CS561 - Assignment 2 : Robot Localization Using HMMs

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Implementation

The approach followed to solve the assignment includes the following steps:

Grid World Representation
The grid world representation includes defining the size of the grid, where each cell corresponds to a potential location of the robot.Obstacles are marked as '0' while empty spaces are marked as '1'.The grid serves as the basis for determining possible movements and sensor readings of the robot.

Transition Model
The transition model calculates the probabilities of transitioning from one grid cell to another based on neighbouring empty cells. It considers the spatial relationships between cells to determine the likelihood of movement. The transition probabilities are essential for predicting the future state of the robot given its current position and intended movement.

Sensor Model
The sensor model calculates the likelihood of observing sensor readings given the true position of the robot.It takes into account sensor errors, such as false positives and false negatives, and environmental uncertainties, such as occlusions and noise.Different sensor models can be implemented based on the type of sensors used by the robot (e.g., proximity sensors, vision sensors).

Filtering (Forward Procedure)
The forward algorithm, also known as filtering, iteratively updates the posterior distribution over the robot's position given a sequence of sensor readings. It incorporates both the transition model and sensor model to compute the likelihood of the robot being in each grid cell.

Viterbi Algorithm
The Viterbi algorithm determines the most likely path taken by the robot based on a sequence of sensor readings. It finds the optimal sequence of states (grid cells) that maximises the likelihood of the observed sensor readings. By considering all possible paths and their associated probabilities, the Viterbi algorithm provides a robust method for tracking the robot's trajectory.

Integration of Hidden Markov Model (HMM)

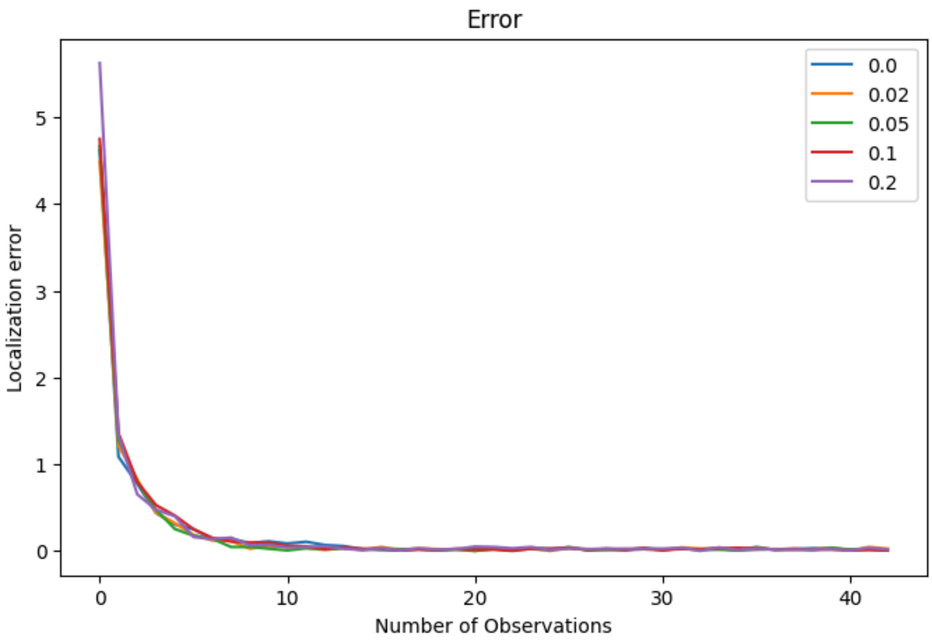
The main function integrates all components of the HMM, including the transition model, sensor model, filtering, and the Viterbi algorithm. It orchestrates the localization process by simulating multiple iterations and varying sensor error rates to evaluate the performance of the HMM

Conclusion

The implemented Hidden Markov Model (HMM) provides an effective framework for localization in a grid world environment. By combining transition probabilities and sensor likelihoods, the algorithm accurately estimates the robot's position even in the presence of sensor errors. The evaluation of localization performance using different sensor error rates helps understand the robustness and reliability of the localization system. Overall, the HMM-based approach demonstrates its effectiveness in solving the localization problem in various scenarios.

Program Output (Plots):

1. **Localization Error Plot :** This plot shows the localization error (Manhattan distance from the true location) as a function of the number of observations.



2. **Path Accuracy Plot :** This plot shows the path accuracy, defined as the fraction of the correct states on the Viterbi path, as a function of the number of observations.