Comprehensive Report: Enhanced Robot Localization Using Sensor Fusion

Sheyda Rastgarmohammadizad, Nana Tufffour-Kwarteng, Ciaran Maher
Data Fusion Architecture, Hanze University of Applied Sciences
Supervised by: Dr. Mehdi Sedighi

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1 Introduction

Robot localization answers the fundamental question: *Where is the robot now?*. Localization is essential for robots to navigate and interact with their environment effectively. This project combines sensor fusion techniques using the Kalman Filter (KF) and Particle Filter (PF) to achieve accurate localization for a Create3 iRobot in a 3x3-meter environment.

2 Selecting a Proper Sensor Fusion Model

Sensor fusion models were selected based on the system's requirements:

- **Kalman Filter:** Applied to smooth noisy IMU orientation data. Its recursive Bayesian framework is effective for linear systems with Gaussian noise.
- **Particle Filter:** Chosen for global localization due to its ability to handle nonlinear motion and non-Gaussian noise.

This hybrid approach ensures robustness, adaptability, and precision, addressing the challenges of robot localization in noisy and nonlinear environments [1].

3 Data Selection and Analysis

The data sources used in this project include:

- **IMU Data:** Provides angular velocity and yaw angle for orientation tracking. Yaw is computed from quaternion data.
- **Wheel Encoders:** Provide displacement and velocity, essential for updating the robot's position in the motion model.
- **TF Data:** Ground truth position data used for evaluating model accuracy.

Each dataset was preprocessed to extract relevant features, such as `delta_yaw`, which represents the change in orientation between timesteps.

4 Developing the Model

The localization model integrates the following components:

4.1 Kalman Filter for Orientation

The Kalman Filter estimates the robot's orientation (`yaw`) by recursively fusing angular velocity with noisy IMU measurements:

$$x_k = Ax_{k-1} + Bu_k, \quad P_k = AP_{k-1}A^T + Q \tag{1}$$

$$K = P_k H^T (HP_k H^T + R)^{-1}, \quad x_k = x_k + K(z_k - Hx_k) \tag{2}$$

4.2 Particle Filter for Localization

The Particle Filter estimates the robot's pose (x, y, θ) by simulating a set of particles. Key steps include:

- **Initialization:** Particles are uniformly distributed in the environment.
- **Motion Model:** Particles are updated based on displacement (`dx, dy`) and orientation changes ($\Delta\theta$).
- **Weight Update:** Particle weights are adjusted based on how well they match observed measurements.
- **Resampling:** High-weight particles are selected to refine the state estimate.

5 Sensor Uncertainties from Experiments

To account for sensor noise:

- Gaussian noise was added to the motion model to represent uncertainties in displacement and orientation.
- Measurement noise was modeled using Gaussian distributions in the Particle Filter.
- The Kalman Filter corrected IMU drift by balancing noisy measurements with predicted states.

6 Fusion of Data to Improve Precision

Sensor fusion improved localization by combining:

- IMU data for orientation smoothing using the Kalman Filter.
- Wheel encoder data for position updates in the Particle Filter.

The hybrid approach leverages the strengths of each filter to address system nonlinearities and sensor noise.

7 Model Evaluation

Model accuracy was evaluated using:

- **Trajectory Comparison:** Visual comparison between estimated and ground truth trajectories.
- **RMSE Computation:**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_i^{\text{true}})^2 + (y_i - y_i^{\text{true}})^2} \tag{3}$$

  Results:

  - RMSE (X-axis): **1.050 meters**
  - RMSE (Y-axis): **0.824 meters**
  - Total RMSE: **1.335 meters**

8 Analyzing System Requirements

The system was designed to meet the following requirements:

- Handle noisy sensor data effectively.
- Provide accurate localization in nonlinear environments.
- Allow integration with additional sensors if required.

9 Applicable Sensor Fusion Architectures

The project demonstrates the feasibility of:

- Using the Kalman Filter for linear, Gaussian noise systems.
- Leveraging the Particle Filter for nonlinear, non-Gaussian systems.

Future work could explore advanced architectures, such as Extended Kalman Filters (EKF) or Unscented Kalman Filters (UKF).

10 Results and Visualization

10.1 Kalman Filter Development

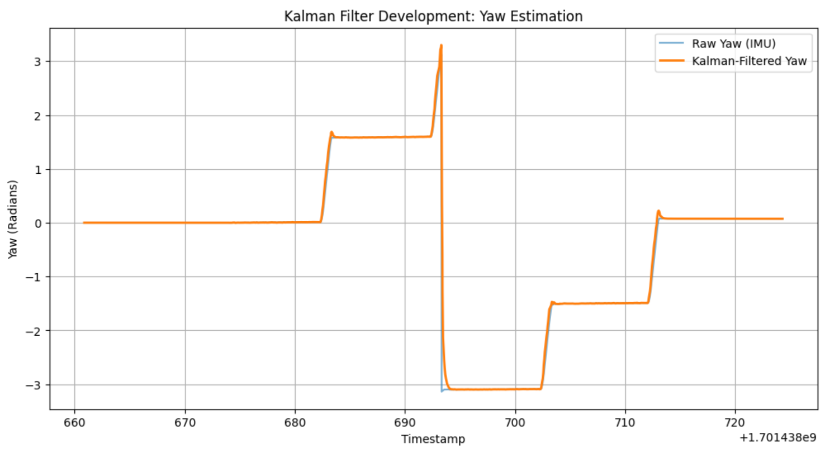

Figure 1: Yaw Estimation: Raw IMU vs Kalman-Filtered

10.2 Particle Filter Visualization

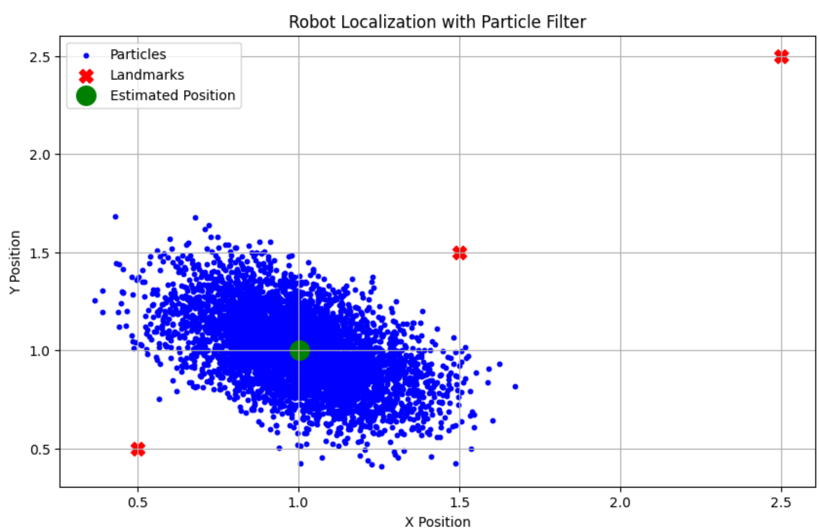

Figure 2: Particle Filter Localization: Estimated Position and Particles

10.3 Trajectory Comparison

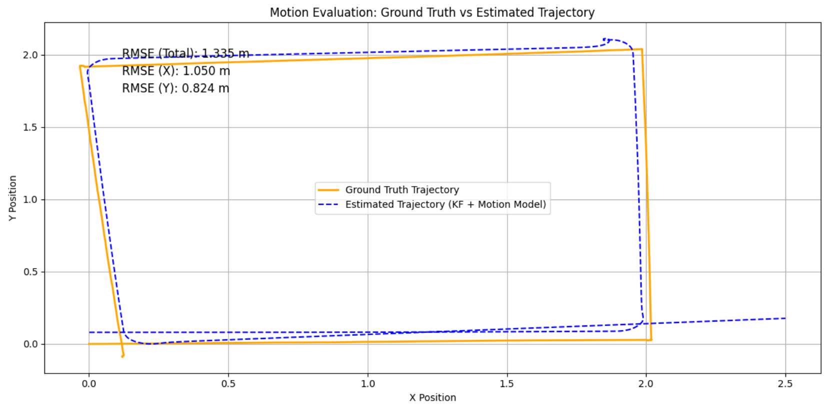

Figure 3: Trajectory Comparison: Ground Truth vs Estimated

11 Conclusion

This project demonstrates the effectiveness of combining Kalman and particle filters for robot localization in a controlled environment. The hybrid approach addressed the challenges posed by nonlinear motion dynamics and noisy sensor data, providing robust and accurate pose estimates.

The Kalman Filter proved to be an excellent choice for smoothing IMU orientation data. By leveraging its ability to recursively estimate states in systems with linear motion models and Gaussian noise, the Kalman Filter effectively reduced the drift and noise inherent in the IMU data. This contributed significantly to the accuracy of the robot's estimated orientation (`yaw`), which directly influenced the reliability of the subsequent position estimation.

The Particle Filter complemented this by tackling the nonlinearity and non-Gaussian noise present in the robot's localization problem. By simulating a distribution of particles and continuously updating their weights based on sensor measurements, the Particle Filter offered a flexible framework to model the robot's pose in complex environments. The resampling step ensured that particles converged on the most likely robot state, reducing the impact of outliers and improving the robustness of the system.

The results, including an RMSE of **1.335 meters** for the total trajectory, indicate that the combined Kalman and Particle Filter approach is capable of delivering precise localization in environments with moderate sensor noise. The RMSE breakdown across the X and Y axes highlights that while the system performed well overall, further optimization may be needed to improve accuracy in specific directions. This is likely due to varying levels of uncertainty in the motion model and measurement updates, which can be addressed in future iterations of the project.

Moreover, the visualization of the trajectory comparisons clearly illustrates the ability of the model to closely follow the ground truth, reinforcing the system's validity. The integration of data from multiple sensors, including IMU and wheel encoders, demonstrates the power of sensor fusion to enhance localization accuracy beyond what any single sensor could achieve alone.

Future work could focus on incorporating additional sensors, such as LiDAR or camera-based systems, to provide richer environmental data for improved particle weight updates. Furthermore, exploring advanced filtering techniques like Unscented Kalman Filters (UKF) or integrating machine learning models for dynamic noise estimation could further enhance the system's performance in more complex or dynamic environments.

In conclusion, the project successfully combined the strengths of the Kalman Filter for orientation smoothing and the Particle Filter for robust pose estimation, addressing key challenges in robot localization. The hybrid approach and its results validate the efficacy of probabilistic methods in navigating the complexities of real-world sensor data, setting a strong foundation for future developments in autonomous robotics.

References

[1] S. Thrun, W. Burgard, and D. Fox. *Probabilistic Robotics.* MIT Press, 2005.

[2] H. F. Durrant-Whyte. *Industrial Robotics.* Ind. Rob., 1994, 21, pp. 11–16.

[3] J. Webster (ed.), *Wiley Encyclopedia of Electrical and Electronics Engineering.* Copyright © 2016 John Wiley & Sons, Inc.