Apriltag Landmark Localization with Right-Invariant EKF on a Low Cost, Educational Robot

WN 24 ROB 530 Final Project

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Overview

- Motivation
- Methods
- Experiments
- Results
- Discussion
- Future Considerations

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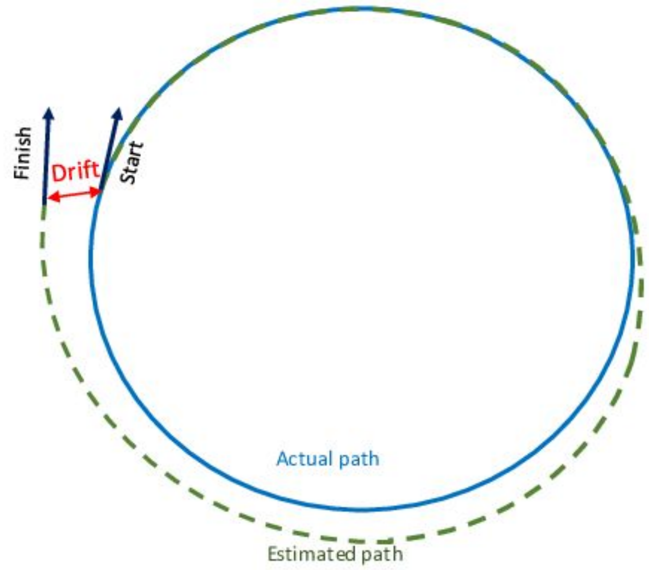
Motivation

- Cost conscious robots in dynamic environments may struggle to achieve robust SLAM performance.

- Odometry tracking sensors (IMU, encoders) are prone to drift, causing poor state estimation.



Visualization of drift in robot pose estimation [1]

Motivation

- Apriltag fiduciary markers provide a cost-effective landmark that is easily detectable with a camera using OpenCV

- We can test a real-world implementation on an MBot

Apriltag detections [2]

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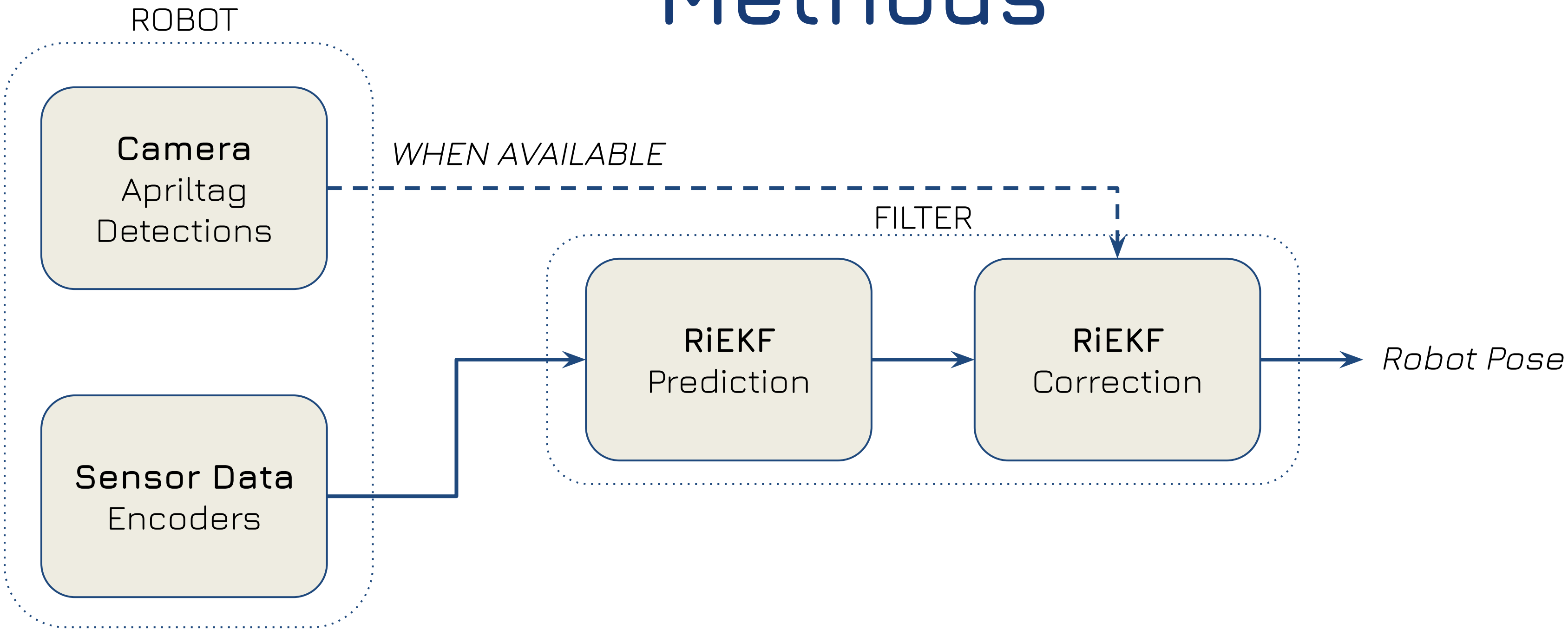
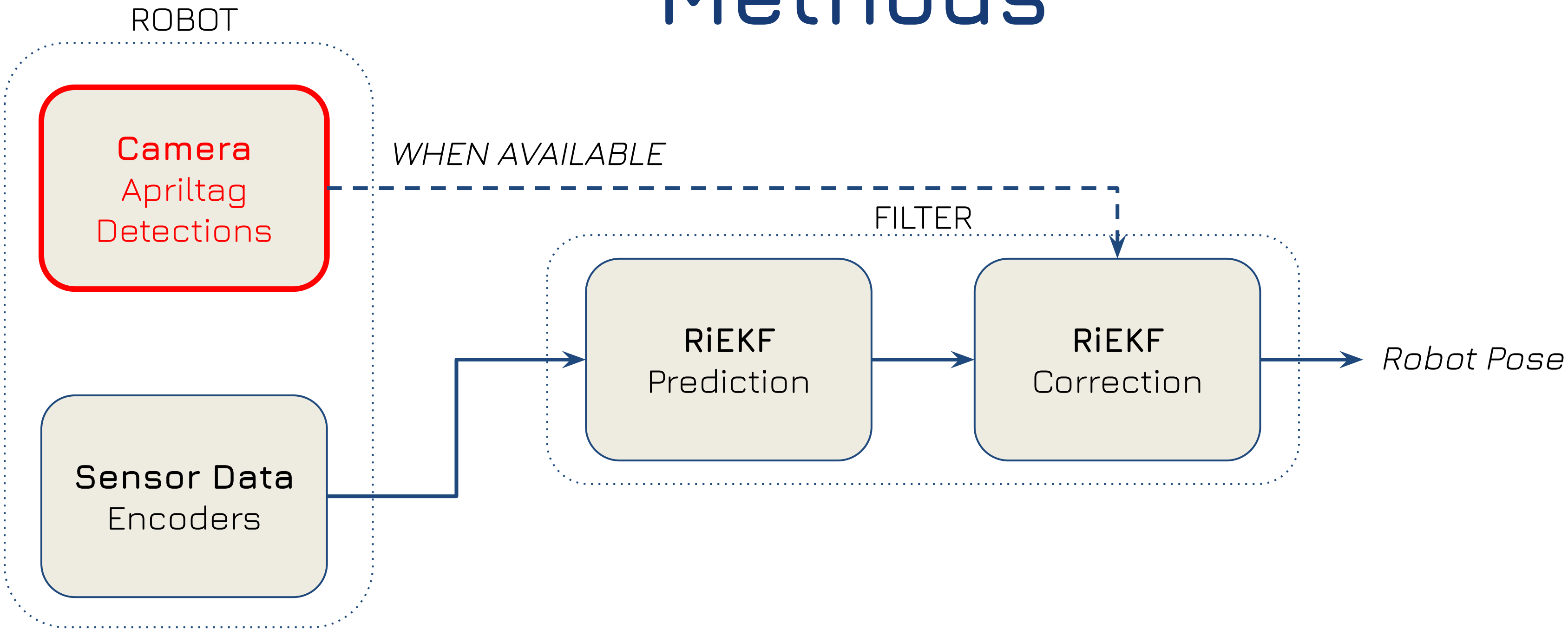
Methods


ROBOT
Camera
Apriltag
Detections
Sensor Data
Encoders
WHEN AVAILABLE
FILTER
RiEKF
Prediction
RiEKF
Correction
Robot Pose

Methods



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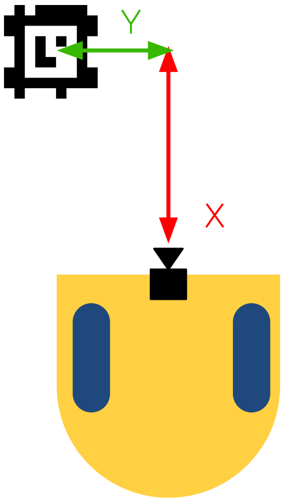
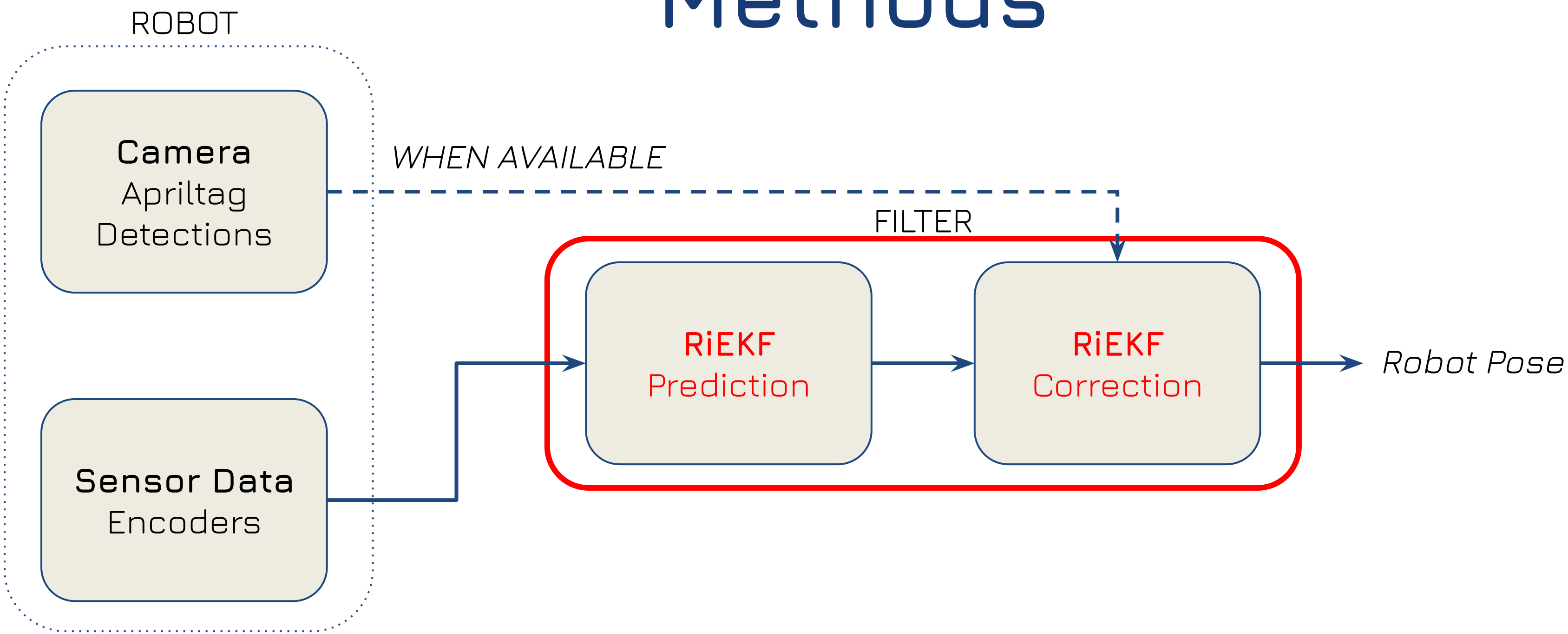
Methods

- We utilize Python and OpenCV to detect Apriltags. The Apriltag library provides X and Y measurements of the apriltags in the robot frame.

- Due to the known size of an Apriltag, determining these locations with a calibrated camera is easy.



Methods


ROBOT
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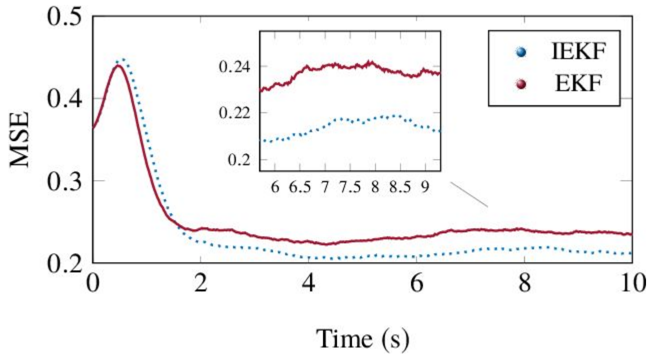
Methods

- RiEKF provides better handling of nonlinear dynamics than traditional EKF by operating within the Lie group

1. Propagate mean and covariance
2. Update mean and covariance



Invariant EKF vs traditional EKF [3]

Methods

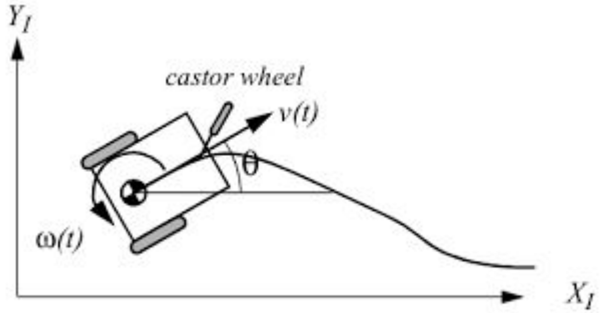
Robot Motion Model:

$$x_{k+1} = x_k - \frac{\hat{v}}{\hat{\omega}} sin(\theta_k) + \frac{\hat{v}}{\hat{\omega}} sin(\theta + \hat{\omega}\Delta t)$$

$$y_{k+1} = y_k + \frac{\hat{v}}{\hat{\omega}} cos(\theta_k) - \frac{\hat{v}}{\hat{\omega}} cos(\theta + \hat{\omega}\Delta t)$$

$$\theta_{k+1} = \theta_k + \hat{\omega}\Delta t$$

Robot motion model [4]



Nonholonomic differential drive robot [5]

Methods

Algorithm 1: RI-EKF Localization

Given: F: Dynamics Model;
X_{init}: Initial State (Lie Algebra);
Σ_{init}: Initial State Covariance;
W: Motion noise covariance;
V: Measurement noise covariance;

$X \leftarrow X_{init}$
$\Sigma \leftarrow \Sigma_{init}$
while *task not complete* **do**
  $v, \omega \leftarrow calcVelFromEncoders()$
  $X, \Sigma \leftarrow \boxed{Prediction(X, \Sigma, v, \omega)}$
  if $AprilTagDections()$ **then**
    $Y_1, Y_2, id_1, id_2 \leftarrow AprilTagDections()$
    $X, \Sigma \leftarrow \boxed{Correction(X, \Sigma, Y_1, Y_2, id_1, id_2)}$

RiEKF algorithm [6]

Algorithm 2: Prediction(X, Σ, v, ω)

$x, y, \theta \leftarrow getState(X)$
$\bar{x}, \bar{y}, \bar{\theta} \leftarrow \mathbf{F}(x, y, \theta, v, \omega)$
$\bar{X} \leftarrow poseMatrix(\bar{x}, \bar{y}, \bar{\theta})$
$u^\wedge = \log\left(X_k^{-1} X_{k+1}\right)$
$X = \exp\left(u^\wedge\right)$
$Ad_X = X u^\wedge X^{-1}$
$\Sigma = \Sigma + Ad_X W Ad_X^T$
Return X, Σ

Algorithm 3: Correction$(X, \Sigma, Y_1, Y_2, id_1, id_2)$

$b_1 = getLandmarkPosition(id_1)$
$b_2 = getLandmarkPosition(id_2)$
$S = H \Sigma H^T + X V X^T$
$K = \Sigma H^T S^{-1}$
$Y = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix}$
$b = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$
$\nu = \begin{bmatrix} X & 0 \\ 0 & X \end{bmatrix} Y - b$
$X = exp^{(K\nu)^\wedge} X$
$\Sigma = (I - KH)\Sigma(I - KH)^T + K(XVX^T)K^T$
Return X, Σ

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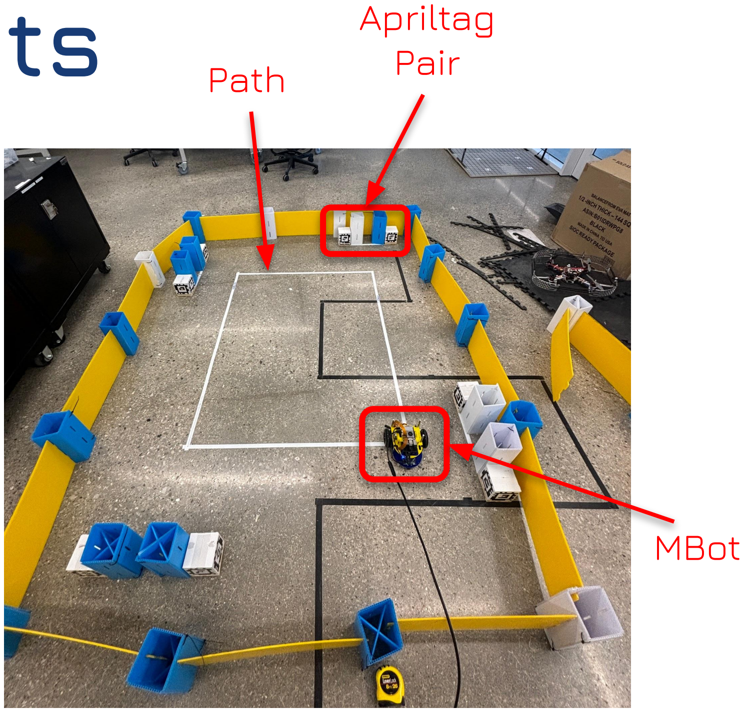
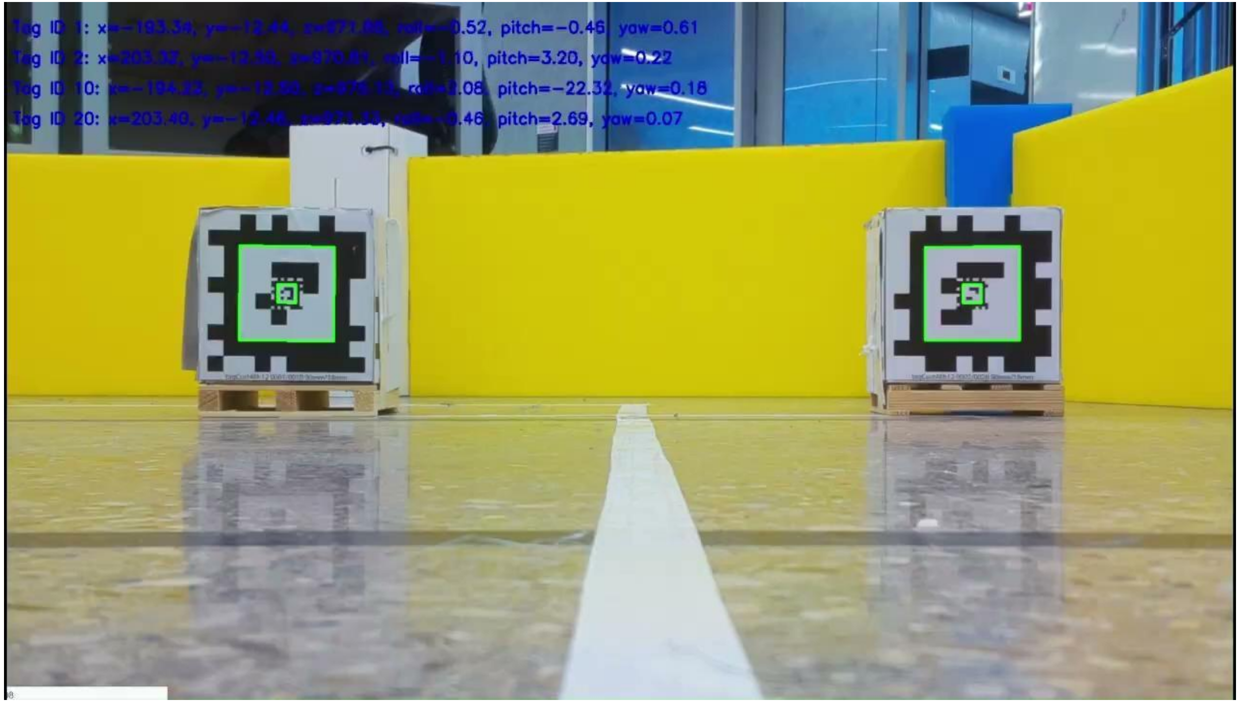
Experiments

- We created our own dataset using an MBot equipped with an Apriltag detector as described in Methods
- Apriltag pairs are placed in observable locations and the MBot is driven in a square.
- Data stored in LCM log file



Experiments



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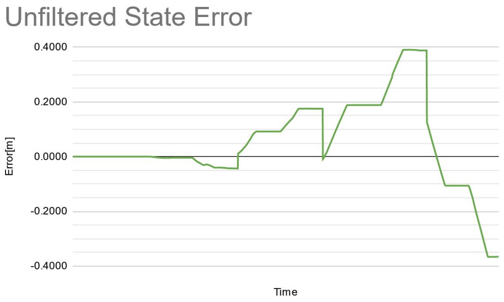
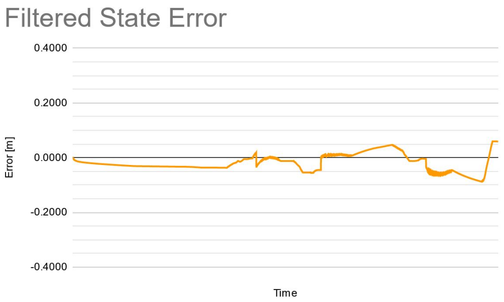
Results

- Filtered position reduced RMSE by over 75% (from 0.16m to .04m)
- RiEKF Parameters:
  - Motion Noise STD: 0.03m/s & 0.01 rad/s
  - Measurement Noise STD: 0.1 m





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Discussion

- Effectively improve robot position estimation over time with landmark localization
  - **>75% error improvement**

- Computationally efficient method of odometry correction

- Experiment setup is time consuming (difficult to setup Apriltags consistently)

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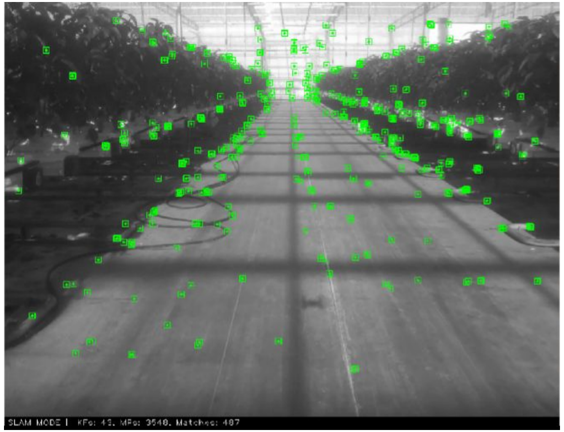
Future Considerations

- Expanding code to work live on the MBot
- Improved motion model
  - IMU sensor fusion
  - Visual odometry
- Simplify setup
  - Bird's eye camera with Apriltag on the robot
  - Eliminating the need for several landmarks + one sensor for multiple bots
- Extending to 3D (i.e. a drone)



Visual odometry output [7]

Thank you for a great semester!

References

[1] Younes, Georges & Asmar, Daniel & Shammas, Elie. (2016). A survey on non-filter-based monocular Visual SLAM systems.

[2] A. Rosebrock, "Apriltags with python," PyImageSearch, https://pyimagesearch.com/2020/11/02/apriltag-with-python/ (accessed Apr. 17, 2024).

[3] Phogat, Karmvir Singh and Dong Eui Chang. "Invariant extended Kalman filter on matrix Lie groups." *Autom.* 114 (2019): 108812.

[4] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. 2005. Probabilistic Robotics (Intelligent Robotics and Autonomous Agents). The MIT Press.

[5] Di Caro, Gianni A. "Lecture 4: (Non) Holonomic Robots, Wheeled Robots, Kinematics." 16-311-Q Introduction to Robotics, Carnegie Mellon University Qatar, Fall 2017

[6] M. Ghaffari, "Lecture notes for mobile robotics," University of Michigan, Ann Arbor, 2021.

[7] Krul, Sander & Pantos, Christos & Frangulea, Mihai & Valente, João. (2021). Visual SLAM for Indoor Livestock and Farming Using a Small Drone with a Monocular Camera: A Feasibility Study. Drones. 5. 41. 10.3390/drones5020041.