

Neuro-Fuzzy Rule Generation for Backing up Navigation of Car-like Mobile Robots

Jin-Il Park, Jae-Hoon Cho, Myung-Geun Chun, and Chang-Kyu Song

Abstract

An automatic neuro-fuzzy rule generation scheme is proposed for backing up navigation of car-like mobile robots. The proposed method is based on the Conditional Fuzzy C-Means (CFCM) and Fuzzy Equalization (FE) methods. The CFCM is adopted to render clusters, which can represent the homogeneous properties of the given input and output fuzzy data, and also the FE method is used to systematically construct the fuzzy membership functions for the ANFIS. From these, a compact size of fuzzy rules can be automatically obtained, which satisfy the given goal. The proposed method has been applied to a truck, and also to a truck-trailer backing up navigation problem, and good results have been achieved in comparison to previous work.

Keywords: *Conditional FCM, Fuzzy equalization, ANFIS, Backing up control, Mobile robot.*

1. Introduction

Most real-world processes are difficult to control effectively because of their nonlinear and time varying behaviors. The navigation of mobile robots in real-world scenarios is one of these processes, where it is difficult to find a control rule for the desired purpose; in fact to accomplish the goal of navigation in mobile robots, several soft computing methods, such as fuzzy controllers, fuzzy logic approaches, neural networks and their combinations have been applied [1-6, 8, 18-23]. When adopting a soft computing technique like fuzzy modeling, the domain knowledge needs to be obtained from human experts, and transformed into fuzzy rules to model the target system and to design a suitable controller based on the model of a system. However, an expert's knowledge is often inconsistent and incomplete, and also there is no formal and effective way of knowledge acquisition, thus depending on human experience results in some difficulties [7].

To solve these problems, researchers have been attempting to automate rule extraction, based on numerical training data. Most methods are intrinsically based on a fusion scheme of fuzzy logic and neural networks, that is, a neuro-fuzzy approach is often used. Here, fuzzy logic permits easy incorporation of the expert knowledge with humanlike if-then rule thinking and neural networks, leading optimization abilities, learning abilities, and connectionist structures. In this way, the learning power of neural networks can be incorporated into fuzzy systems, and also the reasoning process can be provided to the neural networks [9-10]. One of the most widely used method has been the neuro-fuzzy scheme, which is the Adaptive-Network-based Fuzzy Inference System (ANFIS) proposed by Jang [12]. This paper is also proposed on this basic framework of the ANFIS approach.

Applying the ANFIS to real-world problems requires two phases, namely, parameter identification and structure identification. The former is used to adjust the membership functions in the premise part of the rules and the linear coefficients in the consequent part are determined by using the steepest descent and least square estimation methods, respectively. The latter is related to finding a suitable number of rules and a proper partition of the input space. Related to the structure identification, the usual grid partition often encounters problems when there are a moderately large number of inputs which is usually referred to as the "curse of dimensionality" [12].

To alleviate these problems, a novel fuzzy clustering method CFCM [13-14] is proposed here, with the FE [15-16], to perform the identification of the structure for the flexible scatter partitioning. From the information granulation property of the CFCM, the exponential increase of the number of fuzzy rules in the ANFIS, due to grid partitioning of input space can be prevented. The proposed method has been applied to the backing up control of car-like mobile robots, such as truck models [1-3, 5, 8, 21-22] and truck-trailer models [1, 4, 6, 18-19, 23]. From various experimental results, it has been found that the proposed method gives better performance than previous results in this area.

The rest of this paper is organized as follows. A brief description about FE, CFCM, and ANFIS methods is given in Section 2 and then, Section 3 explains the

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details of the proposed scheme, and describes the truck and truck-trailer models together with the experimental results. Concluding remarks are given in Section 4.

2. Previous Works for Fuzzy Clustering and Fuzzy Inference System

A. Fuzzy Equalization (FE) Method for Generating Membership Functions

The concept of the fuzzy equalization originates from the idea of a fuzzy event, as proposed by Zadeh [17]. When a fuzzy set is defined in some universe of discourse in which is given some probability density function (pdf), the probability of the fuzzy event over the support of the fuzzy set is determined such as

$$P(\mathbf{A}) = \int_{\mathbf{A}} p(x) dx \quad (1)$$

where \mathbf{A} is the membership function of the fuzzy set, whereas $p(x)$ denotes the corresponding pdf defined in \mathbf{X} .

Now consider the case that a family of fuzzy sets, say $\mathbf{A} = \{A_1, A_2, \dots, A_G\}$ is given and to make each A_i meaningful, that is, to have the same amount of experimental evidence, it is necessary that

$$P(A_1) = P(A_2) = \dots = P(A_G) = \frac{1}{G} \quad (2)$$

According to the above equalization condition, fuzzy sets become more specific in the regions of \mathbf{X} where pdf attains local minima. In the areas of low values of pdf, fuzzy sets of broader support are needed in order to gain sufficient evidence, as shown in Fig. 1. When a series of triangular fuzzy numbers, with a 1/2 overlap between successive fuzzy sets and the first as well as the last fuzzy set, is defined by a trapezoidal membership function, the fuzzy equalization method can be described as follows [11, 15].

[Step 1] Specify the number of elements of linguistic terms in \mathbf{A} , say “ G ”.

[Step 2] Start from the lower bound of \mathbf{X} denoted by x_{\min} .

[Step 3] Compute the moving value of the integral and then stop once the value has reached the value of $1/2G$ such as:

$$\int_{x_{\min}}^a A_1(x) p(x) dx \quad (3)$$

Denote the value of this corresponding argument by “ a ”.

[Step 4] Determine the upper bound, b , of the support of A_1 so that the probability of the fuzzy event becomes equal to

$$\int_a^b A_1(x) p(x) dx = \frac{1}{2G} \quad (4)$$

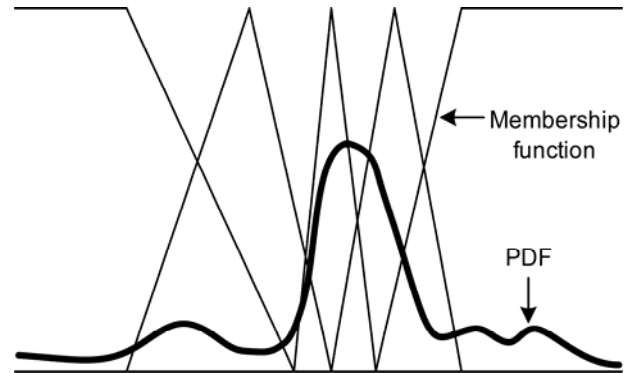


Figure 1. The idea of fuzzy equalization.

[Step 5] For the triangular fuzzy sets (starting from A_2 and A_3, A_4 , etc), compute the probability of the fuzzy event such as

$$\sigma = \int_a^b A_2(x) p(x) dx \quad (5)$$

[Step 6] Optimize the decreasing of the upper bound of support of the fuzzy set, such that it satisfies the condition:

$$\int_a^b A_2(x) p(x) dx = \frac{1}{G} - \sigma \quad (6)$$

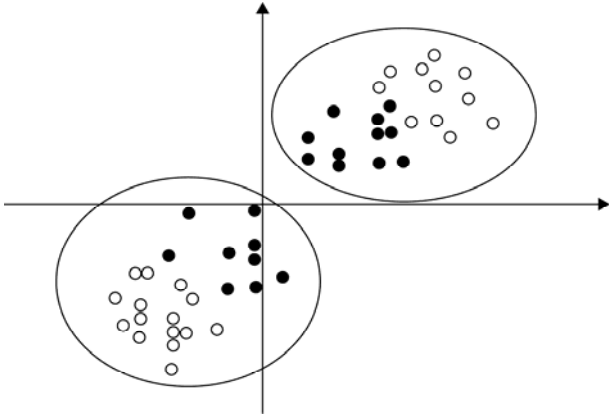
[Step 7] Repeat [Step 5] ~ [Step 6] for the successive fuzzy sets in \mathbf{A} .

B. Conditional Fuzzy C-Means (CFCM) Clustering Method

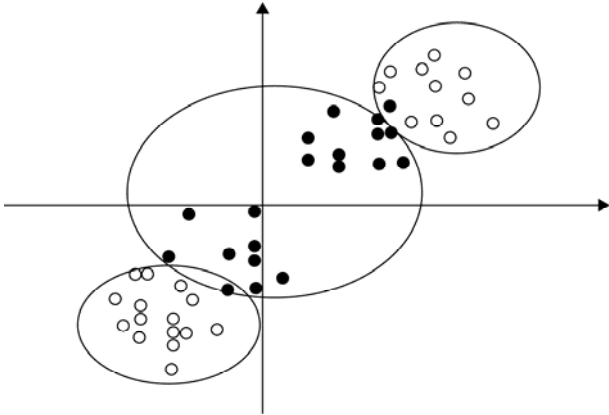
The CFCM has been proposed by Pedrycz [13-14] as a fuzzy clustering method to establish clusters and to preserve homogeneity of the given patterns, with regard to their similarity in the output space, as well as their respective values in input space. To illustrate the CFCM approach, a brief description is given for a simple training set $(\mathbf{X}_k, \mathbf{Y}_k)$, $\mathbf{X}_k = [x_{k1} \ x_{k2}]$ (Fig. 2). The colors (black and white) of the data points reflect the corresponding values assumed by the dependent variable (\mathbf{Y}_k). The conventional clustering method favors two evident clusters (as shown in Fig. 2(a)). The results, however, change when the corresponding values of \mathbf{Y}_k 's are reflected. To preserve homogeneous clusters in the $x_1 - x_2$ space, while requesting that these structures group \mathbf{Y}_k 's with the similar values, Fig. 2(b) shows an extra cluster has been created to preserve the homogeneity with respect to the output variable. The clusters obtained in this way are far more homogeneous than the ones produced by the conventional clustering method.

The CFCM algorithm can be summarized as follows [13].

[Step 1] Select the number of clusters $c(2 \leq c \leq n)$ and the exponential weight $m(1 < m < \infty)$.



(a) Clusters in $x_1 - x_2$ space.



(b) Clusters in the $x_1 - x_2$ space with a conditional variable involved.

Figure 2. The basic principles of the CFCM method.

[Step 2] Choose an initial partition matrix $U^{(0)}$ and a termination criterion ε , and set the iteration index p to 0, where $U = [u_{ij}]$, $i = 1, 2, \dots, c$, $j = 1, 2, \dots, n$.

[Step 3] Calculate the fuzzy cluster centers $c_i^{(p)}$ by using $U^{(p)}$ and

$$c_i = \frac{\sum_{j=1}^n u_{ij}^m x_j}{\sum_{j=1}^n u_{ij}^m} \quad (7)$$

[Step 4] Calculate the new partition matrix $U^{(p+1)}$ by using $c_i^{(p)}$ and

$$u_{ij} = \frac{f_j}{\sum_{k=1}^c \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \quad (8)$$

where f_j describes a level of involvement of x_j in the constructed cluster. That is, the linguistic term defined in the output space is expressed as a fuzzy set. Then, $f_j = A(y_j)$, $j = 1, 2, \dots, n$ stands for a degree of membership of y_j in A .

[Step 5] If $\|J^{(p+1)} - J^{(p)}\| \leq \varepsilon$, then stop. Otherwise, set $p = p + 1$ and go to [Step 3].

$$J = \sum_{j=1}^n \sum_{i=1}^c u_{ij}^m \|x_j - c_i\|^2 \quad (9)$$

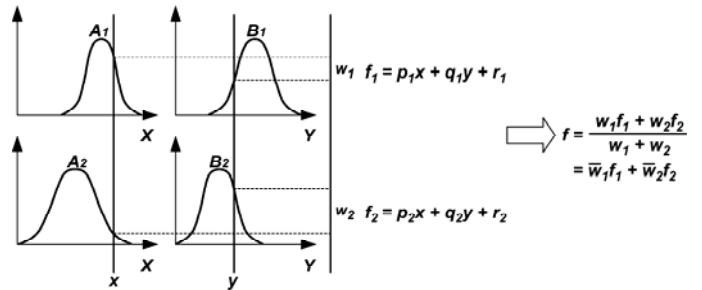
C. Adaptive-Network-based Fuzzy Inference System (ANFIS)

Without loss of generality, consider an inference system consisting of TSK (Takagi-Sugeno-Kang) type of two fuzzy if-then rules, as follows.

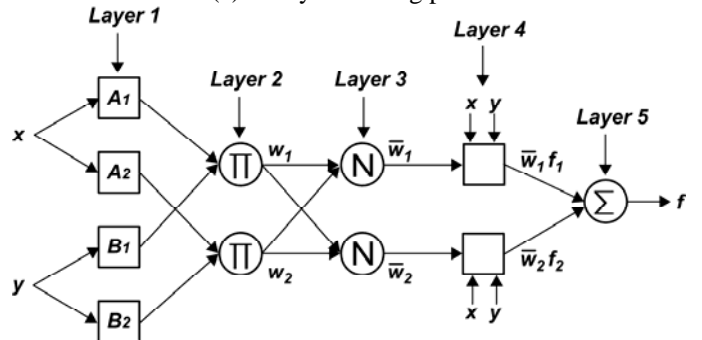
$$R^1 : \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \quad (10)$$

$$R^2 : \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2$$

where x and y are the input variables, A_i and B_i are the linguistic terms, and $\{p_i, q_i, r_i\}$ is a consequent parameter set. The architecture of the resulting ANFIS for the above fuzzy rules is shown in Fig. 3.



(a) Fuzzy reasoning process.



(b) ANFIS architecture.

Figure 3. Structure of ANFIS.

For this ANFIS, the behavior characteristics and learning procedure of each layer adopted in this paper

are described as

[Layer 1] Every node has a membership values as an output, as follows:

$$O_i^1 = u_{A_i}(x), O_{i+2}^1 = u_{B_i}(y) \quad i = 1, 2 \quad (11)$$

Here, the premise membership function is a Gaussian function, expressed as

$$u_{A_i}(x) = \exp \left\{ - \left(\frac{x - c_i}{a_i} \right)^2 \right\} \quad (12)$$

where $\{a_i, c_i\}$ is the premise parameter set. a_i and c_i are the width and center of the Gaussian functions.

[Layer 2] Each node in this layer multiplies the incoming signals.

$$O_i^2 = w_i = u_{A_i}(x) \times u_{B_i}(y) \quad i = 1, 2 \quad (13)$$

[Layer 3] Each node in this layer is a node that calculates the ratio of the i^{th} rule's firing strength of the sum of all rule's firing strengths.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \quad (14)$$

[Layer 4] Each node multiplies the normalized firing strengths and the consequent function.

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad i = 1, 2 \quad (15)$$

[Layer 5] The single node in this layer is a node that computes the weighted average of each rule's output.

$$O_i^5 = y_i^* = \sum_{i=1}^2 \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (16)$$

Considering the training algorithm for the ANFIS, it is necessary to derive the learning algorithm for the premise parameter set $\{a_i, c_i\}$, by minimizing the objective function defined by:

$$E = \frac{1}{2} (y^* - y_d)^2 \quad (17)$$

where y_d is the desired output for input vector $X = [x, y]^T$ and y^* is the output of the fuzzy model. Since the membership function is defined by the premise parameters, the objective function is determined only by them, when the consequent parameter is fixed. So, to reduce the value of the objective function E , the premise parameters are repetitively calculated by the steepest descent method, as follows.

$$\begin{aligned} a_j^i(t+1) &= a_j^i(t) - \eta \frac{\partial E}{\partial a_j^i} \\ c_j^i(t+1) &= c_j^i(t) - \eta \frac{\partial E}{\partial c_j^i} \end{aligned} \quad (18)$$

The consequent parameters of ANFIS are estimated

by LSE and the error between the actual output and the fuzzy model can be minimized by using this hybrid learning procedure.

3. Back up Navigation of Truck and Truck-Trailer

The proposed scheme of generating a neuro-fuzzy rule for the backing up navigation of car-like mobile robots is shown in Figure 4. First, the input-output data pairs are collected from the successful backing up navigation trajectories, and then these are divided into "training" and "testing" data sets. The testing data is applied to validating the obtained neuro-fuzzy rules. With the training data set, the FE method is applied to the desired output data, the steering angle of the truck and the truck-trailer, to automatically generate the membership functions reflecting the distribution characteristics of the output data. Based on the obtained membership functions of output data, the CFCM is performed to generate clusters reflecting their similarity in the output data, as well as their respective values in the input space. From the generated clusters and their centers, the premise fuzzy membership functions can be systematically produced for the input data [9]. And also the consequent parameters of ANFIS are obtained from the hybrid learning scheme. From these, an ANFIS can be automatically constructed having a small number of fuzzy rules.

After completing this kind of structure identification, the parameter identification is carried out by a hybrid learning scheme, using the Least Square Estimate (LSE) and the back propagation algorithm, as in Jang's method [12]. The proposed method has been applied to car-like mobile robots backing up control of a truck model and a truck-trailer model. The detailed experimental procedures are described in the next sections.

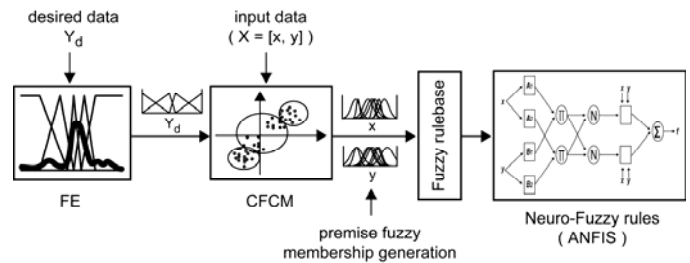


Figure 4. Proposed neuro-fuzzy rule generation scheme.

A. Backing up Control of a Truck

Kong and Kosko [3] proposed a fuzzy control strategy using linguistic rules for the truck backing up control problem, but this cannot use sampled data, and also causes redundant rules due to the grid partition. Wang [2] has proposed a fuzzy rules extraction approach using

numerical input-output data pairs and linguistic information, but as in the method of Kosko, this also causes the redundant rules due to the grid partition. On the other hand, Wong [21-22] and Tang [8] has proposed a fuzzy controller designed by GA (Genetic Algorithms) and PSO (Particle Swarm Optimization). Sudhagar [5] has proposed a neuro-fuzzy logic approach in the design of a controller with a five-layer neural network and 125 fuzzy rules sets.

The truck-backing control problem is to make a truck arrive at the loading dock at a right angle ($\phi = 90^\circ$), and to align the position (x, y) of the truck with the desired loading dock. For the simulation experiments, a simulated truck and loading zone are used, as shown in Fig. 5, and the following nonlinear kinematics [2]:

$$\begin{aligned} x(k+1) &= x(k) + v \cdot t \cdot \cos[\phi(k)] \\ y(k+1) &= y(k) + v \cdot t \cdot \sin[\phi(k)] \\ \phi(k+1) &= \phi(k) + v \cdot t / l \cdot \tan[\theta(k)] \end{aligned} \tag{19}$$

where the backing velocity v and time step t are -5 [m/s] and 0.5 [s]; the length of the truck l is assumed as 4 [m] and the variable ranges are as follows:

$$\begin{aligned} -40 \text{ [m]} \leq x \leq 40 \text{ [m]}, \quad 0 \text{ [m]} \leq y \leq 50 \text{ [m]}, \\ -90^\circ \leq \phi \leq 270^\circ, \quad -45^\circ \leq \theta \leq 45^\circ \end{aligned} \tag{20}$$

The variables are the truck angle ϕ , and the truck x -position coordinate, x , then the control variable becomes the steering-angle signal, θ . Since it is assumed that there is enough clearance between the truck and the loading dock, the truck's y -position can be ignored [2-3].

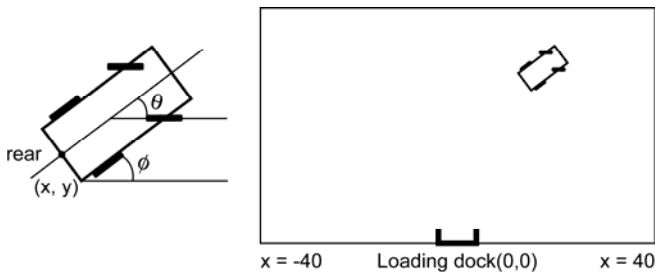


Figure 5. Truck diagram and the truck's parking space.

In order to evaluate the resultant model of the proposed neuro-fuzzy system that is not biased toward the training dataset, and so is likely to have a better generalization capacity to new data, the datasets are divided into training and testing datasets, as shown in Fig. 6. Here, 700 training sets are selected from among those given for modeling, while the other 700 test sets are used for the model validation.

The histogram for the training steering angle of the truck is shown in Fig. 7. After applying the FE method given as the histogram, the fuzzy membership functions can be systematically obtained (see Fig. 8). For each fuzzy set of the output variable θ , two fuzzy clusters are generated. Finally, a fuzzy production system is

extracted, consisting of eight TSK-type fuzzy rules.

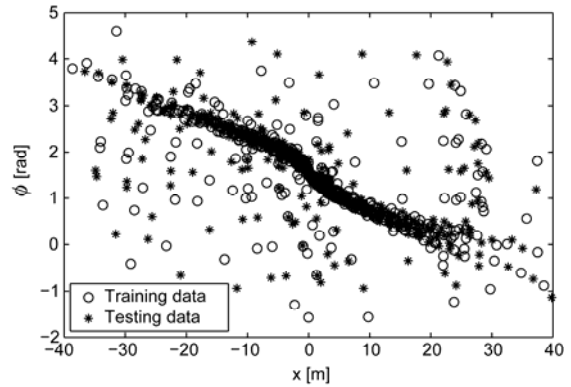


Figure 6. The training data and the testing data.

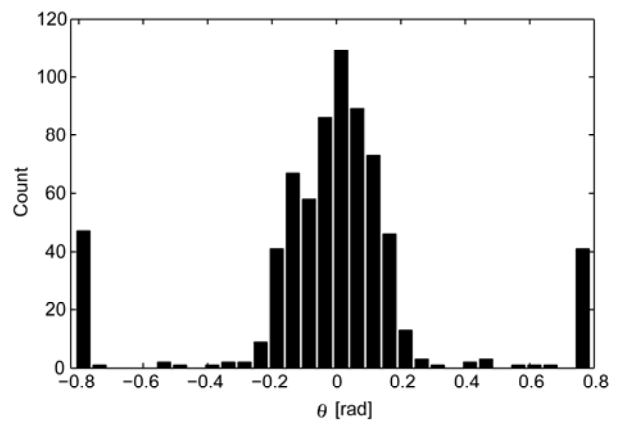


Figure 7. The histogram of the steering angles.

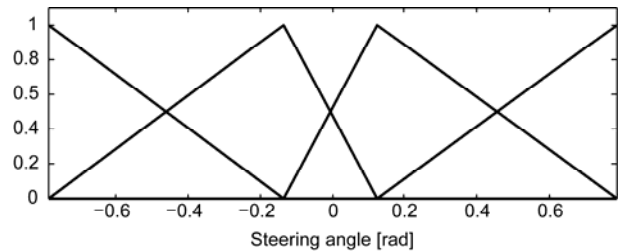


Figure 8. The membership functions generated by the fuzzy equalization.

Table 1. Cluster centers obtained by each method.

Cluster	FCM	CFCM	CFCM & FE
1	(-25.6025, 3.0777)	(-19.8871, 1.4840)	(-19.5830, 1.4842)
2	(-13.2320, 2.4924)	(-16.2700, 2.6919)	(-16.1318, 2.6719)
3	(-4.4739, 2.0349)	(-6.2083, 3.0564)	(-6.6819, 3.0283)
4	(-0.1280, 1.5921)	(-0.4587, 1.6647)	(-1.2418, 1.7409)
5	(1.9929, 1.2910)	(-0.1716, 1.5314)	(0.7922, 1.4270)
6	(7.9575, 0.8355)	(4.7483, -0.1327)	(5.1191, -0.1214)
7	(16.2876, 0.4462)	(16.2657, 0.4265)	(16.3526, 0.4436)
8	(25.4487, 0.1080)	(24.8058, 1.5323)	(24.6216, 1.5352)

After performing 100,000 iterations, three neuro-fuzzy models are obtained, having cluster centers as shown in Table 1. For the comparisons, three different schemes are implemented: FCM, CFCM, and CFCM & FE (the proposed method) based ANFISs. The FCM-based ANFIS uses the conventional fuzzy c-means (FCM) algorithm [9] to generate the clusters. The CFCM-based ANFIS generates the output membership functions without the FE processing, that is, using an even spacing scheme. Fig. 9 shows the training RMSE (Root Mean Squared Errors) curves for each ANFIS model, and the related RMSEs are presented in Table 2. As can be seen, the proposed method shows better performance than the other methods tested.

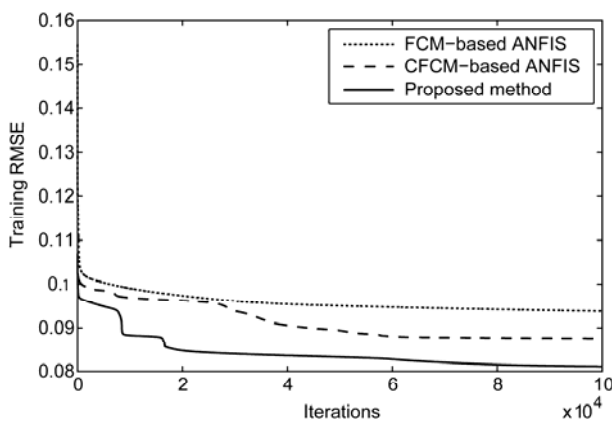


Figure 9. The training RMSE curves for each method-based ANFIS.

Table 2. The comparison of RMSE for the ANFIS based methods.

	Training RMSE	Testing RMSE
FCM-based ANFIS	0.0938	0.1174
CFCM-based ANFIS	0.0876	0.1380
Proposed method	0.0811	0.1080

The finally obtained premise, and consequent parameters are shown in Fig. 10, and the consequent parameters are given in Table 3.

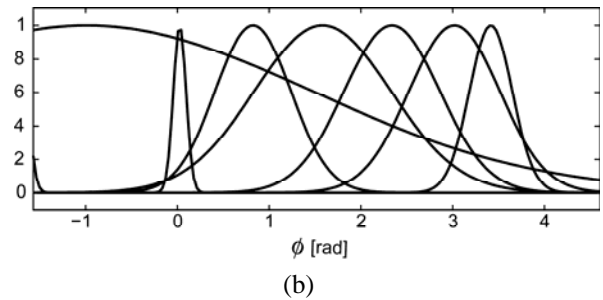
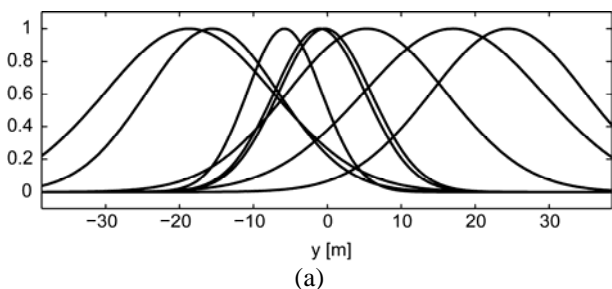


Figure 10. The premise membership functions given by the proposed method.

Table 3. The consequent parameters given by the proposed method.

	p_i	q_i	r_i
Rule 1	0.0167	0.0286	-0.3292
Rule 2	-0.9677	-3.9750	-2.5640
Rule 3	0.0132	0.5413	-0.4970
Rule 4	-0.0013	0.1139	-0.6591
Rule 5	0.0529	1.1070	-1.9720
Rule 6	0.1616	1.4950	-2.0790
Rule 7	0.0171	-0.2910	1.4270
Rule 8	5.335e-05	-0.0108	0.8142

The truck's navigational trajectories from five different initial states are shown in Fig. 11, where their initial states (x, y, ϕ) are $(-30, 40, 80)$, $(-10, 40, 0)$, $(5, 42, 45)$, $(20, 40, -45)$, and $(30, 40, 110)$. From the various simulation experiments, it has been found that the established neuro-fuzzy rules successfully back up the track to the desired position.

Moreover, the proposed method obtained better results with more compact fuzzy rule size, as shown in Table 4. That is, the proposed scheme can solve the problem that the number of fuzzy rules exponentially increases due to grid partitioning of input space, which often arises in the conventional ANFIS approaches.

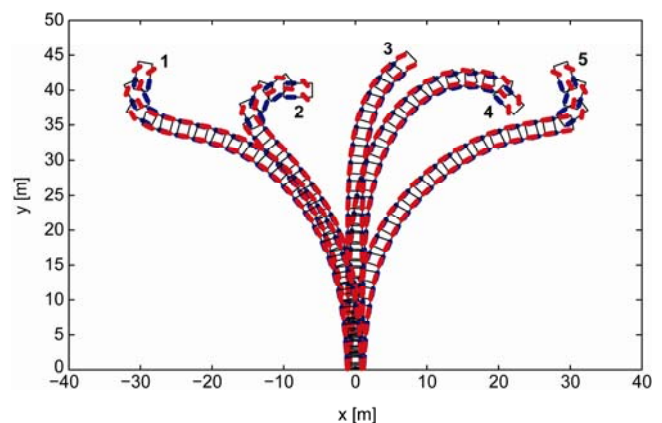


Figure 11. The truck trajectories obtained using the proposed method.

Table 4. Comparison of the number of rules.

	Rule number
Wang [2]	27
Kosko [3]	35
Sudhagar [5]	125
ANFIS (grid partition)	64
Tang [8] (obtained by GA)	10
Proposed method	8

B. Backing up Control of a Truck-Trailer

The backing up control of a truck-trailer is a more complex problem than backing up a simple truck model. Many controller design methods have been proposed for this problem [1, 4, 6, 18-19, 23]. In this paper, the following truck-trailer system model is used [18] (see also Fig. 12).

$$\begin{aligned}
 x_0(k+1) &= x_0(k) + v \cdot t / l \cdot \tan[u(k)] \\
 x_1(k) &= x_0(k) - x_2(k) \\
 x_2(k+1) &= x_2(k) + v \cdot t / L \cdot \sin[x_1(k)] \\
 x_3(k+1) &= x_3(k) + v \cdot t \cdot \cos[x_1(k)] \cdot \sin[\{x_2(k+1) + x_2(k)\} / 2] \\
 x_4(k+1) &= x_4(k) + v \cdot t \cdot \cos[x_1(k)] \cdot \cos[\{x_2(k+1) + x_2(k)\} / 2]
 \end{aligned}
 \tag{21}$$

where

- $x_0(k)$: The angle of the truck referenced to the desired trajectory
- $x_1(k)$: The angle difference between the truck and the trailer
- $x_2(k)$: The angle of the trailer referenced to the desired trajectory
- $x_3(k)$: The vertical position of the trailer tail end
- $x_4(k)$: The horizontal position of the trailer tail end
- $u(k)$: The steering angle of the truck

Here, the length of the truck l and trailer L are 2.8 [m] and 5.5 [m], respectively and the sampling time t and the constant backward speed v are 2 [s] and -1 [m/s], respectively.

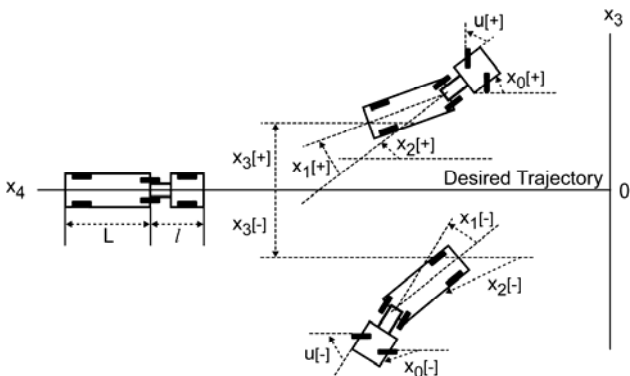


Figure 12 Truck-trailer model and its coordinate system.

The ranges of the variables are assumed to be as follows:

$$\begin{aligned}
 -90^\circ \leq x_1 \leq 90^\circ, \quad -180^\circ \leq x_2 \leq 180^\circ, \\
 -40 \text{ [m]} \leq x_3 \leq 40 \text{ [m]}, \quad -45^\circ \leq u \leq 45^\circ
 \end{aligned}
 \tag{22}$$

Over 10,000 truck-trailer datasets are generated using the fuzzy control system [19], and the datasets are divided into training and test datasets, as shown in Figs. 13 and 14 so that 5,000 training sets are selected for the modeling, while the other 5,000 testing sets are used for the model validation.

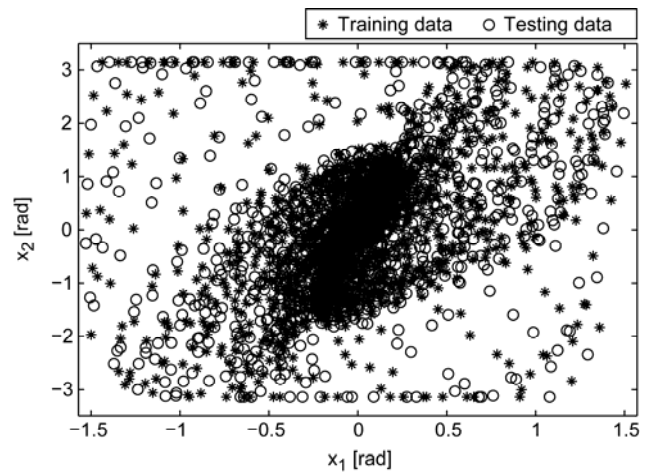


Figure 13. The training data and the testing data (x_1 vs x_2).

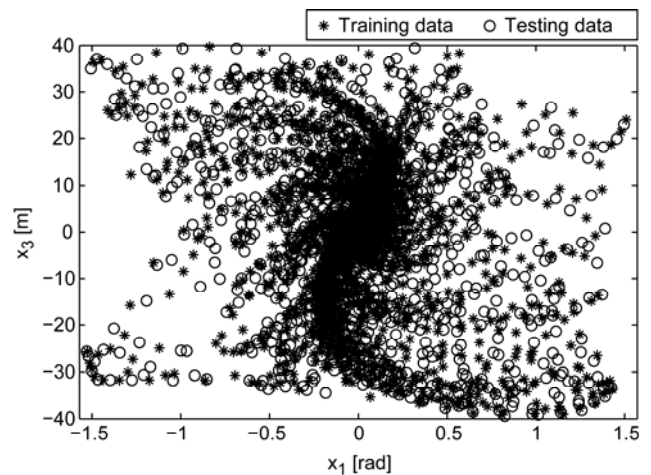


Figure 14. The training data and the testing data (x_1 vs x_3).

The histogram for the training steering angle of the truck-trailer is shown in Fig. 15 and after applying the FE method, the fuzzy membership functions are systematically obtained (see Fig. 16). For each obtained fuzzy set with the output variable u , two fuzzy clusters are generated and finally, a fuzzy production system is extracted, consisting of eight TSK-type fuzzy rules.

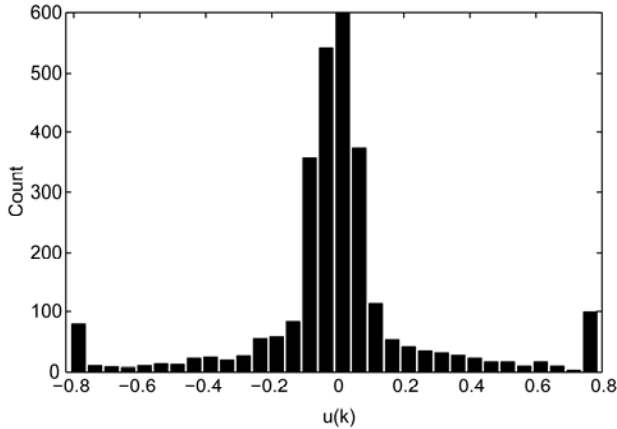


Figure 15. The histogram for the steering angles.

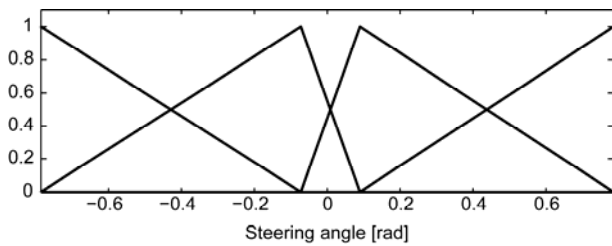


Figure 16. The membership functions generated by the fuzzy equalization.

Table 5. Cluster centers obtained by each method.

Cluster	FCM	CFCM	CFCM & FE
1	(-0.1238, -0.8082, -10.2629)	(-0.8379, -0.2925, 11.6282)	(-0.7484, -0.4238, 11.6374)
2	(-0.1050, -0.3513, -2.0976)	(-0.2006, -0.7531, -6.4547)	(-0.1849, 2.1251, -6.6791)
3	(-0.0443, -1.2245, -21.7440)	(-0.1990, 2.2188, -7.1405)	(-0.1678, -0.7271, -7.4150)
4	(6.12e-05, 8.60e-04, 0.0127)	(-0.0123, 0.0432, 1.3278)	(-0.0205, 0.0131, 1.1269)
5	(0.0793, 1.2551, 21.9029)	(0.0199, -0.0441, -1.7058)	(0.0331, -0.0245, -1.8965)
6	(0.1091, 0.3877, 2.7073)	(0.2591, 0.8854, 6.2442)	(0.2027, 0.8126, 7.5003)
7	(0.1152, 0.8492, 11.8406)	(0.5885, -2.1778, -4.5758)	(0.5663, -1.9800, -6.5222)
8	(0.7600, 1.1562, -18.4743)	(0.8980, 0.8437, -12.8061)	(0.8103, 0.8966, -11.0444)

After performing 10,000 iterations, three neuro-fuzzy models are obtained, with cluster centers as shown in Table 5 and Fig. 17 shows the training RMSE curves for each ANFIS based model, together with the related RMSEs which are summarized in Table 6. The proposed method shows better performances for both the training and the testing datasets than the other methods tested.

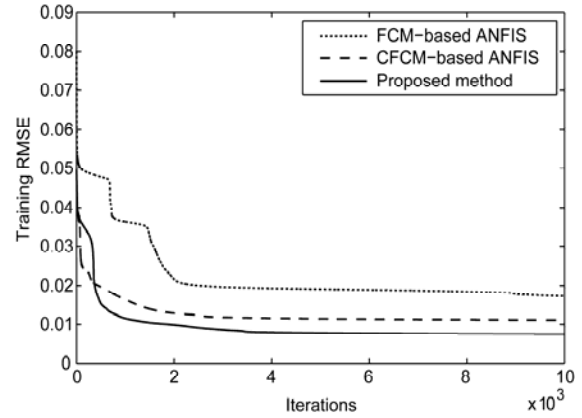


Figure 17. The training error curves for each method-based ANFIS.

Table 6. Comparison of RMSE for ANFIS based methods.

	Training RMSE	Testing RMSE
FCM-based ANFIS	0.0173	0.0297
CFCM-based ANFIS	0.0111	0.0156
Proposed method	0.0074	0.0128

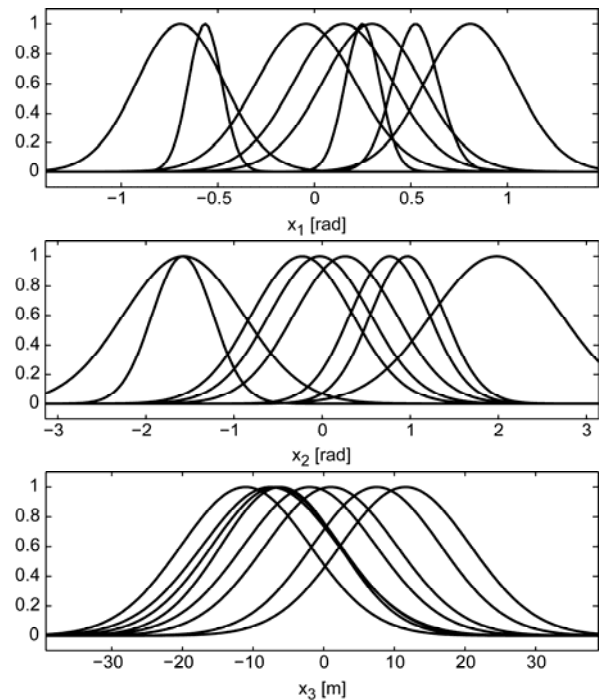


Figure 18. The premise membership functions by the proposed method.

The simulations are performed with different starting positions and initial angles between the truck and the trailer. The truck-trailer trajectories from four initial states $((x_1, x_2, x_3) = [(0, 0, 32), (0, 180, 20), (-45, 90, -10), (0, 30, -32)])$ are shown in Fig. 19. From the various simulation experiments, it has been found that the established fuzzy rules successfully control the truck to

the desired position and the proposed method shows better results that obtained using previous methods; in addition the methods leads to more compact sized fuzzy rules as described in Table 8.

Table 7. The consequent parameters determined by the proposed method.

	p_i	q_i	r_i	s_i
Rule 1	2.0330	-0.5956	0.0254	-0.0539
Rule 2	0.0292	-0.0086	-0.0001	-0.7422
Rule 3	1.3660	-0.3937	0.0243	-1.9390
Rule 4	0.5114	-0.1805	0.0116	-0.0676
Rule 5	2.0760	-0.6079	0.0260	-0.0063
Rule 6	6.2530	-1.7930	0.0774	1.1590
Rule 7	2.0430	-0.5988	0.0255	0.0035
Rule 8	-0.0010	-0.0131	-0.0002	0.7480

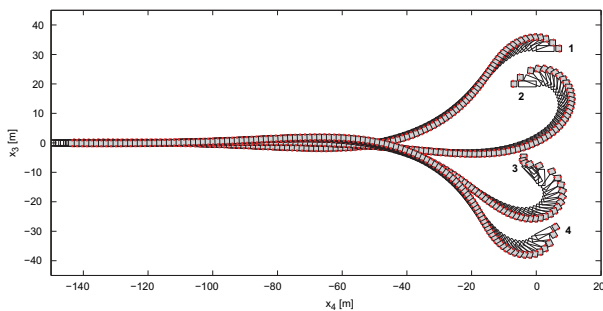


Figure 19. The truck-trailer trajectories obtained using the proposed method.

Table 8. Comparison of the number of rules.

	Rule number
Kosko [1]	735
Zimic [4]	125
Yang [6]	105
ANFIS (grid partition)	512
Proposed method	8

4. Concluding Remarks

The backing up control problems of a truck and a truck-trailer are practical examples in dealing with complex nonlinearity, and they have been investigated by many researchers in the field of soft computing. To take the best performance or behavior, different soft computing methods, such as fuzzy logic, neural networks and their combinations based on expert knowledge have been applied. Soft computing methods constructed from the direct expert's knowledge, result in some difficulties due to the intrinsic properties of

inconsistency and incompleteness of human knowledge. To solve these problems, a fusion scheme of fuzzy logic and neural networks, that is, a neuro-fuzzy system has been widely studied to extract the fuzzy rule depending on the data sets.

This paper has proposed an ANFIS based neuro-fuzzy rule generation scheme with CFCM and FE, and has applied it to truck and truck-trailer backing up navigation problems. Simulation results are presented to show that the proposed method is able to guide the truck, and the truck-trailer to dock, from almost any initial position. Moreover, it has been found that the proposed method renders a more compact number of fuzzy rules having smaller root mean squared error. So, it is expected that this method can be successfully applied in the area of real-time mobile robot navigation and path planning problems.

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