Report
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ME231b – Experiential Advanced Control Design

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1. Characterization of uncertainties

First, we characterized the measurement noise thanks to the experimental run 0. In fact, this run file contains measurements for a stationary bicycle. We extracted the existing measurement values from the file and we plotted the one figure (**Figure 1**) that corresponds to the box plot for the two measurements along x and y. We also plotted the histogram of the two measurements (**Figure 2**).

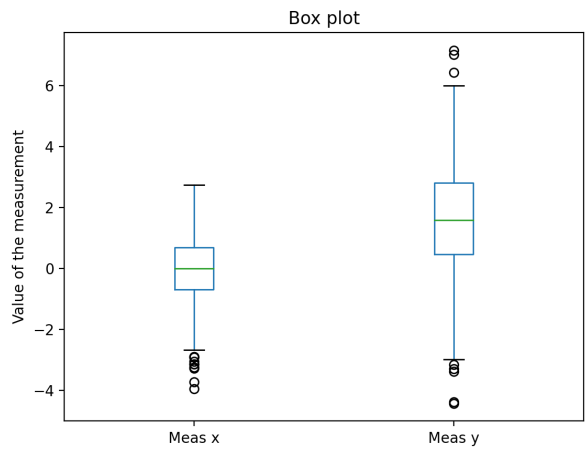

Figure 1 - *Box plot of the measurements x and y*

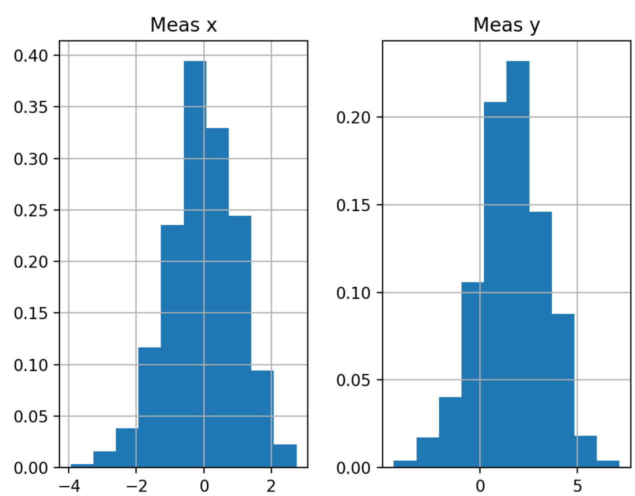

Figure 2 - Histogram *of the measurements x and y*

We can see on figure 1 that the two measurements are symmetric and the distribution seems to be Gaussian according to figure 2.

We also computed the mean and variance of each measurement:

We obtained a mean of -0.019 and variance of 1.09 for the measurement x. For the measurement y, we have a mean of 1.63 and a variance of 2.99 that allow us to characterize the uncertainty due to electrical noise in the sensor, timing imprecision and atmospheric disturbances that warp the path of the GPS signals.

2. UKF estimator

We implemented the UKF filter with our defined state such as:

$$X = [x,\ y,\ \theta]^T$$

We had therefore 6-sigma points and we used Euler discretization to obtain the dynamic of the system:

$$X(k+1) = X(k) + q_k(X(k),\ u(k))$$

With:

$$q_k(X(k),\ u(k)) = [v(k)\cos(\theta(k))\Delta t,\ \ v(k)\sin(\theta(k))\Delta t,\ \ \frac{v(k)}{B} v(k)\tan(\gamma)\Delta t]^T$$

$$u(k) = [\omega(k),\ \gamma(k)]$$

where ω is the pedal speed, γ is the steering angle, and $v(k) = 5r\omega$because the bicycle is geared such that the angular velocity of the rear wheel is 5 times the pedaling speed. We assumed there was no process noise for the system. Instead, we assumed r and B are uniformly distributed in the given range [0.425-5%, 0.425+5%] and [0.8-10%, 0.8+10%], respectively. The values for r and B are defined in our *estInitialize* code so that it does not vary along the run. The estimator was initialized with x(0) = 0, y(0) = 0, $\theta(0) = \pi/4$, and Pm(0) = diag(1,1,1).

We defined the function $h_k(x_p(k))$as the given position measurements $p(k)$ and the variance of the noise as diag(1.09, 2.99), which was characterized in the previous section.

With the two previous functions, and our 6-sigma points we can implement our UKF.

3. Results

The following results were generated using data from run #1. For a better comparison, we also implemented the particle filter to get a sense of how well the UKF would perform.
With the UKF, we obtained the following results (**Figure 3**):

```
Loading the data file # 1
Running the initialization
Running the system
Done running
Final error:
   pos x = -0.18794989859201117 m
   pos y = -0.12234205797032871 m
   angle = 0.14227965358869188 rad
```

Figure 3 - Estimations for the run 1 with the UKF

With the PF, we obtain the following results (**Figure 4**):

```
Final error:
   pos x = -0.69655 m
   pos y = -0.27279 m
   angle = -0.39019 rad
Generating plots
Done
Elapsed time is 2.132069 seconds.
```

Figure 4 - Estimations for the run 1 with the PF

With the PF, however, due to its random nature, results can be unpredictable and vary largely. Every run outputs results that vary not insignificantly compared to the previous run. We tried fixing this issue by adding more particles and repeatedly running the estimator multiple times and taking the average in the end, but by doing this, computation time would largely increase. On the other hand, UKF outputs steady results, and its computation time is much less than that of PF. On average, UKF also produces smaller errors than PF (**Figure 3 & 4**). We conducted multiple runs with both UKF and PF, and our findings still stand. Therefore, we decided to use UKF as our best estimator.