AprilTag-based Trajectory Tracking

for the LIMOS Robot

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Master's degree in artificial perception and robotics

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Outline

Problem

Challenges

Project goal

Phases

Problem description

Problem to solve

- We need a robot that can **learn a path by being guided**.

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- We need a robot that can **learn a path by being guided**.
- Later it must **drive that same path alone**.
- It has to work in normal indoor rooms without fuss.

Challenges

Why this is challenging

- **Hardcoded paths**: someone types coordinates by hand.

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Why this is challenging

- **Hardcoded paths**: someone types coordinates by hand.
- **No flexibility**: any small change means rebuilding code.
- **High barrier**: only experts can tweak routes.

Chosen setup

Selected Platform

- Robot: **LIMOS** with wheels and camera.

Fig. 1 — LIMOS mobile robot

Chosen setup

Selected Platform

- Robot: **LIMOS** with wheels and camera.
- Tags: **AprilTag** to tell where the robot is.

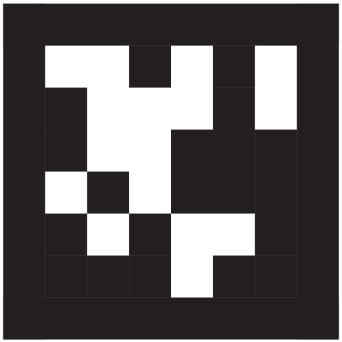

Fig. 2 — AprilTag visual marker

Chosen setup

Selected Platform

- Robot: **LIMOS** with wheels and camera.
- Tags: **AprilTag** to tell where the robot is.
- Together they keep the pose steady while we teach and repeat.

Fig. 1 — LIMOS robot

Fig. 2 — AprilTag marker

Project Goal

Our Goal

- Build a simple **teach and repeat** loop.

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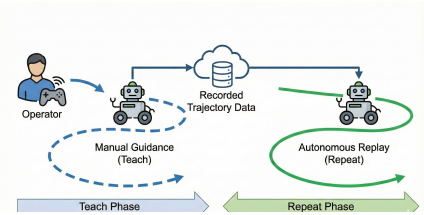

Fig.3 — High-level teach and repeat concept

Project Goal

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- Build a simple **teach and repeat** loop.
- **No coding**: you just guide the robot by hand.

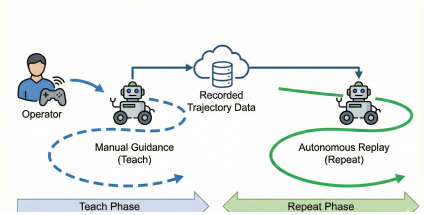


Fig.3 — High-level teach and repeat concept

Project Goal

Our Goal

- Build a simple **teach and repeat** loop.
- **No coding**: you just guide the robot by hand.
- **Auto replay**: it drives the same path accurately later.

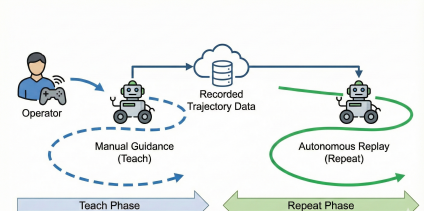


Fig.3 — High-level teach and repeat concept

Phase 1: TF setup and perception

Step 1 — Put tags on the map.

We save where each AprilTag sits:

$$T_{\text{world}}^{\text{tag}}$$

This stays fixed for every next step.

Phase 1: TF setup and perception

Step 2 — Drive the robot once.

The simulator gives the robot pose while it follows a smooth curve:

$$T_{\text{world}}^{\text{camera\_link}}(t)$$

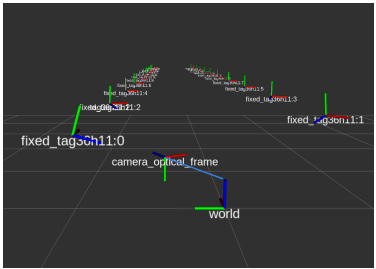


Fig. 4 — World, robot and camera frames

Phase 1: TF setup and perception

Step 3 — Use the real camera frame.

We switch to the optical frame (how the camera really looks):

$$T^{\text{camera\_optical}}_{\text{world}}(t) = T^{\text{camera\_link}}_{\text{world}}(t) \cdot T^{\text{camera\_optical}}_{\text{camera\_link}}$$

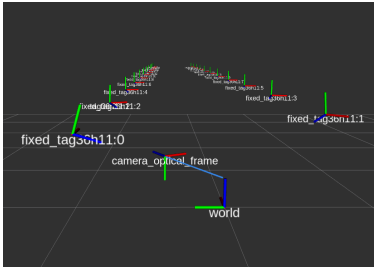


Fig. 4 — World, robot and camera frames

Phase 1: TF setup and perception

Step 4 — Compute clean tag detections.

From the map and pose we get, for each tag:

$$T^{\text{tag}}_{\text{camera\_optical}}(t)$$

This is the clean data that Phase 2 will dirty with noise.

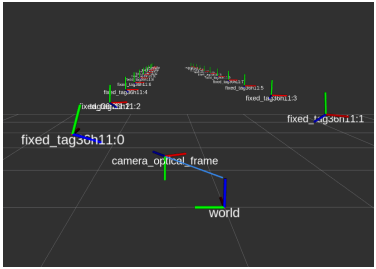


Fig. 4 — World, robot and camera frames

Phase 2: Simulation and dataset generation

Step 1 — Simulate a clean path.

We make a smooth curve and log the true pose:

$$T_{\text{world}}^{\text{camera\_optical}}(t)$$

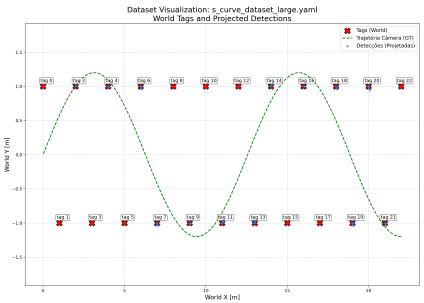


Fig. 5 — Ground truth sinusoid trajectory

Phase 2: Simulation and dataset generation

Step 2 — Compute perfect tag reads.

For every tag and time we compute the clean detection:

$$T^{\text{tag}}_{\text{camera\_optical}}(t)$$

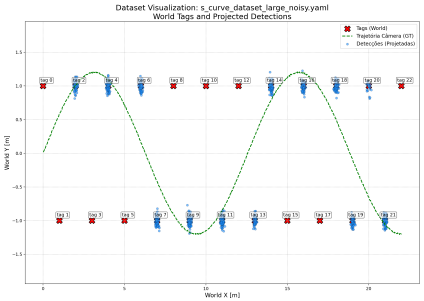
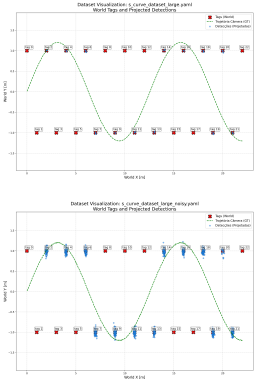


Fig. 6 — Noisy measurements

Phase 2: Simulation and dataset generation

Step 3 — Add noise like real life.

We add Gaussian noise so readings look imperfect, like sensors do.



Clean (top) and noisy (bottom) simulated data

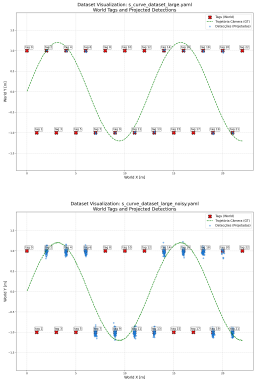
Phase 2: Simulation and dataset generation

Step 4 — Save the dataset.

For each time we save:

- the true pose $T_{\text{world}}^{\text{camera\_optical}}(t)$
- the noisy tag detections $T_{\text{camera\_optical}}^{\text{tag}}(t)$

Phase 3 will test its optimizer on this file.



Clean (top) and noisy (bottom) simulated data

Phase 3: Trajectory Optimization & Recovery

Goal: Fix drift with a simple optimizer

- **Path recovery:** Align the noisy run with the taught path.

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- **Pose graph:** Reduce error between waypoints and simple constraints.

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Goal: Fix drift with a simple optimizer

- **Path recovery:** Align the noisy run with the taught path.
- **Pose graph:** Reduce error between waypoints and simple constraints.
- **Drift fix:** Auto-correct rotation and position drift.

Recovery the Optimal Path Sinusoidal Trajectory

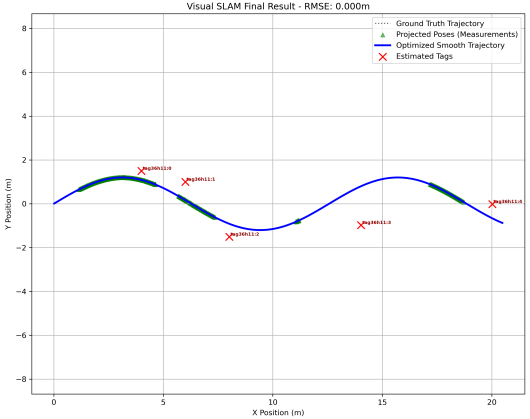


Fig. 7.2 — Trajectory Recovery via Optimization

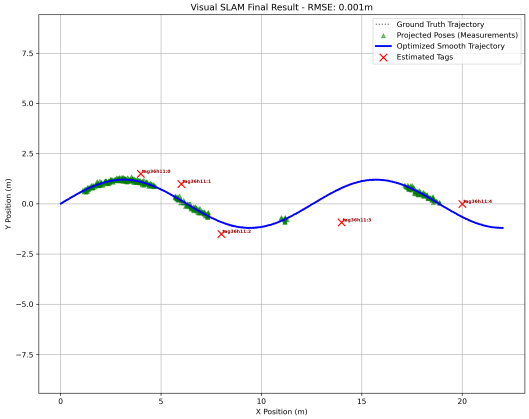


Fig. 7.1 — Simulated Dataset with Gaussian Noise

Quantitative Analysis Sinusoidal Trajectory

Case 1: Optimization without NOISE (Ideal)

Metric	Value
Trajectory RMSE	**0.0000** m
Avg. Tag Position Error	0.0164 m

Tag Estimation Error (Ideal)

Tag Name	X Error	Y Error	Z Error
tag36h11:0	0.00	0.00	0.00
tag36h11:1	0.00	0.00	0.00
tag36h11:2	0.01	−0.01	0.00
tag36h11:3	0.03	0.00	0.00
tag36h11:4	0.02	−0.02	0.00

Case 2: Optimization with NOISE (6 cm)

Metric	Value
Trajectory RMSE	**0.0007** m
Avg. Tag Position Error	0.0239 m

Tag Estimation Error

Tag Name	X Error	Y Error	Z Error
tag36h11:0	0.00	0.01	0.01
tag36h11:1	0.01	0.00	0.00
tag36h11:2	0.00	−0.04	0.01
tag36h11:3	−0.01	0.07	0.00
tag36h11:4	0.00	−0.01	0.00

Tables — Comparison of Optimization Results with and without noise.

Recovery the Optimal Path Sinusoidal Trajectory

The scenario with 23 tags

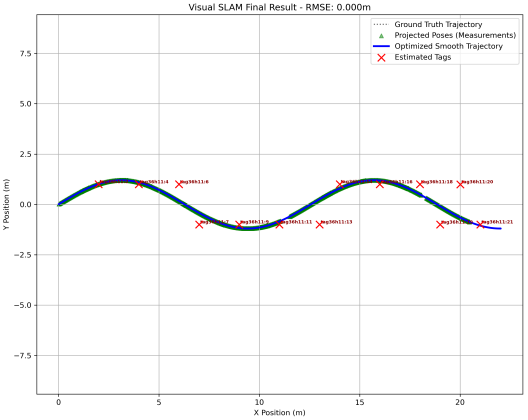


Fig. 8.1 — Trajectory Recovery via Optimization

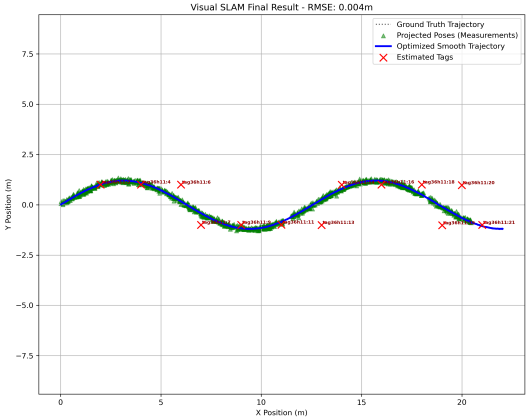


Fig. 8.2 — Simulated Dataset with Gaussian Noise

Quantitative Analysis Sinusoidal Trajectory

The scenario with 23 tags

Case 1: Optimization without NOISE

Metric	Value
Trajectory RMSE	**0.0002** m
Avg. Tag Position Error	0.0019 m

Tag Estimation Error (Sample)

Tag Name	X Error	Y Error	Z Error
tag36h11:2	0.00	0.00	0.00
tag36h11:7	0.00	0.00	0.00
tag36h11:13	0.00	0.00	0.00
tag36h11:18	0.00	0.00	0.00
tag36h11:21	0.00	0.00	0.00

Case 2: Optimization with NOISE (6 cm)

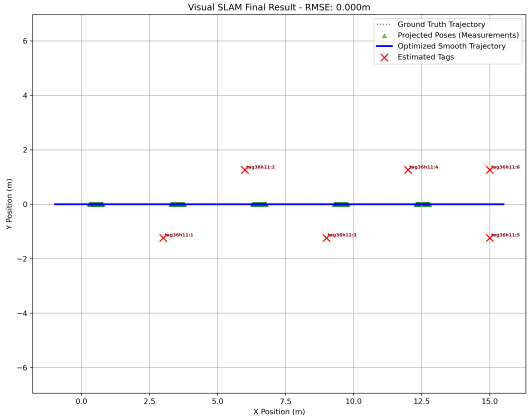
Metric	Value
Trajectory RMSE	**0.0037** m
Avg. Tag Position Error	0.0134 m

Tag Estimation Error (Sample)

Tag Name	X Error	Y Error	Z Error
tag36h11:2	0.01	0.01	0.00
tag36h11:7	0.00	0.00	0.00
tag36h11:13	0.01	0.01	0.00
tag36h11:18	0.00	0.00	0.01
tag36h11:21	0.01	0.00	0.02

Tables — Comparison of Optimization Results with and without noise (Sample of 5 Tags).

Recovery the Optimal Path: Straight Trajectory



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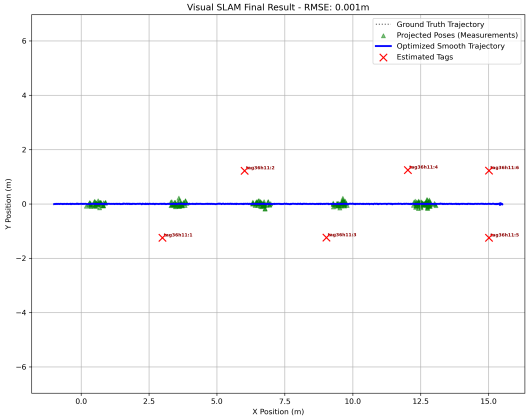

Fig. 8.2 — Simulated Dataset with Gaussian Noise

Quantitative Analysis: Straight Trajectory

Case 1: Optimization without NOISE

Metric	Value
Trajectory RMSE	**0.0017** m
Avg. Tag Position Error	0.0000 m

Tag Estimation Error (Sample)

Tag Name	X Error	Y Error	Z Error
tag36h11:0	0.00	0.00	0.00
tag36h11:1	0.00	0.00	0.00
tag36h11:2	0.00	0.00	0.00
tag36h11:3	0.00	0.00	0.00
tag36h11:4	0.00	0.00	0.00

Case 2: Optimization with NOISE (6 cm)

Metric	Value
Trajectory RMSE	**0.017** m
Avg. Tag Position Error	0.01912 m

Tag Estimation Error (Sample)

Tag Name	X Error	Y Error	Z Error
tag36h11:0	0.01	0.01	0.00
tag36h11:1	0.00	0.00	0.00
tag36h11:2	0.01	0.01	0.00
tag36h11:3	0.00	0.00	0.01
tag36h11:4	0.01	0.00	0.02

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Phase 5: Path recovery algorithm

Goal: Recover when the robot leaves the taught path

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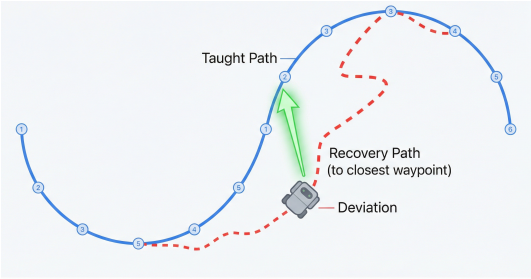
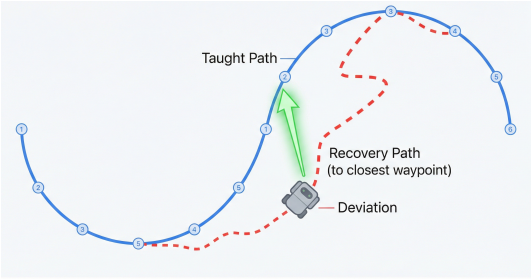


Fig. 10 — Returning to the original path after deviation

Phase 5: Path recovery algorithm

Goal: Recover when the robot leaves the taught path

- **Recovery logic:** Simple rules to steer back to the recorded path.
- **Closest waypoint search:** Use a quick KD-Tree to find the nearest waypoint.
- **Safety validation:** Test recovery moves in sim to avoid bad turns.



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Goal: Demonstrate full teach and repeat autonomy

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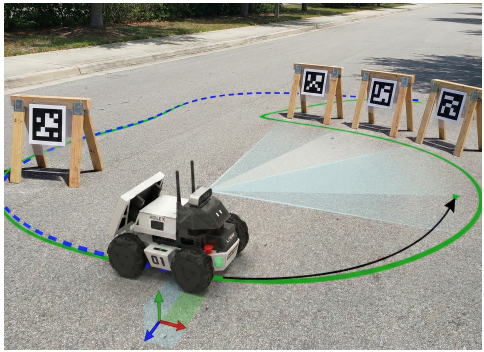
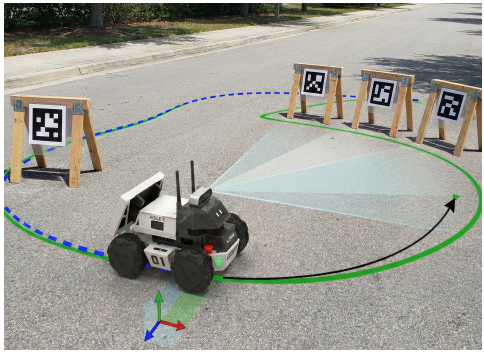


Fig. 11 — Fully integrated teach and repeat behavior

Phase 6: System integration

Goal: Demonstrate full teach and repeat autonomy

- **Controller integration:** Mix Pure Pursuit with the perception and pose stack.
- **Autonomous replay:** Let the robot drive the recorded path on its own.
- **Final system:** A teach & repeat pipeline anyone can run without coding.



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References I

[1] R. Adámek, M. Brablc, P. Vávra, B. Dobossy, M. Formánek, and F. Radil, “Analytical Models for Pose Estimate Variance of Planar Fiducial Markers for Mobile Robot Localisation”, *Sensors*, vol. 23, no. 12, p. 5746, 2023. DOI: 10.3390/s23125746

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Thank you for listening!

Any questions?

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