Australian National University

Single Image Super-Resolution Using a Channel Attention Generative Adversarial Network

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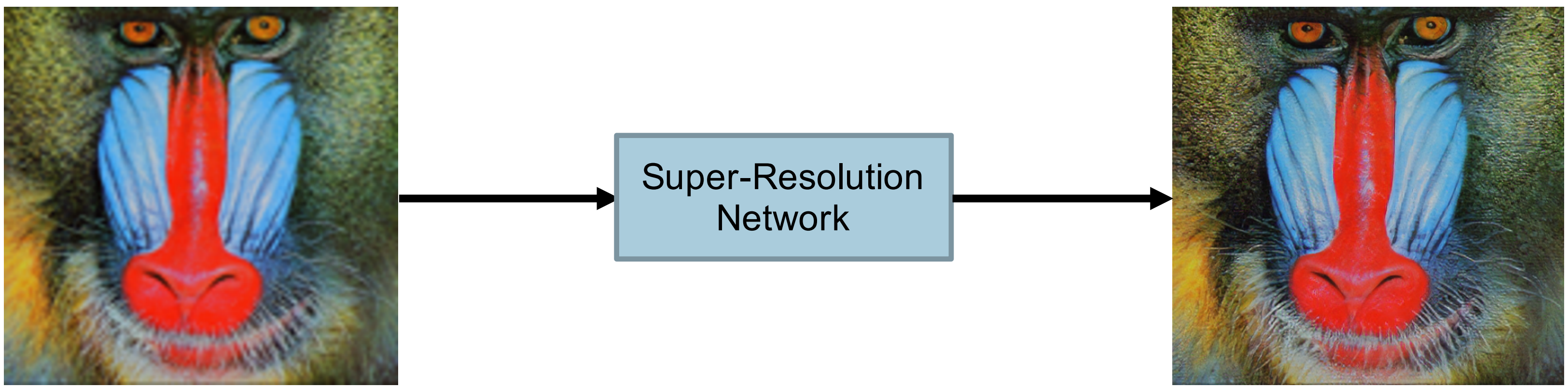
ENGN8536 Project Presentation
Group 8

Super-resolution



Low-resolution

Super-resolution

Key idea: reconstruct required details!

Introduction

- Motivations
  - Require texture information to reconstruct details
  - Features between channels and pixels
  - Using Generative Adversarial Network
- Our Method
  - Proposed a Channel Attention based GAN

Attention + GAN

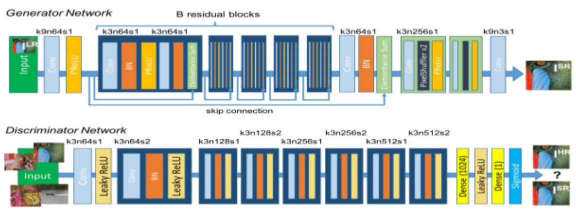
texture reconstructed

LR image

Super-resolution using Attention & GAN

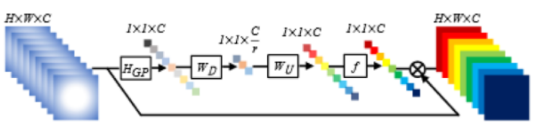
SR image

Related work

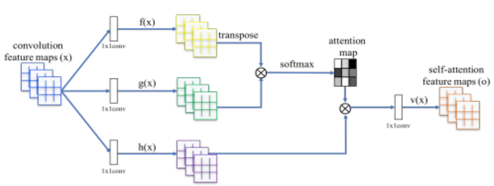


SRGAN

Perceptual Loss: visually satisfying results



Channel Attention



Self Attention

Attention strategies

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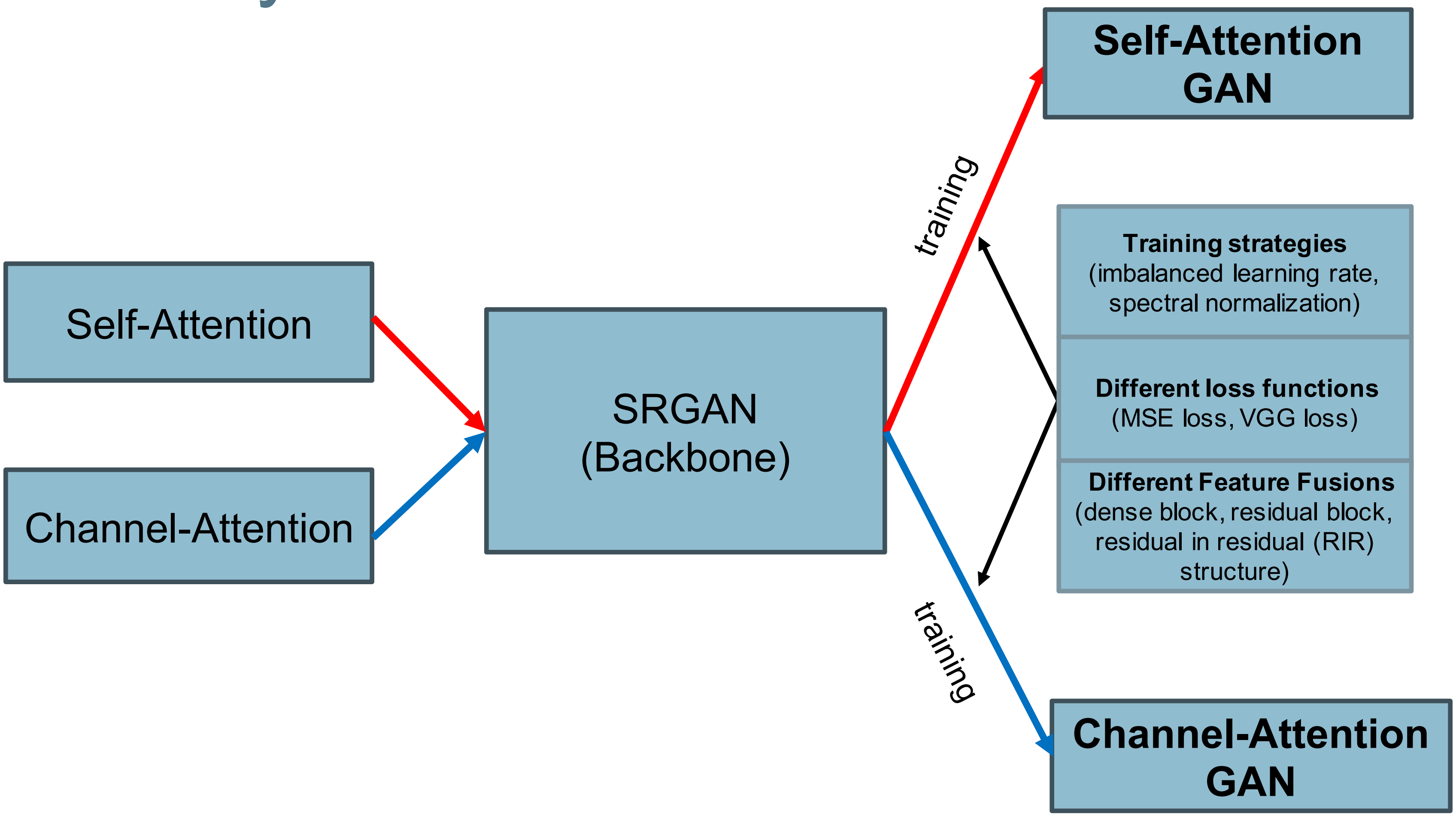
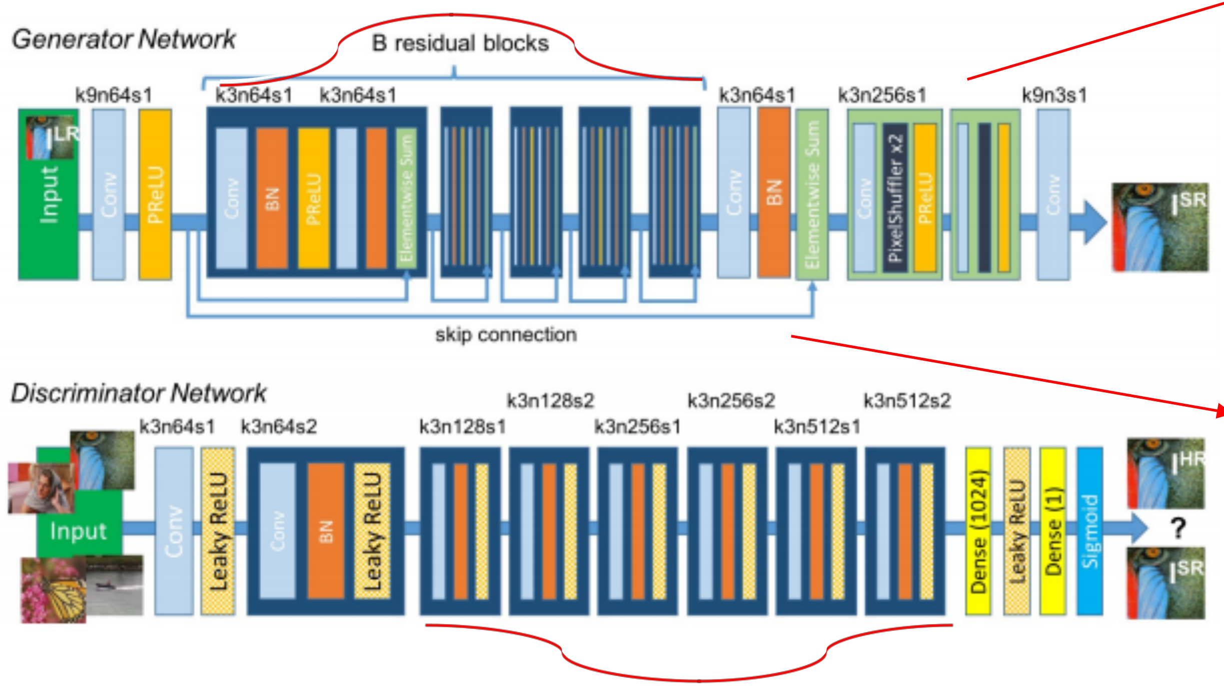
Novelty



Channel Attention GAN Architecture

Channel Attention Blocks

Subpixel convolutional block



Feature fusion of low-level features and high-level features

Channel Attention Blocks

Loss of SR-CAGAN

$$l^{SR} = \underbrace{l_X^{SR}}_{\text{content loss}} + \underbrace{10^{-3} l_{Gen}^{SR}}_{\text{adversarial loss}}$$

Content Loss:

MSE loss *vs* VGG loss

$$l_{MSE}^{SR} = \frac{1}{r^2WH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I_{x,y}^{HR} - G_{\theta_G}(I^{LR})_{x,y})^2$$

$$l_{VGG/i.j}^{SR} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y})^2$$

Loss of SR-CAGAN

$$l^{SR} = \underbrace{l^{SR}_{X}}_{\text{content loss}} + \underbrace{10^{-3} l^{SR}_{Gen}}_{\text{adversarial loss}}$$

Adversarial Loss:

$$l^{SR}_{Gen} = \sum_{n=1}^{N} -\log D_{\theta_D}(G_{\theta_G}(I^{LR}))$$

Channel Attention vs Self Attention

Channel Attention mechanism:

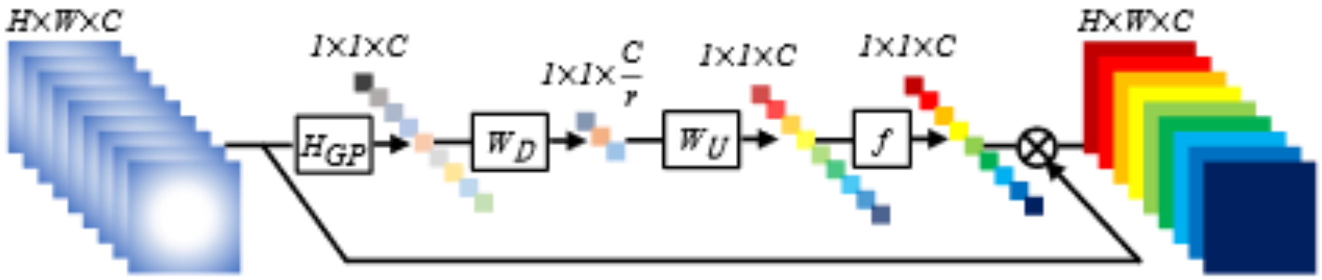


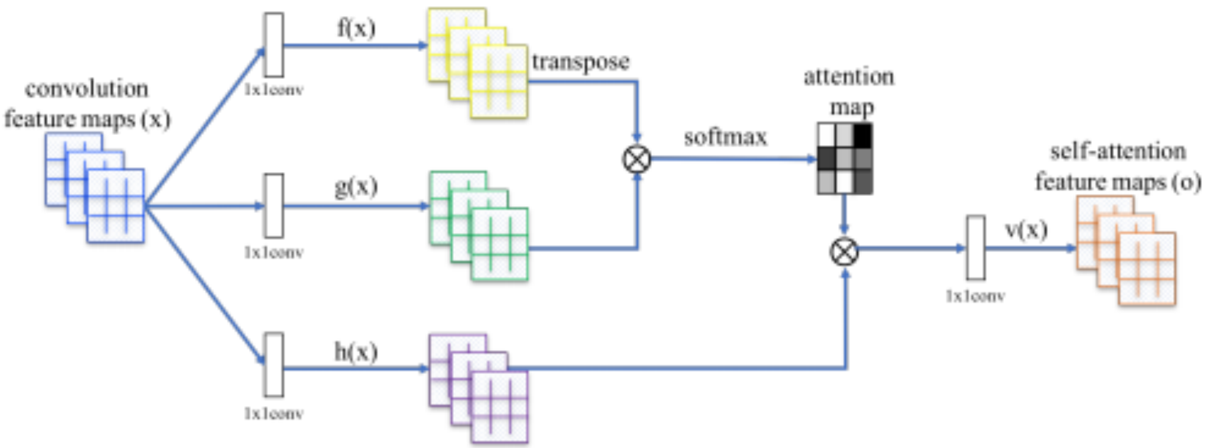
Fig. 3. Channel attention (CA). ⊗ denotes element-wise product

Attention through **channels**!

Capture channel relationships

Channel Attention vs Self Attention

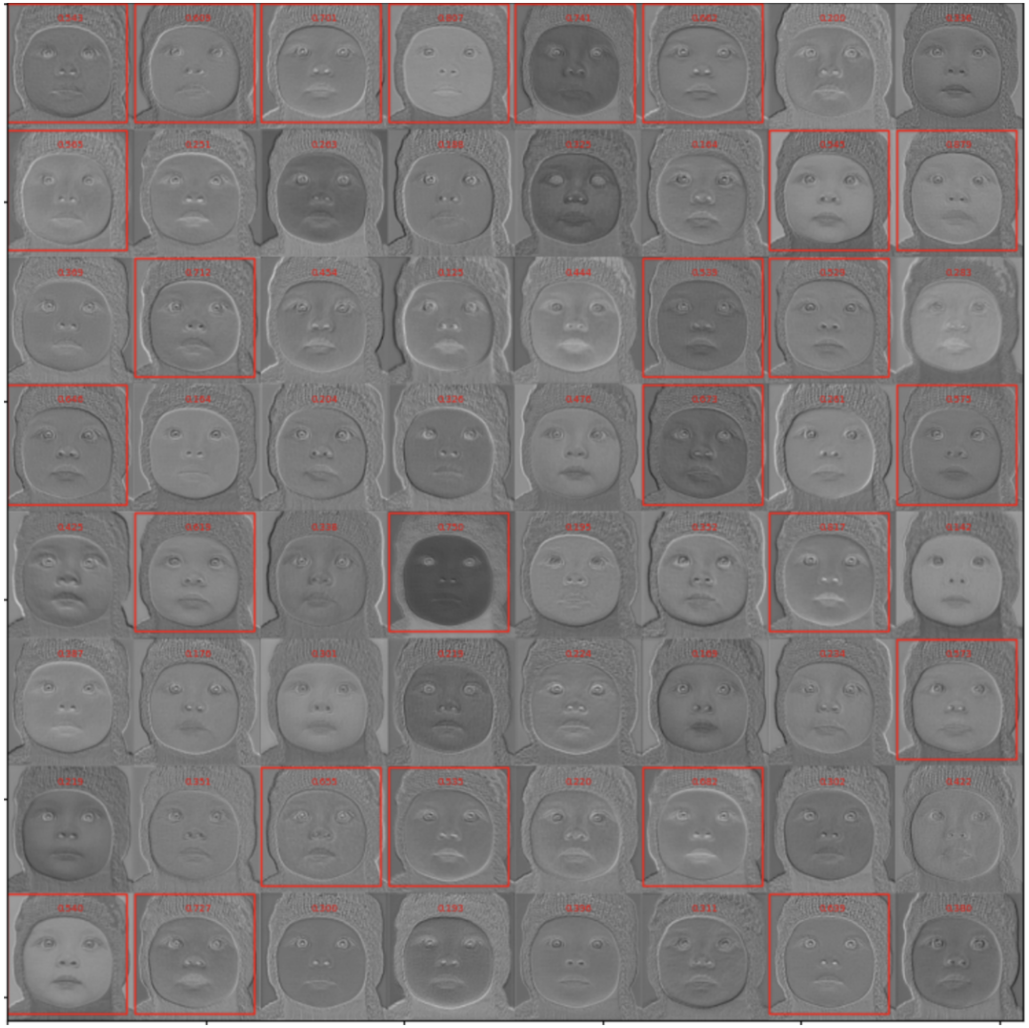
Self Attention mechanism:



Attention through **pixels**!

Capture spatial relationships

Visualization of Channel Attention



Red-boxed channels have larger channel weights(>0.5).

Emphasizing informative channels

Suppresses less useful channels.

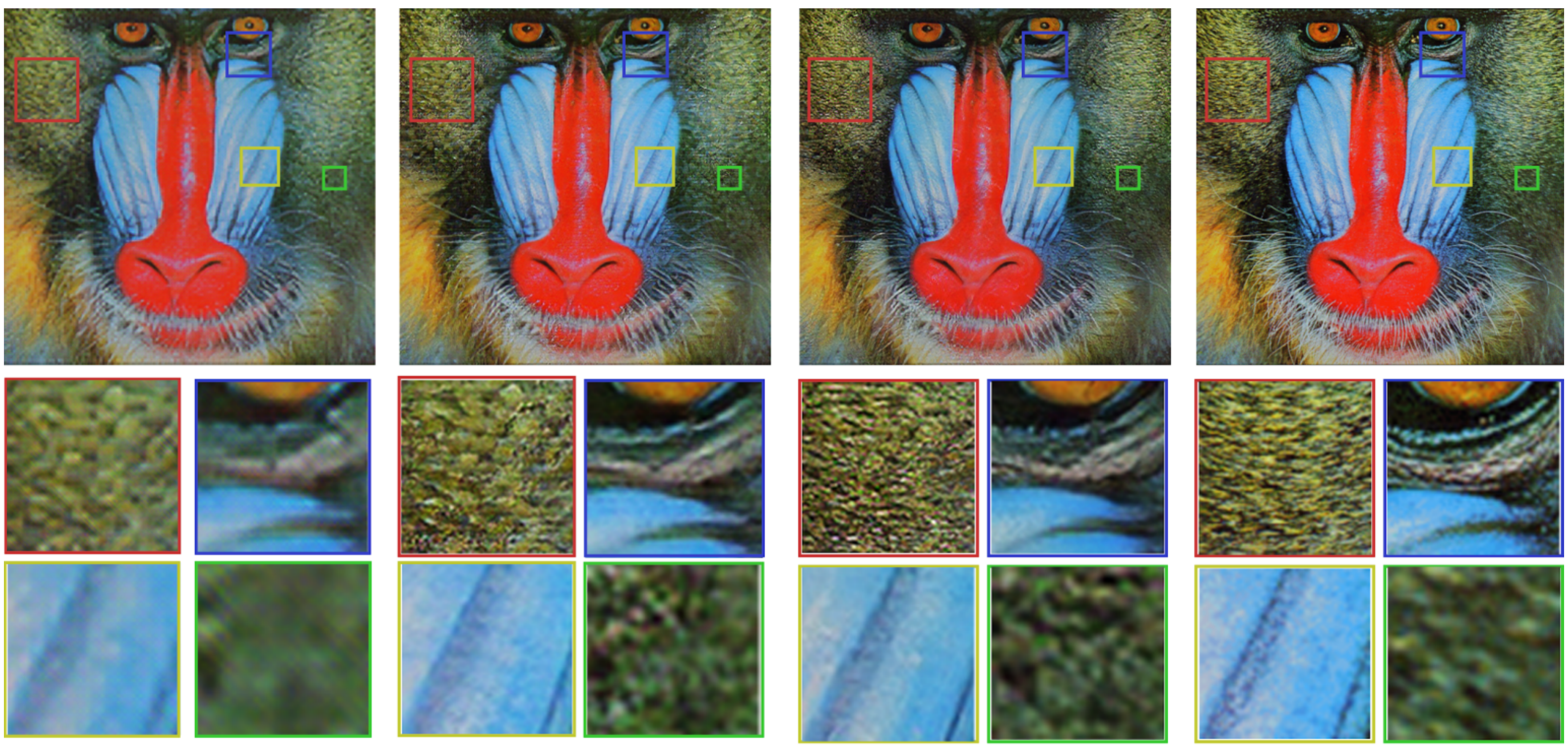
Comparison between different models

dataset / models	Set5			Set14			BSD100		
	PSNR	SSIM	MOS	PSNR	SSIM	MOS	PSNR	SSIM	MOS
SRGAN	26.304	0.825	3.46	24.269	0.690	3.56	23.126	0.634	3.53
Self Attention	27.135	0.828	3.62	25.474	0.727	3.57	23.599	0.646	3.61
Channel Attention	**30.757**	**0.869**	**3.87**	**26.455**	**0.743**	**3.76**	**25.572**	**0.686**	**3.79**

training data: 82k coco images (train2014)
validation data: Set5,Set14 and BSD100
batch size:16
epochs:100

SRGAN vs our Models (4x scaling)

Self Attention vs Channel Attention



bicubic | self attention | **channel attention** | original

Ablation study 1:Channel Attention

Experiments: Different numbers of channel attention
Conclusion: More channel attentions have better performance!

dataset / number of CA	Set5			Set14			BSD100		
	PSNR	SSIM	MOS	PSNR	SSIM	MOS	PSNR	SSIM	MOS
0	27.504	0.828	3.67	25.269	0.660	3.62	23.416	0.674	3.63
4	30.742	0.854	3.77	26.384	0.726	3.67	25.441	0.670	**3.78**
8	**30.811**	0.856	3.78	26.333	0.739	3.63	25.519	0.672	3.70
16	30.757	**0.869**	**3.91**	**26.455**	**0.743**	**3.76**	**25.572**	**0.686**	**3.78**

Ablation study 2:Perceptual loss

Experiments: VGG loss vs MSE loss

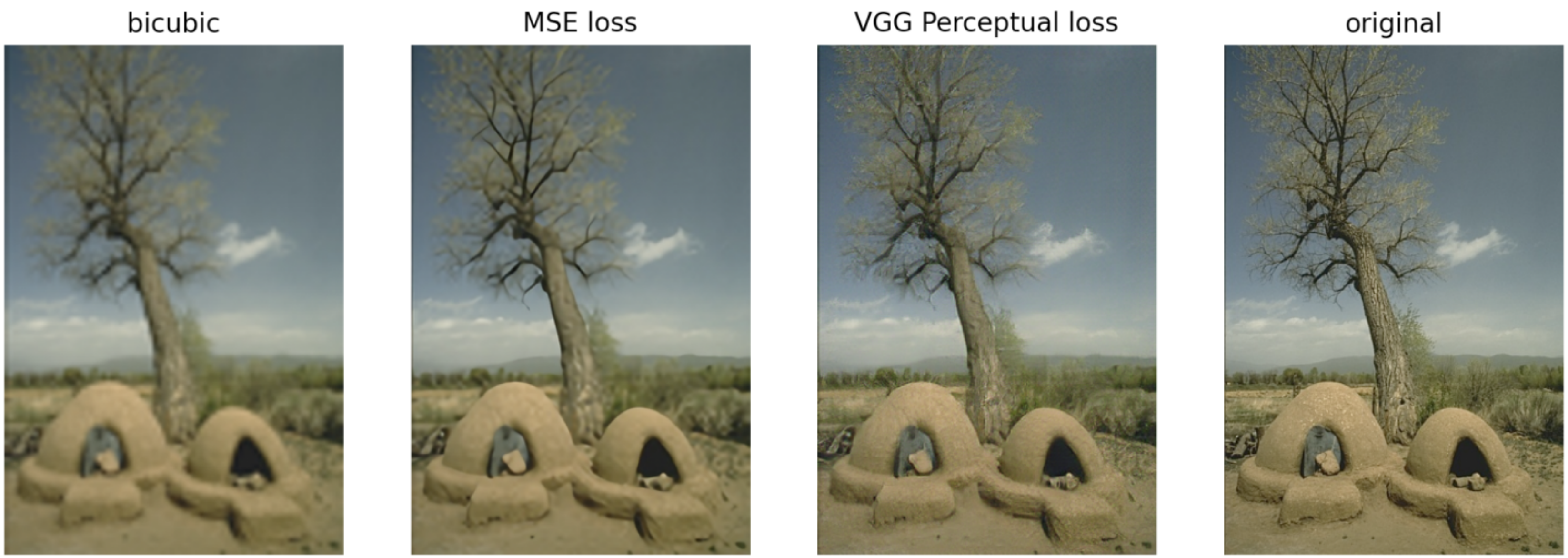
Conclusion:

- MSE loss can get higher PSNR and SSIM score
- But VGG loss has better visual results

number of CA	Set5			Set14			BSD100		
	PSNR	SSIM	MOS	PSNR	SSIM	MOS	PSNR	SSIM	MOS
MSE loss	**33.335**	**0.923**	3.33	**28.588**	**0.800**	3.33	**27.187**	**0.722**	3.37
VGG loss	30.942	0.854	**3.91**	26.384	0.726	**3.88**	25.441	0.670	**3.79**

VGG loss vs MSE loss

PSNR does not necessarily reflect the perceptually better SR results!



PSNR: 28.367 26.476

Ablation study 3:Stabilization strategy

Experiments: Fixed vs Imbalanced learning rate

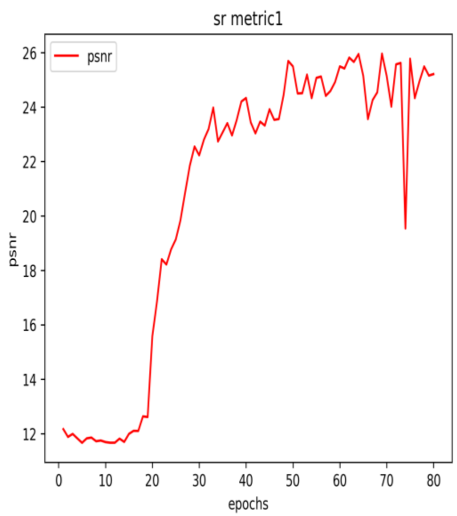
Model is trained on a smaller COCO dataset (6k images)

Conclusion: model with imbalanced learning rate gets better results.

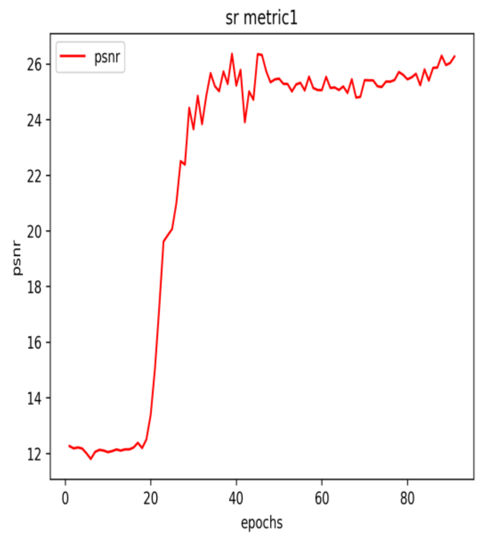
	Set5			Set14			BSD100		
	PSNR	SSIM	MOS	PSNR	SSIM	MOS	PSNR	SSIM	MOS
fixed learning rate	26.039	0.808	3.33	24.848	0.721	3.41	**24.517**	**0.667**	3.**66**
imbalanced learning rate	**26.146**	**0.812**	**3.60**	**25.077**	**0.727**	**3.54**	24.093	0.656	3.54

Stabilization strategies

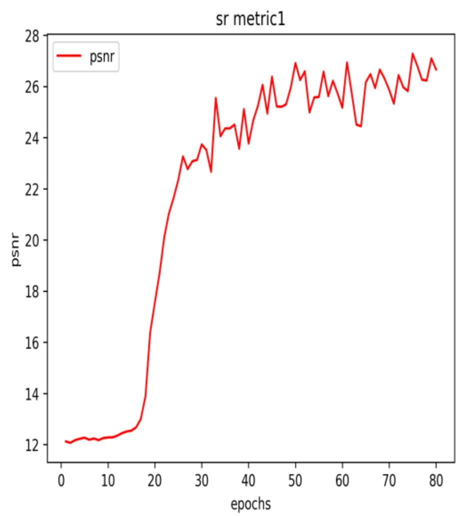
Imbalanced learning rate and **spectral norm** speed up and stabilize the training process



psnr for base model



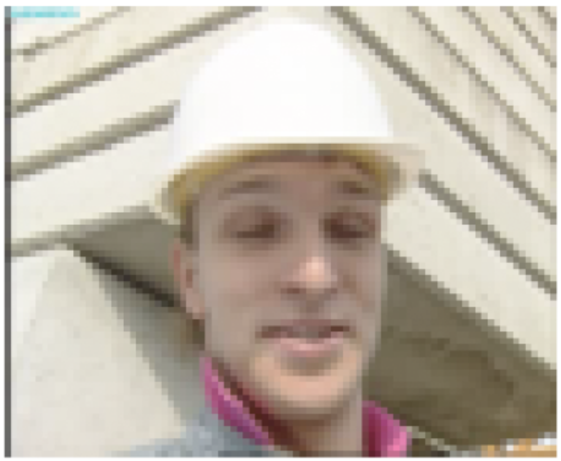
psnr for imbalanced lr



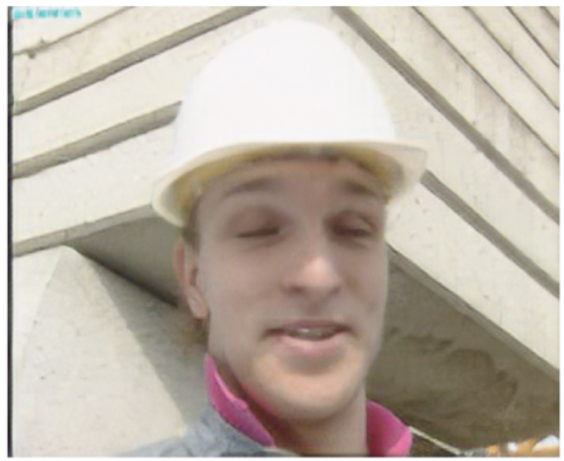
psnr for spectral norm

More results(4x scaling)

4x downsampled lr image



channel attention gan



original

lr: low resolution image (4x downsampled result of the original image)

More results(4x scaling)

4x downsampled lr image

channel attention gan

original

More results(4x scaling)

4x downsampled lr image

channel attention gan

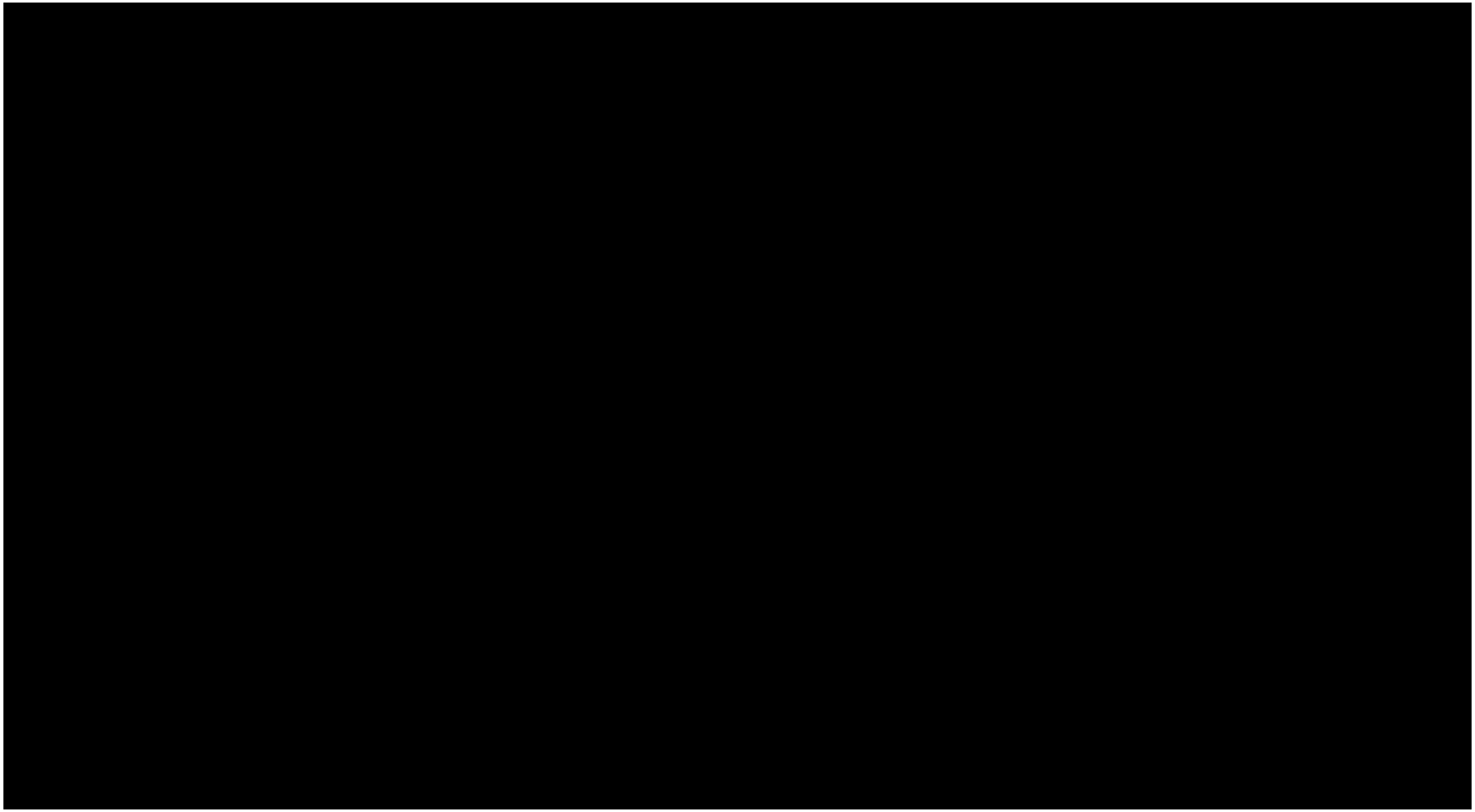
original

More results(4x scaling)

4x downsampled lr image

channel attention gan

Video demo(4x scaling)



Conclusion

- We proposed the Channel-attention GAN and showed channel information is more useful than spatial information on SR tasks.

- Our models outperform SRGAN on SR tasks.

Future work

- To research a better feature-fusion method(e.g. RIR structure)

- To improve the efficiency of our model

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Q&A