Optimization analysis of autonomous obstacle avoidance path for self-driving vehicles based on improved ant colony algorithm

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Abstract. In order to further improve the accurate response and fast response ability of autonomous obstacle avoidance in real dynamic environment, an improved AC (ant colony algorithm) model based on PSO (Particle Swarm Optimization) is proposed to realize the global and fast optimization analysis of autonomous obstacle avoidance path planning for self-driving vehicles. Firstly, an autonomous obstacle avoidance path planning model for self-driving vehicles is established; secondly, the global pheromone is searched by using the cooperation and information sharing mode between particles in PSO; thirdly, the global pheromone updating strategy is used to optimize the path searching ability of AC; finally, an innovative way of integrating PSO and AC is used to obtain the optimal path of autonomous obstacle avoidance for self-driving vehicles. The simulation results show that the AC model is improved by PSO to realize the fast and accurate planning of autonomous obstacle avoidance path for self-driving vehicles.

1. Introduction
Autonomous obstacle avoidance of self-driving vehicles has become a hot topic in the field of unmanned driving vehicles [1]. In order to effectively protect the safety of people and property in the driving state of autonomous vehicles, many artificial intelligence technologies and algorithms are widely used in the design of self-driving path planning [2]. Among them, ant colony algorithm has made outstanding achievements in the application of path planning [3].

However, autonomous obstacle avoidance technology of self-driving vehicles has not been widely promoted by relevant legislation and industry [4, 5]. The reason is that the relevant technology has not reached a mature and controllable level. At the same time, ant colony algorithm itself has problems such as poor convergence response time and easy to get into local optimal solution. For the practical application of autonomous obstacle avoidance path planning for self-driving vehicles, a single algorithm can not solve this problem independently and perfectly. The combination of multiple intelligent algorithms has become the development trend of path planning to solve the problem of autonomous obstacle avoidance for self-driving vehicles. Therefore, the following will focus on an improved ant colony algorithm based on PSO solution.
2. Establishment of Technical Route Optimization for Autonomous Obstacle Avoidance Path of Self-driving Vehicles

In view of the fact that the autonomous obstacle avoidance requirement of the self-driving vehicle has strong real-time response and high controllability, the path planning assessment is severe. Combining the respective advantages of PSO algorithm and AC algorithm, the technical design route of autonomous obstacle avoidance path planning optimization design for auto-driving vehicle is shown in Fig.1.

Fig.1 Optimization design of autonomous obstacle avoidance path for self-driving vehicles based on PSO improved ant colony algorithm

Specific technical route optimization of autonomous obstacle avoidance path for self-driving vehicles:
1. Use the PSO algorithm, and construct the particle collection of time-space is constructed: \( \Omega(p_i) \) \( (x_i, y_i, z_i, t_{pi}) \);
2. Establish particle dynamic search mode and optimize particle fitness function;
3. Dynamically adjust the global pheromone through the fitness function (using loop iteration);
4. Establish an ant colony algorithm to find the shortest path behavior function (establishing pheromone update method);
5. Global pheromone intervention is added in space-time;
6. Through the accumulation of global scope pheromone and the iterative work of path optimization, the planning path of autonomous obstacle avoidance behavior of self-driving vehicles is obtained.
3. Autonomous Obstacle Avoidance Path Optimization Model of AC Improved by PSO

3.1. The Model of fitness function based on PSO

PSO is a population-based stochastic optimization technique, which is inspired by the population behavior characteristics and used to solve optimization problems. The potential solution to each optimization problem can be thought of as a point in the n-dimensional search space, which is called the "Particle". All particles have a fitness value determined by the objective function, and each particle has a velocity to determine its direction and distance. Then the particles follow the current optimal particle to search in the solution space.

Each particle can be regarded as a searching individual in the n-dimensional search space. The current position of the particle is a candidate solution to the corresponding optimization problem. The flying process of the particle is the searching process of the individual. The flying speed of a particle can be dynamically adjusted according to the historical optimal position of the particle and the historical optimal position of the population. Particles have only two attributes: speed and position, speed represents the speed of movement, and position represents the direction of movement. The optimal solution that each particle searches independently is called individual extremum, and the optimal individual extremum in the particle swarm is the current global optimal solution. Speed and position are constantly iterating and updating. Finally, an optimal solution that satisfies the termination condition is obtained.

a. Initialization of PSO algorithm

PSO is used to obtain the best location point in time-space by means of collaboration and information sharing between particles, which meets the requirements of path planning optimization for autonomous obstacle avoidance of self-driving vehicles[6,7].

The velocity vector and the current time-space position of the particle are expressed in formula (1) and (2).

\[ V_{i+1} = c_0V_i + c_1(p_{best_i} - P_i) + c_2(g_{best} - P_i) \]  
\[ P_{i+1} = P_i + V_{i+1} \]  

In the formula (1) and (2), \( V_i \) is the velocity vector of the particle, \( P_{i+1} \) is the position of the particle at time \( t \), \( p_{best_i} \) shows the optimal position of single particle, \( g_{best} \) shows the optimal real-time position of the whole population, \( c_0, c_1, c_2 \) represent the adjustment coefficients of particle swarm in the process of path planning, \( c_0 \) is a random number between 0 and 1, \( c_1, c_2 \) are a random number between 0 and 2. \( V_i \) is the vector sum between \( V_{i+1}, p_{best_i} - P_i \) and \( g_{best} - P_i \), which indicates that the update of particle velocity is affected by current velocity, perception mode and population information.

b. Connotation of fitness function

In the context of path optimization for autonomous obstacle avoidance of self-driving vehicles, the dynamic response fitness function of PSO is defined as follows[8].

\[
\begin{align*}
    f(p_i) &= \begin{cases} 
        (d(pD) + \sum_{i=3}^{p} d(i)) / \text{Ob}, & 0.9 \leq \text{Ob} < 1 \\
        (d(pD) + \sum_{i=3}^{p} d(i)) * 2 / \text{Ob}, & 0.7 \leq \text{Ob} < 0.9 \\
        (d(pD) + \sum_{i=3}^{p} d(i)) * 4 / \text{Ob}, & 0.6 \leq \text{Ob} < 0.7 \\
        (d(pD) + \sum_{i=3}^{p} d(i)) * 8 / \text{Ob}, & 0 < \text{Ob} < 0.6 
    \end{cases}
\end{align*}
\]

In the formula (3), at the time \( t \), \( (x_p, y_p, z_p) \) is the spatial coordinates of particles, \( (x_{s3}, y_{s3}, z_{s3}) \) is the starting point coordinate, \( (x_{e3}, y_{e3}, z_{e3}) \) is the end point coordinate. \( d(pD) = \sqrt{(xp - xd)^2 + (yp - yd)^2 + (zp - zd)^2} \) indicates the estimated value of particle \( p \) from the current position to the end point. \( \sum_{i=3}^{p} d(i) \) indicates the sum of the distances from the starting point to the current
position, \( d(i) = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2} \). \( Ob \) represents Predictive Obstacle Information Quantity. When \( 0.9 \leq Ob < 1 \), \( Ob \) is clear; when \( 0.7 \leq Ob < 0.9 \), \( Ob \) is relatively clear; when \( 0.6 \leq Ob < 0.7 \), \( Ob \) is generally clear; when \( 0 \leq Ob < 0.6 \), \( Ob \) is relatively fuzzy.

3.2. Construction of the global pheromone updating on AC

The basic principle of ant colony algorithm is derived from the shortest path principle of natural ants foraging for food. When ants are searching for food source, they can release pheromone, a secretion characteristic of ants, in the path they have traveled, so that other ants within a certain range can detect and thus influence their future behavior. When more and more ants pass through some paths, they leave more and more pheromones, leading to the increase of pheromone intensity. Therefore, the probability of ants choosing this path is higher, which increases the pheromone intensity of this path. This selection process is called the autocatalytic behavior of ants. The ant walking path is used to represent the feasible solution of the problem to be optimized, and all paths of the whole ant colony constitute the solution space of the problem to be optimized. Ants with shorter paths release more pheromones. As time goes on, the concentration of pheromones accumulated on shorter paths gradually increases, and the number of ants choosing this path is also increasing.

a. Initialization of AC

Information transmission among ants is achieved by means of substances called pheromones. Generally, the pheromone accumulation process of AC is affected by the amount of information in the update process of path planning[9,10].

The information updating method of AC in the process of path optimization is shown in the formula (4).

\[
\tau_{ij}(t + n) = (1 - \rho) \tau_{ij}(t) + C_f \Delta \tau_{ij}
\]

In the formula (4), \( \Delta \tau_{ij} \) represents the total increment of information amount on path \( ij \) in the loop; \( \rho \) indicates the degree of volatilization of the information, ranging from 0 to 1; \( \Delta \tau_{ij} \) represents the increment of information that ant \( k \) leaves on path \( ij \) in this cycle; \( C_f \) represents the incremental correlation coefficient of the amount of information that ant \( k \) leaves on path \( ij \) in this cycle.

b. Dynamic updating strategy of global pheromone

With the fitness function of PSO in the global space-time, the pheromone distribution and accumulation in the global situation are adjusted in the iterative process of AC[11,12].

By adjusting \( C_f \), the global scheduling of pheromone accumulation can be realized. The specific form of \( C_f \) is shown below.

\[
C_f = \begin{cases} 
1 - \frac{f(p_i) - f(p)_{\min}}{f(p)_{\min} - f(p)_{\max}} \cdot R_{best}, & 0.6 \leq \rho < 1 \\
\frac{f(p_i) - f(p)_{\min}}{f(p)_{\max} - f(p)_{\min}} \cdot R_{best}, & 0 < \rho < 0.6 
\end{cases}
\]

In formula (5), \( R_{best} \) represents the optimal planning path statistics, \( f(p)_{\min} \) represents the minimum value of the particle swarm fitness function, \( f(p)_{\max} \) represents the maximum value of the particle swarm fitness function.

4. Simulation and Analysis

In order to verify the feasibility of the path optimization problem of autonomous obstacle avoidance for self-driving vehicle based on improved AC by PSO, simulation and validation are carried out from two dimensions of the optimization degree of the planning path itself and the timeliness of the path planning.

4.1. Planning Path Simulation

According to the path planning requirements for autonomous obstacle avoidance of self-driving vehicle, the comparison work is carried out from the relative optimization degree of the planning path, as shown in Fig. 2.
As shown in Fig. 2, since the complexity of PSO+AC is higher than that of AC’s, in the initial stage of path planning optimization (iteration number < 50), the relative growth rate of PSO+AC path planning optimization is lower than AC’s. With the deepening of the iterative process, the path optimization degree of PSO+AC has obvious advantages. At the same time, between the number of iterations of 90 and 130, the path planning using the AC algorithm once fell into the local optimal solution situation, which indirectly led to a decrease in the relative degree of path planning optimization of the AC.

4.2. Simulation of path planning timeliness
According to the path planning requirements for autonomous obstacle avoidance of self-driving vehicles, a comparison is made in terms of the timeliness of the planning path, as shown in Fig.3.

As shown Fig.3, AC algorithm frequently fluctuates in the whole process of shortest path optimization. Relatively speaking, the fluctuation of PSO+AC algorithm tends to be stable. The reason for this: in the early stage of path planning, PSO was used to drive the dynamic update strategy of global pheromone of AC. At the same time, at T≈751 ms, the PSO+AC method approaches the shortest...
path approached to 94.5% and maintains that state. At T ≈ 792 ms, the AC method approaches the shortest path approach to 77.0% and maintains that state.

5. Conclusion
In the process of analyzing the path optimization of autonomous obstacle avoidance for self-driving vehicles, on the one hand, it improves the timeliness of the actual obstacle avoidance process by combining PSO and AC. On the other hand, in the process of obstacle avoidance, it helps autonomous driving vehicles to accurately select the global optimal path.

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