Lab 2: Monte Carlo Localization
Group 7

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1 Theory Questions

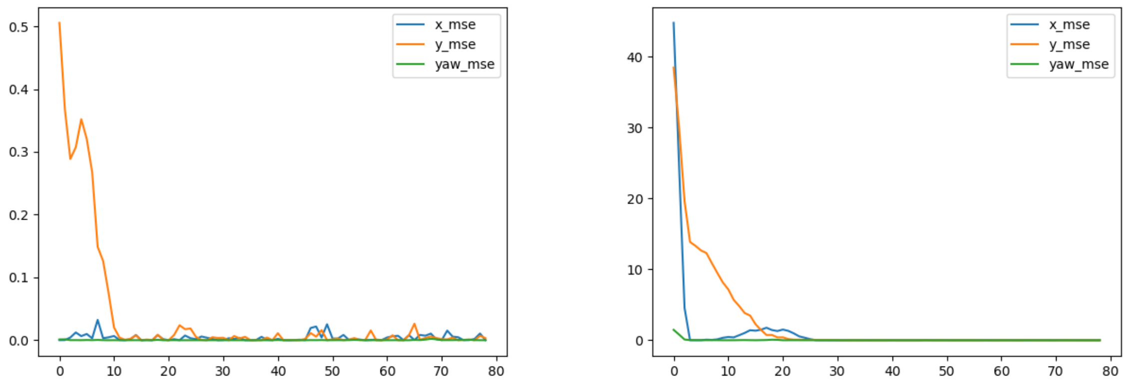
Q1: How does each of the model variance parameters affect the performance of the localizer? Give possible reasons for the behavior you see. The parameters are defined at the top of the file.

Sol: LINEAR_MODEL_VAR_X and LINEAR_MODEL_VAR_Y controls noise in the motion of the robot. ANGULAR_MODEL_VAR controls noise in angular velocity of the robot. Increasing these parameters makes it difficult for the localizer to converge as particles get spread out.

SENSOR_MODEL_VAR controls noise in sensor model. Increasing it will result in noisy sensor data, making it less reliable and as a result causing the particles to spread out.

Figures 1, 2, 3, 4 vary the LINEAR_MODEL_VAR_X, LINEAR_MODEL_VAR_Y, ANGULAR_MODEL_VAR and SENSOR_MODEL_VAR respectively, while keeping other parameters constant.

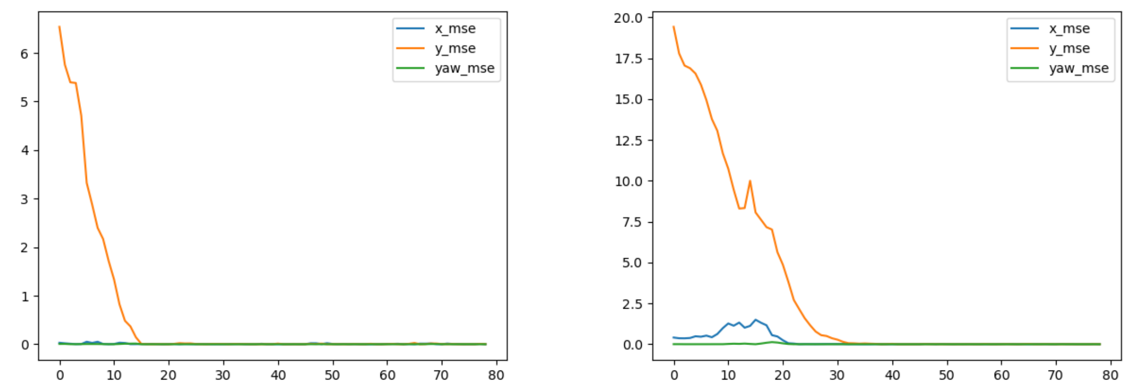
From figures 1 and 2, we can see that on decreasing the LINEAR_MODEL_VAR parameter the initial MSE is low, and increasing the LINEAR_MODEL_VAR parameter the initial MSE is higher. Lower values of variance converge faster while higher values take longer to converge.



(a) LINEAR_MODEL_VAR_X = 0.25

(b) LINEAR_MODEL_VAR_X = 0.75

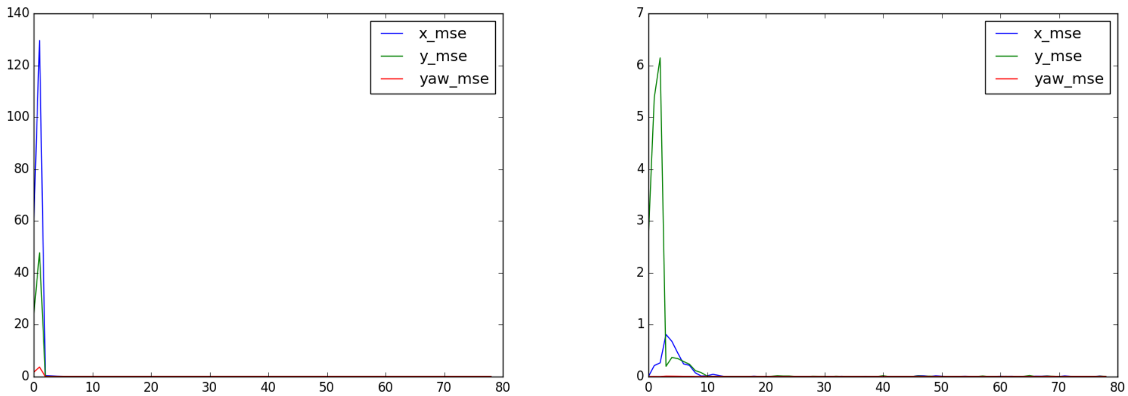
Figure 1: Varying LINEAR_MODEL_VAR_X



(a) LINEAR_MODEL_VAR_Y = 0.25

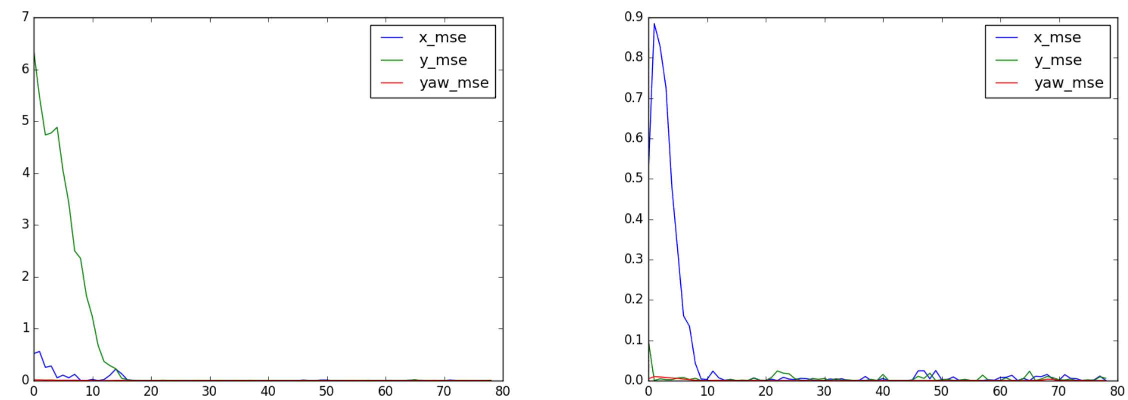
(b) LINEAR_MODEL_VAR_Y = 0.75

Figure 2: Varying LINEAR_MODEL_VAR_Y



(a) ANGULAR_MODEL_VAR = 0.25 (b) ANGULAR_MODEL_VAR = 0.75

Figure 3: Varying ANGULAR_MODEL_VAR



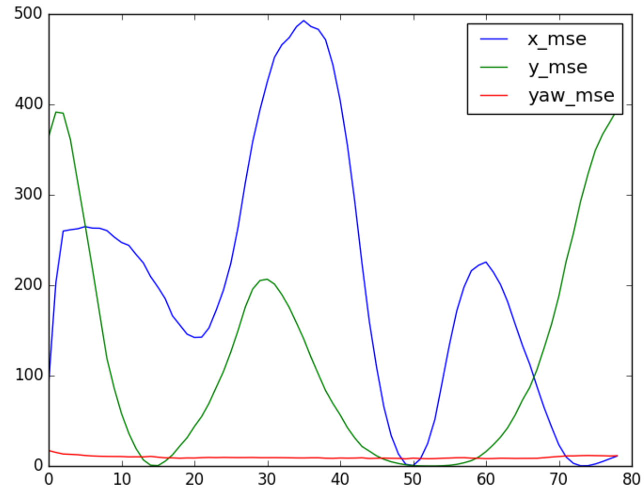
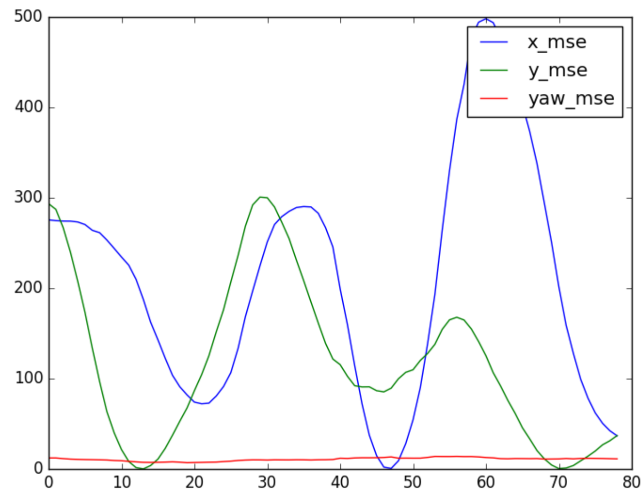
(a) SENSOR_MODEL_VAR = 5 (b) SENSOR_MODEL_VAR = 25

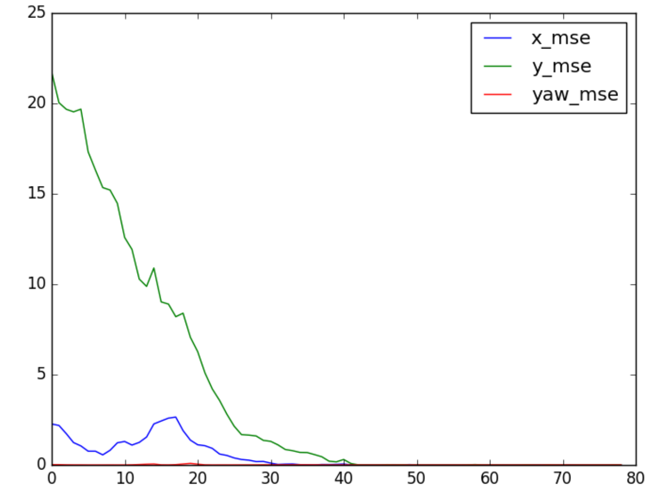
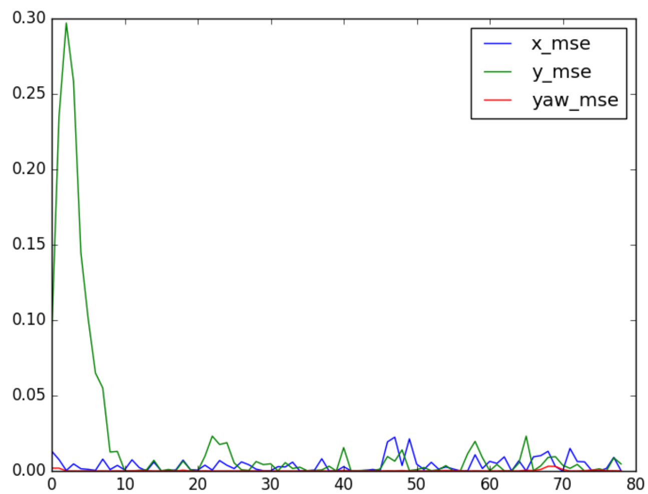
Figure 4: Varying SENSOR_MODEL_VAR

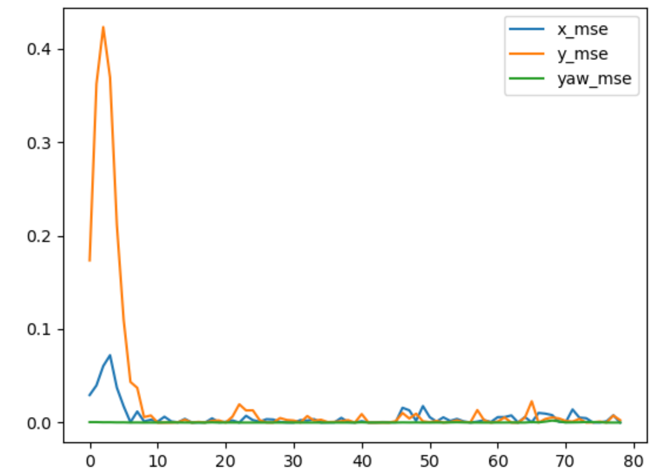
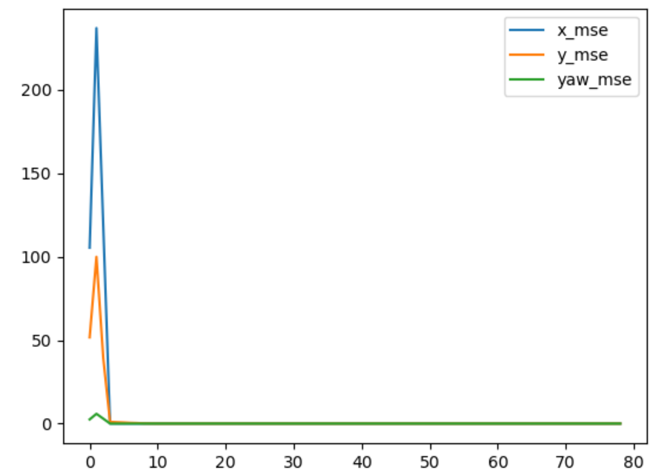
Q2: How does the number of particles affect the behavior of the localizer? The number of particles can be modified at the top of the file.

Sol: Increasing the number of particles results in a better representation of the true state by providing a more accurate posterior distribution. But this slows down the localizer as it requires more computation time.

From the graphs, we can see that on increasing the number of particles from 20 to 2500, the MSE keeps decreasing gradually. However, when we move from 2000 to 2500 particles, we notice that the output becomes more noisy. This is because excessive number of particles lead to increase in number of outliers, resulting in increase in sampling noise.

Number of particles	MSE Graph
20	
50	

200	x_mse y_mse yaw_mse 0 5 10 15 20 25 0 10 20 30 40 50 60 70 80
2000	x_mse y_mse yaw_mse 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0 10 20 30 40 50 60 70 80

2500	
3000	

Q3: Can a particle filter with a single particle perform well? Why or why not? What if it starts in the correct position?

Sol: A particle filter with a single particle will not perform well. The belief is based on a single particle which may not be a good representation of the true state since a single particle has high sensitivity to noise in motion and sensor models, lacks generalization and cannot capture diversity of states.

Even if the particle starts at the correct position it may not work well, since it still has high sensitivity to noise, which might cause it to deviate from the correct position and it would be hard to recover from this.

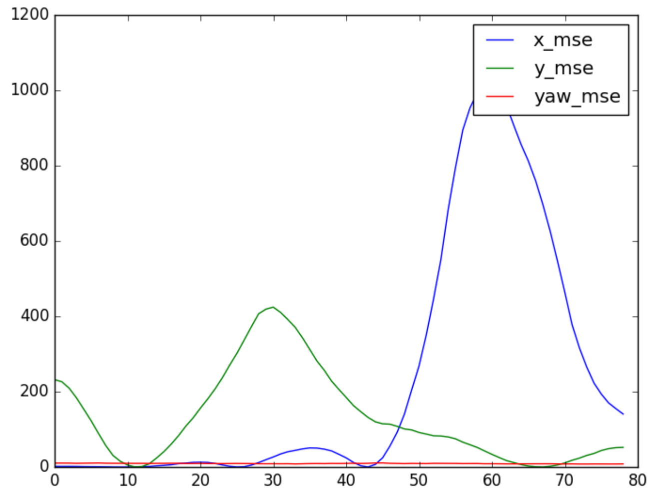


Figure 5: Error graph with 1 particle

2 Error Graph by Localizer for default parameters

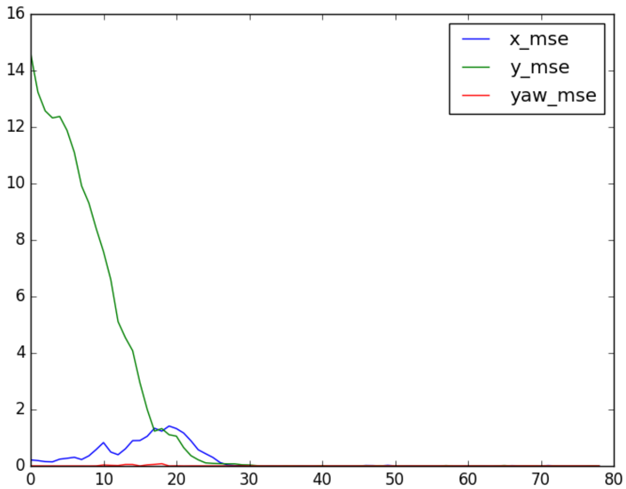


Figure 6: Error graph for linear x=0.5, linear y=0.5, angular=0.3, sensor=15

3 Extra Credit

3.1 Better Noise Model

Q: The noise model for the motion model presented in Section 2.3 of this document is overly simplistic. You can find a better noise model in Section 5.4 of Probabilistic Robotics. Explain why the noise model presented in this lab has poor properties. Implement the better noise model.

Sol: The simple noise model in the lab assumes fixed variance Gaussian noises in the linear and angular velocity errors. This noise model cannot adapt to performance of the system, which means that good and poor systems have the same error.

The noise model introduced in the textbook models can adapt its noise parameters based on the sensor's performance, which improves the accuracy of localization. The error graph of this sophisticated noise model is shown in Fig.7.

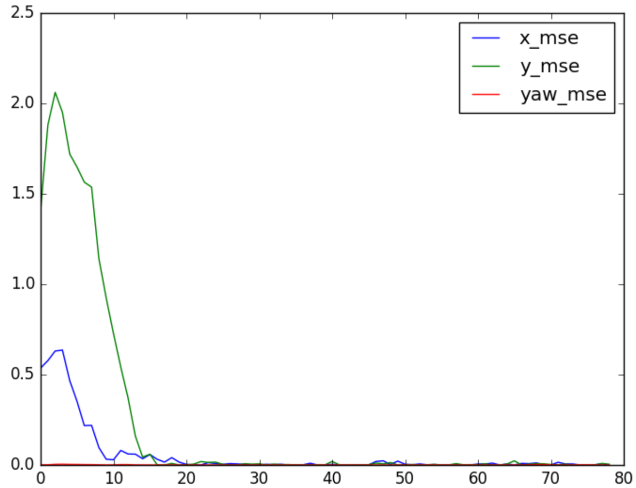


Figure 7: Error graph for Better Noise Model

3.2 Complete Beam Sensor Model

We obtain the maximum sensor value by running the simulation once and noting the maximum of all the sensor values obtained.
Maximum sensor value = 20.1409549713
Since we don't have any dynamic obstacles, we can set z_{short} to a small value. There's also less chance of the sensor missing an object or having the ray being absorbed by black objects in our case. So z_{max} can also be small. Since we have maximum sensor value ~ 20, we can set $\lambda_{short} \simeq 10$, which is roughly half of that. σ_{hit} is chosen to be roughly near the provided SENSOR_MODEL_VAR. In real-world scenarios, these parameters are estimated from true poses and sensor measurements using maximum likelihood estimation.
$z_{hit} = 0.75, z_{short} = 0.1, z_{max} = 0.1, z_{rand} = 0.05$
$\sigma_{hit} = 10, \lambda_{short} = 10$

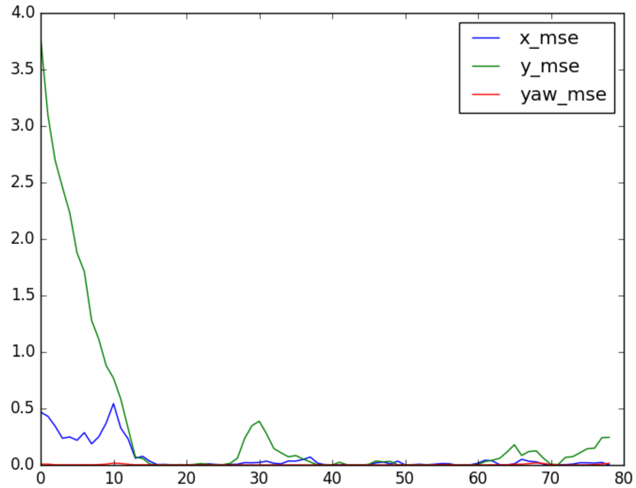


Figure 8: Error graph for Beam Sensor Model

3.3 Particles Clustering

Q: The particle filter is powerful because it can model complex, multimodal posterior distributions. Averaging all particles assumes a unimodal distribution and may yield very unrealistic estimates. Use a clustering algorithm to estimate the particles in the largest mode, and compute their average as a more realistic estimate to concretize the posterior.

Sol: Using the k-means clustering algorithm, as the number of clusters increase, the initial error of the assumptions are larger, as the model commits to a single cluster (which is not necessarily correct). Since these assumptions can be incorrect, the model takes longer to converge to the actual solution. As we keep increasing, a large number of clusters leads to larger initial errors.

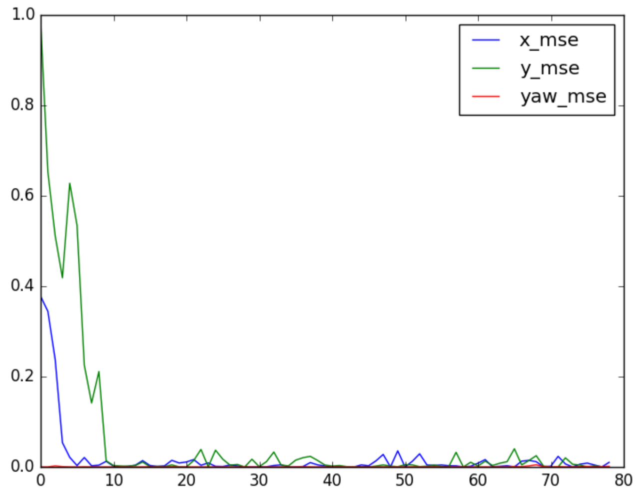


Figure 9: With 2 clusters, the graph looks very similar to the graphs without the clustering algorithms

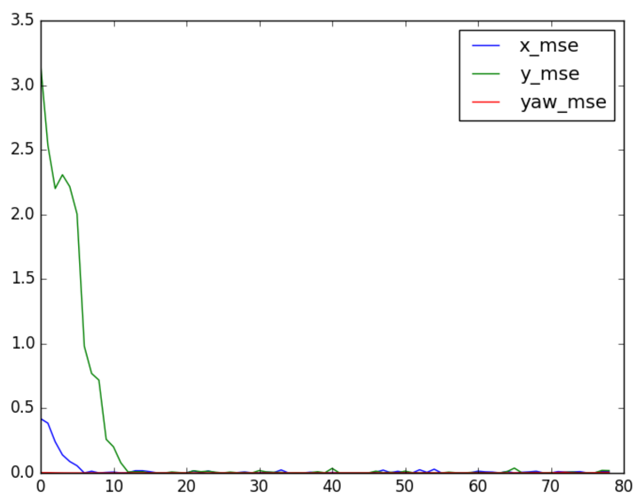


Figure 10: With 10 clusters, there is a larger initial error, but converges after some timesteps

NOTE: Some experiments were run on Mac while others were run on Windows, due to which the graphs are inconsistent in terms of colors.