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Universal Learning Network-based Fuzzy Control

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Abstracts In this paper we present a method to construct fuzzy model with multi-dimension input membership function, which can construct fuzzy inference system on one node of the network directly. This method comes from a common framework called Universal Learning Network (ULN). The fuzzy model under the framework of ULN is called Universal Learning Network-based Fuzzy Inference System (ULNFIS), which possesses certain advantages over other networks such as neural network. We also introduce how to imitate a real system with ULN and a control scheme using ULNFIS.

Keywords ULN, ULNFIS, switch matrix, internal bus, external bus.

1 Introduction

In 1965, Zadeh published the first paper on a novel way of characterizing non-probabilistic uncertainties, which he called " fuzzy set ". The fuzzy logic and fuzzy set theory has now evolved into a fruitful area containing various disciplines, such as calculus of fuzzy if-then rules, fuzzy graphs, fuzzy interpolation, fuzzy topology, fuzzy reasoning, fuzzy inference system, and fuzzy modeling. The applications, which are multi-disciplinary in nature, include automatic control, consumer electronic, database management, computer vision, data classification, decision-making, and so on.

Recently, the resurgence of interest in the field of artificial neural network has injected a new driving force into research field of fuzzy system. The back-propagation learning rule, which drew little attention till its application to artificial neural networks was discovered, is an universal learning paradigm for any smooth parameterized model, including fuzzy inference system. As a result, a fuzzy inference system can now not only take linguistic information from human experts, but also adapt itself using numerical data to achieve better performance. This gives fuzzy inference systems an edge over neural networks, which cannot take linguistic information directly.

In general most multi-input and single output fuzzy models are constructed in feed-forward structure, and the input membership function is built on one dimension. In this paper, we proposed on a novel way to formalize a fuzzy inference system based on universal learning network (ULN), which we called universal learning network-based fuzzy inference system(ULNFIS).

As a case study, we also built a tentative control system which consist of two components: One is called non-linear crane system which is modeled by ULN, and the other is a controller which is realized by ULNFIS. According to the simulation results we can conclude that our method is useful and promising one.

2 Universal Learning Network

2.1 *Basic structure of Universal Learning Networks*

As the name implies, Universal Learning Network is a kind of network structure which comes from full recurrent structure. We can use it as a common tool in modeling and control of large-scale complicated system such as economic, social and living system as well as industrial plants.

The configuration of the ULN is shown in Fig.1. This is the ULN with three nodes. There are two kinds of signal buses, one is internal signal bus that the inside signal of the network flow along, and the other is external signal bus that the outside signal of the network flow along. Each node has multi-input branches with switch unit, which are connected with the two kinds of bus, and one output branch with arbitrary time delay unit which is connected with internal signal bus. The switch unit has two state value of 1 or 0, which represents the connected state of the branch by on or off.

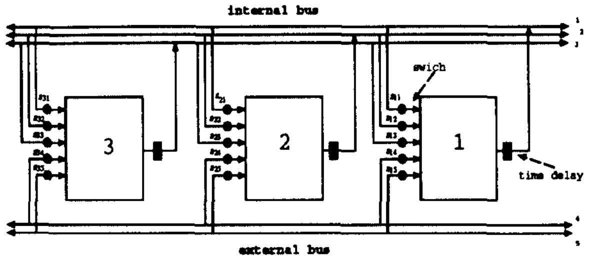

Fig.1 structure of ULN

For a ULN which has J nodes, the numbers of internal signal bus line is J and the numbr of external signal bus line is R, which is constant. Each switch can be labeled by using two parameters, one is the number of node, the other is the number of bus line where the internal signal bus line and external signal bus lines are numbered serially. We can construct a matrix SW(n,m) using switch state s_{ij}.
where

$$n = 1, 2, ..., J; m = 1, 2, ..., J, J + 1, ...J + R$$

The matrix element SW(n,m) whose value is 1 or 0 represents the state on or off of the switch which is connected with node n and signal bus line m. This also shows whether the node n is connected with signal bus line m directly or is cut off. It is obviously, by changing J and state value s_{ij} of the matrix SW(n,m), we can obtain any network structure including feed-forward structure and recurrent one.
In general, each node of ULN can be equipped with a linear or non-linear function with modifiable parameters; by changing these parameters, we can actually change the node function as well as the overall behavior of the ULN.

2.2 *The first order derivatives computation of ULN*

In this section, we introduce the learning rule of ULN which requires calculating first order derivatives (Gradient) of criterion function with respect to parameter variables. In the ULN, the signal on the external bus line is defined as the output of node and the number of the node is the number of the external bus line. For explaining simply, we suppose the nodes of the network have the same time delay D. The output of every node can be expressed by Eq (1)

$$\begin{aligned} h(i,t) &= O_i(\{s_{i1}h(1,t-D), s_{i2}h(2,t-D), \dots, \\ &\quad s_{im}h(m,t-D)\}, \{s_{i1}\lambda_{i1}, s_{i2}\lambda_{i2}, \dots, \\ &\quad s_{im}\lambda_{im}\}) \end{aligned} \tag{1}$$

The O_i represents the function of node i which can be linear or non-linear one, $h(i,t)$ is the value of i node at time t, the λ_{ij} is modifiable parameter of node i which is related to bus line j, and the criterion function is written by Eq. (2):

$$E = e(\{h(i,t)\}, \{\lambda_{ij}\}) \tag{2}$$

First order derivatives of E with respect to parameter λ_{ij} can be written in the form of Eq.(3) and (4).

$$\frac{dE}{d\lambda_{ij}} = \sum_{t\in T} s_{ij}\frac{dh(i,t)}{d\lambda_{ij}}\delta(i,j) + \frac{\partial E}{\partial \lambda_{ij}} \tag{3}$$

$$\delta(i,t) = \sum_{j\in m}\left[s_{ji}\frac{\partial h(j,t+D)}{\partial h(i,t)}\delta(j,t+D)\right] + \frac{\partial E}{\partial h(i,t)} \tag{4}$$

Initial value of $\delta(i,s) = \frac{\partial E}{\partial h(i,s)}$, where s is final evaluation time
Through the introduction of this section, we can understand that ULN is a fundmental tool. It can model real system in nature (in this paper we modeled non-linear crane system by ULN), if the system's function is known. Because of the learning rule coming from the network structure mentioned above , the algorithm is applied to any other network structure.
On the other hand, the ULN can calculate not only first order derivatives, but also n-th order derivatives.

3 Fuzzy Models

The fuzzy inference system is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It has been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision.
The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules, a database or dictionary, which defines the membership function used in the fuzzy rules, and reasoning machanism, which performs the inference procedure upon the rules and given condition to derive a reasonable output or conclusion.
There are three types of commonly used fuzzy inference system: Mamdani fuzzy model, Sugeno fuzzy model, and Tsukamoto fuzzy model. In this paper we adopt Mamdani fuzzy model, whose input membership function is constructed in multi-dimension such as in Eq.(5), the output membership function in Eq.(6), and the output is presented in Eq.(7). In this way we can also change the input membership function of other fuzzy model into multi-dimension.

$$F(i,g,t) = e^{-\frac{1}{2}\left(\sum_{j=1}^{m}\left[\frac{h(j,t)-c(i,g,j)}{\phi(i,g,j)}\right]^2\right)} \quad (5)$$

$$f(j,g,t) = e^{-\frac{1}{2}\left[\frac{h(i,t-D)-C(i,g)}{\Phi}\right]^2} \quad (6)$$

$$h(i,t) = \frac{\sum_{g\in G(i)} F(i,g,t-D)C(i,g)}{\sum_{g\in G(i)} F(i,g,t-D)} \quad (7)$$

where g is the number of rule, i is the number of node, c(i,g,j) is the center of input membership function along j axis, C(i,g) is the center of output membership function, $\phi(i,g,j)$ is the width of input membership function along j axis, Φ is the width of output membership function.

For simplicity, we give the fuzzy model of one input x and one output y with two fuzzy rules. Fig.2 is an illustration of how a two-rule fuzzy inference system of this model derives the overall output y when subjected to crisp input x.

In the fuzzy inference system, the resulting fuzzy reasoning is shown in Fig.2, where the inferred output of each fuzzy rule set is scaled down by the firing strength via the algebraic product. Since input membership function of our model is constructed in multi-dimension, we can obtain the firing strength directly without using other calculation as product or max. Here we remind that the fuzzy model could use two fuzzy rules or more.

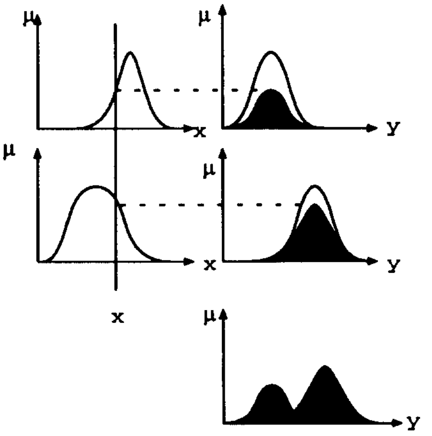

Fig.2 Fuzzy reasoning for two rules

Because the input membership function is constructed in multi-dimension, we can equip it into one node of the ULN (Eq.7), and the method is available to not only other fuzzy model but also the radial basis function.

This fuzzy model is convenient to adjusting the numbers of rules, so in numerical applications we can reduce the numbers of rules to reduce the parameters as few as possible. On other hand we can also adjust the element value of switch matrix to reduce the parameters of input membership function.

4 non-linear crane system modeling

In our simulation there is a non-linear crane system (Fig.3). It has three sub-system: a lift system (Eq.10), a swing system (Eq.9), and a horizontal moving system (Eq.8).

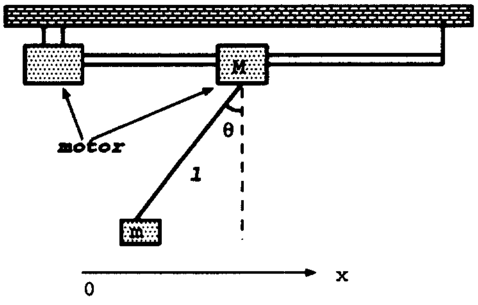

Fig.3 Non-linear crane system

$$\frac{d^2x}{dt^2} = -\frac{mg}{M}\theta - \frac{D+G}{M}\frac{dx}{dt} + \frac{g}{M}u_d \quad (8)$$

$$\frac{d^2\theta}{dt^2} = -\frac{M+m}{lM}g\theta - \frac{D+G}{lM}\frac{dx}{dt} + \frac{G}{lM}u_d \quad (9)$$

$$\frac{d^2l}{dt^2} = -\frac{C+G_m}{m}\frac{dl}{dt} + \frac{G_m}{m}u_m \quad (10)$$

Assuming that $h(J+1,t) = x(t), h(J+2,t) = \dot{x}(t)$, $h(J+3,t) = \theta(t), h(J+4,t) = \dot{\theta}(t), h(J+5,t) = l(t)$, $h(J+6,t) = \dot{l}(t)$, and the time delay of the system as D, the following difference equations are derived.

$$h(J+1,t) = a_{11}h(J+1,\hat{t}) + a_{21}h(J+2,\hat{t}) \quad (11)$$

$$h(J+2,t) = a_{22}h(J+2,\hat{t}) + a_{32}h(J+3,\hat{t}) + b_1u_d(\hat{t}) \quad (12)$$

$$h(J+3,t) = a_{33}h(J+3,\hat{t}) + a_{43}h(J+4,\hat{t}) \quad (13)$$

$$h(J+4,t) = \frac{a_{24}}{h(J+5,\hat{t})}h(J+2,\hat{t}) + \frac{a_{34}}{h(J+5,\hat{t})}h(J+3,\hat{t}) + a_{44}h(J+4,\hat{t}) + \frac{b_1}{h(J+5,\hat{t})}u_d(\hat{t}) \quad (14)$$

$$h(J+5,t) = a_{55}h(J+5,\hat{t}) + a_{65}h(J+6,\hat{t}) \quad (15)$$

$$h(J+6,t) = a_{66}h(J+6,\hat{t}) + b_2u_m(\hat{t}) \quad (16)$$

$$\hat{t} = t - D$$

Using the equations we can easily obtain the model of the crane system by ULN.

The ability of modeling real system by ULN provide us useful tool in modeling and controlling large scale complicated system such as economic, social and life phenomena.

Fig.4 is an illustration of the system structure of our simulation system which consists of two components: non-linear crane system mentioned above, and controller with two nodes which are equipped with fuzzy inference system of two if-then rules.

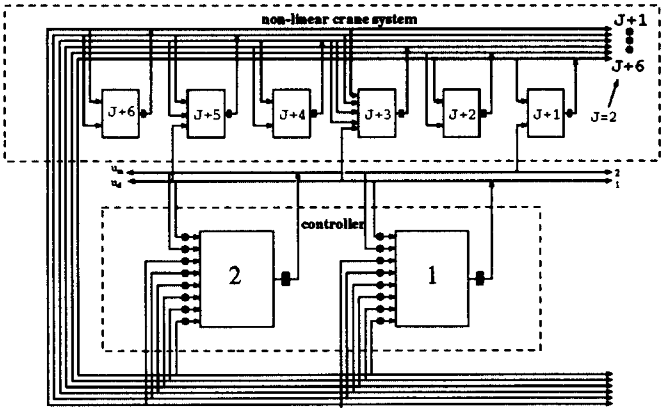

Fig.4 The structure of non-linear crane control system

5 simulation results

Here, we only provide one of the simulation results shown in Fig.5, and Fig.6. These are 6 external inputs structure of $x(t), \dot{x}(t), l(t), \dot{l}(t), \theta(t), \dot{\theta}(t)$, and the controller structure is full recurrent one as shown in Fig.4. The parameters in our system are given by random variable (0,1).The arbitrary time delay is assigned to 1.

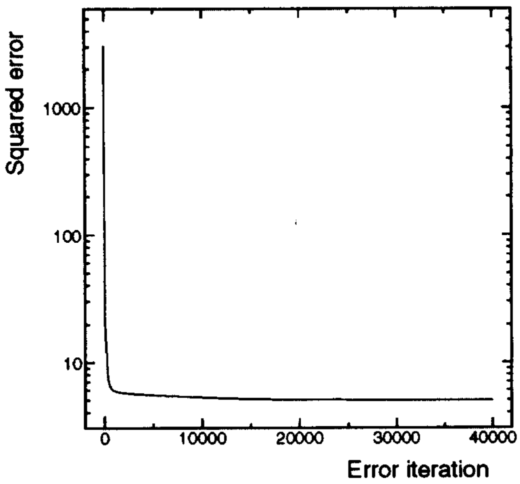

Fig.5 Learning error for crane system

By changing switch matrix, we also performed the task in another controller structure. One is non-recurrent controller with the same inputs mentioned before, another simultions are for full recurrent structure and non-recurrent controller, which have the external input $x(t), l(t), \dot{\theta}(t)$. All of the results are satisfactory.

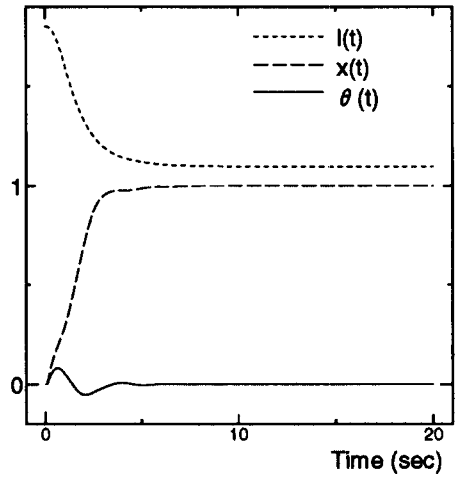

Fig.6 The output of crane system

In our simulations, the goal value of the task is to set $x(t)$ from 0 m to 1.0 m and $l(t)$ from 1.8 m to 1.1 m. we expect the value of $\theta(t)$ as small as possible, so our criterion function is described by Eq.(17)

$$
\begin{aligned}
E &= \frac{1}{2}\sum_{t=0}^{T}[Q_1(1.1 - l(t))^2 + Q_2(1.0 - x(t))^2 \\
&\quad + Q_3\theta^2(t) + Q_4\dot{l}^2(t) + Q_5\dot{x}^2(t) + Q_6\dot{\theta}^2(t) \\
&\quad + Q_7u_m^2(t) + Q_8u_d^2(t)] \qquad (17)
\end{aligned}
$$

where the Q_i is coefficient of criterion function.

6 conclusions

In this paper we proposed a fuzzy model which is based on Universal Learning Network and results of simulation for non-linear crane system are given. Since the ULN has switch matrix and the node including external one is numbered serially, we can obtain any kind of network structure. This feature is useful for further research of structure determination.

References

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