Automatic Parallel Parking System Based on Interval Type 2 Fuzzy Controller

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Abstract

An automatic parking system can reduce the period of time for parking of vehicles, so the vehicle emissions should be reduced, resulting in a benefits for both air quality and fuel consumption. This paper presents the design and simulation of an automatic parallel parking system based on Interval Type 2 Fuzzy Controller (T2FC). T2FC is a further development of the classic fuzzy logic where the membership functions of T2FC is also fuzzy. Tests by several references indicate that the performance of T2FC are better than the classic fuzzy logic. For the case of the automatic parallel parking system will use three fuzzy modules, namely Fuzzy Logic Module for Moving the Vehicle to a Ready-to-Reverse Position, Fuzzy Logic Module for Reversing the Vehicle Into the Parking Space and Fuzzy Logic Module for Navigating the Vehicle Forward Inside the Parking Space. Each module is designed to handle every stage in the process of parallel parking maneuver. The rules of each module have been obtained from heuristic knowledge and numerical data. A simulator software based on LabVIEW 7.1. has been developed to simulate kinematic model of a skid steering vehicle. The simulation software was used to facilitate the evaluation of the proposed T2FC. Simulation result shown that the developed algorithm has the ability to parallel park the vehicle. The system just required a parking space about 1.2 timer longer than the length of a car. Performance of T2FC than compared with Type 1 Fuzzy Controller (T1FC). The simulation result show that the T2FC has better performance than T1FC. Parking duration of T2FC 16% better than T1FC. But Type 2 Fuzzy computation time is more complex than Type 1 Fuzzy algorithm, so T2FC takes 1.8 times slower than T1FC. In application, T2FC needs 1788 units of memory, while T1FC just need 1303 unit memory.

Keywords: Automatic parallel parking system, Interval Type 2 Fuzzy Logic, LabVIEW 7.1, Karnik-Mendel algorithms, Uncertainty

1. Introduction

A. Motivation

An automatic parking system that directs vehicles during parking maneuvers can reduce the period of time for parking of vehicles, reducing vehicle queues due to waiting for the parking of a vehicle, reducing the risk of collision and can help steer the vehicle into a small parking area.And because the system will automatically shorten parking time, vehicle emissions should be reduced, resulting in a benefits for both air quality and fuel consumption.

In[1], Fasciani showed that 350 vehicles that perform automatic parking can save fuel up to 83% and reduce emissions by 77% compared by 350 vehicles that perform manual parking.**Table 1**shows the details of the Fasciani experiments resultsduring experiments 12 hours a day and 365 days per year in North America.

Table 1. Comparison of exhaust emissions and fuel consumption between vehicles parked manually with the automatic parking based on Fasciani Experience [1]

Parking Type	Emissions (ton/year)				Fuel (gal/year)
	VOC	CO	NO_X	CO_2	
Manual	0.216	2.061	0.096	39.5	4.036
Automatic	0.068	0.473	0.017	6.7	689
Reduction (%)	68	77	82	83	83

Although the results would vary for other types of parking conditions, the overall conclusion would remain: in comparison to manual parking, automated parking systems offer significant reductions in air pollutant emissions and fuel consumption.This article focuses on improving the performance of automated vehicle parking system at parallel parking.

B.State of the Art Overview

The number of research based onautomatic parking problem has grown rapidly and continuously in recent years. In[2], Nguyen and Widrow develop a neural network controller for the parking problem. The advantage of the original Nguyen-Widrow approach is that the controller consisting of two neural networks is able to tune itself through a number of training epochs. In[3], Plumer's solution consists of a feed-forward neural network to control the steering of the vehicle using local potential field information. In[4], Kinjo have used genetic algorithms for tuning the neural controllers.

Fuzzy systems have been widely used as an effective tool for modeling non-linear and complex system. 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 their design is simple, fast, inexpensive and easily maintained because the rules can be linguistically interpreted by human experts.

In[5], Riid presented a fuzzy supervisory control system over the PID controller to reduce the complexity of the control problem. Riid demonstrate that problem decomposition leads to more effective knowledge acquisition and improved control performance in fuzzy control. In[6], Kong and Kosko uses both neural networks and fuzzy logic for the same problem. They observed that even that simple fuzzy expert system lead to smoother trajectories than that produced by the two-layer neural network. And in[7], Pourya presents the fuzzy logic enhanced control system that is able to take full control responsibility over the truck and two-trailers system.

Fuzzy controller that replaces human operator has been formulated on the basis of expert knowledge [8] or identified from control data[9]. In this paper, we consider the design of a Fuzzy Logic Systems that is based on rules collected by surveying a group of experts. In this situation, three types of uncertainties can arise[10].

1) Different experts often given different answers to the same question, which results in rules having the same antecedents, but different consequents. Consequently, answers to rule-based questions lead to uncertain consequents.
2) Because words mean different things to different people, and membership functions are associated with words, if we also ask the experts about the membership function parameters, we are likely to get different answers for these parameter values. This results in uncertain membership functions. Consequently, answers to queries about membership functions lead to uncertain antecedents and additional uncertainty about consequents.
3) The data that are used to tune the parameters of fuzzy logic may also be noisy.

Mendel and Karnik [11] have developed a complete theory of type-2 Mamdani Fuzzy Logic Systems. These systems are again characterized by IF-THEN rules, but their antecedents or consequents sets are now type-2. Type-2 fuzzy sets have membership grades that are themselves fuzzy. Corresponding to each primary membership grade (which can be in [0,1]), a secondary membership (which can also be in [0,1]) is used to define the possibilities of primary membership grades. A type-1 fuzzy sets is a special case of a type-2 fuzzy sets; its secondary membership function is a subset with only one element. Type-2 fuzzy sets allow us to handle linguistic uncertainties, as typified by the adage "words can mean different things to different people."

To date, type-2 fuzzy logic systems have been used in decision making[12], solving fuzzy relation equations[13], control of mobile robots [14] and pre-processing of data[15]. In this paper type-2 fuzzy controller for automatic parallel parking system is proposed. As far as the author concerns, there in no work on development of suitable type 2 Fuzzy Controller for parallel parking problem.

C. Content of the Article

This paper explores the use of interval type-2 TSK Fuzzy system, which is well known for its powerful in handling this uncertainties [9].Contribution of this paper is to propose type-2 Fuzzy algorithm suitable for parallel parking problem and compare the performance between the interval type 2 Fuzzy and type 1 Fuzzy.

The paper is organized in six sections. Following this introductions, section 2 contains an overview of interval type 2 fuzzy structure. Kinematic equation and constrains are described in section 3. Type-2 fuzzy controller for parallel parking problem described in section 4 The Simulation results are provided in Section 5. In Section 6, we conclude with conclusion.

2. Interval Type 2 Fuzzy Structure

Type-2 fuzzy sets were originally presented by Zadeh in 1975. The new concepts were introduced by Mendel and Liang allowing the characterization of a type-2 fuzzy set with a superior membership function and an inferior membership function; these two functions can be represented each one by a type-1 fuzzy set membership function. The interval between these two functions represent the footprint of uncertainty (FOU), which is used to characterize a type-2 fuzzy set. Type-2 fuzzy sets allow us to handle linguistic uncertainties, as typified by the adage "words can mean different things to different people".

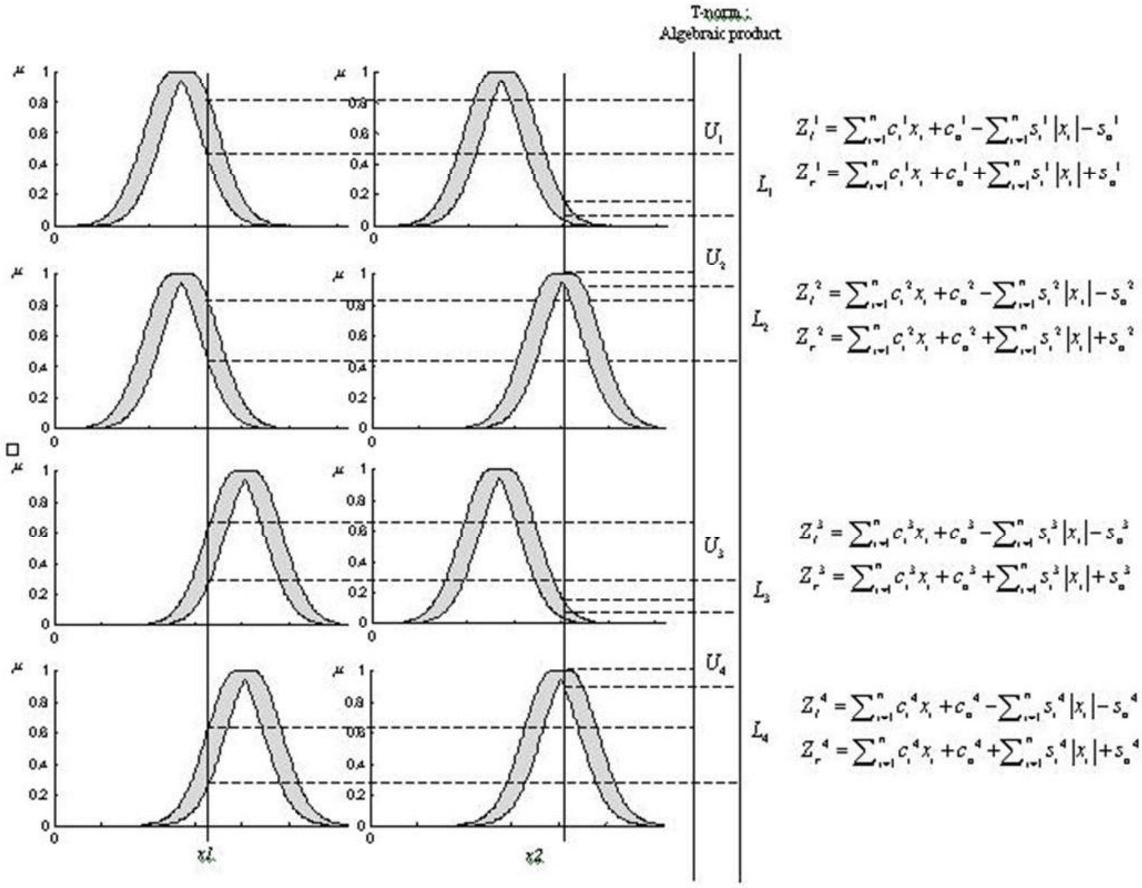

Figure 1. Interval type 2 TSK Fuzzy System Structure

For type-2 TSK models, there are three possible structure[16]:

1. Antecedents are type-2 fuzzy sets, and consequents are type-1 fuzzy sets. This is the most general case and we call it Model I.
2. Antecedents are type-2 fuzzy sets, and consequents are crisp number. This is special case or Model I and we call it model II.
3. Antecedents are type-1 Fuzzy sets and consequents are type-1 fuzzy sets. This is another special case of Model I and we call it Model III.

We use Model I to design interval type-2 TSK Fuzzy system in this paper. A schematic diagram of the proposed T2TSK structure is shown in**Figure 1**, which is organized into *i* input variables and *m* rules.

A. Rule Base

In a first-order type-2 TSK Model I with a rule base of *m* rules and *n* input variables, is denoted as

$$\textbf{IF} x_1 is\ \mu_1{}^b(x_1) \textbf{AND} \ldots \textbf{AND}\ x_a is\ \ \mu_a{}^b(x_a) \quad \textbf{THEN} Z \text{ is } p_1{}^b x_1 + p_2{}^b x_2 + \ldots + p_a{}^b x_a + p_0{}^b \tag{1}$$

where $b \in [0, m]$ and $a \in [0, n]$. The consequent parameter $p_1{}^b, p_2{}^b, \ldots, p_a{}^b, p_0{}^b$, which are type-1 fuzzy sets, has interval, is denoted as

$$p_a{}^b = [c_a{}^b - s_a{}^b, c_a{}^b + s_a{}^b] \tag{2}$$

The membership grades $\mu_1{}^b(x_1)$, $\mu_2{}^b(x_2)$, ..., $\mu_a{}^b(x_a)$are interval sets to, which denoted as

$$\mu_a{}^b = \left[\underline{\mu}_a^b, \overline{\mu}_a^b\right] \tag{3}$$

Where $\underline{\mu}_a^b$ is lower membership function and $\overline{\mu}_a^b$ is upper membership function. These rules let us simultaneously account for uncertainty about antecedent membership functions and consequent parameter values.

B. Fuzzification

This process is transforming the crisp input to a type-II fuzzy variable. The primary membership functions for each antecedent are interval type-2 fuzzy systems described by Gaussian primary membership function with uncertain means, denoted as

$$\mu_a^b(x_a) = \exp\left[-\frac{1}{2}\left(\frac{x_a - m_a^b}{\sigma_a^b}\right)^2\right] \tag{4}$$

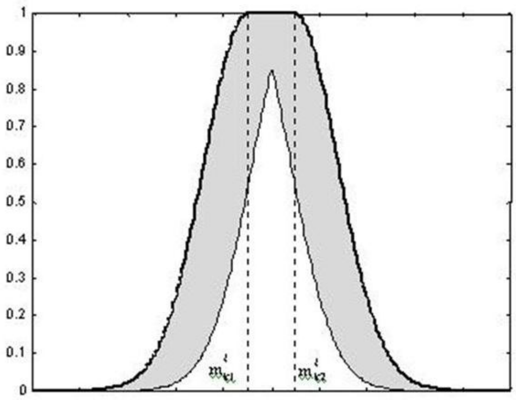

Figure 2. Gaussian interval type-2 fuzzy membership function with uncertain means

where $m_a^b \in [m_{a1}^b, m_{a2}^b]$ is the uncertain mean, with $a = (1,\dots,n)$ is the number of antecedent, $b = (1,\dots,m)$ is the number of rules and σ_a^b is the standard deviation.

There are two kinds of type-2 sets. First is a gaussian type-2 fuzzy set, which the membership grade of every domain point is a Gaussian type-1 set contained in [0,1]. Second is an interval type-2 fuzzy set which the membership grade of every domain point is a crisp set whose domian is some interval contained in [0,1].**Figure 2**shows gaussian interval type-2 fuzzy membership function with uncertain means.

The upper membership function is defind as

$$\overline{\mu}_a^b(x_a) = \begin{cases} N(m_{a1}^b, \sigma_a^b, x_a), & x_a < m_{a1}^b \\ 1, \quad m_{a1}^b \le x_a \le m_{a2}^b & \\ N(m_{a1}^b, \sigma_a^b, x_a), & x_a > m_{a2}^b \end{cases} \tag{5}$$

where

$$N(m_{a1}^b, \sigma_a^b, x_a) = \exp\left[-\frac{1}{2}\left(\frac{x_a - m_a^b}{\sigma_a^b}\right)^2\right] \tag{6}$$

And lower membership function is defind as

$$\underline{\mu}_a^b(x_a) = \begin{cases} N(m_{a2}^b, \sigma_a^b, x_a), & x_a \le \dfrac{m_{a1}^b + m_{a2}^b}{2} \\ N(m_{a2}^b, \sigma_a^b, x_a) & x_a > \dfrac{m_{a1}^b + m_{a2}^b}{2} \end{cases} \tag{7}$$

C. Fuzzy Inference System

Fuzzy inference mechanism applies the fuzzy reasoning on the rules in the rule base in order to derive a mathematically reasonable output or conclusion which represents the problem conditions best. Fuzzy inferences in antecedent using algebraic product, is denoted as

$$\underline{W}^b = \underline{\mu}_1^b(x_1) \times \underline{\mu}_2^b(x_2) \times \dots \times \underline{\mu}_n^b(x_n) \tag{8}$$

and

$$\overline{W}^b = \overline{\mu}_1^b(x_1) \times \overline{\mu}_2^b(x_2) \times \dots \times \overline{\mu}_n^b(x_n) \tag{9}$$

Figure 3shows Fuzzy inference illustrative example of the simplified case with two input variable.

The interval value of the consequent Z^b is $Z^b = [Z_l{}^b, Z_r{}^b]$, where

$$\begin{aligned} Z_l{}^b &= \sum_{i=1}^n c_i^b x_i + c_0^b - \sum_{i=1}^n s_i^b |x_i| - s_0^b \\ Z_r{}^b &= \sum_{i=1}^n c_i^b x_i + c_0^b + \sum_{i=1}^n s_i^b |x_i| + s_0^b \end{aligned} \tag{10}$$

and $Z_l{}^b$ and $Z_r{}^b$ denote the lower and upper values of consequent output for b th rule. c_i^b denotes the center (mean) of $Z^b$and s_i^b denotes the spread of Z^b.

D. Type Reduction

The Karnik-Mendel algorithms is used for determining c_l and c_r. This process takes the type-2 output set and convert it to a type-1 set. The five steps for determining c_r[17]:

[1] Initialize θ_r^b by setting:

$$\theta_r^b = \frac{1}{2}\left[\underline{W}^b + \overline{W}^b\right] \quad b = 1,\dots,n \tag{11}$$

and then compute :

$$c' = \frac{\sum_{b=1}^m \theta_r^b Z_r^b}{\sum_{b=1}^m \theta_r^b} \tag{12}$$

[2] Find $k_r (1 \le k_r \le N-1)$ such that

$$Z_r^{k_r} \le c' \le Z_r^{k_r+1} \tag{13}$$

[3] Set :

$$\theta_r^b = \begin{cases} \underline{W}^b & b \le k_r \\ \overline{W}^b & b \ge k_r + 1 \end{cases} \tag{14}$$

And compute :

$$c'' = \frac{\sum_{b=1}^k Z_r^b \underline{W}^b + \sum_{b=k+1}^m Z_r^b \overline{W}^b}{\sum_{b=1}^k \underline{W}^b + \sum_{b=k+1}^m \overline{W}^b} \tag{15}$$

[4] Check if $c'' = c'$. If yes, stop and set $c'' = c_r$. If no, go to step [5]

[5] Set $c' = c''$ and go to step [2]

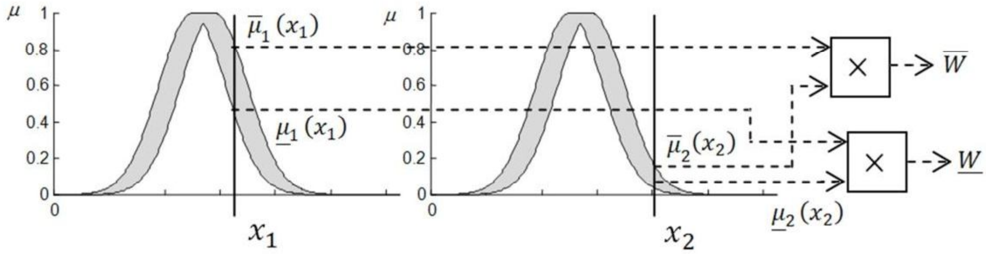

Figure 3. Illustrative example of inference mechanism using algebraic product

For determining c_l, same as previouse procedur, except in step 3, set

$$\theta_l^b = \begin{cases} \underline{W}^b & b \le k_l \\ \overline{W}^b & b \ge k_l + 1 \end{cases} \tag{16}$$

so that :

$$c'' = \frac{\sum_{b=1}^{k} Z_l^b \underline{W}^b + \sum_{b=k+1}^{m} Z_l^b \overline{W}^b}{\sum_{b=1}^{k} \underline{W}^b + \sum_{b=k+1}^{m} \overline{W}^b} \tag{17}$$

E. Defuzzification

Since the resultant type-reduced output is an interval type-1 fuzzy set, the output of fuzzy can be calculate using the average of its lower and upper bounds :

$$y = \frac{c_l + c_r}{2} \tag{18}$$

3. Vehicle Kinematic Equations

Figure 4shows the geometry of the simulated vehicle and desired position. The vehice position is exactly determined by the three state variable $\emptyset$, x and y, where$\emptyset$ is the angle of the truck with the horizontal. The coordinate pair (x,y) specifies the position of the rear center of the truck in the plane. The goal is to make the truck arrive from the arbitrary initial position $(x_i, y_i, \emptyset_i)$ to the parking spot (x_f, y_f) at right angle $(\emptyset_f)$. Control of the vehicle is the angle θ.

The vehicle moves backward of forward by a fixed unit distance every stage. The zone is the plane $[0,10] \times [0,10]$. So, the controller should produce the appropriate steering angle θ at every stage to make the vehicle back up to the parking spot from any initial position and from any angle.

The task here is to design a control system, whose input are $\emptyset \in [-90^o, -270^o]$, $x \in [0,10]$ and $y \in [0,10]$ and whose output is $\theta \in [-30,30]$, to take the vehicle to the desired location and orientation $(x_f, y_f, \emptyset_f)$.

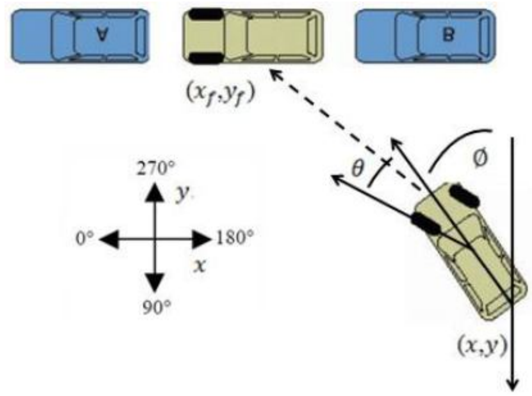

Figure 4. Vehicle kinematic for parallel parking

Since we performed simulations, we needed to known the dynamics of the vehicle procedure. We used the following approximate kinematics (see [18] for details) :

$$x(t+1) = x(t) - \cos(\emptyset(t) + \theta(t)) - \sin(\theta(t))\sin(\emptyset(t)) \tag{19}$$

$$y(t+1) = y(t) - \sin(\emptyset(t) + \theta(t)) - \cos(\theta(t))\sin(\emptyset(t)) \tag{20}$$

$$\emptyset(t+1) = \emptyset(t) - \sin^{-1}\left(\frac{2\sin(\theta(t))}{b}\right) \tag{21}$$

4. Type-2 Fuzzy Logic (T2FL) for Parallel Parking Problem

Based on human expert knowledge for parallel parking problem, the parking process was divided into three steps and a fuzzy controller was designed for each of the steps[19]. The three steps are : 1) reaching a ready to reverse position, 2) reversing the vehicle into the parking space, and 3) adjusting the vehicle forward inside the parking space.

In the first step, the vehicle is navigated to reach a ready-to-reverse position with the vehicle orientation parallel to the parking space (see**Figure 5**).This step is divided into two sub-steps. The task of the first sub-steps is to have the vehicle move forward and the second sub-stpes is to have the vehicle move backward to adjust the desired position and orientation.

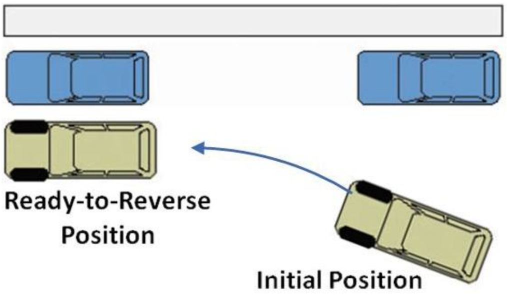

Figure 5. Reach a ready-to-reverse position

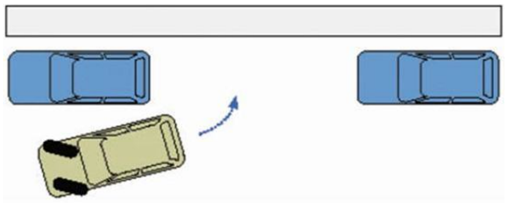

Figure 6. Backward with increasing θ

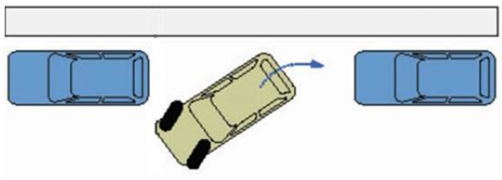

Figure 7. Backward with decreasing θ

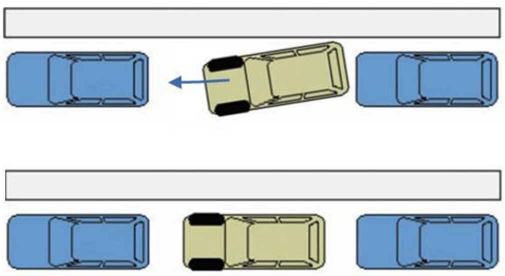

Figure 8. Adjust forward inside the space

In the second step (see**Figure 6**and **7**), the vehicle is first move backward into the maneuvering space with increasing θ until its rear right wheel is at certain distance from the boundary of the parking spot. Then the vehicle is reversed with decreasing θ until one of the rear wheels is very close to the boundary of the parking space.

In the third step, the vehicle is moved forward to adjust its position inside the space (see**Figure 8**). The desired final position of the vehicle is that it is parallel to and at the center of the space. The second and third steps can be repeated several times until the desired final position is reached with some tolerance.

A. T2FL for Moving the Vehicle to a Ready-to-Reverse Position

The first step is to navigated the vehicle to reach a ready-to-reverse position with the vehicle orientation parallel to the parking space. The controller contains T2FLBackward Module and T2FLForward Module. The controller structure is shown in**Figure 9**.First the vehicles will be guided by T2FL Forward Module to reach a ready-to-reverse position. If the orientation of the vehicle is not appropriate (not parallel to the parking space), then the T2FL backward module will be used to guide the vehicle moving backward and then forward again to adjust vehicle orientation.

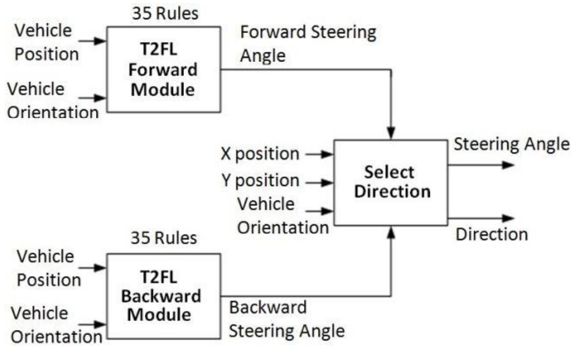

Figure 9. General structur of T2FL for moving the vehicle to a ready-to-reverse position

The input parameters are the vehicle angle $\emptyset$ and the x-position x. The output parameter is the steering signal θ. Positive value of θ are clockwise rotations of the steering wheel. Negative values are counterclockwise rotations. All values are discretized to reduce computation. The resolution of $\emptyset$ and θ is one degree each. The resolution of $x\ is\ 0.1$.

Fuzzy substes of the input and output numerically represent linguistic terms, the sort of linguistic terms an expert might give to describe the control system's behavior. The fuzzy substes for the T2FL for moving the vehicle to a ready-to reverse position are shows in**Table 2**.The membership functions of the variables are given in**Figure 10–Figure 12**.The complete rule base as shows in**Table 3**and**Table 4**.

Table 2. Fuzzy subsets for the T2FL for moving the vehicle to a ready-to-reverse position

Vehicle Position	Vehicle Orientation	Steering Angle
LD : Left-Down	L : Left	NB : Neg-Big
L : Left	LC : Left-Center	NM : Neg-Med
LU : Left-Up	C : Center	NS : Neg-Small
U : Up	RC : Right-Center	Z : Zero
RU : Right-Up		PS : Pos-Small
R : Right	R : Right	PM : Pos-Med
RD : Right-Down		PB : Pos-Big

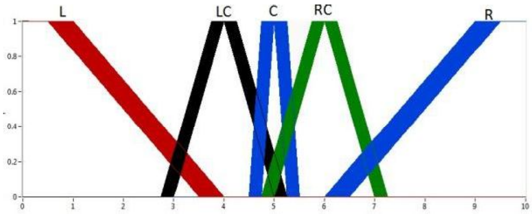

Figure 10. Membership functions for vehicle-position

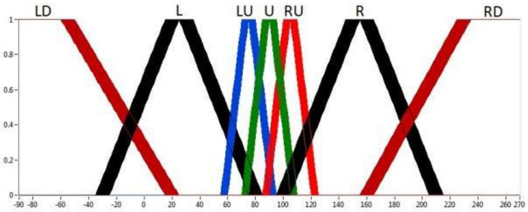

Figure 11. Membership functions for vehicle-orientation

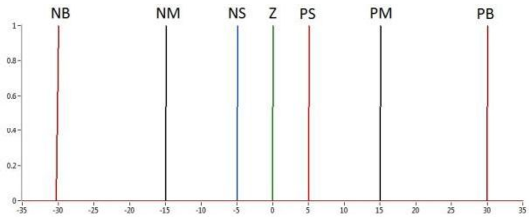

Figure 12. Membership functions for steering-angle

Table 3. T2FL Backward Module

		Vehicle Orientation						
		LD	**L**	**LU**	**U**	**RU**	**R**	**RD**
Vehicle Position	**L**	NS	PS	PM	PM	PB	PB	PB
	LC	NM	NS	PS	PM	PM	PB	PB
	C	NM	NM	NS	Z	PS	PM	PM
	RC	NB	NB	NB	NM	NM	NS	NS
	R	NB	NB	NB	NM	NM	NS	NS

Table 4. T2FL Forward Module

		Vehicle Orientation						
		LD	**L**	**LU**	**U**	**RU**	**R**	**RD**
Vehicle Position	**L**	PB	PB	PM	PM	PS	NS	NB
	LC	PB	PB	PM	PM	PS	NS	NM
	C	PM	PM	PS	Z	NS	NM	NM
	RC	PM	PS	NS	NM	NM	NB	NB
	R	PM	PS	NS	NM	NM	NB	NB

B. T2FL for Reversing the Vehicle Into the Parking Space

This reverse maneuvering into the parking space requires a more complex fuzzy logic controller. This step has two basic sequential goals : 1) back up the vehicle while increasing the orientation angle until the vehicle is very close to the boundary of the parking space, and 2) then back up the vehicle while decreasing the angle.

As shown in **Figure 13**, the coordinate system of the left rear corner of the vehicle in the local coordinate system is defined as (x_a, y_a) and the coordinate of the right rear corner of the vehicle is defined as (x_b, y_b). The size of the rectangular parking space is defined as $h_p \times l_p$. Here, two variables x_{a1} and y_{b1}, are defined by $x_{a1} = x_a/l_p$ and $y_{b1} = y_b/h_p$; they represent the position of the vehicle relative to the parking space.

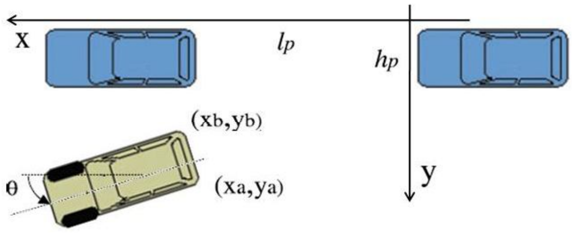

Figure 13. Maneuvering space and local coordinate system

The T2FL for this step has three inputs, x_{a1}, y_{b1} and the orientation angle θ. The output is steering rate $\dot{\theta}$. The membership functions of the variables are given in

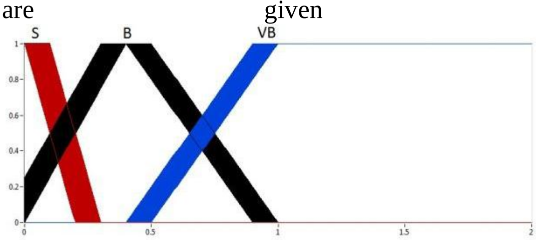

Figure 14–**Figure 17**. The three dimensional fuzzy rules are shown in **Table 5**(see[19]for rationale behing several of the rules).

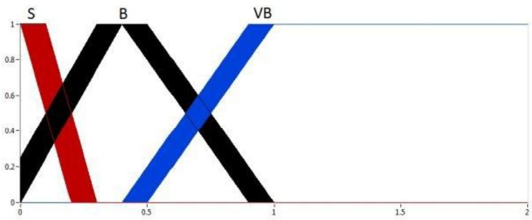

Figure 14. Membership function for input x_{a1}

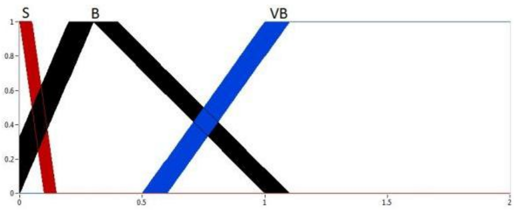

Figure 15. Membership function for input y_{b1}

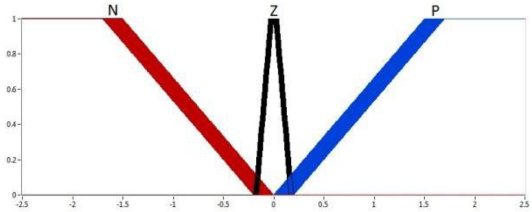

Figure 16. Membership function for input θ

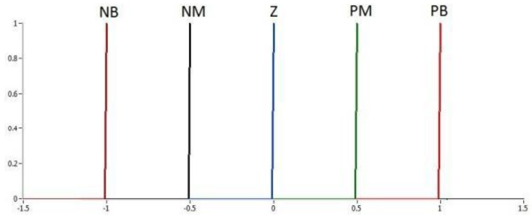

Figure 17. Membership function for output $\dot{\theta}$

Table 5. T2FL for reversing step

	x_{a1} \ y_{b1}	S	B	VB
θ = N	S	PB	PB	
	B	PM	PB	PB
	VB			PM
θ = Z	S	Z	Z	
	B	Z	PB	PB
	VB			Z
θ = P	S	NB	Z	
	B	NM	Z	PM
	VB			NB

C. T2FL for Navigating the Vehicle Forward Inside the Parking Space

The third step is to adjust the orientation of the vehicle while simultaneously move it forward. This is essentially the same task as that of the orientation adjustment described in the first step. Thus the membership functions and fuzzy inference rules are exactly the same as the first step.

5. Simulation Results

A simulator software based on LabVIEW 7.1. has been developed to simulate kinematic model of a skid steering vehicle. A screen snap shot of the designed GUI for navigation of vehicle is shown in **Figure 18**.

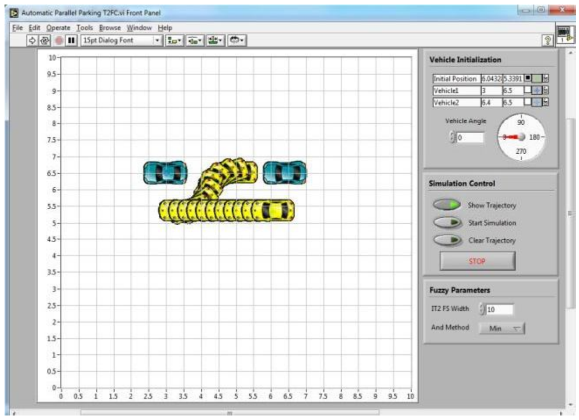

Figure 18. Simulated Parallel Parking based on LabVIEW 7.1

To verify the desribed method, we performed three steps. First, we simulated a large number of parking maneuvers; second we compared the type-2 fuzzy controller with type-1 fuzzy controller; and finally we measure the computational cost.

A. Simulations

In order to verivy the system performance, we simulated a large number of different parking situations. We randomized all the initial conditions: parking area dimensions, vehicle position and orientation.

The critical distance in parallel parking as show in **Figure 19** is between the front-right corner of the vehicle and the parking spot. **Figure 20**shows a histogram plot of minimum front corner distance and the parking spot for all randomized experiments. Zero would indicate a collision of the vehicle with parking boundary. As shown in the histogram, that no collisions occured.

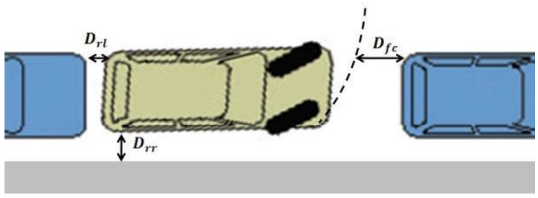

Figure 19. Critical distance D_{fc}, D_{rr} and D_{rl} on parallel parking

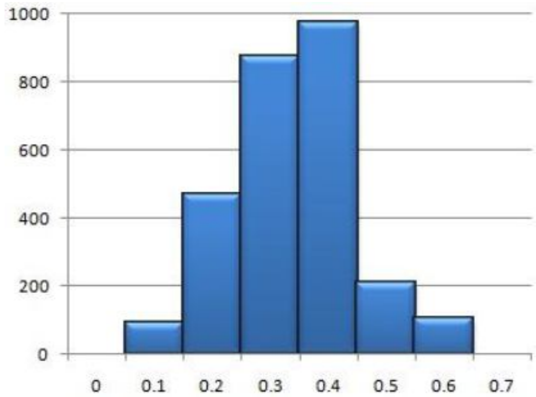

Figure 20. Histogtam of the minimum front corner distance.

Other important performance measure for parallel parking is the required number of moves. **Figure 21**shows a histogram plot of the counted moves until parallel orientation was reached by the simulated vehicle.

Figure 22 and **Figure 23** show simulated parking maneuvers for different size of parking area. It shows that the parking space requires just 1.2 times longer than vehicle length.

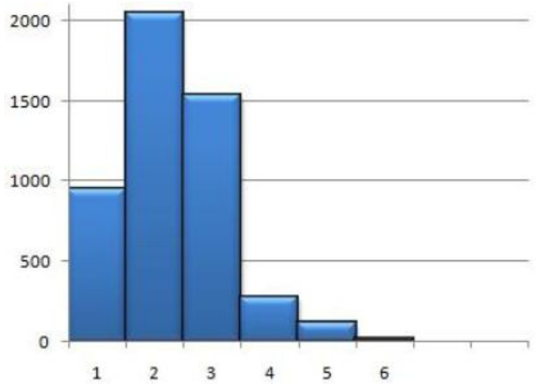

Figure 21. Histogram of the required number of iterations

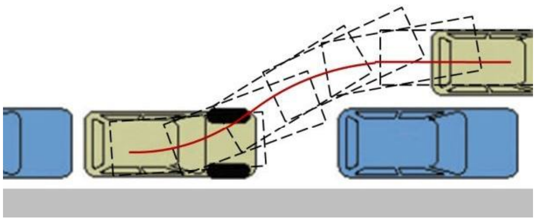

Figure 22. Simulated parking maneuver for a large parking area (length of the parking area= 8.5 m, length of the vehicle = 5.4 m)

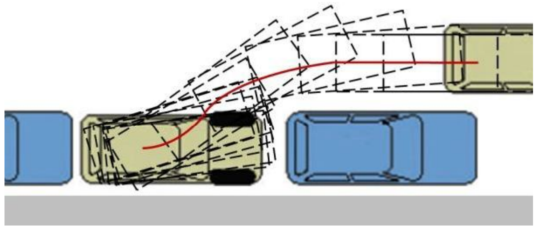

Figure 23. Simulated parking maneuver for a small parking area (length of the parking area= 6.5 m, length of the vehicle = 5.4 m)

B. Comparison with Type-1 Fuzzy Controller

Then the develop controller was compared with type-1 Fuzzy Controller (T1FC). Comparison of parking duration between T2FC dan T1FC for some different parking area dimensions and vehicle orientation are shown in **Table 6**. Example of trajectory comparison between T2FC and T1FC for initial configuration x = 6, y = 3, θ = 180 are shown in**Figure 24.**

The simulation result show that the advantage of type-2 fuzzy controller approach is it provides the shorter parking durations than those obtained by type-1 fuzzy controller. Parking duration of T2FC 16% better than T1FC.

Table 6. Comparison of parking duration between T2FC dan T1FC

No	Vehicle angle	X	Y	Parking length	Parking duration (steps)	
					T2FC	T1FC
1	135	10	3	8.5	18	18
2	135	10	3	7.5	30	48
3	135	10	3	6.5	43	47
4	180	10	3	8.5	21	23
5	180	10	3	7.5	32	37
6	180	10	3	6.5	48	60
7	225	10	3	8.5	22	25
8	225	10	3	7.5	34	39
9	225	10	3	6.5	50	81

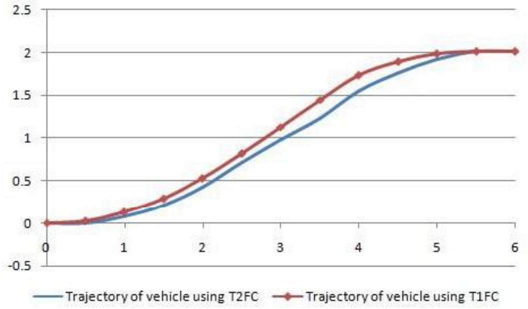

Figure 24. Example of trajectory comparison between T2FC and T1FC for initial configuration x = 6, y = 3, θ = 180

C. Computational Cost

But type-2 fuzzy controller computation time is more complex than type-1 fuzzy controller. **Table 7**show the comparison of type-2 fuzzy controller and type-1 fuzzy controller computation time. So T2FC takes 1.8 times slower than T1FC. In application, T2FC needs 1788 units of memory, while T1FC just need 1303 unit memory.

Table 7. Computation time

	Average of time computation (microsecond)
Type-1 Fuzzy Controller	18750
Type-2 Fuzzy Controller	33854

6. Conclusion

A type-2 fuzzy controller has been described to solve the parallel parking problem. The controller showed good performance in various parking situations. In a small parking area,the system instructed the vehicle to iteratively change the direction of heading until a suitable position was reached. The system just required a parking space about 1.2 timer longer than the length of a car.

Compared with type-1 fuzzy controller, this type-2 fuzzy controller demonstrates advantages on the control performance. Trajectories are composed of circular arcs and straight segments and as a result the type-2 fuzzy controller approach produces shorter trajectories in comparison with type-1 fuzzy controller methods. Parking duration of T2FC 16% better than T1FC. But Type 2 Fuzzy computation time is more complex than Type 1 Fuzzy algorithm, so T2FC takes 1.8 times slower than T1FC. In application, T2FC needs 1788 units of memory, while T1FC just need 1303 unit memory.

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