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Robust Automatic Parking without Odometry using Enhanced Fuzzy Logic Controller

Young-Woo Ryu, Se-Young Oh, *Senior Member, IEEE*, and SamYong Kim

***Abstract*—This paper develops a novel automatic parking algorithm based on a fuzzy logic controller with the vehicle pose for the input and the steering rate for the output. It localizes the vehicle by using only external sensors - a vision sensor and ultrasonic sensors. Then it automatically learns an optimal fuzzy if-then rule set from training data. This is possible using a genetic fuzzy system which optimizes the parameters for the fuzzy logic controller. Furthermore, it also finds the green zone of the ready-to-reverse position where parking is possible just by reversing. It has been tested on a Pioneer mobile robot which emulates the real vehicle.**

I. Introduction

An automatic parking system can park the vehicle for inexperienced drivers. It consists of the exploration for the parking space and the automatic parking algorithm. These processes are more experimental than a logical one. So by transferring the expert driver's parking skill to an automatic parking system, this technology also can be used to alleviate the driving burden and enhance safety in next-generation passenger vehicles. The vehicle with vision [1],[2] or ultrasonic sensors [3]-[5] explores the proper parking space and finds starting position. After exploration, the automatic parking is performed using two main approaches. The path planning approach plans a feasible geometry path in advance, takes into account the environmental model as well as the vehicle dynamics and constraints, and then control commands are generated to follow the reference path [2],[6],[7]. A skill-based approach mimics an experienced driver's parking skill using fuzzy logic [5], neural networks [1],[8] etc. There is no reference path to follow and the control command is generated by considering the orientation and position of the vehicle relative to the parking space. These approaches require the exact vehicle pose relative to the parking space. Daxwanger [1] used neural networks that can transform the video sensor's image of the environment to a corresponding steering angle. Xu et al. [2] and Jiang et al. [3] used the ultrasonic sensor information. For improving the parking performance, Zhao [5] and Adollah [9] found improved fuzzy membership functions using a GA. But the odometry data is not readily available so that image and sonar based localization in outdoor parking is a more practical choice. Further, the automatic parking algorithm must consider various sizes and shapes of the parking lot, the parking stability, the time required, the accuracy in real situations.

This paper proposes an automatic parking algorithm that can be applied to the general outdoor parking. We first propose an improved localization method using a vision and ultrasonic sensors. Using these two sensors in tandem, the parking line sensible via vision and the nearby objects sensible via the sonar can be of great help to localize the vehicle even when using either sensor alone would fail to localize. We also did not use any odometry information in this process since this would be too expensive and cumbersome to be used in actual outdoor vehicles. Then we optimize the rule set and membership functions for the fuzzy logic controller (FLC) by defining a proper performance index for robust parking. The performance index for this optimized fuzzy controller was chosen to take into account the possibility of collision, parking time, and the decency of the final parked pose. In addition, a green zone of the initial stop-to-park position was also found that facilitates the entire automatic parking process. A tight space maneuvering algorithm is also obtained by proper tuning of the fuzzy controllers. In the real experiment, we implemented the general parallel parking and the garage parking.

II. Automatic Parking System

A. System Overview

The automatic parking process consists of several steps as shown in Fig. 1.

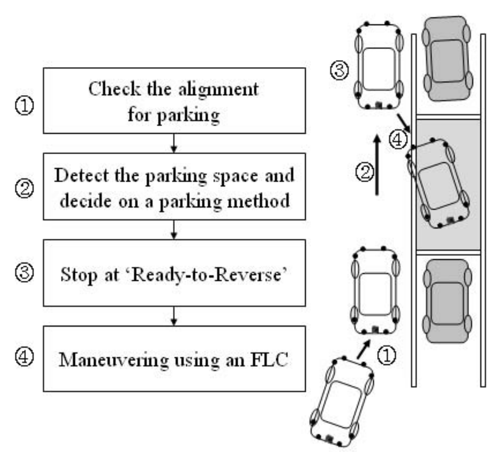

Fig. 1. The entire process of the automatic parking system.

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The authors are with the Department of EE, POSTECH (Pohang University of Science and Technology), South Korea (phone: +82-54-279-2880; fax: +82-54-279-5594; e-mails:{ggr78, syoh, tripledg*}@postech.ac.kr). (*: corresponding author)

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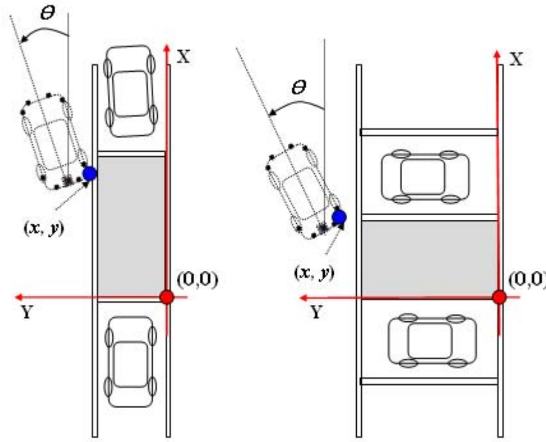
The system first checks the direction of the parking lot and then navigates forward to reach a ready-to-reverse position with the vehicle orientation parallel to the parking space using ultrasonic sensors. After detecting and checking the size of the parking bay, the system makes decision on the possible parking method-'parallel parking', 'garage parking', or 'impossible'. And the vehicle stops at the recommended ready-to-reverse position from which the parking is performed stably. Finally, Maneuvering for the automatic parking is completed an optimized FLC that is designed to achieve some objective.

B. Vehicle Localization

In order to autonomously navigate and perform useful tasks, a vehicle needs to know its exact position and orientation, that is, the vehicle state or its pose vector, $\mathbf{x} = [x\ y\ \theta]$. The relative position can be obtained by vehicle localization with respect to the detected parking space. To obtain this information, to compensate parking space detection errors, and to prevent collision, we use a camera and 16 ultrasonic sensors. Fig. 2 shows the local coordinate system and maneuvering space and Fig. 3 shows the localization procedure. If other vehicles or walls exist, the vehicle state is easily determined by ultrasonic sensors. Because the ultrasonic sensor data may contain error according to the approach direction and the material of the reflected object, they are integrated. If the change of the sensor value is larger than a certain threshold, we can substitute this value with the mean value of the neighbor sensors. But in case of the ready-to-reverse direction with a large approach angle between the vehicle and the parking lot or the position with no objects behind, we can't estimate the vehicle state. In this case, the system estimates the vehicle state from the parking lines in an image. After extracting parking line candidates using the edge and intensity profiles, it transforms the extracted parking lines to the world coordinates. Then we estimate the vehicle state by extracting feature points.

1) Coordinate Transformation: When we transform from the image to the world coordinates using the flat earth assumption, the inverse perspective transform (IPT) is usually applied [10]. But because the used camera for parking has a short focal length and a wide view angle, the acquired image has some radial distortion, and the IPT results incur serious errors. So we use the neural networks that learns the mapping relationship between the image coordinates (u, v) and the world coordinates (x, y) [11]. The used neural networks architecture is 2-5-5-2 multi-layer perceptron which allows us to acquire more precise world positions like in Fig. 4 and Table I.

2) Parking line extraction: Valid parking lines are extracted using the Hough transform in the world coordinates [12]. After discriminating each line as 'rear line', 'left line', or 'right line', etc., and using the crossing points of the parking lines as the feature points, we can obtain the vehicle state $\mathbf{x}$ relative to the parking lot like in Fig. 5. And finally we can reconstruct the top view image like in Fig. 6.



(a) (b)

Fig. 2. Local coordinate systems for (a) Parallel parking. (b) Garage parking.

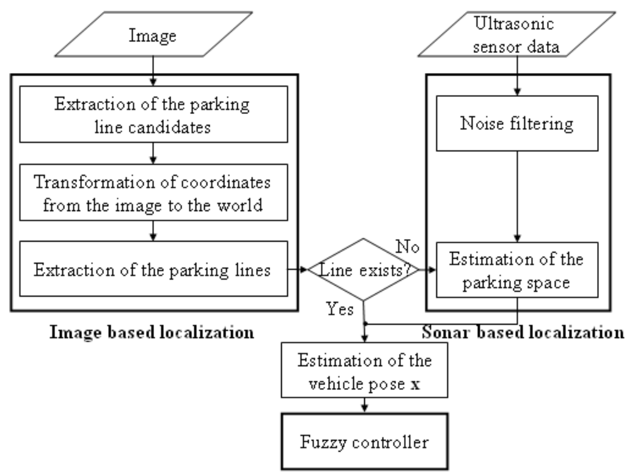
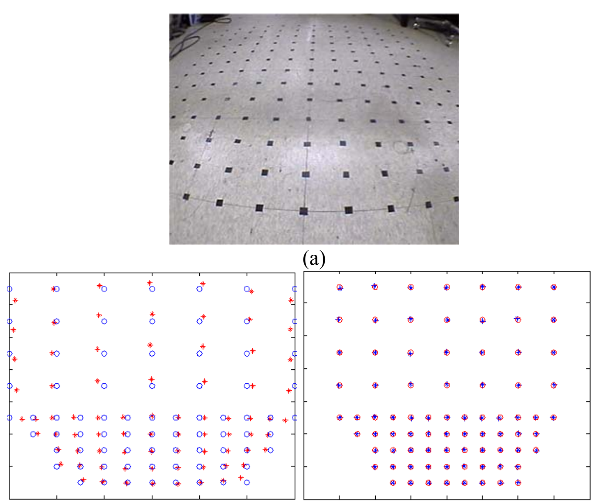


Fig. 3. Localization procedure.

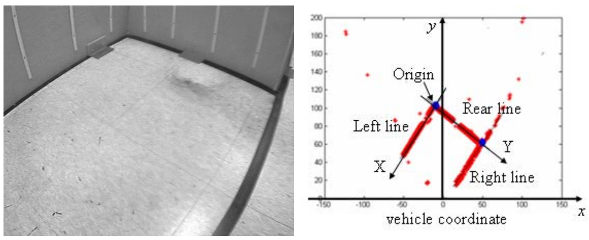


(b) (c)

Fig. 4. Results of the coordinate transformation. (a) Original image (b) IPT result (o : Real position, * : IPT estimated position). (c) NN result (o : Real value, * : NN estimates).

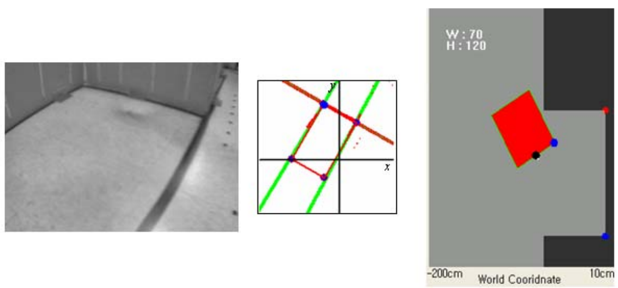
TABLE I
ACCURACY COMPARISON OF INVERSE PERSPECTIVE TRANSFORM AND NEURAL NETWORK ESTIMATION

	Max. error	Mean error
Inverse Perspective Transform	9.78 cm	2.54 cm
Neural Network	1.138 cm	0.391 cm

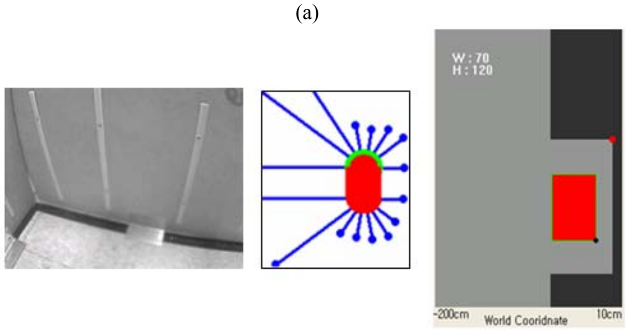


(a) (b)

Fig. 5. Extracted parking lines and feature points. (a) Raw image. (b) Parking lines and feature points.



Original image Vehicle coordinate Vehicle state
(a)



Original image Ultrasonic sensor pattern Vehicle state
(b)

Fig. 6. Results of estimation of the vehicle state. (a) Image based localization. (b) Ultrasonic sensor based localization.

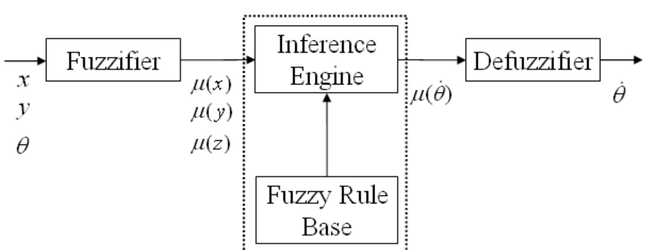


Fig. 7. Structure of the fuzzy controller.

C. *Automatic Parking using a Heuristics Based FLC*

A handcrafted FLC for parking has three input variables (x, y, θ), one output variable $\dot{\theta}$, and 27 IF-THEN rules. The structure of the FLC is shown Fig. 7. The fuzzy rule base consists of multiple rules with multiple antecedents, and the Mamdani's fuzzy inference model is used to determine the output value, and the defuzzification is done by using center of gravity [13]. The fuzzy rule set for parallel and garage parking are shown in Tables II and III. Fig. 8 shows the fuzzy membership functions used.

TABLE II
FUZZY RULE SET FOR PARALLEL PARKING

	$x \backslash y$	S	B	VB
$\theta = \mathrm{N}$	S	PB	PB	NB
	B	PM	PB	PB
	VB	PM	PB	PM
$\theta = \mathrm{Z}$	S	Z	Z	NM
	B	Z	PB	PB
	VB	Z	PM	PB
$\theta = \mathrm{P}$	S	NB	Z	Z
	B	NM	Z	PM
	VB	NM	Z	PM

TABLE III
FUZZY RULE SET FOR GARAGE PARKING

	$x \backslash y$	S	B	VB
$\theta = \mathrm{N}$	S	B	B	M
	B	B	B	M
	VB	M	M	M
$\theta = \mathrm{Z}$	S	B	B	M
	B	B	M	S
	VB	M	S	S
$\theta = \mathrm{P}$	S	M	M	S
	B	M	S	Z
	VB	S	Z	Z

III. IMPROVEMENT OF THE FLC

When we evaluate the performance of the FLC, we consider various factors:

- Possible collision
- Time required for parking
- Accuracy of the parked position
- Compactness of the FLC
- Size of the parking space

Although the FLC introduced in Section II was designed by hand, it was not optimal for various parking scenarios. In this Section, we will optimize the FLC using the above criteria as the cost function.

A. *Modeling of a Vehicle*

For the generation of the training data and training FLC, because it is too difficult to evolve the FLC in the real vehicle, we used a simulator with the vehicle kinematics with skid-steering as in (1), but we consider the constraints for the real vehicle like the minimum and maximum steering angles [5].

$$\begin{aligned}\theta(i+1) &= \theta(i) + \dot{\theta}(i)dt \\ x(i+1) &= x(i) + v(i+1)\cos(\theta(i+1))dt \\ y(i+1) &= y(i) + v(i+1)\sin(\theta(i+1))dt\end{aligned} \tag{1}$$

where

$v(i) = \dfrac{v_r(i) + v_l(i)}{2}$, v_r = right wheel's speed, v_l = left wheel's speed

$\dot{\theta}(i) = \dfrac{v_r(i) - v_l(i)}{w_v}$, w_v = distance between left and right wheels

B. *Extraction of the Fuzzy Rule Set from Training Data*

We can find an improved IF-THEN rule set not by using heuristics as in Section II-C but using the training procedure based on a grade of certainty *CF* in [14]. It constructs a fuzzy-rule-based system that divides the n-dimensional input pattern space $[0,\ 1]^n$ into c disjoint decision areas and *CF* is determined by training patterns in the fuzzy subspace. A fuzzy if-then rule with an empty class consequent is referred to as a dummy rule that has no effect on the classification of a new pattern. The training data contains the consecutive pairs of the vehicle state $\mathbf{x}$ and the corresponding angular velocity $\dot{\theta}$ under various initial positions using manual maneuvering as in Fig. 9. The acquired $\dot{\theta}$ is quantized to 5 classes that are linguistic values for the output membership functions. The IF-THEN rule is optimized by adjusting the parameters of the membership functions as in (2).

$$\begin{aligned}&\text{Rule } R_j : \text{If } x_1 \text{ is } A_{j1} \text{ and } \cdots\ x_n \text{ is } A_{jn} \\ &\qquad \text{then Class } C_j \text{ with } CF = CF_j\end{aligned} \tag{2}$$

where

$A_{j1} \cdots A_{jn}$: Antecedent fuzzy set

C_j : Consequent class

CF_j : Certainty of the fuzzy if-then rule R_j

The grade of certainty for the rule R_j to the input pattern $\mathrm{x_p} = (x_{p1}, x_{p2}, \cdots, x_{pn})$ is:

$$\mu_j(\mathrm{x_p}) = \mu_{j1}(x_{p1}) \cdots \mu_{jn}(x_{pn}) \tag{3}$$

The sum of the grades of certainty for the rule R_j over the class training patterns in each class is:

$$\beta_{\text{class}\,h}(R_j) = \sum_{\mathrm{x_p} \in \text{class}\,h} \mu_j(\mathrm{x}_p) \tag{4}$$

The class h with the maximum $\beta_{\text{class}\,h}(R_j)$ is the consequent C_j, and the grade of certainty CF_j becomes

$$CF_j = (\beta_{\text{class}\,h_j}(R_j) - \bar{\beta}) / \sum_{h=1}^{c} \beta_{\text{class}\,h}(R_j) \tag{5}$$

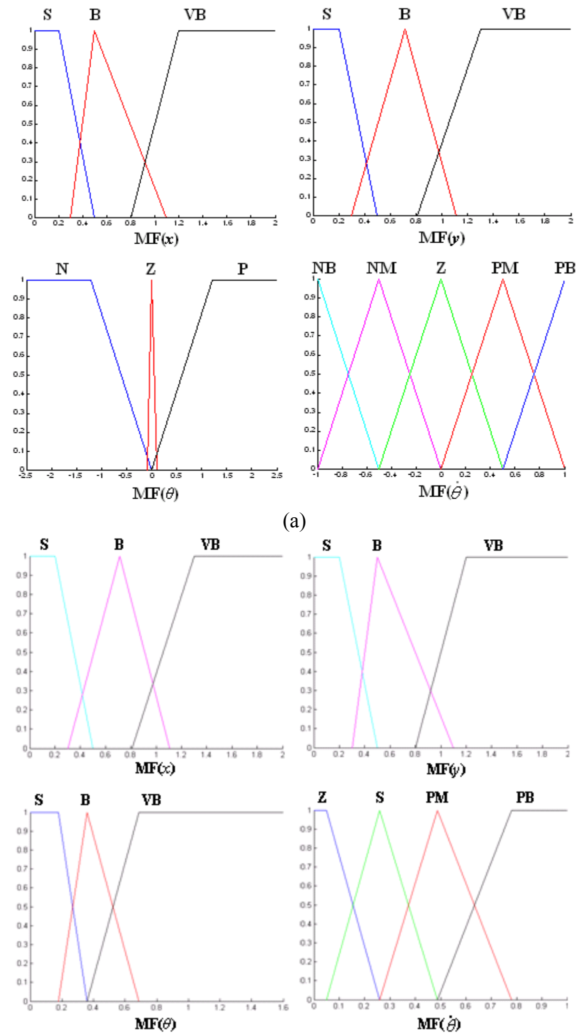
where

c : number of the class

$\bar{\beta} = \sum_{h \neq h_j} \beta_{\text{class}\,h}(R_j) / (c-1)$

Tables IV and V show the *CF* and the consequent classes from the training data for the parallel and garage parking respectively.

While the previous rule set has 27 rules, the new rule set has just 13 and 9 rules respectively. This rule set will be further optimized again by evolutionary strategy (ES) in the next section.



(a)

(b)

Fig. 8. Intuitive MFs for (a) Parallel parking. (b) Garage parking.

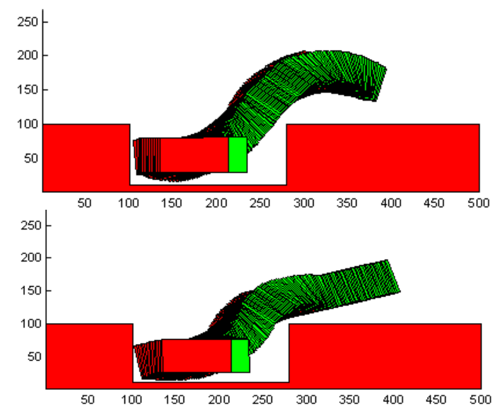


Fig. 9. Training samples for parallel parking.

C. *Fine-tuning of the FLC with Evolution Strategy (ES)*

ES searches the solution space through the use of simulated evolution to choose the most effective parameters for the FLC. In this research, ES optimizes the parameters for both the

membership functions and the rule set until the cost falls within a certain threshold as shown in Fig. 10.
A chromosome of ES contains the left, center, right points for each triangular or trapezoidal membership functions as in Fig.

TABLE IV
GRADE OF CERTAINTY AND CONSEQUENT CLASS FOR PARALLEL PARKING

	$x \backslash y$	S	B	VB
$\theta = \mathrm{N}$	S	1(PM)	0	0
	B	0	0	0.52(PB)
	VB	0	0	0.85(Z)
$\theta = \mathrm{Z}$	S	0.71(Z)	0	0
	B	0	0	0.57(PM)
	VB	0	0	0.73(PB)
$\theta = \mathrm{P}$	S	0.47(NM)	0.87(Z)	0
	B	0.51(Z)	0.37(PM)	0.52(PM)
	VB	0	1(Z)	0.97(PB)

TABLE V
GRADE OF CERTAINTY AND CONSEQUENT CLASS FOR GARAGE PARKING

	$x \backslash y$	S	B	VB
$\theta = \mathrm{N}$	S	0.79(B)	0.31(B)	0
	B	0	0.48(Z)	0
	VB	0	0.61(Z)	1(M)
$\theta = \mathrm{Z}$	S	0.56(B)	0.52(B)	0
	B	0	0	0
	VB	0	0	0
$\theta = \mathrm{P}$	S	0.59(Z)	0.62(S)	0
	B	0	0	0
	VB	0	0	0

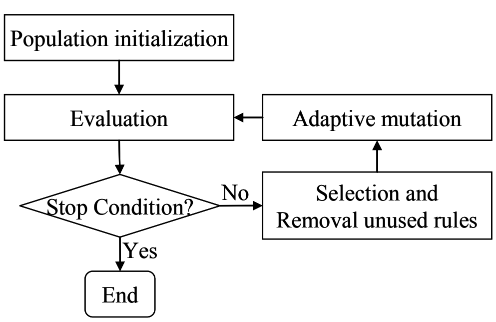


Fig. 10. Optimization process for the membership function.

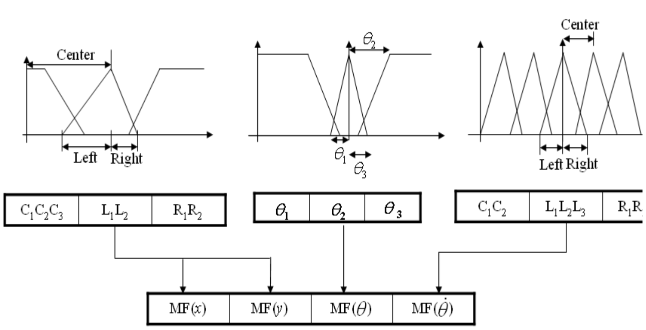


Fig. 11. A chromosome structure of a membership function.

11. Tuning the membership functions requires adjustment of the values of these parameters. Another important issue for the optimization problem is to determine the cost function. In this research, the cost function for ES considers the collision possibility, the time required, and the accuracy of parked position in (6).

$$\text{cost} = w_1 \cdot N_c + w_2 \cdot T + w_3 \cdot e_p + w_4 \cdot e_o \qquad (6)$$

where

w_i : Weight for each subcost

N_c : Occurence of collision (binary)

T : Overall parking time

e_p : Final position error

e_o : Final orientation error

The adaptive mutation used is as follows:

$$\begin{aligned} & \mathrm{x}_i'(j) = \mathrm{x}_i(j) + \sigma_i(j)\mathrm{N}_j(0,1) \\ & \sigma_i'(j) = \sigma_i(j)\ \exp[\tau' \mathrm{N}(0,1) + \tau\, \mathrm{N}_j(0,1)] \\ & \tau = 1\Big/\sqrt{2\sqrt{n}},\ \tau' = 1\Big/\sqrt{2n} \\ & \mathrm{N}(0,1) = \text{Gaussian random number} \\ & \mathrm{N}_j(0,1) = \mathrm{N}(0,1) \text{ using } j \text{ as counter} \end{aligned} \qquad (7)$$

To illustrate the tuning results more clearly, the membership functions with the best performance are shown in Fig. 12. Even though there is no obvious improvement relative to extensive manually tuning, the tuning process with ES is more systematic and results in a significant time saving for the designers. Furthermore, we can remove those rules playing a minor role. The total rule set,

$$S = [s_1 s_2 \cdots s_{13}] = [01 \cdots 0] \qquad (8)$$

where

$s_j = 1$: the the j^{th} candidate rule is included in S.

$s_j = 0$: otherwise case

We can optimize the rule set by a new cost function with the number of the rules added. Finally, 4 and 7 rules for each parallel and garage parking were finally selected like the gray cells in Tables IV and V. We find the membership functions as a function of various sizes of the maneuvering space.

D. *Exploration of the Proper Initial Poses*

Although an optimized fuzzy controller can be found as described earlier, it is important to start from a good ready-to-reverse position, that is, green zone for stable and good parking. After exploring the parking space, the vehicle moves to a good ready-to-reverse position. The system explores certain regions of the ready-to-reverse positions by checking the parking possibility in advance. These regions are defined by quantizing the antecedent variables x, y, θ. If the vehicle is in the valid region so called the green zone, the automatic parking process will ensure right away. Otherwise, the vehicle has to move to a valid region first. Fig. 13 shows this green zone. Bright cells have a good possibility of proper parking.

IV. Experimental Results

The Pioneer 3-AT robot is the autonomous vehicle considered here. The wheels on one side of the robot are mechanically coupled and thus the skid steering is used to maneuver the robot in Fig. 14 (a). It has 16 ultrasonic sensors as in Fig. 14 (b) and a camera with a 120° view angle in the rear that sees in downward direction. Fig. 15 shows that the parking space is represented by the parking markings and possible surrounding obstacles.

Fig. 15 shows the real experiments for parking. The vehicle starts from an initial position of Fig. 15 (a) and then seeks both for a parking space and alignment to it as shown in Fig. 15 (b). When a proper parking space has been found, it will decide on a proper parking scheme and the initial reverse-to-backup position. Finally, the system will use vision and the sonar readings to continuously localize itself to implement the preselected parking control using a properly optimized fuzzy logic controller as shown in Figs. 15 (d)-(f).

And Fig. 16 and 17 show the reconstructed trajectories using the proposed automatic parking system in three different parking areas. One would notice however that in Fig. 15, the perspective parking views make it rather difficult how well the actual control is executed.

In order to help visualization of the parking precision, Figs.

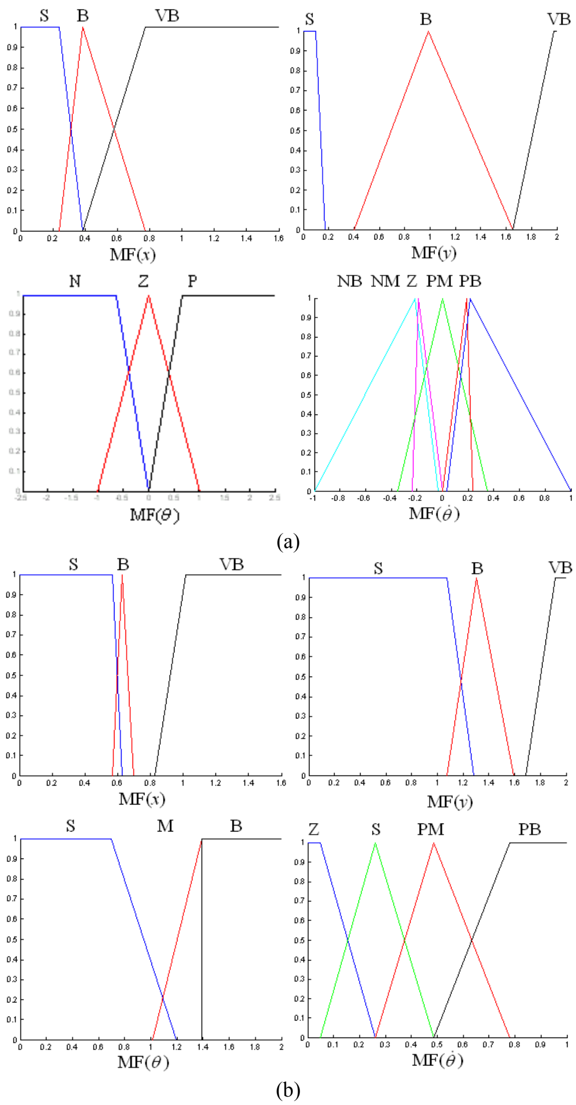
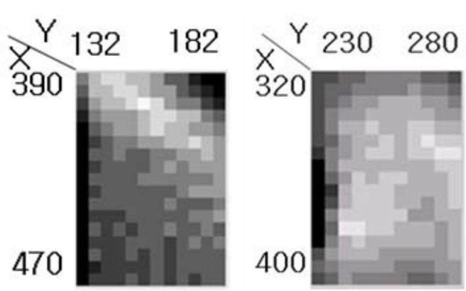
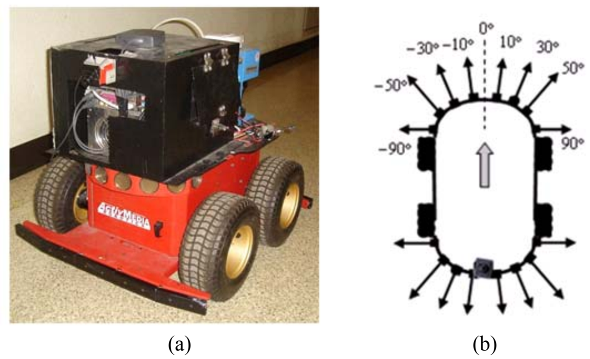


Fig. 12. Optimized MFs for (a) Parallel parking. (b) Garage parking.



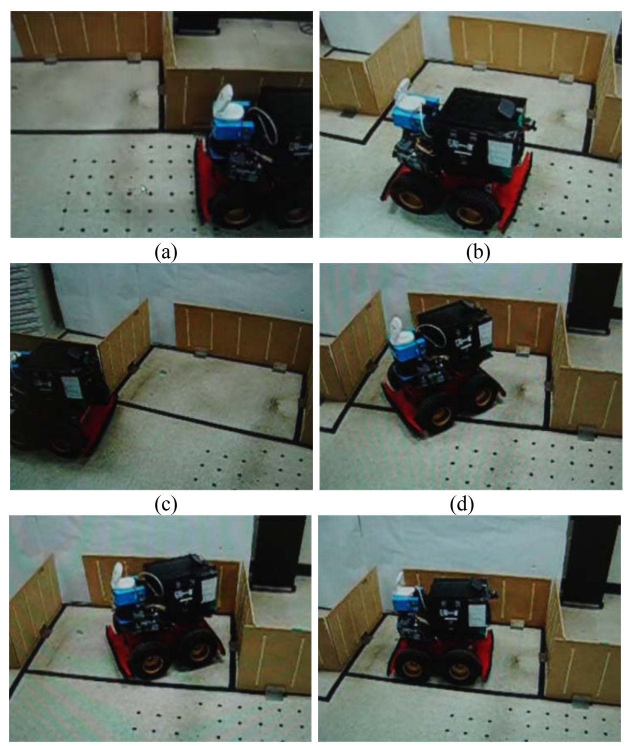
(a) (b)

Fig. 13. Green zone (bright pixels) for good starting positions. (a) Parallel parking. (b) Garage parking.



(a) (b)

Fig. 14. System Hardware. (a) Testbed. (b) Sensor configuration.

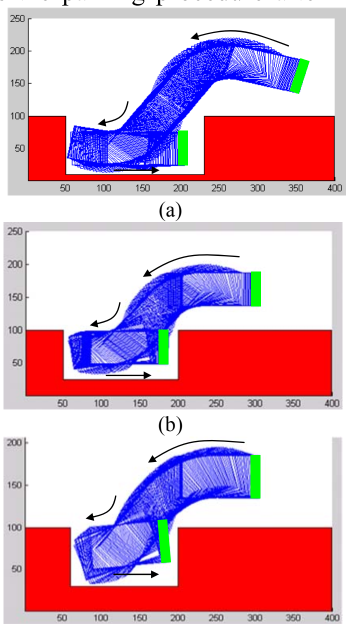


(e) (f)

Fig. 15. Parallel parking procedure. (a) Initial position. (b) Exploration of the space. (c) Ready-to-reverse position. (d) Backup maneuvering. (e) Forward adjustment maneuvering. (f) Final position reached.

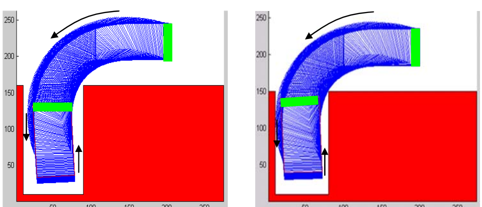
16 and 17 show the reconstructed controlled trajectories seen from the top for three different parking spaces. Although the figures show a stable performance without any collision, the best and most stable result is obtained from a relatively larger park space since the proposed parking scheme does not attempt to find a proper park space but that the whole parking process is carried out at one shot.

Fig. 18 shows the parking procedure after moving to a green zone because the vehicle started from a poor initial pose. For instance, if we start from an initial position in Fig. 18 (a), it would have to go through a time-consuming series of backward and forward maneuver adjustments. However, if we instead decide to adjust the ready-to-reverse position as in Fig. 18 (b), we can eliminate these somewhat tedious backward-forward movements. As shown in Figs. 18 (c) and (d), we are able to parallel park at one shot through this adjustment of the ready-to-reverse position.



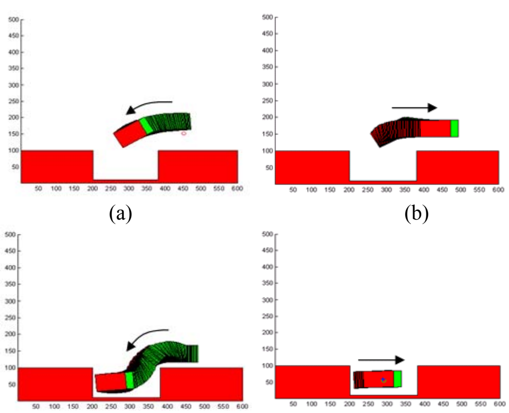
(a) (b) (c)

Fig. 16. Reconstructed trajectory for parallel parking as a function of the size of the maneuvering space. (a) 1.8x1.8 times the dimension of the vehicle. (b) 1.5x1.5 times. (c) 1.4x1.4 times.



(a) (b)

Fig. 17. Reconstructed trajectory for garage parking. (a) 1.5x1.5 times. (b) 1.4x1.4 times.



(a) (b) (c) (d)

Fig. 18. Parking procedure from a poor starting pose for a parking size of 1.8x1.8 times. (a) Initial backup for corrective movement. (b) Move to a green zone. (c) Backup (d) Final adjustment.

V. Conclusion

The proposed system improves the parallel and garage parking performance using a stable localization algorithm and an optimized fuzzy controller. Thus it is possible to park from any position with stability, speed, and precision. For different vehicle platforms, it is just needed to tune the kinematics and weights for each cost of ES. Finally we can improve the current system by recommending a proper steering rate and also by fusing the FLC and some kind of human parking behavior using NN.

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