RnD experiments analysis

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1 Particle Filter Benchmarking: Linear and Rotational Motion Analysis

In this experiment, I conducted analyses comparing the performance of three distinct particle filter algorithms. Specifically, I evaluated AMCL alongside two variants of the optimal particle filter. The first variant involves interpolating 2D lidar data into 3D, while the second directly utilizes 2D lidar data. These experiments were carried out using a TurtleBot3 within a custom environment on ROS Noetic.

The initial experiment was to check the performance of AMCL under default parameters provided by Turtlebot3 package.

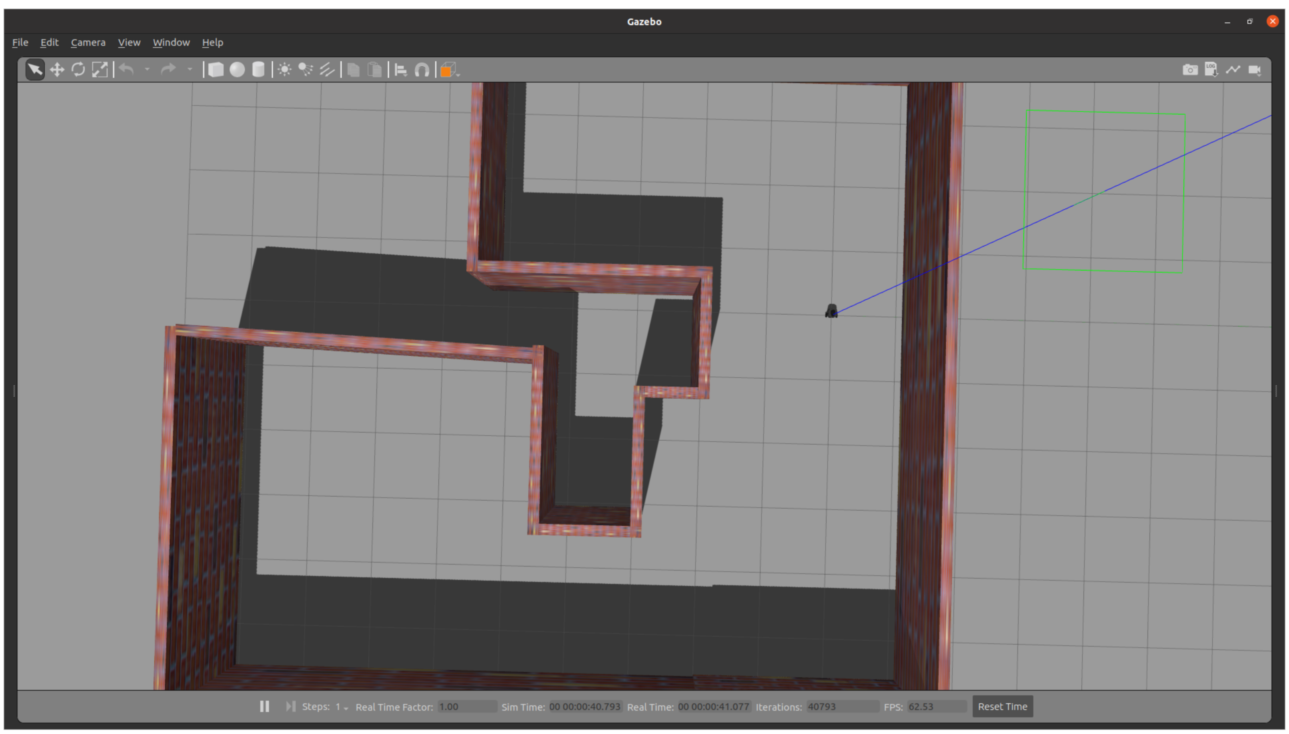

Figure 1: gazebo setup

1. **Linear Motion Accuracy Test:**
   - Turtlebot3 moved linearly along the x-axis with a velocity of 0.22 m/s, covering a distance of approximately 5 meters.
   - Both Odom position and filter position started at (0,0) before the motion.
   - The robot's trajectory during this experiment was a straight line along the x-axis.
   - The experiment was repeated for particle quantities of 1, 3, 50, 100, 250, and 500.
   - Data was collected for the RMSE between Odom and filter positions for each run and an average of the entire run is taken at the end.
   - The same experiment was conducted for two variants of optimal particle filter under similar conditions and the results were plotted.

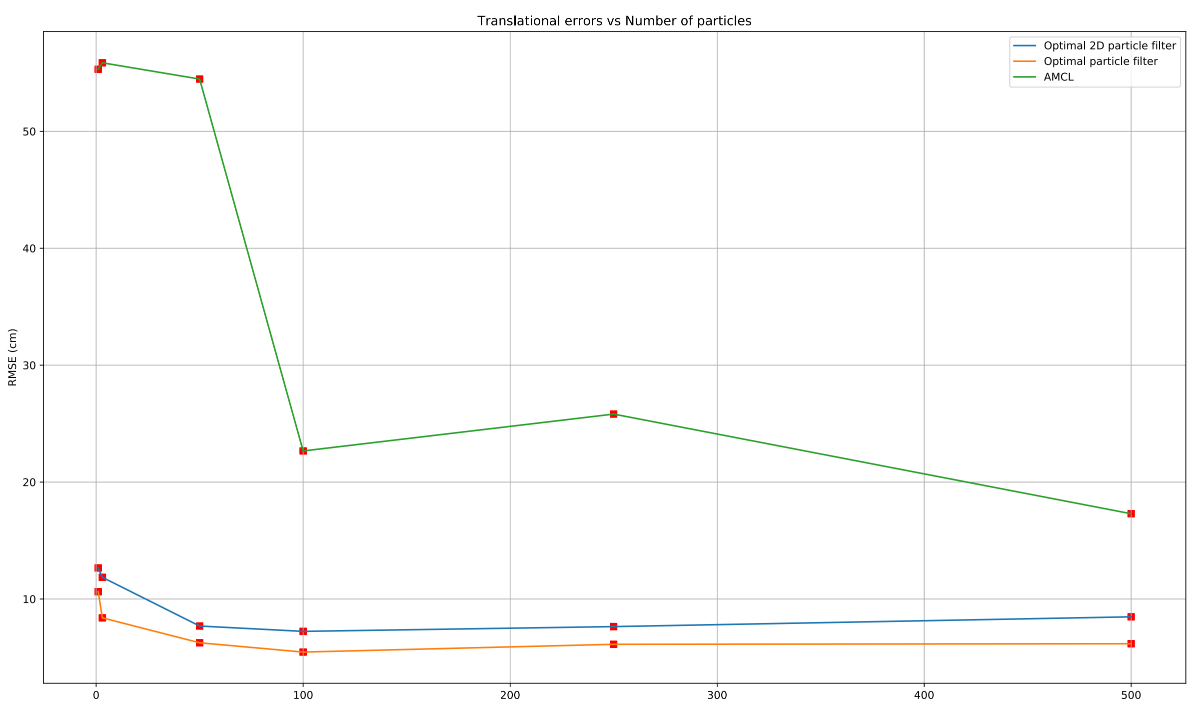

Figure 2: translational error vs number of particles

2. **Rotational Motion Accuracy Test:**

   - Turtlebot3 executed a full circular motion with a constant linear velocity of 0.22 m/s and an angular velocity of -0.5 rad/s.
   - Both Odom position and filter position started at (0,0) before the circular motion.
   - The robot's trajectory during this experiment was a circle.
   - The experiment was repeated for the same particle quantities (1, 3, 50, 100, 250, and 500).
   - Data was collected for the RMSE between Odom and filter positions for each run and an average of the entire run is taken at the end.
   - The same experiment was conducted for two variants of optimal particle filter under similar conditions and the results were plotted.

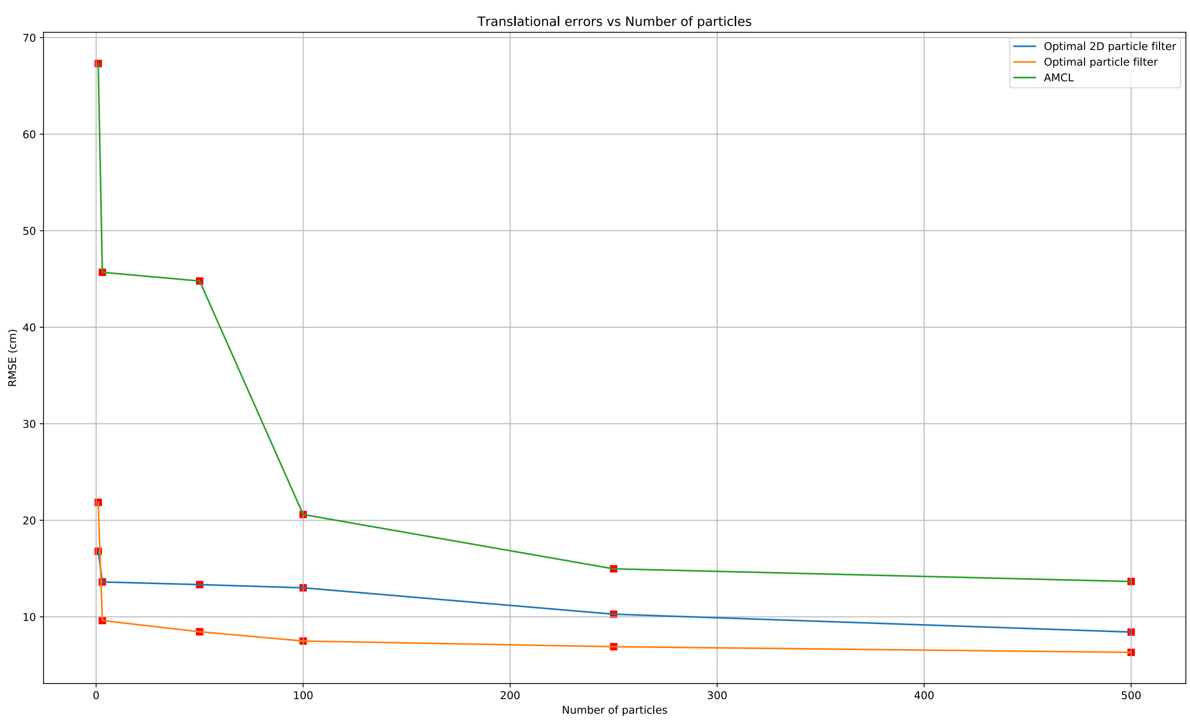

Figure 3: rotational error vs number of particles

3. **Random Motion Accuracy Test:**

   - The Turtlebot3 is subjected to a random motion test with a mix of translational and rotational velocities. Velocities are dynamically determined by a Python code which has predefined velocities.
   - Both Odom position and filter position started at (0,0) before the this motion.
   - The robot's trajectory during this experiment was a mix of translation and rotation.
   - The experiment was repeated for the same particle quantities (1, 3, 50, 100, 250, and 500).
   - Data was collected for the RMSE between Odom and filter positions for each run and an average of the entire run is taken at the end.
   - The same experiment was conducted for two variants of optimal particle filter under similar conditions and the results were plotted.

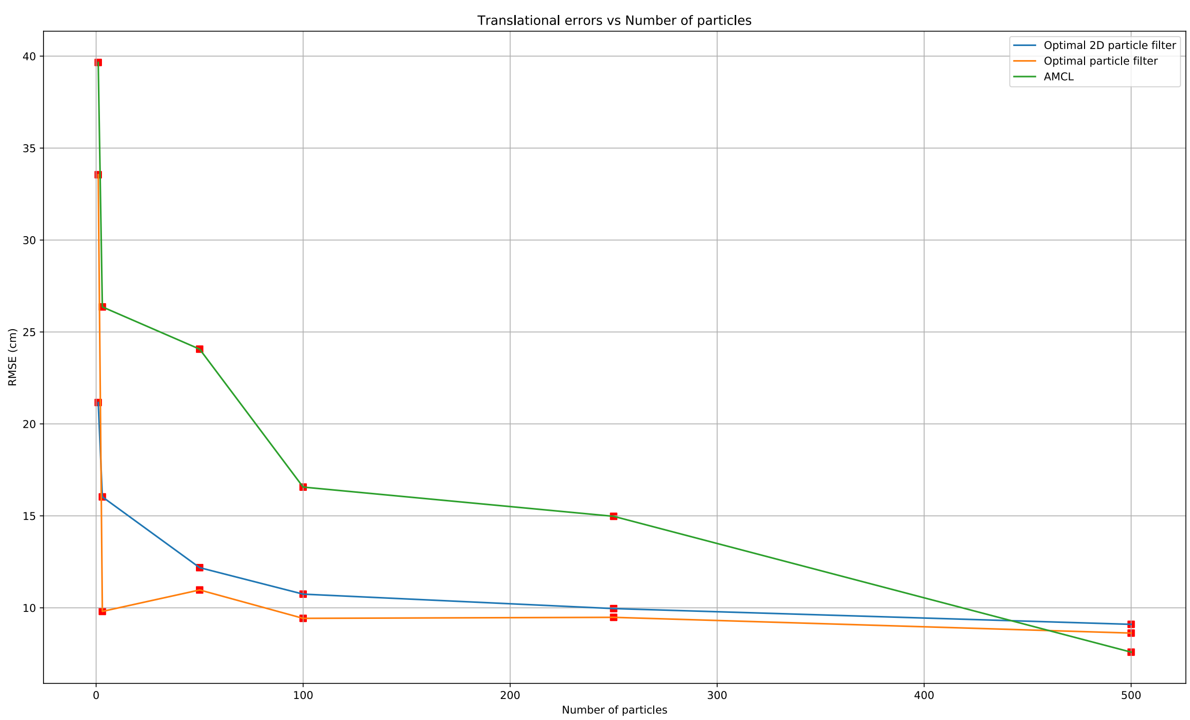

Figure 4: random motion error vs number of particles

In conclusion, the experiment showcased a consistent trend of significantly better accuracy in the optimal particle filter compared to AMCL. Even with fewer particles, such as 1 or 3, the optimal particle filter outperformed AMCL, giving better results compared to the 500 particles in AMCL. This shows optimal particle filter is more efficient, resulting in more accurate localization

2 Dynamic Adaptability of Particle Filter: Adaptive Response to Manual Displacements

In this experiments, With the same setup. I moved the Turtlebot3 manually, lifting the robot and moving along linear x and y axes, and rotational movement. This dynamic scenario aimed to simulate real-world scenarios where the robot encounters robot kidnap problem where the robot is picked and placed at a random position.

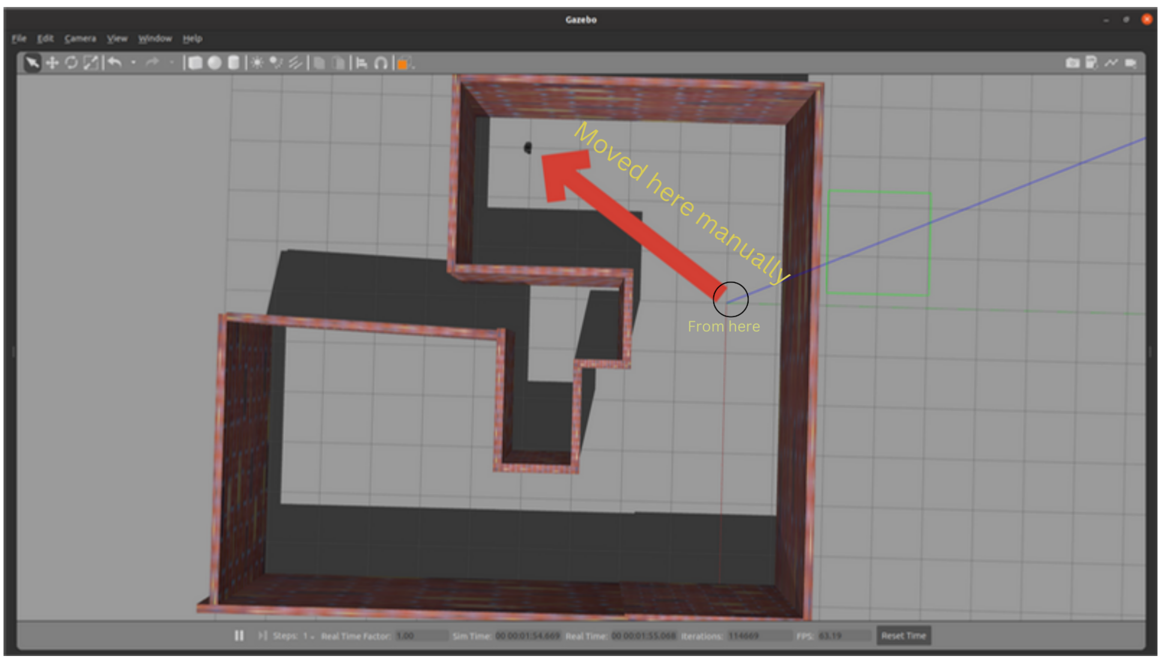

Figure 5: gazebo setup

1. **Linear Motion Accuracy Test:**
   - After manual displacements, an accuracy test for linear motion was performed

- The same experiment as above was done in this experiment and plotted the results for both algorithms

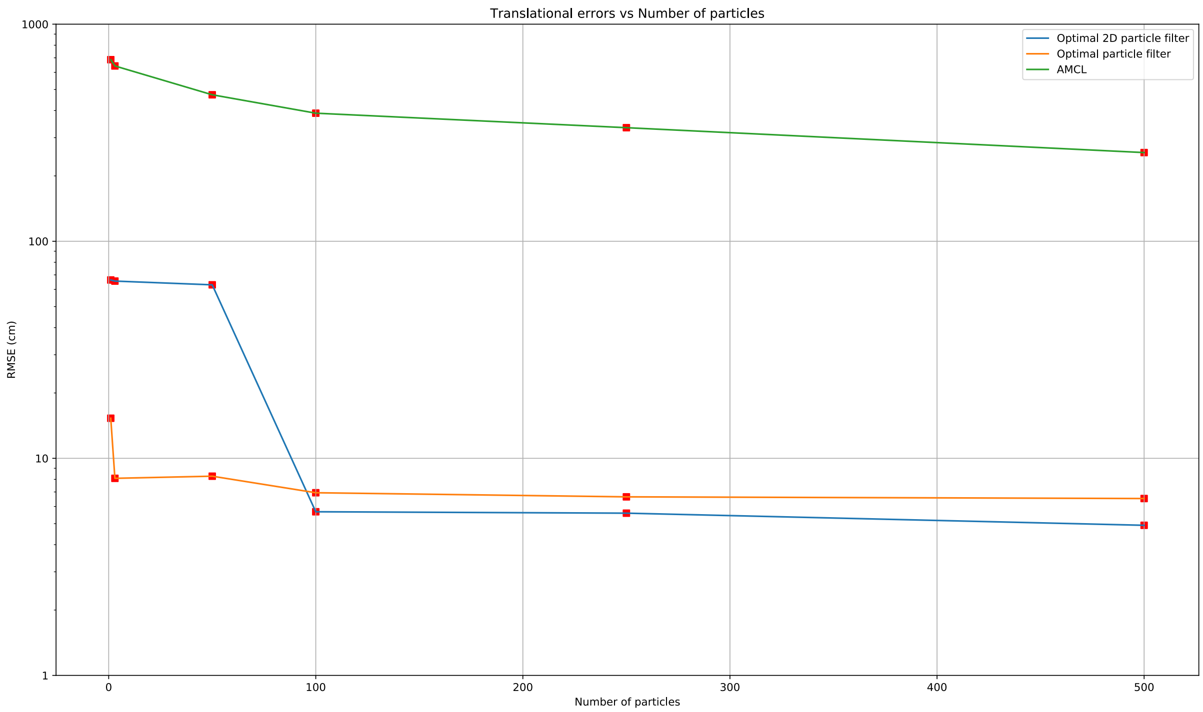

Figure 6: LOG graph of translational error vs number of particles

2. **Rotational Motion Accuracy Test:**
   - After manual displacements, an accuracy test for rotational motion was performed
   - The same experiment as above was done in this experiment and plotted the results for both algorithms

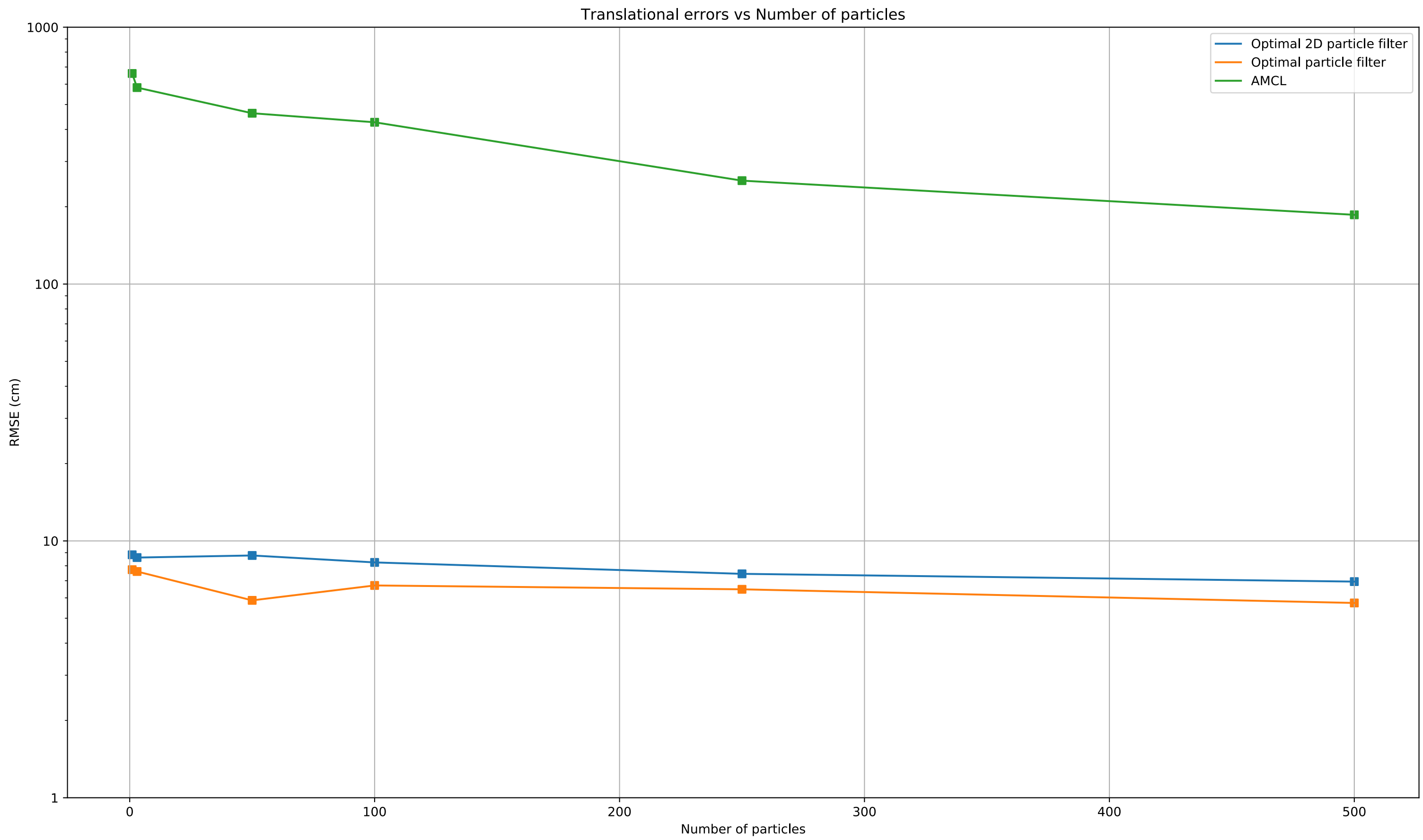

Figure 7: LOG graph of rotational error vs number of particles

3. **Random Motion Accuracy Test:**
   - After manual displacements, an accuracy test for Random motion was performed
   - The same experiment as above was done in this experiment and plotted the results for both algorithms

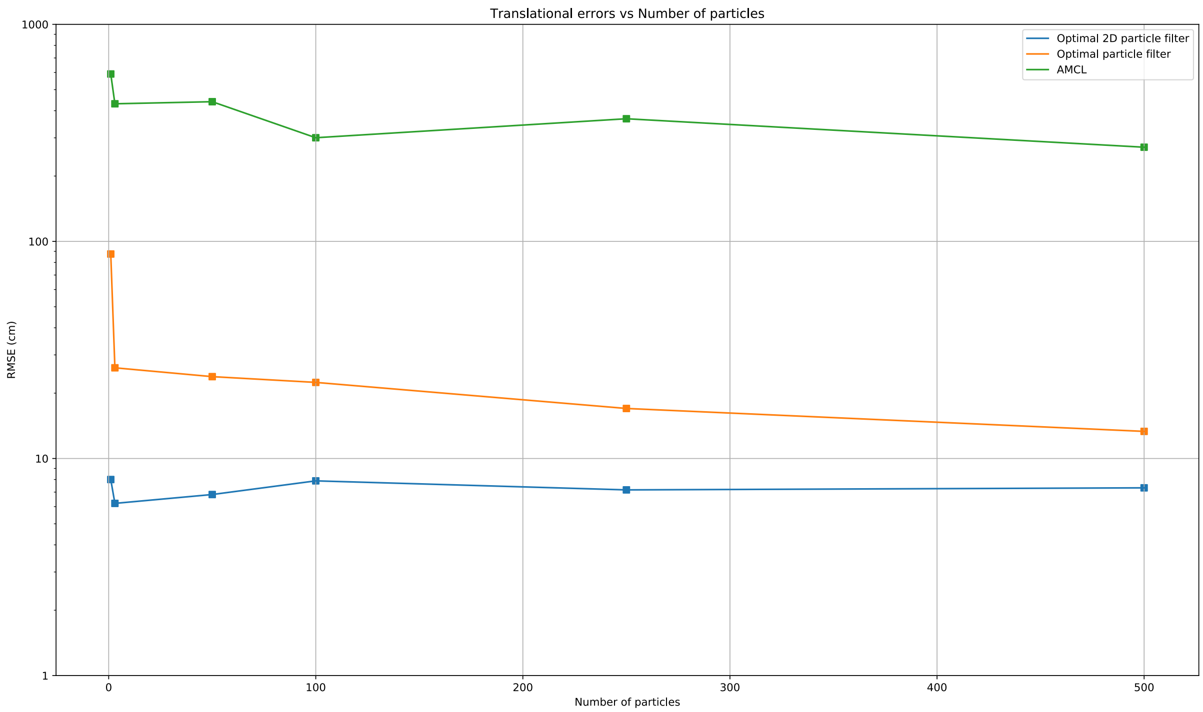

Figure 8: LOG graph of random motion error vs number of particles

4. **Comprehensive Analysis of Particle Filter Performance post Robot Kidnap Scenario:**

   - Conducted extensive analysis after the robot kidnap scenario, plotting individual error values for particles 1, 3, 50, 100, 250, and 500 in each run for both AMCL and Optimal Filter without computing averages.
   - This comprehensive examination provides a detailed insight into the performance of both algorithms across varying particle quantities and how they recover after the robot is placed somewhere else.
   - The plotted results highlight the Optimal Particle Filter's effective recovery post the robot kidnap scenario, in contrast to AMCL, which struggles to regain accurate localization.

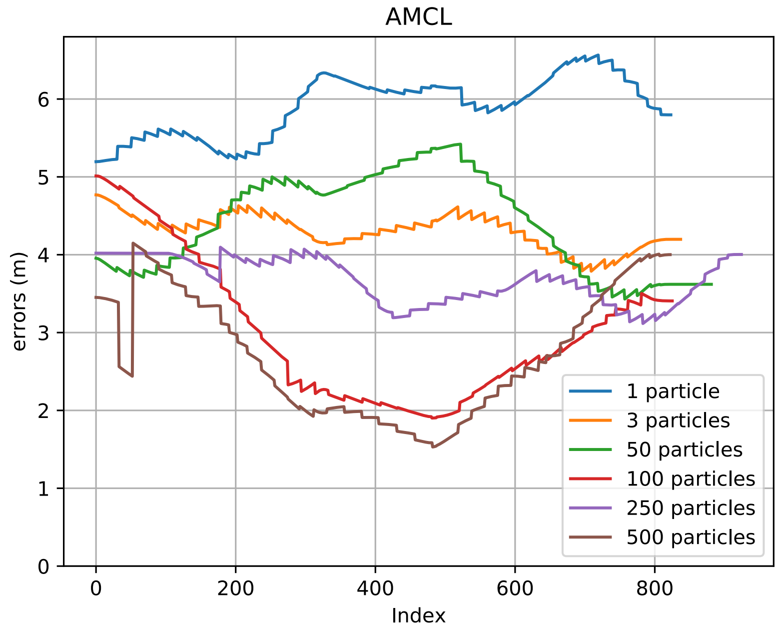

Figure 9: AMCL Errors for Different Particle Quantities

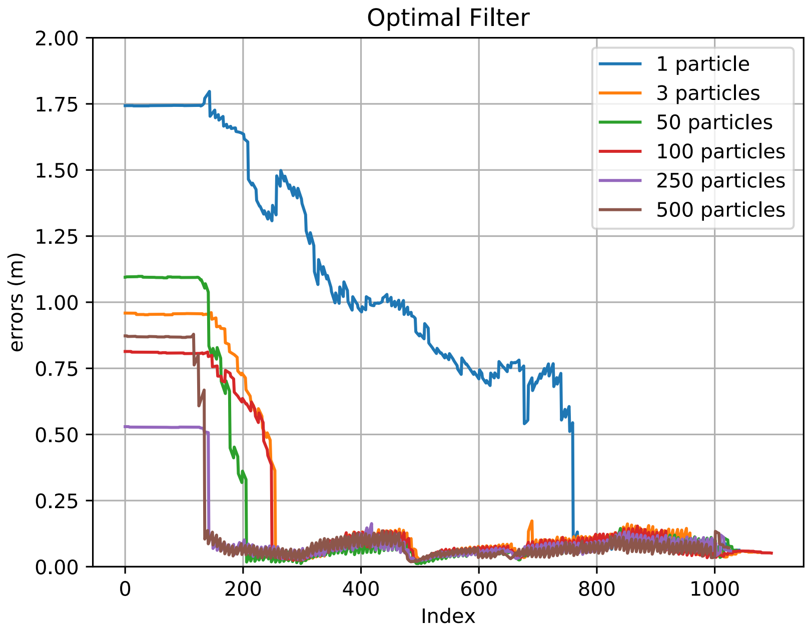

Figure 10: Optimal Filter Errors for Different Particle Quantities

In conclusion, this experiment too showcased a consistent trend of significantly better accuracy in the optimal particle filter compared to AMCL. When faced with a challenging scenario of robot kidnap, where the robot has lifted and placed in different positions, the AMCL algorithm struggled to recover effectively, even with higher particle count of 500. In contrast, the optimal particle filter demonstrated better results, adaptability and efficient localization during the robot kidnap scenario, even with a reduced number of particles. This again shows optimal particle filter is better at handling complex and dynamic situations, highlighting more efficient, resulting in more accurate localization