

Super Resolution

Super resolution is the process of upscaling and or improving the details within an image. Often a low resolution image is taken as an input and the same image is upscaled to a higher resolution



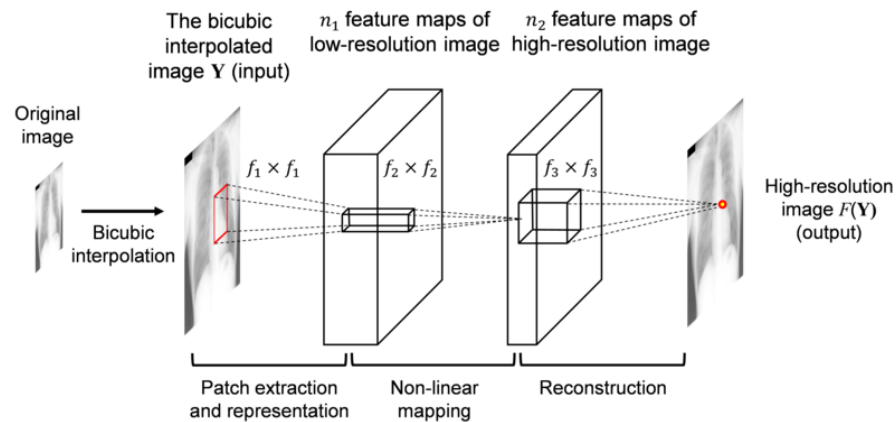


LR – Low Resolution Image
HR – High Resolution Image
SR – Image produced by model

DEEP SISR

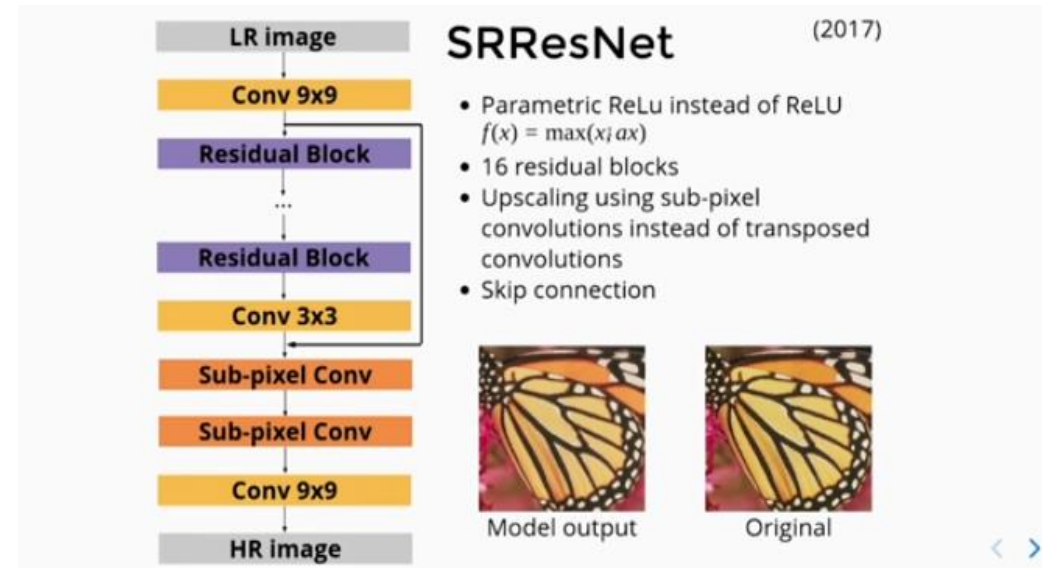
image-to-image mapping
Spatial Alignment

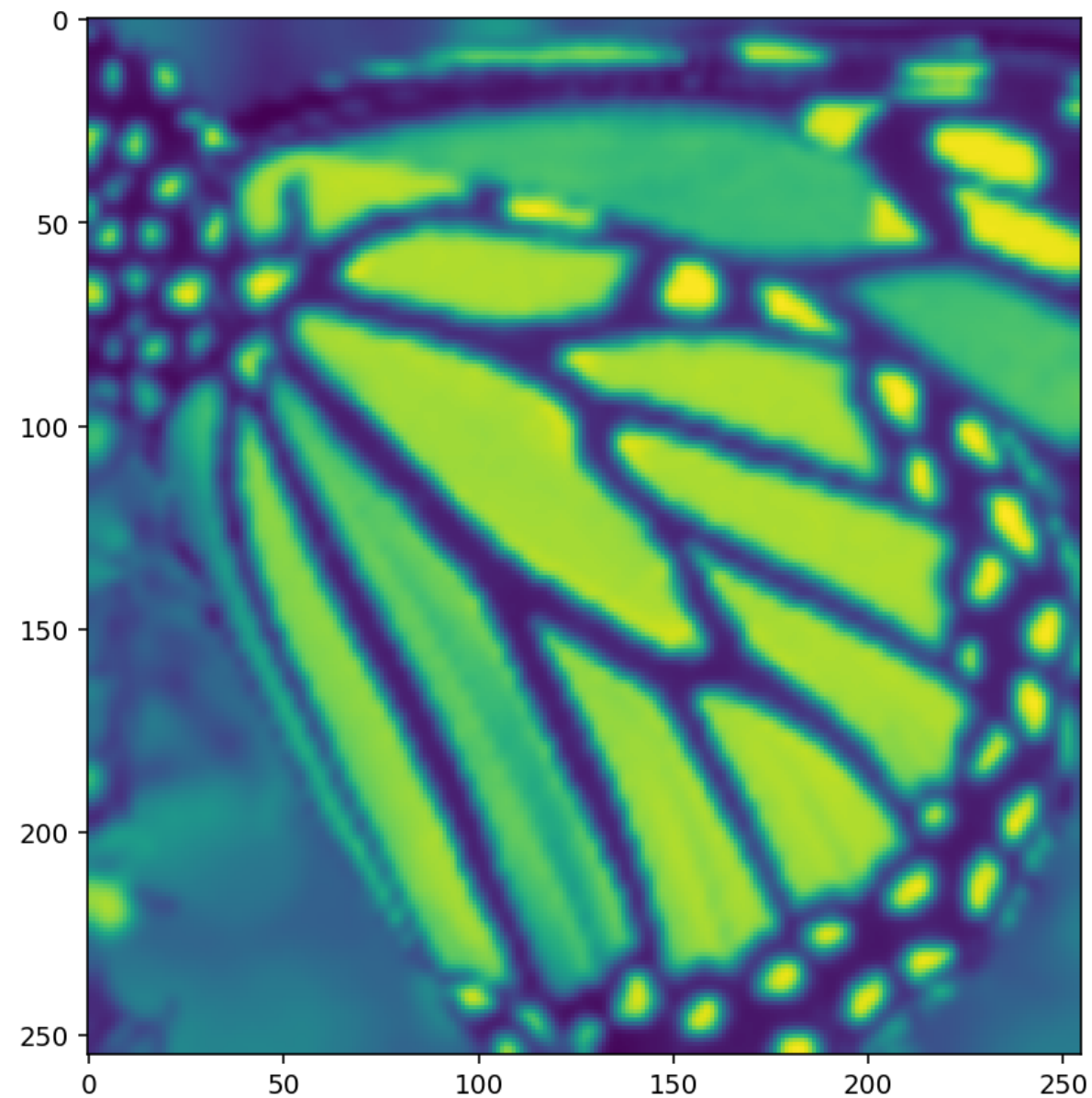
• SRCNN



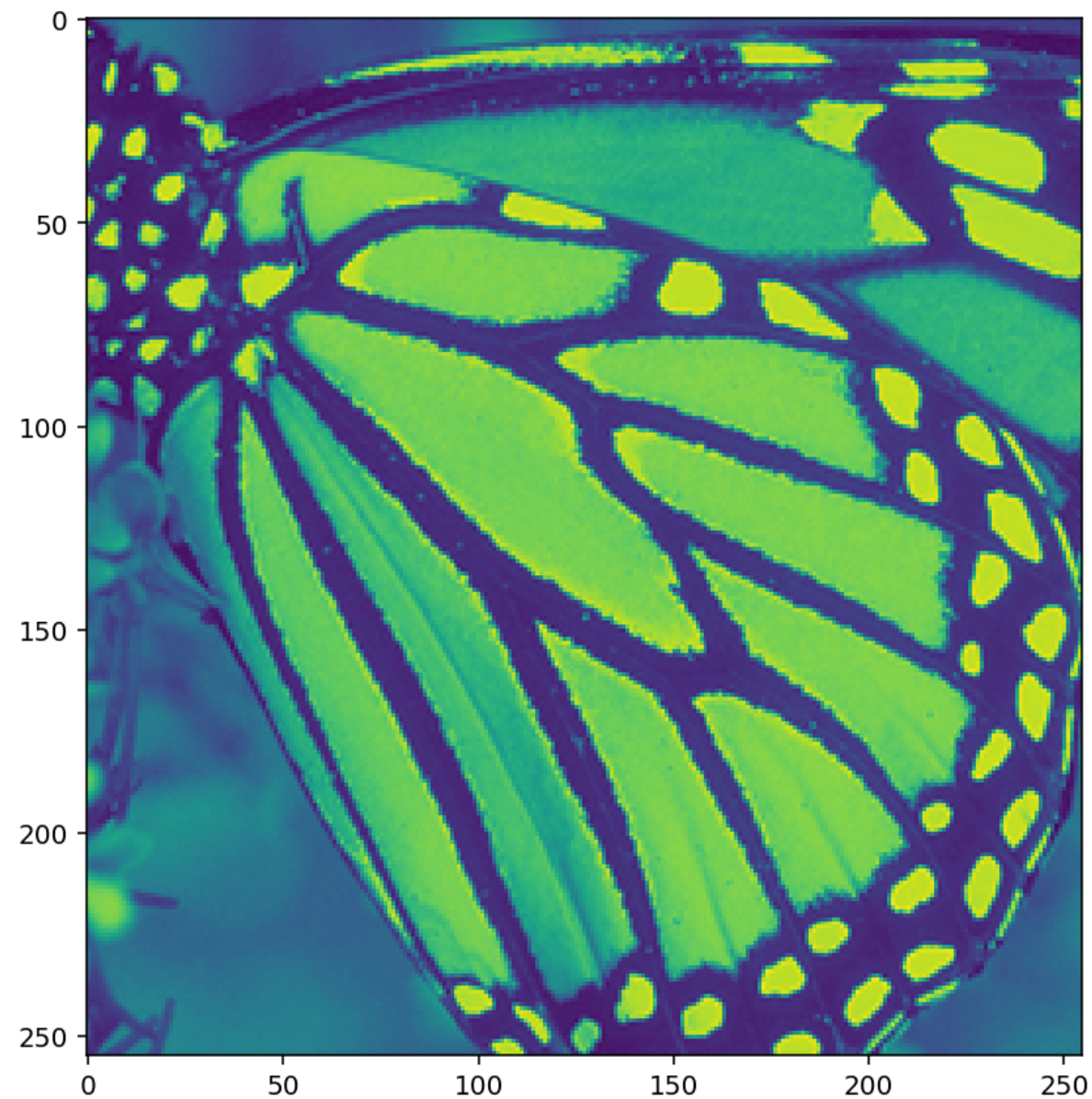
- Bicubic interpolation was replaced by Transpose convolution later
- Multiple Recursive layers

SRResNets





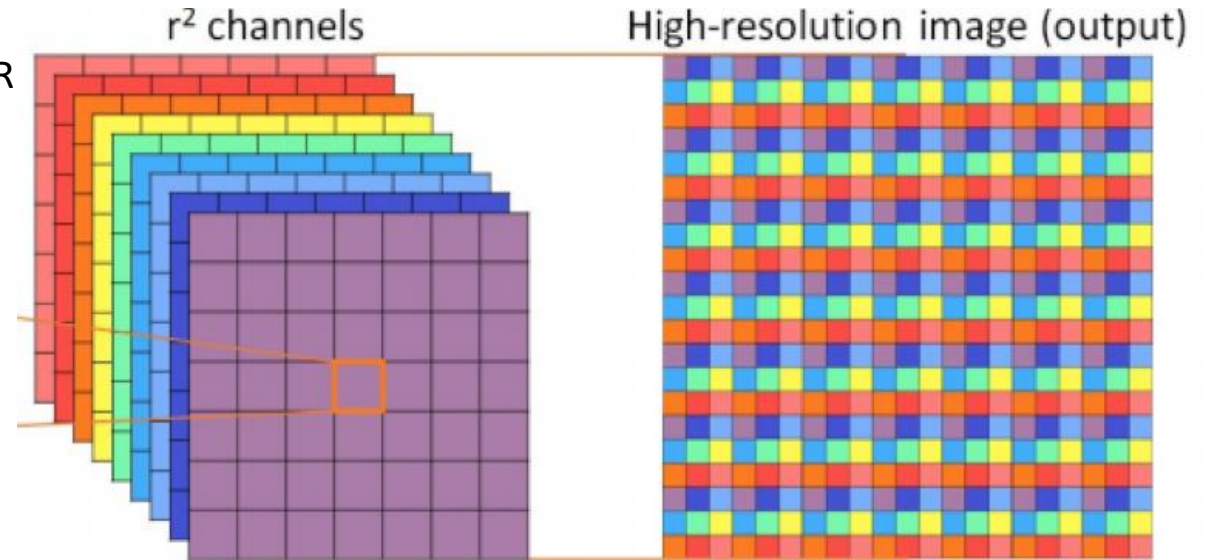
LR- Interpolated



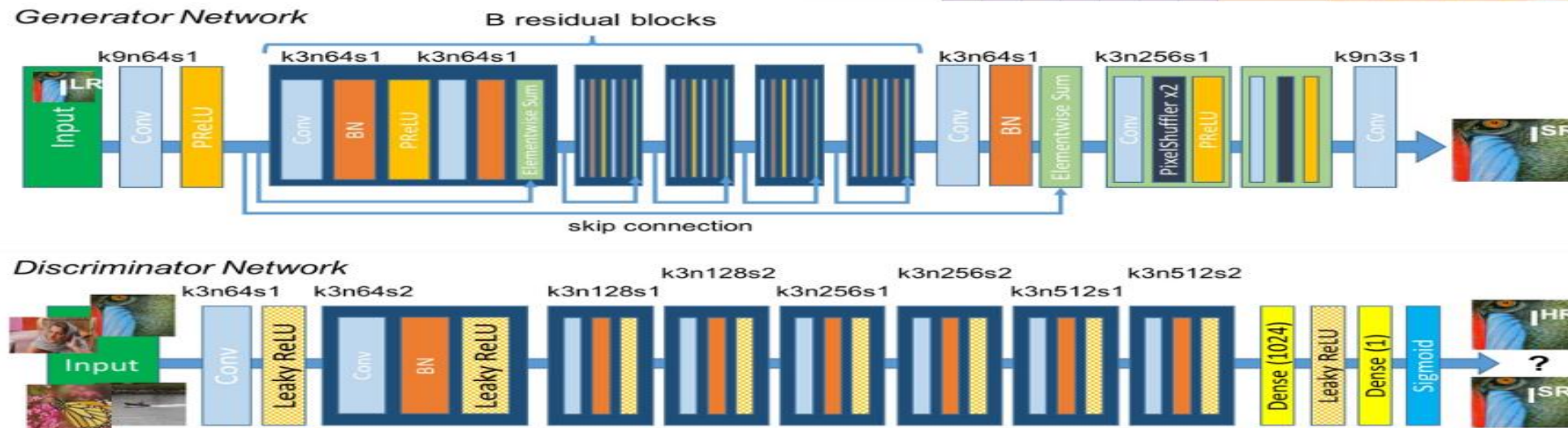
SRCNN

- **Sub-pixel convolution for upsampling (pixel shuffle)**

- 1) R squared channels are produced by convolutions on LR is then pixel reshuffled to produce xR SR.
- 2) This method is faster than other SR methods
- 3) ConvT causes image artifacts (distortions)

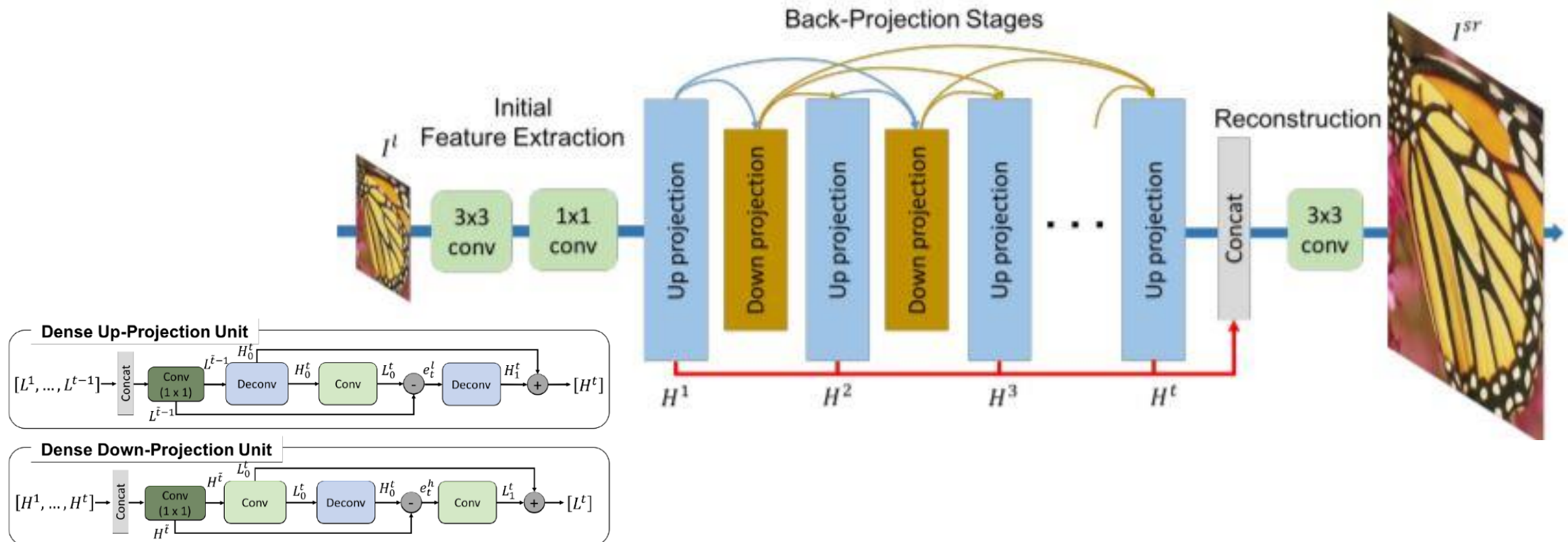


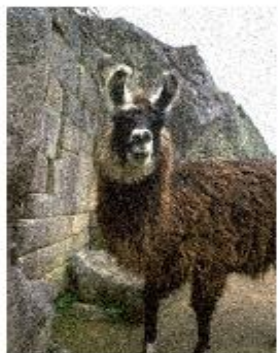
- **SRGAN**



- **DBPN**

- 1) Deep Back-Projection Networks (DBPN) exploit iterative up- and down-sampling layers
- 2) We use error feedbacks from the up- and down-scaling steps to guide the network to achieve a better result





Noisy
 $\sigma = 20$



GT
PSNR/SSIM



BM3D-SR [54]
25.05/0.5868



BM3D-SRNI [55]
25.31/0.6206



Ours
27.03/0.7330

DRLN

DEEP VSR

Temporal alignment

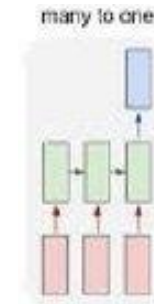
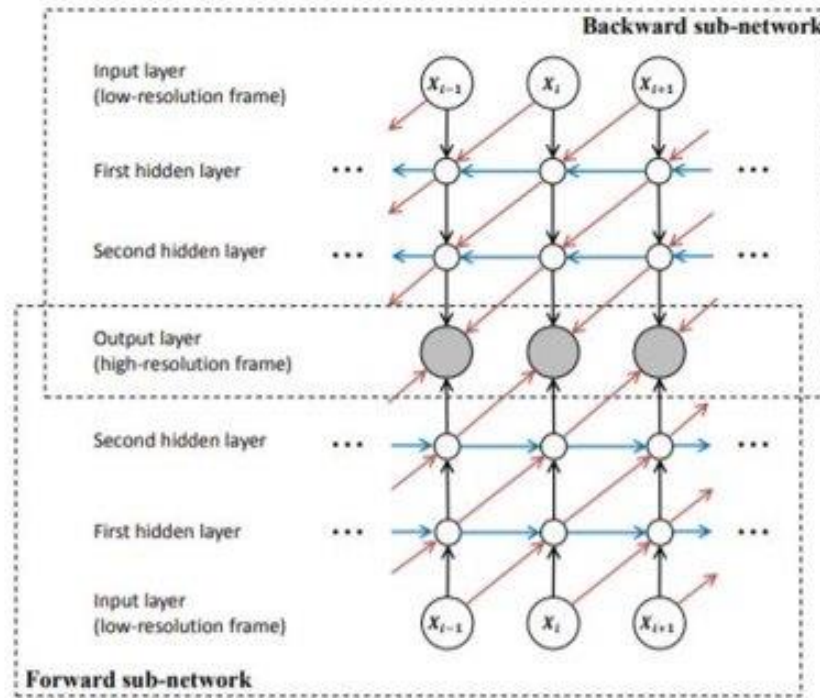
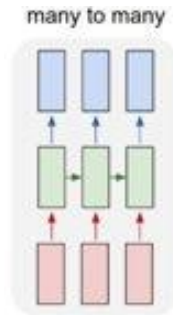
- **Temporal Concatenation**

- SISR for all Frames
- Frames are not temporal smooth (temporal incoherence)
- It doesn't include details/motion from surrounding frames

- **MISR**

- MISR utilizes the missing details available from the neighboring frames $LR(t-n)$, ..., $LR(t)$, ..., $LR(t+n)$ and fuses them for super-resolving LR

- **RNNs**



A sequence of LR frames is mapped to a single target HR frame in a window fashion

- **Optical flow methods**

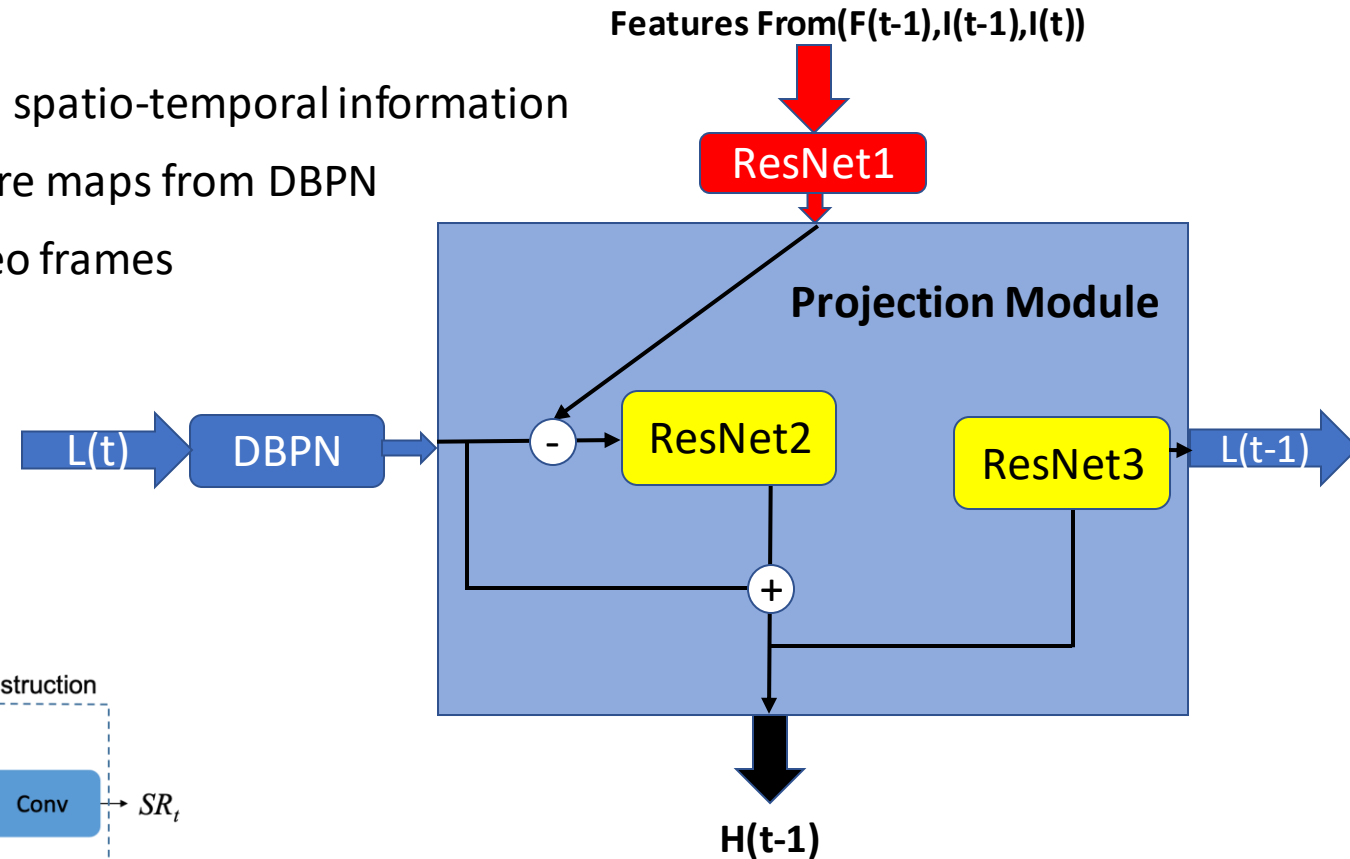
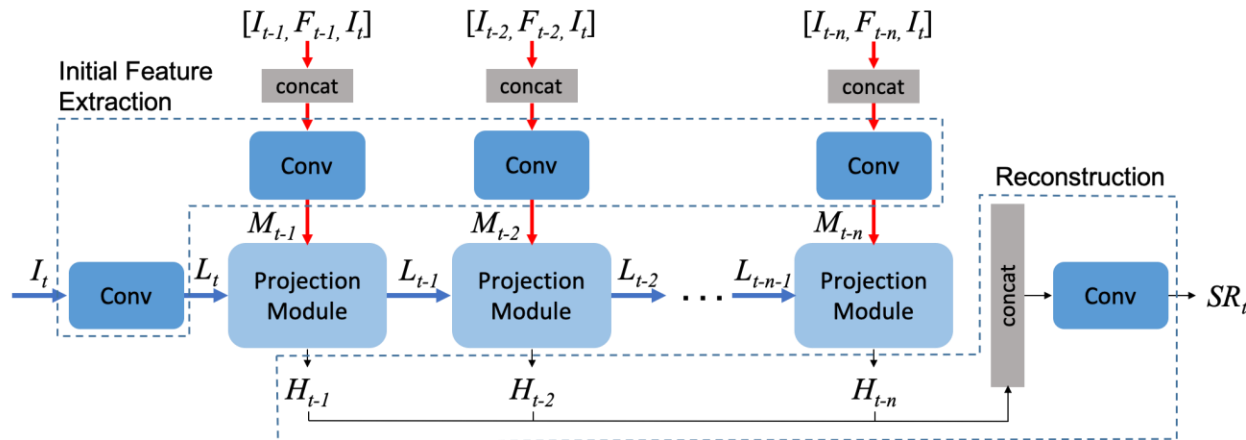
- Separate network to calculate optical flow between neighboring frames $LR(t-n) \dots LR(t+n)$
- Optical flow methods allow estimation of the trajectories of moving objects, thereby assisting in VSR.
- Video frames are Warped using the optical flow method $LR(t-k)$, $LR(t)$, $F(t-k)$

• RBPN

- An RNN-based optical flow method that preserves spatio-temporal information
- RBPN uses the idea of iteratively refining HR feature maps from DBPN
- But extracts missing details using neighboring video frames

I- LR Frames H – Used to construct SR

L- Refined Frame M-Residual Features



MSE Loss is not enough for SR!

- While optimizing MSE during training improves PSNR and SSIM, these metrics may not capture fine details in the image leading to misrepresentation of perceptual quality
- The ability of MSE to capture intricate texture details based on pixel-wise frame differences is very limited
- Minimizing MSE encourages finding pixel-wise averages of plausible solutions that are typically overly-smooth

Perceptual Loss:

- Focuses on perceptual similarity instead of similarity in pixel space.
- Perceptual loss relies on features extracted from the activation layers of the pre-trained VGG-19 network, instead of low-level pixel-wise error measures
- It is the Mean squared distance b/w features extracted from HR and SR

4 Fold Loss

$$\begin{aligned} Loss_{G_{\theta_G}}(SR_t) = & \alpha \times MSE(SR_t, HR_t) \\ & + \beta \times PerceptualLoss(SR_t, HR_t) \\ & + \gamma \times AdversarialLoss(SR_t) \\ & + \delta \times TVLoss(SR_t, HR_t) \end{aligned} \quad (5)$$

where, α , β , γ , δ are weights set as 1, 6×10^{-3} , 10^{-3} and 2×10^{-8} respectively [14].

- **AdversarialLoss**

Limit model “fantasy”, thus improving the “naturalness”

AdversarialLoss(t) = $-\log(D(G(LR(t))))$ (instead of $\log(1 - D(G(LR(t))))$)

- **TV Loss**

It is defined as the sum of the absolute differences between neighboring pixels in the horizontal and vertical directions.

To De-noise the output SR







$$TVLoss_t = \frac{1}{WH} \sum_{i=0}^W \sum_{j=0}^H \sqrt{(G_{\theta_G}(LR_t)_{i,j+1,k} - G_{\theta_G}(LR_t)_{i,j,k})^2 + (G_{\theta_G}(LR_t)_{i+1,j,k} - G_{\theta_G}(LR_t)_{i,j,k})^2} \quad (4)$$

- **MSE Loss**

- **Perceptual Loss**

Discriminator Loss = $1 - D(HR(t)) + D(SR(t))$

Results:

Dataset	Clip Name	VSR-DUF [23]	iSeeBetter	Ground Truth
Vid4	Calendar			
SPMCS	Pagoda			
Vimeo90K	Motion	