Radar Signal Processing: Opportunities for SSPers

Randy Moses

Dept. of Electrical and Computer Engineering
The Ohio State University

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Context

- Advances in digital processing are enabling revolutionary opportunities for radar signal processing

- Opportunities for Statistical Signal Processing
  - Persistent sensing over space and time
  - More sophisticated radar image/volume reconstructions
  - Multi-function radars that can simultaneously perform imaging, detection, moving object tracking and recognition, …
  - Uncertainty analysis and estimation bounds

- Challenges
  - Traditional models for radar backscattering may not apply over wide angles
  - Large data, processing, and communications tasks
Persistent Sensing enables:

- High resolution, volumetric imaging of stationary objects and scenes
- Continuous tracking of moving objects
Outline

- Radar 101
- Revisit modeling assumptions for wide angle radar
- How can sparsity play a role?
  - Parametric Modeling
  - Sparse Reconstruction
- Feature-Based Classification
- Transmit adaptation
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SAR Data Collection

At each point measure:
\[ E(f, \phi, \theta), \ f \in [f_{\text{min}}, f_{\text{max}}] \]
SAR Image Formation

- Traditional approach: tomography

- Tomographic image $I(x,y)$ is a **matched filter** for an isotropic point scatterer at location $(x,y)$. [Rossi+Willsky]
3D Reconstruction

- Large data size and processing requirements
- Filled aperture is difficult to collect
Example: Ohio Stadium

X-Band Radar
3° aperture
1ft x 1ft res
SAR Image Detail
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Persistent, Wide-Angle SAR

Persistent Sensing enables:

• High resolution, volumetric imaging of stationary objects
• Continuous tracking of moving objects

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AFRL Gotcha Radar

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Data Storage: 90 G samples/circle

Image formation: 45 Tflops/sec

Communications: 190 M samples/sec
Wide Angle Scattering Behavior

- At high frequencies, radar backscatter is well-modeled as a sum of responses from canonical scattering terms.
- EM scattering theory provides a rich characterization of backscatter behavior as a function of object shape
  - Azimuth, elevation, frequency dependence
  - Polarization dependence
  - Phase response - range
- Most backscatter does NOT behave like a point scatterer over wide angles
  - Standard imaging is not statistically (close to) optimal
Scattering Model

\[
S'(f, \phi, \theta) = \begin{bmatrix}
A_{HH} & A_{HV} \\
A_{VH} & A_{VV}
\end{bmatrix}
\left(\frac{jf}{f_c}\right)^\gamma M(\phi, \theta) \, e^{j\frac{4\pi f}{f_c} \Delta R(x,y,z;a)}
\]

<table>
<thead>
<tr>
<th>Canonical Shape Type I</th>
<th>Icon</th>
<th>Polarization Type (\beta)</th>
<th>Amplitude Response (M_r(k, \phi, \theta; \Theta))</th>
<th>Calibration Factor (A)</th>
<th>Range Offset (\Delta R_e)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plate</td>
<td>![Plate Icon]</td>
<td>odd</td>
<td>(M_{\text{plate}}(\Theta_{\text{plate}}) = \frac{kA}{\sqrt{\lambda}} \text{sinc} \left[ kL \sin \left( \frac{\phi}{2} \right) \cos \theta \right] \text{sinc} \left[ kH \sin \theta \right] ) (\phi \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right])</td>
<td>(LH)</td>
<td>0</td>
</tr>
<tr>
<td>Dihedral</td>
<td>![Dihedral Icon]</td>
<td>even</td>
<td>(M_{\text{dih}}(\Theta_{\text{dih}}) = \frac{kA}{\sqrt{\lambda}} A \text{sinc} \left[ kL \sin \left( \frac{\phi}{2} \right) \cos \theta \right] \times \left{ \sin \theta, \ \theta \in \left[ 0, \frac{\pi}{2} \right] \right} \times \left{ \cos \theta, \ \theta \in \left[ -\frac{\pi}{2}, -\frac{\pi}{2} \right] \right} )</td>
<td>(2LH)</td>
<td>0</td>
</tr>
<tr>
<td>Trihedral</td>
<td>![Trihedral Icon]</td>
<td>odd</td>
<td>(M_{\text{tri}}(\Theta_{\text{tri}}) = \frac{kA}{\sqrt{\lambda}} \times \left{ -\cos \left( \frac{\phi}{2} - \frac{\pi}{4} \right), \ \phi \in \left[ -\frac{\pi}{2}, 0 \right] \right} \times \sin \left( \frac{\phi}{2} - \frac{\pi}{4} \right), \ \phi \in \left[ 0, \frac{\pi}{4} \right] \right} )</td>
<td>(2\sqrt{3}L^2)</td>
<td>0</td>
</tr>
<tr>
<td>Cylinder</td>
<td>![Cylinder Icon]</td>
<td>odd</td>
<td>(M_{\text{cyll}}(\Theta_{\text{cyll}}) = jk \sqrt{\cos \phi} A \text{sinc} \left[ kL \sin \phi \right] \phi \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right] )</td>
<td>(L \sqrt{r})</td>
<td>2r \cos \phi</td>
</tr>
<tr>
<td>Top-hat</td>
<td>![Top-hat Icon]</td>
<td>even</td>
<td>(M_{\text{top}}(\Theta_{\text{top}}) = A \sqrt{k} \times \left{ \sin \theta, \ \theta \in \left[ 0, \frac{\pi}{2} \right] \right} \times \cos \theta, \ \theta \in \left[ \frac{\pi}{4}, \frac{\pi}{3} \right] \right} )</td>
<td>(\sqrt{\frac{8\pi}{\sqrt{2}}} L)</td>
<td>2r \cos \theta</td>
</tr>
<tr>
<td>Sphere</td>
<td>![Sphere Icon]</td>
<td>odd</td>
<td>(M_{\text{sphere}}(\Theta_{\text{sphere}}) = A \sqrt{\pi r} )</td>
<td>1</td>
<td>2r</td>
</tr>
</tbody>
</table>

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Jackson & RLM: 2009
When the radar measurement extent is ≤ scattering persistence, the isotropic assumption is ~satisfied, and tomographic imaging is ~a matched filter.
For wide-angle measurements the isotropic scattering assumption breaks down.

– Tomography is no longer a matched filter
Scattering Aspect Dependence

Most scattering centers have limited response persistence 20° or less [Dudgeon et al, 1994]

Image response is no longer characterized by a single impulse response shape.
Coherent wide-angle SAR Images

500 MHz Bandwidth
110 degrees az

Coherent wide-angle image is not well-matched to limited persistence scattering behavior

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**GLRT Image Formation**

**GLRT Image:** Image $I(x,y)$ is GLRT output at $(x,y)$ to a limited-persistence scattering center with center $\phi_c$ and width $\alpha$.

$$I(x, y) = \arg\max_{\phi, \alpha} R(x, y, \phi_c, \alpha)$$

$$R(x, y, \phi_c, \alpha) = \text{std image with center } \phi_c, \text{ width } \alpha$$

**Approximation:** fix width $\alpha$; quantize $\phi_c$.

Then the GLRT image is approximately max over sub-aperture images.

**GLRT Image:** pixel $p_{ij} = \arg\max_{\phi_c} p_{ij}^{\phi_c} \approx \arg\max_k p_{ij}^k$
GRLT Imaging

Generalizes Rossi+Willsky matched filter result to wide-angle imaging with limited-persistence scattering

[Diagram of Frequency Data and GLRT Image]

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RLM, Potter, Cetin: 2004
Coherent and GLRT Image

110° Coherent Image

110° GLRT Image

4 GHz bandwidth

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RLM, Potter, Cetin: 2004
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Sparse 3D Radar Reconstruction

- 3D radar reconstruction necessarily will use (very) sparse measurements
- Is the radar reconstruction sufficiently sparse to overcome measurement sparsity?

AFRL Backhoe Data Dome, with sparse “squiggle path” shown
Squiggle Path 3D Tomographic Reconstruction

Top 25 dB voxels shown
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**Parametric: Canonical Scattering Model**

\[
S(f, \phi, \theta) = \sum_{k=1}^{K} \left[ \begin{array}{cc} A_{HH} & A_{HV} \\ A_{VH} & A_{VV} \end{array} \right] \left( \frac{jf}{f_c} \right)^{\gamma_k} M_k(\phi, \theta) e^{j\frac{4\pi f}{f_c} R(x_k, y_k, z_k; a_k)}
\]

- **Polarization Dependence**
- **Frequency Dependence**
- **Aspect Dependence**
- **Location Dependence**

Jackson & RLM: 2009
Nonparametric:
\( l_p \) Regularized Least-Squares

Sparsity

- Measurements \( y (M \times 1) \): sparse sampling of full \((f, az, el)\) radar measurement space
- Reconstruction: \( x (N \times 1) \): sparse set of \((x, y, z)\) locations with significant radar scattering energy

\[
y = Ax + \nu
\]

\[
A = \left[ e^{-j(k_x mx_n + k_y my_n + k_z mz_n)} \right], \quad M \times N
\]

Sparse reconstruction:

\[
\hat{x} = \arg \min_x \|y - Ax\|_2^2 + \lambda \|x\|_p^p \quad p \leq 1
\]
Algorithmic Challenges

- For large scale problems, the algorithm can become very memory and computationally expensive.
  - E.g. for backhoe squiggle problem:
    - $M \approx 10^5$
    - $N \approx 10^7$

- $A$ is structured and may not satisfy RIP for reconstruction samplings of interest.
  - Recent advances [e.g. Austin, Fannjiang] incorporate structure in $x$ to allow high coherence in $A$. 

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Squiggle Path Collection: $l^p$ Regularized LS Reconstruction

Top 30 dB voxels shown; p=1

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Austin, Ertin, RLM, 2011
Backhoe Squiggle Image
Gotcha Vehicle Data
Gotcha $l_p$ Reconstructions: Camry
Radar 101

Revisit modeling assumptions for wide angle radar

How can sparsity play a role?
  – Parametric Modeling
  – Sparse Reconstruction

Feature-Based Classification

Transmit adaptation
Vehicle Classification

- Six sedans from a 10-class problem
- Spatially-varying signatures across large scene
Vehicle Classification; Attributed Point Sets

>95% correct classification

Dungan and Potter, 2011

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Joint Communication and Radar Sensing

Can adaptive transmit waveforms be used to simultaneously sense a scene and communicate sensed data to a receiver?

AFRL Gotcha Radar Communications:
190 M samples/sec

Image at UAV

Communicated image at base station
OSU Software Defined Radar

- Compact
- Wide Bandwidth (125 MHz)
- Real-time (DSP + FPGA)
Joint Sensing-Comm Experiment

- Self-adaptive joint radar/communication system
  - PN transmit signal waveform
- Measured and communicated range-Doppler maps
  - $n^{th}$ range-Doppler map used to adapt $(n+1)^{st}$ waveform set.

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Rossler, Ertin, RLM: 2011
Take-Home Points

- Advances in sampling and digital processing are moving radar systems more firmly in the digital realm.
- Persistence and wide-angle sensing motivate rethinking the models and algorithms for radar processing.
- Effective 3D reconstruction from sparse apertures is possible
  - Surprising fidelity
  - Huge issues in computation, communication remain
- Huge opportunities for SSPers
  - Modeling; tractable algorithms; adaptation; persistent tracking; classification; performance estimation

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Data Resources

- AFRL Sensor Data Management System
  - https://www.sdms.afrl.af.mil
  - Backhoe Volumetric Data (synthetic)
  - Civilian Vehicle Data Domes (synthetic)
  - Gotcha data (measured)
  - SAR-GMTI Challenge Problem

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Thank you!