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Hsuan-Ming Feng
Department of Computer Science and Information Engineering, National Quemoy University, Kinmen, Taiwan, R.O.C

Ching-Yi Chen
Department of Information and Telecommunications Engineering, Ming Chuan University, Taoyuan County, Taiwan, R.O.C., chingyi@mail.mcu.edu.tw

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INTELLIGENT DYNAMIC ACQUISITION LEARNING FUZZY MODELING SYSTEMS DESIGN

Hsuan-Ming Feng[1] and Ching-Yi Chen[2]

Key words: fuzzy modeling system, particle swarm optimization, recursive least-squares.

ABSTRACT

Technologies of fuzzy knowledge-based discovery can be exploited to extract appropriate behaviors for identified modeling problems. A proposed novel data acquisition learning algorithm (DALA) is dynamically applied to examine the initial recognitions of the training data set, where it can automatically establish the number of cluster centers and their associated positions. The characteristics of the training data set are dynamically mined by the DALA, and the primary architecture of the fuzzy system is initially represented with the collected information. Because the prototypes of the collected training data are determined with DALA, the initial populations of the particle swarm optimization (PSO) are generated and distributed around them. The hybrid PSO and recursive least-squares (RLS) learning schemes referred to as RPSO are applied to design an appropriate fuzzy modeling system. The approximation of the proposed fuzzy modeling system shows that it automatically determines suitable fuzzy membership functions and resolves the local optimal problem of identifying appropriate parameters for fuzzy systems to swiftly approach desired functions. A comparison between computer simulations and other modeling methods shows the excellent performance of the dynamic acquisition learning fuzzy modeling system in explaining nonlinear and inverted pendulum function approximations. Simulation results show that the generated fuzzy system with the DALA scheme can be adapted to balance the pole position for various initial conditions. The proposed control rules swiftly recover the sudden and large imported noise.

Paper submitted 01/04/12; revised 01/20/13; accepted 05/21/13. Author for correspondence: Ching-Yi Chen (e-mail: chingyi@mail.mcu.edu.tw).
[1] Department of Computer Science and Information Engineering, National Quemoy University, Kinmen, Taiwan, R.O.C.
[2] Department of Information and Telecommunications Engineering, Ming Chuan University, Taoyuan County, Taiwan, R.O.C.

I. INTRODUCTION

Knowledge-based information systems have important roles and applications in several fields: modeling prediction/control systems, decision support systems, diagnostic systems, and pattern recognition. Fuzzy or neural-fuzzy systems are particularly suitable platforms for modeling the behavior of training patterns, especially for recognized nonlinear problems [2, 5, 14, 15]. Resolutions for nonlinear, controlled, and predicted problems are offered to model the framework of the gathered data set. Thereafter, they can predict their future action based on previous and current observations. Therefore, how to capture the appropriate parameters of the fuzzy modeling system with the proper and required number of fuzzy rules for approximating the desired target is the objective of this study.

Two main objectives require consideration: The first involves ensuring that obtaining an accurate and quick characterization to achieve the fitting curve of a sample data set is suitable; and the second involves building a general and flexible data learning mechanism that is adapted to reconstruct rule-based expert systems for handling wide-range adaptations in various modeling problems [13]. A fuzzy modeling system is commonly generated by training example data with both structure-identified and parameter-learning stages [3, 4]. In the structure-identified step, several efficient mechanisms (specifically based on the data acquisition learning concept) were used to extract features from the input training patterns. They can completely describe the primary character of the identified modeling plan. The objective of the data acquisition learning algorithm (DALA) for each domain center is to approach the maximum similarity between it and the selected data groups; thus, the selected domain centers show the prototype of the identified system for reasonably representing the primary behavior of the training data set.

The fuzzy c-means (FCM) [1] clustering algorithm is the most common technique for separating the given training data set into several groups and determining the selected cluster centers for the associated data points because of the adaptability of the fuzzy inference methodology. However, the shortcomings of the FCM clustering algorithm require that the number of cluster centers be manually predetermined. To improve the traditional FCM clustering learning scheme, how to self-recognize a suitable number of domain centers (points) with the DALA design is the key objective of this study. In this study, the applied novel DALA with flexible computation is for continually evaluating the similarity of the training data. The DALA concurrently adjusts the proper center positions and chooses a suitable number of cluster centers. The choices of the initial situation and type of measure distance are vigorously considered for the desired clustering result even if the previous drawback is overcome. Therefore, the other measuring formula is considered to apply a proper method for evaluating the similarity between a training data set and its associated domain centers. The Gaussian type membership function is considered despite using the traditional Euclidean norm metric to calculate the similarity of the selected cluster centers and the given training data. The novel DALA with special fuzzy type measuring schemes are proposed to dynamically detect the proper number of clustering centers and its associated position value to describe the initial module of the training data set and identify the entire proper architecture of the discussed problems.

The fuzzy modeling system was designed to approximate several nonlinear functions and solve complex problems because of its universal approximation ability [3]. A novel DALA with a fuzzy-based measure is proposed in our studies to extract the domain knowledge from the training data. Thereafter, we assign the selected information from the domain knowledge as initial centers of the membership function to generate the initial architecture of the fuzzy modeling system. In this study, the number of clustering domains is equal to the number of fuzzy rules; each location of primary domain knowledge sequentially represents the initial structure of the proposed fuzzy system. Furthermore, the selected domain centers are randomly distributed around the proposed membership function and the consequent portion of the fuzzy rules [6-8, 21].

The proposed novel DALA is an important step in initializing the architecture of the identified fuzzy modeling system from the training data, but the correctness of the selected clustering results depend on the tuning stratagem of the proposed learning algorithm. The choices of the learning scheme can generally be considered as the following two types: the traditional type is referred to as the local learning methodology, and the second type can be referred to as the global learning methodology. For the traditional approach, the general gradient descent learning type algorithms with typical local learning stratagems are determined to approach the actual functional curve from the training data set [19]. However, the training module has a high probability of meeting local optimal problems when they attempt to identify complex and high dimensional data sets. In another considered situation, the modeling results are always unstable because of the variance in initial conditions [16]. Numerous global type optimal learning algorithms are used to overcome these discussed local optimal problems. For example, genetic algorithms (GA) [20] and particle swarm optimization (PSO) are proposed to regulate the parameters of fuzzy systems for approximating a desired output [6-8, 21]. In this study, the swarm-like population-based evolutional learning algorithm referred to as PSO simulates similar motions to flocking birds or schooling fish to create a self-generation fuzzy modeling system. A main movement of the PSO evolutional learning algorithm involves observing how natural creatures behave as swarms and simulating swarm patterns using computer computations. Each solution in the PSO evolutional learning algorithm is a bird referred to as a particle. Every particle has a velocity that directs the movement of each particle and a fitness value that is estimated by the fitness function to be optimized. The PSO can efficiently yield the optimum solution in the search space based on the guides of the defined fitness function. The PSO was recently used to determine the wide range of optimization solutions through representations of social interactions. Following the completion of the initial organization for the fuzzy modeling system with DALA, a powerful recursive least-squares (RLS)-based PSO (RPSO) technology is proposed to obtain the optimization solutions in the evolutional learning stage. The hybrid-based RPSO algorithm is successively applied to achieve more accurate fuzzy modeling systems when the initial framework of the fuzzy modeling system is generated.

The remainder of this study is separated as follows: Section II details the architecture of the fuzzy modeling systems and the proposed novel DALA. An artificial data set is used to dynamically test the efficiency of the DALA; Section III shows that the RPSO learning algorithm tunes the optimal parameters to approach the desired outputs of fuzzy modeling systems. The PSO recursive-based learning scheme is used to model two nonlinear functions; Section IV presents detailed comparisons with other learning methods; and Section V provides a conclusion with a summary of the contributions to this study.

II. INITIALIZE FUZZY MODELING ARCHITECTURE WITH NOVEL DATA ACQUISITION LEARNING ALGORITHM

The novel DALA automatically determines the required number of fuzzy rules for covering the training data and provides a good configuration for initializing the fuzzy modeling system's architectures. The novel DALA in the design of the initial architecture of fuzzy model systems is described in the following paragraph.

To design the initial architecture of the fuzzy modeling system, let $\underline{v}_i = x_i$, $i = 1, 2, \ldots, N$ be a set of N vectors in an s-dimensional space, where the x_{ij} is represented as ($x_i = x_{i1}, x_{i2}, \ldots, x_{is}$). Our objective is to acquire characterization from the given training data set and group similar points into the same region when diverse points are in different parting areas. We find that points with high relational grades have the same property; thus, we can gather those points into one group. Therefore, determining the required number of fuzzy rules initially involves choosing training data as the reference clustering center's value and identifying similar points that have high relational grades to the referenced estimation value. Thereafter, we can dynamically replace the centers of parting areas by averaging the vectors with high relational grades in a similar manner. The replaced points gradually incline toward the centers of the selected parting area. The novel DALA can be proposed as follows [8]:

Step (1): Define N movable vectors $\underline{v}_i$, $i \in I \equiv \{1, 2, \ldots, N\}$ and let $\underline{v}_i = x_i$; that is, x_i is the initial value of $\underline{v}_i$.

Step (2): Calculate the relational grades between the reference vector $\underline{v}_i$ and the comparative $\underline{v}_j$ by

$$m_{ij} = \prod_{t=1}^{s} \exp\left(\frac{-(\underline{v}_{i,t} - \underline{v}_{j,t})^2}{2\sigma_t^2}\right), \forall i,\ j \in I, \tag{1}$$

where

$$\sigma_t = \sqrt{\frac{\sum_{i=1}^{N}(x_{i,t} - \overline{x}_t)^2}{\pi(N-1)}},\ \overline{x}_t = \frac{1}{N}\sum_{i=1}^{N} x_{i,t},\ t = 1, 2, \ldots, s \tag{2}$$

and

$$r_{ij} = m_{ij} \cdot \mathrm{sgn}(m_{ij}) \tag{3}$$

The definition for the $sgn(\cdot)$ function is

$$sgn(x) = \begin{cases} 0, & if \quad x < \varepsilon \\ 1, & if \quad x \ge \varepsilon \end{cases} \tag{4}$$

where ε is a small-valued constant and our experimental value is $\varepsilon = 0.01$.

Step (3): Calculate $\underline{v}_i'$ using the following equations:

$$\underline{v}_i' = \frac{\sum_{j=1}^{N} r_{ij}\underline{v}_j}{\sum_{j=1}^{N} r_{ij}},\ i = 1, 2, \ldots, N \tag{5}$$

Step (4): If $\sum_{i=1}^{N}\left\|\underline{v}_i - \underline{v}_i'\right\| < \xi$, proceed to Step 5; otherwise let $\underline{v}_i = \underline{v}_i'$ and return to Step 2.

Step (5): We can determine that the number of fuzzy rules is equal to the number of convergent vectors based on the final results $\underline{v}_i$. The original data with the same convergent vector are grouped into the same areas, and the convergent vector is the center of the selected groups.

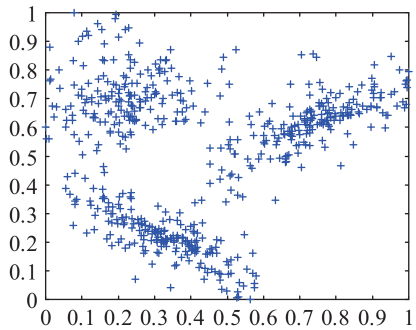

Fig. l. A two dimensional data set.

To describe the learning procedure and dynamic behavior of the training points clearly, Figs. 1 and 2 show the behavior for initializing the basic architecture of the fuzzy modeling systems with the proposed DALA. Fig. 1 shows 579 training data points with 2D spaces, where it contains mixed spherical and elliptical shapes, and the number of clustering centers is three [17]. Figs. 2(a) and 2(b) show the initial condition with contour mapping for the training data set that contains 579 data points and their associated membership functions, respectively. Figs. 2(c) and 2(d) show the next situation after one data learning cycle is finished. Figs. 2(e)-2(f) and Figs. 2(g)-2(h) show the situations after three and five learning cycles are finished, respectively. After the seventh learning cycle, the detected groups and their associated membership functions are shown in Figs. 2(i), 2(j), and 3, respectively. The selected centers are assigned as the center position of the membership function, and the number of partition groups equals the number of fuzzy rules. The proposed DALA can automatically select the proper fuzzy number from the training data set and extract the required information that makes a suitable configuration in the initial fuzzy modeling system.

For the design of the fuzzy modeling system with n-inputs-single-output, the fuzzy IF-THEN rules are used in the complete input variables as n-dimensional patterns (i.e., $x = (x_1, x_2, \ldots, x_n)$). We choose hyper-spheroid membership functions (HE_j) to define a fuzzy set in the input space and combine real value y_j to form the output space:

$$R_j : \text{IF } x \text{ is } HE_j \text{ THEN } y \text{ is } y_j,\ j = 1, 2, .., m \tag{6}$$

where m is the total number of fuzzy rules, y_j denotes a real value of the corresponding jth rule, and HE_j is defined as

$$HE_j(x) = \exp\left(-\left(\sum_{i=1}^{n}\frac{(x_i - a_{j,i})^2}{(b_j)^2}\right)\right) \tag{7}$$

where $a_{j,i}$ and b_j are the center and length for the jth hyper-spheroid function, respectively. The $a_{j,i}$ and b_j are both required parameters for training in the premised portion of the fuzzy rules. When the input vector is applied to the fuzzy rule table and the weighted average defuzzifier is used in this

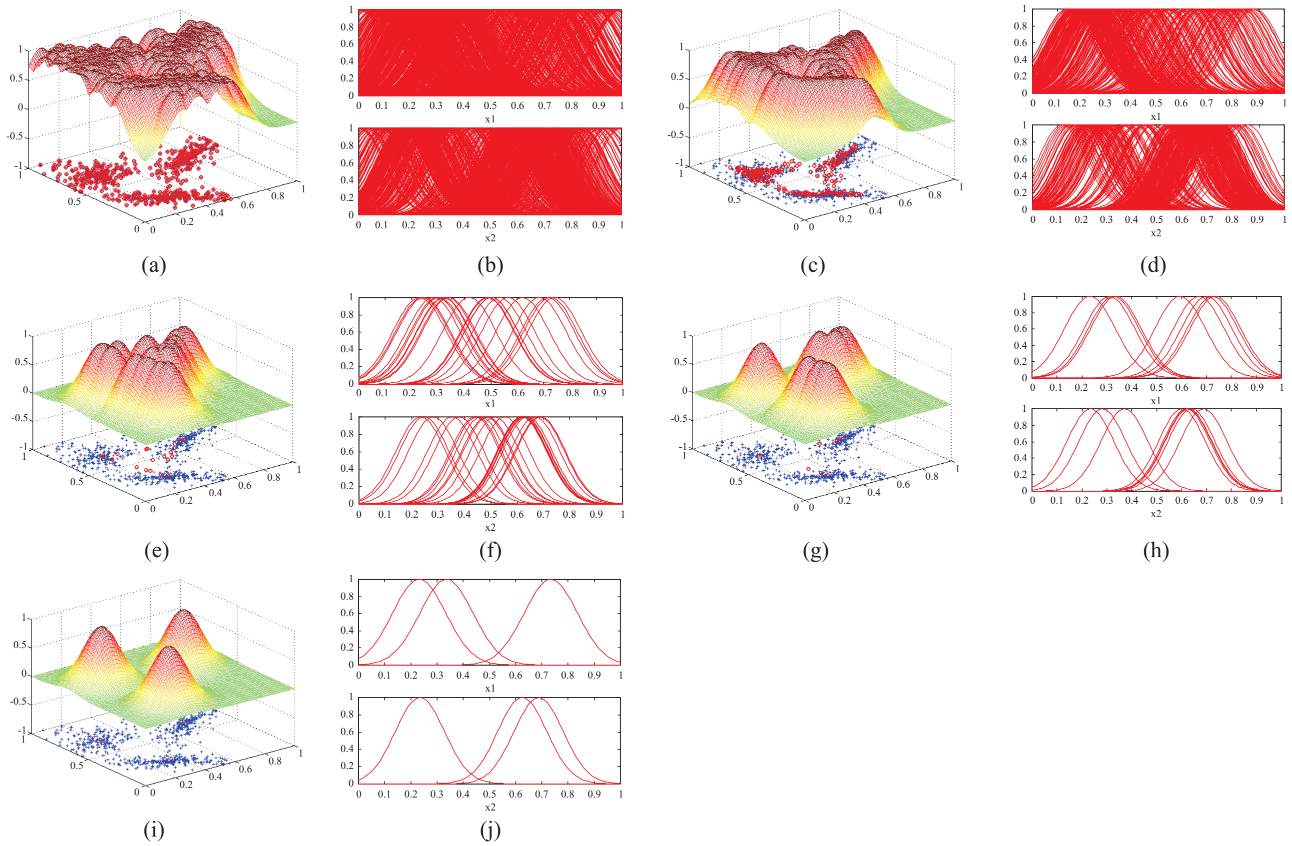

Fig. 2. Dynamic Response of the proposed novel data acquisition learning algorithm scheme. (a) iteration 0, (b) iteration 0, (c) iteration 1, (d) iteration 1, (e) iteration 3, (f) iteration 3, (g) iteration 5, (h) iteration 5, (i) iteration 7, (j) iteration 7.

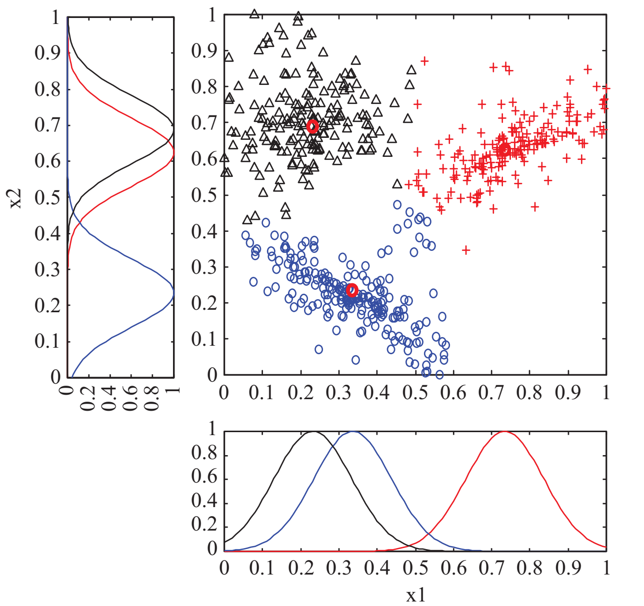

Fig. 3. Distributions of final clustering structure by the novel data acquisition learning algorithm.

fuzzy inference method, the output (y^o) of the fuzzy system can be calculated using the following equation:

$$y^o = \frac{\sum_{j=1}^{m} HE_j(x) \cdot w_j}{\sum_{j=1}^{m} HE_j(x)} \tag{8}$$

The parameter set R ($a_{j,1}, a_{j,2}, \ldots a_{j,n}, b_j, w_j, 1 \le j \le m$) affects the final performance of the fuzzy modeling system to a large extent, because the contour of the jth membership function $HE_j(x)$ is defined by the parameters $\{a_{j,1}, a_{j,2}, \ldots a_{j,n}, b_j\}$ and the consequent partitions are determined by the value w_j. In this study, the final parameter set (R) is extracted by the PSO and powerful RLS to determine the proposed fuzzy modeling system.

III. PARAMETERS TUNING STAGE WITH HYBRID PSO AND RLS LEARNING ALGORITHM

The evolution-based PSO with simplified social models was initially proposed by Kenney and Eberhart in 1995 [11]. In the PSO learning cycle, two important values that contain efficient learning factors direct the affected action in a self-heuristic manner. The first global best (*gbest*) value is referred to as the best particle's solution with the highest fitness value.

The second value is referred to as the personal best (*pbest*) and is each particle's best current solution. The learning formula of the proposed PSO was first introduced by [10, 11].

$$V_d^p(t+1) = \tau \cdot V_d^p(t) + \alpha * rand() * (pbest_d^p(t) - \Re_d^p(t)) + \beta * rand() * (gbest_d(t) - \Re_d^p(t)) \tag{9}$$

$$\Re_d^p(t+1) = \Re_d^p(t) + V_d^p(t+1) \tag{10}$$

where d is the number of dimensions (variables), p is the particle number in the population, V is the velocity vector, τ is the inertia factor, and $\Re$ is the particle's position vector, which additionally denotes possible solutions of the generated fuzzy modeling systems. Parameters α and β are the cognitive and social learning rates, respectively. Moreover, they control the relative influence of the memory of the particle and its neighborhood.

After completing the novel DALA, the collected information is used to organize the initial architecture of the fuzzy modeling system; that is, the number of fuzzy rules is determined (centers of the membership functions are sequentially assigned by the selected values). The RPSO learning schemes are suggested to adjust the parameters of the fuzzy modeling system based on the previous initial configuration. The learning stratagem of this RPSO scheme involves using the PSO learning algorithm to regulate the parameters of the fuzzy modeling systems. Thereafter, a valid RLS learning algorithm is performed to recursively modify the parameters of the fuzzy modeling systems to achieve the desired objectives [6-8, 21]. The RLS learning algorithm is used because the outputs of the fuzzy modeling systems are all approximates to those identified by the nonlinear functions (or desired outputs (y^d)). In this study, the outputs of the fuzzy modeling system can be redefined using (8).

$$y = \sum_{i=1}^{m} q_i * \omega_i \tag{11}$$

where q_i are the normalized values of the ith membership functions corresponding to the input vector x and are defined by

$$q_i = \frac{HE_i(x)}{\sum_{i=1}^{m} HE_i(x)} \tag{12}$$

Therefore, (12) can be represented in the matrix form and is described by

$$y = Q\boldsymbol{\omega} \tag{13}$$

where

$$\boldsymbol{\omega} = [\omega_1, \omega_2, \ldots, \omega_m]^{\mathrm{T}} \tag{14}$$

$$Q = [q_1, q_2, \cdots, q_m] \tag{15}$$

The RLS is determined to modify the subsequent parts ($\boldsymbol{\omega}$) of the fuzzy rules to approximate to the desired output (y^d). This RLS algorithm enables calculating the next new $\boldsymbol{\omega}(k+1)$ value on the basis of the training data pairs and current known parameters $\boldsymbol{\omega}(k)$. Let the initial time step be $k = 1$. Thereafter, the new $\boldsymbol{\omega}(k+1)$ is modified using the following recursive learning iterations:

$$\Im(k+1) = \Im(k) - \frac{\Im(k) \cdot Q^T(k+1) \cdot Q(k+1) \cdot \Im(k)}{1 + Q(k+1) \cdot \Im(k) \cdot Q^T(k+1)},\ k = 1, \cdots, N \tag{16}$$

$$\boldsymbol{\omega}(k+1) = \boldsymbol{\omega}(k) + \Im(k+1) \cdot Q^T(k+1) \cdot (y^d(k) - Q(k+1) \cdot \boldsymbol{\omega}(k)),\ k = 1, \cdots, N \tag{17}$$

In this study, the initial value $Q(1)$ = zero (zero = zero vector), and $\Im(1) = \eta I$, η is a positive large number ($\eta = 100$ in this study), N is the number of training data, and I is an $m \times m$ identity matrix. After N iteration calculations using (16) and (17), the consequent portions ($\boldsymbol{\omega}$) of the fuzzy rules are regulated recursively in this RLS algorithm. The root mean square error (*RMSE*) between the fuzzy modeling systems and the desired outputs is determined to evaluate the efficiency of the fuzzy modeling systems in the parameters-tuning stage. The *RMSE* is calculated as follows:

$$RMSE = \left(\frac{1}{N} \sum_{k=1}^{N} \left(y^d(k) - \frac{\sum_{i=1}^{m} HE_i(x(k)) \cdot w_i}{\sum_{i=1}^{m} HE_i(x(k))}\right)^2 \right)^{0.5} \tag{18}$$

In the RPSO parameter learning method, the presented fitness function is *exp*(-*RMSE*); thus, the RPSO is determined to approach the maximal fitness value. The proposed RPSO learning scheme is applied based on the fitness function's direction to select the optimal parameter set from the fuzzy modeling systems to minimize the *RMSE*. The RPSO learning method is described in the following learning steps:

Step (1): Set the number of generations (G) and initialize $g = 0$.

Step (2): The number of membership functions and their associated center values are defined based on the previous novel DALA. Initialize fuzzy modeling systems with a random selection procedure. Each particle begins at its own position with respect to velocity, including its direction and magnitude.

Step (3): Apply the proposed PSO learning method to train

Table 1. Best parameter values of fuzzy modeling system for Example 1.

	$a_{i,1}$	$a_{i,2}$	b_i	w_i
$i = 1$	-0.4926	0.5018	0.2344	-2.2133
$i = 2$	0.5198	0.5024	0.2397	2.4648
$i = 3$	3.0000	0.5411	1.7658	-0.4664
$i = 4$	2.9899	0.5588	17.7463	0.1177

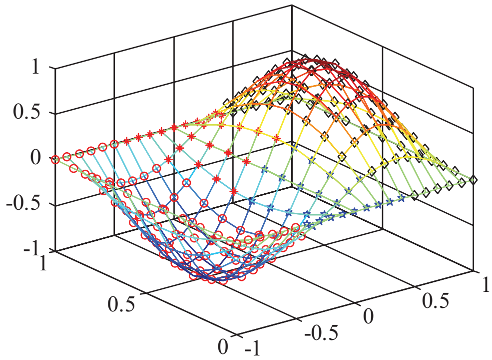

Fig. 4. Distributions of final clustering structure by the novel data acquisition learning algorithm for Example 1.

the initial fuzzy architecture and modify the consequent parts of the selected membership function using the RLS algorithm to derive the near optimal parameters of the fuzzy modeling system.

Step (4): Calculate every particle's fitness value and compare individual evaluation values with the *gbest* and *pbest*. Select the new *gbest* from the entire swarm and *pbest* for every individual particle.

Step (5): Update the velocity and position value for every particle according to (9) and (10).

Step (6): $g = g+1$.

Step (7): If $g = G$, proceed to exit, otherwise proceed to step 3.

Step (8): Desired fuzzy modeling system is generated with the *gbest* parameter set.

IV. ILLUSTRATED SIMULATIONS IN THREE EXAMPLES

Two non-linear approximating function problems and one nonlinear inverted pendulum modeling problem are presented to demonstrate the efficiency of the proposed evolutional learning fuzzy modeling systems. The initial condition setting for the RPSO learning scheme is *pop_size* = 30, G = 150, α=1.2, and β=1.2.

Example 1: Modeling a $\sin(\pi x_1 \cdot \sin(\pi x_2)$ function

In this example, the intelligent fuzzy modeling system is considered for automatically approximating the following nonlinear function [12, 19]:

Table 2. Performance comparisons with different methods for Example 1. The last two rows are from Ref. [12] and Ref. [19].

Methods	No. of fuzzy rules	*RMSE*
DALA + PSO	4	0.1075
DALA + RPSO	4	0.0420
Wong's System [19]	6	0.0648
Lee's System [12]	6	0.0520

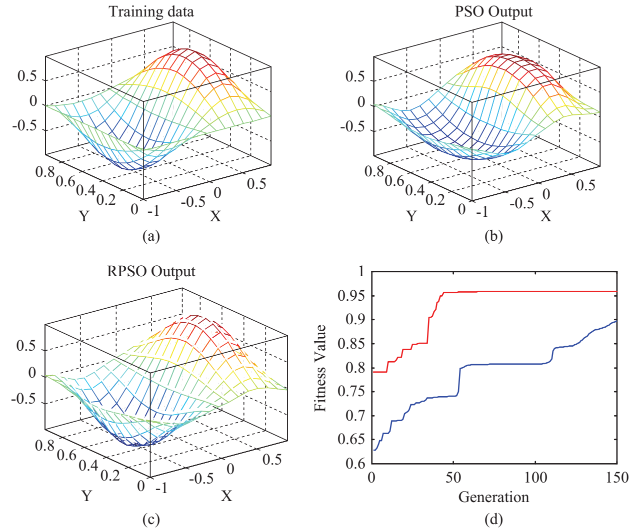

Fig. 5. $\sin(\pi x_1) \cdot \sin(\pi x_2)$ function approximation (a) training data (b) outputs of fuzzy modeling by DALA + PSO (c) outputs of fuzzy modeling by DALA + RPSO (d) fitness value against iteration by DALA + PSO (dashed) and DALA + RPSO (solid).

$$F_1 = \sin(\pi x_1) \cdot \sin(\pi x_2), \tag{19}$$

where 225 pieces of training data are uniformly distributed in the $x_1 \in [-1, 1]$ and $x_2 \in [0, 1]$ range. In the system data acquired and identified step, the novel DALA is applied to determine the required information for constructing the initial architecture of the fuzzy modeling system. Fig. 4 shows the acquired results of the original data point after running the novel DALA. Following the proposed RPSO parameters learning procedure, the parameter set of the selected fuzzy modeling systems are obtained (Table 1). Fig. 5 shows the computer simulations: Fig. 5(a) presents the desired output of the training data, Fig. 5(b) shows the fuzzy modeling system's outputs with the DALA + PSO method, Fig. 5(c) shows the result of the fuzzy modeling using the powerful DALA + RPSO method, and Fig. 5(d) presents the best-of-generation fitness value against the generation number for the DALA + RPSO (solid curve) and DALA + PSO (dashed curve) methods. Computer simulations show that the fitness value of the DALA + RPSO is quickly increased to a high fitness value; thus, the DALA + RPSO learning scheme can swiftly approach the desired outputs. The *RMSE* comparison with other modeling methods is shown in Table 2. A comparison of the

Table 3. Best parameter values of fuzzy modeling system for Example 2.

	$a_{i,1}$	$a_{i,2}$	b_i	w_i
$i = 1$	0.9631	1.1203	3.5931	18.0904
$i = 2$	1.8965	1.8079	0.7631	-1.1996
$i = 3$	3.8680	4.0187	1.4132	7.3583
$i = 4$	3.6193	3.0291	1.3463	3.5426
$i = 5$	5.1000	4.3567	1.1902	1.5096
$i = 6$	3.3063	3.3649	2.1001	-15.9863

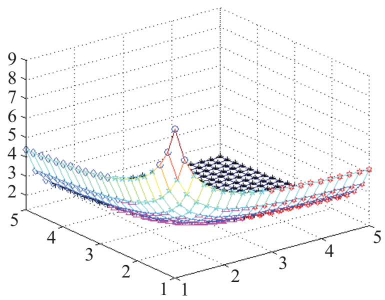

Fig. 6. Distributions of final clustering structure by the novel data acquisition learning algorithm for Example 2.

results indicates that this type of generated fuzzy modeling system's *RMSE* using the DALA + RPSO learning scheme is smaller than that by the DALA + PSO method. This information proves the capability of the proposed DALA + RPSO compared to [13, 19]; it can approximate the unknown function with fewer fuzzy rules and with acceptable accuracy for solving same modeling problem. The constructed DALA + RPSO learning scheme with small membership functions is sufficient for efficiently and automatically generating the desired fuzzy modeling systems.

Example 2: Modeling a two-input nonlinear function

Nonlinear 3D functions are presented as the identifying plant to show the ability of the proposed DALA + RPSO method. The mathematical equation defined by [18] is as follows:

$$F_2 = (1 + x_1^{-2} + x_2^{-1.5})^2 \quad x_1, x_2 \in [1, 5], \tag{20}$$

where 400 collected training data are uniformly distributed in a 3D space, as shown in Fig. 7(a). In the structure-identification stage, the novel DALA is considered for obtaining the characters of the training data and determining the suitable segmentation for generating the initial structure of the fuzzy modeling system. Fig. 6 shows the centers and associated six classified portions of the novel DALA. In the parameter-training procedure, the defined fitness function is presented to *exp*(-*RMSE*). The objective of the proposed learning scheme is to maximize the fitness function value (i.e., minimize the *RMSE* value). The best selected parameters in

Table 4. Performance comparisons with different methods for Example 2.

Methods	No. of fuzzy rules	*RMSE*
DALA + PSO	6	0.6082
DALA + RPSO	6	0.1449
Feng's system [6]	6	0.1481

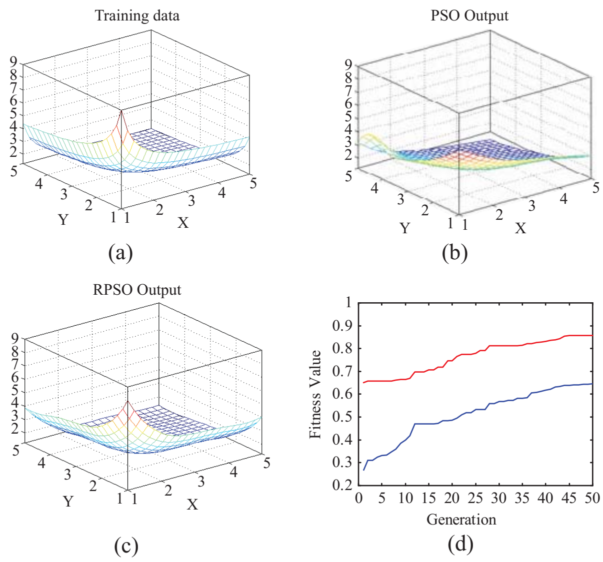

Fig. 7. Function approximation for Example 2, (a) training data (b) outputs of fuzzy modeling by DALA + PSO (c) outputs of fuzzy modeling by DALA + RPSO (d) fitness value against iteration by DALA + PSO (dashed) and DALA + RPSO (solid).

the fuzzy modeling system based on the DALA + RPSO algorithm are shown in Table 3. The simulated modeling results for the two-input nonlinear function by the DALA + PSO and DALA + RPSO learning schemes are shown in Figs. 7(b) and 7(c), respectively. The best-of-generation fitness curve against the generation numbers for the DALA + PSO and DALA + RPSO learning methods is shown in Fig. 7(d). The phenomenon shows that the fitness value of the DALA + RPSO is rapidly approaching a high value. A performance comparison for the two proposed learning schemes and other learning methods are shown in Table 4. We find that the constructed DALA + PSO type fuzzy modeling system with the same fuzzy rules can efficiently approximate the desired surfaces.

Example 3: Nonlinear inverted pendulum function extraction

Controlling an inverted pendulum platform was considered a complex, unstable, and nonlinear problem. The balancing objective in designing a fuzzy modeling system is that it can lead the mounted free-falling pole into a vertical position in a short period by pushing a suitable force on the cart. Let $x_1(t) = \theta$(angle of the pole with respect to the vertical axis) and $x_2(t) = \dot{\theta}$ (angular velocity of the pole). Thereafter, the mathematical equation of the inverted pendulum system is described as follows [9]:

Table 5. Best parameter values of fuzzy modeling system for Example 3.

	$a_{i,1}$	$a_{i,2}$	b_i	w_i
$i = 1$	-0.4929	31.3278	0.1000	0.01
$i = 2$	14.5546	-8.0436	3.4618	44.4943
$i = 3$	32.8267	18.5050	59.9992	25.3495
$i = 4$	-37.6718	-13.8277	26.8835	-79.7197
$i = 5$	49.9816	-35.1988	32.5389	-7.0338
$i = 6$	50.0000	-16.0461	10.4488	23.1600
$i = 7$	21.4449	15.4407	12.8921	53.7205

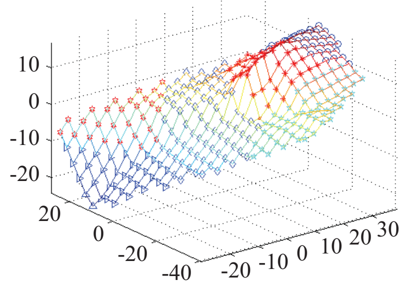

Fig. 8. Distributions of final clustering structure by the novel data acquisition learning algorithm for Example 3.

$$\dot{x}_1 = \dot{\theta} = x_2 \tag{21}$$

$$\dot{x}_2 = H(x_1, x_2, F) = \frac{g \cdot sin(x_1) + cos(x_1)\left(\frac{-F - m \cdot l \cdot x_2^2 sin(x_1)}{m+M}\right)}{l \cdot \left(\frac{4}{3} - \frac{m \cdot cos^2(x_1)}{m+M}\right)} \tag{22}$$

where g (acceleration due to gravity) is 9.8 m/s, M (mass of the car) is 1.0 kg, m (mass of the pole) is 0.1 kg, 1 (is half the length of pole) is 0.5 m, and F is Newton's applied force. To identify the fuzzy modeling system for acquiring the inverted pendulum modeling system's behavior, 400 input-output training data pairs (x_1, x_2, F) were collected from [9], which were successful in balancing the pole to a stable state from several initial conditions. The novel DALA is initially applied in the structure-identification learning stage; it can catch characters of the discussed inverted pendulum training data and regenerate the fuzzy modeling system. It shows the distributed result with its associated seven classified parts in Fig. 8; thus, the decision for configuring the initial architecture of the fuzzy modeling system is completed. The selected fitness function with the defined *exp*(-*RMSE*) formula is manipulated in the proposed DALA + RPSO algorithm. The objective of the proposed learning algorithm in this parameter training procedure is to minimize the *RMSE* value. The best parameters are shown in Table 5. The 3D plot for the training data set (x_1, x_2, F) is shown in Fig. 9(a). The extraction of the results for this inverted pendulum function modeling

Table 6. Performance comparisons with different methods for Example 3.

Model	No. of fuzzy rules	*RMSE*
DALA+ PSO	7	1.2717
DALA + RPSO	7	0.3216

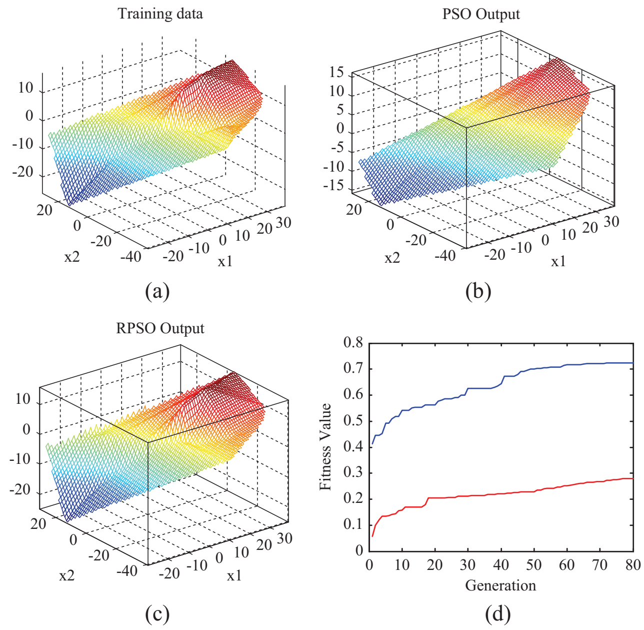

Fig. 9. Inverted pendulum modeling approximation (a) training data (b) outputs of fuzzy modeling by DALA + PSO (c) outputs of fuzzy modeling by DALA + RPSO (d) fitness value against iteration by DALA + PSO (dashed) and DALA + RPSO (solid).

problem by using the DALA + PSO and DALA + RPSO learning scheme are shown in Figs. 9(b) and 9(c), respectively. Fig. 9(d) shows the best-of-generation fitness value against the generation number for DALA + PSO and DALA + RPSO learning methods, respectively. The fitness value for the proposed DALA + RPSO method rapidly increased, which shows the efficiency for solving the nonlinear inverted pendulum modeling problem.

Let e denote the initial angle of the pole and ed the initial angular velocity of the pole in the following simulations. Four various initial control conditions (e = 35 and ed = 20; e = 45 and ed = 20; e = 55 and ed = 20; e = 60 and ed = 20) are applied to demonstrate the strong regulation. Figs. 10(a), 10(b), and 10(c) show the various responses of the pole angle, angle velocity, and input force from time = 0 s to time = 2.5 s, respectively. Fig. 10(d) shows the distributed plots with the related angle and velocity response. The simulated results show the excellent adaptability of the DALA + RPSO algorithm even when the simulated conditions are outside the training bounds [-30, 30].

In the other robust experiment, the extracted fuzzy rules are applied to overcome the sudden and large imported noise at a

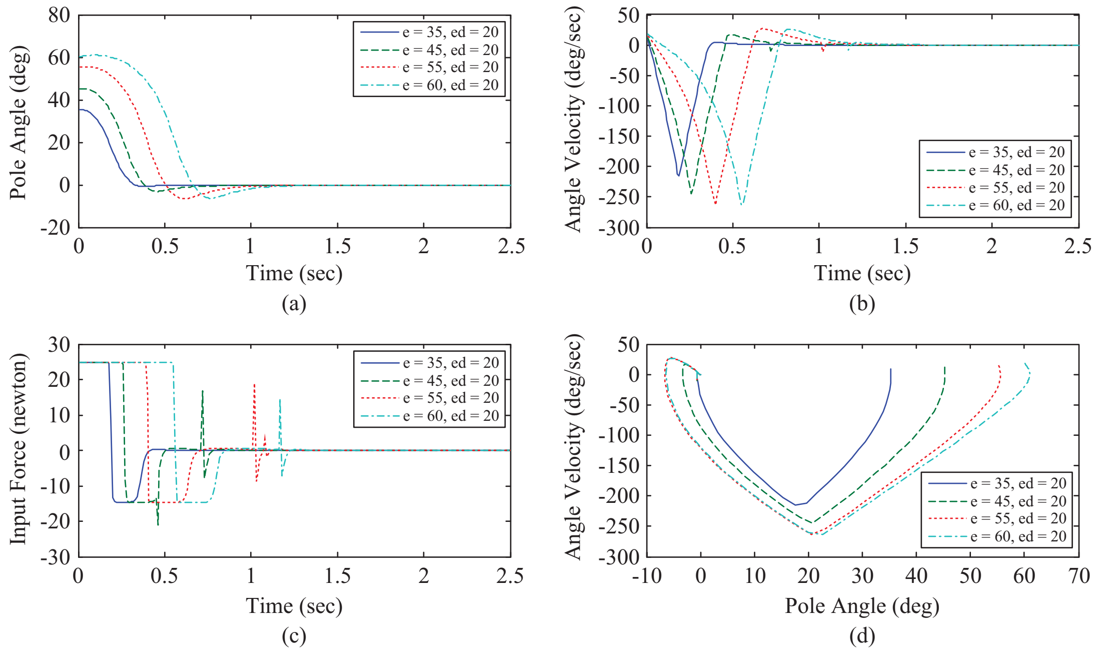

Fig. 10. Multiple runs with the proposed DALA + RPSO method in example 3, (a) pole angles, (b) pole velocities, (c) Forces, and (d) pole angles against pole velocities.

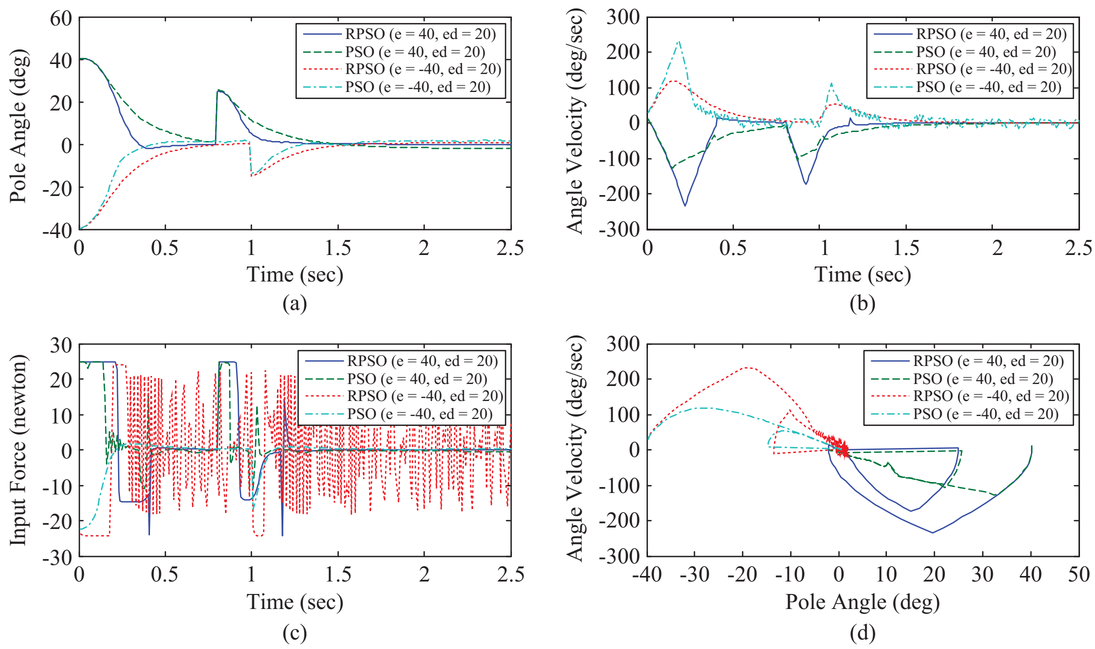

Fig. 11. Simulation results of the proposed method with DALA + RPSO (solid and dotted lines), DALA + PSO (dashed and dashdot lines) type selection in example 3, (a) pole angles, (b) pole velocities, (c) forces, and (d) pole angles against pole velocities.

specific system time. For sudden simulations, we add the positive values for the pole angle (25) and angle velocity (5) at system time 0.8 s. For the other large noise conditions, we provide negative values to the pole angle (-15) and angle velocity (5) at system time 1.0 s. Figs. 11(a), 11(b), and 11(c) show the various responses of the pole angle, angle velocity, and input force from time = 0 s to time = 2.5 s, respectively. Fig. 11(d) shows the distributed plots with the related angle and velocity response. The graphics of the solid and dashed lines are separately described for the different responses of the DALA + RPSO and DALA + PSO learning algorithm at the positive sudden condition. For the other negative initial conditions, the DALA + RPSO and DALA + PSO responses are illustrated by the dotted and dash-dotted lines, respectively.

Table 7. Performance comparisons of the proposed DALA + RPSO and DALA + PSO methods in example 3.

Cases \ Performances		*RT*	*Max-OV*	*RMSE*
Positive sudden noise	DALA + RPSO	0.2800	2.0799	5.0878
	DALA + PSO	0.4500	2.1322	7.7845
Negative sudden noise	DALA + RPSO	0.2500	1.8918	4.3907
	DALA + PSO	0.4000	0.8358	5.5962

The performance comparison of the proposed DALA + RPSO and DALA + PSO methods are shown in Table 7. The *RT* represents the rise time, *Max-OV* denotes the maximal overshoot, and *RMSE* is the root means square errors.

These results indicate that the select fuzzy control system using the proposed method can achieve an excellent response in recovering the big change. The performances show that the DALA + RPSO-based learning algorithm can have a shorter rise time, smaller maximal overshot, and smaller root means square errors than the DALA + PSO-based learning method.

V. CONCLUSION

In this study, the constructed dynamic acquisition learning schemes are suggested to automatically, quickly, and efficiently design an optimal fuzzy modeling system. Several known disadvantages of the traditional FCM clustering algorithm or its variants, such as requiring clusters numbers in advance and local optimal problems, can be overcome using the novel DALA. The DALA is applied to address the drawbacks of the FCM clustering algorithm. Our experiments show accurate data acquiring results and its efficient ability in recovering the behavior of this training data set. Useful data acquiring information is applied to form the initial fuzzy modeling framework. Moreover, computer simulations have established that the generating information of the discussed modeling data set is correct and suitable for assigning the initial architecture of the fuzzy modeling system.

After the initial configuration of the fuzzy modeling system, the RPSO learning algorithm (containing the PSO global learning ability and RLS fast recurrent approximating method) is applied to achieve the desired outputs. Three nonlinear approximation modeling problems are considered to show the efficiency of the proposed RPSO learning algorithm. The simulations show that only a small number of fuzzy rules are necessary for solving nonlinear modeling problems. The generated fuzzy control rules can yield the character of the nonlinear car-pole balance system for the quick recovery of the unexpected imbalance states.

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