Assignment 3 PF

May 6, 2025

0.1 Particle filter

#Process model

$$\dot{\mathbf{x}} = \begin{bmatrix} \dot{\mathbf{p}} \\ G(\mathbf{q})^{-1}(\mathbf{u}_{\omega} - \mathbf{b}_g) \\ \mathbf{g} + R(\mathbf{q})(\mathbf{u}_a - \mathbf{b}_a) \\ \mathbf{n}_{bg} \\ \mathbf{n}_{ba} \end{bmatrix}$$

0.1.1 Particle Filter Algorithm

Predict Step

1. Particle Initialization

Particles are uniformly distributed within an approximate feasible volume of the environment map, representing the initial belief over position and orientation.

2. Sampling IMU Noise

Gyroscope and accelerometer readings are perturbed with zero-mean Gaussian noise to model sensor uncertainty. These noisy inputs are used to compute the state derivative using the process model.

3. State Propagation

Each particle's state is propagated forward in time by integrating the state derivative (e.g., velocity and orientation changes). This results in a new predicted set of particles representing the system's state after motion.

Update Step

1. Observation Model

An observation model is applied to each predicted particle to simulate the expected measurement from that state (e.g., expected sensor reading or landmark observation).

2. Measurement Likelihood

The actual sensor measurements are compared with the predicted observations to compute the likelihood (or error). An importance weight is assigned to each particle based on this likelihood.

3. Weight Normalization

The importance weights are normalized across all particles to form a valid probability distribution.

4. State Estimation

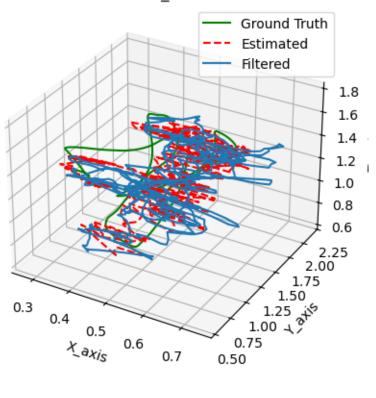
The current position and orientation estimates are obtained as a weighted average over the particle set.

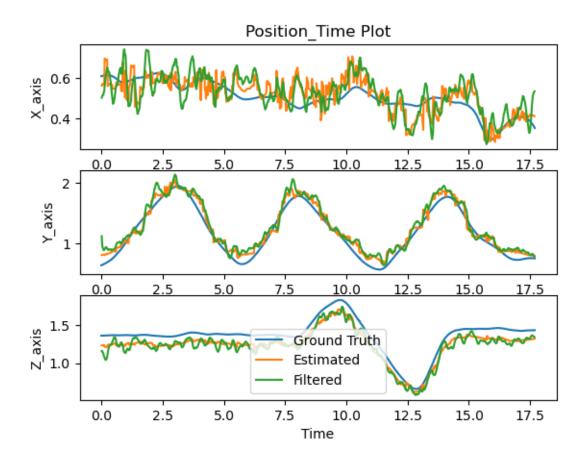
5. Resampling

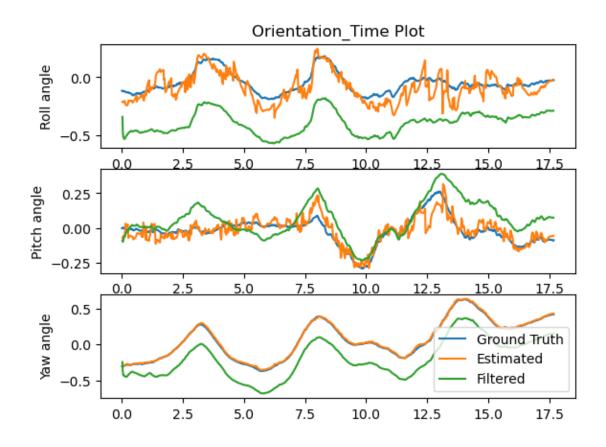
To avoid particle degeneracy, particles are resampled according to their normalized weights using **low-variance resampling**, focusing computational resources on high-likelihood regions of the state space.

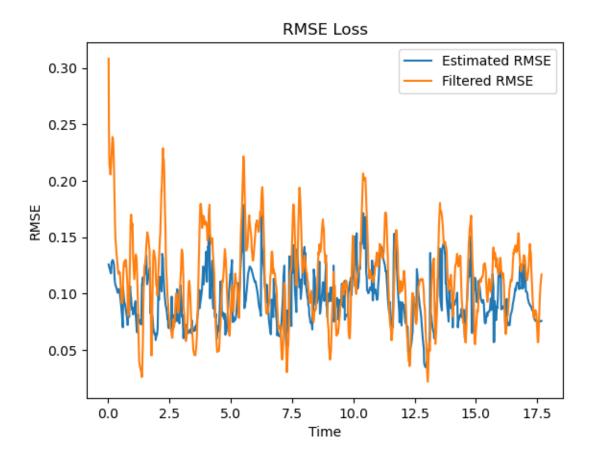
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[13]: #Compute Covariance
import compute_covariance as covariances
R = covariances.average_covariance()
```

0.1.2 Plots



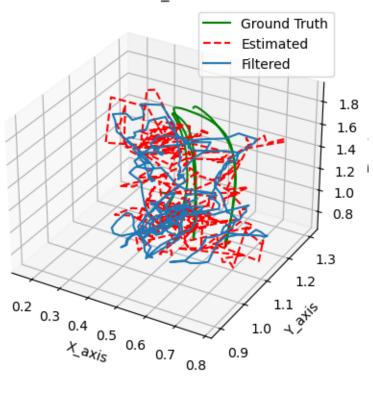


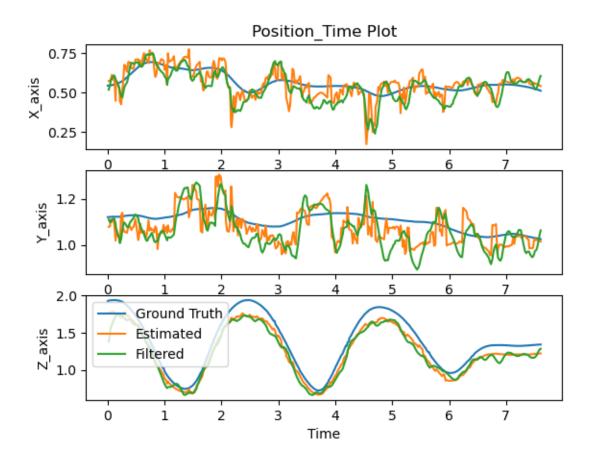


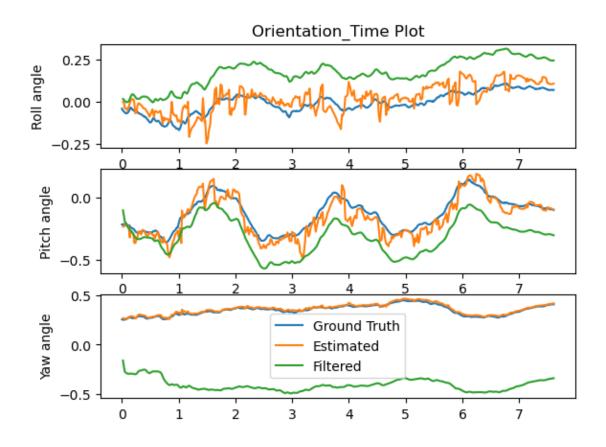


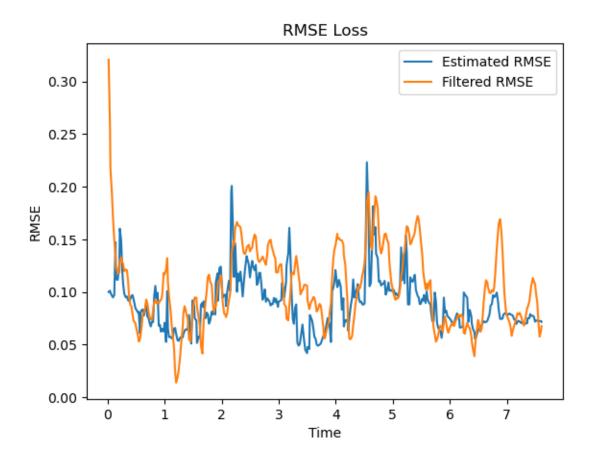
```
from simulation_PF import simulate import plots

estimated, est_t, ground_truth, ground_truth_t, filt_data, partcl_hist, exe_t = simulate(r"data\data\studentdata2.mat", 1000, "weighted_avg", R, Qa=100, squared of the simulate(r"data\data\studentdata2.mat", 1000, "weighted_avg", R, Qa=100, squared of the simulate(r"data\data\studentdata2.mat", 1000, "weighted_avg", R, Qa=100, squared of the simulated of the simu
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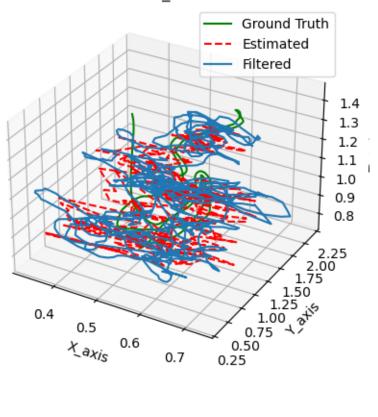


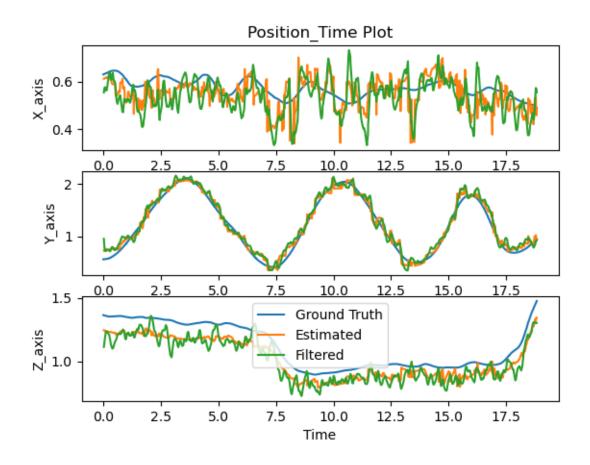


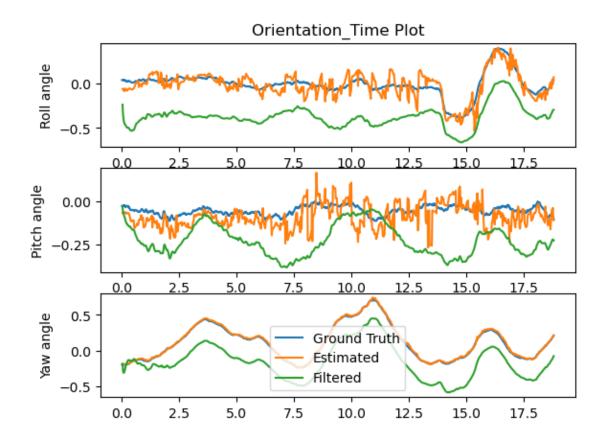
```
from simulation_PF import simulate import plots

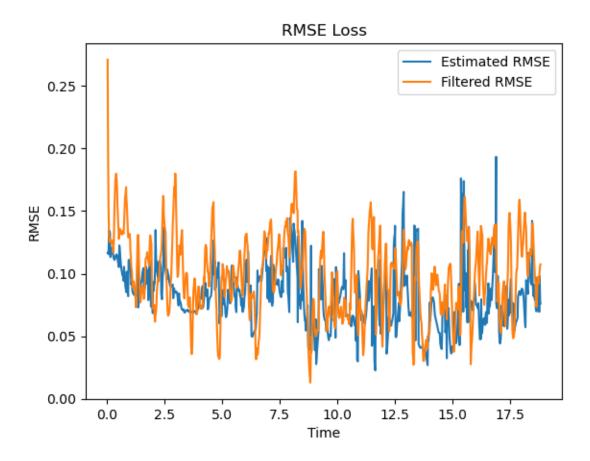
estimated, est_t, ground_truth, ground_truth_t, filt_data, partcl_hist, exe_t = simulate(r"data\data\studentdata3.mat", 1000, "weighted_avg", R, Qa=110, sq=0.1)

plots.plot(estimated, est_t, ground_truth, ground_truth_t, filt_data)
```





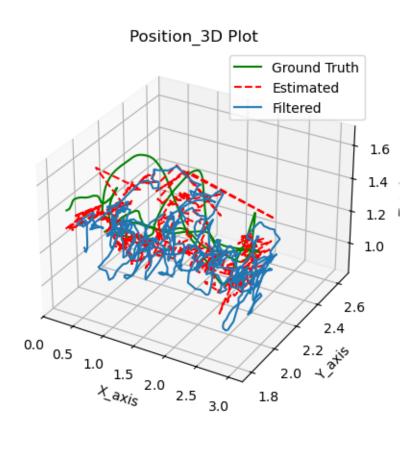


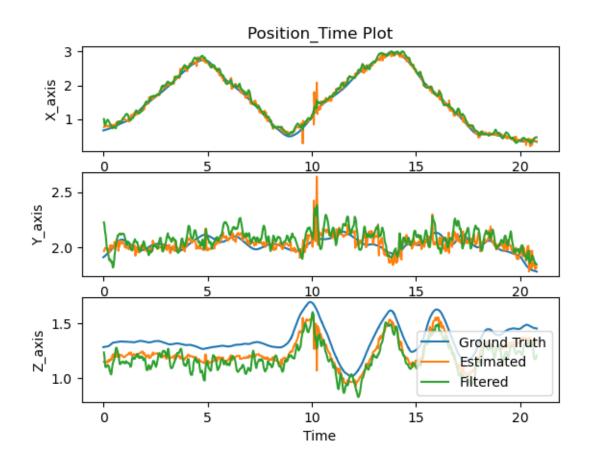


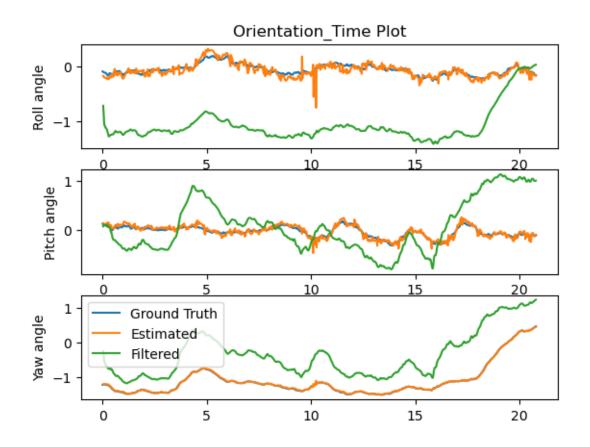
```
from simulation_PF import simulate import plots

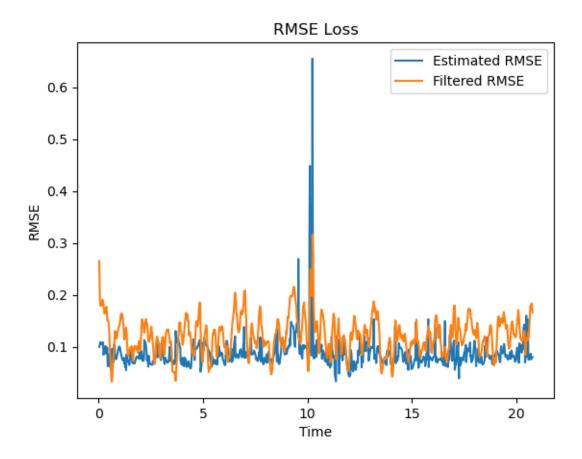
estimated, est_t, ground_truth, ground_truth_t, filt_data, partcl_hist, exe_t = simulate(r"data\data\studentdata4.mat", 1000, "weighted_avg", R, Qa=120, sqg=0.1)

plots.plot(estimated, est_t, ground_truth, ground_truth_t, filt_data)
```





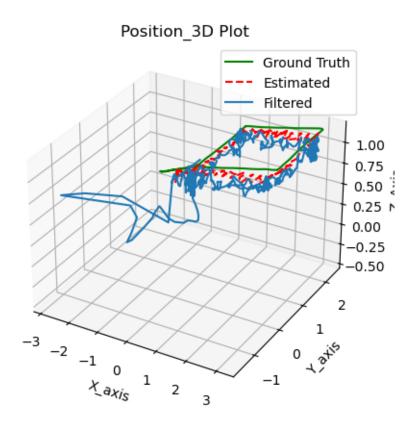


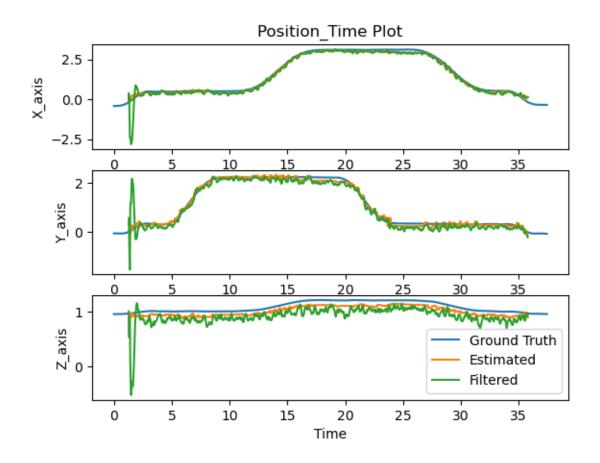


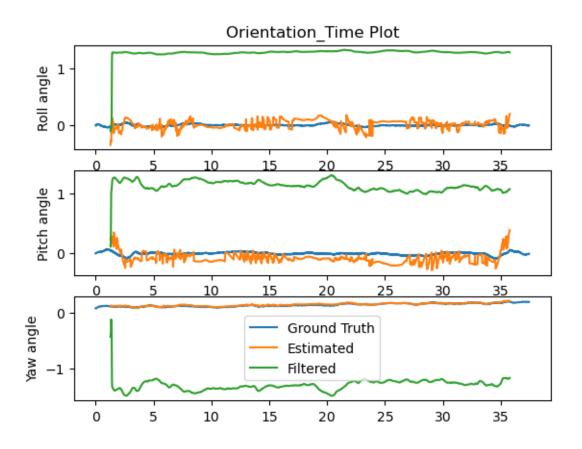
```
from simulation_PF import simulate import plots

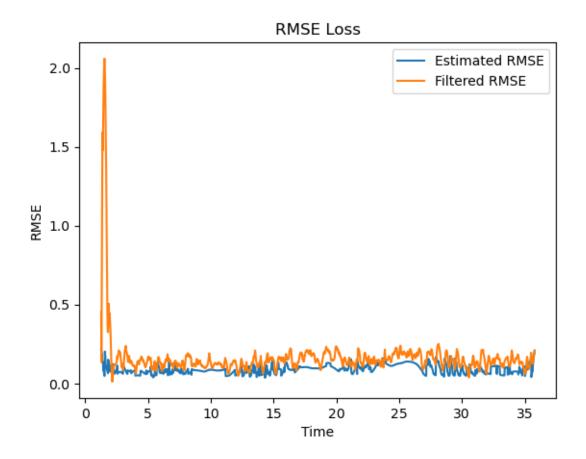
estimated, est_t, ground_truth, ground_truth_t, filt_data, partcl_hist, exe_t = simulate(r"data\data\studentdata5.mat", 1000, "weighted_avg", R, Qa=100, sq=0.01)

plots.plot(estimated, est_t, ground_truth, ground_truth_t, filt_data)
```









```
from simulation_PF import simulate import plots

estimated, est_t, ground_truth, ground_truth_t, filt_data, partcl_hist, exe_t = simulate(r"data\data\studentdata6.mat", 1000, "weighted_avg", R, Qa=110, sq=0.1)

plots.plot(estimated, est_t, ground_truth, ground_truth_t, filt_data)
```

