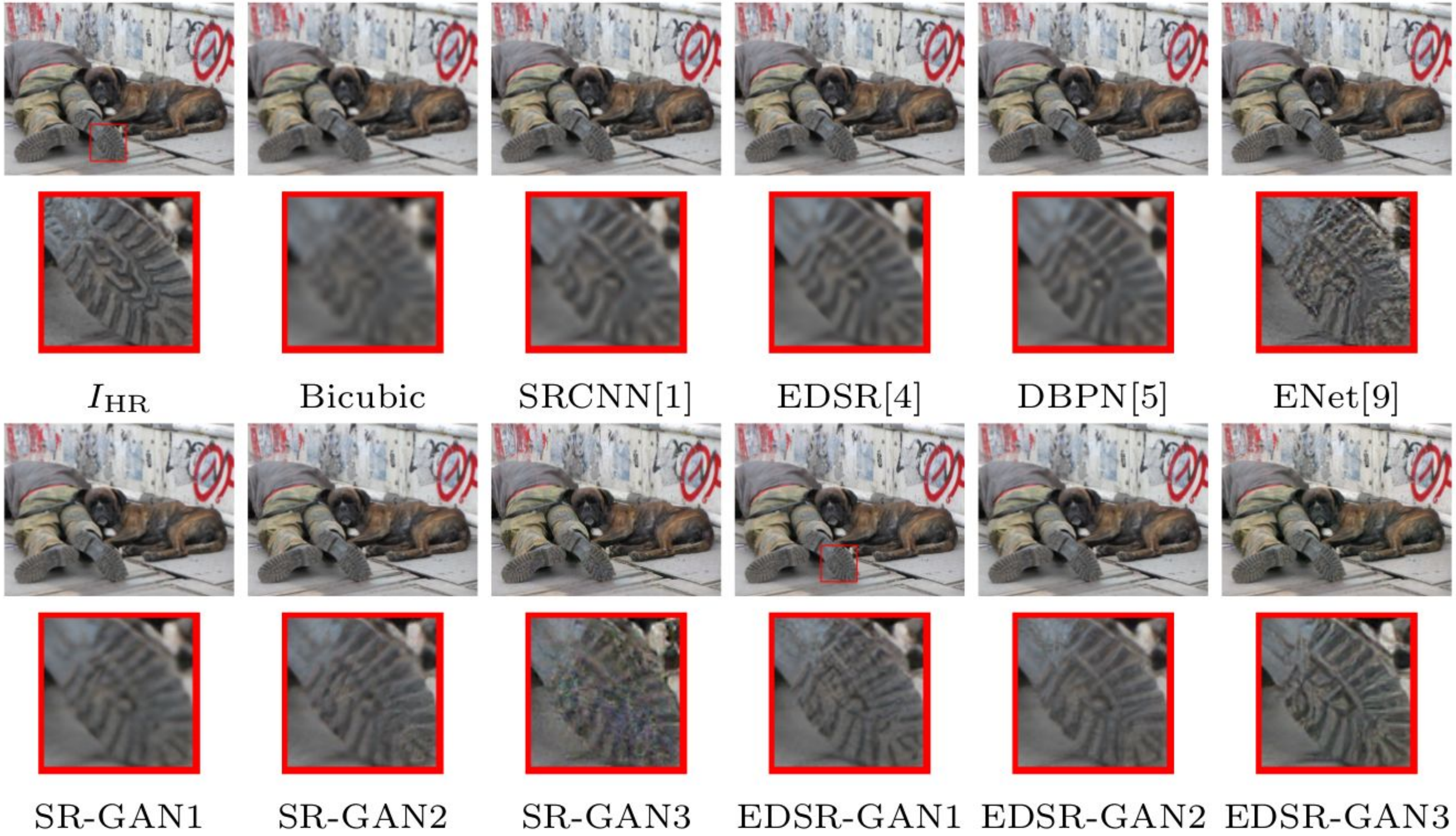
Figure 9. **Visual comparison of algorithms closest to the perception-distortion bound.** The algorithms are ordered from low to high distortion (evaluated by IFC). Notice the co-occurring increase in perceptual quality.

SR Results for x4 - CVPR 2017

bicubic (21.59dB/0.6423) | SRResNet (23.53dB/0.7832) | SRGAN (21.15dB/0.6868) | original

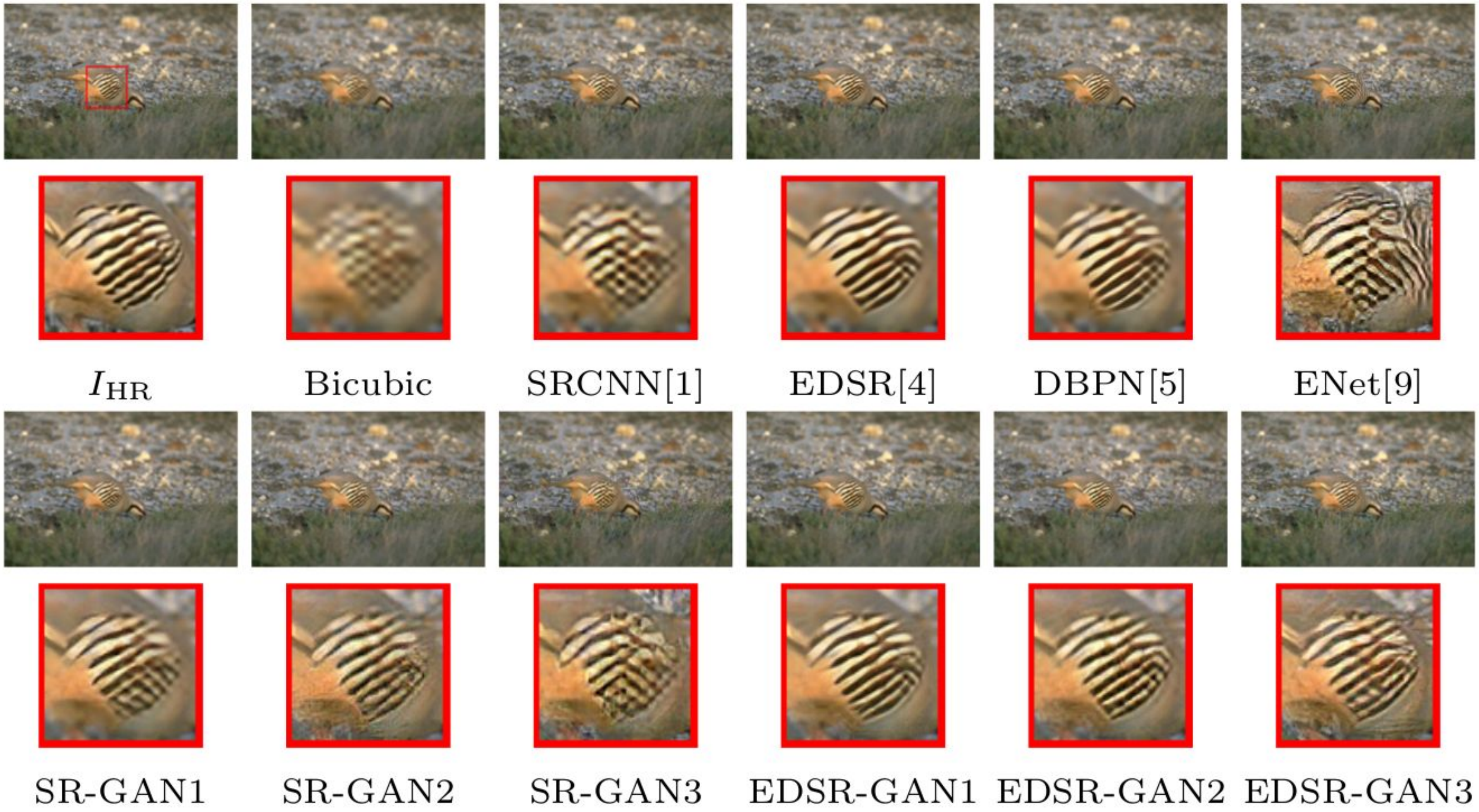


SR Results for x4 - ECCV 2018



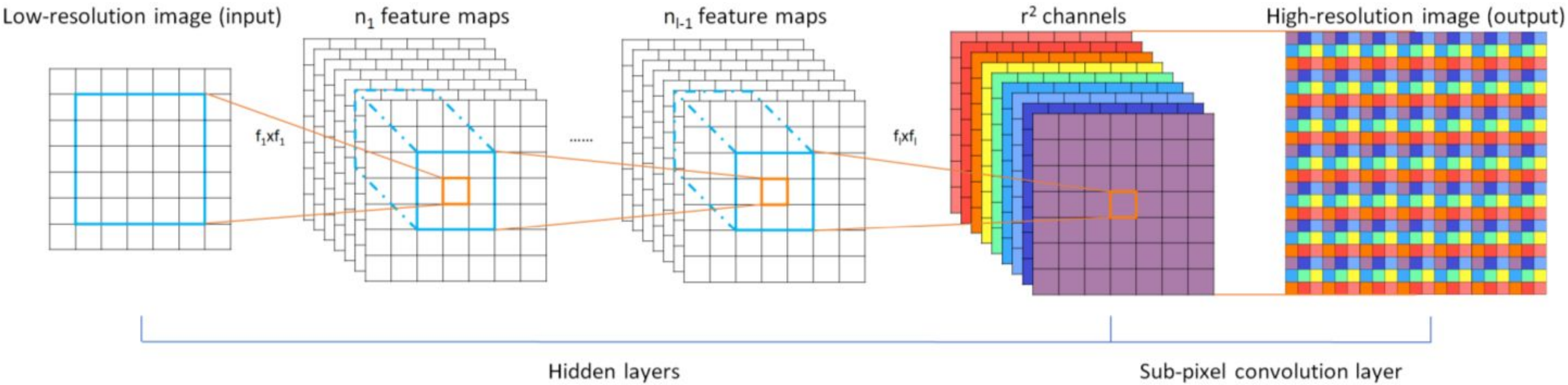
*EDSR - CVPRW 2017, DBPN - CVPR 2018, ENet - ICCV 2017, EDSR-GAN - ECCVW 2018

SR Results for x4 - ECCV 2018



Video super-resolution

Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network (CVPR 2016)



- They perform video SR by applying single image SR in a frame by frame fashion. Speed up achieved by ESPCN allowed them to perform real-time SR of 1080p videos

Real-Time Video Super-Resolution with Spatio-Temporal Networks and Motion Compensation : VESPCN (CVPR 2017)

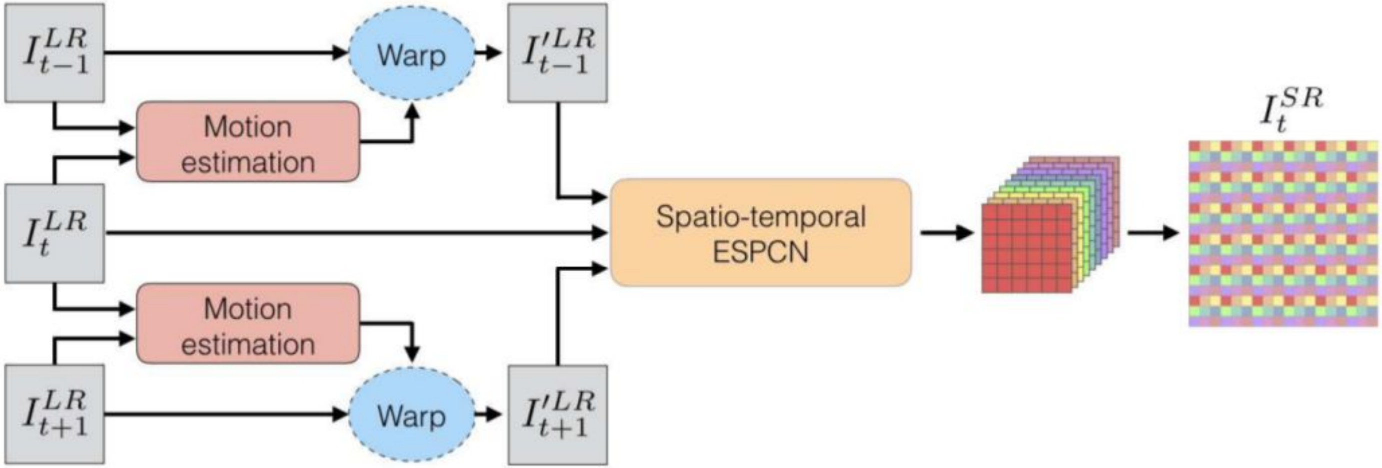


Figure 1: Proposed design for video SR. The motion estimation and ESPCN modules are learnt end-to-end to obtain a motion compensated and fast algorithm.

Frame-Recurrent Video Super-Resolution (CVPR 2018)

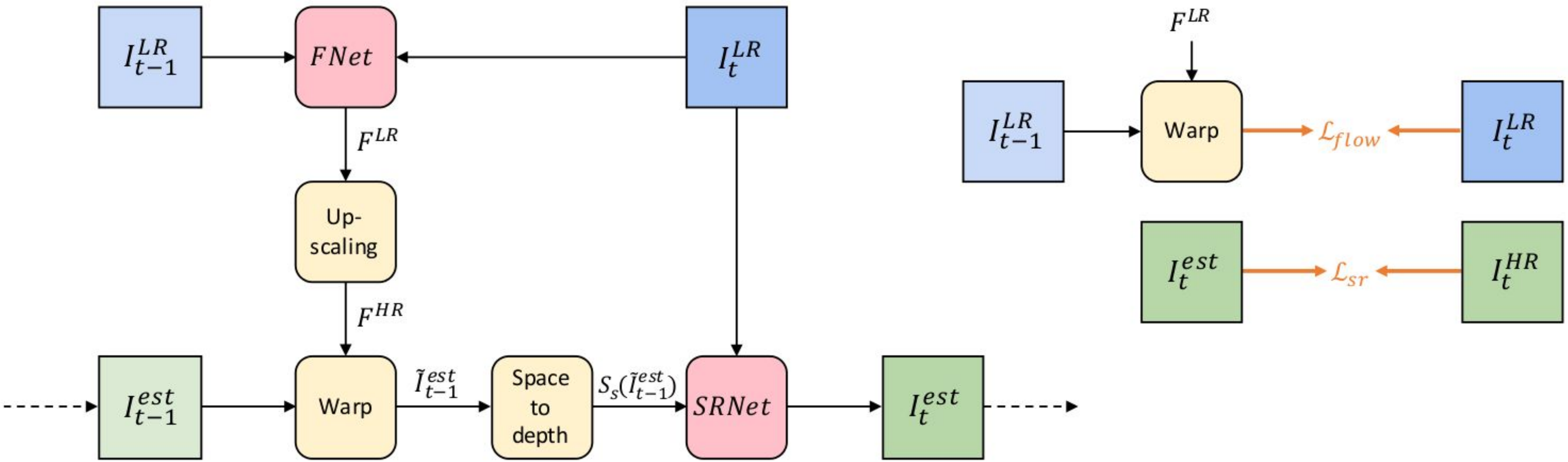


Figure 2: Overview of the proposed FRVSR framework (left) and the loss functions used for training (right). After computing the flow F^{LR} in LR space using FNet, we upsample it to F^{HR}. We then use F^{HR} to warp the HR-estimate of the previous frame I_{t-1}^{est} onto the current frame. Finally, we map the warped previous output $\tilde{I}_{t-1}^{\mathrm{est}}$ to LR-space using the space-to-depth transformation and feed it to the super-resolution network SRNet along with the current input frame I_t^{LR}. For training the networks (shown in red), we apply a loss on I_t^{est} as well as an additional loss on the warped previous LR frame to aid FNet.

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