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Adaptive Control Based on Nonlinear Dynamical System

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Abstract : This paper presents a neuro adaptive control method for nonlinear dynamical systems based on artificial neural network systems. The proposed neuro adaptive controller consists of 3 layers artificial neural network system and parallel PD controller.
At the early stage in learning or identification process of the system characteristics the PD controller works mainly in order to compensate for the inadequacy of the learning process and then gradually the neuro controller begins to work instead of the PD controller after the learning process has proceeded.
From the simulation studies the neuro adaptive controller is seen to be robust and works effectively for nonlinear dynamical systems from a practical applicational point of view.

Keywords : Neuro adaptive controller, nonlinear systems, identification, learning, artificial neural network system

1 INTRODUCTION

Recently, much attention [1]-[2] has been focused on the application of artificial neural network systems [3]-[7] (denoted as ANNSs) to control nonlinear dynamical systems which have unknown structures and parameters under the disturbances.
Until now conventional system identification techniques [8]-[9] have been applied for estimating the unknown structures and parameters of linear or nonlinear dynamical systems based on the mathematical descriptions of the systems.
The ANNS can be used as both a new type of identification method which is able to model the complex systems with unknown structures, nonlinearities, and disturbances and a new type of control method which is able to adapt easily for the sudden changes of the operating conditions of the systems. We have already proposed a neuro identifier for linear and nonlinear dynamical systems based on the ANNS [10] which has a tapped delay line added to the input layer in order to learn dynamic maps or systems. The neuro identifier proposed uses the back propergation method in order to minimize the errors between the output of the ANNS and the output of the system to be identified. Also we developed a new model predictive control method [11] based on the neuro identifier which is robust and satisfactory in the control performance for the cases where the structure of the dynamical system is changed and/or the disturbances are added to the system, etc..
This paper proposes a new neuro adaptive controller, which involves the parallel PD controller, in order to preserve the stability of the system and implements the identification of the system simultaneously based on the ANNSs. The neuro adaptive controller and identifier uses the back propergation method in order to learn the system dynamics.
The numerical simulation studies are performed in order to check both control and identification performances of neuro adaptive controller for two nonlinear dynamical systems. From the results obtained it is concluded that the neuro adaptive controller has robustness in the change of operational conditions, circumstances and disturbances and hence the control uite satisfactory.

2 ARTIFICAL NEURAL NETWORK SYSTEMS

A general view of the M-layers ANNS is shown in Fig.1. The system equation which describes the input-output relation of k-th layer in the ANNS is given by

$$S_j^{(k)} = \sum_i w_{ij}^{(k-1)} y_i^{(k-1)}, \tag{1}$$

$$y_j^{(k)} = f(S_j^{(k)}), \ k=2,\cdots,M \tag{2}$$

where $S_j^{(k)}$ is the sum of the inputs to j-th unit in k-th layer, $y_j^{(k)}$ is the output of j-th unit in k-th layer, f is the sigmoid function given by

$$f(x)=(1-\exp(-x/\mu_0))/(1+\exp(-x/\mu_0)) \tag{3}$$

with the property given as

$$f'=(1+f)(1-f)/\mu_0. \tag{4}$$

It is noted that $y_j^{(1)}=x_j$ and the threshold value is equal to $w_{0j}^{(k-1)}$, and $w_{ij}^{(k-1)}$ is the synapses weight

$w_{ij}^{(k-1)}$ is calculated from the recursive formula given by

$$\Delta w_{ij}^{(k-1)} = -\eta \delta_j^{(k)} y_i^{(k-1)}, \quad (5)$$

$$\text{where } \delta_j^{(n)} = (z_j - y_j^{(n)})(1+y_j^{(n)})(1-y_j^{(n)})/\mu_\theta, \quad (6)$$

$$\delta_i^{(k)} = (\sum_j \delta_j^{(k+1)} w_{ij}^{(k)})(1+y_i^{(k)})(1-y_i^{(k)})/\mu_\theta \quad k=M-1,\cdots,2, \quad (7)$$

and z_j is the teaching signal.

3 MODELING OF INVERSE SYSTEM AND NEURO ADATIVE CONTROL METHOD

3-1 *Modeling of Inverse System*

There are two ways in applying the ANN for modeling or identifying the dynamics of systems. One is to model the input and output relation of the system in forward direction and the other is to model that in backward or inverse direction.

The configuration of direct inverse identification using the ANNS is shown in Fig.2 where U(k) and Y(k) are the known input to the plant and the known output from the plant at sampling time k, respectively. The inputs to the input layer in the ANNS are tapped delayed output given by Y(k-1),···, Y(k-p) and inputs given by U(k-1),···, U(k-q).

The output from the ANNS is $U_N(k)$. The back propergation method is employed as the learning method in order to minimize the error between U(k) and $U_N(k)$.

3-2 *Neuro Adaptive Controller*

The configuration of a neuro adaptive control system using the ANNS is illustrated in Fig.3. In this figure the conventional PD controller shown as linear control system is used in parallel. In the linear PD controller the control law $U_G(k)$ is decided in the way that the error between the desired output $Y_D(k)$ and the output of the system Y(k) at sampling time k is reduced or compensated. Namely, the control law is given by

$$U_G(k) = K_P e(k) + K_D(e(k)-e(k-1)), \quad (8)$$

where K_P is the propotional gain, K_D is the differential gain, and

$$e(k) = Y_D(k) - Y(k). \quad (9)$$

In the meanwhile, since the ANNS predicts the output of the system at sampling time (k+1), the desired value $Y_D(k+1)$ becomes the input to the ANNS. The output $U_N(k)$ from the ANN is obtained in order for that the ANNS provides with the desired value. Hence the neuro adaptive control U(k) for the system is represented by the sum of the output $U_N(k)$ from the neuro controller based on the ANNS and the output $U_G(k)$ from the PD controller as follows.

$$U(k) = U_N(k) + U_G(k). \quad (10)$$

The solid line in Fig.3 shows the signal flow at the neuro adaptive control stages. The inputs for the ANNS at the learning stage are the time series of the output Y(k) of the systems and the output from the ANNS is the control specified by $U_N(k-1)$. Hence the inputs for the ANNS at the learning stage are different from those at the control stage. The learning is performed by the back propergation method which decreases the mean squares error between the real control U(k-1) and the control from the ANNS $U_N(k-1)$ at sampling time (k-1) specified by

$$J = (U(k-1)-U_N(k-1))^2/2 = (U_N(k-1)+U_G(k-1)-U_N(k-1))^2/2 \quad (11)$$

The dotted line in Fig.3 shows the signal flow at the learning or identification stage of nonlinear dynamical system based on the ANNS. The flowchart for the calculation of neuro adaptive controller is illustrated in Fig.4. At the early stage in the modeling the PD controller works mainly in the fashion of assisting the ANNS which has not learned sufficiently the system dynamics.

After the modeling of the system dynamics has been proceeded and hence the ANNS has learned the system, the output of the system tracks well the desired value. Then the input e to the PD controller becomes zero and hence the output of the controller $U_G(k)$ becomes zero. Consequently, the most part of control to the system is decided from the output of the ANNS $U_N(k)$. In her words, the inverse system of the nonlinear dynamical system to be controlled has been modeled inside the ANNS. Then the control action is gradually transfered from the control by the PD controller to that by the ANNS. After the transition has been completed the PD controller still continues to work. Hence, the stability of the control is assured sufficiently by compensating the nonlinear dynamical system with the aid of the PD controller for the cases when the changes of the system to be controlled and the operating conditions are occurred. Therefore we can construct a robust control system.

4 SIMULATION STUDY

A nonlinear dynamical systems is considered as example in the simulation studies of the neuro adaptive controller. Namely the dynamical equation is assumed to be given by

$$\text{Example 1}: Y(K) = 0.8\sin(2Y(k-1)) + 1.2U(k-1), \quad (12)$$

The parameters used for the PD controller and the ANNSs employed are illustrated in Table 1. The desired value is specified as

$$Y_D(k) = 0.8\cos(2\pi k/100) + 0.1 \ . \quad (13)$$

The 100 sampling data is used as one pack or training period. Some of the results in the simulation studies are illustrated in the followings. Figure 5 shows the results when the traing period is 1. Figure 6 shows the results when the traing period is 100. Figure 7 shows the results when a constant disturbance is added example at 900 sampling time. We notice that the results obtained from the simulation studies shows the robustness and adaptiveness of the neuro adaptive controller.

5 CONCLUSIONS

In this paper a neuro adaptive controller based on the PD controller for the nonlinear dynamical systems with the aid of the ANNS is proposed as one of robust and effective control methods and effective methods from a practical applicational point of views. The idea of neuro identifier as well as neuro controller with the parallel PD controller based on the ANNS is presented in order to model the inverse systems of the nonlinear dynamical systems to be controlled.

The numerical studies of the neuro adaptive controller are performed in order to check the identification and control performances. It is seen from the simulation studies that neuro identifiers and controllers developed are able to model quite well the inverse systems of the nonlinear dynamical systems and hence the neuro adaptive controllers are able to control the systems satisfactory.

In addition, the neuro adaptive controllers are robust for the changes of systems and operating conditions and the addition of the disturbances. However training the ANNS requires a long computational time. Hence, in order to get rid of this disadvantages we will introduce a neuro computer hardware in future studies in order to design the practical identifiers and controllers in the real applications.

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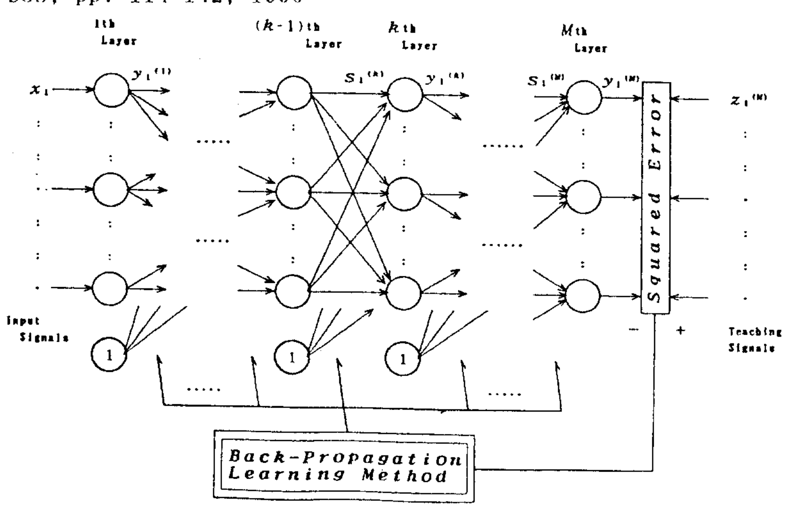


Fig.1 General View of M-layers Artificial Neural Network System based on Back-Propagation Learning Method

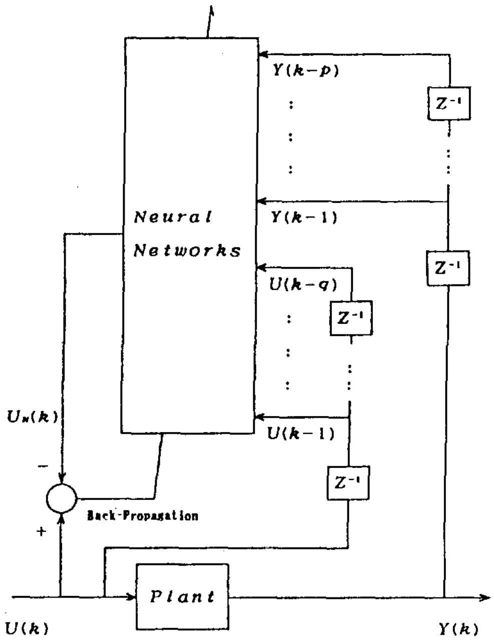


Fig.2 Direct Inverse Identification by using Artificial Neural Network System based on Back-Propagation Learning Method

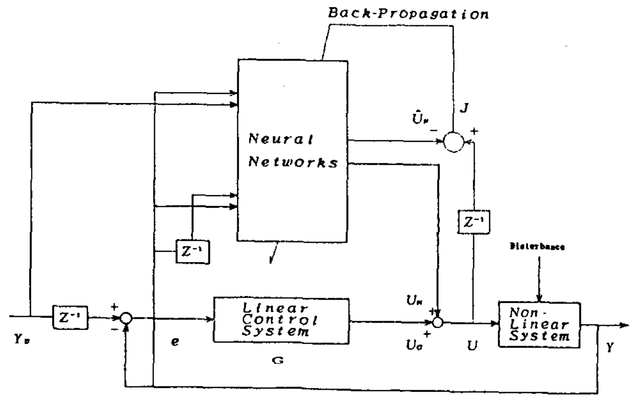


Fig.3 A Structure of Neuro Adaptive Control System by using Artificial Neural Network Systems

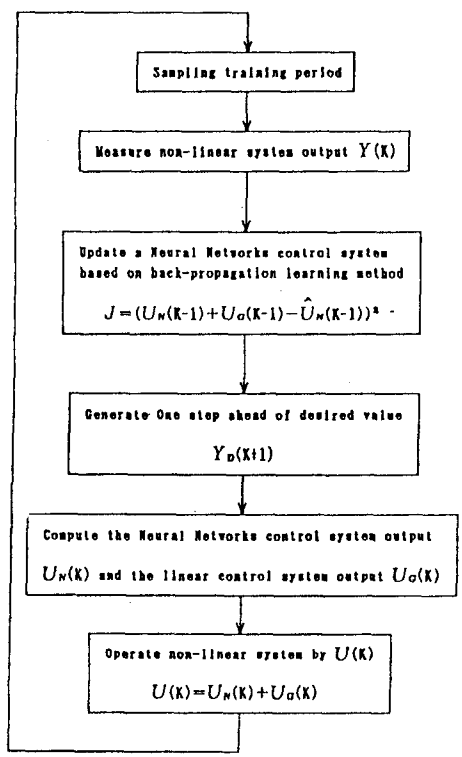


Fig.4 A flow chart of Neuro Adaptive Control System by using Artificial Neural Network Systems

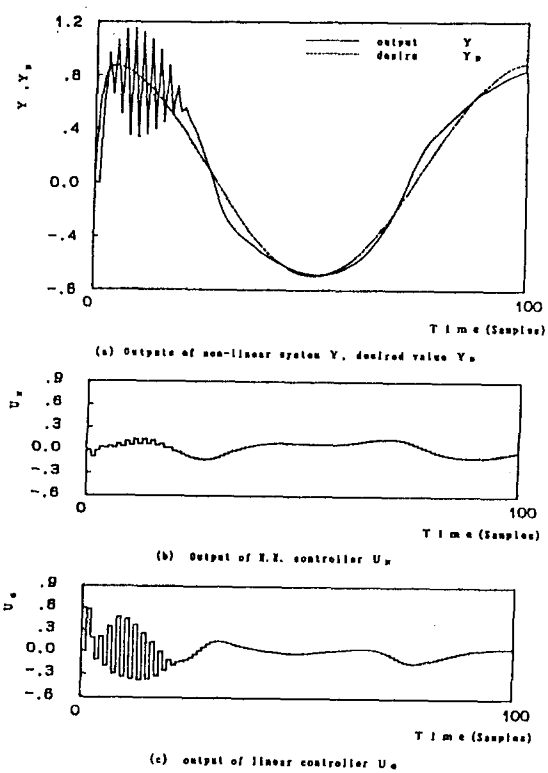
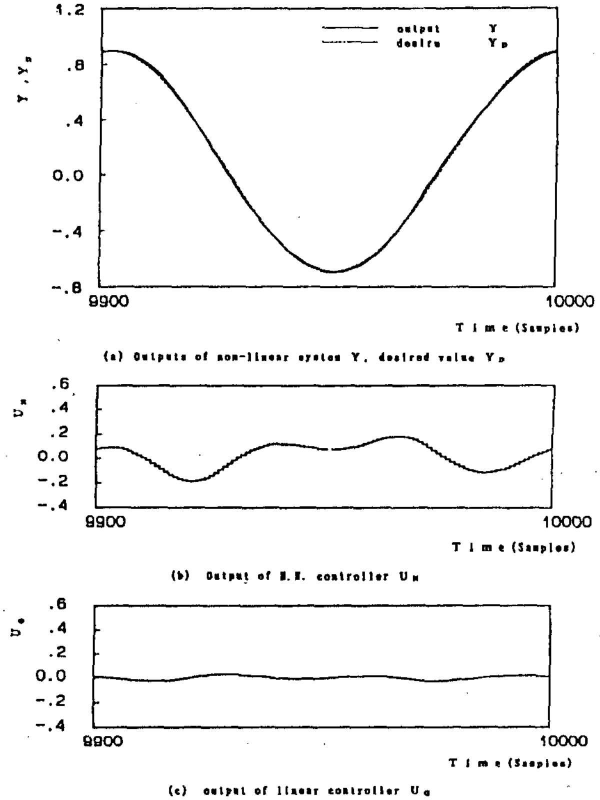


Fig.5 Simulated results for the non-linear dynamical system by Eq.(12) when training period is 1

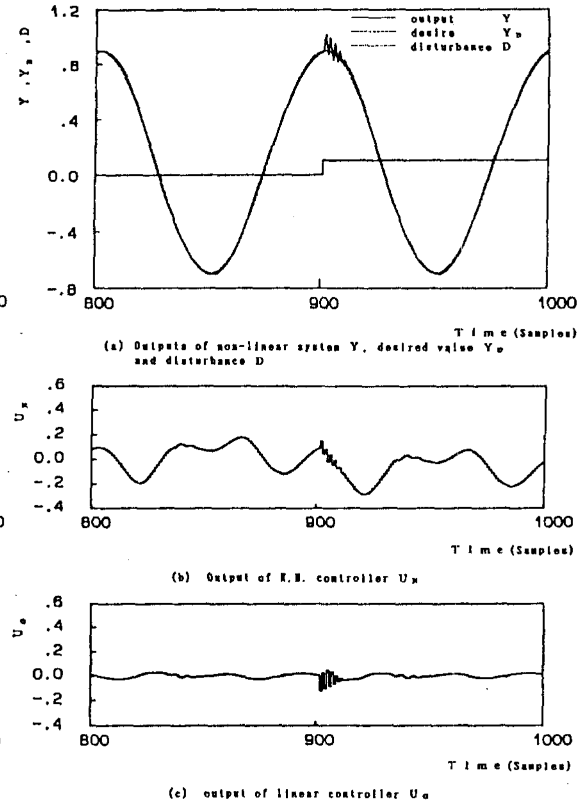


(a) Outputs of non-linear system Y, desired value Y_D

(b) Output of N.N. controller U_N

(c) output of linear controller U_c

Fig.6 Simulated results for the non-linear dynamical system by Eq.(12) when training period is 100



(a) Outputs of non-linear system Y, desired value Y_D and disturbance D

(b) Output of N.N. controller U_N

(c) output of linear controller U_c

Fig.7 Simulated results under the disturbance at 900 sampling time for the non-linear dynamical system by Eq.(12) when N.N. on-line control is taken

Controlled system	Non-linear system equation (12)
Proportional gain K_P	1.0
Differential gain K_D	0.1
Number of layers	3
Input layer units	2(p=2, q=0)
Hidden layer units	6
Output layer units	1
Initial weights W	-0.50~0.50
Learning parameters η	0.3 0.5(offset)
Sigmoid function parameter μ_0	2
Learning repetition	1

Table 1 Conditions of Simulation Studies