Workshop BxDiff & GDR Appamat – *High-precision BRDF Measurement*

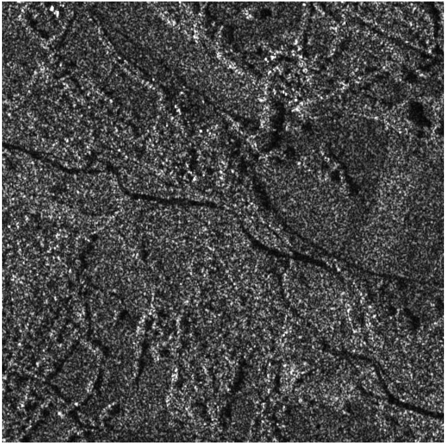
Removing speckle while maintaining resolution: methods in synthetic aperture radar imaging

Loïc Denis, Emanuele Dalsasso & Florence Tupin

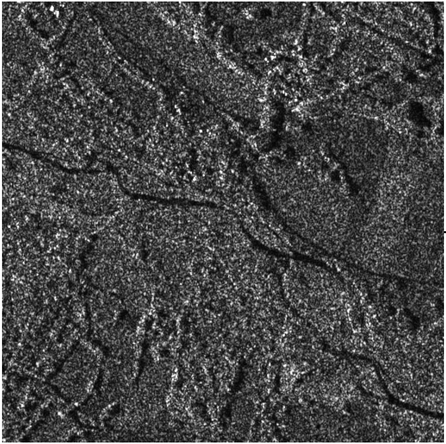
Université de Saint-Etienne, France

Institut Polytechnique de Paris, France

Institut d'Optique Graduate School, December 10, 2021



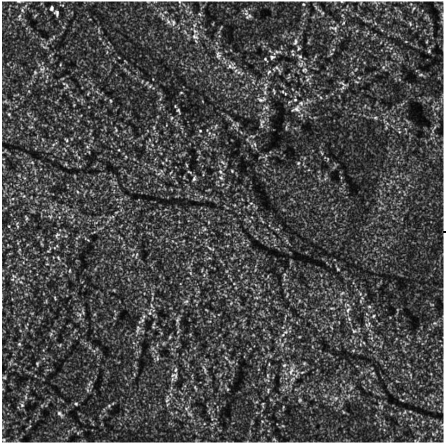
Synthetic aperture radar image
TerraSAR-X stripmap
X-band satellite
(altitude 514km, freq: 9.65GHz)
(spatial resolution: 3m)



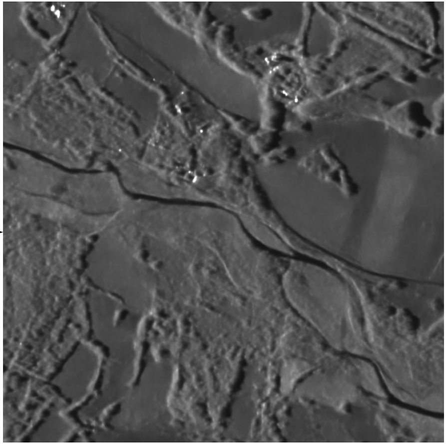
Synthetic aperture radar image
TerraSAR-X stripmap
X-band satellite
(altitude 514km, freq: 9.65GHz)
(spatial resolution: 3m)

?

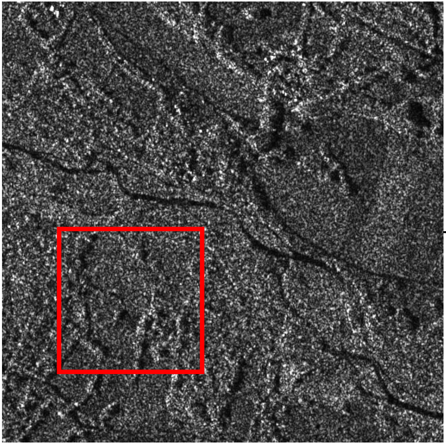
Restored image with a
speckle-reduction algorithm



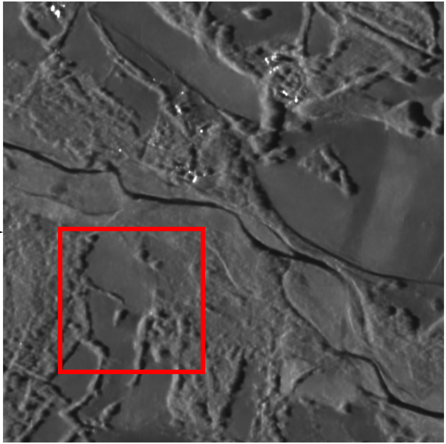
Synthetic aperture radar image
TerraSAR-X stripmap
X-band satellite
(altitude 514km, freq: 9.65GHz)
(spatial resolution: 3m)



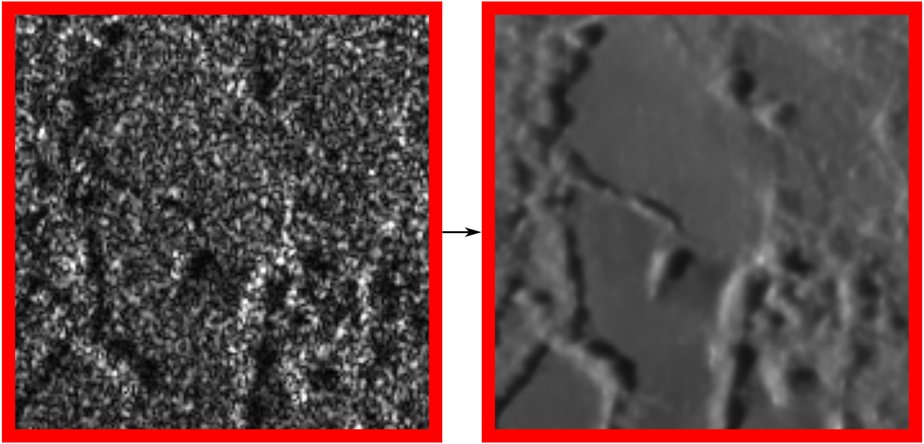
Restored image with a
speckle-reduction algorithm
MERLIN [Dalsasso, Denis, Tupin 2021]



Synthetic aperture radar image
TerraSAR-X stripmap
X-band satellite
(altitude 514km, freq: 9.65GHz)
(spatial resolution: 3m)



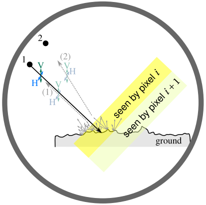
Restored image with a
speckle-reduction algorithm
MERLIN [Dalsasso, Denis, Tupin 2021]



Synthetic aperture radar image
TerraSAR-X stripmap
X-band satellite
(altitude 514km, freq: 9.65GHz)
(spatial resolution: 3m)

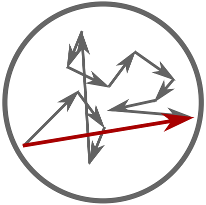
Restored image with a
speckle-reduction algorithm
MERLIN [Dalsasso, Denis, Tupin 2021]

Structure of the presentation



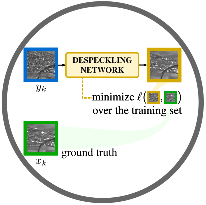
1. Principles of SAR imaging

– acquisition geometry
– applications of SAR imaging
– particularity of SAR data



2. Speckle in SAR images

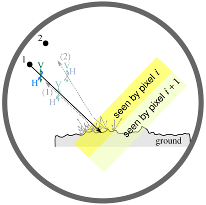
– fully-developed speckle model (Goodman)
– limits of the fully-developed speckle model



3. Speckle reduction techniques: an overview of 40+ years of research

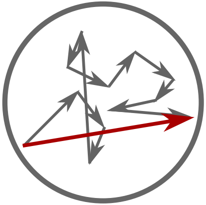
– spatial multi-looking
– patch-based despeckling
– variational approaches
– deep neural networks

Structure of the presentation



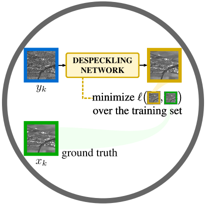
1. Principles of SAR imaging

– acquisition geometry
– applications of SAR imaging
– particularity of SAR data



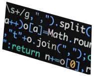
2. Speckle in SAR images

– fully-developed speckle model (Goodman)
– limits of the fully-developed speckle model



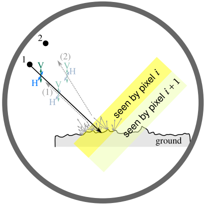
3. Speckle reduction techniques: an overview of 40+ years of research

– spatial multi-looking
– patch-based despeckling
– variational approaches
– deep neural networks

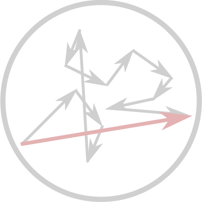


code available!

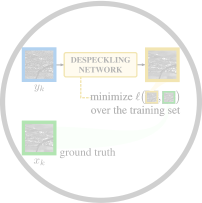
Structure of the presentation



1. Principles of SAR imaging
- acquisition geometry
- applications of SAR imaging
- particularity of SAR data

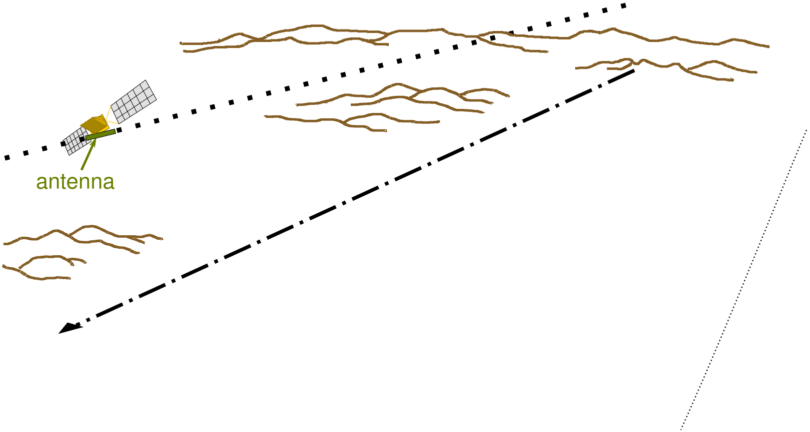


2. Speckle in SAR images
- fully-developed speckle model (Goodman)
- limits of the fully-developed speckle model



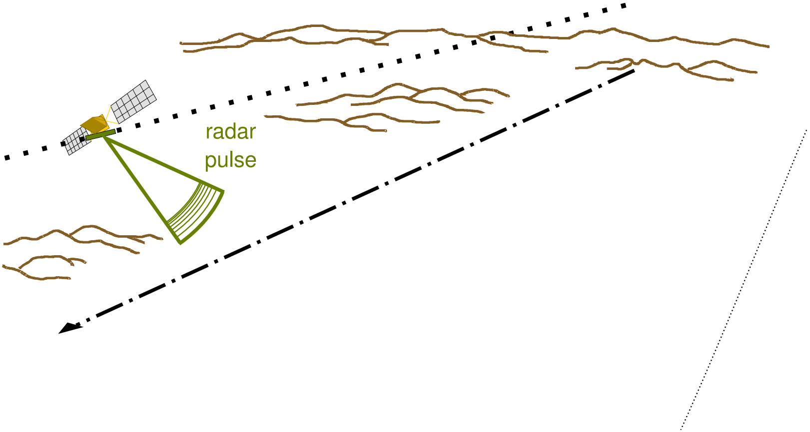
3. Speckle reduction techniques: an overview of 40+ years of research
- spatial multi-looking
- patch-based despeckling
- variational approaches
- deep neural networks

1. Principles of SAR imaging



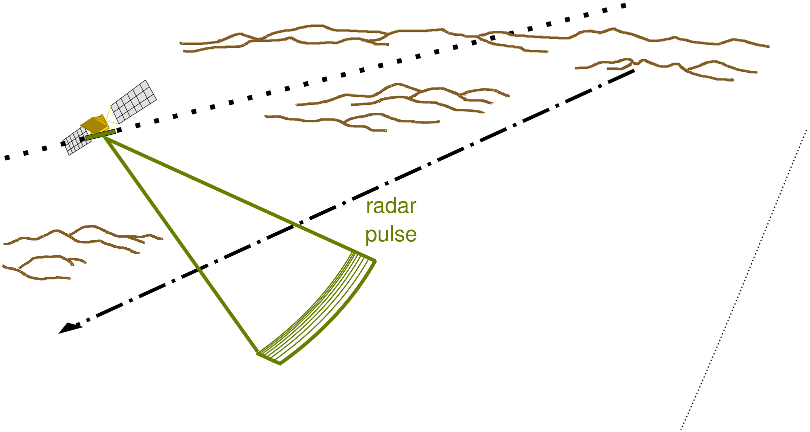
SAR imaging is an active imaging technique. . .

1. Principles of SAR imaging



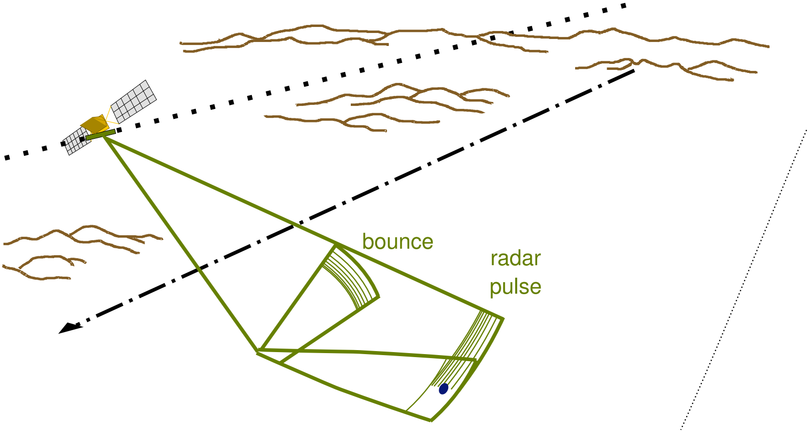
. . . based on the emission of an electromagnetic wave (typ. 10GHz).

1. Principles of SAR imaging

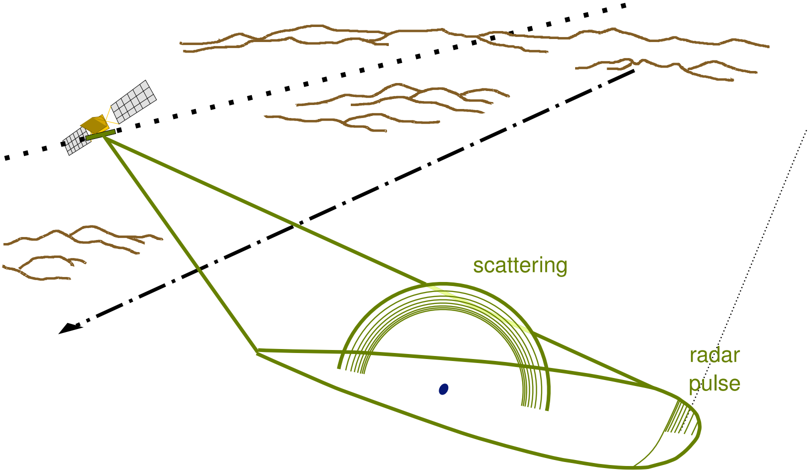


. . . based on the emission of an electromagnetic wave (typ. 10GHz).

1. Principles of SAR imaging

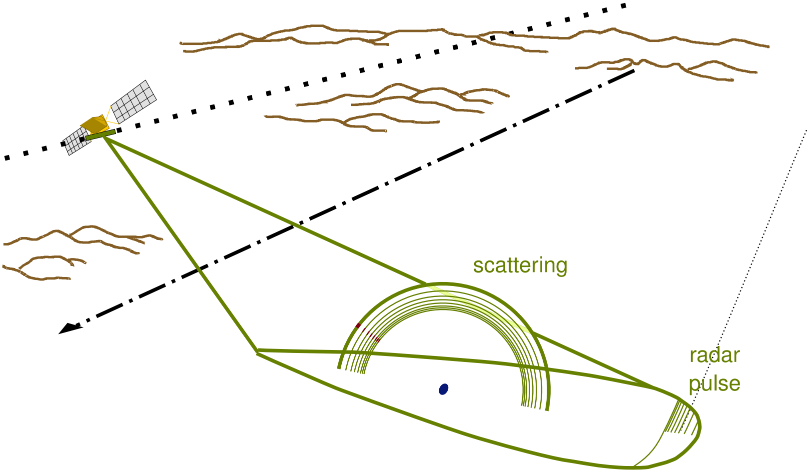


Depending on the scene geometry, the radar pulse is reflected. . .



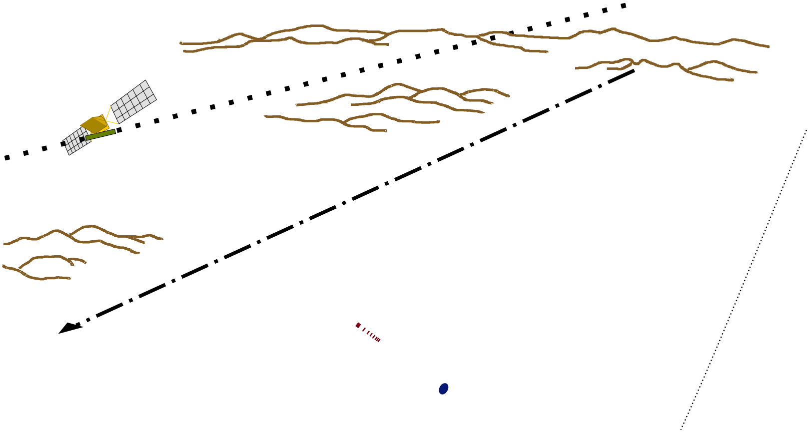
. . . or scattered. . .

1. Principles of SAR imaging

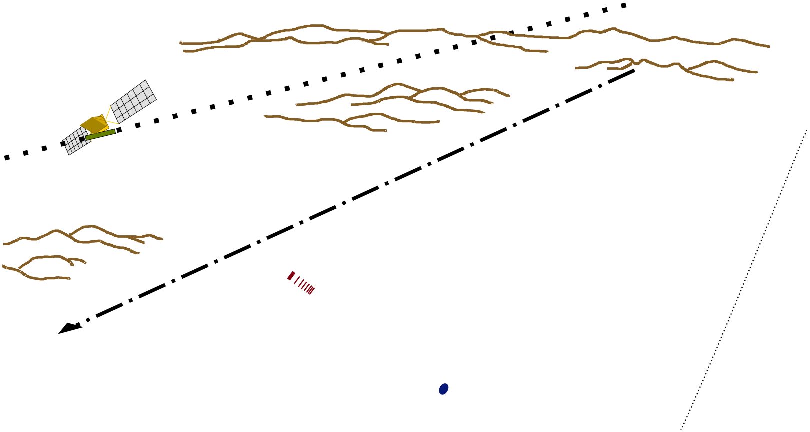


. . . and part of the incident energy is sent back to the antenna.

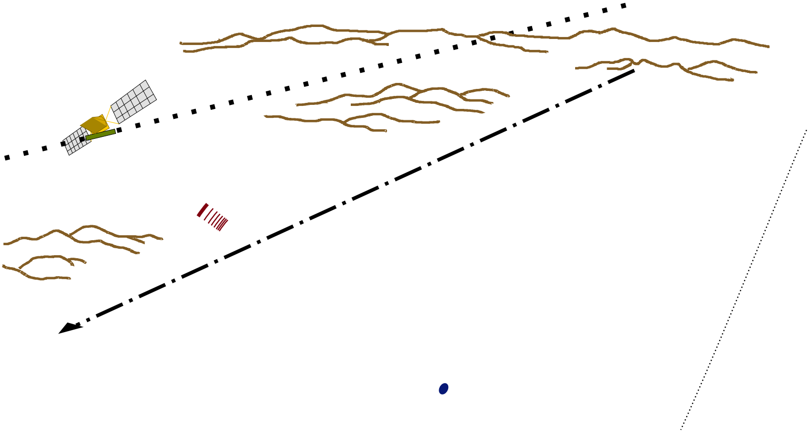
1. Principles of SAR imaging



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

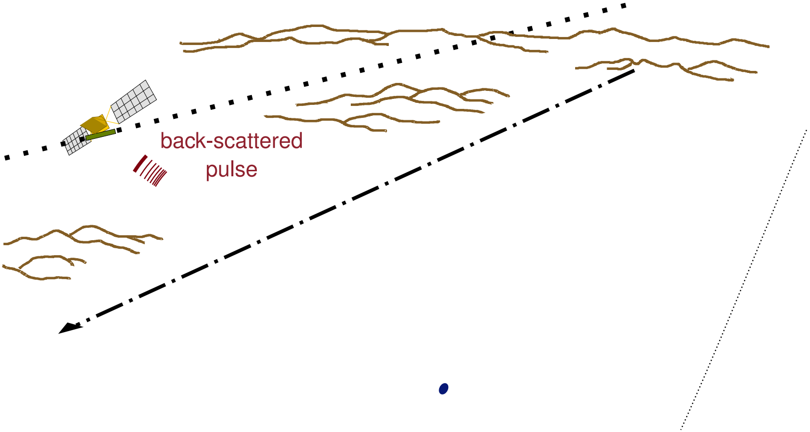


. . . and part of the incident energy is sent back to the antenna.



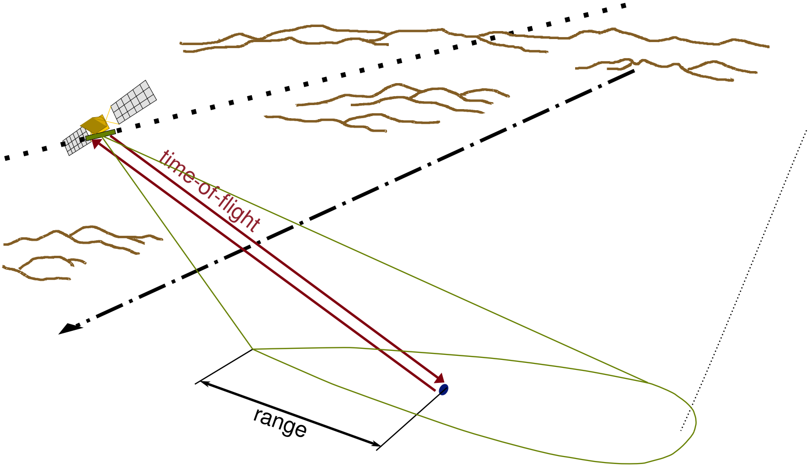
...and part of the incident energy is sent back to the antenna.

1. Principles of SAR imaging



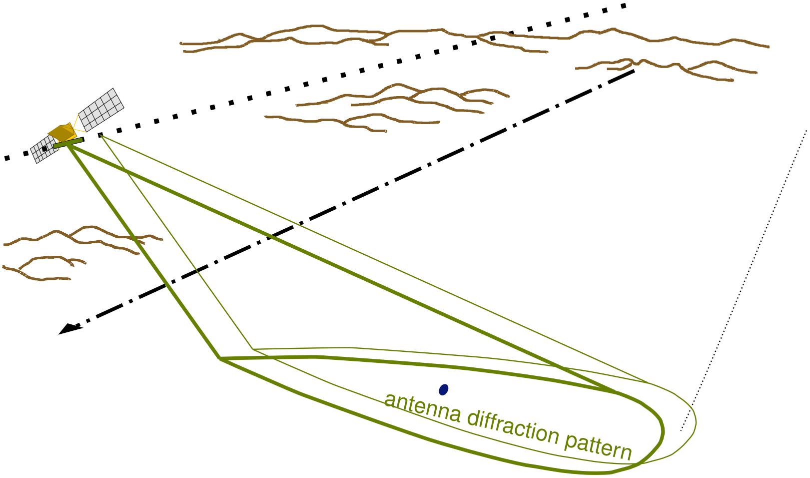
…and part of the incident energy is sent back to the antenna.

1. Principles of SAR imaging

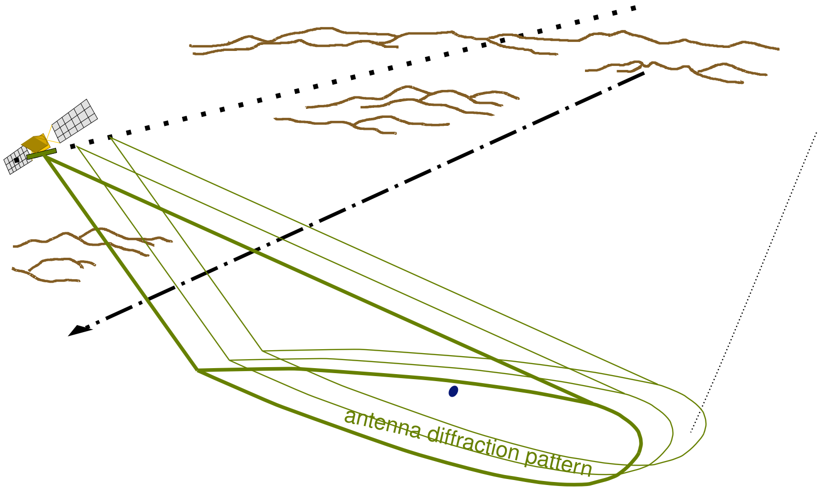


The location on the ground of the scatterer is deduced from the time-of-flight.

1. Principles of SAR imaging

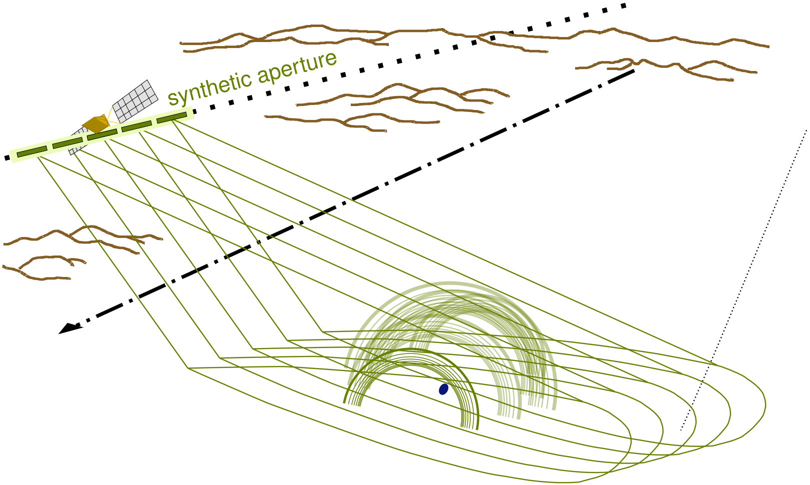


As the satellite moves, the antenna diffraction pattern covers another area. . .

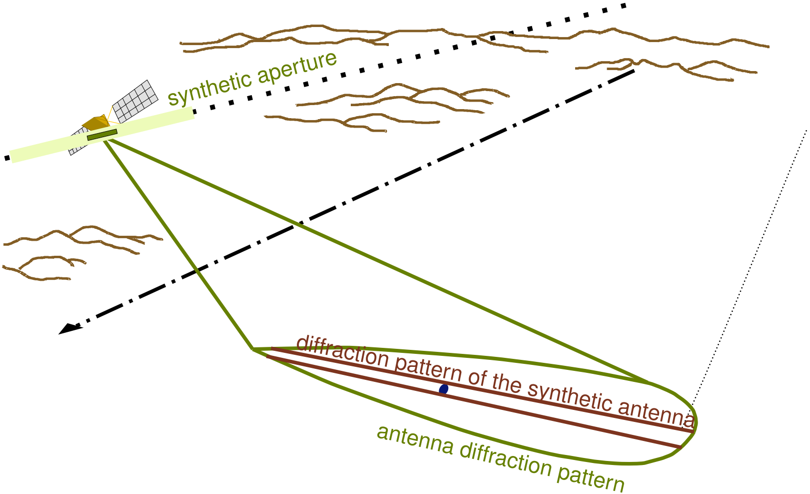


. . . thereby forming a 2D image.

1. Principles of SAR imaging

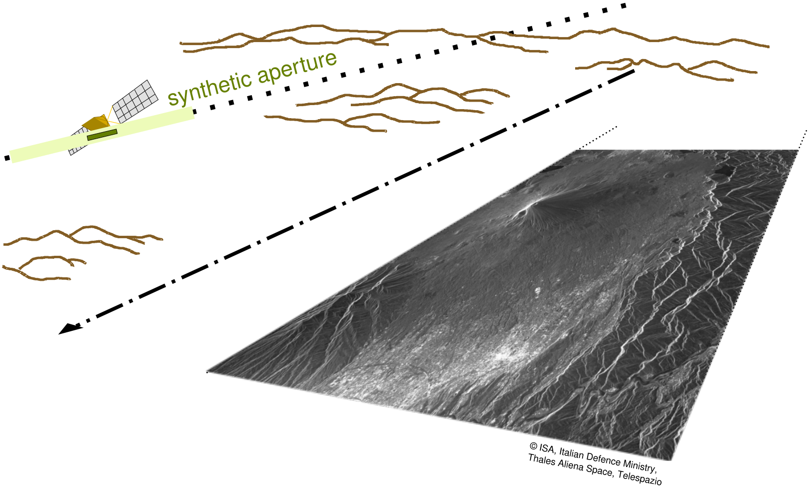


Aperture synthesis consists of numerically combining the echoes. . .

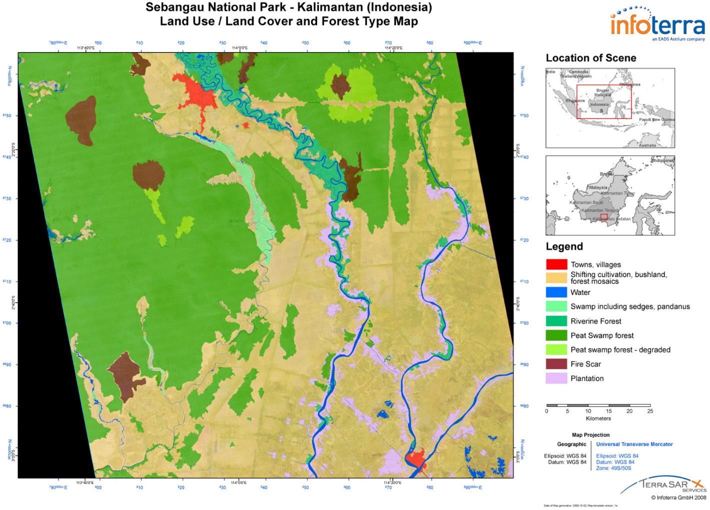


. . . which greatly improves the resolution.

1. Principles of SAR imaging

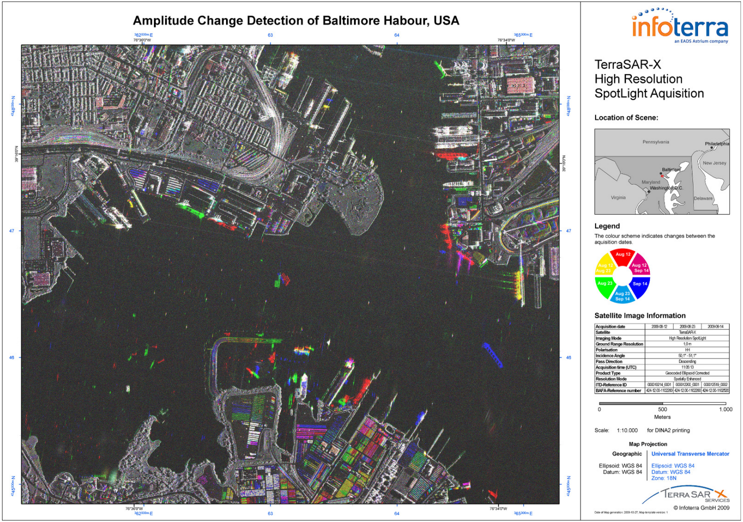


Examples of applications: Study of forested areas

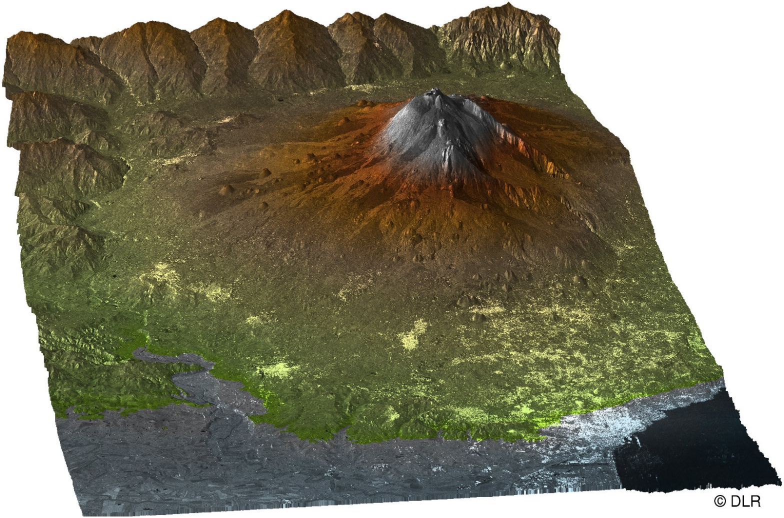


1. Principles of SAR imaging

Examples of applications: Change detection

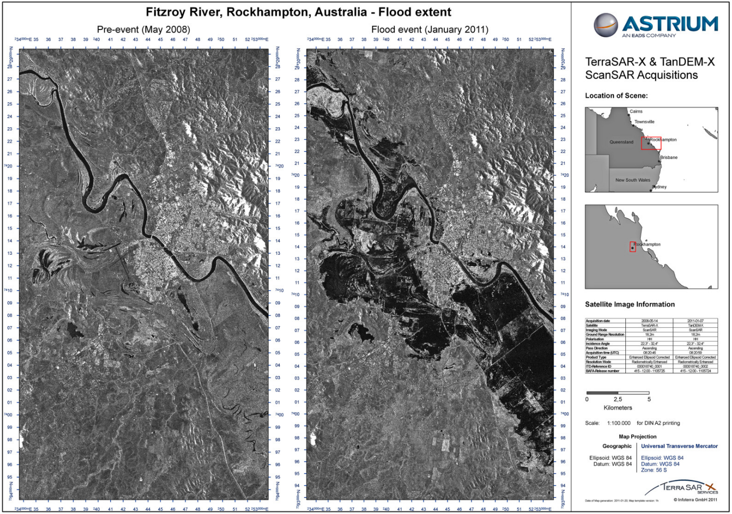


Examples of applications: Digital elevation model



© DLR

Examples of applications: Crisis management (eg: floods)



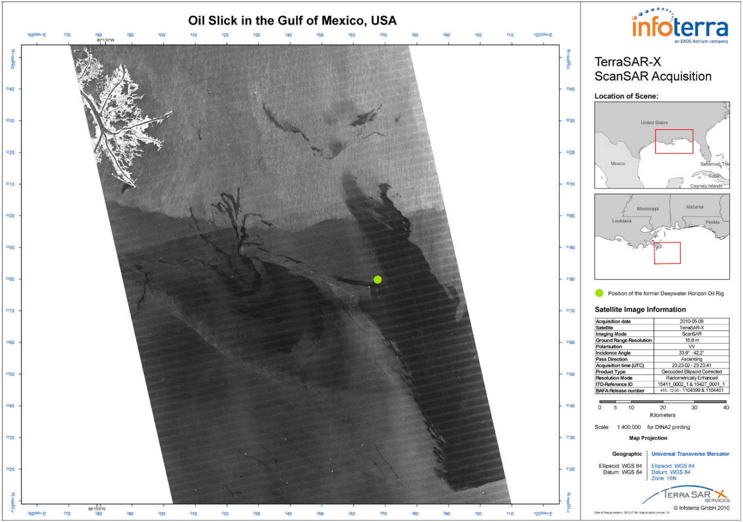
Examples of applications: Crisis management (eg: Tsunami in Japan)

Change detection between two TerraSAR-X images acquired before (20/10/2010) and after (12/03/2011) the tsunami.

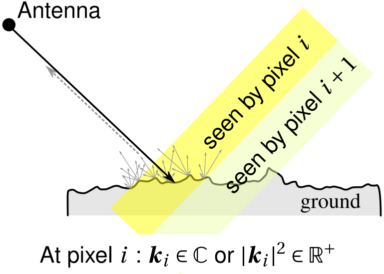
Higashi Airport – Matsushima

Bleu: flooded area
Cyan: damaged building
Magenta: debris

Examples of applications: Pollution monitoring



Particularity of radar images:
The complex amplitude of the field is measured at each pixel.



At pixel i : $\boldsymbol{k}_i \in \mathbb{C}$ or $|\boldsymbol{k}_i|^2 \in \mathbb{R}^+$

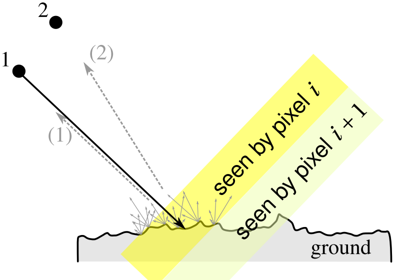
Intensity data:

intensity

airborne SAR images ©ONERA

1. Principles of SAR imaging

Particularity of radar images:
The complex amplitude of the field is measured at each pixel.



At pixel i : $\boldsymbol{k}_i \in \mathbb{C}^2$

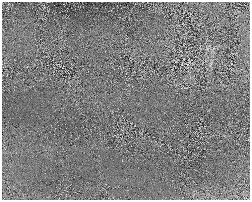
Radar reflectivity : $\langle |[\boldsymbol{k}_i]_1|^2 \rangle \approx \langle |[\boldsymbol{k}_i]_2|^2 \rangle$

Interferometric phase : $\arg\left(\langle [\boldsymbol{k}_i]_1 [\boldsymbol{k}_i]_2^* \rangle\right)$

Coherence : $\dfrac{\left|\langle [\boldsymbol{k}_i]_1 [\boldsymbol{k}_i]_2^* \rangle\right|}{\sqrt{\langle [\boldsymbol{k}_i]_1^2 \rangle \langle [\boldsymbol{k}_i]_2^2 \rangle}}$

Interferometric data:

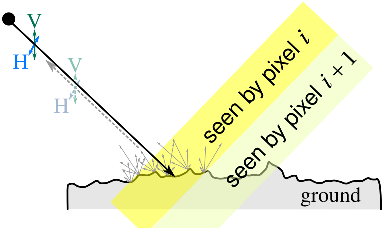

intensity


interferometric phase


coherence

airborne SAR images ©ONERA

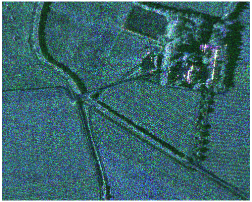
Particularity of radar images:
The complex amplitude of the field is measured at each pixel.



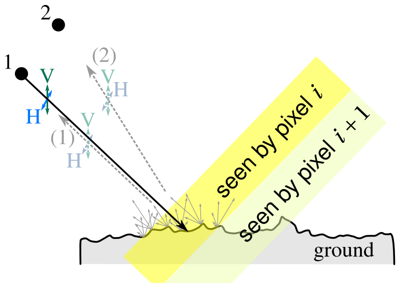
At pixel i : $\boldsymbol{k}_i \in \mathbb{C}^3$
Polarimetric covariance : $\langle \boldsymbol{k}_i \boldsymbol{k}_i^{\mathsf{H}} \rangle$

Polarimetric data:


intensity

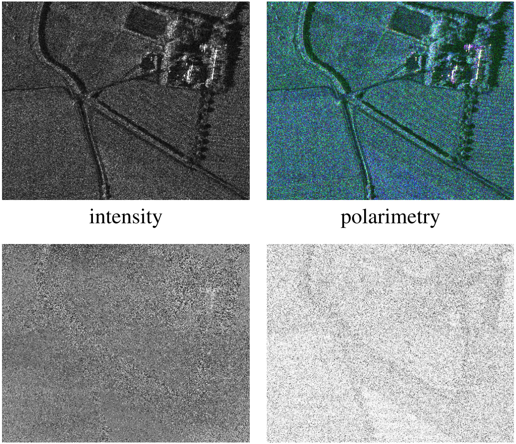

polarimetry

Particularity of radar images:
The complex amplitude of the field is measured at each pixel.



At pixel i : $\boldsymbol{k}_i \in \mathbb{C}^6$

Polarimetric and interferometric data:



intensity

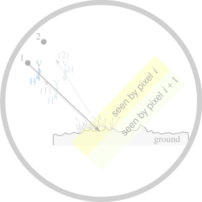
polarimetry

interferometric phase

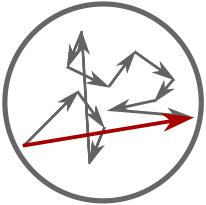
coherence

airborne SAR images ©ONERA

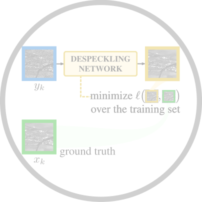
Structure of the presentation



1. Principles of SAR imaging
- acquisition geometry
- applications of SAR imaging
- particularity of SAR data



2. Speckle in SAR images
- fully-developed speckle model (Goodman)
- limits of the fully-developed speckle model



3. Speckle reduction techniques: an overview of 40+ years of research
- spatial multi-looking
- patch-based despeckling
- variational approaches
- deep neural networks

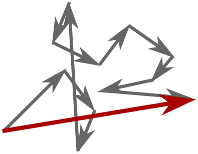
Fully-developed speckle model [Goodman 1963]

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



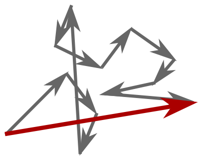
Fully-developed speckle model [Goodman 1963]

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

$\rightsquigarrow$ a random walk in the complex plane

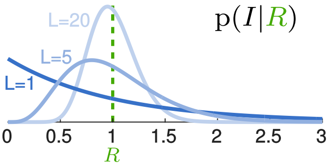
Assumption: rough & homogeneous surface

$\rightsquigarrow$ real and imaginary parts are independent Gaussians



Intensity images: multiplicative noise modeled by a gamma distribution

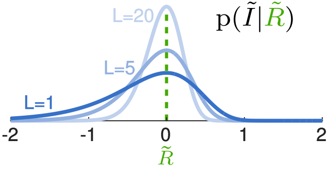
$$\mathrm{p}(I|R) = \left(\frac{L}{R}\right)^L \frac{I^{L-1}}{\Gamma(L)} \exp\left(\frac{-L\,I}{R}\right)$$



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 $\quad \tilde{R} = \log R$



2. Speckle in SAR images

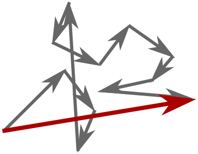
Fully-developed speckle model [Goodman 1963]

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



noisy image = noiseless image + Gaussian noise

additive Gaussian noise

vs

noisy image = noiseless image × exponential noise

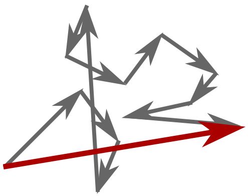
multiplicative speckle noise

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

noisy image = noiseless image + Fisher-Tippett noise

additive Fisher-Tippett noise

Fully-developed speckle model [Goodman 1963]



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

Interferometric and/or polarimetric images:

- diffusion vectors $\boldsymbol{k}$ distributed according to a complex circular Gaussian distribution

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

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

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

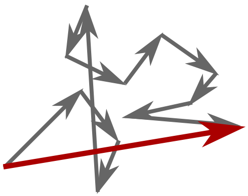
Fully-developed speckle model [Goodman 1963]

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



Interferometric and/or polarimetric images:

- diffusion vectors $\boldsymbol{k}$ distributed according to a complex circular Gaussian distribution

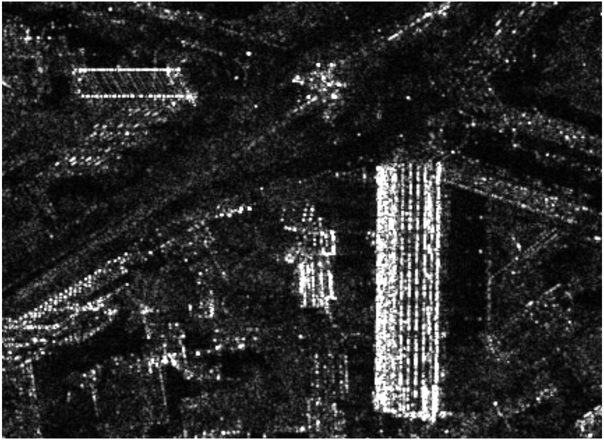
$$\mathrm{p}(\boldsymbol{k}|\boldsymbol{\Sigma}) = \frac{1}{\pi^K |\boldsymbol{\Sigma}|} \exp\big(-\boldsymbol{k}^\dagger \boldsymbol{\Sigma}^{-1} \boldsymbol{k}\big)$$

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

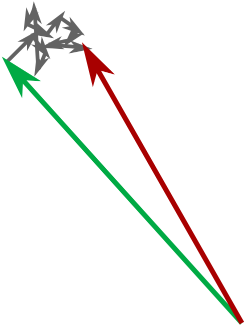
$$\mathrm{p}(\boldsymbol{C}|\boldsymbol{\Sigma}, L) = \frac{L^{LK} |\boldsymbol{C}|^{L-K}}{\Gamma_K(L) |\boldsymbol{\Sigma}|^L} \exp\big(-L\, \mathrm{Tr}(\boldsymbol{\Sigma}^{-1} \boldsymbol{C})\big)$$

Limits of Goodman's fully-developed speckle model:

Very high-resolution images & man-made structures
⇝ strong scatterer echoes dominate
the response in the resolution cell



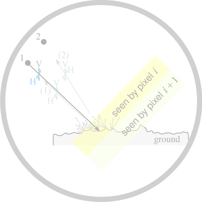
TerraSAR-X Spotlight image (Berlin, Germany) ©DLR



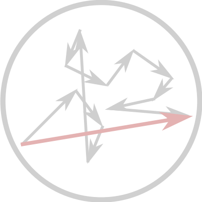
Extended speckle models exist, e.g. Rice, Fisher, or K distribution, SIRV models...

They require additional parameters to model heterogeneity
⇝ difficult to estimate at a pixel-level.

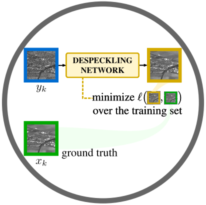
Structure of the presentation



1. Principles of SAR imaging
– acquisition geometry
– applications of SAR imaging
– particularity of SAR data

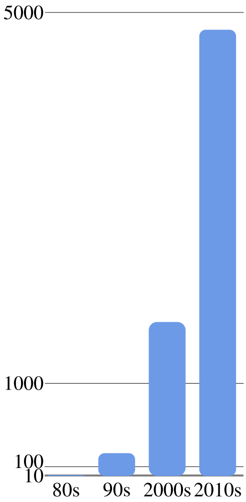


2. Speckle in SAR images
– fully-developed speckle model (Goodman)
– limits of the fully-developed speckle model



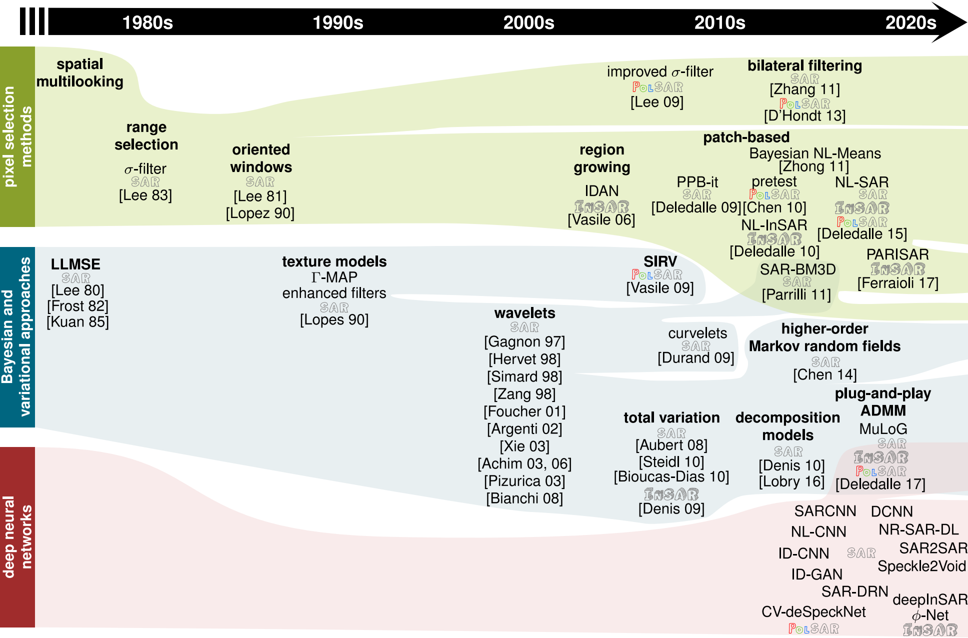
3. Speckle reduction techniques: an overview of 40+ years of research
– spatial multi-looking
– patch-based despeckling
– variational approaches
– deep neural networks

Speckle reduction is an old topic that has been intensively studied:

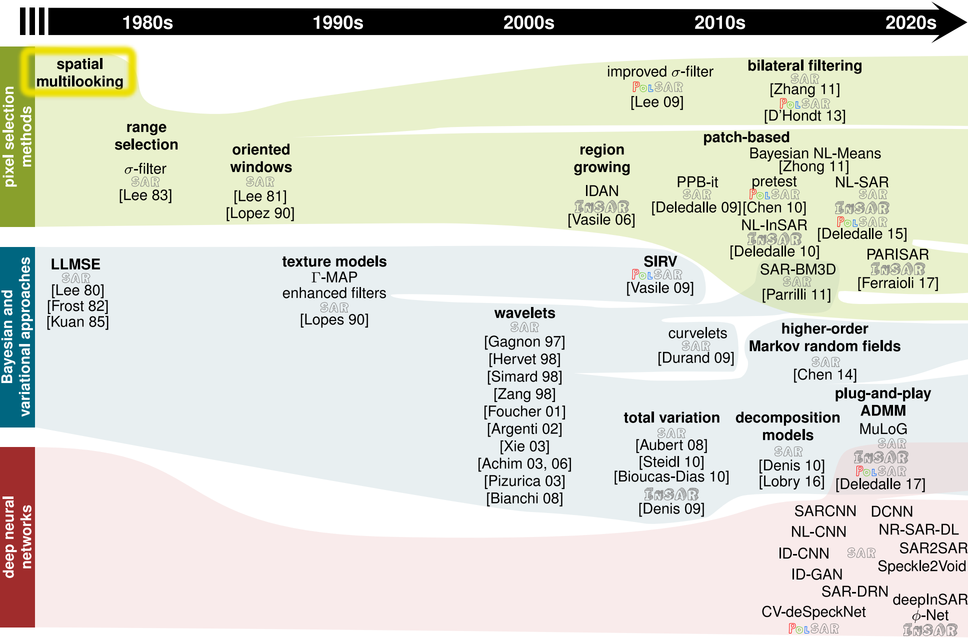


Coarse estimate of the number of papers
published on speckle reduction per decade
(based on a search on Google Scholar)

3. Speckle reduction techniques: an overview of 40+ years of research



3. Speckle reduction techniques: an overview of 40+ years of research



Spatial multi-looking

Key idea: average intensities within a small window

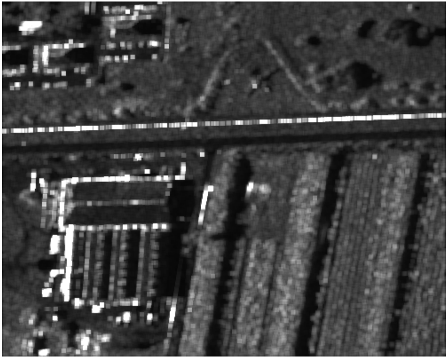
noisy ©ONERA

denoised (3×3 window)

Spatial multi-looking

Key idea: average intensities within a small window

noisy ©ONERA

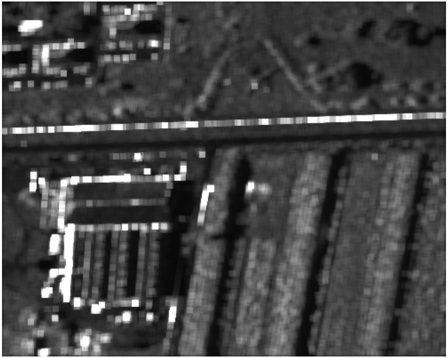


denoised (5×5 window)

Spatial multi-looking

Key idea: average intensities within a small window

noisy ©ONERA

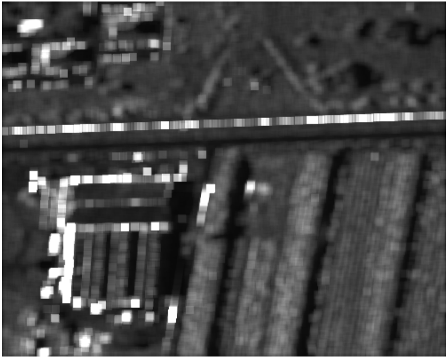


denoised (7×7 window)

Spatial multi-looking

Key idea: average intensities within a small window

noisy ©ONERA



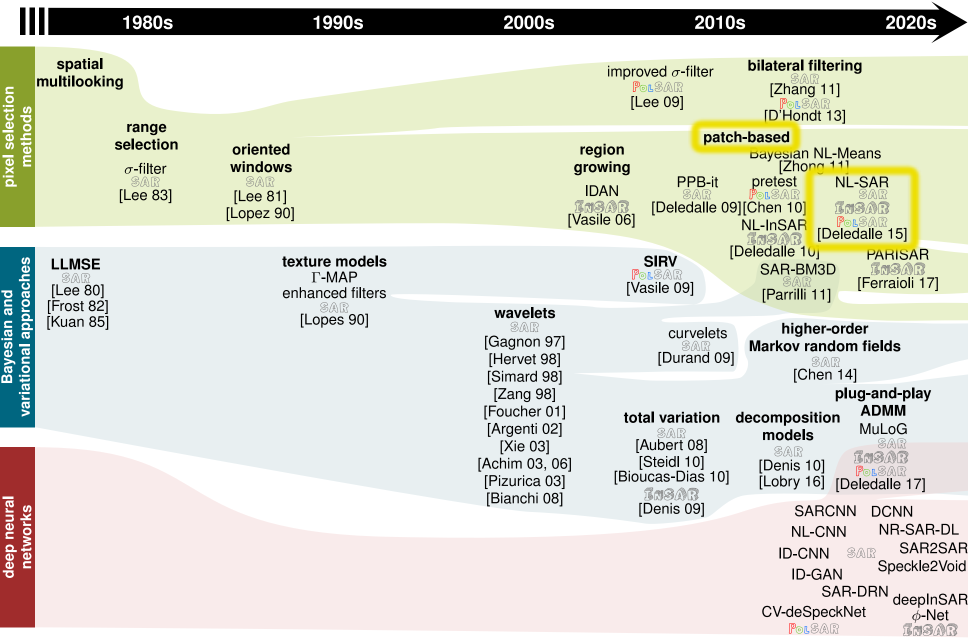
denoised (9×9 window)

simple and fast

strong resolution loss!

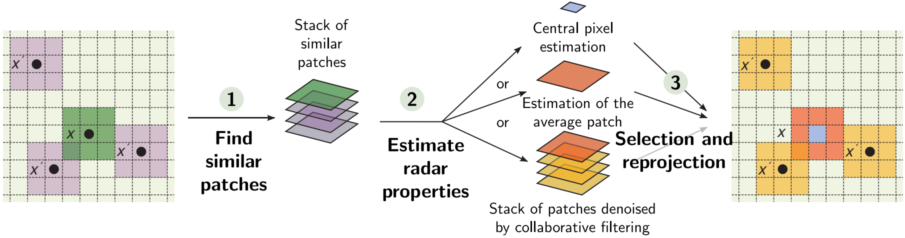
⇝ still in use in several works (e.g. forest/agriculture applications)

3. Speckle reduction techniques: an overview of 40+ years of research



Patch-based: NL-SAR [Deledalle *et al.* IEEE trans. Geosc. Rem. Sens. 2014]

Key idea: weighted average with weights derived from patch comparisons

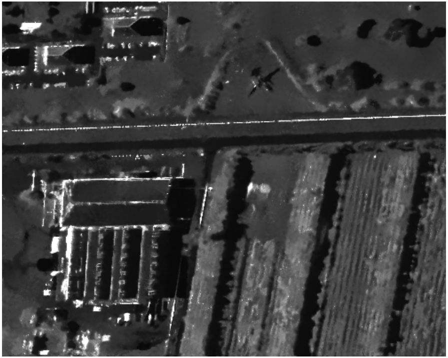


3. Speckle reduction techniques: an overview of 40+ years of research

Patch-based: NL-SAR [Deledalle *et al.* IEEE trans. Geosc. Rem. Sens. 2014]

Key idea: weighted average with weights derived from patch comparisons

noisy ©ONERA

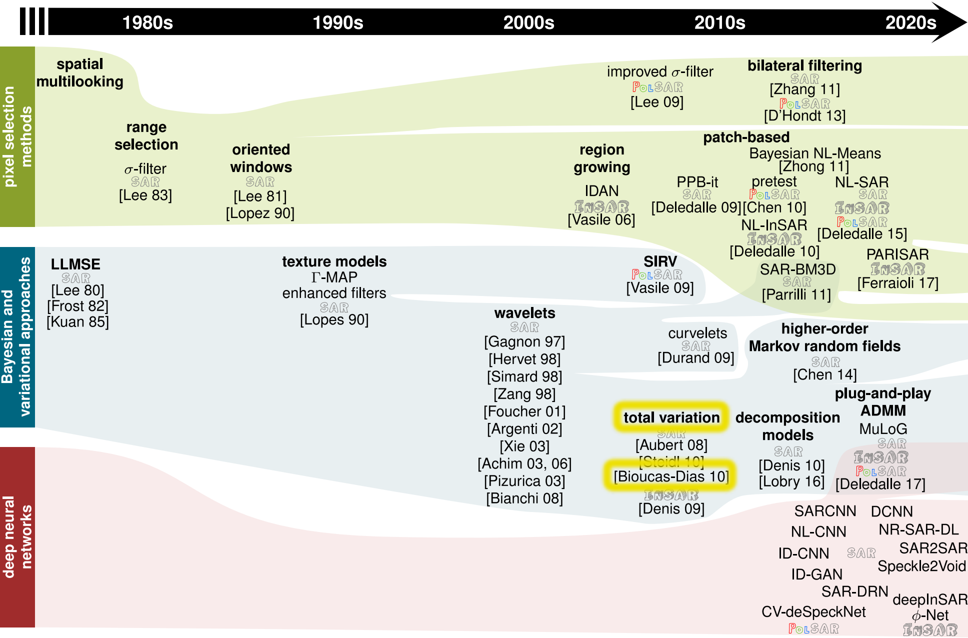


denoised (NL-SAR)

preserves the spatial resolution
also works on polarimetric/interferometric data

some residual speckle may be visible
some low-contrast textures are smoothed

3. Speckle reduction techniques: an overview of 40+ years of research



Variational: total variation minimization [Bioucas-Dias *et al.* IEEE trans. Image Proc. 2010]

Key idea: minimization of a loss function combining data-fidelity and regularity (low total-variation)

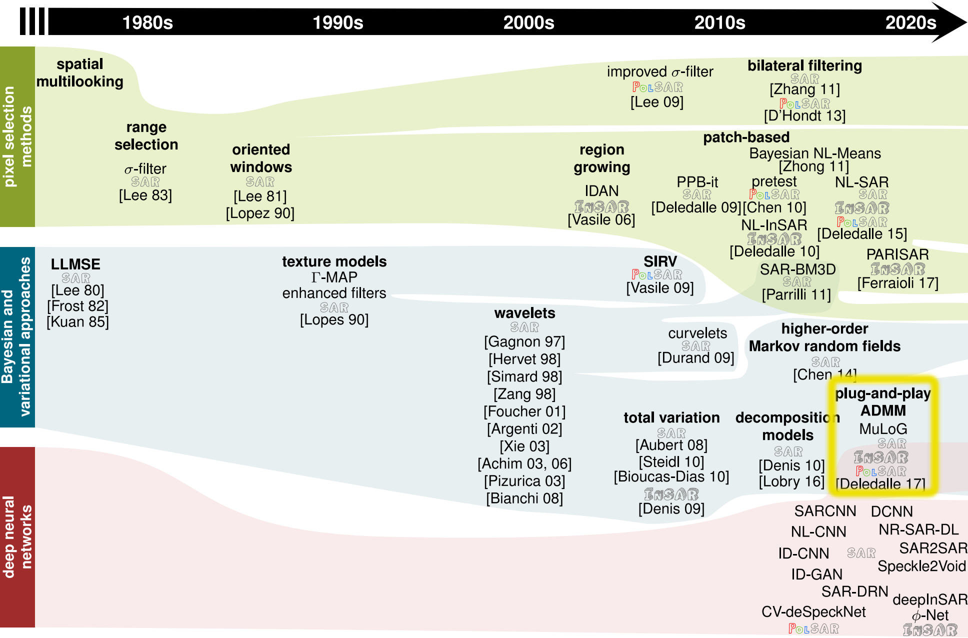
noisy ©ONERA

denoised (TV minimization)

sharp edges

restored image is piecewise constant
↳ staircase artifact in slowly varying areas

3. Speckle reduction techniques: an overview of 40+ years of research



3. Speckle reduction techniques: an overview of 40+ years of research

plug-and-play ADMM: MuLoG [Deledalle *et al.* IEEE trans. Image Proc. 2017]

Key idea: use off-the-shelf Gaussian denoisers

noisy ©ONERA

denoised (MuLoG)

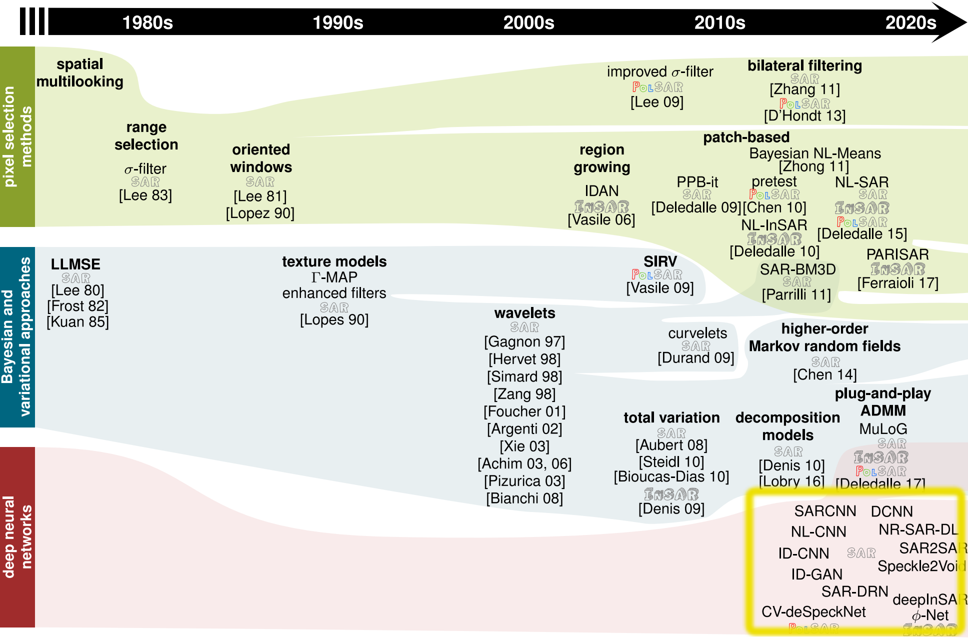
high-quality results

meta-algorithm: can be used with many different denoising algorithms

↳ results can be compared to rule out algorithm-specific artifacts

sensitive to spatial correlations in the speckle fluctuations.

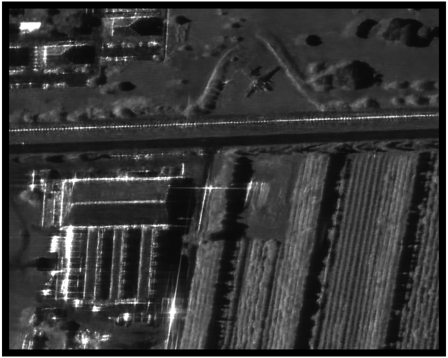
3. Speckle reduction techniques: an overview of 40+ years of research



deep learning: MERLIN [Dalsasso *et al.* IEEE trans. Geosc. Remote Sens., to appear]

Key idea: self-supervised training

noisy ©ONERA

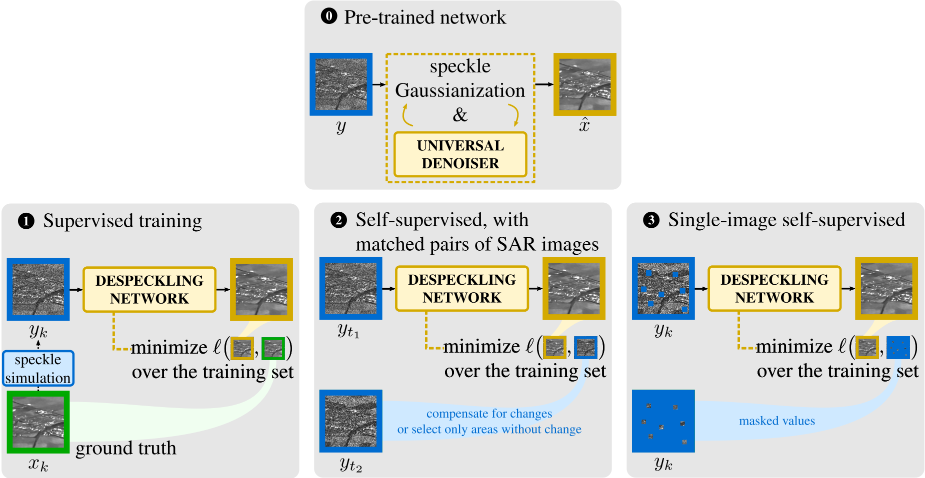


denoised (MERLIN)

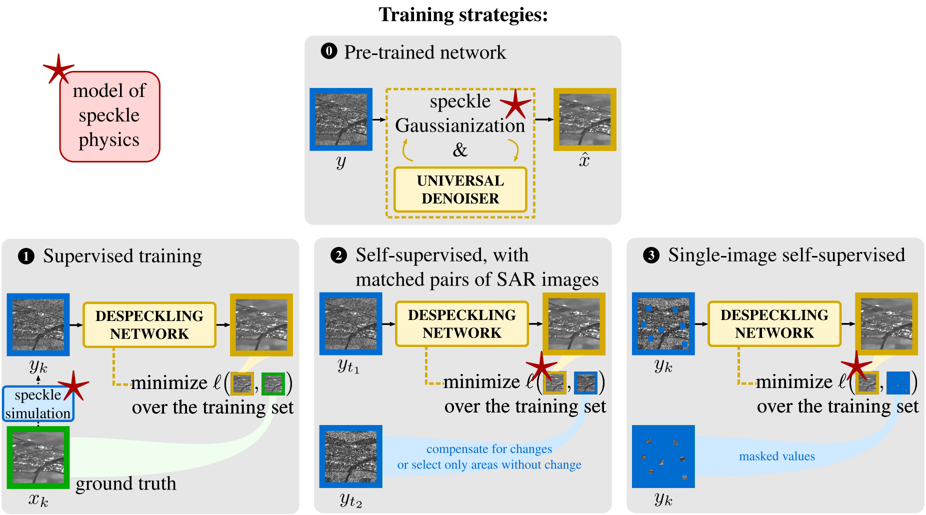
best preservation of the spatial resolution:
trained to handle spatially-correlated speckle without a whitening step.
easy to train (self-supervised)
fast

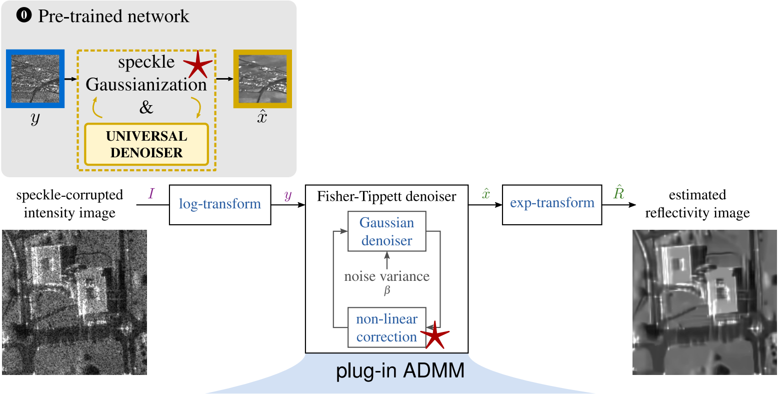
A broad overview of deep-learning strategies for despeckling

Training strategies:



A broad overview of deep-learning strategies for despeckling





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

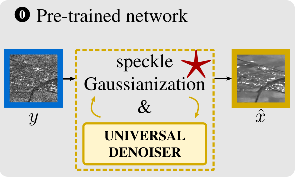
implicit regularization: CNN trained on natural images

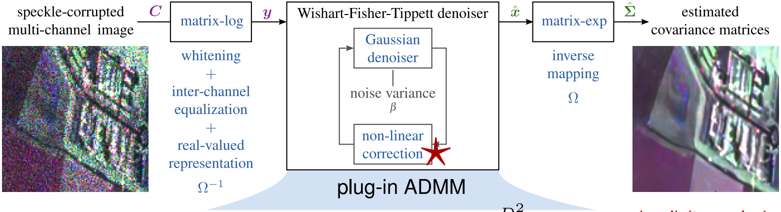
$$\hat{\boldsymbol{d}} \leftarrow \hat{\boldsymbol{d}} + \hat{\boldsymbol{z}} - \hat{\boldsymbol{x}} \; ,$$

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

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)





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

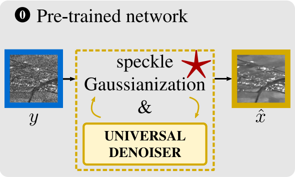
$$\hat{d} \leftarrow \hat{d} + \hat{z} - \hat{x} \,,$$

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

implicit regularization: CNN trained on natural images

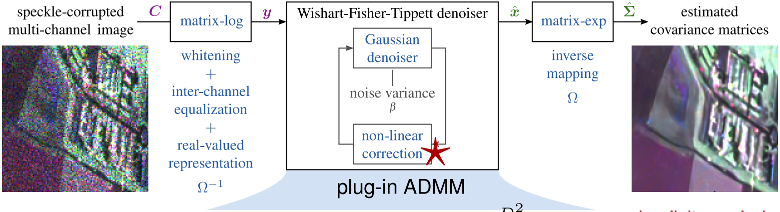
C.A. Deledalle, L. Denis, S. Tabti, & F. Tupin, "*MuLoG, or how to apply Gaussian denoisers to multi-channel SAR speckle reduction?* ", IEEE Transactions on Image Processing, 2017.

Applying a pre-trained network (universal Gaussian denoiser)



requires no training!
generalizes to multi-channel images

network not refined for SAR scenes.



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

implicit regularization: CNN trained on natural images

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

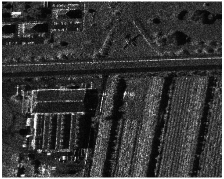
$$\hat{x} \leftarrow \underset{x}{\operatorname{argmin}} \frac{\beta}{2}\|x - \hat{z} - \hat{d}\|^2 - \log p_y(y|x)\,.$$

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)

Restoration results with MuLoG: airborne images with SETHI (©ONERA, images have been pre-processed to reduce sidelobes and limit speckle correlation, pixel size ≈ 70cm)

$D = 1$: SAR intensity images



noisy intensity

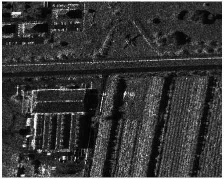
restored reflectivity

C.A. Deledalle, L. Denis, & F. Tupin, "*Speckle reduction in matrix-log domain for synthetic aperture radar imaging*", HAL, 2021.

Applying a pre-trained network (universal Gaussian denoiser)

Restoration results with MuLoG: airborne images with SETHI (©ONERA, images have been pre-processed to reduce sidelobes and limit speckle correlation, pixel size $\approx$ 70cm)

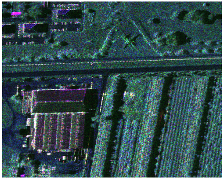
$D = 1$: SAR intensity images



noisy intensity

restored reflectivity

$D = 3$: PolSAR polarimetric images



noisy polarimetry

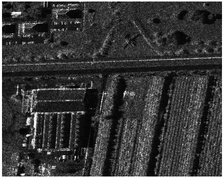
restored polarimetry

C.A. Deledalle, L. Denis, & F. Tupin, "*Speckle reduction in matrix-log domain for synthetic aperture radar imaging*", HAL, 2021.

Applying a pre-trained network (universal Gaussian denoiser)

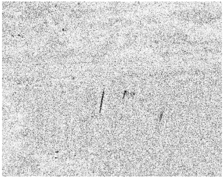
Restoration results with MuLoG: airborne images with SETHI (©ONERA, images have been pre-processed to reduce sidelobes and limit speckle correlation, pixel size $\approx$ 70cm)

$D = 2$: InSAR interferometric images

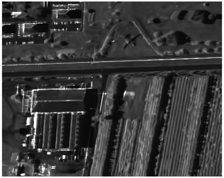


noisy intensity

noisy phase

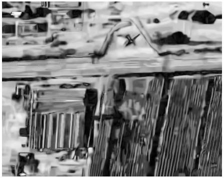


noisy coherence



restored intensity

restored phase



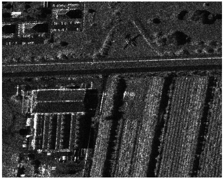
restored coherence

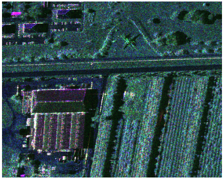
C.A. Deledalle, L. Denis, & F. Tupin, "*Speckle reduction in matrix-log domain for synthetic aperture radar imaging*", HAL, 2021.

Applying a pre-trained network (universal Gaussian denoiser)

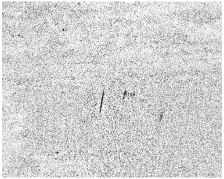
Restoration results with MuLoG: airborne images with SETHI (©ONERA, images have been pre-processed to reduce sidelobes and limit speckle correlation, pixel size ≈ 70cm)

$D = 6$: PolInSAR polarimetric and interferometric images

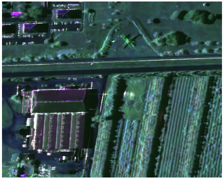

noisy intensity

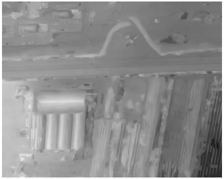

noisy polarimetry

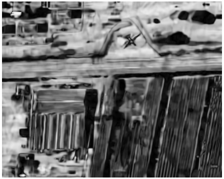

noisy phase


noisy coherence


restored intensity

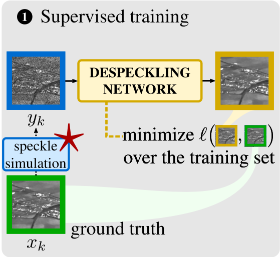

restored polarimetry


restored phase

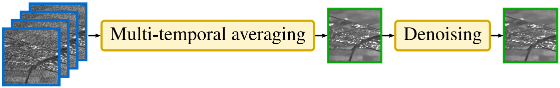

restored coherence

C.A. Deledalle, L. Denis, & F. Tupin, "*Speckle reduction in matrix-log domain for synthetic aperture radar imaging*", HAL, 2021.

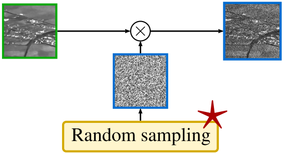
Supervised training of a despeckling network



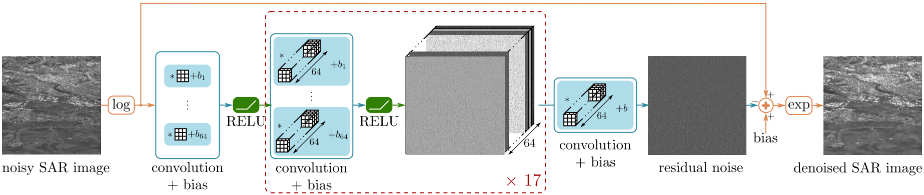
Ground-truth generation:



Speckle simulation:

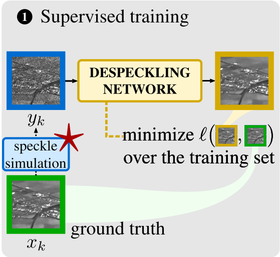


Residual CNN:

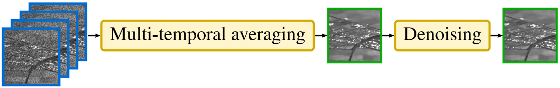


G. Chierchia et al. “*SAR image despeckling through convolutional neural networks*”, IEEE IGARSS 2017.
E. Dalsasso et al. “*SAR Image Despeckling by Deep Neural Networks: from a pre-trained model to an end-to-end training strategy*”, Remote Sensing, 2020.

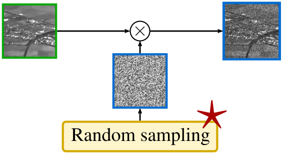
Supervised training of a despeckling network



Ground-truth generation:



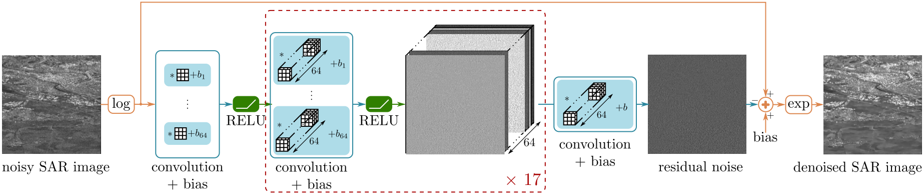
Speckle simulation:



time series provide high-quality ground truth.

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

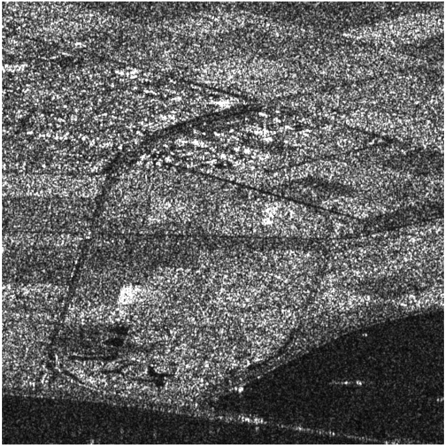
Residual CNN:



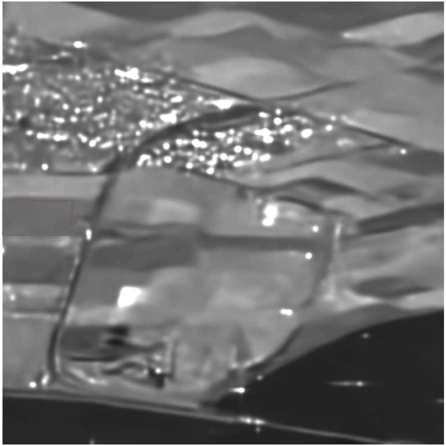
G. Chierchia et al. “*SAR image despeckling through convolutional neural networks*”, IEEE IGARSS 2017.
E. Dalsasso et al. “*SAR Image Despeckling by Deep Neural Networks: from a pre-trained model to an end-to-end training strategy*”, Remote Sensing, 2020.

Supervised training of a despeckling network

Restoration results with SARCNN: Sentinel-1 SLC IW image (©ESA, images have been pre-processed to reduce sidelobes and limit speckle correlation)



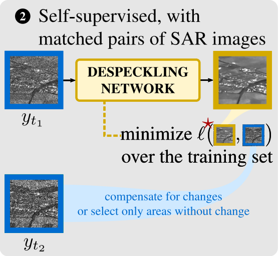
Single-look Sentinel-1 image



Restored image

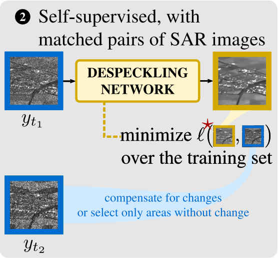
E. Dalsasso et al. "*SAR Image Despeckling by Deep Neural Networks: from a pre-trained model to an end-to-end training strategy*", Remote Sensing, 2020.

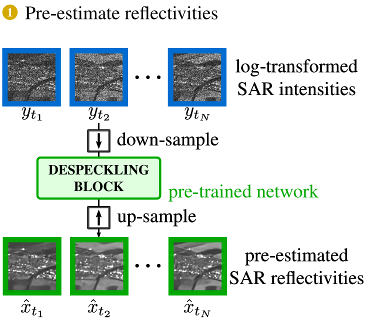
Self-supervised with matched pairs of SAR images



E. Dalsasso et al. "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE JSTARS, 2021.

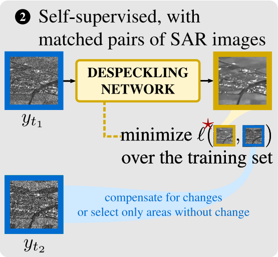
Self-supervised with matched pairs of SAR images

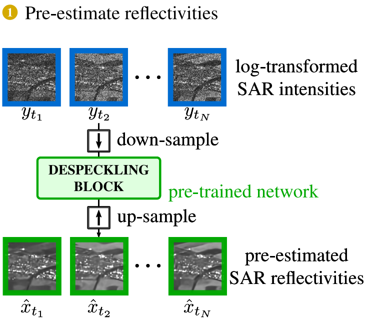


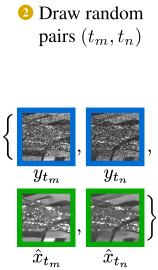


E. Dalsasso et al. "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE JSTARS, 2021.

Self-supervised with matched pairs of SAR images

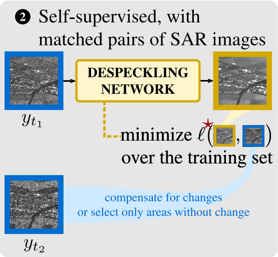


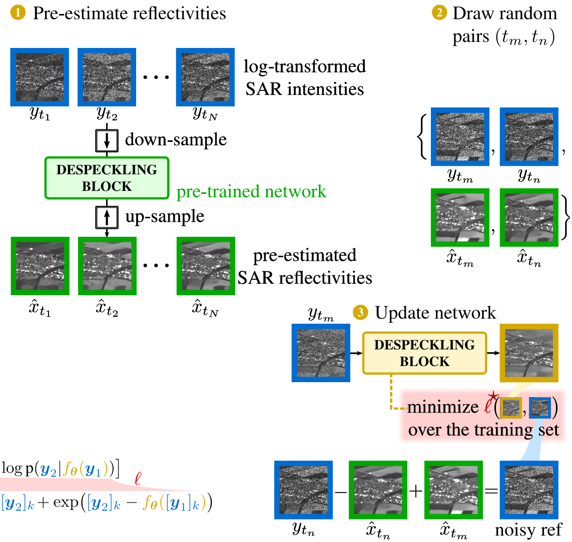




E. Dalsasso et al. "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE JSTARS, 2021.

Self-supervised with matched pairs of SAR images



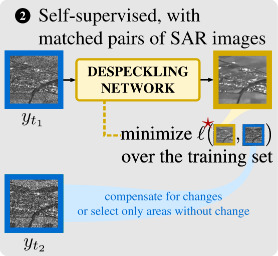


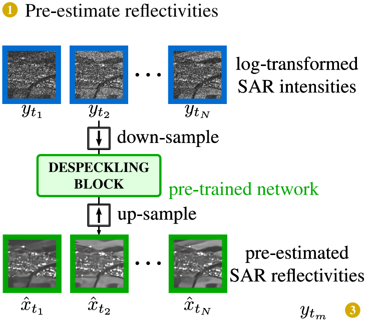
$$\hat{\boldsymbol{\theta}}^{(\text{lik})}_{\text{self-supervised}} \in \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\; \mathbb{E}_X\left[-\log \mathrm{p}(\boldsymbol{y}_2 | f_{\boldsymbol{\theta}}(\boldsymbol{y}_1))\right]$$

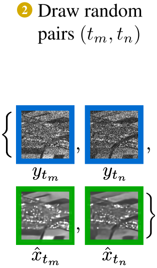
Goodman's speckle model: $\sum_k f_{\boldsymbol{\theta}}([\boldsymbol{y}_1]_k) - [\boldsymbol{y}_2]_k + \exp\left([\boldsymbol{y}_2]_k - f_{\boldsymbol{\theta}}([\boldsymbol{y}_1]_k)\right)$ (ℓ)

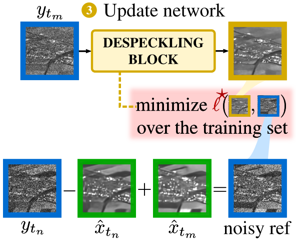
E. Dalsasso et al. "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE JSTARS, 2021.

Self-supervised with matched pairs of SAR images









very good restoration performance

the training procedure is a little heavy

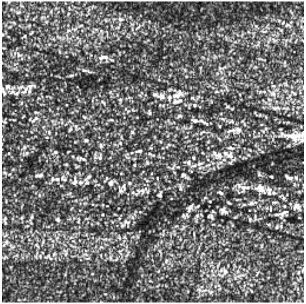
$$\hat{\theta}^{(\text{lik})}_{\text{self-supervised}} \in \underset{\theta}{\operatorname{argmin}} \; \mathbb{E}_X \left[-\log \mathrm{p}(\boldsymbol{y}_2 | f_\theta(\boldsymbol{y}_1)) \right]$$

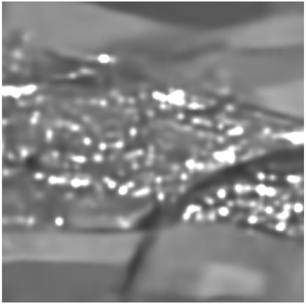
Goodman's speckle model: $\displaystyle \sum_k f_\theta([\boldsymbol{y}_1]_k) - [\boldsymbol{y}_2]_k + \exp\big([\boldsymbol{y}_2]_k - f_\theta([\boldsymbol{y}_1]_k)\big)$

E. Dalsasso et al. "*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*", IEEE JSTARS, 2021.

Self-supervised with matched pairs of SAR images

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

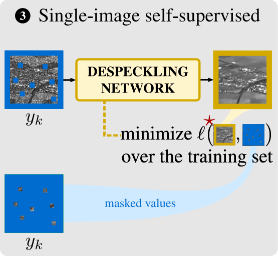

Single-look Sentinel-1 image


Restored image (SARCNN)

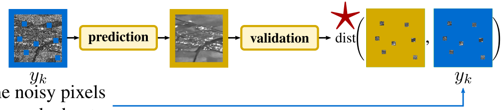

Restored image (SAR2SAR)

E. Dalsasso et al. “*SAR2SAR: a semi-supervised despeckling algorithm for SAR images*”, IEEE JSTARS, 2021.

Self-supervised with a single image



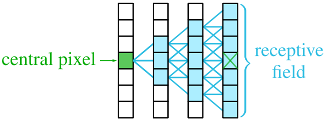
Main idea: train by cross-validation



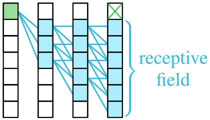
some noisy pixels
are masked out

Improvement 1: alternately mask out each pixel ⇝ dense validation

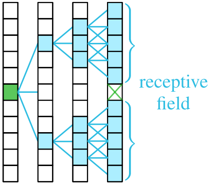
build network architecture to exclude the central pixel
from the receptive field



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



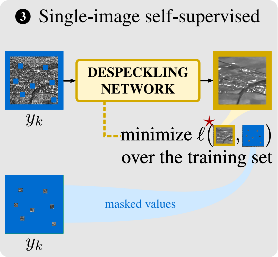
by shifting the convolution kernels
the central pixel is next to the
receptive field



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

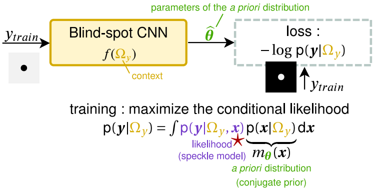


Main idea: train by cross-validation

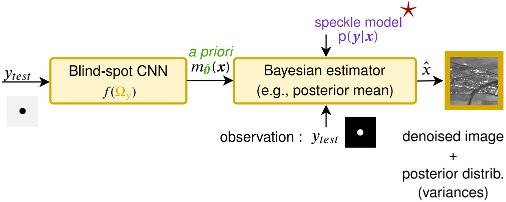
Improvement 2: include the noisy measurement at the central pixel in the final estimation:

$\rightsquigarrow$ Bayesian framework

network training:

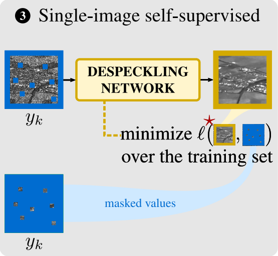


applying the network to denoise an image:

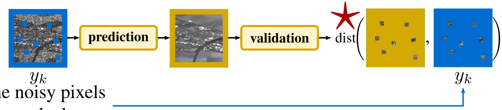


Laine et al. "High-Quality Self-Supervised Deep Image Denoising", NeurIPS 2019.
Molini et al. "Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks", IEEE TGRS 2021

Self-supervised with a single image



Main idea: train by cross-validation

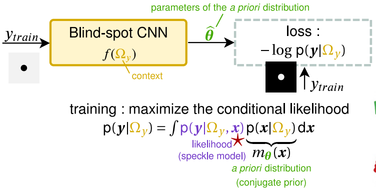


Improvement 2: include the noisy measurement at the central pixel in the final estimation:

$\rightsquigarrow$ Bayesian framework

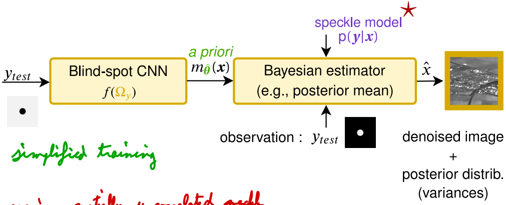
network training:

applying the network to denoise an image:



simplified training

requires spatially uncorrelated speckle

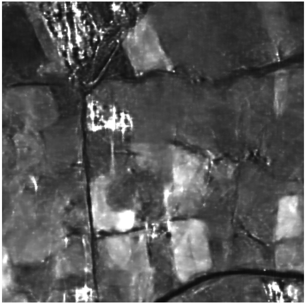


Laine et al. “High-Quality Self-Supervised Deep Image Denoising”, NeurIPS 2019.
Molini et al. “Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks”, IEEE TGRS 2021

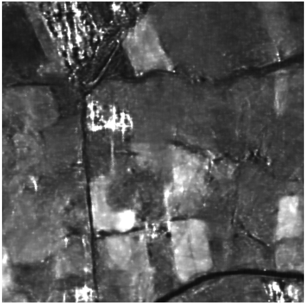
Self-supervised with a single image

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

Single-look TerraSAR-X image



Speckle2Void

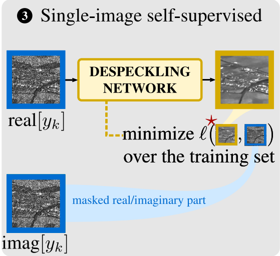


Speckle2Void-NL

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

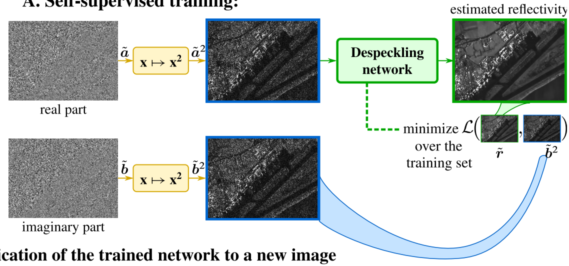
Molini et al. "Speckle2Void: Deep self-supervised SAR despeckling with blind-spot convolutional neural networks", IEEE TGRS 2021

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

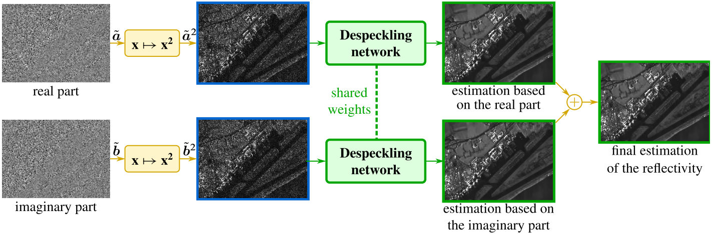


Main idea: speckle in the real and imaginary parts is independent

A. Self-supervised training:

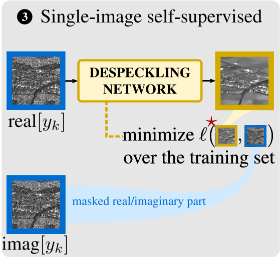


B. Testing: application of the trained network to a new image



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

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

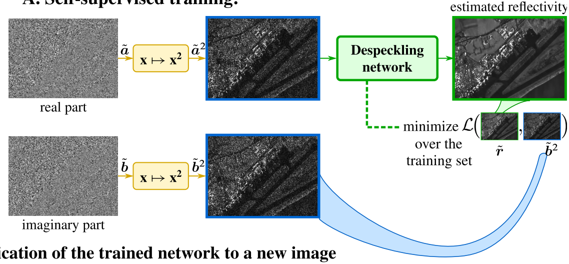


- building the training set is inexpensive
- handles images with spatially correlated speckle
- very good performance

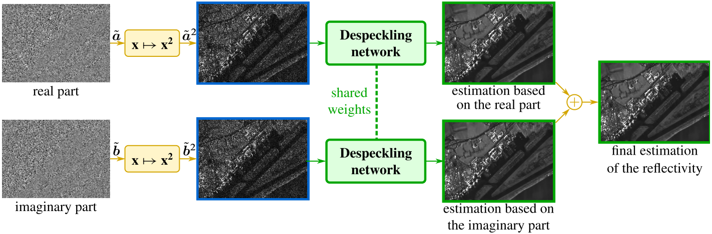
- the real/imaginary parts have a lower SNR than the original image
- requires special care (pre-processing step) for some imaging modalities (e.g., SPOTLIGHT, TOPS)

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

A. Self-supervised training:

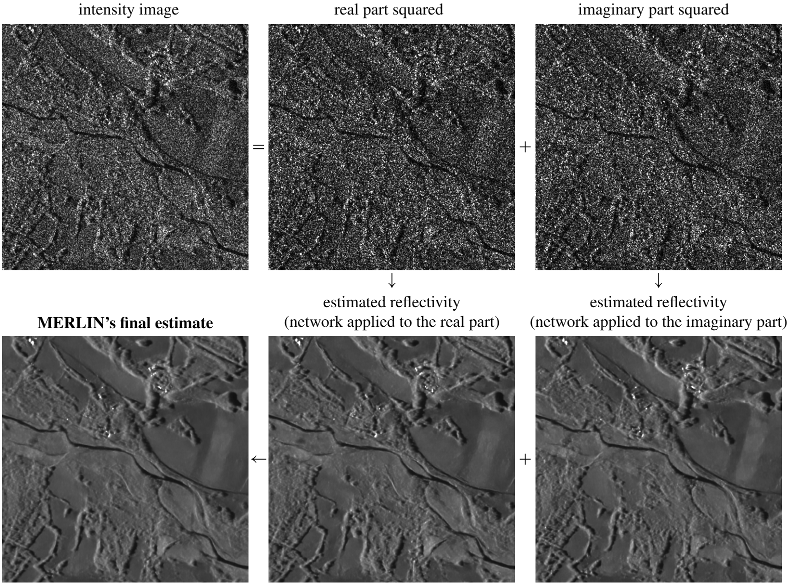


B. Testing: application of the trained network to a new image



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

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



Dalsasso et al. "As if by magic: self-supervised training of deep despeckling networks with MERLIN",to appear in TGRS

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]

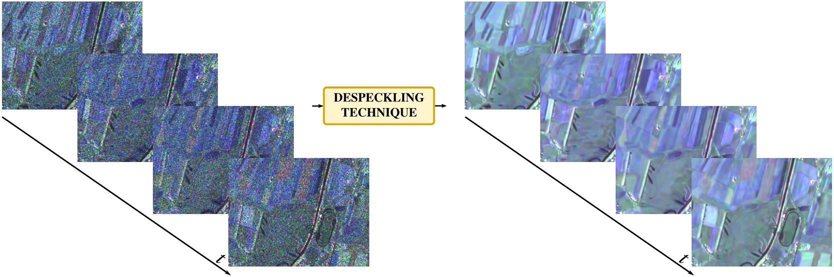
Handling complex-valued information

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

Concluding words

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`