The Study on Position Control of a Flexible Robot Manipulator Using Fuzzy Neural Networks

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퍼지신경망을 이용한 유연성 로봇 매니퓰레이터의 위치제어에 관한 연구

추연규 · 탁한호

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요 약

본 논문은 퍼지신경망을 이용한 유연성 단일 링크 로봇 매니퓰레이터의 위치제어에 관한 논문이다. 제안된 퍼지신경망 모델은 전건부와 결론부에 퍼지집합을 갖는 퍼지규칙으로 구성된 퍼지모델을 표현하고, 퍼지추론을 수행하는 기능을 가진다. 유연성 로봇 매니퓰레이터에 대한 동적모델을 유도하고, 시뮬레이션을 통해 PID 제어기와 비교 분석하였다. 그 결과 제안된 제어기가 PID 제어기보다도 개선된 성능을 확인하였다.

1. Introduction

Today most of the robots often used in industrial fields for automatization and higher efficiency have rigid bodies and thick, heavy manipulators. The bad things about these robots are that they take a lot of space and that actuators require more motion energe, which in turn makes it difficult to promote motion speed. Now a lot of researches are under way to complement such weaknesses by reducing the weight and making the link more flexible[1][2][3].

Y. Sakaw[1] and Z. H. Luo[2] applied optimal control to flexible link and demonstrated its utility. K. S. Yeung[3] applied variable structure control method and did the same. However

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linear optimal control or linear feedback control is *robust within limited linear areas enough for* systems to be sensitive to them when unexpected disturbances happen. Accordingly the regulation of system parameters is necessary in case system environment is unknown or uncertain.

Instead of the established mathematical analytical methods showing conventional control, new control methods utilizing fuzzy and neural network theories are applied to industry by lots of researchers[4][5].

As a result, very favorable simulation performance is reported in the nonlinear or adaptive control of the unknown system and nolinear plants.

This paper aims to actively control the elasticity and position of a flexible robot manipulator by way of the fuzzy neural network controller.

The controller composes the defuzzification part of the fuzzy controller by using single layered GMDP(Generalized Multi-Denderite Product) neural network[6] and adjusts the fuzzy membership function based on the fuzzy-neural network model to control the position of a flexible robot manipulator.

Through computer simulation, its efficiency and correctness are analyzed and compared with the case where a common PID controller is used.

2. Fuzzy Neural Networks controller

As Figure 1 shows, the fuzzy neural network model is composed of the fuzzy inference engine and the defuzzification interface.[5]

The former calculates the maching degree ($\alpha_1, \alpha_2 \cdot \cdot, \alpha_5$) between the antecedent part of fuzzy rules and the input, while the latter composes the linguistic terms of consequent part.

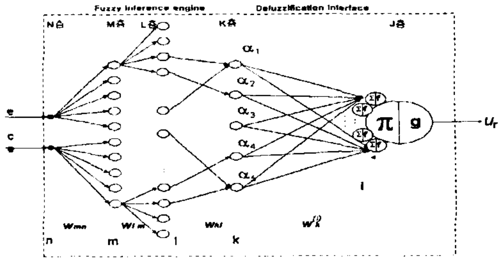


Figure 1. Fuzzy neural network model.

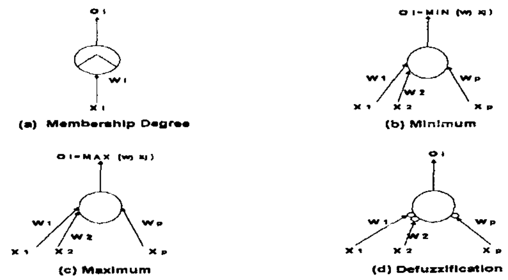


Figure 2. Operation of fuzzy neural network's neuron

Unlike normal neural networks, fuzzy neural network dose not fix neuron operation but uses various operation depending on places.

When fuzzy rules are given and max-min or max-product inference is used, the results of fuzzy inference depend on marching degree in the input and the antecedent part of fuzzy rules.

By using the function approximation capacity of the neural network, parts of consequent composition and defuzzification operation can be made into a single layered GMDP neural network.

In figure 3, e(error) and ce(change of error) of the N layer represent the system's input values, and NB, NM, ZO, PM, PB linguistic terms. Neurons of the M layer compute the membership degree of those values against linguistic terms of input.

Among diverse fuzzy sets against linguistic terms including the shaper of trapezoids and Gaussian function, triangular fuzzy numbers for application were used in the present research.

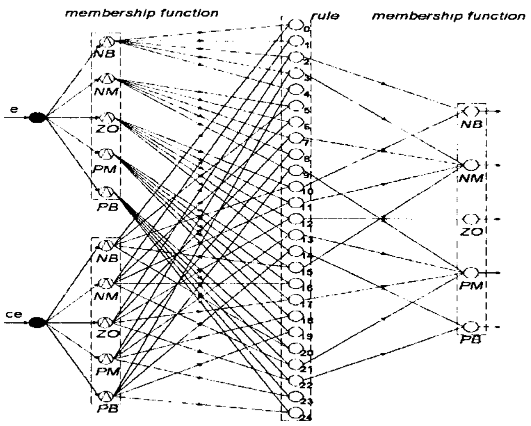


Figure 3. Structure of fuzzy inference part.

In Figure 4, the fuzzy sets F_m, is expressed by three parameters c_m, l_m, r_m, representing triangular center and left/right width.

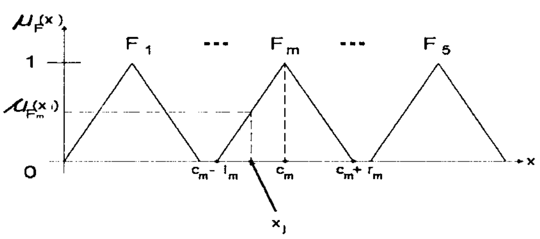


Figure 4. Representation of triangle fuzzy nember.

The membership function μ_{F_m} of F_m is defined as follows.

$$\mu_{F_m}(x_j) = \begin{cases} 1 - \dfrac{x_j - c_m}{r_m} & x_j \in [c_m, c_m + r_m] \\ 1 + \dfrac{x_j - c_m}{l_m} & x_j \in [c_m - l_m, c_m] \\ 0 & otherwise \end{cases} \quad \cdots\cdots (1)$$

Fuzzy inference by fuzzy neural network utilized Mandani's max-min rule at the L and K layers. Unit number and layer relationship were revealed through the analysis of fuzzy rules, shown in table 1.

Table 1. fuzzy rule.

e \ ce	NB	NM	ZO	PM	PB
NB	0	0	NB	NM	0
NM	0	0	NM	0	PM
ZO	NB	NM	ZO	PM	PB
PM	NM	0	PM	0	0
PB	0	PM	PB	0	0

3. Modeling of flexible robot manipulator

Figure 5. shows the manipulator system that has a flexible single link. I_h means the mass moment of inertia of the hub referring to the actuator operating the manipulator plus the part fixing the link to the actuator: M_e , the mass of end effect plus payload at the end-point of the link and J_e , its mass moment of inertia: g , the gravity heading below z axis.

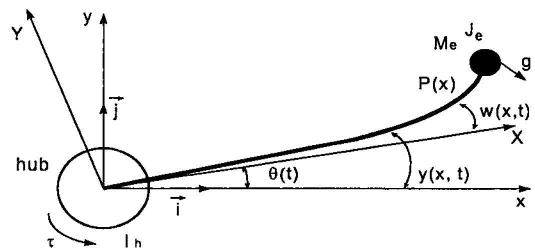


Figure. 5 Flexible single link robot manipulator.

Flexible link were modeled on the thin long uniform Bernoulli-Euller beam which has such great length compared with a cross-section area that shear deformation and rotary inertia effects can be neglected. In the operation they don't show any distortion and it is assumed that they have only bending deformation. The friction of joints and the structural damping of flexible link are neglected in system modelling. The differential equation of motion should be satisfactory to the flexible link with free transverse vibration and the equation is as follows[7]:

$$\rho A(x)\frac{\partial^2 w(x,t)}{\partial t^2}+\frac{\partial^2}{\partial x^2}[EI(x)\frac{\partial^2 w(x,t)}{\partial x^2}]=0 \qquad \cdots\cdots (2)$$

In this equation, ρ is linear mass density, A(x) the cross-section area of the link and EI(x) the bending stiffness of the link. w(x,t) the elastic displacement to x arbitrary point of the link is the linear combination of assumed mode shapes and generalized coordinates, which is approached as follows[8]:

$$w(x,\ t)=\sum_{i=1}^{n}\phi_i(x)q_i(t)=\phi q^T \qquad \cdots\cdots (3)$$

where $\phi_i(x)$, the i th assumed mode shape of the link, is clamped-free eigenfunction, $q_i(t)$, the i th generalized coordinate which is the time function corresponding to $\phi_i(x)$. The link has a moment of inertia I_b and a length l. The angular displacement of the link is denoted as $\theta(t)$, so the total deflection $y(x,t)$ can be represented as

$$y(x,t)=x\theta(t)+w(x,t) \qquad \cdots\cdots (4)$$

The elastic displacement on oprate plane of the system is being approximated by the assumed modes. The assumed modes is the assumed modes with function of space coodinates and the linear combination of generalized coordinates with time function, which is approached as (3). In addition, comparative function which can be satisfied with both the geomatrical boundary conditions that it has mass in end-point of the clamped-free link and the natural boundary condition simultaneously is used for the assumed modes shape. At the clamped end($x=0$), when the zero conditon of deflection and gradient from hub the geomatrical boundary conditions given by bellow.

1) $w(0,\ t)=w_0=0$: The deflection must be zero.
2) $\frac{\partial w(0,\ t)}{\partial x}=0$: The slope of the deflection curve must be zero.

At the free end($x=l$), the shearing force and the bending moment by balance condition the natural boundary condition given by bellow.

1) $EI\frac{\partial^2 w(l,\ t)}{\partial x^2}+J_e[\ \ddot{\theta}+\frac{\partial\ \ddot{w}(l,\ t)}{\partial x}]=0$: The bending moment must be zero.
2) $EI\frac{\partial^3 w(l,\ t)}{\partial x^3}+M_e[-\ \ddot{w}(l,\ t) + \dot{\theta}^2 w(l,\ t)-\ddot{\theta}\, l+g\sin\theta\ ]=0$: The shearing force is zero.

The above boundary condition yield the transcendental equation for the natural frequency βl

$$\cosh(\beta l)\cos(\beta l)\ +\ 1=0 \qquad \cdots\cdots (5)$$

From (3), the eigenfunction $\phi(x)$ can be represented as

$$\phi(x)=c_1\sin\beta x+c_2\cos\beta x+c_3\sinh\beta x+c_4\cosh\beta x \qquad \cdots\cdots (6)$$

where c_i is an arbitrary constant, Substituting boundary conditions, and reform for c_1, c_2, c_3, and c_4.

Kinetic energy come from rotary motion of hub, alignment or rotary motion of flexible link and that of the mass of end point. It is sums to total kinetic energy as following.

$$K = \frac{1}{2} I_h \dot{\theta}^2 + \frac{1}{2} \rho A \int_0^l [\dot{\theta}^2 x^2 + \dot{w}^2 + 2\dot{\theta}\dot{w}x + \dot{\theta}^2 w^2]dx + \frac{1}{2} J_e [\dot{\theta}^2 + 2\dot{\theta}\dot{w}_l' + \dot{w}_l'^2] + \frac{1}{2} M_e [\dot{w}_l^2 + \dot{\theta}^2 w_l^2 + 2\dot{\theta}\dot{w}_l l + \dot{\theta}^2 l^2] \quad \cdots (7)$$

And potential energy in system is the very elastic displacement of flexible link, if it was irrespective of the mass of end-point and gravity of flexible link, the above energy can be demonstrated as follows.

$$V = \frac{1}{2} EI \int_0^l (\frac{\partial^2 w}{\partial x^2})^2 dx + \int_0^l \rho A g [w \sin\theta - x \cos\theta] dx + M_e g [w \sin\theta - x \cos\theta] \quad \cdots (8)$$

The equation of motion can apply the Euler-Lagrange equation.

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{q}_i} - \frac{\partial L}{\partial q_i} = 0, \ i = 1, 2, \ldots, n \quad \cdots (9)$$

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{\theta}} - \frac{\partial L}{\partial \theta} = \tau \quad \cdots (10)$$

where τ is input torque for drive of flexible link from actuator, and $L = K - V$. Substituting (7) and (8) into (9) and (10) gives, without regard to the mass of end-point of flexible link, the mass of inertia and gravity, applied partial differential to generalized coordinates. The kinetic equation of discreted differential equation type is given by

$$\ddot{\theta} = \frac{\tau + \sum_{j=1}^{n} q_j \omega_j^2 \int_0^x \phi_j x dm}{I_h} \quad \cdots (11)$$

$$\ddot{q}_i = -\frac{T}{I_h} \int_0^x \phi_i x dm - q_i \omega_i^2 [1 + \frac{(\int_0^x \phi_i x dm)^2}{I_h}] - \sum_{j \neq i}^{n} \frac{q_j \omega_j^2 \int_0^x \phi_j x dm \int_0^x \phi_i x dm}{I_h} \quad \cdots (12)$$

4. Design of control system

Figure 6. represents the total control system using fuzzy neural network controller, where e and ce are the input of the fuzzy-neural network controller.

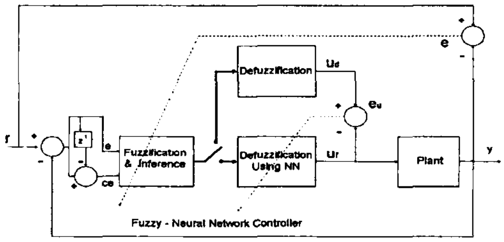


Figure 6. Total control system using fuzzy neural networks controller.

Learning algorithm for defuzzification approximation begins with obtaining the output in the GMDP neural networks.

The local potential function to the ith dendrite of neuron is given by

$$net^{(i)} = \sum_{k=1}^{5} w_k^{(i)} a_k \quad \cdots (13)$$

where $w_k^{(i)}$ is the weight value from the kth input unit(K layer) to the ith dendrite of output layer, a_k is the output of fuzzy inference engine.

Equation (14) applies to the output u_r of GMDP neural network[6].

$$u_r = g(\prod_{k=1}^{5} f(net^{(k)})) \quad \cdots (14)$$

The learning rule is based on the least square error criterion between $u_d^{\,i}$ and u_r^i ;
it is defined by

$$E_u = \frac{1}{2}\sum_i^n (u_d^i - u_r^i)^2 \quad \text{......} (15)$$

where $u_d^{\,i}$ is the expected value and u_r^i is the actual output.

To minimize the error, the weights are required to be updated along the negative gradient direction.

Following the generalized delta rule, we have

$$\Delta w_k^{(i)}(n) = \eta\delta^{(i)}u_r + \xi\,\Delta w_k^{(i)}(n-1) \quad \text{......} (16)$$

where η is called the learning rate according to the gradient descent method, ξ is momentum rate.

$\delta^{(i)}$ is defined as follows:

$$\delta^{(i)} = (u_d - u_r)\, g'\Big(\prod_{i=1}^{5} f(net_k^{(i)})\Big)\, f'(net_k^{(i)}) \prod_{l\neq i}^{5} f(net_k^{(l)}) \quad \text{......} (17)$$

For the input layer,

$$\delta_k = -\frac{\partial E}{\partial net_k} = \sum_i \delta^{(i)} w_k^{(i)} \quad \text{......} (18)$$

Based on the value of δ_k, each parameter (c_m, l_m, r_m) of the M layer is adjusted by the chain rule to modify the language term's membership function to the plant.[5]

$$\Delta c_m = -\eta\frac{\partial E}{\partial c_m} = \eta\sum_k \delta_k \sum_l \frac{\partial o_k}{\partial o_l}\frac{\partial o_l}{\partial o_m}\frac{\partial o_m}{\partial c_m} \quad \text{......} (19)$$

$$\Delta l_m = -\eta\frac{\partial E}{\partial l_m} = \eta\sum_k \delta_k \sum_l \frac{\partial o_k}{\partial o_l}\frac{\partial o_l}{\partial o_m}\frac{\partial o_m}{\partial l_m} \quad \text{......} (20)$$

$$\Delta r_m = -\eta\frac{\partial E}{\partial r_m} = \eta\sum_k \delta_k \sum_l \frac{\partial o_k}{\partial o_l}\frac{\partial o_l}{\partial o_m}\frac{\partial o_m}{\partial r_m} \quad \text{......} (21)$$

5. Simulation

To demonstrate the efficiency of the proposed controller in this study, a comparative analysis was made with common PID controller through an simulation. The simulation were performed using MATLAB software package. The PID controller was simulated using appropriate parameter, which obtained from Ziegler-Nichols rule widely known.

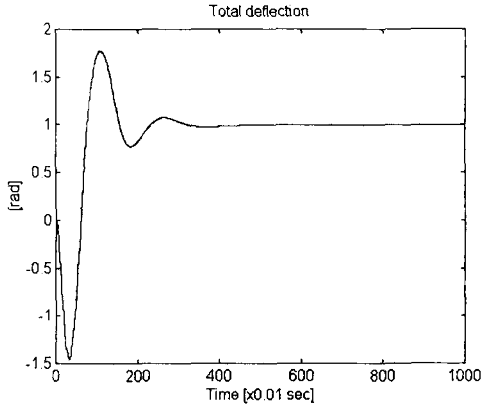
The system parameters used in this study are the length of the link $l=1.2[m]$, the width of the link $w=0.0254[m]$, the thickness of the link $D=0.0032[m]$, mass density $\rho=0.2332[kg/m^2]$, coefficient of elasticity $EI=6.715[N\cdot m^2]$, hub inertia $I_h=0.017[Kg/m^2]$, the material of the hub is aluminum, and the end-point payload of the link not considered.

The reference input used in this simulation is ± 1[rad] step as a position control as to trajectory tracking, we observed the response as to total deflection and elastic displacement in output. Each parameter in the fuzzy neural network controller usedan the linear of PID controller as far as the control of the l 0.4 learning rate, 0.7 moment rate, and 2,000 times of learning.

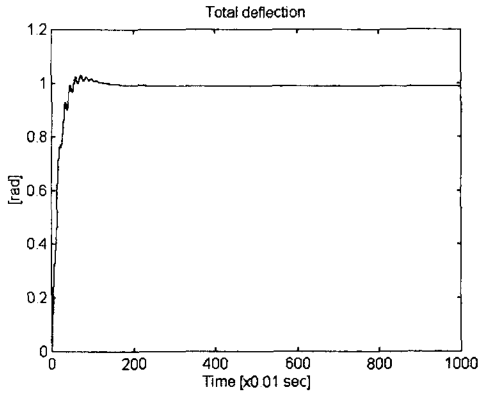
Figure 7. represents location responses against the step input. Here, (a) is those with the PID controller and (b) is those to the fuzzy neural network controller. The latter shows superior control capacity with less early error and qucker convergence.

Figure 8. shows responses to elastic transformation.

Therefore, as noticed in the simulation results, the proposed fuzzy neural networks controller had faster adaptation and better control ability than a common PID controller for position control of the flexible robot manipulator.

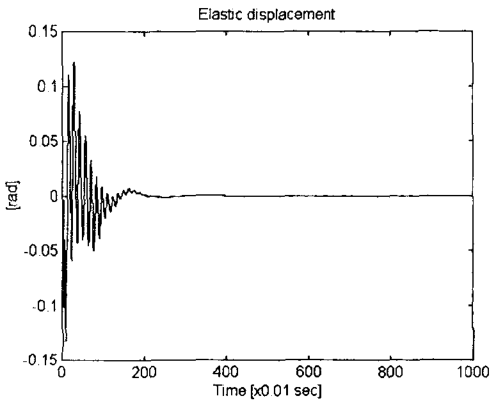


(a) PID controller.

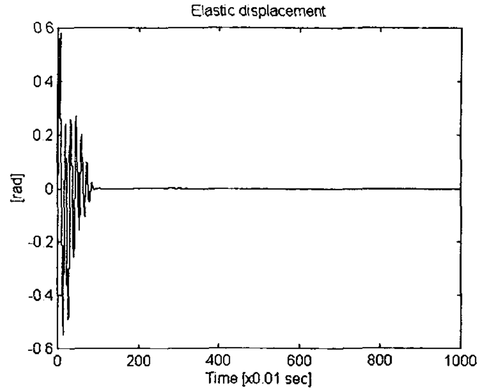


(b) Fuzzy-Neural Networks controller.

Figure 7. Response of total deflection.



(a) PID controller.



(b) Fuzzy-Neural Networks controller.

Figure 8. Characteristics of elastic displacement.

6. Conclusion

This paper presents position control of flexible single link robot manipulator system by fuzzy neural networks. A dynamic models for a flexible robot manipulator is derived, and then a comparative analysis was made with PID controller through a simulation. The results are presented to illustrate the advantages and improved performance of the proposed controller over the PID controller.

The task of study in the future is to incorporate various payloads into the end-point of the link and to demonstrate in the experiment of multi-link that the neural networks controller is more efficient in position control than other conventional ones.

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