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Improved artificial potential field method for mobile robot path planning

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Abstract. Path planning has already been used in areas like robots and unmanned vehicles to prevent collisions in certain environments. A Path planning algorithm is needed to achieve such tasks and Artificial Potential Field (APF) method is one of the methods. However, APF has limitations facing various situations like being stuck in a local minimum such as a dead-end or a narrow path. To solve the problem, First, a side force is added to the algorithm along with two types of definitions of the force direction. Then a variable k_{rep} is proposed to prevent the dead-end situation. Finally, the variable step size is used to improve the efficiency of the algorithm. The simulation results demonstrate the effectiveness of the method. In comparison to APF, the improved APF could prevent the local minimum and reach the target position with fewer processing steps and better performance.

Keywords: path planning, artificial potential field, local minimum.

1. Introduction

Nowadays, autonomous robots and unmanned vehicles have been widely used in industry and daily life. To accomplish a task such as transporting a load or moving a robot arm, collision avoidance between the vehicle and the environment should be considered and an algorithm is required. Path planning algorithms generate commands based on environmental information given by onboard sensors (e.g. ultrasonic sensors) or a certain map, which can be used to solve the problem [1,2]. Global path planning algorithms offer a path that could avoid collapsing into obstacles by using the given map but may cause a collision in a dynamic environment with moving objects and obstacles (e.g. self-driving cars [3,4]). Local path-planning algorithms rely on sensors, which help to improve adaptability to dynamic environments, and have become more popular in recent years.

The artificial potential field (APF) algorithm is first given by Khatib in 1986 which is classified as a local path planning algorithm [5]. The theory of this algorithm is derived from the forces between the particles in the electric field. In such a field, the robot and the obstacles have the same properties which generate a repulsive force inversely proportional to the change in distance. The goal on the other hand has different properties which create an attraction force related to distance. The superposition of these forces gives the direction of the next path and the total force that drag the vehicle to the target.

Traditional forms of APF can be trapped in local minimum easily, which is a major problem of the algorithm (Figure 1). This situation occurred when the attractive force and the combination of the

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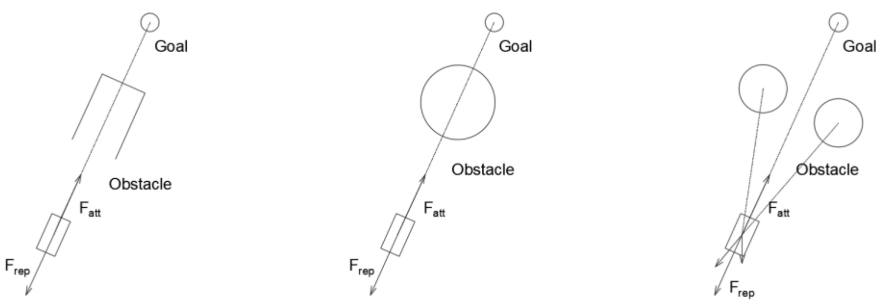
repulsive forces are equal in values but opposite in directions (e.g. a dead-end or a narrow path between two obstacles). To avoid getting into a local minimum, various methods have already been used to improve the algorithm. Some put interest in giving a pre-designed path function to prevent the situation from happening. In [6], a regular hexagon-guided (RHG) pattern is raised. The method provides a hexagon-guided trajectory after reaching the local minimum. The trajectory can be expanded until the vehicle gets rid of the local minimum. Others tried to modify the algorithm itself or add some principle to avoid local minimum. In [7], the researcher decomposes attractive forces and repulsive forces into a new coordinate and calculates the angle of the total force under the new coordinate system. The trigonometric value of this angle is used to plan the next step which could be used to prevent the local minimum. In [5], a robot with two LiDAR sensors is used. By receiving the data from the sensors, the improved algorithm could recognize a local minimum situation and create a virtual wall and obstacles to add additional forces to the vehicle and prevent it from sticking to the local minimum. In [1], a top quark-based mechanism has been used when the vehicle reaches the local minimum to give extra forces to the total force equation to help get rid of the local minimum.

The method listed above could solve the local minimum problem, but some work still needs to be done. Adding a certain path when reaching the local minimum may have problems in a dead-end environment. Setting up a virtual wall could solve the dead-end problem but may have problems in narrow environments. From the present review, adding a side force to the algorithm receive little attention which is a method that needed to be developed. The step length of the algorithm is assigned to a certain value which can be modified in various values under different situations to reduce the generating time of the path.

In this paper, a side force is added to the algorithm to help prevent the local minimum problem. The parameter of repulsive force is also designed to be variable to help prevent the vehicle from entering the local minimum. Variable step size is designed to reduce the calculation time. Such approaches could improve the performance of the algorithm and have better adaptability to different environments.



(a) (b) (c)

Figure 1. Local minimum situations.

(a) dead-end(b) a single obstacle in the path (c) a narrow path

2. Traditional Artificial Potential Field method (APF)

In the given field, the position of the vehicle and the goal are $[x_v, y_v]$ and $[x_g, y_g]$. The attractive force is only attached to the distance calculated by the two coordinates. The further the distance, the greater the value of attractive force (F_{att}). The attraction potential field U_{att} produced by the goal point is [6,8]:

$$U_{att}(X_v) = \frac{1}{2} \cdot k_{att} \cdot \mathrm{d}^2(X_v, X_g) \tag{1}$$

Where k_{att} is the attractive constant, d is the distance between the vehicle and the goal.

The attractive force is the negative gradient of $U_{att}(X_v)$

$$F_{att} = k_{att} \cdot \mathrm{d}(X_v, Y_v) \tag{2}$$

The direction of the force starts from the vehicle and points at the goal.

The repulsive field of the obstacles is just the same as the attractive field but the force direction and the relationship between distance and forces are the opposite. A single obstacle located in $[x_o, y_o]$, the repulsive field is [9,10]:

$$U_{rep} = \begin{cases} \frac{1}{2} \cdot k_{rep} \cdot \left(\mathrm{d}(X_v, X_o)^{-1} - d_0^{-1}\right)^2, \ d \leqslant d_0 \\ 0, \ d > d_0 \end{cases} \tag{3}$$

Where $d(X_v, X_o)$ is the distance between the obstacle and the vehicle and k_{rep} is the repulsive constant. Also, the repulsive force is the negative gradient of U_{rep}. Within the range d_0, the repulsive force should be:

$$F_{rep} = k_{rep} \cdot \left(\mathrm{d}(X_v, X_o)^{-1} - d_0^{-1}\right) \cdot \left(d(X_v, X_o)^{-1}\right)^2 \tag{4}$$

In the equation, the force gets larger when the distance is shortened and it only takes into consideration when the distance between the vehicle and the obstacle is close enough. The direction of the force is parallel to the line that connects the obstacle and the vehicle and points away from the obstacle.

The total force is the combination of repulsive forces and a single attractive force. The total force of the vehicle should be:

$$F_t(X_v) = F_{att}(X_v) + F_{rep}(X_v) \tag{5}$$

In the equation, F_{rep} represents the total repulsive which is the superposition of different vectors.

3. Improved Artificial Potential Field (IAPF)

Since the APF could be trapped by the local minimum, some improvements are proposed in this paper that help to get rid of the local minimum.

3.1. The side force for local minimum

In APF, When the vehicle reaches a local minimum point, the total force (F_t) is almost zero in value, causing the vehicle to a stop and be unable to move. The F_{att} and F_{rep} are almost the same in value but opposite in directions. A side force that breaks the balance of the two forces can be added to the total force in this scenario. By doing so, the value of the total force is nonzero and the direction is the same as the side force. The vehicle is pulled into a new position where the balance of the F_{att} and F_{rep} is broken, which increases the possibility for the vehicle to return to its normal trajectory.

To make sure the local minimum can be fully solved, a mechanism is proposed (Figure 2). For obstacles like the dead-end or the roof-top, the repulsive force given by the side wall may push the vehicle back to another local minimum. To prevent repetitive movements, the direction between the obstacle and the vehicle and the direction between the vehicle and the goal position will be compared if the obstacle is in the range d_0. Obstacles in the fore-hemisphere will be recorded and the side force will not be canceled until no obstacles are in range and located in the front hemisphere. With the mechanism above, the side force can be defined as:

$$F_{side} = k_{side} \cdot b \cdot alpha^{-1} \tag{6}$$

where k_{side} is the side force constant, b is the number of obstacles that match the conditions and alpha is a constant.

The more obstacle in the fore-hemisphere, the greater the side force will be which ensure the vehicle could get rid of the local minimum and lower the possibility to be trapped again by the local minimum.

The direction of the side force is perpendicular to the direction of the direction of F_{rep} (Def 1). A principle is used to decide to point at the left or the right side by counting the obstacles on the left or right side of the vehicle. If one side has a relatively small number of obstacles, the direction of the force will be pointed to that side (Figure 3) to find a shorter path. In this paper, the direction of the side force can also be defined as the vector that is perpendicular to the direction of the vehicle and the goal position (Def 2). Both methods will be tested on the map to judge their effectiveness.

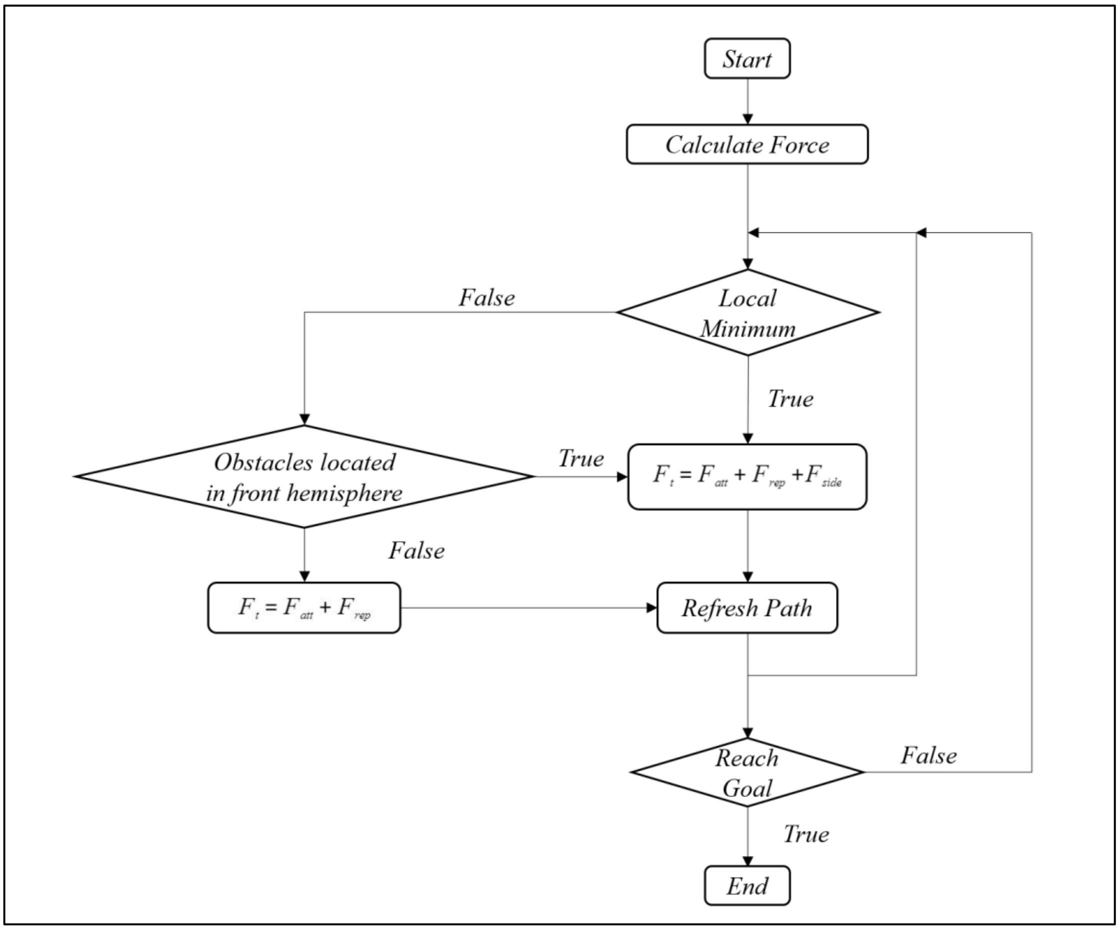


Figure 2. The flow of the mechanism.

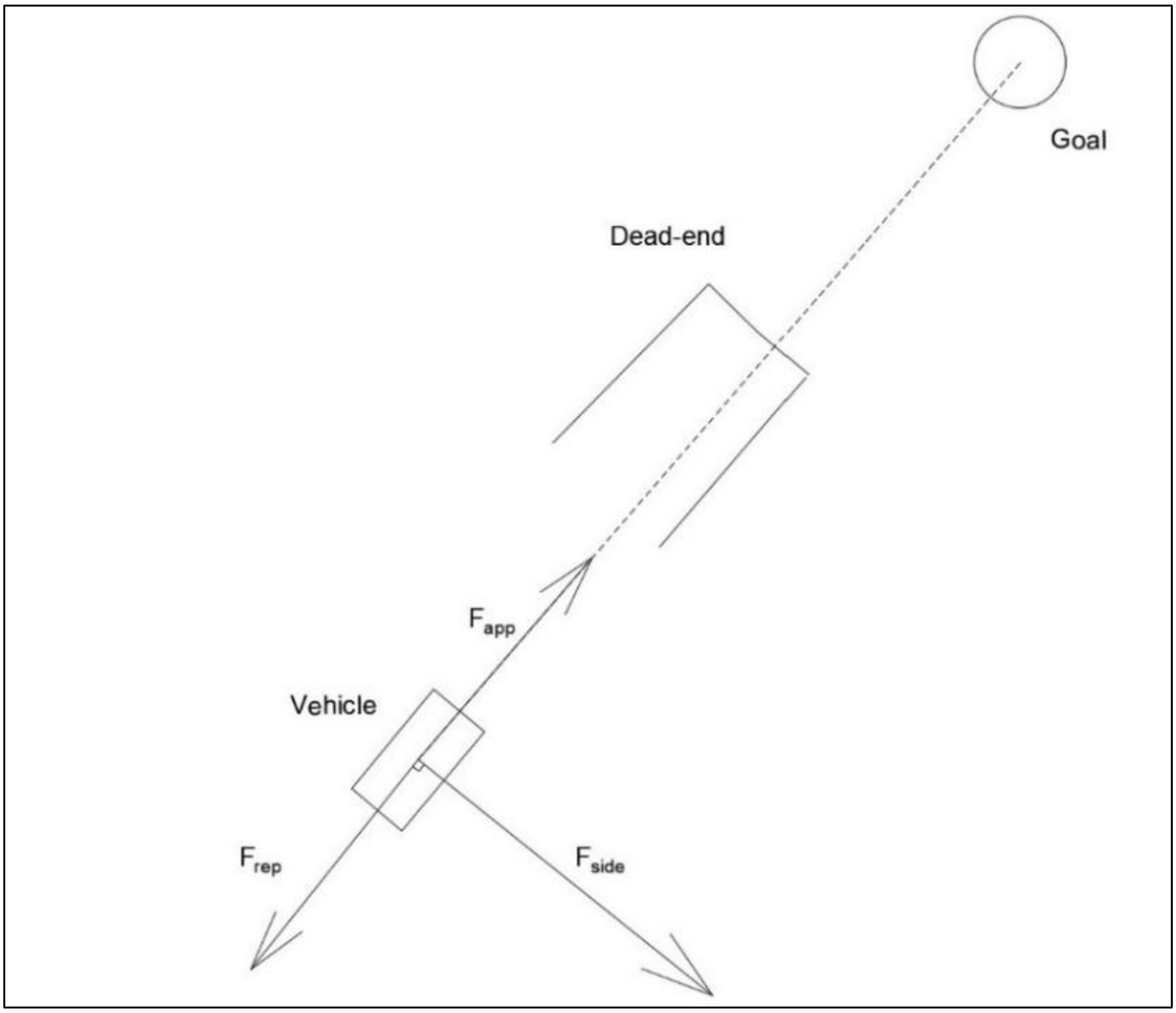


Figure 3. A picture of the side force in a local minimum.

3.2. The variable k_{rep} to prevent a dead-end situation

When the vehicle is stuck in a dead-end on the map, simply applying the side force to the vehicle is no longer an effective approach since there's no space for the vehicle to move aside, especially in narrow dead-ends. Adjusting the constant k_{rep} can be used in limited situations but not all scenarios. To enhance the adaptability of the algorithm, the definition of k_{rep} has changed into the form below:

$$k_{rep} = a - d(X_v, X_o) \tag{7}$$

where a is a constant and $d(X_v, X_o)$ is the distance between the vehicle and each obstacle within the rang d_0. The k_{rep} increases when the distance gets closer instead of the constant value in APF. This method causes the vehicle to fall into the local minimum earlier which effectively prevents the vehicle from entering the dead-end and getting stuck in it.

3.3. The variable step size to improve the efficiency

In APF, the step size is designed to be a constant value for better performance facing the obstacle. In situations where no obstacles in range, the constant step size may be a factor that could increase the requirement of the platform and lower the speed of the algorithm. To solve the problem, the step size is divided into several different constant values and each one has its corresponding phase which relies on the distance between the vehicle and the obstacles. The closer the vehicle is to an obstacle, the smaller the step size is given. What's more, if there are no obstacles in range, the maximum step size will be given until an obstacle appears in the range. This strategy boosts the efficiency of the algorithm and still has the same performance as APF when an obstacle occurs.

4. Result and discussion

To validate the algorithm, Matlab is used to run the simulation. The constant values and the key parameters are listed in Table 1.

Table 1. The parameters used in the simulation.

parameter	value
k_{att}	0.008
k_{side}	4.5/0.01
rep_radius	2.5
alpha	13.7
a	2.464

The rep_radius is the range and a is the constant in the k_{rep} definition. In the simulation, the constant value k is used to record the number of step points. By switching the two different sets of side force directions, the efficiency and the trajectory can be shown to make a comparison.

4.1. Dead-end scenario

In the dead-end situation, the APF couldn't get rid of the local minimum but adding a side force could solve the problem (Figure 4). In the situation where the side step can be varied, the simulation with Def 1 has a much smooth trajectory than the one using Def 2. The mechanism is clearly shown in the result that the side force still exists even if the point is not a local minimum which helps to solve the problem.

In the situation with fixed step size, the simulation with Def 1 could also work but it also showed that it can go into local minimum again. On the contrary, the simulation with Def 2 has a better pattern and only a few zig-zag is shown.

Comparing the k value of the simulation, Def 1 and Def 2 showed little differences in the same conditions. In the variable step size condition, the average step uses is 3454, and in the fixed step size condition, the average use goes more than 24000. This result proved that variable step size could boost the efficiency of the algorithm.

In the figure below, the red and green circle represent the start and the goal seperately. The blue line is the trajectory of the vehicle and the red lines are the obstacles.

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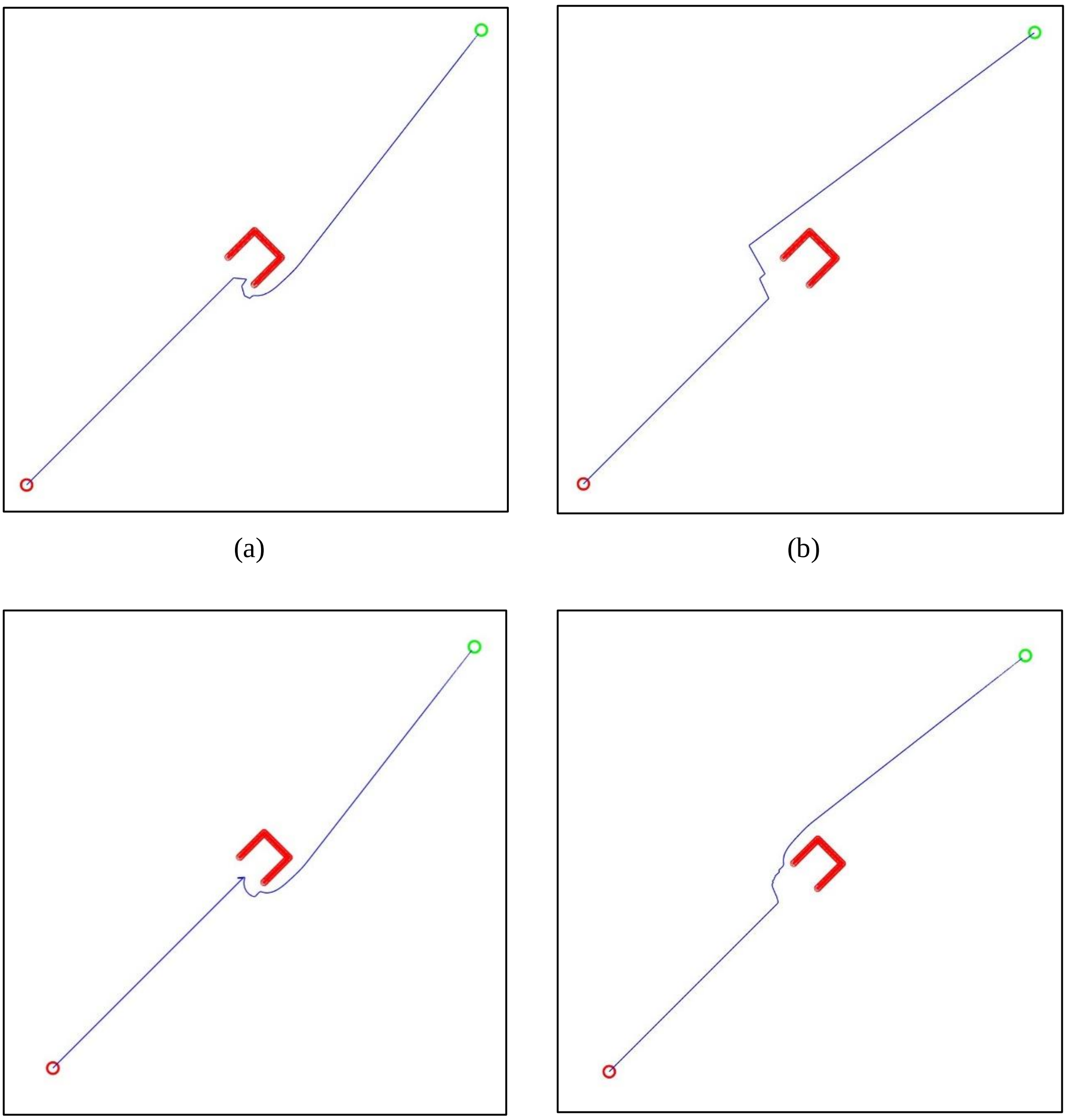

(a) (b) (c) (d)

Figure 4. Trajectory in Dead-end Situation.

(a) variable step size with Def 1 (b) variable step size with Def 2

(c) fixed step size with Def 1 (d) fixed step size with Def 2

4.2. Roof-top scenario

In the roof-top situation, the trajectory shown after the simulation gives a similar look compared with the dead-end scenario (Figure 5). In variable step size conditions, both Def 1 and Def 2 could finish the task but the path of the one using Def 1 is too close to the obstacles which may cause a collision. The one using Def 2 works well but the trajectory has more zig-zag movements which is not as smooth as the one using Def 1.

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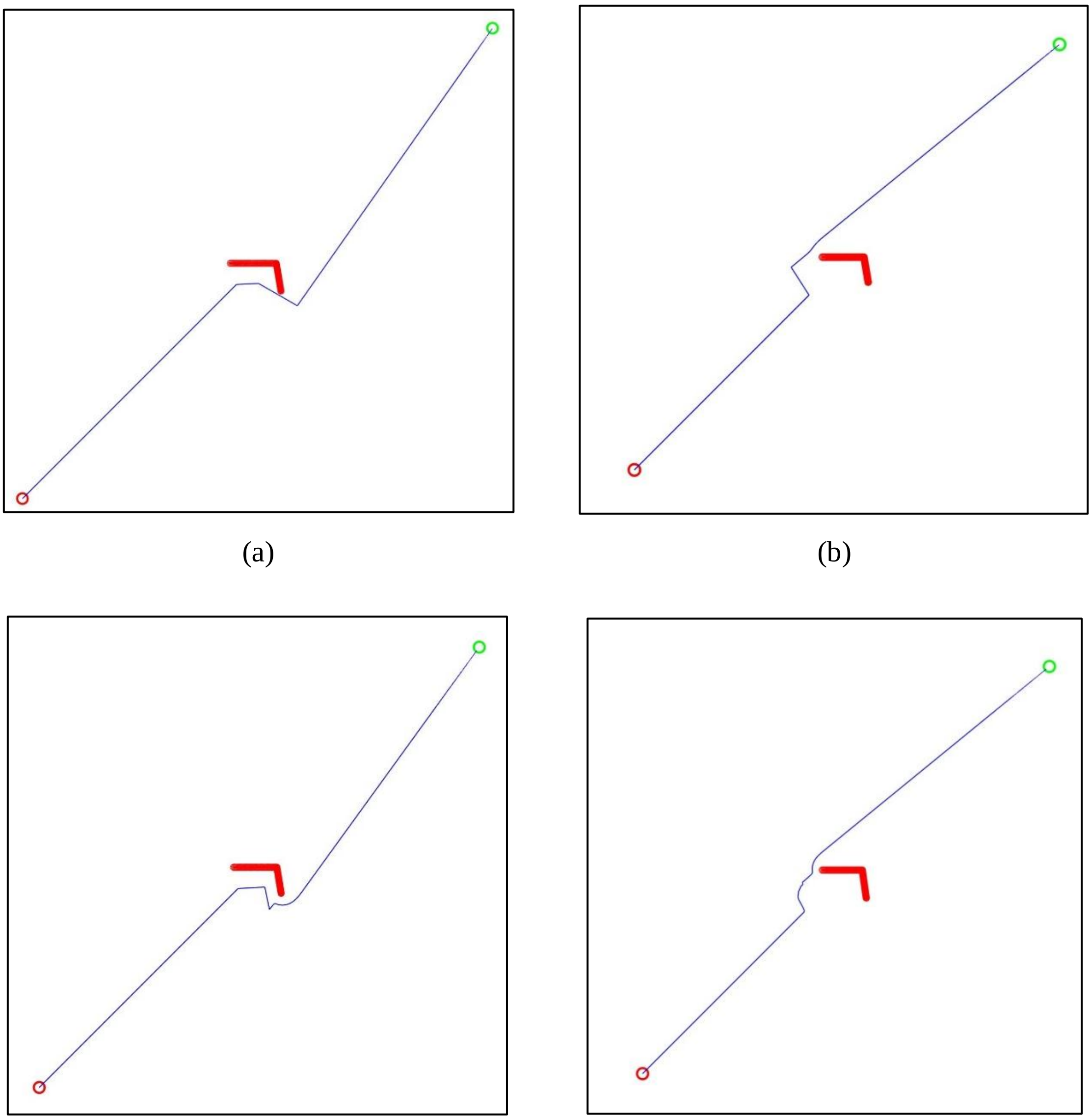
In the situation where the step size is fixed, both the trajectory of Def 1 and Def 2 have a smooth path. The one using Def 2 falls into the local minimum much earlier than the one using Def 1 which is an advantage for the path planning since it has less sharp turns.

Counting the steps the simulation used, the simulation with a fixed step size consumes more time to reach the goal whereas the one with a variable step size uses less time.



(a) (b)

(c) (d)

Figure 5. Trajectory in Roof-top Situation.

(a) variable step size with Def 1 (b) variable step size with Def 2

(c) fixed step size with Def 1 (d) fixed step size with Def 2

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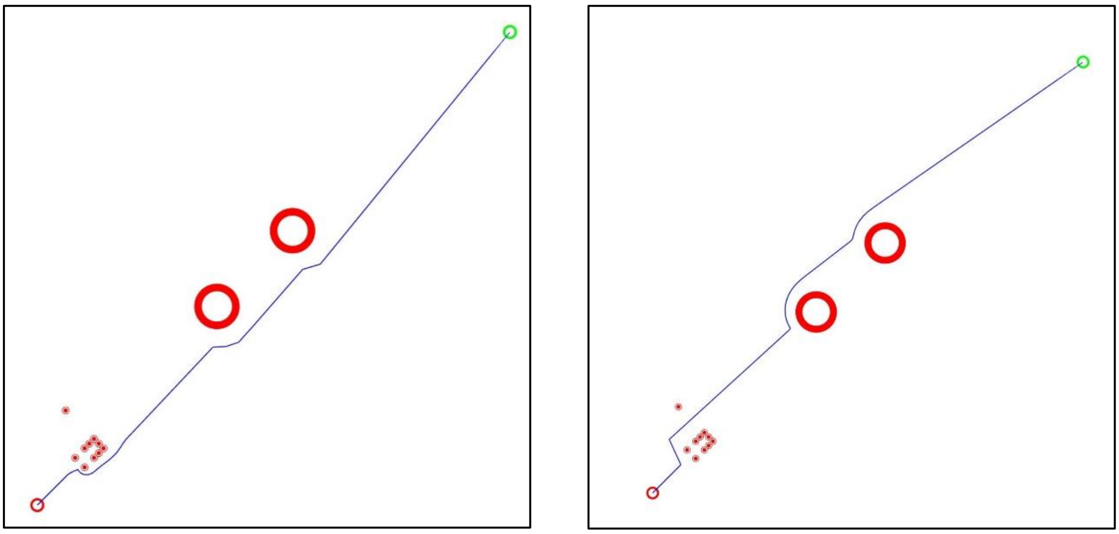
4.3. Mixed scenario

In the mixed environment (Figure 6), the algorithm faces different kinds of obstacles. Regardless of using Def 1 or Def 2 in the simulation, the task can be finished with a similar step number. The difference between definitions is the smoothness of the trajectory. The one using Def 2 clearly has a much smooth trajectory but the one using Def 1 gets much closer to the obstacles.



(a) (b)

Figure 6. Trajectory in mixed obstacle situation.

(a) variable step size with Def 1 (b) variable step size with Def 2

4.4. Discussion

The trajectory indicates that the side force mechanism could solve the local minimum problem and could remain in the total force until the local minimum fully disappeared. The variable k_{rep} prevents the vehicle from getting into the dead-end which solves one of the local minimum problems.

Through the experiment, the Def 1 tend to get close to the obstacles but the Def 2 falls into a local minimum much earlier. The trajectory of Def 2 is always smooth but the trajectory of Def 1 is not. These two phenomena result in the direction of the side force. The trajectory made by Def 2 is smoother because the direction of the lateral force is perpendicular to the direction of movement, which can produce a circular trajectory. The trajectory made by Def 1 is sharper because it is perpendicular to the F_{rep}, which can cause it to continue towards the obstacle even though it has fallen into the local minimum, causing it to be forcibly pushed away from the obstacle, creating a sharp trajectory. For vehicles that need to examine the environment, Def 1 may be more suitable because the range of dead zones that the robot can traverse will be reduced. For vehicles that need a smooth trajectory, Def 2 may be a better choice.

The trajectory also showed that the smoothness of the trajectory has a strong connection to the step size. In the fixed step size condition, the step size is assigned to be the same as the step size in variable conditions when facing multiple obstacles. The result is clear that the smaller the step size is, the smoother the trajectory will be. But on the other hand, the relatively smaller step size could sometimes harm the trajectory since the step it takes is too small and it can easily fall into another local minimum. What's more, the small step size is unnecessary when there are no obstacles around the vehicle. By using the variable step size, the k value dropped significantly, which saved loads of resources and time. Taking these advantages, the variable step size needs further research.

The constant k_{side} may also be the reason why the trajectory is sharp because the side force sometimes may go far beyond the requirements which push the vehicle too far. To some point, it helps to get rid of the local minimum, but it also creates a sharp trajectory. A variable k_{side} is needed to be defined in future works to improve the performance of the algorithm.

5. Conclusion

The research proposed a method to improve the traditional artificial potential field. The total force of the method, the equation of the repulsive forces, and the step size have been improved separately. The simulation results verified the effectiveness of the approach and it proved that the improved algorithm could prevent the vehicle from falling into the local minimum with fewer processing steps and better performance.

Some problems like the sharp trajectory and coherence of the trajectory are found in the research, which should be improved in further research. Also, the adaptability of the algorithm is another point to be studied in the future. The research set up a new direction for improving the artificial potential field and gives a different choice to make path planning for vehicles and drones.

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