Robot Mapping

Assignment: Sheet 6 ,Unscented Kalman Filter SLAM

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1 Exercise 1: The prediction Step

In this section, the motion model is used to update the robot's pose only leaving the landmarks untouched. In this step only the robot covarience matrix and the correlation matrix between the robot pose and lanmdmarks pose are updated.

This is happened by :

- Generate the sigmapoints from the previous estimate μ_{t-1}, Σ_{t-1}
- Pass these points into the motion model, and update the robot's pose $\bar{\mu}_t$ as well as the Σ_{xx}, Σ_{xm} of the covaruience matrix $\bar{\Sigma}_t$ through the update of the second moment

$$\mathcal{X}(1:3,:)_{t+1} = g(\mathcal{X}(1:3,:)_t, u_{t+1}) \tag{1}$$

- So we apply nonlinear transformation for each sigma point in order to map it to the new domain , thus we can find the parameters (moments) of the mapped pdf.
- Compute the first and the second moment of the mapped points

At the end of this step we have $\bar{\mu}_t$ and $\bar{\Sigma}_t$, which will be used in the sensor model linearization.

2 Exercise 2: The correction step

In this step, the output of the prediction step is used to linearize the observation model $h(.)$. This can be done by :

- Generate sigmapoints from the predicted moments $\bar{\mu}_t$ and $\bar{\Sigma}_t$
- if a landmark is observed, pass its associated sigmapoints into the observation model as following (using convention):
  - SigmaPoints(j^{th} landmarks detected by i^{th} measurment)

    $\mathcal{X}(2j+2:2j+3,:)= [\bar{\mu}_t(2j+2, 2j+3), \bar{\mu}_t(2j+2, 2j+3) \pm L(2j+2:2j+3,:)]$

  - Pass these points to the observation model $h(.)$, and then compute the moments of the output of this mapping, which is z_{points} : $\bar{\mu}_{j,x}, \bar{\mu}_{j,y}$.
  - z_{points} are the results of passing $\mathcal{X}(2j+2:2j+3,:)$ vector into $h(.)$, which would result in :

$$\delta = \begin{pmatrix} \delta_x \\ \delta_y \end{pmatrix} = \begin{pmatrix} \mathcal{X}(2j+2:2j+3,:)_x - \mathcal{X}(1,:)_{t,x} \\ \mathcal{X}(2j+2:2j+3,:)_y - \mathcal{X}(2,:)_{t,y} \end{pmatrix} \tag{2}$$

$$z_{points} = \begin{pmatrix} \sqrt{sum(\delta^T .* \delta, 1)} \\ atan2(\delta_y, \delta_y) - \mathcal{X}(3,:)_{t,\theta} \end{pmatrix} = \begin{pmatrix} z_{range} \\ z_{bearing} \end{pmatrix} \tag{3}$$

    where : $\mathcal{X}(k,:)_t \in \mathcal{R}^{2N+1}$, $\delta \in \mathcal{R}^{2x2N+1}$, and $z_{points} \in \mathcal{R}^{2x2N+1}$

  - The z_{points} are the resulted sigmapoints after passing them into the observation function, where from which we compute the expected observation by computing the first moment of each row of the z_{points} vector as follows:

$$z_{expected} = \begin{pmatrix} \sum_i w_m^i z_{rangei} \\ \sum_i w_m^i z_{bearingi} \end{pmatrix} = \begin{pmatrix} \bar{z}_{range} \\ \bar{z}_{bearing} \end{pmatrix} = \bar{z} \tag{4}$$

  - $\bar{z}$ is the expected measurement of the sensor, which is analogous to $h(\bar{\mu}_t)$ is case of EKF.
  - Then, this expected value of measurement is used to compute the innovation matrix S.
- Finally, the Kalman gain is calculated and the final estimate of the first two moments are update, ie. μ_t, Σ_t