MRSS19 + PIA19

SUPER-RESOLUTION FOR SENTINEL-2 IMAGES

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Introduction

Key issue

To obtain Sentinel-2 imagery of higher spatial resolution than the native bands.

Previous studies focused on upsampling of 20m and 60m Sentinel-2 bands to 10 meters resolution taking advantage of 10m bands.

Deep learning-based techniques has become a de facto standard for single-image super-resolution (SISR).

Problem

Neural network learning for super-resolution requires image pairs at both the original resolution (10m in Sentinel-2) and the target resolution (e.g., 5m or 2.5m). But there is no way to obtain higher resolution images for Sentinel-2.

Proposal

To consider images from others sensors having the greatest similarity in terms of spectral bands, which will be appropriately pre-processed.

Deep learning and Single Image Super-Resolution

The objective of SISR is to increase the spatial resolution of an image, considering only the information in the image itself and some acquired knowledge in the form of an algorithm or model.

We focus on **Convolutional Neural Networks (CNNs) forsuper-resolution**. Learning requires pairs of a low resolution image and a high resolution image. Commonly, the pairs of images are obtained out of the same high resolution image by downsampling. **This is the main problem we aim to face in this work, as there are no Sentinel-2 RGB images available at 5m resolution, our objective**.

Architecture

EDRS, Enhanced Deep Residual Networks – 8 ResBlocks and 64 filters.

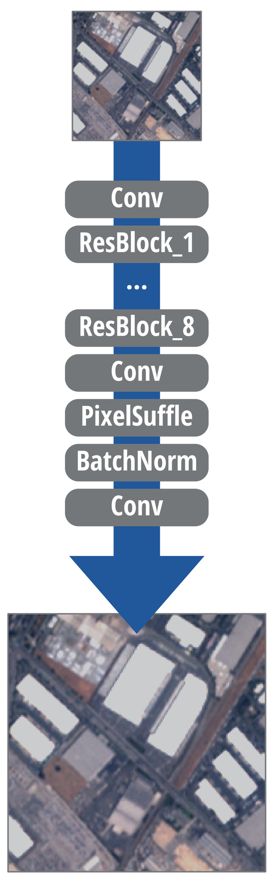
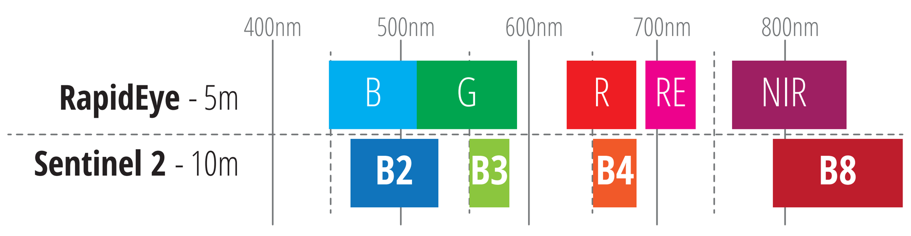


Figure 1. Architecture of EDSR.

Proposal

To use RapidEye satellite images as reference for training. We found that RapiEye (RE) satellite provide images with similar spectral bands to Sentinel-2 (S2).
https://directory.eoportal.org/web/eoportal/satellitemissions/r/rapideye

Figure 2. Comparison between RapidEye and Sentinel-2 spectral bands for RGB and NIR.



Dataset

– Temporarily close image pairs with cloud cover less than 10%
– RapidEye images downloaded using 14 days free trial from Planet https://www.planet.com/ > California (USA)
– Normalization and both automatic and manual validation
– Patchs of 96x96 (S2) and 192x192 (RE).

Figure 3. Example of validated/removed patches in Hayward (red: manual validation, yellow: statistical validation).

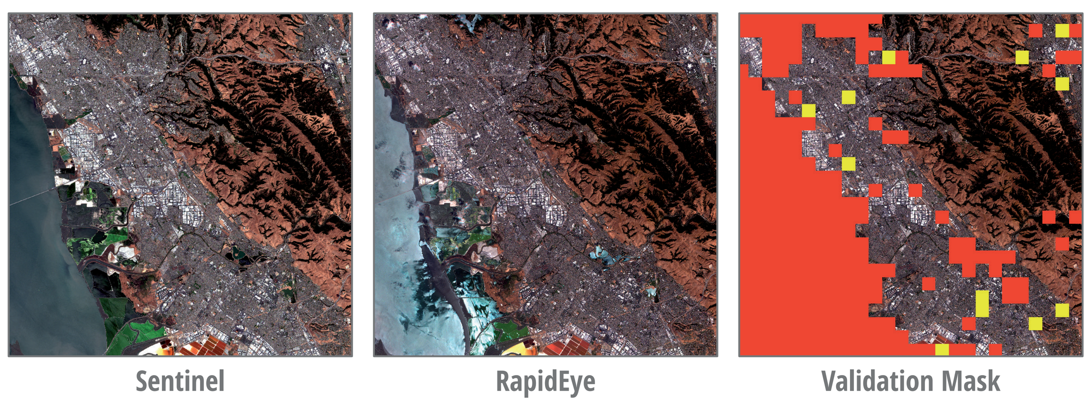
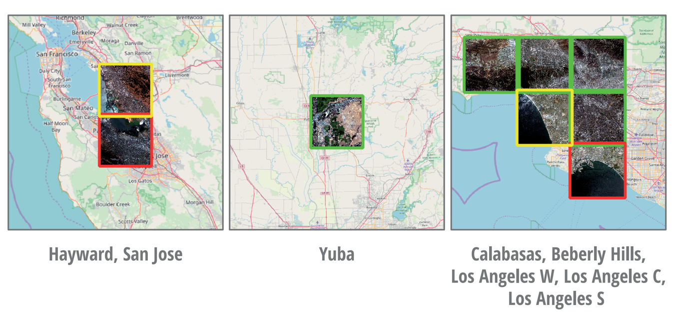


Figure 4. Dataset summary



SET	IMAGES	#PATCHES	RATIO%
Train	5	2918	74.2
Val	2	295	7.5
Test	2	718	18.3
TOTAL	9	3931	100

CITY	SENTINEL DATE	RAPIDEYE DATE	DELAY (D)	DELAY (D)	#PATCHES
Yuba	2018-08-28	2018-08-29	1	TRAIN	616
Calabasas	2018-07-23	2018-07-02	21	TRAIN	581
Beberly Hills	2018-07-23	2018-06-13	40	TRAIN	584
Los Angeles N	2018-07-23	2018-08-05	13	TRAIN	611
Los Angeles C	2018-07-23	2018-08-05	13	TRAIN	526
San Jose	2018-07-09	2018-08-20	42	VAL	72
Los Angeles S	2018-07-23	2018-08-05	13	VAL	223
Hayward	2018-07-09	2018-07-04	5	TEST	414
Los Angeles W	2018-07-23	2018-08-05	10	TEST	304

Network training

Loss function

Pixel Loss (L1) + feature loss (VGG16) + Style loss (VGG16). One-cycle policy, batch size: 16, different learning schemes based on progressive resizing.

Table 1. Configurations considered.

CONFIGURATION	LEARNING SCHEME
1.1 - RE^{20} > RE^{10}	50 ep, lr 5e-3 > 100 ep, lr le-03
1.2 - RE^{10} > RE^{5} (from 1.1)	50 ep, lr 1e-4 > 100 ep, lr le-3
1.3 - SE^{10} > RE^{5} (from 1.1)	50 ep, lr 1e-4 > 30 ep le-5 > 30 ep, lr le-6
1.4 - SE^{10} > RE^{5} (from 1.2)	50 ep, le-3 > 30 ep, lr 1-4 > 30 ep, lr le-5
2.1 - SE^{20} > SE^{10}	50 ep, lr 5.25e-3 > 100 ep, lr 5.25e-3
2.2 - SE^{10} > RE^{5} (from 2.1)	50 ep, lr 2.75e-4 > 30 ep, lr 2.75e-5 > 30 ep 2.75e-6
3.1 - SE^{20} > RE^{10}	50 ep, lr 4.37e-3 > 100 ep, lr le-3
3.2 - SE^{10} > RE^{5} (from 3.1)	50 ep, lr 1e-4 > 30 ep, le-5 > 30 ep, lr le-6
4.1 - SE^{10} > RE^{5}	50 ep, lr 6.31e-3 > 100 ep, lr le-3 > 30 ep, lr le-4 > 30 ep, lr le-5

*RE: RapidEye ; SE: Sentinel2 ; ep: epoch ; lr: learning rate

Evaluation

Paerk signal-to-noise ratio (PSNR) and Structural Similarity (SSIM).

Results

Table 2. Results obtained by the different configurations

	RE^{10} > RE^{5}		SE^{10} > RE^{5}	
CONFIGURATION	PSNR	SSIM	PSNR	SSIM
0.0 - Bicubic	31.68	0.9094	26.80	0.8055
1.1 - RE^{20} > RE^{10}	33.88	0.9389	26.38	0.7989
1.2 - RE^{10} > RE^{5} (from 1.1)	35.49	0.9572	26.95	0.8137
1.3 - SE^{10} > RE^{5} (from 1.1)	32.61	0.9383	27.63	0.8220
1.4 - SE^{10} > RE^{5} (from 1.2)	32.14	0.9395	27.81	0.8285
2.1 - SE^{20} > SE^{10}	33.76	0.9392	26.48	0.7979
2.2 - SE^{10} > RE^{5} (from 2.1)	32.64	0.9404	27.62	0.8220
3.1 - SE^{20} > RE^{10}	31.23	0.9189	26.87	0.7983
3.2 - SE^{10} > RE^{5} (from 3.1)	32.07	0.9288	27.43	0.8178
4.1 - SE^{10} > RE^{5}	32.18	0.9355	27.75	0.8253

Figure 5. Visual comparison between the bicubic interpolation and the proposed method.

Discussion

Numeric results (Table 2)

- Bicubic interpolation can be outperformed by our EDSR-based solution in both scenarios (RE2RE and SE2RE)
- **Model 1.2 works best in RE2RE**, but do not transfer results to SE2RE
  - Not trained in S2 images / Much harder task
- **Model 1.4 works best in SE2RE**
  - Pretraining helps (better than 4.1)
  - But not always (4.1 is better than 2.X and 3.X)

Visual results (Figure 5)

- The proposed approach is **more sharpen and less blurry** than bicubic. Edges are better defined.
- Difficult to differentiate between RE and SE after super-resolution
  - Although **there are details that cannot be recovered**
- **Visual differences are greater than numeric** ones as we are evaluating with RE the super-resolution of SE.

Conclusions and Future Work

We have proposed **a novel way for super-resolving Sentinel-2 RGB bands to 5m resolution**. We considered a satellite with similar spectral bands as reference for learning (**RapidEye**).

We trained a **EDSR network with some modifications** (loss function, proper initialization of Pixel Shuffle and a specific loss function (with feature and style losses).

We studied different **transfer learning strategies based on progressive resizing**.

Remarkable results in terms of PSNR and SSIM and visual inspection showed the avoidance of the blurry effect of bicubic interpolation.

Future work

- **Increase the dataset size** (more images and better co-registered, the least temporal differences, different places)
- **Comparison** with other state-of-the-art CNNs (GANs)
- Super-resolve to **4x scale.**

Acknowledgements

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