IMPLEMENTATION OF NEUROFUZZY CONTROLLER TO ROBOT MANIPULATOR

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ABSTRACT

This paper presents a neurofuzzy controller that is applied to robotic manipulators. Robotic manipulators are highly nonlinear, coupled multivariable dynamical system, and may contain uncertain elements such as friction and load. Many efforts have been made in developing control schemes to achieve the precise tracking control of robot manipulators. For this reason, classical linear controller, such as PID (Proportional, Integral, and Derivative) controller, will provide robustness only over relatively small range operation because of complexity and nonlinearity of the system. Neurofuzzy employed in this system to increase the range operation without lack of robustness. Before considering the actual control system, a neurofuzzy controller must be trained. Two strategies of training are presented in this paper : generalized training and specialized training. In generalized training a neurofuzzy controller is trained off-line. The objective of this training is the controller should performed the ability to follow an input signal over the wide range operation even the transient response is poor. Specialized training is on-line procedure learning. Based on the result of generalized training a neurofuzzy controller is trained to achieve the desired transient response.The results proved the potency of the neurofuzzy in robotic manipulators control systems. Neurofuzzy control systems are essentially nonlinear systems, due to the nature of the nonlinear neurofuzzy controller. Mostly, the nonlinear system is so difficult to be solved. Consequently, the analysis of such systems is complicated, particularly, when a neurofuzzy controller is involved. This is because of the absence of a universal mathematical model.

Keywords : *neurofuzzy controller, robotic manipulators, generalized training, specialized training*

INTRODUCTION

Robots are ideal candidates for material handling operations, manufacturing and measuring devices because of their capacity to pick up, move and release an object, to manipulate both objects and tools and their capacity to explore the three dimensional space.

Nowadays, robotic manipulators are extensively used in the industrial field. The desire of a high-speed or a high-precision performance for this kind of mechanical systems has led to research into improved control systems. These high performance control systems need, in general, the dynamical model of the robotic manipulator in order to generate the control input (Yurkovich, 1992).

Robotic manipulators are highly nonlinear and coupled multivariable dynamical systems. Many efforts have been made in developing control schemes to achieve the precise tracking control of robot manipulators. In the simulation experiments of this paper, the proposed neurofuzzy controller is applied on robotic control to prove its effectiveness.

L. A. Zadeh presented the first paper on fuzzy set theory in 1965. Since then, a new language was developed to describe the fuzzy properties of reality, which are difficult and sometime even impossible to be described using traditional methods. One example in power system is to describe the severeness of power system disturbances accurately. Fuzzy set theory has been widely used in the control area with some application to power system. A simple fuzzy control is built up by a group of rules based on the human knowledge of system behavior.

The translation of the knowledge into fuzzy set theory is not formalized and arbitrary choices concerning for example the shape of the membership function that have be made. Changing shapes of membership functions can drastically influence the quality of the controller. Thus methods for tuning fuzzy controllers are necessary.

Artificial neural networks are highly parallel architectures consisting of simple processing elements, which communicate through weighted connections. They are able to approximate function or to solve certain task by learning from examples. Neural networks can also be used to control problem and they are able to learn from given data. The problem is that learning process takes a lot of time and is not guaranteed to be successful. Furthermore it is not possible to integrate prior knowledge to simplify the learning process.

A combination of both approaches offers possibility to solve the tuning and design problem of the fuzzy control. The combination of neural networks and fuzzy controllers assembles the advantages of both approaches and avoid the drawbacks of them. There are much architecture that has been proposed by researchers to combine the neural networks and fuzzy logic. This research uses an architecture that name as FALCON (Fuzzy Adaptive Learning Control Network). The architecture was firstly proposed by Lin and Lee in 1991.

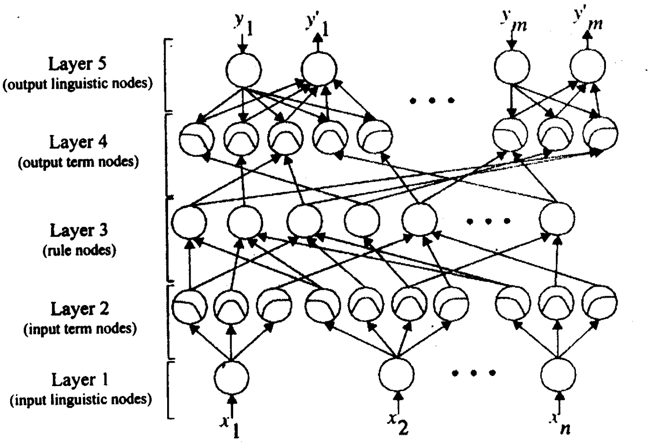


Figure 1.Structure of the FALCON

FALCON is neural network, which functioned as fuzzy inference system. Figure 1 shows the structure of the FALCON. The system has a total of five layers. The nodes in layer 1 are input nodes that represents input linguistic variable, and layer 5 is the output layer. There are two linguistic nodes for each output variable. One is for training data (desired output) to feed into network, and other is for decision signal (actual output) to be pumped out of the networks. Layer 2 and layer 4 are term nodes, which act as membership function representing the term of respective linguistic variables. Each node in layer 3 is rule node that represents one fuzzy logic rule. Thus, all layer 3 nodes form a fuzzy rule base. Links in 3 and 4 function as a connectionist inference engine, which avoids the rule-matching process. Layer 3 links define the predictions of the preconditions of the rule (premise), and layer 4 links defines the consequent of the rule nodes.

DYNAMICS OF ROBOTIC MANIPULATOR

For simplicity, the robotic manipulator to be controlled just has two joints. The structure of the two-joints manipulator is shown in Figure 2 (Sun and Wang, 2004). In Figure 2, m_1 and m_2 are masses of arm1 and arm2 respectively; l_1 and l_2 are lengths of arm1 and arm2; t_1 and t_2 are torque on arm1 and arm2; θ_1 and θ_2 are positions of arm1 and arm2. The dynamics model of two-link robot can be formulated as

$$\mathbf{M(q)\,\ddot{q} + V(q, \dot{q})\,\dot{q} + G(q) = T} \quad (1)$$

where $\mathbf{q} = [\theta_1 \quad \theta_2]^T$ is the joint position vector; $\mathbf{M(q)} \in \mathbf{R}^{\mathbf{nxn}}$ denotes the moment of inertia; $\mathbf{V(q, \dot{q})\, \dot{q}}$ are the Coriolis and centripetal forces; $\mathbf{G(q)}$ includes the gravitational forces; $\mathbf{T} = [t_1 \quad t_2]^T$ is the applied torque vector.

Let $c_i \equiv \cos\theta_i$, $s_i \equiv \sin\theta_i$, $c_{ij} \equiv \cos(\theta_i + \theta_j)$, then $\mathbf{M, V, G}$ in (1) can de described as

$$\mathbf{M(q)} = \begin{bmatrix} m_1 l_1^2 + m_2(l_1^2 + l_2^2 + 2l_1 l_2 c_2) & m_2 l_2^2 + m_2 l_1 l_2 c_2 \\ m_2 l_2^2 + m_2 l_1 l_2 c_2 & m_2 l_2^2 \end{bmatrix},$$

$$\mathbf{V(q, \dot{q})} = \begin{bmatrix} -2m_2 l_1 l_2 s_2 \dot{q}_2 & -m_1 l_1 l_2 s_2 \dot{q}_2 \\ m_2 l_1 l_2 s_2 \dot{q}_1 & 0 \end{bmatrix}, \tag{2}$$

$$\mathbf{G(q)} = \begin{bmatrix} m_2 l_2 g c_{12} + (m_1 + m_2) l_1 g c_1 \\ m_2 l_2 g c_{12} \end{bmatrix}$$

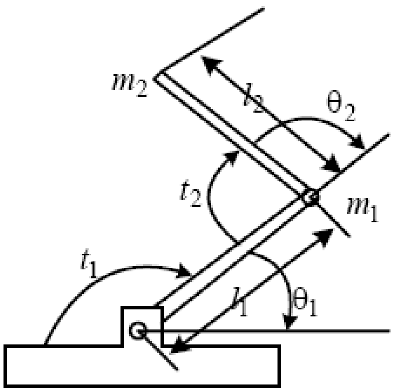


Figure 2**.** Structure of Two-Joints Robot Manipulator

The system structure for the control of two-joints robot manipulator is shown in Figure 3. In this case, the plant in Figure 3 represents the manipulator, the control signal is the torque vector $\mathbf{T}$ and the output of the system is the angle vector $\mathbf{q}$.

NEUROFUZZY CONTROLLER DESIGN

The neurofuzzy logic controller includes three important steps: fuzzification, fuzzy reasoning (decision making) and defuzzification. The inputs to the neurofuzzy controller are the error e(t) and delta error $\Delta e(t)$. This type of fuzzy logic controller can be regarded as a parameter-time varying PD controller. The basic operation of the inference process is to determine the values of the controller output based on the contributions of each rule in the rule base.

It is necessary to choose the proper linguistic variables which formulate the neurofuzzy control rules in order to improve the performance of the neurofuzzy controller. Empirical knowledge and engineering intuition play an important role in choosing linguistic variables and their corresponding membership functions. Essentially, the sensitivity of a variable determines the number of fuzzy subsets. After the fuzzy inference system has been built, it will be tuned by using neural network to increase its performance.

The fuzzy inference system has two universals of discourse in input linguistic and one universal of discourse in output linguistic. The inputs of the neurofuzzy are error vector e(t) and delta error vector $\Delta e(t)$.The output of neurofuzzy is torque vector that drives the robot manipulator. The same neurofuzzy controller is applied in joint1 and joint2. Specialized training is used to improve the performance.

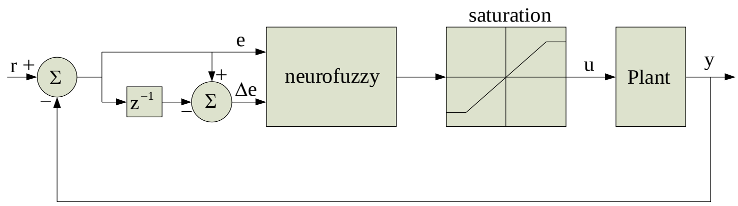
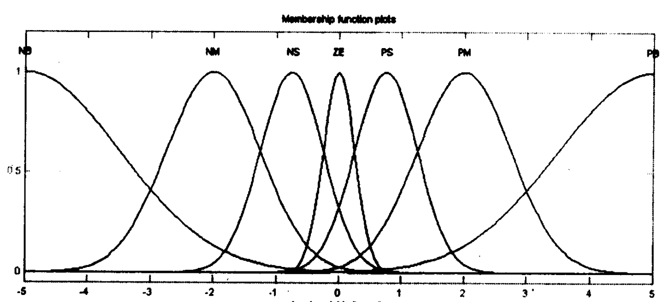
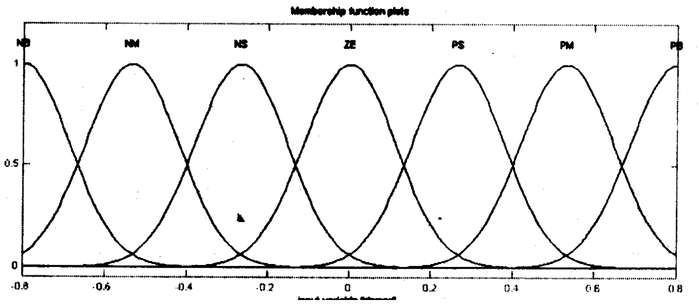


Figure 3 Block Diagram Shows The Proposed Neurofuzzy Controller

Each of the universal of discourse is divided into seven linguistic variables. The linguistic variables are Positive Big (PB), Positive Medium (PM), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Medium (NM), and Negative Big (NB). Figure 4 shows the membership function for universal of error and delta error. Variable linguistic of the control action is shown in Figure 5.



(a)
Membership Function of error



(b)

Membership Function of delta error

Figure 4. Membership Function of Input of Neurofuzzy

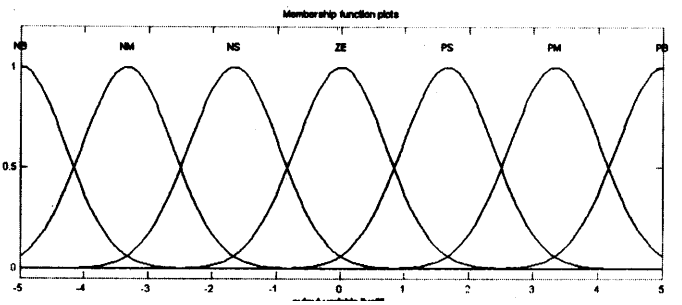


Figure 5. Membership Function of Control Action

Membership function in each universal of discourse uses Gaussian function (Jang, et.al., 1997) that is shown the equation below:

$$\mu(x) = \exp\{\frac{-(x-a)^2}{2b^2}\} \tag{3}$$

which :

$\mu(x)$	= membership degree of x
x	= member of universal of discourse
a	= centre of the membership function
b	= width of the membership function

Using the linguistic variable, the fuzzy rule base can be built as shown in Table 1.

Table 1. Rule base of the proposed controller

$\Delta\omega$ \ $d\Delta\omega$	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	PS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

SIMULATION RESULT AND DISCUSSION

In the simulation, the parameters of manipulator are $m_1 = 4$ kg, $m_2 = 2$ kg, $l_1 = 1$ m, $l_2 = 0.5$ m, $g = 9.8$ N/kg. Initial conditions are given as $\theta_1(0) = 0$ rad, $\theta_2(0) = 0$ rad, $\dot{\theta}_1(0) = 0$ rad/s, and $\dot{\theta}_2(0) = 0$ rad/s. The desired output is given by $\theta_{1r} = 2$ rad and $\theta_{2r} = 1$ rad.

The proposed neurofuzzy control algorithm was compared with the existing PD control used in industry. In this application, it is important to prevent overshoots which seriously affect the quality of the control system.

Figure 6 shows the step responses of PD controller. The system response is coincident with the reference after 3 sec and overshoot appears. For The proposed controller, it could be easily tuned to completely kill the overshoot with a reduction about 30% of the seek time as shown in the Figure 7 compared to the PD controller. It is clear from Figure 6 and Figure 7 that the proposed controller completely meets the design specifications mentioned above.

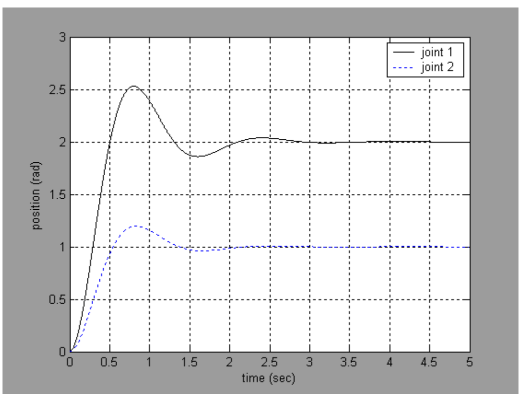


Figure 6. Step Response of Systems based on PD Controller

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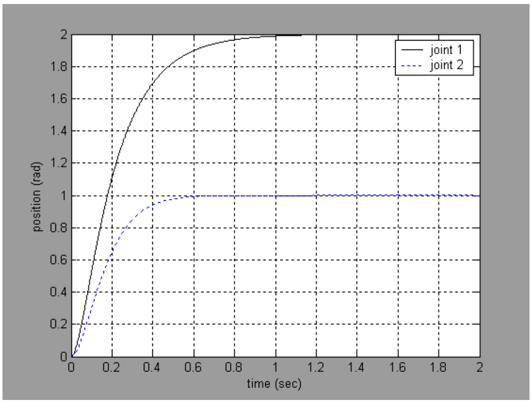

Figure 7. Step Response of Systems based on Proposed Controller

CONCLUSION

The control of robotic manipulators is investigated in this research work with the neuro fuzzy control algorithm for MIMO nonlinear systems. The tracking control of an 2-links robot manipulator to achieve high-precision position control. In the whole design process, no strict constraints and prior knowledge of the controlled plant are required, and the asymptotic stability of the control system can be guaranteed.

A neurofuzzy controller applied in robot manipulators control systems has been reported in this paper. By applying the proposed controller we can get the advantages of the neurofuzzy both at the transient region and at the steady state region to overcome any overshoots.

Simulation results using a mathematical model of robot manipulator show a much better performance using the proposed controller compared to that of the PD controller.

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