The Gauntlet

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1 Strategy

The goal of this challenge was to have the NEATO drive from the global origin of the Gauntlet^{TM} to the BoB (Bucket of Benevolence^{TM}) while sensing and avoiding rectangular obstacles and walls. Our overarching strategy was to establish vector potential fields around the coordinates of the objects in the pen, with the bucket having an attractive field and the obstacles having repulsive fields. The NEATO would then use gradient descent to drive towards the bucket, while steering away from the other objects.

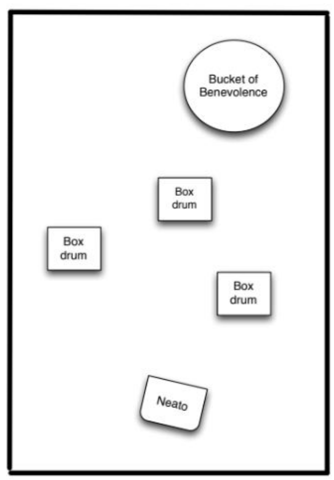

Figure 1: Top down layout of the Gauntlet^{TM}, showing the target bucket, the obstacles, the walls of the pen, and the NEATO itself.

In order to determine the locations of the objects in the Gauntlet^{TM}, we used a random sample consensus (RANSAC) algorithm to develop a rudimentary reconstruction of the boxes and walls of the pen. We began by having the NEATO take LIDAR scans of the Gauntlet. Since both types of obstacles can be represented by line segments, the algorithm tried to find the line of best fit for each segment. It worked by taking two random points out of the point map we got by translating the polar LIDAR scans to Cartesian coordinates of the Gauntlet^{TM} and drawing a line between them. Our algorithm achieved this by finding the unit vector in the direction of the line, and the distance between the points, and then calculating points along the line parametrically. After finding a line, the algorithm would check for "inliers" which are points that lay within a certain threshold d of the line (perpendicularly). We repeated this n times and then stored the line with the most "inliers" as line which (most likely) went through an obstacle or wall. Then we deleted those inliers from the overall data set and continued to run RANSAC until there were less than four inliers in the best line.

A set of evenly spaced points were created along the length of each line segment, so as to represent each obstacle with a similar "density" of data points. Once these points were found, they were translated from the LIDAR reference frame to the NEATO reference fram and then finally the global reference frame of the gauntlet. We deleted all of the points that were detected within a foot of the bucket center coordinates, so that it would not be treated as an obstacle.

In translating the data to the global coordinate system, we first stored each point in a column vector with the first index being the point's x value the second the point's y and the third a 1 (so that it could be transformed) as shown below.

$$Point_{LIDAR} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

With this point, we then applied a transormation to shift the reference frame's origin to that of the NEATO with the following transformation matrix:

$$T_{NEATO} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -d \\ 0 & 0 & 1 \end{bmatrix}$$

where d is the distance from the center of the LIDAR scanner to the center of the NEATO. With this translation done, we then changed to using the basis vectors of the global reference frame of the Gauntlet^{TM} with the following matrix:

$$R_{Global} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

where θ is the angle of the NEATO's heading with respect to the global coordinate system. Lastly, we shifted the origin from that of the NEATO's reference frame with the following translation matrix:

$$T_{Global} = \begin{bmatrix} 1 & 0 & X_N \\ 0 & 1 & Y_N \\ 0 & 0 & 1 \end{bmatrix}$$

where X_N and Y_N are the NEATO's coordinates in the global reference frame. Applying all of these these transformations and change of bases in one matrix multiplication would entail using the following equation

$$Point_{Global} = \begin{bmatrix} 1 & 0 & X_N \\ 0 & 1 & Y_N \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -d \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

This conversion of points to the global reference frame can then be extended to act on a large matrix of points in the form:

$$Points_{LIDAR} = \begin{bmatrix} x_1 & x_2 \dots \\ y_1 & y_2 \dots \\ 1 & 1 \dots \end{bmatrix}$$

This is how we transformed all the Cartesian points from a given LIDAR scan into the global reference frame all at once.

An attractive vector potential field was created at the coordinates of the bucket's center by applying the function to the point:

$$f_1 = 12 * log\sqrt{(x - x_{center})^2 + (y - y_{center})^2} \tag{2}$$

We wanted the attractive characteristics of the bucket to be much greater than the repulsive strength of the points making up the obstacles, so that the NEATO would always tend to move towards the bucket while running. For each of the points making up the walls and boxes, a repulsive potential vector field was created by applying the following function:

$$f = f_1 - 0.1log\sqrt{(x - x_{obstacle})^2 + (y - y_{obstacle})^2} - 0.1log\sqrt{(x - x_{obstacle})^2 + (y - y_{obstacle})^2}... \tag{3}$$

wherein *f1* was the function applied to the bucket. For each step in the simulation, we calculated the gradient at the current location. We then sent the NEATO some distance in the direction opposite (for gradient descent). From there, it repeated the process (scan and gradient calculation) until it reached the coordinates of the bucket.

After calculating the surrounding gradient function at each point we were at in the global coordinate system, we calculated the vector pointing the opposite direction, but with the same magnitude, as the gradient vector at our current position in the vector potential field we created as so:

$$\bigtriangledown f = \begin{bmatrix} \frac{\delta f}{\delta x} \\ \frac{\delta f}{\delta y} \end{bmatrix} \tag{4}$$

and then headed a constant step in that direction.

2 Evaluation

In our final run of the third challenge (where nothing is known except the location of the bucket), it took 48 seconds for the NEATO to reach the bucket from its start at the origin. We achieved this result by running RANSAC about 1100 times in order to get a very accurate representation of the NEATO's surroundings. Below a certain point the trade off of speed and accuracy of obstacle detection becomes not worth it.

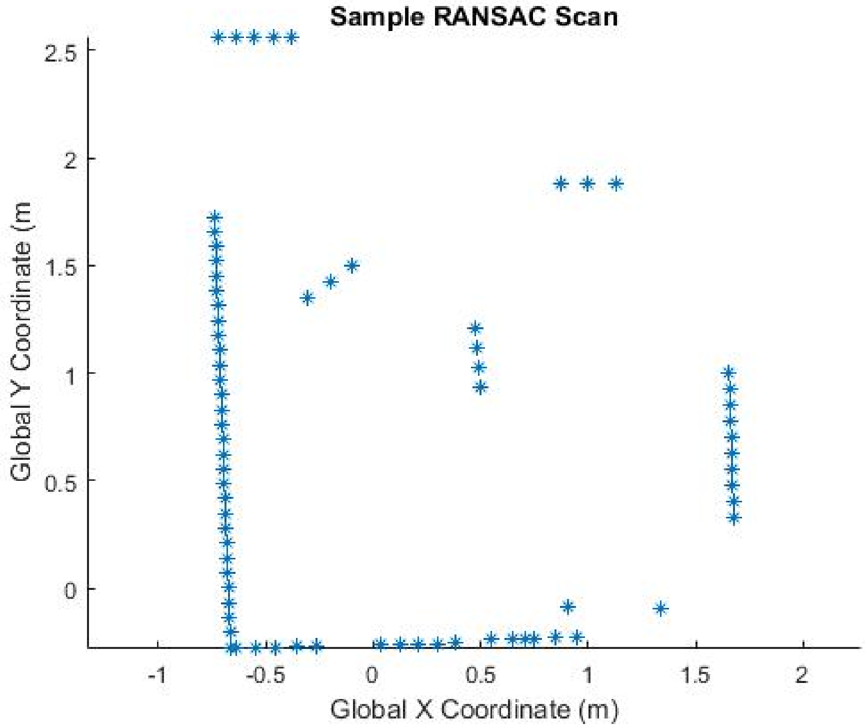

Figure 2: This graph is an example of the result of our RANSAC algrithm. As can be seen, the points are spaced our with about a constant density (except for places where two lines may overlap) which spreads out the charge of the obstacles well.

3 General Process

We began by developing a RANSAC algorithm that could be tested on scan data and identify where the boxes and walls were. From there, we tried to jump straight to having the NEATO identify and avoid obstacles while traveling to the bucket. We soon realized that trying to implement gradient descent and obstacle detection simultaneously was not a wise decision as it soon became very difficult to debug. We then decided to reevaluate and follow a more iterative process for the remainder of the project.

We first tried to implement gradient descent to the bucket without any obstacles. A function with an attractive vector potential field was imposed on the known coordinates of the bucket, and we had the NEATO follow the direction opposite to the gradient at each step until it reached the target.

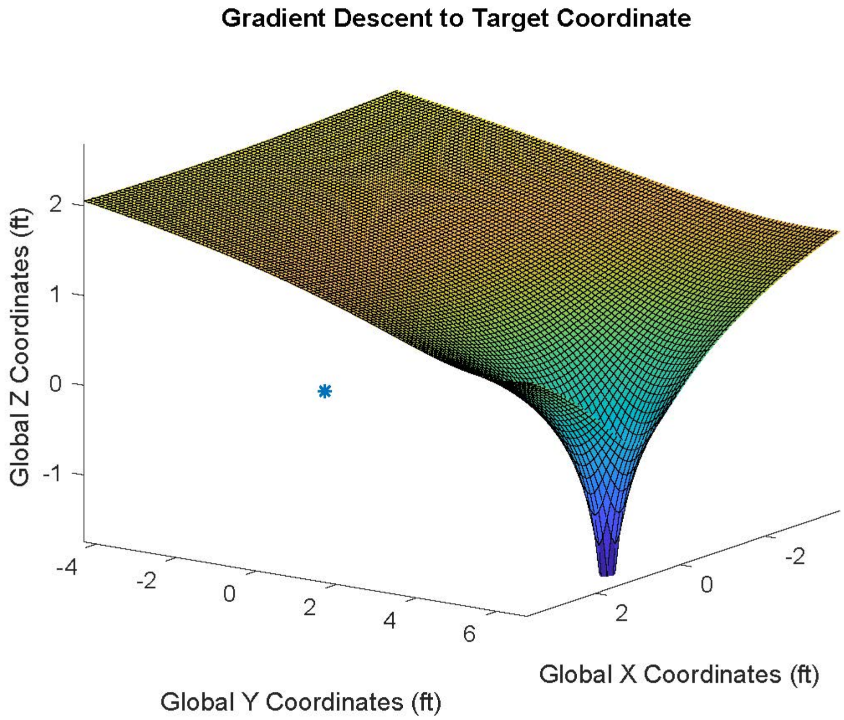

Figure 3: Surface plot of the function imposed on the target coordinate. The X,Y coordinates of the highlighted point indicate the starting position of the NEATO, and the minimum point in the plot represents the position of the bucket.

Next, we implemented basic obstacle avoidance, by finding the centers of the boxes within the Gauntlet, and imposing a function with a repulsive vector potential field upon these points. It was during this stage in the challenge that we realized the importance of making the attractive nature of the bucket much greater than the repulsive nature of the boxes, so that the NEATO would continue in the general direction of the bucket even while adjusting its heading to avoid the boxes. There was some trial and error involved in adjusting the coefficients of the functions in order to achieve the desired behavior.

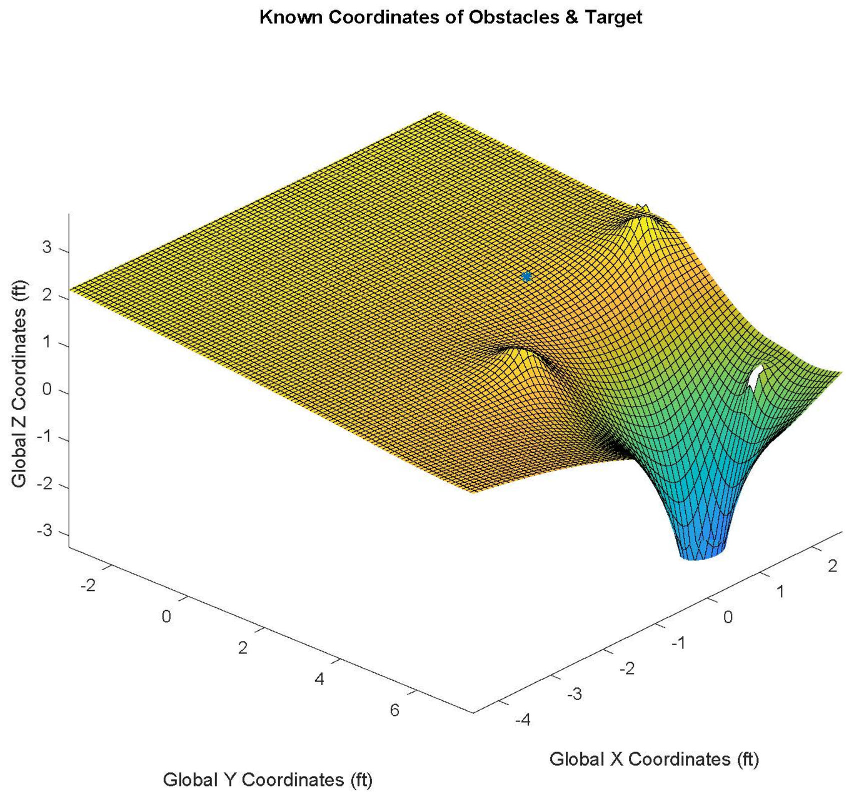

Figure 4: Surface plot of the functions imposed on the obstacle and bucket coordinates. The X,Y coordinates of the highlighted point indicate the starting position of the NEATO. The peaks in the graph represent the boxes, and the minimum point in the plot represents the bucket.

Finally, we put all of the components together. We used RANSAC algorithm to scan for and detect walls and boxes, and gradient descent to make the NEATO approach the bucket while avoiding these obstacles. We were satisfied with the progress that we had made at this point, as we were able to integrate all of the components necessary to have the NEATO reach a known target location. This process could be extended in the future to have the NEATO find and travel to a target at an unknown location, by developing circle detection code to find the bucket from the LIDAR scan, and using the process described in this paper to follow gradient descent to that location, and avoiding surrounding obstacles if the circle is not seen.

4 Video and Code

Video: `https://www.youtube.com/watch?v=8nCLfTmbivU`
Code: `https://github.com/MarkG98/NeatoVectorPotentialField`