PROJECT #2 *(Part A)*

Part A – Sensor Data Fusion / EKF Localization

Introduction
Relevant part of Project 2 is focused on implementing Sensor Data Fusion, in a Bayesian fashion, via applying the EKF approach.
For that purpose, we continue working in our case of study: "localizing a platform". We have seen, in Project 1, that there are diverse sources of information, e.g. provided by sensors' measurements and from a process model such as the kinematic model of the platform. Now, we want to combine those sources of information in a consistent way, in which qualities of those sources of information are considered, for generating estimates of the variables of interest, i.e. the state of our system, the vehicle's pose. Those estimates are required to be permanently provided (i.e. frequently and at any time when required). The estimation process will generate optimal estimates in the form of an expected value and a covariance matrix. The estimation process will operate in real-time, and it will require low processing cost; all those are characteristics which are relevant in industrial and critical applications.

Part A requires implementing an EKF based localizer based on kinematic model and LiDAR measurements.

For solving this part, you will modify your solution implemented for Project1 (or create a new one, from scratch if you prefer)

Your program will maintain estimates of the vehicle pose, i.e. an expected value and an associated covariance matrix.

You will perform the prediction step in the same way you used to run your kinematic model, in Project1. In that way you will always maintain expected value and covariance matrix, statistically describing the vehicle pose, at any time.

In addition, you will perform update steps each time at which observations are available, i.e. when you process a LiDAR measurement, in which you detect OOIs from which you are able to associate some of them with map landmarks. The update will exploit measurements of range (and of bearing if required). Those range and bearing measurements, are the same you already exploited in Project1.PartD.

The data association component will run in the same way you used it in in Project 1; however, in this case, the DA will be based on the prior expected value, before the actual update is applied.

The datasets to be used are not “friendly” such those datasets used in Project 1. These used in Project 2 do contain measurements which are polluted by noise, which is assumed to be WGN, and whose variances are known. LIDAR’s measurements are polluted with noise, in addition to the quantization error and limited angular resolution. Speed measurements and gyroscope measurements are also polluted by noise, in addition to the small quantization errors which were present in the datasets used in P1.

Part A1. Implement the EKF localizer, exploiting only the range observations. Verify that the estimation process is able to estimate all the vehicle states (pose), including the heading.
Comment: : this case is similar to that in which we do not have a LiDAR but we have a sonar, which is able to measure distances to OOI, but no angles.

Part A2. Modify your solution in Part A1, to implement a localizer which only process bearing observations (similar to a camera based one), i.e. not processing range observations.

Part A3. From the implementations in A1 and A2, implement a localizer able to process all available observations (range and bearing measurements, from multiple OOIs.)

Use datasets named Data19b.mat”, Data20b.mat”, Data21b.mat”.
Assume the following characteristics for the noise which polluted the sensors’ measurements

Speed measurements: standard deviation: 5cm/second;
Gyroscope measurements: standard deviation: 1 degree/second
OOIs range observations: standard deviation: 10cm
OOIs bearing observations: standard deviation: 2degrees

Questions about this project: ask the lecturer via Moodle or by email (j.guivant@unsw.edu.au)
The lecturer will show a possible solution working, during lecture time, on week 8.

Part A is worth 40% of project 2.