Applied estimation

Lab2

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1 PART I - Preparatory Questions

Particle Filters:

1 - What are the particles of the particle filter?

Particles are also called samples. They are used to represent the posterior distribution of some random process of a given noise. Each particle represents a possible state.

2 - What are importance weights, target distribution, and proposal distribution and what is the relation between them?

Importance wights is the probability of a measurement regarding a particle. Target distribution represents the belief bel(xt).Proposal distribution represents the bel(xt) based on the prior belief over state xt−1 and the control ut.

The importance weights are ratio between target distribution and proposal distribution evaluated at the particles state.

3 - What is the cause of particle deprivation and what is the danger

The reason for particle deprivation is the lack of good particles, which leads to convergence to an incorrect position. This may be caused by re-sampling to eliminate good particles, resulting in particle reduction. The danger of particle deprivation is that there will be no particles around the real state of the system. After the algorithm discards all particles that are close to the correct state during re-sampling, it cannot recover the lost particles for the real posture.

4 - Why do we resample instead of simply maintaining a weight for each particle always.

The simplest particle filter algorithm faces degradation problems. As time goes by, there are fewer and fewer particles available (very low weight). Therefore, re-sampling is required to replace low-weight particles with copies of high-weight particles.

5 - Give some examples of the situations which the average of the particle set is not a good representation of the particle set.

Consider some extreme cases, such as multiple peaks with the same density at a symmetrical center of gravity, then their average value will appear at the geometric center, but this does not represent their current position.

6 - How can we make inferences about states that lie between particles.

We can use Gaussian kernels method or create bins and calculate it from histogram.

7 - How can sample variance cause problems and what are two remedies?

The sampling steps create more randomness to the particle filter which cause the noise problem. Remedies is

1)Reducing the re-sampling frequency

2)Using a sequential stochastic process instead

8 - For robot localization for a given quality of posterior approximation, how are the pose uncertainty (spread of the true posteriori) and number of particles we chose to use related.

Higher pose uncertainty would result in larger spread of the posteriori, so larger number of particles are required.

2 PART II - Matlab Excercises

2 Warm up problem with the Particle Filter

Question 1

(6) is a simpler model which the angle is fixed with a constant value, while (8) use the angle obtained with the previous time, so it can make smoother predictions in noisy systems. Compare with (8), (6) can do the prediction when target move in a line and with no noise, and there is less computation, but the disadvantage is if there is some noise (6) can not do a good estimate.

Question 2

We can model circular motions with any angular velocity, linear velocity and radius. To do this we need to know initial angular velocity $\omega 0$, initial speed v0 and initial angle $\theta 0$.

Question 3

I'm not sure why we need to keep constant part in the denominator, but since equation (10) is showing the likelihood function, I guess the purpose is for normalization the value into [0, 1].

Question 4

Multinomial resampling: M different random numbers
Systematic resampling: One

Question 5

Vanilla resampling: The probability of it surviving is being drawn in at least one of the M Chances, so probability of not being drawn in any of the M chances is $(1-\omega)^M$, so the surviving probability is $1-(1-\omega)^M$.

Systematic resampling: The probability is 1, hence guaranteed that a particle eventually will be re-sampled with weight $\omega = \frac{1}{M} + \epsilon$. For the other case, the probability of surviving is proportional both to the weight of the particle and to the number of particles being drawn

M. In the limit $\omega = \frac{1}{M}$, the probability of being drawn would be 1, so the proportionality factor has to be M and the survivability probability is $M\omega$.

Question 6

Measurement noise model: Sigma_Q
Process noise model: Sigma_R

Question 7

The number of particles will decrease quickly during the resample process, and finally we can only see one particle, and other particles all converge to this one. And this particle will gradually away from real position, which is because of process noise.

Question 8

The particles will move randomly around the initial state (uniformly distributed) without converging. This is because there is no resampling, so the distribution of particles is the same, and some inaccurate particles are not filtered out.

Question 9

change the deviations of the observation noise model from 0.0001 to 1 gives the very similar result, which the particle cloud does not converge to a real value, because the measurements are expected to be accurate, so they are not classified as outliers.
When the value comes to 10 the particle cloud will last for some time and then converges immediately.
And when the value change from 100 to 10000, at 100 the estimate are follow the true measurements, but with the value increase, there are bigger variance and uncertainty.

Question 10

When the value increases from 0.0001 to 10000, when there is a small value, the particle distribution is relatively concentrated near the initial value, and the convergence speed is relatively slow. As with the deviation increases, the convergence speed of the particles will be faster, but the distribution will gradually spread.

Question 11

If the motion model is not accurate enough to completely match the real motion, it means that there is a greater error, so we need a larger process noise to match, which bring us a larger particle cloud.

Question 12

If the accuracy of the motion model is good, the initial state of the particles will be near the true value, and we only need a few particles to converge to the correct state. If the motion model is not accurate enough, it means that there is a greater error. Therefore, we need more process noise and more particles.

Question 13

We can detect the outliers by comparing predict result with the measurements and the threshold value. If the result is less than value we can think it as an outliers and remove it.
By Playing with the parameters I found when increase Sigma_Q I can make the Estimate Error decrease and I think this may because there are to many outliers which have very big error so we need a big noise. Besides, increase threshold also works.

Question 14

Motion Model	Sigma_Q	Sigma_R	Estimate Error
Fixed	300	25	10.8 +- 5.6
Linear	350	6	8.5 +- 4.0
Circular	300	2	7.0 +- 3.6

According to the table, we can find that in the fixed model are more sensitive to the process noise and we need a much bigger process noise.

3 Main Problem: Monte Carlo Localization

Question 15

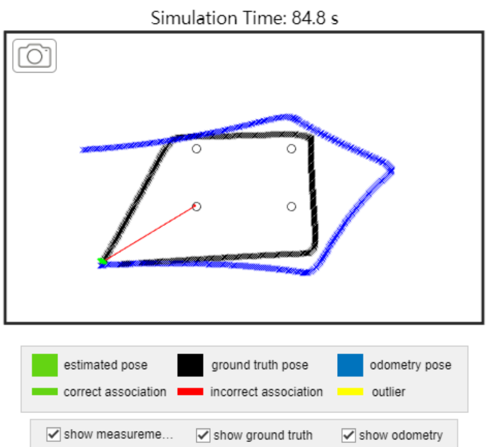
The threshold will affect the aforementioned anomaly detection. The higher the threshold, the easier it is for particles to be detected as abnormal values. And measurement noise will also affect. A very weak noise will give us greater confidence in the measurement results, so more detections will be considered outliers.

Question 16

If we do not detect outliers, the wrong measurements would be taken into consideration and given a big weight, which will make the wrong influence on the next sampling, which may eventually affect the correct convergence.

Dataset 4

Since the landmarks are completely symmetrical and there are four, there are four assumptions at the beginning of the simulation.
Since the landmarks are completely symmetrical and there are four, there are four assumptions at the beginning of the simulation. When using tracking, according to the comparison of Figure 1 and Figure 2, it can be seen that system resampling and polynomial resampling have almost the same effect when the number of particles is 1000. When I use Global, the system has an error in the estimation of the position. Even if I increase the number of particles to 10,000, there will still be an error in the estimation. This situation occurs in both resampling and polynomial resampling. The system will estimate its position as a point centered symmetrically with the true position.



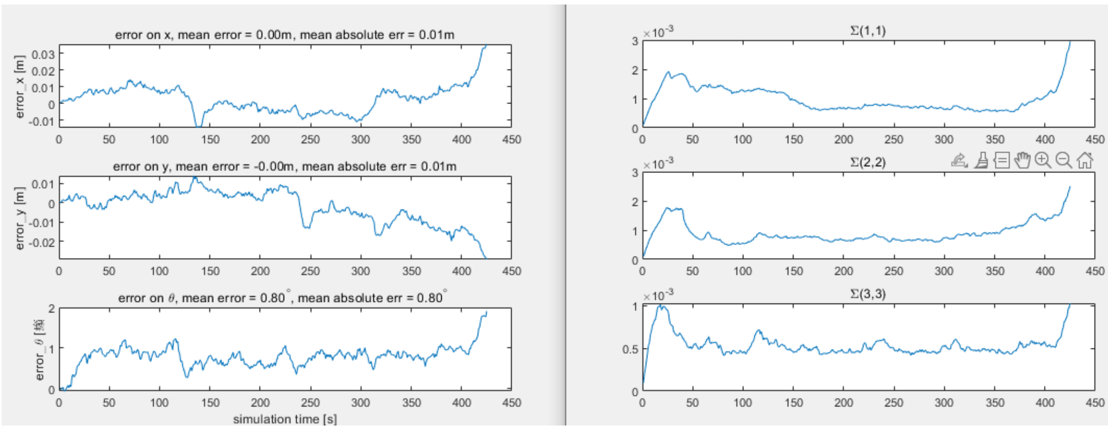
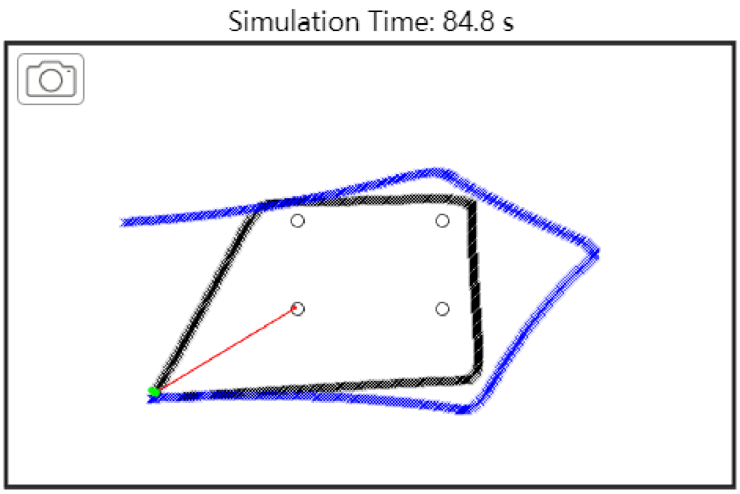


Figure1: Tracking localization with multinomial sampling



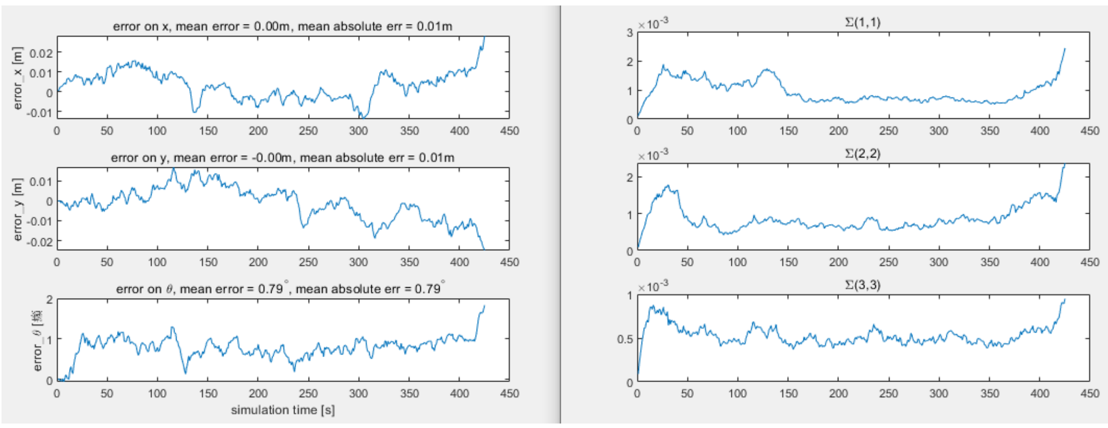


Figure2: Tracking localization with Systematic sampling

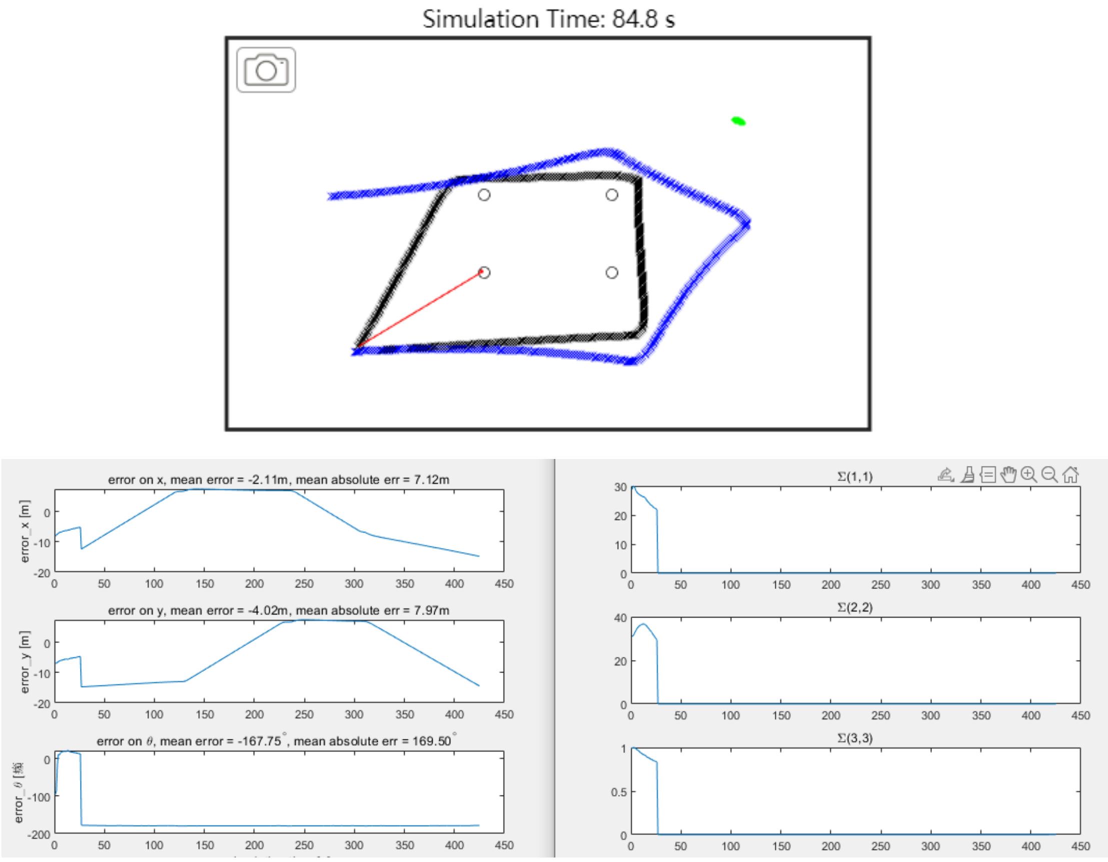


Figure2: Global localization with Systematic sampling

Dataset 5

When the fifth landmark was introduced to break the symmetry, the particles did converge to the correct assumption of the robot position. There were 4 hypotheses at the beginning, but particle deprivation reduced them.

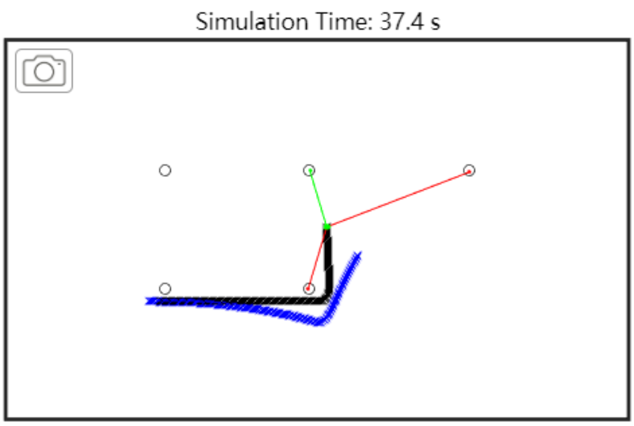


Figure3: The particle hypothesis just after convergence