Towards an Optimal Noise Versus Resolution Trade-off in Wind Scatterometry

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Overview

- Estimation approach
  - Field-wise estimation with statistical signal model
- Implementation
  - MAP estimation
  - Development of priors
- Analysis (QSCAT)
  - Speed histograms
  - Metrics vs. ECMWF
  - Spectra
  - Examples
Estimation Approach

- Field-wise retrieval with statistical signal model (i.e., prior)
  - Simultaneously estimate every WVC for entire rev
  - Prior incorporates spatial covariance ($k^{-2}$ spectrum)
  - No ambiguity removal post wind-retrieval
    - Effectively done by initialization
Estimation Approach

- **Bayes Estimation**
  - Multimodal $\Rightarrow$ local quadratic loss
  - Impractical to implement unless local ball $\Rightarrow 0$
  - Converges to the MAP estimate

- **MAP Estimation**
  - Practical to implement
  - Incorporates the spatial structure of prior
  - Trades off noise and resolution
  - May be biased

Maximize log of posterior distribution (gradient search)

\[
\frac{\partial}{\partial \bar{U}(x)} \log f(\bar{U}(x)|\bar{\sigma}_m^0) = \frac{\partial}{\partial \bar{U}(x)} \left[ \log f(\bar{\sigma}_m^0|\bar{U}(x)) + \log f(\bar{U}(x)) \right]
\]

ML portion Prior
Implementation: MAP Estimation

• ML portion (left side)[1]

\[
\frac{\partial}{\partial U_i(x)} \log f(\sigma^0_m | \vec{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \text{gmf}_n(\vec{U}(x))}{\partial U_i(x)}
\]

• Prior indep Gaussian with spatial cov matrices[2]

\[
f(\vec{U}(x)) = f(U_s(x)) f(U_d(x))
\]

\[
\frac{\partial \log f(U_s(x))}{\partial U_s(x)} = \frac{-1}{2} \mathbf{R}_s^{-1}(U_s(x) - \mu_s(x))
\]

\[
\frac{\partial \log f(U_d(x))}{\partial U_d(x)} = \sin(U_d(x)) \circ \mathbf{R}_d^{-1} \cos(U_d(x)) - \cos(U_d(x)) \circ \mathbf{R}_d^{-1} \sin(U_d(x))
\]


Implementation: Prior Covariance

- Exponential covariance function
  \[ c(x) = e^{-2\pi k_0 |x|} \quad \mathcal{F}\{c(x)\} = \frac{2k_0}{k^2 + k_0^2} \]

- Estimate parameters from L2B12 selected ambiguity using signal and noise model (direction cov of \( \psi = e^{id} \))

\[
\text{cov}(x) = ae^{-b|x|} + c\delta(x)
\]

**TABLE I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Speed</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>12.58</td>
<td>0.924</td>
</tr>
<tr>
<td>(b)</td>
<td>0.01238</td>
<td>0.01029</td>
</tr>
<tr>
<td>(c)</td>
<td>0.678</td>
<td>0.074</td>
</tr>
</tbody>
</table>

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Analysis: Speed Histograms

- 99 QSCAT Revs: 49663-49762
- MAP speed consistent with L2B12 DIRTH, but low speeds are biased slightly lower
Analysis: Metrics w.r.t. ECMWF

Different bias w.r.t. ECMWF

Reduced variability in center of swath
Analysis: Speed and Direction Spectra

- Average speed resolution ~ 25-33 km
- Average direction resolution ~ 50 km
Examples: Tiled Revs

L2B12 DIRTH Speed (m/s)

MAP Speed (m/s)

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Conclusion

• MAP estimation with priors that incorporate spatial structure
  – Outperforms DIRTH in all metrics except speed bias w.r.t. ECMWF
  – Automatically filters (attenuates) signal components that are expected to be noisy
  – Only parameters to tune (given a prior) are $K_p$, WVC posting, and numeric gradient search parameters (i.e., step size, max iterations, and initialization)

• This methodology may be applied to improve several special applications
  – Special priors for hurricanes, fronts, or other storm features
  – Wind and rain estimation with rain priors
  – Coastal and ice-edge applications (can handle sigma0 from mixed surfaces)
Backup Slides
Examples: Tiled Revs

MAP Speed (m/s)
Examples: Tiled Revs

L2B12 Direction (deg.)
Examples: Tiled Revs

MAP Direction (deg.)

Along-track

Cross-track

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Examples: Tiled Revs

L2B12 Speed (m/s)
Examples: Tiled Revs

MAP Speed (m/s)
Examples: Tiled Revs

MAP Direction (deg.)

Along-track

Cross-track
Examples: Tiled Revs

L2B12 Direction (deg.)
L2B12 DIRTH Direction Histogram

DIRTH Direction Histogram Normalized by ECMWF (dB)
L2B12 DIRTH Speed
12.5km MAP Speed
12.5km MAP Direction
Analysis: Speed and Direction Spectra Normalized by $k^{-2}$

- Average speed resolution $\sim 25-33$ km
- Average direction resolution $\sim 50$km
MAP Estimation Implementation

• Maximize log of posterior (gradient search)

\[
\frac{\partial}{\partial \tilde{U}(x)} \log f(\tilde{U}(x)|\tilde{\sigma}_m^0) = \frac{\partial}{\partial \tilde{U}(x)} \left[ \log f(\tilde{\sigma}_m^0|\tilde{U}(x)) + \log f(\tilde{U}(x)) \right]
\]

\[
\frac{\partial}{\partial U_i(x)} \log f(\tilde{\sigma}_m^0|\tilde{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \text{gmf}_n(\tilde{U}(x))}{\partial U_i(x)}
\]

\[
K_n = \left[ \frac{(\sigma_n^0 - T_n(\tilde{U}(x))) - (\alpha_n T_n(\tilde{U}(x)) + \beta_n/2)}{R_{n,n}} + \frac{(\sigma_n^0 - T_n(\tilde{U}(x)))^2(\alpha_n T_n(\tilde{U}(x)) + \beta_n/2)}{R_{n,n}^2} \right]
\]

\[
T_n(\tilde{U}(x)) = \sum_x A_n(x) \text{gmf}_n(\tilde{U}(x))
\]