Statistics / Machine Learning at Paris-Saclay, January 2022
IHES, EDMH

Deep learning strategies for SAR image restoration

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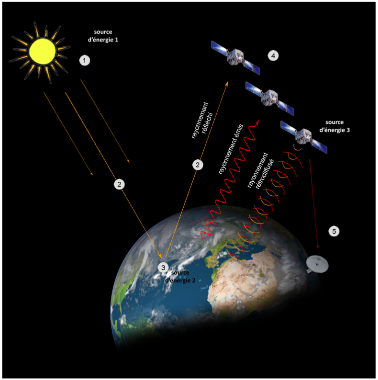
Joint work with L. Denis, E. Dalsasso, and C. Deledalle

26th of January, 2022

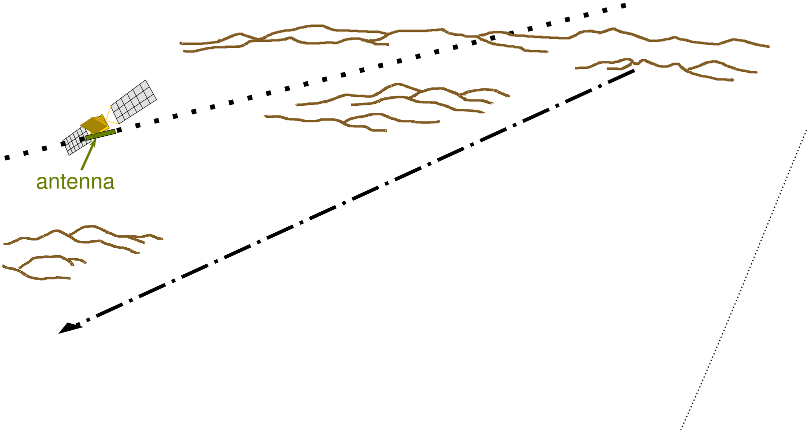
Outline

Principle of SAR imaging

- Active sensor
  - Emission of electro-magnetic waves (GHz)
  - Recording of the backscattered signals by the ground
- Properties
  - All time / all weather sensor
  - Phase of the backscattered signal encoding geometric information
  - Satellite (revisit time) or aerial sensors
- SAR image synthesis
  - Range (time) direction: direction of the wave propagation → chirp emission for improved resolution
  - Azimuth direction: direction of the sensor displacement → synthetic aperture for improved resolution

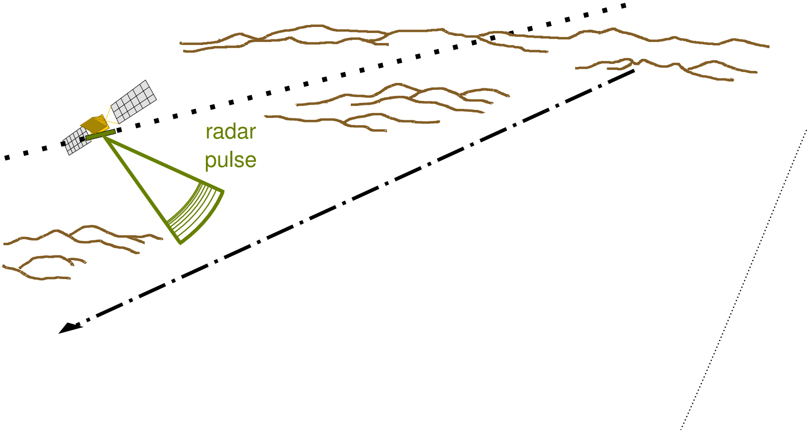


1. Principles of SAR imaging

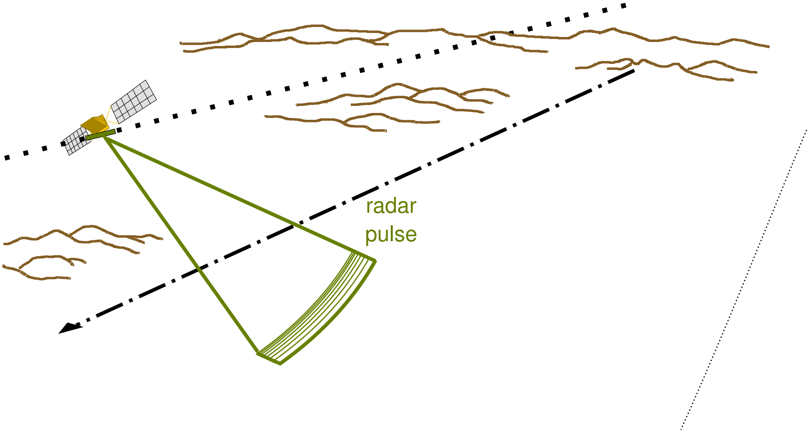


SAR imaging is an active imaging technique. . .

1. Principles of SAR imaging



. . . based on the emission of an electromagnetic wave (typ. 10GHz).



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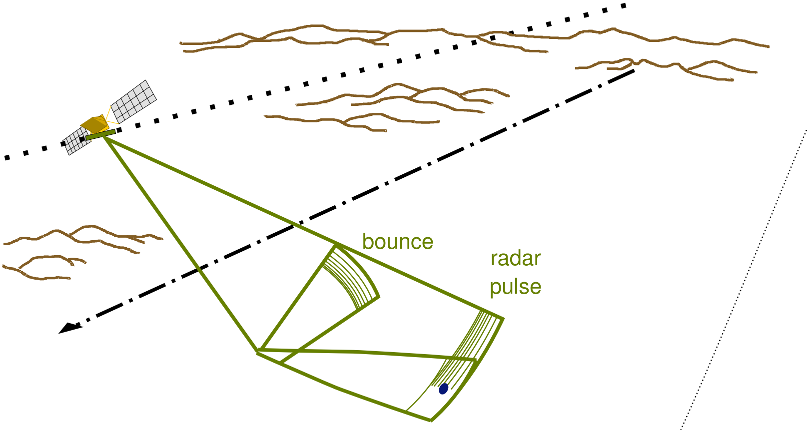
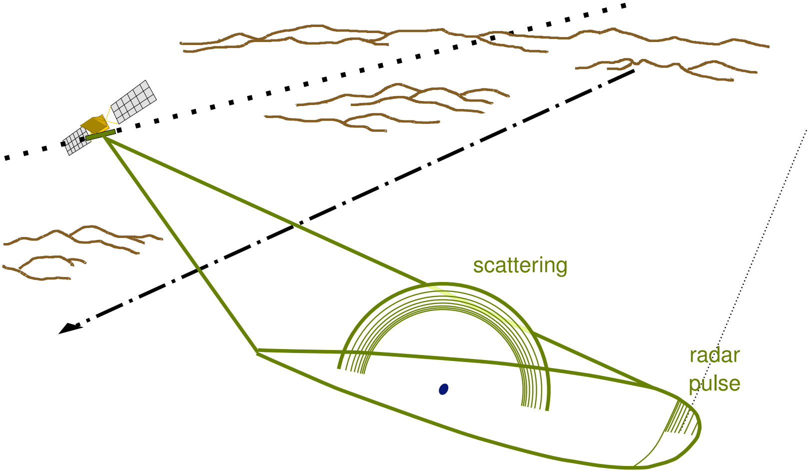
1. Principles of SAR imaging

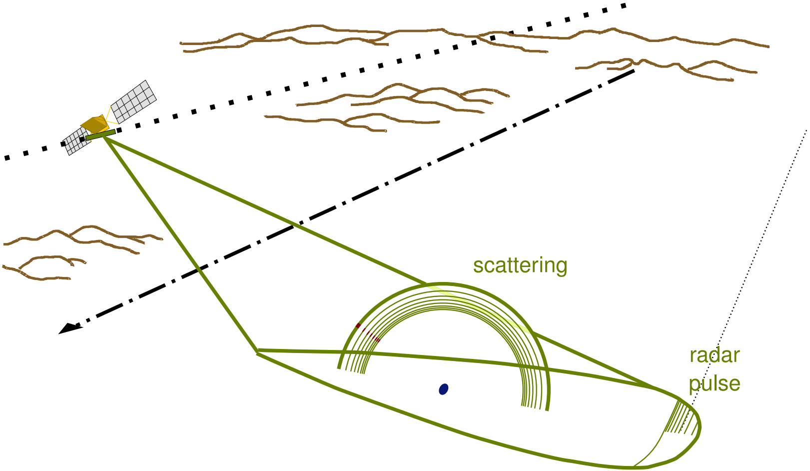


Depending on the scene geometry, the radar pulse is reflected. . .



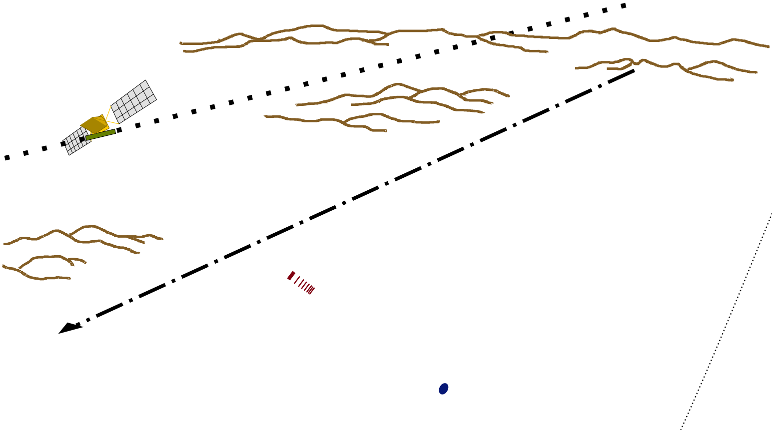
...or scattered...

1. Principles of SAR imaging



. . . and part of the incident energy is sent back to the antenna.

1. Principles of SAR imaging



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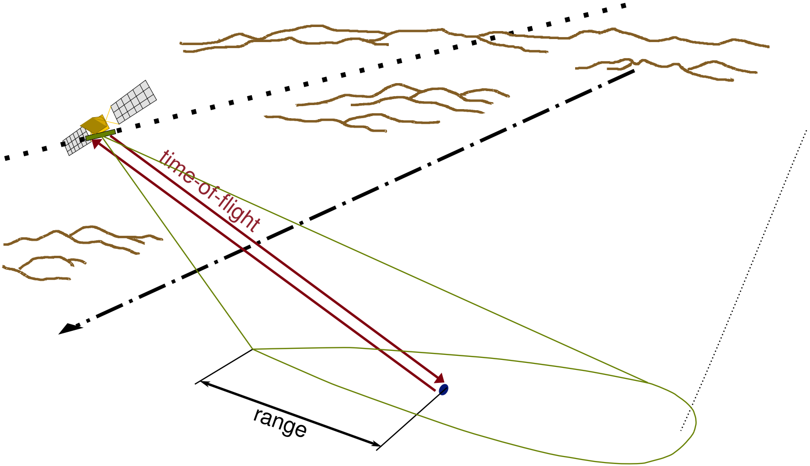
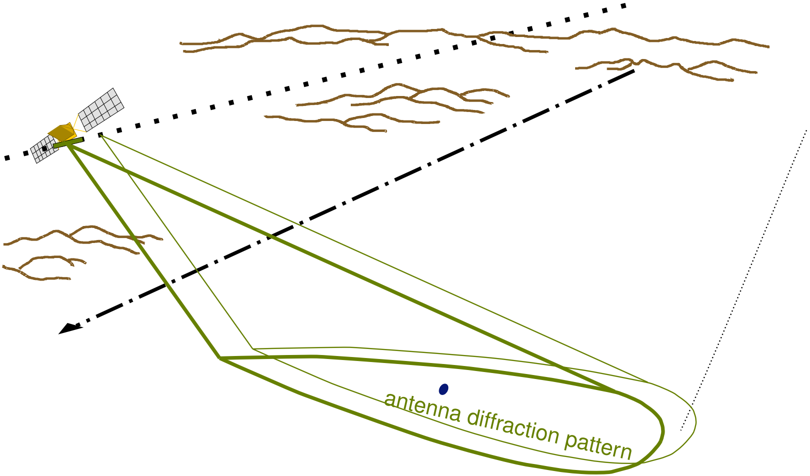
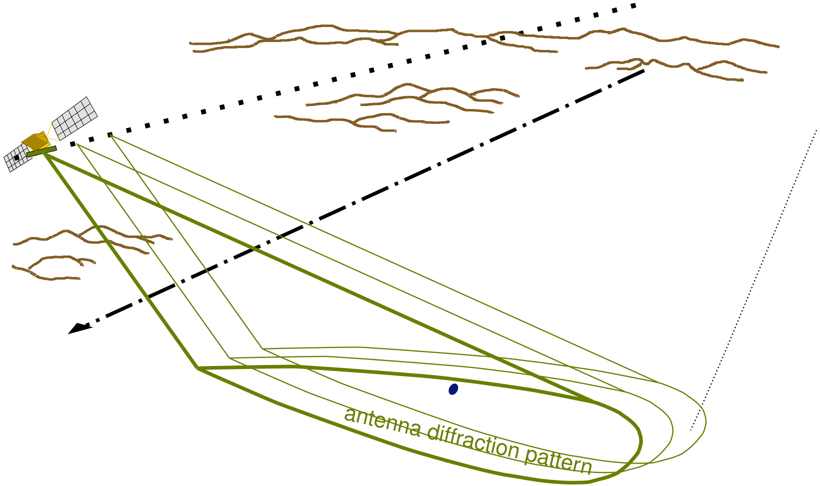


The location on the ground of the scatterer is deduced from the time-of-flight.

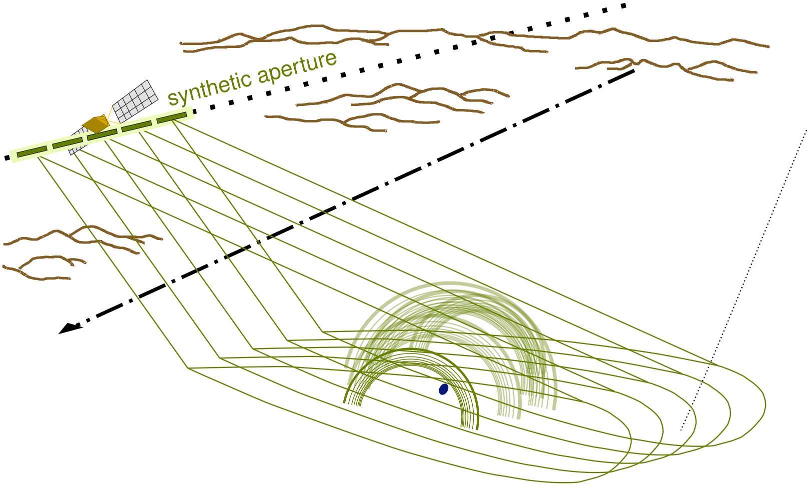


As the satellite moves, the antenna diffraction pattern covers another area. . .

1. Principles of SAR imaging

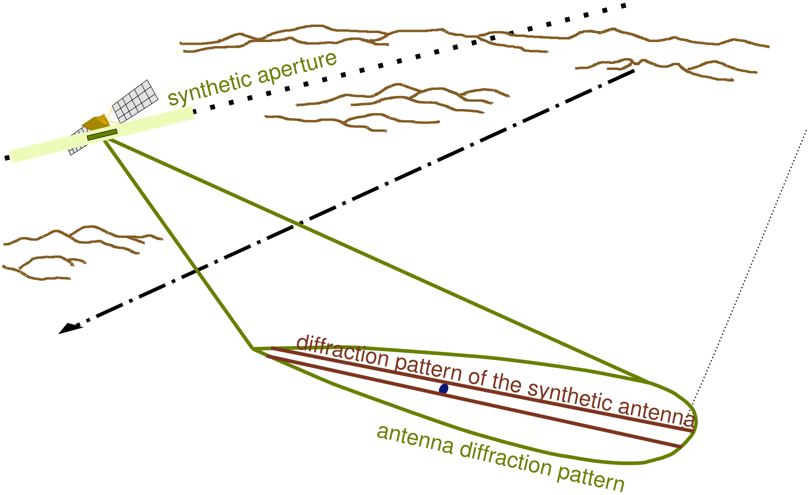


. . . thereby forming a 2D image.



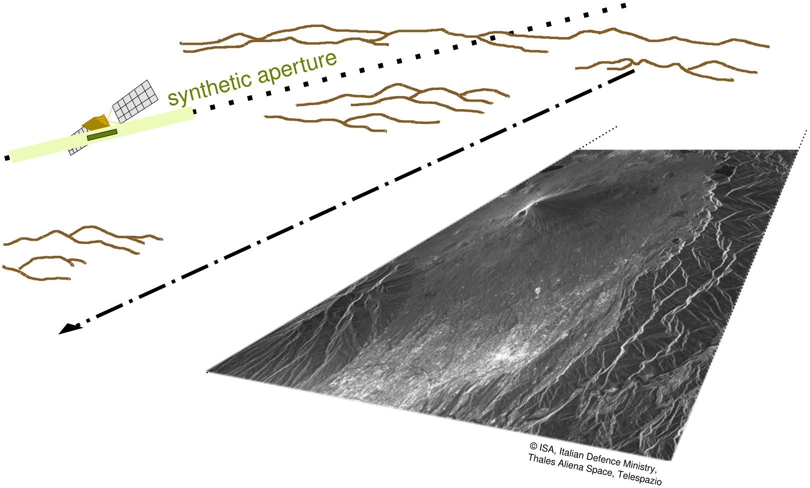
Aperture synthesis consists of numerically combining the echoes. . .

1. Principles of SAR imaging



. . . which greatly improves the resolution.

1. Principles of SAR imaging



SAR data

Different kind of "images"

- single SAR image

  amplitude $\rightarrow$ **object classification**, ...

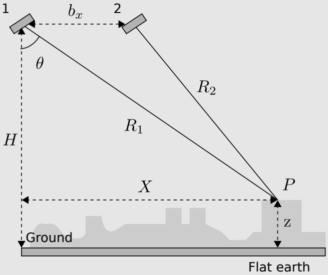
- interferometry: 2 SAR images

  phase difference $\rightarrow$ **elevation**, ...

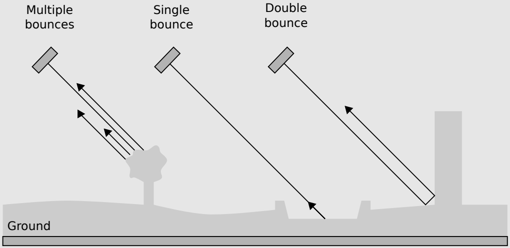
- polarimetry: 3 SAR images

  complex correlation $\rightarrow$ **geophysical properties**

SAR, InSAR, PolSAR, PolInSAR



(a) InSAR



(b) PolSAR

Different kind of "images"

- single SAR image

  amplitude $\rightarrow$ **object classification**, . . .

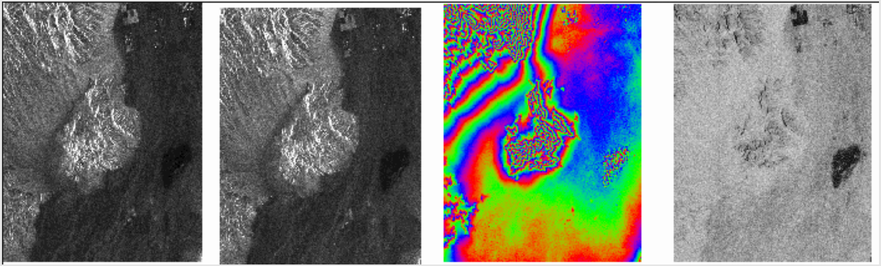
- interferometry: 2 SAR images

  phase difference $\rightarrow$ **elevation**, . . .

- polarimetry: 3 SAR channels

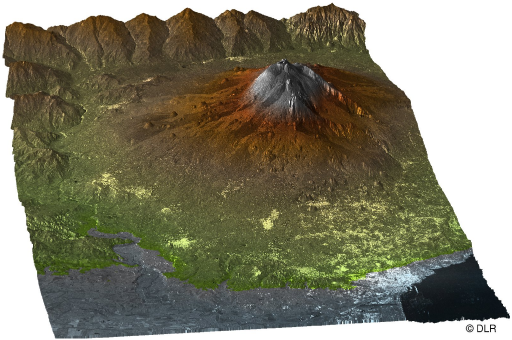
  complex correlation $\rightarrow$ **geophysical properties**

SAR, InSAR, PolSAR, PolInSAR

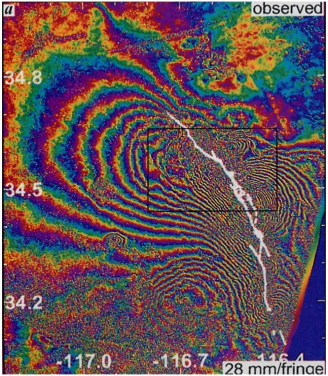


(a) InSAR

SAR imaging applications



(a) InSAR

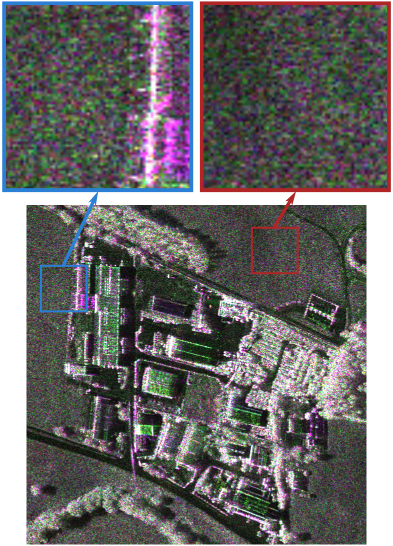


(b) Differential InSAR

Outline

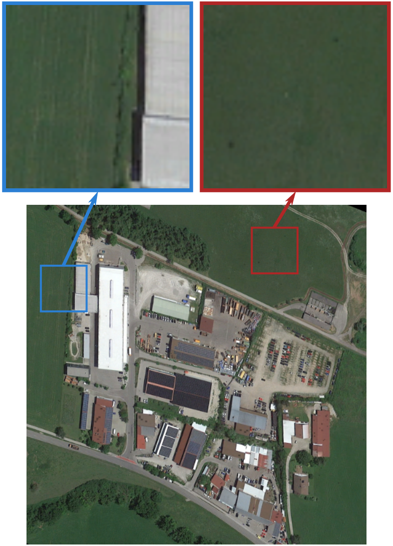
Speckle phenomenon

Speckle fluctuations are a major difference between SAR and optical remote sensing images:



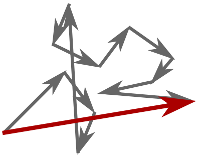
polarimetric SAR image

Pauli representation (HH-VV, 2HV, HH+VV)



corresponding optical image

Fully-developed speckle model [Goodman 1963]



Coherent summation of echoes from each elementary scatterer of the resolution cell:

$\rightsquigarrow$ a random walk in the complex plane

Assumption: rough & homogeneous surface

$\rightsquigarrow$ real and imaginary parts are independent Gaussians

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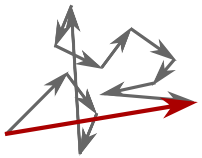
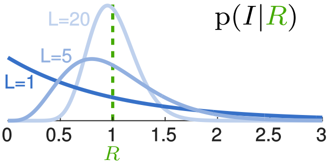


Intensity images: multiplicative noise modeled by a gamma distribution ($I = |z|$ and R being the physical parameter of the scene)

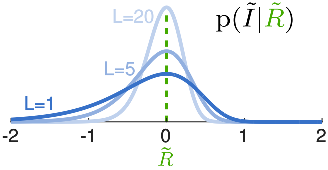
$$\mathrm{p}(I|R) = \left(\frac{L}{R}\right)^L \frac{I^{L-1}}{\Gamma(L)} \exp\left(\frac{-L\,I}{R}\right)$$



Log-transformed intensity images: additive noise modeled by a Fisher-Tippett distribution

$$\mathrm{p}(\tilde{I}|\tilde{R}) = \frac{L^L}{\Gamma(L)} \exp\left[L\left(\tilde{I} - \tilde{R} - \exp(\tilde{I} - \tilde{R})\right)\right]$$

with $\quad \tilde{I} = \log I \quad$ and $\quad \tilde{R} = \log R$



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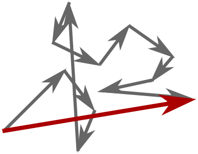
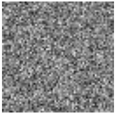
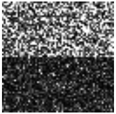
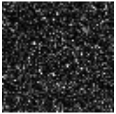


noisy image  $=$ noiseless image  $+$ Gaussian noise 

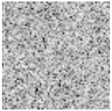
additive Gaussian noise

vs

noisy image  $=$ noiseless image  $\times$ exponential noise 

multiplicative speckle noise

$\downarrow \log$ $\downarrow \log$ $\downarrow \log$

noisy image  $=$ noiseless image  $+$ Fisher-Tippett noise 

additive Fisher-Tippett noise

Fully-developed speckle model [Goodman 1963]

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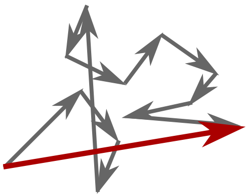

Interferometric and/or polarimetric images:

- diffusion vectors $\boldsymbol{k}$ distributed according to a complex circular Gaussian distribution ($\boldsymbol{\Sigma}$ containing the physical parameters of interest)

$$\mathsf{p}(\boldsymbol{k}|\boldsymbol{\Sigma}) = \frac{1}{\pi^K |\boldsymbol{\Sigma}|} \exp\left(-\boldsymbol{k}^\dagger \boldsymbol{\Sigma}^{-1} \boldsymbol{k}\right)$$

- sample covariance matrix $\boldsymbol{C} = \frac{1}{L} \sum_{i=1}^{L} \boldsymbol{k}_i \boldsymbol{k}_i^\dagger$ distributed according to complex Wishart distributio

$$\mathsf{p}(\boldsymbol{C}|\boldsymbol{\Sigma}, L) = \frac{L^{LK} |\boldsymbol{C}|^{L-K}}{\Gamma_K(L) |\boldsymbol{\Sigma}|^L} \exp\left(-L \,\mathrm{Tr}(\boldsymbol{\Sigma}^{-1} \boldsymbol{C})\right)$$

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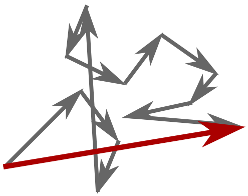

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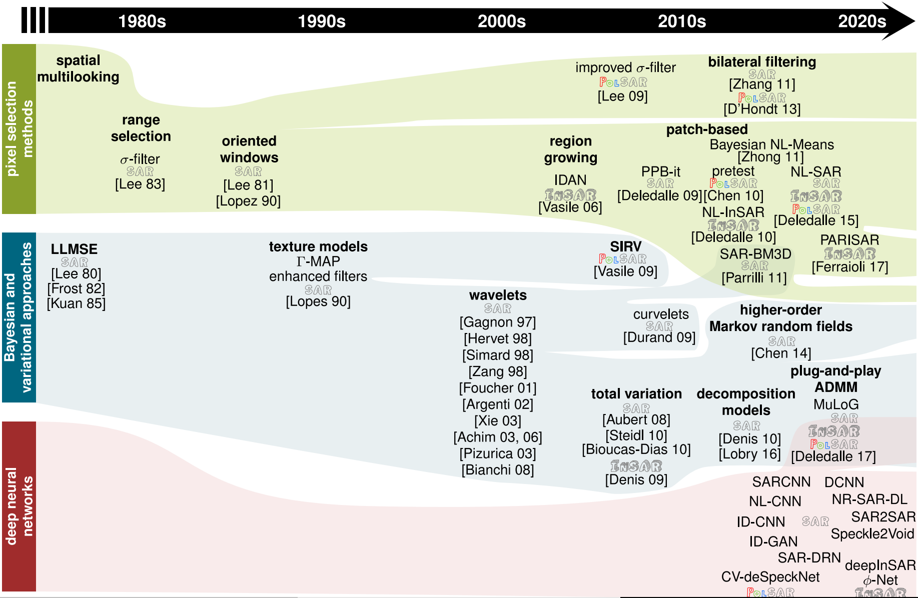
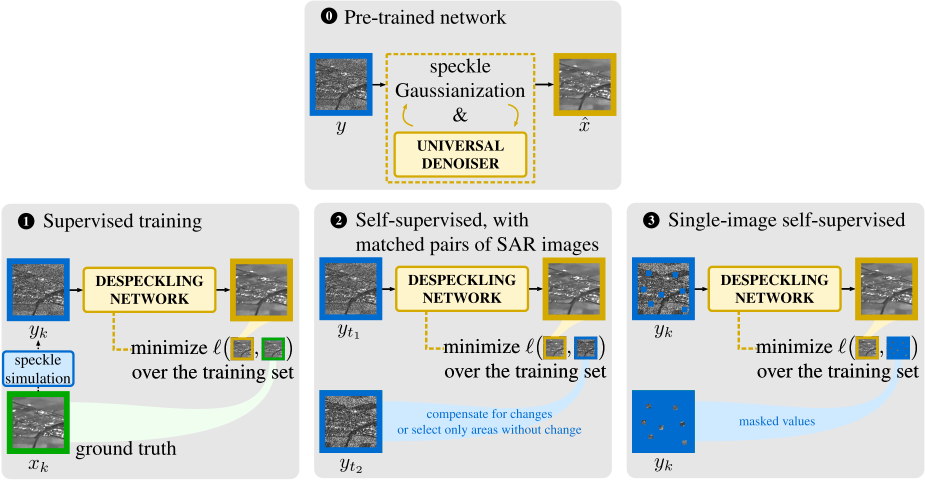
Speckle reduction techniques : an overview of 40+ years of research (L. Denis et al., IGARSS 21)



Outline

A broad overview of deep-learning strategies for despeckling

Training strategies:



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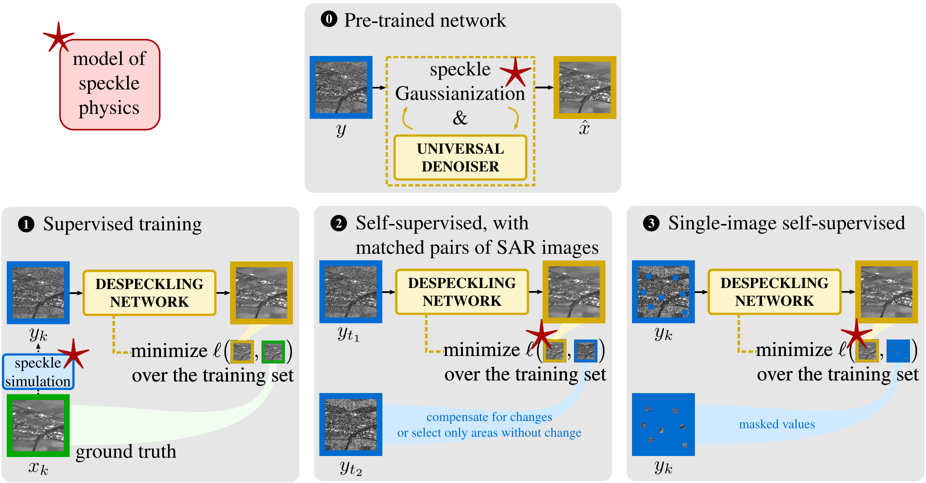
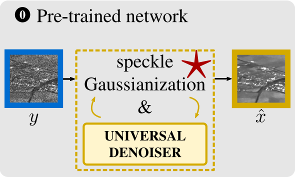
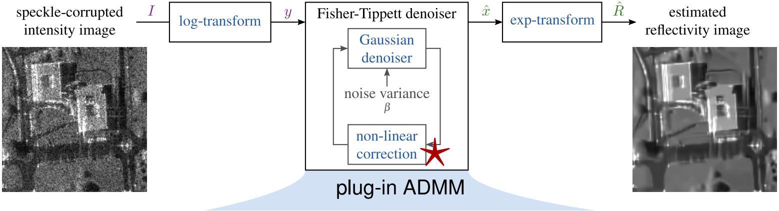


Applying a pre-trained network (universal Gaussian denoiser)





$$\hat{\boldsymbol{z}} \leftarrow \underset{\boldsymbol{z}}{\operatorname{argmin}} \; \frac{\beta}{2}\|\boldsymbol{z} - \hat{\boldsymbol{x}} + \hat{\boldsymbol{d}}\|^2 + \mathcal{R}(z^c) \,,$$

implicit regularization: CNN trained on natural images

$$\hat{\boldsymbol{d}} \leftarrow \hat{\boldsymbol{d}} + \hat{\boldsymbol{z}} - \hat{\boldsymbol{x}} \,,$$

$$\hat{\boldsymbol{x}} \leftarrow \underset{\boldsymbol{x}}{\operatorname{argmin}} \; \frac{\beta}{2}\|\boldsymbol{x} - \hat{\boldsymbol{z}} - \hat{\boldsymbol{d}}\|^2 - \log p_{\boldsymbol{y}}(\boldsymbol{y}|\boldsymbol{x}) \,.$$

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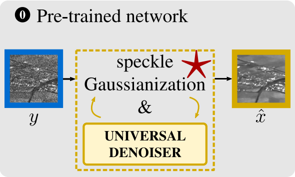

speckle-corrupted multi-channel image → C → matrix-log → y → Wishart-Fisher-Tippett denoiser → $\hat{x}$ → matrix-exp → $\hat{\Sigma}$ → estimated covariance matrices

matrix-log: whitening + inter-channel equalization + real-valued representation Ω^{-1}

Wishart-Fisher-Tippett denoiser: Gaussian denoiser, noise variance β, non-linear correction

matrix-exp: inverse mapping Ω

plug-in ADMM

$$\hat{z} \leftarrow \underset{z}{\operatorname{argmin}} \ \frac{\beta}{2}\|z - \hat{x} + \hat{d}\|^2 + \sum_{c=1}^{D^2} \mathcal{R}(z^c) \ ,$$

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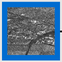
C.A. Deledalle, L. Denis, S. Tabti, & F. Tupin, "*MuLoG or how to apply Gaussian denoisers to multi-channel SAR speckle reduction ?*", IEEE Transactions on Image Processing, 2017.

Applying a pre-trained network (universal Gaussian denoiser)

0 Pre-trained network



y

speckle Gaussianization & **UNIVERSAL DENOISER**

$\hat{x}$

requires no training!
generalizes to multi-channel images

network not refined for SAR scenes.

speckle-corrupted multi-channel image $\boldsymbol{C}$ → matrix-log → $\boldsymbol{y}$ → Wishart-Fisher-Tippett denoiser → $\hat{\boldsymbol{x}}$ → matrix-exp → $\hat{\boldsymbol{\Sigma}}$ → estimated covariance matrices

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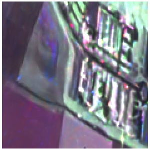

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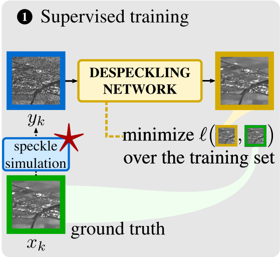
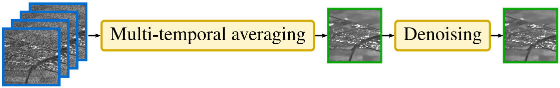
implicit regularization: CNN trained on natural images

C.A. Deledalle, L. Denis, & F. Tupin, "*A Generic Variance-Stabilization Approach for Speckle Reduction in SAR Interferometry and SAR Polarimetry*", IGARSS, 2018.

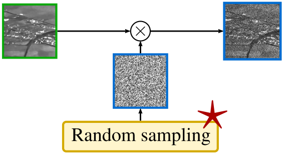
Supervised training of a despeckling network



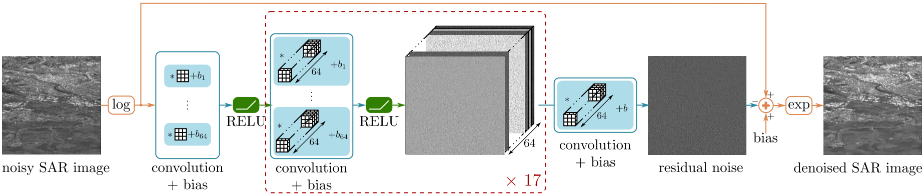
Ground-truth generation:



Speckle simulation:



Residual CNN:



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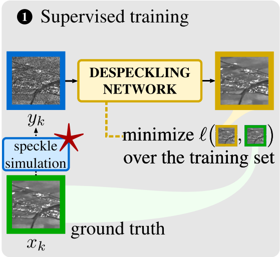

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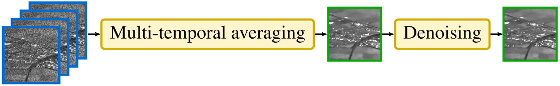

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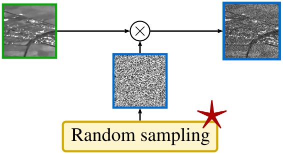
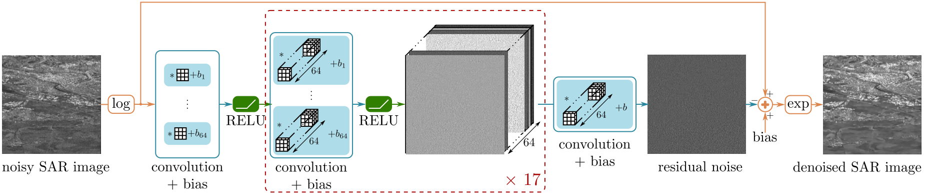


time series provide high-quality ground truth.

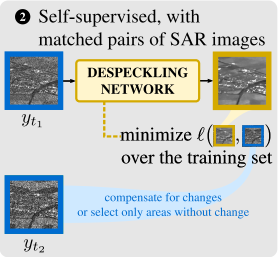
if speckle correlations are ignored in the simulation, requires some downsampling ⇒ resolution loss

Residual CNN:

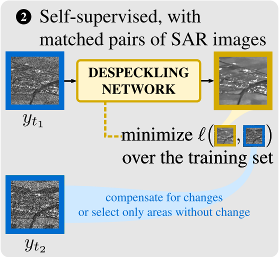


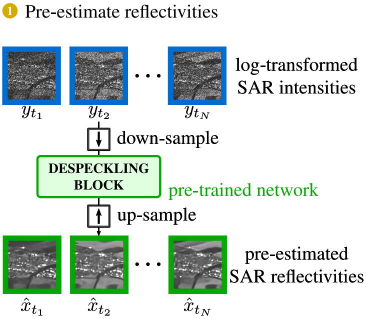
E. Dalsasso, X. Yang, L. Denis, F. Tupin, "*SAR Image Despeckling by Deep Neural Networks: from a pre-trained model to an end-to-end training strategy*", Remote Sensing 2020.

Self-supervised with matched pairs of SAR images

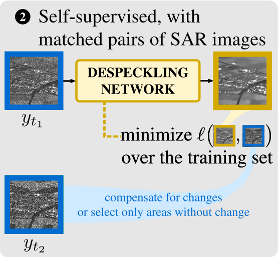


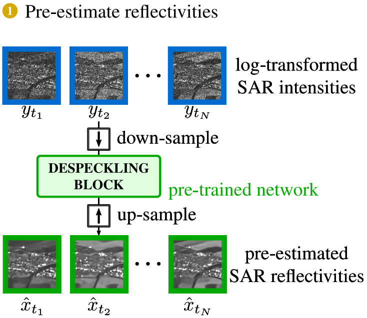
Self-supervised with matched pairs of SAR images

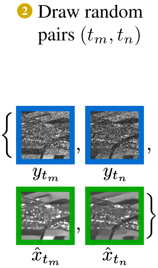




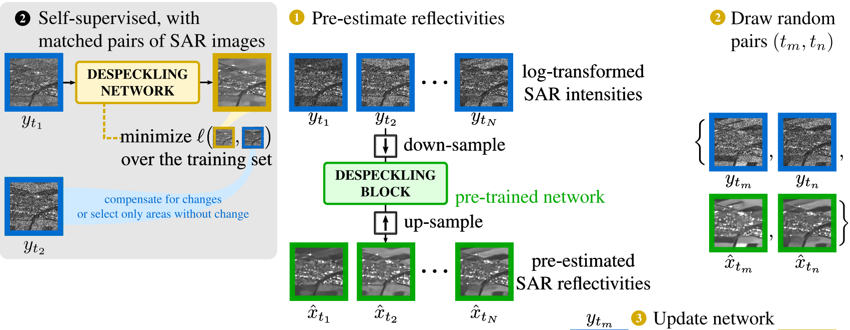
Self-supervised with matched pairs of SAR images

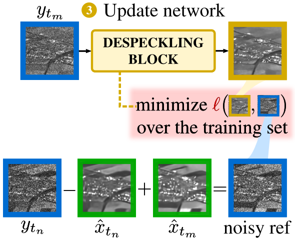






Self-supervised with matched pairs of SAR images

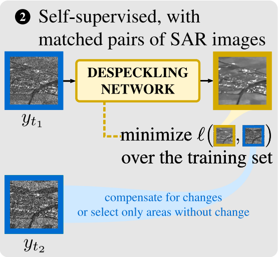


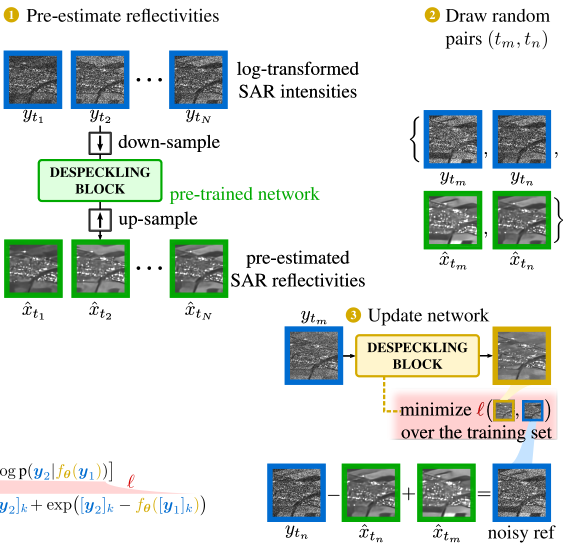


$$\hat{\boldsymbol{\theta}}^{(\text{lik})}_{\text{self-supervised}} \in \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \; \mathbb{E}_X \left[-\log \mathrm{p}(\boldsymbol{y}_2 | f_{\boldsymbol{\theta}}(\boldsymbol{y}_1)) \right] \quad \ell$$

Goodman's speckle model: $\sum_k f_{\boldsymbol{\theta}}([\boldsymbol{y}_1]_k) - [\boldsymbol{y}_2]_k + \exp\left([\boldsymbol{y}_2]_k - f_{\boldsymbol{\theta}}([\boldsymbol{y}_1]_k)\right)$

Self-supervised with matched pairs of SAR images





very good restoration performance

the training procedure is a little heavy

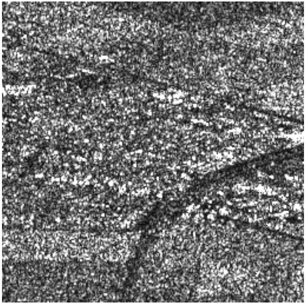
$$\hat{\theta}^{(\text{lik})}_{\text{self-supervised}} \in \underset{\theta}{\arg\min}\ \mathbb{E}_X\left[\underbrace{-\log p(\boldsymbol{y}_2 | f_\theta(\boldsymbol{y}_1))}_{\ell}\right]$$

Goodman's speckle model: $\sum_k f_\theta([\boldsymbol{y}_1]_k) - [\boldsymbol{y}_2]_k + \exp\left([\boldsymbol{y}_2]_k - f_\theta([\boldsymbol{y}_1]_k)\right)$

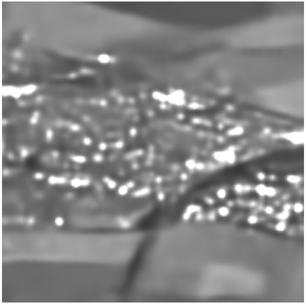
E. Dalsasso, L. Denis, F. Tupin, "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021.

Self-supervised with matched pairs of SAR images

Restoration results with SAR2SAR: Sentinel-1 SLC IW image (©ESA, image not pre-processed)



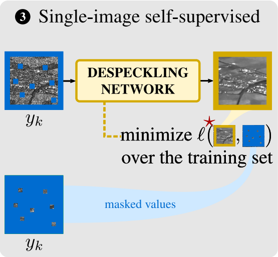
Single-look Sentinel-1 image



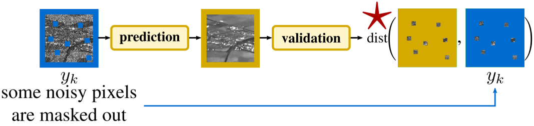
Restored image (SARCNN)

Restored image (SAR2SAR)

Self-supervised with a single image

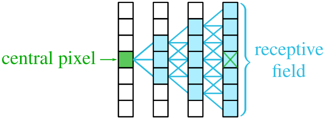


Main idea: train by cross-validation

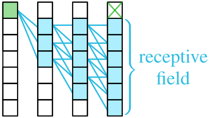


Improvement 1: alternately mask out each pixel ⇝ dense validation

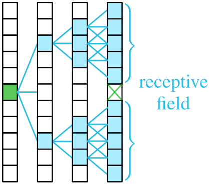
build network architecture to exclude the central pixel
from the receptive field



with conventional convolutions
the central pixel is at the center of
the receptive field



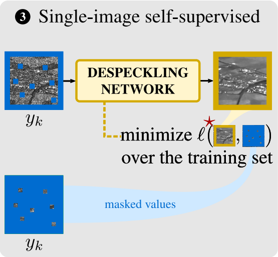
by shifting the convolution kernels
the central pixel is next to the
receptive field



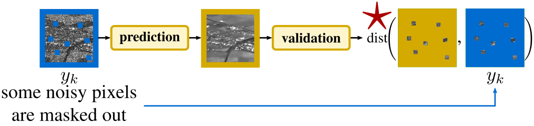
combining dilated convolutions
and conventional convolutions
can also exclude the central pixel

Laine et al. “High-Quality Self-Supervised Deep Image Denoising”, NeurIPS 2019.
Molini et al. “Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks”, IEEE TGRS 2021

Self-supervised with a single image



Main idea: train by cross-validation

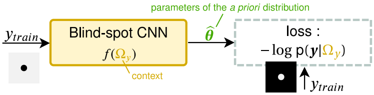


Improvement 2: include the noisy measurement at the central pixel in the final estimation:

$\rightsquigarrow$ Bayesian framework

network training:

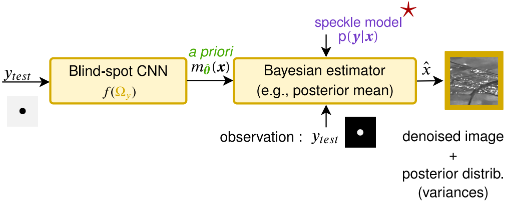
applying the network to denoise an image:



training : maximize the conditional likelihood

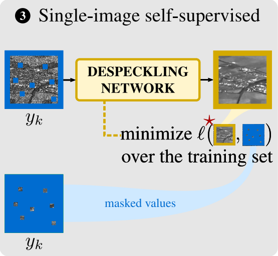
$$p(\boldsymbol{y}|\Omega_y) = \int \underbrace{p(\boldsymbol{y}|\Omega_y, \boldsymbol{x})}_{\text{likelihood (speckle model)}} \underbrace{p(\boldsymbol{x}|\Omega_y)}_{m_{\boldsymbol{\theta}}(\boldsymbol{x})} \, d\boldsymbol{x}$$

a priori distribution (conjugate prior)

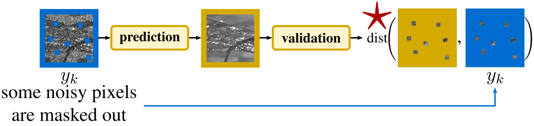


Laine et al. “High-Quality Self-Supervised Deep Image Denoising”, NeurIPS 2019.
Molini et al. “Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks”, IEEE TGRS 2021

Self-supervised with a single image



Main idea: train by cross-validation



Improvement 2: include the noisy measurement at the central pixel in the final estimation:

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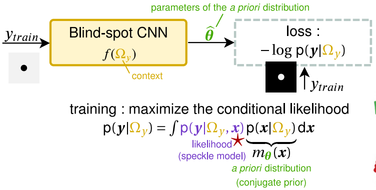
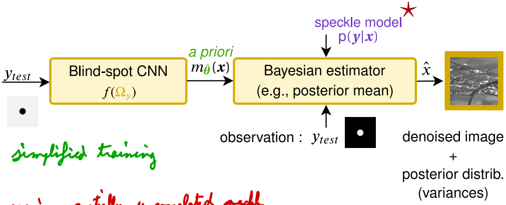




simplified training

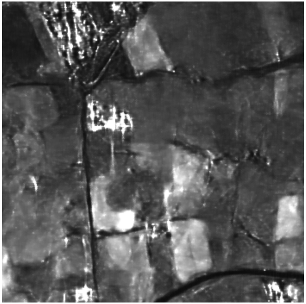
requires spatially uncorrelated speckle

Laine et al. “High-Quality Self-Supervised Deep Image Denoising”, NeurIPS 2019.
Molini et al. “Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks”, IEEE TGRS 2021

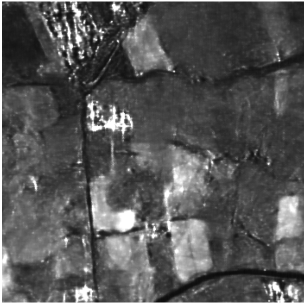
Self-supervised with a single image

Restoration results with Speckle2Void: TerraSAR-X image (©DLR, image pre-processed)

Single-look TerraSAR-X image



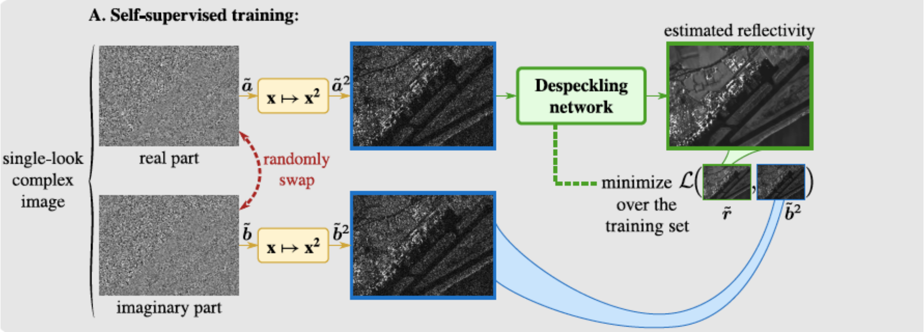
Speckle2Void



Speckle2Void-NL

(source: results provided by the Authors at `https://diegovalsesia.github.io/speckle2void`)

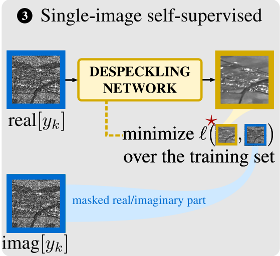
Self-supervised with a single image: real-/imaginary-part decomposition



$$
\begin{aligned}
\mathsf{p}_Z(z) = \mathsf{p}_Z(a+jb) &= \frac{1}{\pi r}\exp(-(a^2+b^2)/r) \\
&= \underbrace{\frac{1}{\sqrt{2\pi}\sqrt{r/2}}\exp(-a^2/r)}_{\mathcal{N}(0,r/2)}\underbrace{\frac{1}{\sqrt{2\pi}\sqrt{r/2}}\exp(-b^2/r)}_{\mathcal{N}(0,r/2)}\,,
\end{aligned} \tag{1}
$$

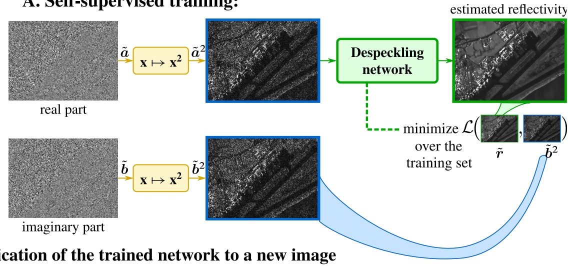
$$
\mathcal{L}(\tilde{\boldsymbol{r}},\tilde{\boldsymbol{b}}) = \sum_k \frac{1}{2}\log(\tilde{r}_k) + \frac{\tilde{b}_k^2}{\tilde{r}_k}\,, \tag{2}
$$

Self-supervised with a single image: real-/imaginary-part decomposition

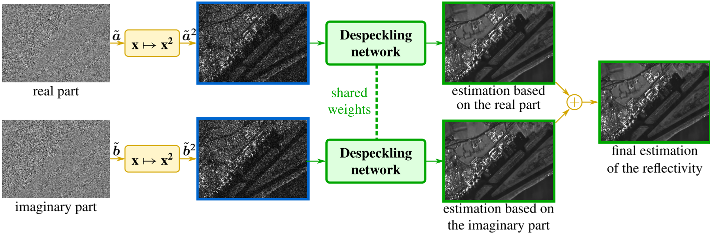


Main idea: speckle in the real and imaginary parts is independent

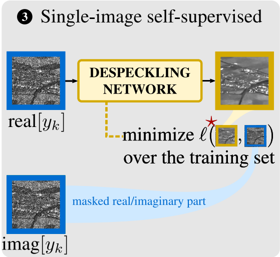
A. Self-supervised training:



B. Testing: application of the trained network to a new image

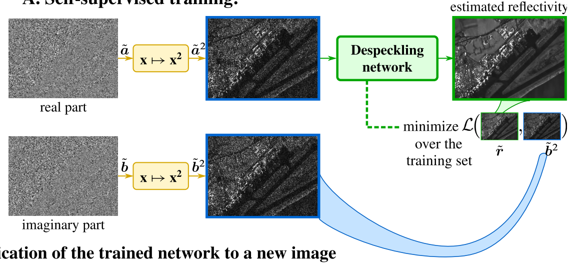


Dalsasso et al. “As if by magic: self-supervised training of deep despeckling networks with MERLIN”, to appear in IEEE Trans Geosc. Remote Sens.



Main idea: speckle in the real and imaginary parts is independent

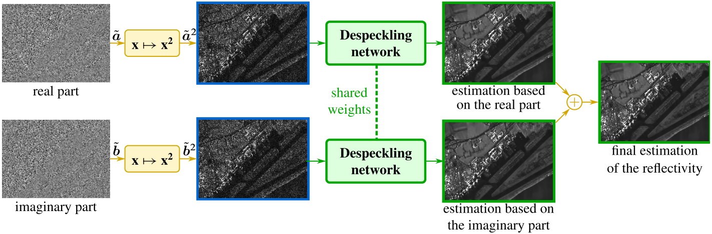
A. Self-supervised training:



- building the training set is inexpensive
- handles images with spatially correlated speckle
- very good performance

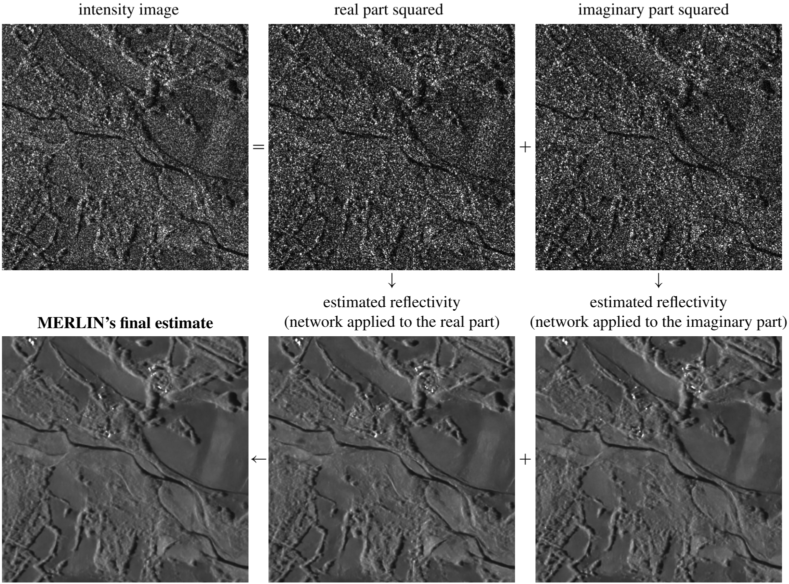
- the real/imaginary parts have a lower SNR than the original image
- requires special care (pre-processing step) for some imaging modalities (e.g., SPOTLIGHT, TOPS)

B. Testing: application of the trained network to a new image



Dalsasso et al. “As if by magic: self-supervised training of deep despeckling networks with MERLIN”, to appear in IEEE Trans Geosc. Remote Sens.

Self-supervised with a single image: MERLIN (TerraSAR-X image ©DLR)



Other considerations when designing a deep network for despeckling:

Network architecture

- deep convolutional (DnCNN [Zhang 17, Chierchia 17,])
- U-Net ([Ronneberger 15])
- non-local ([Cozzolino 19, 20], [Denis 19], [Molini 21])

Loss function

- $\ell_2, \ell_1, \|\nabla \boldsymbol{x} - \nabla \boldsymbol{x}^{\text{true}}\|_2^2$, total variation
- perceptual loss
- neg-log-likelihood, Kullback-Leibler [Vitale 21]
- GAN [Wang 17]

Robustness to speckle correlations

- several methods assume a spatially decorrelated speckle:
  – (blind) speckle decorrelation by inversion of the SAR transfer function
  – downsampling
  it is essential for these methods that images be pre-processed
- other methods are robust to speckle correlations (e.g. trained on correlated speckle) [Cherchia 17, Dalsasso 21]

Handling the high dynamic range

- log-scale [Chierchia 17]
- image normalization
- clipping [Molini 21]

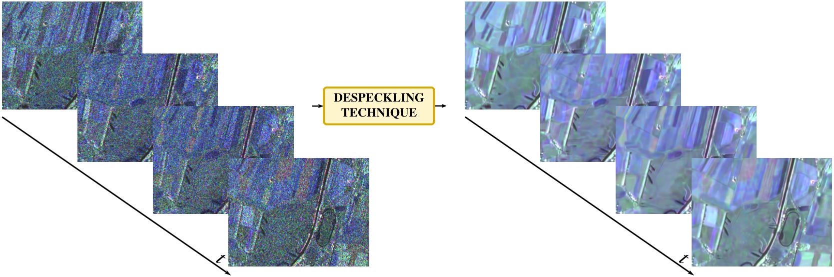
Handling complex-valued information

- extraction of real/imaginary parts [Sica 20]
- matrix log [Deledalle 17, Mullissa 20-21]

Outline

Conclusion

- Speckle reduction in SAR imaging is a well-studied topic
- It is still a very active research topic:
  – deep neural network approaches
  – self-supervised training
  – multi-channel despeckling (interferometry, polarimetry)
  – multi-temporal processing



RadarSat-2 images ©Canadian Space Agency

- there are many resources available (codes)
  <!> check input type ($\sqrt{I}$, I or complex amplitude)
- spatial correlations of the speckle field is an issue for many algorithms

Further reading

Recent review papers on the topic:

Detailed presentation of Bayesian and wavelets techniques:

[Argenti *et al.* 2013] F. Argenti, A. Lapini, T. Bianchi, & L. Alparone
A tutorial on speckle reduction in synthetic aperture radar images,
IEEE Geoscience and remote sensing magazine, 2013

Detailed presentation of patch-based approaches:

[Deledalle *et al.* 2014] C. Deledalle, L. Denis, G. Poggi, F. Tupin, & L. Verdoliva
Exploiting patch similarity for SAR image processing,
IEEE Signal Processing Magazine, 2014

Deep learning techniques:

[Zhu *et al.* 2021] X. Zhu, S. Montazeri, M. Ali, Y. Hua, Y. Wang, L. Mou, Y. Shi, F. Xu, & R. Bamler
Deep Learning Meets SAR: Concepts, Models, Pitfalls, and Perspectives,
IEEE Geoscience and Remote Sensing Magazine

[Fracastoro *et al.* 2020] G. Fracastoro, E. Magli, G. Poggi, G. Scarpa, D. Valsesia, & L. Verdoliva
Deep learning methods for SAR image despeckling: trends and perspectives,
ArXiV preprint

[Rasti *et al.* 2021] B. Rasti, Y. Chang, E. Dalsasso, L. Denis, & P. Ghamisi
Image Restoration for Remote Sensing: Overview and Toolbox,
to appear in IEEE Geoscience and Remote Sensing Magazine, preprint ArXiV available

Further reading

References to the methods illustrated in the presentation:

Patch-based methods:

[Deledalle *et al.* 2009] C. Deledalle, L. Denis & F. Tupin
Iterative weighted maximum likelihood denoising with probabilistic patch-based weights,
IEEE trans. on Image Processing, 2009.
code: `https://www.charles-deledalle.fr/pages/ppb.php`

[Deledalle *et al.* 2015] C. Deledalle, L. Denis, F. Tupin, MA. Reigber & M. Jäger,
NL-SAR: A unified nonlocal framework for resolution-preserving (Pol)(In) SAR denoising,
IEEE trans. on Geoscience and Remote Sensing, 2015.
code: `https://www.charles-deledalle.fr/pages/nlsar.php`

Total variation minimization:

[Bioucas-Dias *et al.* 2010] J. M. Bioucas-Dias, M. A. Figueiredo,
Multiplicative noise removal using variable splitting and constrained optimization,
IEEE trans. on Image Processing, 2010.

Plug-in ADMM:

[Deledalle *et al.* 2017] C. Deledalle, L. Denis, S. Tabti & F. Tupin
MuLoG, or how to apply Gaussian denoisers to multi-channel SAR speckle reduction?,
IEEE trans. on Image Processing, 2017.
code: `https://www.charles-deledalle.fr/pages/mulog.php`

Further reading

References to the methods illustrated in the presentation (continued):

Deep learning techniques:

[Dalsasso *et al.* 2020] E. Dalsasso, L. Denis & F. Tupin
SAR Image Despeckling by Deep Neural Networks: from a pre-trained model to an end-to-end training strategy,
Remote Sensing, 2020.
code: `https://gitlab.telecom-paris.fr/ring/SAR-CNN`

[Dalsasso *et al.* 2021a] E. Dalsasso, L. Denis & F. Tupin
SAR2SAR: A Semi-Supervised Despeckling Algorithm for SAR Images,
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020.
code: `https://gitlab.telecom-paris.fr/ring/sar2sar`

[Molini *et al.* 2021] A. Molini, D. Valsesia, G. Fracastoro, & E. Magli
Speckle2Void: Deep Self-Supervised SAR Despeckling with Blind-Spot Convolutional Neural Networks,
IEEE trans. on Geoscience and Remote Sensing, 2021.
code: `https://github.com/diegovalsesia/speckle2void`

[Dalsasso *et al.* 2021b] E. Dalsasso, L. Denis & F. Tupin
As if by magic: self-supervised training of deep despeckling networks with MERLIN,
IEEE trans. on Geoscience and Remote Sensing, to appear.
code: `https://gitlab.telecom-paris.fr/ring/MERLIN`

Acknowledgments

Fundings:

https://perso.telecom-paristech.fr/tupin/radarteam/staffEN.php
https://gitlab.telecom-paris.fr/ring/
https://alys.wp.imt.fr