Deep learning for the super resolution of SAR images

Y. Adarrab[1], D. Colombo[1], A. Daly[1], I. Hinostroza[2], C. Ren[2], J. Fix[1,3]
[1]CentraleSupélec, 57000 Metz, France
[2]Université Paris-Saclay, CentraleSupélec, SONDRA, 91190 Gif-sur-Yvette, France
[3]Université de Lorraine, CentraleSupélec, CNRS, Loria, 57000 Metz, France

Abstract

In this study, we are interested in **Synthetic Aperture Radar** (SAR) data, in particular those captured during campaigns carried out by unmanned aircraft. SAR data is data captured by a radar antenna placed underneath either an aircraft or a satellite and pointing to the sides. Our work considered horizontally polarised transmitting antenna and horizontally polarised measuring antenna (HH). During its flight path, the aircraft emits waves of varying frequency (a chirp) and the backscattered signal conveys information about the reflectivity of the imaged scene (its distance, its velocity, objects). From these measurements, one can for example detect ground movements, objects or buildings, segregate land use, etc... In contrast to optical measurements, SAR data can be captured day and night and are not as disturbed as optical measurements ; for example, they can penetrate a cloud layer and, depending on the working wavelength, snow, foliage... However, the quality of object detection or segmentation is dependent on the frequency of the chirp and this study **investigates the ability to infer high resolution SAR image from low resolution ones**.

SAR data preparation

- Scene: Los Angeles bay extending over 16.34 (range) x 40.00 (azimuth) kms
- SLC L-band SAR data from `uarvsar.jpl.nasa.gov`
- Polarisation: HH
  Bandwidth: 80 MHz
  Slant range resolution: 1.67 m
  Azimuth resolution: 0.6 m

The SLC data slice is cropped into 4808 images of size 512 × 512 (corresponding to a rectangle of size 850 × 307 ms (range x azimuth).

In order to obtain low resolution images, we filter the half information of the high resolution image in the frequency domain of range and azimuth which are also called the spectral band and the spectro-angular band respectively. Hanning window is then applied to mitigate the side lobes effect. Finally, the low resolution is obtained from the magnitude of the latter image in the spatial domain. Fig.1 shows an example of pairwise low-high resolution of SAR images.

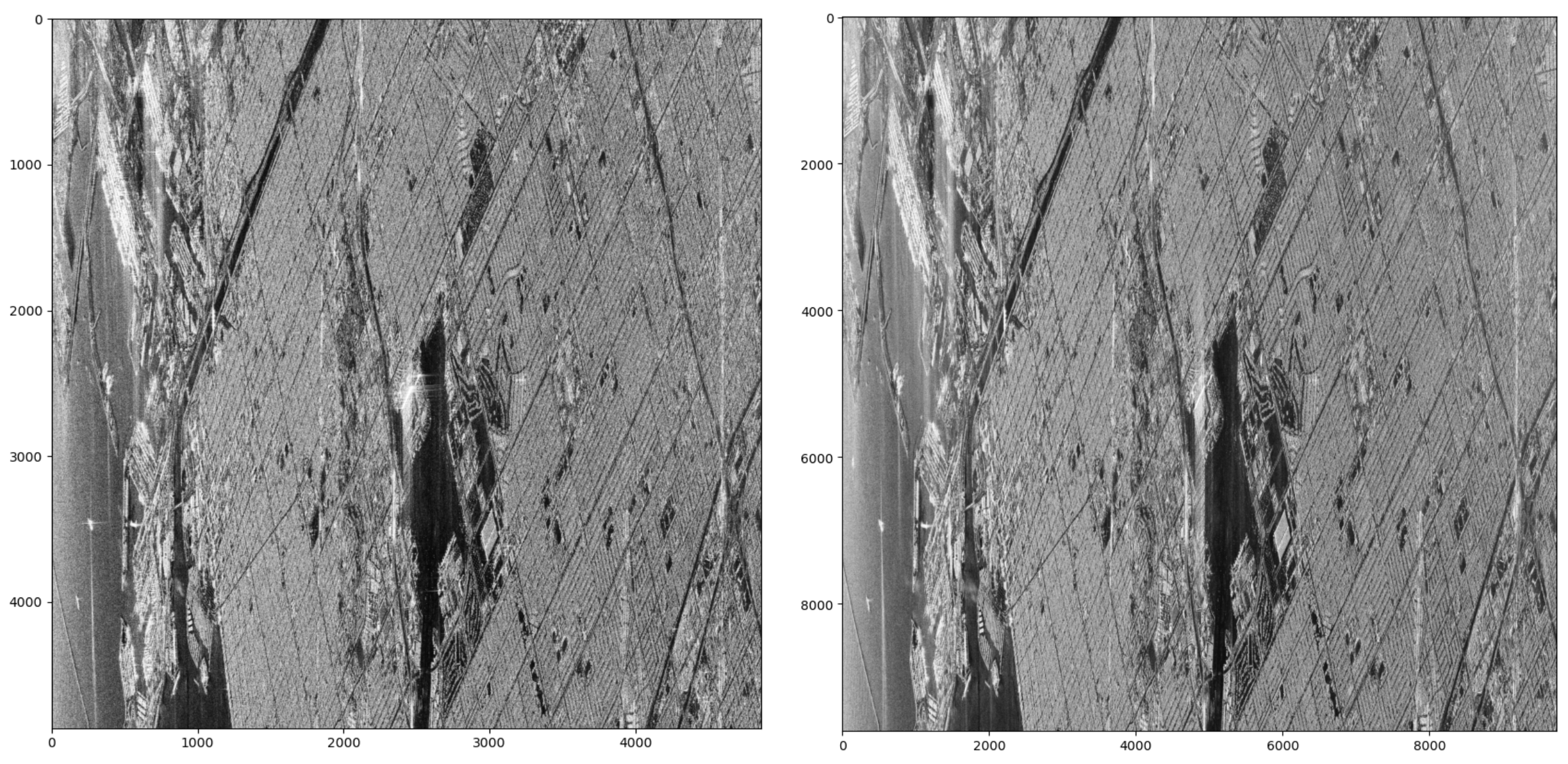
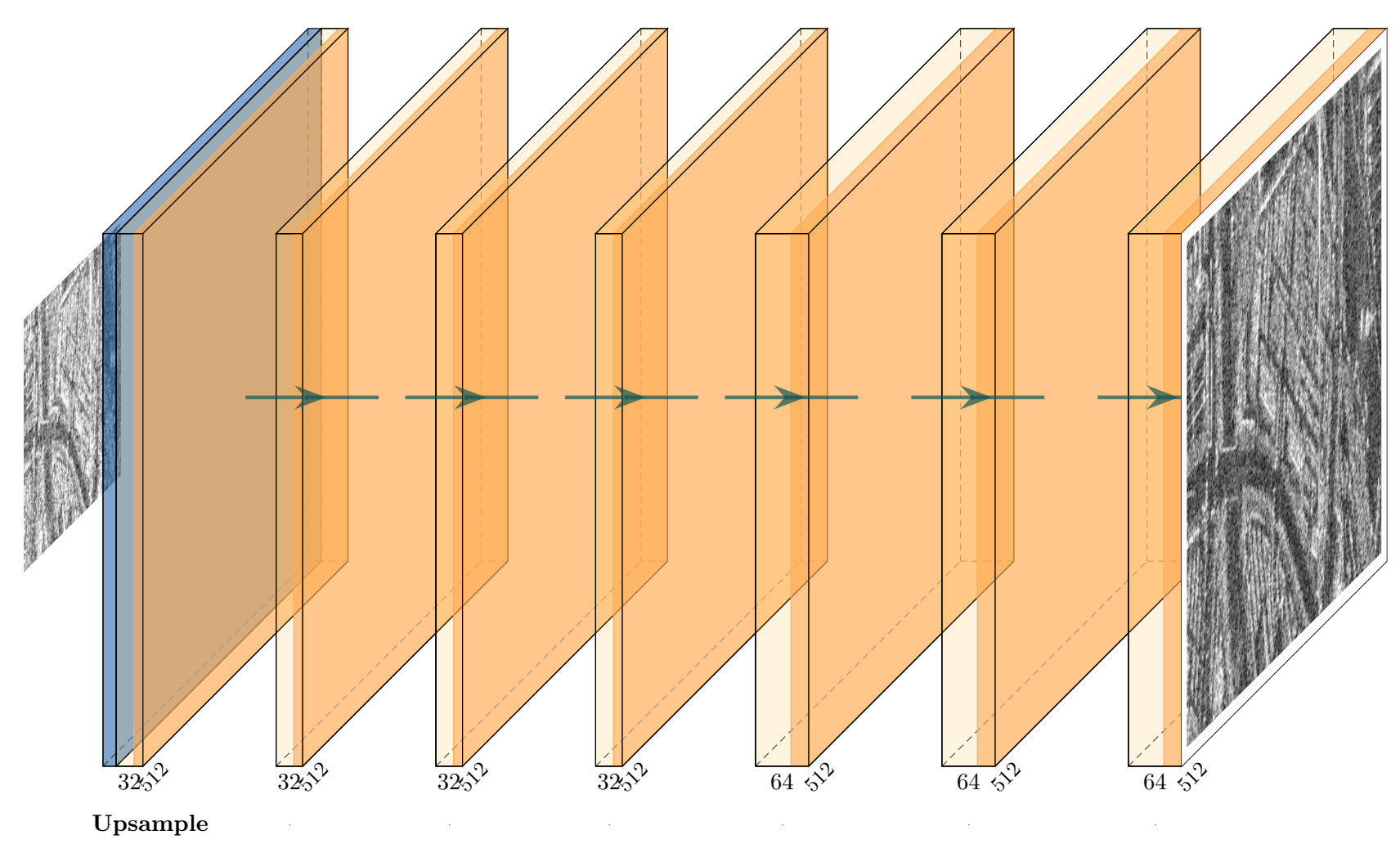


Figure 1: Left) Simulated low resolution SAR, right) Original high resolution SAR

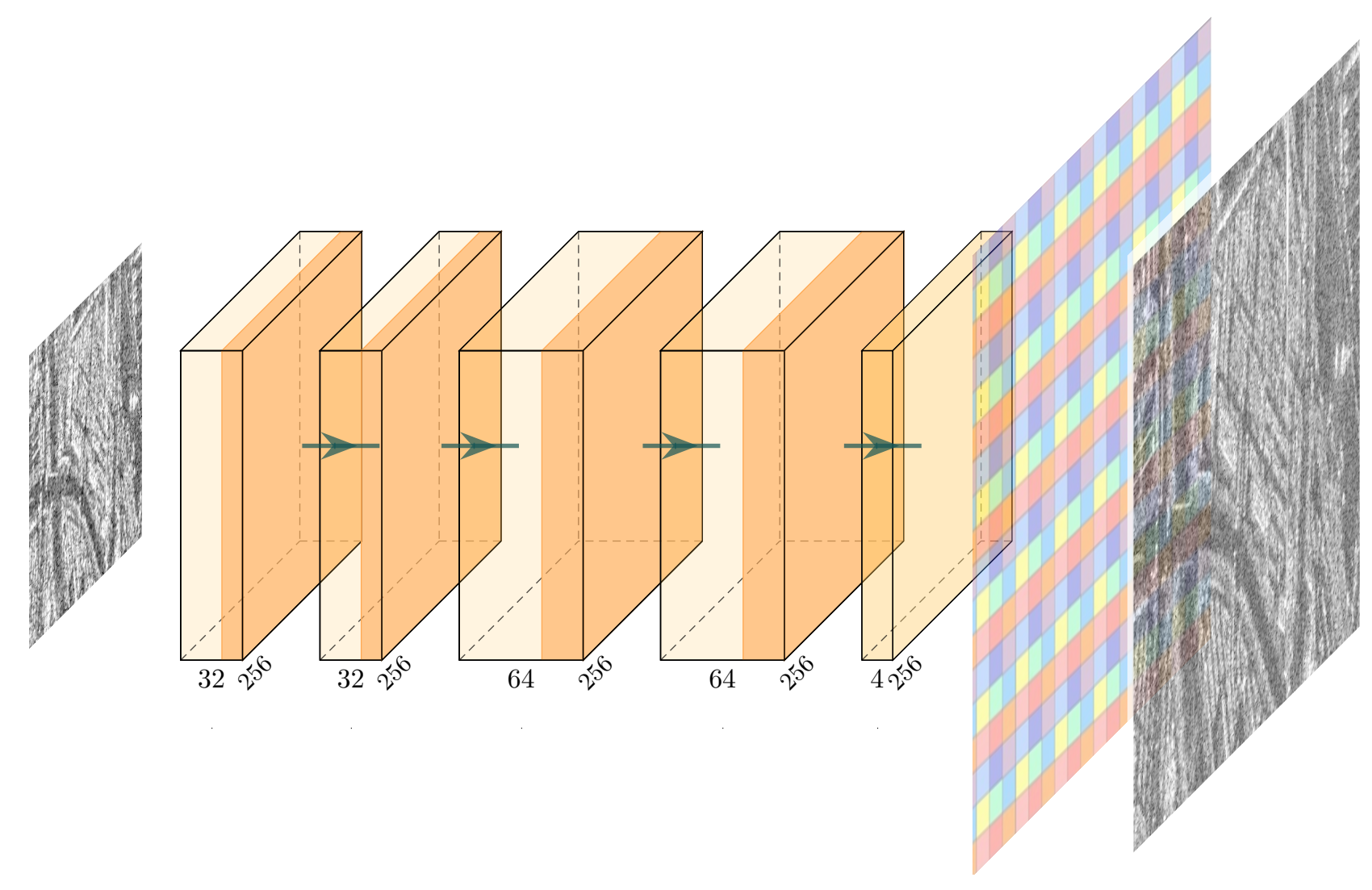
Deep learning for super resolution

We consider three architectures for performing super resolution, depicted below.

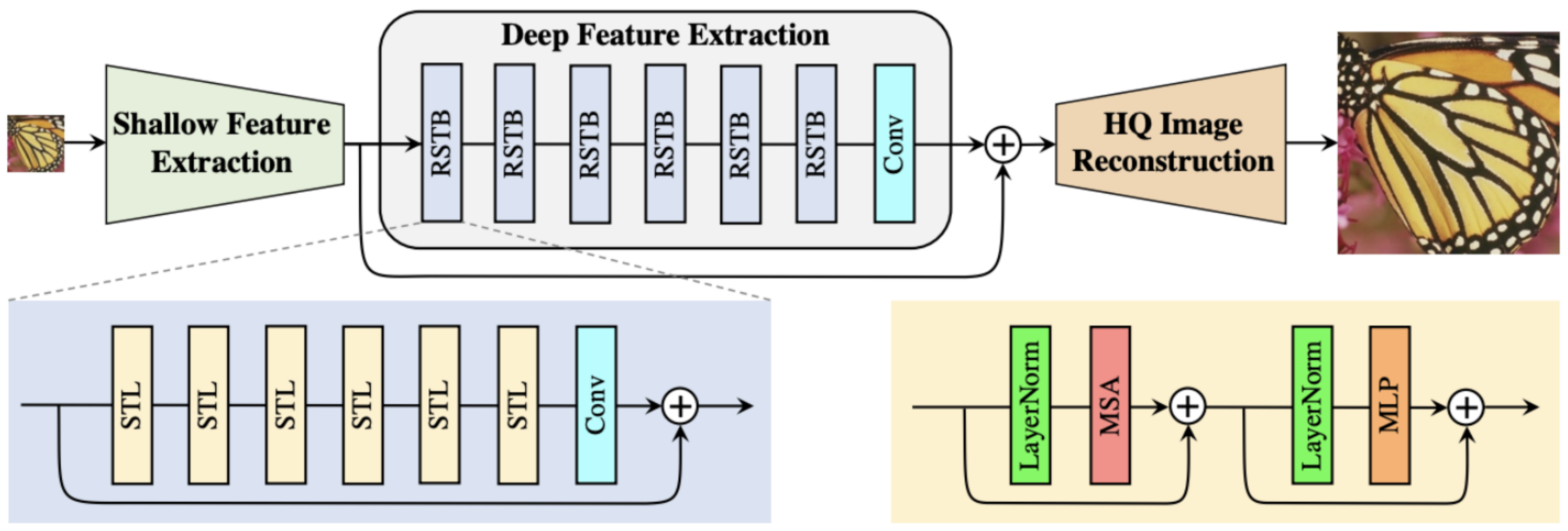
Upsample-Conv



Conv-PixelShuffle



Swin Transformer[1]



(a) Residual Swin Transformer Block (RSTB)

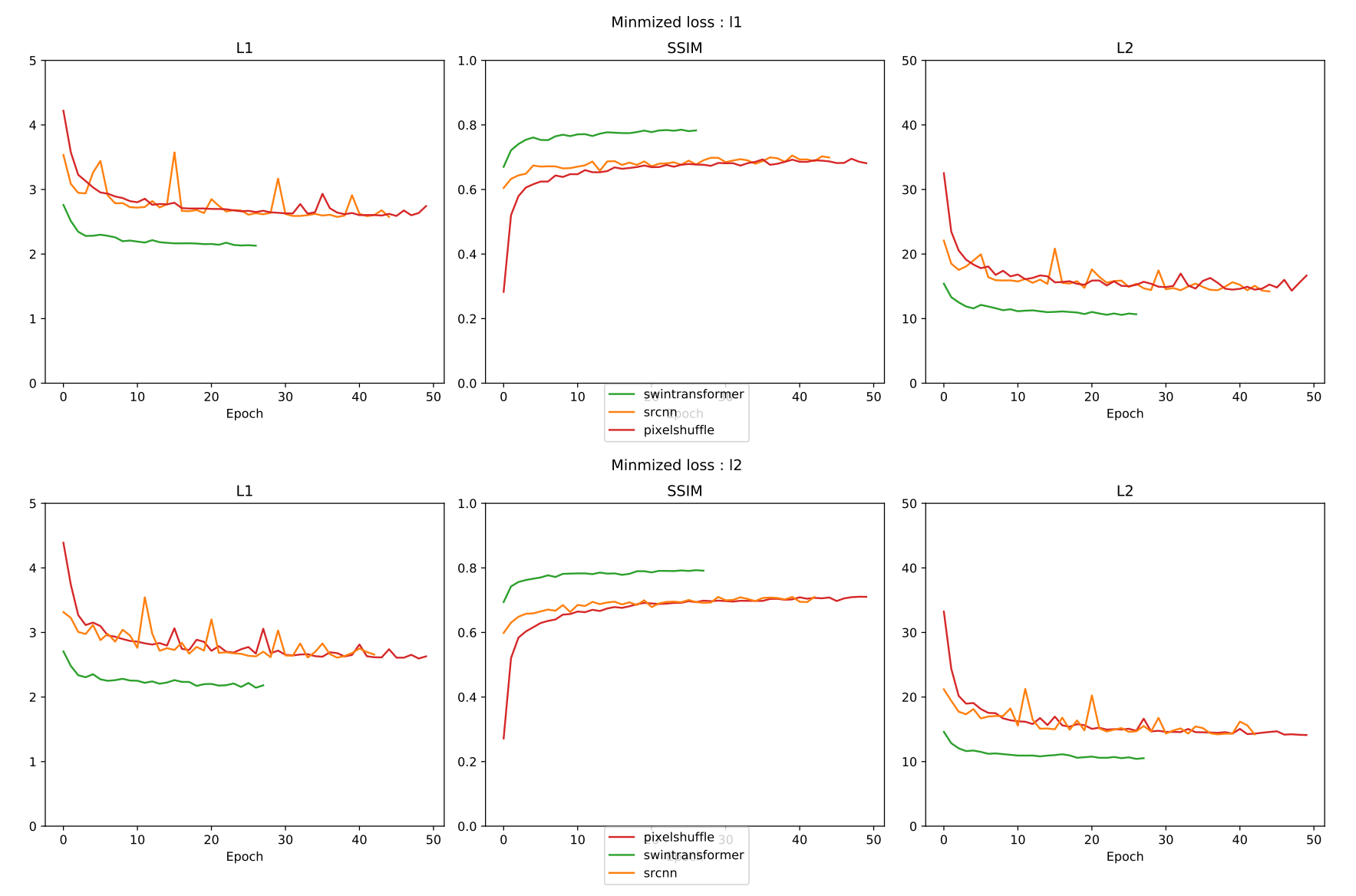
(b) Swin Transformer Layer (STL)

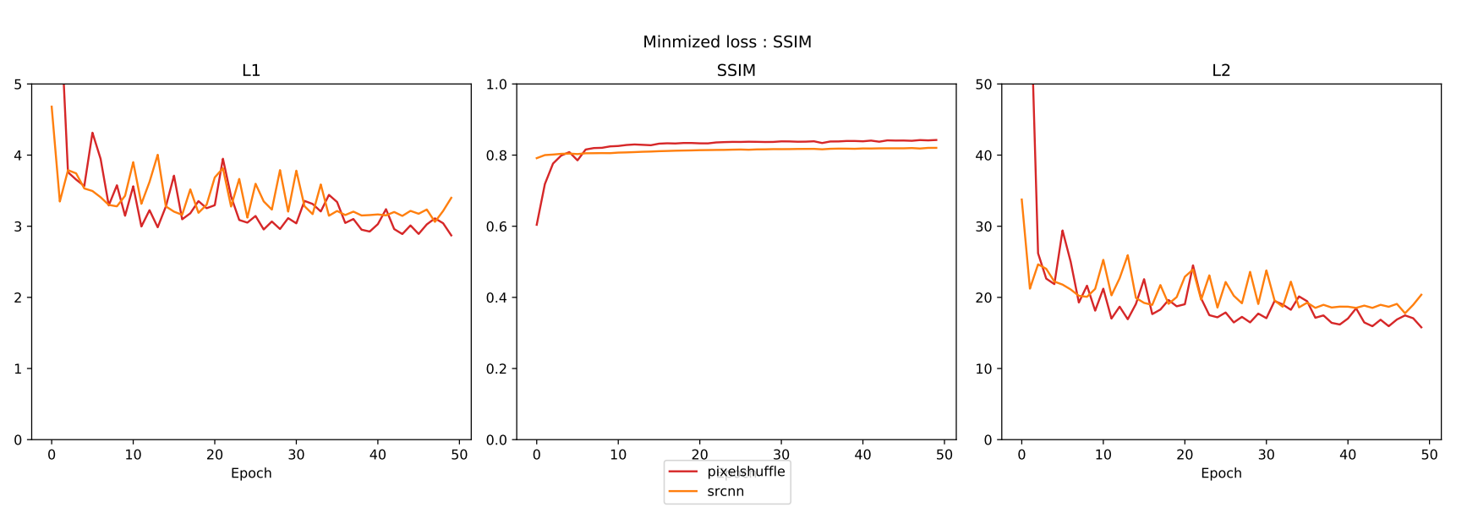
And three losses between the target z and its reconstruction $\hat{z}$:

L1	L2	SSIM [2]
$\sum_{x,y} \lvert\hat{z}(x,y) - z(x,y)\rvert$	$\sum_{x,y} (\hat{z}(x,y) - z(x,y))^2$	$l(z,\hat{z}) = \frac{2\mu_z\mu_{\hat{z}}+C_1}{\mu_z^2+\mu_{\hat{z}}^2+C_1}$ $c(z,\hat{z}) = \frac{2\sigma_z\sigma_{\hat{z}}+C_2}{\sigma_z^2+\sigma_{\hat{z}}^2+C_2}$ $s(z,\hat{z}) = \frac{\sigma_{z\hat{z}}+C_3}{\sigma_z\sigma_{\hat{z}}+C_3}$

Results

Experiments on "fake" high resolution SAR : 256 × 256 → 512 × 512
Learning curves and metrics on the validation set (20%).





Method	L1	SSIM	L2
Nearest	8.99	0.33	102.95
Bilinear	**8.69**	0.34	**95.74**
Bicubic	8.84	**0.36**	98.18

Tested on an independent SLC slice, north of Los Angeles :

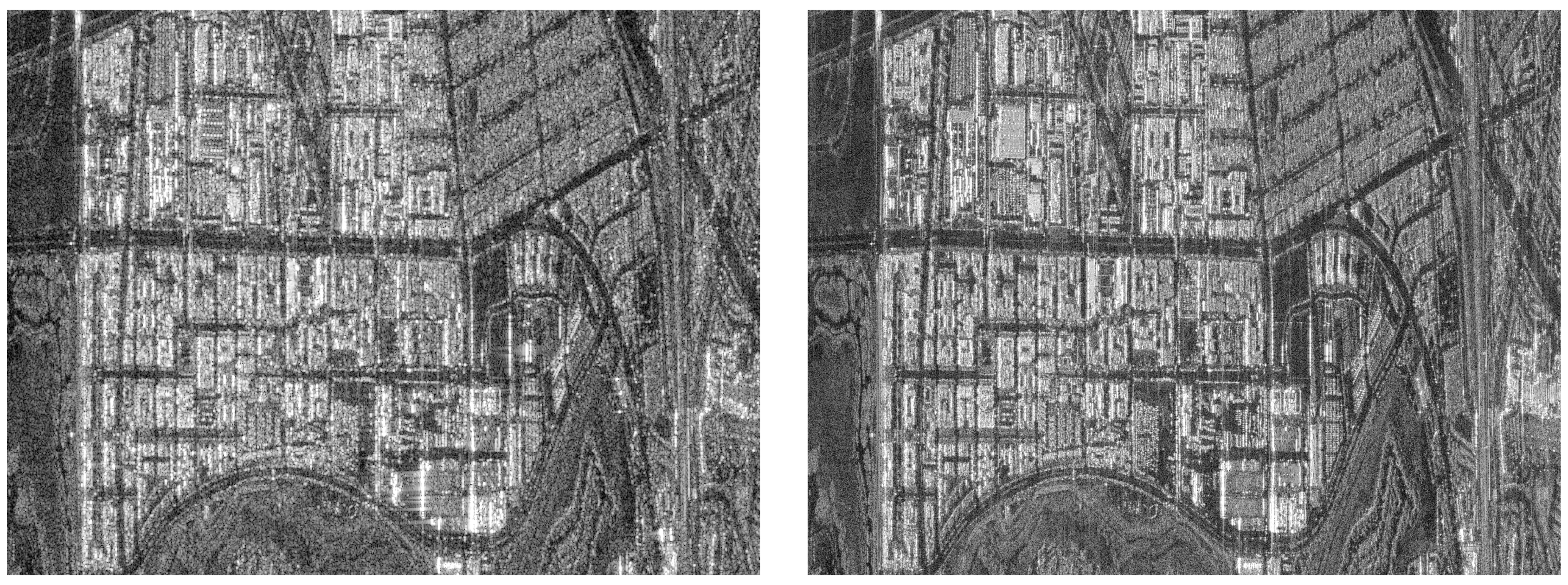


Figure 2: Left) Low resolution, Right) High resolution

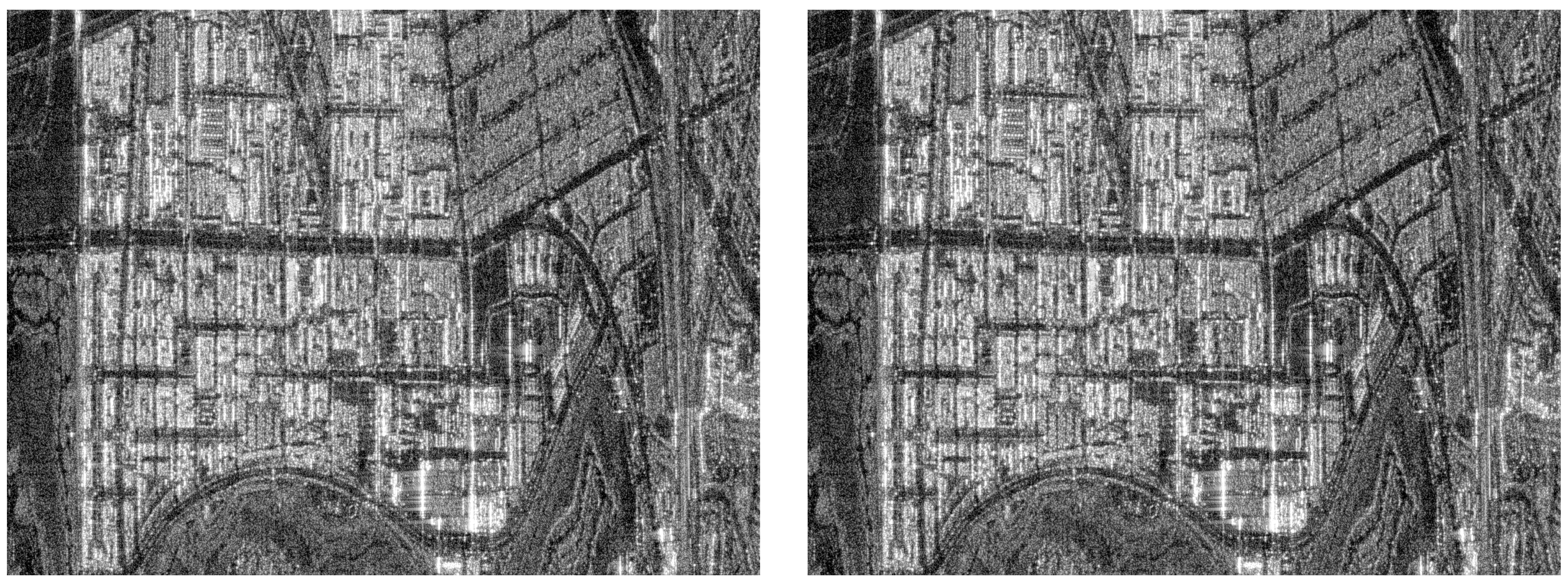


Figure 3: Left) Prediction with a Pixel Shuffle model trained on the SSIM loss, Right) Prediction with a SRCNN model trained on the SSIM loss

Discussion

Predictors learned from data (SRCNN, PixelShuffle, SwinTransformer) all outperforms naïve upsampling baselines. The metrics seem to be better when the SSIM loss is minimized compared to minimizing either the L1 or L2 losses. The PixelShuffle and SRCNN models perform relatively well for a much smaller training time compared to the SwinTransformer although the SwinTransformer performs slightly better than the other models.

The experiments have been performed with reconstructed high resolution (padding the low resolution in the Fourier domain). Training on the original SAR images, the reconstructions were blurred.

References

[1] J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool, and R. Timofte.
Swinir: Image restoration using swin transformer.
In *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, pages 1833–1844, 2021.

[2] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli.
Image quality assessment: from error visibility to structural similarity.
IEEE Transactions on Image Processing, 13(4):600–612, 2004.

https://sondra.fr **June 21, 2022** **chengfang.ren@centralesupelec.fr, israel.hinostroza@centralesupelec.fr, jeremy.fix@centralesupelec.fr**