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# Performance Analysis of the OBB-TM Algorithm for LiDAR-based Pose Estimation of Non-Cooperative Space Targets

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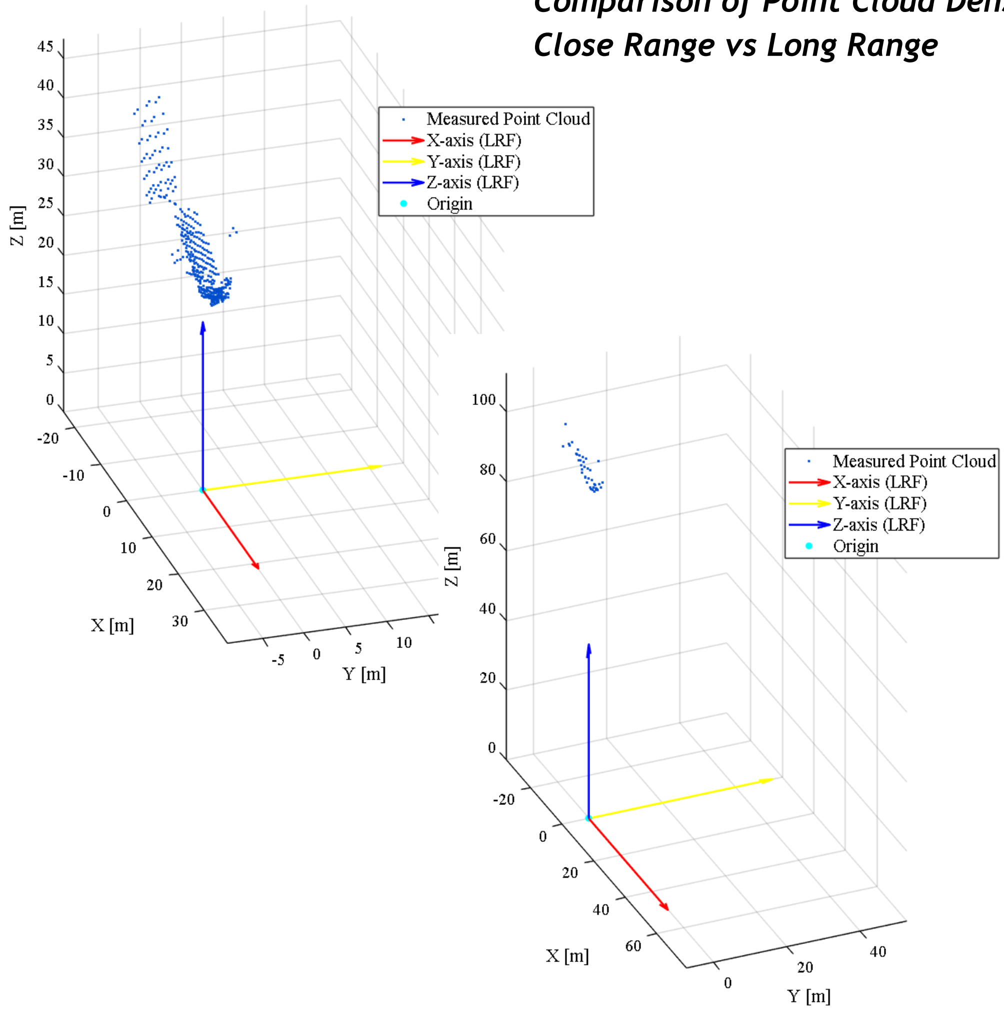
# Context: The Need for Autonomous Navigation

- Crowded Orbital Environment
  - Exponential growth of satellites & debris.
- Critical Proximity Operations
  - On-Orbit Servicing (OOS).
  - Active Debris Removal (ADR).
- The «Non-Cooperative» Challenge
  - No markers, No communication.
  - Uncontrolled dynamics (tumbling).
- Why Autonomous Pose Estimation?
  - Ground control is too slow (latency).
  - Real-time relative navigation is the key enabler.

# The LiDAR Sensor

- Why LiDAR for Space?
  - Active Sensing.
  - Independence of illumination conditions.
  - No scale ambiguity.
- Measurement Principle:
  - Time-of-Flight → range $r$.
  - Direction of ray→ Azimuth and Elevation.
  - Result → 3D point clouds.
- The Critical Limit: Sparsity
  - Point density drops with distance $(1/d^2)$.

***Comparison of Point Cloud Density: Close Range vs Long Range***



# Problem Statement & Thesis Objectives

## The Technical Gap → Research Objectives

### The Technical Gap

- **Initialization Challenge:**
  - Need for a robust global estimate without a priori knowledge.
  - Global search is computationally expensive.
- **Geometric Ambiguity:**
  - Symmetric targets → non-unique solutions.
  - Local optimization converges to incorrect poses.
- **Data Quality:**
  - Lack of local features at long range hampers standard initialization methods.

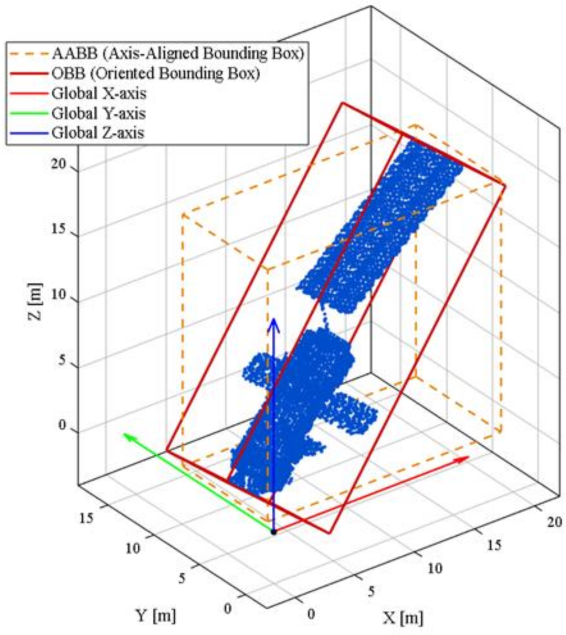
### Research Objectives

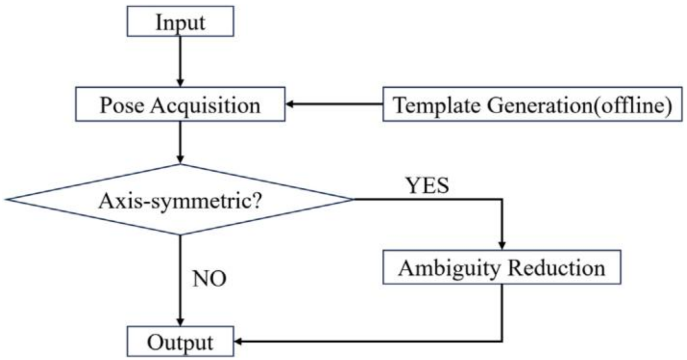
- **Implement OBB-TM Algorithm:**
  - Leverages PCA to reduce the search space to 1-DOF.
- **Ambiguity Reduction (AR):**
  - Resolves symmetry-induced errors.
- **Robustness validation:**
  - Analysis on impact of resolution and distance.

# Methodology: The OBB-TM Algorithm

- The Key Concept: Oriented Bounding Box (OBB)
  - ➢ Defined as the tightest rectangular box enclosing the object.
  - ➢ Extracted via PCA of the point cloud (Model-Based approach).
- Why OBB? (Dimensionality Reduction)
  - ➢ Aligns the measured cloud to a Canonical Frame (Z-axis = Elongation).
  - ➢ *Crucial Benefit*: Decouples Position and Attitude.
  - ➢ Reduces the search space to 1-DOF.
- The Pipeline:

  Offline Database → Online Alignment →1-DOF Matching.

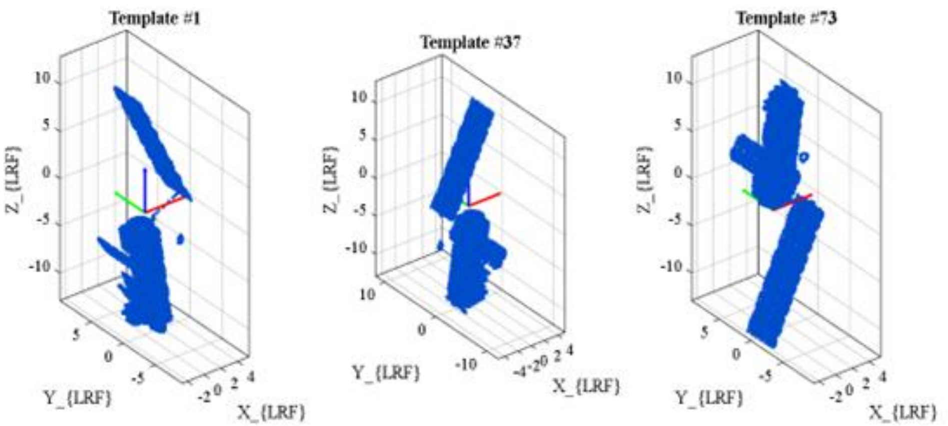


# Offline Phase: The 1-DOF Datatbase

- **Goal:** Create a lightweight search database.

- **PCA on Target Model:**
  - Extracts Principal Axes (Eigenvectors of Covariance Matrix).
  - Construct the OBB aligned with Principal Axes.
  - Defines a Canonical Frame (Z-axis = Elongation axis).



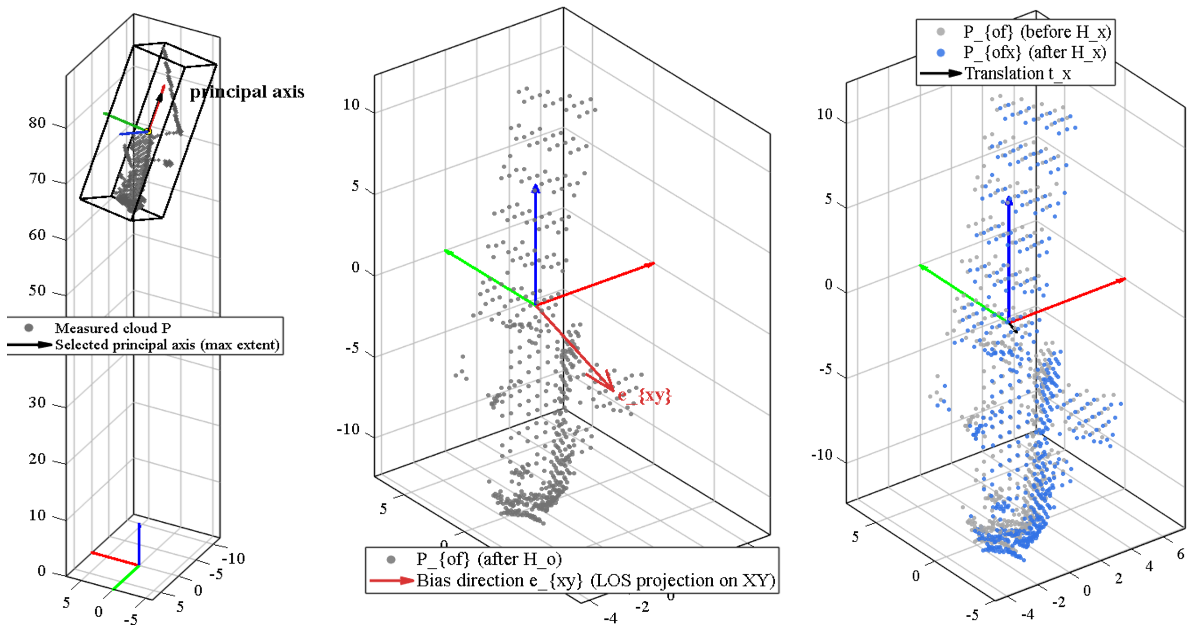

- **Database Generation:**
  - Rotate model around Z-axis (1 Degree-of-Freedom) with fixed step $\sigma$.
  - Flipped database around X-axis.
  - *Result:* Drastic reduction in storage vs full 3D sphere sampling.

# Online Phase: Alignment

- **Input:** Measured Sparse Point Cloud.

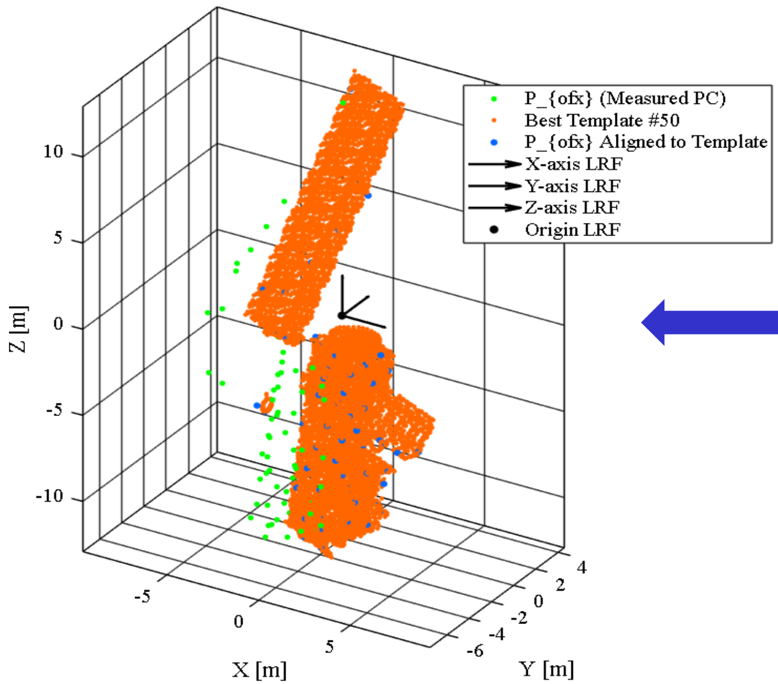
- **Step 1: PCA Alignment**
  - Extract principal axes of the measured cloud.
  - Align measured cloud to the Canonical Frame (First Pose Transformation).
  - *Result*: Target is now aligned with the Z-axis (up to a rotation).

- **Step 2: Centroid Correction:**
  - Compensate for bias due to Partial Views.
  - Shift centroid perpendicularly to optical axis.



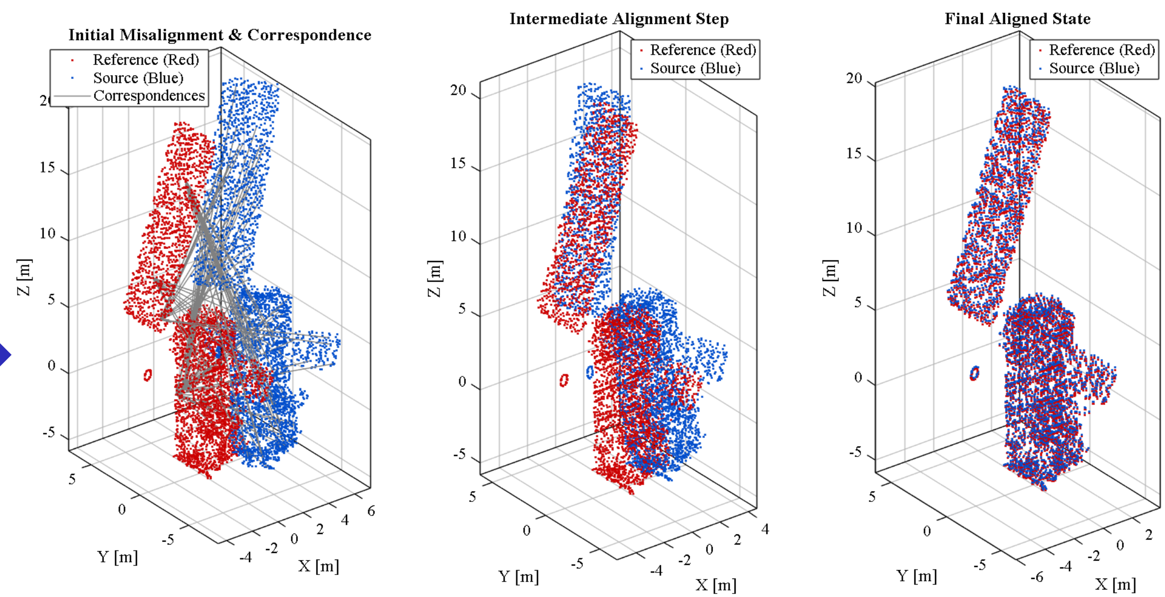

*Measured Point Cloud → First Pose Transformation → Centroid Correction*

# Online Phase: Matching




- Step 3: Template Matching:
  - Compare aligned cloud with the 1-DOF database.
  - *Metric*: Minimum ICP residual error.
  - *Output*: Coarse Pose ($H_0$).

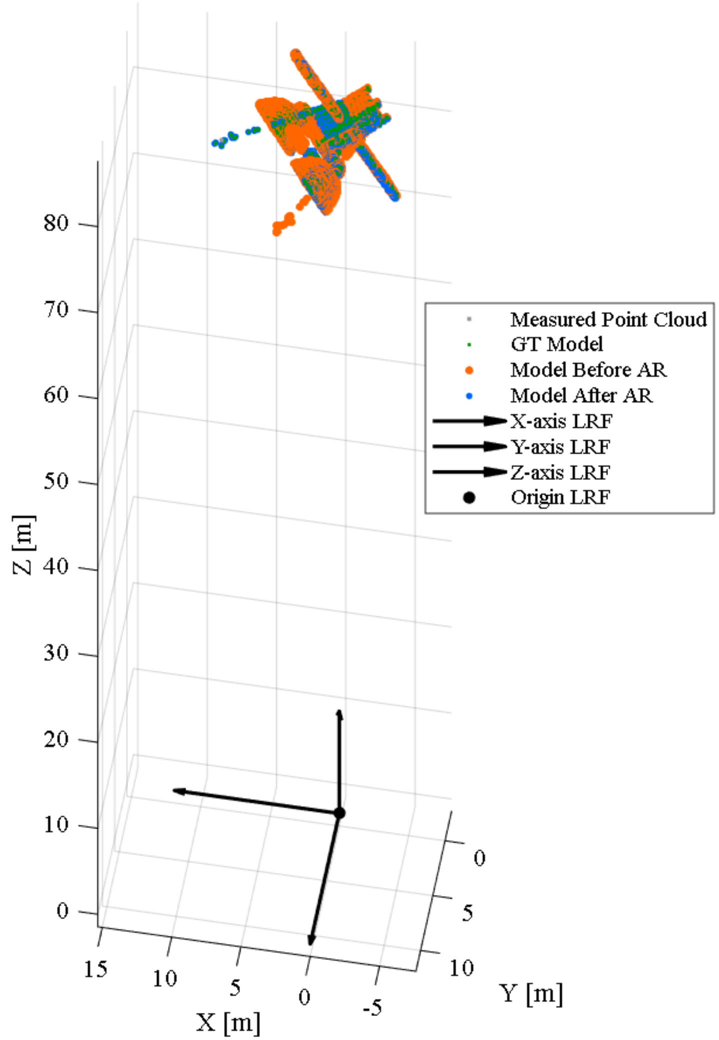
- Step 4: Fine Refinement:
  - Run standard ICP starting from $H_0$.
  - *Output*: Refined Pose (H).



# Ambiguity Reduction (AR) Strategy

- The Structural Symmetry Problem:
  - Symmetric targets generate identical point clouds from opposite viewing angles.
  - Standard matching (ICP/TM) may converge to a local minimum.

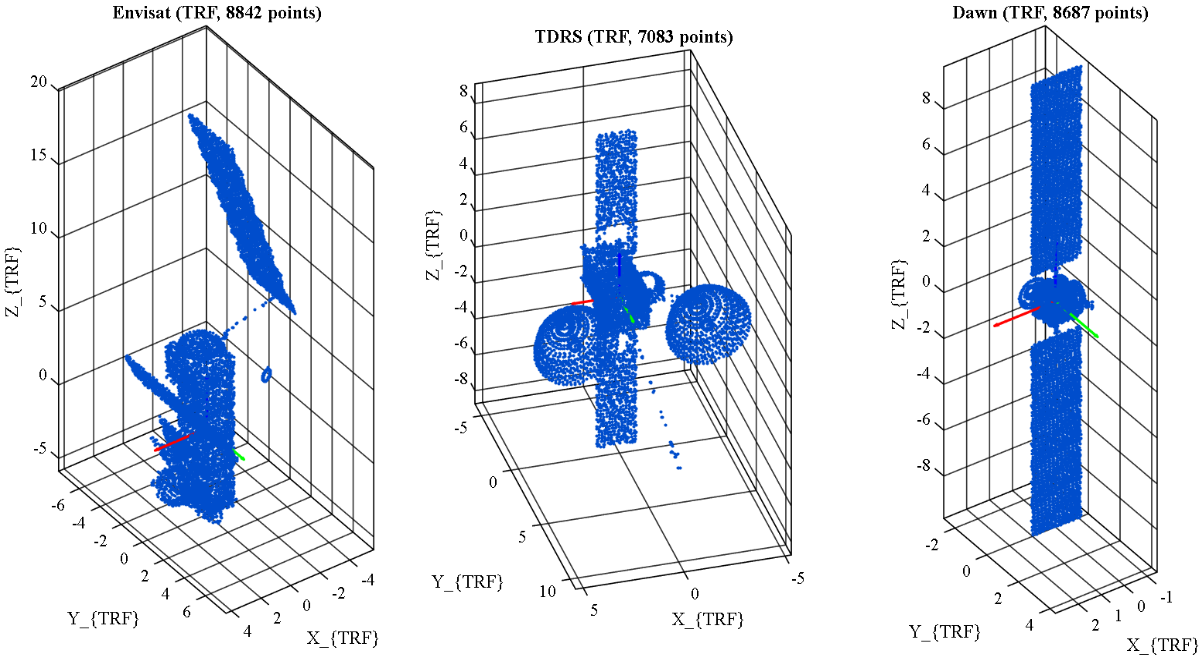
- The AR Solution – Hypothesis testing:
  - *Hypothesis 1:* The estimated pose $H$ (from TM).
  - *Hypothesis 2:* A candidate symmetric pose $H_{sym}$.
  - *Validation:* Perform ICP refinement on both.
  - *Decision:* Select the pose with the lowest Residual Error ($f$).



# Simulation Setup & Cases Studies

- High-fidelity LiDAR Simulator:
  - Geometric Ray-Tracing + Sensor Noise.
  - Field of View : 45° X 45°.
  - Angular Resolution: 0.1°, 0.2°, 0.5°, 1.0°.
  - Max Range: 300m.
  - Range noise $\sigma_r$: 0,025m.
  - *Angular Noise* $\sigma_\theta$: 0,0007rad.

- Extensive Simulation Campain:
  - MATLAB Environment.
  - Distance: 20m → 120m.
  - Attitude Space: Uniform sampling (Roll/Yaw $\pm 180°$, Pitch $\pm 90°$).




***The three targets on which the algorithm is tested, with different symmetry properties.***

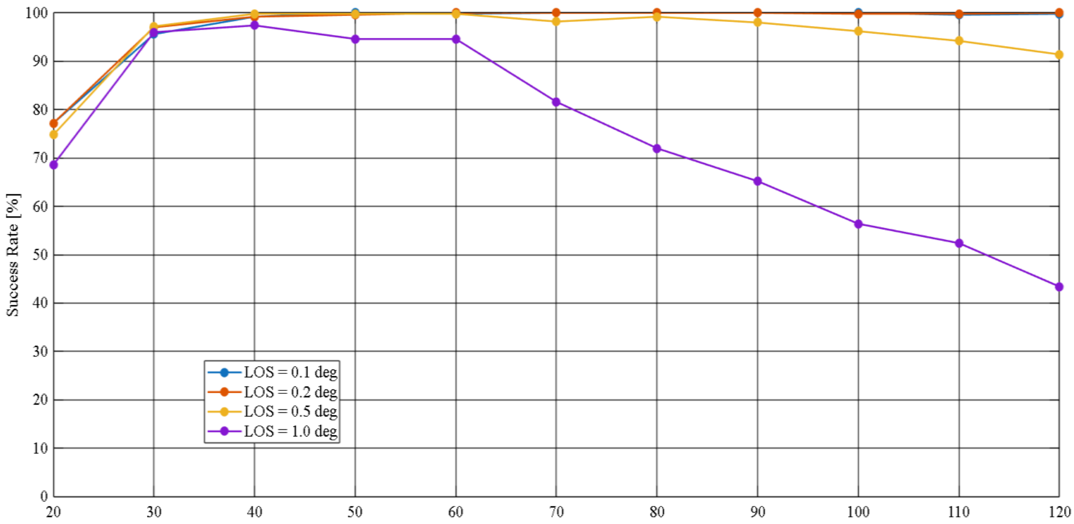
# Algorithm Settings & Metrics

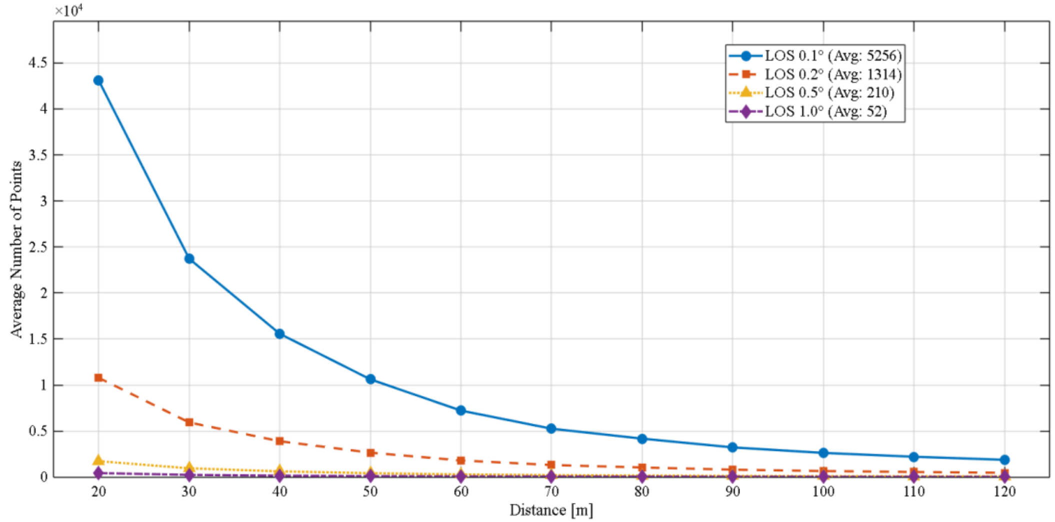
- OBB-TM Configuration:
  - Template Database Step: 5° (1-DOF rotation).
  - Total Templates: 144 templates.

- Success Criteria:
  - Translation Error: $< 0.2\text{m}$.
  - Rotation Error: $< 5°$.
  - Success Rate (SR): % of acquisition satisfying both criteria.

# Results: Baseline Performance (Envisat – asymmetric)

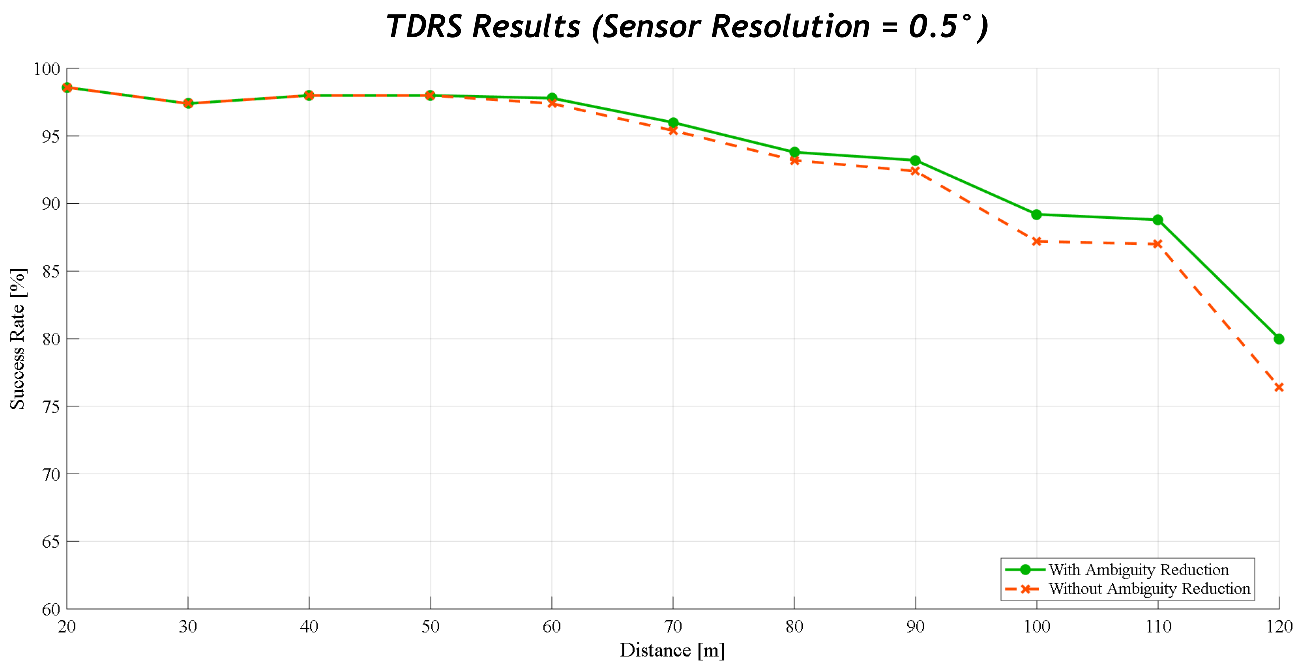
- Robustness Analysis:
  - SR > 97% at fine resolutions (0.1°, 0.2°).
  - Accuracy (Success Cases):
    - Mean Pos. Error: ~0.06 m.
    - Mean Ang. Error: ~0.7°.
- Close-Range Anomaly (<30m):
  - Target exceeds sensor FOV→Centroid Bias→Initialization Failure
- Sparsity Limit:
  - At coarser sensor resolutions and longer distances.
  - Performance drops when Points < 50-100.
  - PCA fails with sparse data.



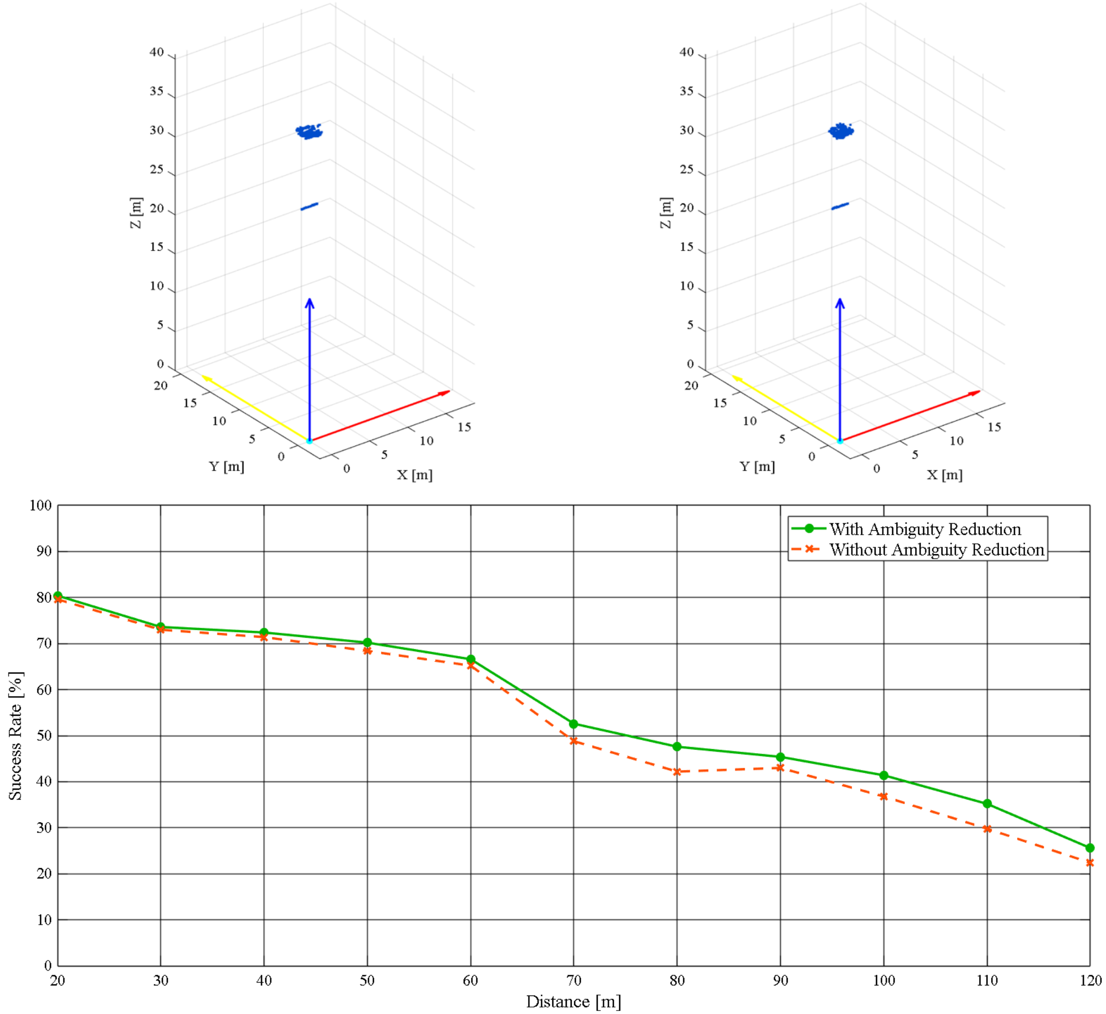
# Results: Ambiguity Reduction Success (TDRS)

- Symmetry impact (NO-AR):
  - SR decreases with distance.
  - *Reason*: point cloud sparsity.
- AR Effectiveness:
  - SR recovered even at higher distances.
  - Successfully flips incorrect poses.
- Why AR works on TDRS?
  - *Volumetric geometry*: high point cloud density.
  - Asymmetric features.



# Results: The Limits of AR (Dawn)

- Dawn Geometric Challenge
  - Minimal cross-sectional area → sparse, disconnected point clusters.
  - "Edge-On" Viewing Geometry: When viewing solar panels from the side (Pitch ~90°), the target appears as a thin line.
- Performance ceiling
  - SR capped at ~80% regardless of AR.
  - AR provides marginal improvements.
  - Sparsity and viewing geometry dominate over symmetry-induced errors.
- Impact on PCA
  - Eigenvectors align with cluster spacing, not true axes.



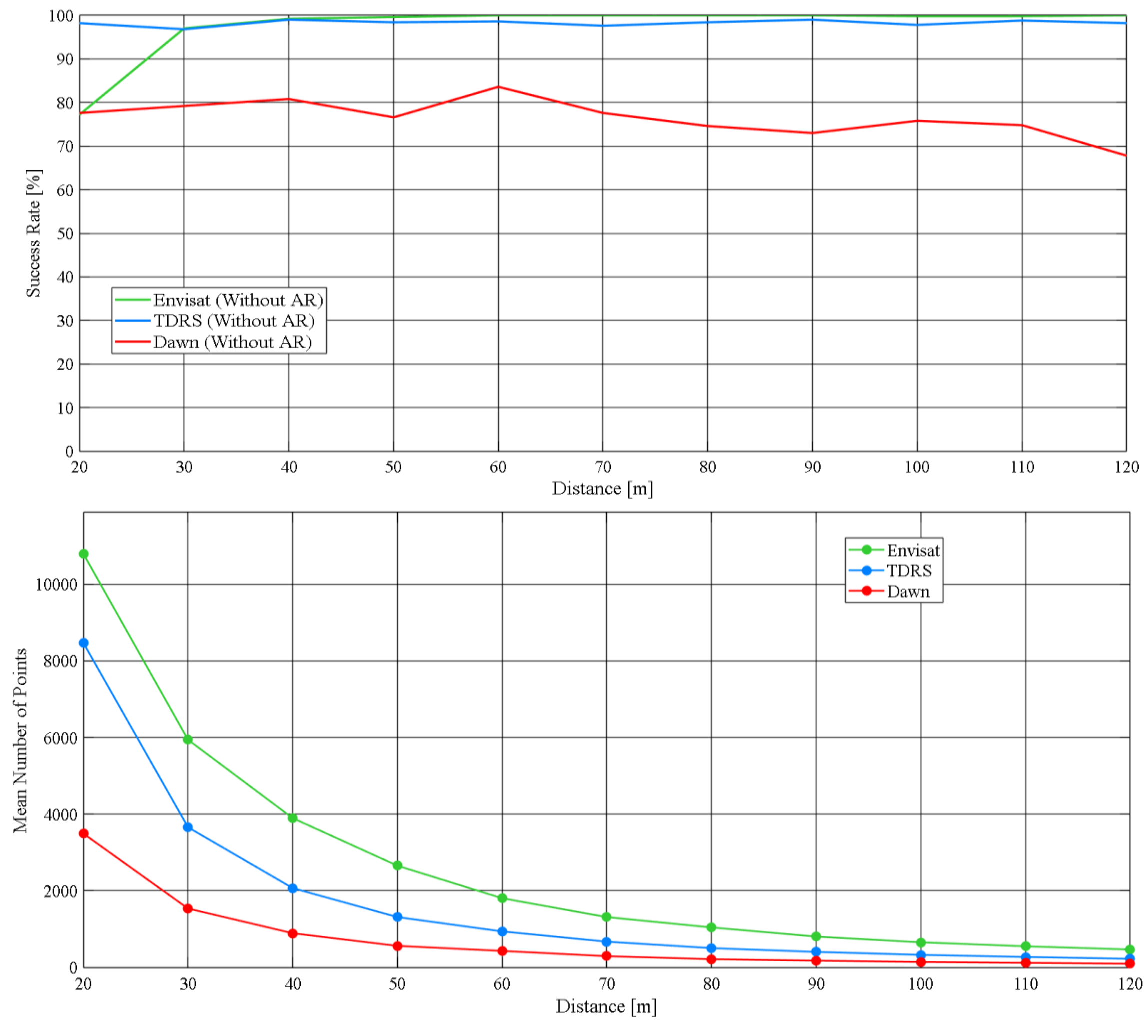

*Dawn Results (Sensor Resolution = 0.5°)*

# Target Geometry as Performance Predictor

- **Key Findings:**
  - Point Cloud density drives success.
  - Target geometry and viewing geometry dominate symmetry.

- **Operational Implication:**
  - Target's effective observability (point distribution around boresight axis), not just symmetry, determines pose estimation reliability.

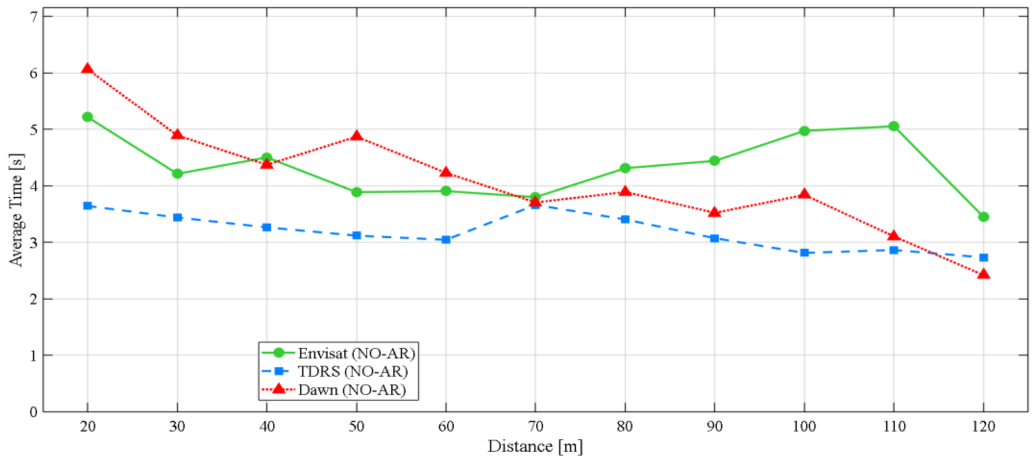
*SR and Measured Points Comparison (Sensor Resolution = 0.2° - NO AR)*

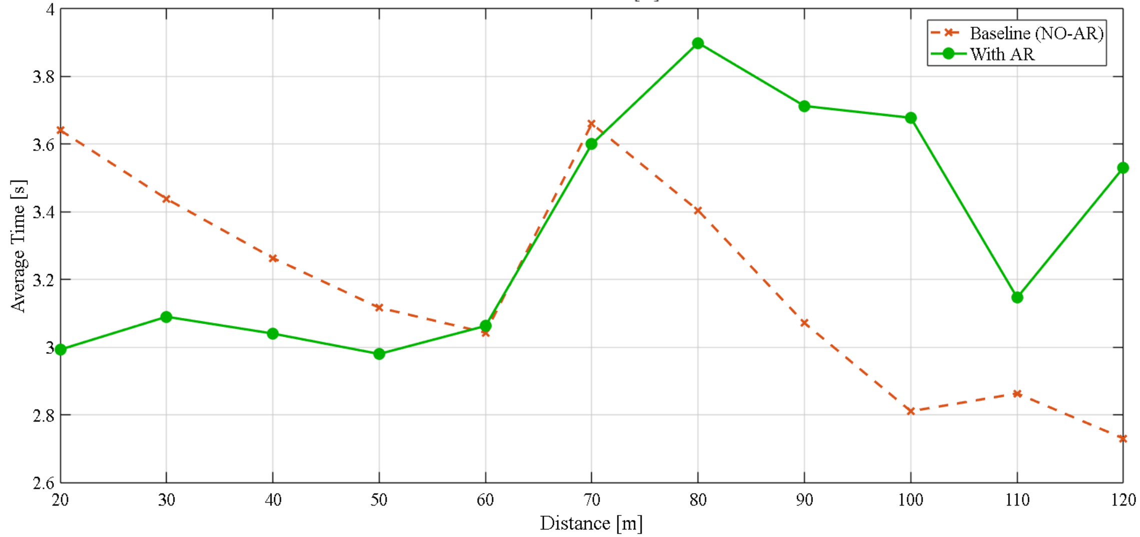


# Computational Efficiency

- **Measured Execution Times:**
  - MATLAB Environment.
  - *Run Time:* 1.0–5.7 seconds per frame across all configurations.
  - *Note:* Code is not optimized for flight (interpreted language).
  - Analysis serves as a comparative benchmark, not absolute performance.
- **Key Findings:**
  - Distance & Resolution Scaling:
    - Execution time decreases at long range + coarse resolution.
  - Ambiguity Reduction Overhead:
    - Modest cost: +10–20%.

***Average Execution Time all target NO AR(up) and TDRS with AR (down)***
***(Sensor Resolution=0.5°)***



## Conclusions

- Methodology Validation:
  - OBB-TM achieved an overall SR >90% across the three tested targets, in fine resolution scenarios .
  - 1-DOF search enables 1-5.7s performance.
  - Geometry dominates performance.
- Role of AR:
  - Prevents catastrophic 180° errors.
  - Modest improvements (0-5%).
  - Limited by sparsity and geometry.
- Operational Guidelines:
  - FOV threshold ≥30m for large targets.
  - Sensor resolution of 0.2°-0.5° optimal for most scenarios.
  - Compact targets require ≤0.2° sensor resolution.

## Future Works

- Sensor fusion:
  - Combine LiDAR + Camera to resolve ambiguities or featureless targets.
- Enhanced AR logic:
  - *Current:* Binary decision (lowest residual error→swap pose).
  - *Proposed:* Probabilistic confidence weighting considering residual error ratio.
  - Threshold based on sensor noise.
- Hardware Acceleration