

PA*: Optimal Path Planning for Perception Tasks

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Abstract. In this paper we introduce the problem of planning for perception of a target position. Given a sensing target, the robot has to move to a goal position from where the target can be perceived. Our algorithm minimizes the overall path cost as a function of both motion and perception costs, given an initial robot position and a sensing target. We contribute a heuristic search method, PA*, that efficiently searches for an optimal path. We prove the proposed heuristic is admissible, and introduce a new goal state stopping condition.

1 INTRODUCTION

The problem of motion planning has been widely studied before, but usually perception is not considered when determining the cost of a path. In this work we plan for motion and sensing, finding a path for the robot that minimizes both the distance traveled and the distance to a sensing target. As we show in Figure 1, a sensing target can be perceived from multiple locations. We show two possible paths that perceive the target from different goal positions, resulting in different motion and perception costs. Our proposed approach solves the problem of finding a path to a position g in a 2D gridmap that minimizes the total cost, $cost_m + \lambda cost_p$, where λ is a weight parameter.

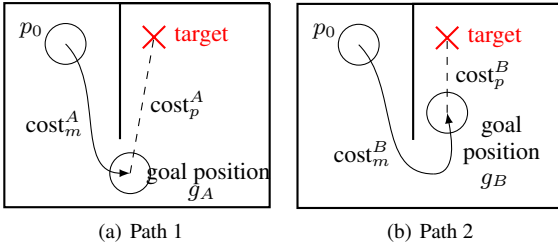


Figure 1. The cost of a path is the sum of the motion cost ($cost_m$) and the perception cost ($cost_p$), proportional to path size and perception distance.

Many robotic applications consider perception separately from planning, with both being computed interleaved. It has been used for tasks as varied as robot localization [1] or object recognition [2], where perception is controlled in order to achieve a goal. However, recently perception got a more active role in planning. An example is object detection, where the next moves of the robot should be planned to maximize the likelihood of correct object classification [5]. Another example is the inspection problem. In order to determine a path that can sense multiple targets, a neural network approach was used to solve the NP-hard Watchman Routing Problem [4]. In the same topic, it has also been shown that perception

planning and path planning can be solved together [3], selecting the most relevant perception tasks depending on the current goal.

Our contribution for solving the perception planning problem is the PA* algorithm, a heuristic search based on A* for gridmaps, and extended to deal with perception tasks. In the next section we explain the PA* algorithm in more detail.

2 PA*: OPTIMAL PERCEPTION PLANNING

We have to find a path ρ that not only minimizes distance traveled, but also minimizes the perception cost. The path is a sequence of positions in a grid, $\{s_0, s_1, \dots, s_n\}$, such as the sensing target T is perceived from some position in ρ . The total cost of path ρ is

$$cost(\rho) = cost_m(\rho) + \lambda cost_p(\rho, T) \quad (1)$$

where λ is a weight parameter that trades-off motion and perception. The motion cost is proportional to the path size, and the perception cost increases with the minimum distance between ρ and T .

Theorem 1. For the optimal ρ^* , the position that minimizes the distance from the path to sensing target T is the final position s_n .

Proof. If there were another position s_i in the middle of the path that had the smallest distance to the target, then there would be a different path ending in s_i with minimal cost, contradicting the hypotheses that the path ρ^* from s_0 to s_n is the one that minimizes cost. \square

In PA* the total cost is given by the sum of $g(s_0, n)$, the path distance from the starting position s_0 to the current node n , and $h(n, T)$, a heuristic of both the motion and perception costs from n to T .

$$f(n) = g(s_0, n) + h(n, T) \quad (2)$$

If the heuristic used is admissible, i.e., always less or equal than the true value, then the path returned is guaranteed to be optimal. Therefore, the choice for the heuristic is based on the euclidean distance between the current node and the target, without considering any obstacles, as shown in Figure 2. We assume that from position n the robot can still move to q , from where it senses the target.

$$h(n, T) = \min_q (||n - q|| + \lambda c_p(||q - T||)) \quad (3)$$

The sensor accuracy is modeled by c_p , with cost increasing with sensing distance. The variable α represents the percentage of the distance to the target that is traveled, and $1 - \alpha$ the percentage of the distance d that is sensed, where $d = ||n - T||$. In order to have the optimal solution, we need to find α that makes cost minimal.

$$\alpha^* = \underset{\alpha}{\operatorname{argmin}} \alpha d + \lambda c_p((1 - \alpha)d) \quad (4)$$

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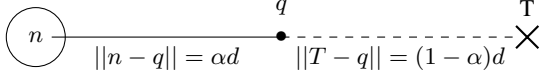


Figure 2. From robot position n and perception target T , without obstacles, the optimal goal lies in the straight line between those points. The image shows a solution with motion αd and sensing distance $(1 - \alpha)d$.

Theorem 2. *If using the straight line solution in PA*, the heuristic is admissible, i.e. it is always less than the true cost.*

Proof. The direct distance between robot position n and target T is d . The motion distance plus the sensing distance equals d' . Because it might be a non-straight path to the target, $d' = d + \epsilon$, with $\epsilon \geq 0$. The robot moves a percentage of this path $\alpha d'$, and senses the rest $(1 - \alpha)d'$. The overall cost is

$$\begin{aligned} \alpha d' + \lambda c_p((1 - \alpha)d') &= \alpha(d + \epsilon) + \lambda c_p((1 - \alpha)(d + \epsilon)) \\ &\geq \alpha d + \lambda c_p(d - \alpha d) \geq \alpha^* d + \lambda c_p((1 - \alpha^*)d) \end{aligned} \quad (5)$$

proving the straight line solution yields minimum cost. \square

For any specific perception function, it is possible to find the optimal sensing position as a function of the distance $\|n - T\|$. With α^* known before-hand, the heuristic is easy to use during search. In our model we assume circular omnidirectional sensing, with a limited range r_p , so the optimal sensing distance d_s^* is $(1 - \alpha^*)d$ if $(1 - \alpha^*)d \leq r_p$, or r_p if $(1 - \alpha^*)d > r_p$. The heuristic becomes:

$$h(n, T) = (\|n - T\| - d_s^*) + \lambda c_p(d_s^*) \quad (6)$$

It is possible to adapt the cost functions to the problem in hand (e.g., sensor and target properties), and then determine the heuristic for that specific problem just by solving for α^* offline.

2.1 Stopping Condition

In perception planning, it is possible to have paths with minimum cost that have a non zero heuristic at the goal state. We introduce a function that represents the cost of sensing from the current node:

$$f^s(n) = g(s_0, n) + \lambda c_p(\|n - T\|) \quad (7)$$

This function accounts for the cost of moving to the current node n , and sensing the target from that position. It takes no obstacles into consideration. Because the heuristic is admissible, $f^s(n) \geq f(n)$. When $f^s(n)$ and $f(n)$ are the same, sensing from the current position is equal to the optimal. At goal positions, besides testing for line-of-sight with ray casting, the following condition has to hold:

$$f^s(n) - f(n) = 0 \Leftrightarrow \lambda c_p(\|n - T\|) = h(n, T) \quad (8)$$

2.2 Addition of Expanded Nodes to Priority Queue

In the solution presented until now, nodes are expanded using a heuristic that estimates how much the robot should move in order to have an optimal path. However, as search continues, the estimated optimal path might not be feasible. We propose a solution that turns PA* into an optimal search algorithm. When a node n is added to the priority queue, its priority is given by $f(n)$. However, as node n is expanded for the first time, not only its neighbors will be added to the priority queue, but the node n itself will be added again, now

using as priority the cost $f^s(n)$. This approach makes it possible to “backtrack” to previous nodes. The stopping criteria becomes $priority(n) = f^s(n)$, with $priority(n)$ being $f(n)$ for the first time a node is added in the priority queue, and $f^s(n)$ for the second time.

3 RESULTS

In order to test the performance of our algorithm, we tested it against a breadth-first search (BFS), comparing node expansion. Our results are based on 1470 feasible search instances. As expected theoretically and shown in Figure 3, PA* has always a better performance than BFS. For large λ , sensing cost has a big weight, so the robot will move as close as possible to the target. In the limit, all the state space is searched for large λ , trying to find a better solution. We can see that the best performance of PA* is for lower λ , which makes robot sense from further away.

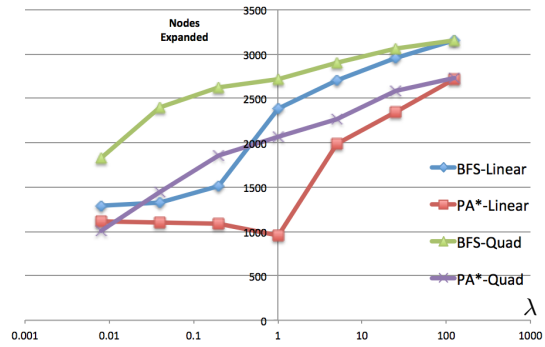


Figure 3. Number of nodes expanded by PA* and Breadth-First Search (BFS) as a function of λ , for linear and quadratic perception functions.

4 CONCLUSIONS

In this work we introduced the problem of motion planning for perception tasks, considering both motion and perception costs. We proposed PA*, an extension of A* for perception problems, and contributed heuristics to solve the planning problem, proving their admissibility. In the future we want to extend our approach with more complex perception cost functions.

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