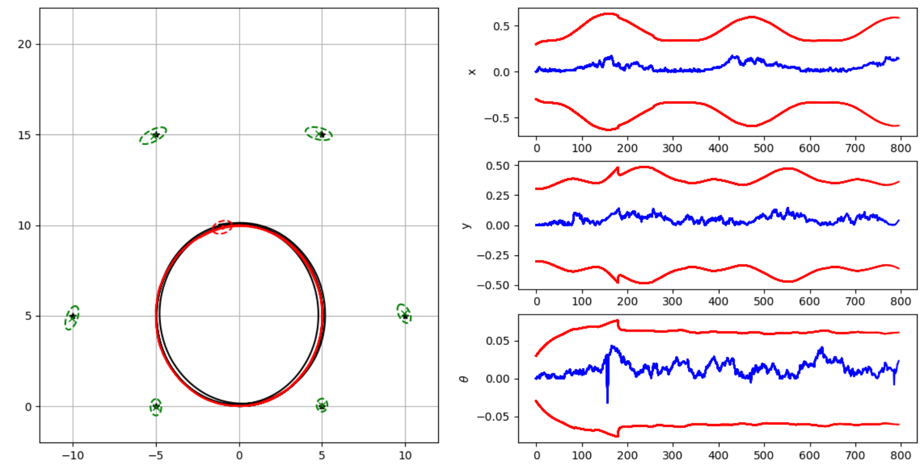
Q1

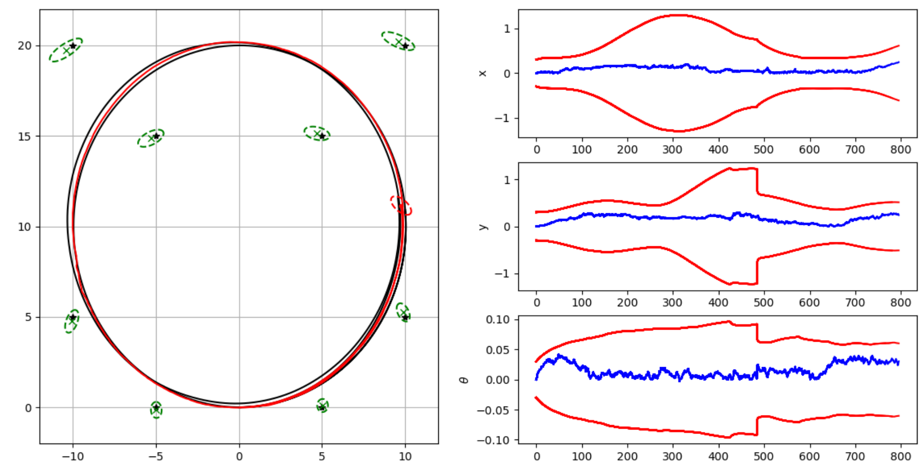
A short loop and a dense map



Mean (var) translation error : 7.958291e-02 (1.909932e-03)

Mean (var) rotation error : 1.349330e-02 (8.294954e-05)

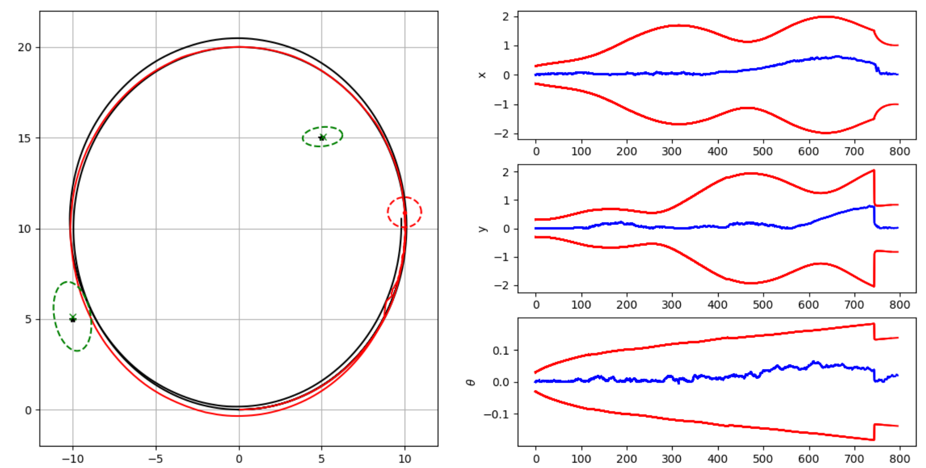
A long loop and a dense map



Mean (var) translation error : 1.861350e-01 (7.661070e-03)

Mean (var) rotation error : 1.557626e-02 (1.237731e-04)

A long loop and a sparse map



Mean (var) translation error : 2.589345e-01 (7.417010e-02)

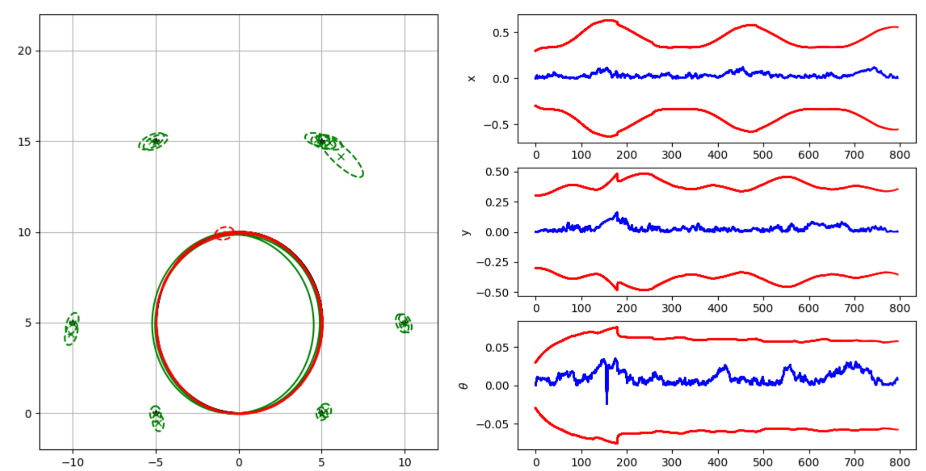
Mean (var) rotation error : 2.024193e-02 (3.326657e-04)

From the above figures, we can conclude that a small loop with many landmarks achieves the least uncertainty and error. When we evaluate the impact of number of landmarks, we can see that with a dense map (figure 2), the translation error and rotation error are small comparing to a long loop with few landmarks. Comparing the covariance of the landmarks, the loop with few landmarks estimate the position of landmark with more uncertainty.

Q2

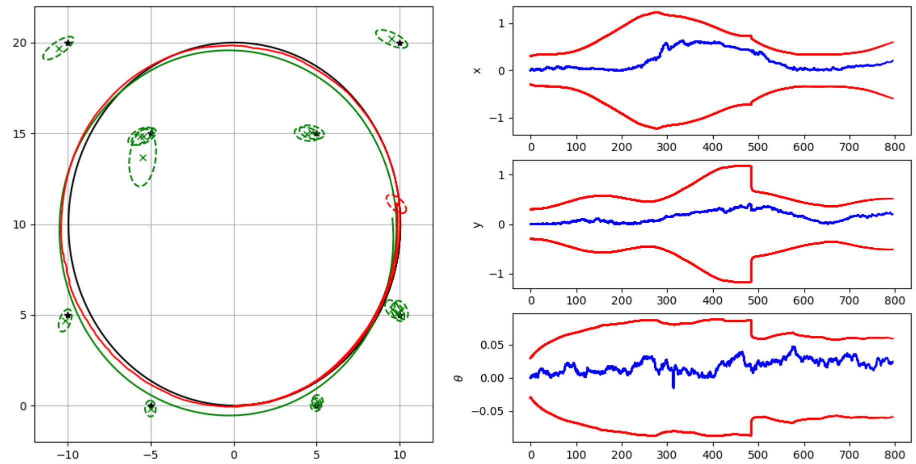
Set M_DIST_TH = 5.0

A short loop and a dense map



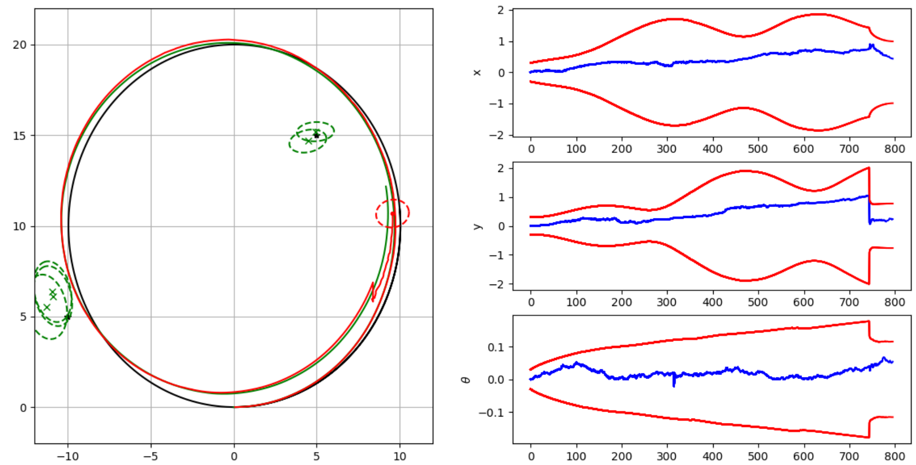
Mean (var) translation error : 5.202149e-02 (8.848887e-04)
Mean (var) rotation error : 1.061769e-02 (6.557009e-05)

A long loop and a dense map



Mean (var) translation error : 2.586875e-01 (4.943806e-02)
Mean (var) rotation error : 1.845922e-02 (1.006317e-04)

A long loop and a sparse map

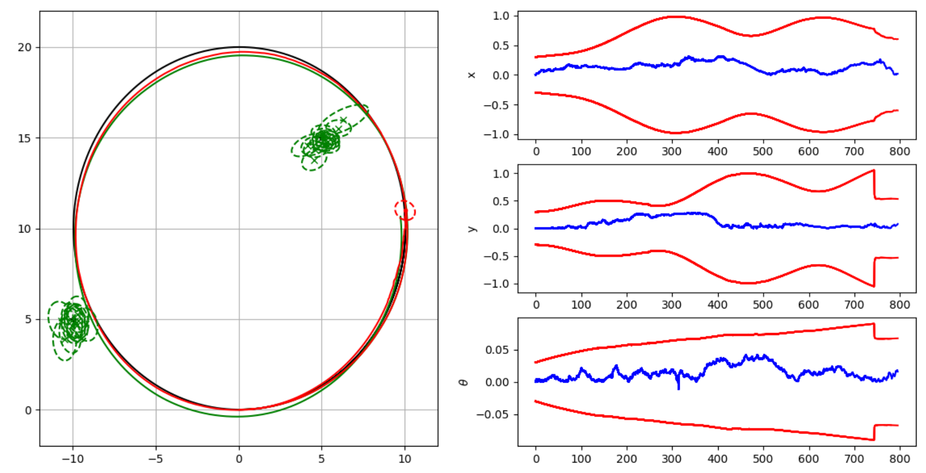


Mean (var) translation error : 6.035280e-01 (1.171333e-01)
Mean (var) rotation error : 2.022804e-02 (2.017402e-04)

Comparing the results with Q1, we can find that, without true landmark ids, the algorithm need to search the landmark and estimate their positions. The estimated results contain more uncertainty and the error of the trajectory is high. When comparing the loops with different number of landmarks, the loop with few landmarks results in big covariance for landmark estimation and also causes a larger error.

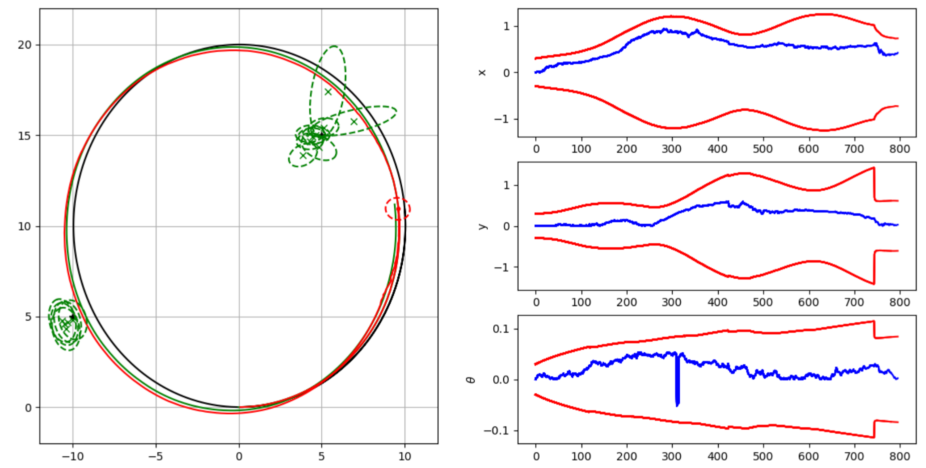
Q3

Smaller (0.5*)



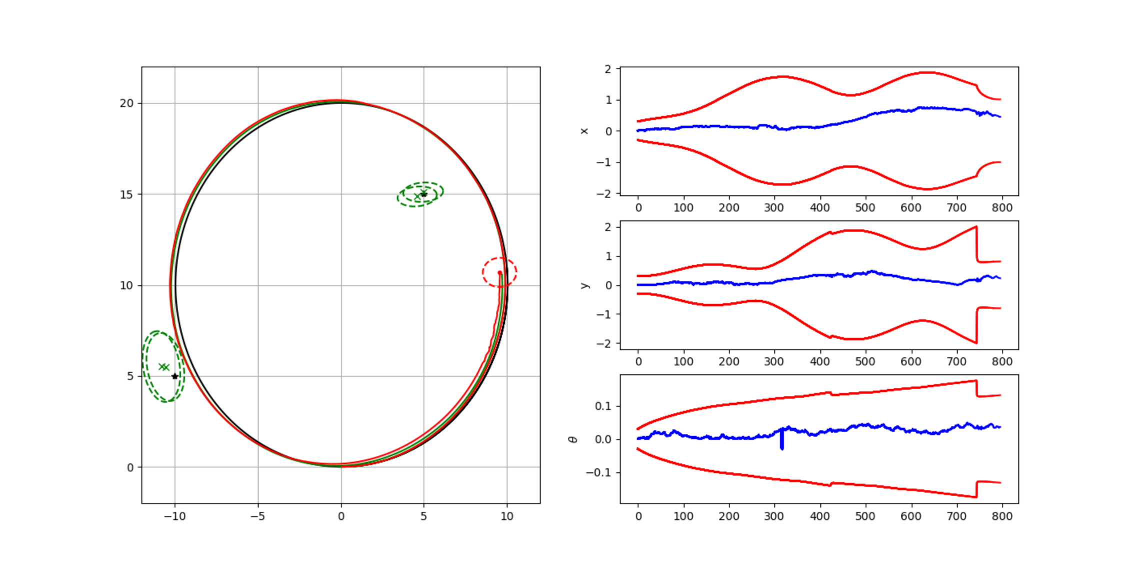
Mean (var) translation error : 1.755585e-01 (1.038556e-02)
Mean (var) rotation error : 1.446177e-02 (1.098320e-04)

Equal



Mean (var) translation error : 6.049365e-01 (6.421971e-02)
Mean (var) rotation error : 2.165627e-02 (2.483051e-04)

Larger (2*)



Mean (var) translation error : 3.845888e-01 (6.434715e-02)
Mean (var) rotation error : 2.113269e-02 (1.732483e-04)

With less noise (case Smaller), which means more accurate input and measurement, the mean translation and rotation error of the total estimation is small. From visual inspection, we can also find that less noise results in better map quality. Comparing the estimation of landmarks in above three cases, case Smaller shows the less covariance of noise in estimation which means less uncertainty.

Comparing the error maps, we can see that with less noise, the error value and corresponding variance are smaller.

Q4

When we use the bearing only SLAM, we could not measure the distance between the current point and the landmarks within range. Without the position of landmarks, we can not correct the measurements during the EKF pipeline. This paper proposed a bearing only method to estimate the position of landmarks by multiple observation.

- Firstly, it assumes that the landmark is in the range from S_{min} to S_{max}, at orientation α (known)
- Then, it generate a Gaussian distribution to describe the position of landmark.
- With a distribution, it produces multiple positions of the landmark.
- Go to next point and observe the landmark, repeat the above steps.
- Finally, sum the distributions and find the point with maximum probability as the landmark.

Unfortunately, I didn't implement the code.