Lab 5 - Searching For Objects

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October 28, 2016

1 Data/Analysis

1.1 Perform at least 10 trials of object recognition using an object other than the Styrofoam block and note the number of false positives.

After exposing the robot to 10 different non-Styrofoam objects, only one false positive was observed. Thus, the success rate for identifying when an object is not the appropriate block was observed to be 90%.

1.2 Repeat the above step, but using the Styrofoam block each time, noting the total number of false negatives.

After exposing the robot to the Styrofoam block ten times, the robot successfully identified that it was a Styrofoam block each time. Thus, no false negatives were observed and the apparent rate it which the robot can detect a Styrofoam block was 100%.

1.3 Run through the search program at least 5 times, recording the average time taken to localize, to find a block, and then to travel to the destination. Also estimate the localization and final destination errors for each trial.

1.3.1 Localization

Figure 1: Localization Statistics

Trial No.	Localization Time (s)	Euclidean Distance Error (cm)	Heading Error (°)
1	25.9	1.7	8.3
2	23.5	2.0	7.4
3	27.0	0.4	7.6
4	26.2	1.3	9.7
5	25.5	1.3	2.0
Average	24.7	1.34	7.0

After 5 trials, the average time taken for the robot to localize was 24.7 seconds. This falls within the acceptable range for the competition. However, significant error was observed. The average error in displacement from localization (measured as euclidean distance) was approximately 1.34cm, and the average error in heading was observed to be approximately 7.0°.

1.3.2 Finding a block

Throughout the five trials, the robot took on average 11.56 seconds to find a block (and identify that it's a Styrofoam block) that was situated approximately in the center of the board, oriented orthogonally to the coordinate axes. Once again, the robot successfully identified that the block was a Styrofoam block 100% of the time.

Figure 2: Search Statistics)

Trial No.	Time (s)
1	11.0
2	12.2
3	12.2
4	9.8
5	12.6
Average	11.56

1.3.3 Arriving at the final destination

Figure 3: Destination Statistics

Trial No.	Time to Destination (s)	Destination Error (cm)
1	13.5	12.3
2	13.3	11.0
3	13.4	10.9
4	13.4	14.4
5	13.0	6.3
Average	13.32	11.0

After finding the Styrofoam block (positioned and oriented as described above), the robot took, on average, 13.32 seconds to position the block in the target destination. Unfortunately, there was significant error in the block's final position. This error ranged from 6.3cm to 14.4cm, averaging at approximately 11.0cm.

2 Observations and Conclusions

2.1 What differences, if any, were observed in the behavior/performance of your earlier code when combined in a larger system? Explain any discepancies

. Odometry and localization suffered painfully upon their integration to the larger system. This was mainly due to the lack of a color sensor for those purposes. Since only one color sensor is available and needed to be used for analyzing objects, it could not be used to detect gridlines without sacrificing a lot of time to implement its own motor and control. As a consequence, the odometry had no sensory feedback, and this led the error in odometry to accrue to a large extent. This was observed when the robot misplaced the Styrofoam block by an average of 11.0cm. Furthermore, the localization routine had to resort to using only the ultrasonic sensor, and couldn't use the color sensor to further improve its measurements. The ultrasonic sensor is susceptible to much more noise than the color sensor, so its readings are not as accurate. To diminish this effect, a median filter was implemented for the ultrasonic readings, however the ultrasonic sensor still could not measure distances as accurately as the light sensor did in Lab 4. Thus, larger errors in heading and position after localization were observed.

2.2 How reliable was your object detection? What factors influence the reliability of object detection? Where would you expect your code to break down? What steps can you take to make detection more robust?

In the conditions under which the robot was tested, the object detection was extremely reliable. As seen in **Data Analysis**, no false negatives occured, and false positives were observed very infrequently. The object detection implemented for this robot was based on the ratio of red to green color values, and was far from robust. The code would likely break down in conditions where ambient light is different from that in the lab. To make the detection more robust, ambient light can be taken into account to offer some prediction as to how the expected of the color of the Styrofoam block the be. Then, colors may be interpreted as three-dimensional vectors, and the classification of objects can be done by analyzing the euclidean distance between two colors. Furthermore, instead on relying solely on color, the object detection can also attempt to measure the dimensions of the block that it is detecting. Then, these dimensions may be compared with those of the Styrofoam block.

2.3 What aspect of this lab did you find most difficult? What aspect of this lab did you find most surprising or unexpected?

The most difficult parts of this lab were reliably searching for objects and reducing the likelihood of the robot crashing into obstacles. The searching algorithm was difficult to conceive, because due to the lack of a rotating ultrasonic sensor, the search algorithm had to ensure that the robot approaches the obstacles it detects at an appropriate angle. This was very difficult to code and test because so many cases are possible. Furthermore, as the robot dragged the block from behind, its "effective radius" - that is to say, the furthest point of the robot from its center of rotation, was very large. Therefore, when the robot turned, it covered an enormous amount of area. It was very difficult to reduce the occurances of the robot hitting obstacles when it was turning for this reason. Surprisingly, the robot was exceptionally good at identifying obstacles. As mentioned previously, errors in obstacle identification were rare, which was unexpected given previous bad experiences with other sensors during this lab and previous experiments.