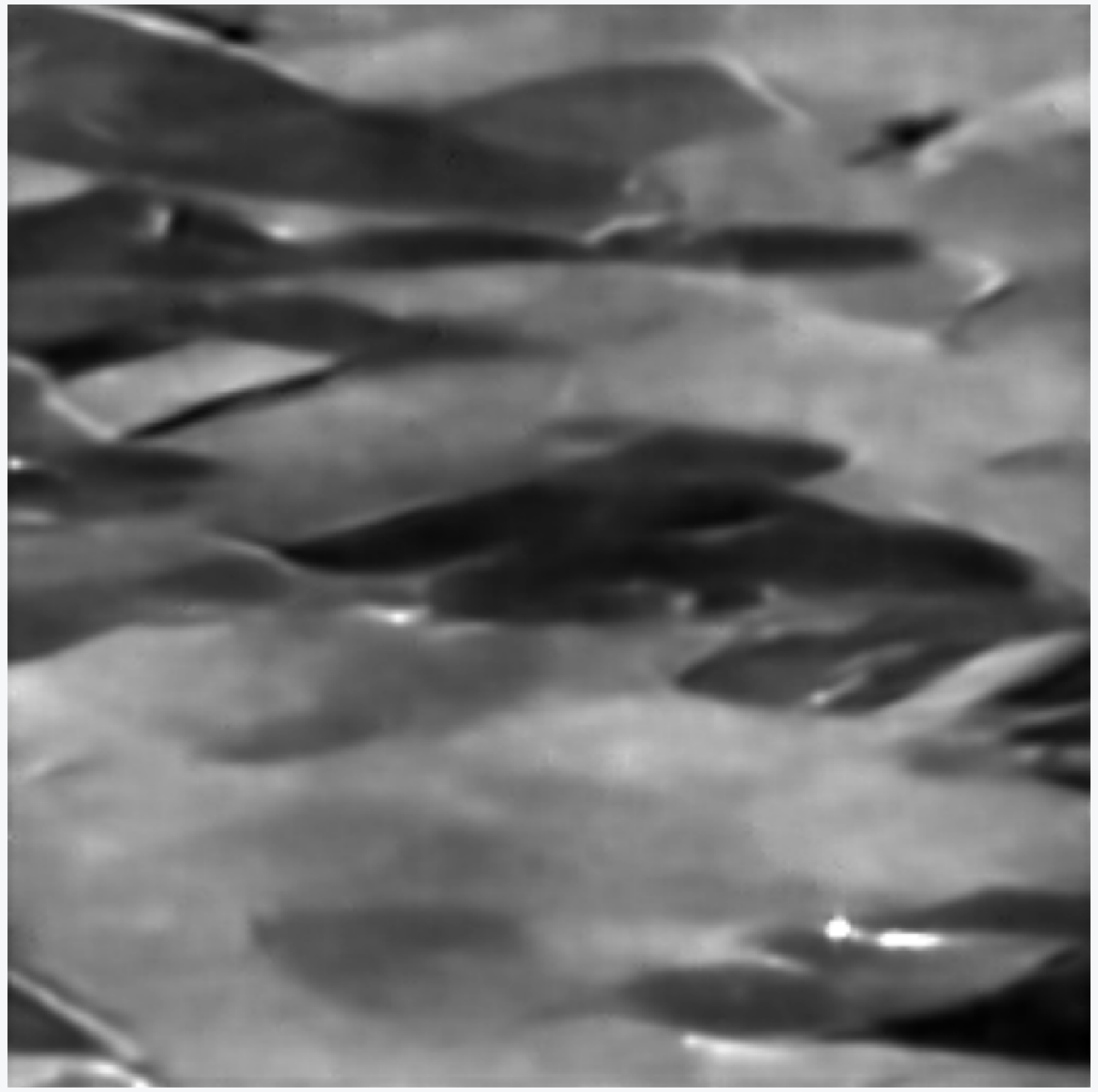


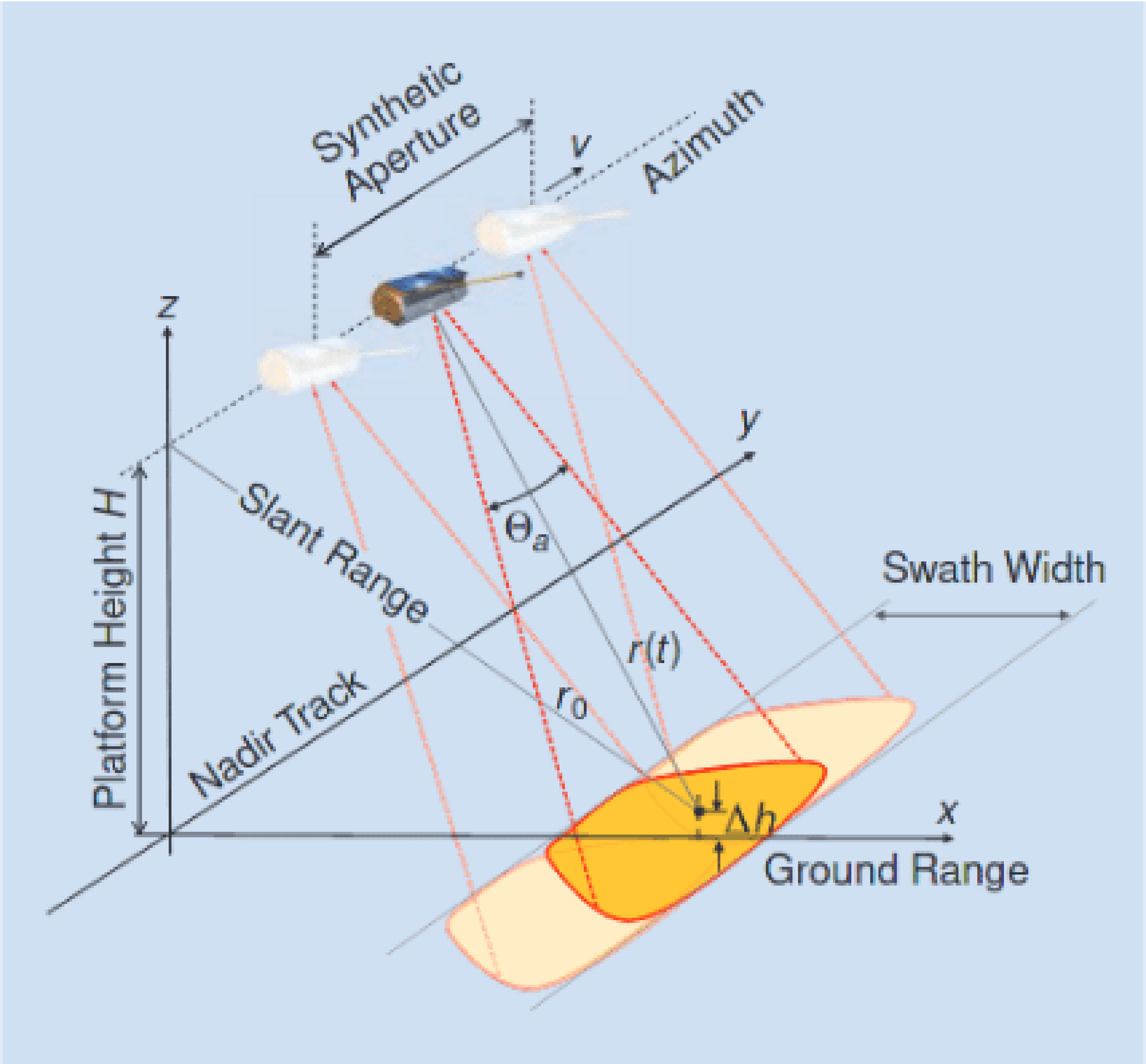
SAR image time serie denoising

Marie Diez
Framers : Florence Tupin
& Ines Meraoumia
& Emanuele Dalsasso

Outline :

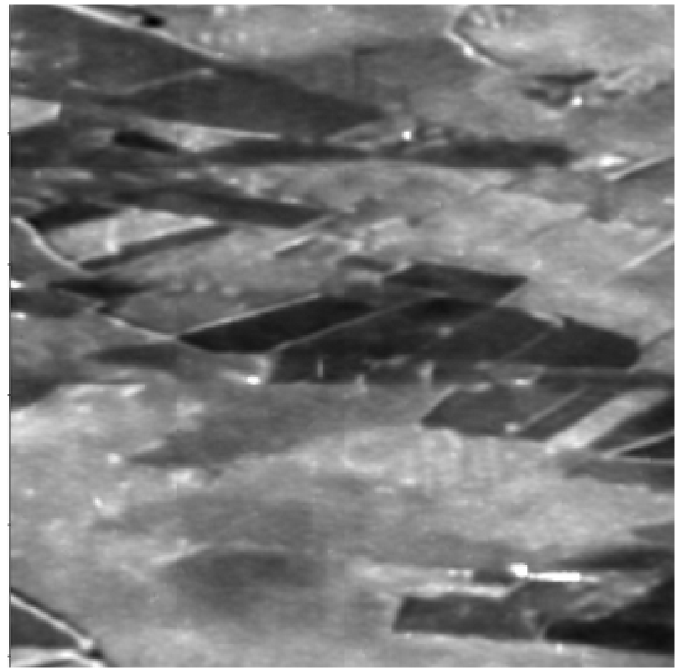
- Context of the project & related works
- Main points of the implementation
    - Implemented methods
    - Discussion on the results
- Conclusion + link with other approaches

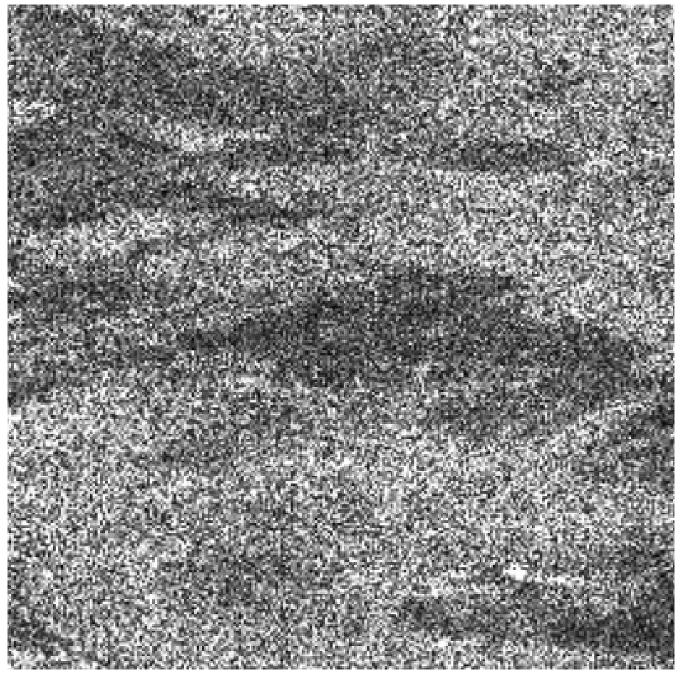
I. Context of the project



SAR = synthetic aperture radar

→ Noisy images : speckle noise





→ Speckle statistic

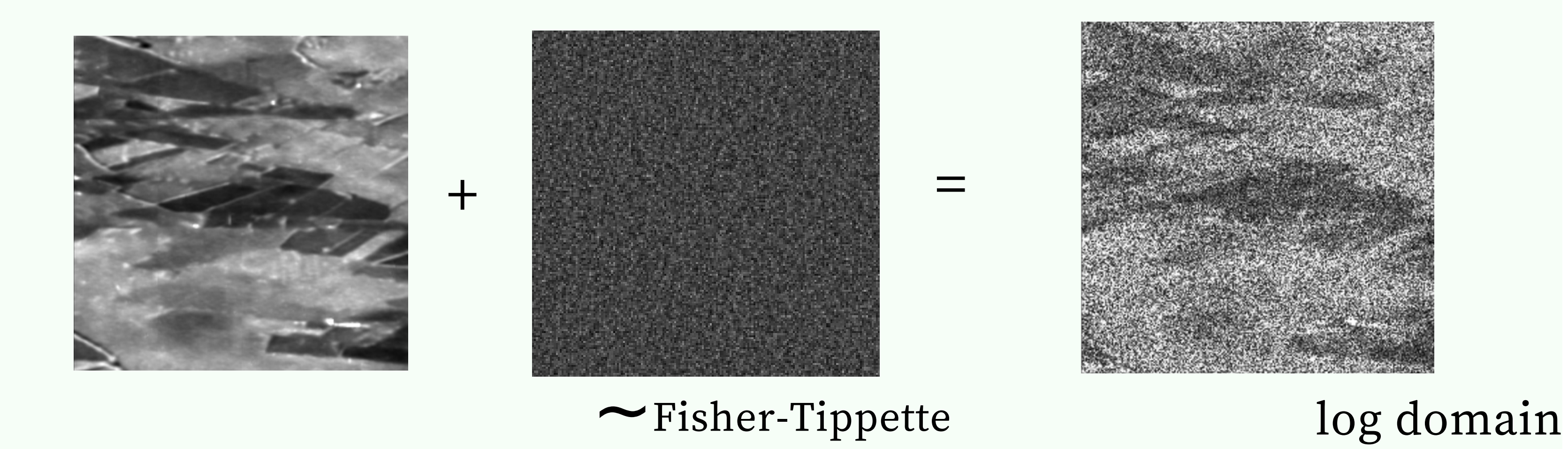
$$y = x * n \quad \sim \quad \mathrm{p}(n) = \frac{L^L}{\Gamma(L)} n^{L-1} \exp(-Ln) \quad \text{Goodman}$$

$$\tilde{y} = \tilde{x} + \tilde{n} \quad \sim \quad \mathrm{p}(\tilde{n}) = \frac{L^L}{\Gamma(L)} e^{L\tilde{n}} \exp\left(-Le^{\tilde{n}}\right) \quad \text{Fisher-Tippette}$$

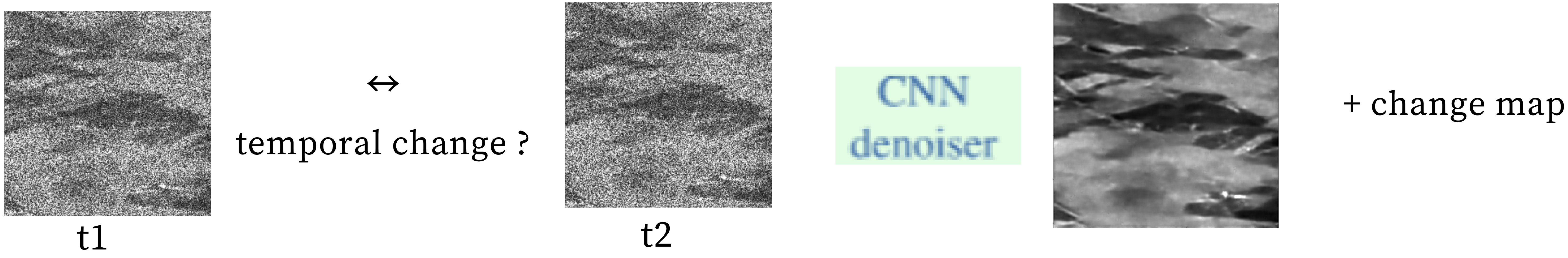
→ Goal : speckle denoising with deep learning

I. Project

Issue deep : lake of ground truth images → work on artificial speckle noise



Idea of the project → Supervised multi-temporal denoiser with consideration of temporal changes by the prediction of a change map



→ help the network with multi temporal information

I. Related works

Idea of some despecking methods :

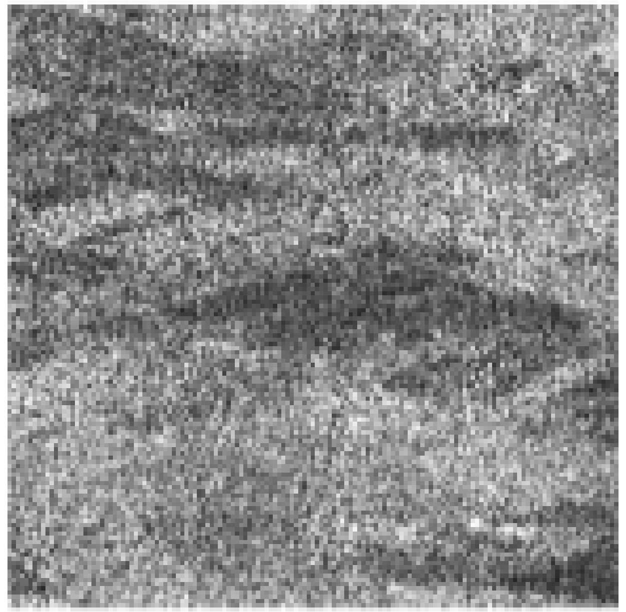
- SAR_CNN → supervised training with adaptation of AGWN denoiser to speckle statistics
- SAR2SAR → change compensation + fine tune on real image to undle spatial correlation of speckle
- RABASAR → multi-looking (average) of time serie
- RABASAR-SAR2SAR → multi-looking of time serie with SAR2SAR

→ Project work on notion of change map within a multi-temporal serie

II. Implemented methods

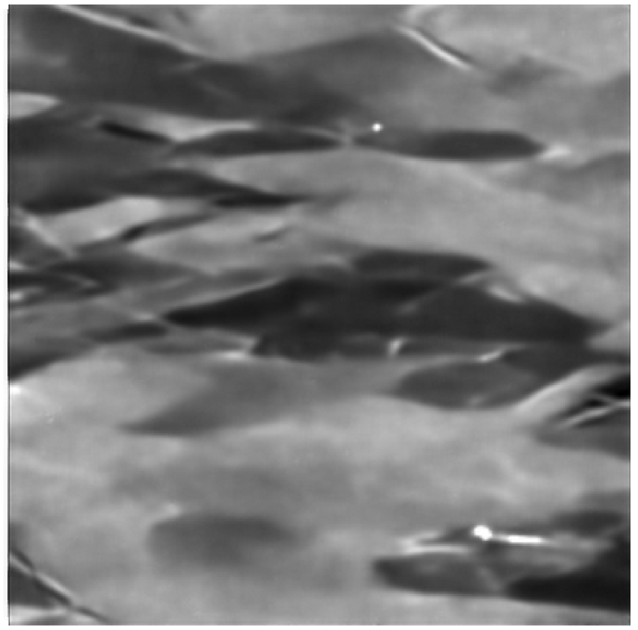
- Basic network
- Extension of the basic network
- Introduction of a change map
- Invariance of the change map to temporal permutations

II. Basic network



X noisy

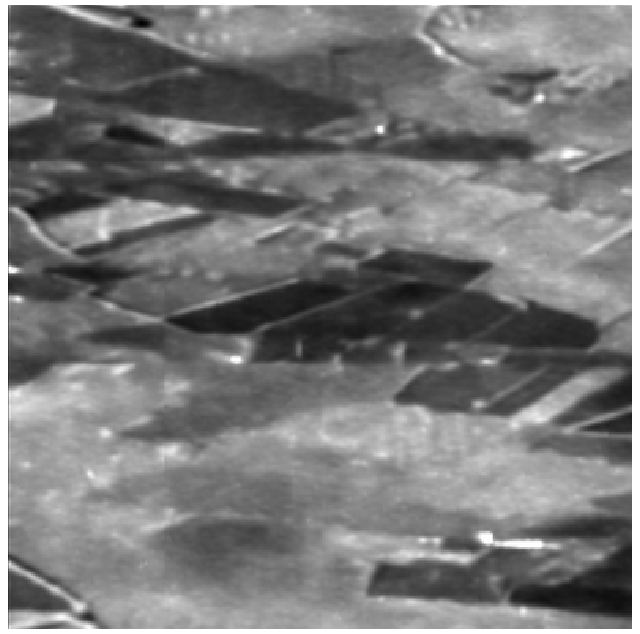
Unet



Y

↔

Absolute difference



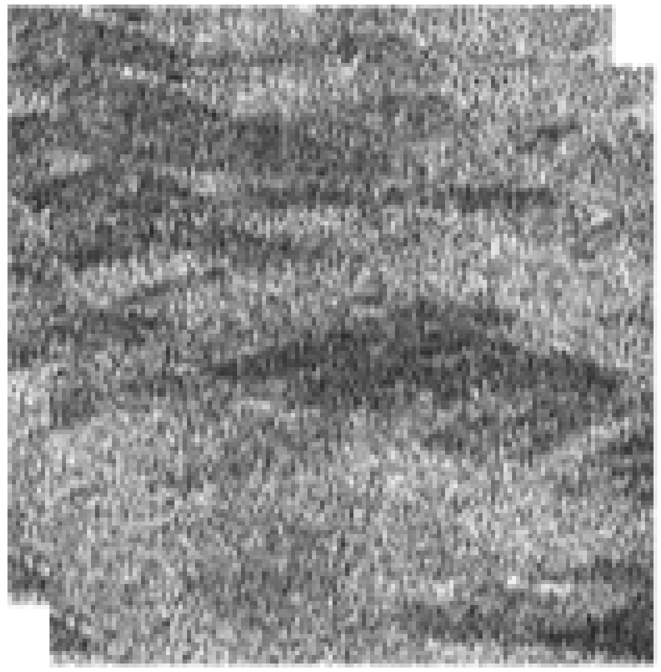
X

$$Loss = \alpha(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|X_{1i}-Y_1 i|))$$

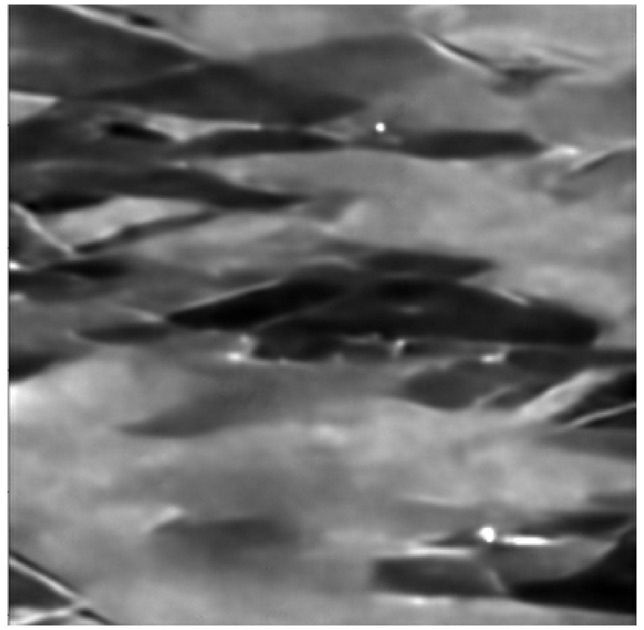
→ Good denoising but loss of structures and details

II. Extension of the basic network

Duplicate informations :



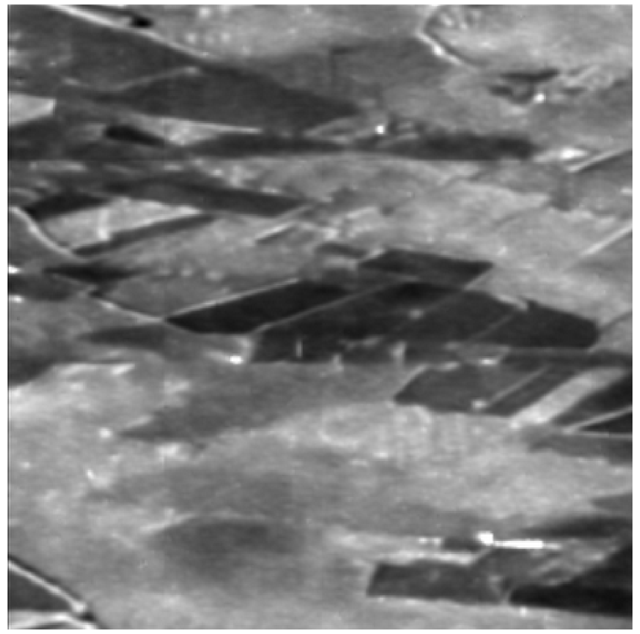
X noisy



Y

$\leftrightarrow$

Absolute difference



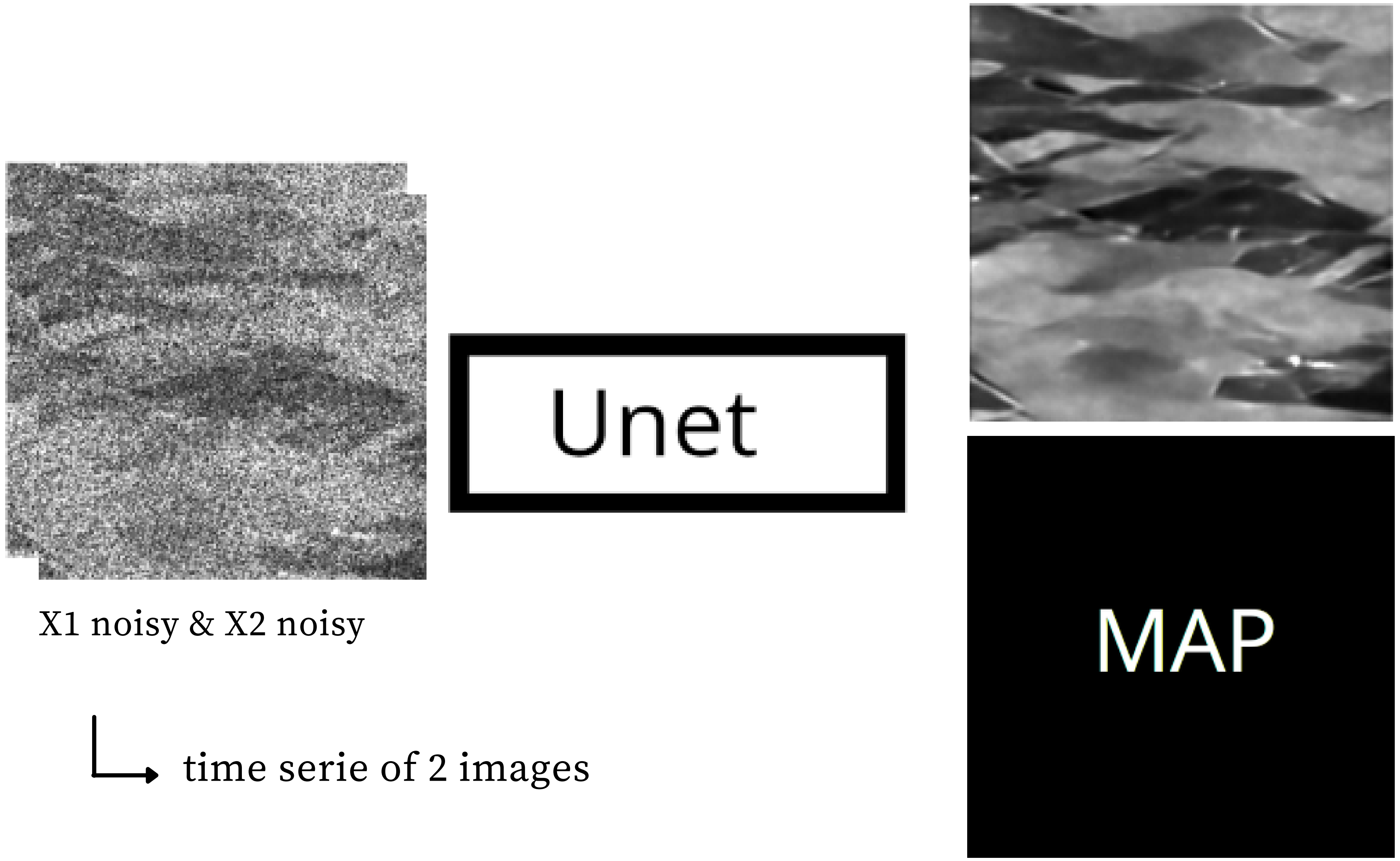
X

$$Loss = \alpha(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|X_{1i} - Y_1 i\,|))$$

→ more structure and details

→ introduce multi-temporal information

II. Change map



Y1

X1 noisy & X2 noisy

$\hat{d}$

→ binary map

→ gray level map

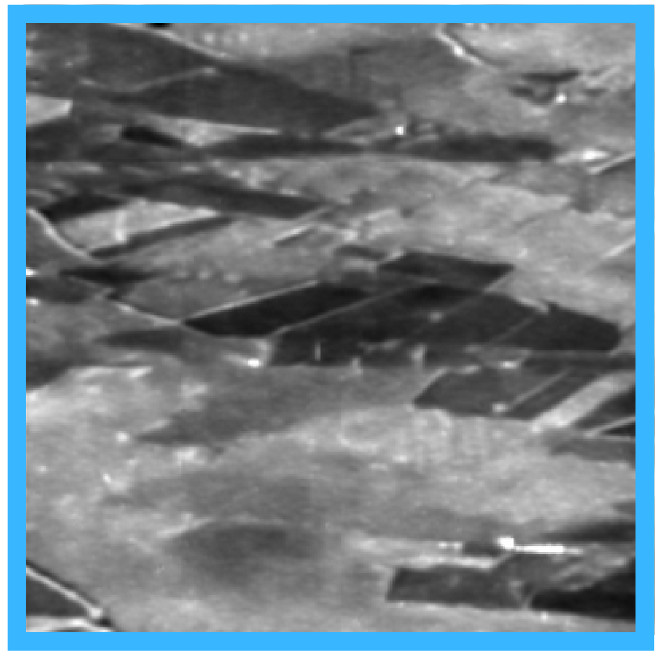
time serie of 2 images

$$Loss = \quad Loss_1 + \quad Loss_2$$

II. Gray level map

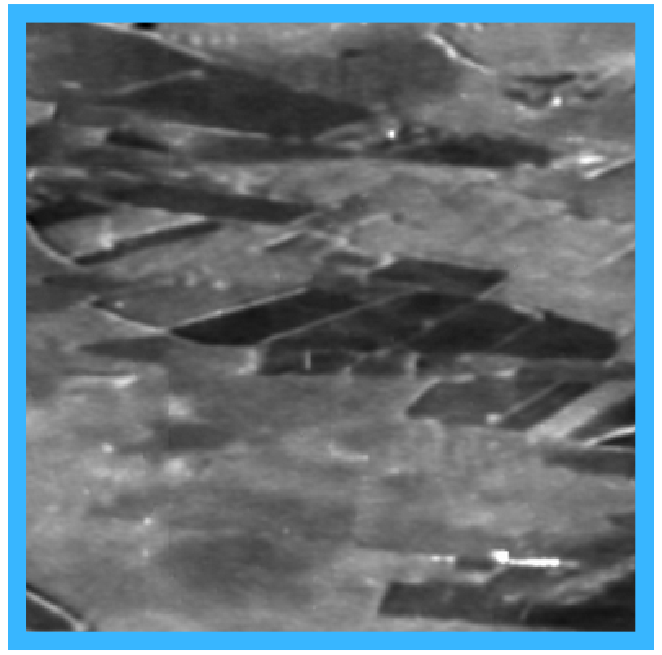
d_1^*

=



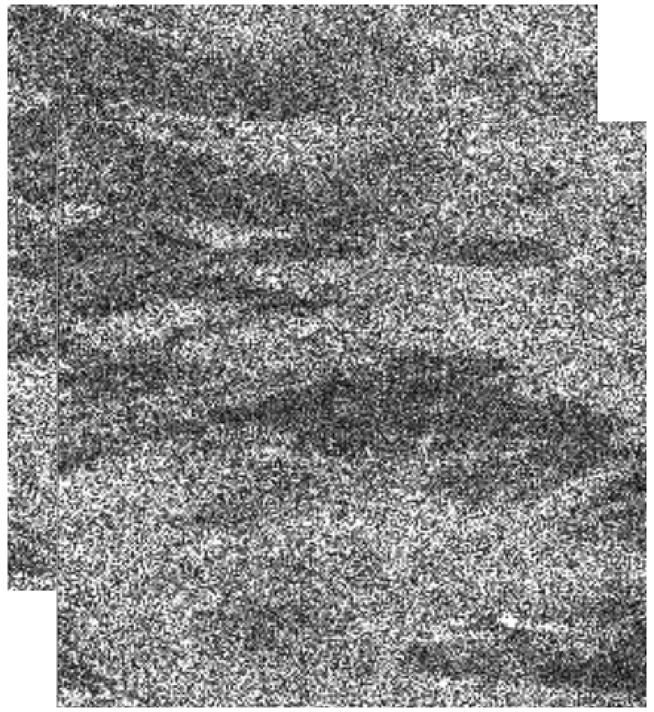
x1

-

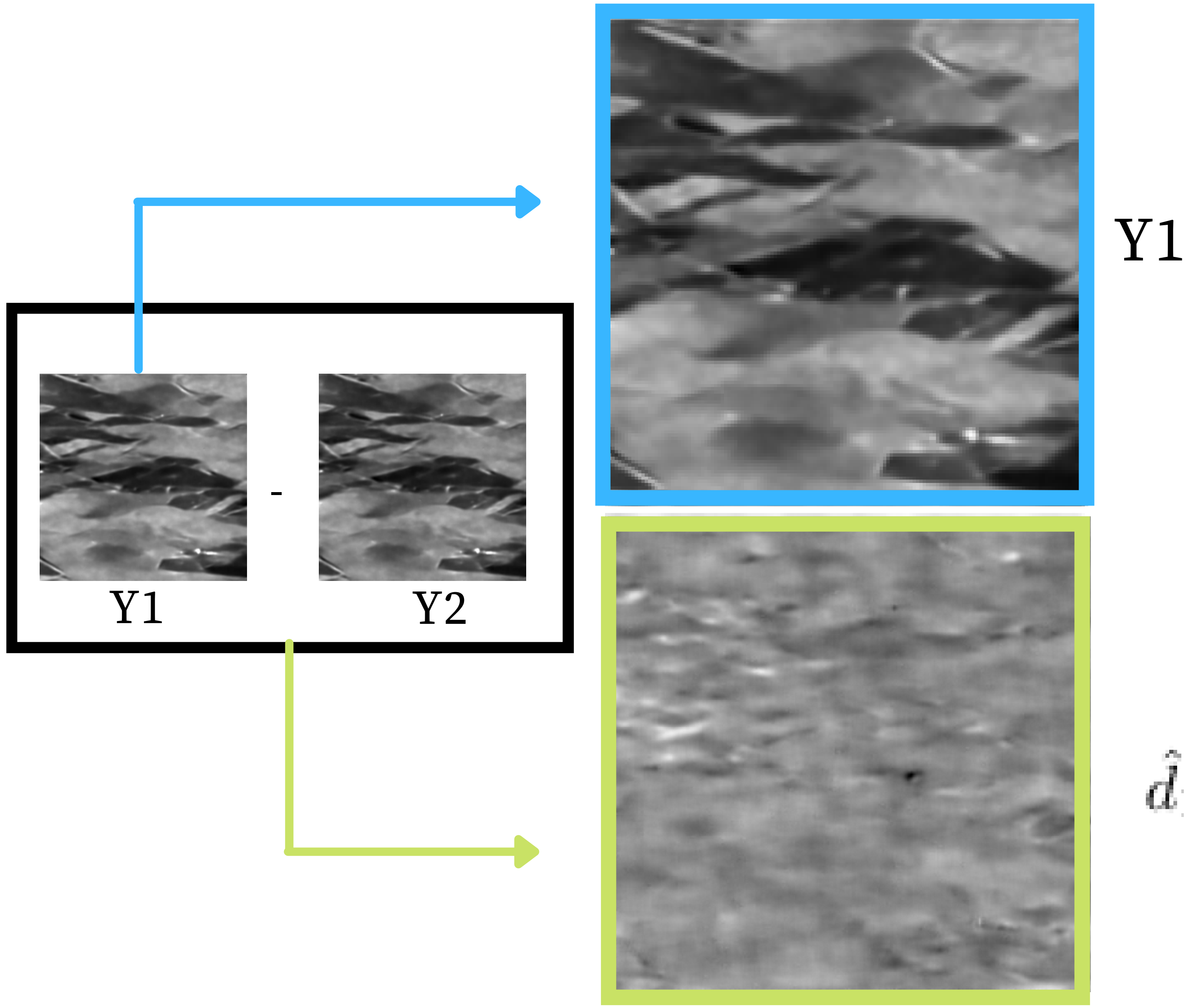


X2

II. Gray level map



noisy X1 & noisy X2



$$\begin{cases} d^* = Y1 - X2 \\ \hat{d} = Y1 - Y2 \end{cases}$$

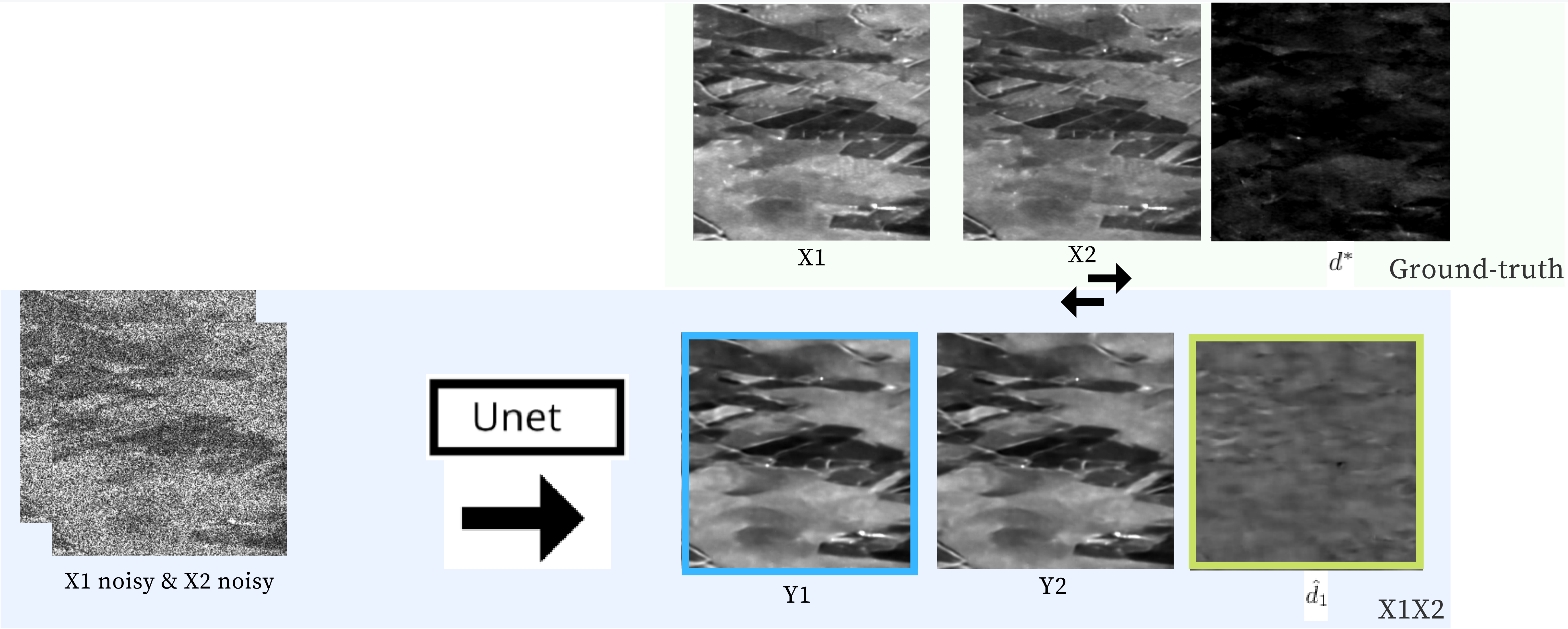
→ Implicit prediction of Y2

→ Redondancy of Y1

→ help network to take more information to help improving denoising + robustness

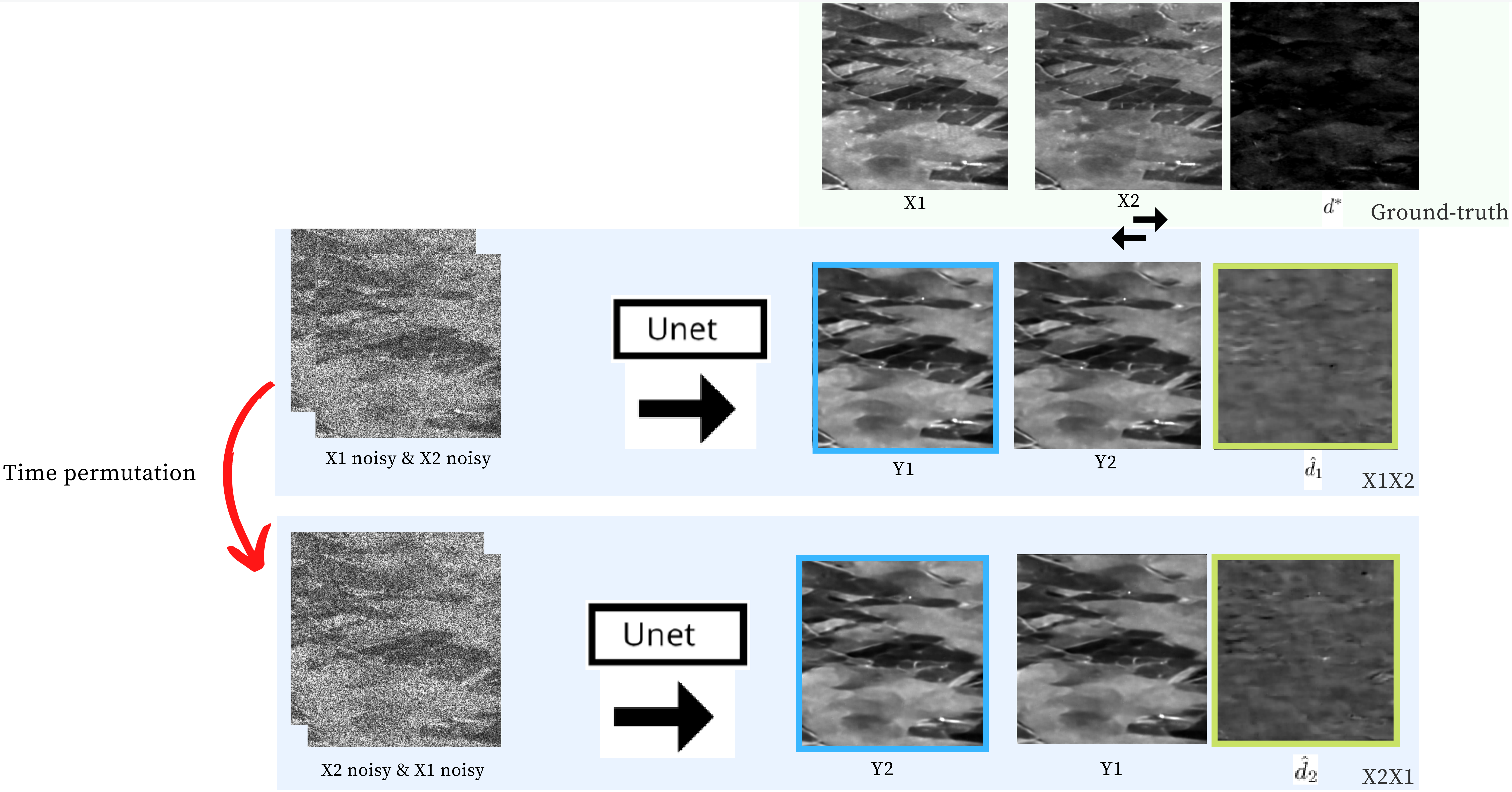
$$Loss = \left(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|X1_i - Y1i + cn|\right) + \left(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|\hat{d} - Y1_i + X2_i|\right)$$

II. Level gray map - x1x2 / x2x1



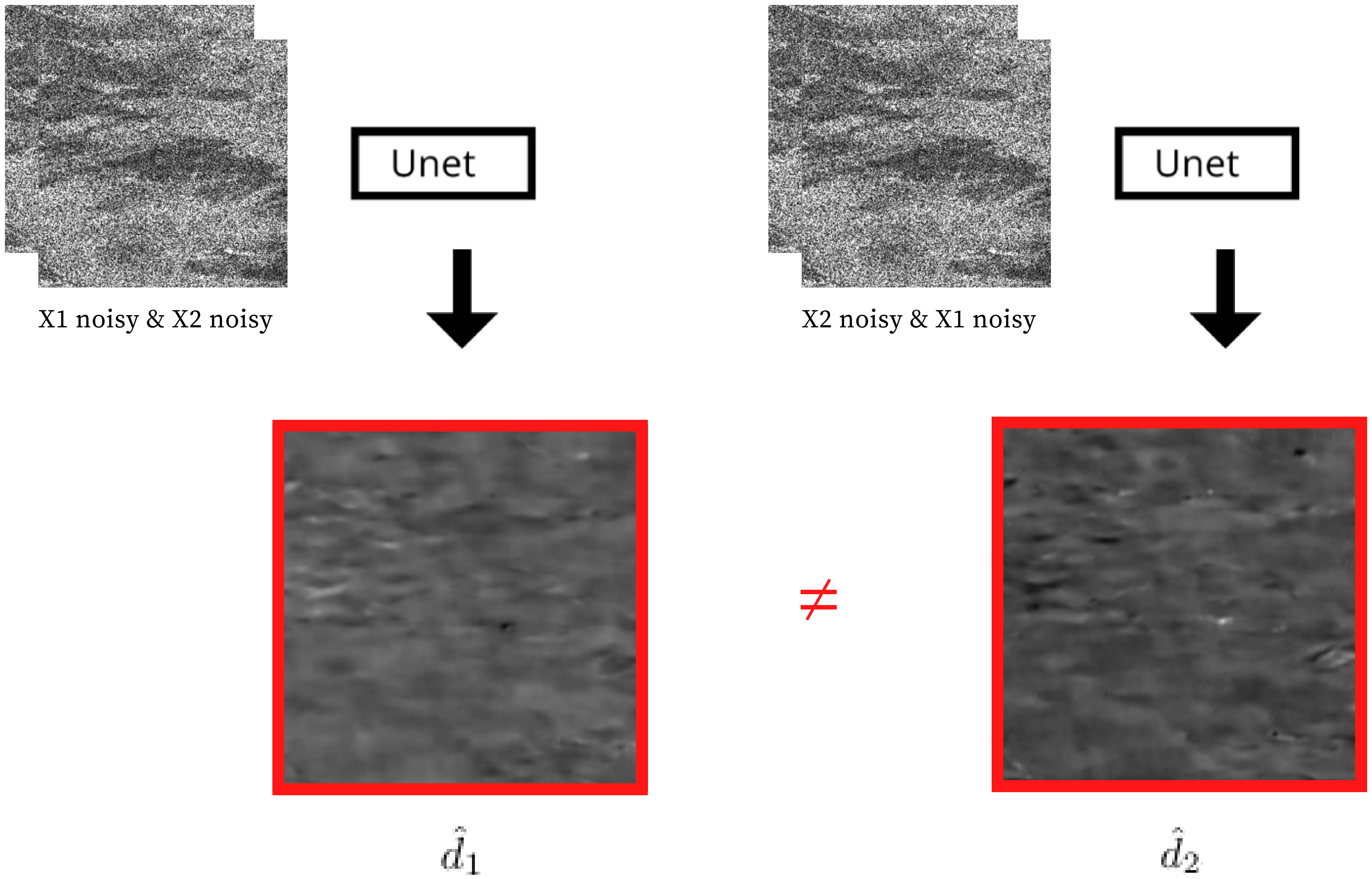
→ Multi-temporal denoising with changing map prediction

II. Level gray map - x1x2 / x2x1



→ Multi-temporal denoising with changing map prediction

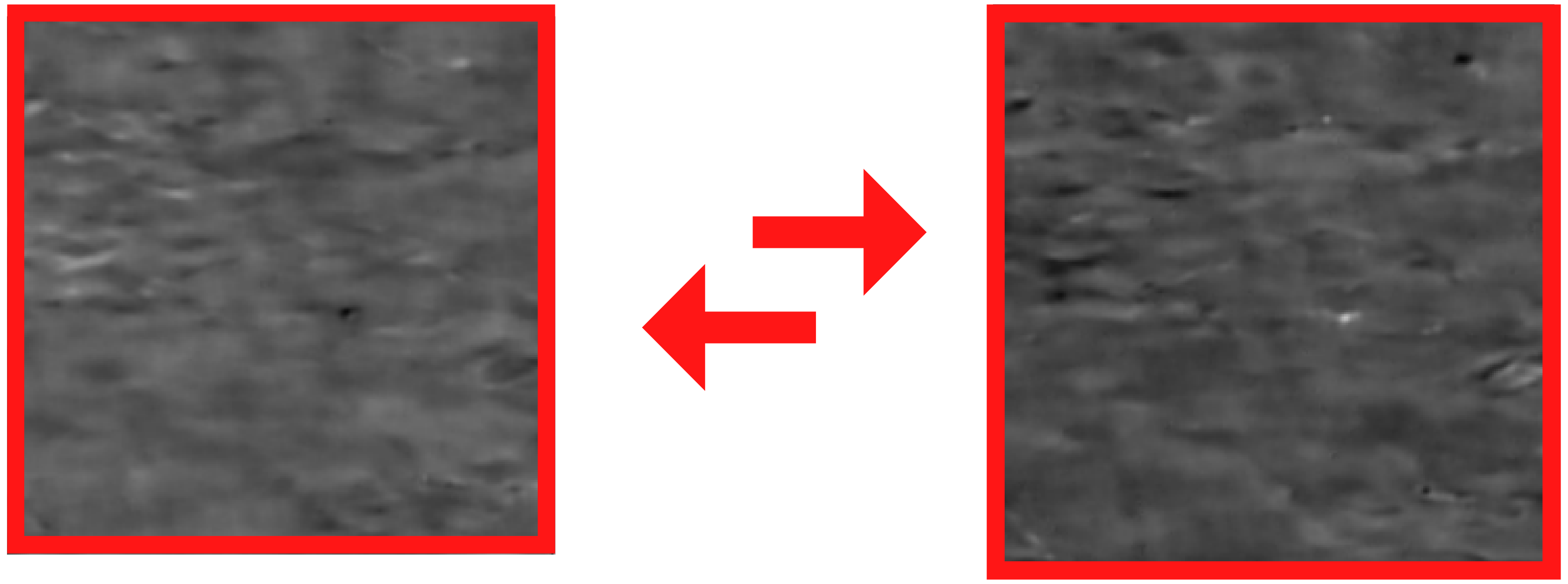
II. Invariance of the change map x1x2 vs x2x1



→ Problem : not invariant to temporal permutations

II. Invariance of the change map

→ Siamese network



$\hat{d}_1$ $\hat{d}_2$

$$Loss_3 = \gamma(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|\hat{d}_{1i} - \hat{d}_{2i}|)$$

$$Loss = (\frac{1}{batch\_size}\sum_{i=0}^{N-1}|X_{1i} - Y_1 i + cn|)) + (\frac{1}{batch\_size}\sum_{i=0}^{N-1}|\hat{d} - Y_{1i} + X_{2i}|) + \gamma(\frac{1}{batch\_size}\sum_{i=0}^{N-1}|\hat{d}_{1i} - \hat{d}_{2i}|)$$

II. Results - Visual evaluation of change map

optimize

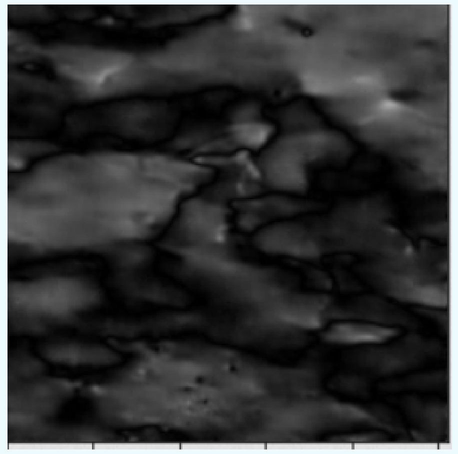
$$Loss = \quad Loss_1 + \quad Loss_2 + \gamma Loss_3$$

Ground truth d_1^*

Ground truth d_2^*

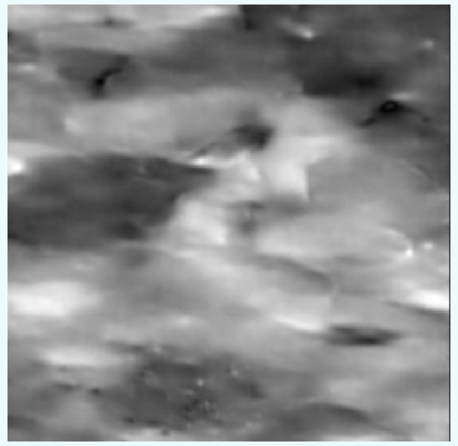
$\hat{d}_1$

SC_MAP - x1x1



$\hat{d}_1$

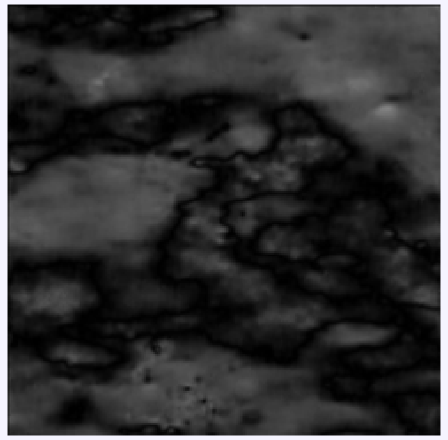
SC_MAP - x1x2



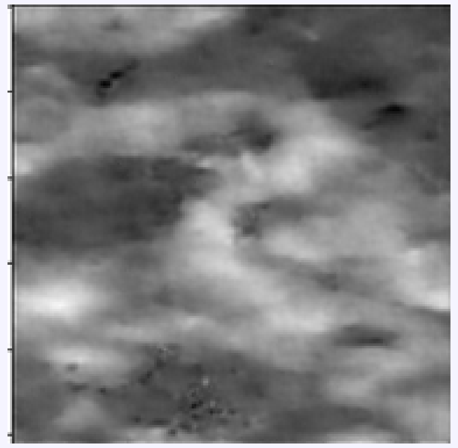
$\hat{d}_2$

SC_MAP - x2x1

Change map without permutation invariance

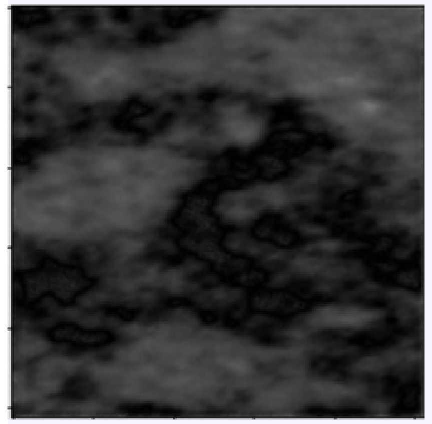


$\hat{d}_1$

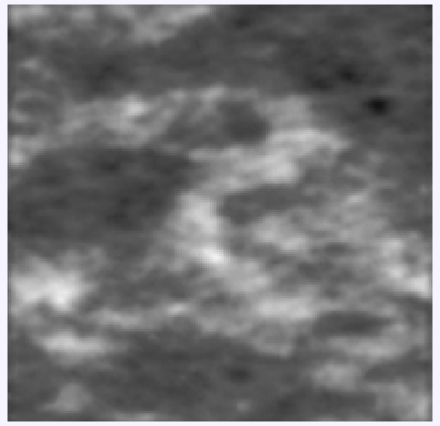


$\hat{d}_2$

SCM_SIAMESE - γ = 0.1



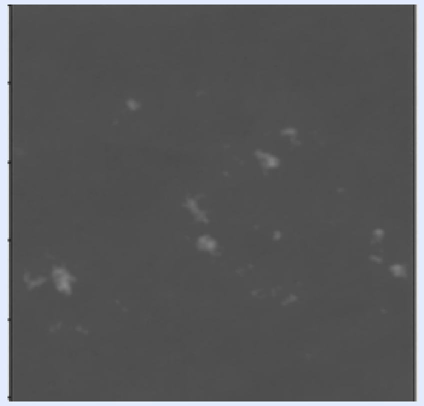
$\hat{d}_1$



$\hat{d}_2$

SCM_SIAMESE - γ = 0.2

$\hat{d}_1$



$\hat{d}_2$

SCM_SIAMESE - γ = 0.5

$\hat{d}_1$

$\hat{d}_2$

SCM_SIAMESE - γ = 1

$\hat{d}_1$

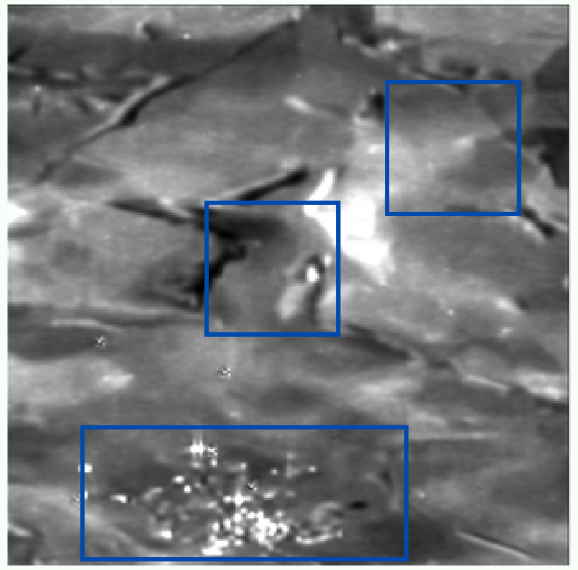
$\hat{d}_2$

SCM_SIAMESE - γ = 2

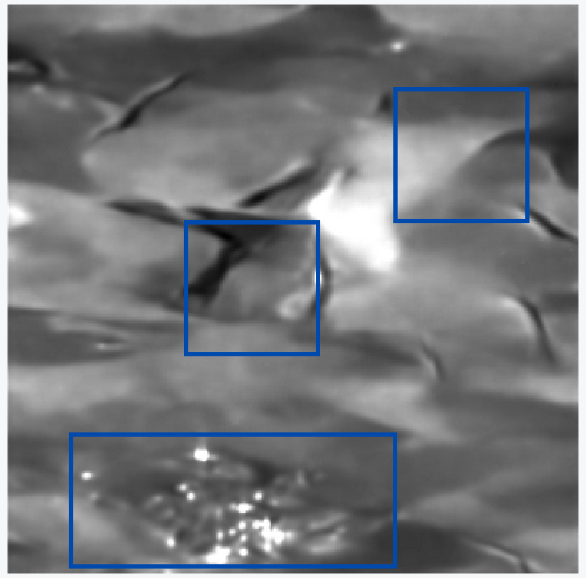
Uniform changing map

Change map with permutation invariance

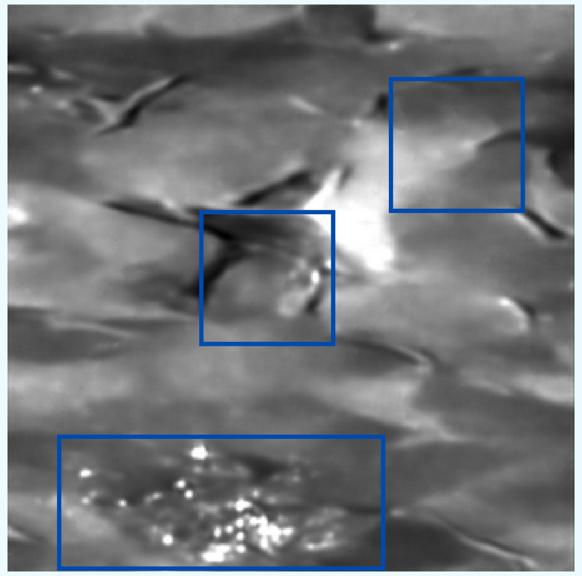
II. Results - Visual evaluation of denoising



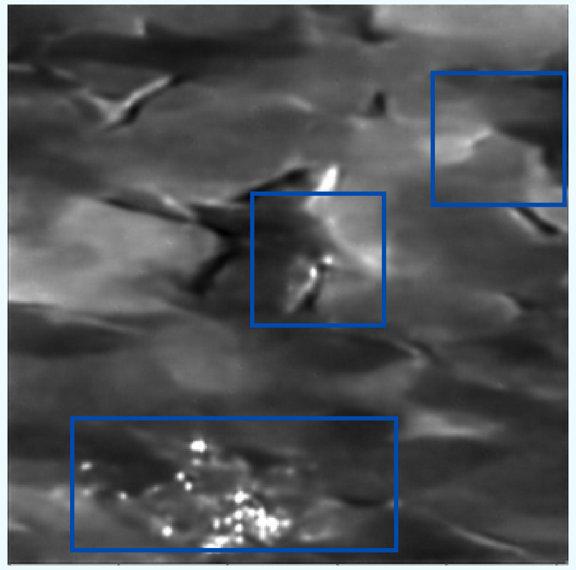
Ground-truth x1



Basic netwok

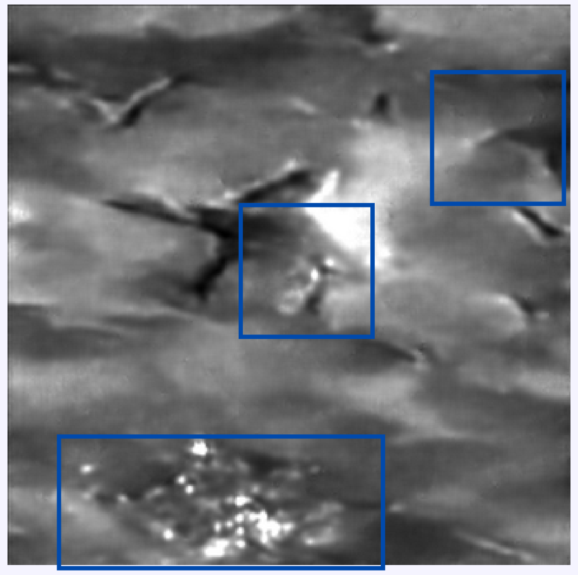


SC_MAP - x1x2

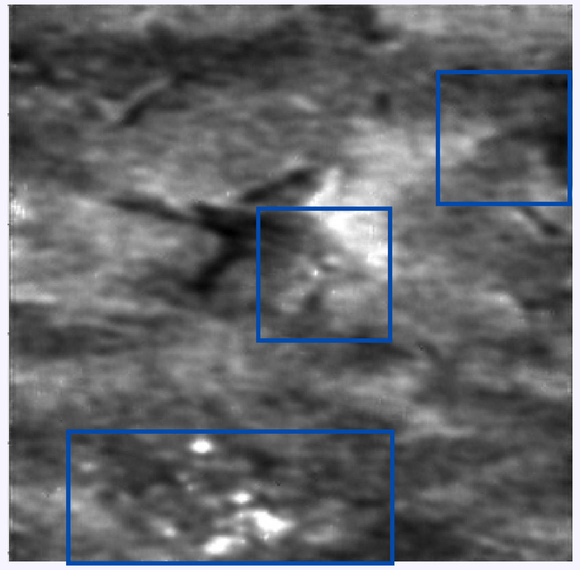


SC_MAP - x2x1

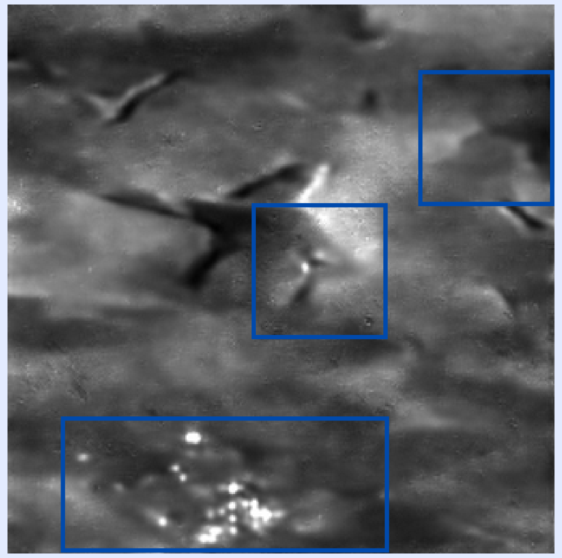
Change map without permutation invariance



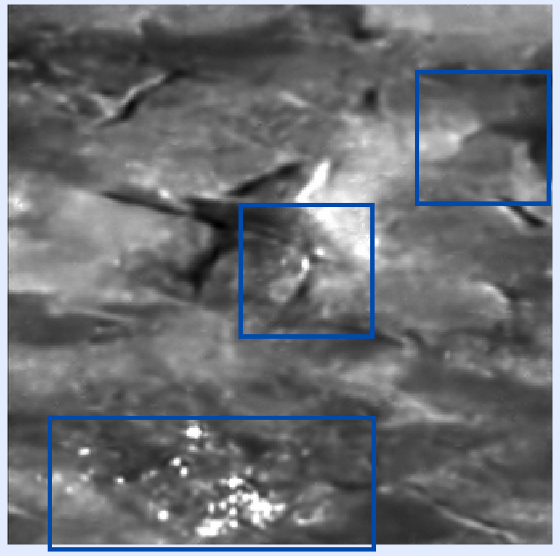
SCM_SIAMESE - γ = 0.1



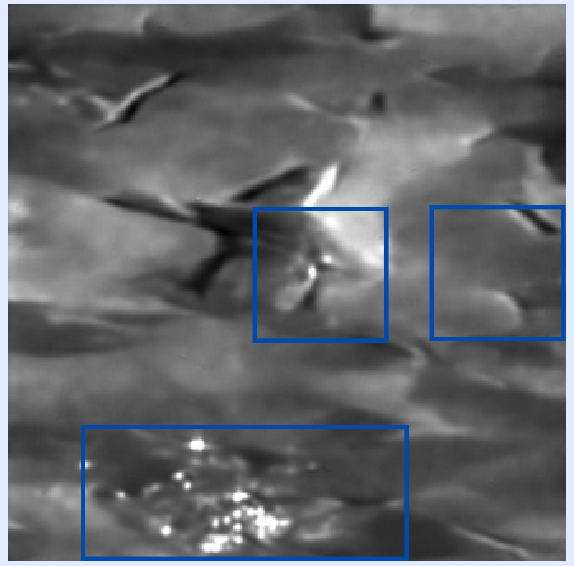
SCM_SIAMESE - γ = 0.2



SCM_SIAMESE - γ = 0.5



SCM_SIAMESE - γ = 1



SCM_SIAMESE - γ = 2

Uniform changing map

Change map with permutation invariance

III. Conclusion

- Multi-temporal time serie denoising → consideration of temporal change with change map prediction
- Invariant to temporal permutation

→ improve result

- Encouraging result

→ Extension : 3 images in the time serie

III. References + link

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→ Supervised approach

→ notion temporal change
But don't train on real image, don't take real speckle correlation

→ use multi-temporality

Thank you !