Optimization of an Intelligent Controller for Parallel Autonomous Parking

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Abstract

Autonomous parking has become the research focus. Fuzzy controller was ofen used to solve the nonlinear and time-varying problem of the autonomous parking. According to the shortcomings of traditional fuzzy controller, a new ant colony algorithm based on idle ant effect was proposed. Firstly, the fuzzy controller was designed based on the kinematic equations. Then, multi-colony parallel optimization was adopted to improve the data initialization, path construction and pheromone update. The method guaranteed the completeness of the membership function and made the fuzzy parameters with higher precision. Finally, both traditional controller and the designed controller were used for the autonomous parking, the experimental results showed that, comparing with the traditional fuzzy controller, the designed controller can improve the stability problem with less error and faster response speed.

Keywords*: autonomous parking, fuzzy controllers, multi-colony evolvement, ant colony algorithm*

1. Introduction

In recent years, the number of the car has greatly increased. The parking space for the driver sharply reduced, the accidents are especially prone to occur when rev ersing the car for these less experience driver. In order to riding comfort, driving convenience, and safety. Most vehicle manufacturing companies are investing in improvement of driving safety and development of intelligent driving assistant systems. The autonomous parking problem has become the research focus.

Two problems should be solved for the autonomous parking system. One is how to plan the path; another is how to design a controller to track the path. In earlier studies, a lot of research was carried out by using the robot as the experimental objects for navigation or avioding obstacles [1,2], this may cause more error, but the method gives us some inspiration.

For the path planning problem, it can be defined as finding the shortest paths connecting two given initial and final configurations [3]. But the problem about this path is that the curvature profile is discontinuous between arcs and straight lines, this means the vehicle should stop at the discontinuous point. Since instantaneous changes in steering mechanisms are physically impossible, it results in errors of the state of the vehicle at these transition points. To solve this problem, clothoids, cubic spirals, B-spines, quintic polynomials, etc., are proposed. Lyon [4] presented a comparison of three s-shaped curves for parallel parking a vehicle subject to nonholonomic constraints; Kwon H. and Chung W. [5] proposed the KPP (Korea University Path Planner) and compared with conventional RRT (Rail Rapid Transit). For the control problem, a lot of researches have been carried out. A fuzzy logic control algorithm was employed to design the parking controller [6, 7] based on a model vehicle test or simulation work. Reference [8] designed a fuzzy position controller for an autonomous mobile robot with six ultrasonic sensors. In [9], an intelligent autonomous parking controller by integrating sensor data capable of obtaining the surrounding data of the vehicle is proposed. Zhu and Rajamani [10] proposed a nonlinear state feedback controller for roadside autonomous parking.

However, previous research has the following drawbacks. Firstly, it was difficult to plan the accurate path. Secondly, the vehicle's geometric kinematics were not considered when design the controller. In addition, when design the fuzzy controller, expertise and trial-and-error work should be used, which was not convenient for practical application. In this paper, an intelligent fuzzy controller based on improved ant colony algorithm is designed for the

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autonomous parking system. The simulation experimental results demonstrate the effectiveness of the developed controller. This paper is organized as follows. In Section 2, kinematic equations are described and then, the intelligent controller was designed and aslo, the optimization of the fuzzy controller is explained. Experimental results are given in Section 3 to show the validity of the proposed fuzzy controller.

2. Design of the Intelligent Controller

2.1. Kinematic Equations

In the low speed range, we don't consider the impact of the tire slide, and the wheels deflection meets the relationship named Ackerman Steering any time. In this process, all the wheels make a circular motion around the same instantaneous center. Figure 1 is the sketch map of vehicle kinematic model. Suppose x, y is the coordinates of the vehicle rear axle midpoint and v is the moving speed of the of the front wheel center which we assume it to be constant. The posture of the vehicle can be ascertained from the three state variables (x, y, φ), the kinematic equations are as follows:

$$\begin{aligned} x' &= v\cos\varphi\cos\Phi; \\ y' &= v\sin\varphi\cos\Phi; \\ \varphi' &= v\sin\Phi / L; \end{aligned} \tag{1}$$

where, L is the wheelbase, φ is the intersection angle of the vehicle's positive direction and the horizontal position, Φ is the steering angle of the front axle center.

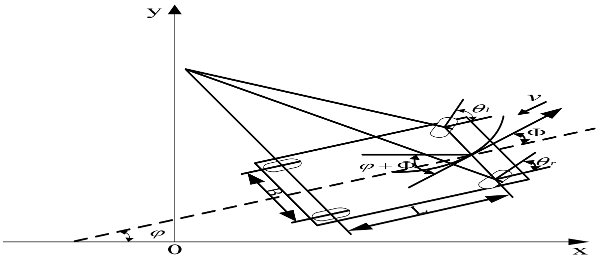

Figure 1. The Vehicle Kinematic Model

2.2. Design of Autonomous Parking Controller

Since the vehicle autonomous parking control process has a non-autonomous property and uncertainty behavior, each parking trajectory and initial and target positions are different. Generally speaking, the purpose of the parking path tracking control is executed by monitoring the steering angle only. So the output of the controller should be the front wheel steering angle command.

For a traditional fuzzy controller, one of the state variables is chosen to describe the parking path and to derive the front wheel steering angle control command. The specified parking path can be represented by three desired state variable trajectories, namely x_{rd}, y_{rd}, ψ_d. Take x_r as analysis, the desired and real vehicle accelerations in the x direction can be derived from equation (1):

$$\begin{cases} \ddot{x}_{rd} = \left[\dfrac{d}{dt}(-V_r\cos\psi_d)\right] = V_r\dot{\psi}_d\sin\psi_d - \dot{V}_r\cos\psi_d \\ \ddot{x}_r = V_r\dot{\psi}_d\sin\psi - \dot{V}_r\sin\psi = -\dfrac{V_r^2}{L}\tan\delta\sin\psi - \dot{V}_r\cos\psi \end{cases} \tag{2}$$

Define the errors of three desired state variables as:

$$\begin{aligned} e_{1x} &= x_{rd} - x_r \\ e_{1y} &= y_{rd} - y_r \\ e_2 &= \psi_d - \psi \end{aligned} \qquad (3)$$

From equation (2), the fuzzy control law can be expressed as:

$$\delta = \tan^{-1}\left[\frac{L}{V_r^2 \sin\psi}(-V_r\dot{\psi}_d \sin\psi_d + \dot{V}_r \cos\psi_d - \dot{V}_r \cos\psi - \lambda_1\dot{e}_{1x} - \lambda_2 e_{1x})\right] \qquad (4)$$

Similarly, the control law for choosing the state variables y can be described as:

$$\delta = \tan^{-1}\left[\frac{L}{V_r^2 \cos\psi}(-V_r\dot{\psi}_d \cos\psi_d - \dot{V}_r \sin\psi_d + \dot{V}_r \sin\psi - \lambda_1\dot{e}_{1x} - \lambda_2 e_{1x}\right] \qquad (5)$$

In order to avoid the singularity problem, the control law should be limited in the range from $-\frac{\pi}{2}$ to $\frac{\pi}{2}$. The 2D parking path can be confirmed by the state variables x and y, the main task of the fuzzy controller is to derive the front wheel steering angle control command. The fuzzy inputs membership function shown in Figure.2 is divided into 11 fuzzy subsets from -1 to 1 with intervals of 0.2.The membership function used for the fuzzification is a triangular type. The function can be expressed as

$$\mu(x) = \frac{1}{W}(-|x-a| + W) \qquad (6)$$

where W is the distribution span of the membership function and a is the parameter corresponding to the value 1 of the membership function. A linear interpolation fuzzy operation scheme is employed for interference and defuzzification of the fuzzy variable from fuzzy control rules to obtain the front-wheel steering angle control command in each control step.

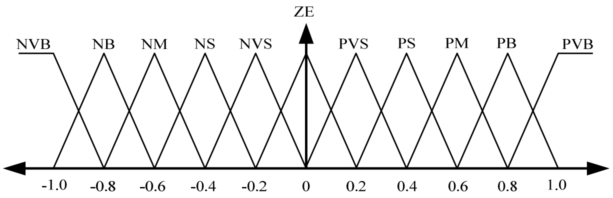

Figure 2. Fuzzy Inputs Membership Function

2.3. Optimization of the Fuzzy Controller Parameters

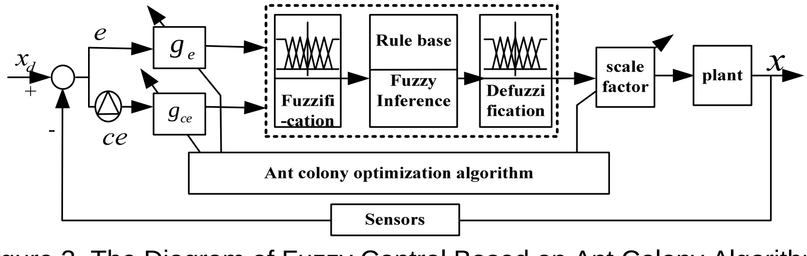

Figure 3. The Diagram of Fuzzy Control Based on Ant Colony Algorithm

In order to get a good performance, the fuzzy parameters of fuzzy controllers should be optimized. In this paper, a method of multi-colony evolvement ant colony algorithm shown in Figure 3 was proposed to optimize the parameters.

2.3.1. The principle of multi-colony evolvement ant colony algorithm

If the traditional ant colony algorithm is used to optimal the parameters, there is only one ant species, which will lead to the same initialization of the algorithm, and the pheromone of different parameter are consistent. Two kinds of parameters are divided into independent sub-populations according the different characteristics of the fuzzy parameters, and then form different species of ants' distribution. The membership functions and the fuzzy rules restrict and relate each other, they work together to constitute a fuzzy control system. In the evolutionary process, multi-population sharing a target function reflects the output of the system characteristics. In this way, the fuzzy set parameters can be realized optimization at the same time, which ease the problem of excessive number iteration ants and speed up the convergence. The principle diagram is shown in Figure 4.

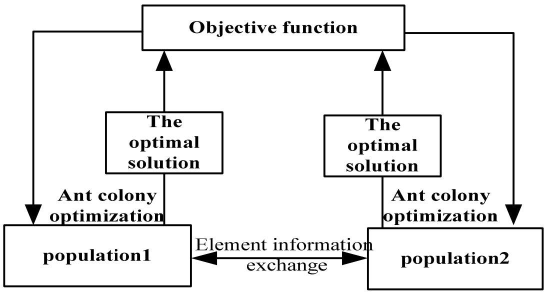

Figure 4. Multigroup Evolutionary Algorithm Principle Diagram

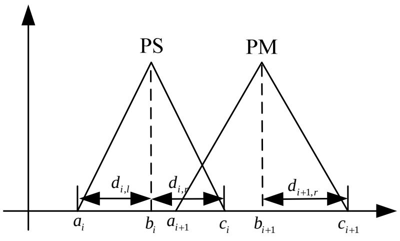

Figure 5. Adjacent Membership Function

2.3.2. Realization of multi-colony evolvement ant colony algorithm

According to literature [11], it is known that the ant colony algorithm including algorithm initialization, path building, pheromones updating. The pheromones updating process can be seen in Reference [12]. The paper only discusses algorithm initialization, path building process.

The algorithm initialization is divided into position distribution and pheromone initialization. The position distribution initializes the shape of the membership to keep it completeness. In the paper, the membership functions of fuzzy due dates represented by triangle function. Suppose the shape of the triangle membership is determined by left end point a, center point b, and right end point c. As is shown in Figure.5 take adjacent membership functions positive small (PS) and positive middle (PM) for example. For the i th triangle, set left width as $d_{i,l}$, right width as $d_{i,r}$. Set the triangle right span coefficient as k_i, set the triangle center point as b_i, and overlapping factors as α_i. The right span coefficient k_i can be represented as

$$k_i = \begin{cases} \mathrm{sgn}(\frac{d_{i,r}}{b_i}) & b_i \in (-1,1) \\ \mathrm{sgn}(\frac{b_i}{d_{i,r}}) & else \end{cases} \tag{7}$$

when k_i, b_i and α_i is known, the membership of the fuzzy subset PS can be calculate as follows:

The right width of the i th triangle is

$$d_{i,r} = \begin{cases} \frac{\mathrm{sgn}(b_i)}{k_i} & b_i \in (-1,1) \\ k_i \cdot \mathrm{sgn}(b_i) & else \end{cases} \tag{8}$$

So the left end point a_i and right end point c_i of the i th triangle are

$$\begin{cases} a_i = b_i - \dfrac{b_{i+1} - b_i}{1-\alpha} + k_i \cdot \operatorname{sgn}(b_i) \\ c_i = b_i + k_i \cdot \operatorname{sgn}(b_i) \end{cases} \tag{9}$$

Since the right span coefficient $k_i \in (0,1)$, the left width is calculated according to α_i and the adjacent right width of the membership functions, this keep the adjacent membership functions in fellowship state and keep the triangle form a reasonable shape, which keep the membership functions completeness.

When optimize the fuzzy rules, the starting position is no longer random distribution, but to make the ants onto the rules position. The optimization problem can be transformed into the optimization of the output variables. We fixed input variables, put the output variable in an arrangement. Each rule adopts a decimal number to express.

When begin to the path building, each ant moves to the next target from the start node according to the probability transfer function. In the i th travel, the transition probability an ant transfer from the node (d,i) of the son space d to the node $(d+1, j)$ of the son space $d+1$ is

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{s \in allowed_k} \tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & j \in X_{d+1} \\ 0 & j \notin X_{d+1} \end{cases} \tag{10}$$

where, p_{ij} is the probability the ant transfers from i to j; is attracting strength of the ant j; η_{ij} is the difference of the target function that the ant K move from node i to node j. The closer the two node target function, the closer to approach the optimal point.

3. Results and Analysis

In order to demonstrate that our intelligent autonomous parking controller is feasible and effective. A one-tenth scale model vehicle was chosen as the platform for parking experiments. Both the proposed fuzzy controller based on ant colony algorithm and the traditional fuzzy controller are implemented on this model vehicle. The basic architecture of the vehicle consists of the following eight modules: the robot mechanism unit, the NIOS-embedded system unit, the DC motor unit, the servo motor unit, the ultrasonic range sensor unit, the PDA unit, the wireless module unit, and the power regulator unit.

The model uses the NIOS development board as platform for developing embedded systems. The computer-aided design tool is used to implement the hardware design, including the processor core configuration, synthesis, place, and route. The processor core configuration tool is realized by verilog hardware description language (VHDL) and graphical user interface (GUI).The assignment of I/O, including the ultrasonic signals and the motor driving signals, is set in the GUI, and the function of the hardware is realized by MATLAB code.

3.1. The traditional fuzzy controller

The trajectory of the vehicle’s motion and the tracking error of the steering angle are shown in Figure 7 and Figure 8. It can be known that the model car follows the specified autonomous path backwards to the target position with a small tracking error.The relative error in XY direction is from -0.024m to 0.01m, the steering angle tracking error is between -0.86° and 0.78°. The error peak of the initial steering angle is due to the large initial velocity error of the rear-wheel PI speed control, which will cause a motion trajectory estimation error in the control law calculation. If the vehicle’s velocity can be accurately controlled and measured, those errors can be reduced. Relatively speaking, the error is a little big and the control performance is not very good.

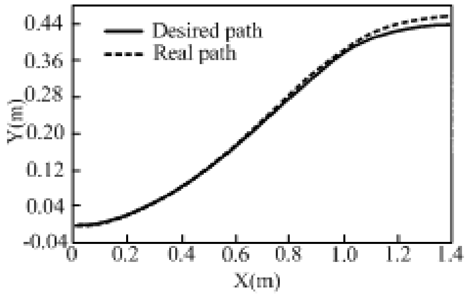

Figure 7. Trajectory Comparison Chart of the Vehicle

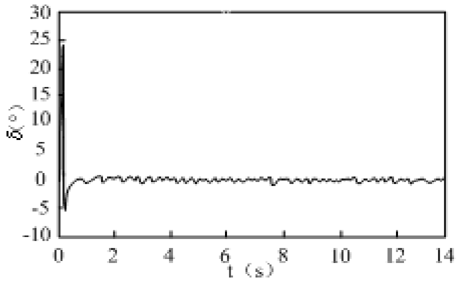

Figure 8. The Steering Angle Tracking Error with Adopting Regular Controller

3.2. Fuzzy controller based on ant colony algorithm

Figure 9 and Figure 10 are trajectory of the vehicle's motion and the tracking error of the steering angle respectively. From the Figures, we can come to the conclusion that the model vehicle follows the specified autonomous parking path backwards to the target position with a much smaller tracking error by using fuzzy controller based on improved ant colony algorithm than using the traditional fuzzy controller. The relative error in XY direction is from -0.009m to 0.014m, the steering angle tracking error is between -0.56° and 0.57°. The error peak of the initial steering angle is due to the large initial velocity error of the rear-wheel PI speed control, which will cause a motion trajectory estimation error in the control law calculation. If the vehicle's velocity can be accurately controlled and measured, those errors can be reduced. Generally speaking, the error using this intelligent controller is much smaller compared with the traditional controller.

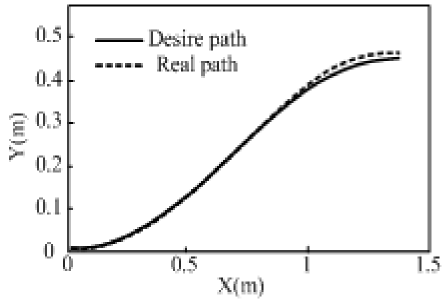

Figure 9. Trajectory Comparison Chart of the Vehicle

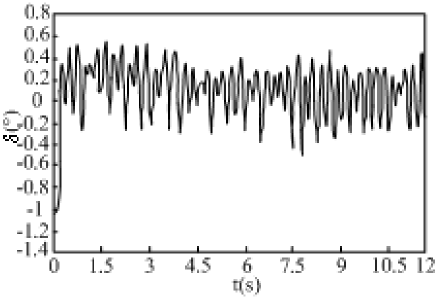

Figure 10. The Steering Angle Tracking Error with Adopting Ant Colony Algorithm

Table 1. Autonomous Parking Path Tracking Control Performance Comparison

Control method	Velocity					
	0.1m/s			0.15m/s		
	Error X(m)	Error Y(m)	Angle error δ (deg)	Error X(m)	Error Y(m)	Angle error δ (deg)
Regular controller	-0.024	-0.011	-0.86~0.78	0.018	-0.02	-0.81~0.79
New controller	-0.005	-0.01	-0.56~0.49	-0.009	-0.014	-0.57~0.57

Table 1 gives out the comparison between the two controllers. It can be seen that the error is much smaller using the new controller than using the regular controller. Obviously, the dynamic control performance of the fuzzy controller based on improved ant colony algorithm is better than that of the traditional fuzzy controller.

4. Conclusion

A novel fuzzy controller based on improved ant colony algorithm is proposed for reversed roadside parallel autonomous parking. The algorithm adopted multi-colony parallel optimization based on tradition ACO algorithm. After optimizing the fuzzy controller, the method improves the quality of the solution space and raises the searching speed. It not only can improve the stability problem of previous research but also can reduce the computing time and database. A PC based one-tenth model vehicle is constructed to investigate this autonomous parking operation status and to evaluate the control performance and system robustness. The experimental results show that this intelligent controller can achieve reasonable tracking control accuracy for this autonomous parking system. Generally, the experimental results are better than those of the traditional fuzzy controller because the new controller can improve the stability problem with less error and faster response speed. We believe that the autonomous parking system development and real scale implementation will be the topics of future work.

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