Artificial Intelligence in Control Engineering exercise

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1 Problem

2 Configuration

3 Implementation

3.1 Particle Filter

To solve the Paticle Filter problem, we implement follow below steps:

- Prediction

  Process model:

$$x_t = x_{t-1} + V_t \Delta t \cos(\theta_t + \varphi_{t-1}) \tag{1a}$$

$$y_t = y_{t-1} + V_t \Delta t \cos(\theta_t + \varphi_{t-1}) \tag{1b}$$

$$\varphi_t = \varphi_{t-1} + \frac{V_t \Delta t \sin\theta_t}{WB} \tag{1c}$$

  Measurement model:

$$r_t = \sqrt{(x_t - x_L)^2 + (y_t - y_L)^2} \tag{2a}$$

$$b_t = \arctan\frac{y_t - y_L}{x_t - x_L} + \varphi_t \tag{2b}$$

  - Measurement model
  - Implementing a loop with M step which is numbers of particles
  - Using process model and control signals u_t in **VG** which are affected by thermal noise to calculate coordinate $x_t^{[m]}$ of robot.
  - Combining coordinate of robot from above step and coordinate of landmarks in **lm** to calculate range r_t and bearing angle b_t.
  - Calculating importance factor $w_t^{[m]}$ depend on probability density function fomula with μ is matrix of expected range and bearing which are from **Z**.

$$f_x(x_1, x_2, ..., x_N) = \frac{1}{(2\pi)^{\frac{N}{2}} \|\Sigma\|^{\frac{1}{2}}} exp\left(\frac{-1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)\right) \tag{3}$$

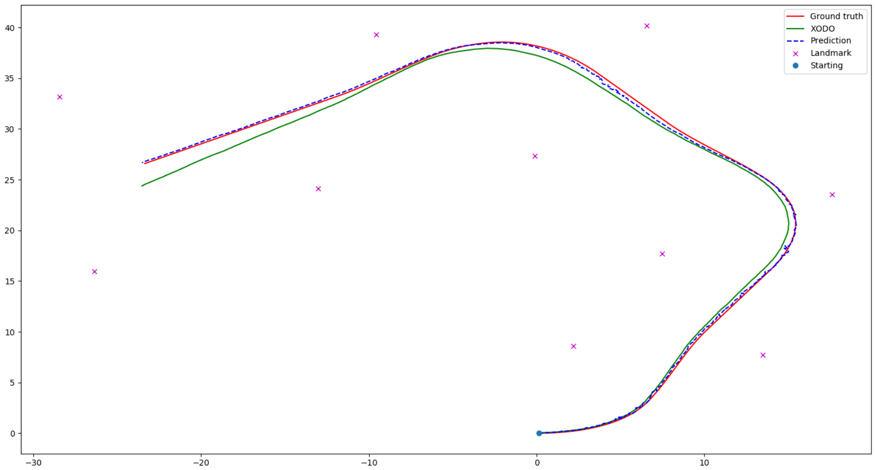
- Selection
  - Implementing a loop with M step.
  - Choosing a index in range $[1, M]$ for $x_t^{[m]}$ with probabilities $w_t^{[m]}$.

3.1.1 Python code

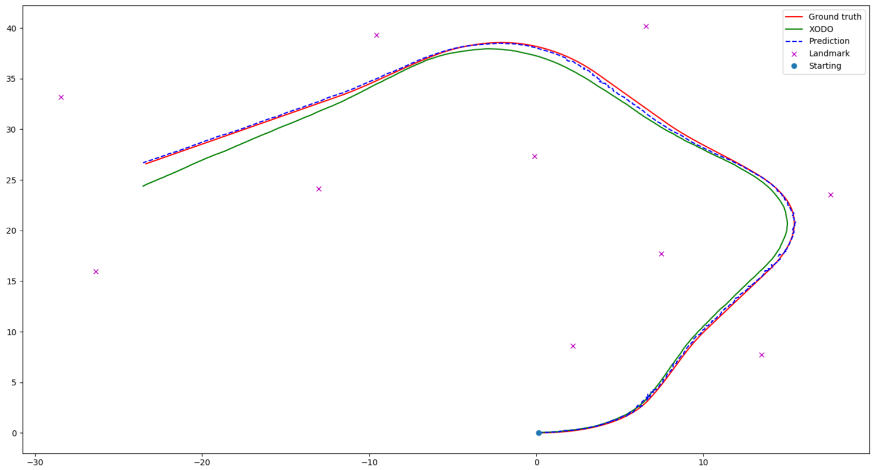
```python
#------------------------------------------------------------------------------
#   Libraries
#------------------------------------------------------------------------------
import numpy as np
from scipy.io import loadmat
from utils.particle_filter import ParticleFilter


#------------------------------------------------------------------------------
#   Parameters
#------------------------------------------------------------------------------
n_particles = 100
sigma_v, sigma_g = 0.5, 3/180*np.pi
sigma_r, sigma_b = 0.2, 2/180*np.pi
wb = 4
time_step = 0.025
particle = "max"


#------------------------------------------------------------------------------
#   Main execution
#------------------------------------------------------------------------------
# Load data
data = loadmat("data20171107.mat")
landmarks, X_gt, Z, U, X_ODO = data["lm"], data["XTRUE"], data["Z"], data["VG"], data["XODO"]
n_steps = X_gt.shape[1]


# Create a Particle Filter instance
particle_filt = ParticleFilter(
    n_particles=n_particles,
    n_steps=n_steps,
    landmarks=landmarks,
    sigma_v=sigma_v,
    sigma_g=sigma_g,
    sigma_r=sigma_r,
    sigma_b=sigma_b,
    wb=wb,
    time_step=time_step,
)


# Perform loops
x_start = X_gt[:, 0, np.newaxis]
X_record, W_record = particle_filt.loop_over_steps(x_start, U, Z)


# Visualize the result
mse = particle_filt.compute_MSE(X_gt, X_record, W_record, particle)
print("MSE: %.6f" % (mse))
particle_filt.visualize(X_gt, X_ODO, X_record, W_record, particle)
```

3.1.2 Result

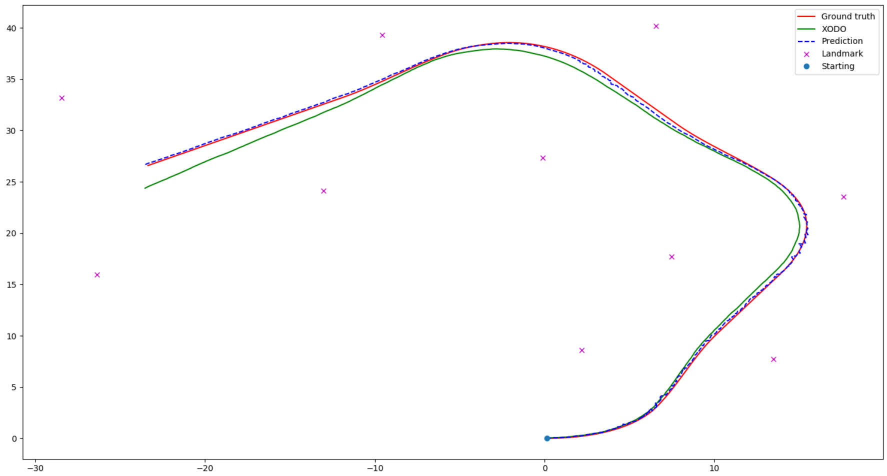
- Comment:
  - Overall, three trajectories of Prediction fits Ground truth with the same patterns. However, the best fit is belong to trajectoty with choosing max w_t, so the root mean square is smallest.
  - Line of XODO which is calculated from process model is different from Ground truth because of effect on range and bearing angle from thermal noise, while Prediction is calculated and chosen with importance factor w_t. That is the reason why line of Prediction is better than XODO.



(a) Trajectories with max w_t. $RMS = 11.289769$



(b) Trajectories with median w_t. $RMS = 11.428931$



(c) Trajectories with min w_t. $RMS = 11.475249$

Figure 1: Trajectories of Ground truth (XTRUE), XODO, Prediction and root mean square (RMS) of Prediction compared to Ground truth.