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APF Method of Dynamic Obstacle Avoidance with Relative Velocity

Yonghao Shu[1*], Dehan Shen[2], Mohan Chen[3]

[1]*College of Liberal Arts, University of Minnesota Twin City, Minneapolis, USA*
[2]*Automatic Control & Systems Engineering, University of Sheffield, Sheffield, U.K.*
[3]*Suzhou Foreign Language School, Suzhou, China*
**Corresponding Author. Email: SHU00037@umn.edu*

Abstract. The Artificial Potential Field (APF) method is a widely adopted approach in autonomous mobile robot path planning due to its mathematical simplicity and computational efficiency. However, its application in dynamic obstacle avoidance remains limited by the static assumptions in its algorithmic logic, leading to challenges in realistic scenarios. This paper addresses these limitations by introducing a novel refinement to the APF method for dynamic obstacle avoidance. Our approach redefines the repulsive field as an adaptive elliptical model, with the obstacle as the focal point and the relative velocity between the robot and the obstacle dictating the major axis. This innovation accounts for realistic motion dynamics, including varying speeds and directions, to enhance safety and path optimization. To validate the effectiveness of the proposed method, we developed new algorithms and tested them in a virtual environment, demonstrating improved adaptability and efficiency compared to traditional APF approaches.

Keywords: Artificial Potential Fields, Dynamic Obstacle Avoidance, Autonomous Driving

1. Introduction

Automatic vehicles are developing rapidly and are in high demand. It is quite imaginable that if autonomous vehicles are fully integrated into transportation systems, social life will be more efficient, as behaviors such as random parking, arbitrary lane changes, and congestion can be technically avoided. However, under the current state of autonomous vehicles, unexpected accidents still occur. For instance, on October 2, 2023, an autonomous vehicle operated by Cruise collided with a pedestrian in San Francisco. The pedestrian had initially been struck by another human-driven vehicle and was then run over by the autonomous vehicle. This incident led the California Department of Motor Vehicles (DMV) to suspend Cruise's permit for autonomous vehicle operations later that month [1]. This tragic event highlights the ongoing challenges autonomous vehicles face in dynamic obstacle avoidance, particularly in handling complex, real-time interactions with pedestrians and other vehicles in urban environments.

The ultimate goal of obstacle avoidance is to arrive at the target point with minimal operational cost while avoiding all obstacles. Static obstacle avoidance has been extensively studied using algorithms such as Artificial Potential Fields (APF), machine learning-based methods, and A*.

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Among these, the APF method stands out for its intuitive mathematical model and straightforward computational logic, making it a preferred choice for many researchers despite its limitations in handling dynamic scenarios.

Recent studies have explored APF's applications and limitations in various environments. For instance, Ge and Cui [4] integrated the APF method with simulated annealing to address the issue of local minima. Similarly, Batinovic et al. [7] and Peng et al. [8] applied APF to three-dimensional environments, such as unmanned aerial vehicle navigation, demonstrating its adaptability to various domains. Li and Wang [3] incorporated decision tree methods to enhance APF's dynamic obstacle avoidance capabilities. Furthermore, Omar and Gu [2] reviewed APF's theoretical foundation and identified key areas for improvement, particularly in addressing its inherent tendency to get stuck in local minima. Li et al. [10] introduced a novel improvement combining fuzzy algorithms and relative velocity potential fields for Unmanned Aerial Vehicles (UAVs).

In addition to these algorithmic advancements, practical applications of APF in multi-robot and multi-agent systems have also been explored. Zhang et al. [9] combined APF with deep reinforcement learning to improve multi-robot path planning. Such studies have demonstrated APF's potential to adapt to complex, real-time scenarios, particularly in autonomous vehicle navigation.

Despite these advancements, challenges remain. Traditional APF approaches often assume a fixed repulsive field around obstacles, which may not reflect real-world dynamics. Gao [5] proposed an elliptical repulsive field model to address this, but this approach still lacked accuracy in representing the varying risks associated with different obstacle velocities. Inspired by Zhao [6], we aim to further improve the APF model by incorporating relative velocity into the repulsive field's parameters, making it more adaptive to dynamic scenarios. Our approach builds upon these foundational studies to propose a novel refinement of the APF method for dynamic obstacle avoidance.

2. Theoretical foundations of APF

The APF method of obstacle avoidance starts with static obstacles. A classical static obstacle avoidance algorithm assigns an obstacle to a circular, fixed-radius repulsive field, and robots entering the field are subjected to a specific formula of repulsive forces. At the same time, the robot is also affected by the gravitational field generated by the target and therefore constantly searches for a path to the target point. The common repulsion field functions are:

$$U_{rep}(x) = \begin{cases} k_{rep}\left(\frac{1}{x_u - x_{ob}} - \frac{1}{x_0}\right)^2, & (x_u - x_{ob}) < x_0 \\ 0, & (x_u - x_{ob}) \geq x_0 \end{cases} \tag{1}$$

Where k_{rep} is the repulsion gain coefficient, x_{ob} is the position of the obstacle, $x_u - x_{ob}$ is the Euclidean distance between the UAV and the obstacle, and x_0 is the influence radius of the obstacle.

The algorithm can avoid the obstacle and reaches the target point, and the trajectory of its avoidance segment exhibits a distinctly circular feature.

However, this algorithm is not applicable in the field of dynamic obstacle avoidance. It completely ignores the effect of obstacle speed, and therefore can be dangerous and deviate from the path optimization principle during dynamic obstacle avoidance.

To solve this problem, Gao [5] proposed a solution idea. He changed the shape of the repulsive field from a circle to an ellipse with the direction of the obstacle's velocity as the long axis, thus

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leaving a corresponding avoidance space for the existence of velocity (Figure 1).

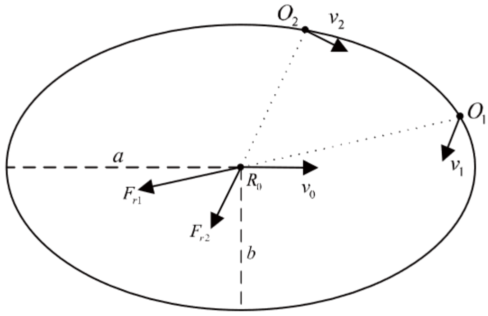

Figure 1. Ellipse repulsive field [5]

Still, this model is not perfectly reasonable for self-driving cars. For example, the rear of the forward direction of an obstacle is relatively safer, so the repulsive force should have a smaller area of influence. Also, the model has significant distortions when dealing with situations where the obstacle speed is perpendicular to the robot speed. There is no clear literature on the improvement of these aspects in artificial driving environments, but treatments in similar situations give us ideas to deal with the above issues.

3. Proposed work

The idea of this article is to improve the existing elliptic model. Firstly, the ellipse with the obstacle being the geometric center shall be changed to an ellipse with the obstacle as the focal point and the direction of the obstacle velocity as the longer major axis; secondly, the parameter of the long axis of the ellipse shall be changed from a constant to a function of the velocity of the obstacle; and thirdly, the interaction between the obstacle and the robot is taken into account, with an emphasis on the effect of the relative velocities on the parameters of the repulsive force field.

As mentioned before, the repulsive force field in the case of dynamic obstacle avoidance is unlikely to be an ellipse geometrically centered on the obstacle. Due to inertia, it is more dangerous along the direction of velocity, as braking, deceleration, and other maneuvers need to allow for distance. The repulsive field in the opposite direction of velocity should be reduced, since in real life it is unlikely that the vehicles will suddenly gain backward velocity; all we need to consider here is to allow space to avoid rear-end collisions. Similarly, the repulsive fields on the sides of the robot need to be relatively small, as it is not possible to gain sudden lateral velocity.

However, this alone is still not very close to reality. The above model does not provide very scientific guidelines for obstacle avoidance when the robot speed is perpendicular to the obstacle speed. Hence, it is the velocity of the obstacle relative to the robot rather than the velocity of the obstacle that really determines the extent and shape of the repulsive field.

Therefore, the shape of the repulsive field shall be an ellipse with the obstacle as the focal point and the direction of the obstacle's velocity relative to the robot as the major axis (the longer piece of the major axis).

We have built an algorithm for the above model and simulated it in MATLAB, which will be illustrated in detail in the next section.

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4. Methodology and experimental validation

In this chapter, we conducted simulation experiments using MATLAB to investigate three obstacle avoidance algorithms: the traditional APF method for static obstacle avoidance, the elliptical repulsive potential field considering obstacle velocity for dynamic obstacle avoidance, and the dynamic obstacle avoidance algorithm considering relative velocities between the robot and obstacles.

We set up 10 fixed-position obstacles and performed obstacle avoidance using the traditional APF method. The green point represents the starting point, the red point represents the destination, the blue points represent the obstacles, and the pink line represents the simulated path. As shown in Figure 2, the path generated by the traditional APF algorithm veers away from the obstacles when approaching them, resulting in trajectories that closely resemble arcs.

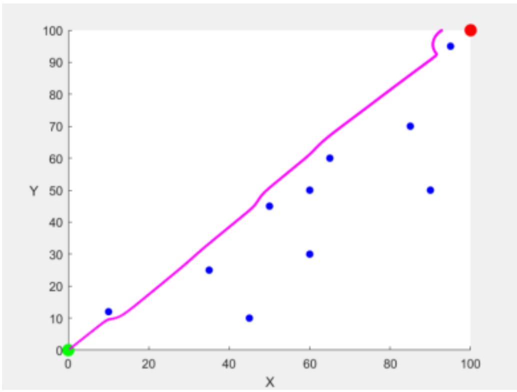

Figure 2. Static obstacle avoidance using the traditional APF algorithm

Next, we introduced a single obstacle and conducted experiments using both the improved APF algorithm considering obstacle velocity and the improved APF algorithm considering relative velocities between the robot and obstacles. As depicted in Figure 3, an ellipse represents the repulsive field around the obstacle, with a blue point located at one focus of the ellipse, representing the obstacle's position, and a red point at the other focus, representing the robot's position. It is evident that when considering the relative velocities between the robot and obstacles, the robot's path becomes more flexible, and the avoidance trajectory is more efficient, allowing for smoother and more convenient navigation around obstacles. And the same conclusion can also be drawn from Figure 4 and Figure 5. The pink dots represent other obstacles, which also have elliptical potential fields. However, for the sake of observation, only the potential field of the blue obstacle is depicted in the figure.

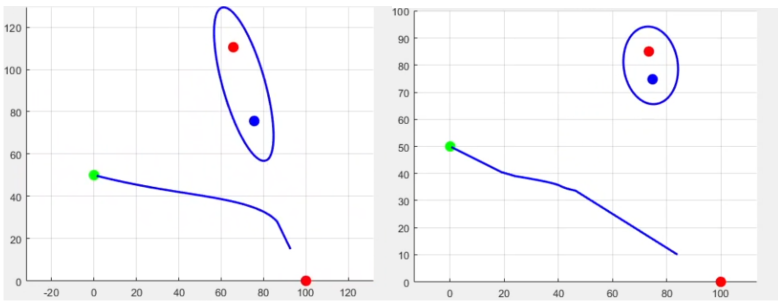

Figure 3. Comparison between the algorithm considering obstacle velocity and the algorithm considering relative velocities between the robot and obstacles

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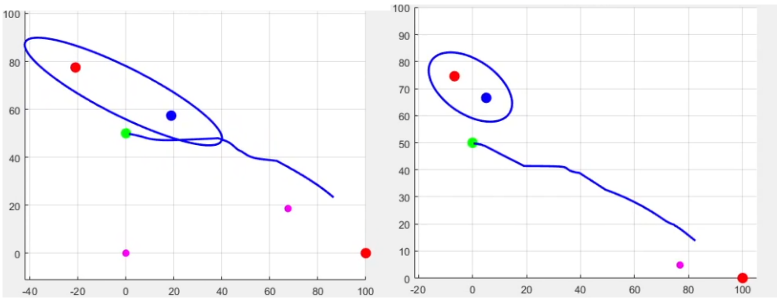

Figure 4. Comparison of the paths generated by the two algorithms when setting up three obstacles

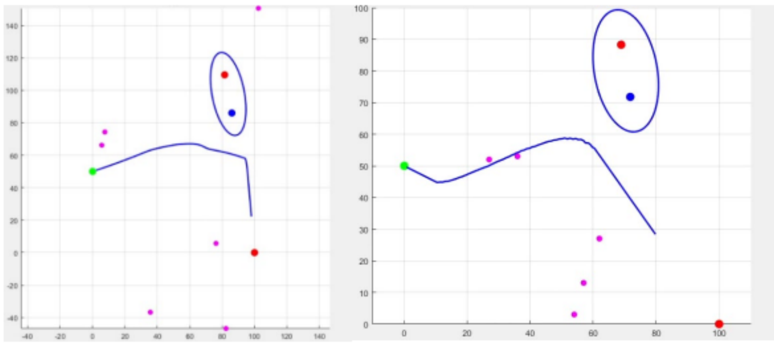

Figure 5. Comparison of the paths generated by the two algorithms when setting up seven obstacles

Subsequently, in the improved algorithm of the APF based on relative velocity, we adjust the magnitude of the velocity influence factor to observe the changes in repulsive forces generated by the repulsive potential field. In Figure 6, it can be observed that when the Kv value is 0, the robot is not influenced by repulsive forces related to relative velocity, resulting in a less smooth planned path. When the Kv value is set to 0.2, the robot takes into account the influence of relative velocity, generating a much smoother avoidance path. However, when the Kv value is set to 0.4, the robot's avoidance path becomes too large in amplitude. Therefore, setting Kv appropriately is crucial for the reliability of the algorithm.

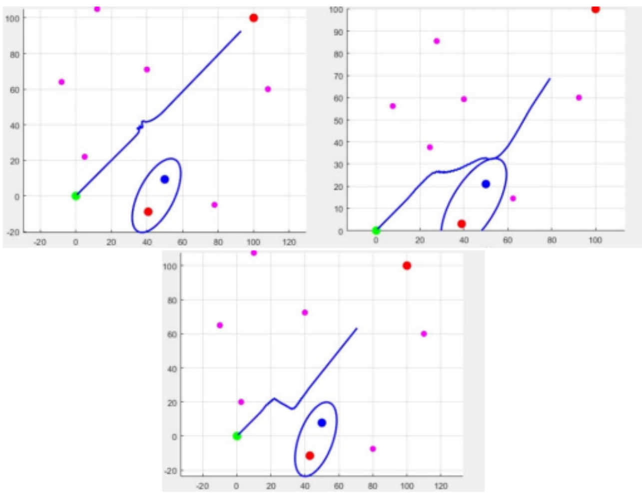

Figure 6. Comparison of the results of the improved algorithm based on relative velocity when the kv values are set to 0, 0.2, and 0.4, respectively

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5. Conclusion

In this study, a modified and more realistic dynamic obstacle avoidance algorithm based on the APF method is proposed. We have adapted the repulsive field of the obstacle in a dynamic case, improving it to an ellipse with the obstacle as the focal point and the direction of the obstacle's velocity relative to the robot as the major axis (the longer piece of the major axis). The minor axis of this ellipse is an empirical constant, considering the safe distance and turning radius of the actual vehicle. The major axis of this ellipse is the sum of the safe distance constant and the empirical polynomial with relative velocity as the variable. The results of the simulations are generally as expected. When the relative speed between the obstacle and the robot is high, the robot starts to take evasive maneuvers at a relatively long distance to avoid large turns, acceleration or deceleration, and dangerous situations. At small relative speeds, the trajectory of the cart is optimized and will take evasive action over a shorter distance.

Still, this article still has several shortcomings. Firstly, the formula for the range of repulsive fields and force fields still need more improvement to be close to reality. This article proposes an idea that provides a formula that can satisfy the basic route planning task in general, but it does not explore too much whether it is an optimal solution or not, and thus there is room for optimisation.

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