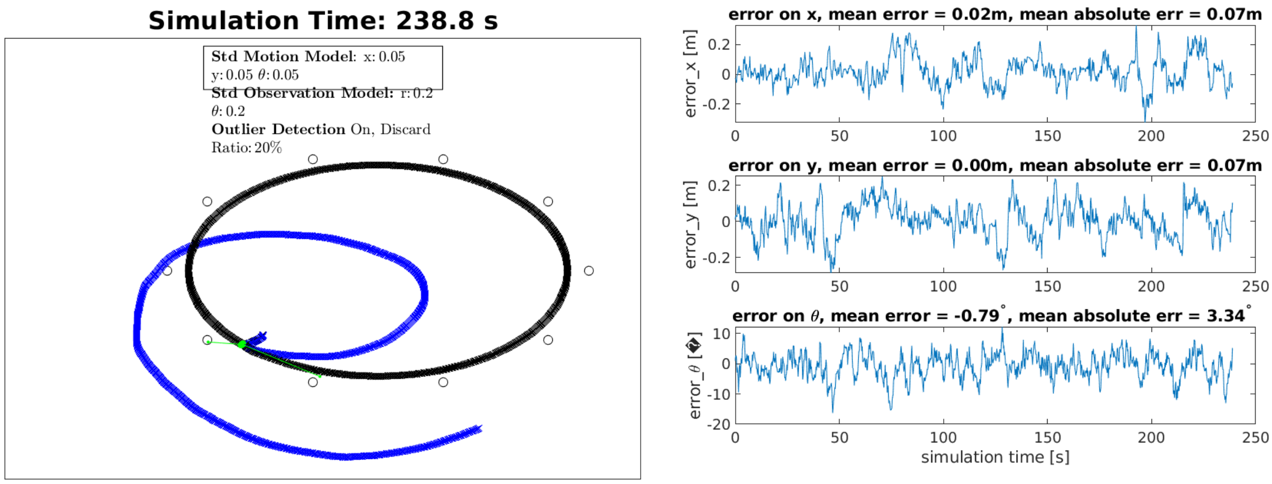

Fig 8. Visalization and error statistics of dataset 2

Dataset 3

The third dataset distinguishes of the two others because of the different simulated noises. While association does not play a big role if turned off, once the batch update is turned off, the estimation deteriorates. Averaging off noise and outliers with batch update is vital in this case.

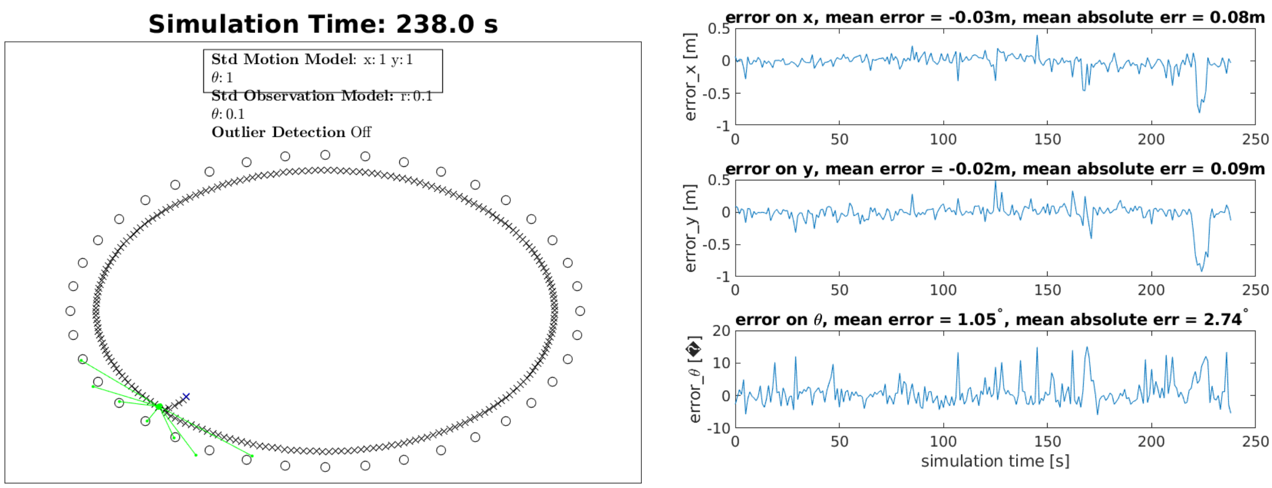

Fig 9. Visalization and error statistics of dataset 3

Lab 2

PART I

Preparatory Questions

1.**What are the particles of the particle filter?**

States of the state space at which the posteriori probability density is estimated. In Localization another way is thinking of particles as possible locations of the robot.

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

Target distribution is the probability distribution to be estimated, in other words the posteriori distribution. Proposal distribution is called the distribution we sample from, which makes use of the model. Importance weights adjust for the difference between the sampled distribution and the target distribution.

3.**What is the cause of particle deprivation and what is the danger?**

Particle deprivation happens when there are not enough particles to cover all the space. The dagner is that there may not be particles in vicinity of correct state.

4.**Why do we resample instead of simply maintaining a weight for each particle?**

Resampling makes sure that a redistribution of the particles to places of higher possibiliy takes place. In that way the computational power is concetrated in places of bigger importance.

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

The average is not a good representation always when the particles have not converged, i.e. when there re still outlier particles. One case is at the beginning when the uncertainty is still big and lots of particles have not yet converged. Another example comes from localization in symmetrical environments where the particles are distributed equally in different poses.

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

Place a kernel(e.g. Gaussian kernel) around each particle and estimate the additive effect on the state of interest which than correspond to the density on that state. Other ways can be to fit a Gaussian to the mean and variance of particle set or form a histogram where state space is seperated in bin and each bin has a number of particles.

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

This problem can manifest itself as a loss of diversity in the particle population which translates to an approximation error. Two major strategies for variance reduction include low variance sampling and sampling less frequently.

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

The higher the number of particles we use the better can the posteriori probability estimation be done, i.e. the lower the uncertainty.

PART 2

Matlab Exercises

9.**What are the advantages/drawbacks of using (5) compared to (7)? Motivate.**

(5) assumes a constant angle and is so simplier whereas (7) includes the angle which is in the mean time part of the state. While more complicated (7) allows for the discription of more complicated models.

10.**What types of circular motions can we model using (8)? What are the limitations (what do we need to know/fix in advance)?**

Only circular motions with constant angular and linear velocity which need to be known in advance.

11.**What is the purpose of keeping the constant part in the denominator of (10)?**

It is kept for normalizing purposes to make sure that the likelihood is a probability distribution.

12.**How many random numbers do you need to generate for the Multinomial re-sampling method? How many do you need for the Systematic re-sampling method?**

For the Multinomial re-sampling we need to generate M random variables whereas for the Systematic re-sampling only 1.

13.**With what probability does a particle with weight w =1/M + ϵ survive the re-sampling step in each type of re-sampling (vanilla and systematic)? What is this probability for a particle with 0 ≤ w < 1/M? What does this tell you? Hint: it is easier to reason about the probability of not surviving, that is M failed binary selections for vanilla, and then subtract that amount from 1.0 to find the probability of surviving.**

A particle with weight w =1/M + ϵ survives vanilla resampling with probability and the systematic resampling with probabilty 1. For importance weight smaller than 1/M the survuval probability for the vanilla corresponds the already presented formula whereas for the sequential resampling the probabilty is w/1. We can say that the probability to survive is proportional to the weight eventhough both methods follow different approaches.

14.**Which variables model the measurement noise/process noise models?**

Σ_Q and Σ_R respectively.

15.**What happens when you do not perform the diffusion step?(You can set the process noise to 0)**

When the diffusion place doesn't take place the particles diverge.

16.**What happens when you do not re-sample? (set RESAM-PLE MODE=0)**

The particles do not converge.

17.**What happens when you increase/decrease the standard deviations(diagonal elements of the covariance matrix) of the observation noise model? (try values between 0.0001 and 10000)**

When observation noise covariance matrix is big the variance of the particles position stays big since all weights are approximately equally big from a certain point. On the other hand when the covariance matrix gets small allmost all particles have very small weights, but once a particle is very close to the real position the resampling tends to choose that particle many times and so all particles converge to the real position.

18.**What happens when you increase/decrease the standard deviations (diagonal elements of the covariance matrix) of the process noise model? (try values between 0.0001 and 10000)**

When the the covariance decreases a lot the process noise isn't considered enough which leads the particles movie in wrong directions. A higher covariance matrix of the process noise counts for any possible noise of the model. While the position of the particles have a bigger covariance their mean is still able to approximate the real position. If the process noise is made too big than the particle filter works as if there were no model and the estimations depends only on the measurements which would deverge in case of outliers or not modelled noise.

19.**How does the choice of the motion model affect a reasonable choice of process noise model?**

Wrong model is compensated with higher process noise.

20.**How does the choice of the motion model affect the precision/accuracy of the results? How does it change the number of particles you need?**

The not correct motion model would require a higher process noise which and so keeps a particle cloud with a bigger variance. In order to cover a bigger variance distribution the number of particles needed is bigger.

21.**What do you think you can do to detect the outliers in the third type of measurements? Hint: What happens to the likelihoods of the observation when it is far away from what the filter has predicted?**

Similiar to EKF we can use a threshold on the average likelihood of the observation from all particles to detect the outliers.

22.**Using 1000 particles, what is the best precision you get for the second type of measurements of the object moving on the circle when modeling a fixed, a linear or a circular motion (using the best parameter setting)? How sensitive is the filter to the correct choice of the parameters for each type of motion?**

Since the modeling of measurements noise doesn't depend on the motion model a 20x bigger (Lab2/Formulas/sigma_R.png) than the one given brings in the best results. Using the fixed motion model we came to the conclusion that using a big enough is very important for the particles to not diverge. The best results were achieved for a Σ_R 10x bigger than the one given. On the other hand the linear and circular motion modell are stable. The best results for the linear motion modell are achieved for same modell noise covariance. Whereas for the circular motion modell a 20x smaller Σ_R than the given one is the best choice.

Main problem

Monte Carlo Localization

23.**What parameters affect the mentioned outlier detection approach? What will be the result of the mentioned method if you model a very weak measurement noise |Q| → 0?**

The outlier detection method is affected by the measurement noise covariance and the threshold. By modelling the measurement model with a very weak measurement noise, almost all measureents would be detected as outliers. This happens because the peaks are very tight and a smoll deviation from the right peak would force the likelihood to not pass the threshold.

24.**What happens to the weight of the particles if you do not detect outliers?**

If an outlier measurement is not detected the weights of the particles corresponding to these measurements are given more weights than they should which would give a wrong set of particles after the re-sampling.

Dataset 4

How many valid hypotheses do you have for these 4 landmarks? Start with 1.000 particles. Does your filter keep track of all hypotheses reliably? How about 10.000 particles? What do you think is the reason? Try multinomial sampling. How well does it preserve multiple hypotheses? How well are your hypotheses preserved when you model stronger/weaker measurement noises?

The global localization with 1000 particles tends to converge towards the wrong position as is shown in Fig 1.

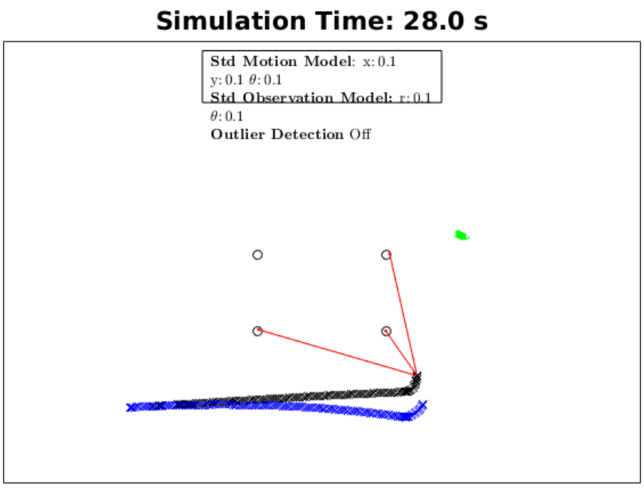

Fig 1. Global Localization with 1000 particles on Dataset 4

Observing Fig 2 we can say that global localization with 10000 particles has 4 valid hypothesis and it is not able to converge toward only one of them since the enviroment is perfectly symetric respective to the place from where the measurements are taken

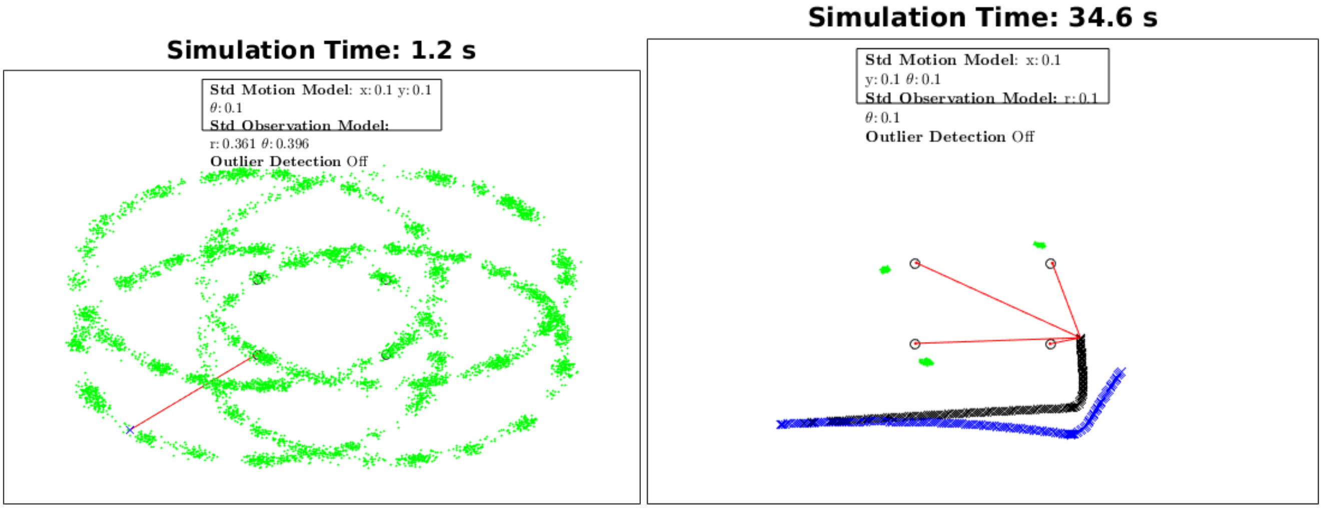

Fig 2. Global Localization with 10000 particles and systematic resampling on Dataset 4

On the other hand, using multimonial resampling does not preserve the 4 hypothesis as it is more biased to choose particle of higher weight

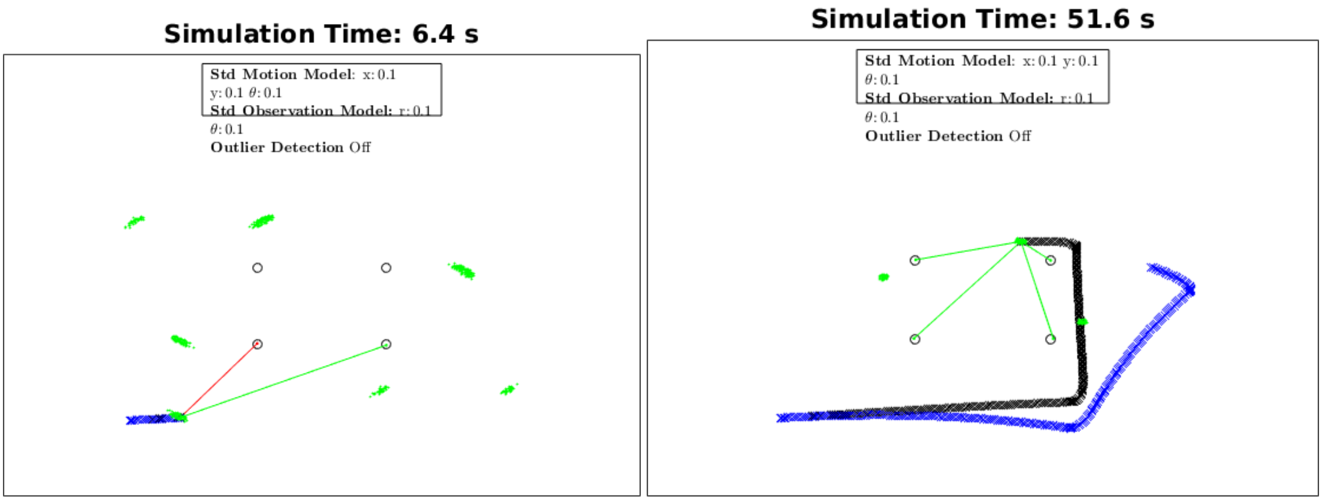

Fig 3. Global Localization with 10000 particles and withmultinomial resampling on Dataset 4

Changing the measurement noise models also affects the hypotheses preservation. Figure 4 shows the results for stronger measurement noise and Figure 5 for very weak noise. For stronger noise the hypotheses are preserved although are more spread. For weaker noise the hypotheses disappear fast and in this case converge to the correct one. The reason may lie in the fact that the landmarks don't form a real square but rather a rectangle which can be considered if the measurement are very good and we model them with very low noise at the same time.

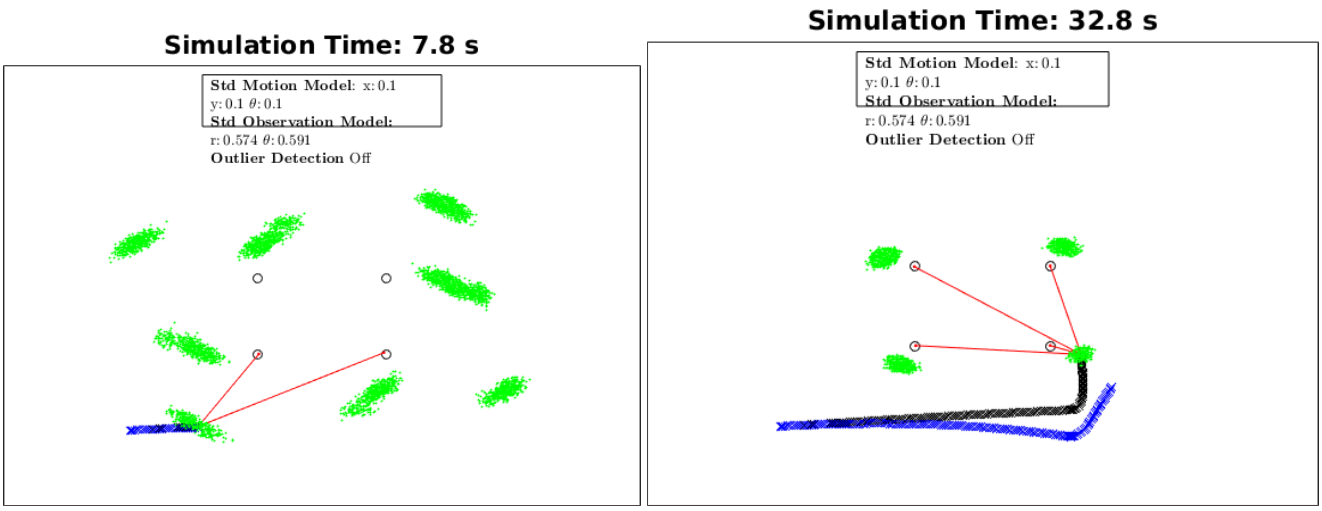

Fig 4. Global Localization with 10000 particles and strong measurement noise on Dataset 4

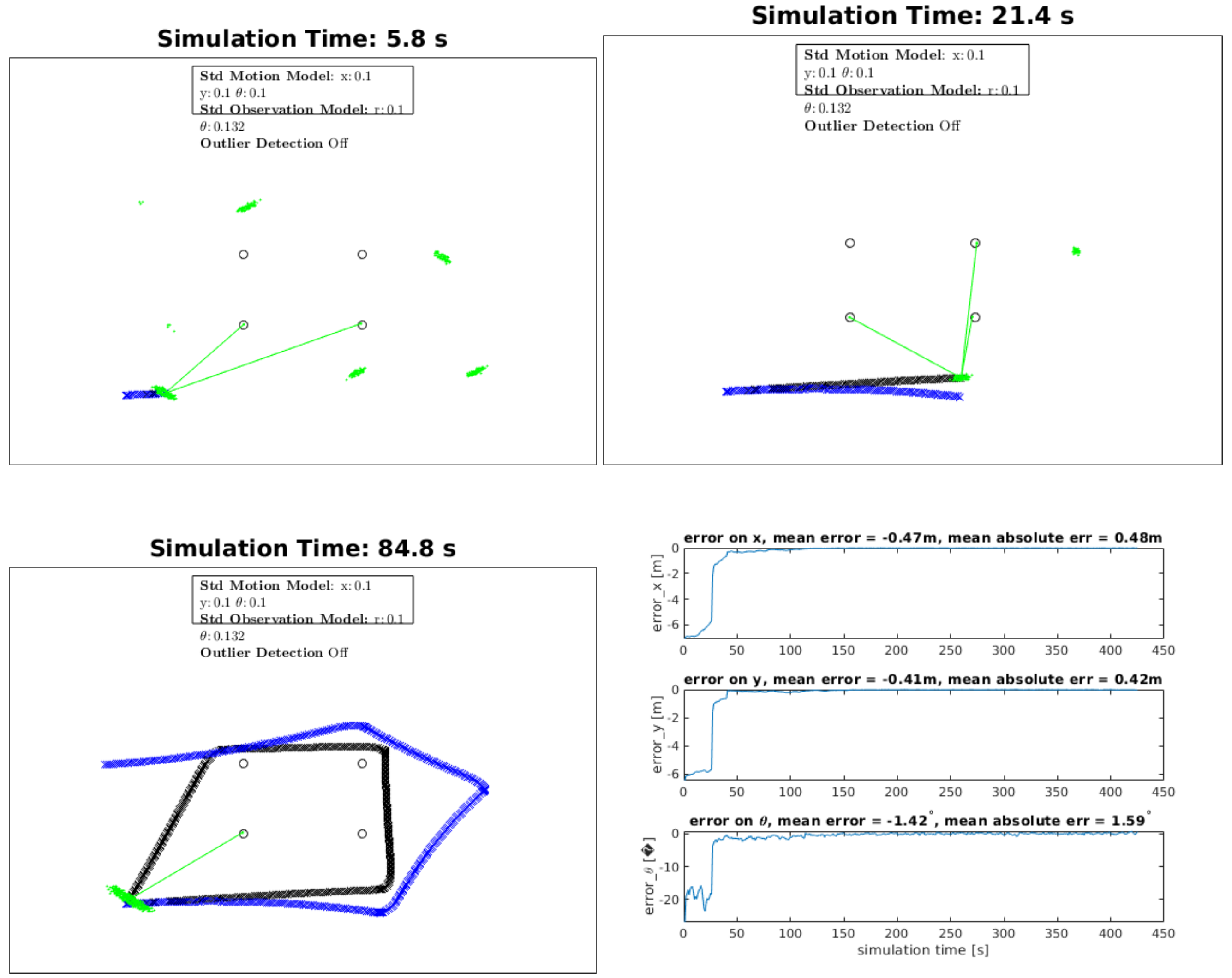

Fig 5. Global Localization with 10000 particles and weak measurement noise on Dataset 4

Dataset 5

Does your filter converge to the correct hypothesis? Include in your report an image just before and just after the convergence.

The filter is able to converge only after breaking the symmetry when observing the outlier on the right at second 37.

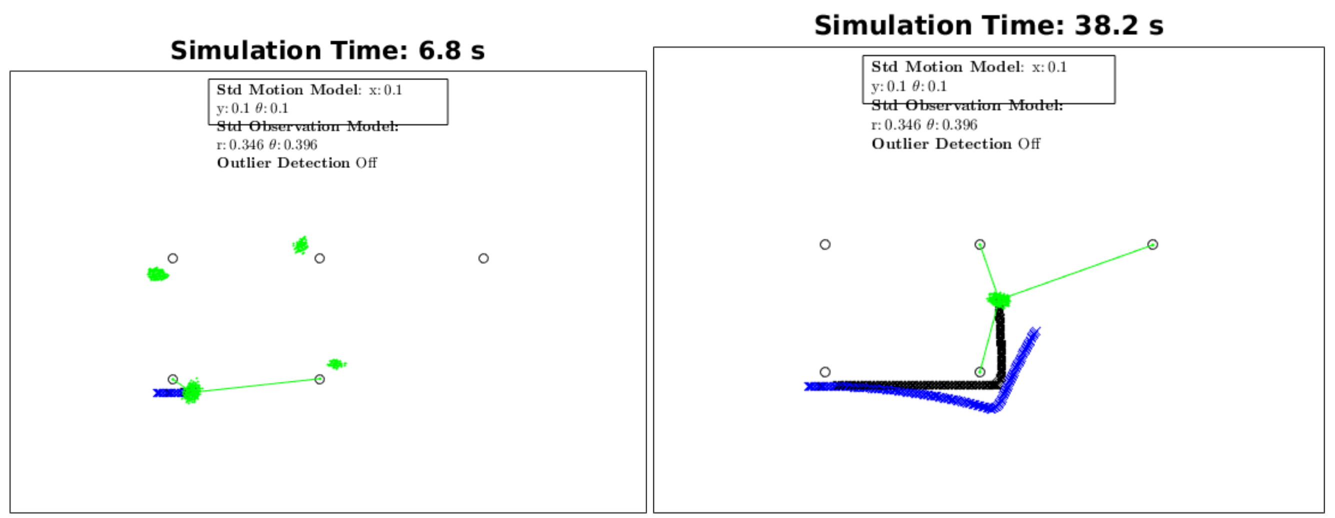

Fig 6. Global Localization with 10000 particles and default settings on Dataset 5