Localisation and Mapping Assignment Report

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I. Introduction

This report presents the outcomes of the Localisation and Mapping assignment for the Advanced Vision for Localisation and Mapping module.

II. Task 1: Robot Control

- **Requirements:** Implement a closed-loop ROS/MATLAB controller to explore at least 50% of the environment without collisions and provide a ground-truth path figure.
- **Reflection:** Achieved 100% coverage without collisions but found tuning the forward and centring gains challenging, causing small oscillations at the center turns (around markers 3 and 7).
- **Achievements & Challenges:** Successfully navigated the maze collision-free; required a 0.1 m hysteresis to stabilise the controller at sharp turns. Robot path is shown in Figure 1.

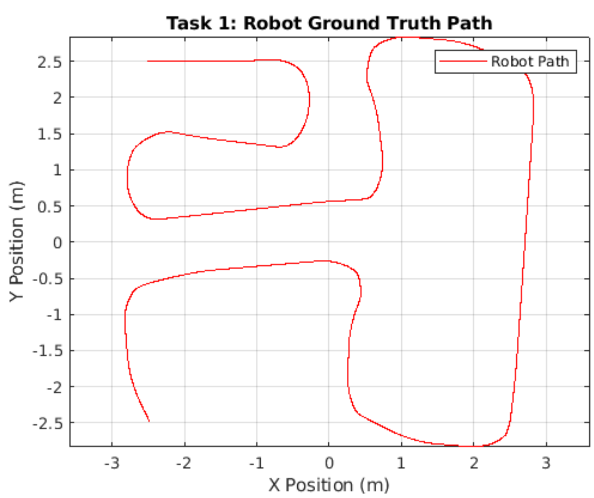

Fig. 1: Ground truth path of the robot exploring the environment.

III. Task 2: Motion Model

- **Requirements:** Generate a noisy pose estimate using a velocity motion model with the given noise parameters and include an overlay figure of ground truth vs noisy path.
- **Reflection:** The motion model effectively captured drift, and repeated runs showed consistent final deviations, highlighting the model's stability yet accumulating error.
- **Achievements & Challenges:** Implemented `sample_velocity_motion_model` correctly and saved outputs in `task2_data.mat`. Robot path is shown in Figure 2.

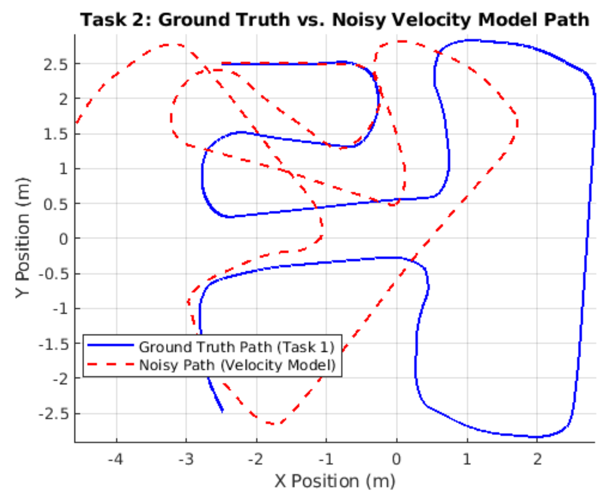

Fig. 2: Overlay of ground truth path (solid blue) and noisy pose estimate (dashed red) generated by the velocity motion model.

IV. Task 3: Mapping

- **Requirements:** Build an occupancy grid from ground-truth poses and LiDAR data, plus map ArUco marker positions; include two figures (occupancy grid and ArUco map).
- **Reflection:** The occupancy grid displays walls, produces a little bit of noise at turns; ArUco detections were robust overall but low-angle views of markers 4 and 5 yielded less than 70 observations.
- **Achievements & Challenges:** Packaged all datasets in 'task3_dataset/'; adjusted detection thresholds to balance false negatives and spurious detections but accepted lower sample counts for occluded markers. Occupancy grid is shown in Figure 3. ArUco marker map is shown in Figure 4.

V. Task 4: Extended Kalman Filter Localisation

- **Requirements:** Fuse noisy odometry and known ArUco landmark measurements via an Extended Kalman Filter; provide path overlay and L2-norm error figures.

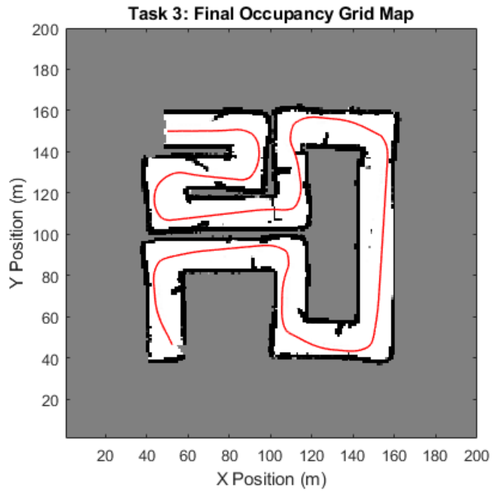

Fig. 3: Occupancy grid map generated from ground truth pose and LiDAR data.

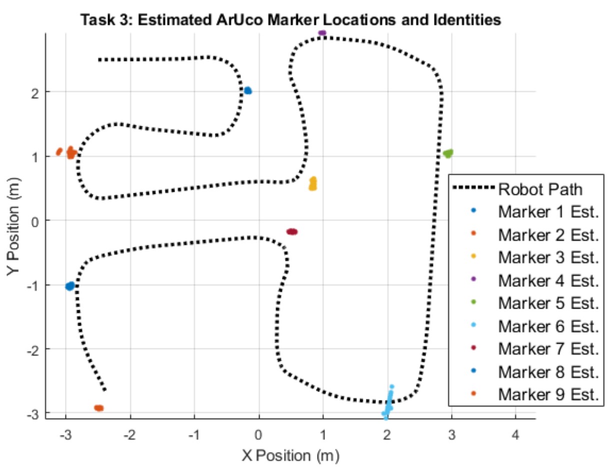

Fig. 4: Estimated ArUco marker locations and identities overlaid on the robot path.

- **Reflection:** EKF successfully mitigated drift overall, but around markers 4-5 low detection counts induced overcorrection in the estimate.
- **Achievements & Challenges:** Derived and validated analytical Jacobians; encountered sensitivity to sparse landmark observations causing occasional jumps in the filter update. Robot path is shown in Figure 5. L2 norm error is shown in Figure 6.

VI. Task 5: Particle Filter Localisation

- **Requirements:** Implement a Particle Filter, and include trajectory and L2-norm error figures.
- **Reflection:** PF matched EKF accuracy but at much longer runtime; reducing from 100 000 to 1 000 or 100 particles increased peak error rapidly.
- **Achievements & Challenges:** Deployed systematic resampling effectively; balanced error vs computational load by benchmarking multiple particle counts. Particle filter path is shown in Figure 7. L2 norm error is shown in Figure 8.

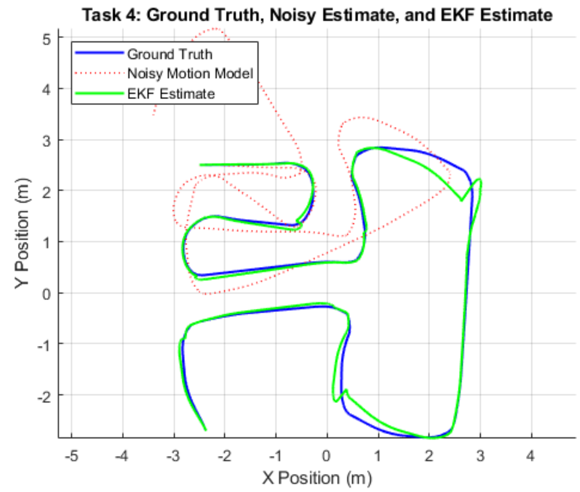

Fig. 5: Ground truth (blue), noisy motion model (red dashed) and EKF estimate (green).

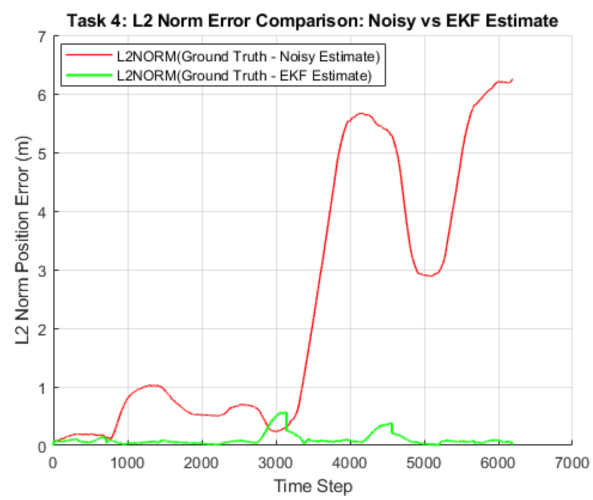

Fig. 6: L2 norm error of noisy estimate (red) vs EKF estimate (green) over time.

VII. Conclusion

The exploration achieved over 100% coverage without collisions, and the mapping pipeline generated occupancy grids and ArUco marker positions. The Extended Kalman Filter minimised the pose error compared to raw odometry, while the Particle Filter offered a very similar performance at the cost of higher computational expense.

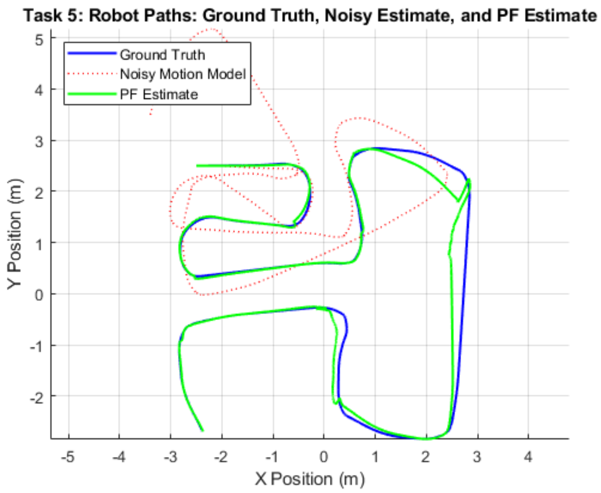

Fig. 7: Particle filter localisation performance compared to ground truth and noisy estimate.

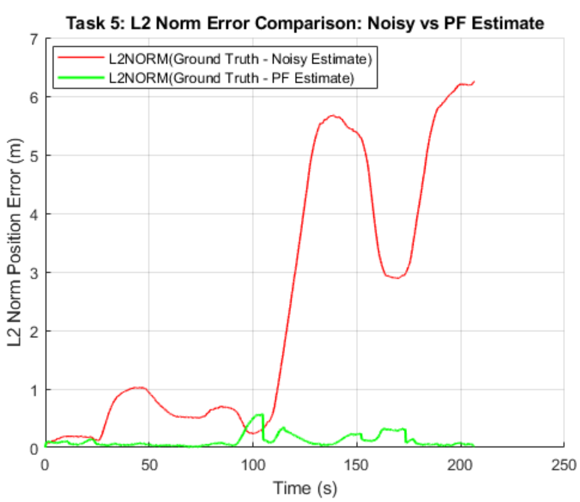

Fig. 8: L2 norm error of noisy estimate (red) vs PF estimate (green) over time.