

# A graph neural network for multiple-image super-resolution

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Introduction

Proposed  
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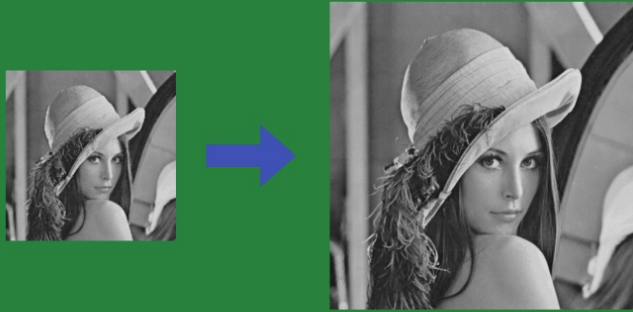


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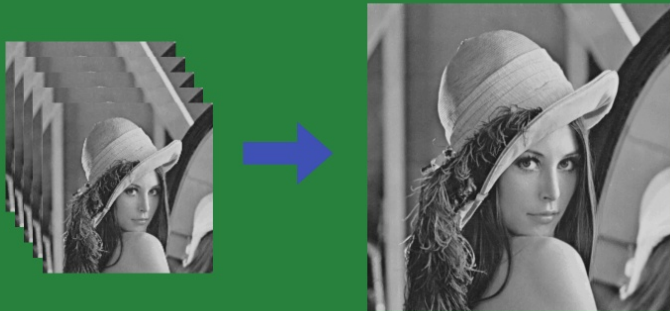


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# Image super-resolution



**Single-image super-resolution (SISR)**



**Multi-image super-resolution (MISR)**

Related  
work

Contribution

# Related work

**DeepSUM** - Andrea Bordone Molini, Diego Valsesia, Giulia Fracastoro, and Enrico Magli, “**DeepSUM: Deep neural network for super-resolution of unregistered multitemporal images**”, IEEE TGRS, vol. 58, no. 5, pp. 3644–3656, 2020

**RAMS** - Francesco Salvetti, Vittorio Mazzia, Aleem Khaliq, and Marcello Chiaberge, “**Multi-image super resolution of remotely sensed images using residual attention deep neural networks**”, Remote Sensing, vol. 12, no. 14, pp. 2207, 2020

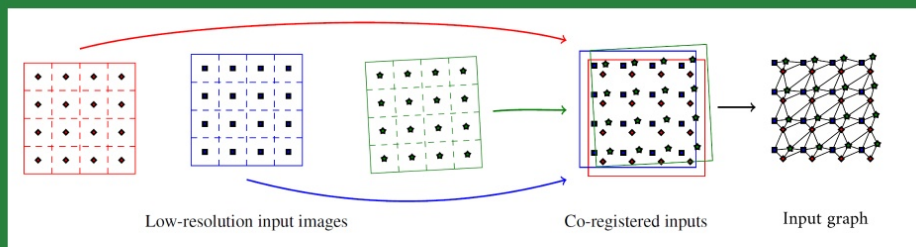
**HighRes-net** - Michel Deudon, Alfredo Kalaitzis, Israel Goytom, Md Rifat Arefin, Zhichao Lin, Kris Sankaran, Vincent Michalski, Samira E Kahou, Julien Cornebise, and Yoshua Bengio, “**HighRes-net: Recursive fusion for multi-frame super-resolution of satellite imagery**”, arXiv preprint arXiv:2002.06460, 2020.

## Common limitations:

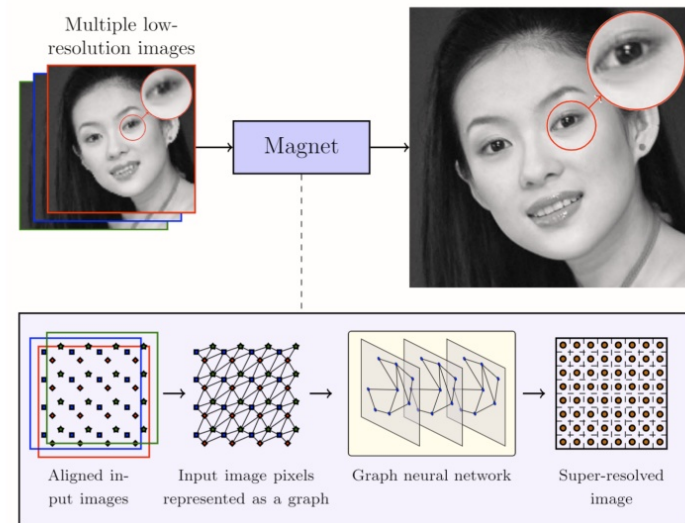
- Fixed number of input images for training and inference
- Potential information loss if pre-registration is performed

# Contribution

## Representation of images as a graph



## Magnet: Multiple-image graph neural network



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# Proposed Method

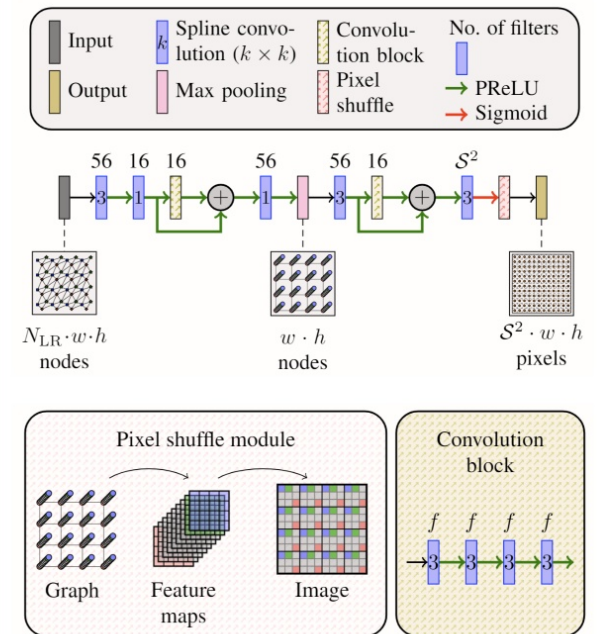
## Images-to-graph conversion

- multiple input images represented as a single graph
- each pixel represents one node
- node positions are adjusted by shifts between input images
- values of translated nodes remain unchanged
- no co-registration means no loss of information

## Graph neural network - Magnet

- graph on the input, tensor on the output
- continuous kernels using spline-based convolutions [1]
- arbitrary number of input images
- low number of trainable parameters: 176.7k

[1] Matthias Fey, Jan Eric Lenssen, Frank Weichert, and Heinrich Muller, "SplineCNN: Fast geometric deep learning with continuous B-spline kernels," in Proc. IEEE CVPR, 2018, pp. 869–877



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# Experimental setup

Seven datasets:

- DIV2K
- BSDS100
- historical
- Manga109
- Set5
- Set14
- Urban100

Training set: **1130** DIV2K images

Validation set: **279** DIV2K images

Test sets: **338** images from the rest of the datasets

Low-resolution images were created by downscaling the original ones by a factor of three and applying random subpixel shifts.

Training

Results



# Training

Adam optimizer:

- $\beta_1 = 0.9$
- $\beta_2 = 0.999$
- learning rate =  $1e^{-3}$  down to  $1e^{-4}$

Loss function:

- shifted PSNR - choosing the highest PSNR score calculated 49 times per example where each time a different translation is applied to the output image (from  $[-3, 3]$  range for each axis).

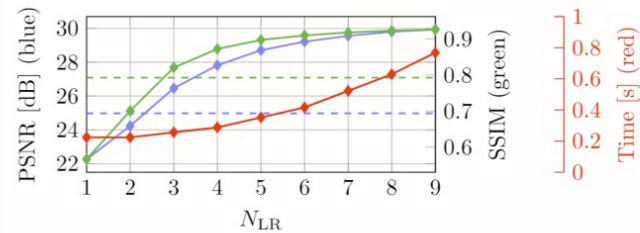
Two hundred epochs (no early stopping):

- models chosen based on PSNR score on validation set

## Hardware & Software:

- NVIDIA RTX 2080Ti GPU (11 GB VRAM)
- Python 3.8.5
- Pytorch 1.7
- Pytorch Geometric

# Results

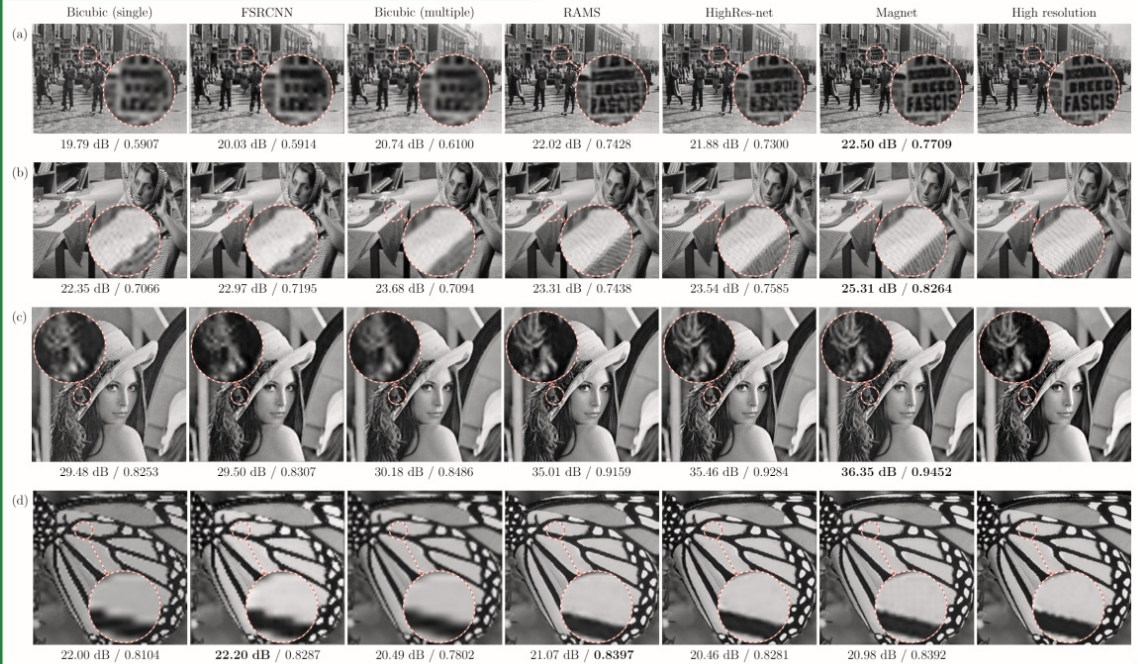


Reconstruction accuracy and time (for 256 x 256 images) obtained with Magnet using different number of low-resolution images. The dashed lines show the performance obtained with bicubic interpolation.

Dataset →		Set5		Set14		BSD100		Manga109		Historical		Urban100		
Method ↓	Model size ↓	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	
Bicubic (single)*		—	29.21	0.8671	25.14	0.7737	25.47	0.7530	25.80	0.8427	20.94	0.6816	23.64	0.7200
FSRCNN*	17.1k	29.18	0.8620	25.25	0.7742	25.73	0.7563	25.79	0.8405	21.24	0.6827	23.81	0.7215	
Bicubic (multiple)		—	29.72	0.8737	25.83	0.7856	26.35	0.7669	26.18	0.8463	21.79	0.6966	24.43	0.7333
RAMS	1058.1k	32.53	0.9294	28.77	0.8798	29.41	0.8814	30.08	0.9337	23.68	0.8194	27.97	0.8703	
HighRes-net	591.8k	32.75	0.9350	29.07	0.8843	29.44	0.8818	30.15	0.9358	23.79	0.8196	27.74	0.8625	
MagNet	176.7k	<b>33.33</b>	<b>0.9387</b>	<b>30.68</b>	<b>0.9207</b>	<b>30.54</b>	<b>0.9122</b>	<b>30.69</b>	<b>0.9451</b>	<b>24.86</b>	<b>0.8613</b>	<b>28.70</b>	<b>0.8990</b>	

\* Single-image SR techniques

Reconstruction accuracy obtained using different methods for six benchmark datasets.



Examples of the reconstruction outcomes with PSNR and SSIM scores under the corresponding image.

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# Conclusions

- the first time a graph neural network has been used for MISR problem
- graph-based representation allows for effective fusion of information
- lightweight yet highly accurate model
- our method allows for raw data input with arbitrary number of low-resolution images

## Future plans:

- researching more sophisticated graph-building procedures
- tests on deeper and more complex architectures
- detecting and adjusting node positions based on image rotation
- fusing input images of different spatial resolution
- real data applications

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