Reactive navigation of autonomous vehicle

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Abstract. Research on dynamic path planning for autonomous vehicle has been increased significantly in recent years because of the percentage of car accidents reduced by autonomous driving. The functions of Artificial Potential Fields (APF) as mentioned in previous studies, particularly nonlinear constraint, speed and safe distance, are seldom discussed or mentioned. In this paper, we focus on the need for vehicle safety. Thus, this study proposes a fuzzy artificial potential field path planning algorithm (FZ-APF) for local path planning in vehicle. FZ-APF introduces the distance factor to solve the well-known drawbacks of the traditional APF like goal non-reachable with obstacle nearby (GNRON) problem. However, FZ-APF not only optimizes path but also deals with the constraints of vehicle like the limit of steering angle at different speeds. Therefore, FZ-APF introduces longitudinal potential function to make the planned path accord with vehicle characteristics. In addition, to achieve more safe and efficient FZ-APF for vehicle, the fuzzy technique which adjusts the parameters at any moment according to the current speed and safety distance of the vehicle is added into FZ-APF. Numerical simulations are presented and validate the proposed algorithm under some complicated test scenarios. Experiment eventually illustrates the efficiency of this FZ-APF algorithm using an autonomous vehicle prototype.

1. Introduction

In recent years, the applications of autonomous vehicles in industry and military are attracting more attention[1]. At present, autonomous system can handle sample driving scenarios. Such as Google’s unmanned vehicles, which have been tested on more than 16 million miles of roads in the United States. Now, the applications of autonomous technology are suitable for the structured road. However, the applications of autonomous system as mentioned in previous studies, particularly the unstructured road, are seldom discussed or mentioned. Many algorithms of unmanned vehicles route planning are improved from robot path planning. The artificial potential field method is a relatively mature and real-time planning method in the study of path planning and was first proposed by Khatib [2]. However, there are many defects in this algorithm. Koren and Borenstein [3] described the defects such as the local minimum problem, the goal non-reachable with obstacle nearby (GNRON) problem, oscillations in narrow passages. In order to overcome the problem that the artificial potential field has a local minimum, various researchers [4] have proposed some improvements. For example, A new harmonic potential function [5]. For the goal non-reachable with obstacle nearby (GNRON) problem, Jia and Wang [6] improved the potential function to handle this problem. But the difference lies in that our study pays more attention on path planning from the perspective of vehicle-safety standards. For
the road planning of unstructured roads, this paper divides the problems of traditional artificial potential into the following cases:

- The speed and safe distances between vehicle and obstacles play critical roles in Vehicle Safety. The higher the speed, the longer the safe distance. As the safety distance increases, the possibility of collision between vehicle and obstacle decreases. Figure 1 shows that smooth trajectory is planned by the traditional APF. Although the smooth trajectory can avoid the obstacles, it is appropriate for low speed. If the speed of the vehicle is high, the safety distance is so small that the vehicle can’t respond in time and will hit the obstacles before turning to the designated position. Therefore, the safe distance should be adjusted based on the different speed in order to minimize the possibility of the collision between the vehicle and the obstacles. For this purpose, we optimize the influence scope of obstacle to adjust the safe distance.

- The route planning of autonomous driving is limited by the steering constraints of the vehicle itself, such as the spatial constraints which the barriers block the line for vehicle motion. As shown in Figure 1 (b), the route curvature is too small to conform to the constraints of the vehicle steering mechanism and there are many possibilities that the vehicle rolls and knocks into the obstacles.

Hence, the artificial potential field algorithm should consider the parameters of the vehicle steering constraint in order to improve the safety performance of vehicle, so that the accidents won’t happen due to the small turning radius.

2. The Path Planning Algorithm With The Traditional APF approach

Artificial potential field (APF) in the field of robot path planning was first proposed by Khatib in 1986. The basic principle is to build two kinds of potential field, the Attraction Field (AF) which the target point generates attraction on the object, the Repulsion Field (RF) which obstacles generate repulsion on the robot. As shown in Figure 2, we take the mobile robot and the goal point as the particle and take the obstacle area as a circle. The robot avoids obstacles and reaches the destination under the combined force in the two-dimensional space.

Figure 2. The force model of artificial potential field

The attractive potential field function $U_{\text{att}}(X)$ and the repulsive potential field function $U_{\text{rep}}(X)$ of traditional APF are constructed as the following equations.

$$F_{\text{att}}(X) = -\nabla U_{\text{att}}(X) = \alpha |X_g - X_o|$$

(a) Safe car distance (D) is too small  
(b) The turning radius of the vehicle is too small
Where $a$ is the gain of attraction field, $\beta$ is the gain of repulsion field, $X = (x, y)$ denotes the current position of a moving object in Two-dimensional space, $X_g$ is the goal, $X_o$ is the obstacle, $\rho(X, X_g)$ is the distance between the robot $X$ and the goal $X_g$, $\rho(X, X_o)$ is the distance between the robot $X$ and the obstacle $X_o$, $\rho_o$ is the influence scope of the obstacle.

The total force $F_{\text{total}}$ of the robot is calculated as follow.

$$ F_{\text{total}} = F_{\text{at}} + F_{\text{rep}} $$

(3)

However, the robot can't arrive at the target if $F_{\text{total}}$ is 0 before mobile robot arriving at the goal. To solve the problem, FZ-APF was proposed in this paper.

3. Improved traditional APF for autonomous vehicle

3.1. Improved attractive potential field

The repulsive force on the vehicle is close to the attractive force, it leads to the total force of the vehicle approach zero before the vehicle arrives at the goal. In order to solve this problem, the attractive potential functions are improved by introducing the relative distance $\rho(X_q - X)$. The new attractive potential function is:

$$ F_{\text{at}}(X) = \begin{cases} 
      a\rho(X_q - X)\rho^2(X_q - X) + a\rho^2(X_q - X)\rho(X_q - X), & |X - X_o| \leq \rho_o \\
      a\rho(X_q - X), & |X - X_o| > \rho_o 
   \end{cases} $$

(4)

Where $\rho(X_q - X)$ denotes Euclidean distance from the vehicle $X$ to the start position.

3.2. Improved repulsion field

The gain of repulsion field $\beta$ and the influence scope of the obstacle $\rho_o$ in traditional APF algorithm are fixed. However, vehicle speed influences the value of these parameters in actual conditions. There is a linear relationship between vehicle speed and vehicle minimum safety distance. The faster the speed, the longer the safety distance should be. In APF algorithm, vehicle safety distance represents for the influence scope of the obstacle. Therefore, the parameters should be adjusted appropriately at different speeds to avoid obstacles. In this paper, combined with adaptive fuzzy logic control rules, it is able to optimize these parameters depending on the speed.

Adaptive Fuzzy Controller Design This will be followed by a description of the fuzzy nature of the problem and a detailed presentation of how the required membership functions are defined. In this paper, two different types of controller structure are proposed. These structures include one similar standard, there are two inputs and one output. With the input of Fuzzy parameters, including speed and safe distance, the output is called Gain represented as the parameter $\beta$ or the parameter $\rho_o$. In order to describe the patterns, the following new fuzzy variables with Gaussian-type membership function have been presented (Figure 3.) and defined:

- **Speed($v$):** it means the current speed ($ZV$: low speed, $MV$: medium speed, $FV$: high speed) of vehicle.

$$ \text{Speed}(v) = \begin{cases} 
      ZV & \text{if } v < 30 \\
      MV & \text{if } 30 \leq v < 80 \\
      FV & \text{if } 80 \leq v < 150 
   \end{cases} $$

(5)

- **Angle($\varepsilon$):** it represents the direction angle $\varepsilon$ ($Ze$: small angle, $M\varepsilon$: medium angle, $F\varepsilon$: big angle) between the minimum Euclidean distance of the vehicle from the obstacle and the direction of the vehicle movement.

$$ \text{Angle}(\varepsilon) = \begin{cases} 
      Ze & \text{if } 0 \leq \varepsilon < \pi/12 \\
      M\varepsilon & \text{if } \pi/12 \leq \varepsilon < \pi/3 \\
      F\varepsilon & \text{if } \pi/3 \leq \varepsilon < \pi 
   \end{cases} $$

(6)

- **Distance($\rho$):** it shows the distance $\rho(X, X_o)$ ($ZD$: short distance, $MD$: safe distance, $FD$: long distance) from the vehicle to the barriers.
Distance $\rho (\mathbf{r}) = \begin{cases} 
ZD & \text{if } \rho (X, X_0) < 30 \\
MD & \text{if } 30 \leq \rho (X, X_0) < 60 \\
FD & \text{if } 60 \leq \rho (X, X_0) < 100 
\end{cases}$ \hspace{1cm} (7)

Figure 3. the minimal distance $\rho (X, X_0)$ and direction angle $\varepsilon$

We have described it by the following fuzzy sets: Null-Affective(NA), Small-Affective(SA), Medium-Affective(MA), Big-Affective(BA). The defined fuzzy patterns described above could be used in Table 1 and Table 2.

| $\rho (X, X_0)$ | $\mathbf{E}$ |
|-----------------|----------------|
| ZE              | M$E$           |
| F$E$            |                |

Table 1 Controller 1 fuzzy rules

| $\varepsilon$ | $\rho (X, X_0)$ | $\mathbf{E}$ |
|----------------|-----------------|
| ZE             | ZE              |
| M$E$           | M$E$           |
| F$E$           | F$E$           |

Table 2 Controller 2 fuzzy rules

3.3. Kinematic and Dynamic models of vehicle

In this section, the characteristics and environment under which vehicle nonlinear constraint is designed are described. We assume that the vehicle is a rigid object and ignore the effects of air and other factors on the vehicle. Figure 4 shows the dynamic model of vehicle at different moments, whose kinematic model equations of vehicle model can be formulated as:

\[
\theta_{i+1} - \theta_i = d_{\theta} = 2 \tan \theta_r d_x / (2l - b \tan \theta_r) \hspace{1cm} (8)
\]

where $d_x$, $d_{\theta}$, and $\theta_i$ are the moving distance between adjacent moments, the central angle of the vehicle and the heading angle of the vehicle in the global coordinate, $(x_i, y_i)$ is the location of the vehicle at different times $i$ in two-dimensional space, located at the mid-point of the rear-wheel axle, $l$ is the wheelbase, $b$ is the distance between rear wheels, $\theta_r$ is the steering angle.

In the potential field, the path point is in the Cartesian coordinate system $(i)$, the angle between the total force and the $(x)$ axis is $\mu_i$.

\[
\mu_i = (F_{\text{attr}} + F_{\text{rep}}) / (F_{\text{attr}} + F_{\text{rep}}) \hspace{1cm} (9)
\]

where $F_{\text{attr}}$ and $F_{\text{rep}}$ are the longitudinal and lateral forces of vehicle in attraction field, $F_{\text{rep}}$ and $F_{\text{rep}}$ are the longitudinal and lateral forces of vehicle in repulsion field.

Based on the APF algorithm, we plan out the path in order to meet the vehicle steering constraint, the constraint can be got according to equation (10):

\[
0 \leq \mu_i \leq d_{\theta} \hspace{1cm} (10)
\]
In this paper, to avoid excessive turning radius, the longitudinal force $F_Z$ is added to the potential field:

$$
\mu_i = \left( \frac{F_{atry} + F_{rep_y} + F_Z}{F_{atrx} + F_{rep_x}} \right) \leq d_0
$$

$$
F_Z = \begin{cases} 
\omega \rho(X_q - X) & \mu_i > d_0 \\
0 & \mu_i \leq d_0 
\end{cases}
$$

Where $\rho(X_q - X)$ is the distance from the mid-point of the rear-wheel to the X-axle, $\omega$ is coefficient.

Composition of forces $F_{total}$ acting on vehicle is presented as the equation:

$$
F_{total} = \begin{cases} 
F_{atc} + F_{rep} & 0 < \mu_i \leq d_0 \\
F_{atc} + F_{rep} + F_Z & \mu_i > d_0 
\end{cases}
$$

4. Vehicle motion planning Simulation

4.1. Simulation and Analysis of attractive Field

Two trajectories from the traditional navigation algorithm and the improved navigation algorithm are showed in Fig. 7(a). In the environment with obstacles around the target point, the vehicle navigates along the red line and reaches the target directly, at the same time, it avoids obstacles without any difficulty, but when it navigates along the blue line, it can’t reach the destination. The value of the attractive potential field is shown as Fig.7(b). The improved APF is different from the traditional algorithm. When the vehicle enters the influence scope of the obstacles, the value of the attractive potential field will continue to increase. The improved algorithm overcomes the situation that the resultant force is zero when it does not reach the destination.

Figure 5. Trajectory and gravitational field

4.2. Simulation and Analysis of repulsion Field

The repulsive force gain coefficient and the influence scope of the obstacle in the traditional artificial potential field algorithm are both unchanged, however, in fact they are affected by vehicle speeds. Figure 6 (a) shows the variation of these parameters at different speeds. It can be seen from the figure, the improved algorithm parameters changes with speed when the speed reaches the limit value, and the limit value increases with the increase of angle. Fig. 8(b) shows the three paths of a car which reach to the goal and avoid the obstacles under different speed.
The vehicle steering angle difference and the path of travel in the non-structural environment of unmanned vehicles are respectively showed in Fig. 9. The default parameters for the potential have been set up as follows: the vehicle speed \( v = 5 \text{m/s} \) and the most of the wheel steering angle \( \theta_c = 0.83 \).

As result in Fig. 9(b), a safe driving route has been found under the traditional artificial potential field algorithm planning, however, it does not meet the steering characteristics of the vehicle and the driving route is not smooth. As can be seen from Figure 7 (a), the blue line as the traditional algorithm depicts that during the car maneuvering, the car steering angle could be set arbitrarily and the course error and change in error could be larger some time. Instead, the red line as the improved algorithm depicts that it meets basic limit condition of the kinematic and dynamic theories of vehicle.

5. Conclusion

In this paper, we propose a novel path planning algorithm of autonomous vehicle, Fuzzy-artificial potential field (FZ-APF). This method, based on the potential field framework, is a truly reactive navigation method for it reacts to safe distance and speeds as well as recalculates an optimal path in real-time. Adding dynamics and kinematic constraints to this method solves the problem that the artificial potential field method cannot be directly applied to the path planning of autonomous vehicle. The simulation results indicate that this method has rapid dynamic response speed and high stability, as well as good following capability and strong robustness. This method has certain application value in the driverless trajectory planning field.

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