Problem Set 8

AA279D: Dyn, Nav, Ctrl of DSS
Spring Quarter 2022/2023
Due: May 31, 2023, Wed, 11:59AM PT
Prof. Simone D'Amico

Submission Instructions

Please briefly document all tasks outlined below in a report which will grow during the course. You should include a table with change logs since the last submission, and an index for sections at the beginning. Please submit your report as a single PDF file to the course Canvas website. It should include narrative, plots, tables, code, and interpretations. You should use typesetting software like LaTeX or Microsoft Word to produce your document. Do not submit extra files.

Topics

Week 8. Continuation of project. Implementation of filter(s).

Problem 1: Navigation filter

You have set up the foundation of your extended and unscented Kalman filters in the previous problem set. It is now time to implement them as an estimator in MATLAB/Simulink or your preferred programming language. Be sure to perform the following steps:

- Generate ground truth signals using a clearly-described propagator for your distributed space system
- Convert the ground truth into measurements and corrupt them by adding representative noise
    - Note that you can generate noise as a zero-mean Gaussian random vector with pre-selected standard deviation in MATLAB as *sqrtm(sigma)*randn(n, 1)*, where sigma is a covariance matrix, and n is your desired vector size.
    - Be sure to use reasonable standard deviations for your measurements, consistent with your mission and sensors and choice of units.
- Set an initial estimate and covariance, x_0 and P_0. The estimate should be close to, but not exactly equal to the true initial state. The covariance can be set to a diagonal matrix (especially with uncorrelated state parameters), with elements equal to the variance of your initial state parameters.
- Define the process and measurement noise covariances, $\boldsymbol{Q}$ and $\boldsymbol{R}$, which represent the uncertainty in the dynamics and measurement models, respectively. You may wish to define $\boldsymbol{Q}$ similar to $\boldsymbol{P}_0$, but much smaller. Meanwhile $\boldsymbol{R}$ may be a diagonal matrix with elements equal to the variance of each measurement.
- Combine all of the previous parameters and mechanize your extended and/or unscented Kalman filter. Recall the steps involved in a single iteration of the filter:

    - Predict the evolution of the state and covariance with your dynamics model and state transition matrix to the time of the incoming measurement
    - Generate the pre-fit residuals by comparing the expected measurement against the true measurement
    - Update the state and covariance prediction using the filter measurement update step
    - Generate the post-fit residuals by comparing the updated expected measurement against the true measurement.
- Illustrate the functionality and performance of the filter by plotting the following parameters: true and estimated states, estimation error (difference between true and estimated states), superimpose estimated covariance bounds (estimated state error), indicate true statistics (mean and std of true state error at steady-state, e.g. last orbit), plot pre-fit and post-fit residuals and compare them with injected noise.

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