Stabilization Control of Nonlinear System Using Adaptive Neuro-Fuzzy Controller

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적응 뉴로-퍼지 제어기를 이용한 비선형 시스템의 안정화 제어

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ABSTRACT

In this paper, an stabilization control method using adaptive neuro-fuzzy controller(ANFC) is proposed for modeling of nonlinear complex systems. The proposed adaptive neuro-fuzzy controller implements system structure and parameter identification using the intelligent schemes together with optimization theory, linguistic fuzzy implication rules, and neural networks from input and output data of processes.

The results show that the proposed method can produce the intelligence model with higher accuracy than other works achieved previously.

요 약

본 논문에서는 적응 뉴로-퍼지 제어기를 이용하여 비선형 복합시스템 모델의 안정화 제어 방법에 적용한다. 제안된 적응 뉴로-퍼지 제어기는 언어적 퍼지추론, 프로세스의 입출력 데이터를 이용하는 신경회로망, 최적이론 등이 포함된 인공지능을 시스템구조와 파라메터 검증에 필요한 도구로 이용한다. 그 결과 제안된 방법이 이전에 연구되었던 다른 방법보다 아주 높은 인공지능 모델을 제시하였다.

키워드: adaptive neuro-fuzzy controller, parameter identification, linguistic fuzzy implication rules

Ⅰ. INTRODUCTION

Fuzzy systems has the ability to make use of knowledge expressed in the form of linguistic rules, thus they offer the possibility of implementing drawback is the lack of a systematic expert human knowledge and experience. Their main methodology for their design. Usually, tuning parameter of membership functions is a time consuming task. Neural networks learning techniques can automate this process, significantly reducing development time, and resulting in better performance. The merger of neural networks and fuzzy logic led to the creation of neuro-fuzzy controllers which are curren

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tly one of the most popular research fields. There are some very interesting architectures for neuro-fuzzy controllers proposed by Jang[1] and Nomura[2].

Recently to cope with the control problems a lot of experts are conducting a study of control methods to which neural networks or fuzzy system are applied, as opposed to existing mathematical analytical ones, on parallel process, nonlinear mapping, pattern recognition, industrial application, medicine, expert system, etc.[3, 4].

Besides neuro-fuzzy controllers are characterized by nonlinearity, learning ability and optimalizing ability, and by making practical use of these characteristics and appling them to nonlinear control, adaptive control, etc. good results have been achieved[5].

The proposed adaptive neuro-fuzzy controller(ANFC) implements system structure and parameter identification using the intelligent schemes together with optimization theory, linguistic fuzzy implication rules, and neural networks from input and output data of processes. Inference type for this adaptive neuro-fuzzy controller is presented as simplified inference.

This study focuses on how to use neuro- fuzzy controllers based on adaptive controller and bring under stabilization control of nonlinear complex systems.

To demonstrate the efficiency of the adaptive neuro-fuzzy controller presented in this study, a neuro-fuzzy controller based adaptive controller was designed and then a comparative analysis was made with LQR controller through an simulation.

Ⅱ. LEARNING PROCESS

The learning procedure we present is based on the stochastic approximation method for the adjustment of parameters of a nonlinear system. The method corresponds to supervised learning, developed in the form of a closed loop adaptation(Fig. 1).

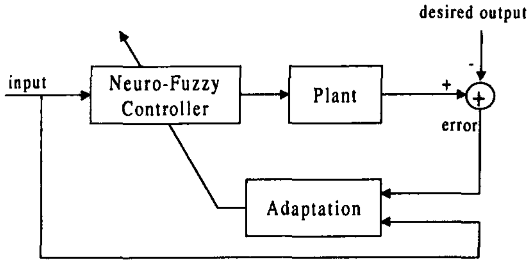

Fig. 1 Closed loop adaptation.
그림 1. 폐루프 적응

Using it, an adaptive algorithm adjusts the parameters of the system, thus altering its response characteristics by minimising a measure of the error, thereby closing the performance loop.

Suppose that the parametric model of one linear or nonlinear system is given in the following form:

$$\dot{x}=f(x,\ u,\ z,\ t) \cdots\cdots\cdots\cdots (1)$$

$$y=g(x,\ u,\ z,\ t) \cdots\cdots\cdots\cdots (2)$$

where x is a state vector, u an input vector, z a parameter vector and y is the output vector.

All solutions to parameter estimation problems consist of finding the extremum of a criterion function V considered as a function of the parameters of the nonlinear system. The criterion function is usually given by:

$$V=E(e^2(t)) \cdots\cdots\cdots\cdots (3)$$

or

$$V=\frac{1}{N}\sum_{t=1}^{N}e^2(t) \cdots\cdots\cdots\cdots (4)$$

where E denotes the mathematical expectation and N is the number of training patterns. Most learning algorithms are based on the minimisation of the cost function given by:

$$V=\frac{1}{2}e^2(t)=\frac{1}{2}(y(t)-y_d(t))^2 \cdots\cdots (5)$$

where y_d is the desired output provided by an expert. The Minimisation of this function can be done in several ways[6].

Here we will use the criterion (eq. 5) and apply the method of stochastic approximation to identify the parameters of the fuzzy system. It is an iterative procedure given by:

$$z(t+1)=z(t)-\Gamma\Delta_z V[z(t)] \cdots\cdots (6)$$

where z is the vector of parameters to adapt, Γ is a predefined constant and $\Delta_z V$ is the notation for gradient of V with respect to z:

$$\Delta_z V=[\frac{\partial V}{\partial z_1},\ldots,\frac{\partial V}{\partial z_n}] \cdots\cdots (7)$$

III. ADAPTIVE NEURO-FUZZY CONTROLLER

Learning methods for fuzzy controller usually involve the application of conventional adaptive control techniques. Since these techniques are used also in training neural networks, for example, the least square algorithm, many adaptive fuzzy controllers are effectively adaptive neuro-fuzzy controllers. An interesting architecture for a adaptive neuro- fuzzy controller has been proposed by Jang [1], and we now develop a simple adaptive neuro-fuzzy controller and a learning procedure.

As shown in Fig. 2, which is comprised by the input layer(the layer 1), fuzzification(the layer 2), application of T-norm(the layer 3), normalization(the layer 4), defuzzification(the layer 5), and output layer(the layer 6), is adopted to implement the adaptive neuro-fuzzy controllers in this study.

One important task in the structure identification of the adaptive neuro-fuzzy controller is the partition of the input space, which influences the number of fuzzy rules generated. Another feature of the adaptive neuro- fuzzy controllers is that it can optimally determine the consequent part of fuzzy if-then rules during the structure learning phase.

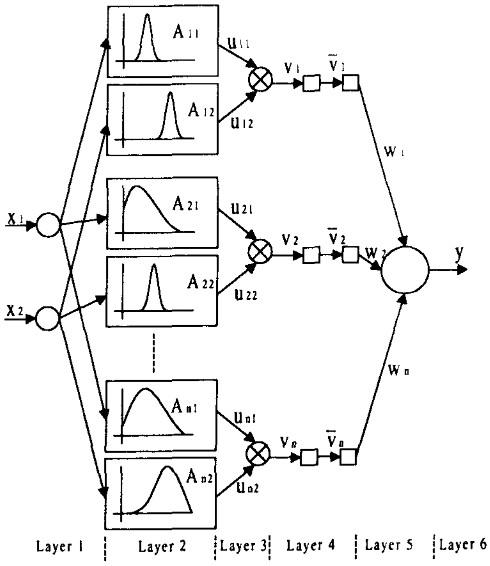

Fig. 2 Adaptive neuro-fuzzy controllers.
그림 2. 적응 뉴로퍼지 제어기

Assume that a fuzzy controller has m inputs $x_1, x_2, \ldots, x_m$ and one output y and that we define n linguistic rules in the form:

R_i: **IF** x_1 is in A_{i1} **and** x_2 is in A_{i2} **and** ... **and** x_m is in A_{im} **then** y is y_i

$i=1, \ldots, n \cdots\cdots (8)$

where x_i and y are the input variables, respectively, i is the index of the rule, A_{ij} is a fuzzy set for i_th rule and j_th linguistic variable defined over the universe of discourse for j_th variable and y_i is the position of a symmetric membership function of the output variable with its width neglected during the defuzzification process.

Every membership function in this controller is defined as a Gaussian function. For the application of the rules we need to define a fuzzy inference mechanism, and in this case, we will take the product operator as T-norm. This means that the firing strength of every rule is:

$$v_i=u_{i1}u_{i2}\ldots u_{im}, \quad i=1,\ldots,n \cdots (9)$$

where u_{ij} is the degree of membership of x_j in the fuzzy set A_{ij}. The consequent part of the rules are required to be crisp values, and if defuzzification is by the centre of gravity method, this crisp value is given by:

$$y=\frac{\sum_{i=1}^{n} v_i w_i}{\sum_{i=1}^{n} v_i}=\sum_{i=1}^{n} \bar{v}_i \ \bar{w}_i \quad \cdots\cdots (10)$$

The general scheme of this system with two inputs and one output is represented in Figure 2, and in fact this representation is analogous to the architecture of a feedforward artificial neural networks. The second layer performs a fuzzification for each linguistic rule. Outputs from this layer are membership values and they are fed into the next layer which performs a T-norm operation -product- (eq. 9). The result is a firing strength for each rule and in the next layer, firing strengths are normalized (eq. 10).

As learning, In the fuzzy controller presented above, z(eq. 6) is given by:

$$z=(a_{11},\ldots,a_{nm},b_{11},\ldots,b_{nm},w_1,\ldots,w_n) \quad \cdots\cdots (11)$$

There are three of parameters to adapt: centre value a_{ij}, width values b_{ij} and consequent values w_i. The number of parameters to adapt is $p=2nm+n$ and the vector which minimises the loss function is defined by:

$$\left(-\frac{\partial V}{\partial z_1},\ -\frac{\partial V}{\partial z_2},\ldots,-\frac{\partial V}{\partial z_p}\right)=0 \quad \cdots (12)$$

leading to the learning rule:

$$z_k(t+1)=z_k(t)-\Gamma\frac{\partial V(z)}{\partial z_k},\ k=1,\ldots,p \quad \cdots\cdots (13)$$

If the neuro-fuzzy controller is defined with Gaussian membership function, it follows from (eq. 9, 10, and 13) and from the equation for the membership function that the equation for the adaptation of the parameters are:

$$a_{ij}(t+1)=a_{ij}(t)\Gamma a\frac{v_i}{\sum_{i=1}^{n} v_i}(y-y_d)(w_i-y)\frac{(z_j-a_{ij}(t))}{b_{ij}^2} \quad \cdots\cdots (14)$$

$$b_{ij}(t+1)=b_{ij}(t)\Gamma b\frac{v_i}{\sum_{i=1}^{n} v_i}(y-y_d)(w_i-y)\frac{(z_j-a_{ij}(t))^2}{b_{ij}^3} \quad \cdots\cdots (15)$$

$$w_i(t+1)=w_i(t)\Gamma w\frac{v_i}{\sum_{i=1}^{n} v_i}(y-y_d) \quad \cdots (16)$$

Ⅳ. SIMULATION RESULTS

In this section, we appled the adaptive neuro-fuzzy controller which is proposed to the rotating inverted pendulum system stabilizing problem. The rotating inverted pendulum includes nonlinear dynamics which is difficult to control and is shown in Fig. 3. For now, dissipative elements such as bearing friction are neglected, but will be added to the system later[7]. The equation for the total kinetic energy of the system is :

$$K_t=K_{l1}+K_{l2} \quad \cdots\cdots (17)$$

where

$$K_{l1}=\frac{1}{2}I_1\ \dot{\theta}_1^{\,2}+\frac{1}{2}M_e r^2\ \dot{\theta}_1^{\,2} \quad \cdots\cdots (18)$$

$$K_{l2}=\frac{1}{2}(I_m+I_b)(\ \dot{\theta}_1+\ \dot{\theta}_2)^2+\frac{1}{2}M_m V_m^2+\frac{1}{2}M_b V_b^2 \quad \cdots\cdots (19)$$

The equation for the potential energy of the system is :

$$P_t=gr(M_m+M_b+M_e)\cos(\theta_1)+g(M_m L_m+M_b L_b)\cos(\theta_1+\theta_2) \quad \cdots (20)$$

With the kinetic and potential energies defined, the corresponding Lagrangian equations of motion are easily derived. The Lagrangian is defined as the sum of the kinetic minus the sum of the potential energies :

$$L=\sum K_i-\sum P_i \quad \cdots\cdots\cdots\cdots (21)$$

Following Lagrange's method, each energy function is differentiated appropriately. Q represents the input torque for the generalized coordinate, while θ_i represents the generalized coordinate.

$$Q_i=\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}_i}\right)-\frac{\partial L}{\partial \theta_i} \quad \cdots\cdots\cdots (22)$$

Starting with coordinate θ_1:

$$\tau_i=\frac{d}{dt}\left(\frac{\partial K}{\partial \dot{\theta}_1}-\frac{\partial P}{\partial \dot{\theta}_1}\right)-\left(\frac{\partial K}{\partial \theta_1}-\frac{\partial P}{\partial \theta_1}\right) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (23)$$

These equations may now be written in actual linear state space form as :

$$\dot{x}^*=A_i x^*+B_i u^*+\tau \quad \cdots\cdots\cdots (24)$$

Now it is simple to add in the damping dynamics to the linearized equation of motion :

$$\frac{d}{dt}\begin{pmatrix}\dot{\theta}_1\\ \dot{\theta}_2\\ \theta_1^*\\ \theta_2^*\end{pmatrix}=\begin{pmatrix}a_{11} & a_{12} & a_{13} & a_{14}\\ a_{21} & a_{22} & a_{23} & a_{24}\\ 1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\end{pmatrix}\begin{pmatrix}\dot{\theta}_1\\ \dot{\theta}_2\\ \theta_1^*\\ \theta_2^*\end{pmatrix}+\begin{pmatrix}a_1\\ a_2\\ 0\\ 0\end{pmatrix}u+\begin{pmatrix}\tau_1\\ \tau_2\\ 0\\ 0\end{pmatrix} \quad \cdots\cdots (25)$$

where is $a_{11}=-\dfrac{M_{22}^*b_1}{det(M)}$, $a_{12}=\dfrac{M_{12}^*b_2}{det(M)}$,

$a_{21}=\dfrac{M_{21}^*b_1}{det(M)}$, $a_{13}=\dfrac{M_{22}^*G_{11}-M_{12}^*G_{21}}{det(M)}$,

$a_{14}=\dfrac{M_{22}^*G_{12}-M_{12}^*G_{22}}{det(M)}$, $a_{22}=\dfrac{-M_{11}^*b_2}{det(M)}$,

$a_{23}=\dfrac{M_{11}^*G_{21}-M_{21}^*G_{11}}{det(M)}$, $a_1=\dfrac{M_{22}}{det(M)}$,

$a_{24}=\dfrac{M_{11}^*G_{22}-M_{21}^*G_{12}}{det(M)}$, $a_2=\dfrac{M_{21}}{det(M)}$.

To demonstrate the efficiency and satisfactory of the neuro-fuzzy controller presented in this study, a neuro-fuzzy controller based adaptive controller was designed and then a comparative analysis was made with LQR controller through an simulation. In this Fig. 4, the neural networks is configured in parallel to a LQR controller.

This scheme consists of a fixed gain LQR controller that makes the overall system stable, and a feedforward controller which updates its internal weights to generate the control signal u_{NF} in the process of becoming an inverse model of the plant. During the initial training period, the control signal u_{NF} was very insignificant. The learning trials increased u_{NF} become dominant over u_C. For the proposed adaptive neuro-fuzzy controller, parameter used 7 input membership functions.

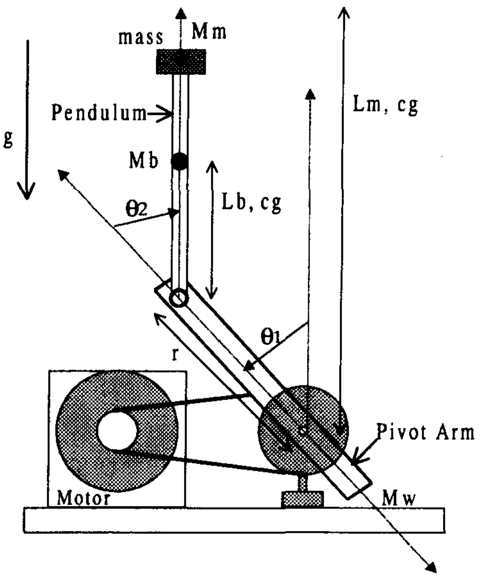

Fig. 3 Structure of the rotating inverted pendulum.
그림 3. 회전형 도립진자의 구조

For the ANFC, we specify the input variable as the performance error $e(k)$, which is the error between the reference input and actual system, and the rate of change of the performance error $\Delta e(k)$.

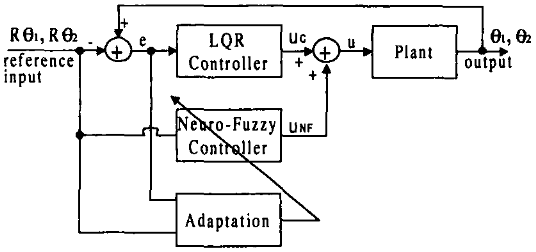

Fig. 4 Total control system.
그림 4. 제어시스템

In the initial parameter, θ_1, θ'_1, θ_2, θ'_2 is 0.5, 0.1, 5.0, 0, respectively. The gain K for LQR controller was [-16.85, -13.24, -70.4, -67.9]. The parameters of the system is

M_W : 0.403kg, M_b : 0.081kg, M_m : 0.189kg, J_m : 2.2597e-4kg-m^2, $I_{enc,cg}$: 3.3e-5kg-m^2, M_e : 0.154kg, M_s : 0.1kg, M_{gl} : 0.138kg, I_{shaft} : 2.1844e-5kg-m^2, K_t :0.13436902Nm/A.

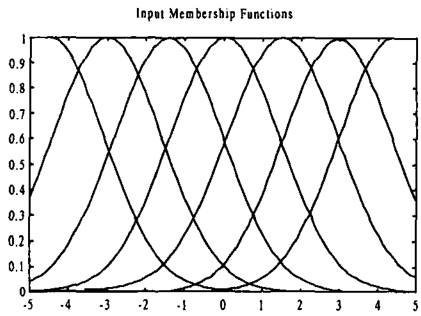

Fig. 5 Input membership functions
그림 5. 입력 멤버쉽 함수

Fig. 6 represents the stabilization response of pivot arm from the random position to the center. Here, we can see that the adaptive neuro-fuzzy controller gets stable with less change more quickly than the LQR controller. Fig. 8 show the responses to pivot arm′ velocity.

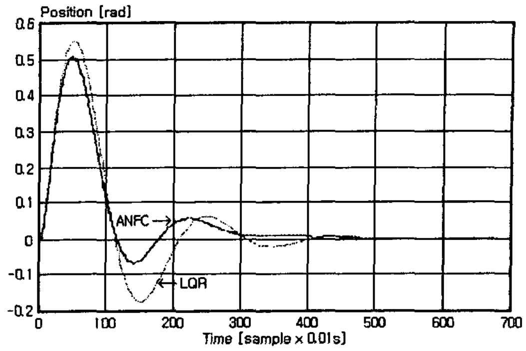

Fig. 6 Position of pivot arm.
그림 6. 중심축의 위치

Fig. 7 is about the responses to pendulum′ position change, where the adaptive neuro-fuzzy controller was also superior. Fig. 9 is concerning the responses according to pendulum′ velocity.

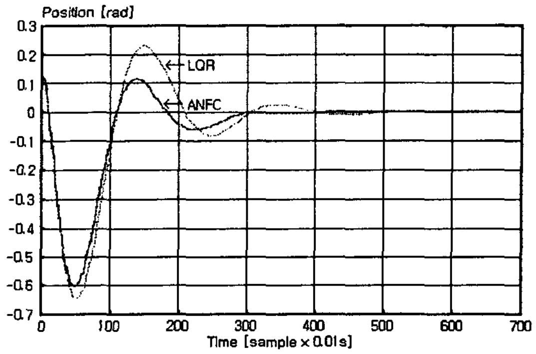

Fig. 7 Position of pendulum.
그림 7. 진자의 위치

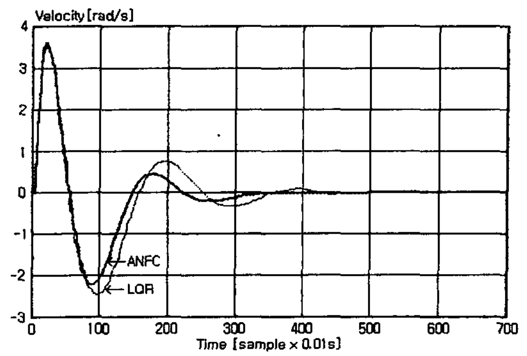

Fig. 8 Velocity of pivot arm.

그림 8. 중심축의 속도

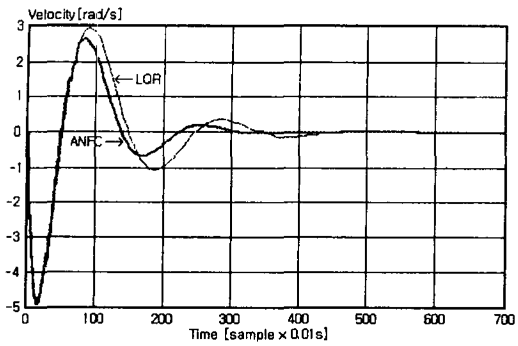

Fig. 9 Velocity of pendulum.
그림 9. 진자의 속도

Simulation results confirm that the adaptive neuro-fuzzy controller also has a few errors in the early stage of learning, much fewer than the LQR controller though. As learning continues, however, it shows no if any errors and good responses.

V. CONCLUTION

In this paper, we proposed the adaptive neuro-fuzzy controller with application to rotating inverted pendulum.

With simulation results, the proposed adaptive neuro-fuzzy controller is more effect than the LQR controller results in the convergence time. As compared to LQR controller, it provides improved performance. Thus, this proposed algorithm is very useful for fuzzy logic control because the needs for the expert knowledge are relative much lower compared to conventional fuzzy logic control.

Further research should be made along the lines of providing the effects of the adaptive neuro-fuzzy controller by consecutive simulation and experiments.

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