ELEC 448: Introduction to Robotics

Short Paper Report

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Introduction

The topic of the chosen paper concerns the use of ant colony optimization (ACO) in solving path planning problems in robots. This is applied by randomly generating a set of paths to a destination, evaluating which paths are better than others, and repeating this process until a good enough path is found.

Background

The technical problem this paper aims to solve is called the travel salesman problem (TSP). The goal of this problem is to travel from an initial position to a destination position. In the accompanying experiments, positions (1, 1) and (20, 20) were respectively used.

The paper outlines an ACO algorithm applied to minimize the path length travelled by the robot, which is based on the Ant System (AS) algorithm [1]. From a present state (x, y) (with x, y integers) the ant travels to an adjacent state {(x+1, y), (x+1, y+1), (x, y+1), (x-1, y+1), (x-1, y), (x-1, y-1), (x, y-1), (x+1, y-1)} randomly. The probability of traveling to an adjacent state is dependent on the accumulated “pheromone” attributed to that state, and a global attraction vector directed toward the destination point. Pheromone is allocated more strongly to states that have been used previously by shorter paths. Indeed, the amount of pheromone deposited on a state is inversely related to the length of the shortest path associated with that state. In the next round of path simulations, this causes the ants to choose states that have been associated with more optimal routes. Finally, when the pheromone is updated, the pheromone deposited in previous rounds is scaled down by a *pheromone forgetting parameter*, which has the effect of weighing recently deposited pheromone more heavily. This is done because as more simulations are performed, the algorithm should theoretically approach an optimal solution.

Various numbers of obstacles were randomly positioned in the area between the initial position and the destination. These obstacles served merely as invalid positions which the robot could not occupy; there was no penalty for approaching an obstacle too closely.

Discussion

The paper comes to the questionable conclusion that there is a “random decreasing nonlinear trend” between number of obstacles and path length. In other words, the robot is able to find a shorter path to the destination when there are more obstacles. Intuitively, this seems unlikely. Ultimately the obstacles have little effect on the robot’s path. Because there is no penalty for coming near an obstacle, the obstacles only serve as inadmissible states. Aside from there being zero probability that the ants enter them, they have no effect on the ants’ behaviour.

The following figure plots the data from Table 1 [2] with a linear trendline. However, running a linear regression on this data yields an R^2 value of approximately 0.6, which coupled with the shallow slope of the trendline indicates a weak correlation if any between path length and number of obstacles.

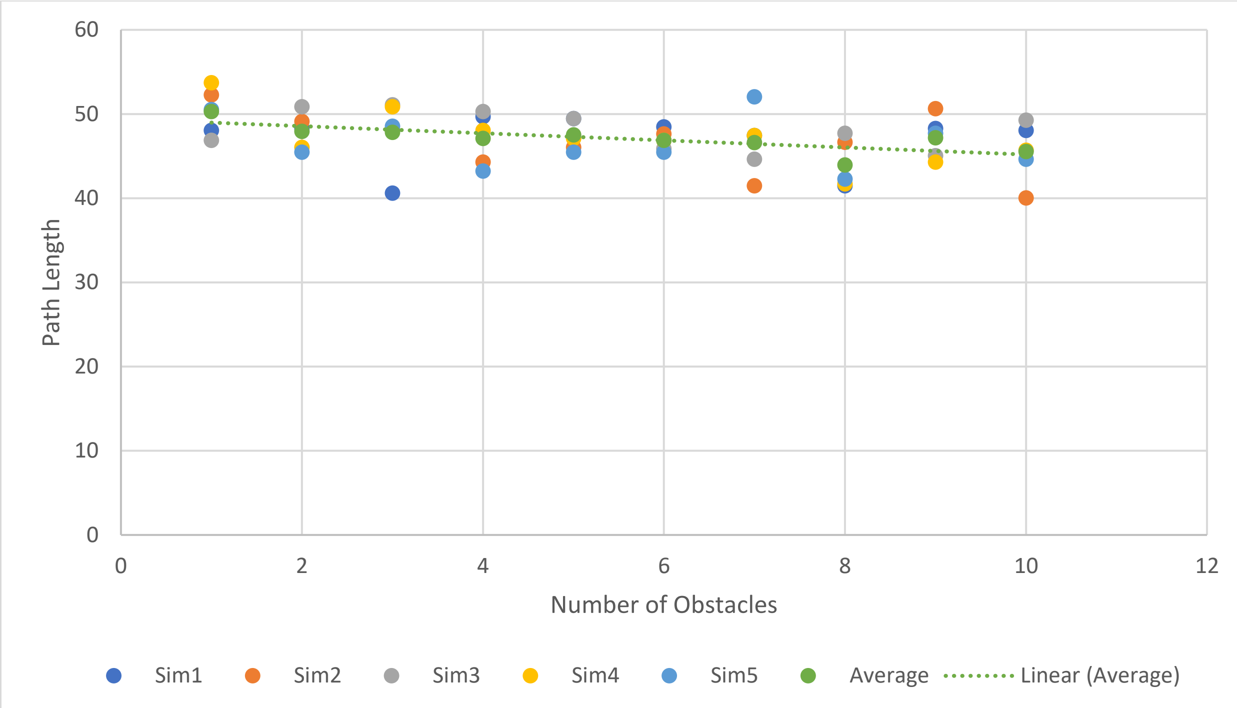

Figure 1: Simulation results giving optimal path lengths using the given ACO algorithm.

It is worth noting that while the original paper acknowledges a “random decreasing nonlinear trend” between path length and number of obstacles, it offers no cause for this relation. In my opinion, it is likely that there is no relation, and the appearance of a trend would disappear if more trials were performed. I have substantial doubt that the authors believe that they could improve the optimal path length by adding hundreds of obstacles.

Conclusion

The equations are nearly illegible, the conclusions drawn by the authors are questionable, writing errors are abundant, and the “optimal” paths seen in Figures 4 through 12 are clearly far from optimal. In many cases the paths cross over themselves, traveling in loops. Furthermore, not once did the algorithm achieve a path length of less than 40. This is relevant because if the robot were to travel straight up to y=20 and then straight across to x=20, it would achieve a path length of 38. Traveling directly on a diagonal from (1, 1) to (20, 20) could yield an even lower path length, with minor alterations to avoid obstacles without substantial cost to the path length. It is not clear from any of these “best tours” (Figures 4-12) whether the algorithm is even converging to a good solution, letalone an optimal solution. Even via the “smoothness of solutions” claimed by the paper, Figure 12 clearly would not converge to an optimal solution, as an optimal path would not travel below the obstacle at (18, 10). In conclusion, based on this paper’s methodology and results I question the ability of ant colony optimization to solve the problem of path planning.

References

[1] M. Dorigo and T. Stützle, "Ant Colony Optimization," 2004.

[2] R. Rashid, N. Perumal, I. Elamvazuthi, M. K. Tageldeen, M. A. Khan and S. Parasuraman, "Mobile Robot Path Planning Using Ant Colony Optimization," IEEE International Symposium on Robotics and Manufacturing Automation (ROMA), 2016.