# Sliding Mode ANFIS-Based MIMO Fuzzy Neural Network Control for Robotic Systems

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**Abstract**

This paper develops a design methodology of sliding mode ANFIS-Based multi-inputs multi-outputs (MIMO) fuzzy neural network (AMFNN) control for robotic systems. This control system consists of a sliding mode (SM) controller and an AMFNN controller. The SM controller is used to deal with uncertain parts of system dynamics and external disturbances and the AMFNN controller is served as a controller approaching the ideal controller of SM controller to stabilize the system. The ANFIS-Based laws of the AMFNN parameters are derived so that the stability and convergence of the system's parameters of AMFNN can be guaranteed. The simulation results reveal that the better performances are possessed by the proposed AMFNN control compared with the adaptive fuzzy neural network (AFNN) control and state feedback control.

***Keywords:*** *ANFIS, multi-inputs multi-outputs (MIMO), fuzzy neural network, Robotic system, Sliding mode control.*

## 1. Introduction

Many neural-networks-based control technologies have been proposed to demonstrate their performances for control of dynamic systems. The most useful property of neural networks is their ability to approximate linear or nonlinear mapping through learning. Based on this property, neural-network-based controllers have been developed to compensate for the effects of nonlinearities and system uncertainties, thus improving the stability, convergence and robustness of the control system [1]-[3]. The concept of incorporating fuzzy logic into a neural network referred to as a fuzzy neural network (FNN) has become a significant research topic. Based on the automation of neural networks by introducing learning capacities, the design and implementation of fuzzy logic control systems have become very active areas of researching in recent years [4]. Recently, The Adaptive Network-based Fuzzy Inference System (ANFIS) [5] has been applied in many area of researches and has been embedded in toolbox of MATLAB$^{TM}$ [6-9].

To deal with the multi-inputs multi-outputs (MIMO) nonlinear control systems, some adaptive fuzzy control and neural fuzzy control systems have been proposed [10-13]. Robotic systems are well known MIMO nonlinear systems that have to encounter nonlinearities and various uncertainties in their dynamic models, such as friction, disturbance, and load changing, and it is very difficult to reach excellent performance when the control algorithm is completely based on the robotic plant model [14, 15]. Recently, many new adaptive control schemes are proposed for rigid robotic manipulator perturbed by unknown uncertainties and disturbances [16-19].

In this paper, a sliding mode (SM) controller [15] is employed with ANFIS-Based MIMO FNN (AMFNN) controller to deal with robotic system's tracking control. The ANFIS-Based laws of the AMFNN parameters are derived so that the stability of the system and convergence of the parameters of AMFNN can be guaranteed. In the simulation examples, a robotic control system is presented to illustrate the effectiveness of the proposed design method.

## 2. Problem Formulation for MIMO Nonlinear System

Consider an M-dimensional MIMO time invariant nonlinear system, the system states model equation must be expressed as matrix form. To reduce the complexity, the *o-th* column of *M*-th order state matrix of the MIMO system can be expressed as following canonical form.

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}(t)) + \boldsymbol{G}(\boldsymbol{x}(t))\boldsymbol{u}(t) + \boldsymbol{d}(t), \qquad \boldsymbol{y} = \boldsymbol{x} \quad (1)$$

where $\boldsymbol{u}(t)$ and $\boldsymbol{y}$ denote the control inputs and outputs and $\boldsymbol{d}$ denotes the unknown bounded disturbance. For simplicity, the aforementioned functions are abbreviate denoted as $\boldsymbol{x}$, $\boldsymbol{d}$, $\boldsymbol{u}$, $\boldsymbol{f}$, and $\boldsymbol{G}$ in the following discussions. In this paper, the control law will be discussed at first; then the overall control law will be derived by the same way.

The objective of a control system is to design a controller of $\boldsymbol{u}$ such that the system output $\boldsymbol{x}$ can track a desired signal $\boldsymbol{x}_d$ .Then an ideal control law $\boldsymbol{u}^*$ can be designed such as to achieve an error dynamic equation [15]. However, the un-modeled dynamics and external disturbance are always unknown in practice, so that $\boldsymbol{u}^*$ is difficult to design. Recently, many literatures have been proposed to solve this problem. But they are suffered problems of complex manipulations and not good enough performances. In this paper, the controller is designed simply by using a sliding mode ANFIS-Based MIMO fuzzy neural network (AMFNN) controller to cope with model free problem such as to let the states to be closed to the region of desired states; meanwhile, the sliding mode controller is used to maintain the systems' states in the sliding surface; finally letting $\boldsymbol{u}$ approximating the $\boldsymbol{u}^*$ such as to achieve better performance and satisfy the stability convergence; that is $\lim_{t\to\infty} \boldsymbol{e} = \boldsymbol{0}$. The controller is designed as

$$\boldsymbol{u} = \boldsymbol{u}_{AMFNN} + \boldsymbol{u}_{SM} \tag{2}$$

where $\boldsymbol{u}_{AMFNN}$ is an ANFIS-Based MIMO controller and the $\boldsymbol{u}_{SM}$ is a sliding mode controller.

## 3. Sliding Mode ANFIS-Based MIMO Fuzzy Neural Network Design

The ANFIS uses a hybrid learning algorithm to identify the membership function parameters to generate Takagi-Sugeno type fuzzy inference systems (FIS). It uses the method of combination of least-squares and back-propagation gradient descent methods to train FIS membership function parameters to model a given set of input/output data. The principle of ANFIS is briefly described as follows [5].

$$R_i: \textit{If } x \textit{ is } A_1 \ \ldots \textit{and } y \textit{ is } B_1$$
$$\textit{then } h_1 = p_1 x + q_1 y + r_1 \tag{3}$$

where $R_i$ denotes the $i$th fuzzy rules, $i$=1, 2,..,$r$; $A_i$ is the fuzzy set in the antecedent associated with the $k$th input variable at the $i$th fuzzy rule, and $p_{i1},..., p_{in}$, $r_i$ are the fuzzy consequent parameters.

Based on defuzzification. The output $u$ can be calculated as

$$h = \frac{w_1}{w_1+w_2} h_1 + \frac{w_2}{w_1+w_2} h_2$$
$$= \overline{w}_1 u_1 + .. + \overline{w}_2 u_n \tag{4}$$

where $w_i$ is the $i$th node output firing strength of the $i$th rule, and $\overline{w}_1 = \frac{w_1}{w_1+..+w_n}$ ,.., $\overline{w}_n = \frac{w_n}{w_1+..+w_n}$ .

Because the fuzzy inference system is a Takagi-Sugeno type, i.e., $h_i = p_i x + q_i y + r_i$ , Eq. (4) can be rewritten as

$$h = \overline{w}_1 h_1 + \overline{w}_2 h_2$$
$$= (\overline{w}_1 x_1) p_{i1} + .. + (\overline{w}_1 x_n) p_{in} + (\overline{w}_1) r_1$$
$$+$$
$$\vdots$$
$$+ (\overline{w}_n x_1) p_{i1} + .. + (\overline{w}_n x_n) p_{in} + (\overline{w}_n) r_n . \tag{5}$$

The hybrid learning algorithm developed in [5] can be applied to (5) directly. A two inputs neural network structure of ANFIS is shown in Fig. 1. In the hybrid algorithm, functional signals go forward till layer 4 of Fig. 1 and the consequent parameters $p_{i1}, p_{i2}, r_i$ are identified by the *least squares estimate* (LSE) approach. In the *backward pass*, the error rates propagate backward and the premise parameters $x_1$, $x_2$ are updated by the gradient descent approach.

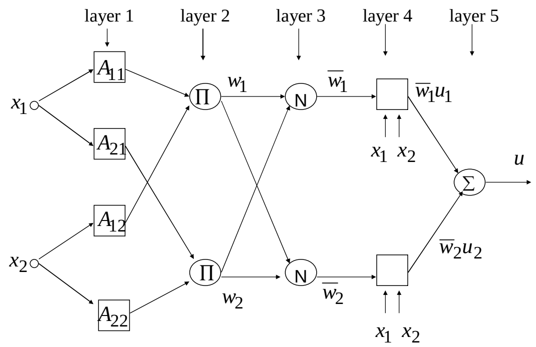


Fig. 1. A two-inputs one-output ANFIS architecture

## 4. Simulation Results of Robotic Control

In this section, an MIMO nonlinear system of robotic system is illustrated to verify the effectiveness of the proposed design method. The robotic system is a two-link, articulated manipulator which positions can be described by a joint angle vector $\boldsymbol{q} = [q_1 \quad q_2]^T$ , and the actuator input is the torque vector $\boldsymbol{u} = [\tau_1 \quad \tau_2]^T$ applied to the manipulator joints. The nonlinear dynamics of such a robotic manipulator is a two-inputs two-outputs coupled system which can be written as following form [15]

$$\boldsymbol{H}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{L}(\boldsymbol{q}) = \boldsymbol{u} , \tag{6}$$

where $\boldsymbol{H}(\boldsymbol{q})$ is the $2 \times 2$ manipulator inertia matrix, $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}}$ is the vector of centripetal and Coriolis torques, and $\boldsymbol{L}(\boldsymbol{q})$ is the gravitational torque vector. The control problem for such a system is to design the control law such that the required actuator inputs to the robot are sufficient to perform the tracking control. Assuming that the robotic manipulator is in the horizontal plane ( $\boldsymbol{L}(\boldsymbol{q}) \equiv 0$ ), the dynamic equation can be written explicitly as [15]

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix}+\begin{bmatrix} -h\dot{q}_2 & -h(\dot{q}_1+\dot{q}_2) \\ h\dot{q}_1 & 0 \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix}=\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} \quad (7)$$

where

$$\begin{aligned} H_{11} &= a_1+2a_3\cos q_2+2a_4\sin q_2, \\ H_{12} &= H_{21}=a_2+a_3\cos q_2+a_4\sin q_2, \\ H_{22} &= a_2, \\ h &= a_3\sin q_2-a_4\cos q_2, \end{aligned} \quad (8)$$

with

$$\begin{aligned} a_1 &= I_1+m_1 l_{c1}^2+I_e+m_e l_{ce}^2+m_e l_1^2, \\ a_2 &= I_e+m_e l_{ce}^2, \\ a_3 &= m_e l_1 l_{ce}\cos\delta_e, \\ a_4 &= m_e l_1 l_{ce}\sin\delta_e, \end{aligned} \quad (9)$$

the parameters values of the robotic system are given as $m_1=1$, $l_1=1$, $m_e=2$, $\delta_e=30^\circ$, $I_1=0.12$, $l_{c1}=0.5$, $I_e=0.25$, $l_{ce}=0.6$.

Equation (7) can be rewritten as a state equation

$$\ddot{\boldsymbol{q}}=\boldsymbol{f}_q(\dot{\boldsymbol{q}})+\boldsymbol{G}_q(\boldsymbol{q})\boldsymbol{u} \quad (10)$$

where

$\dot{\boldsymbol{q}}=[\dot{q}_1 \quad \dot{q}_2]^T$ , $\boldsymbol{f}_q(\dot{\boldsymbol{q}})=\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix}$ ,

$\boldsymbol{G}_q(\boldsymbol{q})=\begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}$ and $\boldsymbol{u}=[\tau_1 \quad \tau_2]^T$. Because the state of (10) is $\dot{\boldsymbol{q}}$, it is necessary to make transformation for this state equation with state vector of $\boldsymbol{q}$ such that the error dynamic equation of $\tilde{\boldsymbol{q}}$ can be established. By defining the states as $x_1=q_1$, $x_2=q_2$, $x_3=\dot{q}_1$ and $x_4=\dot{q}_2$, then, fourth order equation of (10) can be obtained.

The joint angle error vector is defined as $\boldsymbol{e}=\boldsymbol{x}_d-\boldsymbol{x}$, the controller can be designed as

$$\boldsymbol{u}=\hat{\boldsymbol{u}}_{AMFNN}+\boldsymbol{u}_{SM} \quad (11)$$

Where $\hat{\boldsymbol{u}}_{AMFNN}$ represents the estimated AMFNN controller. The robot, which is initially at rest at ($q_1=0^\circ, q_2=0^\circ$), is commanded to follow a desired trajectory $q_{d1}(t)=30^\circ(1-\cos(2\pi t))$ and $q_{d2}(t)=45^\circ(1-\cos(2\pi t))$. Moreover, 50% mass uncertainties of $m_1$ and $m_e$ is also simulated to illustrate the robust control performance. For simulation results, the proposed controller in (14) will be compared with adaptive fuzzy neural network (AFNN) controller and state feedback controller to verify the effectiveness of the proposed control methodology. ANFIS is designed as in Fig. 2. The simulation results are shown in Fig. 3. The simulation results show that the AMFNN controller can cooperate with sliding mode controller to achieve better and robust control performance than the AFNN control and state feedback control.

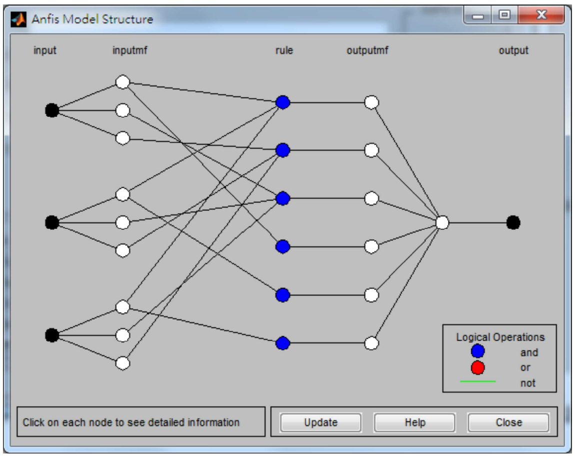


Fig. 2. The ANFIS structure diagram

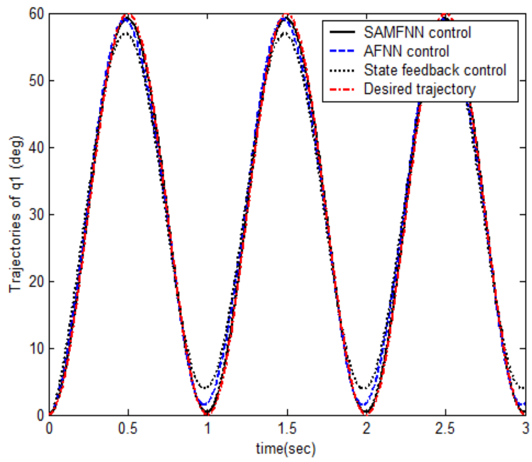


Fig. 3(a). Tracking trajectories of $q_1$

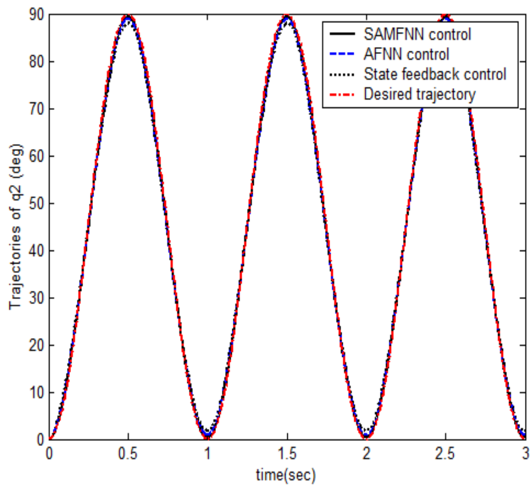


Fig. 3(b). Tracking trajectories of $q_2$

## 5. Conclusions

A sliding mode ANFIS-Based multi-inputs multi-outputs (MIMO) fuzzy neural network (AMFNN) control for robotic system has been developed in this paper. This control system consists of a sliding mode (SM) controller and an AMFNN controller. The SM controller is used to deal with uncertain parts of system dynamics and external disturbances, and the AMFNN controller presents a controller to approach the ideal controller of SM controller to stabilize the system. The ANFIS-Based laws of the AMFNN parameters are derived so that the stability of the system and convergence of the parameters of AMFNN can be guaranteed. The simulation results reveal that the proposed control methodology possesses better performances by comparison with adaptive fuzzy neural network (AFNN) control and state feedback control.

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