Mobility Improves Accuracy: Precise Robot Manipulation with COTS RFID Systems

Haoyu Wang†, Si Chen‡, and Wei Gong†*
†University of Science and Technology of China
‡Simon Fraser University

CONTENT

1. Motivation
2. System Design
3. Evaluation
4. Conclusion

1 Motivation

Background

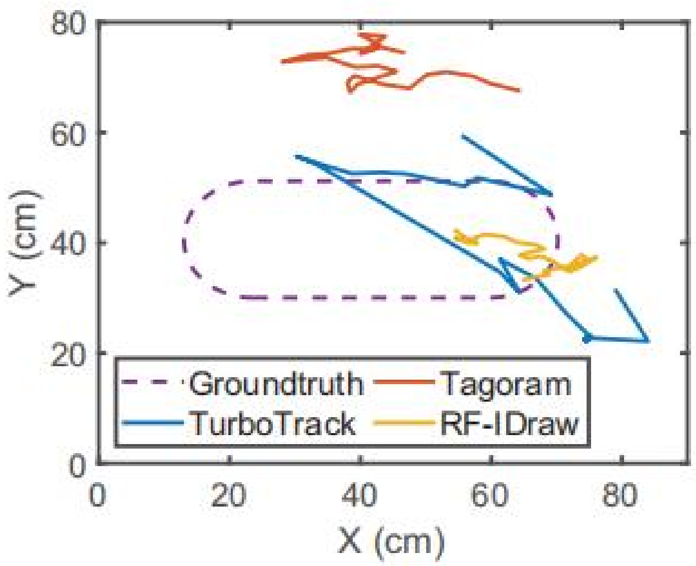
Robotics has been evolving significantly over the past decades, becoming more capable, agile, and precise. This robot precision is the key enabler to future applications and **RFID localization** is an appealing solution.

- Real-time
- Cost-effective
- Highly accurate
- Occlusion-handleable

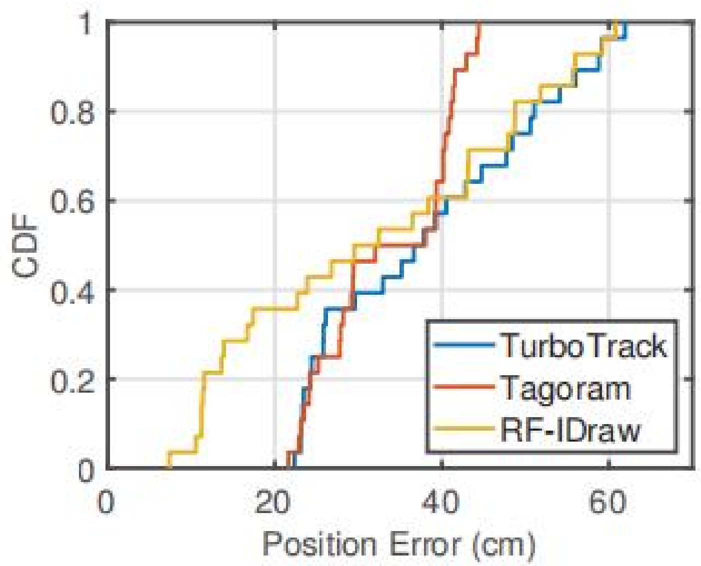
Motivation

Standard Test: We employ a **COTS reader** with 4 antennas to continuously localize a tag moving at **40 cm/s** along a predefined track.

- **Oversimplified mobility models**
- **Low-rate asynchronous reading**

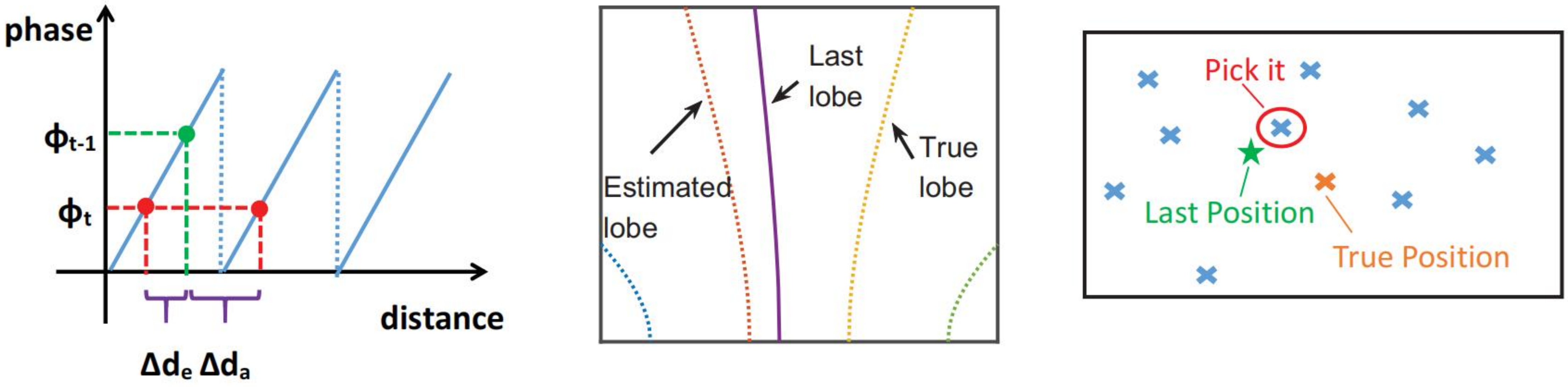


(a) Trajectories at 40 cm/s



(b) CDF comparison

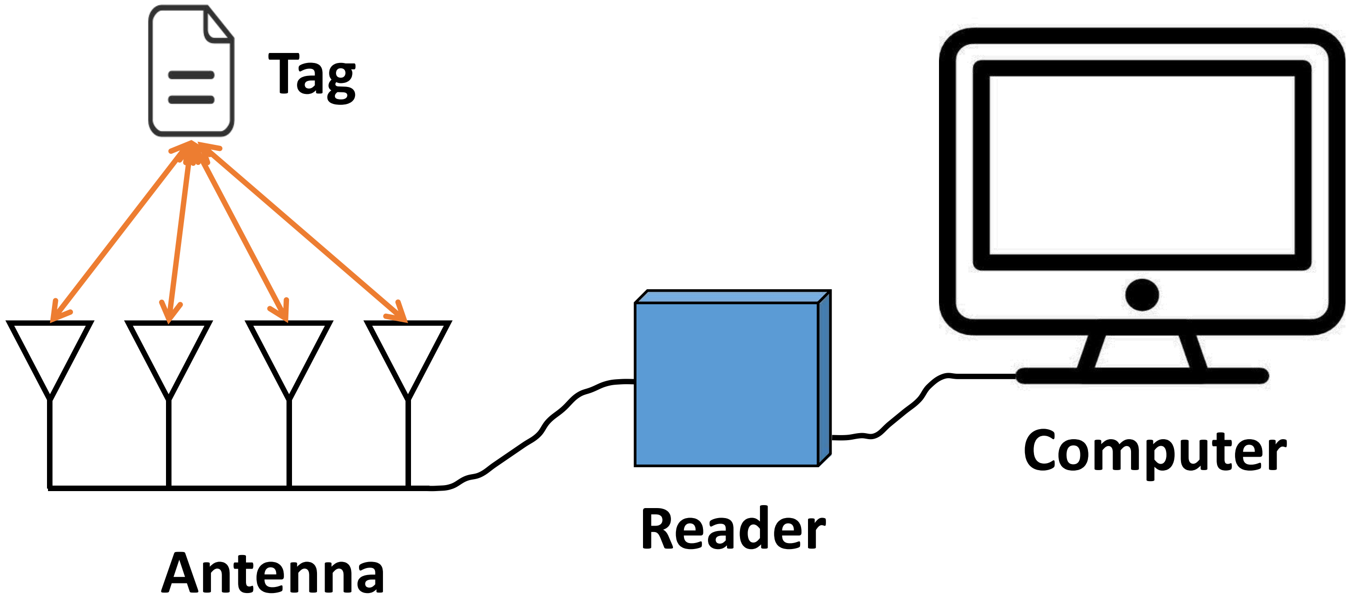
Motivation: Oversimplified Model

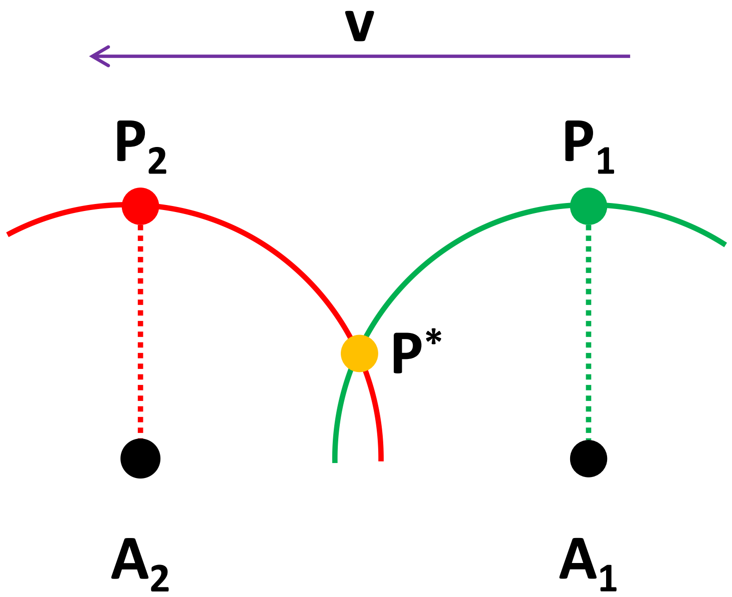


(a) Tagoram (b) RF-IDraw (c) TurboTrack

Mobility has to be properly modeled to deal with **fast-moving** objects.

Motivation: Asynchronous Reading





Low-rate asynchronous readings shouldn't be approximated as **synchronous**.

Contribution

- We design GLAC, **the first mobile 3D localization system** that supports robot object manipulation using only **COTS** devices. It enables robots to locate an object with an accuracy of **millimeter-level** and a timescale of **tens of milliseconds**.

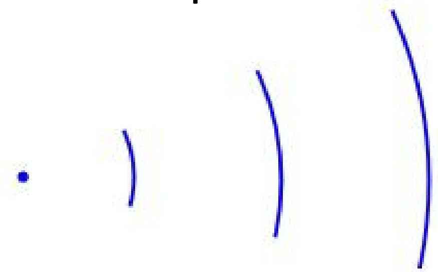
- GLAC presents a novel RF-tracking framework formulated using the HMM.
  - It leverages the object's **mobility** for disambiguation;
  - It can estimate the object's **velocity** in addition to its location using only a **single phase measurement**;
  - It employs a **fast inference algorithm** that uses nearest neighbor pruning and solid geometry.

- A real-time **prototype** of GLAC is implemented, and extensive real-world **experiments** show its capability of millimeter-level tracking in real-time.

2 System Design

Hidden Markov Model (HMM)

Problem definition: given a time series of phase measurements $(\phi_0, \phi_1, .., \phi_k)$, find the most probable location series $(P_0, P_1, .., P_k)$.

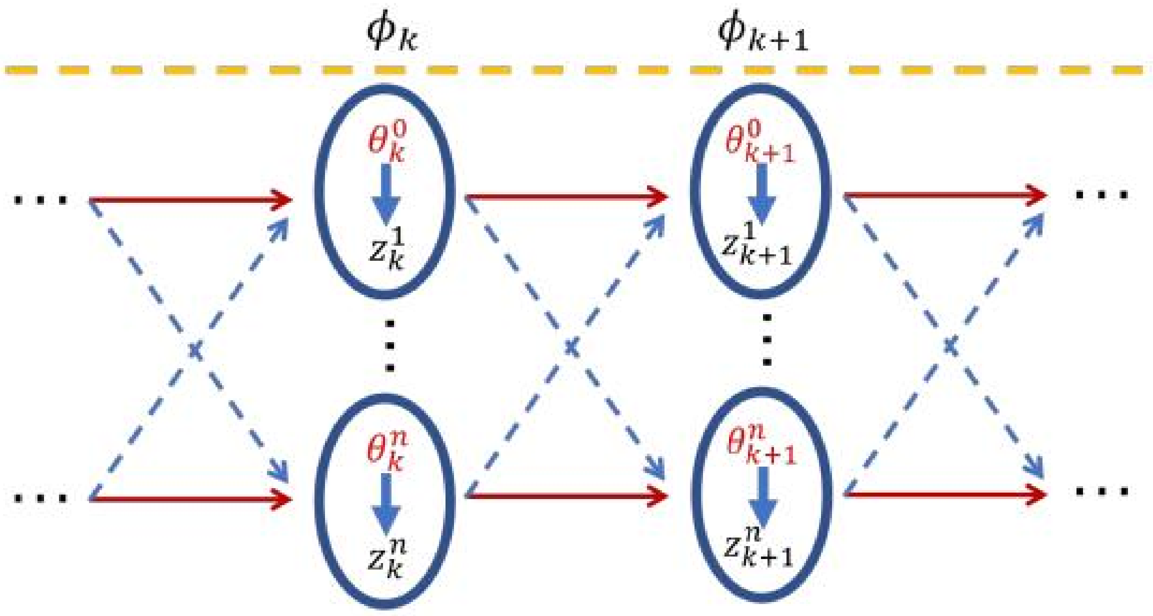


Given a distance observation series $(Z_0, Z_1, .., Z_k)$, find the most probable state series $(\theta_0, \theta_1, .., \theta_k)$.

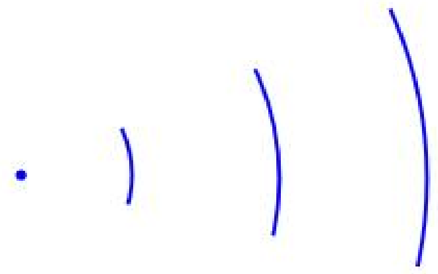
$$\phi = 2\pi \times \frac{2z}{\lambda} + \delta \mod 2\pi$$

$$\boxed{\phi_k \Rightarrow Z_k = (z_k^0, z_k^1, .., z_k^n)}$$

$$\boxed{\theta_k = (P_{x,k}, P_{y,k}, V_{x,k}, V_{y,k})^T}$$



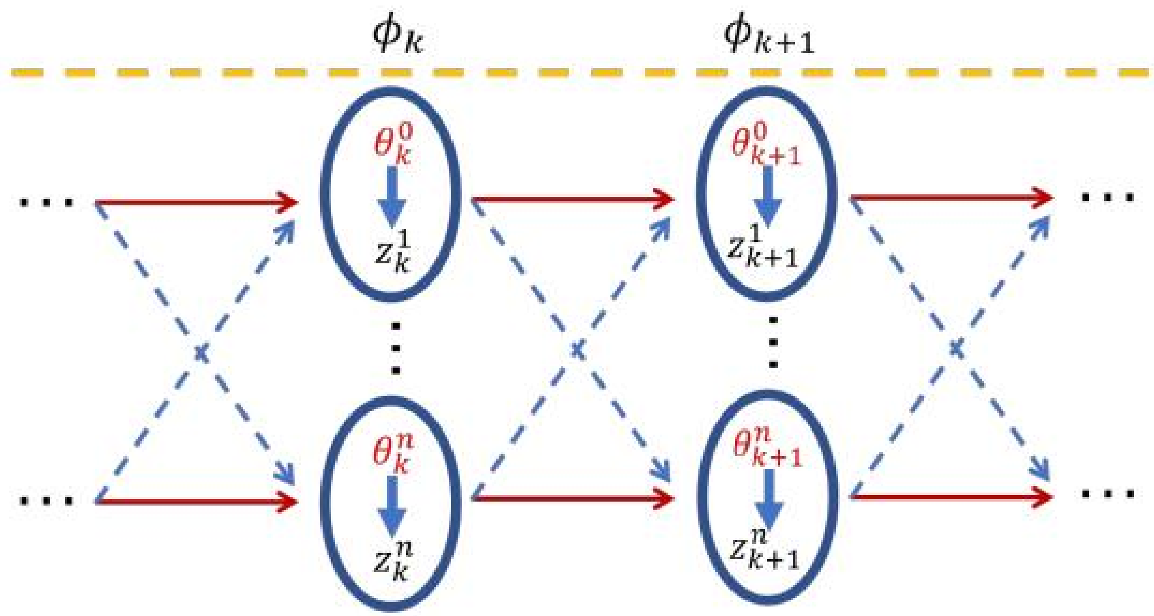
Hidden Markov Model (HMM)



$$\phi = 2\pi \times \frac{2z}{\lambda} + \delta \mod 2\pi$$

Gaussian error

$$\boxed{\phi_k \Rightarrow Z_k = (z_k^0, z_k^1, .., z_k^n)}$$



Mixed Gaussian $\Rightarrow$ **Multiple** Gaussian

Extended Kalman Filter (EKF)

State Definition

$$\theta_k = \begin{pmatrix} P_{x,k} \\ P_{y,k} \\ V_{x,k} \\ V_{y,k} \end{pmatrix}$$

- Position in X axis
- Position in Y axis
- Velocity in X axis
- Velocity in Y axis

Transition Equation

$$\theta_k = f(\theta_{k-1}) + s_k = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \theta_{k-1} + s_k$$

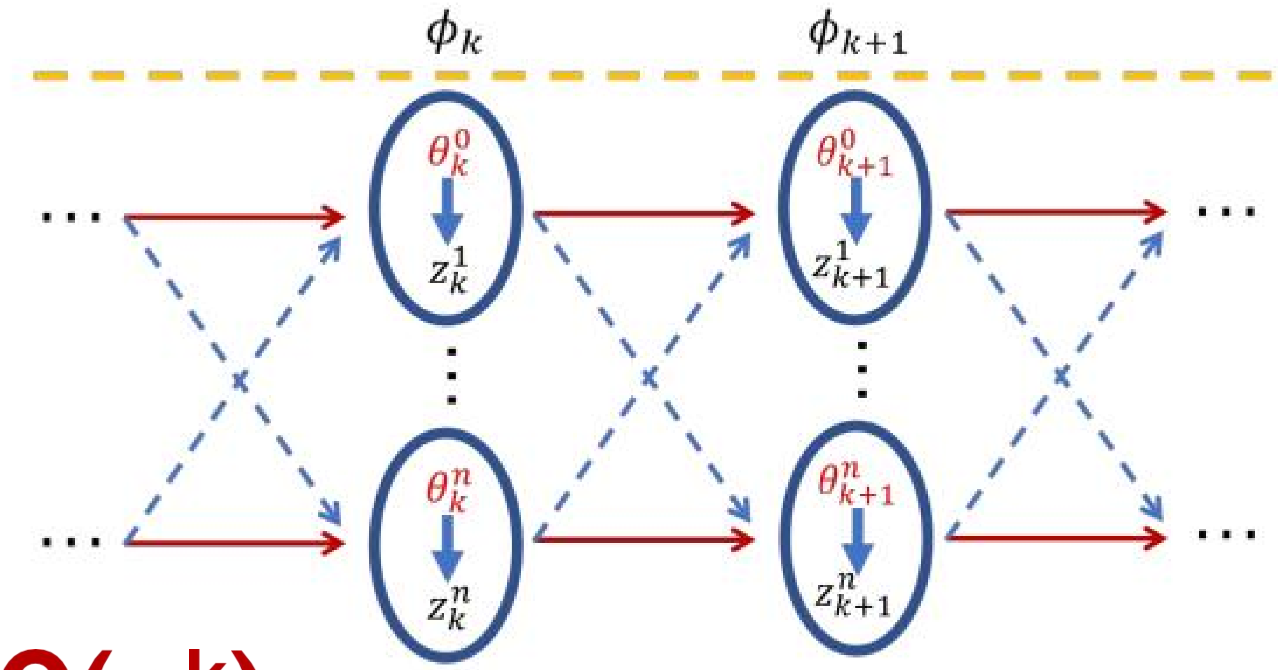
Observation Equation

$$z_k = h(\theta_k) + v_k = (\sqrt{(P_{x,k} - A_x)^2 + (P_{y,k} - A_y)^2}) + v_k$$

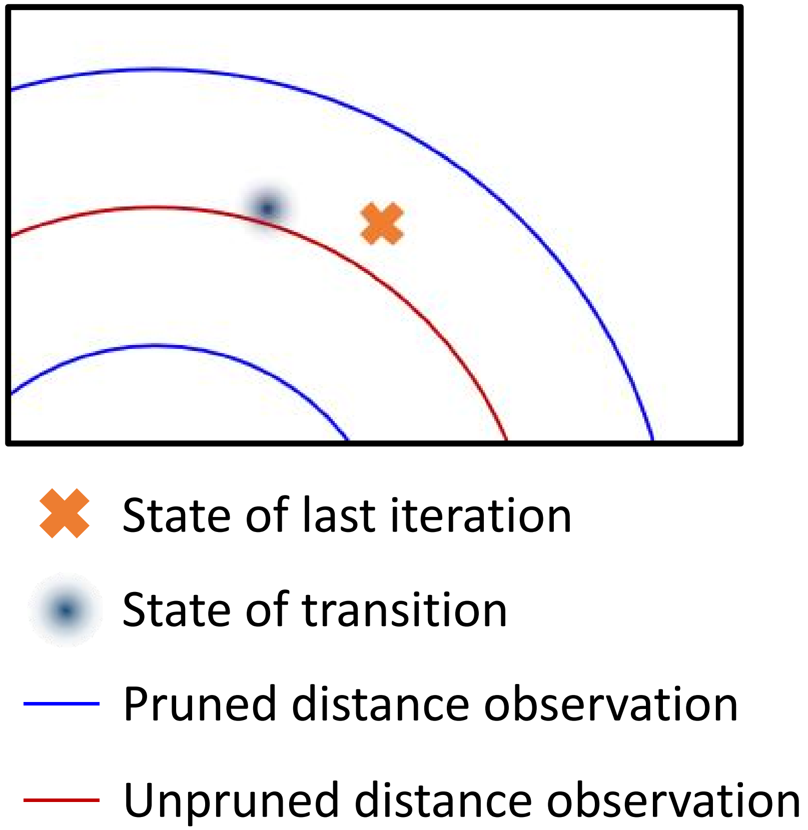
We keep a Kalman filter for each trajectory to handle the Gaussian errors. Only a **single phase measurement** is needed to estimate the next state. Due to the nonlinearity, **EKF** is used.

$$\begin{aligned}
\theta'_k &= f(\theta_{k-1}) \\
\Sigma'_k &= A\Sigma_{k-1}A^T + Q \\
K'_k &= \Sigma'_k C^T (C\Sigma'_k C^T + R)^{-1} \\
\theta_k &= \theta'_k + K'_k(z_k - h(\theta'_k)) \\
\Sigma_k &= (I - K'_k C)\Sigma'_k
\end{aligned}$$

Nearest Neighbors Pruning

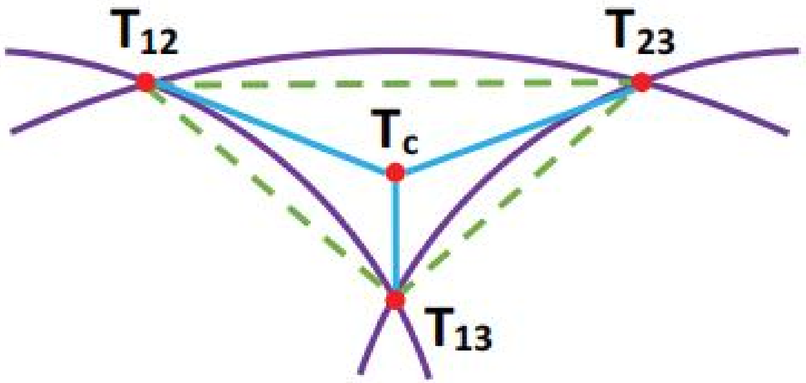


$O(n^k)$



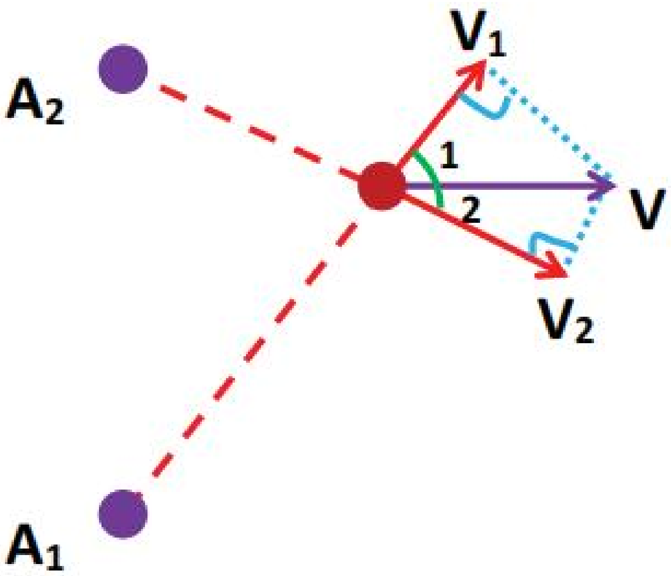
Nearest neighbors pruning ensures that the number of candidate trajectories is **not growing over time**, achieving great time efficiency.

Initial State Pruning



(a) Position estimation

- Interpolation
- Trilateration
- Perimeter pruning



(b) Velocity estimation

- Projected velocity estimation
- Least squares method

Optimal Trajectory

Initial likelihood:

$$L_0 = \prod_{i=1}^{M} P(\theta_0|\hat{\phi_{i,0}}) \propto \prod_{i=1}^{M} P(\hat{\phi_{i,0}}|\theta_0) = \prod_{i=1}^{M} \mathcal{F}(d_0^i; z_0^*, R_0)$$

Combining observations from multiple antennas

Likelihood update:

$$L_{k+1} = L_k P(z_{k+1}^*|\theta_{k+1}) P(\theta_{k+1}|\theta_k)$$

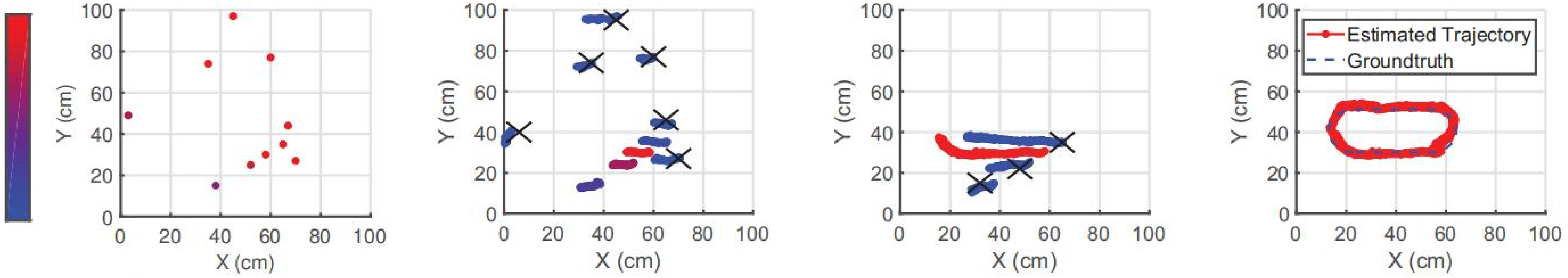
$$P(z_{k+1}^*|\theta_{k+1}) = \mathcal{F}(d_{k+1}; z_{k+1}^*, R_{k+1})$$

$$P(\theta_{k+1}|\theta_k) = \mathcal{F}(\theta_{k+1}; \theta_k, Q_{k+1})$$

Based on observation

Based on transition

Working Process



(a) Initial estimation (t=0) (b) t=1s (c) t=5s (d) t=15s

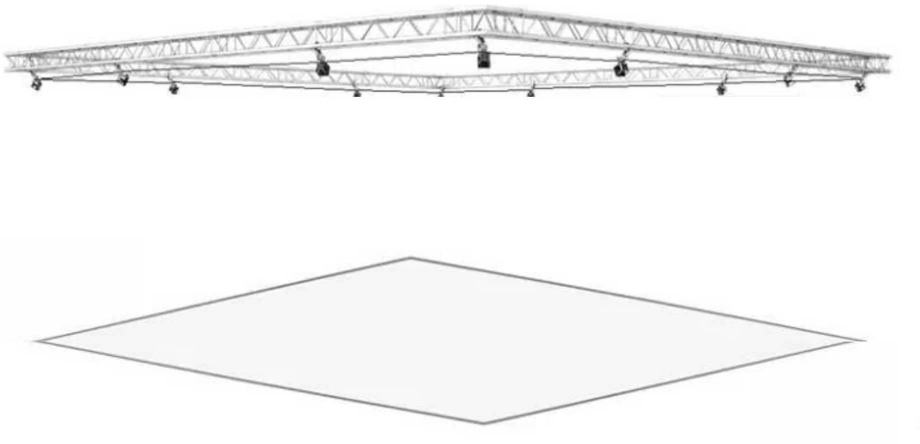
Quick Stop: The trajectory whose likelihood is below the threshold L_{th} will be deleted and not updated anymore.

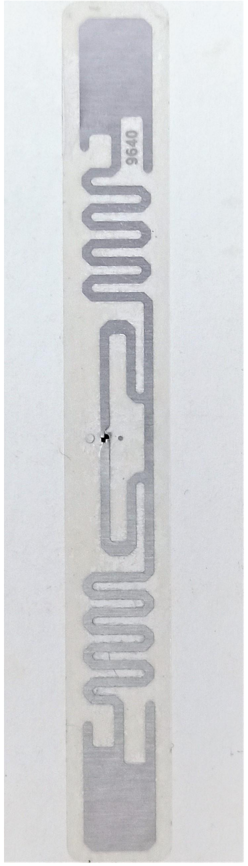
3 Evaluation

Implementation

- Hardware:
  - ThingMagic M6e RFID reader
  - 4 omnidirectional antennas
  - RFID tags

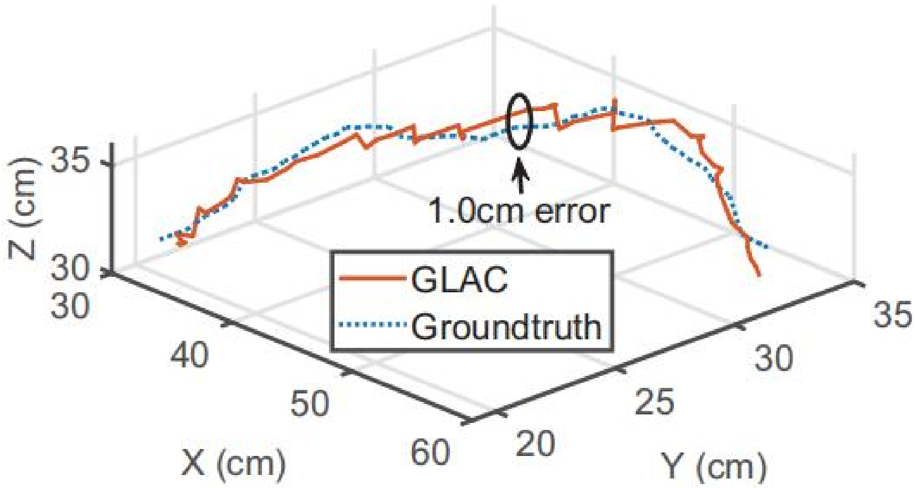
- Groundtruth: OptiTrack



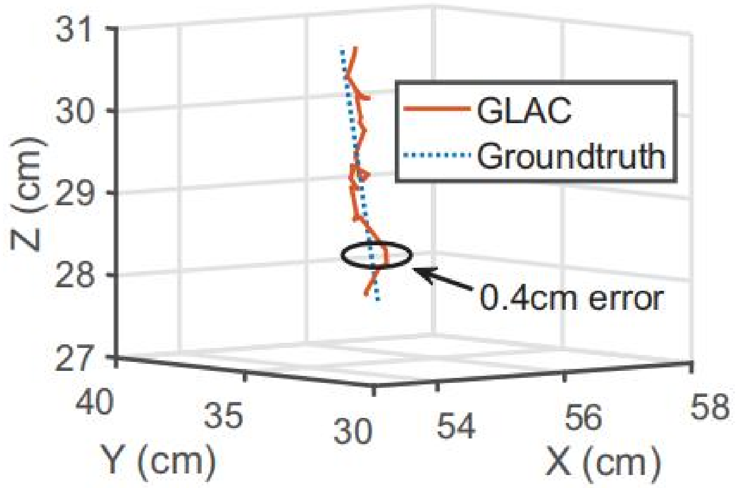


Robotic Arm Tracking

(a) Robotic arm and target tag

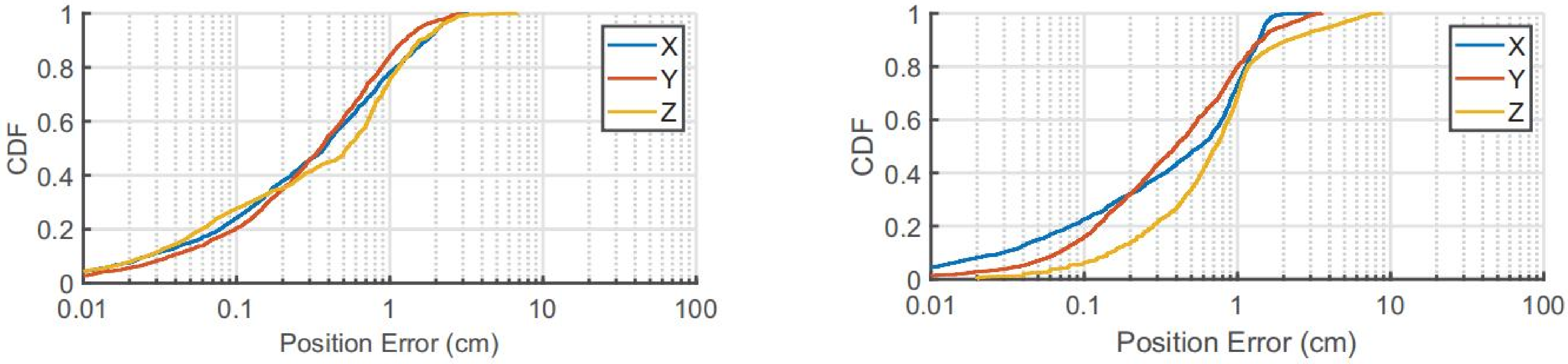


(b) Rotating



(c) Lifting

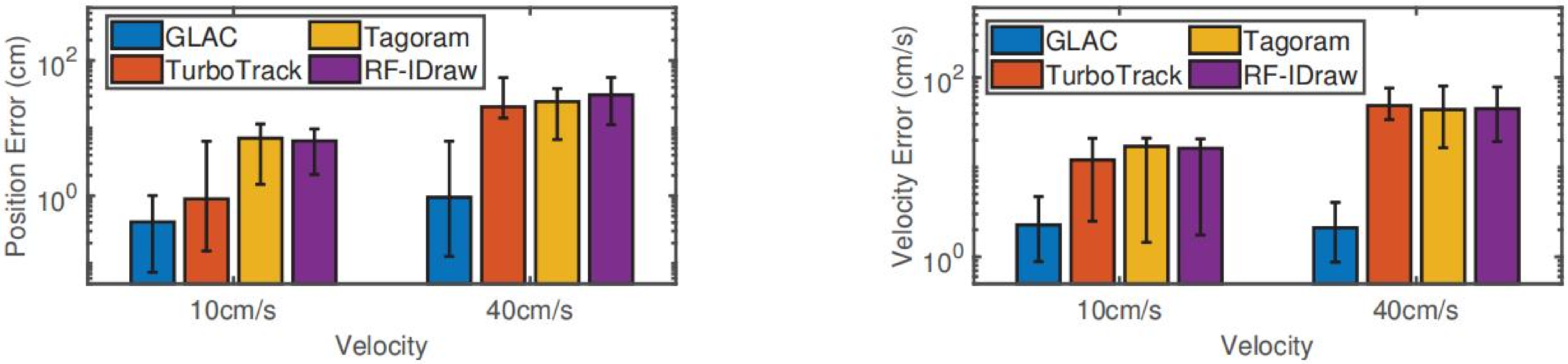
3D Tracking



(a) LoS (b) NLoS

The median position error of GLAC is less than 1 cm in both LoS and NLos in all dimensions achieving **millimeter accuracy**.

Mobility Comparison



(a) Position error (b) Velocity error

GLAC achieves better performance than existing systems. Especially in **high-speed** scenarios, the performance gap is more than **20 times**.

Time-Efficiency Comparison

	Reading	Computation	Total
GLAC	28ms	78us	28ms
TurboTrack	111ms/4.0×	408us/5.2×	111ms/4.0×
Tagoram	111ms/4.0×	1896ms/24300×	2007ms/72×
RF-IDraw	111ms/4.0×	3us/0.038×	111ms/4.0×

GLAC achieves the **best overall time-efficiency** among all thanks to shortest reading time brought by **single-phase update** and decent computation time resulted from our **fast inference scheme**.

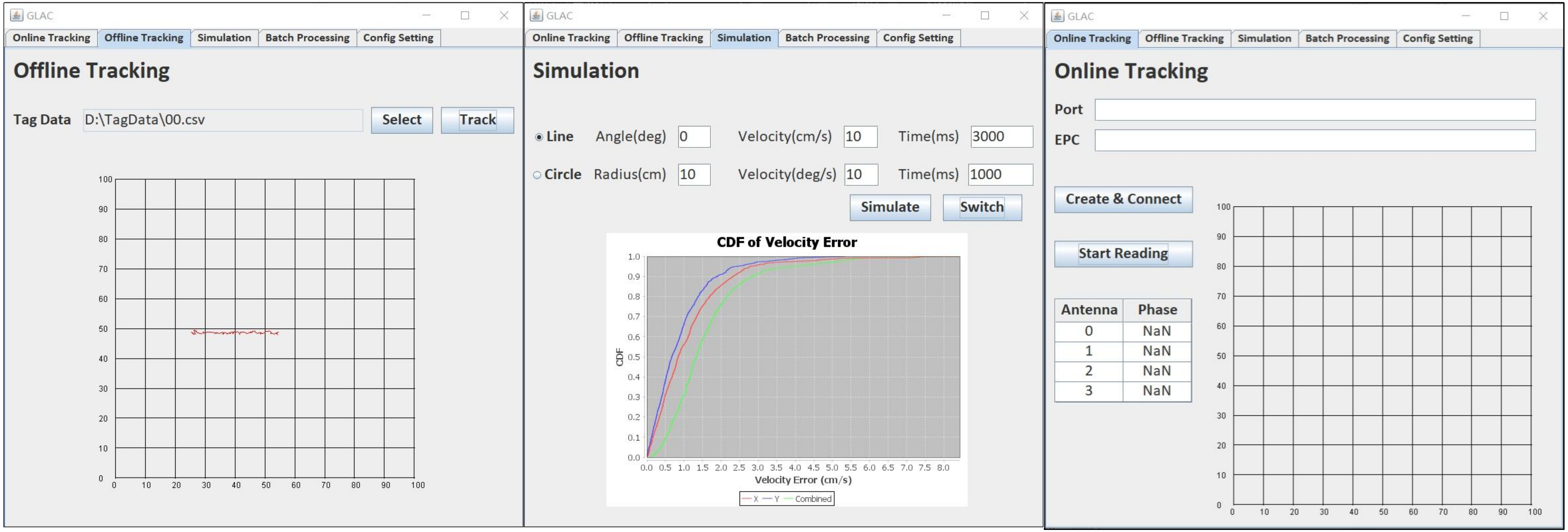
4 Conclusion

Conclusion

- We discover that **oversimplified mobility model** and **low-rate asynchronous reading** are harmful to tracking precision, especially for fast-moving objects.
- With the novel **HMM framework** and **fast inference technology**, GLAC achieves **millimeter-level accuracy** without requiring any extra hardware and restrictive mobility for tags and readers.
- GLAC paves the way for fast and wide adoption of cheap and readily available commercial RFIDs in robotic applications demanding high-precision, e.g., welding, assembly, and surgeries.

Artifact

- **Artifact Certified**
- **Result Certified**



Q&A

THANKS FOR YOUR WATCHING

Acceleration Upper Bound

- We suppose
  - wavelength λ = 0.3 m
  - reading cost t = 0.03 s

- Therefore, as long as the acceleration is not too large, the **nearest neighbor purning** works.

$$\frac{1}{2}at^2 < \frac{1}{2} \times \frac{1}{2} \times \lambda$$

$$a < \frac{\lambda}{2t^2} = 166.7m/s^2$$

Gains of Mobility Modeling

State Definition

$$\theta_k = \begin{pmatrix} P_{x,k} \\ P_{y,k} \\ V_{x,k} \\ V_{y,k} \end{pmatrix}$$

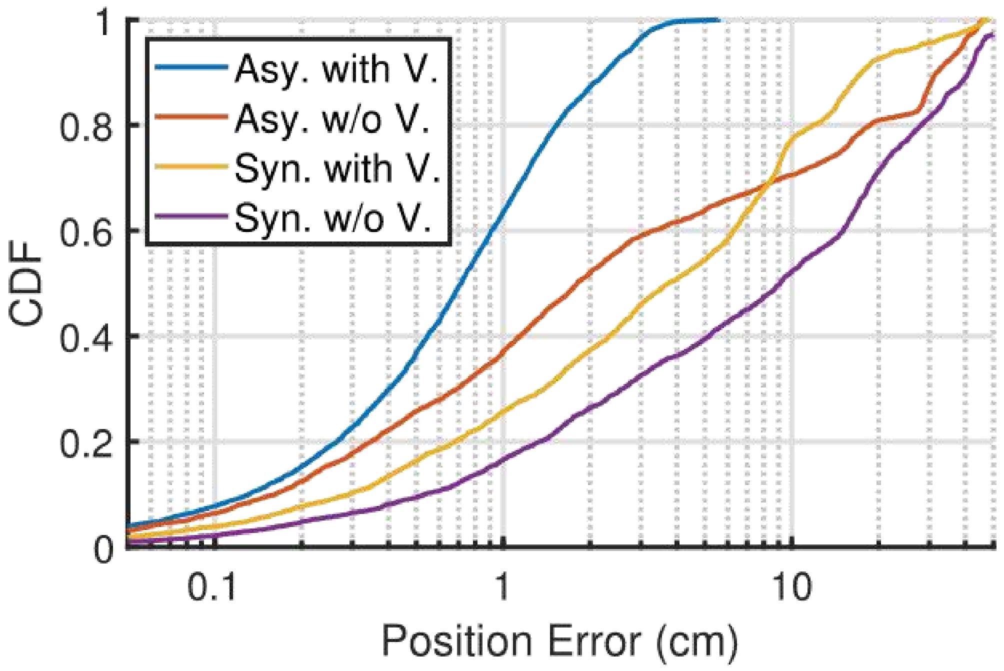
- Position in X axis
- Position in Y axis
- Velocity in X axis
- Velocity in Y axis

Transition Equation

$$\theta_k = f(\theta_{k-1}) + s_k = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \theta_{k-1} + s_k$$

Observation Equation

$$z_k = h(\theta_k) + v_k = (\sqrt{(P_{x,k} - A_x)^2 + (P_{y,k} - A_y)^2}) + v_k$$



$$\theta_{\mathbf{k+1}} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \theta_{\mathbf{k}} + \mathbf{s_k}.$$

$$\mathbf{z_k} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \theta_{\mathbf{k}} + \mathbf{u_k}.$$