

The saved water chamber pot system bases on the extenics-based fuzzy model

Hung-Jin Chen

Department of Information and Computer Science Engineering

De Lin Institute of Technology

Taipei, Taiwan, 236, R.O.C.

hjchen@dlit.edu.tw

Abstract- This article involved the grey relational analysis in Grey theory and integrating Extenics into Fuzzy theory, in order to fast modeling and anti-noise function. After involving the extension theory and calculating the active membership degree with traditional methods at known datum, then investigating the double sides of the corresponding membership function can be adjusted in order to matter element transformation in extension thinking. That meaning is the membership degree extend from $[0,1]$ to $[-1,1]$ and create the corresponding extended correlation function extending from traditional classic membership function. During the extension region adjusting, we can retard the mutual interference in tuning membership functions dynamically. Thereby, the problem of learning cure too long can be terminated and expedite the parameters tuning process, inference speed and slow down the system error outputs. Besides, To verify the feasibility of the proposal extended fuzzy inference system, we realize the model to "the saved water chamber pot" in order to control the water of flush time and muddy degree, expecting there is a precision time in flush time and reaching the purpose of saving water.

Keyword: matter element, neuro network, fuzzy model, grey relational analysis, extended correlation function, extension theory.

1. Introduction

The slow learning rate is a main problem in the intelligence control system and can't be satisfied the requirement of the real time control system in fast and time-variant system. Hence, how to develop the practical controller with the specifications with fast modeling, fast inferring, fast converge and provided with learning capability are urgent in intelligence control system. Recently, grey system using it's less data modeling characteristic, can compensate statistical theory's defects that needs loss of data. To obtain a satisfactory fuzzy model, some systematic methods which can adjust the model were proposed [1-2]. In order to solve the incompatible or contradictory problems, Cai [3] created the formal concept of extension set which extends the logic

value from $[0,1]$ to $(-\infty,+\infty)$. This allows us to define a set which includes any data in the domain. In other words, the membership degree extend from $[0,1]$ to $[-1,1]$ and create the corresponding extended correlation function extending from traditional classic membership function. To distinguish the classical set from the extended set depends on how we define the extended relational function. For present, water resource saving and utilize become a new issue, for verifying the proposal model, the "saved water chamber pot flushing system" is implemented to response this issue.

2. The extenics-based fuzzy model

In this proposal, we consider how to integrate the extension theory into the well-known fuzzy inference. The extension theory, first proposed by Cai in 1983, solves the contradiction and incompatible problems [1]. The range of the extension set is $[-\infty, \infty]$ which differs from the fuzzy set in $[0,1]$. This means that an element belongs to any extension set with different degree. Define the extended relational function by $k(x)$ to represent the degree of an element belonging to a set. A degree between zero and one, i.e., $0 \leq k(x) \leq 1$, corresponds to the normal fuzzy set. $k(x) \leq -1$ implies that the element x is hard to belong to the set.

When $-1 < k(x) < 0$, this means that the element

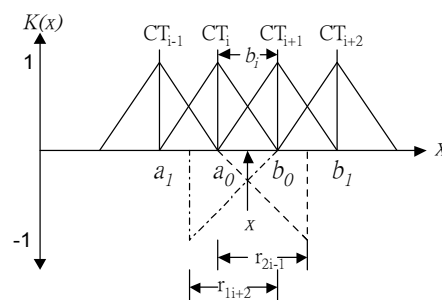


Fig. 1. The extended membership function.

X still has a chance to be included into the set if the set was adjusted. Thus, the extension set theory focuses on the subset with range between -1 and zero.

Assuming the isosceles membership functions with 50% overlap with their neighbors are used. Since a triangular membership function is characterized by its center and base, both the center and base of the triangle are adjusted in our current model. Based on the extended theory and from Fig. 1, we can define the matter element as follows:

$$R_c = \left[\begin{array}{l} x, C_1, < CT_i - b_i, CT_i + b_i > \\ , C_2, < CT_{i+1} - b_{i+1}, CT_{i+1} + b_{i+1} > \end{array} \right]$$

$$R_e = \left[\begin{array}{l} x, C_3, < CT_{i-1} + b_{i-1}, CT_{i-1} + b_{i-1} + r_{2i-1} > \\ , C_4, < CT_{i+2} - b_{i+2} - r_{i+2}, CT_{i+2} - b_{i+2} > \end{array} \right] \quad (1)$$

where R_c and R_e are the normal (or classical) set and extended set, respectively.

We can derive the correlation functions for each region depicted in Fig. 1. From Fig. 1, a datum fallen into the left extended set, C_3 region, will have a relational degree as follows:

$$k_{i-1j}(x) = \frac{c_{i-1j} + b_{i-1j} - x_j}{r_{2i-1j}} \quad (2)$$

In the above equation, c_{i-1} , b_{i-1} , and r_{2i-1} are the center, half base, and left extended width of the i -1th membership function, respectively. Similarly, a datum in the right extended set, C_4 region, will result in a relational degree as follows:

$$k_{i+2j}(x) = \frac{x_j - c_{i+2j} + b_{i+2j}}{r_{i+2j}} \quad (3)$$

For datum located in the classical fuzzy set, C_1 region, the relational degrees can be defined as follows:

$$k_{ij}(x_j) = \frac{c_{ij} + b_{ij} - x_j}{b_{ij}} \quad (4)$$

Similarly, the relational degree of C_2 region can be written as follows:

$$k_{i+1j}(x_j) = \frac{x - c_{i+1j} + b_{i+1j}}{b_{i+1j}} \quad (5)$$

For the fuzzy rules with singleton-type w_i in the consequents, the inferred output is obtained as follows:

$$y_c = \left(\sum_{j=i-1}^{i+2} k_j(x)w_j \right) / \sum_{j=i-1}^{i+2} |k_j(x)| \quad (6)$$

Note that the denominator in Eq.(6) differs from the conventional method in that the absolute value is considered. Since the correlation degree is negative in the extended region, taking the absolute value can prevent the denominator from becoming zero. Denote the desired output for a pattern by y_d . The error function is defined as follows:

$$E = \frac{1}{2} (y_c - y_d)^2 \quad (7)$$

We can use the gradient descent method [3-5] to adjust the related paramters.

The new value for the to-be-adjusted parameter in the next step is then defined as follows:

$$p(t+1) = p(t) - k_p \frac{\partial E}{\partial p} \quad (8)$$

where k_p is the learning rate.

3. Simulation and realized

After defining the extended relational functions and using the gradient descent method to refine the system parameters, the next step is to verify the effectiveness of the presented model. Assuming the isosceles triangular membership functions are used in the underlying simulations. The following fifth-order polynomial function [6] is used as the model for the single-input-single-output case.

$$y = 3x(x-1)(x-1.9)(x+0.7)(x+1.8),$$

$$-1.5 \leq x \leq 0.5.$$

When 201 sample data are generated from upper equation, Fig. 2 plots the simulation results from the proposed extended fuzzy inference model. Under the same initial conditions, Fig. 4 shows the simulation results from 5000 iterations. We also perform the simulation when the consequent part of fuzzy rule is replaced by the linear combination of the inputs. Table 1 compares the results from different iterations with singleton and linear fuzzy rules.

Table 1. The MSE from different cases for the fifth-order function

Type\No.	1,000	2,000	3,000	4,000	5,000
Singleton	0.010213	0.008422	0.005377	0.031291	0.004538
Linear	0.015850	0.008883	0.005659	0.003211	0.004307

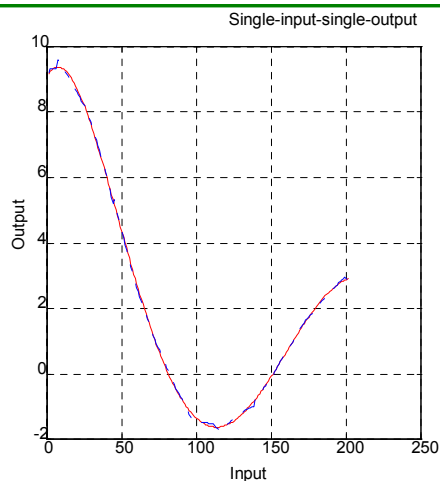


Fig. 2(a). The simulation result for the fifth-order function. The average error is 0.052182 and the final MSE value is 0.004538. The results are from 5000 iterations.

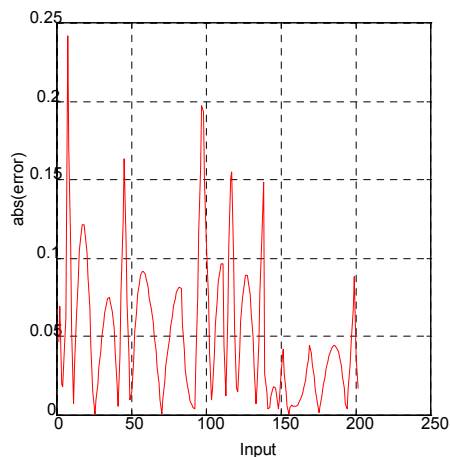


Fig. 2(b). The absolute error for each sample point for the fifth-order function. The results are from 5000 iterations.

To verify the proposed model, “the fuzzy water saving flushing system” is realized by using 89C51 C language to construct extenics-based fuzzy control’s kernel parts — fuzzified, rule base, fuzzy inference, and defuzzication. All the model theories are programmed, compiled and saved in CPU chip, and can be connected directly to PC for fuzzy variables adjusting. The block diagram of electronically hardware is shown in Figure 4 and consists of 11 parts. And, the perspective of stool is illustrated in Figure 5.

As we know, the stool’s quantity and the water’s dirty degree in stool decide the quantity of water to be used for flushing. Namely, those effective parameters can be translated to optical signal which be read into 89C51 to active fuzzy mapping, then to construct extenics-based fuzzy inference in order to decide the flushing time. The following steps are the key skills to construct the fuzzy works.

1) Decide the physical input signal: The flush system has several input variables, such as the quantity of droppings in the bowl seat, water dirty degree, outlet pipe size and U-type pipe shape, etc.. Which one parameter is correlation with the optimal flush time can be measurement by grey relation analysis with Grey system’s theory. After several times experiment, we found the correlation between quantity of droppings in the bowl seat, i.e. the transparency rate, and flash time are superior than others. Hence, we use the physical signal of droppings quantity or water dirty degree’s to translate into digital signal by the electronic photon diode in order to active the input membership function.

2) Fuzzified the input signals: This function utilize the system measurement and translate to it’s membership function. A ladder-shaped membership function as Figure. 5 is used. For example, when the transparency rate is low, it means some droppings block the light. We can use (0,0,64,128) to describe this membership’s degree. We adapt two sets of

photon sensitive element to average the transparency rate and its membership function show on the Figure.5’s left hand side and upper side.

3) Rule base: This function is derived from expert experience or by training samples. And the general forms of fuzzy rule can be expressed as follow:

R_i : If x_1 is A_{i1} and x_2 is A_{i2} and... x_n is A_{in} , then y is w_i

There are 3 labels in each input signal and 2 input signals are adapted in this flush system. Hence, 9 rules are list as follow and Figure 6 depicts the rule base map.

R_1 : If x_1 ’s is little and x_2 ’s is little then flush 9 sec.

...

R_9 :If x_1 ’s much and x_2 ’s is much then flush 5 sec.

Where little is meaning the light is blocked very much, i.e. the transparency rate is low. Contrarily, the transparency rate is high.

4) Extenics-based fuzzy inference: This function is base on max-min or similar infer to simulate human thinking for decision making. The inference output is

termed as $k_i = \prod_{j=1}^n A_{ij}(x_j)$.

5) Defuzzication. The center of gravity defuzzication as Eq.(6) is acted as the flush time for controlling the closing water tank. The conclusion part of fuzzy rule is a singleton style that can be described in bottom side of Figure 6.

4. Conclusion

In this proposal, we focused on the fast modeling, fast inferring and fast converge issues. The fast modeling can be made by Grey theory and fast inferring mechanism can be approached by integrating Extenics into Fuzzy theory to retard the mutual interference in tuning membership functions dynamically. To evidence the proposal model can be work well, the “saved water chamber pot flushing system” based on extenics-based fuzzy model is implemented.

Acknowledgment

This work was supported by the National Science Council, Taiwan, ROC, under Grant NSC92-2213-E-237-001.

References

- [1] K. Nozaki, H. Ishibuchi, and H. Tanaka, “A simple but powerful heuristic method for generating fuzzy rules from numerical data,” *Fuzzy Sets and Systems*, vol. 86, pp.251-270, 1997.
- [2] M. Sugeno and T. Yasukawa, “A fuzzy-logic-based approach to qualitative modeling,” *IEEE Trans. Fuzzy Systems*, vol. 1, no. 1, pp.7-31, 1993.

- [3] W. Cai, "The extension set and noncompatible problem," *J. of Scientific Exploration*, vol. 1, pp.81-93, 1983.
- [4] M. Sugeno and T. Yasukawa, A fuzzy-logic-based approach to qualitative modeling, *IEEE Trans. Fuzzy Systems* 1(1) (1993) 7-31.
- [5] M. Sugeno and T. Yasukawa, A fuzzy-logic-based approach to qualitative modeling, *IEEE Trans. Fuzzy Systems* 1(1) (1993) 7-31.
- [6] J.A. Dickerson and B. Kosko, "Fuzzy function approximation with ellipsoidal rules," *IEEE Trans. Systems, Man, and Cybernet. part B: Cybernetics*, vol. 26, no.

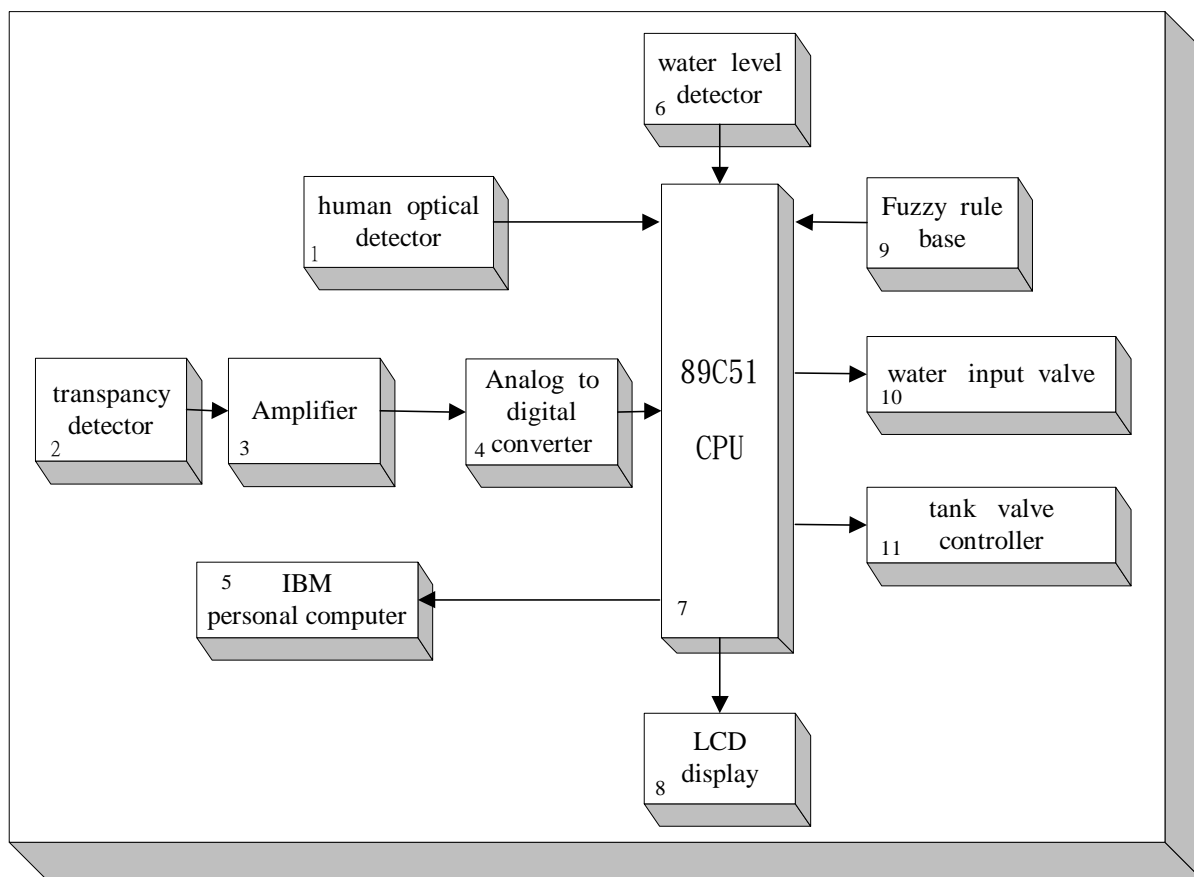


Figure 4 The block diagram of system hardware

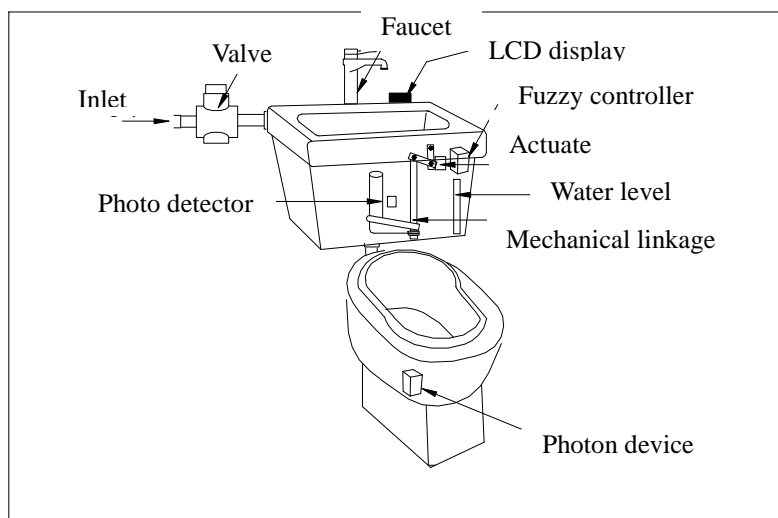


Figure 5 The perspective of stool

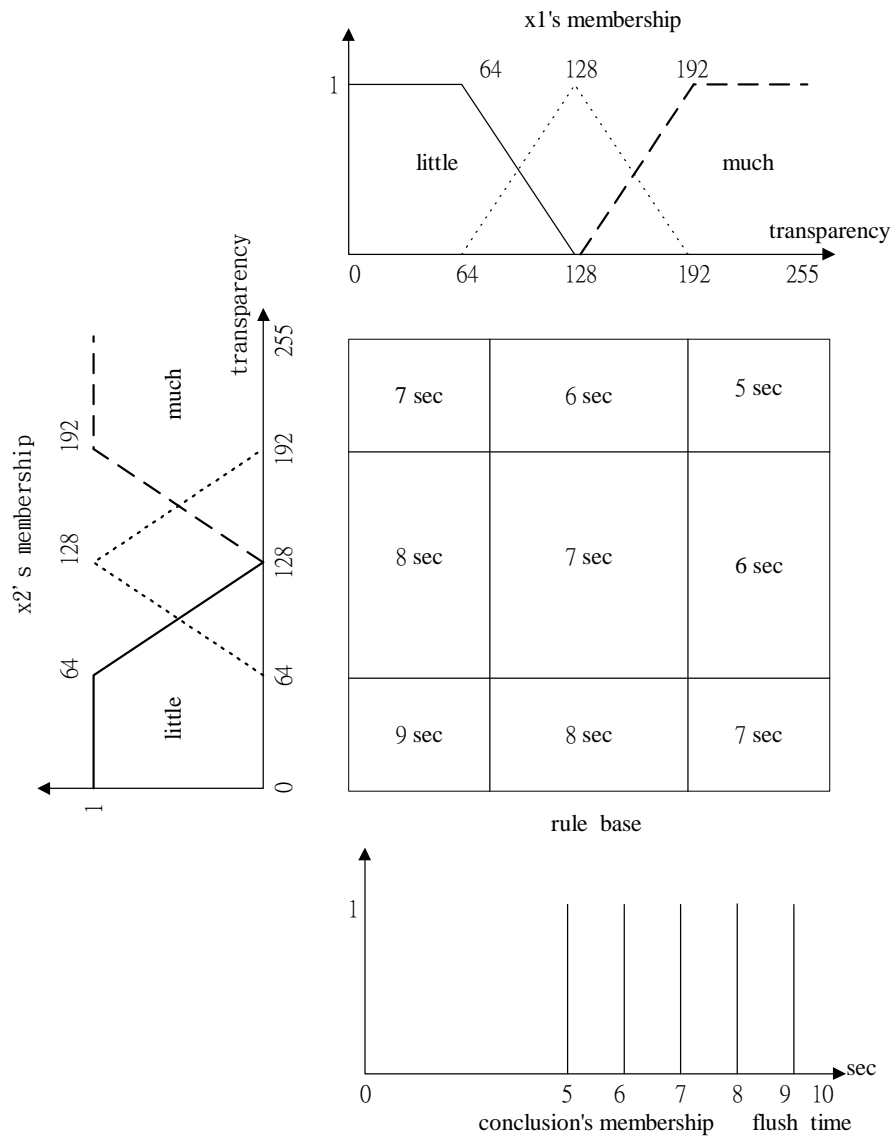


Figure. 6 The inference rules map of “saved water chamber pot”