Localization using poles & signs detected by a lidar

UTC - ARS4 - Estimation for robotic navigation

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I. System modeling

A. State vector

In order to represent the pose of the vehicule in the 2D space, we can use the following state vector $\mathbf{x}_t$:

$$X = \begin{bmatrix} x \\ y \\ \theta \\ v \\ \omega \end{bmatrix}$$

with :

- x, y : Coordinates of the vehicule (ENU working frame).
- θ : Heading of the vehicule (ENU working frame).
- v : Longitudinal speed.
- ω : Angular speed.

B. Dynamic space state model

The evolution of the system can be define as follows :

$$X_{t+1} = f(X_t, u_t) + q_t$$

with :

- $\mathbf{u}_t = [v_t, \omega_t]^T$: speed inputs.
- $\mathbf{q}_t \sim \mathcal{N}(0, Q)$: model noise.

Thanks to the Euler method, that uses the derivatives definition to define the value of the next iteration of the discrete space state, we have :

$$X_{k+1} = X(t) + \Delta.\dot{X}(t),$$

Using basic definitions of geometry and automatic control, we can define the nonlinear function f such that (assuming constant speeds between 2 samples) :

$$\begin{aligned} x_{t+1} &= x_t + v_t \Delta t \cos(\theta_t), \\ y_{t+1} &= y_t + v_t \Delta t \sin(\theta_t), \\ \theta_{t+1} &= \theta_t + \omega_t \Delta t, \\ v_{t+1} &= v_t, \\ \omega_{t+1} &= \omega_t. \end{aligned}$$

Consequently, we have

$$f(X_t, u_t) = \begin{bmatrix} x_t + v_t \Delta t \cos(\theta_t), \\ y_t + v_t \Delta t \sin(\theta_t), \\ \theta_t + \omega_t \Delta t, \\ v_t, \\ \omega_t. \end{bmatrix}.$$

II. Observation Model

We can define observation as the reception of GNSS and Lidar information. In the model, we describe it as :

- GNSS $(x_{GNSS}, y_{GNSS}, \theta_{GNSS})$

  $$\begin{aligned} x_{\text{GNSS}} &= x \\ y_{\text{GNSS}} &= y \\ \theta_{\text{GNSS}} &= \theta \end{aligned}$$

  with $\sigma_x^2 = \sigma_y^2 = 0.2$ and $\sigma_\theta^2 = 0.01$

- Lidar $(x_{lidar}, y_{lidar}, x_{map}, y_{map})$

  To process LiDAR observation, we make a change of variables in polar coordinates to compute the estimated observation:

  $$\hat{\rho}^i = \sqrt{(x^i_{map} - x_t)^2 + (y^i_{map} - y_t)^2}$$

  $$\hat{\lambda}^i = \arctan 2(y^i_{map} - y_t, x^i_{map} - x_t) - \theta_t$$

  And so we can compare it with the real observation in polar coordinates

  $$\rho^i = \sqrt{(x_{lidar})^2 + (y_{lidar})^2}$$

  $$\lambda^i = \arctan 2(y_{lidar}, x_{lidar})$$

The global observation model equation can be finally written as follows (defining M as the map informations):

$$\mathbf{z}_t = g(X_t, M),$$

with

$$\mathbf{z}_t = \begin{bmatrix} x_{\text{GNSS}} \\ y_{\text{GNSS}} \\ \theta_{\text{GNSS}} \\ \rho^i \\ \lambda^i \end{bmatrix}, \quad g(X_t, M) = \begin{bmatrix} g_{\text{GNSS}} \\ g_{\text{LiDAR}} \end{bmatrix} = \begin{bmatrix} x_t \\ y_t \\ \theta_t \\ \hat{\rho}^i \\ \hat{\lambda}^i \end{bmatrix}.$$

As Lidar obervations are received at a higher frequency than GNSS observations (10Hz vs. 1Hz), they will enable us to update our state estimation more frequently.

III. Simulation Implementation

The initial state for the simulation refered to the first position of the GNSS sensor. We have

$$x_0 = \begin{bmatrix} \text{gnss(1).x} \\ \text{gnss(1).y} \\ \text{gnss(1).heading} \\ \text{v(1)} \\ \text{omega(1)} \end{bmatrix}$$

Initial covariance matrix P is set to

$$P = \begin{bmatrix} 0.5 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0.1 \end{bmatrix}$$

Initial process noise matrix Q is set to

$$Q = \begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0.001 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0.001 \end{bmatrix}$$

For the simulation, we decided to separate the two observation models and implement 2 separate Kalman filters. In this way, we can correct the state with two types of independent observations.

A. Extended Kalman Filter

To apply EKF, we need to compute the jacobians of the observation and evolution models. We have :

$$\begin{aligned} F &= \frac{\partial f}{\partial X} \\ &= \begin{bmatrix} 1 & 0 & -v\Delta t\sin(\theta) & \Delta t\cos(\theta) & 0 \\ 0 & 1 & v\Delta t\cos(\theta) & \Delta t\sin(\theta) & 0 \\ 0 & 0 & 1 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \end{aligned}$$

$$C_{\text{GNSS}} = \frac{\partial g_{\text{GNSS}}}{\partial X} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

$$C_{\text{LiDAR}} = \begin{bmatrix} -\frac{\Delta X}{r} & -\frac{\Delta Y}{r} & 0 & 0 & 0 \\ \frac{\Delta Y}{r^2} & -\frac{\Delta X}{r^2} & -1 & 0 & 0 \end{bmatrix}$$

With

$$\begin{aligned} \Delta_X &= x_{map} - x_t \\ \Delta_Y &= y_{map} - y_t \\ r &= \sqrt{\Delta_X^2 + \Delta_Y^2} \end{aligned}$$

The results using just GNSS data are better than with the use of LiDAR measurements (Figure n°1 & 2)

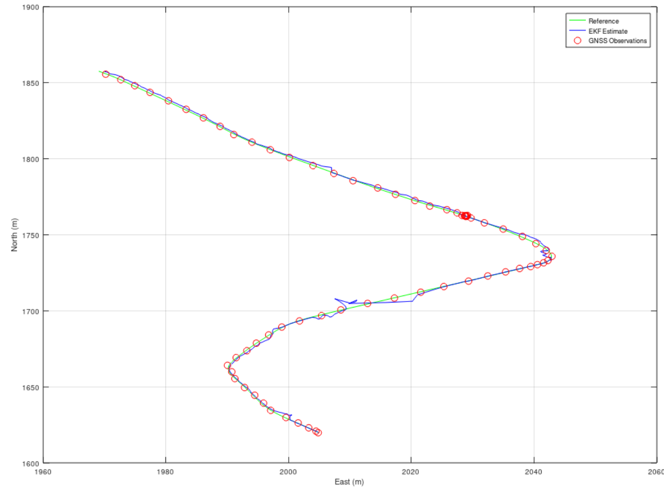

Fig. 1. EKF Localization with GNSS and Lidar Observations

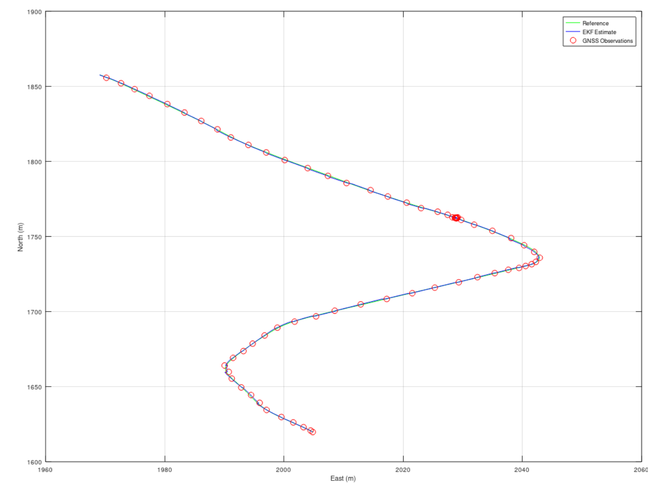

Fig. 2. EKF Localization with GNSS Observations

B. Unscented Kalman Filter

IV. Real Implementation

A. Multi sensor data fusion

B. Extended Kalman Filter

C. Unscented Kalman Filter

V. Conclusion