

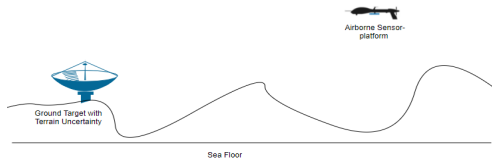
Sensor Fusion and Optimal Platform Trajectory Planning for Ground Target Localization with Terrain Uncertainty and Measurement Biases

Dipayan Mitra and Ratnasingham Tharmarasa

Estimation, Tracking and Fusion Laboratory
Department of Electrical and Computer Engineering
McMaster University
Canada

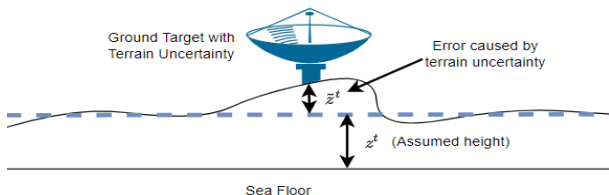
mitrad1@mcmaster.ca

July 7, 2022



- 3-D ground target localization with biased **angle-only sensor**.
- Two key sources of uncertainties:
 - **Measurement bias**, i.e. bias in the elevation and bearing angles.
 - **Terrain uncertainty**.
- Ground target can be:
 - Stationary.
 - Moving with a nearly constant velocity (CV).

- How to make the 3-D localization problem observable?
 - The target height from the sea level is available.
 - Height information is obtained from a Digital Terrain Elevation Database (DTED).
- Height information obtained from DTED has uncertainty.
- Neglecting terrain uncertainty leads to:
 - Localization error.
 - Optimistic performance bounds.

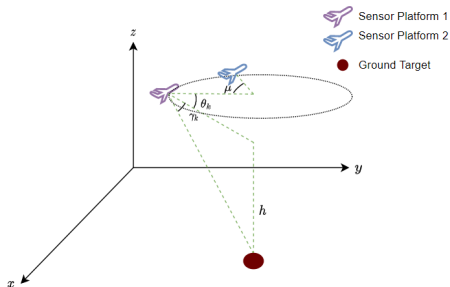


- Tracking a ground target in 3-D using angle-only airborne sensor.
- Ground target height from the sea level is assumed to be known with terrain uncertainty.
 - Sources of uncertainties: terrain uncertainty and measurement bias.
- Bias estimation using a target of opportunity.
 - Optimal number of target of opportunity.
 - Optimal sensor trajectory.
- Target localization using bias compensated non-linear filtering.
- Evaluation of biased posterior Cramer Rao Lower Bound (PCRLB) and estimator performance evaluation.

¹D. Mitra, A. Balachandran, R. Tharmarasa, "Ground Target Tracking Using an Airborne Angle-Only Sensor with Terrain Uncertainty and Sensor Biases," *Sensors*, 22, no. 2:509, January 2022, pp. 1-26.

- Challenges:
 - Presence of measurement bias causes **delay in error convergence**.
 - Estimation **accuracy** is **low**.
- Proposed solution:
 - Range sensor addition to improve localization accuracy.
 - Error convergence is attained faster.
 - Platform **trajectory optimization** for estimation.
 - Ground target localization while handling biases.
 - Bias compensation.
 - Bias estimation.

- Localizing a ground target using two airborne sensor platforms.
 - Ground target has terrain uncertainty.
 - Platform 1 contains biased angle-only sensors.
 - Platform 2 contains unbiased range sensor.
- Optimal platform trajectory based on performance bound.



- Biased angle-only measurements $\theta_k \in [-\pi, \pi]$ and $\gamma_k \in [-\frac{\pi}{2}, \frac{\pi}{2}]$.
- From 3-D geometry,

$$\theta_k^{\text{true}} = \tan^{-1} (y_k^t - y_k^{p1}, x_k^t - x_k^{p1}) \quad (1)$$

$$\gamma_k^{\text{true}} = \tan^{-1} \left(\sqrt{(x_k^t - x_k^{p1})^2 + (y_k^t - y_k^{p1})^2}, z_k^t - z_k^{p1} \right) \quad (2)$$

- True height of the ground target from the sea level is z_k^t .
- Assumed height containing **terrain uncertainty** $z_g = z_1^t + \tilde{z}^t$.
 - Error associated to terrain uncertainty $\tilde{z}^t \sim \mathcal{N}(\tilde{z}^t; 0, \sigma_{z^t}^2)$.
- Measurement model for platform 1,

$$\mathbf{z}_k = \mathbf{h}_a(\mathbf{x}_k^t, \mathbf{x}_k^{p1}) + \mathbf{b}_k + \mathbf{w}_k \quad (3)$$

- Bias vector $\mathbf{b}_k = [\theta_{b_k}, \gamma_{b_k}]$.
- $\mathbf{h}_a(\mathbf{x}_k^t, \mathbf{x}_k^{p1}) = [\theta_k^{\text{true}}, \gamma_k^{\text{true}}]^T$.
- Measurement noise $\mathbf{w}_k \sim \mathcal{N}(\mathbf{w}_k; 0, \mathbf{R}_k)$, where $\mathbf{R}_k = \text{diag}(\sigma_\theta^2, \sigma_\gamma^2)$.

- Unbiased range measurements,

$$r_k = \sqrt{(x_k^t - x_k^{p2})^2 + (y_k^t - y_k^{p2})^2 + (z_k^t - z_k^{p2})^2} \quad (4)$$

- Measurement model for platform 2,

$$\mathbf{z}_k^r = \mathbf{h}_r(\mathbf{x}_k^t, \mathbf{x}_k^{p2}) + \mathbf{w}_k^r \quad (5)$$

- $\mathbf{h}_r(\mathbf{x}_k^t, \mathbf{x}_k^{p2}) = [r_k]$.
- Measurement noise \mathbf{w}_k^r is a zero-mean Gaussian with variance $\sigma_{r_k}^2$.
- Range measurements might not be available for all time-steps.

- Bias compensated measurements

$$\mathbf{z}_k^c = \mathbf{h}_a(\mathbf{x}_k^t, \mathbf{x}_k^{p1}) + \mathbf{b}_k - \mathbf{b}_k^{\text{prior}} + \mathbf{w}_k^c \quad (6)$$

- Bias prior $\mathbf{b}_k^{\text{prior}} = [\theta_{b_k}^{\text{prior}}, \gamma_{b_k}^{\text{prior}}]$.
- Measurement noise $\mathbf{w}_k^c \sim \mathcal{N}(\mathbf{w}_k^c; 0, \mathbf{R}_k^c)$.
- Bias compensated covariance
 $\mathbf{R}_k^c = \text{diag}((\sigma_\theta^2 + \sigma_{\theta_{b_k}^{\text{prior}}}^2), (\sigma_\gamma^2 + \sigma_{\gamma_{b_k}^{\text{prior}}}^2))$.
- Considering terrain uncertainty (only for initialization)
 $\mathbf{R}_1 = \text{diag}(\sigma_{z^t}^2, (\sigma_{\theta_k}^2 + \sigma_{\theta_{b_1}}^2), (\sigma_{\gamma_k}^2 + \sigma_{\gamma_{b_1}}^2))$
- Unscented Kalman Filter (UKF) is used for non-linear filtering with zero point initialization.

- **No bias compensation** is performed.
- Bias states are stacked with the target state.
 - Joint state initialization as $\mathbf{x}_1 = [x_1, 0, y_1, 0, z_g, \theta_{b_k}^{\text{prior}}, \gamma_{b_k}^{\text{prior}}]$.
 - For stationary target $\mathbf{x}_1 = [x_1, y_1, z_g, \theta_{b_k}^{\text{prior}}, \gamma_{b_k}^{\text{prior}}]$.
 - $\theta_{b_k}^{\text{prior}}$ and $\gamma_{b_k}^{\text{prior}}$ can be zero.
- UKF is used for non-linear filtering.
- Information on terrain uncertainty **not used** after initialization.

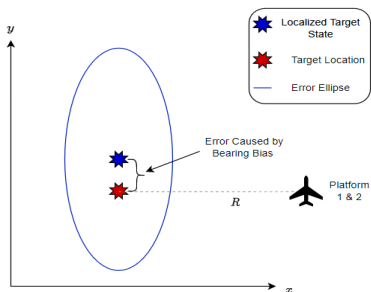
- Posterior Cramer Rao Lower Bound (PCRLB) is used.
- With $\mathbf{Z}_K = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_K]$,

$$\mathbf{C}_k = \mathbb{E} \left[(\hat{\mathbf{x}}_k^t(\mathbf{z}_k) - \mathbf{x}_k^t)(\hat{\mathbf{x}}_k^t(\mathbf{z}_k) - \mathbf{x}_k^t)^T \right] \geq \mathbf{J}_k^{-1} \quad (7)$$

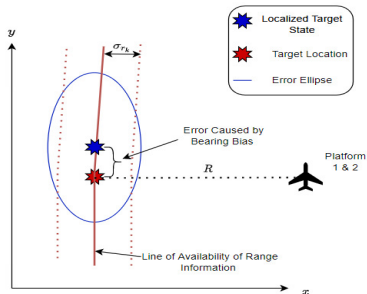
- Fisher Information Matrix (FIM) or \mathbf{J}_k ,

$$\mathbf{J}_{k+1} = \left(\mathbf{F}_k \mathbf{J}_k^{-1} \mathbf{F}_k^T + \mathbf{Q}_k \right)^{-1} + \mathbf{J}_z(k+1) \quad (8)$$

- Measurement contribution $\mathbf{J}_z(k) = \mathbb{E} \left[q_k \mathbf{H}_k^T \mathbf{R}_k^{-1} \mathbf{H}_k \right]$.
- For angle-only sensors $\mathbf{H}_k = \frac{\partial \mathbf{h}_a(\mathbf{x}_k^t, \mathbf{x}_k^{p1})}{\mathbf{x}_k^t}$.
- For range-only sensor $\mathbf{H}_k = \frac{\partial \mathbf{h}_r(\mathbf{x}_k^t, \mathbf{x}_k^{p2})}{\mathbf{x}_k^t}$.
- For range and angle measurements $\mathbf{J}_z(k) = \mathbf{J}_z^a(k) + \mathbf{J}_z^r(k)$.
 - $\mathbf{J}_z(k) = \mathbf{J}_z^a(k)$ or $\mathbf{J}_z(k) = \mathbf{J}_z^r(k)$, based on the availability of the sensor.

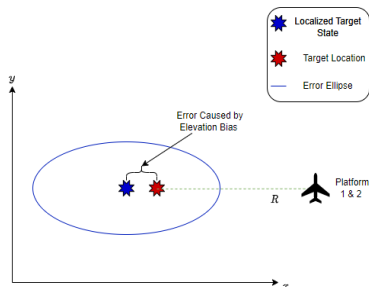


(a) Localization affected by θ_{b_k}

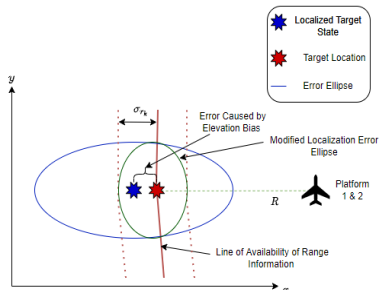


(b) Range sensor fusion with θ_{b_k}

Figure: Target state and the localization estimates in presence of biases in the angle measurements with $\mu = 0$.

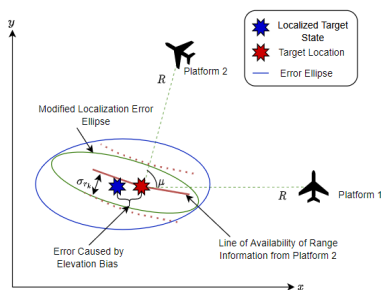


(a) Localization affected by γ_{b_k}

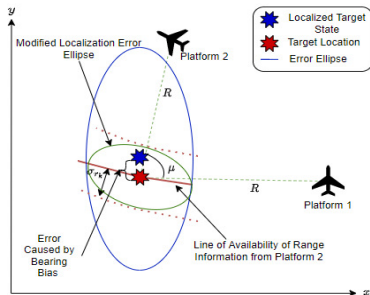


(b) Range sensor fusion with γ_{b_k}

Figure: Target state and the localization estimates in presence of biases in the angle measurements with $\mu = 0$.



(a) Range sensor fusion with γ_{b_k}



(b) Range sensor fusion with θ_{b_k}

Figure: x-y plane projection of stationary target state and the localization estimates with sensor fusion and $\mu > 0$.

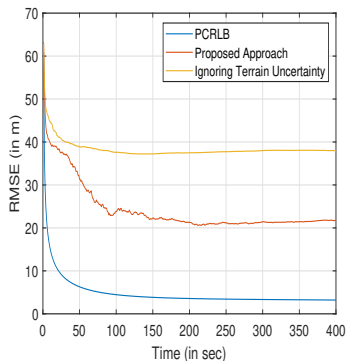
- Goal: Finding optimal μ by optimizing PCRLB.
- Measurement contribution of the FIM,

$$\mathbf{J}_z(k) = \mathbf{J}_z^a(k) + \mathbf{J}_z^r(k) \quad (9)$$

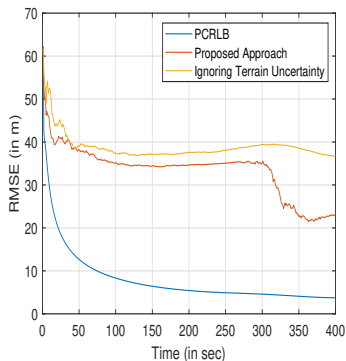
- Sampling rate of the range sensor might be different from the angle-only sensors.
- $\mathbf{J}_z^r(k)$ might not be available for all the time-steps.
- The optimization problem is formulated as,

$$\begin{aligned} \arg \min_{\mu} \sum_{k=1}^K \text{Tr}[\mathbf{J}_k^{-1}] \\ \text{s.t. } \mu \in [0, 360^\circ] \end{aligned} \quad (10)$$

- The **bias** in the angle-only measurements are **smaller** →
Choose $\mu = 0$.
- For **larger bias** in the angle-only measurements → **Increase separation** between the platforms.



(a) Stationary ground target



(b) Moving ground target

Figure: Comparison of the RMSE of the proposed approach with an approach that ignores the terrain uncertainty, when the $\sigma_{z_t} = 30$ m.

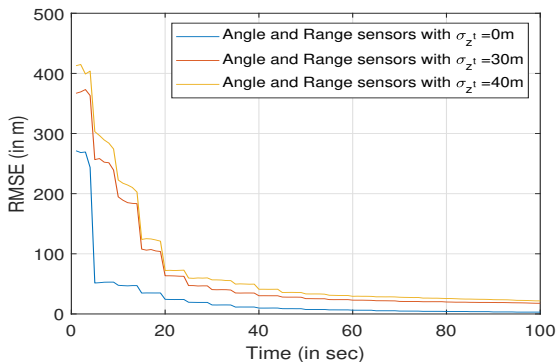


Figure: Ground target localization errors for various terrain uncertainties using range sensor fusion for the platform separation angle $\mu = 0^\circ$.

- Higher terrain uncertainty leads to higher localization error.

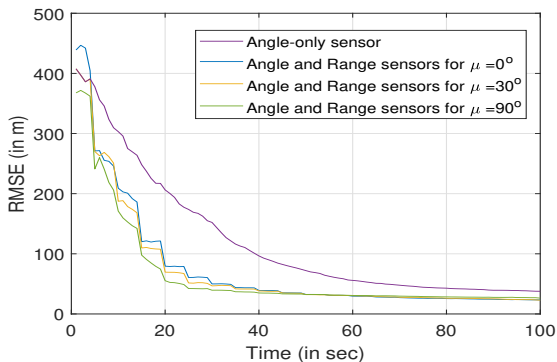
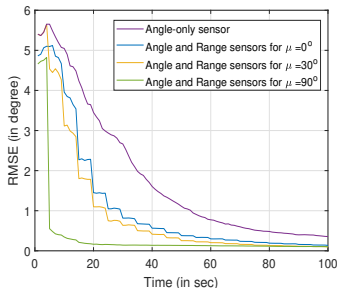
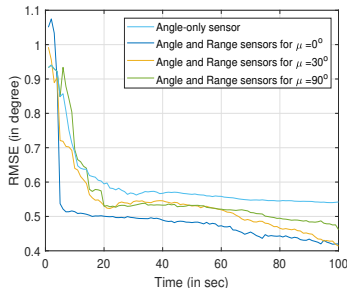


Figure: Comparison of errors in target state localization using range sensor fusion for various degrees of separations between airborne platforms.

- $\mu = 90^\circ$ leads to faster reduction in RMSE for localization.



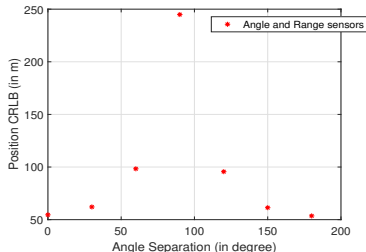
(a) Bearing bias estimation errors



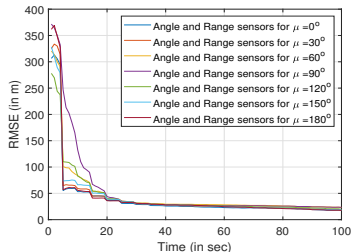
(b) Elevation bias estimation errors

Figure: Comparison of bias estimation errors for various angles of separation.

- $\mu = 90^\circ$ is optimal for bearing bias estimation.
- $\mu = 0^\circ$ is optimal for elevation bias estimation.



(a) PCRLB comparison at time = 5 s



(b) Target localization error

Figure: Comparison of ground target localization error for various μ with $\sigma_{\theta_b} = 1^\circ$, $\sigma_{\gamma_b} = 1^\circ$ and $\sigma_{z^t} = 30\text{m}$.

- Impact of the higher μ on reducing localization error fades away for small biases.
- Terrain uncertainty primarily impacts localization accuracy \rightarrow Increasing μ has no effect in reducing RMSE.

- Localization of a ground target using,
 - Biased angle-only sensors.
 - **Additional range** sensor → **Improves error convergence.**
- Uncertainties present →
 - Measurement bias uncertainty.
 - Terrain uncertainty.
- Proposed localization approaches →
 - Use **bias compensated** measurements with **inflated initial covariance.**
 - Joint estimation of the bias and the target states. (**Recommended method, if time is not a constraint**)
- **PCRLB** based optimal platform trajectory planning →
 - Choose 90° separation for **higher bearing biases.**
 - Choose 0° separation for **lower bearing biases.**

Backup Slides

- Ground target state $\mathbf{x}_k^t = [x_k^t, \dot{x}_k^t, y_k^t, \dot{y}_k^t, z_k^t]$.
- State evolution of ground target,

$$\mathbf{x}_{k+1}^t = \mathbf{F}_k \mathbf{x}_k^t + \mathbf{G}_k \mathbf{v}_k \quad (11)$$

- Process noise $\mathbf{v}_k \sim \mathcal{N}(\mathbf{v}_k; 0, \sigma_v^2)$.
- For a stationary ground target $\dot{x}_k^t = \dot{y}_k^t = 0$ and $\mathbf{F}_k = \mathbf{I}$.
- Platform 1 and 2 with states $\mathbf{x}_k^{p1} = [x_k^{p1}, \dot{x}_k^{p1}, y_k^{p1}, \dot{y}_k^{p1}, z_k^{p1}]$ and $\mathbf{x}_k^{p2} = [x_k^{p2}, \dot{x}_k^{p2}, y_k^{p2}, \dot{y}_k^{p2}, z_k^{p2}]$.
 - Platforms follow a 'coordinated turn model'.
 - Ground target remains at the centre of the circle.
 - Circle radius R and the constant speed v are known a-priori.
 - Turn rate $\omega = \frac{v}{R}$ rad/s.
 - Angle of separation is μ .

Platform radius (R)	3000 m
Platform speed (v)	50 m/s
Platform height (z_1^{p1})	700 m
Standard deviation of terrain uncertainty (σ_{z^t})	30 m
Range measurement standard deviation (σ_{r_k})	5 m
Bearing measurement standard deviation (σ_{θ_k})	0.4°
Elevation measurement standard deviation (σ_{γ_k})	0.2°
Sampling time of the angle-only sensor (T_1)	1 s
Sampling time of the range sensor (T_2)	5 s
Mean bearing bias (θ_{b_k})	0°
Bearing bias standard deviation ($\sigma_{\theta_{b_k}}$)	5°
Mean elevation bias (γ_{b_k})	0°
Elevation bias standard deviation ($\sigma_{\gamma_{b_k}}$)	1°

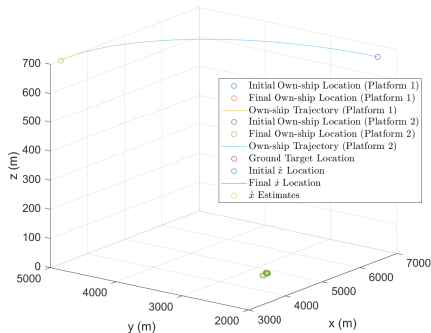


Figure: Target own-ship geometry along with the estimates for the airborne platform separation angle $\mu = 0^\circ$.

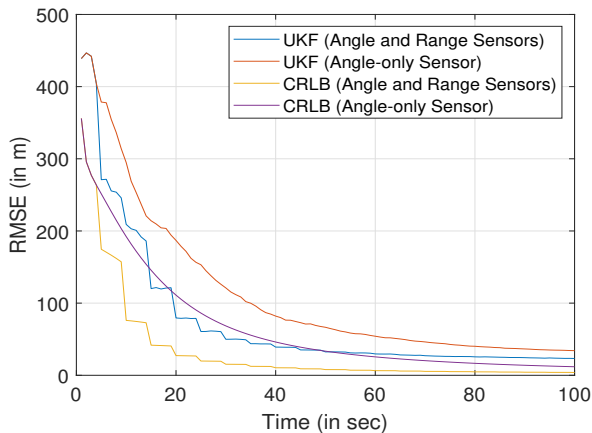
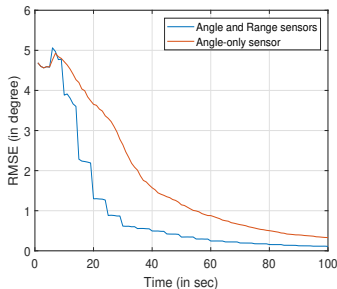
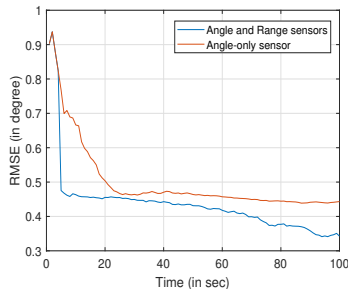


Figure: Ground target localization error using range sensor fusion for the platform separation angle $\mu = 0^\circ$ and $\sigma_{z^t} = 30\text{m}$.



(a) Bearing bias estimation



(b) Elevation bias estimation

Figure: Bias estimation errors for the airborne platform separation angle $\mu = 0^\circ$.