MULTILINEAR SUPER-RESOLUTION: FROM 2-D TO N-D

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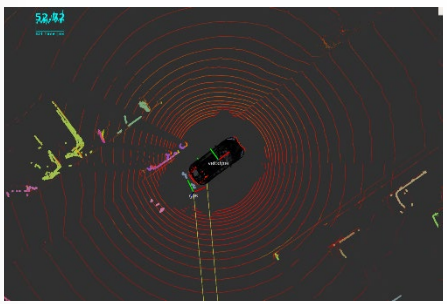
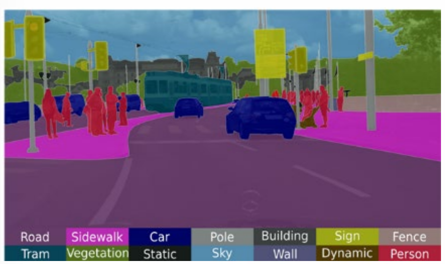
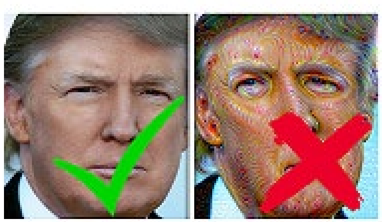
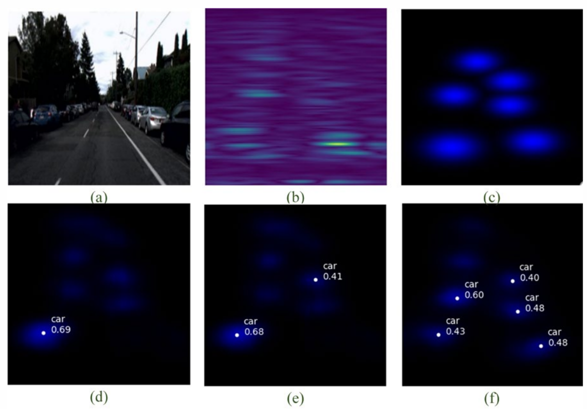
About Me

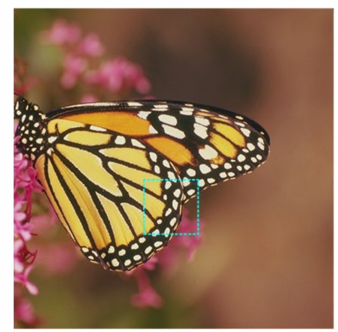
- Deep learning-based image processing and computer vision
  - DeepFake detection, Few-shot learning, ADAS application (vision), Medical signal analysis, and hyperspectral image restoration

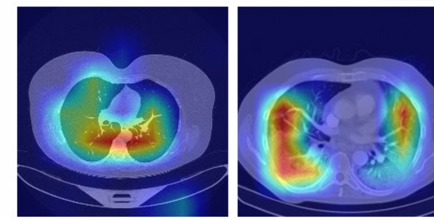


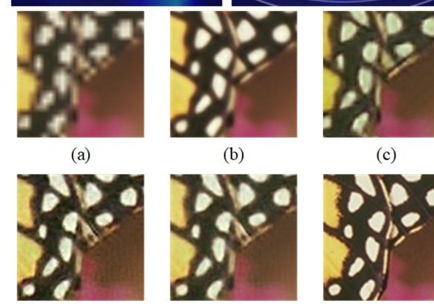


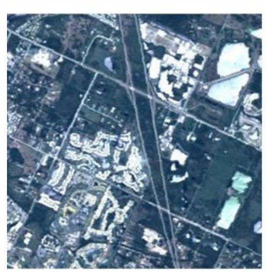




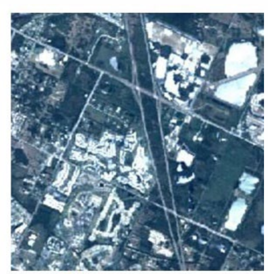




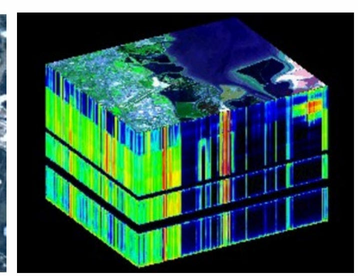




C-Type Ground Truth



1% Super-resolved image



Outline

- Overview of Deep Learning
  - Super-resolution
- Deep super-resolution
  - Structured image super-resolution
    - Face hallucination
  - 2-D image super-resolution (generic images)
  - *N*-D image super-resolution (Hyperspectral images)
- Summary

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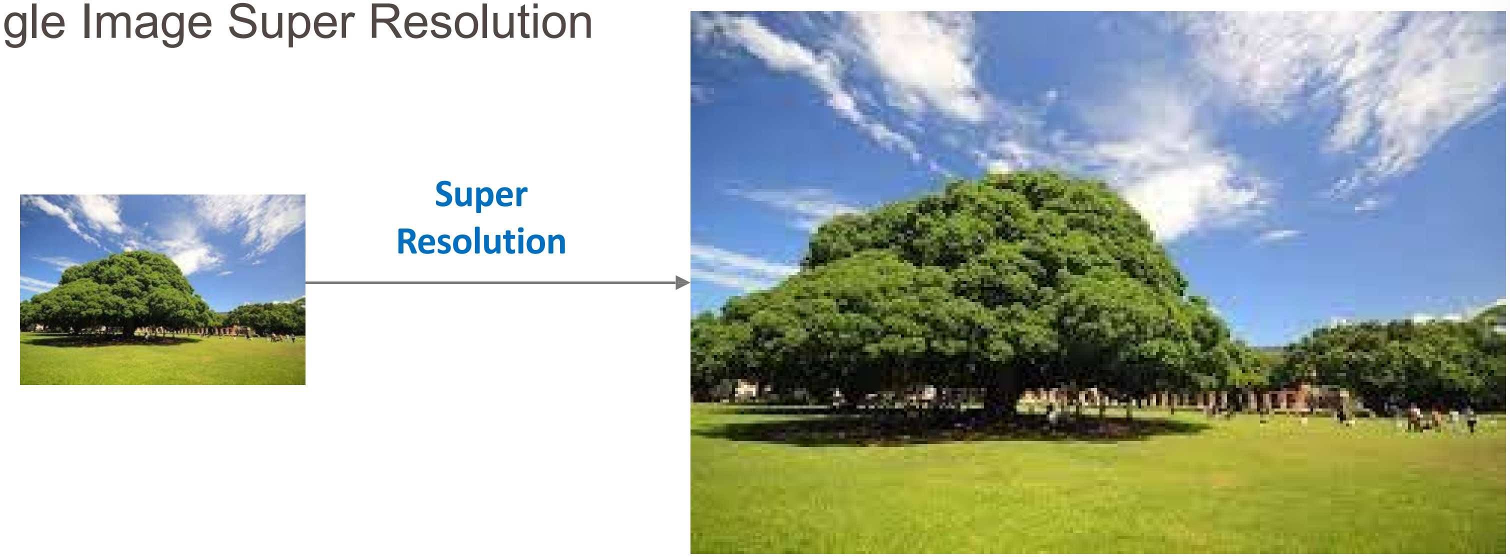
IMAGE SUPER-RESOLUTION

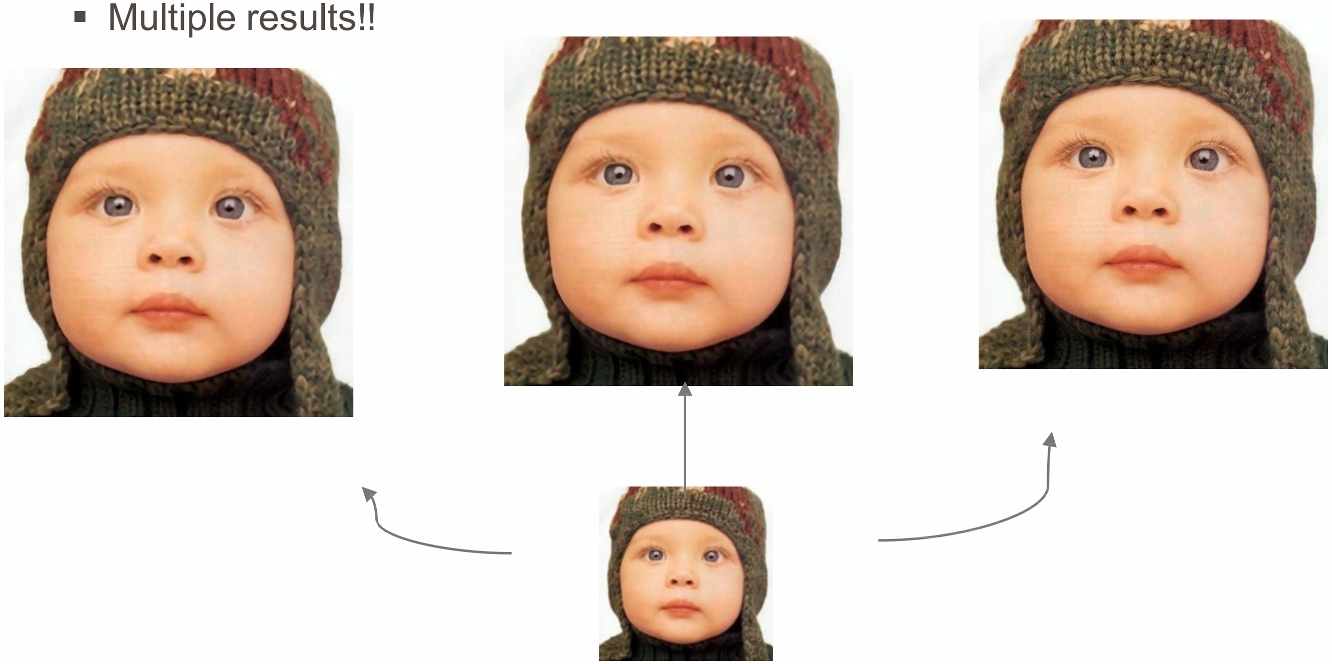
What is Super Resolution?

- Super Resolution
  - Restore High-Resolution(HR) image(or video) from Low-Resolution(LR) image(or video)
  - According to the number of input LR images, SR can be classified SISR or MISR
  - Efficient & Popular
  - Single Image Super Resolution



What is Super Resolution?

- Single Image Super Resolution
  - Restore High-Resolution(HR) image(or video) from Low-Resolution(LR) image(or video)
  - Ill-Posed Problem.. (Regular Inverse Problem) → We can't have ground truth from LR image
    - Multiple results!!



LR

What is Super Resolution?

- Interpolation-based Single Image Super Resolution
  - In image upscaling task, bicubic or bilinear or Lanczos interpolation is usually used.
  - Fast, easy.. but low quality..

Super Resolution

Deep SR

bilinear

Deep Learning for Single Image Super Resolution

- First Deep Learning architecture for Single Image Super Resolution
- SRCNN(2014) – three-layer CNN, MSE Loss
  - Early upsampling
- Compared to traditional methods, it shows excellent performance.

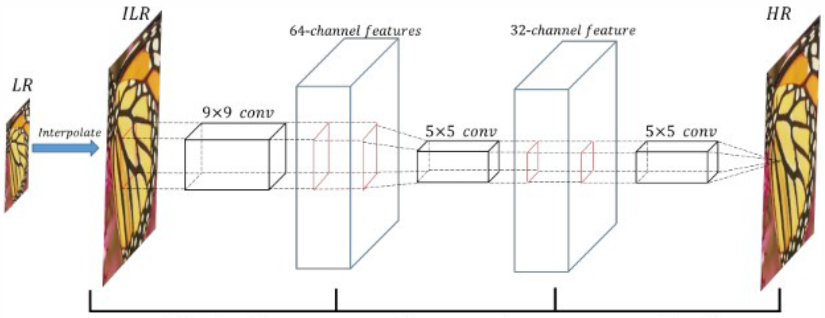
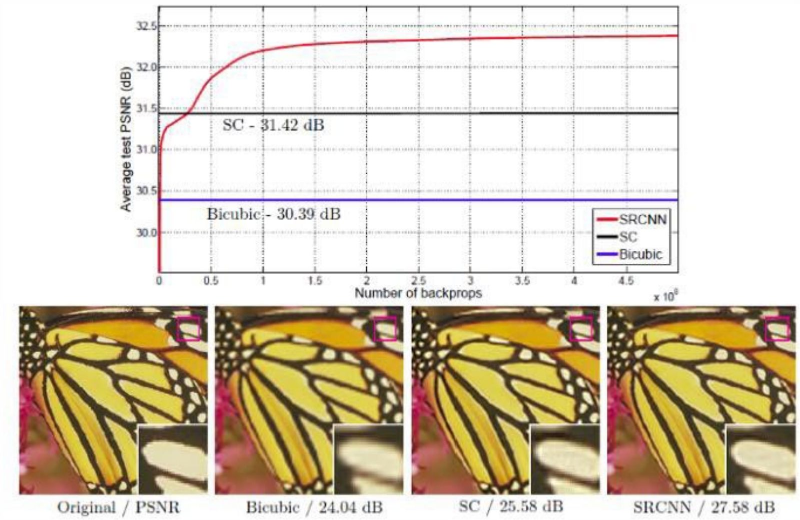


Figure 2: Sketch of the SRCNN architecture.

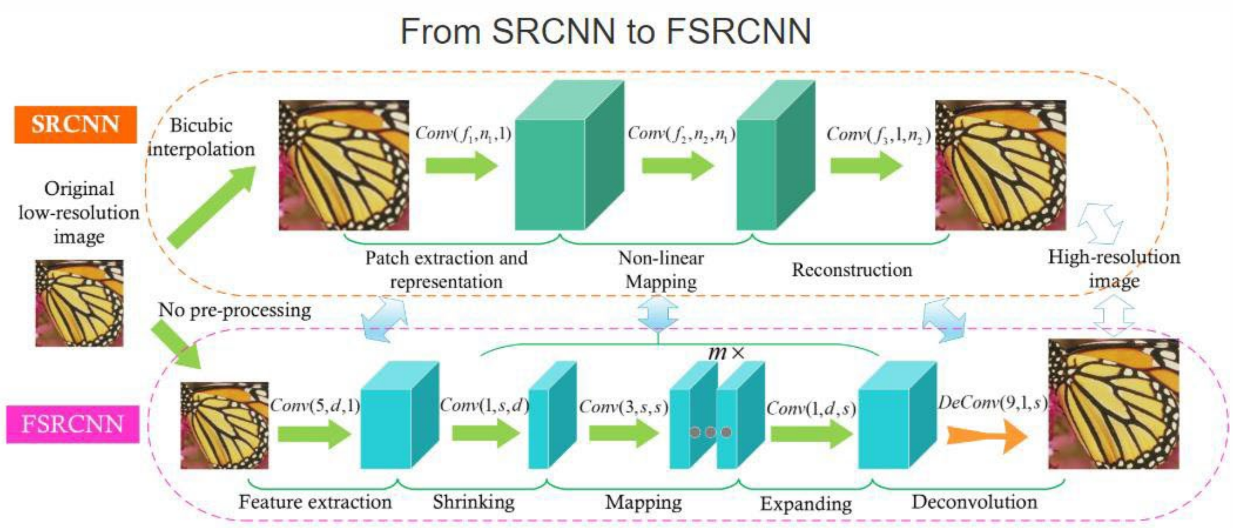


Reference: "Image Super-Resolution Using Deep Convolutional Networks", 2014 ECCV

Deep Learning for Single Image Super Resolution

- Efficient Single Image Super Resolution
- FSRCNN(2016), ESPCN(2016)
  - Late Upsampling
  - Deconvolution or sub-pixel convolutional layer

Inefficient in Memory, FLOPS



Reference: "Accelerating the Super-Resolution Convolutional Neural Network", 2016 ECCV

Deep Learning for Single Image Super Resolution

- ESPCN(Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel
  - Convolutional Neural Network)
  - Use sub-pixel convolutional layer (pixel shuffler or depth_to_space)
  - This sub-pixel convolutional layer is used in recent SR models

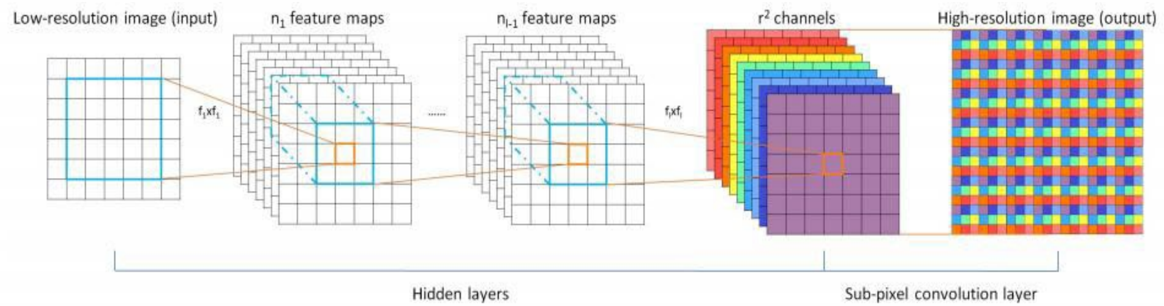


Figure 1. The proposed efficient sub-pixel convolutional neural network (ESPCN), with two convolution layers for feature maps extraction, and a sub-pixel convolution layer that aggregates the feature maps from LR space and builds the SR image in a single step.

Reference: "Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network", 2016 CVPR

Deep Learning for Single Image Super Resolution

- VDSR(Accurate Image Super-Resolution Using Very Deep Convolutional Networks)
  - VGG based deeper model(20-layer) for Super-Resolution → large receptive field
  - Residual learning & High learning rate with gradient clipping
  - MSE Loss, Early upsampling

Epoch	10	20	40	80
Residual	36.90	36.64	37.12	37.05
Non-Residual	27.42	19.59	31.38	35.66
Difference	9.48	17.05	5.74	1.39

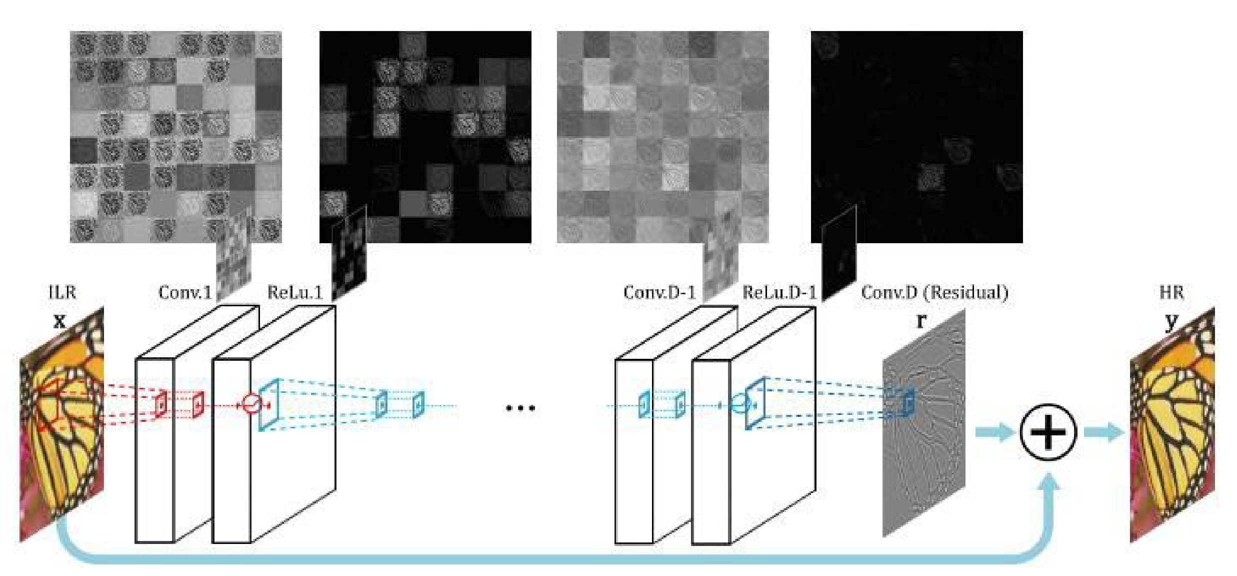
(a) Initial learning rate 0.1

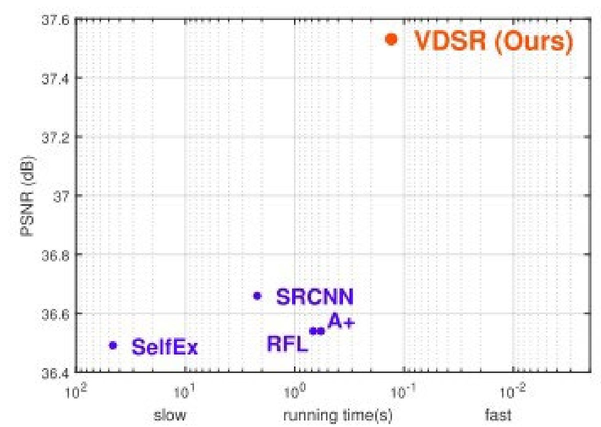
Epoch	10	20	40	80
Residual	36.74	36.87	36.91	36.93
Non-Residual	30.33	33.59	36.26	36.42
Difference	6.41	3.28	0.65	0.52

(b) Initial learning rate 0.01

Epoch	10	20	40	80
Residual	36.31	36.46	36.52	36.52
Non-Residual	33.97	35.08	36.11	36.11
Difference	2.35	1.38	0.42	0.40

(c) Initial learning rate 0.001

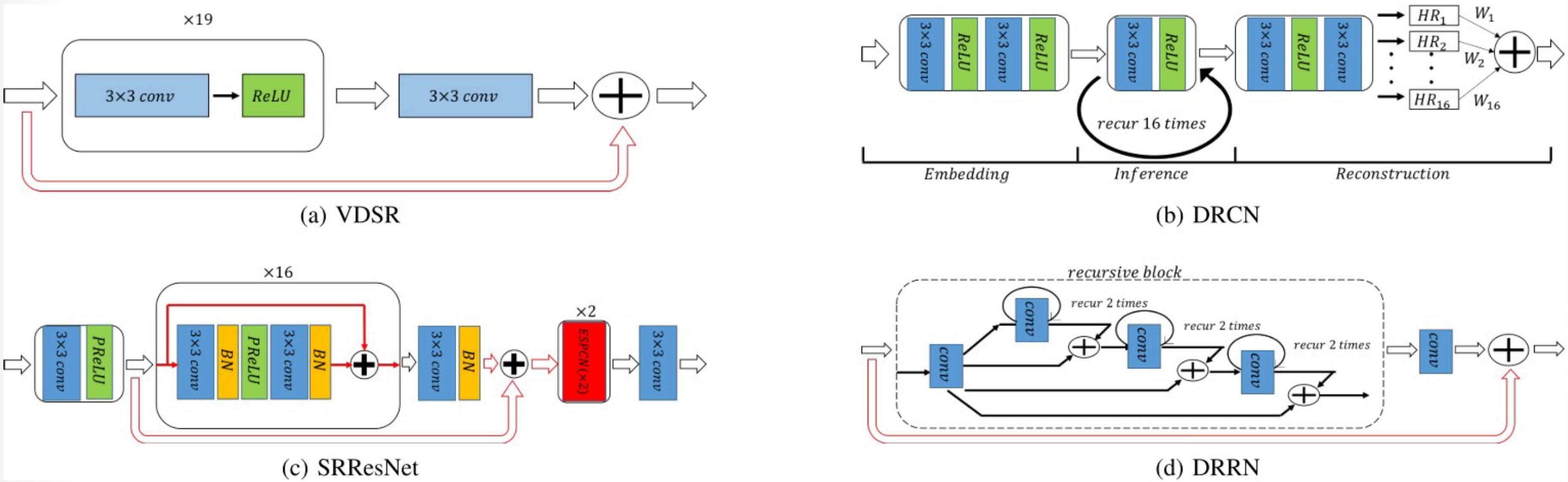




Reference: "Accurate Image Super-Resolution Using Very Deep Convolutional Networks", 2016 CVPR

Deep Learning for Single Image Super Resolution

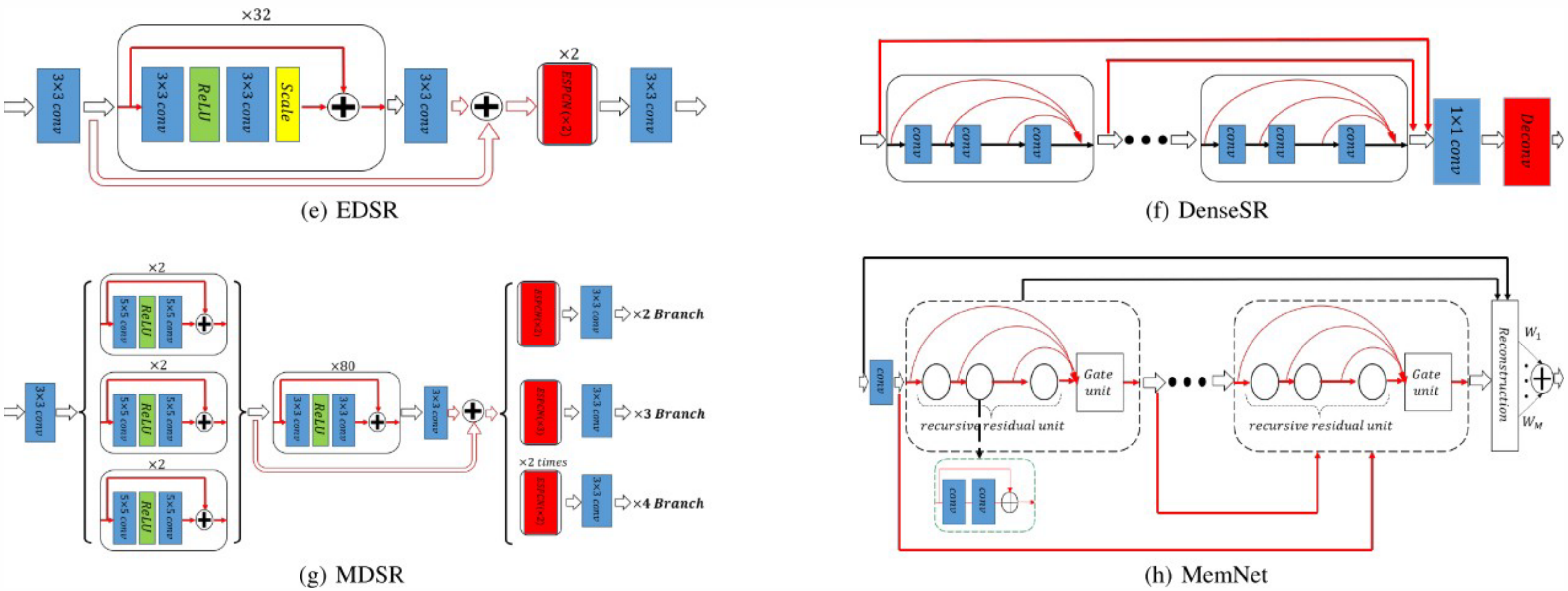
- Deeper Networks for Super-Resolution after VDSR
  - DRCN(Deeply-recursive Convolutional network), 2016 CVPR
  - SRResNet, 2017 CVPR
  - DRRN(Deep Recursive Residual Network), 2017 CVPR



Reference: "Deep Learning for Single Image Super-Resolution: A Brief Review", 2018 IEEE Transactions on Multimedia (TMM)

Deep Learning for Single Image Super Resolution

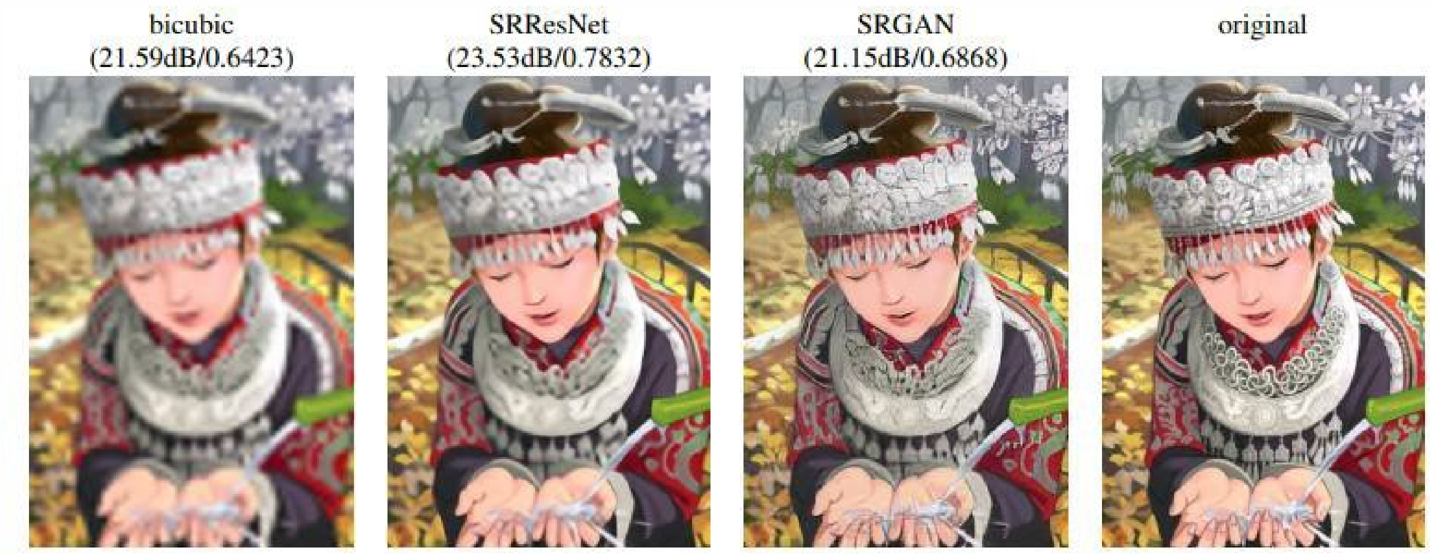
- Deeper Networks for Super-Resolution after VDSR
  - EDSR, MDSR (Enhanced Deep Residual Network, Multi Scale EDSR), 2017 CVPRW
  - DenseSR, 2017 CVPR
  - MemNet, 2017 CVPR



Reference: "Deep Learning for Single Image Super-Resolution: A Brief Review", 2018 IEEE Transactions on Multimedia (TMM)

Deep Learning for Single Image Super Resolution

- Generative Adversarial Network(GAN) for Super-Resolution
  - SRGAN(Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network)
  - First GAN-based SR Model, MSE Loss → Blurry Output → GAN loss + Content loss = Perceptual loss



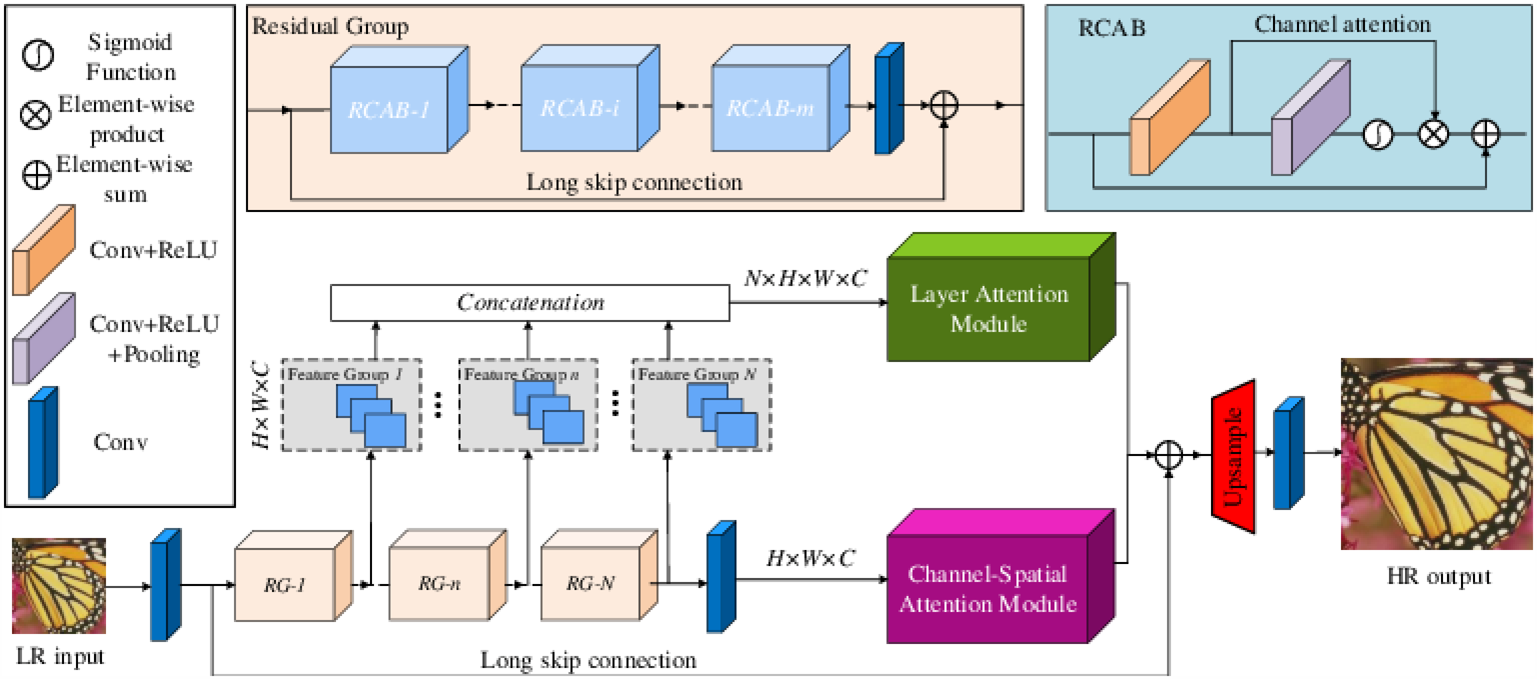
Reference: "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network", 2017 CVPR

Deep Learning for Single Image Super Resolution

- Generative Adversarial Network(GAN) for Super-Resolution
  - SRGAN, EnhanceNet, SRFeat, ESRGAN

Reference: "A Deep Journey into Super-resolution: A survey", 2019 arXiv

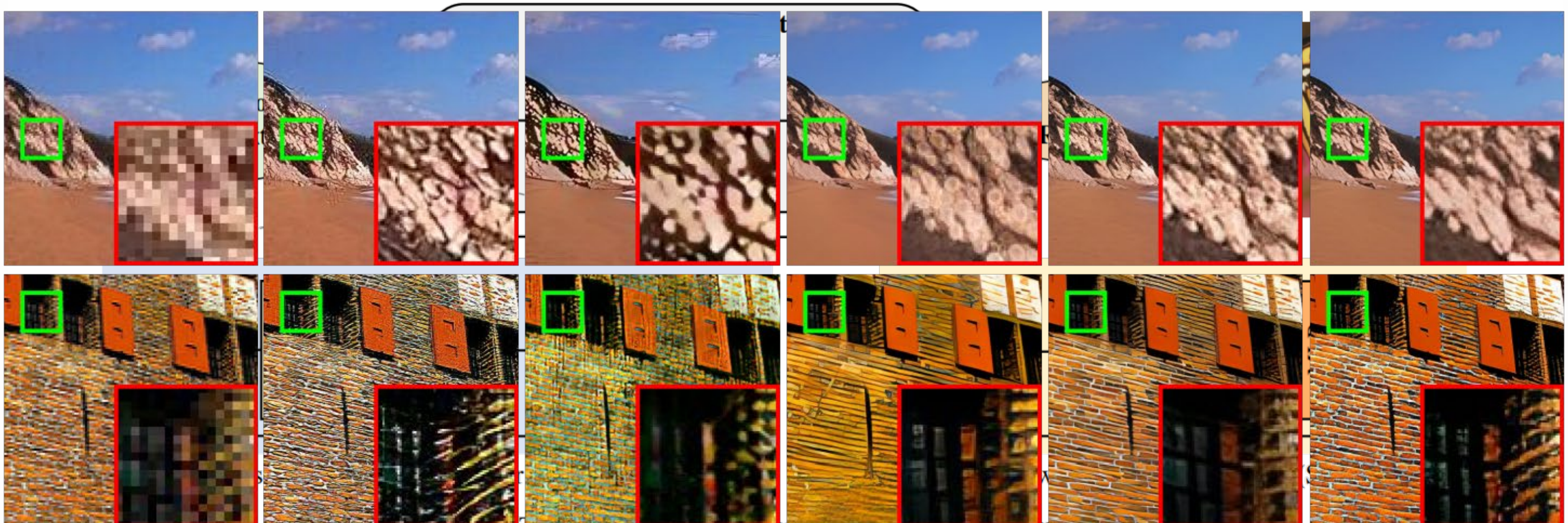
HANet, ECCV 2020



- Bring the “attention” module to the generator

Swin-IR (2021, CVPR-W)

- This paper employ the same feature extraction modules for all restoration tasks, but use different reconstruction modules for different tasks.

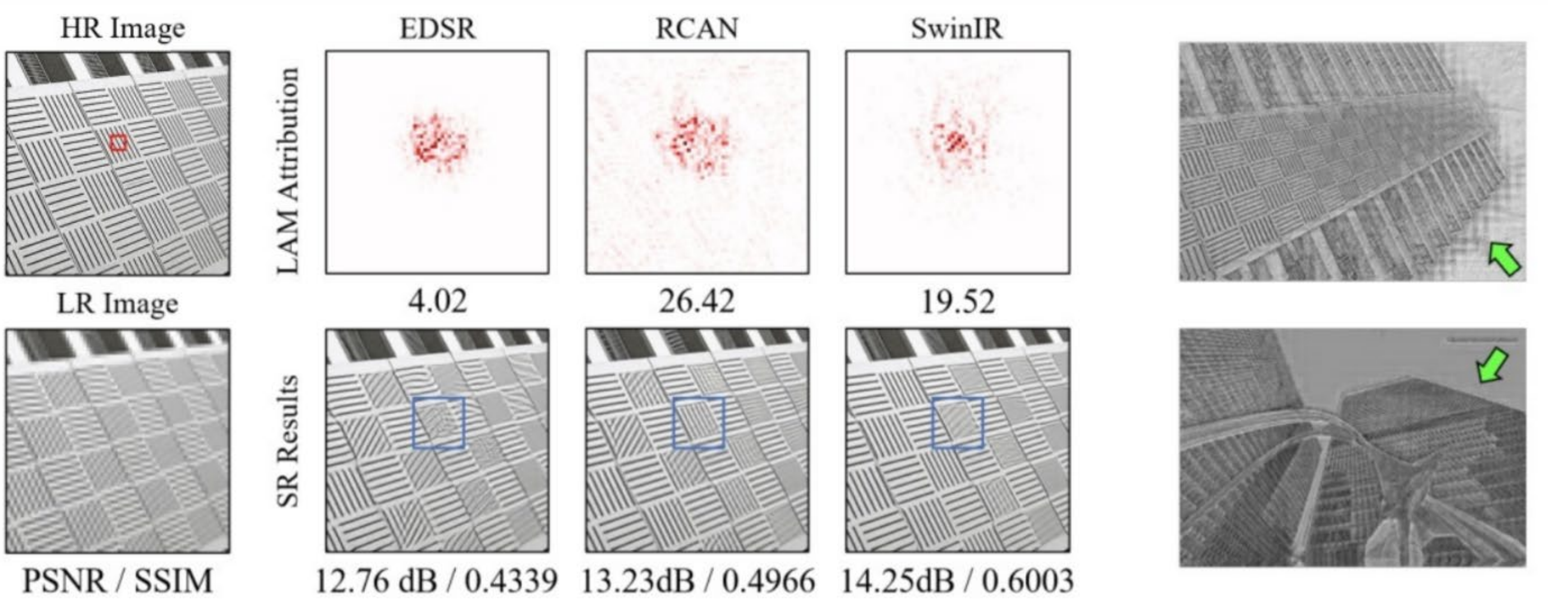


LR (×4) | ESRGAN [81] | RealSR [37] | BSRGAN [89] | Real-ESRGAN [80] | **SwinIR** (ours)

Figure 5: Visual comparison of **real-world image SR** (×4) methods on real-world images.

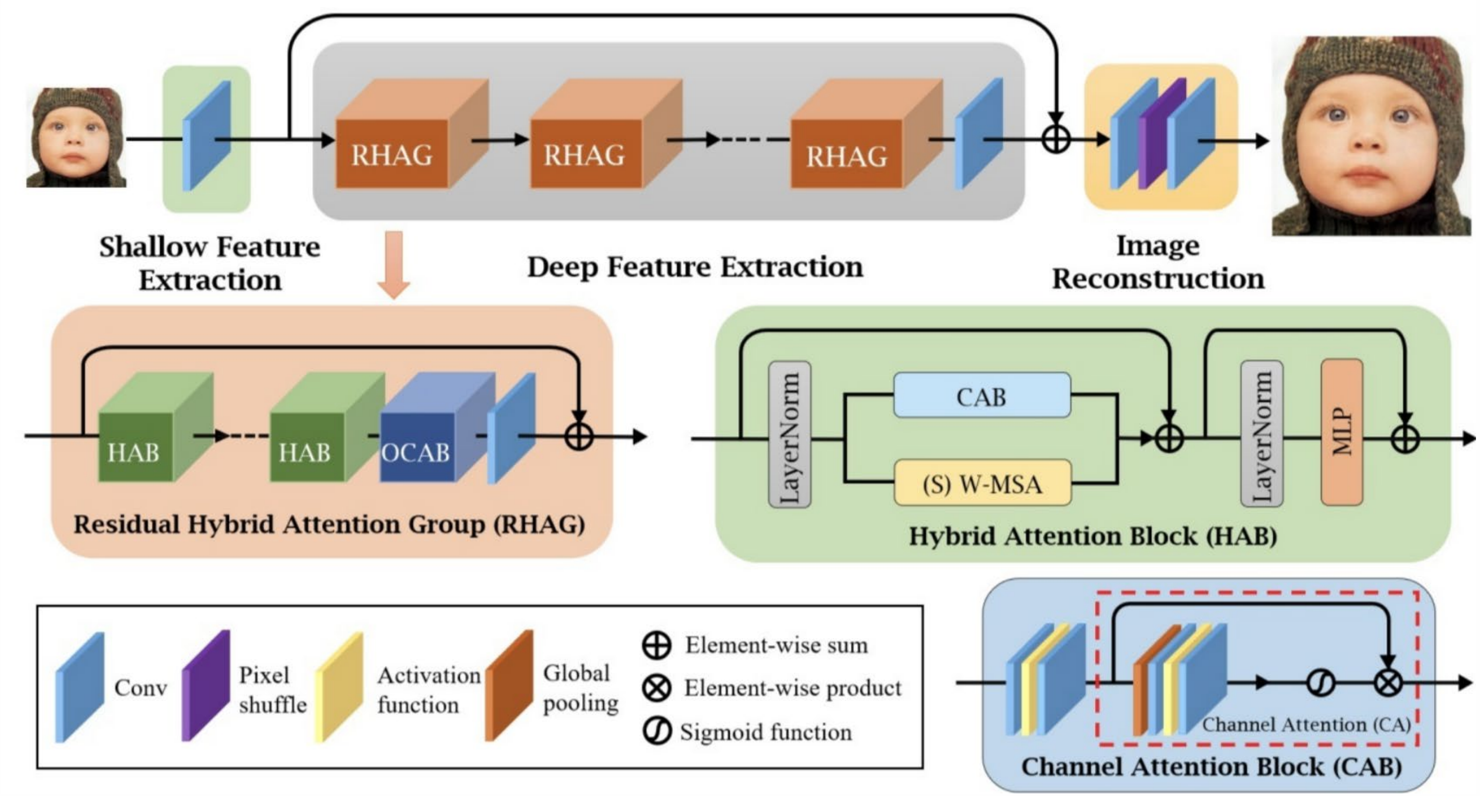
HAT (arXiv 2022)

- Activating More Pixels in Image Super-Resolution Transformer
  - Check the activation of Grad-LAM

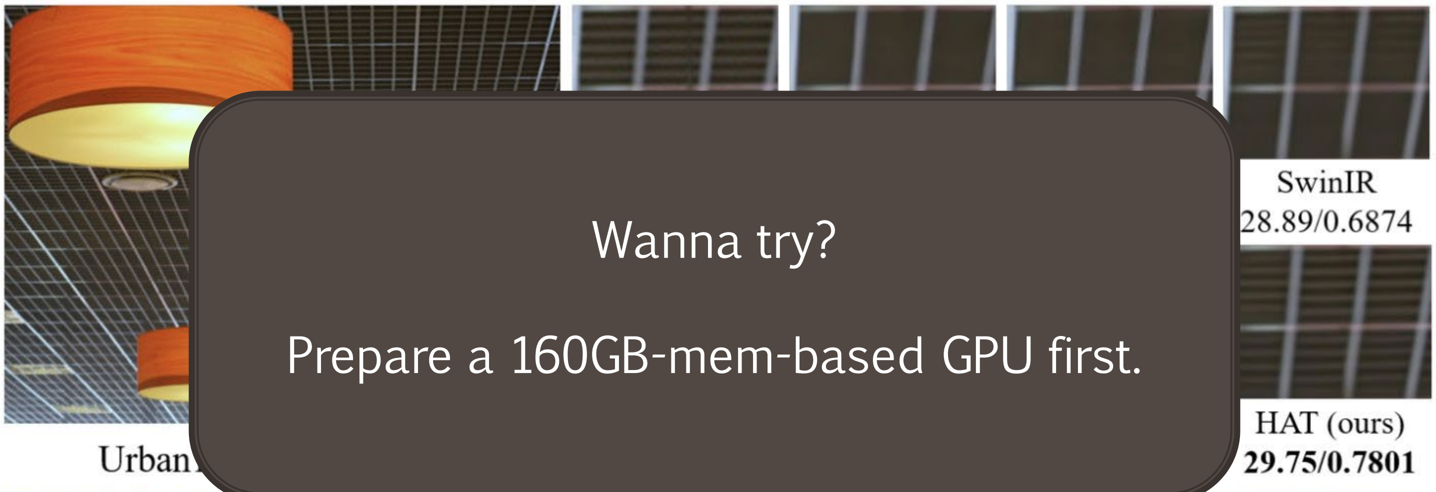


(a) LAM [14] results for different networks. (b) Blocking artifacts.

HAT


RHAG
RHAG
RHAG
Shallow Feature Extraction
Deep Feature Extraction
Image Reconstruction
HAB
HAB
OCAB
Residual Hybrid Attention Group (RHAG)
LayerNorm
CAB
(S) W-MSA
LayerNorm
MLP
Hybrid Attention Block (HAB)
Conv
Pixel shuffle
Activation function
Global pooling
Element-wise sum
Element-wise product
Sigmoid function
Channel Attention (CA)
Channel Attention Block (CAB)

Results of HAT



Wanna try?

Prepare a 160GB-mem-based GPU first.

- Refer to `./options/train` for the configuration file of the model to train.
- Preparation of training data can refer to this page. ImageNet dataset can be downloaded at the official website.
- The training command is like

```
CUDA_VISIBLE_DEVICES=0,1,2,3,4,5,6,7 python -m torch.distributed.launch --nproc_per_node=8 --master_port=4321
```

- Note that the default batch size per gpu is 4, which will cost about 20G memory for each GPU.

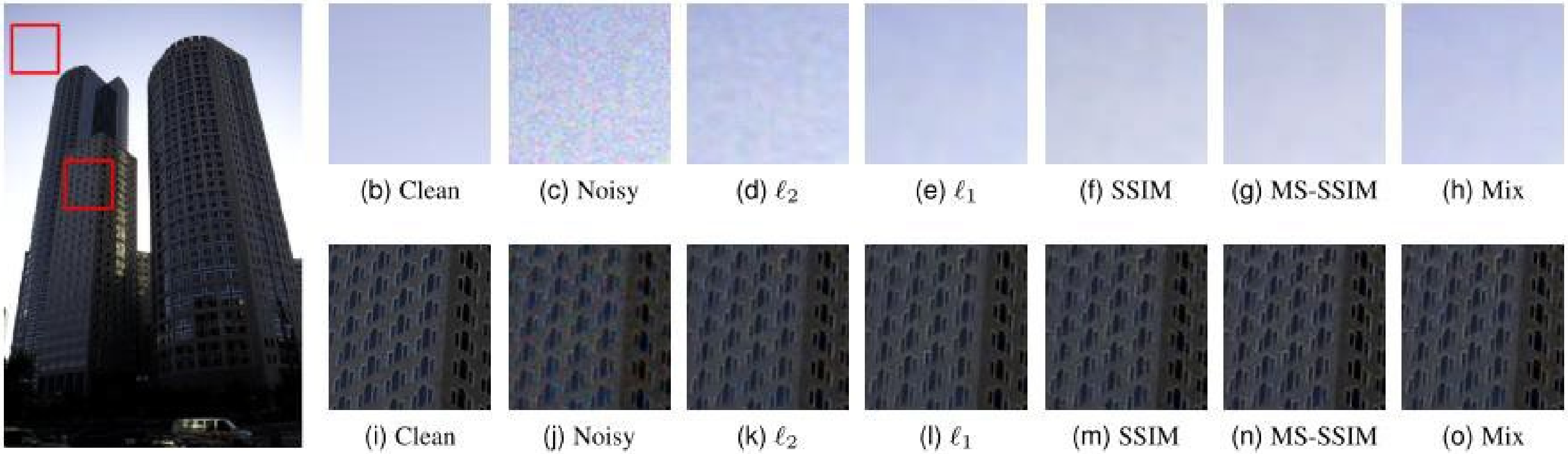
WHAT’S NEXT?

Finding the issues in current SRs

Some Issues for Super Resolution

- Loss function
  - Propose a various loss function methods in Image Restoration task
  - Report the best result when using mixed loss with MS-SSIM loss + $l1$ loss

$$\boxed{\mathcal{L}^{\text{Mix}} = \alpha \cdot \mathcal{L}^{\text{MS-SSIM}} + (1-\alpha) \cdot G_{\sigma_G^M} \cdot \mathcal{L}^{\ell_1}, \qquad (14)}$$



(a) Clean image

Reference: "Loss Functions for Image Restoration with Neural Networks", 2016 IEEE TCI

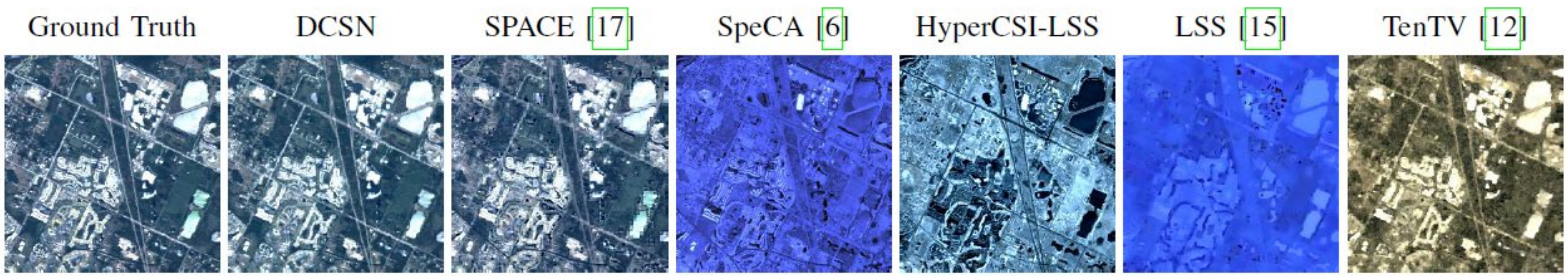
Some Issues for Super Resolution

- GAN Loss achieves a high visual quality
- L1/SSIM losses achieves a high fidelity
- However, we don’t have a metric that can consider both of them

- We show that one of the critical problem in loss functions is “resolution-aware” information
  - Feature distance does not fit “resolution”
    - Good quality != High resolution
      - E.g., defocused sample/background?

Some Issues for Super Resolution

- How about multilinear super-resolution
  - E.g. Hyperspectral data



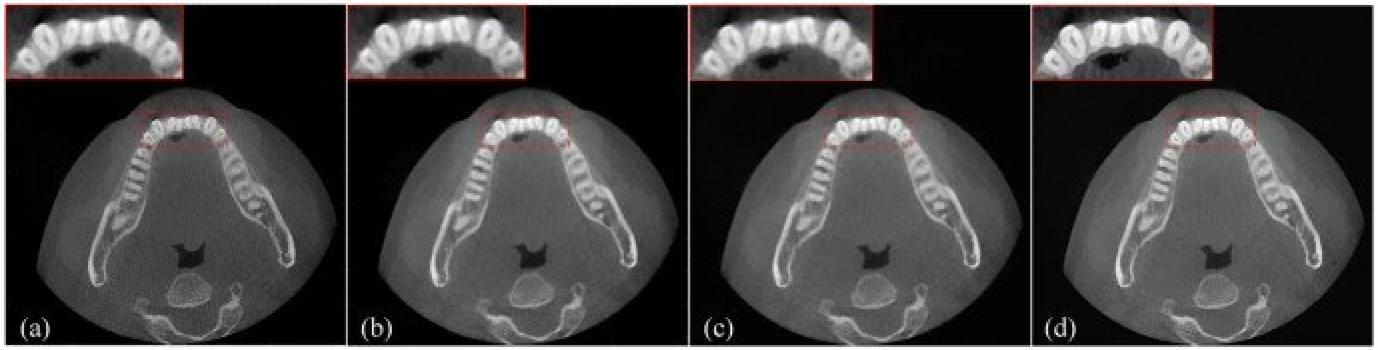
  - Data range? 0-255 for RGB but not for Multi- and Hyper-spectral images
  - Super-resolution on “spectral” or “spatial”?

Hsu, Chih-Chung, et al. "Sigan: Siamese generative adversarial network for identity-preserving face hallucination." *IEEE Transactions on Image Processing* 28.12 (2019): 6225-6236.

Some Issues for Super Resolution

- How about the structured image super-resolution?
  - Face hallucination

- How about multilinear super-resolution
  - E.g. medical imaging data



Hsu, Chih-Chung, et al. "Sigan: Siamese generative adversarial network for identity-preserving face hallucination." *IEEE Transactions on Image Processing* 28.12 (2019): 6225-6236.

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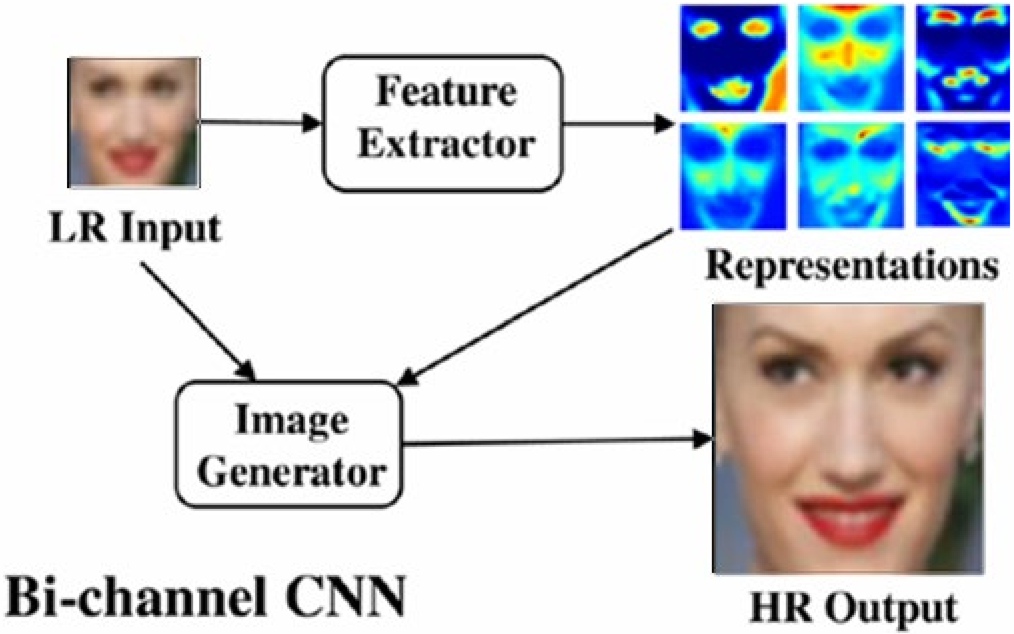
CNN-based Approach (AAAI'15)

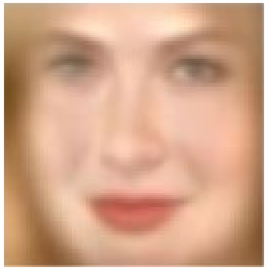
- Using CNN to learn the dictionary and its coefficients



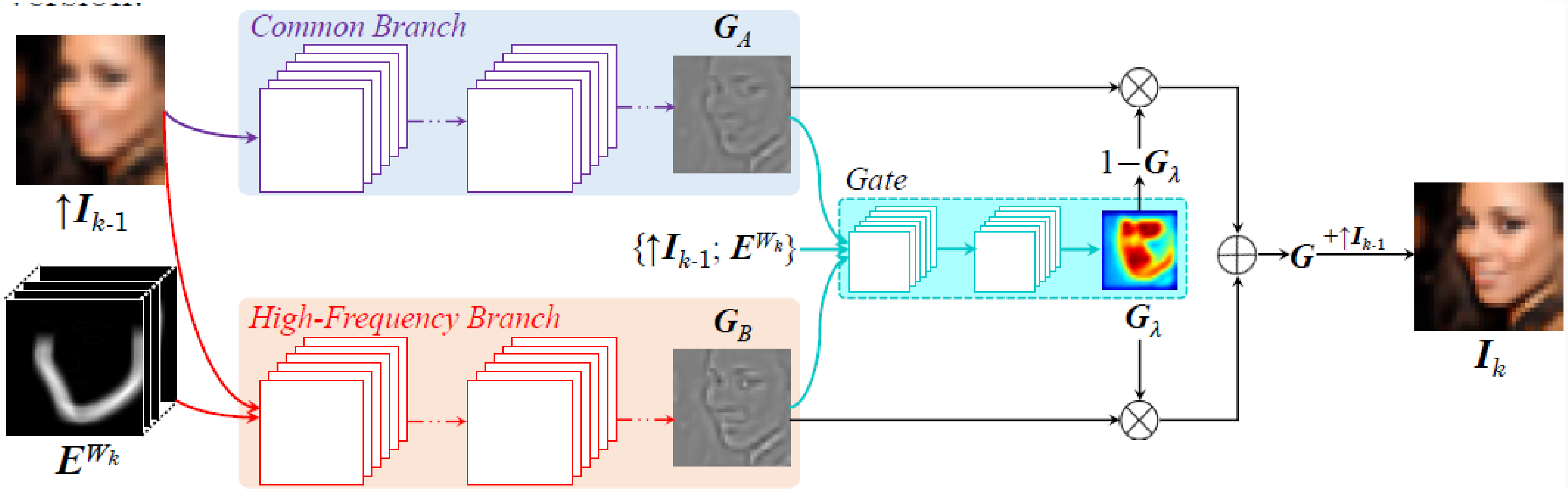
Zhou, Erjin, et al. "Learning Face Hallucination in the Wild." *AAAI*. 2015.

CNN-based Approach (AAAI'15)

- Pros
  - First approach based on deep neural network (DNN)
  - Alignment is unnecessary
  - State-of-the-art result (2015)
- Cons
  - The visual quality of reconstructed face image will be poor when
    - Extreme low-resolution
      - i.e. 8x8
    - Identity-unrecognizable



Cascaded CNN Approach (ECCV'16)



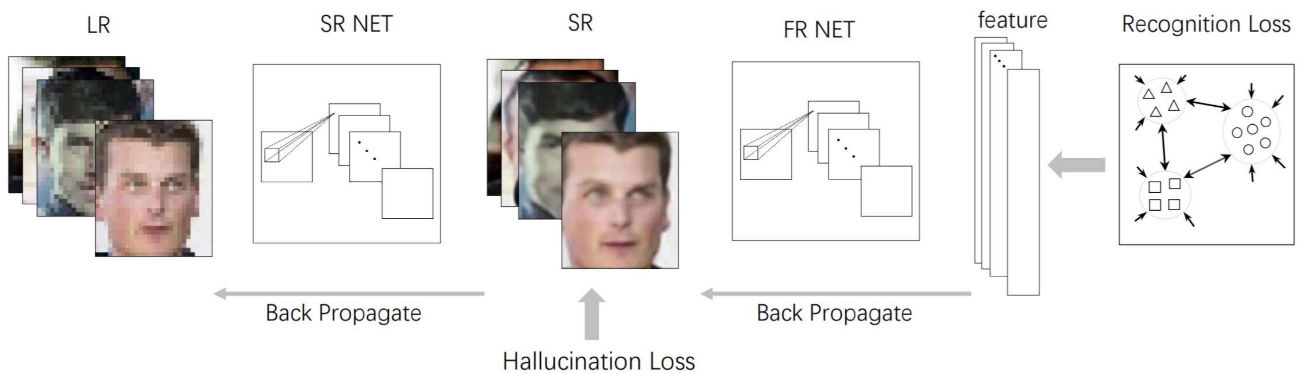
- Cascaded multiple CNN to enhance visual quality
- Gate network can be used to fusion of two nets

Zhu, Shizhan, et al. "Deep cascaded bi-network for face hallucination." *European Conference on Computer Vision*. Springer International Publishing, 2016.

Cascaded CNN Approach (ECCV'16)

- Pros
  - The best performance so far
  - Alignment-free
  - More realistic
- Cons
  - It is very hard to train
    - Released code has no training codes
  - A lot of parameters need to be tuned manually
  - Extreme low-resolution inputs
    - Cannot obtain promising results

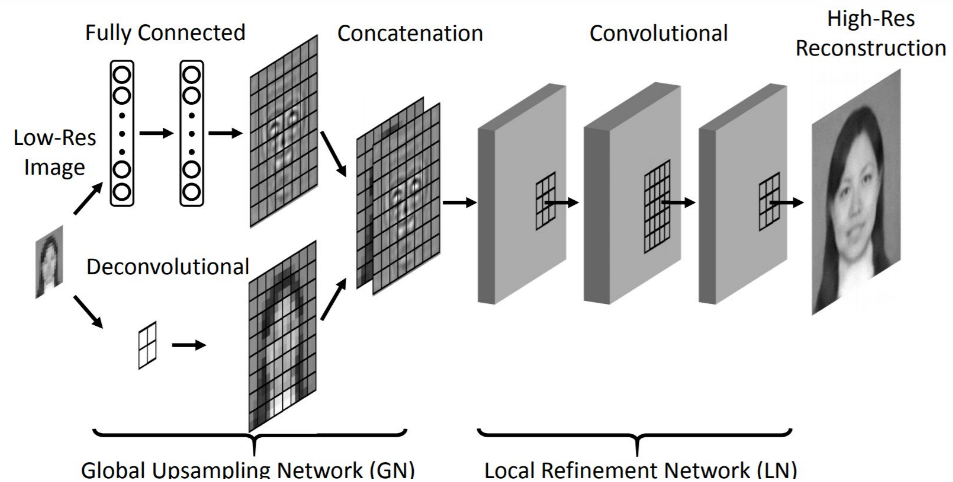
Deep Joint Face Hallucination and Recognition (ArXiv'16)



- Pros
  - First joint face hallucination and recognition
- Cons
  - Quality of the reconstructed face may be unrealistic
    - No related experiments can be verified…

Wu, Junyu, et al. "Deep Joint Face Hallucination and Recognition." *arXiv preprint arXiv:1611.08091* (2016).

GAN (Generative Adversarial Net) for Face Hallucination



- Use discriminator to refine the upsampling network
  - Dissimilar to the ground truth

Tuzel, Oncel, Yuichi Taguchi, and John R. Hershey. "Global-Local Face Upsampling Network." *arXiv preprint arXiv:1603.07235* (2016). [no code]

GAN for Face Hallucination (II)

- Discriminator is used to judge the visual quality

Yu, Xin, and Fatih Porikli. "Ultra-resolving face images by discriminative generative networks." *ECCV*, 2016. [no code]

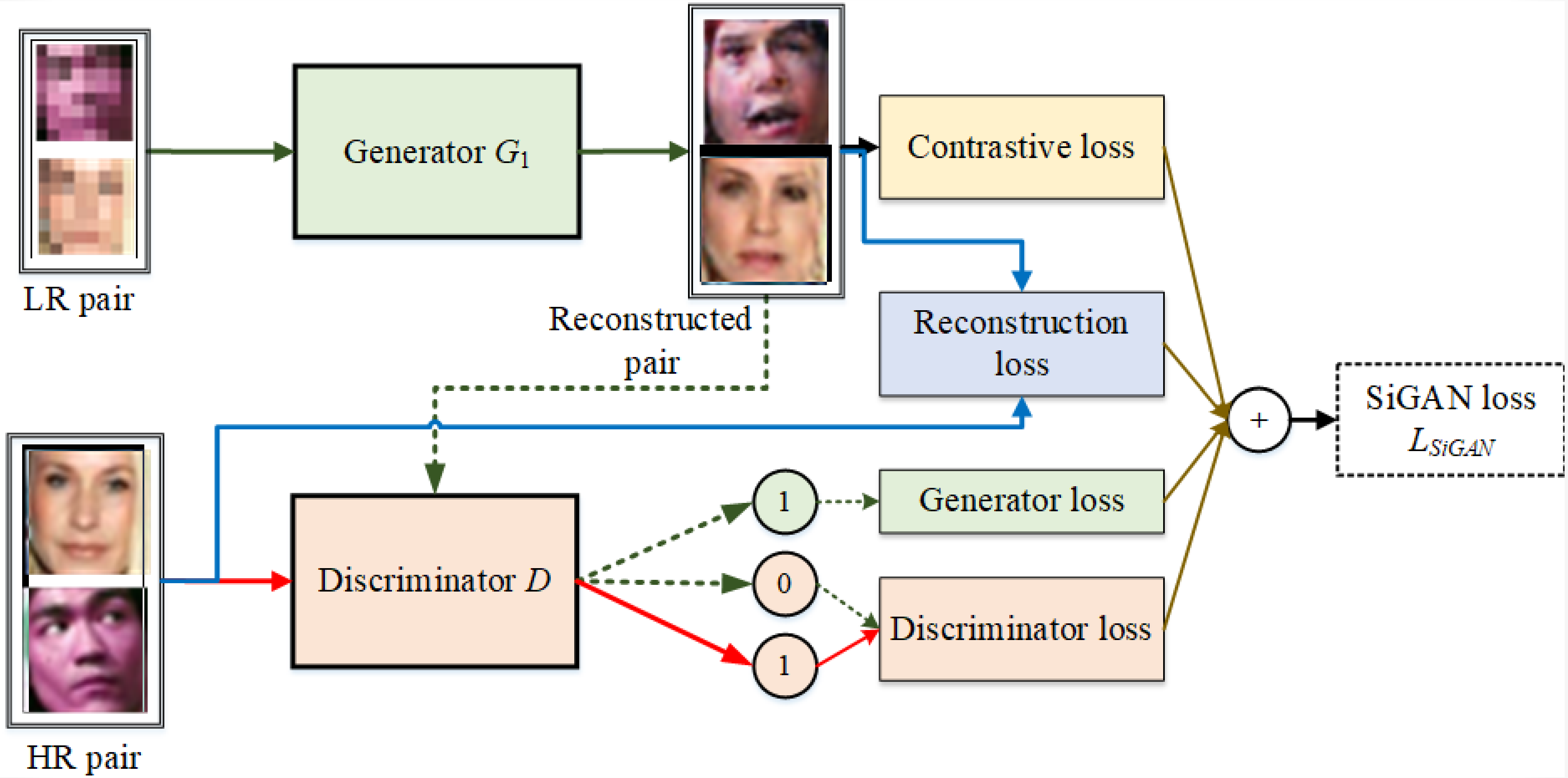
GAN-based Face Hallucination

- Pros:
  - High visual quality of the reconstructed image
- Cons:
  - May be identity-unrecognizable

Our Solution

- Key idea
  - Label embedding
    - Use the label information to fine-tune the generator
    - Identity-recognizable reconstruction
  - We propose “Siamese GAN” (SiGAN)
    - Label information will guide the “generator” how to obtain both high-visual quality and identity-recognizable result
    - Partial label information needs only

The Proposed SiGAN



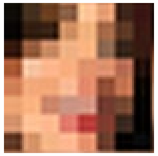
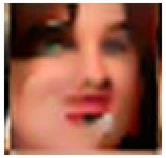
The Loss Function of The Proposed SiGAN

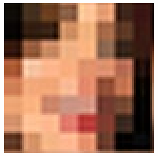
- Loss function for our generator

$$\min_G \max_D V(D,G) = E_D\left[\log D(\mathbf{x}_1^{HR})\right]$$
$$+E_G\left[\log\left(1 - D(G(\mathbf{x}_1^{LR}))\right)\right] + E_C\left[G(\mathbf{x}_1^{LR}), G(\mathbf{x}_2^{LR})\right],$$

  - subject to $\|y^{HR} - y^{SR}\|_1 < \epsilon$

  - SR result: $G(\mathbf{x}^{LR})$
  - E_C represents contrastive loss

D [G() = ] = 0

D [G() = ] = 1

Contrastive Loss for SiGAN

- If we directly minimize Ew(X1, X2)
  - The energy and the loss can be made zero by simply making Gw(X1) a constant function
  - We don't want to see that
- By adding a contrastive term
  - The loss function can be

CNN's parameters

The same or not (0/1)

Partial loss function for a genuine pair

$$L(\mathrm{W}) = \sum_{i=1}^{P} L(\boxed{W}, \boxed{(Y,} \boldsymbol{x}_1, \boldsymbol{x}_2)^i)$$

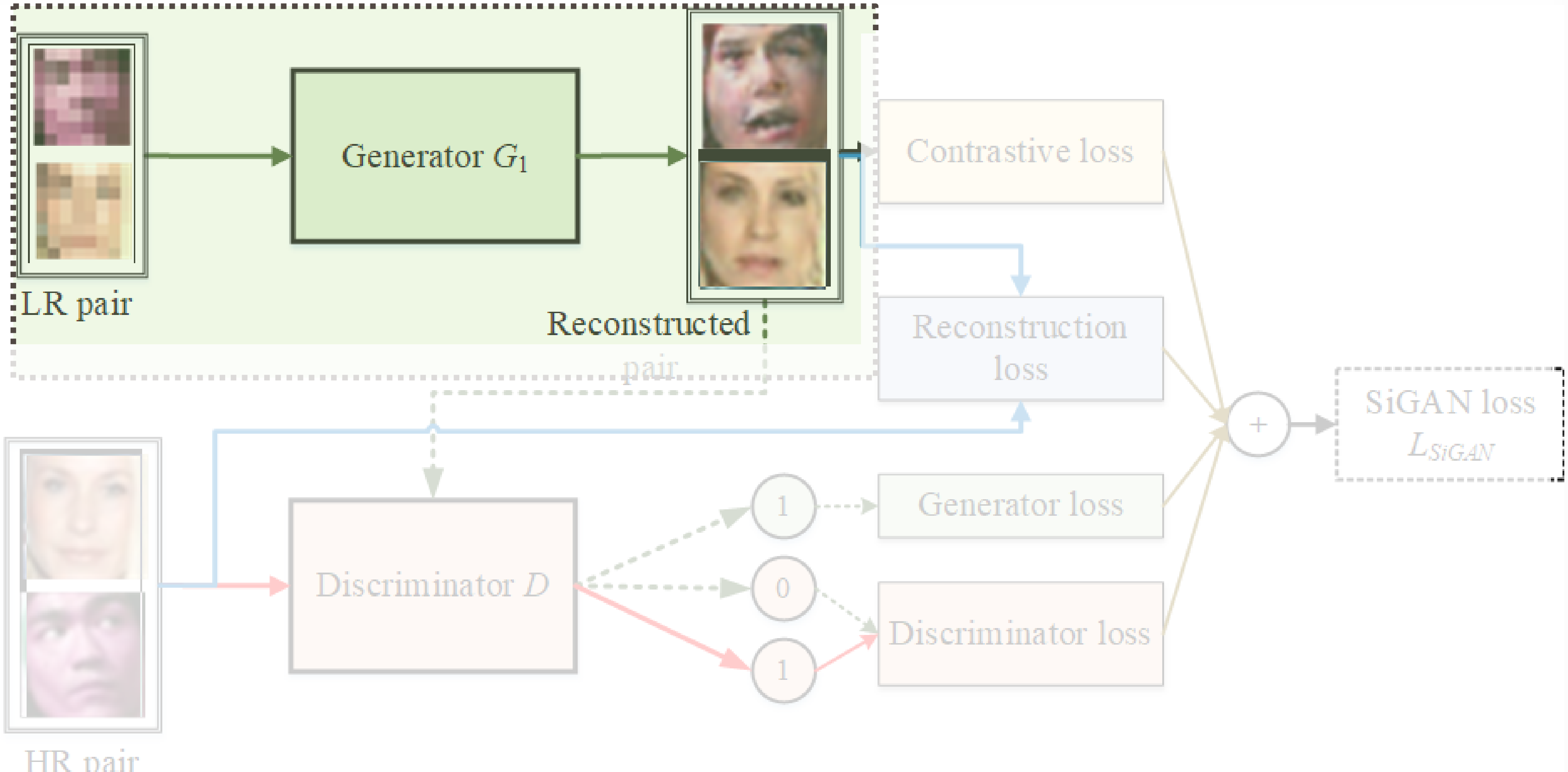
$$L(W, (Y, \boldsymbol{x}_1, \boldsymbol{x}_2)^i) = y \boxed{L_G}\left(E_w(\boldsymbol{x}_1, \boldsymbol{x}_2)\right) + (1-y)\boxed{L_I}(E_w(\boldsymbol{x}_1, \boldsymbol{x}_2))$$

$$L_{\mathrm{G}} = \frac{1}{2}(E_w)^2$$

$$L_{\mathrm{I}} = \frac{1}{2}[\max(0, margin - E_w)]^2$$

Partial loss function for an impostor pair

Test Stage of The Proposed SiGAN



A simple forward process

Experiment Settings

- LR: 8x8
- HR: 32x32 (4x upscaling factor)
- #Identities of training set: 10,575
- #Training images: 491,131
- #Test images: 3,283
- Face recognition engine: FACENET (State-of-the-art)

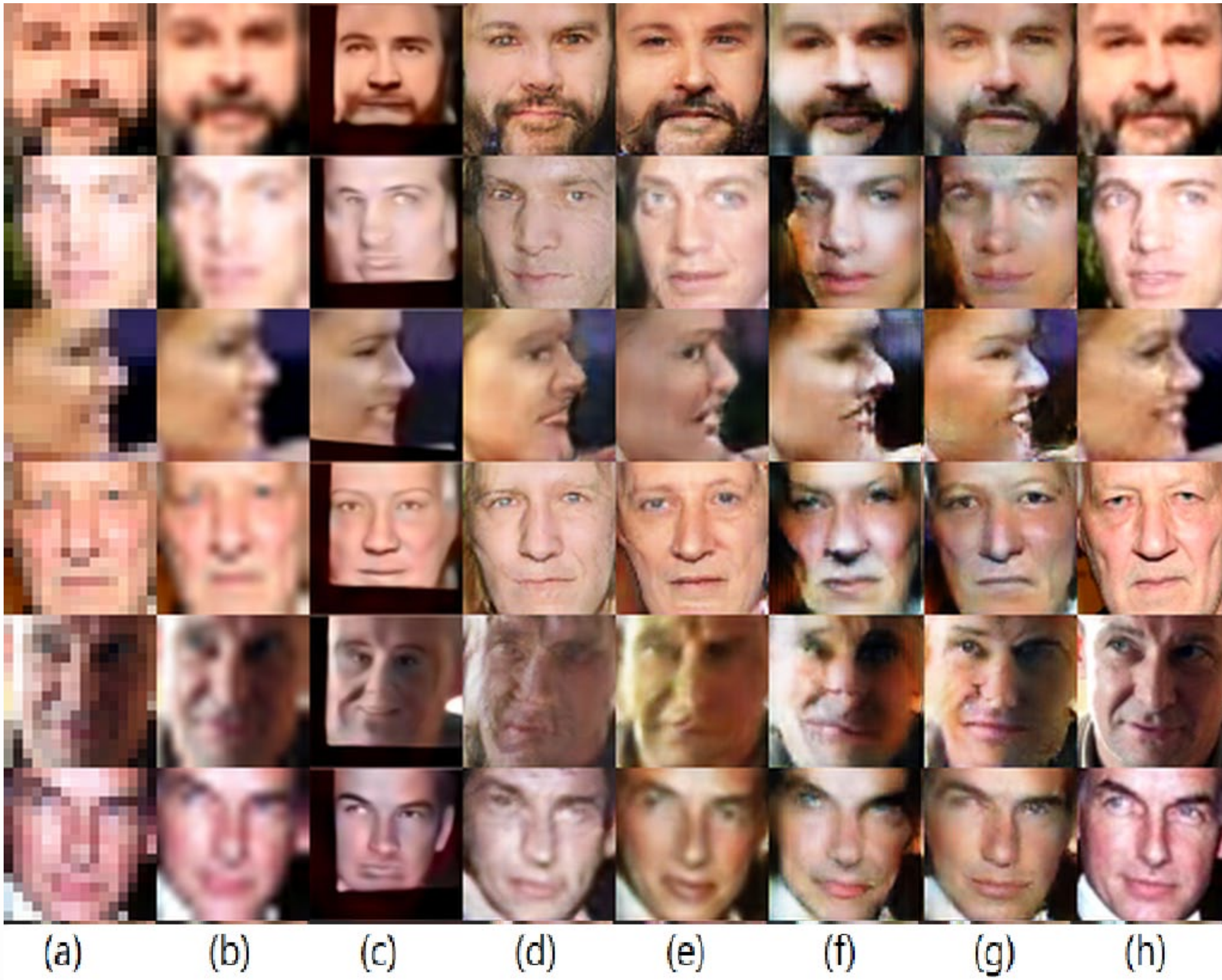
Subjective Result (8x8→32x32)

- Face hallucination: Identity-recognizable reconstruction

(a) (b) (c) (d) (e) (f) (g) (h) (i)

(a) LR face image
(b) Bicubic interpolation
(c) ECCVCNN
(d) GAN
(e) UR-DGN
(f) Pixel-Recurrent (Google)
(g) Ours w/o label
(h) Ours
(i) Original HR face image

Subjective Result (16x16➔64x64)



(a) LR face image
(b) Bicubic interpolation
(c) ECCVCNN
(d) GAN
(e) UR-DGN
(f) Pixel-Recurrent (Google)
(g) Ours
(h) Original HR face image

Objective Results

Method	Top-1	Top-5	Top-10
HR (32×32)	30.4%	51.2%	59.6%
LR (8×8)	10.7%	19.5%	33.1%
Bicubic	10.8%	20.1%	34.4%
DFCG [11]	9.3%	17.7%	21.4%
UR-DGN [9]	9.9%	18.6%	22.7%
DCGAN [22]	4.6%	10.9%	16.8%
PRSR [25]	10.8%	18.8%	24.4%
SR-GAN [15]	8.8%	11.1%	19.4%
Wavelet-SRNet [17]	12.8%	20.2%	30.3%
SiGAN (ResNet)	15.8%	27.5%	40.4%
SiGAN (DenseNet)	15.1%	26.8%	40.3%

Face recognition rate comparison
LR=8x8

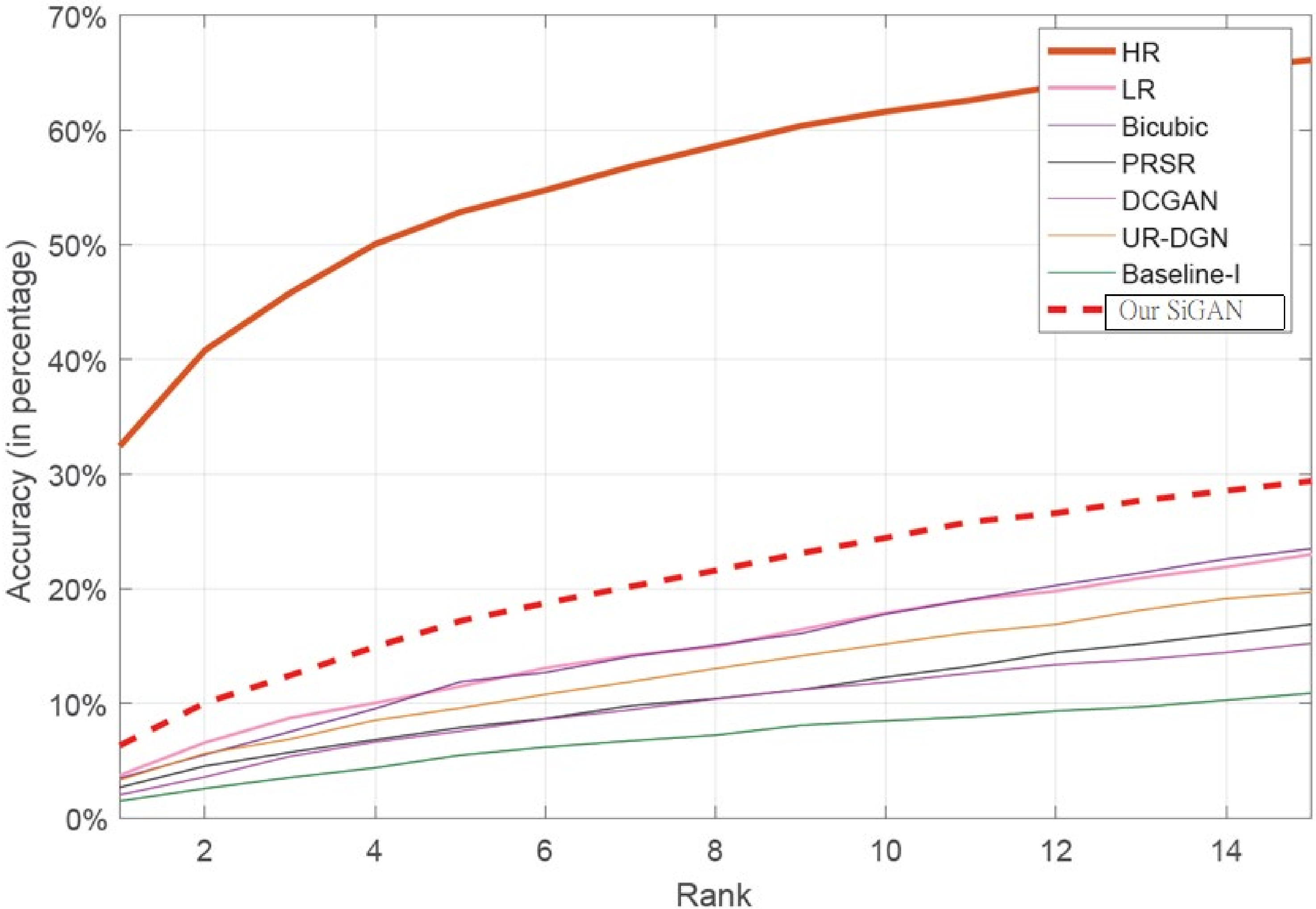
HR=32x32

Face recognition rate comparison
LR=16x16

HR=64x64

Method	Top-1	Top-5	Top-10
HR (64×64)	36.8%	55.9%	63.8%
LR (16×16)	12.4%	27.4%	37.1%
Bicubic	11.6%	27.5%	37.6%
DFCG [11]	9.6%	23.7%	34.8%
UR-DGN [9]	12.2%	29.0%	38.7%
DCGAN [22]	9.3%	24.9%	33.9%
PRSR [25]	13.3%	29.7%	40.1%
SR-GAN [15]	11.6%	23.2%	36.3%
Wavelet-SRNet [17]	12.0%	25.5%	38.8%
SiGAN (ResNet)	17.9%	32.9%	48.1%
SiGAN (DenseNet)	18.3%	33.5%	50.0%

Objective Result (8x8)



Summary of Our SiGAN

- Contributions
  - Label information is embedded in the generator of GAN
    - A Guider for the generator
  - High visual quality and identity-recognizable reconstruction
  - Faster hallucination process

Outline

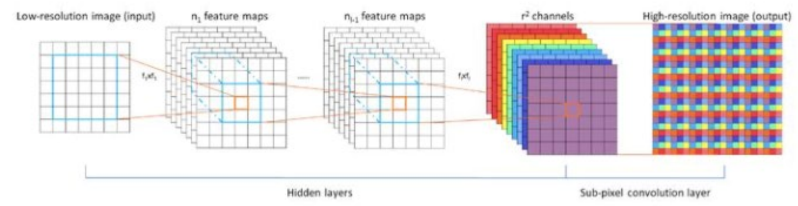
- Overview of Deep Learning
  - Image super-resolution
- Deep super-resolution
  - Structured image super-resolution
    - Face hallucination
  - 2-D image super-resolution (generic images)
  - *N*-D image super-resolution (Hyperspectral images)
- Summary

RESOLUTION-AWARE ADVERSARIAL LEARNING

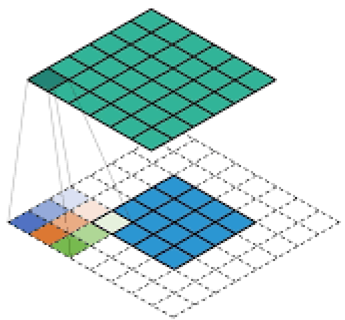
IEEE ICCV 2019 AIM Workshop and IEEE SAM 2020, Oral

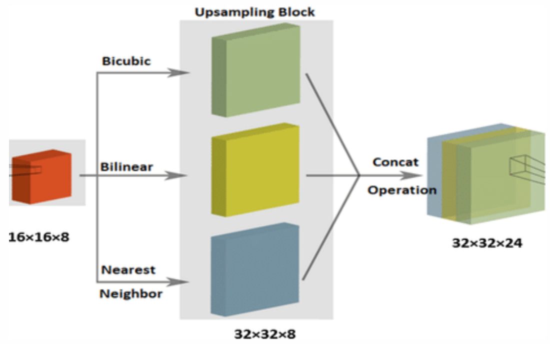
What's Issue in the SISR?

- Knowing upsampler in SISR usually could be
  - Pixel-shuffle conv (as known sub-pix. conv.)
  - Interpolation + conv.
  - Transposed conv.



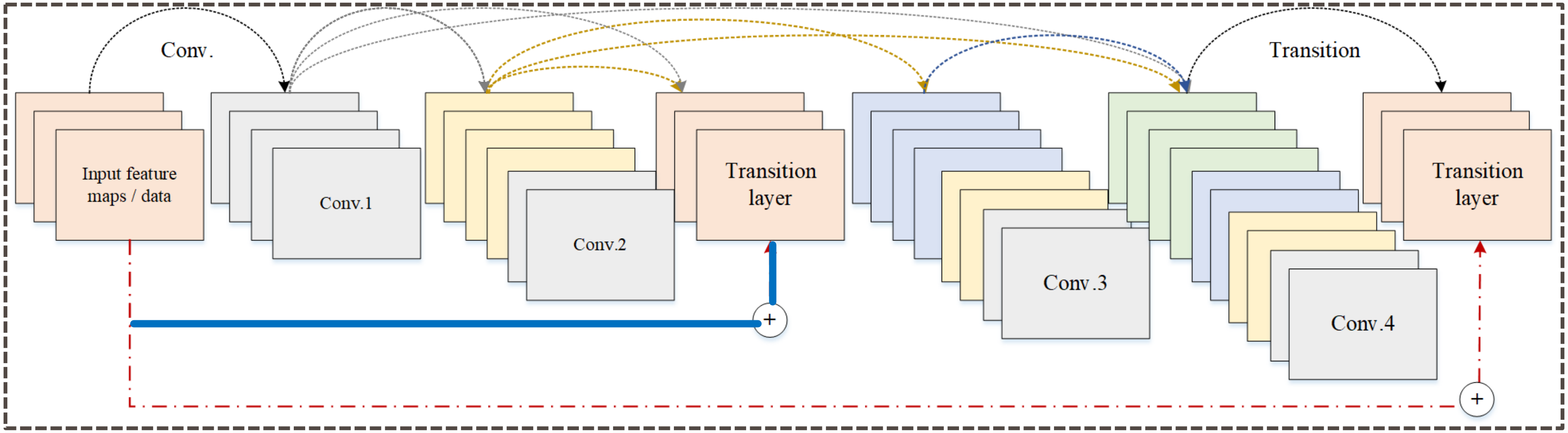
- Each type of the upsamplers could be some advantages
  - Only one type of the upsamplers could fail in some case
    - Texture vs. Edge vs. Smoothing regions.





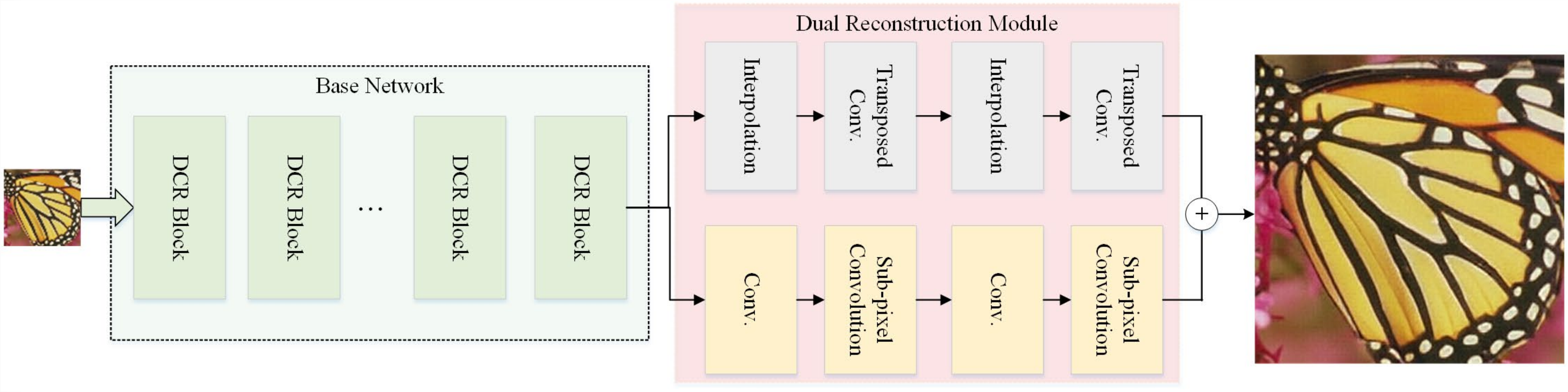
Backbone Selection

- ESRGAN [ECCV'18] presents a great performance at image quality.
  - Based on RDB (residual dense block)
- We revisit the RDB to explore more information



Bring the advantages of different upsamplers

- Dual reconstruction branch aims at reconstructing the high-spatial-resolution feature map by integrating two upsamplers together. +
  - Pixel-shuffle + Transposed Conv + Interpolation
  - Three versions of fine details!!!
    - Merged by “conv” again!



Augmented Training

- To improve the performance, three loss functions, as suggested in ESRGAN, is used in our method

$$L_p(\mathbf{x}_{HR}, \mathbf{x}_{SR}) = \frac{1}{N^2 - 1} \sum_{i=1}^{N^2} |\mathbf{x}_{SR} - \mathbf{x}_{HR}|,$$

  - Keep the spatial fidelity

$$L_{GAN}(D, G) = E_D\left[\log D(\mathbf{x}_{HR})\right] + E_G\left[\log\left(1 - D(G(\mathbf{x}_{LR}))\right)\right]$$

  - Enhance the visual quality

$$L_{feat}(\mathbf{x}_{HR}, \mathbf{x}_{SR}) = \frac{1}{M} \sum_{i=0}^{M-1} ||f_e(\mathbf{x}_{SR})(i) - f_e(\mathbf{x}_{HR})(i)||_1,$$

  - Keep the semantic similarity

Experimental Settings

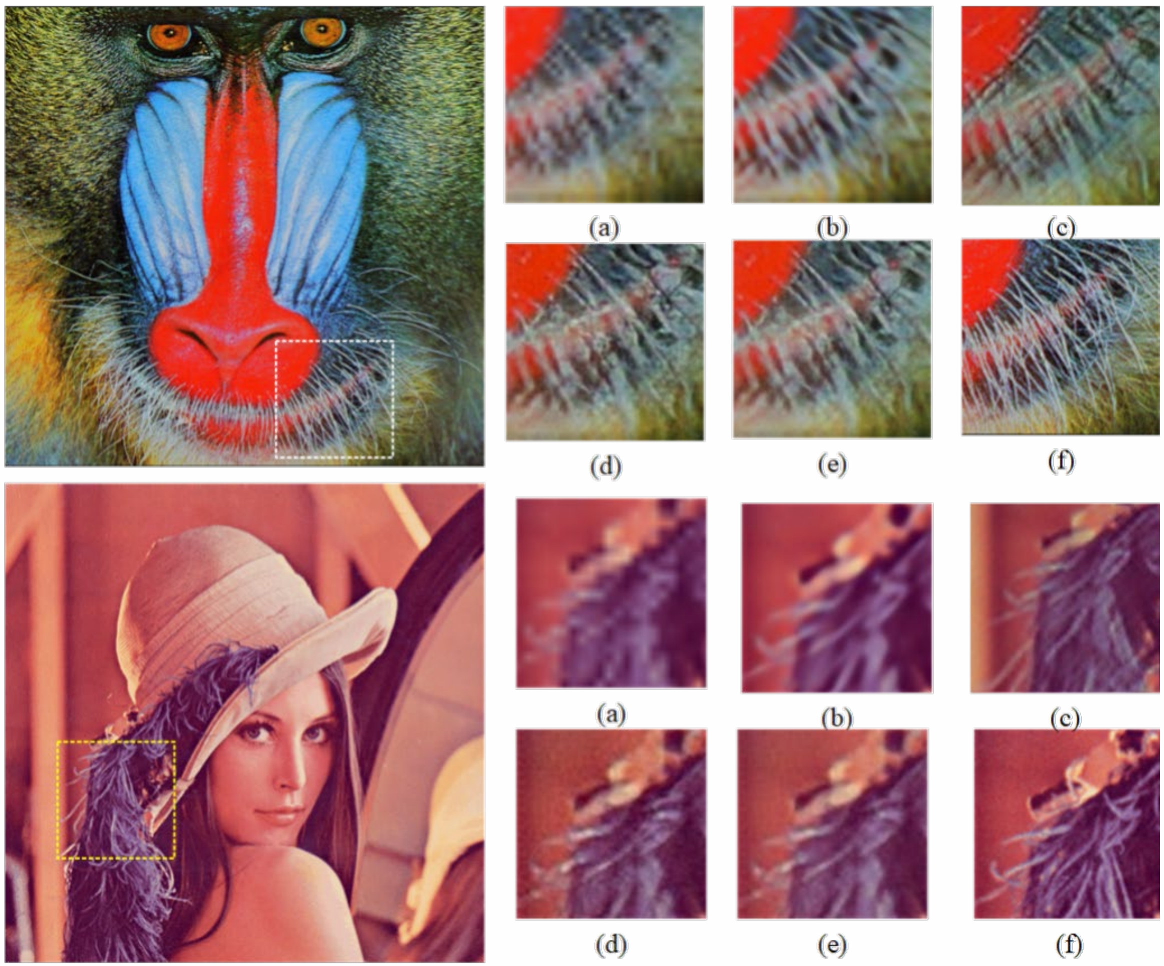
- Standard benchmark datasets
  - DIV2K + Filcker2K
- Training hyperparameters
  - #Iterations: 60000
  - Patch size: 160*160
  - Optimizer: SGD (it is also important)
  - Initial weight value: 1e-4 (good one)
  - Metrics: PSNR/SSIM

Subjective Quality Comparison

Table 3. Ablation study on the proposed method for Set5 and Set14.

Method	Set5		Set14	
	PSNR	SSIM	PSNR	SSIM
Baseline-I (SAM)	27.61	0.640	24.89	0.600
Baseline-I (VAM)	27.32	0.639	24.32	0.590
Baseline-I (VAM+SAM)	27.61	0.641	25.30	0.607
Baseline-II (SAM)	27.57	0.641	25.52	0.612
Baseline-II (VAM)	27.21	0.639	24.62	0.589
Baseline-II (VAM+SAM)	27.82	0.640	25.47	0.611
SAM-SR (ours)	27.64	0.648	24.85	0.596
VAM-SR (ours)	27.85	0.648	25.25	0.607
SAM+VAM (ours)	**28.03**	**0.649**	**25.60**	**0.616**

Objective Quality Assessment

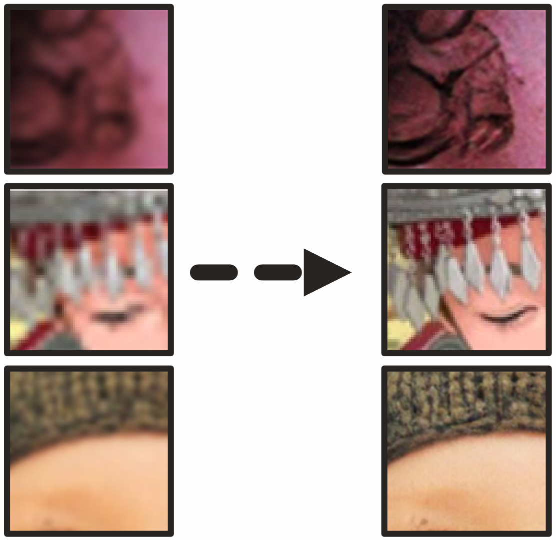


SO, WHAT’ S NEXT?

We notice that…

A loss function seems not reasonable.

GAN based Super Resolution



Reconstruction Error

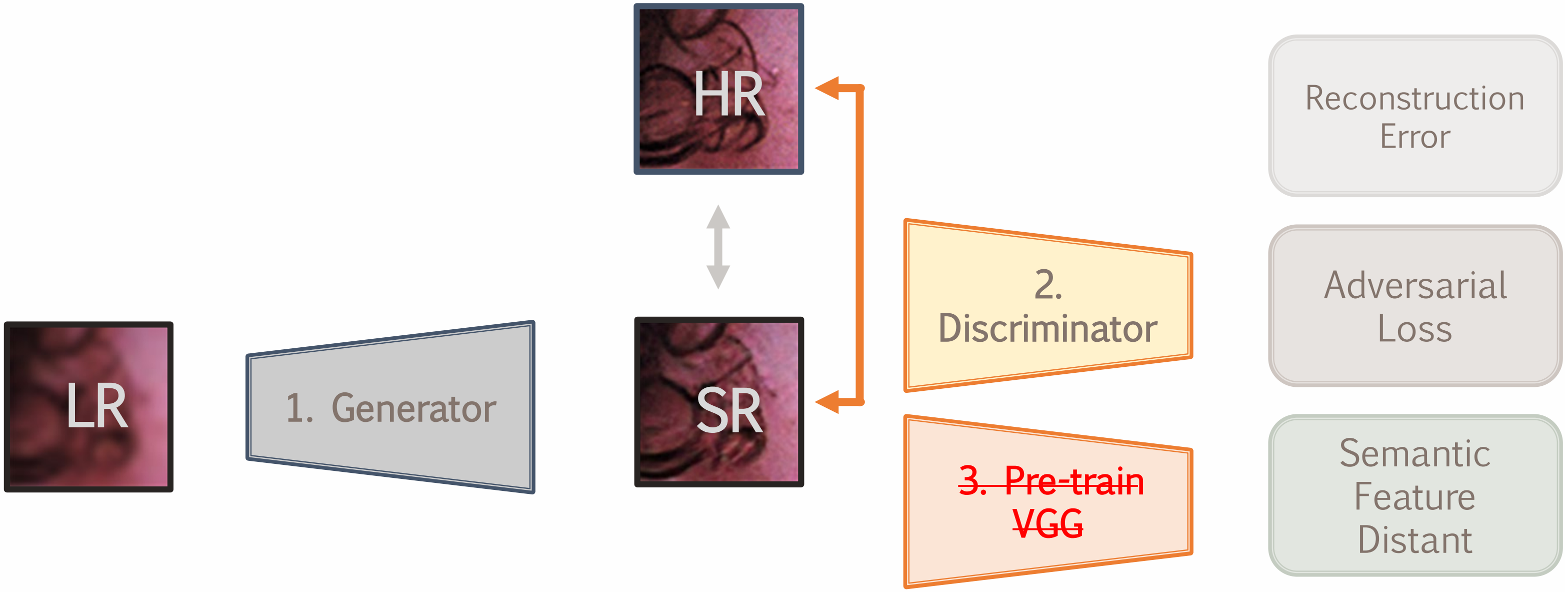
Adversarial Loss

Semantic Feature Distant

fidelity

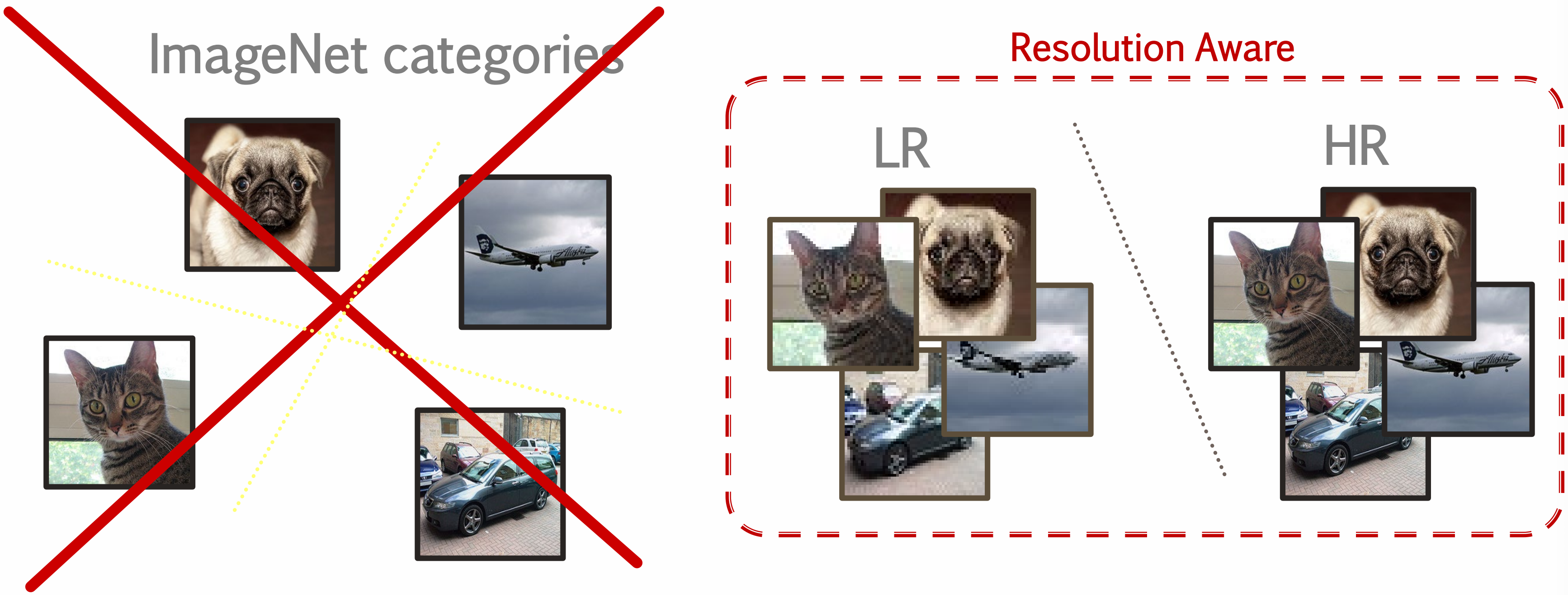
visual quality

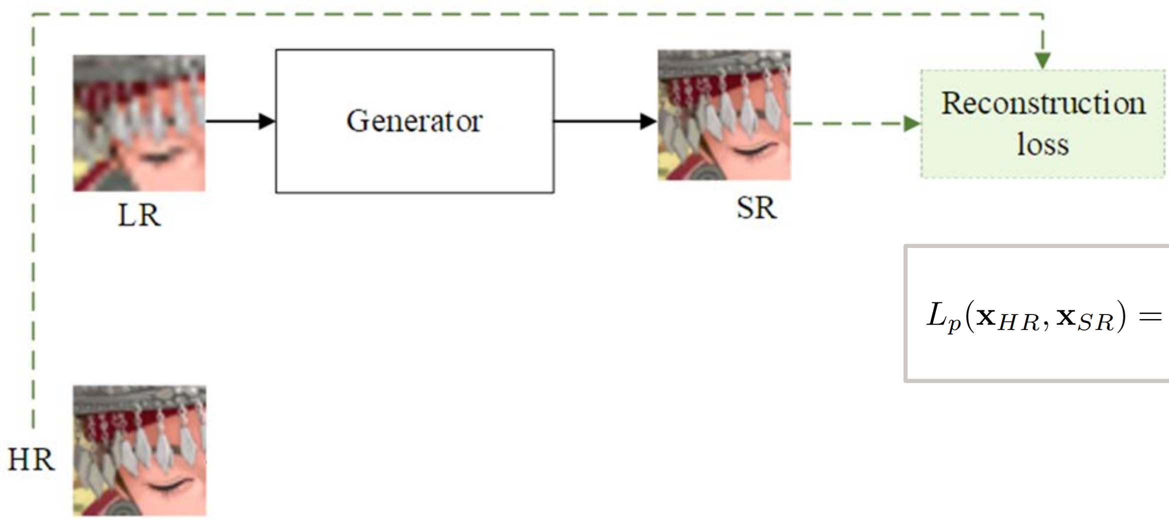
GAN based Super Resolution



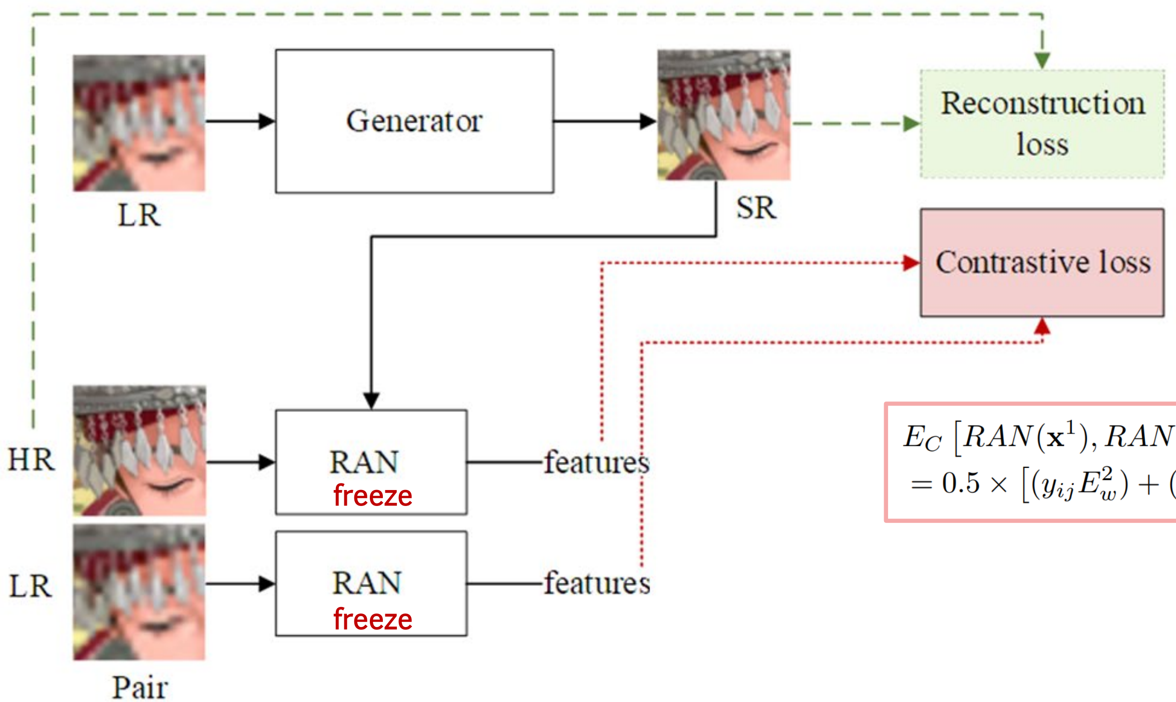
Not for measuring the features of the HR and LR

Resolution Aware feature Network (RAN)

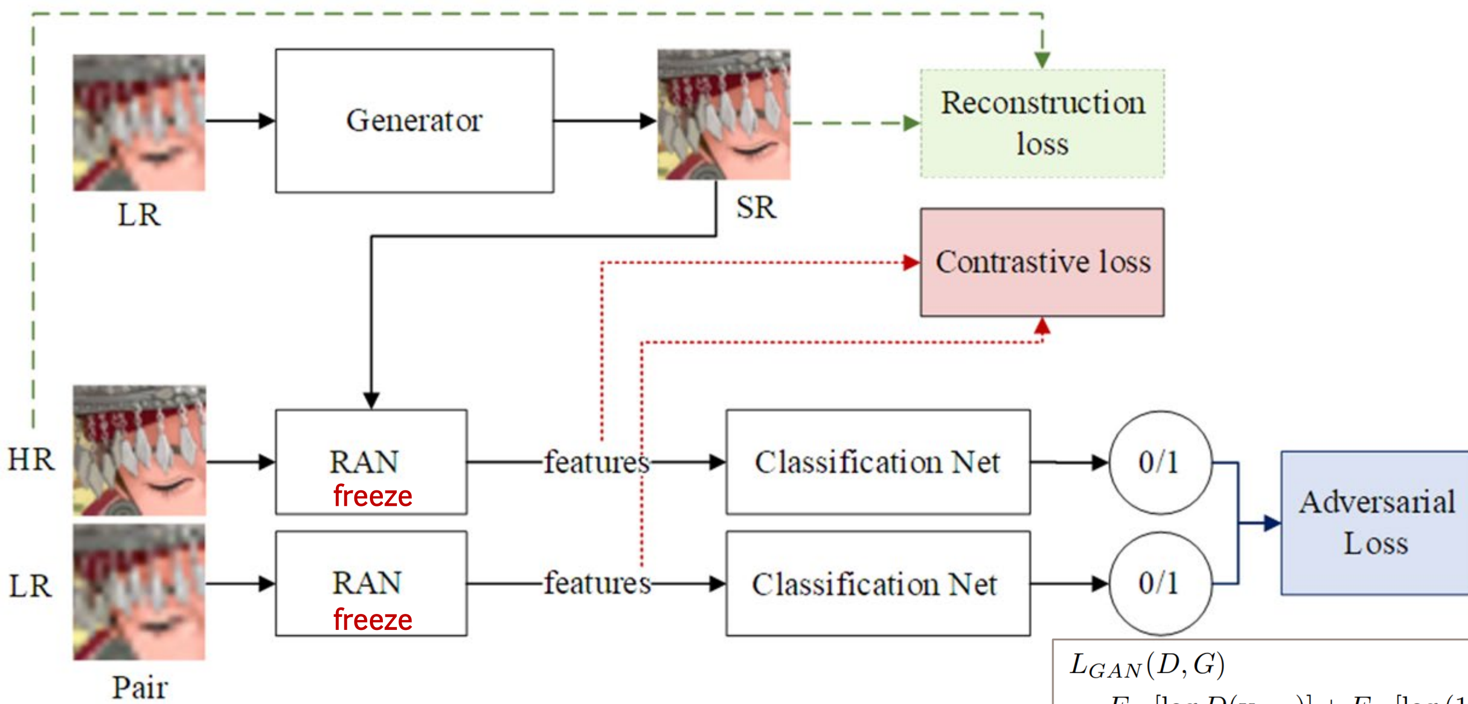




$$L_p(\mathbf{x}_{HR}, \mathbf{x}_{SR}) = \frac{1}{N^2 - 1} \sum_{i=1}^{N^2} |\mathbf{x}_{SR} - \mathbf{x}_{HR}|$$

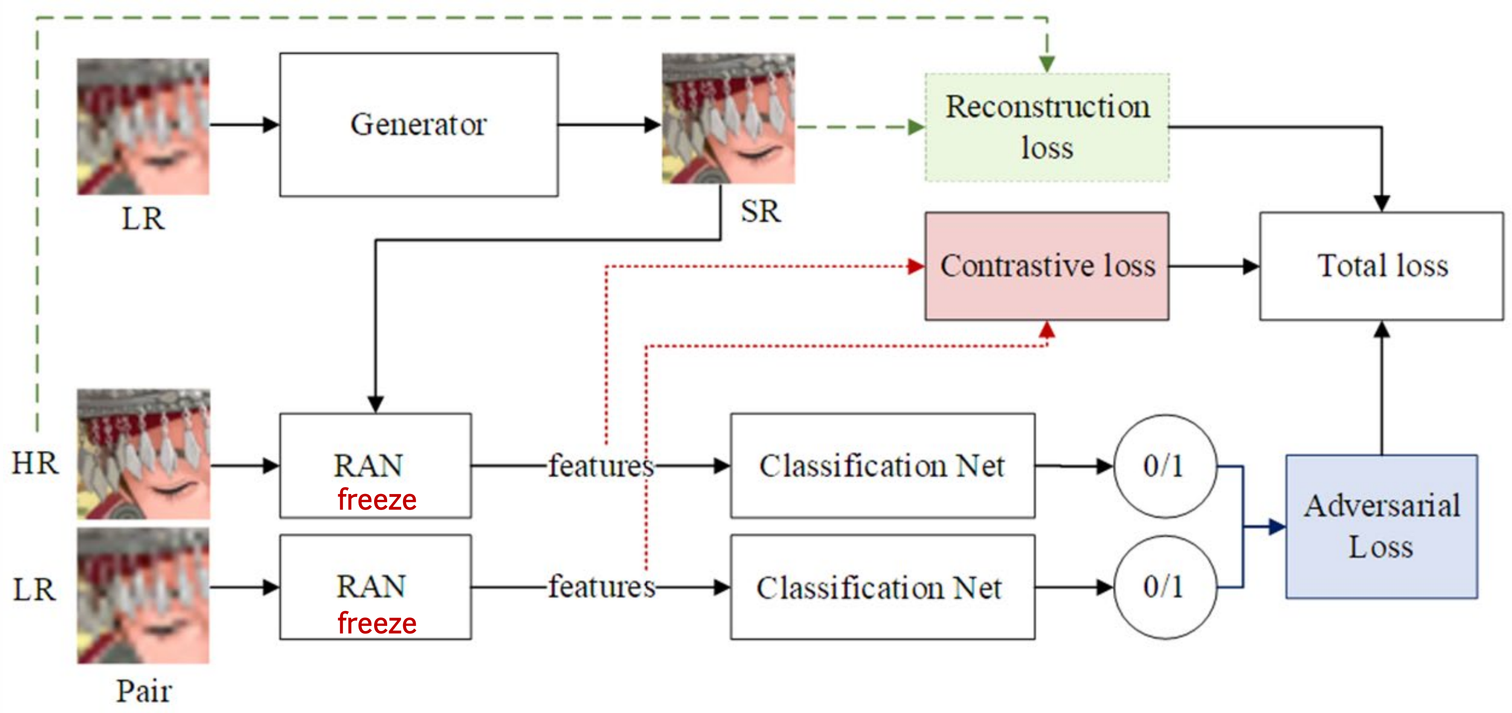


$$E_C\left[RAN(\mathbf{x}^1), RAN(\mathbf{x}^2)\right]$$
$$= 0.5 \times \left[(y_{ij} E_w^2) + (1 - y_{ij}) \times max(0, (m - E_w)_2^2)\right]$$



$$L_{GAN}(D,G) = E_D\left[\log D(\mathbf{x}_{HR})\right] + E_G\left[\log\left(1 - D(G(\mathbf{x}_{LR}))\right)\right]$$

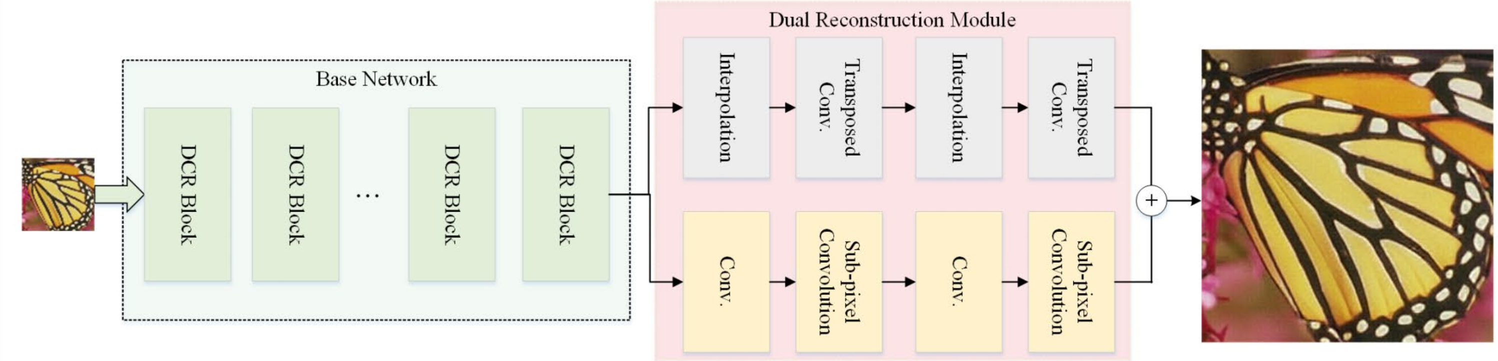
Couple Adversarial Training (CAT)



Network Structure

- RAN / Discriminator (VGG16)

- Generator (DRSR)
  - Hswish -> Swish



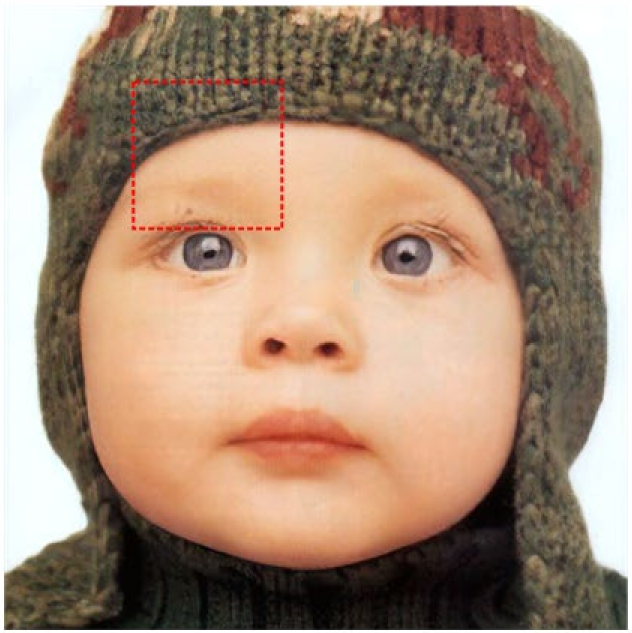
RESULTS

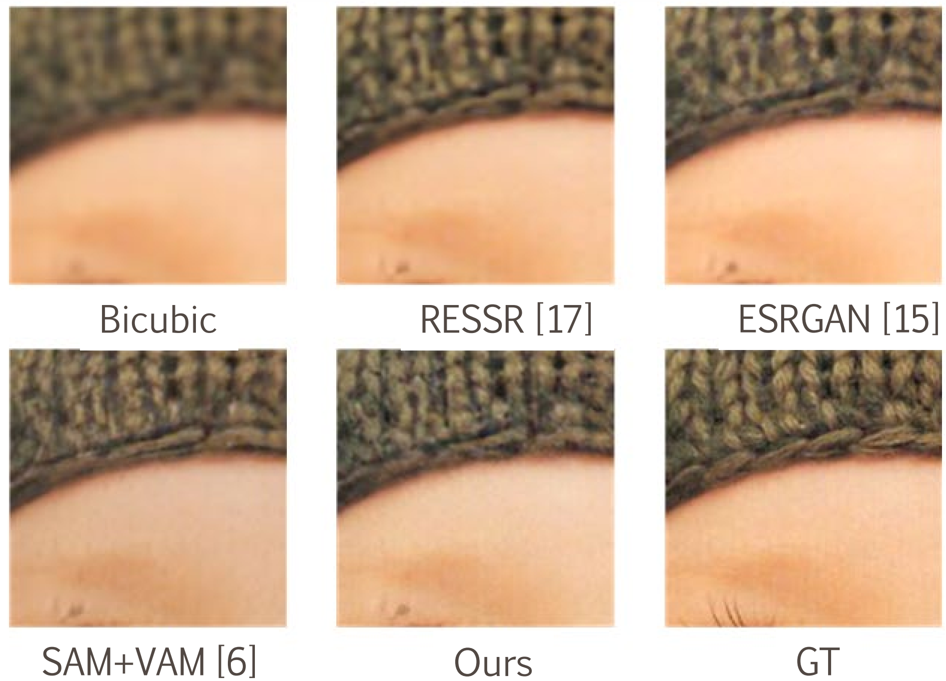
Objective Quality Comparison

TABLE I
PERFORMANCE COMPARISON AMONG THE DIFFERENT SR METHODS EVALUATED ON SET5 [9], BSD100, [11] AND URBAN100 [9].

Method	Set5		BSD100		Urban100	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
MSRResNet [15]	**30.28**	**0.864**	26.27	0.712	24.62	0.766
ESRGAN [15]	29.06	0.814	25.57	0.682	24.15	0.712
SAM+VAM [6]	29.18	0.823	25.86	0.705	24.22	0.726
RESSR [17]	30.11	0.860	26.22	0.709	24.65	0.766
Baseline (ours)	29.25	0.858	**27.76**	**0.779**	**24.99**	**0.802**
Proposed	29.66	0.848	26.51	0.723	24.54	0.759

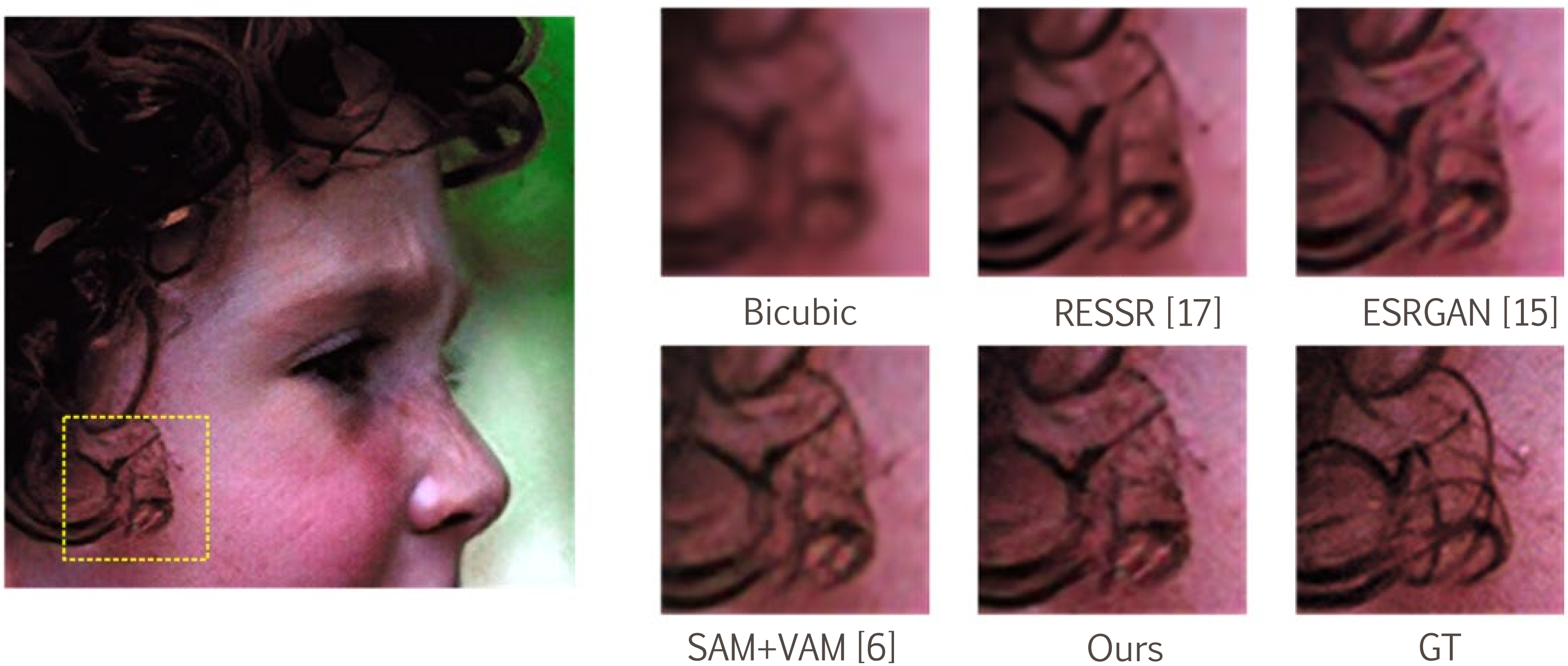
Subjective Quality Comparison





Subjective Quality Comparison

Subjective Quality Comparison



Conclusion

- Resolution Aware feature Network (RAN)
  - Get the resolution-aware information to the deep neural network
- Combined contrastive loss to learn the discriminative features to "Resolution"
- Excellent both visual and objective quality of the reconstructed images

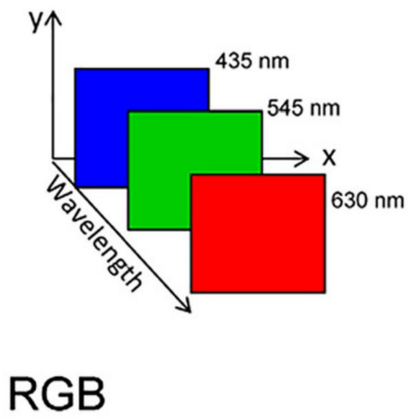
Outline

- Deep super-resolution
  - Traditional super-resolution
  - 2-D image super-resolution (generic images)
  - *N*-D image super-resolution (Hyperspectral images)
- Summary

HYPERSPECTRAL IMAGE SR + COMPRESSION

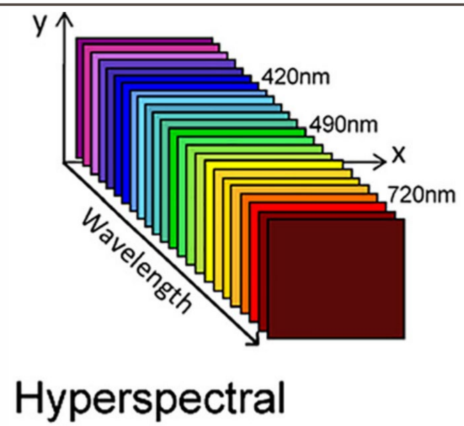
ACVLAB / IHCL

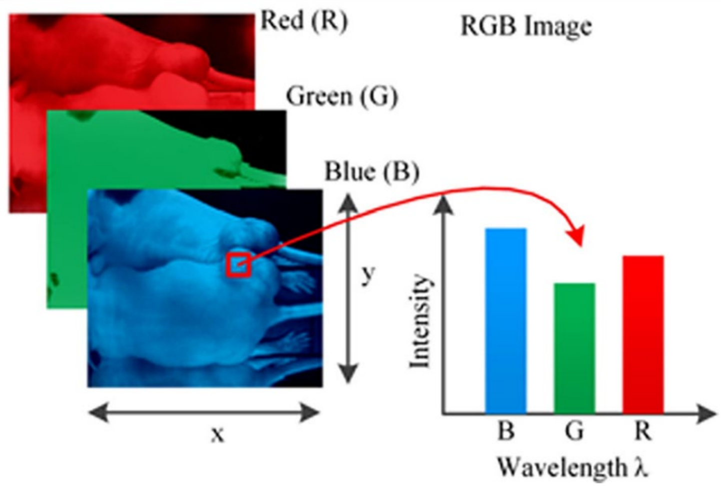
Hyperspectral Image (HSI)

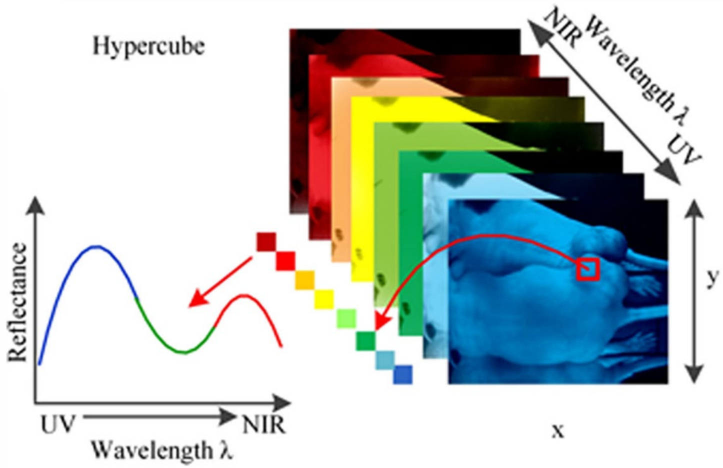


Many applications

Remote sensing, medical imaging, matter recognition...



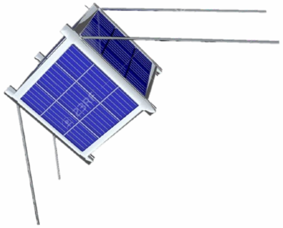




[Metha'18] N. Mehta et al., "Single-Cell Analysis Using Hyperspectral Imaging Modalities," ASME Journal of Biomechanical Engineering, vol.140, Feb, 2018

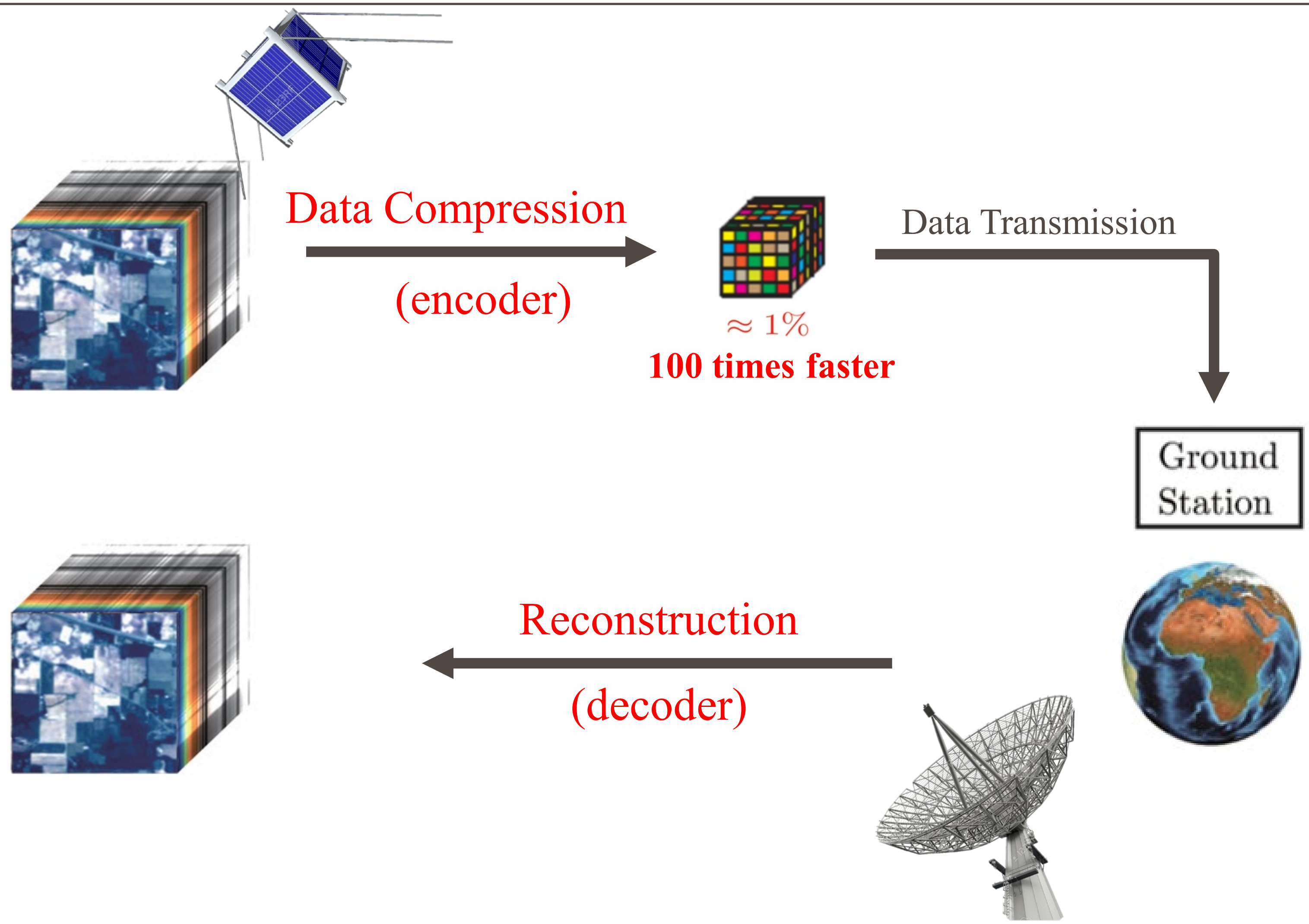
We are talking about one application: remote sensing

- Assumed we have a miniaturized satellite
  - Issues:
    - Data storage usage
    - Memory usage
    - Limited computing resource



- We achieved
  - Fast/Lightweight compressed sensing
  - 1% sampling rate (100x compression ratio)
  - State-of-the-art performance under a lower sampling rate
  - Robust to channel noise

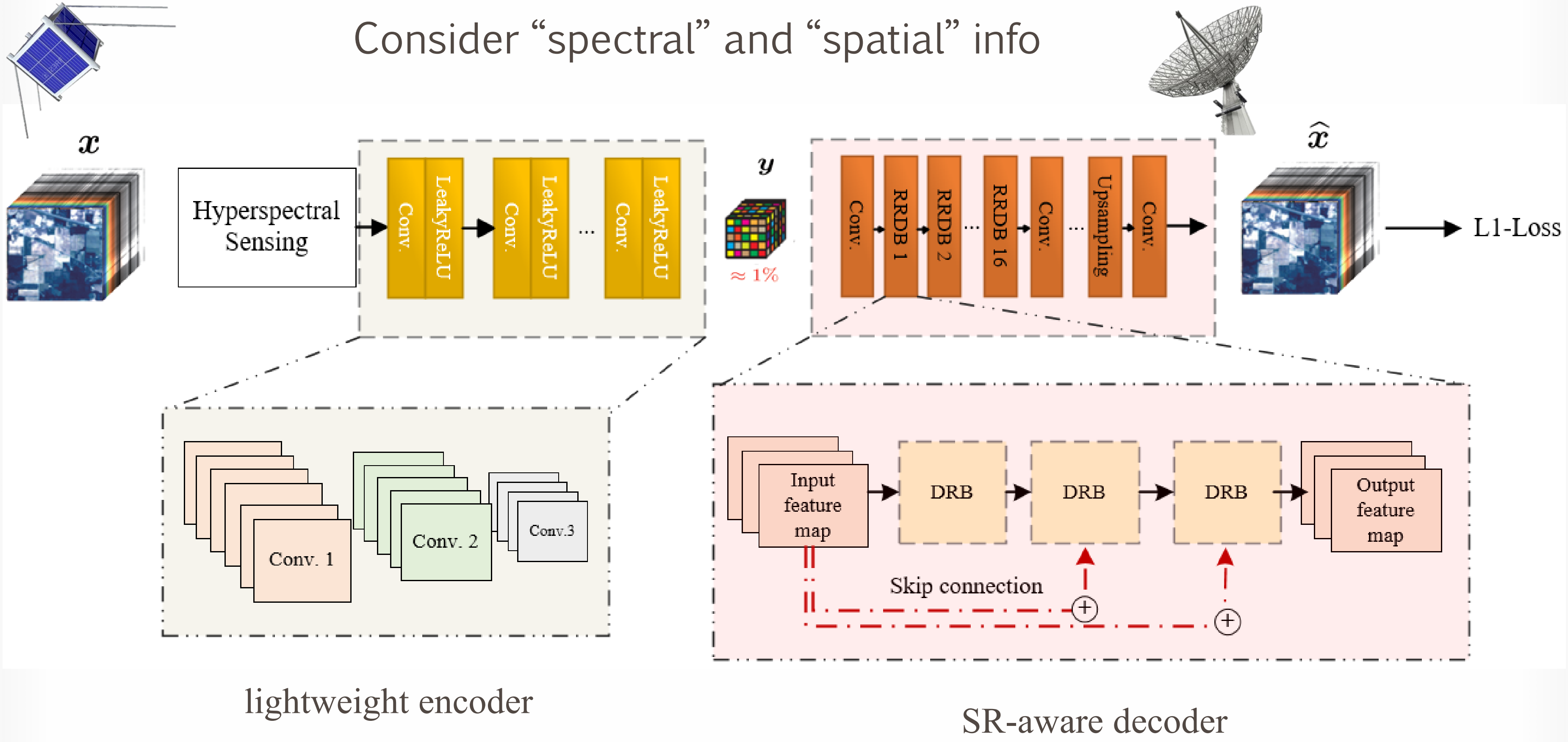
Introduction



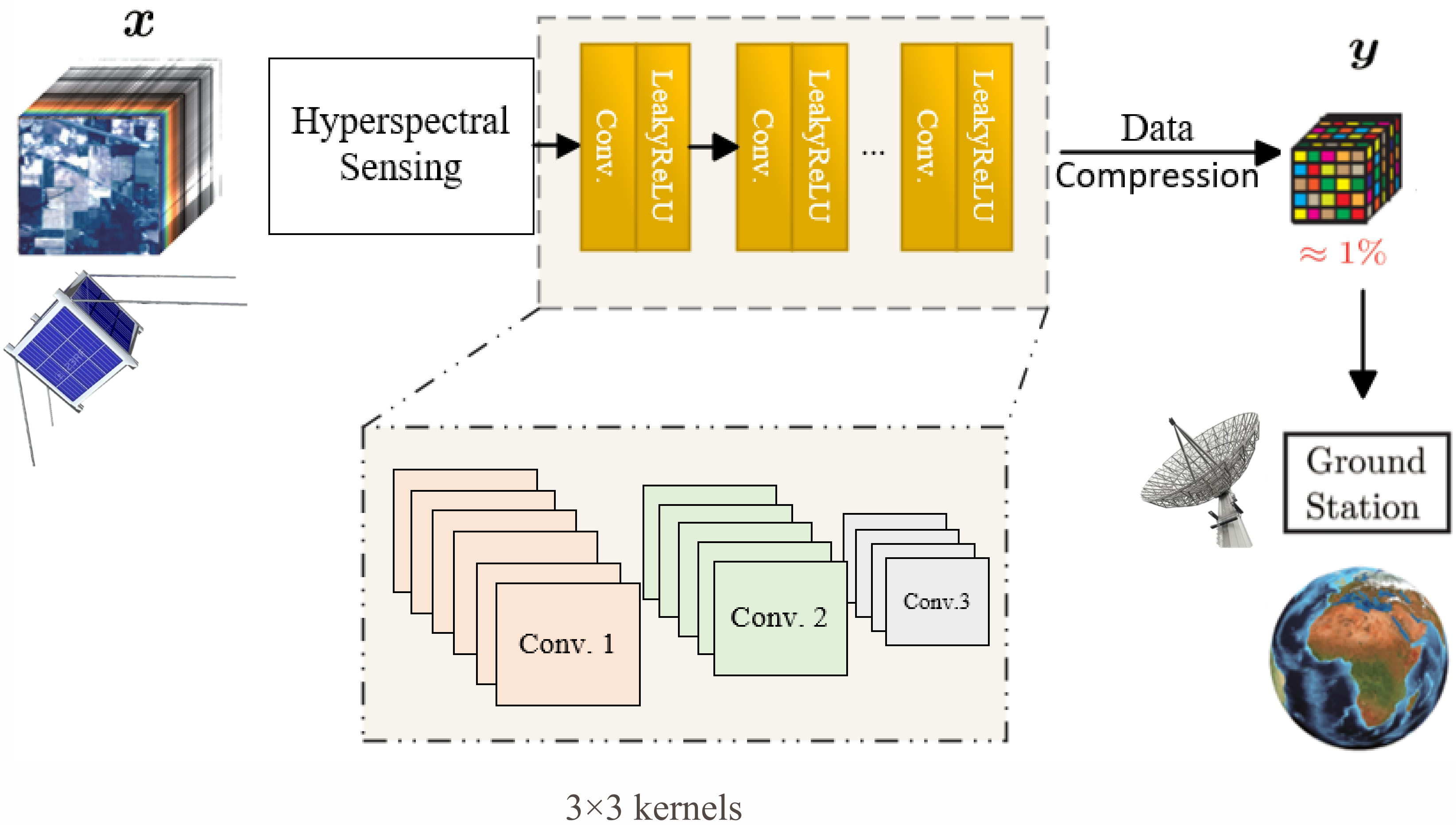
Proposed HCSN

Hyperspectral **C**ompression **S**uper-resolution **N**etwork

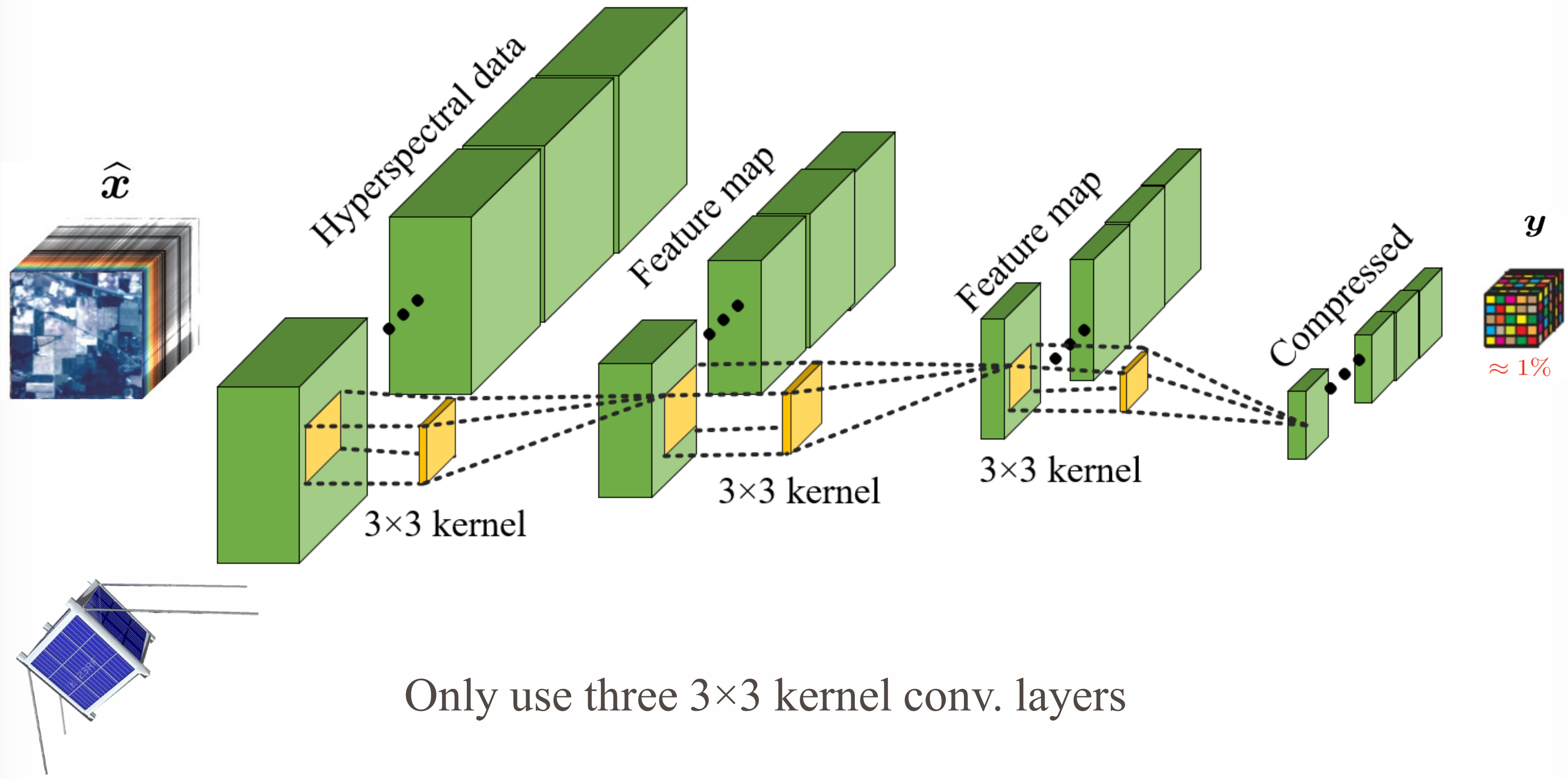
Consider “spectral” and “spatial” info



Lightweight Encoder

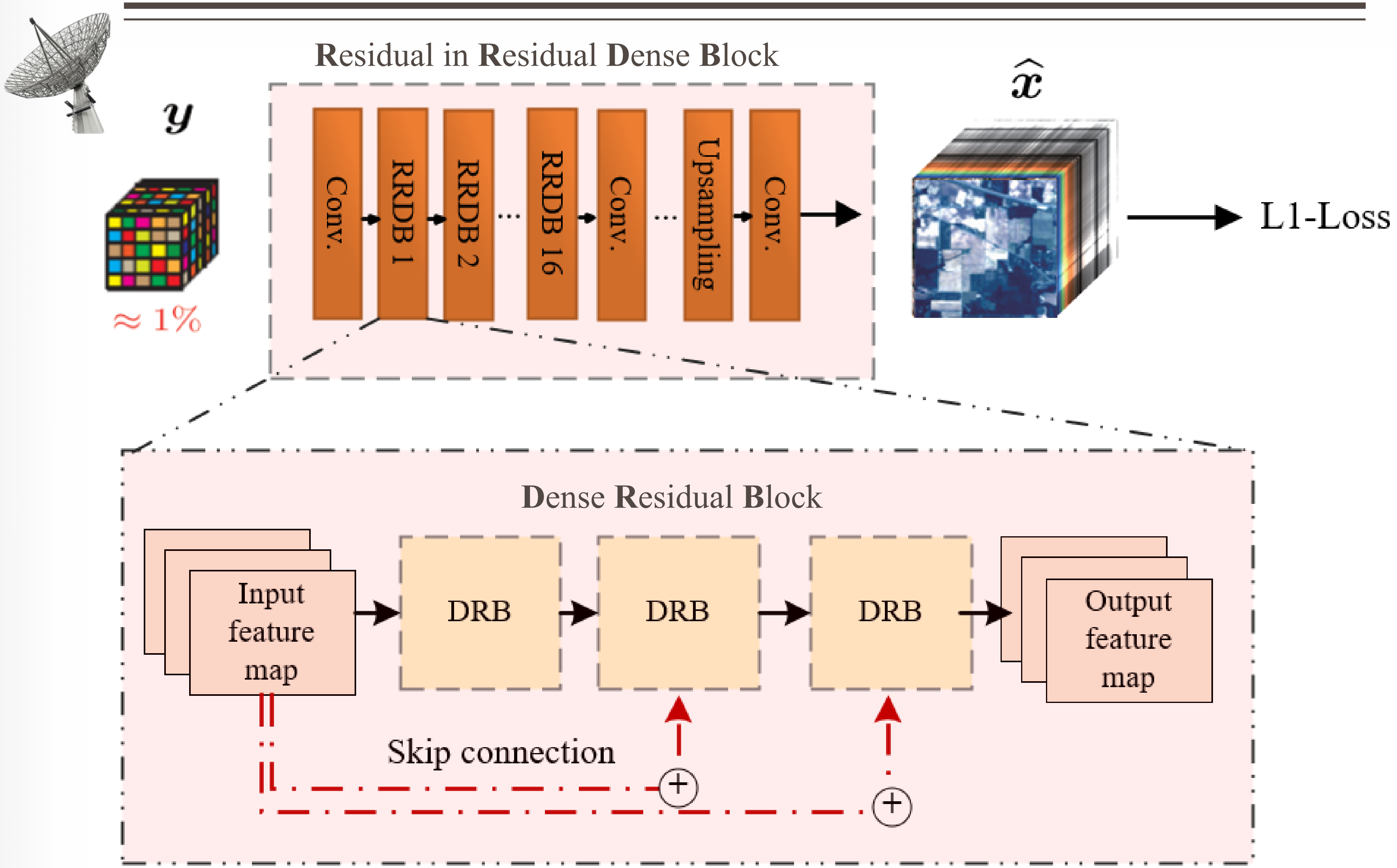


Lightweight Encoder

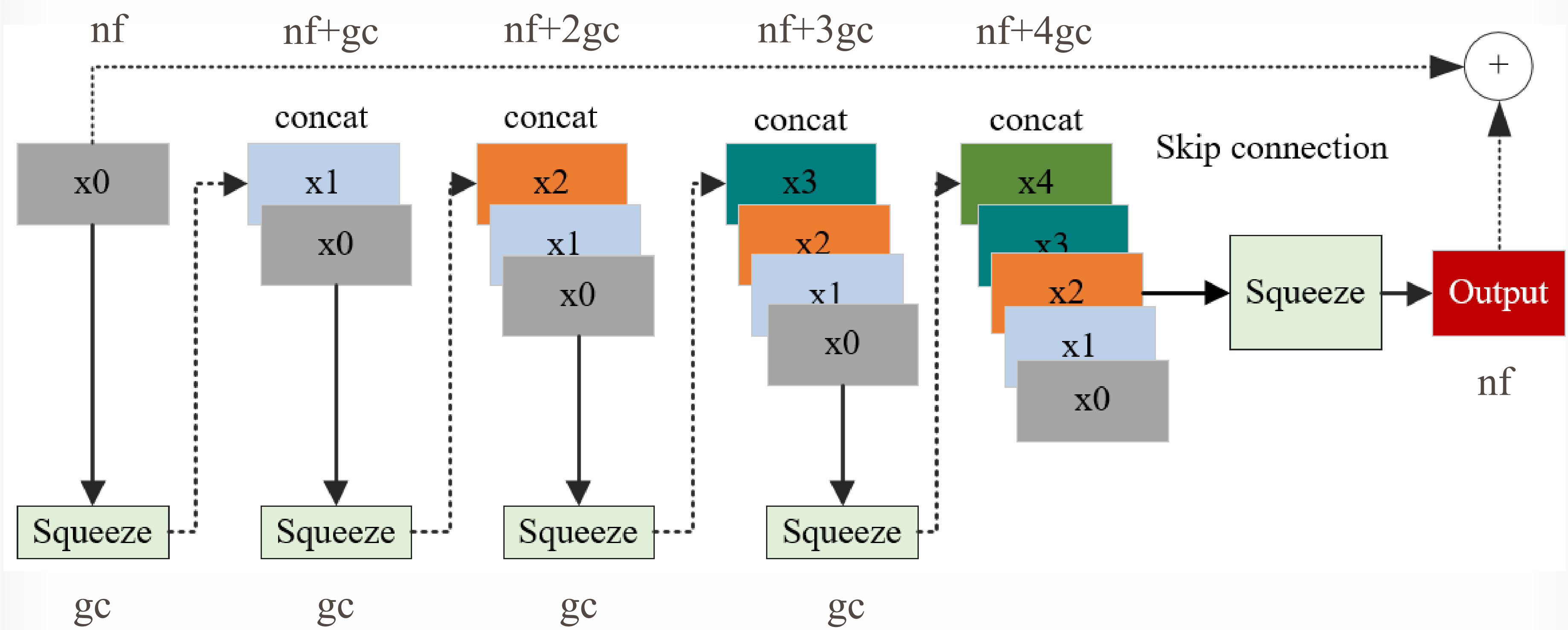


Only use three 3×3 kernel conv. layers

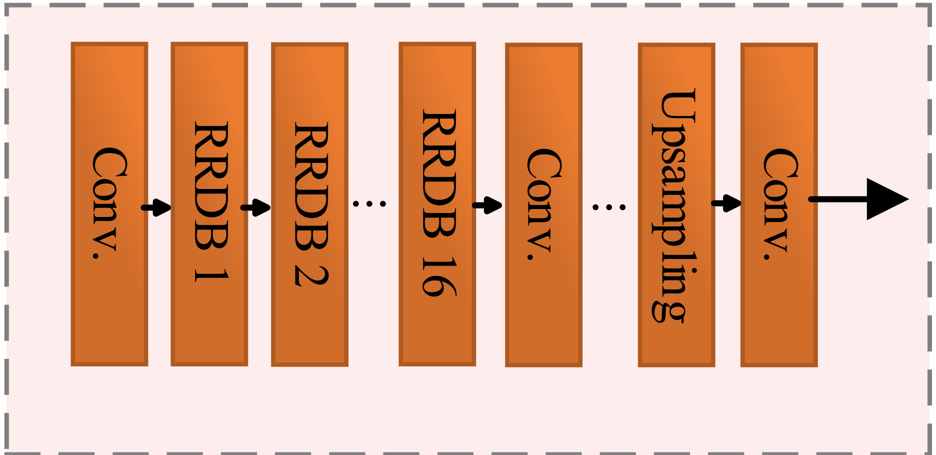
SR-aware Decoder

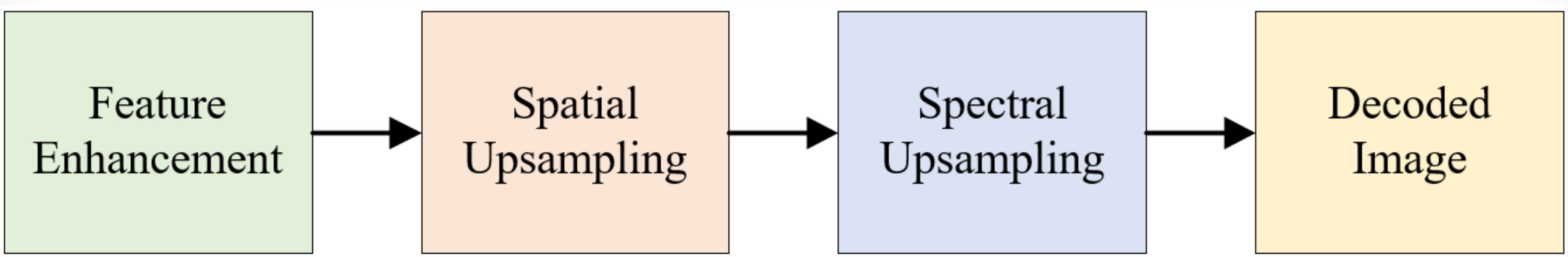


Dense Residual Block (DRB)



SR-aware Decoder





Experiment

- We train the proposed HCSN with 2,537 sub-image sized of 256×256×172
  - *Provided by IHCL / Prof. C.H. Lin.*
- 2,537 sub-images acquired by AVIRIS sensor:
-     - 102 images for city areas (C-type)
-     - 1,870 images for mountain areas (M-type)
-     - 272 images for farm/grass areas (F-type)
-     - 293 images for lake/coastline areas (L-type)
- Randomly selected 90%, 10% for training set and testing set

Aviris Data Portal. [Online]. Available: https://aviris.jpl.nasa.gov/dataportal/.

Experiment

- Spectral compressive acquisition (SpeCA) [Martín’16]
- Spatial/spectral compressed encoder (SPACE) [Lin’20]
- Locally similar sparsity-based hyperspectral unmixing compressive sensing (LSS) [Zhang’16]
- Compressive sensing via joint tensor Tucker decomposition and weighted 3-D total variation regularization (TenTV) [Wang’17]

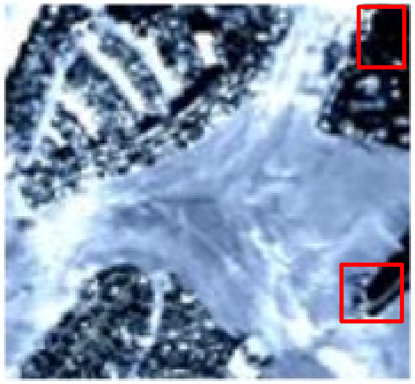
[Martín’16] G. Martín and J. M. Bioucas-Dias, “Hyperspectral blind reconstruction from random spectral projections,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 9, no. 6, pp. 2390–2399, June 2016.
[Lin’20] C.-H. Lin, J. M. Bioucas, T.-H. Lin, Y.-C. Lin, and C.-H. Kao, “A new hyperspectral compressed sensing method for efficient satellite communications,” in Proceedings of the 11th IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM), Hangzhou, China, Jun. 2020. *(Special Session: Unsupervised Computing and Large-Scale Optimization for Multi-dimensional Data Processing)*
[Zhang’16] L. Zhang, W. Wei, Y. Zhang, H. Yan, F. Li, and C. Tian,“Locally similar sparsity-based hyperspectral compressive sensing using unmixing,” IEEE Transactions on Computational Imaging, vol. 2, no. 2, pp. 86–100, June 2016.
[Wang’17] Y. Wang, L. Lin, Q. Zhao, T. Yue, D. Meng, and Y. Leung, “Compressive sensing of hyperspectral images via joint tensor Tucker decomposition and weighted total variation regularization,” IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 12, pp. 2457–2461, Dec 2017.

Experiment

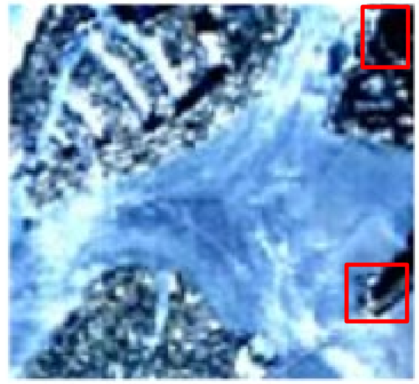
- (Spatial quality) PSNR (dB) – Peak Signal-to-Noise Ratio
- (Global quality) RMSE (degree) – Root Mean Square Error
- (Spectral quality) SAM (degree) – Spectral Angle Mapper

Test Set / Method	C-type	M-type	F-type	L-type
	PSNR↑ / RMSE↓ / SAM↓			
SPACE	24.129/613.661/7.207	29.161/140.415/3.743	29.674/64.151/3.121	27.727/209.757/4.446
SpeCA	9.299/784.867/42.863	15.377/234.735/21.510	11.701/407.530/33.036	14.024/225.772/22.006
TenTV	20.208/570.255/26.247	18.533/260.221/22.972	20.401/248.994/18.714	18.824/314.248/25.523
LSS	7.002/615.037/48.546	0.427/232.486/57.256	3.848/259.960/50.781	2.380/341.429/55.669
HyperCSI-LSS	25.078/278.263/8.704	26.146/51.421/4.907	25.943/82.299/5.732	25.897/83.626/5.779
HCSN (ours)	**34.274/65.120/2.016**	**33.729/30.620/1.631**	**35.908/17.408/1.380**	**35.566/21.558/1.408**
HCSN (C)	34.551/62.437/1.862	30.260/50.947/3.584	34.267/19.361/1.908	33.463/24.162/2.187
HCSN (M)	33.188/78.269/2.731	33.752/30.652/1.595	35.327/18.978/1.550	34.567/27.795/1.801
HCSN (F)	32.834/77.508/2.718	30.074/68.014/4.873	35.750/17.657/1.357	33.137/29.138/2.339
HCSN (L)	33.666/70.175/2.272	31.806/39.403/2.538	34.541/20.117/1.770	34.972/22.456/1.528

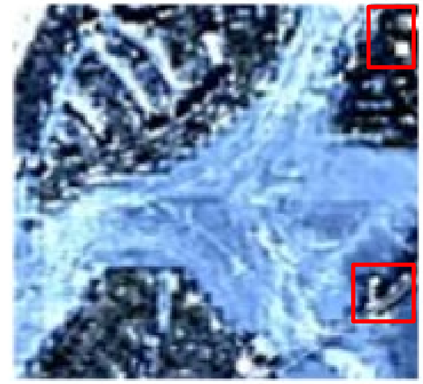
Experiment



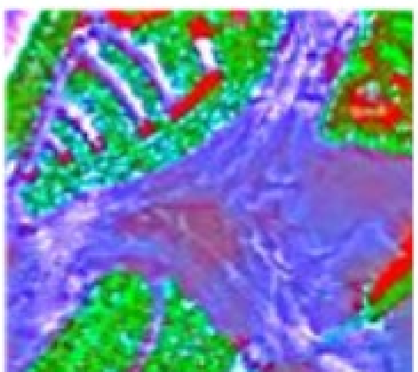
(a) Ground Truth



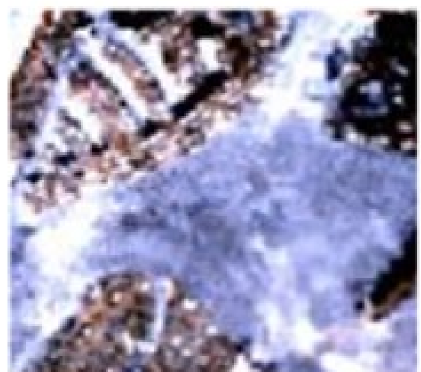
(b) HCSN
SAM: **2.958**



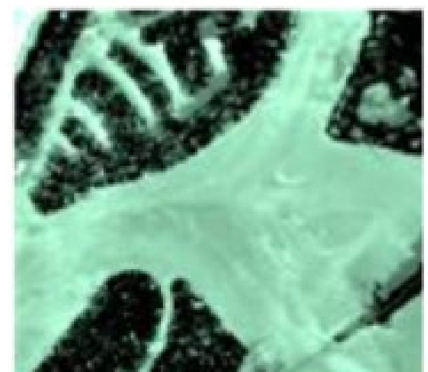
(c) SPACE
SAM: 6.019



(d) LSS
SAM: 59.563



(e) TenTV
SAM: 26.258



(f) SpeCA
SAM: 27.787

Conclusion in HSI SR

- A new deep neural network for HSI compression/reconstruction
- Fast compression by the lightweight encoder
- An efficient decoder which decode the spatial and spectral super-resolution

Outline

- Overview of Deep Learning
  - Supervised – Unsupervised
- Deep super-resolution
  - Traditional super-resolution
  - Structured image super-resolution
    - Face hallucination
  - 2-D image super-resolution (generic images)
  - *N*-D image super-resolution (Hyperspectral images)
- Summary

Outline

- Deep super-resolution
  - Traditional super-resolution
  - 2-D image super-resolution (generic images)
  - *N*-D image super-resolution (Hyperspectral images)
- Summary

Summary

- Single image super-resolution still remains several issues to be overcome
  - Good metric beyond GAN loss
    - Visual quality vs math equation
  - Different types of images have different requirements
    - Network architecture design
    - Applications
  - Finding a good prior for super-resolution always works
    - Such as “face hallucination”

QA session

For more information,
Please visit https://cchsu.info