Ecological applications with repeat-pass Pol-InSAR

Marco Lavalle, Kosal Khun, Maxim Neumann, Razi Ahmed, Marc Simard and Scott Hensley

Jet Propulsion Laboratory, California Institute of Technology
Outline

• Introduction and motivation

• **Part I: The RMoG model**
  - Modeling assumptions
  - Consequences of the RMoG model

• **Part II: Inversion of the RMoG model**
  - Inversion using single-baseline Pol-InSAR data
  - Numerical simulations
  - UAVSAR experiments
Background

- Cancellation of DESDynI lidar motivated us to look for alternative approaches for ecosystem science

- DESDynI Science Steering Group and broader ESWG recognize the potential of Pol-InSAR

- Terrestrial Ecology funded Pol-InSAR algorithm development and field experiments

- NASA CCE workshop in Oct 2011 addressed the problem of temporal decorrelation
Motivation and objectives

- Current and forthcoming **low-frequency SAR missions** (ALOS-1/2, BIOMASS, DESDynI) collect repeat-pass data

- The **use of repeat-pass Pol-InSAR data** is predicated on solving/mitigating the problem of temporal decorrelation

- **Objective is** to provide a model-based algorithm that “compensates for” temporal decorrelation while forest parameter are estimated

Canopy height estimated from 2-day repeat-pass JPL/UAVSAR data (Harvard Forest, MA)
The RMoG model

- Random-motion-over-ground (RMoG) model: RVoG model + refined Zebker’s model

- Physical model of temporal-volumetric coherence proposed in late 2009 and improved throughout 2010-2012

- Exponential structure function for volumetric decorrelation

- First-order expansion of arbitrary temporal function for temporal decorrelation (time-dependence dropped)
Key properties of the RMoG model

- 4 structural + 2 temporal = 6 model parameters

- Temporal and volumetric decorrelations are mixed and not separable

\[ \gamma = e^{j\varphi_g} \frac{\mu \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu + 1} \]

\[ \gamma \neq \gamma_t \gamma_v \]

- RMoG temporal decorrelation depends on vegetation structure (e.g. canopy height)

\[ p_1 = \frac{2\kappa_v}{\cos(\theta - \alpha)}, \quad p_2 = p_1 + j\kappa_z, \quad p_3 = -\frac{\Delta\sigma^2}{2h_r} \left( \frac{4\pi}{\lambda} \right)^2 \]
Key properties of the RMoG model

Coherence locus of RMoG temporal decorrelation

RMoG temporal decorrelation depends on wave polarization through the ground-to-volume ratio

Part II

Inversion of the RMoG model
From RMoG model to RMoG forward problem

- **RMoG forward problem** formulated as mapping of ten-dimensional real vector into five-dimensional complex vector

- Each coherence observation has a **different** ground-to-volume ratio

- **Domain** of RMoG forward problem is a subset of the 10-dimensional real space

- **Codomain** of RMoG forward problem is a subset of the 5-dimensional complex space


RMoG inverse problem

- The codomain of the RMoG forward problem is not the coherence locus.

- Two coherence observations are sufficient to estimate the coherence locus, but not the RMoG model parameters.

- Values of RMoG model parameters are inferred from vector of observations.

- The RMoG forward problem is ambiguous if two vectors of model parameters map in the same coherence vector.
RMoG inversion strategy

1. Coherence phase optimization → end points of visible line

2. Unit circle intersection → approximate ground phase

3. Constrained least-square optimization of non-linear, complex problem using interior-point algorithm and analytically-derived gradient

\[
\begin{align*}
\hat{\gamma}_1 e^{-j\varphi_{gt}} &= e^{j(\varphi_g - \varphi_{gt})} \frac{\mu_1 \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_1 + 1} \\
\hat{\gamma}_2 e^{-j\varphi_{gt}} &= e^{j(\varphi_g - \varphi_{gt})} \frac{\mu_2 \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_2 + 1} \\
\hat{\gamma}_3 e^{-j\varphi_{gt}} &= e^{j(\varphi_g - \varphi_{gt})} \frac{\mu_3 \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_3 + 1} \\
\hat{\gamma}_4 e^{-j\varphi_{gt}} &= e^{j(\varphi_g - \varphi_{gt})} \frac{\mu_4 \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_4 + 1} \\
\hat{\gamma}_5 e^{-j\varphi_{gt}} &= e^{j(\varphi_g - \varphi_{gt})} \frac{\mu_5 \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_5 + 1}
\end{align*}
\]

\[
F = \sum_{i=1}^{5} |\gamma_i - \hat{\gamma}_i|^2
\]

\[
\gamma_i = e^{j\varphi_g} \frac{\mu_i \gamma_{tg} + \gamma_{vt} e^{-j\varphi_g}}{\mu_i + 1}
\]

\[
\hat{\gamma}_i = \hat{\gamma}_1 + F_i \left( e^{j\varphi_{gt}} - \hat{\gamma}_1 \right), \quad F_i = \frac{F_5}{4} (i-1)
\]

\[
\sigma_v \geq \sigma_g
\]

RMoG inversion: Existence and uniqueness of the solution

RMoG numerical simulations

- **large range** of model parameters
  \[ \varphi_g \in [-\pi, \pi] \text{ rad} \]
  \[ h_v \in [0, 30] \text{ m} \]
  \[ \kappa_e \in [0.1, 0.3] \text{ dB m}^{-1} \]
  \[ \sigma_g = 0 \text{ cm} \]
  \[ \sigma_v = 0 \text{ cm} \]
  \[ \mu_{\text{max}} \in [0, 10] \text{ dB} \]
  \[ \mu_{\text{min}} \in [-10, -30] \text{ dB} \]

- **UAVSAR** radar and acquisition geometry
  \[ k_z = 0.12 \text{ m}^{-1} \]
  \[ \lambda = 0.2384 \text{ m} \]
  \[ \theta = 45 \text{ deg} \]

- **300 RMoG coherence** simulations and RMoG inversions
RMoG inversion: Existence and uniqueness of the solution

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  - \( h_v \in [0, 30] \text{ m} \)
  - \( \kappa_e \in [0.1, 0.3] \text{ dB m}^{-1} \)
  - \( \sigma_g \in [0, 1] \text{ cm} \quad (\gamma_t \simeq 0.87) \)
  - \( \sigma_v \in [1, 2] \text{ cm} \quad (\gamma_t \simeq 0.57) \)
  - \( \mu_{\text{max}} \in [0, 10] \text{ dB} \)
  - \( \mu_{\text{min}} \in [-10, -30] \text{ dB} \)

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RMoG model VS real world: UAVSAR experiments
Validation of temporal decorrelation model ($b_\perp = 0$)

Quebec (Canada); 45 min temporal interval; ~zero vertical wavenumber; L-band UAVSAR


LVIS lidar canopy height

UAVSAR HV-coherence ($\mu \approx 0$)

validation of dependence of temporal decorrelation on canopy height
Validation of temporal decorrelation model \((b_\perp = 0)\)

Quebec (Canada); 45 min temporal interval; ~zero vertical wavenumber; L-band UAVSAR

Tree height from Pol-InSAR UAVSAR data

Harvard Forest, MA (US); 2 days temporal interval; 0.075 m$^{-1}$ vertical wavenumber; L-band

Canopy-dominated coherence

Ground-dominated coherence

Estimated ground topography

Estimated canopy height
Tree height from Pol-InSAR UAVSAR data VS lidar LVIS

Harvard Forest, MA (US); 2 days temporal interval; 0.075 m$^{-1}$ vertical wavenumber; L-band

![Histogram of Canopy Height](image)
RMoG temporal parameters from Pol-InSAR UAVSAR data

Harvard Forest, MA (US); 2 days temporal interval; 0.075 m$^{-1}$ vertical wavenumber; L-band

Dynamic motion of scattering elements at ground (mean TempDec = 0.97)

Dynamic motion of scattering elements in the canopy (mean TempDec = 0.67)
Comparison UAVSAR time series and weather data

Coherence, precipitation and wind data (Harvard Forest, MA)

effects of the rain
Conclusions

- In repeat-pass Pol-InSAR scenario **temporal decorrelation must be modeled** in order to extract ecosystem structural parameters.

- We have proposed a **physical model** of temporal decorrelation and a **new method for extracting canopy height** from single-baseline, repeat-pass Pol-InSAR data.

- Model and method validated with numerical simulations and **JPL/UAVSAR data**.

- Attractive avenue for **estimating forest parameters using Pol-InSAR data** from proposed radar missions (DESDynI, ALOS-2, BIOMASS, SENTINEL-1).