





Introduction to

Polarimetric

SAR Tomography

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SAR & Hyperspectral multi-modal Imaging and sigNal processing, Electromagnetic modeling



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SAR tomography basics

Application of PolTomoSAR

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Acknowledgements



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SAR Tomography basics

SAR imaging: resolution improvement based on signal diversity

2-D imaging limitations over 3-D scenes: SAR interferometry

2-D SAR and inSAR imaging limitations over complex (really 3-D) scenes:

SAR tomography

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Radar response model



Born approximation at order 1:

valid for media with weak dielectric contrast



$$\psi_{s_i}(\mathbf{r}) \approx \int_{V_i} f_i(\mathbf{r}') \psi_h(\mathbf{r}') \frac{\mathrm{e}^{jk|\mathbf{r}-\mathbf{r}'|}}{|\mathbf{r}-\mathbf{r}'|} \mathrm{d}(\mathbf{r}')$$

Consequence: linear response model (does not account for multiple interactions)



$$s_r(\tau) = \sum_i a_{c_i} u(\tau - \tau_i) e^{-j\omega_c \tau_i}$$

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1 scatterer located at distance d_o



- mono-chromatic waveform $u(\tau)=1$

$$s_r(\tau) = a_c e^{-j\omega_c \tau_0} \in \mathbb{C} \quad \stackrel{?}{\longrightarrow} \quad \left\{ \begin{array}{cc} a_c & \in \mathbb{C} \\ d_0 & \in \mathbb{R} \end{array} \right.$$

No, ill-conditioned estimation

- bi-chromatic waveform $\ u(\tau) = \mathrm{e}^{-j\pm\Delta\omega\tau}$

$$\begin{cases} s_{r_1} = a_c e^{-j(\omega_c \pm \Delta \omega)\tau_0} \\ s_{r_2} = a_c e^{-j(\omega_c \pm \Delta \omega)\tau_0} & \longrightarrow d_0, a_c \end{cases}$$

2 frequencies for 1 scatterer

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Several scatterers



- measurements at many spectral locations $\omega_0, \omega_1, \dots$
- wide bandwidth (rich spectrum) waveform



1-D imaging using SPATIAL diversity





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1 scatterer located at distance x₀: **2** azimuth positions

$$\mathbf{s}_{r_i}(\pm \Delta x_a) = a_{c_i} \,\mathrm{e}^{-jk\sqrt{r_i^2 + (x_0 \mp \Delta x_a)^2}} \longrightarrow x_0, a_c$$

Several scatterers: many azimuth positions

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2-D imaging of several scatterers

- 1-D range imaging using spectral diversity (wide bandwith waveform)

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- 1-D imaging in azimuth using spatial diversity (wide azimuth aperture)





2-D SAR imaging





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2-D SAR imaging





Range compressed SAR image

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DEM of Mt Etna, Italy



Loss of a dimension

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2-D SAR imaging: cylindrical ambiguity



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SAR interferometry



Additional spatial diversity

1 scatterer → **2** positions: <u>SAR interferometry</u>



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SAR interferometry





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Range focused signal (x-d domain)

2-D focused signal (x-r domain)





$$s(x, r) = a_c$$

$$h_r(d - r_0)$$

$$h_a(x - x_0)$$

$$exp(-j\frac{4\pi}{\lambda_c}r_0)$$

→ complex reflection coefficient
 → delayed range impulse response
 → delayed azimuth impulse response
 → two-way propagation phase

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Coherent information

$$s_{1} = |a_{c_{1}}| \exp\left(-j\frac{4\pi}{\lambda_{c}}r_{1} + j + \phi_{obj_{1}}\right)$$
$$s_{2} = |a_{c_{2}}| \exp\left(-j\frac{4\pi}{\lambda_{c}}r_{2} + j + \phi_{obj_{2}}\right)$$

InSAR assumptions (small B)

$$|a_{c_1}| \approx |a_{c_2}|, \quad \phi_{obj_1} \approx \phi_{obj_2}$$

InSAR phase difference

$$\phi_{12} = \arg(s_1 s_2^*) = \frac{4\pi}{\lambda_c}(r_2 - r_1) = k_c \Delta r_{12}$$

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 $\theta = f(H, \mathbf{r_1}, \mathbf{h})$

Local linearization

$$\Delta \phi_{12} = k_z \Delta h + k_{fe} \Delta r_1$$
$$= \Delta \phi_{topo} + \Delta \phi_{fe}$$

$$k_z = \frac{k_c B_\perp}{r_1 \sin \theta}, \quad k_{fe} = k_z \cos \theta$$

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InSAR topography estimation





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SAR imaging of 3-D scenes



Urban areas



Mixture of **several contributions** in the elevation direction



Pauli-coded SAR image



Optical image



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SAR imaging of 3-D scenes



BIOSAR II, Boreal forest, L band







Multibaseline InSAR (MB-InSAR) tomography

Several mixed scatterers → many across-track positions

Acquisition geometry





Vertical focusing

- Vertical aperture : L_{tomo}
- Resolution : $\delta_z = \delta_n \sin \theta$ with $\delta_n = \frac{\lambda R_0}{2L_{tomo}}$

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Multibaseline InSAR (MB-InSAR) tomography

Several mixed scatterers \rightarrow many across-track positions

Acquisition geometry



Processing options

- Direct 3-D imaging: coherent combination of M SAR acquisitions
- M x 2-D focusing & coherent processing of M-InSAR quantities

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SAR imaging of 3-D scenes



Direct 3-D imaging of an Alpine glacier at L band







TomoSAR Image - 25 m below the Ice surface → 7th A



TomoSAR Image - 50 m below the Ice surface



SAR imaging of 3-D scenes



M x 2-D imaging of a Boreal forest at L band

SAR: 2D Imaging





400

600



z = 20 m above the terrain



z = 10 m above the terrain



z = 25 m above the terrain



Power distribution in height direction

4400

0

200

azimuth [m]

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Multiple baselines : Illumination from multiple points of view



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Multiple baselines : Illumination from multiple points of view



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Multiple baselines : Illumination from multiple points of view







Multiple baselines : Illumination from multiple points of view



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TomoSAR Resolution





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TomoSAR Resolution





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TomoSAR Processing

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 $I(r,x) = \int_{C} A(x,y,z) \cdot e^{-j\frac{4\pi}{\lambda}R(x,y,z)} dxdydz$

C = resolution cell

SAR pixel = Integral of all

contributions within the resolution cell

• Each elementary scatterer is phase-

rotated according to its distance from

the Dodor



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 $I_n(r,x) = \int_{C_n} A(x,y,z) \cdot e^{-j\frac{4\pi}{\lambda}R_n(x,y,z)} dxdydz$

*C***n** = *resolution cell for*



SAR pixel = Integral of all

contributions within the resolution cell

• Each elementary scatterer is phase-

rotated according to its distance from

the Radar

Multiple baselines

- Resolution cell is oriented at different angles for different baselines
- Range migration: Targets at different cross-range positions appear at different range positions for different baselines

Exact TomoSAR focusing

requires 3D Back-Projection

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Relaxing the model...



Hyp 1: range migration is negligible

small aperture, small bandwidth, targets are distributed in a small angular sector

$$\square I_n(r,x) = \int_C A(x,y,z) \cdot e^{-j\frac{4\pi}{\lambda}R_n(x,y,z)} dxdydz$$

C = resolution cell

Only phase terms vary w.r.t. baselines





Hyp 2 : locally-plane wave approximation (across-track scene extent << R)

b_n = **normal baseline** of the *n*-th view *w*.*r*.*t*. the Master

esa

view $b_n = (\theta_n - \theta_M) \cdot R_M(ref)$



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Relaxed model



$$I_{n}(r,x) = exp\left\{-j\frac{4\pi}{\lambda}R_{n}(ref)\right\} \cdot \int_{C} A(r',x',v)exp\left\{-j\frac{4\pi}{\lambda}r'\right\} \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_{n}}{r}v\right\} dx'dr'dv$$
Common
Solving the integral w.r.t. r' and x' one gets
$$I_{n}(r,x) = exp\left\{-j\frac{4\pi}{\lambda}R_{n}(ref)\right\} \cdot \int_{C} s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_{n}}{r}v\right\} dv$$
Flat earth phase (w.r.t. reference)
$$s(r,x,v) = cross-range \text{ projection of}$$
target reflectivity within the SAR
resolution cell at (r,x)

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SAR Tomography as a Fourier imaging process: M-Fwd 2-D imaging

Focused SLC SAR image

Fourier Transform of s(r,x,v) the scene complex reflectivity (cross-range coord.)

$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv$$

 $I_n(r,x)$: SLC pixel in the *n*-th image s(r,x,v): cross-range projection of target reflectivity within the SAR resolution cell at (r,x) b_n : normal baseline for the *n*-th image

 λ : carrier wavelength

ivity transmitted

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SAR Tomography as a Fourier imaging process: Backwd 3D imaging

⇒ The cross-range distribution of the complex reflectivity can be retrieved by Fourier transforming SLC data with respect to the normal baseline

 $\hat{s}(r, x, v) = DFT\{I_n(r, x)\}$ DFT = Discrete Fourier

Transform **over the b**_s

In other words... $I_{n}(r,x) = \int s(r,x,v) \exp\left(-j\frac{4\pi}{\lambda r}b_{n}v\right) dv$ $i_{n}(r,x) = observation$ s(r,x,v) = unknown $\hat{s}(r,x,v) = estimate$

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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



= reference position

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TomoSAR focusing – examples



$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



= reference position

Note: Constant amplitude factors omitted

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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



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- *Terrain* = *extended target*
- ⇔ It does not project into a

peak

⇔ Cross-range spread

= reference position

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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



= reference position

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TomoSAR focusing – examples



$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$

Case 3: terrain



- *Terrain* = *extended target*
- ⇔ Cross-range spread

depends on terrain slope



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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



Terrain = extended target

⇔ Cross-range spread

depends on terrain slope



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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$



- *Terrain* = *extended target*
- ⇔ Cross-range spread

depends on terrain slope

= reference position

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TomoSAR focusing – examples



$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)$$



= reference position

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$$I_n(r,x) = \int_C s(r,x,v) \cdot exp\left\{-j\frac{4\pi}{\lambda}\frac{b_n}{r}v\right\}dv \quad \hat{s}(r,x,v) = \sum_n I_n(r,x)\exp\left(+j\frac{4\pi}{\lambda r}b_nv\right)dv$$

Case 4: terrain + *forest*

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= reference position

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Ambiguity





DFT produces *periodic* results

- ⇒ Ghost targets appearing at known position w.r.t. the real one
- Also referred to as ambiguous targets, or replicas
- Same range as the real target
- Displaced in cross-range

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ground range







Baseline design tips

- Ambiguity $_{EE}$ baseline spacing
- Resolution $_{= E}$ baseline aperture
- ⇒ Baseline spacing: small enough to ensure that ambiguous targets stay away from the real ones
- ⇒ Baseline aperture: large enough to meet resolution requirement
- \Rightarrow How many passes ?

$$N \ge \frac{b_{ap}}{\Delta b} = \frac{v_a}{\Delta v}$$

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ansmitted pulse



eight,

s(z)

TomoSAR forward model

$$I_n(r,x) = \int_C s(r,x,v) \cdot \bar{exp} \left\{ -j \frac{4\pi}{\lambda} \frac{b_n}{r} v \right\} dv$$

Change of variable from cross range to height

 $z = v \cdot \sin \theta$

 $I_n(r,x)$: SLC pixel in the *n*-th image s(r,x,v): cross-range projection of target reflectivity within the SAR resolution cell at (r,x)

 b_n : normal baseline for the *n*-th image





 k_z is usually referred to as **vertical** wavenumber or phase to height conversion factor

$$k_{z}(n) = \frac{4\pi}{\lambda r} \frac{b_{n}}{\sin \theta}$$

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3-D SAR imaging



Co-registration on a reference plane

Valid for $z \in z_{ref} \pm \Delta z_{val}/2$



$$s(x, y, z) = \sum_{i=1}^{M} s_i(x, r_{i_{ref}}) e^{jk_c r_{i_{ref}}}$$
$$r_{i_{ref}} \approx r_{1_{ref}} + k_{z_i} z$$





3-D SAR imaging



3-D Synthetic Aperture imaging

$$s(x, y, z) = \sum_{i=1}^{M} s_i(x, r_{i_{ref}}) e^{jk_{z_i}z}$$

Beamformer-like formulation

Ē

SLC data



$$\Rightarrow \mathbf{y} = [y_1, \dots, y_M]^T \qquad \mathbf{a} = [1, e^{-jk_{z_2}z}, \dots, e^{-jk_{z_M}z}]^T$$
$$\mathbf{a} = [1, e^{-jk_{z_2}z}, \dots, e^{-jk_{z_M}z}]^T$$

Ctooring vootor

3-D Fourier imaging is equivalent to the Beamformer spectral analysis method

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Principles of spectral analysis



Example: sum of monochromatic signals



Principles of spectral analysis





Principles of spectral analysis



Stationary signal
$$E(|s(t)|^2) = I \quad \forall t \quad \rho_{ss}(\tau) = ACF(s(t))$$

 $\hat{\Phi}(f) = E(|\hat{S}(f)|^2) = I \int_{-\frac{\Delta T}{2}}^{+\frac{\Delta T}{2}} \rho_{ss}(\tau) e^{-j2\pi f\tau} d\tau$
Tomographic equivalence $s_m = \sum_{i=1}^{N_s} a_c(z) e^{jk_{z_m}z} \quad m = 1, \dots, M$

$$\tilde{\Phi}_{ss}(z) = \mathcal{E}(|a_c(z)|^2) = I \sum_{m=-M/2}^{M/2-1} \gamma_{1m} e^{-j2\pi k_{z_m} z}$$

$$\gamma_{mn} = \frac{\mathcal{E}(s_m s_n^*)}{\sqrt{\mathcal{E}(|s_m|^2 \, \mathbb{E} \, |s_n|^2)}} \qquad \longrightarrow \qquad \mathbf{R} = \begin{bmatrix} 1 & \gamma_{12} & \dots & \gamma_{1N} \\ \gamma_{21} & 1 & & \\ \vdots & \ddots & \vdots \\ \gamma_{N1} & \cdots & 1 \end{bmatrix}$$

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Current paradigm for forested areas: retrieve the *vertical distribution of backscattered power* based on the observed *InSAR coherences*



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Bace Tomographic imaging using specan



Acquired signal (single scatterer)

 $\mathbf{y} = a_c \, \mathbf{a}(z_0) + \mathbf{n}$ with $\mathbf{a}(z_0) = [1, e^{jk_{z_2} z_0}, \dots, e^{jk_{z_M} z_0}]^T$

Used approach: linear filtering

$$f(\mathbf{w}) = \mathbf{w}^{\dagger} \mathbf{y} = \sum_{i=1}^{M} w_i^* y_i$$

Beamformer

$$\mathbf{w}_{BF} = \frac{\mathbf{a}(z)}{M}$$

- (Fast) filter maximizing the output SNR
- SNR maximized at $z = z_0$:
- Use: compute

$$P_B(z) = |\mathbf{w}_B^{\dagger}(z)\mathbf{y}|^2$$

estimate parameters from the max



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🖶 Hungaria Tomographic imaging using specan



East: resolution

Uniform baseline sampling

$$\mathbf{a}(z) = [1, \mathrm{e}^{j \mathrm{d}k_z z}, \dots, \mathrm{e}^{j(M-1) \mathrm{d}k_z z}]^T$$

$$|f(z)| = |a_c| \frac{\mathbf{a}^{\dagger}(z)\mathbf{a}(z_0)}{N} = \frac{|a_c|}{M} \frac{|\sin(\pi\Delta k_z(z-z_0))|}{|\sin(\pi dk_z(z-z_0))|}$$
 Slow: ambiguity

Spatial features of a tomogram

- rapidly varying: resolution
- band-limited: sidelobes
- sampled: ambiguities

$$\delta z = \frac{2\pi}{\Delta k}, \quad z_{amb} = \frac{2\pi}{\mathrm{d}k}, \quad \delta z = \frac{z_{amb}}{M}$$



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Comographic imaging using specan





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Comographic imaging using specan





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esa

Beamformer features

- Excellent statistical accuracy
- Fourier resolution (depends on Δk)
- Cannot handle closely spaced scatterers

Capon's solution

Capon's approach

- Linear filter (fast)
- Aims to minimize spatial perturbations & sidelobes

$$\mathbf{w}_{C} = \operatorname*{arg\,min}_{\mathbf{w}} \mathbf{E}(|\mathbf{w}^{\dagger}\mathbf{y}|^{2}) \quad \text{s.t.} \quad \mathbf{w}^{\dagger}\mathbf{a}(z) = 1$$
$$\mathbf{w}_{C} = \frac{\mathbf{R}^{-1}\mathbf{a}(z)}{\mathbf{a}^{\dagger}(z)\,\mathbf{R}^{-1}\mathbf{a}(z)}, \quad \mathbf{R} = \mathbf{E}(\mathbf{y}\mathbf{y}^{\dagger})$$
$$\widehat{\mathbf{R}} = \frac{1}{L}\sum_{l=1}^{L}\mathbf{y}(l)\mathbf{y}^{\dagger}(l)$$

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Comographic imaging using specan





Capon: significantly improved resolution

• For regular baselines, BF & Capon are equally affected by ambiguities



Irregular baseline sampling: logscale distribution



- BF: strongly affected by ambiguities
- CAPON: unsynchronized ambiguity are considered as perturbations and filtered. Good resolution performance preserved

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Over speckle affected environments

- $\mathbf{w}_i^{\dagger}\mathbf{y}, i = B, C$ is a Random Variable (1 realization is not representative)
- Power Spectral Density

$$P_i(z) = \mathbf{E}(|\mathbf{w}_i^{\dagger}\mathbf{y}|^2) = \mathbf{w}_i^{\dagger}\mathbf{R}\mathbf{w}_i$$
$$P_{BF}(z) = \mathbf{a}^{\dagger}(z)\mathbf{R}\mathbf{a}(z), \quad P_C(z) = \frac{1}{\mathbf{a}^{\dagger}(z)\mathbf{R}^{-1}\mathbf{a}(z)}$$

• In practice

$$\widehat{\mathbf{R}} = \frac{1}{L} \sum_{l=1}^{L} \mathbf{y}(l) \mathbf{y}^{\dagger}(l)$$

- BF: quite stable w.r.t L
- Capon may suffer from a poor covariance matrix conditioning

$$\Rightarrow$$
 Diagonal Loading

$$\widetilde{\mathbf{R}} = \widehat{\mathbf{R}} + \alpha \mathbf{I}_M, \quad \alpha \ge 0$$

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Comographic imaging using specan



Tropical forest profile at P band



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Covariance matrix model for discrete scatterers

$$\mathbf{y} = \sum_{i=1}^{N_s} s_i \, \mathbf{a}(z_i) + \mathbf{n} = \mathbf{A}\mathbf{s} + \mathbf{n} \quad \Rightarrow \quad \mathbf{R} = \mathbf{A}\mathbf{R}_{ss}\mathbf{A}^{\dagger} + \sigma_n^2 \mathbf{I}_N$$

Steering matrix $\mathbf{A} = \begin{bmatrix} \mathbf{a}(z_1), \dots, \mathbf{a}(z_{N_s}) \end{bmatrix}$

Covariance matrix eigen-decomposition (N < N)



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Covariance matrix model for discrete scatterers

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Covariance matrix eigen-decomposition (N < N)

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MUSIC principle

$$\mathbf{A} = \mathbf{T}\mathbf{V}_s, \quad \mathbf{V}_s^{\dagger}\mathbf{V}_n = \mathbf{0} \quad \Rightarrow \quad |\mathbf{a}(z_i)^{\dagger}\mathbf{V}_n|^2 = 0 \,\forall \mathbf{a}(z_i) \in \mathbf{A}$$

MUSIC criterion

$$P_M(z) = \frac{1}{|\mathbf{a}(z)^{\dagger} \widehat{\mathbf{V}}_n|^2}$$

Remarks

- The noise space dimension has to be estimated
- MUSIC is well adapted to DISCRETE scatterers, not to continuous reflectivities (i.e. forest canopies)
- The values reached by the criterion DO NOT correpond to the PSD (profile intensity)
- CAPON is **NOT** HR, MUSIC **YES**

Comographic imaging using specan



Critical configuration (3 images) in an urban environment at L band



Strictly speaking, Capon's technique is not HR, but is very convenient and can be easily derived in the full-pol case

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ease study: BIOSAR 2 data



Multi-baseline InSAR coherences and phases - VV



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Case study: BIOSAR 2 data



BF



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CAPON: processing OK ?



Singular covariance matrix \rightarrow increase the number of samples

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MUSIC: processing OK ?



Singular covariance matrix \rightarrow increase the number of samples

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InSAR phases, polarization & TomSAR esa

L-band BIOSAR2, Capon tomograms



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InSAR phases, polarization & TomSAR esa

 ϕ_{1i}

 $h_i =$

Spatial diversity InSAR heights



InSAR phases, polarization & TomSAR esa

Polarimetric diversity



$$h_p = \frac{\phi_{1i_p}}{k_{z_i}}$$



Strong-baseline dependence -> Tomography

Reed for full-rank Polarimetric SAR Tomography CESA





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Cull-rank Polarimetric SAR Tomography





• SKP decomposition (Tebaldini 2009)

3-D POLSAR covariance matrices

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pplication to 3-D forest analysis





- DLR E-SAR
- L-Band
- 21 tracks: average baseline 20m
- Tomographic resolution $\delta_z = 2m$



PAULI

Dornstetten airborne

PolTomSAR data set



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Scattering Mechanism Decomposition



SKP decomposition

Ground-volume decomposition implies:

• Separation of Structural Properties

=> Separated Tomographic Imaging of Ground-only and Volume-only Contributions



• Separation of Polarimetric Properties

=> Evaluation of the Ground to Volume Backscattered Power Ratio for each polarization

P-Band HH



P-Band HV

L-Band HH



L-Band HV



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Application of PolTomoSAR to the characterization of complex media

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3-D IMAGING OF AN URBAN AREA USING A MINIMAL POL-TOMSAR CONFIGURATION CSA

Urban area test site

- Images over Dresden, 2000
- DLR's E-SAR at L-Band
- Resolution : 0.5 m \times 2.5 m
- Fully polarimetric
- Dual-baseline InSAR

Baselines	H _{am}
10 m	55-73 m
40 m	14-18 m

3 PolSAR images



Pauli-coded SAR image



Optical image



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- L-band intermediate-resolution data sets
 - \Rightarrow High-Resolution (HR) tomographic estimators
- 3 images
 - $\Rightarrow N_s = 2$
- Sum of diverse (polarimetric & statistical) contributions
 - \Rightarrow FP-NSF model adaptive estimator.

VV refectivity tomograms (Ns = 2)



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FP-NSF α tomogram



- FP-MUSIC: less sidelobes than SP case
- FP-NSF: better characterization

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Surface elevation map







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Building reconstruction



Difference between LiDAR and estimated surface

- projection of SAR imaging
- vegetation between B1 and B2

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Building reconstruction



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POLITOMSAR IMAGING OF CONCEALED OBJECTS

Above ground and under foliage objects observed at L band

- DLR E-SAR image over Dornstetten, Germany
- L-Band
- 21 tracks : average baseline 20m
- $\delta_z = 2m$







Huang, Y.; Ferro-Famil, L. & Reigber, A. "Under-Foliage Object Imaging Using SAR Tomography and Polarimetric Spectral Estimators", IEEE TGRS 2011

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POLITOMSAR IMAGING OF CONCEALED OBJECTS

VV refectivity tomograms



Capon : limited resolution \Rightarrow overestimated H_{truck}

MUSIC :

+7

- \bigcirc Sub-canopy truck ⇒ hybrid scatterer
- ③ Uncovered
 - \Rightarrow coherent scatterer
- Spurious sidelobes.



POLITOMSAR IMAGING OF CONCEALED OBJECTS

Power spectrum of a mixed environment

• H-distributed scatterers : Continuous Spectrum Forest canopy :





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POL-TOMSAR IMAGING OF CONCEALED OBJECTS

Isolated Scatterer Extraction



Overestimated IS

- Bare soil, sub-canonpy ground
- Under-foliage truck



Overestimated number of IS

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POLETOMSAR IMAGING OF CONCEALED OBJECTS

Compressive sensing solution



- a few wavelet components
- a few discrete contributions

$$\mathbf{B} = \begin{bmatrix} \mathbf{I}_{(N_o \times N_o)} & \mathbf{0} \\ \mathbf{0} & \Psi_{(N_v \times N_v)} \end{bmatrix} \in \mathbb{R}^{(N_s \times N_s)} \qquad \mathbf{p} = \begin{bmatrix} \mathbf{p}_o^T & \mathbf{p}_v^T \end{bmatrix}^T \in \mathbb{R}^{+N_s \times 1}$$

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CPOL-TOMSAR IMAGING OF CONCEALED OBJECTS



a) Capon



(b) MUSIC



(c) Proposed method with merging



(d) Ground and underfoliage scattering (\mathbf{p}_o) estimated by proposed method with merging



(e) Canopy power (\mathbf{p}_v) estimated by proposed method with merging





(a) Capon



(b) MUSIC



(c) Proposed method with merging



(d) Ground and underfoliage scattering (\mathbf{p}_o) estimated by proposed method with merging





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Tropical forest test site and objectives

- TropiSAR Campaign, 2009 •
- ONERA SETHI
- P-Band
- 6 tracks
- $\delta_{az} = 1.245m$ $\delta_{rg} = 1m$
- $\delta_z = 12.5m$
- Ground truth
 - LiDAR data
 - Biomass measurements for 16 ROIs

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Courtesy ONERA

The Calibration site Rochambeau Other site Marais de Kaw

Arbocel

Objectives

- Tree height, underlying ground topography estimation
- Forest vertical structure characterization
- Biomass monitoring

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Tropical forest test site : Paracou



• Tropical forest environments (savannah, undisturbed forests, logged plots...)

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• Highly varying ground topography





Tree height and ground topography estimation



HH







Estimated profiles match LiDAR

HH profiles : similar to FP case

LIDAR - TomSAR -











Estimated results (ground range)



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TomSAR-LiDAR [m]	Mean	Std
Δz_g	0.005	4.6
Δz_{top}	1.6	7.4
ΔH_{v}	0.9	7.7

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Tropical forest biomass estimation Cesa

Ground/Volume separation:



Ground/tree top heights estimation:



Tropical forest biomass estimation Cesa



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Some objectives of PolTomoSAR remote sensing esa

SAR remote sensing: important asset for environmental monitoring

- Coverage, resolution, penetration, robustness
- \circ EM properties \leftrightarrow physical features
- $\circ\,$ Towards systematic and highly frequent space observations at low cost
 - \rightarrow model-based approaches, assimilation, big data ...

EM scattering from dense (snow, ice) multi-component (forest) media: may be complex

- Exaggeratedly numerous physical parameters vs. simplistic description
- Arbitrary level of computing complexity, simplifying assumptions
- Some parameters cannot be measured at a sufficient scale
- $\circ \rightarrow \text{EM}$ "radar ground truth" needed

Direct characterization of complex EM responses

- \rightarrow SAR Tomography (TomoSAR): High-Res 3D imaging
- \rightarrow SAR Polarimetry (PolSAR): dielectric, structure (roughness,

volume) properties

 \rightarrow enhanced component separation

Ground Based-SAR, airborne campaigns

- \rightarrow VHR (cm up to m) local properties, EM "ground truth"
- \rightarrow preparation of spaceborne missions.




Ground Based SAR



Measurements by a Ground based Synthetic Aperture Radar system, developed and implemented by the SAPHIR team at the University of Rennes 1

- Signal Tx and Rx controlled by a VNA
- Available frequency bands: 3 GHz to 35 Ghz (C,X,Ku bands)
- \circ Dynamic range $\approx 90 \text{ dB}$
- Sealed in a metallic box when operating works under a snow fall
- \circ Box + VNA = 40 Kg





Ground Based SAR



 \circ 2D synthetic antenna by collecting parallel passes \rightarrow 3D imaging (TomSAR)



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Ground Based SAR



The IETR GBSAR system allows to obtain multiple parallel passes in three ways:





6 equivalent tracks	5
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Additional tracks

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Refractive index estimation



Iterative procedure for estimation of refractive indices (hyp. horizontal layers):



- Usual scattering models may overestimate volume contribution

+ Keyogeophysical factors snow hand messnsing

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SAR Tomography over fjord ice



Data acquisition carried out in March 2013 at the Kattfjord, Tromsø, Norway



- Seasonal ice life of 3-4 months
- ° Tomographic X-band measurements at VV and HV
- \circ Temperature from -8° to -2°
- \circ The fjord ice: low salinity sea ice
- \circ Dry snow cover on top
- Significant amount air bubbles within the ice layer
 - 0.5 mm to 7 mm diameter
 - Irregularly shaped
 - Randomly oriented

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sea



SAR Tomography over fjord ice



- Same tilt effect as snow-pack tomography
- Corrected assuming
 - refractive index of snow = 1.4
 - refractive index of fjord ice = 1.7

Uncorrected

• Normalized intensity is presented to highlight contrasts (interfaces)



- 0.2 0.6 -0.2 0.5 -0.6 0.3 -0.8 0.2 4.5
- Three clearly visible interfaces Ο
 - Air/snow
 - Snow/ice 0
 - Ice/seawater

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SAR Tomography over fjord ice



• VV & HV tomography Corrected intensity (VV) Corrected intensity (HV) -60 0.2 0.2 -80 Height [m] Height [m] -70 -0.2 -0.2 -90 -80 -0.4 -100-0.6 -90 -0.8-0.8 -110-1001.5 2 4.5 1.5 3.5 4.5 25 3.5 5 2 2.5 5 3 3 Ground range [m] Ground range [m] Corrected normalized intensity (VV) Corrected normalized intensity (HV) 0.7 0.2 0.2 0.6 0.6 Height [m] Height [m] 0.5 0.5 -0.2 -0.2 0.4 0.4 -0.4 0.3 0.3 -0.6 0.2 0.2 -0.8 -0.8 0.1 3.5 4.5 4.5 1.5 2 2.5 3 4 5 1.5 2 3 3.5 5 Ground range [m] Ground range [m]

- Weaker air/snow and stronger snow/ice and ice/seawater scattering at HV than at VV
- \Rightarrow Mostly polarized contributions from regular spherical snow grains
- \Rightarrow Depolarized contributions from irregular air bubbles in the ice layer
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3-D imaging of a dry glacier



Test site: Mittelbergferner, Austrian Alps

- temperate glacier at the main ridge of the Alps in Tyrol
 - main test area is a flat plateau in the upper part of the glacier between 3000 and 3200 m



3D Focusing

esa





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3D Focusing





TomoSAR Vertical Section - HH - North-East Heading



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😔 🔤 Comparison to 200 MHz GPR Transects 🌑 CSA



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3D Polarimetry





(normalized) HH - red (normalized) HV - green (normalized) VV - blue







TomoSAR Image - 25 m below the Ice surface



TomoSAR Image - 50 m below the Ice surface







Towards <u>spaceborne</u> SAR tomography

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Current paradigm for forested areas: **retrieve the** *vertical distribution*

of backscattered power based on the observed InSAR coherences

(Nx1)

data vector

Remarks:

SLC data

- R is (semi-)positive definite => P(z) ≥ 0 physically consistent !
- Equivalent to coherent focusing if inversion is carried out using linear methods (Fourier)
- $^\circ$ Non-linear methods can be used to achieve super-

resolution/ side-lobe rejections

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Coherence matrix

(NxN)

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Spaceborne SARs collect multiple baselines are usually collected by flying multiple passes

Random motions on the order of a fraction of a wavelength are prohibited !!!

Urban tomography: motion due to subsidence/wind/thermal dilation

 \Rightarrow can be accounted for using suitable models

Forest tomography: random motion of scattering element within the vegetation, changing water content, terrain moisture

- P-Band scattering: larger branches, trunks \rightarrow coherence may be preserved at few days
- L-Band (and higher frequencies) scattering: need for simultaneous acquisitions

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Single pass InSAR: a way out of temporal decorrelation



Intrinsically robust to temporal decorrelation, since the images forming each interferometric pair are acquired nearly simultaneously.

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Space office Coherent vs Incoherent TomoSAR esa

Coherent Tomography



- **R** is (semi-)positive definite $\Rightarrow P(z) \ge 0 \rightarrow$ physically consistent ! Ο
- Equivalent to coherent focusing if inversion is carried out using 0 linear methods (Fourier)
- Assumption: Frozen Forest = Stable Scatterers 0



Frozen stationary forest

Non-frozen stationary forest \rightarrow Temporal decorrelation

Physical source: motion and EM changes of scattering elements

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Incoherent Tomography



The solution is no guaranteed to be ≥ 0 Ο

 \Rightarrow Countermeasures needed to enforce positive definitiveness

- Not equivalent to coherent focusing convergence in expected Ο value if proper weighting is applied
- Assumption: Stationary Forest = Stable Structure 0



- Non-frozen, non-stationary forest
- \rightarrow Structural variations

Physical source: seasonality, weather conditions, soil moisture, forest growth

L band spaceborne mission projectesa

SAOCOM-CS: a passive Companion Satellite to SAOCOM

In 2013, ESA received an offer from the National Commission for Space Activities of Argentina (CONAE) to launch a small satellite with the SAOCOM-1b satellite, and to collaborate during the mission exploitation phase





SAOCOM-CS



ESA EE9 Mission proposal

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L band spaceborne mission projectesa

SAOCOM paramete	ers Description				
Orbit	Sun-synchronou orbit	is nearly circular	frozen polar		
Repeat cycle	16 days (one sat	ellite)			
Mission lifetime	5 years				
Payload	L-band fully-po	larimetric SAR			
Central frequency	1275 MHz				
Incidence angle	$20-50^{\circ}$				
Spatial resolution	5 m (Stripmap)				
Bandwidth	Up to 45 MHz				
Noise Equivalent S	Sigma –27.9 (Stripm	ap single-polari	saton worst		
SAOCOM-CS	Measurement	Maturity .		×	
Application Field	Geometry	Level		\bigvee	\times
Boreal forests	Tomographic	Science	\sim		\checkmark
		driver	\times \times		\frown
Tropical forests	Tomographic	In-orbit	\searrow	\times	\wedge
		demonstrator	/ /		\checkmark
3D ice motion	AT Bistatic, Perp.	In-orbit	\times		\sim
	Bistatic	demonstrator			
Surface and asset	AT Bistatic, Perp.	In-orbit	\langle / \rangle		
deformation	Bistatic	demonstrator			
Soil moisture	Perp. Bistatic,	In-orbit	\times		
	Specular	demonstrator			
Ice subsurface	Tomographic	In-orbit			
structure		experiment			
Arid zones	Perp. Bistatic	In-orbit			
Other	A 11	experiment In orbit	/	1. 5-5-0	
ouner	All	In-orbit			
experiments		experiment			

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L band spaceborne mission projectesa

Campaign	BioSAR 2008 - ESA
System	E-SAR - DLR
Site	Krycklan river catchment, Northern Sweden
Scene	Boreal forest Pine, Spruce, Birch, Mixed stand
Topography	Hilly
Tomographic Tracks	6 + 6 – Fully Polarimetric (South-West and North- East)
Carrier Frequency	P-Band and L-Band
Slant range resolution	1.5 m
Azimuth resolution	1.6 m
Vertical resolution (P- Band)	20 m (near range) to >80 m (far range)
Vertical	6 m (near range) to 25 m (far







Base office SAOCOM-CS Tomography (from airborne



Data simulation

- Range filtering from 100 MHz to 40 MHz 0
- Degraded azimuth resolution from 1.6 m to 8 m

Tomographic pre-processing

- Incoherent processing based on 5 InSAR 0 pairs (w.r.t. a common Master)
- Coherence interpolation onto a regular 0 baseline grid

Tomographic focusing

- **Beamforming** approach with triangular Ο weights
- Capon filtering to achieve super-resolution 0

capabilities Coherence vector

(Nx 1)

Regularized coherence vector $(N \times 1)$

Reconstructed coherence matrix $(N+1 \times N+1)$







Multi-baseline InSAR coherences and phases - VV

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Vertical sections





SAOCOM-CS Tomogram - P(z) - HH

Focusing method: Beamforming

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Vertical sections





Focusing method: Capon

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Height retrieval performance



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European Space Agency





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$$\mathbf{s}_{r_i}(\pm \Delta x_a) = a_{c_i} \,\mathrm{e}^{-jk\sqrt{r_i^2 + (x_0 \mp \Delta x_a)^2}} \longrightarrow x_0, a_c$$

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$$s_1 = |a_{c_1}| \exp\left(-j\frac{4\pi}{\lambda_c}r_1 + j + \phi_{obj_1}\right)$$
$$s_2 = |a_{c_2}| \exp\left(-j\frac{4\pi}{\lambda_c}r_2 + j + \phi_{obj_2}\right)$$

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$$\check{z}$$
 ! %1 1 < \check{c} (\check{r} 1 2 \check{t} * * \check{r} ° \check{r} /
 $\phi_{12} = \arg(s_1 s_2^*) = \frac{4\pi}{\lambda_c}(r_2 - r_1) = k_c \Delta r_{12}$

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$$\begin{array}{ll} \Delta\phi_{12} &= k_z \Delta h + k_{fe} \Delta r_1 \\ &= \Delta\phi_{topo} + \Delta\phi_{fe} \end{array}$$

$$k_z = \frac{k_c B_\perp}{r_1 \sin \theta}, \quad k_{fe} = k_z \cos \theta$$

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azimuth