## Homework #4 Report

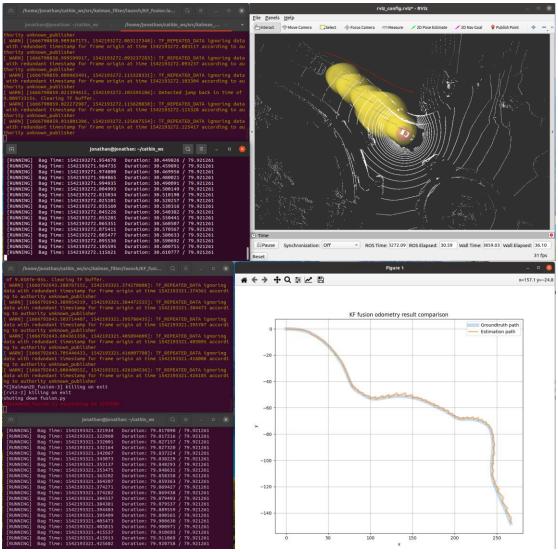
[EECN30168] Self-Driving Cars 2022

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## 1. Introduction

In this homework, our goal is to apply the Kalman filter we implemented in the previous homework on a real set of self-driving car data. Furthermore, we need to visualize the result through "rviz", and make further adjustments to our program through the observations to the output result, as shown in the following session.

## 2. Result



## 3. Discussions

For the implementation of the Kalman filter, I followed the algorithm in the following figure.

```
1: Algorithm Kalman_filter(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t):
2: \bar{\mu}_t = A_t \ \mu_{t-1} + B_t \ u_t
3: \bar{\Sigma}_t = A_t \ \Sigma_{t-1} \ A_t^T + R_t
4: K_t = \bar{\Sigma}_t \ C_t^T (C_t \ \bar{\Sigma}_t \ C_t^T + Q_t)^{-1}
5: \mu_t = \bar{\mu}_t + K_t (z_t - C_t \ \bar{\mu}_t)
6: \Sigma_t = (I - K_t \ C_t) \ \bar{\Sigma}_t
7: return \mu_t, \Sigma_t
```

For the prediction function, I first calculated the predicted state estimate x. I obtain the expected state estimate x by adding the dot product of the transition matrix A and the state estimate x, and the dot product of the transition matrix B and the control vector u. Then I calculate the error matrix P by adding up the covariance of the state transition error Q with the dot product of the transition matrix A, the error matrix P, and the transform of the transition matrix A.

For the update function, I first calculate the innovation covariance S, which can be found in the parentheses in the equation of the optimal Kalman gain K in the algorithm above. For the innovation covariance S, I added up the measurement error R with the dot product of the observation matrix H, the error matrix P, and the transform of the observation matrix H. Then I obtained the optimal Kalman gain K by calculating the dot product of the error matrix P, the transform of the observation matrix H, and the inverse of the innovation covariance S matrix.

Then I'll calculate the measurement post-fit residual y, which is the subtraction of the dot product of the observation matrix H and the state estimate x to the matrix z. With the measurement post-fit residual y, we can get the final state estimate x by adding the state estimate x itself with the dot product of the optimal Kalman gain K and the measurement post-fit residual y.

Lastly, for the error matrix P, we first initialize a 3x3 matrix I

with np.eye(), which with ones on the diagonal and zeros elsewhere. Then we calculate the error matrix P by calculating the dot product of the subtraction of the dot product of the optimal Kalman gain K and the observation matrix H from the 3x3 matrix we just created and the error matrix P itself. Finally, we get the final error matrix P, and the following figure is the plotting result of the Kalman filter I implemented.

Besides, the matrix "A" is the identity matrix, and then matrix "B" will calculate the middle angle according to the position of the last msg received from the GPS, the current position of the radar odometry and the position of the msg of the GPS this time. This corrects the direction error accumulated by the radar odometry.

The matrix "u" in the Kalman filter can be obtained by subtracting the previous point from the current odometry point. However, since the radar odometry is very inaccurate, we will need the rotation matrix mentioned above to correct it.

For the covariance matrices of GPS & radar odometry are R and Q matrix, which are set as below. When the value of Q is larger, it means that the prediction based on the current state is more inaccurate. When R is larger, it means that the observation is more inaccurate. That is to say, the ratio of Q to R will determine the offset of the result to the observation point.