2008 American Control Conference
Westin Seattle Hotel, Seattle, Washington, USA
June 11-13, 2008

Designing a Hierarchical Fuzzy Controller for Backing-up a Four Wheel Autonomous Robot

Pourya Shahmaleki, Mojtaba Mahzoon

Abstract— **Fuzzy controller, formulated on the basis of human understanding of the process or identified from measured control actions, can be regarded as an emulator of human operator. Truck backer-upper system is a typical problem in nonlinear motion control of nonholonomic robots. Controller design, however, may become difficult, especially if the number of state variables is large. This paper recommends a fuzzy control design method for this problem. The addressed problem is the diagonal parking for an autonomous vehicle in which it has to successfully back up to a constrained domain. The fuzzy controller is based on a hierarchical scheme, which is a combination of two fuzzy modules. The rules of each module have been obtained from heuristic knowledge and numerical data. The goal of the control system is to provide short paths with continuous curvature. Approximated trajectories are composed of circular arcs of minimum turning radii and straight line segments. Compared with traditional controller, this fuzzy controller demonstrates advantages on the control performance, convenience and feasibility.**

I. Introduction

One of the most important problems in robotics is motion planning problem, which its basic controversy is to plan a collision-free path between initial and target configurations for a robot. The truck backer-upper control is a typical nonlinear control problem that cannot be solved by the conventional control techniques. The goal of controller is to back up a truck to a loading dock from any initial position as quickly and precisely as possible. Backing a truck to the loading dock or parking spot is a difficult task even for a skilled truck driver. The research in parking problem is derived from the study of general motion planning for autonomous robots. In the past few decades, many algorithms have been developed for robot parking planning [1]–[4]. In the framework of motion planning for nonholonomic systems, the wheeled robots have attracted a significant amount of interest. The path planner of a wheeled autonomous robot has to meet nonholonomic constraints and then the movement direction must always be tangent to its trajectory [1]–[10]. If no obstacles exist on path of the robot, then the robot task is to find the shortest path connecting two given initial and final configurations.

September 20, 2007.
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The attempts to solve the truck backer-upper problem, rooted in computational intelligence, can be divided into two groups. The first group of methods seeks the solution through self tuning using neural networks, genetic algorithms or a combination of both. The second group of solutions, based on fuzzy logic, regards the controller as an emulator of human operator. Truck backer-upper problem, which was studied by Nguyen and Widrow [11], has been investigated by many researchers in the field of computational intelligence (for example; chang in [12], Schoenauer in [13], Wang in [14] and Yu et al. in [15]).

Fuzzy systems have been widely used as an effective tool for modeling non-linear and complex system, where classical methods are unsuccessful due to their complexities or their imprecision. Fuzzy controllers, formulated on the basis of human understanding of the process or identified from measured control actions, can be regarded as emulators of human operators. Fuzzy logic control has more advantages because it can compensate the bad influence by nonlinearity and uncertainties based on advanced human expertise experience, also because it has strong robustness independent of a mathematical model. The other advantages of Fuzzy controllers are that their design is simple, fast, inexpensive, and easily maintained because the rules can be linguistically interpreted by the human experts. Riid et al. [16] presented a fuzzy supervisory control system over the PID controller to reduce the complexity of the control problem and enhance the control performance. Riid and Rustern in [17] demonstrate that problem decomposition leads to more effective knowledge acquisition and improved control performance in fuzzy control. The methodology allows solving complex control problems (truck backer-upper) without loss of functionality that is very difficult with all-in-one approaches and saves design expenses. Li and Chang in [18] addressed the parking problem of a mobile robot by tracking feasible reference trajectories via a fuzzy sliding-mode control. Chen and Zhang in [19] have reported a fuzzy controller to park a truck with suboptimal distance trajectories. They chose arcs of circle of minimum turning radii connected with parabolic curves as the optimal trajectories, but the desired parabolic curve to follow has to be given to the controller. More recently Li and Li in [20] have presented the fuzzy control system based on a hybrid clustering method and neural network.

The path planners described in this paper combine two fuzzy modules that provide desired angle value for front wheel so as to generate short paths with continuous

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curvatures. Approximated trajectories are composed of circular arcs of minimum turning radii and straight line segments.

II. THE TRUCK BACKING-UP PROBLEM

The problem addressed in this paper is the diagonal parking of a truck in a constrained domain. The initial state of the truck position is represented by three state variables x, y and φ in Fig. 1. A truck kinematics model is based on the following system of equations [20]:

$$\begin{cases} x(t+1) = x(t) - \cos(\varphi(t)+\theta(t)) - \sin(\theta(t))\sin(\varphi(t)), \\ y(t+1) = y(t) - \sin(\varphi(t)+\theta(t)) + \cos(\varphi(t))\sin(\theta(t)), \\ \varphi(t+1) = \varphi(t) - \arcsin\left(\dfrac{2\sin(\theta(t))}{b}\right), \end{cases} \quad (1)$$

where (x,y) are the coordinates of the vehicle rear axle midpoint, φ is the robot orientation with respect to the vertical line, b is the length of the truck and the control variable is the steering angle θ, that is the angle of the front wheel with respect to the truck. The truck only moves backward with fixed speed.

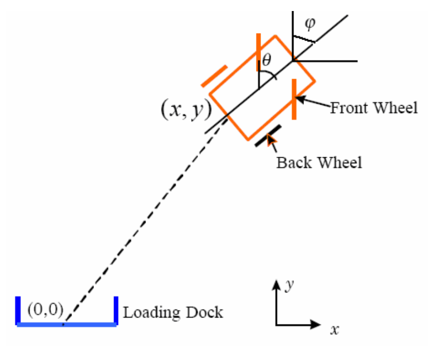


Fig. 1. Diagram of truck and loading dock.

III. THE FUZZY CONTROL SYSTEM

The truck and the loading zone are shown in Fig. 1. The robot has two front steering wheels and two rear driven wheels that cannot move sideway. The coordinate pair (x,y) specifies the rear center position of the truck in the plane. The angle φ increases from -180 toward 180 in a clockwise direction and the steering angle θ is taken as positive if the steering wheel is turned to the right and negative, otherwise. The loading zone is the plane $x:[-25,25]$, $y:[0,25]$.

The goal of this research is to design a Fuzzy Logic Controller (FLC) able to back up the truck into a docking situation from any initial position that has enough clearance from the docking station. The controller should produce the appropriate steering angle $\theta = [-40°, 40°]$ at every stage to make the truck back up to a configuration with $x = 0, y = 0, \varphi = 0$ (that is the desired parking space) from any initial position (x, y and φ) and to stop there.

Thus controller is a function of state variables:

$$\theta = f(x, y, \varphi). \quad (2)$$

The y coordinate is not used because the straight segments of approximated trajectories are always horizontal. Also typically it is assumed that enough clearance between the truck and the loading dock exists so that the truck *y*-position coordinate *y* can be ignored, simplifying the controller function to:

$$\theta = f(x, \varphi). \quad (3)$$

Hence only x-position and truck orientation angle φ are inputs of the fuzzy controller and the steering angle θ is the output.

As shown in Fig. 2, the suboptimal goal is that the backward driving involves short trajectories made up of arcs of circle of minimum turning radii and straight line segments, which meet the kinematic constraints in (1).

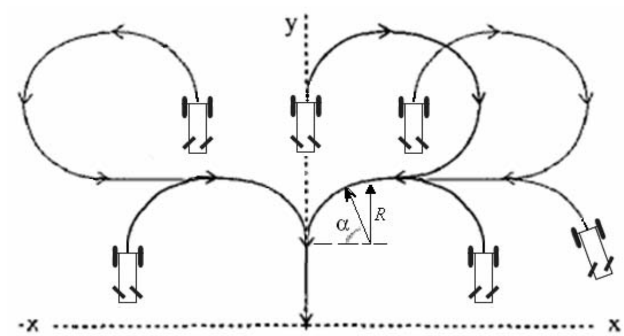


Fig. 2. Ideal trajectories.

Analyzing the shortest paths geometrically, a mathematical expression for the steering angle θ which produces curvature of these short paths can be found:

$$\theta = \begin{cases} 40^\circ & if \quad \varphi > \alpha \\ 0^\circ & if \quad \varphi = \alpha \\ -40^\circ & if \quad \varphi < \alpha \end{cases} \quad (4)$$

where the angle α (depends on x) associated with the switching in the steering angle(θ) sign can be calculated as follows:

$$\alpha = \begin{cases} Sign(x) \cdot \cos^{-1}\left(\dfrac{R - |x|}{R}\right) & if \quad |x| < R \\ Sign(x) \cdot \dfrac{\pi}{2} & if \quad |x| \geq R \end{cases} \quad (5)$$

R being the minimum turning radius corresponding to the maximum curvature (γ) which has a constant value (γ =1/R).

A. Hierarchical approach

In this section the hierarchical structure used in the present article is introduced .The scheme is basically made up of two rule bases (Fig. 3).

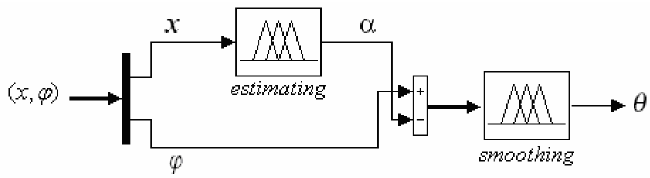


Fig.3. Structure of hierarchical approach

The first one ("estimating") provides approximately the value of the angle α depending on the input variables x. The second one ("smoothing") provides the desired value for steering angle (θ) depending on the value of difference φ-α. Two triangular and two trapezoidal membership functions (LB, LS, RS and RB) are selected to cover the x universe of discourse and four rules are included in the rule base "estimating". The consequents of the rules (mf1, mf2, mf3, and mf4) are singletons. Also the "center of gravity" method is used for defuzzification.

The rule bases (estimating and smoothing) implements a zero-order Takagi–Sugeno inference method.
The rules are:

1) if (x = LB) → α= mf1
2) if (x = LS) → α= mf2
3) if (x = RS) → α= mf3
4) if (x = RB) → α= mf4,

The rule base "smoothing" also contains two triangular and two trapezoidal membership functions and four rules. The rules are:

1) if (diff = MZ) → θ= nf1
2) if (diff = NZ) → θ= nf2
3) if (diff = PZ) → θ= nf3
4) if (diff = RZ) → θ= nf4,

where MZ, NZ, PZ and RZ are fuzzy sets represented by triangular and trapezoidal membership functions (they cause the smooth switching in the steering angle θ when φ is around α). nf1, nf2, nf3, nf4 are singleton values associated with the angle front wheels. The membership functions for the variables x and diff are shown in Fig.4.

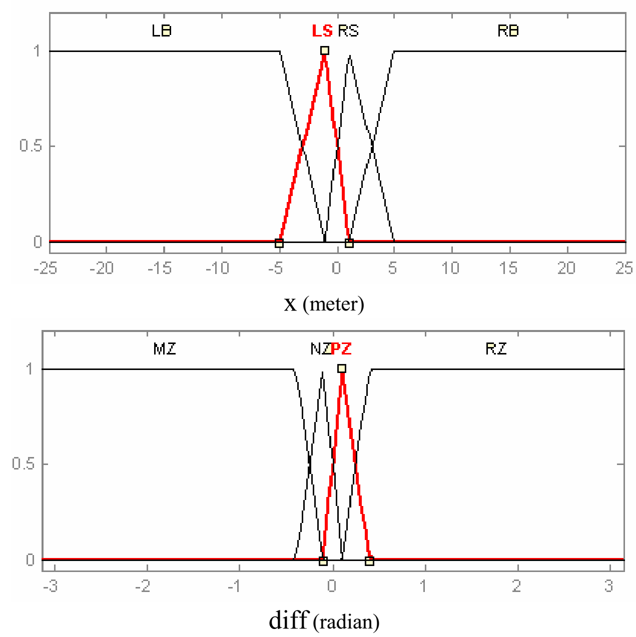


Fig. 4. Membership functions for x and diff variables.

The resulting control surface is shown in Fig. 5. It illustrates the smooth transition between the maximum and minimum values of the steering angle when φ is somewhat greater or smaller than α.

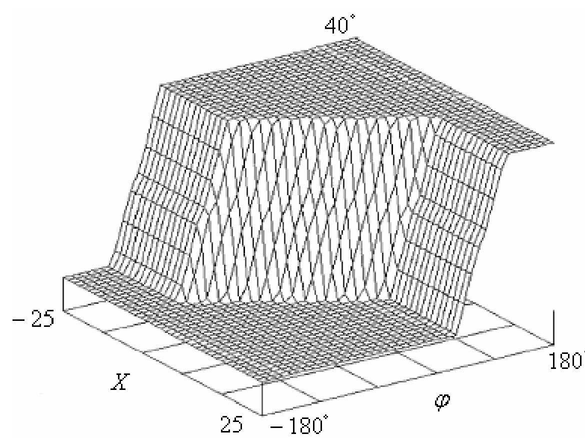


Fig. 5. Control surface of the fuzzy control system

The "estimating" module for the hierarchical approach provides a fuzzy approximation for the angle α. The advantage of using this module instead of giving α analytically is that the required computational cost is reduced. Using normalized triangular and trapezoidal membership functions for the antecedents of the rules and a zero-order Takagi–Sugeno inference engine makes this approximation piecewise linear, which means that only several additions and products need to be implemented. The computational cost of additions and products is less than that of a nonlinear function such as Arcos ( ) in (5).

Fig. 6 shows the variations of θ versus x and φ corresponding to (4) and (5). These equations are associated with an on–off control because the θ value presents abrupt changes, and would require stopping the robot to perform this switching. Two fuzzy modules (hierarchical) described previously are zero-order Takagi–Sugeno systems whose input membership functions always overlap each other. Hence, the subgoal of providing continuous-curvature and short paths is achieved.

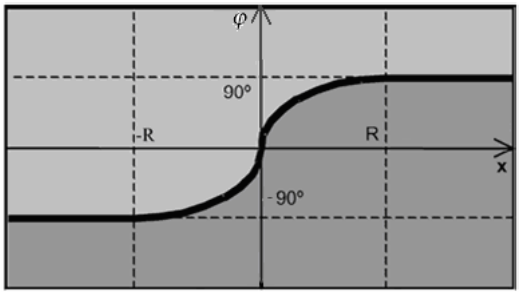
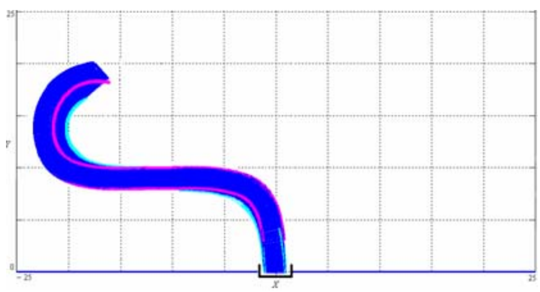
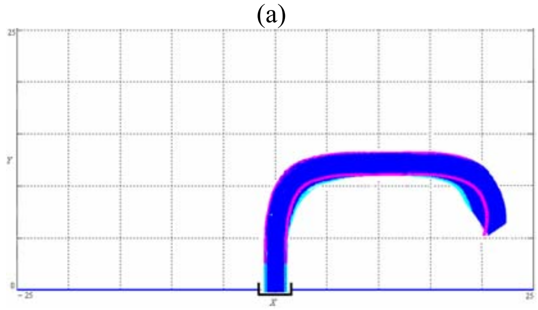


Fig.6. Steering angle θ versus x and φ for short paths. The dark color presents the θ=-40° and the light one presents θ=40°.

Simulated results using the present hierarchical scheme for the different initial positions are shown in Fig.7. In this figures, t indicates the parking duration. It can be seen how the generated paths (Fig.7) are very close to the ideal paths (Fig.2) made up of circular arcs and straight lines.



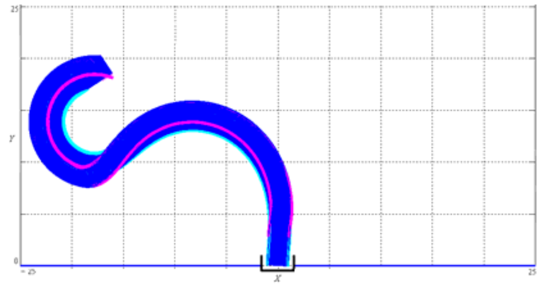
(a)



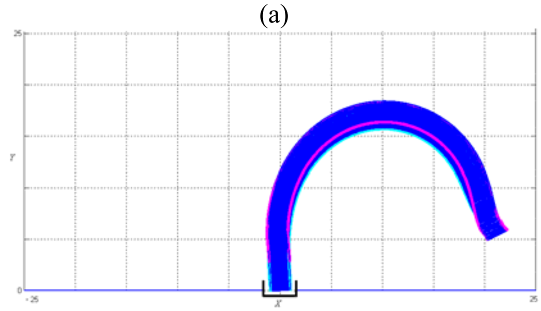
(b)

Fig.7. Results of the parking maneuver corresponding to the initial configurations (a) x=-20, y=18.4, φ=60°, t=78 steps. (b) x=17.5, y=8, φ=162°, t=72 steps.

Further, according to the robot kinematics equations, the work of Li and Li [20] has been used for comparison. Fig.8 shows simulated results of Li and Li [20] for the same initial conditions of Fig.7.



(a)



(b)

Fig.8. Simulated results of the parking maneuver corresponding to the initial configurations (a) x=-20, y=18.4, φ=60°, t=93 steps. (b) x=17.5, y=8, φ=162°, t=86 steps. [20]

An advantage of this approach is that the rules are linguistically interpretable and the controller generates paths with 8 rules compared with 35 used by [17]. Besides it provides the higher smoothness near the target configuration (x=0). Also, parking durations are shorter than those obtained by [20] under the same initial conditions. In this paper, trajectories are composed of circular arcs and straight segments but in other methods, trajectories are composed of circular arcs.

IV. CONCLUSIONS

A fuzzy control system has been described to solve the truck backer-upper problem which is a typical problem in motion planning of nonholonomic systems. In this paper the proposed controller has a hierarchical structure composed of two modules which adjust the proper steering angle of front wheels similar to what a professional driver does. The recommended approach is compared with other methods.

The hierarchical approach generates paths with a small number of rules. The computational cost is also less because we don't have to work with nonlinear functions such as "Arcos ( )". Compared with traditional controller, this fuzzy controller demonstrates advantages on the control performance, convenience and feasibility. Trajectories are composed of circular arcs and straight segments and as a result the hierarchical approach produces shorter trajectories in comparison with other methods.

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