An Intelligent Obstacle Avoidance Method in Unmanned Driving

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Abstract. This paper proposes an intelligent obstacle avoidance method in unmanned driving. This method first establishes a simplified model for the obstacle avoidance problem in unmanned driving, and constrains the car from kinematics, physics, travelable area, and critical collision. Then list the equations and uses the direct collocation method to discrete the equation. The problem is turned into a nonlinear programming problem.

Keywords—evadible system; unmanned driving; artificial intelligence; direct collocation method; nonlinear programming

1. Introduction

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With the improvement of the urban transportation system, the number of private cars is increasing. At the same time, the rapid development of Internet technology has brought revolutionary changes to the automotive industry. On the basis of artificial intelligence, unmanned driving becomes possible. In the early 1970s, developed countries such as the United States, Britain, and Germany began to study driverless vehicles. After a long period of development, driverless vehicles have made breakthrough progress in terms of feasibility and practicality [1]. In 1995, Navllab-V, an unmanned vehicle developed by Carnegie Mellon University in the United States, completed an unmanned driving experiment across the east and west of the United States [2]. In 2005, in the "Grand Challenge" competition organized by the US Department of Defense, the unmanned car transformed by Stanford University passed through deserts, tunnels, muddy riverbeds and rugged and steep mountain roads [3].

In the unmanned vehicles, the intelligent obstacle avoidance system is an important part. Only by carrying out reliable route planning to avoid obstacles can the safety of unmanned driving be ensured and the probability of traffic accidents can be reduced. The current trajectory planning algorithm can be divided into two types: traditional algorithm and intelligent algorithm according to the principle of driving path planning. Traditional path planning algorithms include artificial potential field method [4] and heuristic search algorithms, such as A* algorithm [5], Dijkstra algorithm [6], RRT algorithm [7] and so on. In literature [8], A* algorithm and Dijkstra algorithm are compared in terms of search speed.
and search efficiency. The traditional artificial potential field method is easy to fall into the dilemma of local minimum [9]. In view of the strong randomness of the RRT algorithm, the idea of gravity in the artificial potential field method is introduced into the RRT algorithm in literature [10], which improves the real-time performance of the algorithm, but still has the disadvantages of unsmooth planned path [11]. Intelligent algorithms mainly include ant colony algorithm [12], fuzzy logic algorithm [13], neural network algorithm and genetic algorithm [14] and so on. Intelligent algorithms have greatly improved the shortcomings of traditional algorithms. But they have high requirements for computer hardware and are difficult to apply on a large scale in ordinary vehicles.

Based on the ‘discrete optimization’ idea of the Gaussian pseudospectral method, this paper adopts the direct collocation method that has been widely used in the aerospace field to design the intelligent obstacle avoidance system in unmanned driving. Compared with the indirect method, the direct collocation method discretizes and parameterizes the continuous optimal problem and uses numerical approximation methods to optimize the performance indicators. It does not have to solve the necessary conditions for the more complex and difficult optimal solution. The Gaussian pseudospectral method is a direct method, which discretizes the system control variables and state variables at a limited discrete point. Its advantages are low sensitivity to the initial value of numerical iteration and its exponential convergence rate, which is faster than the rate of any polynomial.

2. Introduction to the third-order Simpson method

The direct collocation method [15] is to divide the entire time process of the system into N segments under the assumption that the control variable is linear, and the two end points of each segment are called ‘nodes’. Between the two nodes, a polynomial is used to represent the relationship of state variables over time. According to the different polynomial order, the direct collocation method can be divided into low-order trapezoid method, Simpson method and high-order fourth-order and fifth-order methods. This system uses the third-order Simpson method.

Within \([t_0, t_f]\), the continuous time is divided into N segments, and each interval is \([t_i, t_{i+1}]\), \(i = 0, 1, 2, \ldots, N-1\). Assuming \(h_i = t_i - t_{i-1}\), \(s = \frac{(t - t_i)}{h_i}\), then \(s \in [0, 1]\), on the interval \([t_i, t_{i+1}]\), the state variable \(x\) can be expressed by a cubic polynomial

\[
x = c_0 + c_1 s + c_2 s^2 + c_3 s^3
\]

The boundary conditions of this formula are

\[
\begin{align*}
x_i &= x(0) \\
x_i &= \frac{dx}{ds} \bigg|_{s=0} \\
x_2 &= x(1) \\
x_2 &= \frac{dx}{ds} \bigg|_{s=1}
\end{align*}
\]

From (1) and (2) we can get the matrix

\[
\begin{bmatrix}
x_1 \\
x_3 \\
x_2 \\
x_2
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
1 & 1 & 1 & 1 \\
0 & 1 & 2 & 3
\end{bmatrix} \begin{bmatrix}
c_0 \\
c_1 \\
c_2 \\
c_3
\end{bmatrix}
\]

Solve the linear equations (3) to get (4)
\begin{equation}
\begin{bmatrix}
  c_0 \\
  c_1 \\
  c_2 \\
  c_3 \\
\end{bmatrix} = 
\begin{bmatrix}
  1 & 0 & 0 & 0 \\
  0 & 1 & 0 & 0 \\
  -3 & -2 & 3 & -1 \\
  2 & 1 & -2 & 1 \\
\end{bmatrix} = 
\begin{bmatrix}
  x_1 \\
  x_1 \\
  x_1 \\
  x_2 \\
\end{bmatrix}
\end{equation}

At \( s = \frac{1}{2} \), substitute (4) into (1) to get

\begin{align}
  x_{ci} &= \frac{x_i + x_{i+1}}{2} + \frac{h_i}{8}(f_i - f_{i+1}) \\
  x_{ci} &= \frac{3(x_i + x_{i+1})}{2h_i} - \frac{f_i + f_{i+1}}{4}
\end{align}

In the above formula, \( f_i \) and \( f_{i+1} \) respectively represent the function value of the state function \( f(x,u,t) \) at the two ends of the i-th interval, namely

\begin{align}
  f_i &= f(x_i,u_i,t_i) \\
  f_{i+1} &= f(x_{i+1},u_{i+1},t_{i+1})
\end{align}

The third-order Simpson method takes the state quantity at each node, the control quantity and the control quantity at the distribution point as optimization decision variables, and the distribution point is taken as the midpoint of each interval, it can get

\begin{equation}
Z = \begin{bmatrix}
  x_0^T, u_0^T, \ldots, x_N^T, u_N^T
\end{bmatrix}
\end{equation}

3. Formatting the text

3.1. Establishment of smart car motion model

The vehicle kinematics model of this paper is shown in Figure 1.

![Unmanned car motion model](image)

**Figure 1.** Unmanned car motion model

As shown in Figure 1, the position of the unmanned car is \( O \), the coordinates of the center of the rear axle of the car are \( (x,y) \), and the coordinates of the center of the front axle of the car are \( (x_1,y_1) \). \( \theta \) is the yaw angle of the vehicle, \( \delta \) is the steering angle of the front wheels, \( L \) is the wheelbase, and \( v \) is the vehicle speed. The vehicle in the picture is subject to motion constraints as follows:
\[
\begin{align*}
x &= v \cos \theta \\
y &= v \sin \theta \\
\theta &= v \tan \frac{\delta}{L}
\end{align*}
\]  

(10)

The vehicle is also mechanically constrained by its own steering system. Assuming that the minimum and maximum steering angles of the vehicle are \( \delta_{\text{min}} \) and \( \delta_{\text{max}} \) respectively, we can get

\[
\delta_{\text{min}} \leq \delta \leq \delta_{\text{max}}
\]

(11)

In addition, assume that the speed of the vehicle is constant, that is \( v = v_0 \).

3.2. The establishment of intelligent obstacle avoidance scene

The obstacle avoidance scene established by this paper is shown in Figure 2.

Suppose that the smart car needs to pass the front obstacle car to reach \((x_1, y_1)\) in the area of \( x \in \left[-\frac{l}{2}, \frac{l}{2}\right] \), \( y \in \left[-\frac{h}{2}, \frac{h}{2}\right] \) and the front wheel axle of the obstacle car is located at \( M_1(x_b', y_b') \), and the rear wheel axle of the obstacle car is located at \( M_2(x_b'', y_b'') \).

Assuming that the size of the obstacle car and the smart car are the same, the simplified model of the obstacle car is shown in Figure 3.
As shown in Figure 3, the entire car can be reduced to a rectangle with length $a$ and width $b$, and the front and rear of the car can be reduced to two circles with a radius of $\frac{\sqrt{2}b}{2}$.

The critical conditions for a collision between a smart car and an obstacle car are shown in Figure 4.

Figure 4 shows that there is a minimum critical distance when the smart car body is tangent to the front and rear circles of the obstacle car. Therefore, the constraint conditions for avoiding car collision can be obtained as follows

$$
\begin{align*}
\left( x - x'_1 \right)^2 + \left( y - y'_1 \right)^2 &\geq \left( \frac{\sqrt{2} + 1}{2} - b \right)^2 \\
\left( x - x'_2 \right)^2 + \left( y - y'_2 \right)^2 &\geq \left( \frac{\sqrt{2} + 1}{2} - b \right)^2 \\
\end{align*}
$$

In summary, the obstacle avoidance problem of smart cars can be transformed into an optimal control problem to solve the following conditions
$$\min J = \sum_{k=0}^{N-1} (t_{k+1} - t_k)$$

$$x = v \cos \theta$$

$$y = v \sin \theta$$

$$\theta = \frac{v \tan \delta}{L}$$

$$\delta_{\text{min}} \leq \delta \leq \delta_{\text{max}}$$

$$x \in \left[ \frac{-l}{2}, \frac{l}{2} \right]$$

$$y \in \left[ \frac{-h}{2}, \frac{h}{2} \right]$$

$$(x_k - x_{0,5})^2 + (y_k - y_{0,5})^2 \geq \left( \frac{\sqrt{2} + 1}{2} b \right)^2$$

$$(x_k - x_{0,5})^2 + (y_k - y_{0,5})^2 \geq \left( \frac{\sqrt{2} + 1}{2} b \right)^2$$

(13)

### 3.3. Solution to the problem of intelligent obstacle avoidance

This paper uses the direct collocation method in the second section to solve the problem.

First, discretize \((t_0, t_f)\) into N time segments, each time segment is \((t_k, t_{k+1})\), where \(k = 0, 1, 2, \ldots, N\), then N+1 nodes can be obtained as

$$t = [t_0, t_1, \ldots, t_N]^T$$

Then according to the method in Section 2, the continuous state and control variables are discretized at the nodes in the area of \((t_k, t_{k+1})\), and the midpoint \(t_{k+0.5} = \frac{(t_k + t_{k+1})}{2}\) of each time segment is used as the distribution point, and the state variables and control variables are respectively determined at the distribution point. After discretization, the state variables and control variables after discretization are as follows

$$x = \left[ x_0, x_{0.5}, x_1, \ldots, x_{N-1}, x_{N-0.5}, x_N \right]^T$$

$$y = \left[ y_0, y_{0.5}, y_1, \ldots, y_{N-1}, y_{N-0.5}, y_N \right]^T$$

$$\theta = \left[ \theta_0, \theta_{0.5}, \theta_1, \ldots, \theta_{N-1}, \theta_{N-0.5}, \theta_N \right]^T$$

$$\delta = \left[ \delta_0, \delta_{0.5}, \delta_1, \ldots, \delta_{N-1}, \delta_{N-0.5}, \delta_N \right]^T$$

(15)

After converting the state variables and control variables, the kinematic constraints are converted. Using the third-order Simpson integral formula

$$h \left( \frac{x_k + 4x_{k+0.5} + x_k}{6} \right) + x_k - x_{k+1} = 0$$

(16)

The kinematic equation constraint (1) can be transformed into
The objective function \( \min J = \int_{t_0}^{t_f} dt \) can be converted to

\[
\min J = \sum_{k=0}^{N-1} (t_{k+1} - t_k)
\]  

The car’s own constraints (11) can be transformed into

\[
\delta_{\text{min}} \leq \delta \leq \delta_{\text{max}}, \quad k = 0, 0.5, 1, \ldots, N \quad 0.5, N
\]  

The restriction of the area where the car can travel can be converted into

\[
\begin{align*}
x_k & \in \left[ -\frac{l}{2}, \frac{l}{2} \right] \\
y_k & \in \left[ -\frac{h}{2}, \frac{h}{2} \right]
\end{align*}
\]  

The critical constraint of collision (12) can be converted to

\[
\left\{ \begin{array}{l}
(x_k - x_{k'})^2 + (y - y_{k'})^2 \geq \left( \frac{\sqrt{2} + 1}{2} b \right)^2 \\
(x_k - x_{k'})^2 + (y - y_{k'})^2 \geq \left( \frac{\sqrt{2} + 1}{2} b \right)^2 \\
(k = 0, 1, 2, \ldots, N)
\end{array} \right.
\]  

In summary, by establishing a simplified model for the obstacle avoidance problem of the intelligent car, and separately applying kinematics, physical, travelable area, and collision critical constraints to the intelligent car, the route planning problem in unmanned driving can be simplified to the nonlinear programming problem shown in the equation (22). For the solution of this nonlinear programming problem, this paper will use the software package SNOPT [16] in Matlab.
4. Conclusion
This paper presents a method of intelligent obstacle avoidance path planning in unmanned driving. This method first builds a model of the car's movement and obstacle avoidance and constrains the intelligent car from the four aspects of kinematics, physics, travelable area, and critical collision. Then the direct collocation method in the direct optimization method is applied to convert the optimal trajectory planning problem into a nonlinear programming problem. The direct collocation method transforms the dynamic parameter problem into the static parameter problem, thereby overcoming the disadvantages of traditional algorithms such as large amount of calculation, poor real-time performance, and sensitivity to initial guesses of variables. This method can better plan a smooth obstacle avoidance path, and has good real-time and adaptability. It has good application value in actual intelligent vehicle control. At the same time, this method also has certain shortcomings. For example, the modeling in this article is based on the situation that the size of the obstacle car is the same as that of the unmanned car. And the dynamic characteristics of the vehicle steering system are ignored, the role of the suspension system is ignored, the vertical and pitch motions are not considered, and the control variables are assumed to be linear. The route planning method of unmanned driving still needs more research from scholars to ensure the safety and reliability of driving.

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