CS3630 Project 3 Report (Fall 2022)

Name: Anthony Wong

GT Email: awong307@gatech.edu

GT Username: awong307

Q1.1 Representing Gaussian’s

1. What are the two broad categories of representing uncertainty in continuous State Space? And which one are we using?

   - Exact Parameterized PDFs
   - Discrete Approximations to Probability Distributions

2. Which representation are we using in Project 3?

   - Discrete Approximations to Probability Distributions

Q2.1 Markov Localization

1. What are the optimizations applied in the predictive step function to reduce the latency and boost performance?

    - Make the outer loop over the previous image and threshold on the density
    - Make use of the fact that logistics.gaussian is vectorizes such that we can process an entire row of the predictive image at once

Q2.2 Markov Localization

1. What is the error of Markov Localization given different motion sigmas? Report the error here.

- Motion sigma = 1.0
    - 1.349592078587504
- Motion sigma = 2.0
    - 1.5188921378124645
- Motion sigma = 3.0
    - 2.651801659077752

Q2.2 Markov Localization

2. What is the running time of Markov Localization at Motion sigma = 1.0? Report using wall time in seconds.

32.24456483423 seconds

Q2.3 Markov Localization Analysis

Please provide an explanation for your observations. How does changing motion sigma affect trajectory error and sample (probability) distribution as observed in the generated slide shows?

When motion sigma increases, the sample distribution will have a higher variance. This means we will have more deviations from the mean, which then means we will have a greater error. We see this in the slide shows which displays a wider cluster.

Q3.1 Monte Carlo Localization

How does changing the motion sigma affect the error of localization? Report the error here.

- Motion sigma = 1.0
  - 9.8059902375072
- Motion sigma = 2.0
  - 10.331095302428983
- Motion sigma = 3.0
  - 10.595793255819173

Q3.2 Monte Carlo Localization Analysis

Please provide an explanation for your observations. Does changing motion sigma in particle filtering have similar effects on trajectory error and sample distribution as Markov localization? Why or why not?

This has a similar effect as it does on Markov localization. A larger motion sigma here also increases the variance in our distribution which results in more error. We can again see this as our samples are clustered over a wider area.

Q3.3 Monte Carlo Localization – Sample Size

1. How does changing the sample size affect the running time of localization? Report the wall time in seconds, e.g. 6 s.

- Sample Size = 500
  - 5.458530400002928 seconds
- Sample Size = 1000
  - 8.120754127001419 seconds
- Sample Size = 2000
  - 13.131151589997899 seconds
- Sample Size = 5000
  - 26.51536159600073 seconds
- Sample Size = 10,000
  - 48.41022890399836 seconds

Q3.3 Monte Carlo Localization – Sample Size

2. How does changing the sample size affect the error of localization? Report the error here.

- Sample Size = 500
  - 9.632337635219292
- Sample Size = 1000
  - 9.67158421519086
- Sample Size = 2000
  - 9.758215588455503
- Sample Size = 5000
  - 9.36077277237067
- Sample Size = 10,000
  - 9.480144337922846

Q3.4 Monte Carlo Localization

Please provide an explanation for your observations. How does changing sample size affect running time and error?

Changing sample size does increases the runtime because there are more samples to perform operations over at each time step. This does not change the error however because each particle abides by the same distribution so even if there are more, they will be spread the same throughout the state space, leading to similar error.

Q3.5 Monte Carlo Localization

1. Describe the initial distribution of the samples and the generated slide show for each distribution.

The uniform distribution shows the samples generally evenly spaced throughout the state space. The node-centered distribution has the samples focused in one single cluster at the bottom-left corner. The multi-modal distribution shows the samples focused into a couple of clusters placed randomly throughout the state space.

Q3.5 Monte Carlo Localization

2. How does changing the initial distribution affect the error of localization? Report the error output here.

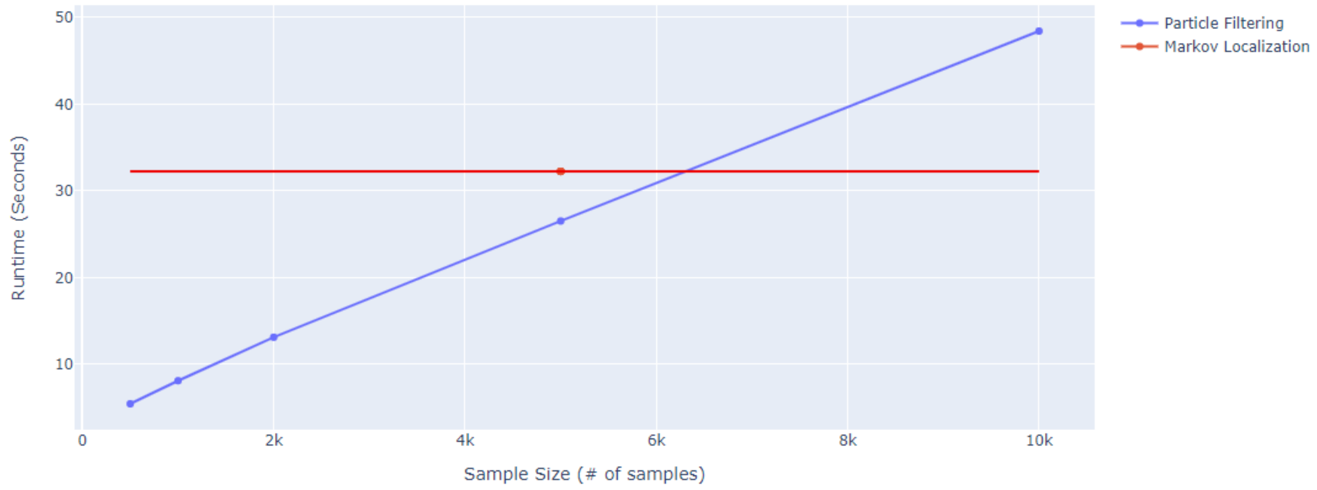
- Uniform distribution
    - 9.171582132221163
- Node-centered distribution
    - 0.6903956565061083
- Multi-modal distribution
    - 4.932051954106404

Q3.6 Monte Carlo Localization

How does changing the sample initialization affect the functionality of Monte Carlo Localization? How will unbalanced initialization (such as multimodal distribution) affect the localization process and sample distribution? Support your answer with the observations you found above.

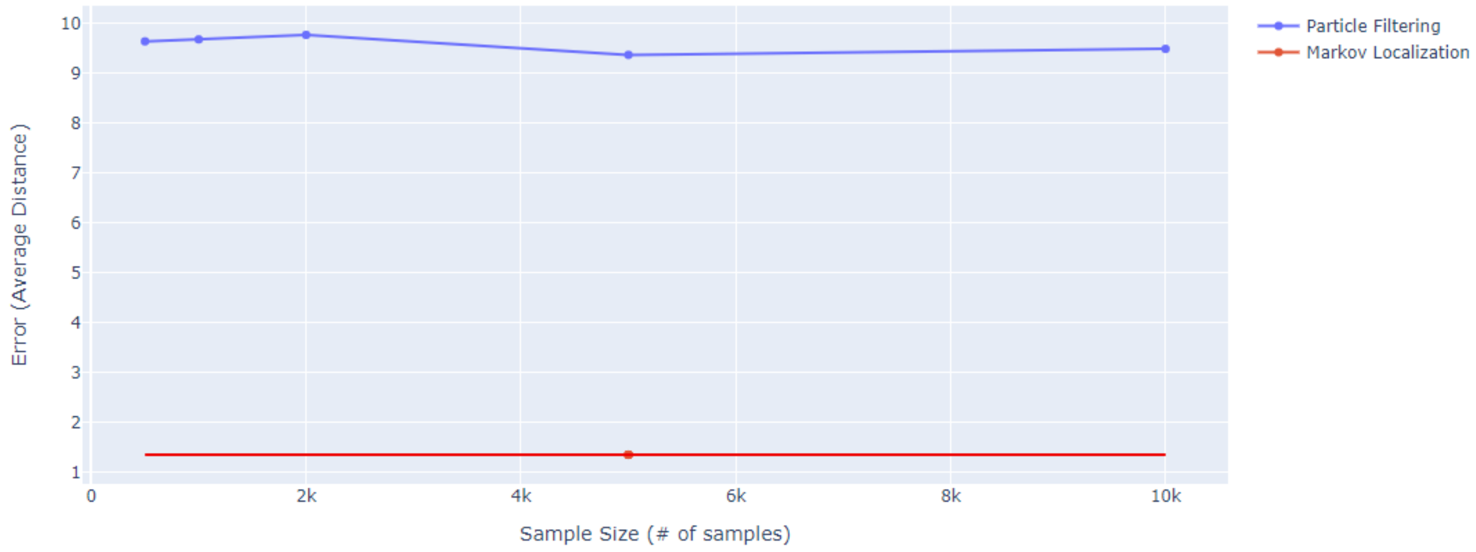
For Monte Carlo Localization to work the best, the initial distribution should have most of its samples near the initial ground truth. In this scenario, node-centered does this well as it places most of the samples near the initial ground truth in the bottom-left. Both multi-modal and uniform have their samples more spread around elsewhere thus making the performance worse.

Q4.1 Localization Comparison – Running Time



- Explain the correlation between running time and sample size.
  - As sample size increases, the running time for Particle Filtering also increases. This follows because we are iterating over our samples per timestep.
- At approximately which sample size will the running time of Monte Carlo localization reach that of Markov localization?
  - The occurs at approximately 6200 samples.

Q4.2



- Explain the correlation between error and sample size.
  - For Particle Filtering, the error seems constant regardless of sample size.
- How does the error of the two algorithms compare?
  - Markov Localization has significantly less error compared to Particle Filtering
- At approximately what sample size is the error of Particle Filtering similar to that of Markov localization?
  - It never is

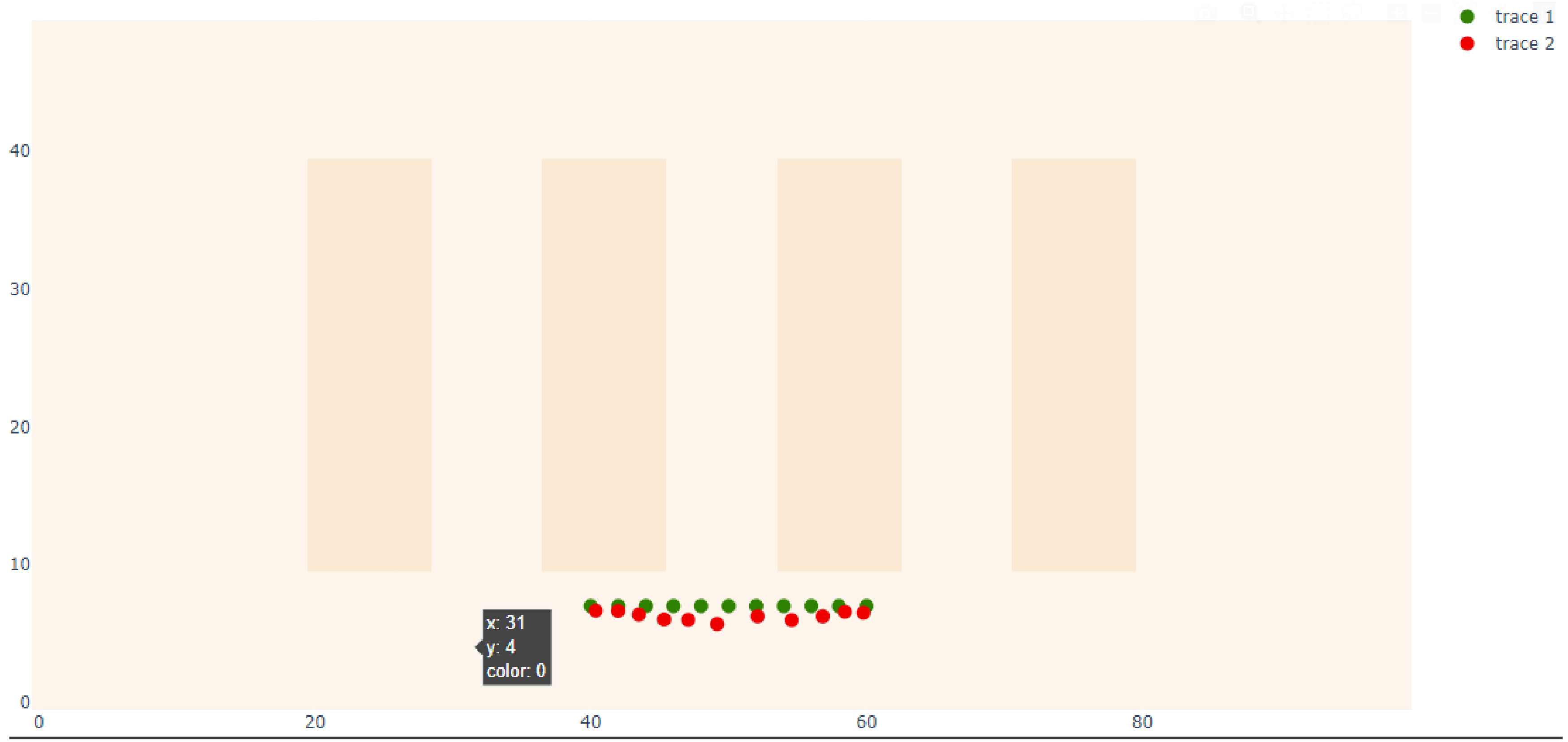
Q4.3

Explain under what configuration (sample size etc.) would you prefer Monte Carlo localization over Markov localization and vice versa?

- Monte Carlo localization is preferred where run time is very important. This means when state space is large, Markov localization's runtime will increase exponentially. When state spaces are small, we can use Markov localization because the runtime issue is minimized while we maintain a better accuracy. Additionally, we must ensure we don't overextend in sample use for Monte Carlo as we have found in this situation that at some point, Markov localization becomes more efficient.

Q5.1

Error: 0.9036420212800599



Q5.2

Error: 6.131237890794406