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Field-Enriched A* search algorithm for robot motion in path planning

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Abstract. Path planning in unknown or complex environments is a central issue in the fields of automation and robotics. To address this global path planning problem while maintaining the smoothness of robot motion, as well as to ensure safety by keeping away from obstacles, this paper propose an innovative method called Field-Enriched A* Planner (FEAP), which incorporates the repulsive potential field into the heuristic computation of the A* search algorithm. The research modified the heuristic mechanism of the A* algorithm by incorporating both attraction and repulsion factors from the Artificial Potential Field method, thereby enhancing the influence of obstacles in the decision-making process. The repulsive potential field enhances obstacle avoidance, ensuring smoother robot motion during the path planning process. The simulation experiments are conducted on the proposed method and compare it with common path planning algorithms. Results from the experimental trials demonstrate that the new method can effectively enhance the smoothness of robot motion while ensuring a safe path is identified.

Keywords: Path Planning, A* Algorithm, Artificial Potential Field, Robotics.

1. Introduction

Automation and robotics constitute significant areas of study in the field of advanced engineering and computer science. Among the various problems associated with these disciplines, path planning has been identified as a substantial challenge that researchers continually strive to address. Essentially, path planning is a critical aspect of robotic navigation, which requires the identification of an optimal path from an initial point to a designated endpoint in an area abundant with obstacles.

In the world of robotics, the path is not merely a route; it must meet certain optimization objectives that greatly depend on the requirements of the task. These objectives could include identifying the shortest possible path, the quickest route, or the safest path that keeps the robot farthest from potential hazards. The complexity of the path planning problem therefore extends beyond mere obstacle avoidance to optimizing the selected path based on a variety of factors.

Over the years, scholars have proposed a plethora of techniques to solve this complex problem. Early methods, for instance, primarily employed graph-based techniques such as A* and Dijkstra's algorithms [1]. A* search algorithm, a heuristic search method, is widely recognized for its ability to determine a route from the initial point to the final point while evading obstacles. However, these conventional algorithms, although effective, do not consider other environmental factors that might influence the path's optimization.

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In response to this issue, recent research has moved toward bio-inspired swarm intelligence algorithms that incorporate various environmental factors into the decision-making process [2]. For instance, the artificial potential field method, a physical field simulation technique, allows for the consideration of these factors. This method creates a force field that reacts to elements like obstacles and targets, subsequently guiding the robot along the path towards its target.

Despite these advancements, the current methods of path planning are not without their drawbacks. While the A* search algorithm is effective in finding a path and avoiding obstacles, it falls short in considering the smoothness of robot motion [3]. This factor is crucial in many applications, including autonomous driving and automatic navigation, where jerky or sudden movements could lead to inefficiencies or even catastrophic results. Moreover, the A* algorithm tends to prioritize the shortest path and may not adequately ensure the safety distance from the obstacles. This insufficient buffer could reduce the safety of the robot, especially in dynamic environments where obstacles could be unpredictable. The artificial potential field method, though adept at creating smooth motion paths, may encounter problems such as trapping the robot in a local minimum, thus preventing it from reaching its target [4].

This paper, therefore, presents a novel method that amalgamates the A* search algorithm with the APF method. This integrated approach aims to resolve the identified limitations of the individual techniques by considering both the smoothness of robot motion and obstacle avoidance during the route development phase. The effectiveness of this novel approach is evaluated through a series of simulation experiments and comparisons with conventional path planning algorithms.

2. Problem Formulation

2.1. Robot Model

This study investigates the problem pertaining to robotic trajectory determination on a two-dimensional plane. The robot is considered as a point mass, with the direction of movement considered to be the same as the direction of the robot. It is presupposed that the robot's path is periodically planned, and within the same period, the robot moves in a straight line along a fixed direction.

2.2. Problem Description

This paper focuses on the path planning problem for a single robot in a multi-obstacle environment. The robot model is described above. In this model, the moving space is considered as a two-dimensional bounded region that includes a start point, a target point and multiple obstacles. The target point and obstacles are treated as circular areas.

The robot starts from a specific initial state and needs to navigate to the target region while successfully avoiding all obstacles. When the robot's proximity to the target falls below a certain limit, it can be considered that the robot to have reached the target region.

In this research, the primary focus revolves around two critical aspects:

2.2.1. Path Smoothness. The robot's journey from its starting point to the target destination should ideally be as smooth as possible. This involves minimizing sudden or sharp turns and providing a seamless route for the robot to navigate. The smoother the way, the less complex the motion control required, improving the overall operational efficiency of the robot [5].

2.2.2. Safety or Obstacle Avoidance. As the robot navigates through the environment, safety is of paramount importance. The robot must be able to not only identify potential obstacles but also maintain a safe distance from them. This becomes particularly crucial when the robot operates in a dynamic environment, where obstacles might unpredictably appear and disappear.

The first issue is a path optimization problem, which requires a careful consideration of the robot's motion characteristics and potentially a new way to define and measure "smoothness" in the path planning context.

The second problem relates to risk management and safe navigation strategies. Here, the core is to explore the balance between maintaining a safe distance from obstacles and still achieving the intended goal within a reasonable time frame.

2.3. Performance Evaluation

2.3.1. Path Smoothness. Suppose the path consists of a sequence of nodes: $n_1, n_2, n_3, \ldots\ldots, n_k$. Traversing this sequence and comparing the directions of movement between every three consecutive nodes: n_i, n_{i+1}, n_{i+2}, if the direction from n_i to n_{i+1} differs from that from n_{i+1} to n_{i+2}, it can be considered that this a turn at node n_{i+1}. All such turns along the path are tallied, and the aggregate count of turns is then rationed by the overall length of the path. This ratio serves as a measure of the path's smoothness, with a higher ratio indicating a less smooth path.

2.3.2. Obstacle Avoidance. Obstacle Avoidance is evaluated through observation of the planned trajectory. The further the path is from obstacles, the stronger the obstacle avoidance capability is demonstrated.

3. Path Planning Algorithm

3.1. Potential Field Method

The Artificial Potential Field (APF) approach is a recognized method extensively employed in robotics for path determination and guidance. It fabricates a virtual potential field throughout the workspace where the robot's operation is anticipated. The robot is perceived as a particle propelled by the influence of this potential field [6].

In APF, an alluring potential field gravitates the robot towards the target while a repulsive potential field drives the robot away from the obstacles. These dual fields collectively compose the total potential field impacting the robot. The robot charts its course by progressing in the direction of the negative gradient (i.e., the direction of maximum descent) of the comprehensive potential field. This principle mirrors the idea of a sphere descending a slope under the impact of gravity [7].

The attractive potential field, often associated with the goal, is typically given by a parabolic potential of the form:

$$F_a = \frac{1}{2}\zeta||q - q_{\text{goal}}||^2 \tag{1}$$

where:

q is the current position of the robot,

q_{goal} is the position of the goal,

ζ is a positive constant that determines the strength of the attractive field.

The repulsive potential field, associated with the obstacles, is typically given by:

$$F_r = \begin{cases} 0.5\eta(1/||q - q_{\text{obstacle}}|| - 1/Q_{\text{star}})^2 & \text{if } ||q - q_{\text{obstacle}}|| < Q_{\text{star}} \\ 0 & \text{if } ||q - q_{\text{obstacle}}|| \geq Q_{\text{star}} \end{cases} \tag{2}$$

where:

q_{obstacle} is the position of the nearest obstacle,

η is a positive constant that determines the strength of the repulsive field,

Q_{star} is the distance at which the repulsive potential field becomes effective.

The comprehensive potential field influencing the robot is the vectorial sum of the enticing and the deterrent fields:

$$\boldsymbol{F}_{\text{total}} = \boldsymbol{F}_{a} + \boldsymbol{F}_{r} \tag{3}$$

The robot moves in the direction given by the negative gradient of the total potential field:

$$\delta q = -\alpha \nabla \boldsymbol{F}_{\text{total}} \tag{4}$$

where α is the step size.

It is important to note that while the APF can effectively guide the robot around obstacles and towards the goal, it is not without limitations. The method can result in the robot getting stuck in local minima if the repulsive fields from multiple obstacles interact to create a point of equilibrium [8,9]. This is a common issue in complex environments with numerous obstacles [10]. The next section, discusses the incorporation of the A* algorithm to mitigate this limitation.

3.2. A Search Algorithm*

The A* Search Algorithm is a renowned path finding method recognized for its efficacy and precision. It is an extension of Dijkstra's Algorithm, a technique to traverse graphs that pinpoints the shortest path between two nodes, and applies notions of cost and heuristic to identify the most favorable route.

In the A* framework, each node within a graph (depicting the search space) is affiliated with a cost value, symbolizing the expenditure to transition to that node from the origin. Likewise, each node is linked to a heuristic value, indicative of the projected cost to shift from that node to the target node. Typically, the heuristic is provided by a distance measure, like Euclidean distance, from the node to the goal. The aggregate cost, for a node is ascertained by the summation of these two values:

$$f(n) = g(n) + h(n) \tag{5}$$

The A* algorithm operates by initializing an open list with the start node, and a closed list for nodes that have already been evaluated. It iteratively selects the node in the open list with the lowest total cost, evaluates all its neighbours, and updates their cost values. If a node is reached again via a different path with a lower cost, this cost is updated. The algorithm proceeds until it reaches the goal node or if there are no more nodes to evaluate (in which case a path does not exist). Once the goal is reached, the path is reconstructed from the goal to the start by backtracking through the parent nodes.

The A* algorithm efficiently finds the shortest path in the search space and can handle complex environments with numerous obstacles. However, for a dynamic environment or an environment with unknown obstacles, the algorithm needs to be rerun every time a change is detected. To overcome this limitation, a combination of the Potential Field Method and the A* algorithm is proposed in the next section.

3.3. Field-Enriched A Algorithm*

The crux of the A* algorithm lies in the evaluation function $f(n)$, composed of the heuristic function $h(n)$ and the actual cost $g(n)$ from the starting point to node *n*. In conventional A* algorithms, $h(n)$ typically represents the estimated distance from node n to the target, such as the Euclidean distance. However, in the new method, $h(n)$ is redefined to simultaneously consider the pull of the goal point and the repulsion of obstacles. The workflow is shown on Algorithm1.

For robots with direction, it's possible to explicitly consider direction in the robot's decision-making. This requires the introduction of direction as part of the robot's state in the path planning algorithm. It is vital to note that the traditional A* algorithm typically only considers four or eight directions (if diagonals are taken into account) in a grid environment. This means that the robot's action space has been discretized. However, the Artificial Potential Field method, as a continuous optimization strategy, can push the robot in any direction. This raises a question of how to combine these two completely different strategies. This problem can be solved by following the A* thought process, maintaining each step of movement as horizontal or vertical, performing trajectory interpolation. For this, it is necessary to divide the artificial potential field at each state into horizontal and vertical components.

Let $d(n)$ represent the length from node n to the intended target, O represents the set of all obstacles, and $d(o,n)$ represents the length from node n to obstacle o. The new heuristic function $h'(n)$ can be defined as:

$$h'(n) = \alpha \cdot d(n) + \beta \cdot \sum_{o \in O} \frac{1}{d(o,n)^2} \tag{6}$$

where α and β are weight factors used to adjust the proportion of the target's attraction and the obstacles' repulsion in $h'(n)$. $\frac{1}{d(o,n)^2}$ represents the total repulsion of node n from all obstacles; the smaller $d(o,n)$ is, the stronger the repulsion.

Therefore, the new evaluation function $f'(n)$ can be expressed as:

$$f(n) = g(n) + h'(n) \tag{7}$$

Under this setting, when the A* algorithm searches for a way from the starting point to the destination, it tends to choose nodes that are close to the target and far from the obstacles, thus planning a path that both avoids obstacles and facilitates smooth robot motion.

It should noted that the selection of α and β significantly affects the performance of the algorithm. If α is too large, it may cause the robot to be unable to effectively avoid obstacles; if β is too large, it may cause the robot to stay too far away from the obstacles, preventing it from finding the optimal path. Therefore, in practical use, the best values of α and β need to be determined experimentally.

Algorithm1: FEAP Algorithm

Input: The initial position *Spoint*, the target position *Epoint*, the obstacle environment *Matrix*.
Output: Path from start point to end point *P*.

```
Procedure FEAP(Matrix, Spoint, Epoint, alpha, beta, n, m)
    Initialize all arrays (G, F, openlist, closelist, parentx, parenty) with values of Matrix
    Initialize openlist[Spoint] to 0
    while true:
        Set num to +inf
        for each point (p, q) in the map:
            if openlist[p, q] is 0 and closelist[p, q] is not 1:
                if F[p, q] >= 0 and num > F[p, q]:
                    Set num to F[p, q]
                    Set Nextpoint to [p, q]
        Set closelist[Nextpoint] to 1
        for each neighbor point of Nextpoint:
            Calculate distance from Nextpoint to this neighbor
            if neighbor is obstacle or closed:
                Continue
            if neighbor is unexplored:
                Update G and F of neighbor
                Update parent of neighbor
            if neighbor is explored and current path is shorter:
                Update G, F and parent of neighbor
```

```

            if neighbor is end point or num is +inf:
                Update parent of end point
                break
        if end point has been reached or no path found (num is +inf):
            break
    Initialize an empty path P
    while end point's parent is not start point:
        Add end point to path P
        Move to parent of end point
    Add start point to P
    return P
```

4. Simulation

This simulation sets up a bounded two-dimensional area with a range of 120×120. One mobile robot starts at position (3,3). The goal is a point located at (120,120). In addition, there are several obstacles with a range of sizes.

To evaluate the proposed modification of the A* algorithm incorporating artificial potential fields, a series of experiments was conducted. The traditional A* algorithm served as the baseline, while the modified version of the A* algorithm was tested with three different repulsion factors, β =5, 10, and 20.

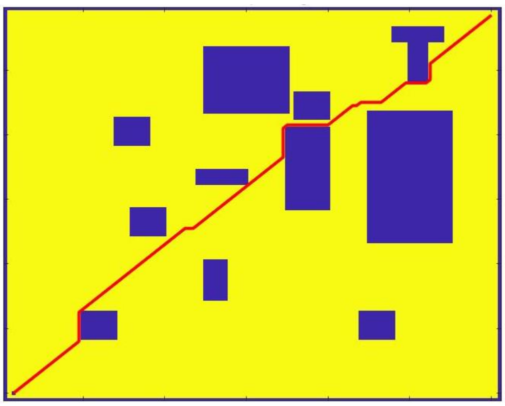

Figure 1. A* Algorithm Path planning

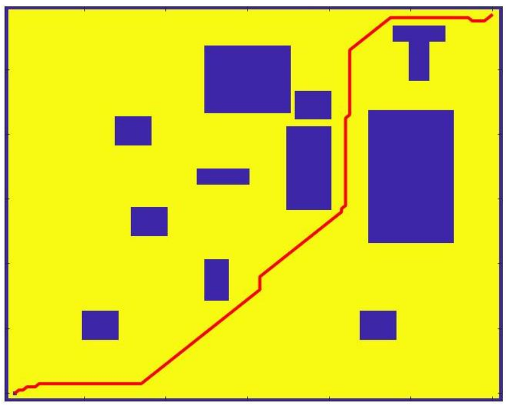

Figure 2. FEAP Path planning with β=5

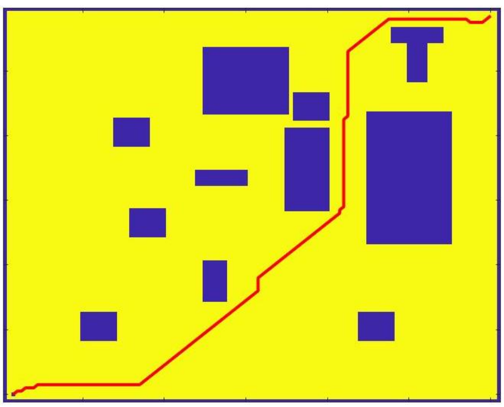

Figure 3. FEAP Path planning with β=10

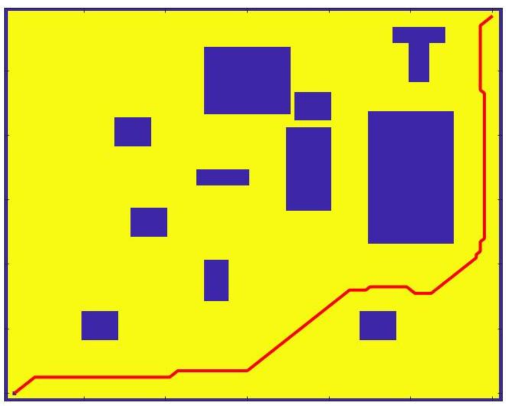

Figure 4. FEAP Path planning with β=20

Table 1. Performance Evaluation of Path Planning

	A* Planner	FEAP Planner (β =5)	FEAP Planner (β =10)	FEAP Planner (β =20)
Steps Conducted	142	170	172	189
Smoothness Factor	0.1418	0.1065	0.1287	0.0957
Obstacle Avoidance	No	YES	YES	YES

The evaluation of performance is shown in Table 1. The findings of the conducted experiment suggest that while the conventional A* algorithm performs with fewer computational steps to achieve its final destination, it frequently devises a trajectory that perilously grazes adjacent obstacles. Observing Figure 2, 3 and 4 yields the FEAP methodology exhibits a superior capacity to devise a path maintaining an appreciable distance from proximal obstacles, thereby effectively addressing the exigency for safe obstacle avoidance, compared to the path planned utilizing traditional A* Algorithm which is demonstrated in Figure 1.

A noteworthy observation pertains to the influence of the repulsion factor, denoted by β . An increase in β invariably coerces the path to be charted more centrally within the navigable terrain. The underlying reason is that a larger β value exerts a more substantial repulsive force against obstacles, which in turn nudges the planned trajectory into safer, open spaces.

However, the implications of an overly large β cannot be overlooked. An inflated β value can be counterproductive for the overall trajectory planning, as it could compel the robotic entity to opt for overly elongated paths, significantly deviating from the most direct route. This proclivity for maximising the distance from obstacles at the expense of an optimally short route underscores the critical necessity of a judicious selection of the β value. The goal is to strike a delicate equilibrium between ensuring an adequate distance from obstacles and optimizing path length.

To elaborate on the specific contexts, a larger β value might be more appropriate in situations such as nuclear radiation fields, where the focus would be on maintaining as much distance as possible from potentially hazardous obstacles. On the other hand, in time-critical scenarios such as disaster relief missions, where swiftness of navigation is paramount, a smaller β would be preferable to avoid excessive detours and ensure rapid arrival at the destination.

In summation, the experimental evidence lends strong credence to the proposed hypothesis, suggesting that incorporating artificial potential fields into the heuristic function of the A* algorithm effectively bolsters the ability of autonomous robots to sustain a prudent distance from obstacles throughout the path planning process.

5. Conclusion

This paper probes the nuances of path planning and optimization. An avant-garde methodology, coined as the Force Enhancing A* algorithm using Potential fields (FEAP) is proposed, aiming to resolve the intricate issue of global path planning while ensuring obstacle avoidance and continuity in robot motion. This strategy integrates a repulsive potential field into the heuristic computation of the esteemed A* search algorithm. The repulsive influence of obstacles is ingeniously incorporated into the heuristic function during the A* search procedure, harnessing the power of the repulsive potential field. This approach significantly augments obstacle avoidance capabilities, consequently fostering smoother, more predictable robot motion during the course of path planning.

A comprehensive series of simulation experiments were meticulously conducted on the novel method, pitting it against some of the more traditional path planning algorithms. The gleaned experimental results provide compelling evidence that the proposed method substantially enhances the fluidity of robot motion, while concurrently ensuring a safe and efficient path is devised.

As a future direction for research, it would be worthwhile to extend the scope of the proposed FEAP method to accommodate multi-robot systems, investigating the impact of inter-robot interactions on path planning. Potential refinements to the heuristic function could also be examined, with the objective of improving the algorithm's efficiency or adaptability to dynamic, unpredictable environments. Lastly, it would be insightful to carry out real-world experiments in addition to simulations, to understand the practical challenges and adjustments required for successful implementation of the FEAP method.

References

[1] Patle B K, Babu L G, Pandey A, Parhi D R K and Jagadeesh A 2019 A review: On path planning strategies for navigation of mobile robot Defence Technol. 15 582–606
[2] Zhang Z, He R and Yang K 2022 A bioinspired path planning approach for mobile robots based on improved sparrow search algorithm Adv. Manuf. 10 114–13
[3] Warren C W 1993 Fast path planning using modified A* method Proc. IEEE Int. Conf. on Robotics and Automation (Atlanta, GA, USA) vol 2 pp 662–667
[4] Wu Z, Su W and Li J 2019 Multi-robot path planning based on improved artificial potential field and B-spline curve optimization Proc. Chinese Control Conf. (CCC) (Guangzhou, China) pp 4691–4696
[5] Gomez E J, Martinez Santa F and Sarmiento F H M 2013 A comparative study of geometric path planning methods for a mobile robot: Potential field and Voronoi diagrams Engineering Mechatronics & Automation
[6] Li G, Yamashita A, Asama H and Tamura Y 2012 An efficient improved artificial potential field based regression search method for robot path planning Proc. IEEE Int. Conf. on Mechatronics and Automation (Chengdu, China) pp 1227–1232
[7] Pradhan S K, Pradhan D R, Panda A K et al 2006 Applied Intelligence 25 321–333
[8] Qixin C, Yanwen H and Jingliang Z 2006 An Evolutionary Artificial Potential Field Algorithm for Dynamic Path Planning of Mobile Robot Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (Beijing, China) pp 3331–3336
[9] Qi N, Ma B, Liu X, Zhang Z and Ren D 2008 A modified artificial potential field algorithm for mobile robot path planning Proc. 7th World Congress on Intelligent Control and Automation (Chongqing, China) pp 2603–2607
[10] Zhu Q, Yan Y and Xing Z 2006 Robot Path Planning Based on Artificial Potential Field Approach with Simulated Annealing Proc. 6th Int. Conf. on Intelligent Systems Design and Applications (Jian, China) pp 622–627