ME 656: Simulation Lab 2

The experiment was performed by running the RRT algorithm through 100 trials and finding the three subject paths namely, (1) shortest path, (2) path with minimum terminal state uncertainty, and (3) path with maximum terminal state uncertainty. A sample trial was run, and the resultant path parameter values yielded the outcome shown in Table 1.

Table 1. Outcome of a sample 100-trial run of the RRT algorithm to find the shortest path, the path with minimum terminal state uncertainty, and the path with maximum terminal state uncertainty.

No.	Path	Path Length	Uncertainty
1	Shortest	102	73.27
2	Minimum Terminal State Uncertainty	112	11.54
3	Maximum Terminal State Uncertainty	115.77	179.27

The shortest path generated by running the RRT algorithm through 100 trials is shown in Figure 1. The red ellipses represent the localization uncertainty in each point along the path. The vertical semimajor axis of each ellipse represents the standard deviation of the y-position estimate's error, while the horizontal semimajor axis represents that of the x-position estimate's error.

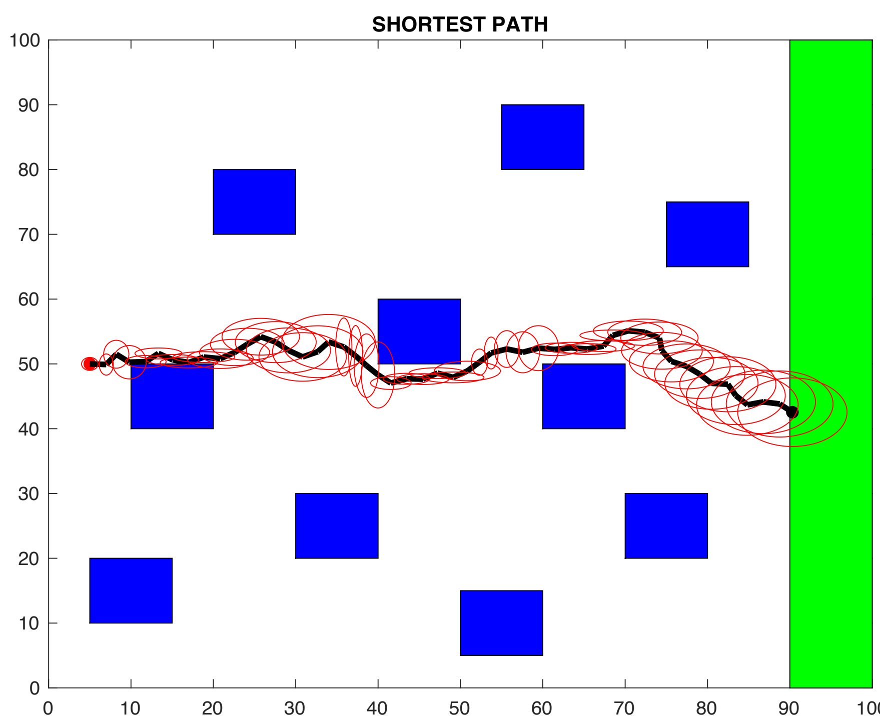

Figure 1. The figure shows a sample of the shortest path generated by RRT algorithm performing 100 trials. The red ellipses represent the standard deviation of the position estimate's error or simply, the uncertainty in localization.

The path length and terminal state uncertainty corresponding to Figure 1 is shown in the first row of Table 1. By further observation of the figure, one can see that the path length is minimized by making the robot travel very near the boundaries of the each close obstacle. Since the uncertainty at each point is only curbed around obstacle, it means that the uncertainty in the terminal state is a somehow controlled; although, not as good as that of the path with minimum terminal state uncertainty as shown in Figure 2. Another important thing to note about the shortest path is that since it optimizes the traversable space around nearby landmarks, it positions the robot at states where it comes very near the obstacle edges. In reality, if the robot makes a significant error in measurement, this increases the risk of collision.

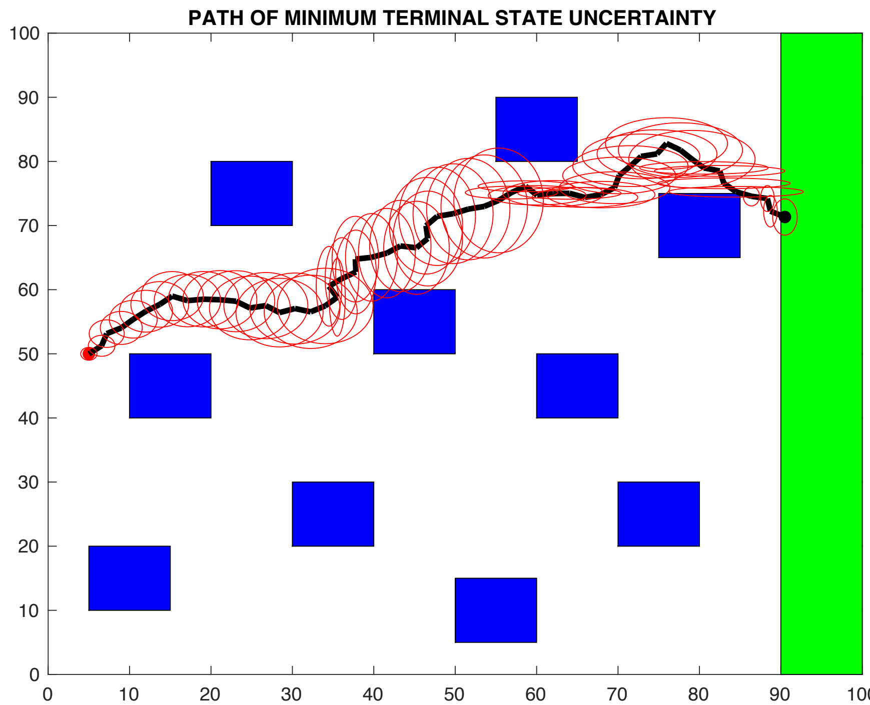

Figure 2. The figure shows a sample path that has the minimum terminal state uncertainty generated by RRT algorithm performing 100 trials. The red ellipses denote the uncertainty in localization.

Figure 2 shows the path that yields the minimum uncertainty at the terminal state (position within the goal region). As seen in the case of the shortest path, the uncertainty in state estimate is significantly curbed when the robot is within the range of a known landmark. So, it is very intuitive that the path with the minimum terminal state uncertainty is the one where the robot's final position falls within the range of the obstacle closest to the goal region. In the map there's only one obstacle that is substantially close to the goal region as shown in the figure. If the objective is to land the robot in a position where it is most certain about its state (regardless of other factors), then this is the best one to use. It is important to note, though, that since RRT is a random sampling-based algorithm, the probability of finding this path increases directly proportional to how many trials are done. Although, the same is true for all other cases as well. This leads to more required computational power and relatively slower convergence.

The path length and terminal state uncertainty corresponding to Figure 2 is shown in the second row of Table 1. From the figures, one can see that the path with minimum terminal state uncertainty does not guarantee a shorter path. In fact, it is always a trade-off between path length and uncertainty that one needs to consider in the context of this paper. Re-inspecting the map, one can see that the obstacle closest to the goal region is positioned above the mid-line (y = 50). While the shortest path tries as hard as possible to land the robot near the tip of this line, the path of minimum terminal state uncertainty tries as equally hard to pull the robot into the state where it lands near the obstacle closest to the goal region. This explains why the path length is longer.

Lastly, Figure 3 shows that path with maximum terminal state uncertainty. This is the worst-case scenario, and it is rather counter-intuitive to implement this path for two main reasons. The first reason is that the fact that it yields a maximum final state uncertainty means that it travels least around obstacles to minimize the path length. This leads to the second reason which is, since it rarely utilizes the landmarks, the error is uncurbed, and growth of localization uncertainty is maximized as represented by the data on the third row of Table 1. Visually, it is represented by the growth of the sizes of the ellipses as the path draws closer to the goal.

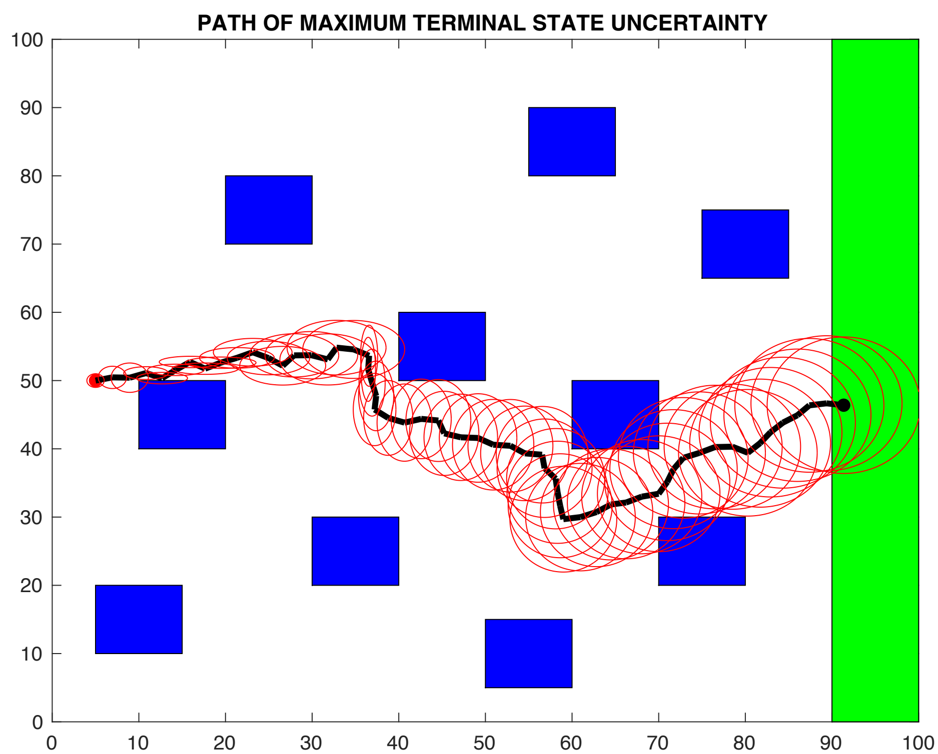

Figure 3. The figure shows a sample path that has the maximum terminal state uncertainty generated by RRT algorithm performing 100 trials. The red ellipses denote the uncertainty in localization.

Depending on whether the goal is to minimize path length or the uncertainty at the goal, one may choose to implement either of the first two paths discussed above, but never the path with maximum terminal state uncertainty. It is also noteworthy that if one decides to go with the shortest path, then the risk of collision is increased as it travels more around the vicinity of obstacle edges. Of course, it still depends on how accurate the measurements and how stable the environment is when it comes to the implementation.

To identify a high-quality path, one may increase the number of trials that the RRT algorithm is run (e.g. 200, 500, 1000). Again, since RRT is a random sampling-based algorithm, increasing the trial count does not guarantee the highest quality path, but rather just increases the probability of finding it. That said, there's not one specific number of trials needed to guarantee the overall optimal path. This is proven by the data shown in Tables 2 and 3 when the trials runs are increased to 500 and 100, respectively.

Table 2. Outcome of a sample 500-trial run of the RRT algorithm to find the shortest path, the path with minimum terminal state uncertainty, and the path with maximum terminal state uncertainty.

Trial Count = 500			
No.	**Path**	**Path Length**	**Uncertainty**
1	Shortest	99.89	15.47
2	Minimum Terminal State Uncertainty	110	11.54
3	Maximum Terminal State Uncertainty	125.7	254.47

Table 3. Outcome of a sample 1000-trial run of the RRT algorithm to find the shortest path, the path with minimum terminal state uncertainty, and the path with maximum terminal state uncertainty.

Trial Count = 1000			
No.	**Path**	**Path Length**	**Uncertainty**
1	Shortest	100	47.42
2	Minimum Terminal State Uncertainty	108	9.56
3	Maximum Terminal State Uncertainty	130	251.87