Super-resolution of satellite imagery using GANs

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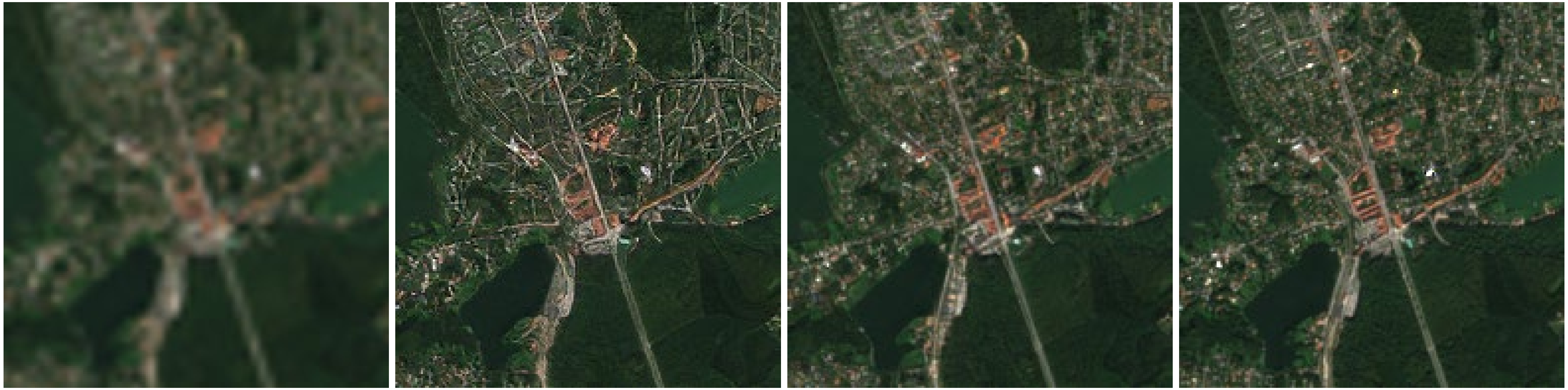


Introduction

- We have many type of satellite imageries.
  - MODIS (500m/px. High spectral quality, daily)
  - Landsat / Sentinel(30-10m/px. High spectral quality, few per month)
  - Planet (3m/px. Low spectral quality, daily)
  - WorldView (0.3 m/px. Medium spectral quality, on request)
  - …
  - And even more when we are going back in time …

- How to combine all this different type of images ?
  - Required for complex and/or long term analysis

How to combine different data

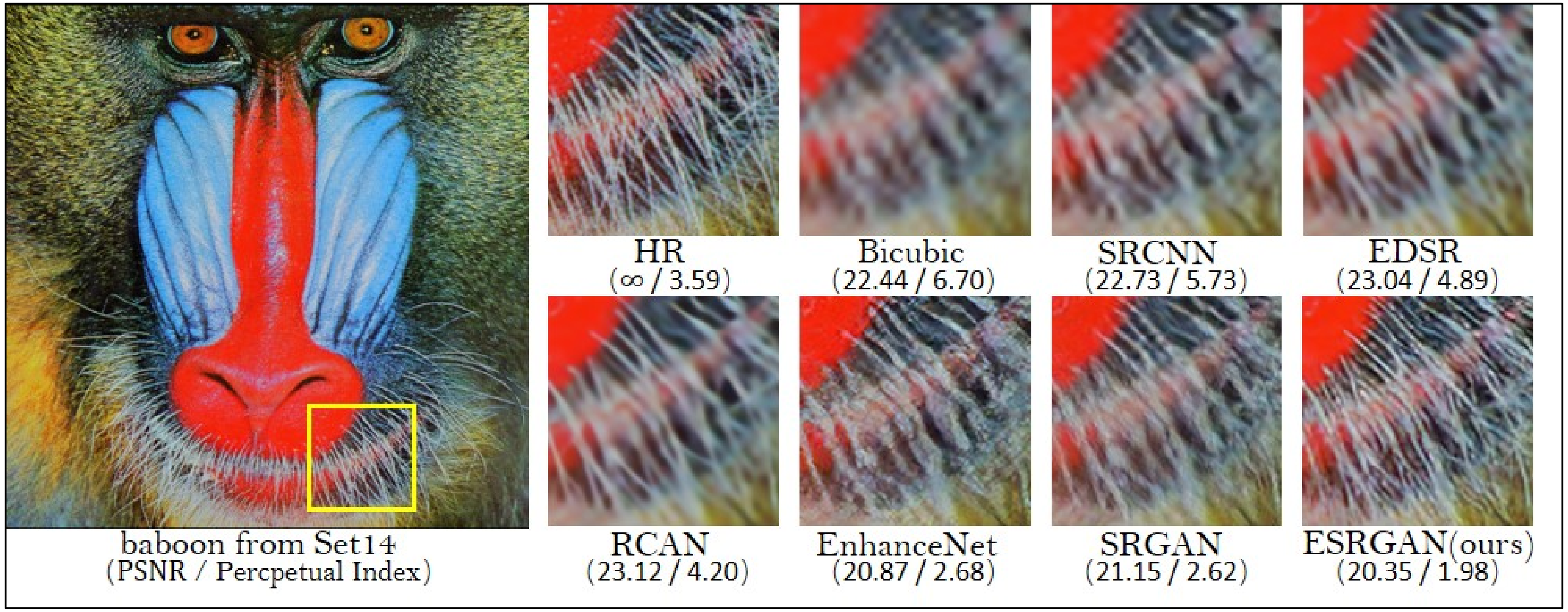
- Decimate the data to the same level
  - Average and remove extra information that is not common to all the sensors
  - Easy and fast
  - Often used
  - Why invest in good sensors ?

- Statistically improve the data to the high quality by artificially creating enhanced images
  - Uses all the information available
  - Homogenizes the data
  - Enhanced analysis

- Is this challenge only in remote sensing ?

Single-image super-resolution in other fields

- Increasingly explored in computer vision
- Implemented in most new TVs



Wang, X., Yu, K., Wu, S., Gu, J., Liu, Y., Dong, C., Qiao, Y., & Loy, C. C. (2019). ESRGAN: Enhanced super-resolution generative adversarial networks. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11133 LNCS, 63–79. https://doi.org/10.1007/978-3-030-11021-5_5

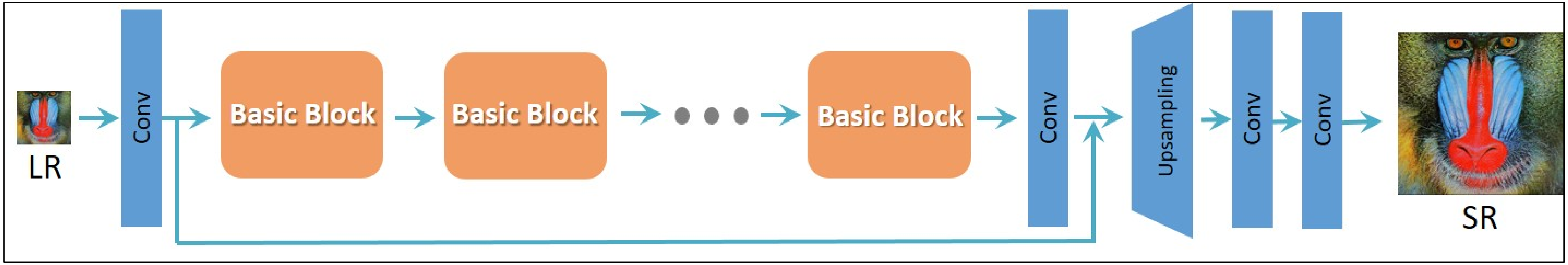
- The goal is to improve image quality for the end user while decreasing computational power needs

ESRGAN

- Winner of the PIRM 2018 Challenge with the best perceptual index

- Does most computation in the LR feature space

- How does the generically trained network perform with satellite images?



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Generic training

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Dataset

- 87 Sentinel-2A images from every continents
  - Selected for low cloud coverage
  - Around 12’000 km^2 per image → ~ 1 million km^2
- 41’052 LR/HR pairs
  - 8’200 used for validation
  - 32’852 used for training

Results

Results

Results

Metrics

	PSNR [dB] ↑	SSIM ↑	PSNR_Y [dB] ↑	SSIM_Y ↑	LPIPS ↓
Bicubic	27.5905	0.7193	NC	NC	0.4616
Sentinel-2A GENERIC	27.1807	0.7013	29.1101	0.7358	0.1425
Sentinel-2A SPECIFIC	**27.8012**	**0.7239**	**29.8063**	**0.7577**	**0.1088**

- Bicubic interpolation has better pixel to pixel metrics than the generically trained GAN.
- However, the interest of the GAN is clear from a structural point of view.
- With a specifically trained model we can achieved both, better pixel to pixel and structural metrics.

Testing the trained model on Lansat-8 images

- Is this training specific to remote sensing or to a given sensor ?
  - Let's give a try to a real case
- We use Landsat-8(30m) data instead of degraded Sentinel-2

- →The training is related to the sensor and cannot be generalized between sensors

Conclusion

- Generic training
  - Easy (pretrained)
  - Datasets easily accessible
  - Introduces spatial structures that are not existing in satellite imagery

- Specific training
  - Better estimation (pixel to pixel) than bicubic interpolations
  - Specific for each situation
  - Requires pair of images (lots of them)
  - Hard to go back in time (pair of image do not exist)

Future of the project

- Improve the architecture so that it is more specific to satellite images
  - Accepts more than 3 input layers
  - Find a loss function not focused on human perceptual quality

- We want to explore real X-sensor situation
  - Landsat 8 → Sentinel 2
  - Sentinel 2 → Planet

Thanks for your attention

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Questions ?