ME 134 Lab 4
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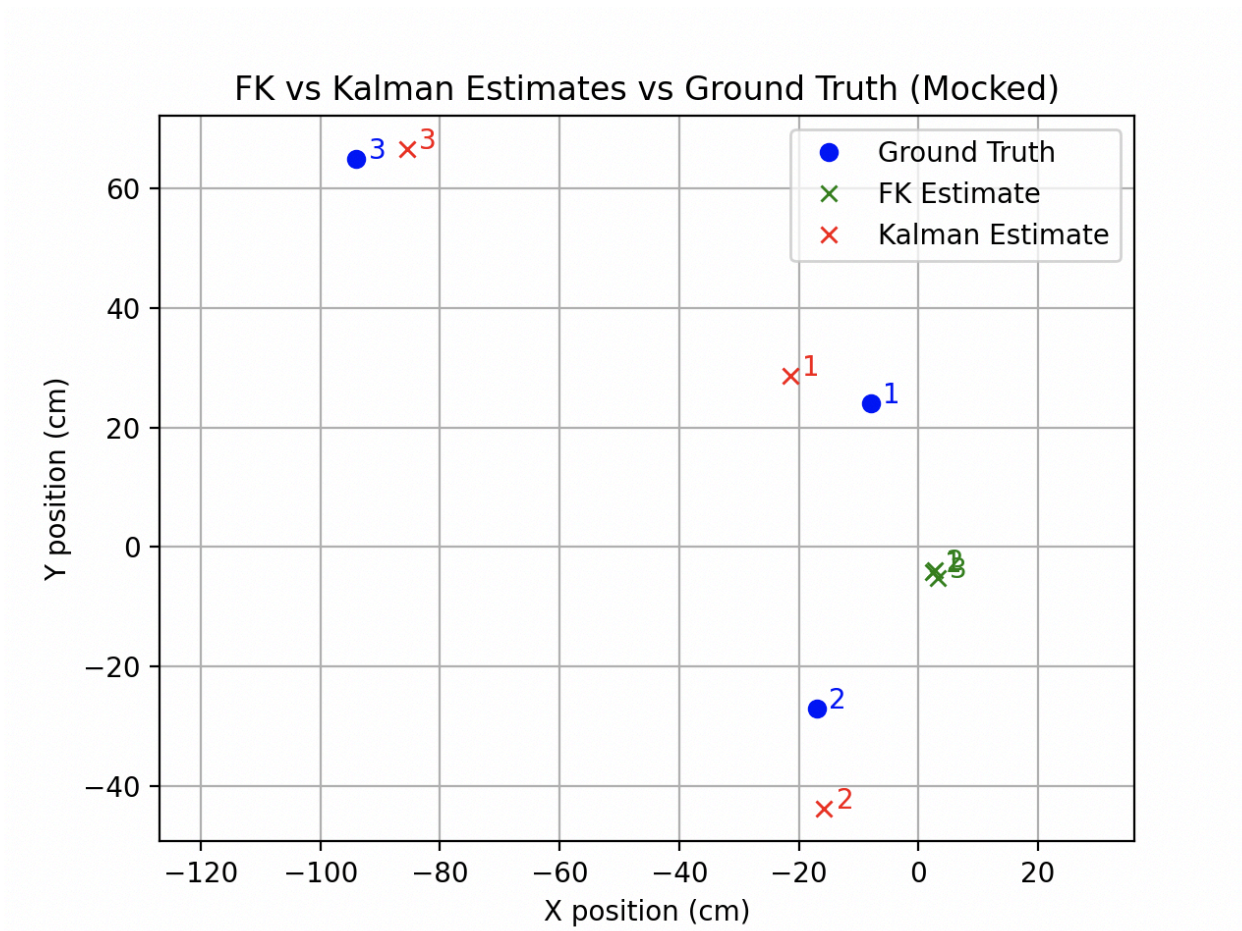
SP25

LAB 4

GitHub: https://github.com/djohnsen21/ME134-lab-4
Video: https://tufts.box.com/s/lg1qfacn0ztxxaob94yxnk29jy1kfhr9

Image:



In terms of accuracy, the final position from the Kalman filter was generally a bit closer to the ground truth than forward kinematics. The difference became most noticeable when the robot had to turn more sharply. In those cases, FK alone tended to over- or under-shoot the heading, which then affected the final x/y position due to compounding error in the direction of motion. The Kalman filter, by correcting the angle with the gyroscope, helped reduce this drift slightly.

If we had disabled the Kalman update step, we would have only had forward kinematics driven by encoder data. In this case, small errors in wheel speed measurements and any slip would go uncorrected, and that error would just keep accumulating over time. In particular, we would see drift in theta, which then throws off the x/y estimate as the robot moves. Since the gyro doesn't drift in the same way as the encoders do, fusing the gyro into the model is helpful because the Kalman filter provides a smart way to balance the two.

One clear moment where the Kalman filter made a difference was after sharp turns. In Trial 2, the robot made a tight right turn followed by a diagonal drive. The FK-only estimate had the robot ending way off to the side, while the Kalman version ended much closer to where the robot actually was. It seems like the gyro was especially helpful here in correcting the heading during and after the turn, which prevented the directional drift from getting too bad.

We have to make some assumptions for this model to work. The prediction step assumes perfect wheel contact and no slip, but when the robot spins quickly or changes direction fast, those assumptions break down. The inner wheel often skids a little or loses traction, which throws off the encoder readings and the kinematic model. The Kalman filter can't fully fix this if the gyro also gets noisy during fast spins, but it at least helps lessen the worse effects.

In conclusion, the Kalman filter generally brought the robot's theta estimate back in line with reality more effectively than forward kinematics. The reason for this is that FK often estimates the robot pointing in the wrong direction, which leads to big errors when the robot drives straight again. Kalman-corrected theta estimates were much more stable, especially right after spin-heavy segments. In the final plot comparing all three trials, the Kalman-filtered end positions were consistently closer to the actual measured positions than FK. The Kalman Filter outperformed FK consistently enough to show that sensor fusion improves position estimation, especially in cases with sharp rotational motion or uneven surfaces where encoders are not the most trustworthy.