Combining Interferometric Radar and Laser Altimeter Data to Improve Estimates of Topography

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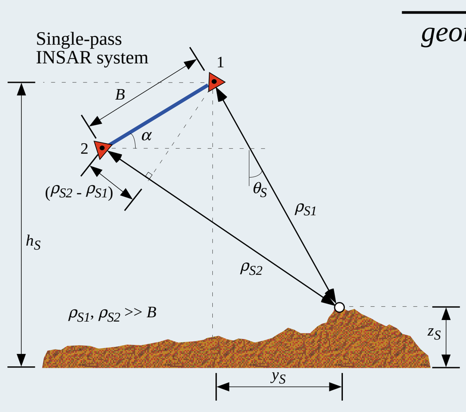
Introduction

- Research Objective
  - Estimate ground surface topography and vegetation heights from interferometric synthetic aperture radar (INSAR) and laser altimeter (LIDAR) data
- Difficulties
  - INSAR can image large areas, but computed elevations lie between ground surface and vegetation canopy
  - LIDAR provides vegetation canopy heights, but coverage area is limited
  - Combining INSAR and LIDAR data is problematic because sensors have different resolutions and do not directly measure same physical quantities
- Proposed Solution
  - Invert INSAR scattering model to estimate ground elevations and vegetation heights [1]
  - Process LIDAR data to obtain ground elevations and vegetation heights [2]
  - Combine transformed INSAR and LIDAR data in a multiresolution framework to obtain improved estimates of ground elevations and vegetation heights [3]

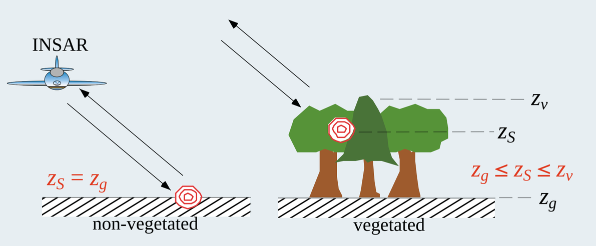
The INSAR Measurement

- Terrain topography can be determined over large areas using INSAR
  - Two complex-valued SAR images acquired simultaneously (single-pass INSAR)
  - Cross-correlation between two SAR images yields phase ϕ used to determine terrain heights z_S
- Vegetation introduces error into height measurements
  - Scattering from both ground and vegetation leads to ambiguity ($z_g \le z_S \le z_v$)

$$\underbrace{\phi = \frac{2\pi}{\lambda}(\rho_{S2} - \rho_{S1})}_{geometry} \approx \underbrace{\frac{-2\pi}{\lambda} B\sin(\theta_S - \alpha)}_{system\ parameters} \rightarrow \begin{array}{l} z_S = h_S - \rho_{S1}\cos\theta_S \\ y_S = \rho_{S1}\sin\theta_S \end{array}$$



h_S	= altitude of antenna 1
B	= baseline distance
α	= baseline angle
θ_S	= incidence angle
ρ_{S1}	= path length from antenna 1
ρ_{S2}	= path length from antenna 2
y_S, z_S	= target coordinates



INSAR Scattering Model

- Relate INSAR measurement to ground and vegetation heights [1]
  - Electromagnetic scattering model $\boldsymbol{M}$ used to relate observations $\mathbf{b}$ to terrain parameters $\mathbf{x}$
  - Observation vector $\mathbf{b}$ is 4-element vector containing magnitude and phase for two INSAR images

$$\mathbf{b} = \boldsymbol{M}(\mathbf{x}) \qquad \mathbf{x} = \begin{bmatrix} \Delta z_v \\ z_g \\ \tau \end{bmatrix}$$

Δz_v = vegetation height above ground
z_g = ground elevation
τ = vegetation extinction coefficient

- Transform inverse problem into constrained nonlinear optimization problem
  - Estimates are pixel-based
  - Inequality constraints bound feasible region X

$$\min \ \|\boldsymbol{M}(\mathbf{x}) - \mathbf{b}\|_2^2 \quad \text{subject to} \quad \mathbf{x} \in X \subseteq \mathbb{R}^3 \ \text{and} \ \{\theta_S \mid 0 < \theta_S < \pi/2\}$$

- Objective function and constraints are twice differentiable and convex on feasible region
- Solve as sequential quadratic programming problem to estimate $\mathbf{x}$ [4]

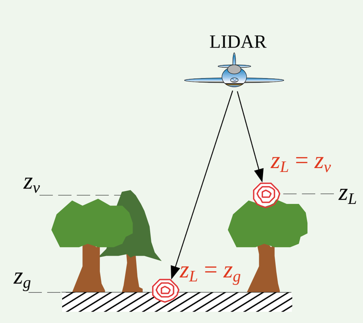
The LIDAR Measurement

- Relate LIDAR measurement to ground and vegetation heights [2]
  - LIDAR measures z_v directly
  - Processing required to obtain z_g
    - >> Compute height statistics in 50 x 50 moving window
    - >> Threshold height standard deviations to isolate non-vegetated pixels
    - >> Linearly interpolate between non-vegetated pixels
  - Obtain Δz_v from z_v-z_g

$$z_v = z_L \quad \forall (n_1, n_2) \in N$$

$$z_g = \begin{cases} z_L, & \forall (n_1, n_2) \in N \mid \sigma_L \le \text{threshold} \\ \text{linearly interpolate}, & \text{otherwise} \end{cases}$$

N = set of all pixels in image
σ_L = standard deviation of within-pixel heights



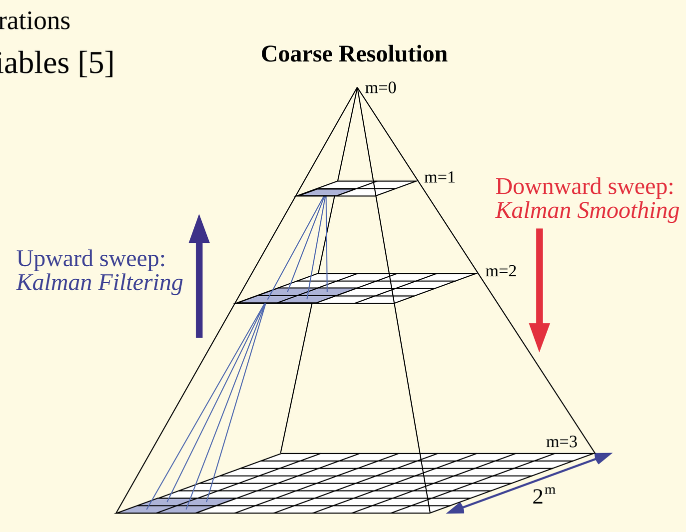
Data Fusion Framework

- Kalman smoothing on a quad-tree
  - Begins with fine-to-coarse sweep up the tree (Kalman filtering with merge step) [3]
  - Followed by coarse-to-fine sweep down the tree (Kalman smoothing)
  - Accommodates sparse and irregularly spaced measurements
  - Allows heterogeneous stochastic data models
  - Is non-iterative with constant computational complexity per node
    - >> For N nodes at finest scale, have 4N/3 nodes on the tree → O(N) operations
  - Computes minimum mean squared error estimates of state variables [5]
  - Allows explicit separation of state variables and observations

Linear Dynamic Model

$x(s)=A(s)x(s\bar{\gamma})+B(s)w(s)$ state equation
$y(s)=C(s)x(s)+v(s)$ measurement equation

m	= scale
s	= node index on multiresolution tree
$s\bar{\gamma}$	= backshift from s (coarse to fine)
$x(s)$	= state variable
$w(s)$	= white noise process ~N(0,1)
$y(s)$	= sensor measurement
$v(s)$	= measurement noise process ~$N(0,R(s))$
$A(s)$	= coarse-to-fine state transition
$B(s)$	= stochastic detail model
$C(s)$	= measurement model/selection matrix



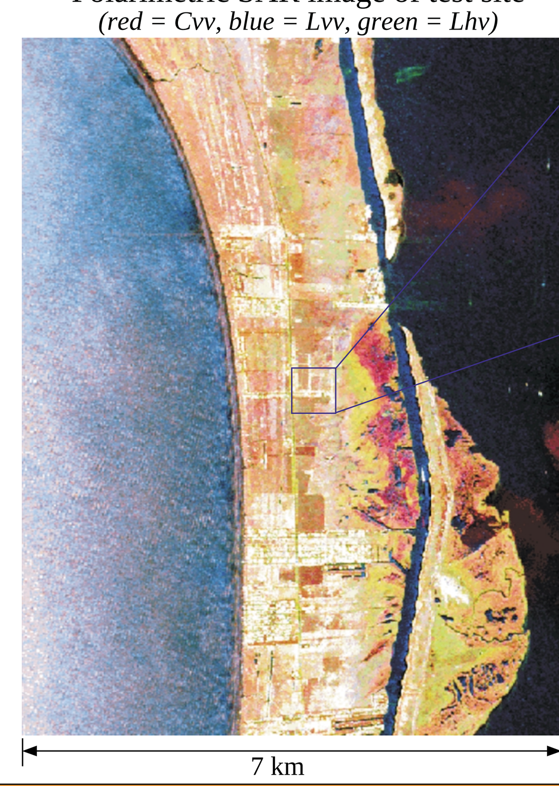
Model Identification

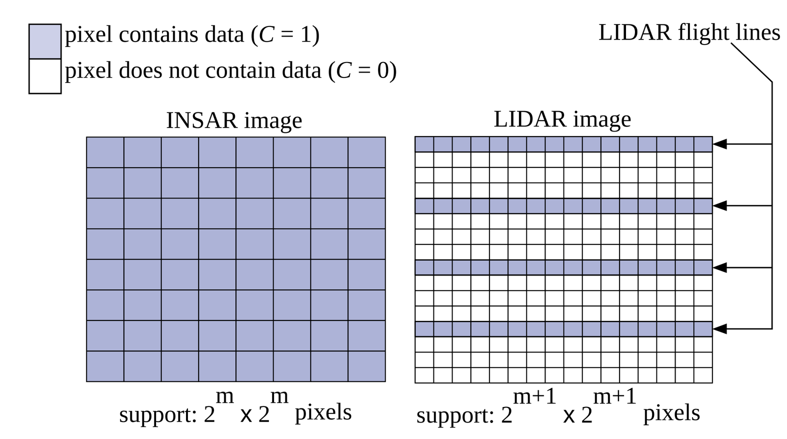
- Select stochastic model structure
  - Many natural processes, such as topography, exhibit self-similar statistics across resolution scales
  - 1/*f*-like stochastic models capture this characteristic
    - >> Variance of stochastic detail $B(s)$ decreases with increasing resolution
- Determine model coefficients
  - Unforced state variable is correlated through scale → $A(s)$=1
  - B_0 and μ selected to match power spectra of data model and observations, $B(s)=B_0 2^{(1-\mu)m/2}$, $\mu>1$

Data from Test Site

- Representative acquisition scenario
  - Dense INSAR coverage with 20 m x 20 m pixels
  - Sparse LIDAR coverage with 10 m x 10 m pixels
  - LIDAR data acquired at finest scale (scale = 6), INSAR at next coarser scale (scale = 5)

Polarimetric SAR image of test site
(*red = Cvv, blue = Lvv, green = Lhv*)

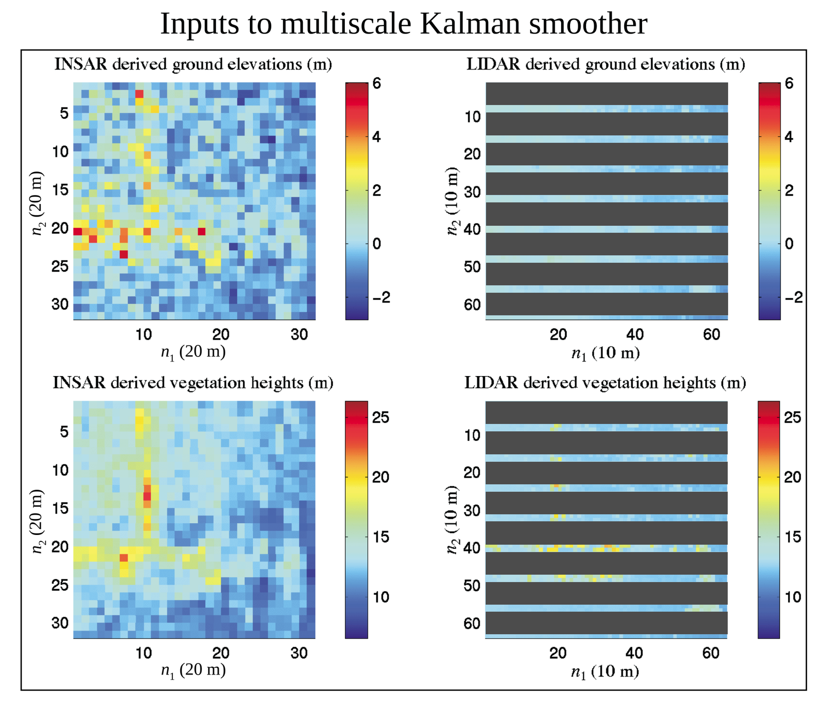




Results

- Run times
  - Nonlinear optimization: 40 min for 64 x 64 image, 10^{-4} estimate tolerance (MATLAB, single-processor Sun Ultrasparc)
  - LIDAR vegetation removal: < 1 min for 64 x 64 image, 10 m postings (C, 4-processor SGI Origin 2000) [2]
  - Multiscale Kalman smoothing: < 2 min for 2^6-scale quad-tree (MATLAB, single-processor Sun Ultrasparc)
- Mean squared errors for both ground elevations and vegetation heights are reduced

Inputs to multiscale Kalman smoother

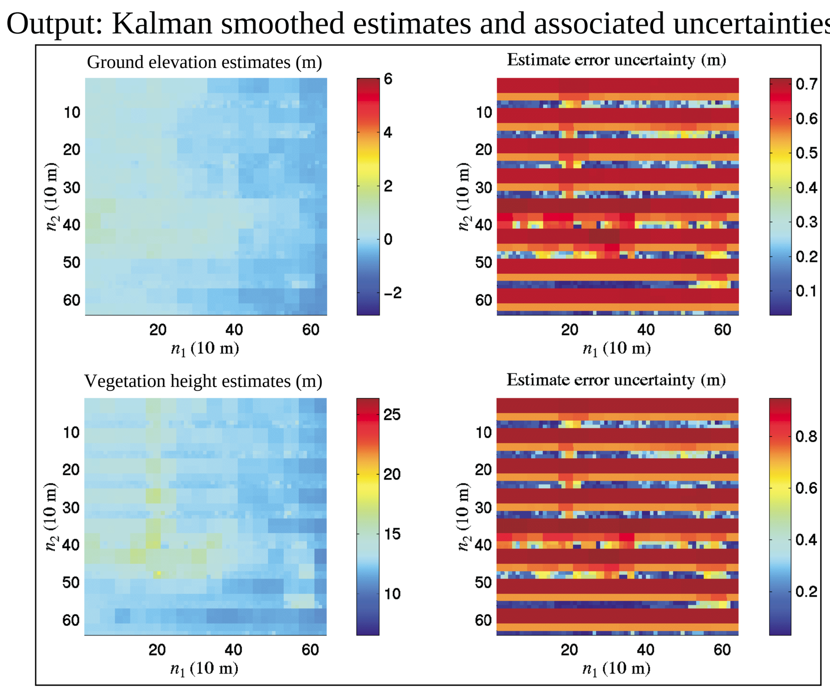


B_0=0.9, μ=1.5 } Bare surface estimation
B_0=3.0, μ=2.0 } Vegetation height estimation

Mean squared errors before multiscale estimation

Bare surface estimation	
MSE: C = {0 or 1}	1.97 m^2
MSE: C = {1}	2.38 m^2
MSE: C = {0}	1.83 m^2
Vegetation height estimation	
MSE: C = {0 or 1}	4.76 m^2
MSE: C = {1}	5.35 m^2
MSE: C = {0}	4.57 m^2

Output: Kalman smoothed estimates and associated uncertainties



Mean squared errors after multiscale estimation

Bare surface estimation	
MSE: C = {0 or 1}	0.056 m^2
MSE: C = {1}	0.018 m^2
MSE: C = {0}	0.069 m^2
Vegetation height estimation	
MSE: C = {0 or 1}	1.41 m^2
MSE: C = {1}	0.993 m^2
MSE: C = {0}	1.56 m^2

Error measures:
- Field measurements confirm LIDAR data approximate ground truth
- Before multiscale estimation:
  Error = (inverted INSAR data - processed LIDAR data)
- After multiscale estimation:
  Error = (Kalman smoothed estimates - processed LIDAR data)

Conclusions

- Combining physical modeling with multiscale estimation improves parameter estimates
  - Multiscale approach is natural for fusing multiple sources of data with different resolutions
  - Target and scale dependent measurement variances allow proper integration of multiple data types
  - Optimal (mean squared sense) estimates of state variables are obtained, conditioned on physical modeling and observations
- Key contributions:
  - Combining physical modeling with multiscale estimation to accommodate nonlinear measurement-state relationships
  - Improving estimates of ground elevations and vegetation heights for remote sensing applications

Future Work

- Estimate model coefficients directly in lieu of matching power spectra
- Use linear signal modeling to determine heterogeneous *A(s)*
- Develop vector-valued stochastic model
  - Exploit interdependencies between estimated parameters

References

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[5] R. Brown and P. Hwang, *Introduction to Random Signals and Applied Kalman Filtering*, 3rd ed., Wiley, New York, NY, 1997.

Acknowledgments

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