PHD Extended Target Tracking Using an Incoherent X-band Radar: Preliminary Real-World Experimental Results

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Introduction

- X-band radars are used for both civil and military applications, e.g.:
  - Weather monitoring
  - Air traffic control
  - Maritime vessel traffic control
  - Wave motion estimation
  - Surface current retrieval
  - Bathymetry map construction
- Marine X-band radar: typically multiple detections per object

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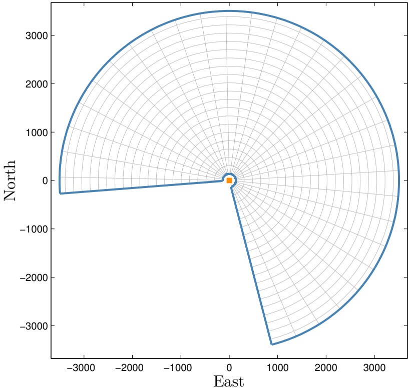
- Marine X-band radar: typically multiple detections per object
- **Problem formulation:**
  - **1:** Process raw radar data to produce detections.
  - **2:** Process detections with Multi Target filter to produce target tracks.

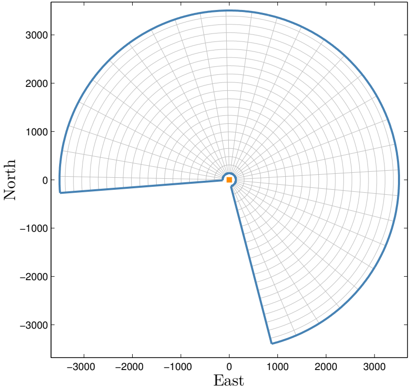
Acquisition system



- Data acquired by marine incoherent X-band radar
- Mounted in Tuscany, Italy, close to Costa Concordia wreckage

Detection strategy

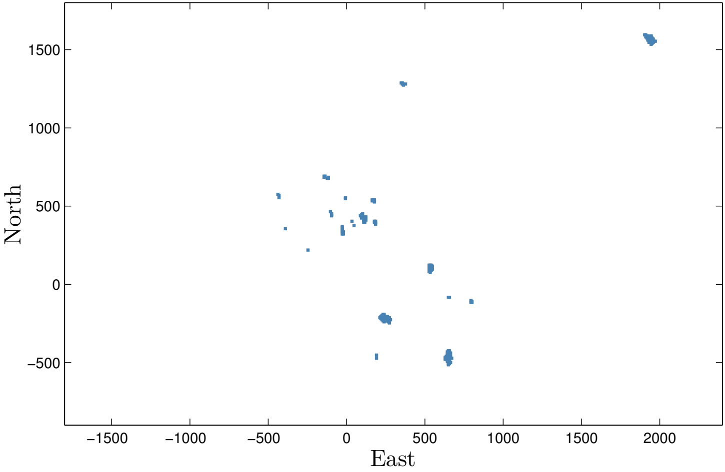
Parameter	**Value**
Rotation period (Δt)	2.41 s
Range res (Δr)	7 m
Azimuth res ($\Delta \varphi$)	$0.9°$
Radar scale	3069 m
View sector	$260°$



- Order Statistic-Constant False Alarm Rate (OS-CFAR) detector
- Weibull distribution for the sea-clutter.

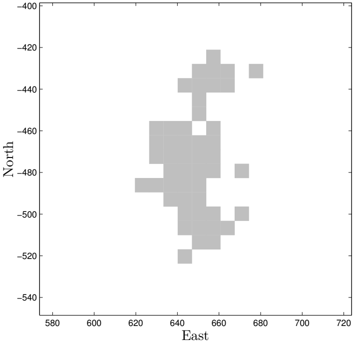
Radar detections

- Approx 1 minute of data (30 time steps)



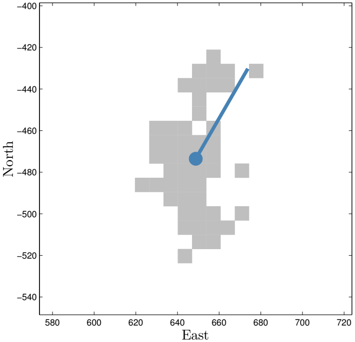
Target modeling

Estimate:



Modeling choices:

Target modeling



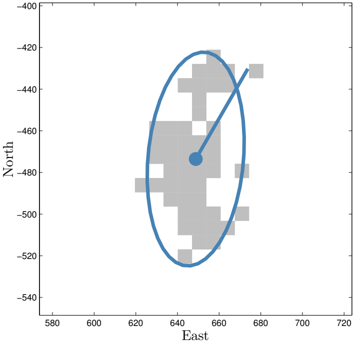
Estimate:

- Position and motion

Modeling choices:

- Only linear motion parameters: velocity and acceleration

Target modeling



Estimate:

- Position and motion
- Size and shape

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- Only linear motion parameters: velocity and acceleration
- Elliptic shape (random matrix model)

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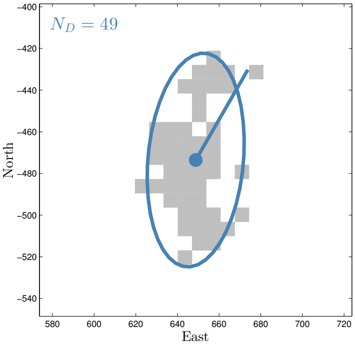


Estimate:

- Position and motion
- Size and shape
- Number of detections

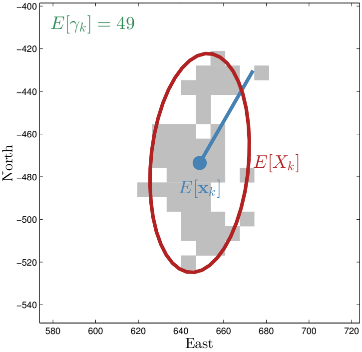
Modeling choices:

- Only linear motion parameters: velocity and acceleration
- Elliptic shape (random matrix model)
- Number of detections is Poisson

Target state

Extended target state: $\xi_k = (\gamma_k, \mathbf{x}_k, X_k)$

- Poisson rate: γ_k.
- Kinematics vector: $\mathbf{x}_k = [\mathbf{p}_k \ , \ \mathbf{v}_k \ , \ \mathbf{a}_k]^{\mathrm{T}}$
  position $\mathbf{p}_k$, velocity $\mathbf{v}_k$, acceleration $\mathbf{a}_k$
- Extension matrix: X_k



Gamma Gaussian inverse Wishart distributed

$$p\left(\xi_k \middle| \mathbf{Z}^k\right) = \mathcal{G}\left(\gamma_k \, ; \, \alpha_{k|k}, \beta_{k|k}\right) \mathcal{N}\left(\mathbf{x}_k \, ; \, m_{k|k}, P_{k|k} \otimes X_k\right)$$

$$\times \mathcal{IW}_d\left(X_k \, ; \, v_{k|k}, V_{k|k}\right)$$

$$= \mathcal{GGIW}\left(\xi_k \, ; \, \zeta_{k|k}\right)$$

$$\zeta_{k|k} = \left\{\alpha_{k|k}, \beta_{k|k}, m_{k|k}, P_{k|k}, v_{k|k}, V_{k|k}\right\}$$

Detection likelihood model

- **Detection set likelihood:**

$$p\left(\mathbf{Z}_k \middle| \xi_k\right) = N_{z,k}! P\left(N_{z,k} \middle| \xi_k\right) \prod_{j=1}^{N_{z,k}} p\left(\mathbf{z}_k^{(j)} \middle| \xi_k\right)$$

i.e. detections assumed independent

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- **Poisson cardinality likelihood:**

$$P\left(N_{z,k} \middle| \xi_k\right) = P\left(N_{z,k} \middle| \gamma_k\right) = \mathcal{PS}\left(N_{z,k};\ \gamma_k\right).$$

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- **Clutter:** independent uniformly distributed, Poisson dist. in number.

Process model

- Kinematics state:

$$\mathbf{x}_{k+1} = \left(F_{k+1|k} \otimes \mathbf{I}_d\right) \mathbf{x}_k + \mathbf{w}_{k+1},$$

where $\mathbf{w}_{k+1}$ is zero mean Gaussian and

$$F_{k+1|k} = \begin{bmatrix} 1 & T_s & \frac{1}{2}T_s^2 \\ 0 & 1 & T_s \\ 0 & 0 & e^{-T_s/\theta} \end{bmatrix},$$

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- Measurement rate, extension state are approx. constant over time,

$$\gamma_{k+1} \approx \gamma_k, \qquad X_{k+1} \approx X_k$$

Multi target filter: ET-PHD filter

- **PHD:** approximated by GGIW mixture

$$D_{k|k}(\xi_k) = \sum_{j=1}^{J_{k|k}} w_{k|k}^{(j)} \mathcal{GGIW}\left(\xi_k\,;\,\zeta_{k|k}^{(j)}\right)$$

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- **Prediction:** new + surviving existing

$$D_{k+1|k}(\xi_{k+1}) = D_{k+1}^{b}(\xi_{k+1}) + D_{k+1|k}^{s}(\xi_{k+1}),$$

Spawning not necessary here

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- **Correction:** detected new + detected existing + not detected existing

$$D_{k|k}(\xi_k) = D_{k|k}^{b}(\xi_k) + D_{k|k}^{d}(\xi_k) + D_{k|k}^{m}(\xi_k),$$

PHD prediction

- **Birth PHD:** Uniform distribution for position $\mathbf{p}_k$

$$D_k^b(\xi_k) = w_k^{(b)} \mathcal{U}(\mathbf{p}_k) \mathcal{N}\left([\mathbf{v}_k,\ \mathbf{a}_k]^{\mathrm{T}}\ ;\ m_k^{(b)}, P_k^{(b)} \otimes X_k\right) \times \mathcal{G}\left(\gamma_k\ ;\ \alpha_k^{(b)}, \beta_k^{(b)}\right) \mathcal{IW}_d\left(X_k\ ;\ v_k^{(b)}, V_k^{(b)}\right)$$

- **Surviving targets PHD:**

$$D_{k+1|k}^s(\xi_{k+1})$$

  - $\mathbf{x}_k$: Predicted using motion model $F_{k+1|k}$
  - γ_k, X_k: keep expected value, increase variance

See paper and Beard et al, IEEE TAES 2013, for details

PHD correction

New targets: $D^b_{k|k}(\xi_k)$

- Generates at least one measurement when it appears, i.e. $P_D = 1$
- Initial position: centroid of cluster
- Initial extension: spread of cluster
- Initial rate: number of detections in cluster

See paper for details

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Existing targets: $D^{d}_{k|k}(\xi_k) + D^{m}_{k|k}(\xi_k)$

- Probability of no detection is higher for targets with lower γ_k

See paper for details

Extraction, track maintenance, reduction

$$D_{k|k}(\xi_k) = \sum_{j=1}^{J_{k|k}} w_{k|k}^{(j)} \mathcal{GGIW}\left(\xi_k ; \zeta_{k|k}^{(j)}\right)$$

- **Extraction:** Components are extracted if $w > 0.5$

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- **Track maintenance:**
  - First extraction: unique label ℓ assigned
  - Label kept through prediction and correction
  - Confirmed track: $w > 0.5$ three time steps

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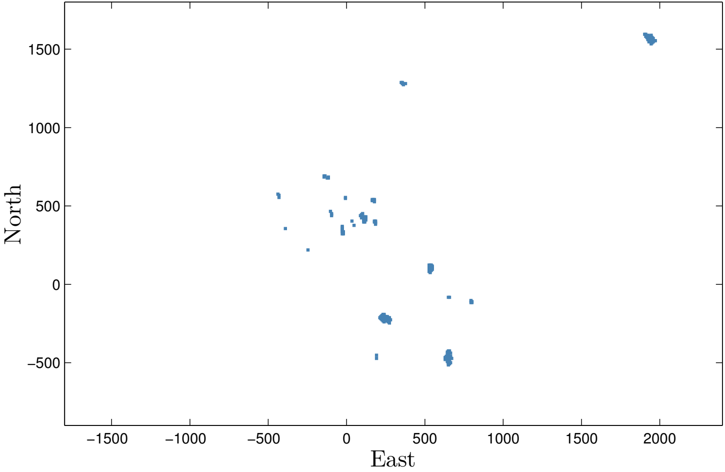
- **Reduction:**
  - Pruning: $w < 10^{-3}$ or $E[\gamma_k] < 1$
  - Merging: identical labels, sym KL-div < 10, merged weight $\tilde{w} < 1.1$
  - Non-unique labels: Keep label for highest weight. Prune other components

$$\text{if} \qquad \max w \geq 1 \qquad \text{or} \qquad \frac{\max w}{\sum w} > 0.8,$$

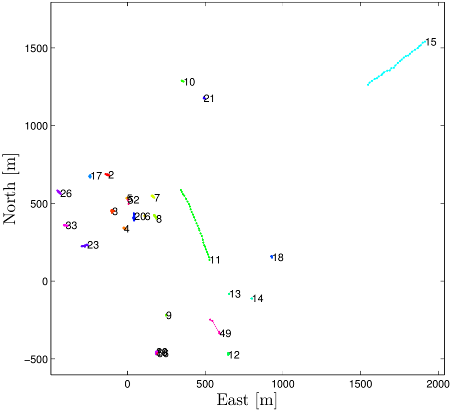
else reset their labels.

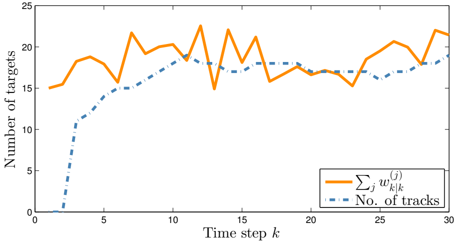
Results

- Time to process one radar scan: 0.8 sec average, 1.5 sec max
- Radar antenna rotation period: 2.41 sec



Results: all target tracks

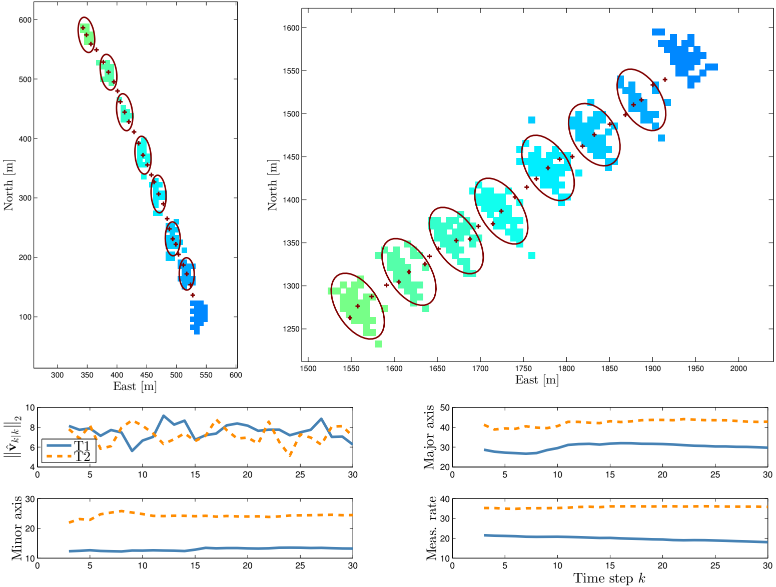




With track management:

- Less variable cardinality estimate
- Improved clutter suppression
- Slower initiation

Results: Tracks 1 & 2



Ongoing & Future work

Larger datasets:

- Currently working on one with 217 radar scans (9 mins)

More datasets:

- Multiple sites
- Ground truth for (some) targets

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Improved detection model:

- Reflection point: r_k, α_k. Detections

$$\mathbf{y}_k = [y_k^r, y_k^\alpha]^{\mathrm{T}}, \qquad y_k^r = r_k + w_k^r, \qquad y_k^\alpha = \alpha_k + w_k^\alpha.$$

  Pre-processing into Cartesian coordinates $\mathbf{y}_k \rightarrow \mathbf{z}_k$:
  - Constant along-range noise
  - Across-range noise increases with range
  - Higher noise var $\Rightarrow$ Cartesian Gaussian approx more crude
- Current detection likelihood does not capture this,

$$\mathcal{N}\left(\mathbf{z}_k^{(j)}; H_k \mathbf{x}_k, X_k\right)$$

Thank you for listening!

Questions?