

A GRAPH NEURAL NETWORK FOR MULTIPLE-IMAGE SUPER-RESOLUTION

Poster number: 2861

Tomasz Tarasiewicz, Jakub Nalepa and Michał Kawulok
Silesian University of Technology, Gliwice, Poland



Silesian University
of Technology

Background

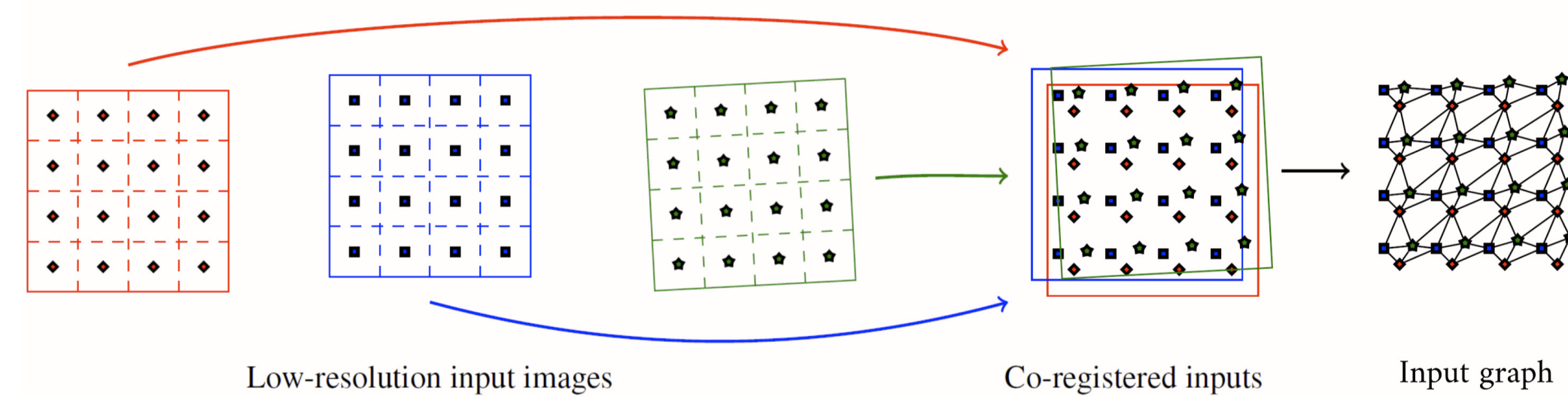
Super-resolution (SR) reconstruction is a common term for a variety of techniques aimed at generating a high-resolution (HR) image from a low-resolution observation (LR).

There are two main approaches to the problem:

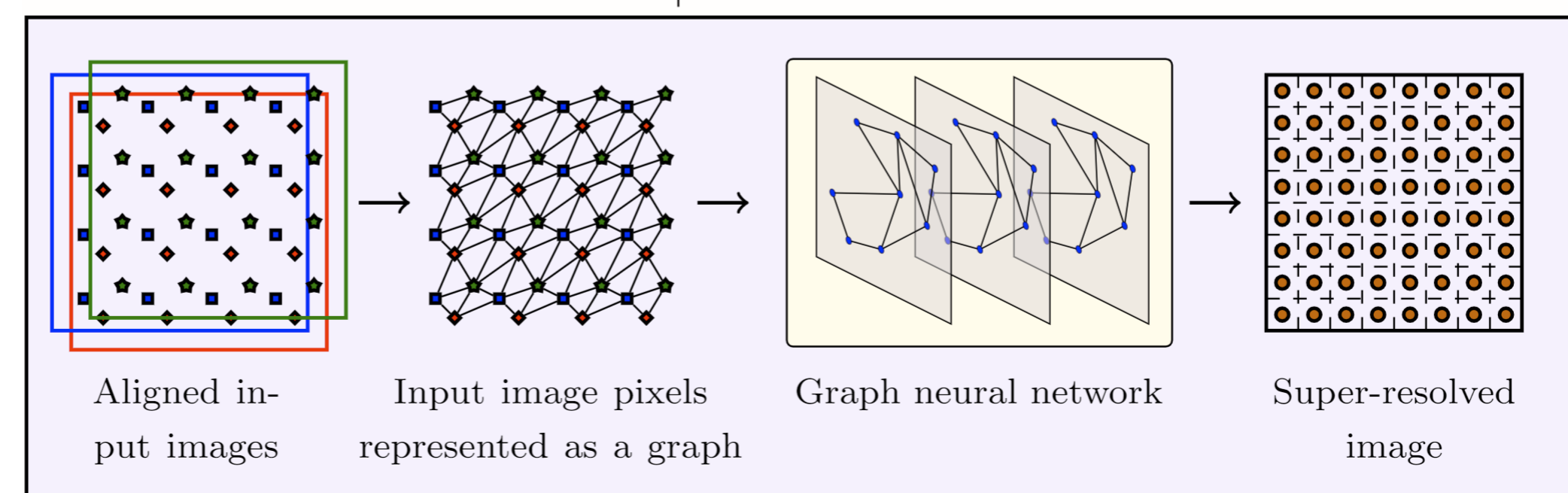
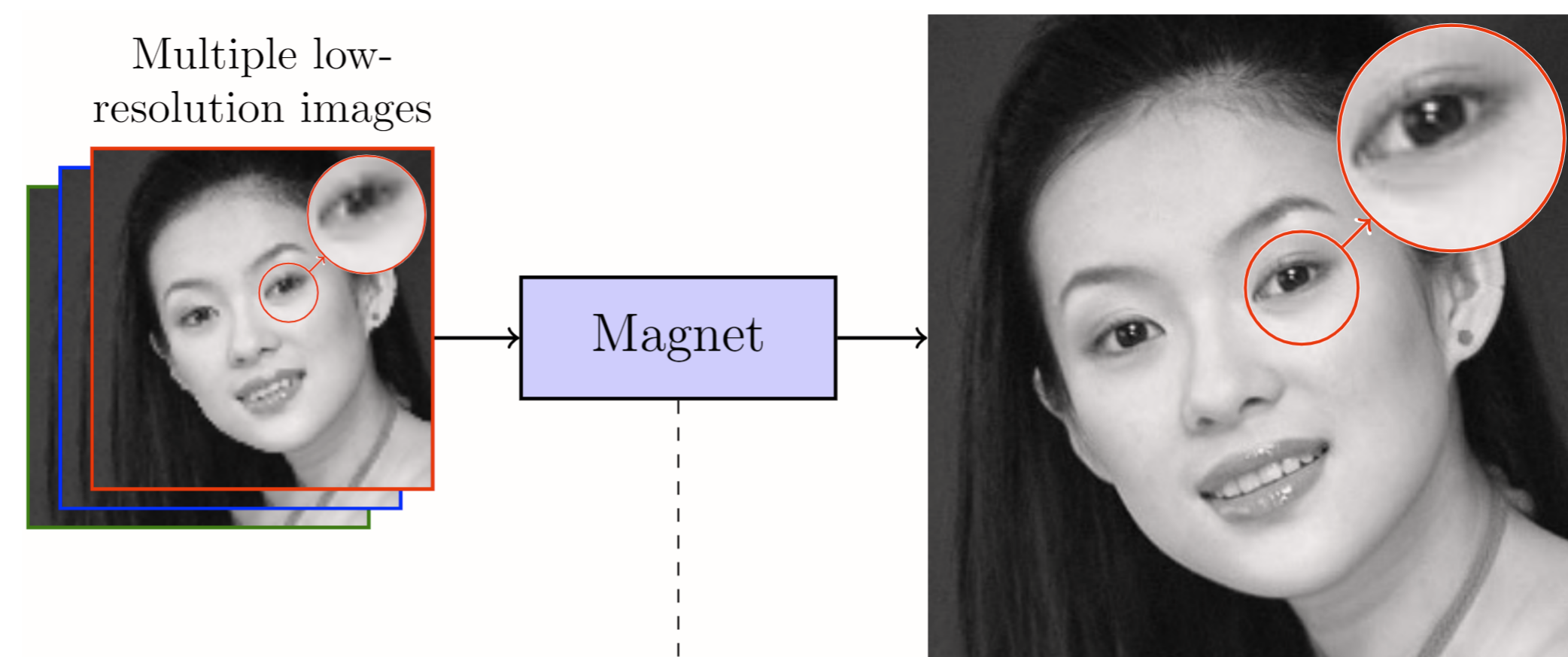
- Single-image SR (SISR): focuses on modeling the relation between low- and high-resolution visual data from a single LR observation;
- Multi-image SR (MISR): additionally benefits from information fusion from multiple LRs representing the same scene.

Contribution

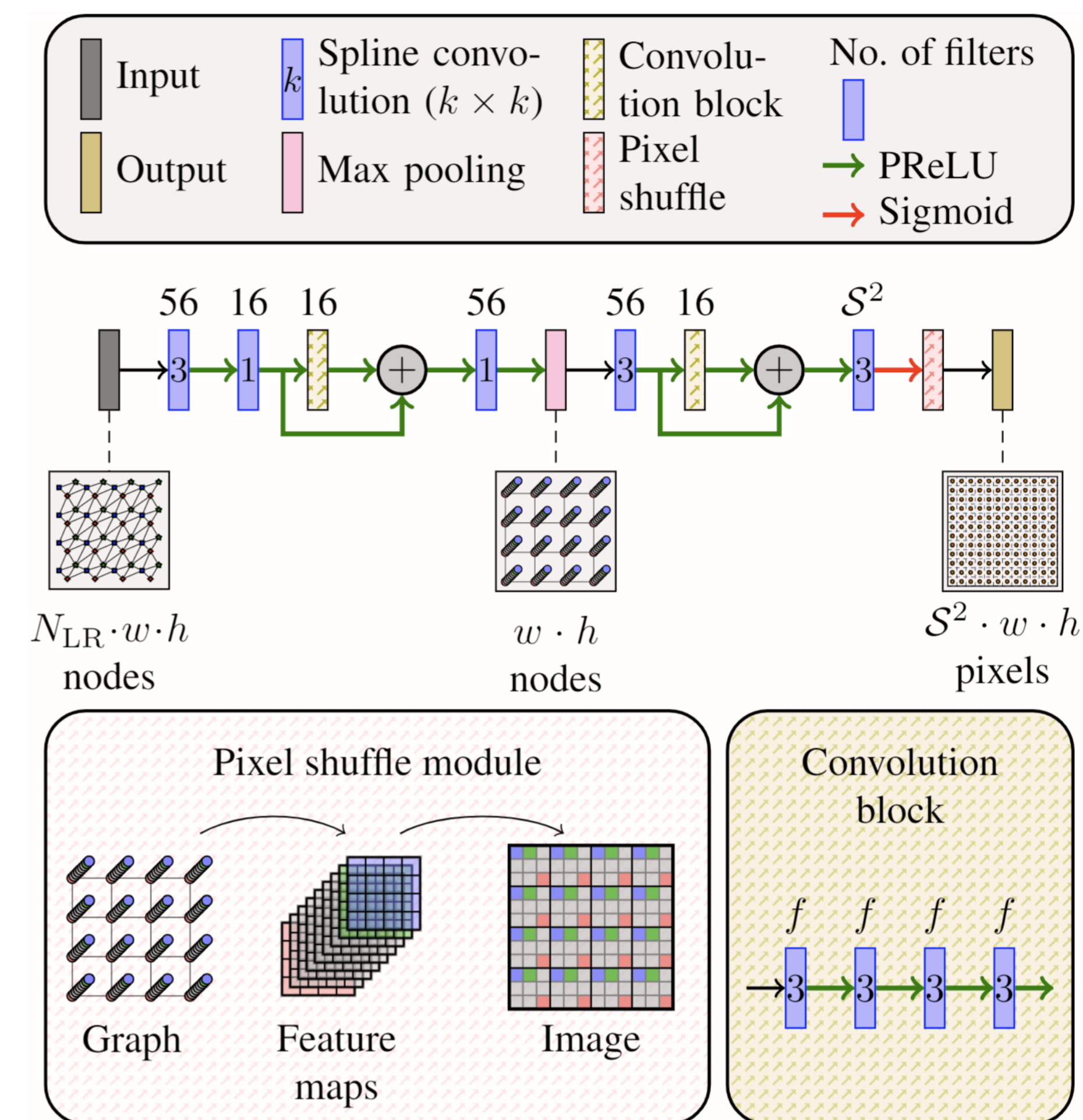
- Images-to-graph conversion
 - » Multiple input images composed as a single graph
 - » Each pixel represents a node
 - » Node positions are adjusted by shifts between LRs
 - » Edge weights indicate distance between nodes



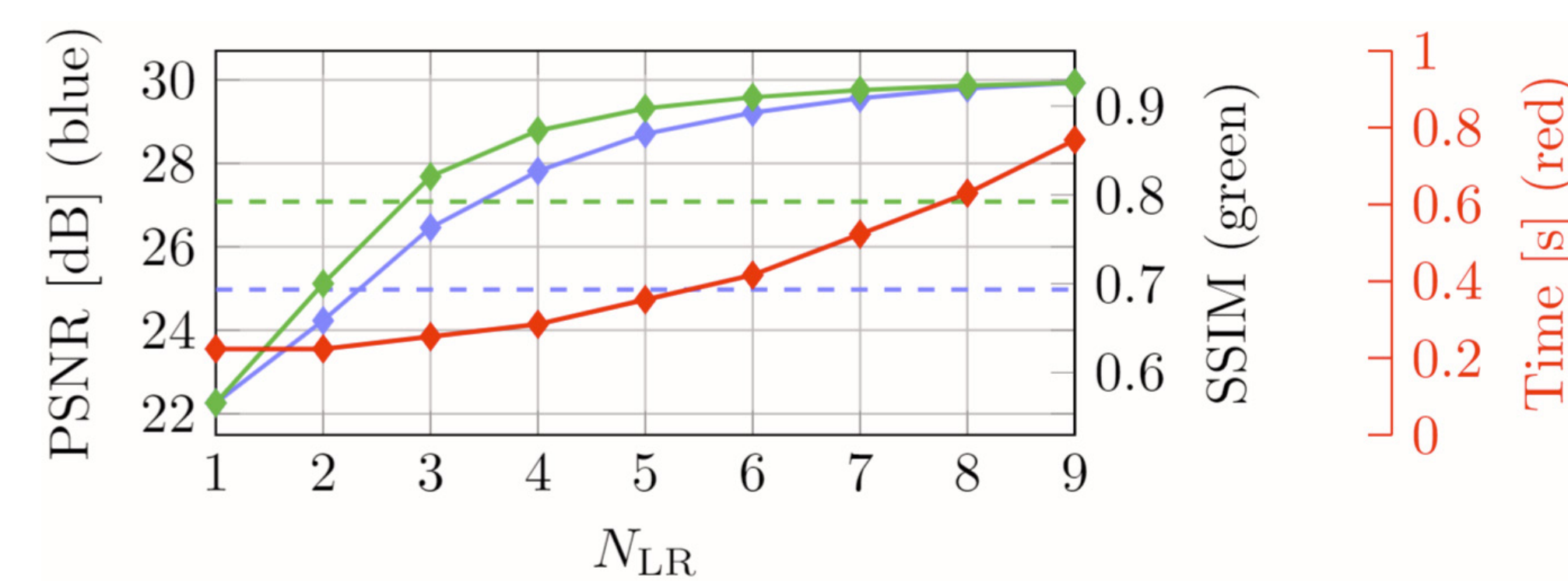
- Magnet—a **m**ultiple-**i**mage **g**raph neural **n**etwork
 - » Graph on the input, matrix on the output
 - » Continuous kernels thanks to spline-based convolutions
 - » Arbitrary number of input images per stack
 - » Allows for arbitrary upscaling factor
 - » Low number of parameters—about 176k



Model architecture



Experiments: Variable stack size



Reconstruction accuracy and time (for 256×256 LRs) obtained with Magnet using different number of input images N_{LR} . The dashed lines show the performance obtained with bicubic interpolation.

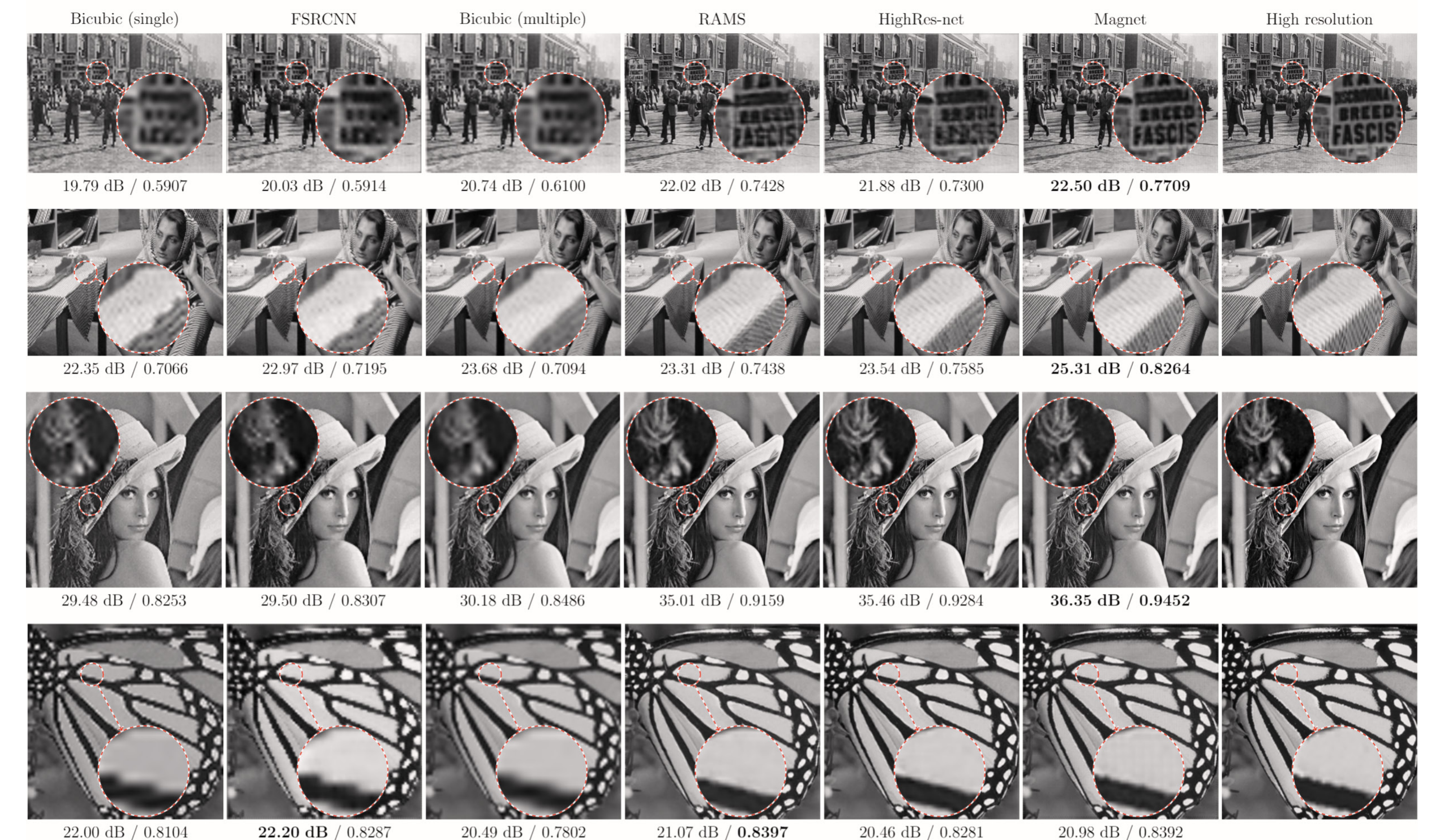
Experiments: Reconstruction outcome evaluation

Reconstruction quality obtained using different methods for six benchmark datasets. The best score for each set is boldfaced.

	Dataset →	Set5	Set14	BSD100	Manga109	Historical	Urban100
Method ↓	Model size ↓	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic (single)*	—	29.21	0.8671	25.14	0.7737	25.47	0.7530
FSRCNN*	17.1k	29.18	0.8620	25.25	0.7742	25.73	0.7563
Bicubic (multiple)	—	29.72	0.8737	25.83	0.7856	26.35	0.7669
RAMS	1058.1k	32.53	0.9294	28.77	0.8798	29.41	0.8814
HighRes-net	591.8k	32.75	0.9350	29.07	0.8843	29.44	0.8818
MagNet	176.7k	33.33	0.9387	30.68	0.9207	30.54	0.9122

* Single-image SR techniques

Examples of the reconstruction outcomes for four images that originate from Historical, Set14 and Set5 benchmark datasets. PSNR/SSIM are reported under the corresponding image, and the best results are boldfaced.



Conclusions

- To the best of our knowledge, it is the first time a graph neural network has been exploited for MISR problem.
- Graph-based representation of the input LR images allows for effective fusion of the information from different LR observations.
- Despite being a lightweight model, Magnet outperforms other state-of-the-art techniques that we tested.
- As for now, our work was focused only on fully artificial data which means that each tested LR was created by downscaling and translating original HR image.

Next steps

- Experiments on deeper and more advanced architectures
- Real data applications
- More sophisticated graph creation procedures
- Taking advantage of rotations between LRs