УДК 621.865.8

© **Chao Xie**[1,2]

# NOVEL CMAC NEURAL NETWORK BASED ROBOT INTELLIGENT CONTROL

## 1. Introduction

Numerous robot control schemes have been studied during the past decade, one approach involves using a dynamic model of the robot to calculate the joint driving torques for the specified trajectory. However, generally speaking, it is difficult to derive an accurate dynamic model for the controlled robot since there exist some unknown factors (such as uncertainty and parameter variation), so the scheme of calculated torque controllers can not always provide satisfactory result [1, 2].

As is well known, Robotic manipulator with multi-joints are very complex control problem due to the model uncertainty and the external disturbances, in practice, it is impossible to obtain their accuracy relationship functions. Therefore, the independent joint control system of direct-drive robot with conventional control methods cannot give satisfactory performance. Although the methods of variable-structure control, adaptive control and fuzzy control have improved the control performance, they cannot be used easily in practice because they rely on the detailed mathematical model of the robot [3, 4].

Recently there are many discussions on the use of neural networks in robot control. This paper proposes a type of efficient intelligent control method of robotic joint based on a novel CMAC-type neural network. The implementation of the controller needs no robot model knowledge. This feature enable the robot to perform fast tracking tasks with high performance, the simulation results verify that the control strategy is effective.

## 2. Dynamics of robotic joint

*A. Continuous Dynamic Model of Robotic Joint*

The controlled plant is a robotic manipulator with two joints: shoulder joint and elbow joint. The aim is to design the joint controller to perform fast tracking task. The dynamic model of the two joints in continuous form are respectively described as:

$$\begin{aligned}&(1.19+0.31C_2)\ddot{q}_1+(0.13+0.15C_2)\ddot{q}_2-0.31S_2\dot{q}_1\dot{q}_2-\\&-0.15S_2(\dot{q}_2)^2+5.25\sqrt{|\dot{q}_1|}\,sgn(\dot{q}_1)=\tau_{1E}\end{aligned} \tag{1}$$

$$(0.13+0.15C_2)\ddot{q}_1+0.32\ddot{q}_2-0.15S_2\dot{q}_1^2+\left(3.72-2.08\sqrt{|\dot{q}_1|}\right)sgn(\dot{q}_2)=\tau_{2E} \tag{2}$$

where $\tau_{1E}$ and $\tau_{2E}$ are respectively the applied driving torques for shoulder and elbow; $\ddot{q}_1$ and $\dot{q}_1$ the shoulder joint acceleration and velocity; $\ddot{q}_2$, $\dot{q}_2$ and $q_2$ the elbow joint acceleration, velocity and position, and $C_1=\cos q_1$, $C_2=\cos q_2$, $S_1=\sin q_1$, $S_2=\sin q_2$.

*B. Discrete Dynamic Model of Robotic Joint*

For the control algorithm is implemented by computer, according to Eq.1 and Eq.1, when we choose sampling time $t_s=0.06s$, we can respectively conclude the dynamic models of the shoulder joint and elbow joint in discrete form as follows:

$$\begin{aligned}q_1(k)=\Big(&0.31*sin\,q_2(k-2)\big(q_1(k-1)-q_1(k-2)\big)\big(q_2(k-1)-q_2(k-2)\big)/0.06^2+\\&+0.15\,sin\,q_2(k-2)\big(q_2(k-1)-q_2(k-2)\big)^2/0.06^2-\\&-5.25\sqrt{|(k-1)-q_1(k-2)|/0.06}\times\\&\times\big(q_2(k)-2q_2(k-1)+q_2(k-2)\big)/0.06^2\Big)\cdot 0.05^2/\\&/\big(1.19+cos\,q_2(k-2)\big)+2q_1(k-1)-q_1(k-2)\end{aligned} \tag{3}$$

$$q_2(k) = -\left(3.72 - 2.08\sqrt{\left|(q_1(k-1) - q_1(k-2))/0.05\right|} \cdot sign\left((q_2(k-1) - q_2(k-2))/0.05\right) + \right.$$
$$+ 0.15 sin q_2(k-2)\left(q_1(k-1) - q_1(k-2)\right)^2/0.05^2 - \left(0.13 + 0.15 cos q_2(k-2)\right) \times \tag{4}$$
$$\left. \times \left(q_1(k) - q_1(k-1) + q_1(k-2)\right)/0.05^2\right) * 0.05^2/0.32 + 2q_2(k-1) - q_2(k-2)\, \tau_{1E}(k-2)$$

According to Eq.3 and Eq.4 , we can conclude the inverse dynamic model of the joint in discrete forms as

$$\tau_{1E}(k) = f_1\left(q_1(k), q_1(k-1), q_1(k-2), q_2(k), q_2(k-1), q_2(k-2)\right) \tag{5}$$

$$\tau_{2E}(t) = f_2\left(q_1(k), q_1(k-1), q_1(k-2), q_2(k), q_2(k-1), q_2(k-2)\right) \tag{6}$$

## 3. Robotic joint intelligent control scheme based on FFI-AMS neural network

As described by Eq.5 and Eq.6, $f_1(\cdot)$ and $f_2(\cdot)$ respectively represent nonlinear functions describing the corresponding inverse robot dynamics of shoulder joint and elbow joint, however, the two relationship functions are very complex duo to the model uncertainty and the external disturbances, moreover, there exists strong between the robotic joint, so the scheme based on accurate mathematic model is not feasible, we present a intelligent control scheme of the robot joint.

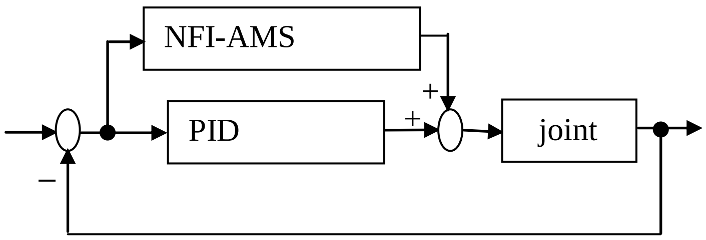


Fig.1 Block of intelligent control scheme

The control scheme includes two main parts: NFI-AMS -based intelligent controller and PD controller. The former is used as a feed forward unit in parallel with the later which is used as a feedback unit, The control block diagram is shown in Fig.1. The NFI-AMS is used to learn the inverse dynamic model of the robot joint and calculate the driving torques required to follow the desired trajectory exactly. In fact, the FFI-AMS-based controller plays even more important role during the whole control process [5].

However, the functions $f_1(\cdot)$ and $f_2(\cdot)$ are difficult to be determined accurately in practice [6], and the involved complex computations are uneasy to be implemented as an essential part of real-time controller. As described in Section 1, the NFI-AMS has a strong ability of approximating any function relationship, just based on this point, we apply NFI-AMS to learn the function relations described by Eq.5 and Eq.6. The NFI-AMS is used to predict the driving torques required to follow a desired trajectory, There exist two independently NFI-AMS (NFI-AMS 1 and NFI-AMS 2) served as feed forward units in parallel with respective PD controllers in the manipulator control system, which is shown in Fig.1.

The NFI-AMS – based robot joint intelligent control method is proposed as following formula.

$$u = u_{NFI-AMS} + u_{PID} \tag{7}$$

where $u_{NFI-AMS}$ represents the control signal of NFI-AMS _based controller, and $u_{PID}$ he control signal of PID controller.

## 4. Design of NFI-AMS_based controller

A. Newton's Forward Interpolation Based Associative Memory System (NFI-AMS)

In order to reduce the computational effort, it is necessary to develop an implicit expression, in which all the discrete differences (instead of the function values themselves) of $f(s_1, s_2, \cdots, s_N)$ are directly used in the interpolation algorithm. A $N$ -variable high-order polynomial function can be approximated by

$$
\begin{aligned}
f(s_1, s_2, \cdots, s_N) &= \phi_\mu(s_1, s_2, \cdots, s_N) + R_\mu(s_1, s_2, \cdots, s_N) \approx \\
&\approx \phi_\mu(s_1, s_2, \cdots, s_N) = \sum_{l_1+l_2+\cdots+l_N=0}^{\mu} c_{l_1,l_2\cdots l_N} \Delta^{(l_1,l_2,\cdots,l_N)} f(s_1, s_2, \cdots, s_N)
\end{aligned}
\tag{8}
$$

It can be easily proved that total number $c_{l_1,l_2\cdots l_N}$'s is

$$
n_c = n_\mu = C_{N+\mu}^{\mu} \tag{9}
$$

Tolle et al. indicated that the weights number strictly depended on the coefficient of a $N$ -variable polynomial function in the form of

$$
\begin{aligned}
f(s) = f(s_1, s_2, \cdots, s_N) &= a_0 + \sum_{j=1}^{N} a_j s_j + \sum_{j=1}^{N} \sum_{j_2=j_1}^{N} a_{j_1} a_{j_2} s_{j_1} s_{j_2} + \cdots + \\
&+ \sum_{j=1}^{N} \sum_{j_2=j_1}^{N} \cdots \sum_{j_\mu=j_\mu-1}^{N} a_{j_1} a_{j_2} \cdots a_{j_\mu} s_{j_1} s_{j_2} \cdots s_{j_\mu}
\end{aligned}
\tag{10}
$$

where $s = [s_1, s_2, \cdots, s_N]$. Thus, the total number of its coefficients is

$$
n_\mu = 1 + C_N^1 + C_{N+1}^2 + \cdots + C_{N+\mu-1}^{\mu} + = C_{N+\mu}^{\mu} \tag{11}
$$

So $n_\mu$ pieces of independent information is enough to approximate $\mu$-th order polynomial function in a specified $N$ -dimensional input space.

*B. Dedsign of NFI-AMS_based Controller*

NFI-AMS is used to model the inverse dynamic of the joint, i.e., Eq.5 and Eq.6, respectively. With uncertainty and external coupling of the joint control system for the robot, the NFI-AMS should be able to learn on-line and satisfy the performance in real time [9, 10].

NFI-AMS1 is designed for shoulder joint, and NFI-AMS2 for elbow joint. Both the two NFI-AMS have the same structure with six-dimensional input and one-dimensional output. Let the input state vector $x_1$ to NFI-AMS1 be formed from the variables $q_1(k), q_1(k-1), q_1(k-2), q_2(k), q_2(k-1)$ and $q_2(k-2)$, and the function $\hat{f}_1(\cdot)$ of NFI-AMS1 correspond to the function $f_1(\cdot)$. Similarly, let the input state vector $x_2$ of NFI-AMS2 be formed from the variables $q_2(k)$, $q_2(k-1), q_2(k-2), q_1(k), q_1(k-1)$ and $q_1(k-2)$, the function $\hat{f}_2(\cdot)$ of FFI-AMS_NN2 correspond to the function $f_2(\cdot)$. The parameters of both two NFI-AMS s are as follows: input dimension: $N = 6$; output dimension: $N_p = 1$.

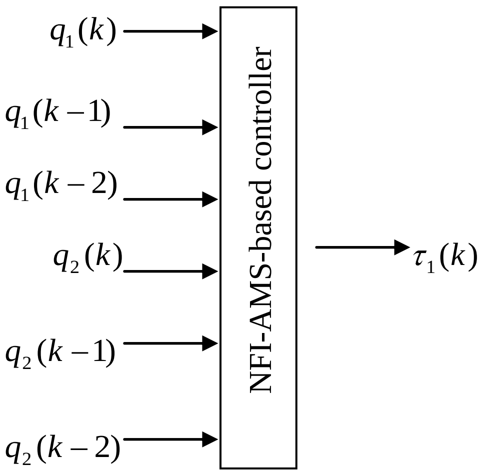


Fig.2. The structure of the NFI-AMS based controller

Each control cycle consists of a training period and a controlling period. At the beginning of each control cycle, a training step is executed, The observed state of the system during the previous control cycle is used as input to the NFI-AMS which produces $\hat{f}_i(x_{io})$, so the training data pairs for the two NFI-AMS is respectively chosen as follows:

$$q_1(k), q_1(k-1), q_1(k-2), q_2(k), q_2(k-1), q_2(k-2) \Rightarrow \tau_1(k)$$

The different between the predicted torque $\hat{f}_i(x_{io})$ and the actual applied command $\tau_{iE}$ during the previous control cycle is used for adjusting the weights stored in the NFI-AMS cells.

After the training period, the learning step is executed. The trajectory planner determines the desired state of the system for the next control cycle (i.e., the desired positions, velocities and accelerations of the actuators) based on the given desired trajectory. The desired next states $s_{ir}$ (i = 1, 2) is then sent to the two NFI-AMS networks. The outputs of NFI-AMS $\hat{f}_i(s_{ir})$ (i = 1, 2) are assumed to be estimates of the driving torques required to achieve respective desired states and added to the outputs of the corresponding PD controllers so as to form the resultant control commands sent to the robot manipulator joints.

As the NFI-AMS can be continually trained on successive control cycles, each NFI-AMS function $\hat{f}_i(s_{io})$ gradually forms an approximation of the corresponding inverse system dynamic characteristics $f_i(s_{io})$ over particular regions in the state space [7]. Finally, if the future control situation of robot manipulator is similar to previously trained one, then the NFI-AMS can output a suitable driving torque. As a result, the state errors will be small and the NFI-AMS will finally take over the control functionality from PD controller. The NFI-AMS _based controller is shown as Fig. 2.

## 5. SIMULATION AND RESULTS

The robot has two rotate joints, in which they can rotate horizontally with 360 degrees. In order to verify the proposed control method, the elbow joint of the robot manipulator is taken as the example and the simulation tests are made. The tracking output and error curves of shoulder joint are shown respectively as Fig.3 and Fig.4. The simulation results fully demonstrate that the proposed control scheme has a more accurate tracking performance than PID controller.

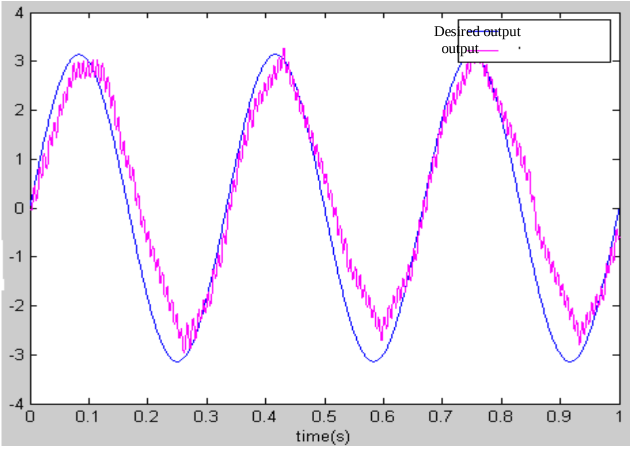


Fig.3 Elbow joint racking result of PID controller.

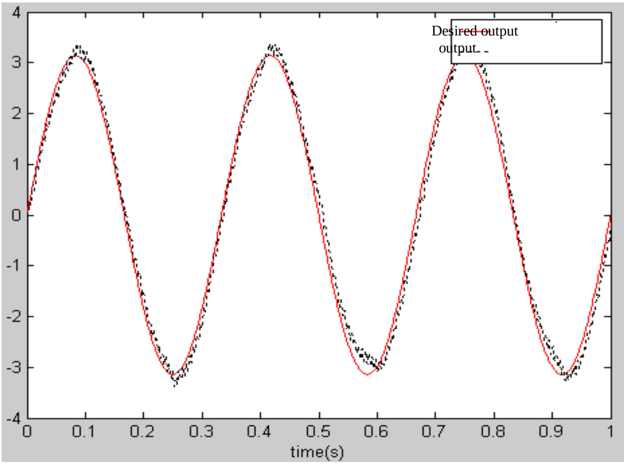


Fig.4 Elbow joint racking result of intelligent controller based on NFI-AMS.

## References


1. Miller, W.T. CMAC: An Associative Neural Network alternative to Back-Propagation / W. T. Miller, F. H. Glanz // Proc. IEEE. – 1990. – Vol. 78. – P. 1561–1567.
2. Xu Ning-shou. A Novel Associative Memory based on Sharp angled Hat Spline Functions / Xu Ning-shou // The IEEE Int. Conference on Systems, Man and Cybernetics, Beijing China, 1996. – P. 381–386.
3. Wang Jun-song. Associative Memory Systems-based Robot Intelligent Control System / Wang Jun-song // Bei-Jing Polytechnique University Master Paper. 1998

4. Xu Ning-shou. A New Content-addressing Mechanism of CMAC Associative Memory System / Xu Ning-shou // Proc. of the 13th IFAC World Congress, USA, 1996. – P. 347–382.
5. Xu Ning-shou. Associative Memory-based Intelligent Control of Ship-steering Systems / Xu Ning-shou // Proc. European Control Conference, ECC-95, Rome.
6. Xu Xing-shou. Generalized SHSF-type Associative Memory System / Xu Xing-shou, Zhi-Hong Yang // Proc. of the 13th IFAC World Congress, USA, 1996. – P. 775–780.
7. Xu Ning-shou. An Innervated Structure System Scheme Using Associative Memory Systems / Xu Ning-shou // Research on Complex System Control Problems / Academia Simca, 1995. – P. 763–768.
8. Chen S. A clustering technique for digital communications channel equalization using radial basis function networks / S. Chen, B. Mulgrew, P. M. Grant // IEEE Trans. Neural Networks, 1993. – Vol. 4, July. – P. 570–578.
9. Bingulac S. P. On the compatibility of adaptive controllers : (Published Conference Proceedings style) / S. P. Bingulac // Proc. 4th Annu. Allerton Conf. Circuits and Systems Theory, New York, 1994. – P. 8–16.
10. Faulhaber G. R. Design of service systems with priority reservation / G. R. Faulhaber // IEEE Int. Conf. Communications : Conf. Rec., 1995. – P. 3–8.

***Chao Xie*[1,2]*.*** «Новая CMAC-нейронная сеть для интеллектуального управления роботом».

В данной статье предложен метод интеллектуального управления робототехническим соединением с помощью высокоорганизованной системы с ассоциативной памятью, основанной на Интерполяции (NFI-AMS), каким является новый тип CMAC нейронной сети. Система NFI-AMS способна проследить желательную траекторию с высокой точностью. Динамика

робототехнического соединения и проект диспетчера, основанного на NFI-AMS, сформулирована. Было проведено много исследований, результаты которых показали, что управление выполняется эффективно.

***Chao Xie*[1,2]. «**Нова CMAC-нейрона мережа для інтелектуального керуванням роботом».

В даній статті запропоновано засіб інтелектуального керування робототехнічним з'єднанням, за допомогою високоорганізованої системі з асоціативною пам'ятью, заснованій на інтерполяції (NFI-AMS), яким є новий тип CMAC нейронної мережі. Система NFI-AMS здатна до слідкування бажаної траєкторії з високою точністю. Динаміка робототехнічного з'єднання та проект диспетчера, заснованого на NFI-AMS, сформульовані. Було проведено багато досліджень, результати яких показали, що керування виконується ефективно.

***Chao Xie*[1,2]**. «Novel CMAC Neural Network Based Robot Intelligent Control»

This paper proposed a robotic joint intelligent control method via a high-order Associative Memory System based on the Newton's Forward Interpolation (NFI-AMS), which is a novel CMAC-type neural network, NFI-AMS is capable of tracking the desired trajectory with high accuracy. Dynamics of robotic joint and design of the NFI-AMS-based controller is formulated. A lot of simulations are conducted, and the simulation results have shown that the control strategy is feasible and efficient.

***Index Terms*:** Associative Memory System, Robot, Intelligent control