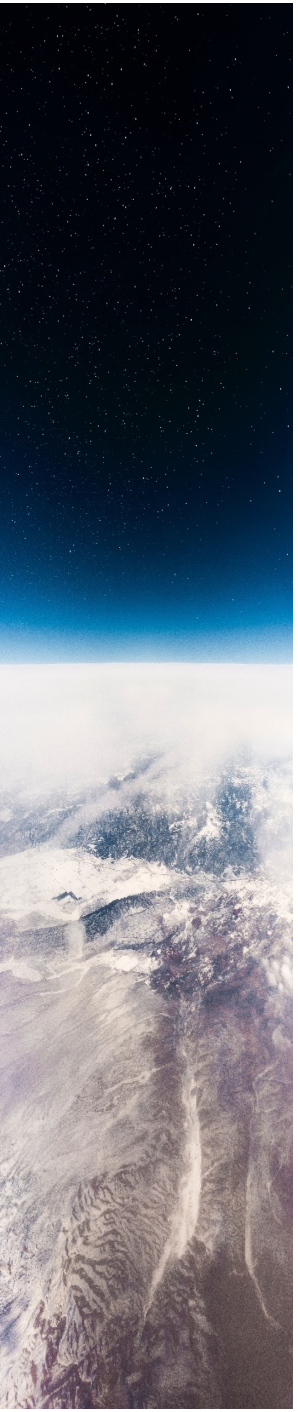

Compressive imaging and deep learning based image reconstruction methods in the "SURPRISE" EU project

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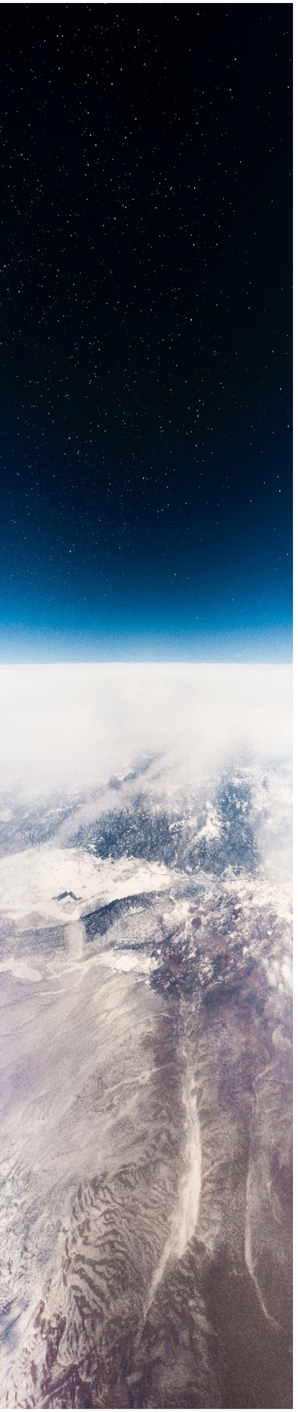
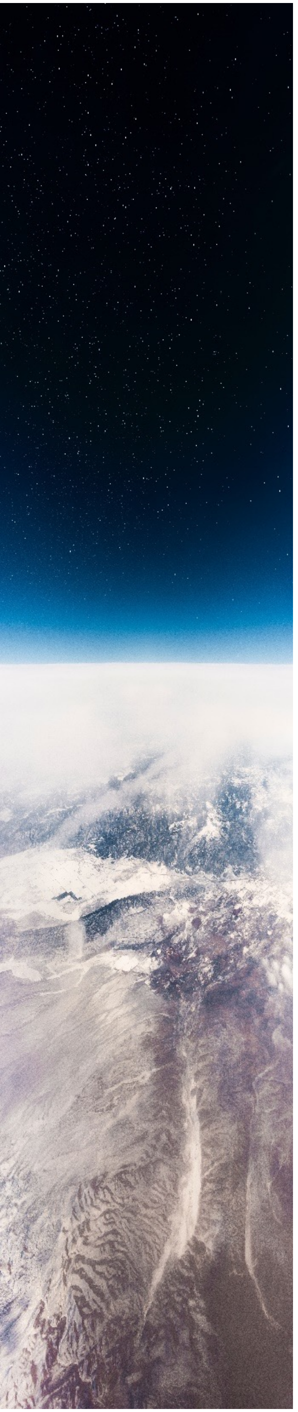


The SURPRISE project

SUper-Resolved comPRessive InStrument in the visible and medium infrared for Earth observation applications (SURPRISE)

Start date: 1 January 2020 – duration: 3 year

- Technologies: compressive sensing + SLM + deep learning
- Consortium: CNR-IFAC, CSEM, POLI-TO, ACRI-ST, SAITEC, RESOLVO, IPMS, LEONARDO



Main objectives

- Implement a demonstrator of a super-spectral EO payload in the Visible-Near InfraRed (VNIR) and Medium InfraRed (MIR) with enhanced performance in terms of at-ground spatial resolution, on-board data processing and encryption functionalities.

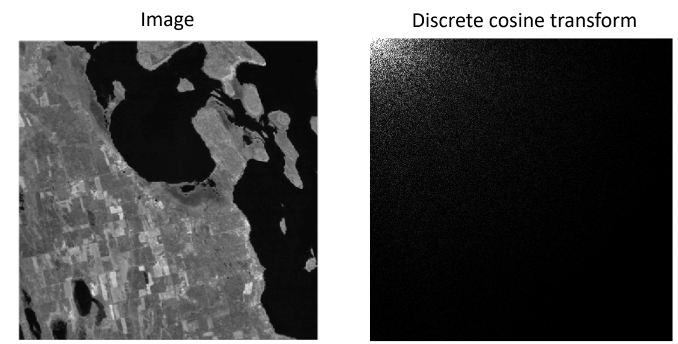
- Demonstrate the functioning of SLM technology in relevant environment, with particular reference to its operation in the MIR.

- Analyse the impact of enhanced performance on EO application products and services.

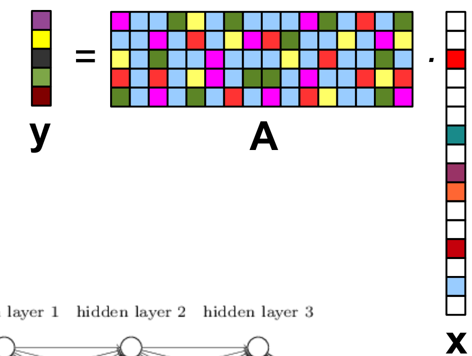
- Uptake of disruptive technological research by EU industry.

CS in a nutshell

- CS exploits the fact that images have a compact representation in **some** domain



- Linear image sensing process: $y = Ax$



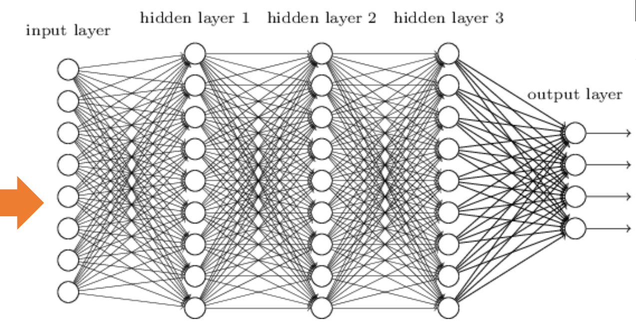
- Non-linear image reconstruction:

$$\min_{x} \|x\|_{0/1} \;\; s.t. \;\; y = Ax$$
$$\min_{x} TV(x) \;\; s.t. \;\; y = Ax$$

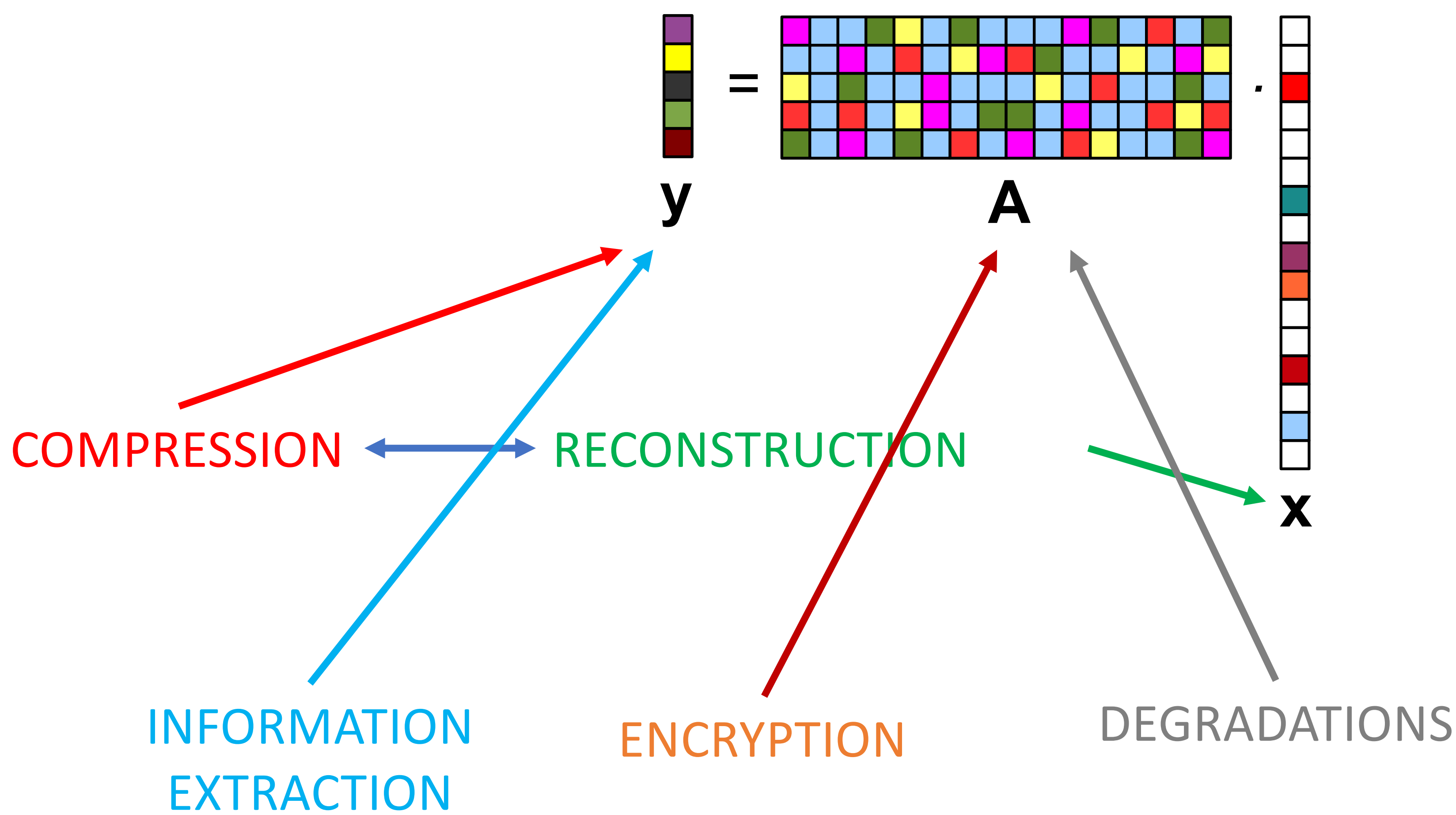
Iteratively minimize a cost function using gradient descent

… … …

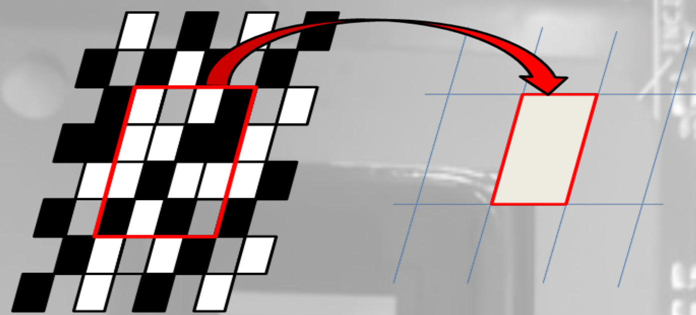
Employ **deep learning** as non-linear model → training set



Role of CS in SURPRISE



SLM technology and super-resolution



SLM (high resolution + masking) *Low-resolution detector*

VIS-NIR+MWIR

A super-resolution imaging system is an imaging system whose resolution is enhanced with respect to the one dictated by the number of pixel of the detector.

- Super-resolution optical system → **SLM with a high number of micromirrors**. Each pixel of the detector integrates the light coming from NxN SLM elements.
- A series of measurements is acquired using a different coding mask for each measurement.
- If the number of measurements are less than NxN, we obtain an **inherent data compression**.
- The random pattern of micromirror positions can also be used as encryption key

Image reconstruction - model-based

- Performs minimization of the TV norm of the reconstructed image

$$\mathrm{TV}(\mathbf{X}) = \sum_{i,j} \sqrt{|(\mathbf{X})_{i+1,j} - (\mathbf{X})_{i,j}|^2 + |(\mathbf{X})_{i,j+1} - (\mathbf{X})_{i,j}|^2}$$

- Assumption: image gradient is sparse (image is piece-wise smooth)

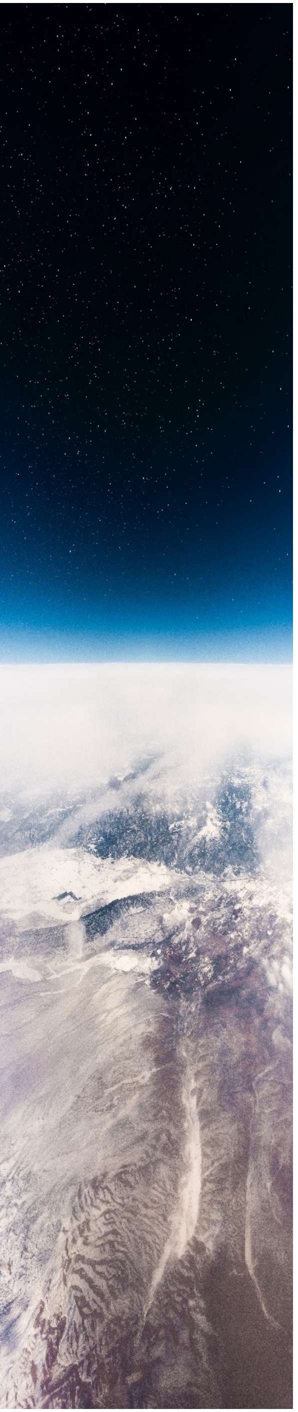
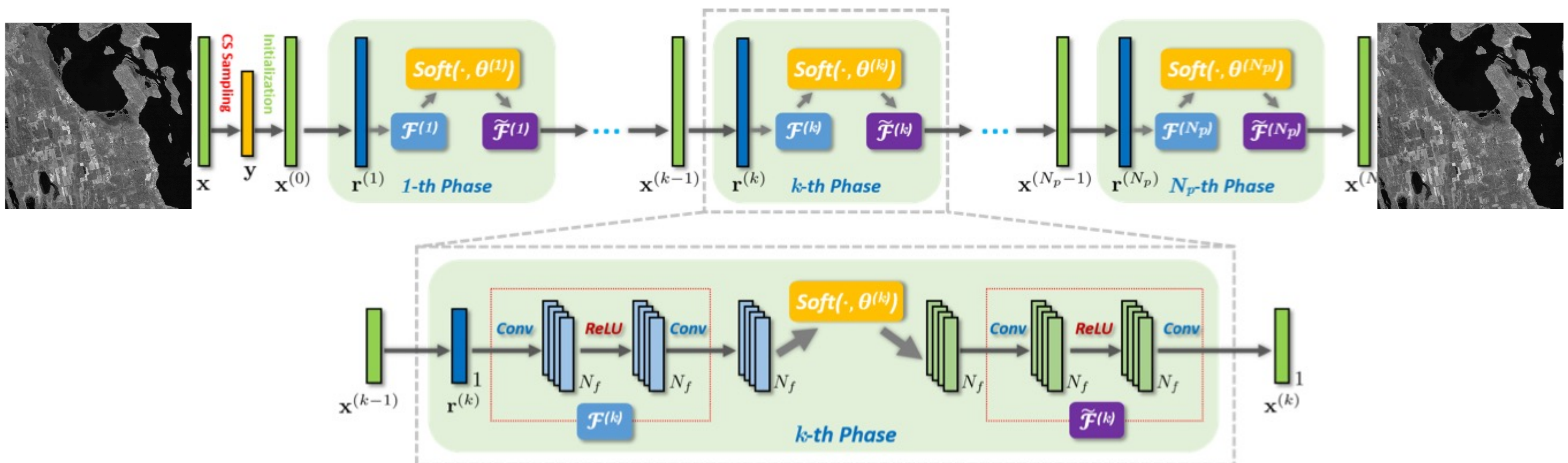


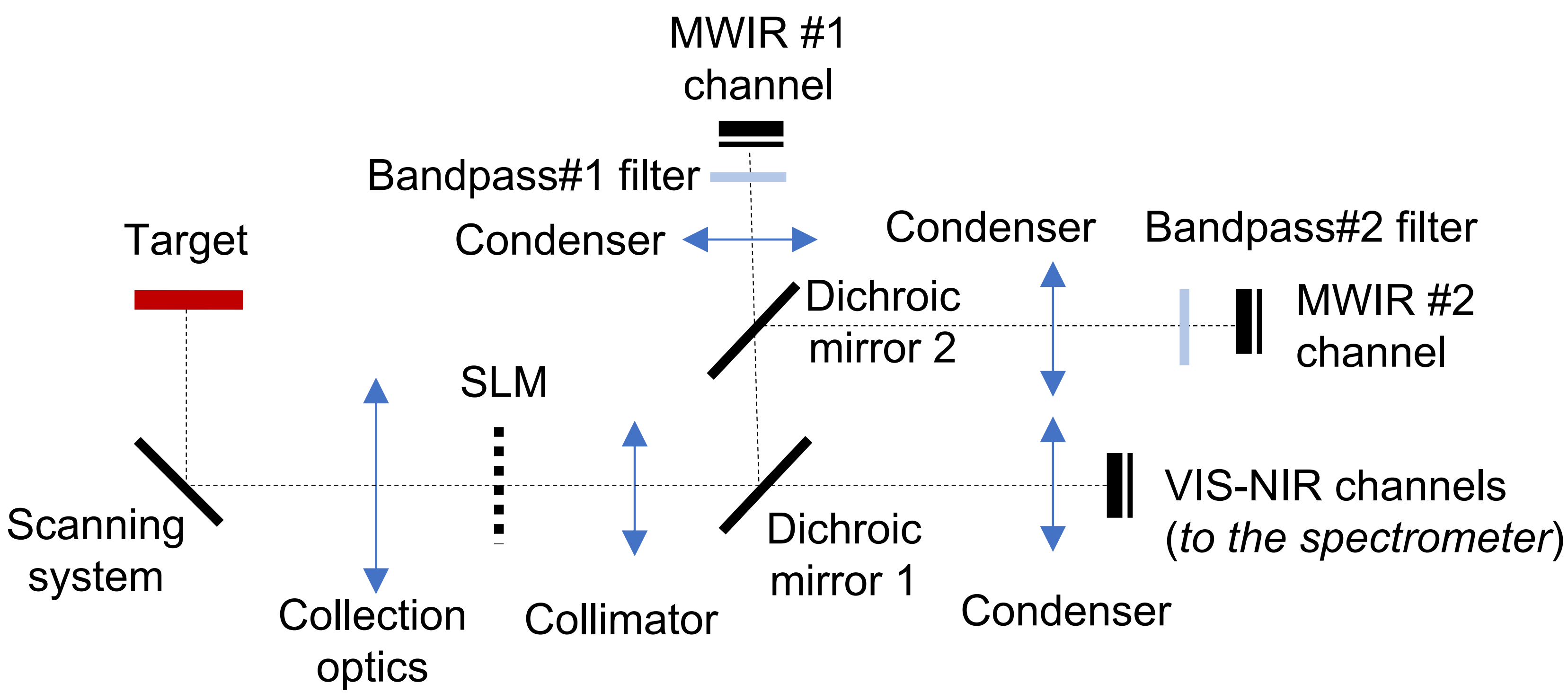
Image reconstruction – deep learning

- **Instead of solving a complex numerical problem…**

…deep learning learns a suitable reconstruction algorithm optimizing the signal representation (e.g., see ISTA-Net algorithm below)



Optical layout



Acquisition model

- Macro-pixels and spectral channels are sensed individually
- For a given spatial position *P* and band *i*:

$$y_i^P = \mathrm{A}_i^{\mathrm{P}} x_i^P$$

with $\mathrm{A}_i^{\mathrm{P}}$ an *m x n* matrix
  - *m* is the number of measurements
  - *n* is the number of micropixels (i.e., the superresolution factor)
- Letting $\alpha \simeq 0$ and $\beta \simeq 1$:

$$\begin{bmatrix} y_{i1}^P \\ y_{i2}^P \\ y_{i3}^P \end{bmatrix} = \begin{bmatrix} \alpha & \alpha & \beta & \beta \\ \beta & \beta & \alpha & \beta \\ \alpha & \beta & \beta & \alpha \end{bmatrix} \begin{bmatrix} x_{i1}^P \\ x_{i2}^P \\ x_{i3}^P \\ x_{i4}^P \end{bmatrix}$$

Full acquisition model

- For the *j*-th measurement:

$$y_{ij}^P = \mathbf{1} H A_{ij}^P x_i^P + \eta_{ij}^P$$

where H is the point spread function (or other linear degradation), and $\mathbf{1}$ is a vector containing all ones.

Performance – image reconstruction

- Natural images, image size 32x32, binary mask pattern
- Variable block size and amount of compression

M=256, 25% compression		
Micro-Pixels & Mask	**ISTA-Net+ Average PSNR**	**TVAL Average PSNR**
2×2, 1 mask	29.22	23.56
4×4, 4 masks	29.11	23.95
8×8, 16 masks	29.93	25.80

M=512, 50% compression		
Micro-Pixels & Mask	**ISTA-Net+ Average PSNR**	**TVAL Average PSNR**
2×2, 2 masks	33.38	26.40
4×4, 8 masks	34.12	27.31
8×8, 32 masks	34.88	29.58

Simulation of SURPRISE instrument

- Image size 388x20, block size 4x4, 10 bands
- Spatial resolution: 250 m. Spectral resolution: 40 um
- <u>No</u> re-training or fine-tuning of reconstruction algorithm

Image	Average PSNR
Argentario_020712	24.20
Argentario_020914	27.63
Firenze_021219	32.80
Firenze_100714	26.54
SanRossore_120810	31.99
Umbria100325	30.56
Venezia_010607	30.77
Venezia_010607	29.67

Results on simulated image (“lawn”)

- CS ratio 25%, 4x4 mask, PSNR = 29.21 dB

Original

Reconstructed

Results on simulated image (“travertino”)

- CS ratio 75%, 32x32 mask, PSNR = 32.79 dB

Original

ISTA-Net

Results on simulated image ("travertino")

- CS ratio 75%, 32x32 mask, PSNR = 29.45 dB

Original

TV

Conclusions

- Deep learning: powerful concept for image reconstruction of a compressive imaging instrument
- Enables super-resolution (final # of pixels > # of detected pixels)
- Very flexible, low complexity
- Also enables compensation of optical degradations in the image reconstruction process
- Also natively enables secrecy (on top of compression)