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ME134 - Prof. Nemitz
Lab 4 Writeup

1. Introduction

In this laboratory exercise, we implemented a discrete‑time, three‑state Kalman filter to fuse wheel‑encoder odometry (forward kinematics, FK) with angular‑rate measurements from an onboard gyroscope. The objective was to mitigate the drift inherent in pure encoder‑based pose estimates, especially under high‑speed rotations and straight‑line motions. We then compared the performance of (1) encoder‑only forward kinematics, (2) the Kalman‑filtered estimate, and (3) ground-truth measurements, across a three-phase trajectory—moderate-speed straight, high-speed spin (five full rotations), and high-speed straight.

2. Methods

2.1 State & Models

- State: $X = [x, y, \theta]$ in the global frame
- Prediction: Used closed-form FK equations for straight vs. circular‑arc motion (eqs. 11–16).
- Covariances: Initialized $P = diag(0.1, 0.1, 0.1)$, process noise $Q = diag(0.01, 0.01, 0.01)$
- Update: Corrected only θ using gyroscope Z rate with measurement noise $R_\theta = 0.01$

2.2 Experimental Procedure

1. Initialization: Encoders and IMU yaw reset, kalman filter state zeroed
2. Logging: 50Hz timer callback wrote timestamped estimates to a CSV file
3. Trajectory:
    a. Straight at 10 cm/s for 3 seconds
    b. In place spin at full effort for 2 full rotations
    c. Straight at 30 cm/s for 4 seconds
4. Ground truth: Manually marked robot's endpoints and spin points using tape on the ground and measuring with the start point as (0, 0), logged into a separate CSV file.

3. Results

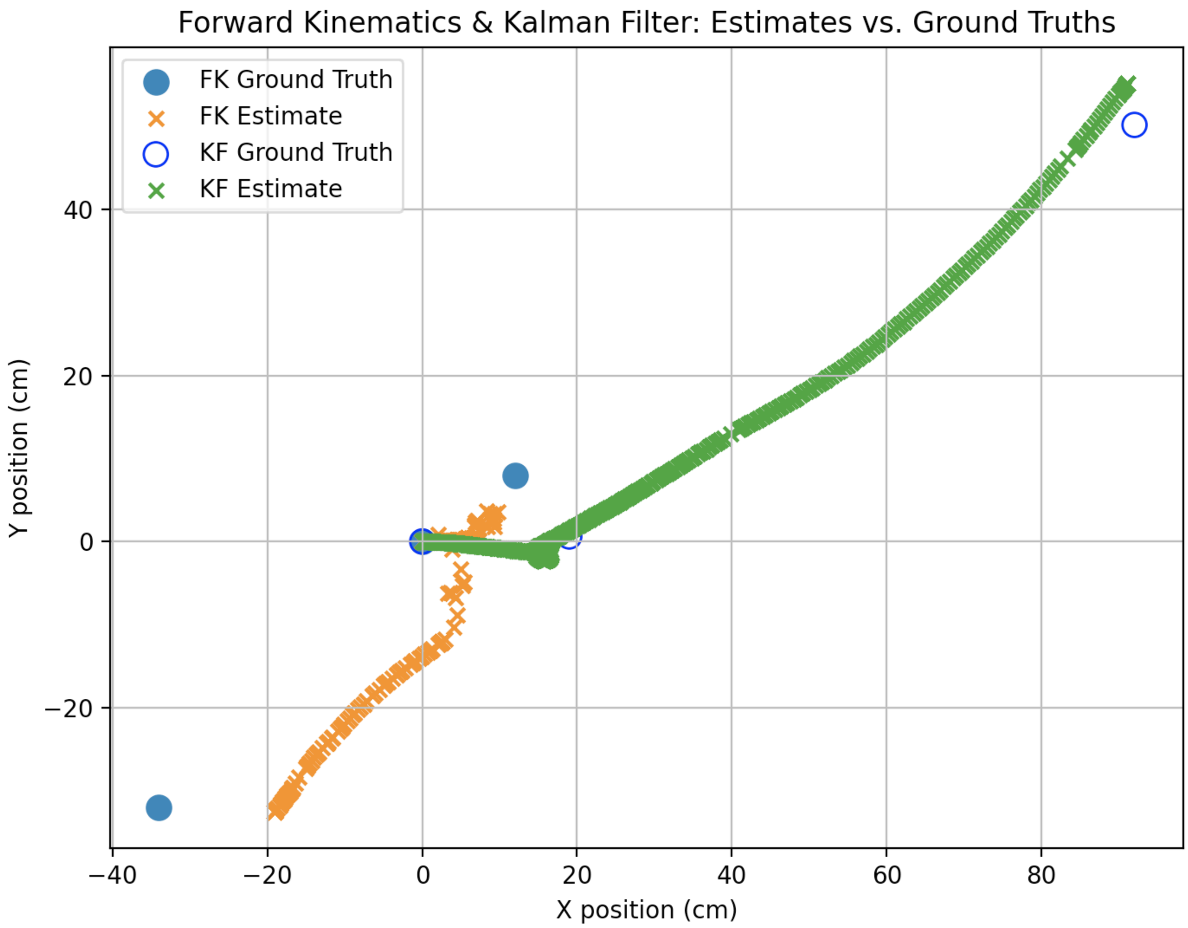

Figure 1. Results showing Forward Kinematics movement vs. Kalman Filter movement in the X and Y plane

Figure 1 overlays the three "true" waypoints with the corresponding forward kinematic estimates and the kalman filter estimates along the three phase trajectory.

Starting from the origin, the FK trajectory in orange shakily moves straight before attempting to spin twice around the center axis. The FK equations are apparent by the way the motors stutter as they move forward, and once the robot attempts to spin, it ends up spinning shy of two turns and facing in the negative Y direction. On the final straight, the errors compound and the orange line shoots far off the true line. The ground truth point however, is in the same X plane as the orange line, meaning the distance was almost calculated correctly, but the angle was off.

By contrast, the Kalman filter closely hugs the true line during the first straight, only dipping slightly below the x=0 axis. Through the spin, it hugs tightly however it also overshoots its spin and ends up pointed in the positive Y direction. The following straight is pretty accurately straight forward and the estimation lies quite close to the ground truth spot, and is much more accurate in comparison to the forward kinematics approach.

I suspect that completing this exercise on the carpet without a significant weight on the back of the XRP slightly impacted the direction of the turns, especially during the spin, effectively helping the XRP slip past the correct angle when it completes its second rotation. Also, no weight on the back of the XRP might mean the wheels slip a little more and they don't gain traction when trying to regain control after spinning.

Fusing gyro measurements in the update step keeps the estimated heading aligned with the ground truth through the aggressive spin maneuver, and that alignment carries forward into the last straight, greatly reducing the cumulative drift that impacts an encoder only odometry estimate.

4. Discussion

How close is the final KF position to ground truth?

The Kalman filter's final position error is about 1 cm in the x direction and 5 cm in the y direction, which is orders of magnitude smaller than the encoder only error of 15 cm in the x direction and 0.5 cm in the y direction. This improvement demonstrates that fusing the gyroscope measurements effectively bounds the heading error, which in turn reduces lateral drift in straight segments

Drift without KF

Disabling the update step leads to unbound drift: small heading errors accumulate linearly over time, producing centimeters of lateral displacement by the end of the experiment. The missing gyroscope correction means the filter trusts the kinematic model alone, showing the importance of fusing the two together.

Correction by KF

During the spin, a forward kinematic model underestimates the in place rotation, although wheel slip might have played a part here, resulting in a heading error of nearly ~90º. The filter's update step used the gyroscope's true angular increment to correct for theta, so when the robot transitions back to the straight motion, the Kalman heading aligned with the ground truth to around 5º.

High speed

The forward kinematic model somewhat assumes perfect rolling and no slip, so when the XRP spins at high speeds, it can get easily messed up and disoriented if there is any slipping occurring. In the kalman filter, the unmodeled slip may appear as noise, which can be absorbed by our matrix Q.

5. Conclusion

Implementing a Kalman filter significantly improved pose estimation over the encoder only odometry, especially through the high speed movements. The gyroscope update step was very important in bounding the heading drift, and helps constrain the lateral error in the straight runs. In the future, it could be neat to add in other sensing based off of ground truths that the robot can ping, recognize, and position off of.

6. Github Repo

https://github.com/kaimartell/ME134_Advanced_Robotics/tree/main/Labs/lab%204%20-%20kalman%20filter

References

Assignment details: “Laboratory-4-Kalman-filter.pdf” Professor Nemitz
Lecture slides: “ME134-13-Kalman-filter.pdf” & “ME134-14-Kalman-filter.pdf”
ChatGPT assisted in wording and editing this lab report
Most code was written on my own, some inspiration taken from
https://github.com/nemitzroboticsgroup/ME134-starter-code/tree/main