Discrete Bayes Filter for 1-D Robot Motion

Implementation Overview

This project simulates the use of a discrete Bayes filter to track the position of a robot in a 1D world of 20 cells. The robot's movement is probabilistic, with uncertainty modeled through predefined transition probabilities. Commands included nine forward moves followed by three backward moves.
The belief state is initialized with full certainty at the robot's starting position (cell 10). For each command, the belief vector is updated using the motion model and normalized. Boundary conditions ensure accurate updates at the edges, preventing invalid movements outside the world.

Results

After executing the commands, the final belief distribution reveals a wide spread due to stochastic errors in movement. The highest probability cell corresponds to the most likely final position.

Notable observations include:

- **Uncertainty Spread:** The belief distribution becomes increasingly diffuse with each step, reflecting growing uncertainty.
- **Boundary Effects:** Near the edges, belief mass accumulates due to restricted movement options.
- **Dynamic Adjustments:** The belief state adapts effectively to the forward and backward commands, demonstrating the filter's robustness.

Final Belief Distribution:

- The belief is highest around cell 13, indicating the robot's likely final position after the sequence of commands.
- Visualization confirms positional probabilities and highlights uncertainty propagation.

Key Metrics:

- **Most likely position**: Cell 13.
- **Distribution spread:** Significant, with reduced confidence compared to earlier steps.

Discussion:

This implementation illustrates the utility of the Bayes filter for tracking robot positions under motion uncertainty. The results align with expected behaviors, including belief spread over multiple cells and accumulation near boundaries. The filter's adaptability and accuracy make it a vital tool for navigation in uncertain environments.

Conclusion:

The discrete Bayes filter effectively tracks a robot's position in a probabilistic setting. The observed belief evolution highlights the importance of accounting for uncertainty in robot navigation. The model provides actionable insights for further refinement, including:

1. Sensor Integration: Adding sensory data can improve accuracy.
2. Higher Dimensions: Extending the approach to multi-dimensional spaces.
3. Parameter Optimization: Exploring how varying probabilities impact belief evolution.

The final belief distribution confirms the method's reliability, showcasing its potential in real-world applications.