적응 뉴로-퍼지 제어기를 이용한 회전역진자 시스템의 제어

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A Study on Adaptive Membership Function For Fuzzy Inference System

Abstract

In this paper, a new adaptive neuro-fuzzy control(ANFC) system using neural network based fuzzy reasoning is proposed to make a fuzzy logic control system more adaptive and more effective. In most cases, the design of a fuzzy inference system relies on the method in which an expert or a skilled human operator would works in that special domain. However, if he has not expert knowledge in any nonlinear environment, it is difficult to control in order to optimize. Thus, the proposed adaptive structure for the fuzzy reasoning system can be controlled more adaptive and more effective in nonlinear environment for changing input membership functions and output membership functions. ANFC can be adapted a proper membership function for nonlinear plant, based upon a minimum number of rules and an initial approximate membership function. Rotary inverted pendulum system is simulated to demonstrate the efficiency of the proposed ANFC.

Ⅰ. Introduction

Fuzzy theory was initiated by Lotfi A. Zadeh in 1965 with his seminal paper *"Fuzzy Sets"*. Fuzzy inference systems have been successfully applied in various areas for intelligent control to expert system [2][9][10].

In most cases, the design of a fuzzy inference system relies on the method in

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which an expert or a skilled human operator would operate in that special domain [9][10]. However, if he has not expert knowledge for any nonlinear environment, it is difficult to control in order to optimize. Thus, using the pro- posed adaptive structure for the fuzzy inference system can be controlled more adaptive and more effective in nonlinear environment for changing input member- ship functions and output membership functions. Several algorithms of adaptive fuzzy membership functions have been proposed in [2]-[6].

With rapid development of techniques for neural networks and fuzzy logic systems, the neuro-fuzzy systems are attracting more and more interest since they are more efficient and more powerful than either neural networks or fuzzy logic system [2][9]-[12]. Many effective learning algorithm of neuro-fuzzy systems were developed and many structure of neuro- fuzzy systems were proposed. For exam- ple, Wang's several adaptive fuzzy systems [2], Jang's adaptive network based fuzzy inference systems(ANFIS) [3], Lin's neural networks based fuzzy logic control and decision system [6], etc.

In the application aspect, neuro-fuzzy systems have been widely used in control system, intelligent robot, pattern recog- nition, consumer products, medicine, expert systems, fuzzy mathematics, information retrieval, etc.

This paper is organized as follows.

In section Ⅱ, we propose a new adaptive neuro-fuzzy controller(ANFC) for the structure, operations, and learning algorithm.

We compare the proposed ANFC with the conventional fuzzy inference systems through simulation results in section Ⅲ. Rotary inverted pendulum control system is simulated to demonstrate the efficiency of the proposed ANFC. The conclusions and further works are given in section Ⅳ.

Ⅱ. Learning Algorithm of Adaptive Neuro-Fuzzy Control System

This section represents the structure and learning algorithm of the adaptive network which is fact a superset of all kinds of feedfoward neural networks with supervised learning capability [4]-[8]. An adaptive network is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, part or all of the nodes are adaptive, which means each output of these nodes depends on the parameters pertaining to this node, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure.

Neural networks are essentially low- level computational structures and algorithm that offer good performance in dealing with sensory date, while fuzzy logic techniques often deal with issues such as reasoning on a higher level than neural networks [2][5][9][10].

However, since fuzzy systems do not have much learning capability it is difficult for a human operator to tune the fuzzy rule and membership functions form the training data set. Thus, a promising approach for reaping the benefits of both fuzzy systems and neural networks is to merge or fuse them into an integrated system. The proposed ANFC aim at a proper membership function for nonlinear plant, based upon a minimum number of rules and an initial approximate membership function.

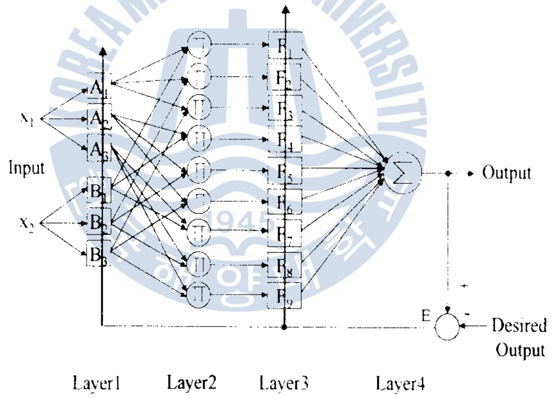


Fig. 1 Adaptive Neuro-Fuzzy Control (ANFC)

The proposed ANFC algorithm consists of 4 layers which are Layer 1(a input membership function), Layer 2(a fuzzy AND operation), Layer 3(a fuzzy OR operation), and Layer 4(defuzzification) in depicted Fig. 1.

The functions of each layer describe the following algorithm for two input x_1, x_2, respectively.

Layer 1 This layer is a square node i with a node function for input membership function depends on incoming input signals.

$$O_{1,i} = \mu_{Ai}(x_1) \tag{1}$$

$$O_{1,i} = \mu_{Bi}(x_2) \tag{2}$$

where x_1, x_2 are the input to node i, and A_i, B_i are the linguistic labels for node function. Namely, $O_{1,i}$ is the membership function of A_i, B_i and it specify the degree to which the given x_1, x_2 satisfy the quantifier A_i, B_i, respectively.

$\mu_{A_i}(x_1)$, $\mu_{B_i}(x_2)$ choose to be gaussian membership function for input x_1, x_2. Each node represents one membership function for one linguistic term.

Input membership functions in this layer are an defined by

$$O_{1,i} = \mu_{A_i}(x_1) = \exp\left[-\left(\frac{x_1 - c_i}{\alpha_i}\right)^2\right] \quad \text{for } i = 1, 2, \cdots, k \tag{3}$$

$$O_{1,i} = \mu_{B_i}(x_2) = \exp\left[-\left(\frac{x_2 - m_i}{\beta_i}\right)^2\right] \quad \text{for } i = 1, 2, \cdots, l \tag{4}$$

where c_i, α_i, m_i, β_i are centers and widths of $\mu_{A_i}(x_1)$, $\mu_{B_i}(x_2)$, respectively.

Layer 2 This layer labeled Π performs fuzzy AND operation.

Every node in this layer is a fixed node, which operates the incoming signal from every set of the membership function nodes for their corresponding input. Each node output indicates the firing strength of a rule. For instance,

$$O_{2,i} = \min(\mu_{Ai}(x_1), \mu_{Bi}(x_2)) \tag{5}$$

Layer 3 Every node in this layer performs a fuzzy OR operation for the output membership function.

An adaptive node function is a gaussian membership function for the output layer. Each node represents a simple output membership function. The link weight of this layer is equal to 1.

$$O_{3,i} = \max(O_{2,i}) \quad \text{for } i = 1, 2, \cdots, k \times l \tag{6}$$

Layer 4 The single node in this layer is a fixed node labeled Σ, which performs the overall output as the summation of all incoming signals. It transits the fuzzy output to crisp signal used for control. This function can be used to computes the center of area defuzzification method. The function of the node can be describe by

$$O_{4,i} = \frac{\sum_{i=1}^{k \times l} s_i \sigma_i O_{3,i}}{\sum_{i=1}^{k \times l} \sigma_i O_{3,i}}$$

$$\text{for } i = 1, 2, \cdots, k \times l \tag{7}$$

Tuning Parameters

The Proposed ANFC network structures are adjust the parameter of input and output membership functions optimally. The back propagation learning algorithm is employed to fine-tune the membership functions for desired output. Considering a single output, the aim is to minimize the error function by

$$E = \sum_{i=1}^{n} \frac{1}{2} (T_i - O_i)^2 \tag{8}$$

where T_i, O_i are the desired output and the measured output, respectively.

To represent the learning rule, we shall show the computation of $\frac{\partial E}{\partial O}$, layer by layer, starting at the output nodes, and we will use gaussian membership function with center s_i and width σ_i as the adjustable parameters for these computations.

Layer 4 Every node in this layer needs to be tuned the center and width of the output membership function. The adaptive rule of the center s_i is derived as

$$\begin{aligned} \frac{\partial E}{\partial s_i} &= \frac{\partial E}{\partial O_{4,i}} \frac{\partial O_{4,i}}{\partial s_i} \\ &= -[T_i(t) - O_i(t)] \frac{\sigma_i O_{3,i}}{\sum \sigma_i O_{3,i}} \end{aligned} \tag{9}$$

Hence, the center parameter is updated by

$$s_i(t+1) = s_i(t) + \eta[T_i(t) - O_i(t)] \frac{\sigma_i O_{3,i}}{\sum \sigma_i O_{3,i}} \quad (10)$$

where η is the learning parameter.

Similarly, the adaptive rule of the width σ_i is derived as

$$\frac{\partial E}{\partial \sigma_i} = \frac{\partial E}{\partial O_{4,i}} \frac{\partial O_{4,i}}{\partial \sigma_i} = -[T_i(t) - O_i(t)] \frac{s_i O_{3,i}(\sum \sigma_i O_{3,i}) - (\sum s_i \sigma_i O_{3,i}) O_{3,i}}{(\sum \sigma_i O_{3,i})^2} \quad (11)$$

Hence, the center parameter is updated by

$$\sigma_i(t+1) = \sigma_i(t) + \eta[T_i(t) - O_i(t)] \frac{s_i O_{3,i}(\sum \sigma_i O_{3,i}) - (\sum s_i \sigma_i O_{3,i}) O_{3,i}}{(\sum \sigma_i O_{3,i})^2} \quad (12)$$

The error to be propagated to preceding layer is derived as

$$\delta_4 = -\frac{\partial E}{\partial O_{4,i}} = T_i(t) - O_i(t) \quad (13)$$

Layer 3 In this layer, no parameter needs to be regulated. Only the error need to be computed.

$$\delta_{3,i} = -\frac{\partial E}{\partial O_{3,i}} = -\frac{\partial E}{\partial O_{4,i}} \frac{\partial O_{4,i}}{\partial O_{3,i}} \quad (14)$$

$$\frac{\partial O_{4,i}}{\partial O_{3,i}} = \frac{s_i \sigma_i(\sum \sigma_i O_{3,i}) - (\sum s_i \sigma_i O_{3,i}) \sigma_i}{(\sum \sigma_i O_{3,i})^2} \quad (15)$$

$$-\frac{\partial E}{\partial O_{4,i}} = T_i(t) - O_i(t) \quad (16)$$

Hence, the error signal is

$$\delta_{3,i}(t) = [T_i(t) - O_i(t)] \quad (17)$$

$$\frac{s_i\sigma_i(\sum\sigma_i O_{3,i})-(\sum s_i\sigma_i O_{3,i})\sigma_i}{(\sum\sigma_i O_{3,i})^2}$$

Layer 2 In this layer, only the error need to be computed.

$$\begin{aligned}\delta_{2,i} &= -\frac{\partial E}{\partial O_{2,i}} = -\frac{\partial E}{\partial O_{3,i}}\frac{\partial O_{3,i}}{\partial O_{2,i}} \\ &= -\frac{\partial E}{\partial O_{3,i}} = \delta_{3,i}\end{aligned} \tag{18}$$

Layer 1 Every node in this layer needs to be tuned the centers and widths of the input membership functions. The adaptive rule of the center c_i is derived as

$$\begin{aligned}\frac{\partial E}{\partial c_i} &= \frac{\partial E}{\partial O_{1,i}}\frac{\partial O_{1,i}}{\partial c_i} \\ &= \frac{\partial E}{\partial O_{1,i}}\frac{2(x_1-c_i)}{a_i^2}\end{aligned} \tag{19}$$

where

$$\frac{\partial E}{\partial O_{1,i}} = \frac{\partial E}{\partial O_{2,i}}\frac{\partial O_{2,i}}{\partial O_{1,i}} \tag{20}$$

where from equation (4.16),

$$\frac{\partial E}{\partial O_{2,i}} = -\delta_{3,i} \tag{21}$$

$$\begin{aligned}\frac{\partial O_{2,i}}{\partial O_{1,i}} &= \delta_{1,i} \\ &= \begin{cases} 1 & \text{if } O_{1,i} = \min \\ & (\textit{input node } i) \\ 0 & \textit{otherwise}\end{cases}\end{aligned} \tag{22}$$

$$c_i(t+1) = c_i(t) + \eta\delta_{1,i}\frac{2(x_1-c_i)}{a_i^2} \tag{23}$$

So the update rule of c_i is defined by

$$c_i(t+1) = c_i(t) \tag{24}$$

$$-\eta[T_i(t)-O_i(t)]\frac{2(x_1-c_i)}{\alpha_i^2}$$

Similarly, the update rule of α_i is derived as

$$\frac{\partial E}{\partial \alpha_i} = \frac{\partial E}{\partial O_{1,i}}\frac{\partial O_{1,i}}{\partial \alpha_i} = \frac{\partial E}{\partial O_{1,i}}\frac{2(x_1-c_i)}{\alpha_i^3} \tag{25}$$

$$\alpha_i(t+1) = \alpha_i(t)+\eta\delta_{1,i}\frac{2(x_1-c_i)}{\alpha_i^3} \tag{26}$$

Hence, the update rule of α_i becomes

$$\alpha_i(t+1) = \alpha_i(t) - \eta[T_i(t)-O_i(t)]\frac{2(x_1-c_i)^2}{\alpha_i^3} \tag{27}$$

Similarly, the update rule of m_i, β_i are derived as

$$m_i(t+1) = m_i(t) - \eta[T_i(t)-O_i(t)]\frac{2(x_2-m_i)}{\beta_i^2} \tag{28}$$

$$\beta_i(t+1) = \beta_i(t) - \eta[T_i(t)-O_i(t)]\frac{2(x_2-m_i)}{\beta_i^3} \tag{29}$$

Ⅲ. Simulation Results

In this section, we appled the adaptive neuro-fuzzy controller(ANFC) which is proposed to the rotary inverted pendulum stabilizing problem [13][14].

The rotary inverted pendulum includes nonlinear dynamics which is difficult to control.

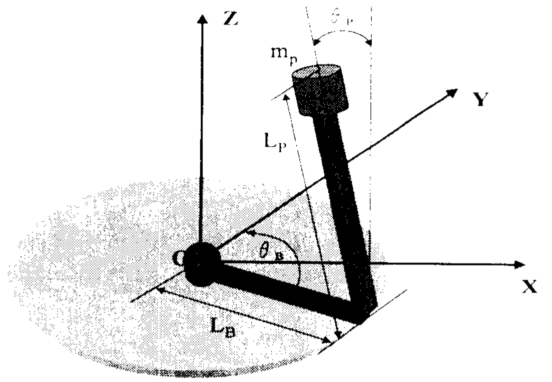


Fig. 2 Rotary Inverted Pendulum System

We must be satisfied two conditions for control of the rotary inverted pendulum. First, it is a position control that any position moves to the objective position. Second, it is a balance control that is stabilized the pole to inverted forward.

Fig. 2 shows the rotary inverted pendulum system.

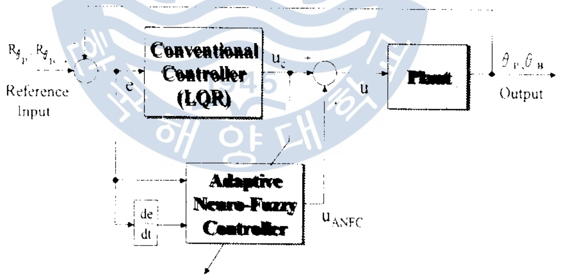


Fig. 3 Proposed Adaptive Neuro-Fuzzy Controller

The proposed ANFC performs the minimization for the conventional controller (LQR) output(Fig. 3).

The dynamic equation of the rotary inverted pendulum system are presented follows.

$$K_P = \frac{1}{2} m_P[(L_B \dot{\theta}_B + L_P \dot{\theta}_P \cos(\theta_P))^2 + (L_P \dot{\theta}_P \sin(\theta_P))^2] \quad (30)$$

$$K_B = \frac{1}{2} J_B \dot{\theta}_B^2 \quad (31)$$

$$P_P \;=\; m_P g L_P \cos(\theta_P) \tag{32}$$

where K_P; K_B, P_P are the kinetic energy for the pole of the rotary inverted pendulum, the kinetic energy for the base link of the rotary inverted pendulum, and the potential energy for the pole of the rotary inverted pendulum, respectively. m_p is mass of pole.

The dynamic equation of the rotary inverted pendulum system solved using the Lagrangian equation. It's equation determines to the kinetic energy and potential energy in generalized coordinate.

By using a above equation, we obtain by Lagrangian equation as follows.

$$\begin{aligned}(m_P L_B^2 + J_B)\ddot{\theta}_B &+ m_P L_B \ddot{\theta}_P L_P \cos(\theta_P) \\ &- m_P L_B \dot{\theta}_P L_P \sin(\theta_P) \;=\; T\end{aligned} \tag{33}$$

$$\begin{aligned}m_P L_B L_P \ddot{\theta}_P \cos(\theta_P) &- m_P L_P L_B \dot{\theta}_P \dot{\theta}_B \sin(\theta_P) \\ &+ m_P L_P^2 \ddot{\theta}_P - m_P g L_P \sin(\theta_P) \;=\; 0\end{aligned} \tag{34}$$

A torque T by DC motor is given the following form.
That is

$$u \;=\; V \;=\; I R_m + K_m \omega_m \tag{35}$$

$$T \;=\; I K_m \;=\; \frac{K_m}{R_m} V - \frac{K_m^2}{R_m}\,\omega_m \tag{36}$$

where u, ω_m are the plant input and rotate speed[rad/s] of the motor.

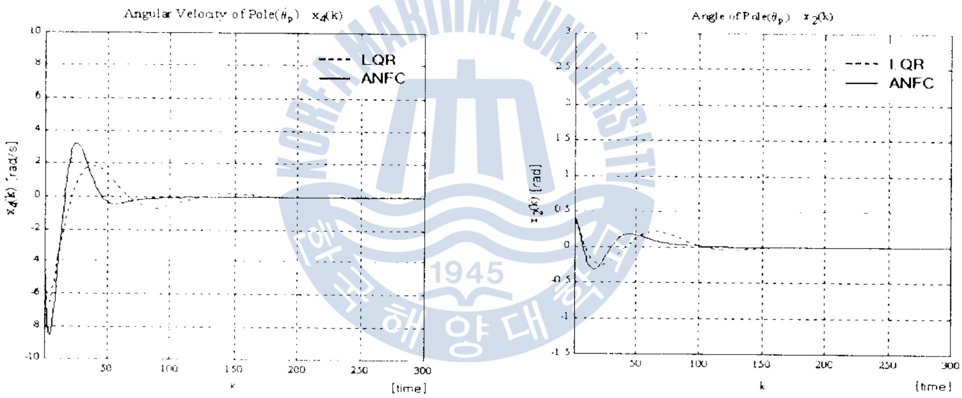
Table 1 System Parameters of the Rotary Inverted Pendulum

Parameter	Symbol	Value	Unit
Length of Pole	L_P	0.305	m
Mass of Pole	m_P	0.210	Kg
Length of Base Link	L_B	0.145	m
Inertia of Base Link	J_B	0.0044	Kgm^2
Motor Armature Resistance	R_m	2.6	Ω
Motor Voltage Constant	V	±5.0	V
Motor Torque Constant	K_m	0.00767	V/rads

Thus, we can find the state equation as following system parameters(Table 1). That is

$$\begin{bmatrix} \dot{\theta}_B \\ \dot{\theta}_P \\ \ddot{\theta}_B \\ \ddot{\theta}_P \end{bmatrix} = \begin{bmatrix} 1 & -0.0031 & 0.0088 & 0 \\ 0 & -1 & 0.0006 & 0.01 \\ -0.5935 & 0.7787 & 0 & -0.0031 \\ 0.6036 & 1 & 0.1063 & 1.031 \end{bmatrix} \begin{bmatrix} \theta_B \\ \theta_P \\ \dot{\theta}_B \\ \dot{\theta}_P \end{bmatrix} + \begin{bmatrix} 0.0022 \\ 1 \\ 0.4161 \\ -0.1942 \end{bmatrix} u \qquad (37)$$

where sampling time is 0.01sec.



(b) Angular Velocity of the Pole (b) Angle of the Pole

Fig. 4 Simulated results of proposed ANFC for the Rotary Inverted Pendulum Angle of the Base -Link and the Pole (------- : LQR, ————: ANFC)

For the proposed ANFC, parameter used 7 input membership functions and 49 output membership functions. In the initial parameter, θ_B, θ_P, $\dot{\theta}_B$, $\dot{\theta}_P$ are 0.5, 0.1, 5.0, 0, respectively. Learning parameter, η is 0.03.

Fig. 4 shows the simulated results of proposed ANFC for the rotary inverted pendulum Angle of the Base-Link and the Pole. LQR is dashed line and ANFC is solid line.

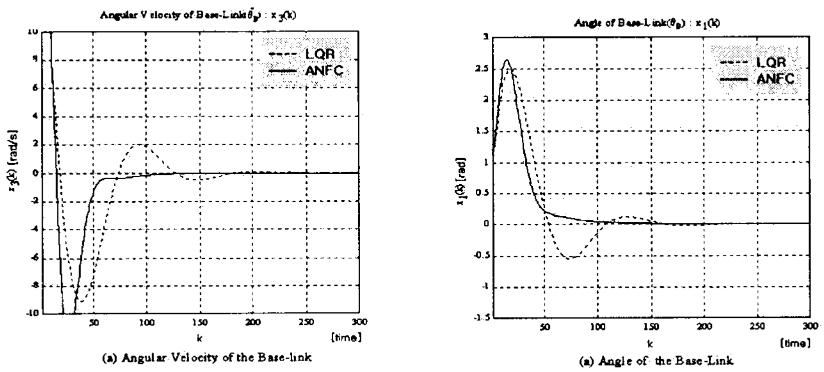


Fig. 5 Simulated results of proposed ANFC for the Rotary Inverted Pendulum Angular Velocity of the Base-Link and the Pole (------: LQR, ——: ANFC)

Fig. 5 shows the Rotary Inverted Pendulum angular velocity of the Base- Link and the Pole.

The proposed ANFC result(solid line) is more effect than the conventional controller(LQR) result(dashed line) in the convergence time. As compared to conventional controller, it provides improved performance. Thus, the proposed method can be controlled more adaptive and more effective in rotary inverted pendulum for changing an input member- ship functions and output membership functions.

Ⅵ. Conclusions and Further Works

In this paper, we proposed adaptive neuro-fuzzy controller(ANFC) with application to rotary inverted pendulum.

With simulation results, the proposed ANFC results is more effect than the conventional controller(LQR) results in the convergence time. As compared to conventional controller, it provides improved performance. Although LQR is robust controller but the proposed method can be controlled more adaptive and faster convergence time than conventional controller (LQR) in nonlinear environment for changing an input membership functions and output membership functions. As it were, the proposed ANFC has learning ability which can be used in the fine tuning of membership functions to mini- mize the output error of the control. Moreover, the rule base can be generated automatically by the proposed ANFC. A simple structure and a high speed computation are the most advantage in proposed ANFC. Thus, this proposed algorithm is very useful for fuzzy logic control because the needs for the expert knowledge are relative much lower com- pared to conventional fuzzy logic control. However, this algorithm must be attended learning parameter, η which effects for learning speed and the convergence time.

Further works, we will establish more effect and more reinforcement algorithm. Also, the lack of stability analysis for both neural networks and fuzzy controllers is the major reason why conventional control literature is resistant to these controller.

Therefore, we think that the establish ment of stability analysis for ANFC can greatly expand the application domains of neuro-fuzzy controller.

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