NTNU
Kunnskap for en bedre verden

Department of Engineering Cybernetics

TTK4250 - Sensor Fusion

Graded Assignment 2

Group 1
Finn Gross Maurer
Magnus Hellebust Haaland
Tarek El-Agroudi

Word count: 1184
November, 2022

1 Simulated data

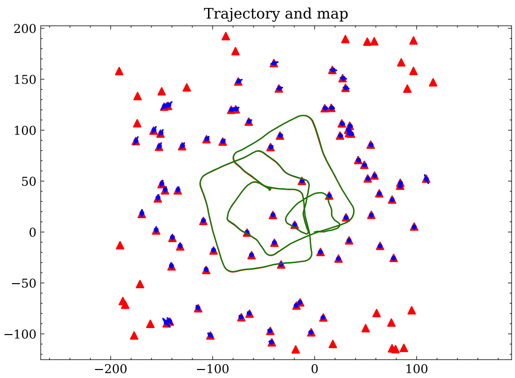

Figure 1: Trajectory and map, default tuning.

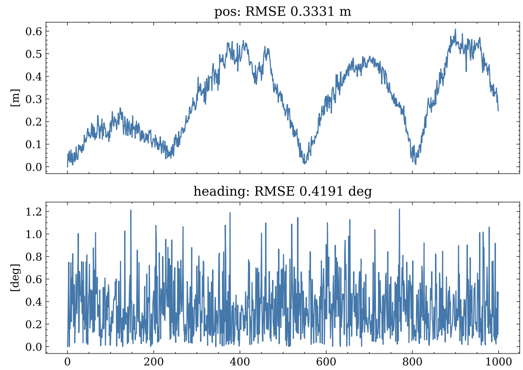

Figure 2: Pose RMSE, default tuning.

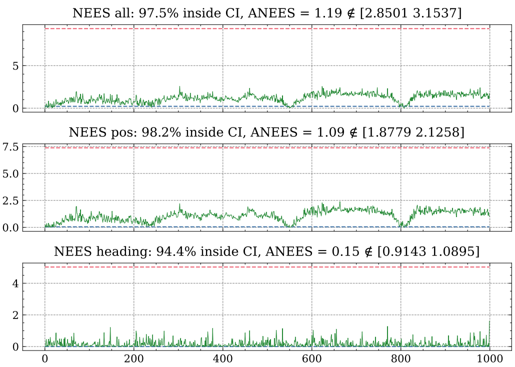

Figure 3: Pose NEES, default tuning.

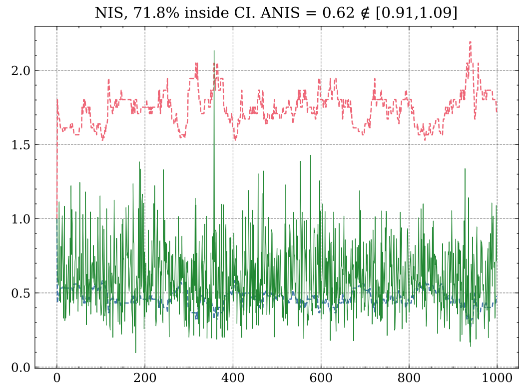

Figure 4: NIS, default tuning.

1.1 An optimal configuration of Q and R

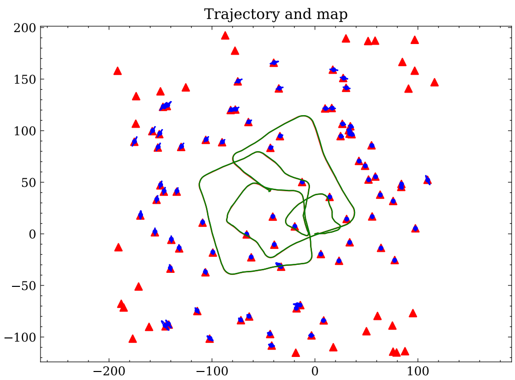

Figure 5: Trajectory and map, ”optimal” tuning.

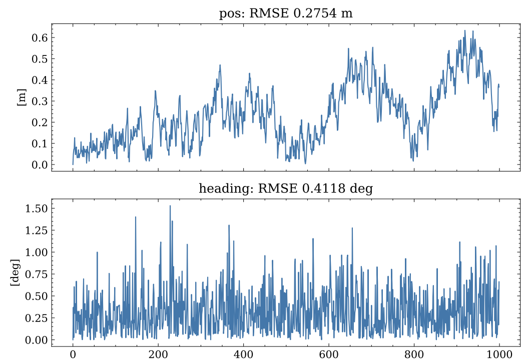

Figure 6: Pose RMSE, ”optimal” tuning.

The initial trajectory and map in figure 1 shows a trajectory that follows the ground truth, as well as landmark estimates that coincide with real landmarks. To point us in the right direction for an “optimal” tuning, the NIS and NEES in figures 3 and 4 indicate that the EKF is slightly underconfident in the model because both the ANEES and ANIS (as well as the curves in general) are below the lower chi squared bounds. Decreasing the process noise Q from $diag([0.1, 0.1, 1\,\text{deg}]^2)$ to $diag([0.017, 0.017, 0.5\,\text{deg}]^2)$ gives the trajectory and NEES in figures 5 and 7. The total ANEES is now roughly in the middle of the χ^2 bounds. Note that while we have here tuned for the pose NEES, this only indirectly tells us something about the consistency of landmark estimates. The latter is better convayed by the NIS, whose increase also reveals better landmark consistency.

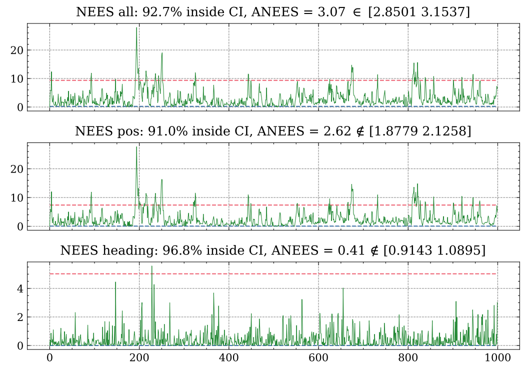

Figure 7: NEES, "optimal" tuning.

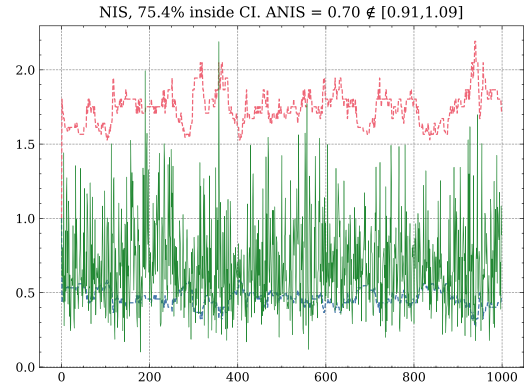

Figure 8: NIS, "optimal" tuning.

In order to have some other metric for optimality, we observe that the position RMSE has decreased from 0.333 in figure 2 to 0.275 in figure 6 , confirming that the results are slightly better.

1.2 Increasing the measurement covariance, landmark "loop closure"

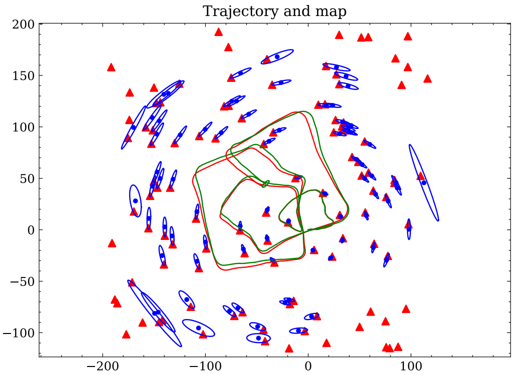

Figure 9: Trajectory and map, R increased by a factor of 10.

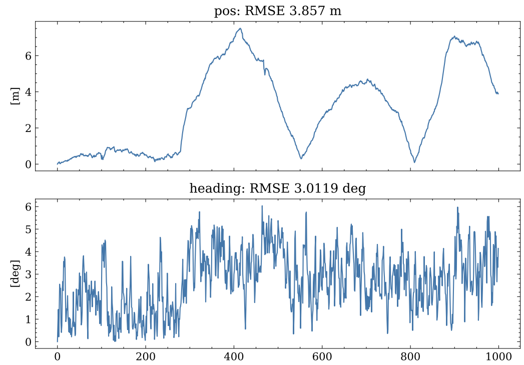

Figure 10: RMSE, R increased by a factor of 10.

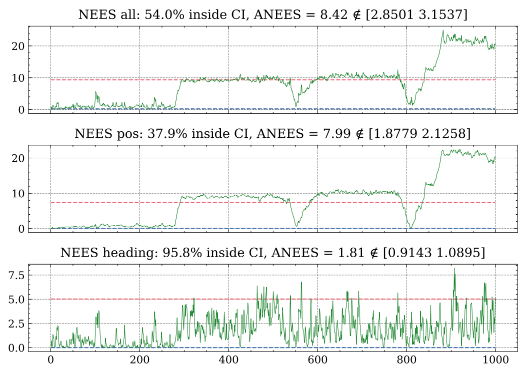

Figure 11: NEES, R increased by a factor of 10.

By increasing the measurement covariance R by a factor 10 we assume worse sensors. The resulting map estimates in figure 9 show correspondingly larger landmark covariances. Furthermore, the increase led to overconfident estimates as can be seen by the increasing NEES in figure 11. Note from this and the increasing RMSE in figure 10 that we experience a drifting position estimate. However, this drift seems to be compensated for at specific points in time, where the RMSE drops. By comparing with the trajectory we suspect that these drops occur when the car returns to a location - or observes landmarks - that it has seen before. It can then update its position accordingly.

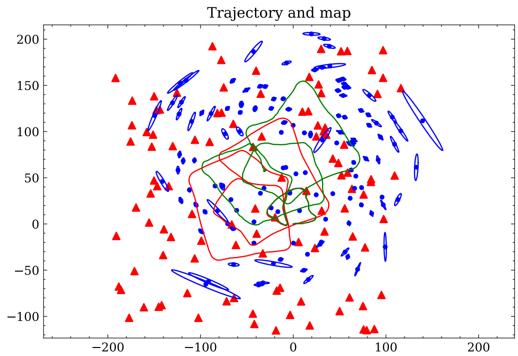

Figure 12: Trajectory and map, R increased by a factor of 10 and Q decreased by a factor of 10.

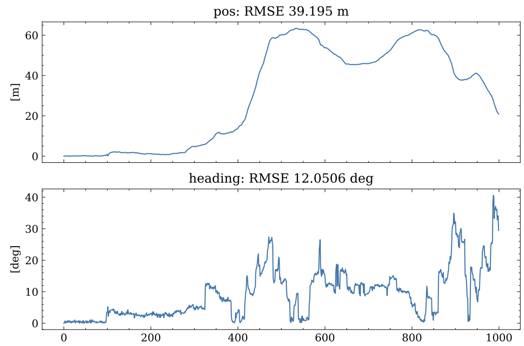

Figure 13: RMSE, R increased by a factor of 10 and Q decreased by a factor of 10.

This landmark "loop closure"[1] does not work unconditionally however. If we further increase overconfidence by decreasing the process noise Q by a factor 10, we get the results in figures 12 and 13. Clearly, we fail dramatically now, as we no longer get significant corrections in the RMSE upon loop closure. This is likely because we now have drifted so much that measurements from a previous location are associated with different landmarks upon seeing them again, thus preventing the position correction.

1.3 Tuning the JCBB compatability thresholds

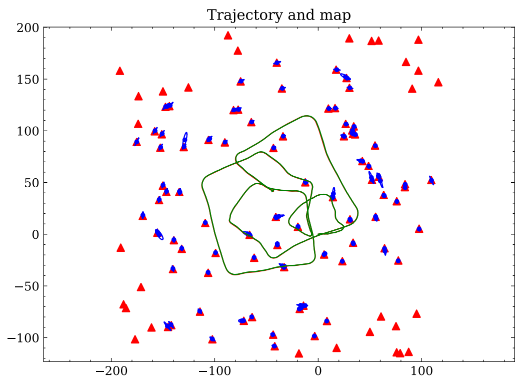

Figure 14: Trajectory and map, JCBB alphas increased by a factor of 200.

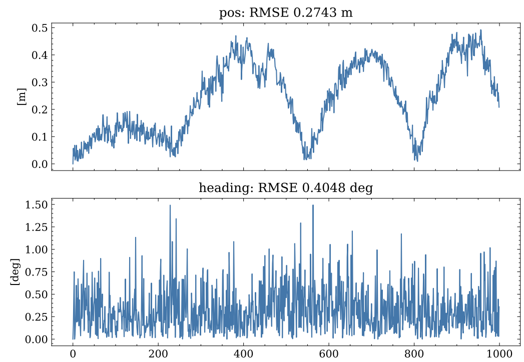

Figure 15: RMSE, JCBB alphas increased by a factor of 200.

Figure 14 shows the trajectory and map for the default tuning with the confidence interval threshold for both individual and joint compatibility increased by a factor of 200. Because of a much higher requirement for individual compatibility, the probability that a measurement is mapped to a landmark in the first place is reduced. Furthermore, for each individually compatible landmark, the probability of returning a jointly compatible association is reduced. Both effects lead to the creation of new landmarks as opposed to mapping to existing ones.

[1]Not to be confused with active loop closure, where the estimates are warped to fit the re-observation of landmarks

Surprisingly enough, the increase in compatibility thresholds did not change the performance in terms of pose RMSE significantly. However, the clear under-association leads to an erroneous map estimate, which shows the importance of giving the associations enough "leeway" to account for measurement noise.

One might expect an opposite perturbation of the confidence thresholds to yield a case of over-association, i.e. that measurements are associated to the same landmark when they originate from separate landmarks. This does not occur because of the "at-most-one" assumption, which ensures that measurements in the same time step cannot be associated to the same landmark. This may become a shortcoming of the algorithm if the point-landmark assumption fails to hold, as we here likely will get multiple different measurements from the same landmark.

As a final note, we observed significant increases in simulation time for both the case of increased and decreased thresholds. In the former case, we sacrifice performance due to the creation of new landmarks and the eventual explosion of the state space dimension. In the latter case, we lose performance because the algorithm considers virtually all landmarks for each measurement.

2 Real data

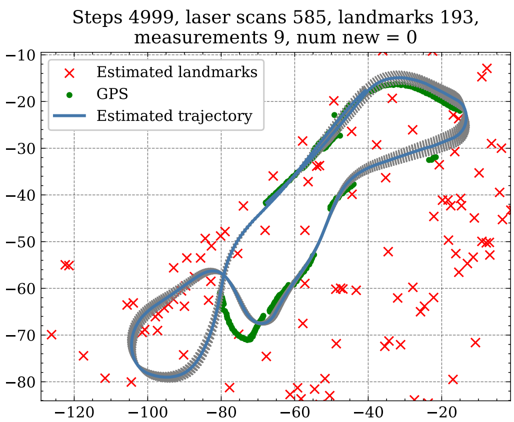

Figure 16: Trajectory and map, default tuning.

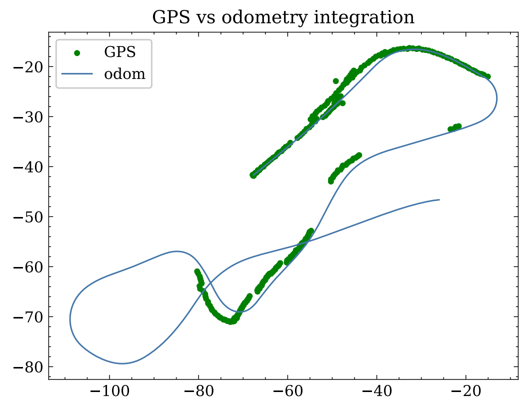

Figure 17: GPS vs pure odometry integration, default tuning.

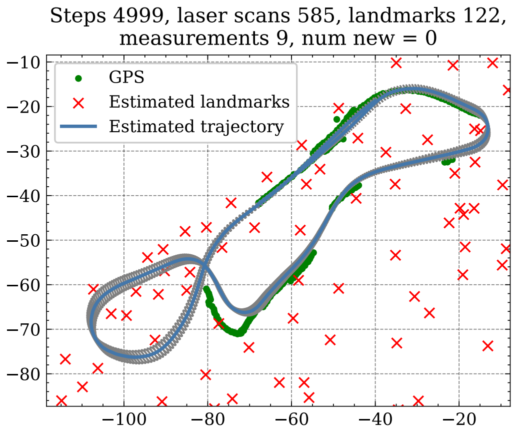

Figure 18: Trajectory and map, "optimal" GPS consistency tuning.

2.1 Drift and tuning GPS consistency

In figure 16, we have plotted the default parameter trajectory with both the covariance ellipses and GPS measurements overlayed. We immediately observe a drift between the position estimates and the GPS measurements. While this drift becomes quite significant during the middle of the trajectory, the "loop closure" landmark corrections reduces the error towards the end of the trajectory, which is reflected in the smaller covariance ellipses. Comparing with the pure odometry dead reckoning in figure 17, we see that although dead reckoning actually is better initially, it drifts quite a lot during the bottom left loop, showing the need for landmark corrections.

The covariance ellipses indicate another problem, namely that the estimates are *inconsistent* with the GPS measurements, which can be considered to roughly represent a ground truth. In an attempt to tune for consistency as well as less drift initially we decrease the process noise Q by a factor of 10 and increase the measurement noises by a factor of 4, yielding the results in figure 18. The initial drift is now reduced and the covariance ellipses more often cover the GPS measurements indicating improved consistency. Note furthermore that the number of landmarks estimated has decreased from 193 to 122. This occurs because the normalised landmark innovation depends on Q and R, and the more even spacing of trees could seem more realistic than the cliques observed in the default case.

The drift highlights a significant problem with this EKF-SLAM, namely that we only use landmark measurements to correct the position while the prediction is pure dead reckoning from encoder and steering angle measurements. If we in addition used GPS measurements to correct the position estimates - aided SLAM - we could account for much of the drift [1].

2.2 JCBB compatibility thresholds

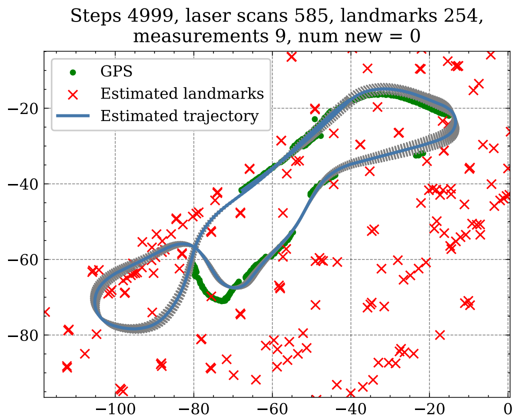

Figure 19: Trajectory and map, increased JCBB alphas.

Another difference from the simulated case is that we now have real landmarks. Factors like multiple measurements from the same landmark as well as the possibility of clutter could mean that we should be more stringent in creating new landmarks, as to not increase the state space dimension too much. Increasing the individual and joint alphas from 1×10^{-4} and 1×10^{-6} to 1×10^{-1} and 1×10^{-2}, respectively, gives the results in figure 19. We observe a significant increase in the number of landmarks which may be unrealistic from domain knowledge (trees in the Victoria desert park are not that densely distributed [2]).

Note that, without prior knowledge or some ground truth on landmarks, we have little way of knowing if we are estimating too many landmarks! One could however postulate that an increase in running time per iteration indicates either under or over-association, and could tune the JCBB alphas based on this.

2.3 Tuning after experimental NIS

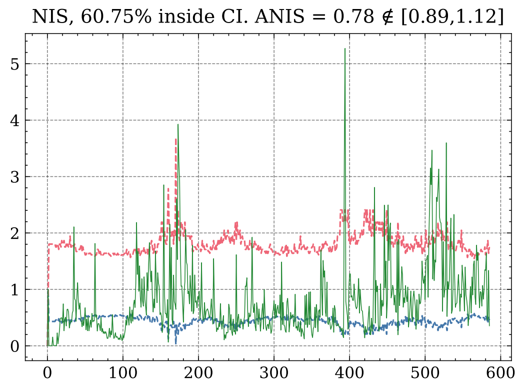

Figure 20: NIS, default tuning.

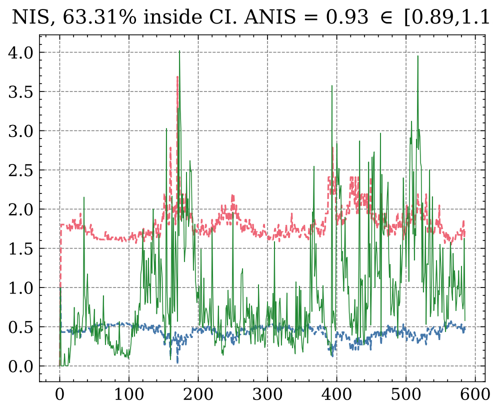

Figure 21: NIS, "optimal" NIS tuning.

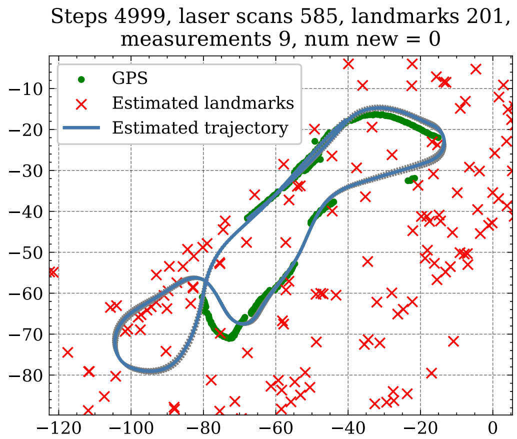

Figure 22: Trajectory and map, "optimal" NIS tuning.

Since the GPS is quite unstable and we cannot always analyse consistency in terms of it, we study the NIS in figure 20. Being slightly on the lower side, we decrease the process noise Q by a factor 5 and get the results in figures 21 and 22. The resulting NIS is higher overall indicating better consistency. Note especially how it is larger towards the end of the trajectory, where we in section 2.1 discovered that the odometry had drifted the most. The spikes in the NIS likely coincide with landmark observations far from the estimates, demonstrating again the drift of EKF-SLAM in between landmark corrections.

This must not be exaggerated, as too much trust in the odometry integration approaches the highly sub-optimal dead reckoning results from figure 17.

Bibliography

[1] Edmund Brekke. *Fundamentals of Sensor Fusion*. 3rd ed. 2022.

[2] *Victoria Park*. http://www-personal.acfr.usyd.edu.au/nebot/victoria_park.htm. Accessed: 2022-11-13.