EE 690
"Self Localization and Mapping (SLAM) for Robotics"

Spring 2015

Project # 1
Introduction to Linear Kalman Filter and Extended Kalman Filter

(due Tuesday February 10th, 2015 via e-mail)

For all parts provide the Matlab code and a write-up with plots and a discussion on the results.

Part 1:

Given a Matlab data file '**data01.mat**' that contains the vectors with the true x, y coordinates (rx and ry) and x and y velocities (vx and vy) of a vehicle, and a Matlab file '**project01a_name.m**' that contains the template for your program with the initial generation of the measurements:

$$\mathbf{z}_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix} + \mathbf{v}_t$$

where $\mathbf{v}_t$ has an associated covariance matrix equal to **R.**

Using the constant velocity model provided in the lecture notes, implement a Linear Kalman Filter (KF) and provide outputs of the filter for various values of the process noise ($\sigma_w^2 = 1, 10, 100$) and the measurement covariance matrix. Provide the output plots in a report and include discussions/explanations on the observed behavior of the filter.

Part 2:

In this part we going to use **velocity measurements** and extend the state vector to include acceleration as well, or:

$$x = \begin{bmatrix} x_t \\ \dot{x}_t \\ \ddot{x}_t \\ y_t \\ \dot{y}_t \\ \ddot{y}_t \end{bmatrix}$$

See '**project01b_name.m**' for the Matlab template. Extend the dynamics model (state propagation equations) for this model. Without proof, the process noise covariance matrix is now given by:

$$
\mathbf{Q} = \sigma_w^2 \begin{bmatrix} \frac{\Delta t^5}{20} & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{6} & 0 & 0 & 0 \\ \frac{\Delta t^4}{8} & \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} & 0 & 0 & 0 \\ \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{\Delta t^5}{20} & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{6} \\ 0 & 0 & 0 & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} \\ 0 & 0 & 0 & \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t \end{bmatrix}
$$

Implement a Linear Kalman Filter (KF) and provide outputs of the filter for various values of the process noise ($\sigma_w = 1, 10, 100$) and the measurement covariance matrix. Provide the output plots in a report and include discussions/explanations on the observed behavior of the filter.

Part 3:

In the final part of this project we are going to design, implement and evaluate an Extended Kalman Filter (EKF) using a constant velocity dynamics model (like in Part 1). The measurements are two range measurements to two different beacons at locations (x_1, y_1) = (-50000, 50000) and (x_2, y_2) = (50000,50000). The measurement equation is given by:

$$
\mathbf{z}_t = \mathbf{h}(\mathbf{x}_t) = \begin{bmatrix} \sqrt{(x_t - x_1)^2 + (y_t - y_1)^2} \\ \sqrt{(x_t - x_2)^2 + (y_t - y_2)^2} \end{bmatrix}
$$

Implement the EKF and provide outputs of the filter for various values of the process noise ($\sigma_w = 1, 10, 100$). Provide the output plots in a report and include discussions/explanations on the observed behavior of the filter.

Note that initial values for the state estimate covariance matrix, **P**, diagonal elements must be chosen large so it converges quicker (e.g. in the 1000-10000 range).