Robust Automatic Parking without Odometry using an Evolutionary Fuzzy Logic Controller

Young-Woo Ryu, Se-Young Oh, and Sam-Yong 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 the training data, using an evolutionary fuzzy system. Furthermore, it also finds the green zone for the ready-to-reverse position in which parking is possible just by reversing. It has been tested on a 4-wheeled Pioneer mobile robot which emulates the real vehicle.

Keywords: Automatic parking, evolutionary strategy, fuzzy logic controller, neural network.

1. INTRODUCTION

An automatic parking system (APS) can park the vehicle for inexperienced drivers. Though some automobile companies have recently developed parking assistance systems (PAS) or APS, issues on safety and cost still remains for commercialization. APS consists of two parts: the exploration of the parking space and parking into that space. These maneuvers are more heuristic than algorithmic. Consequently, transferring the expert driver's parking skill to an automatic parking system can alleviate the driving burden and enhance safety in the next-generation passenger vehicles. For prior work, a vehicle with vision [1,2] or ultrasonic sensors [3-5] explored the proper parking space and then found the proper starting position. Given the starting position, the automatic parking was performed using two main lines of approaches. The path planning approach plans a feasible reference path in advance, taking into account the environmental model as well as the vehicle dynamics and constraints and then the control commands are generated to follow the reference path [2,6,7]. On the other hand, a skill-based approach mimics an experienced driver's parking skill using the 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 an exact vehicle pose relative to the parking space. Daxwanger [1] bypassed pose estimation by using a neural network that can directly map the video sensor's image of the environment to a corresponding steering angle. However, this approach may not generalize well in untrained environments. Xu *et al.* [2] and Jiang et al. [3] used the ultrasonic sensors for parking. Ultrasonic sensors normally have the distance error to the angle of reflection as well as can not obtain the distance in a parking lot without obstacles. In order to improve the parking performance, Zhao [5] and Adollah [9] optimized the fuzzy membership functions using a genetic algorithm (GA) based on heuristic rules. However, they did not consider parking performance factors such as the collision possibility and the overall parking time. Furthermore, all this research used the odometry data obtained from the wheel encoders, which is not really practical. We think that image and sonar based localization will be a more practical choice for automatic parking. Further, the automatic parking algorithm must consider various sizes and shapes of the parking lot, control stability, parking time, parking accuracy in real experiments.

This paper proposes a robust parking algorithm that can be applied to the general outdoor parking. We first propose an improved vehicle localization method using both vision and ultrasonic sensors in mutually complementary modes. Using these two sensors in tandem, the parking space marker obtained via vision and the nearby objects sensed via the sonar can help to localize the vehicle even when either sensor alone would fail to localize. Second, we do not use any odometry information in this process since it would be

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too expensive and cumbersome to be used in real vehicles. Third, we optimize the rule set and membership functions for the fuzzy logic controller (FLC) by developing a proper performance index function for robust parking. The performance index for our fuzzy controller takes into account the possibility of collision, parking time, and the decency of the final parked pose. Furthermore, an initial exploration to find a proper initial ready-to-reverse position (this is a point in a "green zone") improves on the overall parking stability as well as the elapsed time for parking. Also, a tight space maneuvering case is easily handled by proper tuning of the fuzzy controllers. Finally, through simulation and real experiments, we successfully implemented two parking maneuvers: parallel parking and garage parking.

2. VEHICLE LOCALIZATION AND FUZZY LOGIC CONTROL USING A HEURISTIC RULE SET

2.1. System overview

The automatic parking process consists of several steps as shown in Fig. 1. The system first checks the direction of the parking space 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'. The vehicle then stops at the recommended ready-to-reverse position from which the parking maneuver starts. Finally, control for the automatic parking is executed using an optimized fuzzy logic controller that is designed to achieve an objective function.

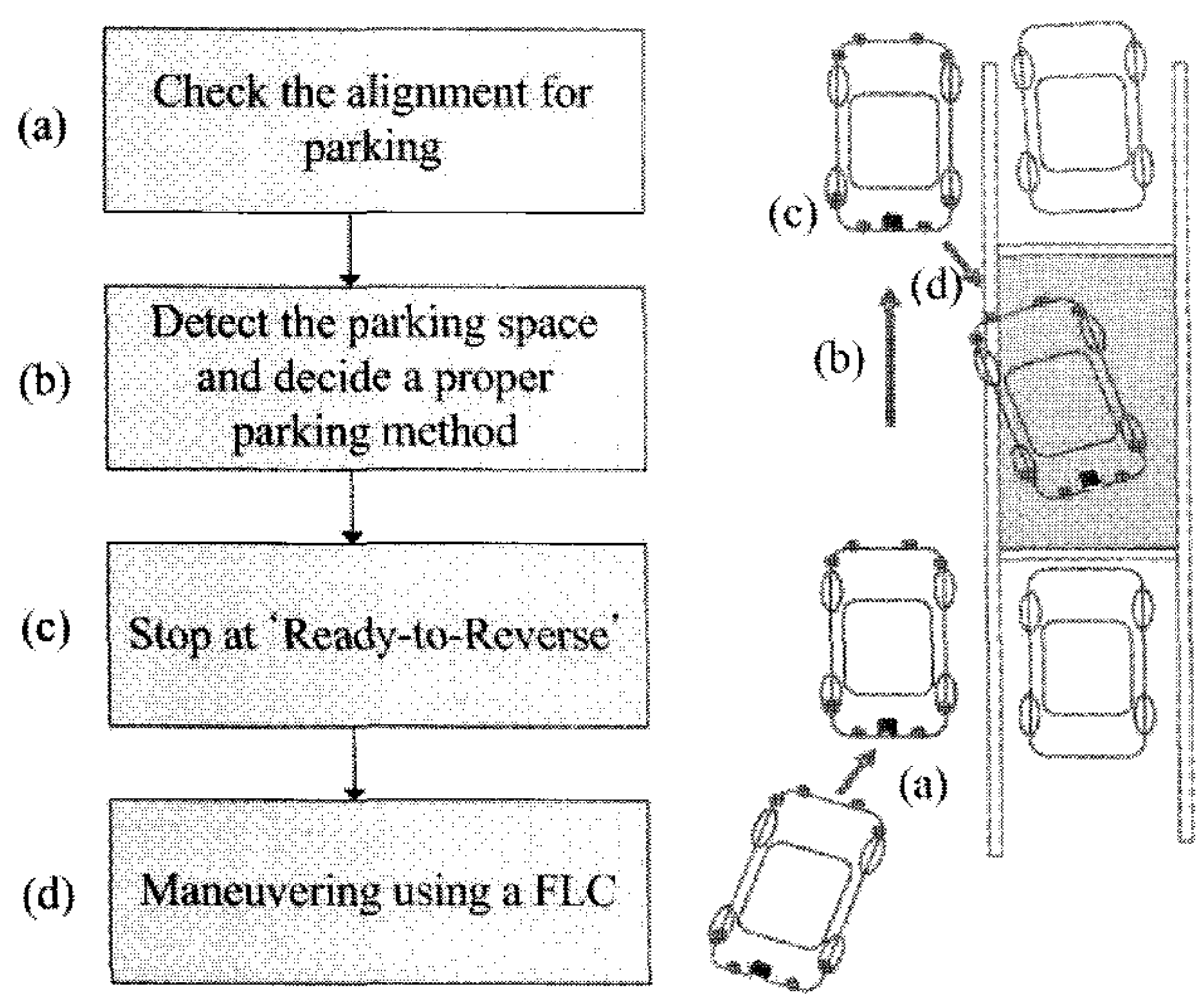
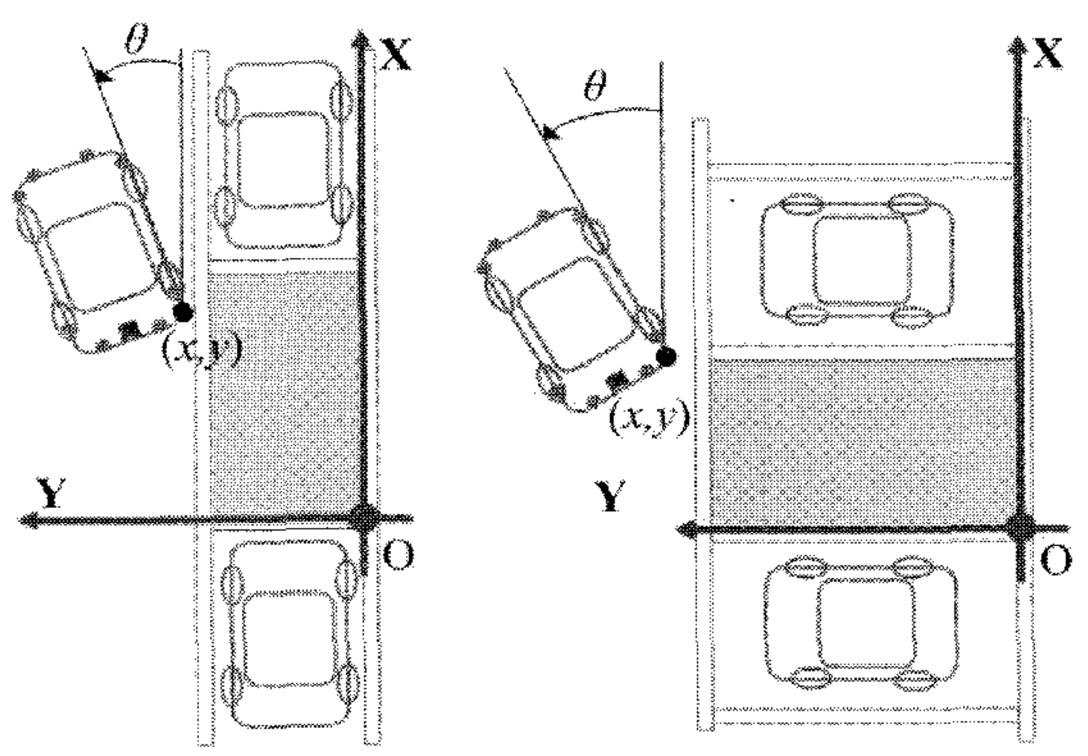


Fig. 1. The entire process of the automatic parking system.

2.2. Vehicle localization

In order to autonomously drive itself, a vehicle needs to know its exact position and orientation, that is, the vehicle state or pose vector, $\mathbf{x} = [x\, y\, \theta]$. But the vehicle localization must be carried out with respect to the detected parking space. To obtain this information and also to compensate for possible parking space detection errors and to prevent collision, we use a camera and 16 ultrasonic sensors. Fig. 2 shows the local coordinate system and the 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 ultrasonic sensor value is larger than a certain threshold, we can handle this noise with the mean value of the both neighboring sensors among ultrasonic sensor array. But in case of a ready-to-reverse direction with a large approach angle between the vehicle and the parking space 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 space markers in an image. After extracting parking space marker candidates using the



(a) Parallel parking. (b) Garage parking.

Fig. 2. Local coordinate systems.

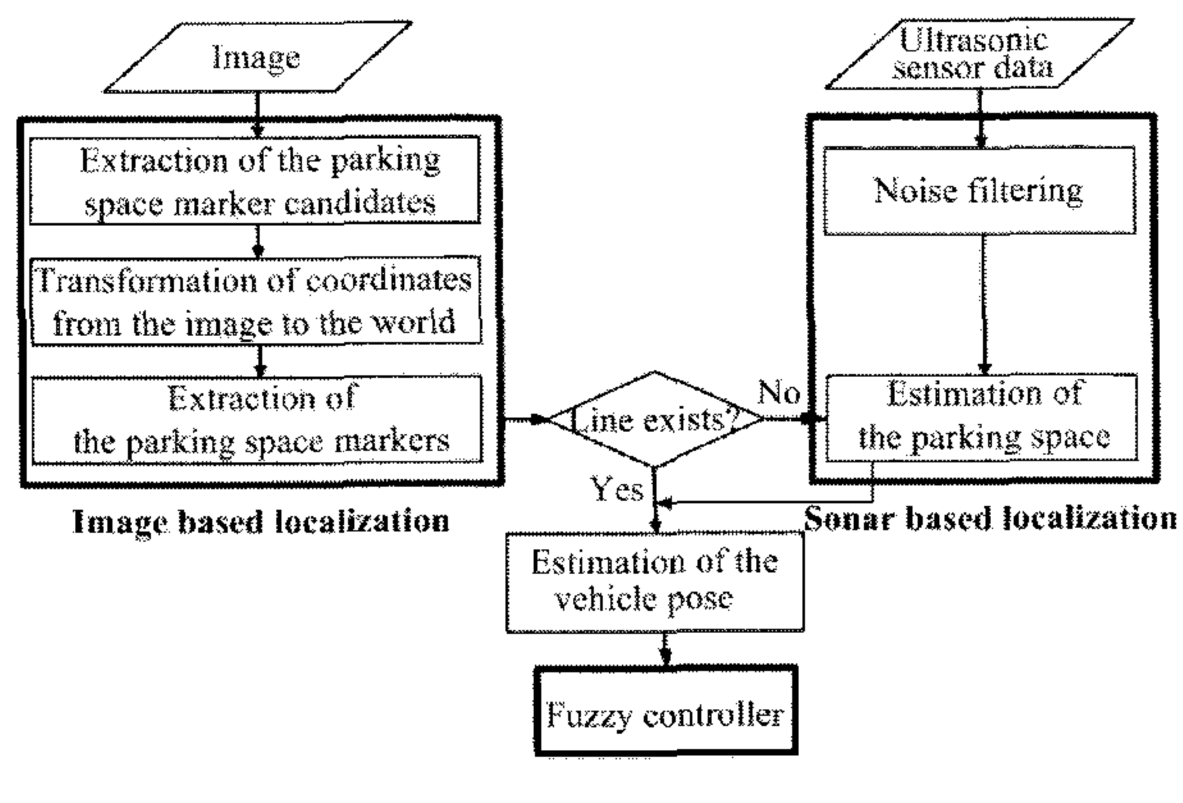
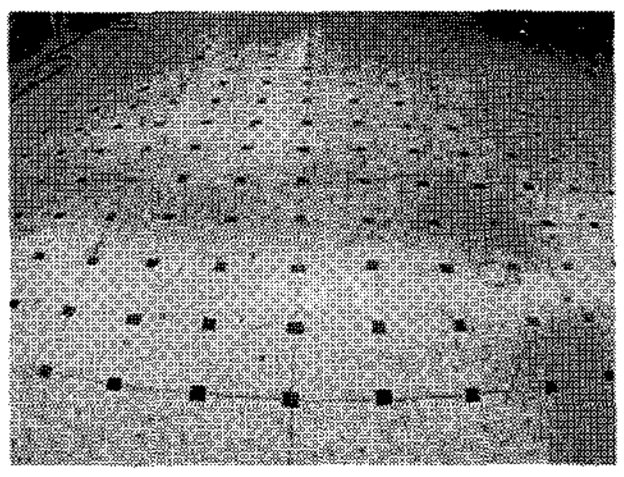
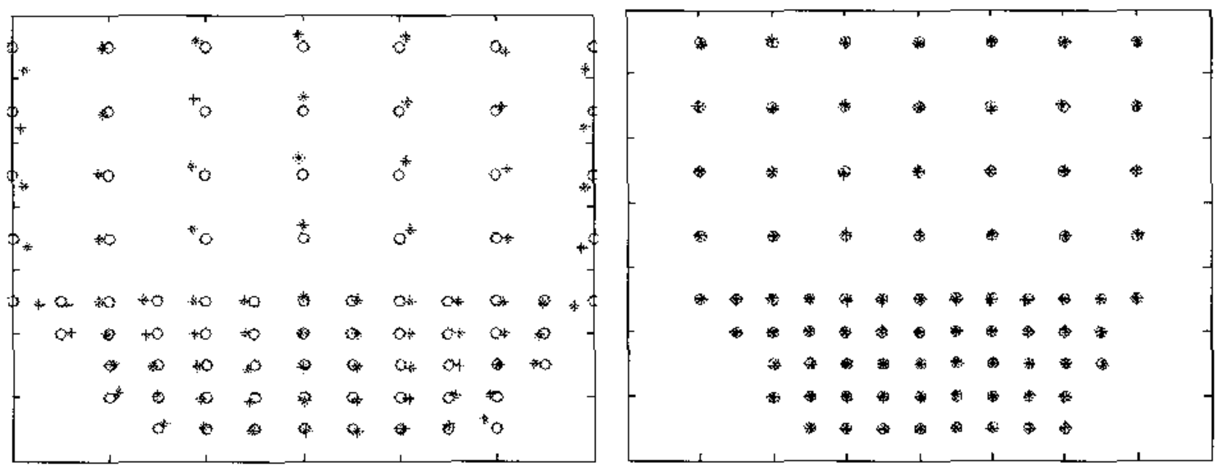


Fig. 3. Localization procedure.



(a)



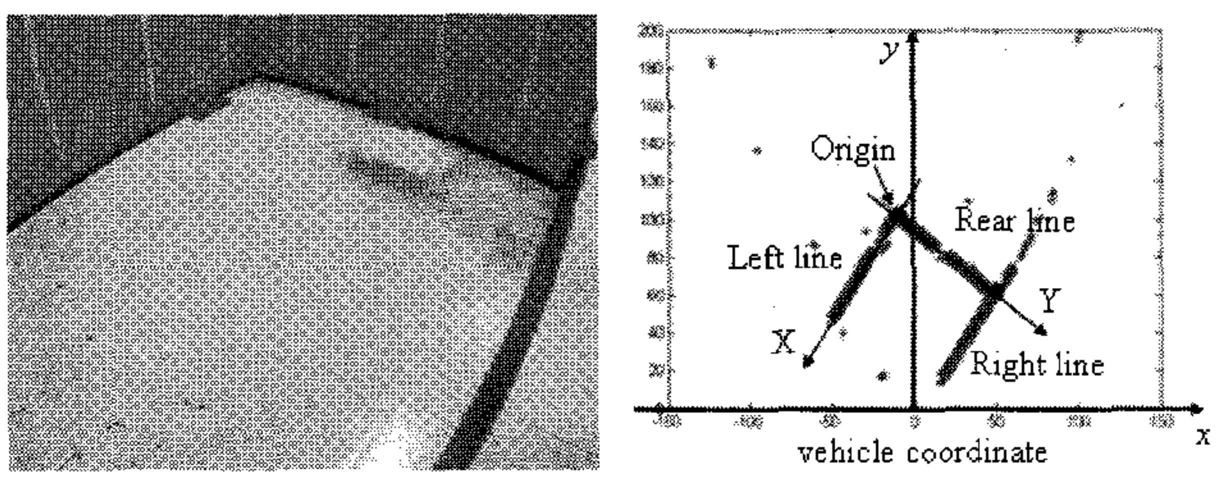
(b)

(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 1. Accuracy comparison of inverse perspective transform and neural network estimation.

	Max. error	Mean error
IPT	9.78 cm	2.54 cm
NN	1.138 cm	0.391 cm



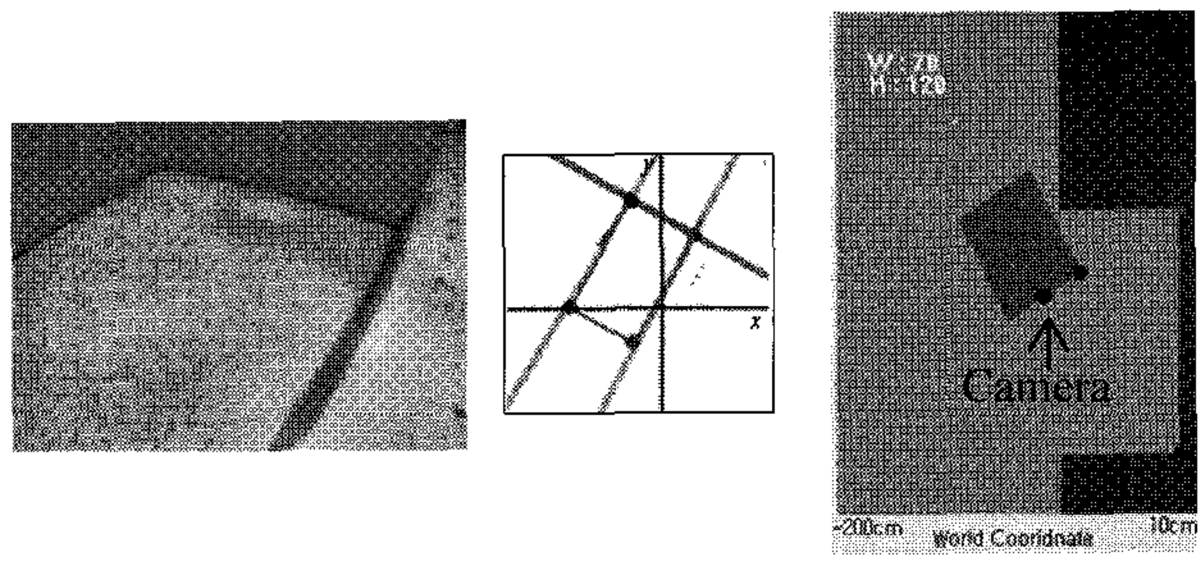
(a) (b)

Fig. 5. Extracted parking space marker and feature points. (a) Raw image (b) Parking space markers and feature points.

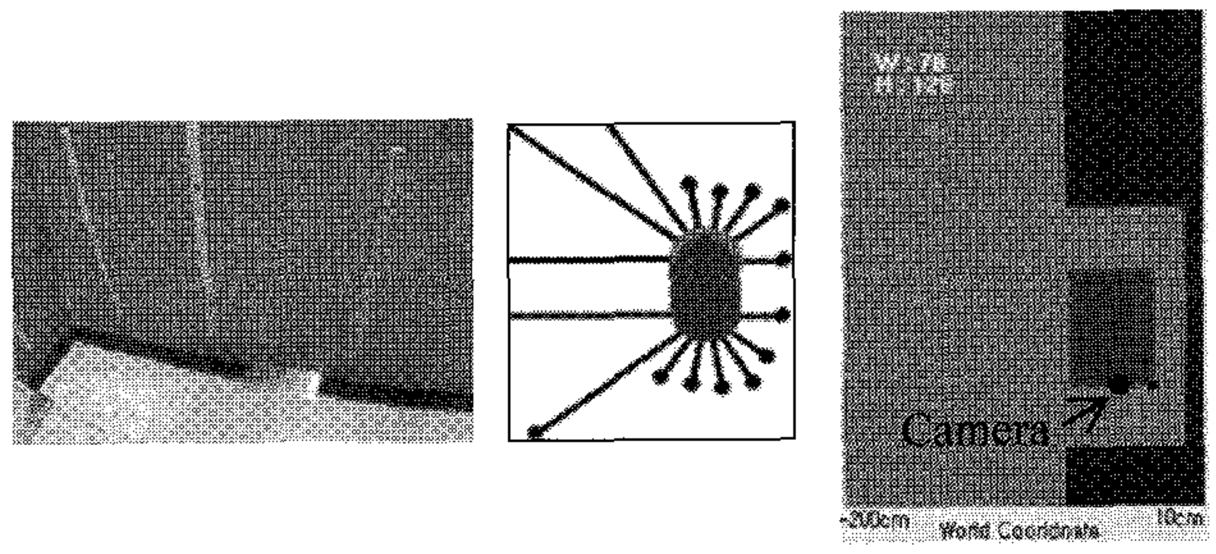
edge and intensity profiles, we transform the extracted parking space markers to the world coordinates. Then we estimate the vehicle state by extracting feature points.

2.2.1 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 camera used 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. Therefore, we used a neural network that learns the mapping between the image coordinates (u,v) and the world coordinates (x,y) [11].



(a) Image based localization (original image, vehicle coordinate, and vehicle state within the environment).



(b) Ultrasonic sensor based localization (original image, the sensor pattern, the vehicle state within the environment).

Fig. 6. Results of the vehicle state estimation.

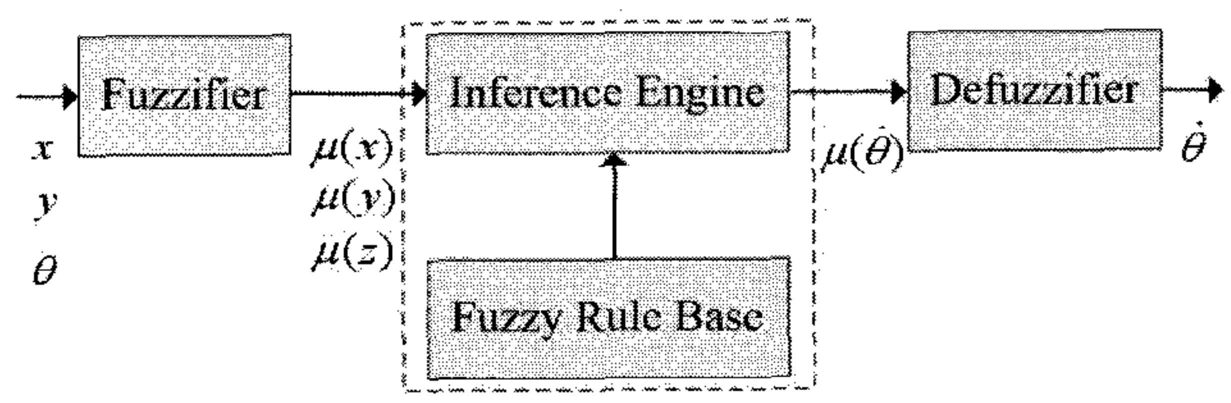


Fig. 7. Structure of the fuzzy controller.

The neural network architecture was a 2-5-5-2 multi-layer perceptron which enables us to acquire more precise world positions as shown in Fig. 4 and Table 1. We used 89 grid points in a 390cm×380cm area for camera and world coordinate calibration.

2.2.2 Parking space marker extraction

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

2.2.3 Automatic parking using a heuristic 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 in Fig. 7. The fuzzy rule base consists of multiple rules

Table 2. Fuzzy rule set for parallel parking.

	x/y	S	B	VB
$\theta=$ N	S	PB	PB	NB
	B	PM	PB	PB
	VB	PM	PB	PM
$\theta=$ Z	S	Z	Z	NM
	B	Z	PB	PB
	VB	Z	PM	PB
$\theta=$ P	S	NB	Z	Z
	B	NM	Z	PM
	VB	NM	Z	PM

Table 3. Fuzzy rule set for garage parking.

	x/y	S	B	VB
$\theta=$ N	S	B	B	M
	B	B	B	M
	VB	M	M	M
$\theta=$ Z	S	B	B	M
	B	B	M	S
	VB	M	S	S
$\theta=$ P	S	M	M	S
	B	M	S	Z
	VB	S	Z	Z

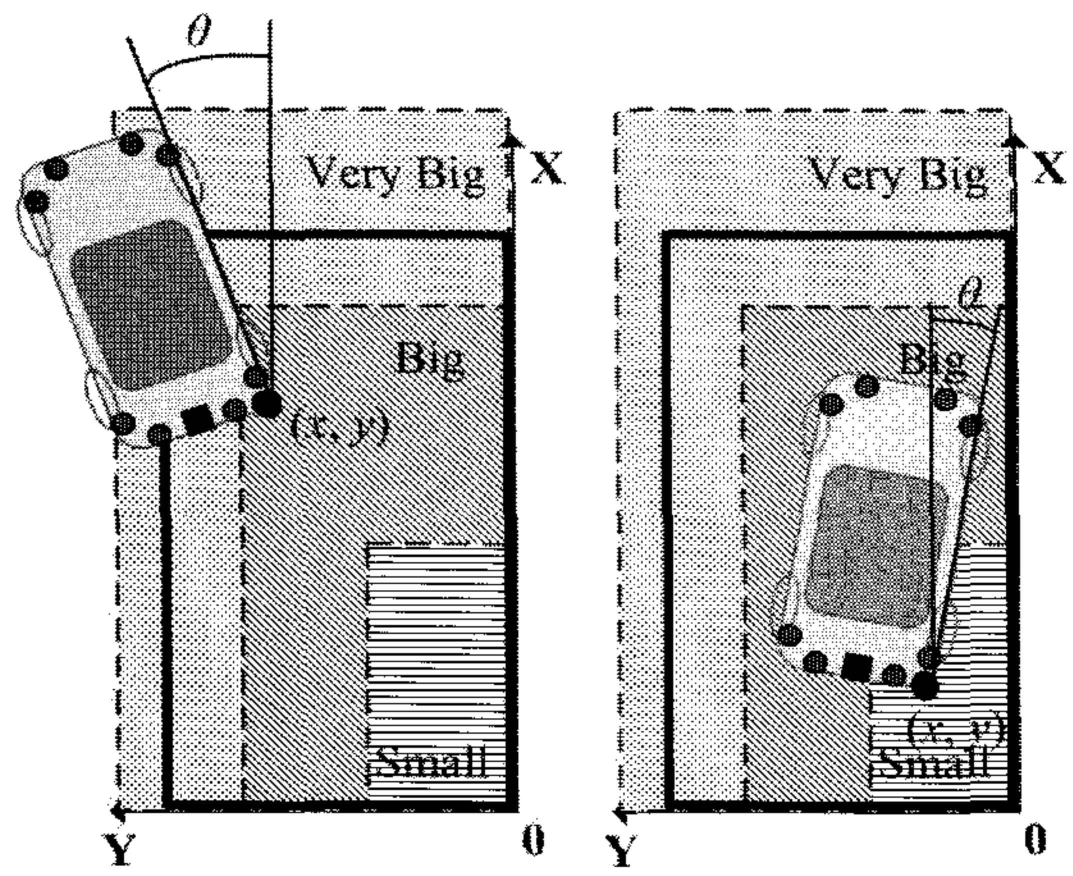


Fig. 8. Elicitation of some fuzzy rules for parallel parking. (a) Rule $[x\ y\ \theta\ \dot{\theta}]$=[B B P Z] (b) Rule $[x\ y\ \theta\ \dot{\theta}]$=[S S N PB].

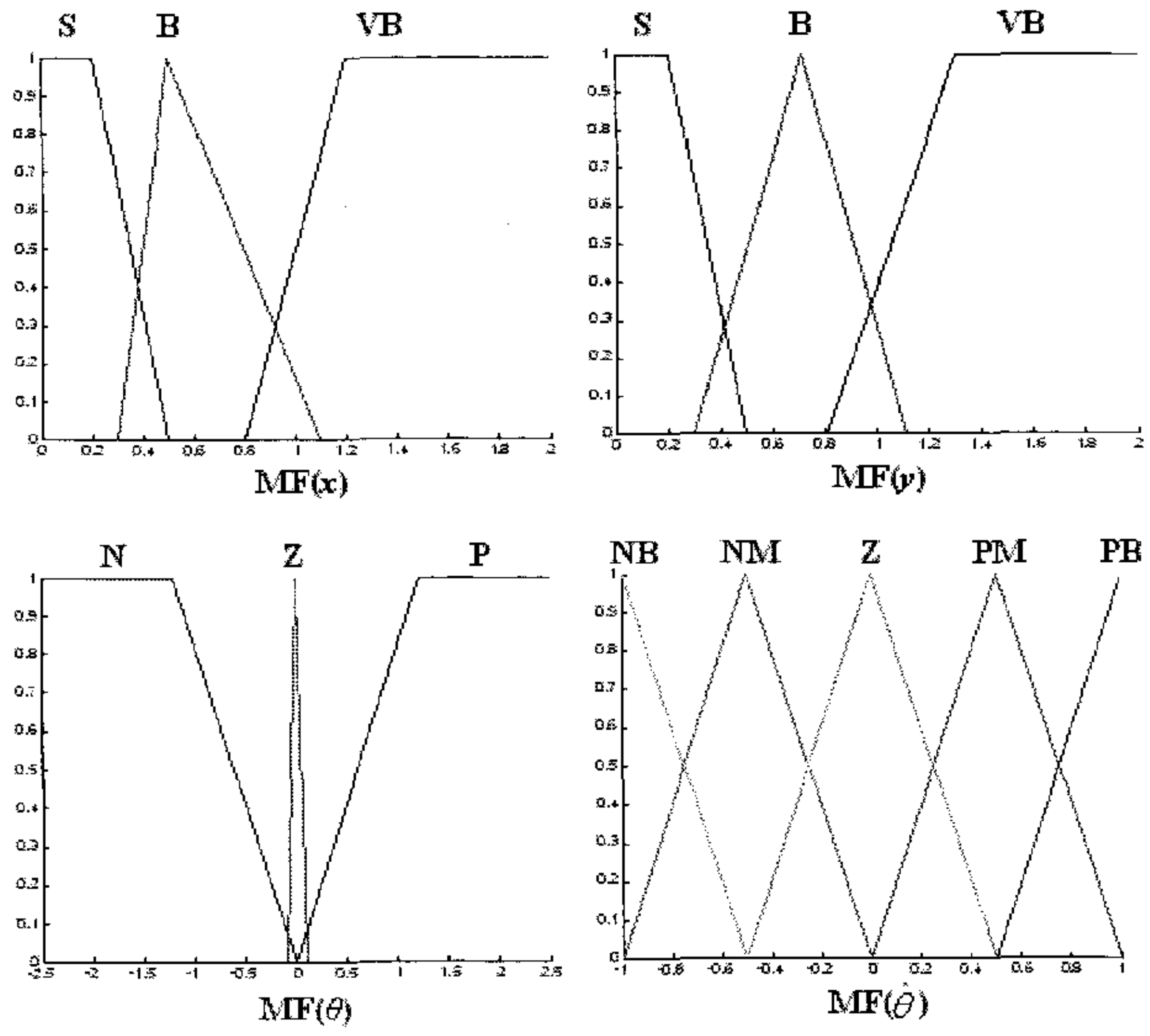
with multiple antecedents and the Mamdani's fuzzy inference model is used to determine the output value, and the defuzzification is done by using center of gravity [13]. The fuzzy rule set for parallel and garage parking are shown in Tables 2 and 3. Fig. 9 shows the fuzzy membership functions used.

The fuzzy rule set used for parallel and garage parking are shown in Tables 2 and 3. The abbreviations represent the linguistic values of each variable as follows:

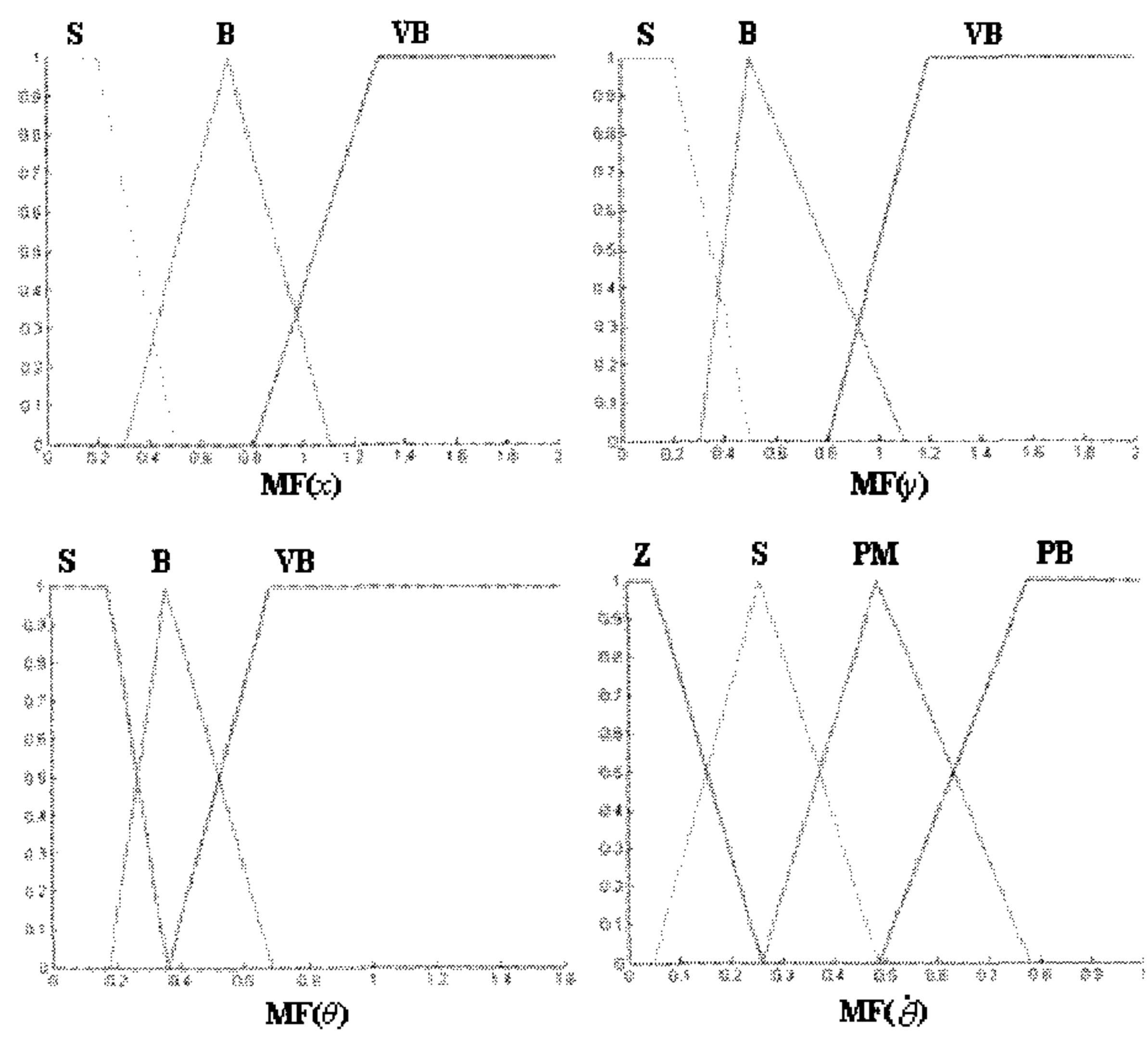
{NB, NM, N, Z, S, M, B, P, PM, PB}={Negative big, Negative medium, Negative, Zero, Small, Medium, Big, Positive, Positive medium, Positive big}.

Based on this fuzzy partitioning, the qualitative description looks like:

- In case of $[x\ y\ \theta\ \dot{\theta}]$=[B B P Z] for parallel parking as Fig. 8(a), if the vehicle is near the outer boundary of the parking space with a positive orientation, it should maintain the current orientation for driving toward the parking space.
- In case of $[x\ y\ \theta\ \dot{\theta}]$=[S S N PB] for parallel parking as Fig. 8(b), if the vehicle is near the origin with a negative orientation, the vehicle should turn in a large angle counterclockwise to get aligned with the parking space.



(a) Parallel parking.



(b) Garage parking.

Fig. 9. MFs.

3. FUZZY LOGIC CONTROLLER USING AUTOMAIC RULE GENERATION THROUGH EVOLUTIONARY STRATEGY

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

- Possible collision
- Parking time
- Accuracy of the parked position
- Compactness of the FLC
- Size of the parking space

Although the FLC introduced in Section 2 was designed by hand, it was not optimal under various parking scenarios. In this section, we will optimize the FLC using the above criteria as the cost function.

3.1. Modeling of a vehicle

For the generation of the training data as well as training FLC, 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 $v(i) = \frac{v_r(i) + v_l(i)}{2}$, v_r =velocity of the right side wheel, v_l =velocity of the left side wheel $\dot{\theta}(i) = \frac{v_r(i) - v_l(i)}{w_v}$, w_v =distance between the left side and right side wheels.

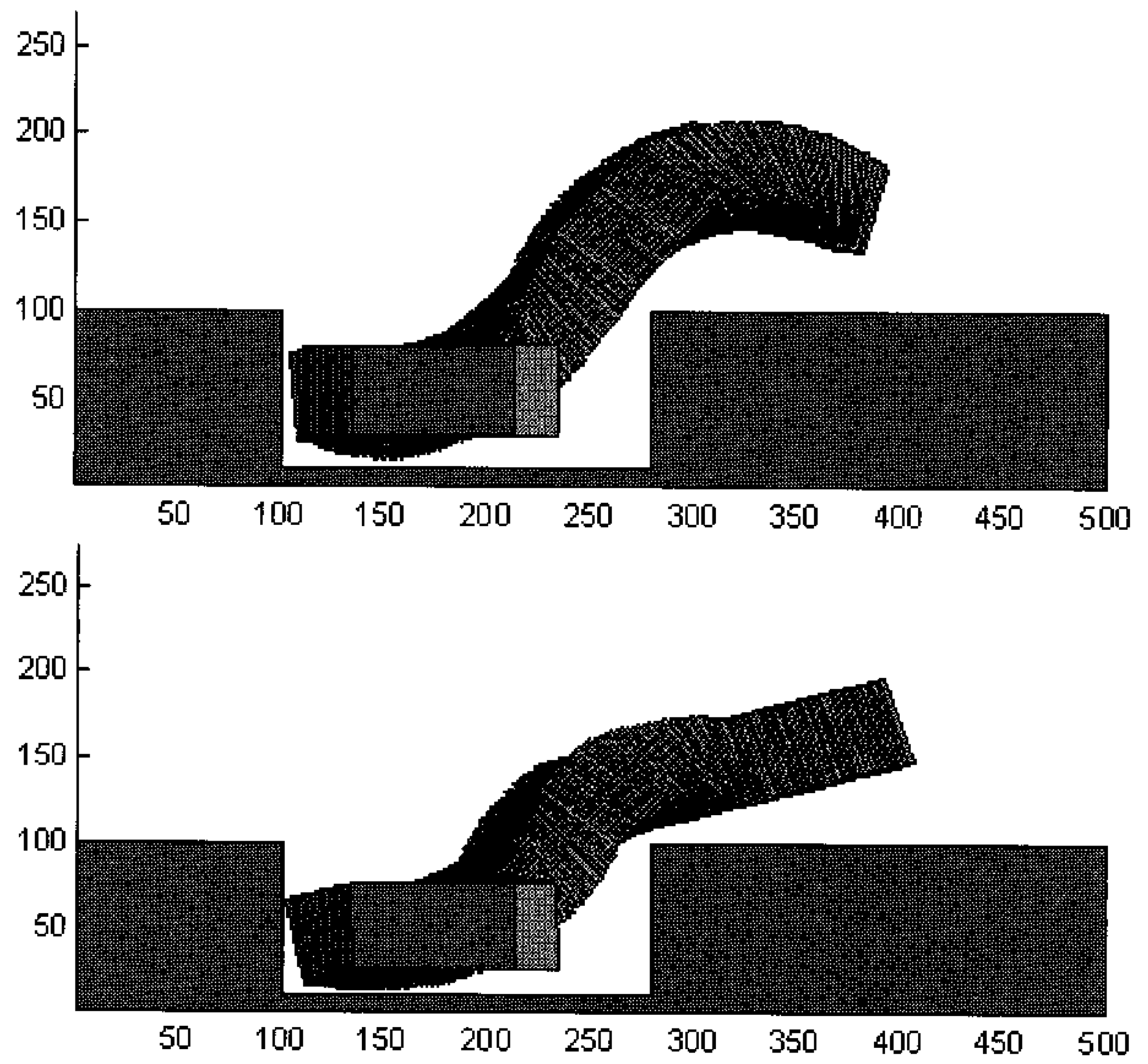


Fig. 10. Training samples for parallel parking (the green portion indicates the vehicle front).

3.2. Extraction of the fuzzy rule set from training data

We can greatly improve on the parking performance of the heuristic rules set given in Section 2.2.3 by evolving the fuzzy rule set embedding the grade of certainty concept (*CF:* Certainty Factor) as in [14]. *CF* represents weights of fuzzy if-then rules. Because some fuzzy if-then rules increase the complexity for the optimization, we can simplify and find the best set of fuzzy if-then rules from training data using CF. 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 calculated by the training patterns defined in vehicle state space. 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. 10.

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).

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

where

$A_{j1} \dots A_{jn}$: 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

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

Table 4. Grade of certainty and consequent class for parallel parking.

	x/y	S	B	VB
$\theta = N$	S	1(PM)	0	0
	B	0	0	0.52(PB)
	VB	0	0	0.85(Z)
$\theta = Z$	S	0.71(Z)	0	0
	B	0	0	0.57(PM)
	VB	0	0	0.73(PB)
$\theta = P$	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 5. Grade of certainty and consequent class for garage parking.

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

Tables 4 and 5 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 by evolutionary strategy (ES) in the next section.

3.3. Fine-tuning of the FLC with evolutionary 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. 11.

A chromosome of ES contains the left, center, and right points for each of the triangular or trapezoidal membership functions as in Fig. 12.

Tuning the membership functions requires adjustment of the values of these parameters. Another

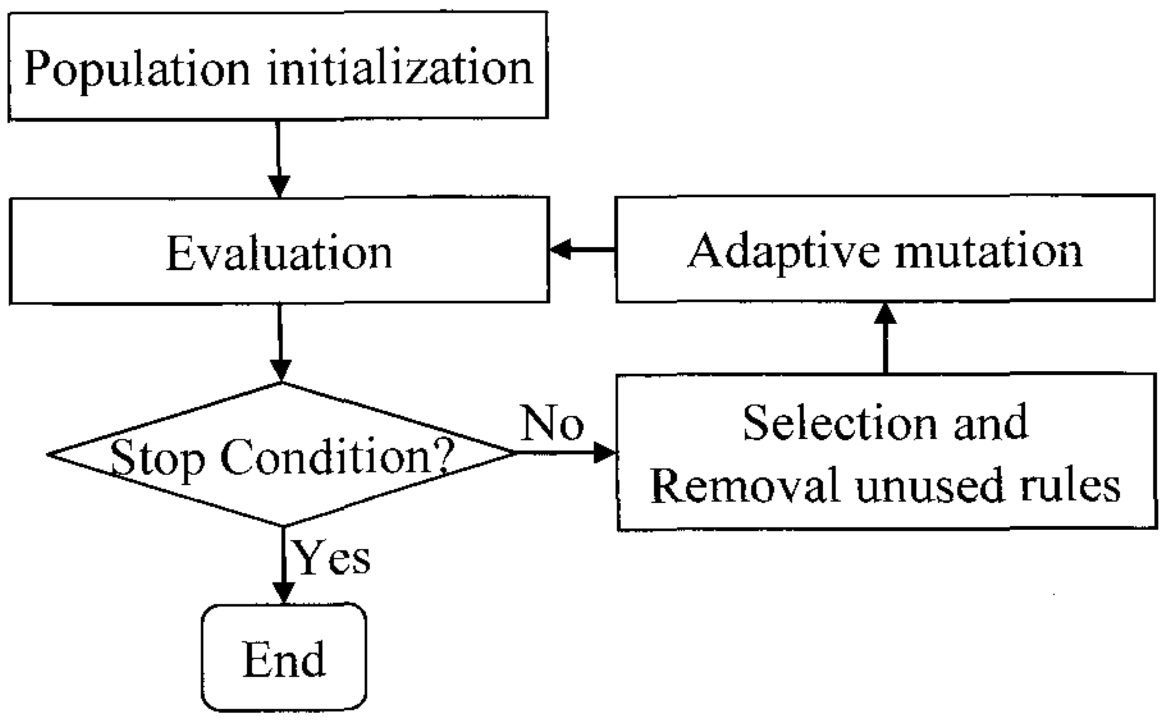


Fig. 11. Optimization process for the membership function.

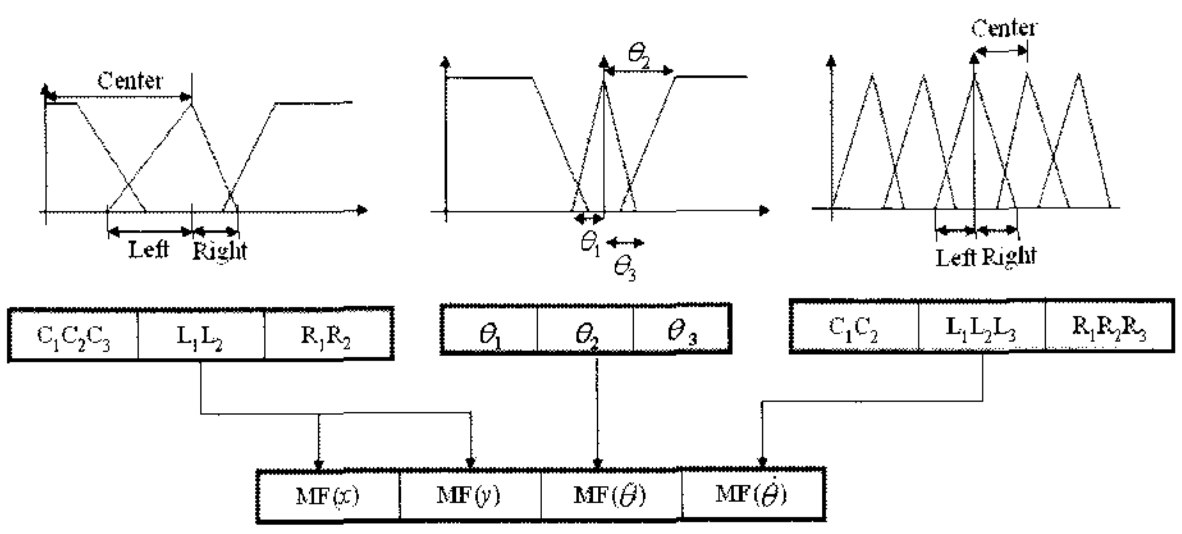


Fig. 12. A chromosome structure of a membership function.

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 elapsed parking time, and the accuracy of the parked position as follows:

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

where

w_i : Weight for eachsubcost

N_c : Occurenceof collision (binary)

T : Overall parkinmg time

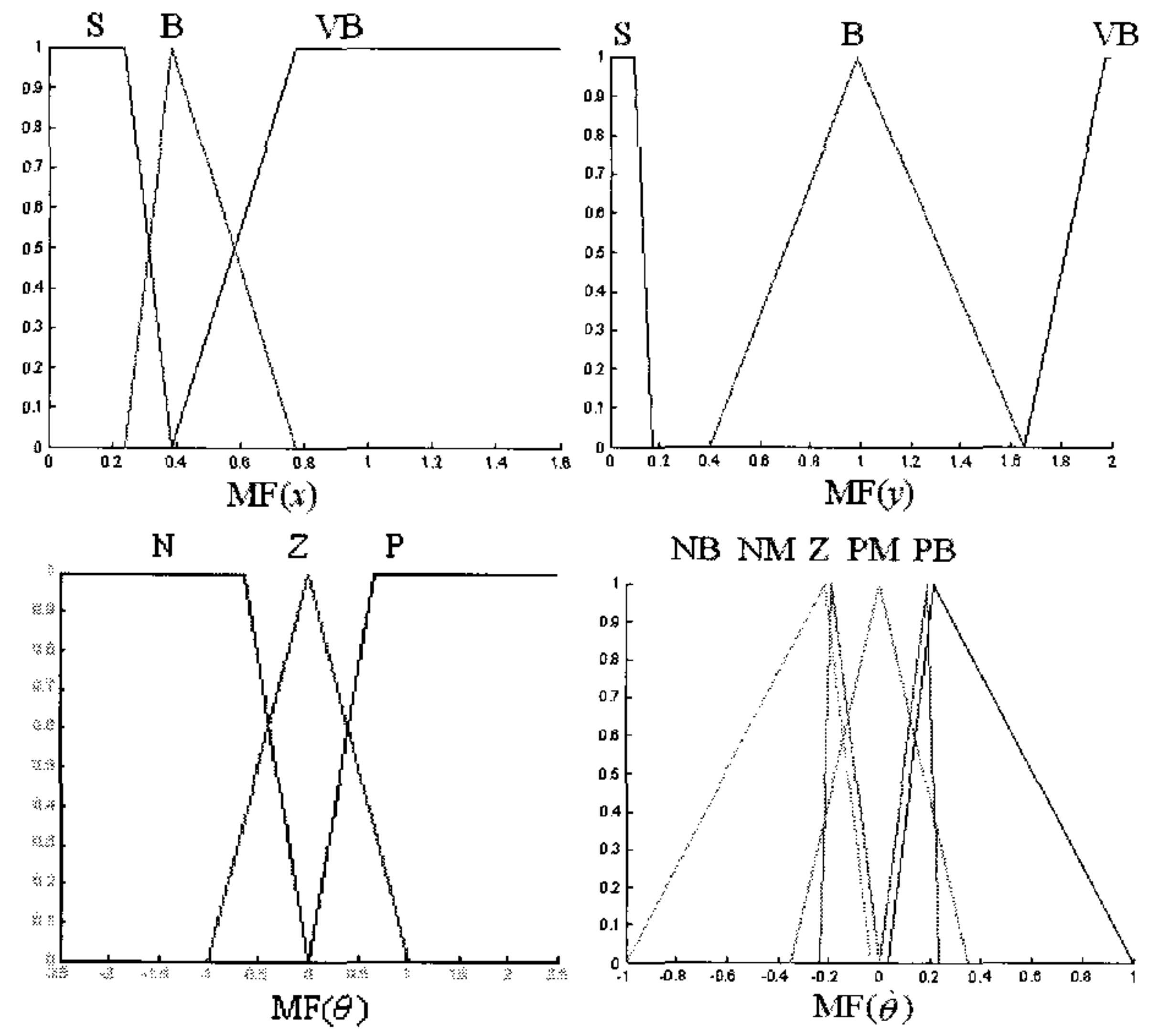
e_p : Final position error

e_o : Final orientation error.

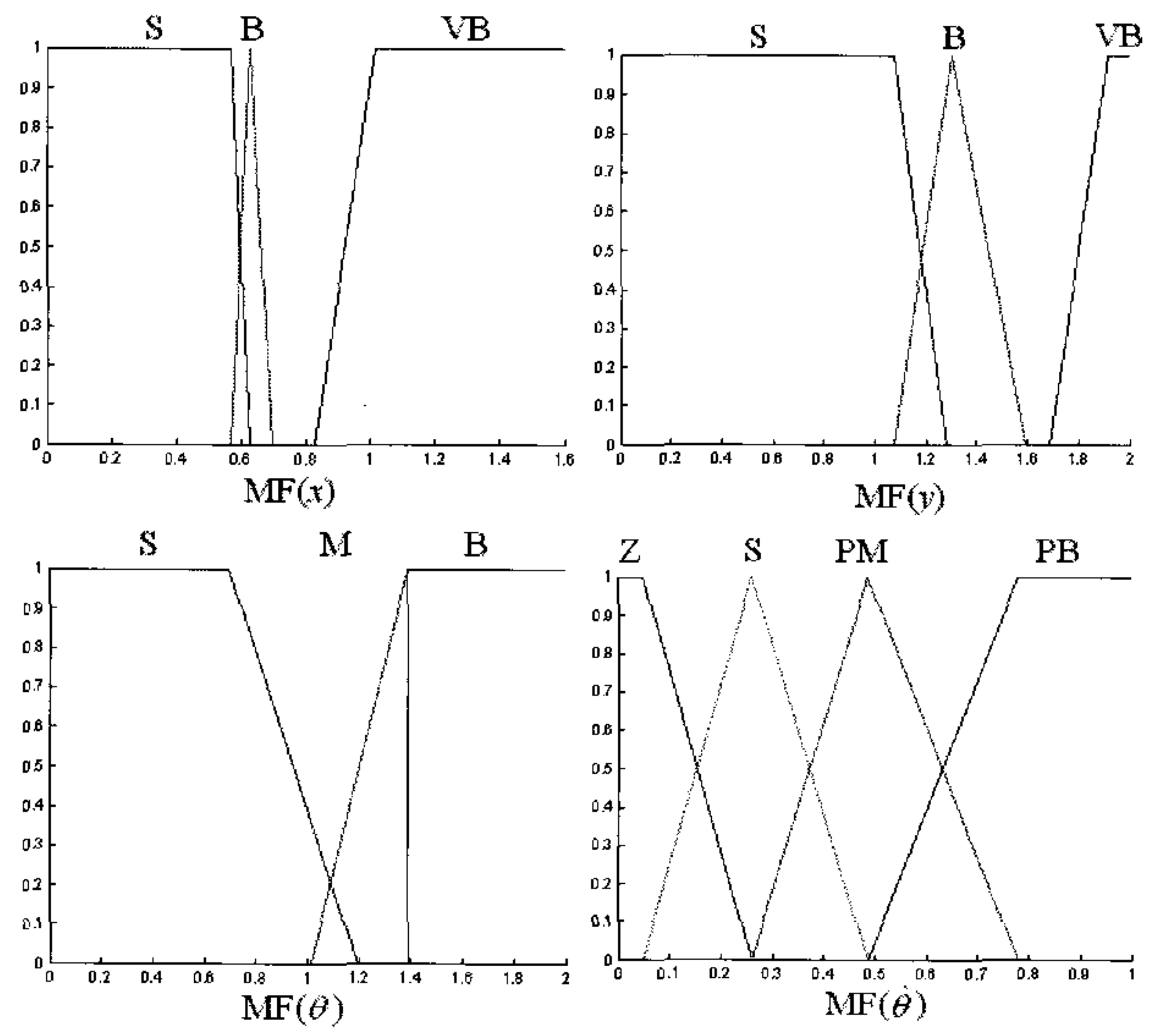
The adaptive mutation used is as follows:

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

To illustrate the tuning results, the membership functions with the best performance are shown in Fig. 13. Even though there is no obvious improvement relative to extensive heuristic tuning, the tuning process with ES is more systematic and results in a significant time saving for the designer.



(a) Parallel parking.



(b) Garage parking.

Fig. 13. Optimized MFs.

Furthermore, we can remove those rules playing a minor role. The total rule set,

$$S = [s_1\ s_2\ \cdots\ s_{13}] = [0\ 1\ \cdots\ 0], \tag{8}$$

where

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

$S_j = 0$: otherwise case.

We can optimize the rule set using 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 4 and 5. We find the membership functions as a function of different sizes of the maneuvering space.

3.4. Exploration of the proper initial poses

Although an optimized fuzzy controller can be found as described earlier, it is also important to start

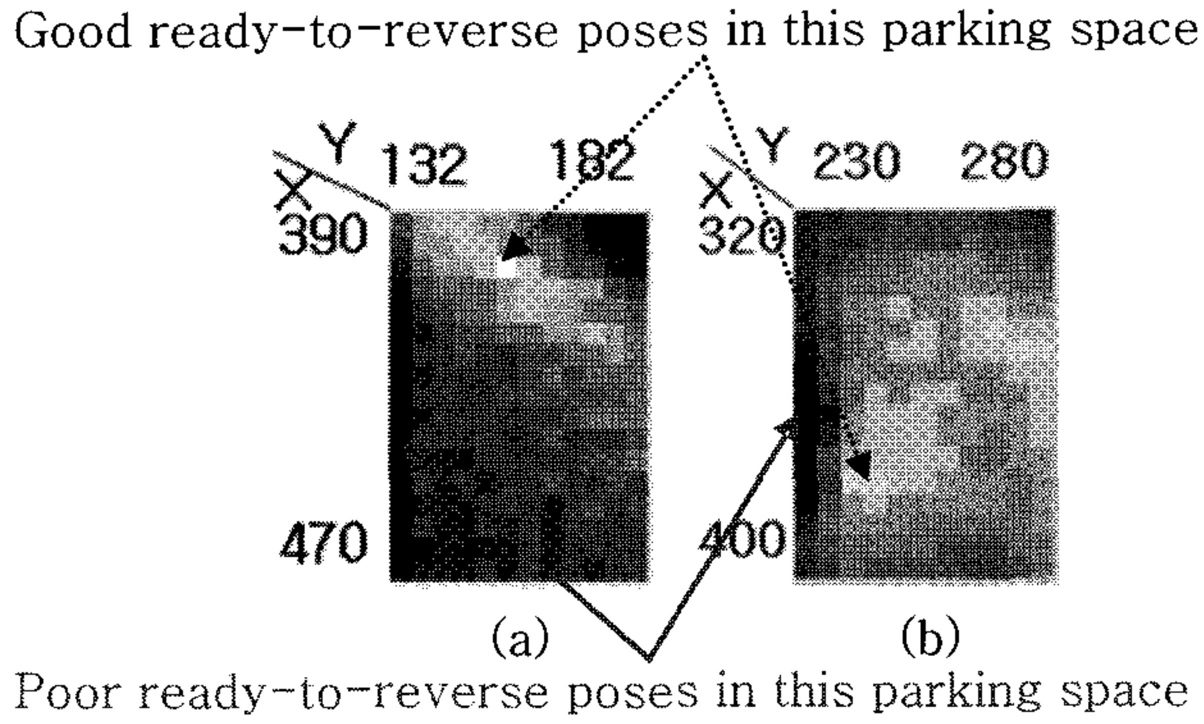


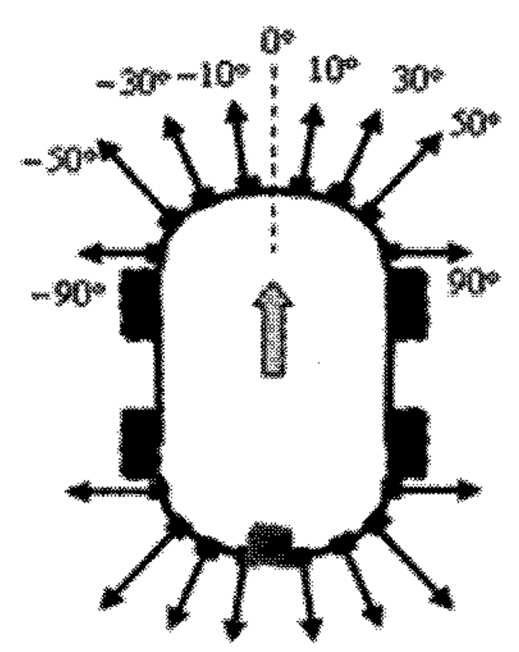
Fig. 14. Green zone (bright pixels for representing the vehicle center position) for good starting poses. (a) Parallel parking (b) Garage parking.

from a good ready-to-reverse position, that is, the 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 start right away. Otherwise, the vehicle has to move to the green zone first. Fig. 14 shows this green zone. Bright cells have a good possibility of proper parking. For moving to the green zone, because it is not required to the exact position and pose in green zone, we applied simple PD controller.

4. 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 skid steering is used to maneuver the robot in Fig. 15(a). It has 16 ultrasonic sensors as in Fig. 15(b) and a camera with a 120° view angle in the rear that looks in downward direction.

(a) Testbed.



(b) Sensor configuration.

Fig. 15. System hardware.

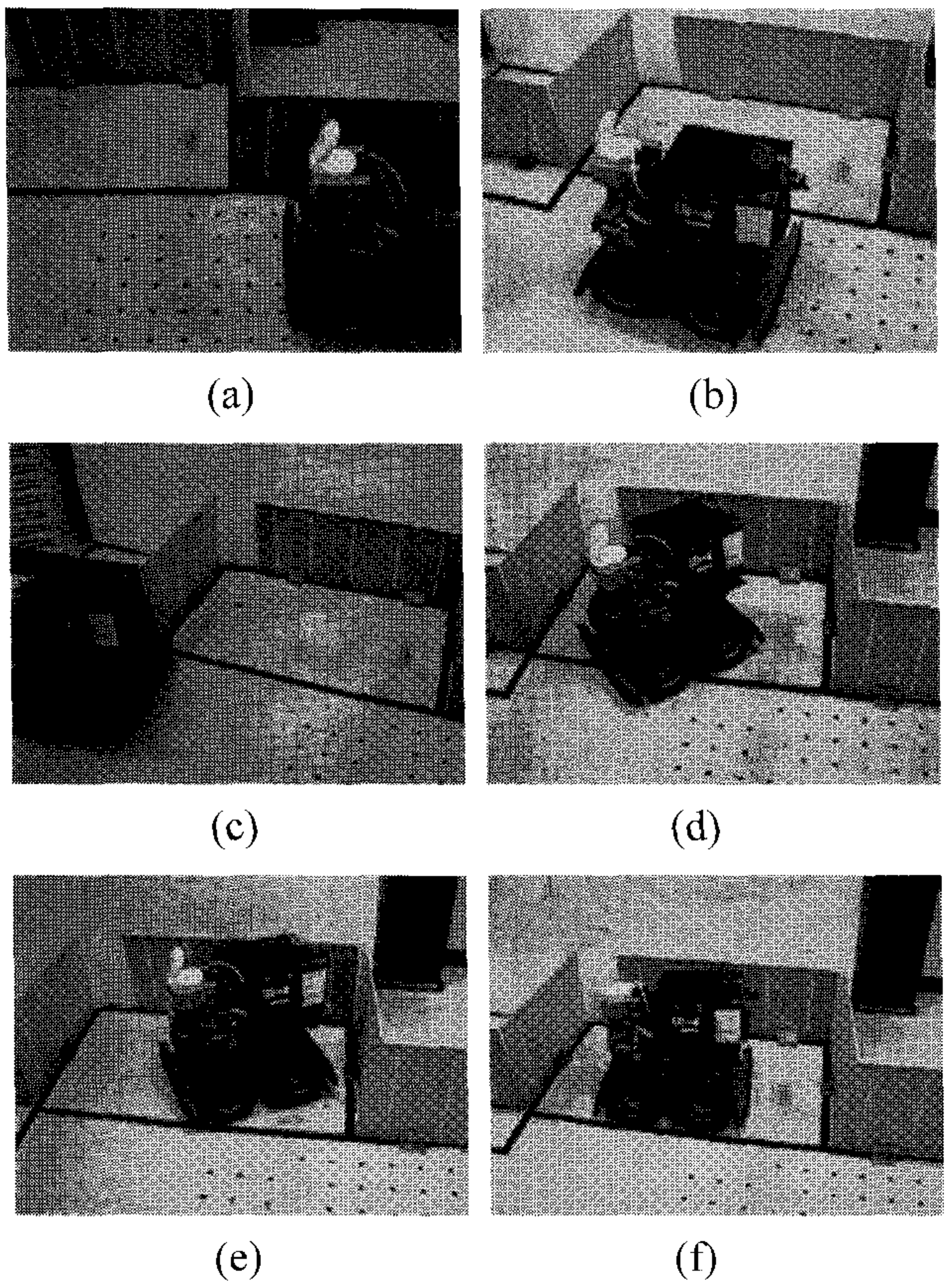
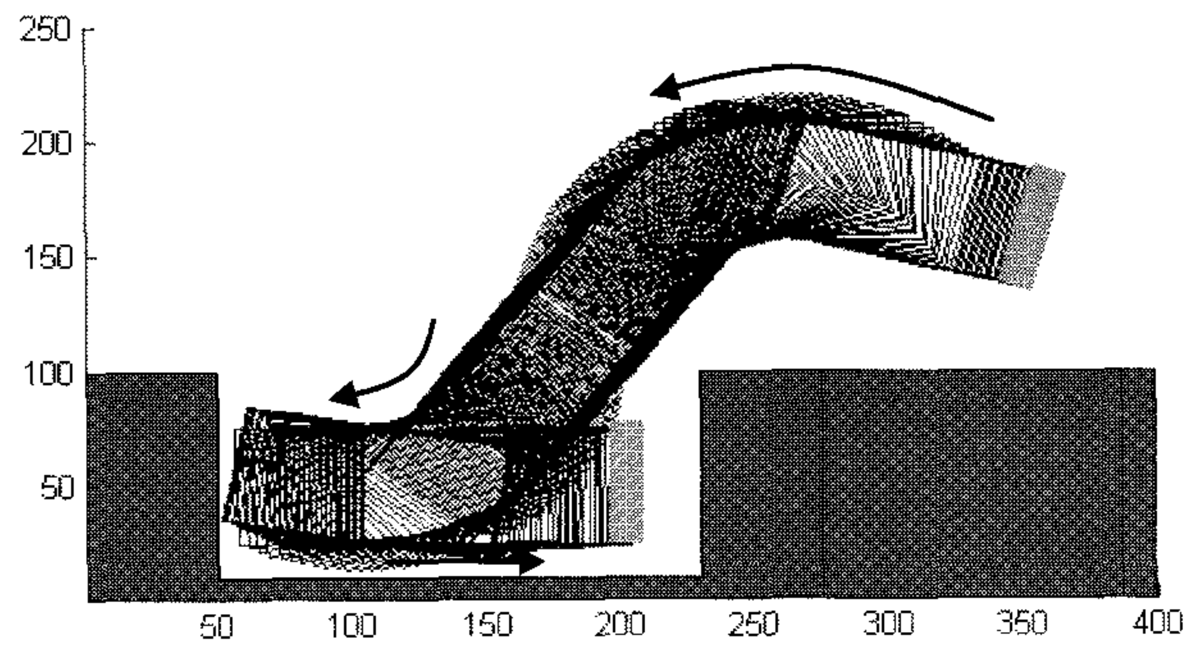


Fig. 16. Parallel parking procedure. (a) Initial position (b) Exploration of the space (c) Ready-to-reverse position (d) Backup maneuvering (e) Forward adjustment maneuvering (f) Final position reached.

The parking space is represented by the parking markings and possible surrounding obstacles as in Fig. 16, showing the real experiments. The vehicle starts from an initial position of Fig. 16(a) and then seeks both for a parking space and alignment to it as shown in Fig. 16(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. 16(d)-(f).

Figs. 17 and 18 show the reconstructed trajectories using the proposed automatic parking system in three different parking areas. The vehicle trajectories are reconstructed by applying the vehicle localization procedure in Section 2.2. One would notice however that in Fig. 16, the perspective parking views make it rather difficult to judge how well the actual control is executed. In order to help visualization of the parking precision, Figs. 17 and 18 show the reconstructed controlled trajectories seen from the top.

Although these figures exhibit a stable performance without any collision, the best and most stable result is obtained from a relatively larger parking space

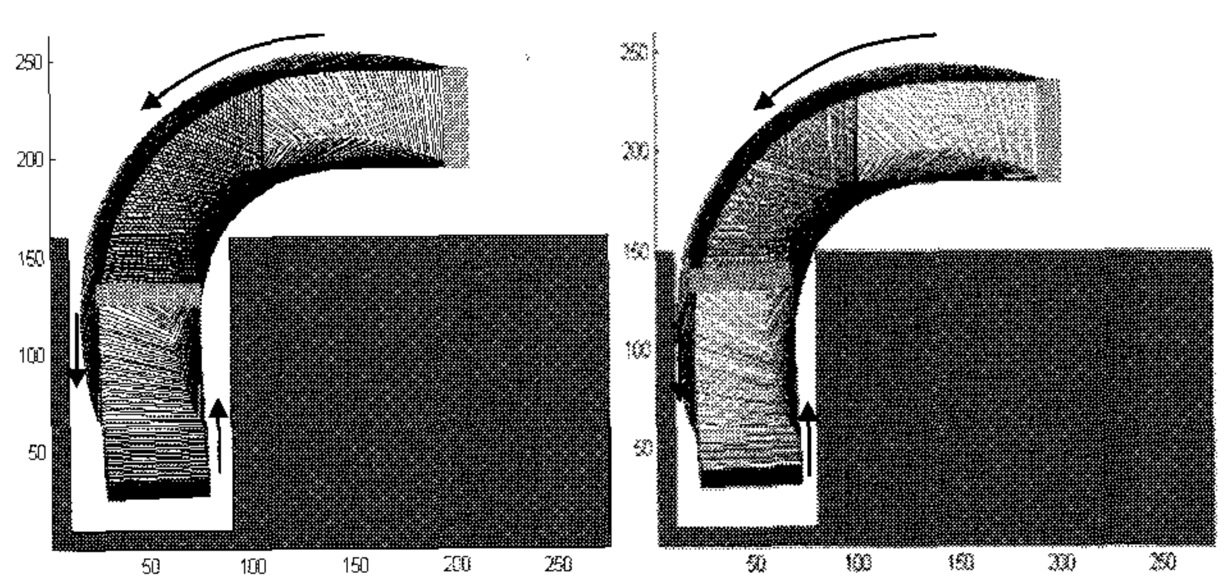


(a) 1.8×1.8 times the dimension of the vehicle.

(b) 1.5×1.5 times.

(c) 1.4×1.4 times.

Fig. 17. Reconstructed trajectory for parallel parking as a function of the size of the maneuvering space.



(a) 1.5×1.5 times. (b) 1.4×1.4 times.

Fig. 18. Reconstructed trajectory for garage parking.

since the proposed parking scheme does not attempt to seek a good parked position but to achieve the whole parking process at one shot (with just a single

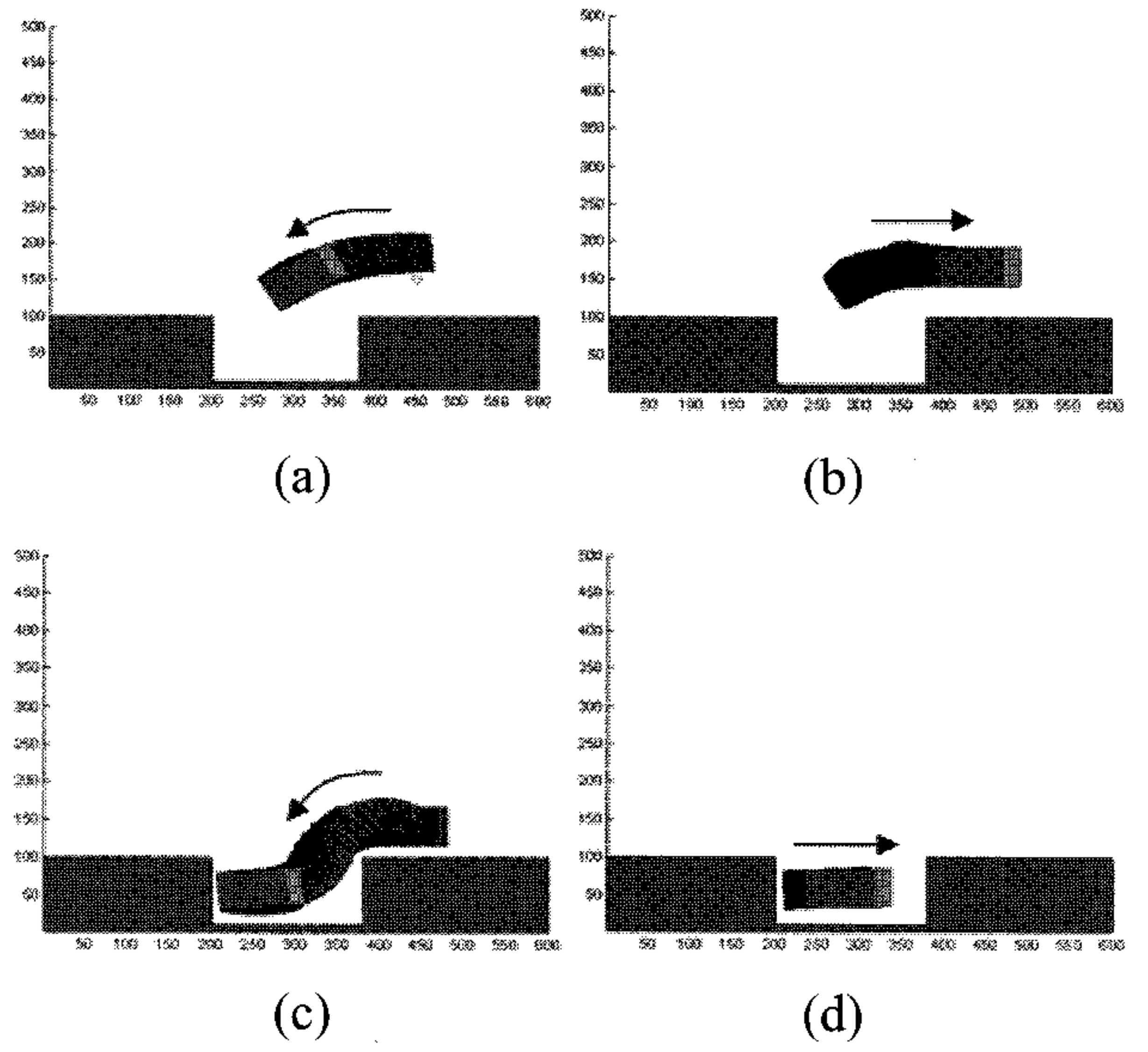


Fig. 19. Parking procedure from a poor starting pose for a parking size of 1.8×1.8 times the vehicle width. (a) Initial backup for corrective movement (b) Move to a green zone (c) Backup (d) Final adjustment.

back up motion).

Fig. 19 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 of Fig. 19(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. 19(b), we can eliminate these tedious backward-forward movements. As shown in Figs. 19(c) and (d), we are able to parallel park at one shot through this adjustment of the ready-to-reverse position.

5. CONCLUSIONS

We developed a novel automated parking utilizing a robust localization algorithm, an automated fuzzy controller design, based on initial search of a good ready-to-reverse position. Our contributions are:

1) Efficient localization: For fully automatic parking, it is required to exactly estimate the relative position and heading of the vehicle. The rear ultrasonic sensors that have been commonly used for parking assistance cannot usually extract this information. The sensor system for APS must have a vision and range sensors for covering all-around directions. The proposed localization draws upon this sensor configuration and can operate well without odometry. Because the reactive control uses raw signals of the sensors, it is required to newly train according to the different sizes and shapes of the parking lot. In contrast, our position-based control facilitates the controller design.
2) Fuzzy controller optimization: We used the FLC which is suitable for position based control. Because the fuzzy rule set is constructed not from heuristics but from the training data, it is made compact and efficient by removing unnecessary rules. Further, the membership functions are optimized by considering the collision possibility, the elapsed time, and the accuracy of the parked position. This process can improve the stability of parking in spite of variations of the parking space.
3) Good starting vehicle pose for parking: The proposed system calculates a green zone for the proper initial positions for the parking maneuver. Starting from a good ready-to-reverse position usually makes the ensuing parking control a lot easier.

Our system can also adapt to different vehicle platforms by tuning the kinematics and weights for each cost of ES. In the future, we can also apply the current system as it is to a parking assistance system (without any control). Finally, we could also train our FLC with a neural network emulating some kind of human parking behavior.

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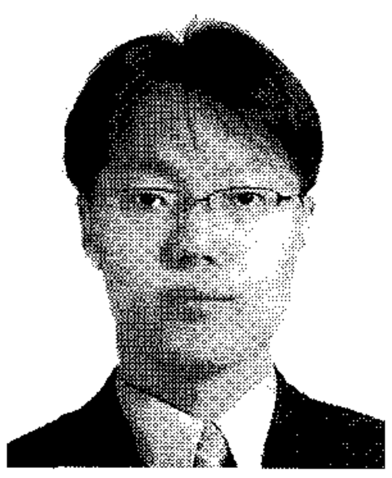

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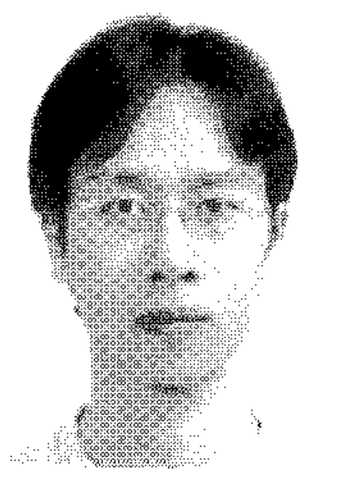

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