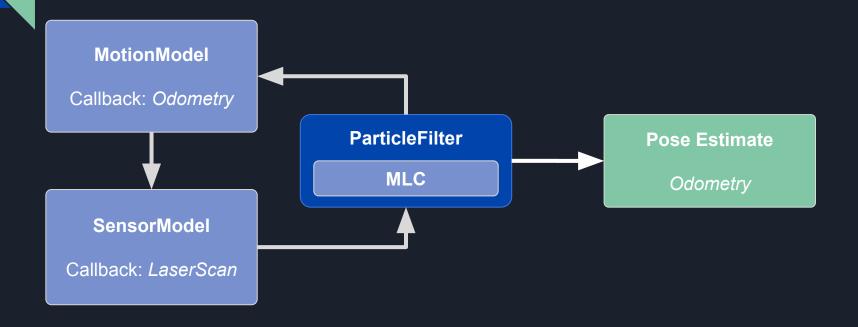
RSS Lab 5

Team Bird-Planes

Joshua, Isaac, Lilly, Mario

Components of Localization



Module 1: Motion and Sensor Models

Motion Model

$$X_k = R\Delta X + X_{k-1}$$

$$R = \begin{bmatrix} \cos(\theta_{k-1}) & -\sin(\theta_{k-1}) & 0 \\ \sin(\theta_{k-1}) & \cos(\theta_{k-1}) & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad X_{k-1} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \theta_{k-1} \end{bmatrix}$$

$$X_{k-1} = \begin{bmatrix} X_{k-1} \\ Y_{k-1} \\ \theta_{k-1} \end{bmatrix}$$

Rotation Matrix (r 🗆 W)

Particle (W)

Motion Model **evaluates** a series of N particles at a time

$$X_k = R\Delta X + X_{k-1}$$

We receive...

$$\begin{bmatrix} X_{k-1}^{(0)} \\ X_{k-1}^{(1)} \\ \cdots \end{bmatrix} = \begin{bmatrix} x_0 & y_0 & \theta_0 \\ x_1 & y_1 & \theta_1 \\ & & &$$

Nx3 Matrix of Particles (W)

Odometry (r)

Motion Model **generates** a different Rotation Matrix for each particle

$$X_k = R\Delta X + X_{k-1}$$

To reflect probable future states, we calculate...

$$R_{i} = \begin{bmatrix} \cos(\theta_{i}) & -\sin(\theta_{i}) & 0 \\ \sin(\theta_{i}) & \cos(\theta_{i}) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_{k}^{(0)} \\ X_{k}^{(1)} \\ \cdots \end{bmatrix} = \begin{bmatrix} x_{0} & y_{0} & \theta_{0} \\ X_{1} & y_{1} & \theta_{1} \\ \cdots \end{bmatrix}$$

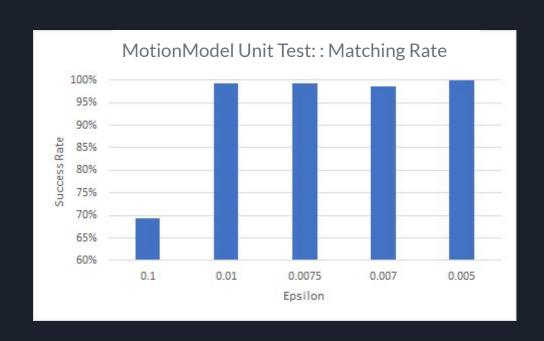
Rotation Matrix for Each
Particle

Nx3 matrix of updated particles given the transformed odometry

When Motion Model **injects noise** into Odometry, the response is **stable** for SD below 0.01

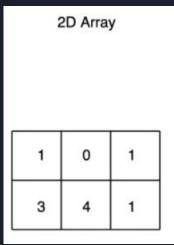
For standard deviation of noise ε :

$$X_k = R [\Delta X \pm norm(0, \epsilon)] + X_{k-1}$$



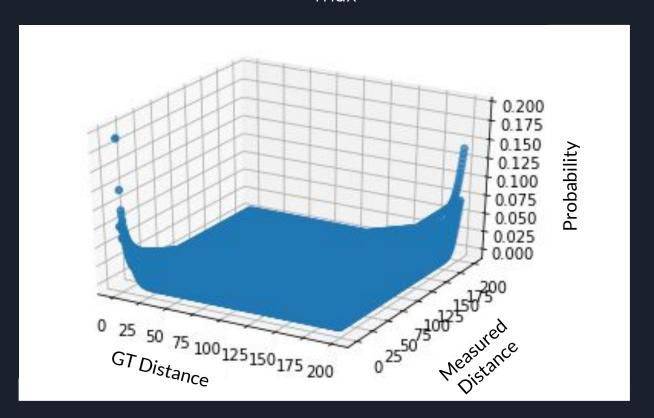
Sensor Model is **probabilistic** with weighted contributions

- 1. P (Detecting known obstacle)
- 2. P (Short measurement)
- 3. P (Missed measurement)
- 4. P (Random measurement)



$$p(z_k|x_k, m) = \alpha p|_{hit} + \alpha p|_{short} + \alpha p|_{max} + \alpha p|_{rand}$$

Sensor Model **precomputes** probability over the discrete range $0 \le z \le z_{max}$



Sensor Model

- 1. Ray Tracing
- 2. Convert meters to pixels
- 3. Clip scans
- 4. Evaluate probabilities

$$p(z_k|x_k,m) = p(z_k^{(1)},\dots,z_k^{(n)}|x_k,m) = \prod_{i=1}^n p(z_k^{(i)}|x_k,m)$$

Module 2: Particle Filter (via MCL)

1a. Odometry Callback

odom -> MotionModel -> parts

1b. Laser Callback

scan -> SensorModel-> probs

2. Monte Carlo (MCL)

Rate: 20 Hz

Sample and Average

particles(200) -> sample(20)
 sample -> pose est

3a. Visualize Particles

sample -> PoseArray

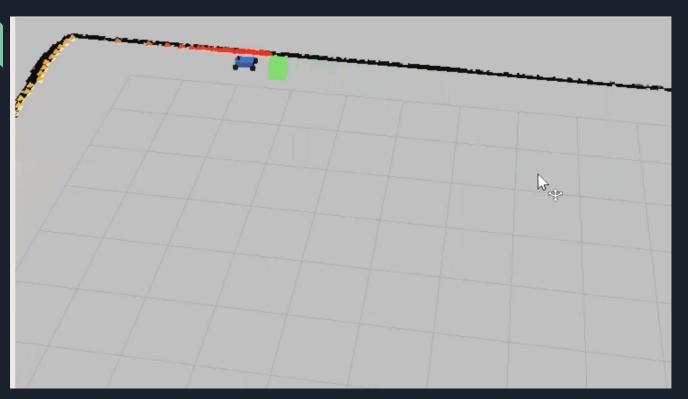
3b. Visualize Estimate

post_est -> Marker

3c. Publish Estimate

pose_est -> Odometry

rviz: **Particles** and **Pose Estimate**

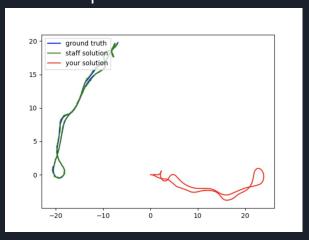


Next Steps for Particle Filter



Tesse implementation

- 1. Record rosbags
- 2. Create error graphs
- 3. Optimization
- 4. Troubleshoot autograder
- 5. Troubleshoot tesse implementation



Conclusion

Technical

- **Submodules:** MotionModel and SensorModel were validated more efficiently than submodules in Lab 4
- **Integration:** correct implementation, poorly tuned.

Communications

- Working in pairs >> Working alone
 - Github: version safety with "active" branches (e.g. dev_sensor, dev_motion)
- Limited communication between pairs

Thank You

Questions?

1a. Odometry Callback

1b. Laser Callback

2. Monte Carlo (MLC)

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