NTNU
Kunnskap for en bedre verden

DEPARTMENT OF MARINE TECHNOLOGY (MSMIR)

TTK4250 - SENSOR FUSION

Guided Assignment 2: Report

Authors :
Madhushree Sannigrahi (Student Number: 128570)
Abhimanyu Bhowmik (Student Number: 128581)

October 2024

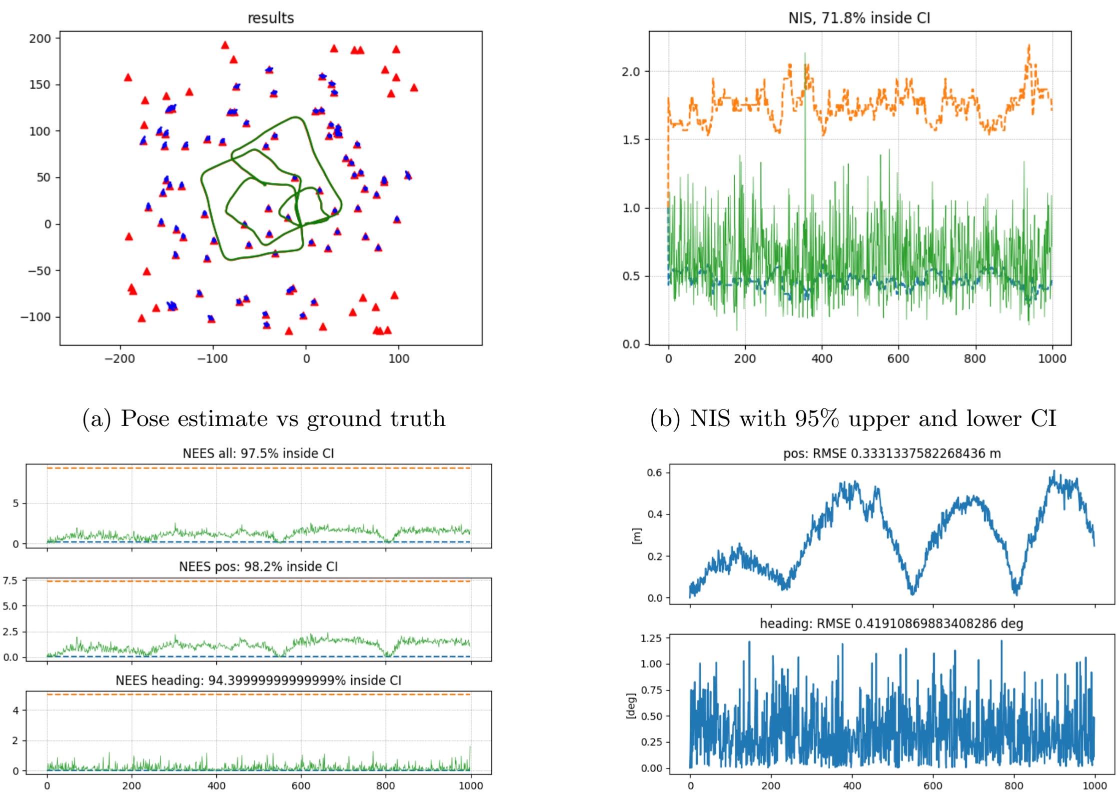
1 Task 2: EKF SLAM on Simulated Data

To begin with the simulated data, the initial tuning values provided to us were quite good. as can be seen in Figure 1. We have 3 parameters to tune, namely Q (process noise), R (measurement noise), and α (JCBB parameter).

$$Q = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 3.046 \times 10^{-4} \end{bmatrix}, R = \begin{bmatrix} 0.01 & 0 \\ 0 & 3.046 \times 10^{-4} \end{bmatrix}, \alpha = \begin{bmatrix} 0.001 \\ 0.0001 \end{bmatrix}$$

The EKFSLAM was tested on the simulated data for 1000 iterations to analyze its performance under different values of tuning parameters. Higher process noise values indicate more uncertainty about how the robot transitions between states. Higher values of measurement noise indicate a lower trust in sensor accuracy, leading the filter to weigh the prediction (from the motion model) more heavily than sensor observations Brekke 2024.

JCBB α are threshold values for the Joint Compatibility Branch and Bound algorithm for data association. This affects how the EKF decides if a detected landmark matches a known landmark. Higher α values lead to a lenient matching criterion, increasing the risk of wrong associations. On the other hand, lower α values enforce stricter compatibility, reducing the chance of matching the wrong landmark and potentially rejecting true matches.



(a) Pose estimate vs ground truth

(b) NIS with 95% upper and lower CI

(c) NEES all, NEES pose, NEES heading

(d) RMSE values for pose and heading

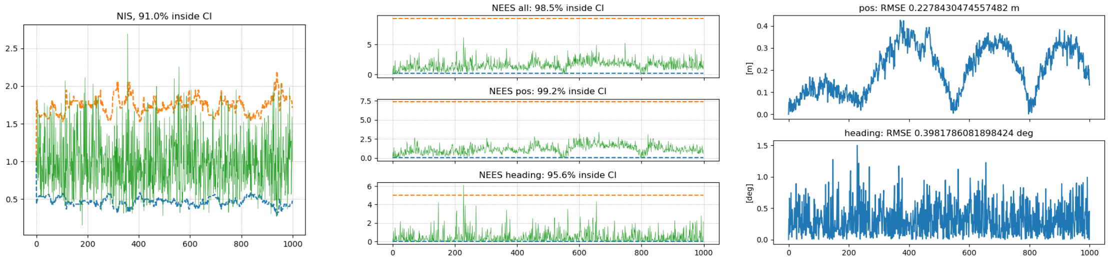
Figure 1: Results with the initial tuning values for Reference

1.1 Case 1: Best-Case Scenario

The EKF performs well when Q and R accurately reflect the uncertainties. As it is simulated data, the uncertainties of both motion and measurements are generally lower than that of real-world data. Also, we can see with the initial data, that the system is underconfident (fig. 5(b)). Thus we lowered the noise values as:

$$Q = \begin{bmatrix} 0.0025 & 0 & 0 \\ 0 & 0.0025 & 0 \\ 0 & 0 & 7.569 \times 10^{-6} \end{bmatrix}, R = \begin{bmatrix} 0.0049 & 0 \\ 0 & 2.4649 \times 10^{-4} \end{bmatrix}, \alpha = \begin{bmatrix} 1 \times 10^{-4} \\ 1 \times 10^{-5} \end{bmatrix}$$

In this case, we reduced both, the process and measurement noise which makes the EKF more confident in the motion model and sensor readings. This helps in achieving better consistency and lower error, as seen in the NIS and NEES graphs in Figure 2(a) and (b). A lower α value was used, which led to fewer incorrect landmark associations, which might have contributed to better NIS and NEES values. We reduced the variance of the heading angle more than the position, leading to a better orientation estimate as seen in Figure 2(c). The overall lower RMSE value shows that the tracking error is very low and the filter performed well in this case.



(a) NIS with 95% upper and lower CI (b) NEES all, NEES pose, NEES heading (c) RMSE values for pose and heading

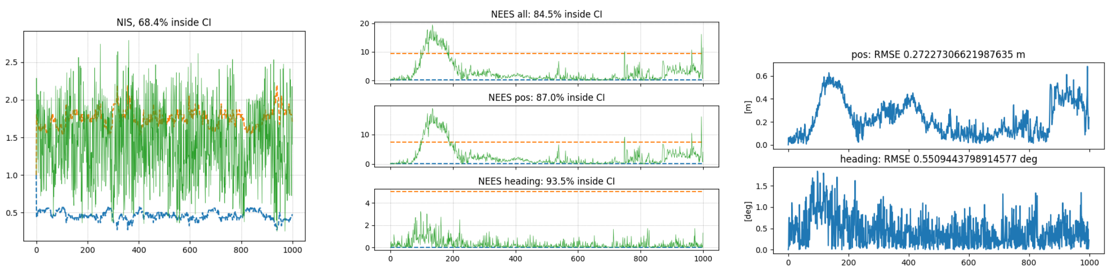
Figure 2: Results with Case 1 on Simulated Dataset

1.2 Case 2: Similar Error with Bad Consistency

In this case, we took the tuning parameters similar to the initial values, slightly reducing the measurement model noise.

$$Q = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 3.046 \times 10^{-4} \end{bmatrix}, R = \begin{bmatrix} 6.4 \times 10^{-3} & 0 \\ 0 & 7.615 \times 10^{-5} \end{bmatrix}, \alpha = \begin{bmatrix} 0.001 \\ 0.0001 \end{bmatrix}$$

This made the system more reliant on the sensor readings and considered them accurate, thus causing the filter to give an overconfident position estimate as can be seen in graph 3(a) and table 1. The unexpectedly lower ANEES suggests that the filter might be underconfident in the heading. This is because the EKF trusts the heading measurements less as R has relatively higher bearing noise than position noise.



(a) NIS with 95% upper and lower CI (b) NEES all, NEES pose, NEES heading (c) RMSE values for pose and heading

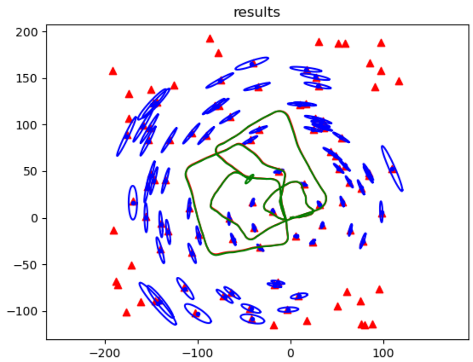
Figure 3: Results with Case 2 on Simulated Dataset

Consequently, the RMSE graph (3 (c)) shows a higher heading error than the position, suggesting that the orientation is more prone to drift. Only 68.4% of innovations inside the confidence interval (CI) (3 (a)) indicates that the filter's innovation predictions are not fully consistent with the actual measurements.

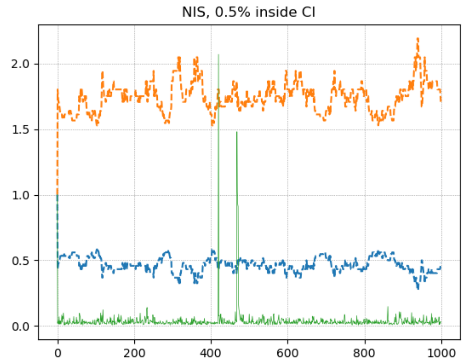
1.3 Case 3: Extreme case scenario

In this case, our goal was to reduce the number of detected landmarks in the map. To achieve this, we increased the noise covariance R so that the EKF would have less trust in the measurement.

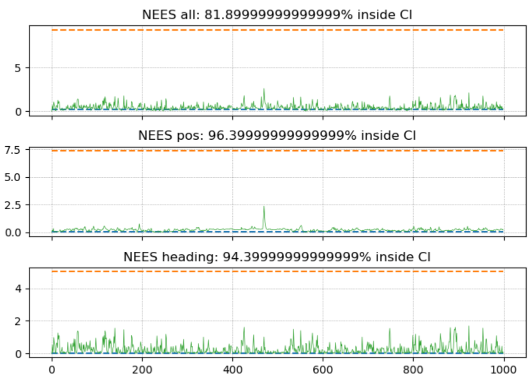
$$Q = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 3.046 \times 10^{-4} \end{bmatrix}, R = \begin{bmatrix} 1.0 & 0 \\ 0 & 0.0109 \end{bmatrix}, \alpha = \begin{bmatrix} 1e-7 \\ 1e-8 \end{bmatrix}$$



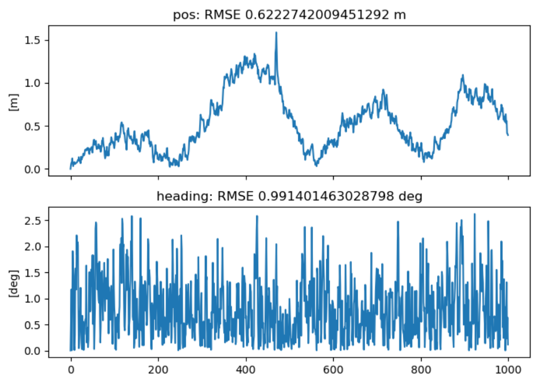
(a) Pose estimate vs ground truth



(b) NIS with 95% upper and lower CI



(c) NEES all, NEES pose, NEES heading



(d) RMSE values for pose and heading

Figure 4: Results with Case 3 on Simulated Dataset

Then we tried to lower the JCBB α values. If the JCBB α values are set lower, only the most confident landmark associations will be made. This adjustment should naturally reduce landmark quantity. However, as we can see in figure 4 (a), the number of landmarks doesn't reduce but we can see the elongated, banana-shaped ellipses which are due to the discrepancy between heading and positional uncertainty. This is more evident for the landmarks that are far from the robot, as orientation errors can distort position estimates over long distances. This increased noise covariance resulted in an extremely underconfident EKF system as can be seen in very low ANEES value in table 1 and in figure 4 (b). However, the NEES graphs in fig 4 (c) are not as bad as the NIS graph in fig 4 (b). This is because the error is not significantly higher, as seen in figure 4 (a), the estimated and true trajectories almost overlap each other with minor shifts where the covariance ellipse of the landmarks are bigger (landmarks are far away from the robot). Similarly, we do not observe a large increase in RMSE values, which again correlate to the localization accuracy of the EKF SLAM.

Table 1: ANEES values for different cases with Simulated data

Case	ANEES all		ANEES pos		ANEES heading	
	Value	CI	Value	CI	Value	CI
Original	1.191	[2.850, 3.154]	1.088	[1.878, 2.126]	0.152	[0.914, 1.090]
Case 1	1.567	[2.850, 3.154]	1.176	[1.878, 2.126]	0.442	[0.914, 1.090]
Case 2	2.879	[2.850, 3.154]	2.644	[1.878, 2.126]	0.290	[0.914, 1.090]
Case 3	0.453	[2.850, 3.154]	0.217	[1.878, 2.126]	0.244	[0.914, 1.090]

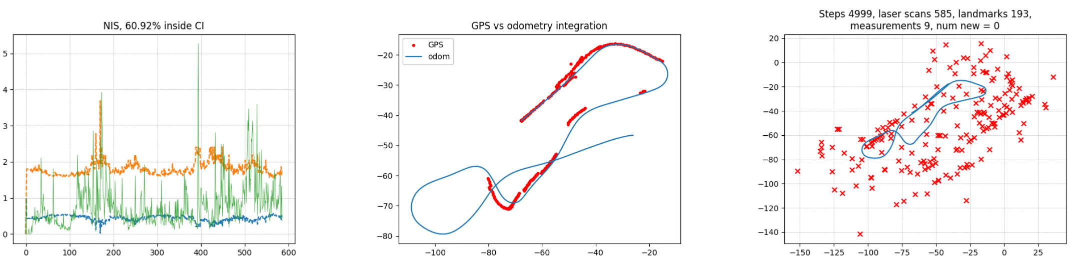
This case highlights the limitations of the EKFSLAM system over this simulated dataset that simply adjusting the measurement noise or JCBB α doesn't sufficiently affect the association threshold to eliminate the less confident landmarks.

2 Task 3: EKF SLAM on Victoria Park dataset

Just like the simulated data, we also got the Victoria Park dataset with good initial tuning values. The initial tuned values were:

$$Q = \begin{bmatrix} 6.25 \times 10^{-12} & 0 & 0 \\ 0 & 1.562 \times 10^{-12} & 2.945 \times 10^{-9} \\ 0 & 2.945 \times 10^{-9} & 6.853 \times 10^{-6} \end{bmatrix}, R = \begin{bmatrix} 0.01 & 0 \\ 0 & 3.0462 \times 10^{-4} \end{bmatrix}, \alpha = \begin{bmatrix} 1 \times 10^{-5} \\ 1 \times 10^{-6} \end{bmatrix}$$

For this project, we only used 5000 iterations to test the performances of the tuning values and the EKF as it was a good balance between runtime and analysis. To evaluate the system consistency, a normalized NIS graph was plotted (figure 5(a)) along with the ANIS, and to make up for the lack of proper GPS data, the estimated trajectory was plotted against the GPS data, which was considered the ground truth (figure 5(b)). The estimated trajectory was also plotted against the detected landmarks showcasing the performance of EKF SLAM (figure 5(c)). Another thing to note is that in areas where GPS measurements were available, we observe that the trajectory with odometry and GPS are almost similar. However, in areas where GPS signals are lost, the trajectories are vastly different. Conversely, the trajectory generated by EKFSLAM in figure 5(c) is almost consistent in places with or without GPS measurements. Thus, we can infer that EKFSLAM is one of the best approaches for GPS-denied environments.



(a) Normalized NIS with 95% upper and lower CI (ANIS = 0.777)

(b) Estimated trajectory (blue) vs GPS (red)

(c) Estimated trajectory (blue) vs landmarks (red)

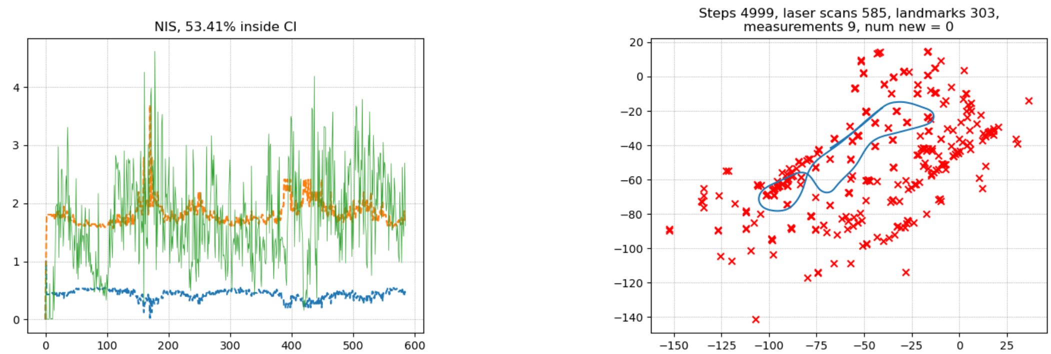
Figure 5: Results with initial tuning parameters for reference

2.1 Case 1: Most detected landmarks

In this case, we reduced the measurement noise quite a lot in comparison to Q and α.

$$Q = \begin{bmatrix} 4.0 \times 10^{-12} & 0 & 0 \\ 0 & 1.0 \times 10^{-12} & 1.396 \times 10^{-9} \\ 0 & 1.396 \times 10^{-9} & 3.046 \times 10^{-6} \end{bmatrix}, R = \begin{bmatrix} 0.0025 & 0 \\ 0 & 7.615 \times 10^{-5} \end{bmatrix}, \alpha = \begin{bmatrix} 5 \times 10^{-6} \\ 5 \times 10^{-7} \end{bmatrix}$$

This has made the system overconfident in the measurement as seen in the normalized NIS graph(6(a)). Reduced measurement noise may also lead to some false detection of landmarks as the EKF places a lot of trust in the measurement. As seen in Figure 6(b), some landmarks appear to have been counted multiple times. The tracking accuracy has also increased a lot as we see in figure (6(b)) that there is almost no gap between the overlapping trajectories in -50 to -75 x-coordinate and -40 to -20 y-coordinate. This is mostly because the duplicate landmarks increased redundancy in the state space, which resulted in more accurate localization in the update step. The unusually high ANIS value of 1.725 also suggests an overconfident system.



(a) Normalized NIS with 95% upper and lower CI (ANIS = 1.725)

(b) Estimated trajectory (blue) vs landmarks (red)

Figure 6: Results with Case 1 on Victoria Park Dataset

Table 2: NIS values for different cases in Victoria Park Dataset

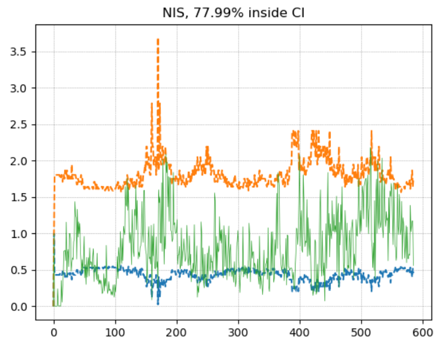
Case	Average NIS	95% CI
Original	0.777	[0.025, 3.689]
Case 1	1.725	[0.025, 3.689]
Case 2	0.815	[0.025, 3.689]
Case 3	0.449	[0.025, 3.689]

2.2 Case 2: Best Consistency

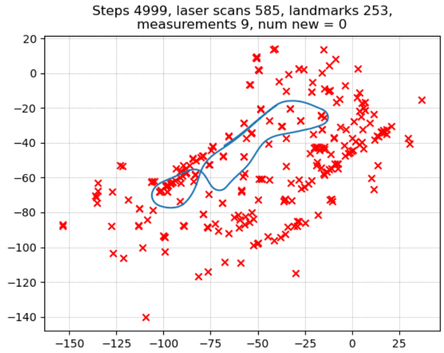
Learning from the previous case, we increased the measurement noise, while also increasing the alpha value to improve the landmark detection to prevent system overconfidence over sensor data.

$$Q = \begin{bmatrix} 3.025 \times 10^{-11} & 0 & 0 \\ 0 & 7.562 \times 10^{-12} & 7.779 \times 10^{-9} \\ 0 & 7.779 \times 10^{-9} & 9.869 \times 10^{-6} \end{bmatrix} R = \begin{bmatrix} 0.0064 & 0 \\ 0 & 0.000225 \end{bmatrix}, \alpha = \begin{bmatrix} 0.01 \\ 0.001 \end{bmatrix}$$

We can see from the graph (7(a)), that the EKF was initially underconfident, which increased over time, resulting in a higher NIS percentage in the confidence interval. This might be due to the presence of fewer landmarks at the beginning. As the vehicle proceeded, more landmarks started appearing, thus increasing the confidence. We can also notice that whenever there is a cluster of duplicate landmarks in figure (7(b)), there is a spike in confidence as seen in the NIS values. As we have increased the α, thus decreasing the landmark threshold, there appears to be some false detection of the landmarks. The tracking accuracy was also better than the initial values, like in the previous case. The ANIS value of 0.815 is slightly higher than the original parameters, which shows overall better confidence in the EKF.



(a) Normalized NIS with 95% upper and lower CI (ANIS = 0.449)



(b) Estimated trajectory (blue) vs landmarks (red)

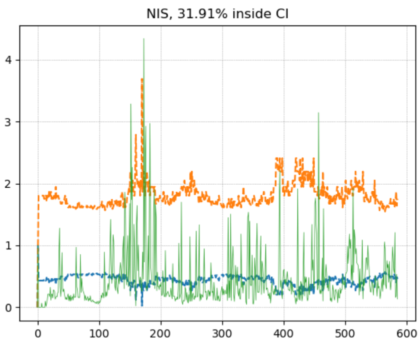
Figure 7: Results with Case 2 on Victoria Park Dataset

2.3 Case 3: Least Landmarks

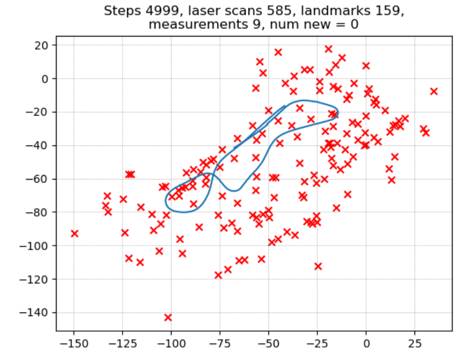
In this case, we increase increased the measurement noise a lot while decreasing the α value. Unlike the simulated case, we can clearly see the reduced number of landmarks in the image 8(b). Higher measurement noise made the system mistrust the sensor data and reduced the correlation between the detected landmarks. While, on the other hand, the high threshold value of the JCBB removed all the less correlated landmark values, making it incredibly difficult for the EKF to detect the landmarks. This resulted in a few landmarks being undetected and a very underconfident filter as portrayed by low ANIS value and the figure 8(a). Consequently, we can also see a wide gap in the overlapping part of the trajectory in figure 8(b), which has widened significantly in comparison to the other cases.

$$Q = \begin{bmatrix} 1.406 \times 10^{-11} & 0 & 0 \\ 0 & 3.062 \times 10^{-12} & 6.047 \times 10^{-9} \\ 0 & 6.047 \times 10^{-9} & 1.218 \times 10^{-5} \end{bmatrix} R = \begin{bmatrix} 0.0225 & 0.0 \\ 0.0 & 1.218 \times 10^{-3} \end{bmatrix}, \alpha = \begin{bmatrix} 5.0 \times 10^{-6} \\ 1.0 \times 10^{-7} \end{bmatrix}$$

With all the above experiments, we observe that any slight change in the measurement noise affects the performance and consistency of the filter a lot. This shows the high sensitivity of EKFSLAM to measurement noise assumptions. This is a problem in real-world scenarios, as we can have not-so-reliable sensors or if the sensor noise changes over time then it will affect our performance a lot. Moreover, in the high measurement noise environments, EKF SLAM's linearization errors become more pronounced especially when combined with associations that the JCBB algorithm might struggle with due to high uncertainty. In our opinion, UKF or other methods which doesn't linearise process and measurement models might be a better solution for those scenarios.



(a) Normalized NIS with 95% upper and lower CI (ANIS = 0.815)



(b) Estimated trajectory (blue) vs landmarks (red)

Figure 8: Results with Case 3 on Victoria Park Datset

Bibliography

Brekke, Edmund (Aug. 2024). *Fundamentals of Sensor Fusion: Target Tracking, Navigation and SLAM*. 5th. Unpublished manuscript.