Creating a Particle Filter in C++

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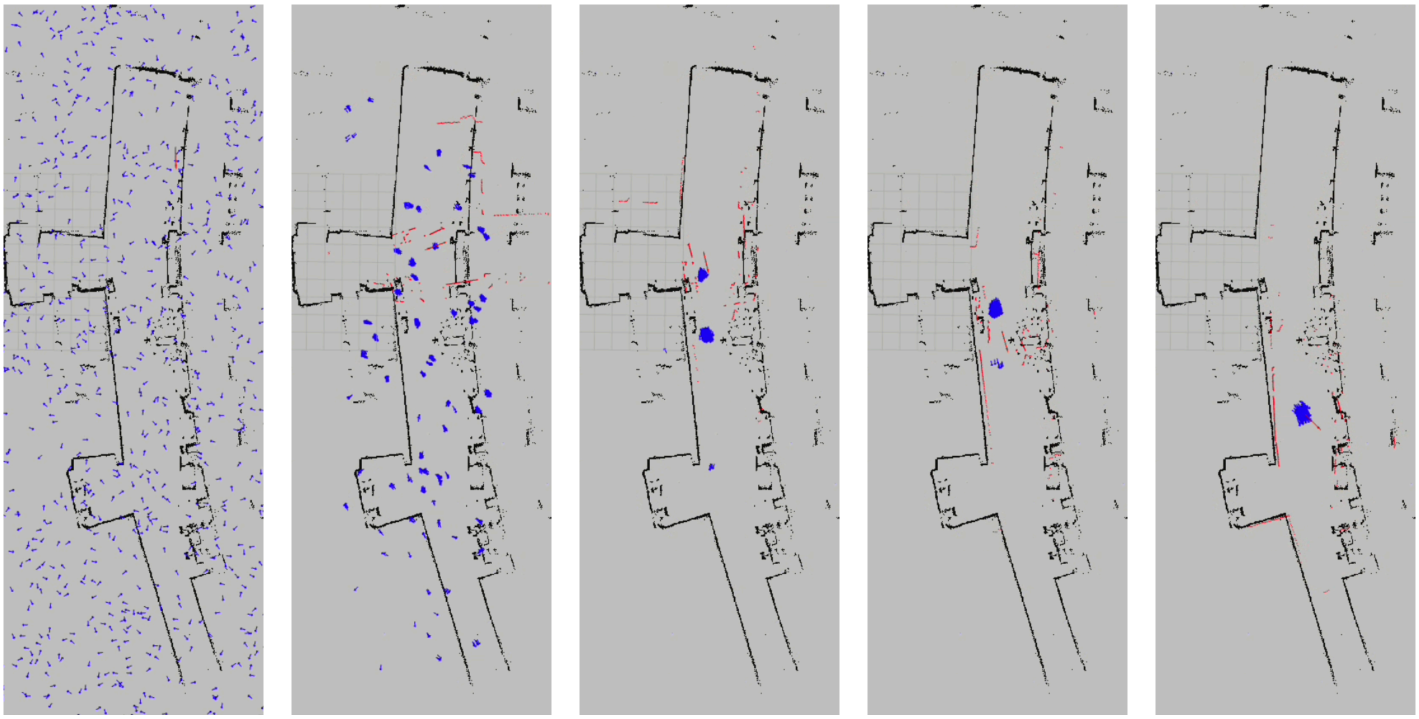


t = 31s t = 33s t = 36s t = 43s t = 61s

Figure 1: From left to right, our particle filter begins and correctly converges on our robot pose.

1 Project Goal

The goal of this project was to implement a working Particle Filter in C++. A Particle Filter is a type of localization algorithm commonly used in robotics when the map of a robot is known, but not the specific location within the map. For instance, given a map of a house, we would like to determine where a Rumba robot is.

A particle filter works by generating many possible guesses of the robot's location, called particles. Initially, these guesses are spread randomly across the map. As the robot moves and collects LiDAR data–essentially describing what it sees–we compare each particle's prediction of the environment to the robot's actual observations. Particles that closely match what the robot sees are considered "good" guesses. Over time, we focus more on these good guesses, creating new particles around them. Gradually, the particles cluster tightly together, indicating that we've likely found the robot's true position. In simple terms, it's like playing a game of "hot or cold" with the robot, where we put more effort into the guesses that are getting "hotter."

For our specific implementation, we were given a bag (or recording file) of a robot moving around a known map, which contained LiDAR and odometry data over time, and a map of where our robot was driving around.

2 Approach

Our approach began with helper code given from the assignment, where we had to implement several algorithm steps, including the core of the algorithm of resampling and updating the particles over time as the robot moved throughout the map.

The core structure of our Particle Filter is the same throughout others; we sample particles, update the particle's motion over time, use data (LiDAR scans) to update the weights of these particles, and resample these particles around high weights to eventually converge.

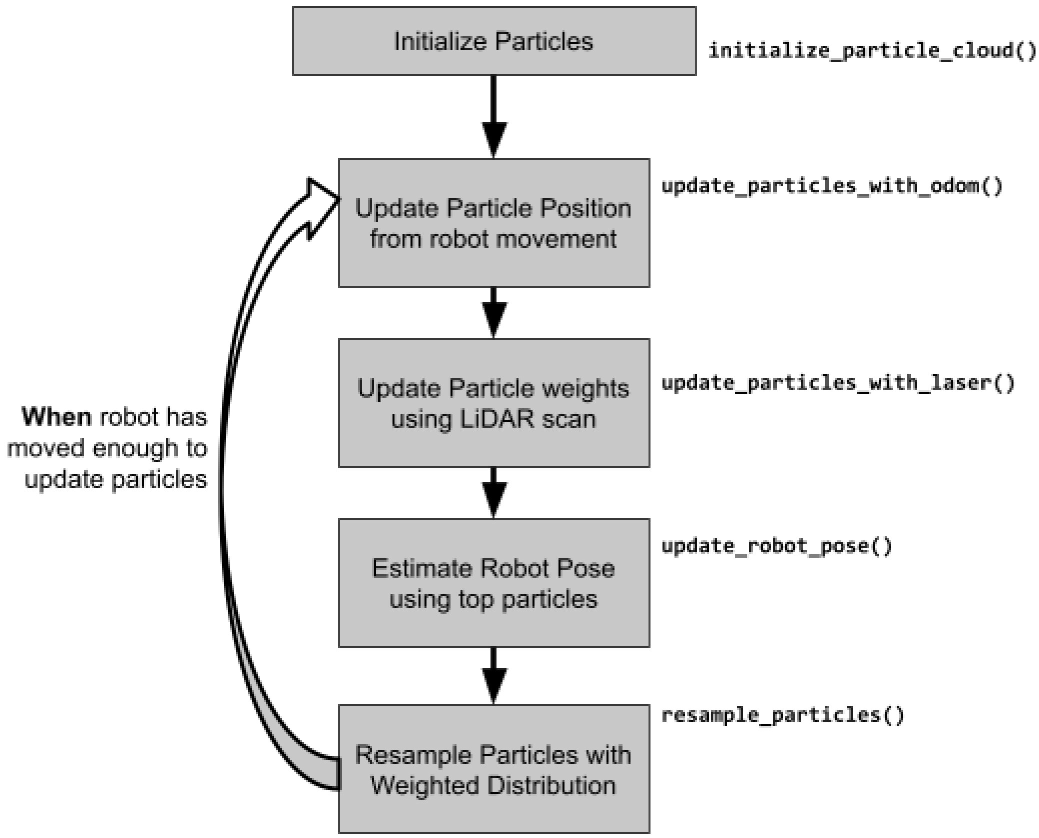


Figure 2: Flow chart of our particle filter algorithm.

The key differences in our approach, which we detail more in the TODO section, were how we assigned weights to particles and how we resampled these particles. For example, we developed two methods of resampling: (a) where we did a hybrid approach of sampling the top particles and randomly assigning the rest, and (b) where we simply resampled all particles. We found our ladder implementation to be better.

The main topics in our node were the /particle_cloud and /map topic. As the bag recording of the robot driving around the map played, subscribers to the odom and scan topic read data to update our particles and publish them to the /particle_cloud for visualization in rviz. There are additional /map and /tf topics that serve as utility topics to help us visualize the map and perform coordinate system transformations.

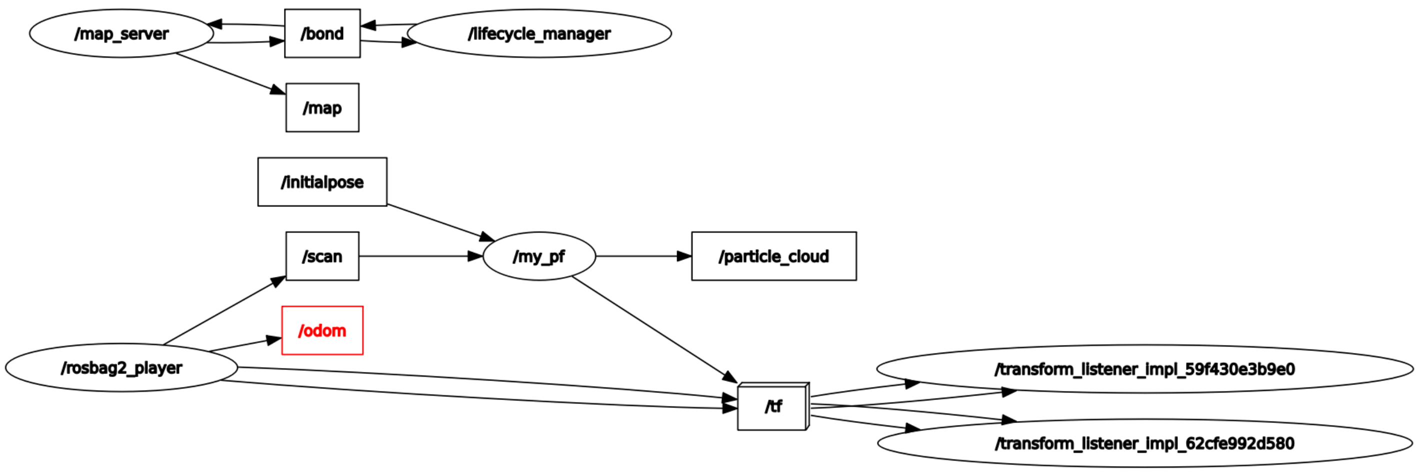


Figure 3: Node/Topic graph of our code.

3 Implementation of each TODO Item

For each todo we specify the goal of the method and our implementation

3.1 Particle Filter Constructor

Goal

Define other constant parameters for the Particle Filter's operation, such as noise standard deviations for the motion and sensor models.

Implementation

We added constants that describe noise we use during our resampling process:

```
// resampling constants
  position_noise_scale = 0.05;
  angle_noise_scale = 0.1;
```

These values were determined after multiple iterations. Overall, we found that too much noise would make the particles less likely to converge. If the noise was too small, the particle could converge too quickly and create a situation where there were two diverged clusters.

3.2 Update Robot Pose

Goal

Calculate the robot's best estimated pose (a weighted average of the particles) and use it to update the map to odom coordinate frame transform.

Implementation

The code below shows us averaging the top particles and updates the estimated robot pose to be the average of these particles. We chose to only use the top particles because during the early loops of the particle filter, not all the particles have converged and it would be inaccurate to use all of them in calculating the average.

```
// average the top particles
  for (int i = 0; i < thresh && i < (int)particle_cloud.size(); i++)
  {
```

```
    x += particle_cloud[i].x;
    y += particle_cloud[i].y;
    theta += particle_cloud[i].theta;
    counter++;
  }

  x /= counter;
  y /= counter;
  theta /= counter;
```

3.3 Update Particles with odom

Goal

Update the locations of each particle given how much the robot moved according to the odom, adding noise to better model the motion.

Implementation

First we calculated the delta/change in between the current odom pose and the next odom pose (x, y, theta). The delta between these two tells us how much the robot moved. With this delta, and a random number generator to mimic noise, we add the deltas to particles alongside the noise to get the new positions.

```
particle.x += delta_x + odom_linear_noise * noise_x;
particle.y += delta_y + odom_linear_noise * noise_y;
particle.theta += delta_theta + odom_angular_noise * noise_theta;
```

3.4 Resample particles

Goal

Implement the Resampling step to replace low-weight particles with copies of high-weight particles, focusing the particle cloud on promising areas.

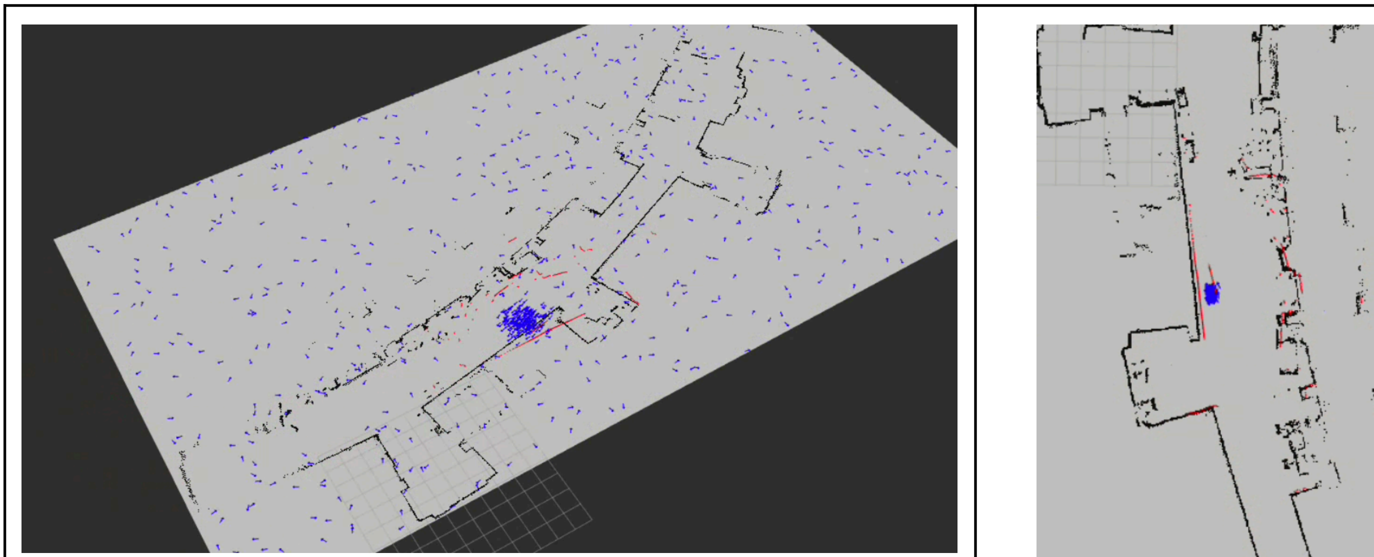
Implementation

Our approach for resampling particles was to create a weighted distribution of the particles based on their weights, and to sample from this distribution to naturally choose more particles that have a higher weight.

We first normalized all particle weights, to ensure we were creating valid probability distribution. We then used the draw_random_sample helper function to perform weighted sampling. This function used the probability distribution to select particles, having a higher likelihood of selecting the highly weighted particles multiple times while lowly weighted particles might not get selected at all.

For each sampled particle, we added Gaussian noise to keep the particles diverse and to prevent the particle cloud from clumping around a single point. We add position noise 0.05 std and angular noise 0.1 rad std to each of the resampled particles. Then we normalize the angle to [-pi, pi] for proper orientation. Then we reset all the particles to weight 1.0 to prevent weight accumulation.

We originally tried using a more complex approach where we would only weighted sample the top 30% of particles in a distribution and randomly choose the other 70% but this approach was not as successful as the prior. This hybrid approach led to too much randomness and it did not effectively focus particles on higher probability regions. On the other hand, the pure weighted sampling approach naturally concentrated the particles into areas they were needed while still maintaining diversity through the noise.



Method #1 (Hybrid) Convergence

Method #2 (Simple) Convergence

Figure 4: Comparing the convergence quality between our two resampling methods.

3.5 Update particles with laser

Goal

Create weights for each particle determined by how well their laser scan maps onto the actual map, where higher weights correlate to a laser scan that aligns with the environment better.

Implementation

First we process each laser reading to see where it hits in the map frame. For each particle, we transform the laser endpoints using the particle's position and orientation, then check how close these endpoints are to actual obstacles in the map.

```
// where does this laser hit in map frame
float ang = particle.theta + ti;
float ri_adj = ri + laser_range_noise * noise_dist(gen);
float x_endpoint = particle.x + ri_adj * std::cos(ang);
float y_endpoint = particle.y + ri_adj * std::sin(ang);
```

We accumulate the distances and use an inverse-square formula to calculate weights where particles whose laser scans hit walls get high weights, while those that miss obstacles get low weights.

3.6 Initialize particle cloud

Goal

Generate and distribute particles all across the map that also represent our assumption to where the robot is located.

Implementation

First we clear the map of all existing particles. Then within the bounding box of the map, we create random coordinates for each particle using a random number generator for x, y, and theta. We then check whether or not the particle is within the map using the validation function, where if get_closest_obstacle_distance() returns a finite value we keep the particle.

3.7 Normalize particles

Goal

Ensure all particle weights are valid by making sure all weights add up to 1.0. This would mean the probability distribution is valid, allowing for resampling.

Implementation

To do this, we first iterate through the particle cloud summing up all the weights of the particles. We then divide each particle by this total sum, which then normalizes the weights. This makes it so when we resample the particles are proportionate to their weights.

```
float weight_sum = 0.0;
for (size_t i = 0; i < particle_cloud.size(); i++) {
   weight_sum += particle_cloud[i].w;
}
for (size_t i = 0; i < particle_cloud.size(); i++) {
   particle_cloud[i].w /= weight_sum;
}
```

4 Challenges Faced

4.1 C++ Bugs

We encountered buggy code in parts of existing skeleton code. We found this frustrating because we assumed that the existing code was working fine.

The issue was that the get_obstacle_bounding_box method (a helper function) was incorrectly implemented. Though it was supposed to get the bounds of our map, the use of UINT8 accidentally limited the bounds of the function to a maximum of 255, which was problematic for the MAC map because it had dimensions ~530 x ~1450

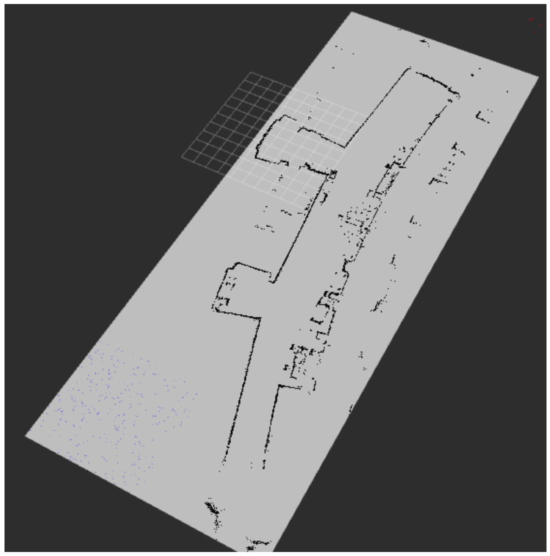


Figure 5: Particles only generated in the bottom left of the map due to the bug.

Another issue we faced was that after we got the particles to generate randomly everywhere, some particles would begin generating and clumping outside of the map. To solve this issue we implemented a validation check that runs get_closest_obstacle_distance() and checks if it returns a finite value. If it does that means the particle is within the map and if not we remove those particles.

Improvements

We would like to try using a whole LiDAR scan or portion of it instead of just the closest distance. We currently use the closest distance to assign weights to particles because that is what was recommended by the course, but we are curious to see how our algorithm behaves if we compare the shape of our lidar scans.

We would like to do more visualization or different types of visualizations. The other C++ group localized the robot in the gauntlet map and we thought this was a cool initiative to take. Other groups also implemented a visual representation of where the actual neato was, which is interesting to us because we could compare the neato to the particles themselves. Other graphs we think would be helpful to implement as well would be graphs to highlight the weight distribution or how LiDAR scans compare to each other.

Lessons Learned

Don't trust existing C++ code. Once we removed the expectation of working code and permitted ourselves to edit the existing code, we became more confident in our solution.

It was hard to split up the code for this project because we initially just divided the TODO items but we didn't know how much work each todo was so some people had more work than others. For this project, the work distribution was that Khoi worked on the particle motion and weight updates, and 1st implementation of resampling. David worked on the normalization, updating robot position, c++ debugging, and 2nd implementation of the resampling algorithm. Splitting up also created another obstacle for us, being that we had to sync our work and test it together after both implementations were done. We took this as an opportunity to debug and work together to solve any issues. Having two separate devices running our code was helpful because it allowed us to eliminate RViz issues and times where components were simply not loading properly.