A Design Method of Model Following Control System using Neural Networks

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Abstract

A design method of model following control system using neural networks is proposed. An unknown nonlinear single-input single-output plant is identified using a multilayer neural networks. A linear controller is designed for the linear approximation model obtained by linearinzing the identification model. The identification model is also used as a plant emulator to obtain the prediction error. Deficient servo performance due to controlling nonlinear plant with only linear controller is mended by adjusting the linear controller output using the prediction output and the parameters of the identification model. An optimal preview controller is adopted as the linear controller by reason of having good servo performance lowering the peak of control input. Validity of proposed method is illustrated through a numerical simulation.

1. Introduction

Using artificial neural networks, simply called neural networks, various methods of nonlinear system identification and control system designing are proposed[1]-[3]. In most cases, however, nonlinear controllers using neural networks, named neural controllers, are designed as inverse system of plant or a part of theirs, since neural networks represent input-output function of any systems without its internal information like a black box. This means that such neural control system is not able to be applied to one class of plant, whose inverse systems are unstable, for instance, non-minimum phase systems. Furthermore, we can hardly analyze stability of system which include neural controllers. After all there are a few difficulties in direct usage of neural networks as controllers.

On the nonlinear system control field, it is one of the simple technique that a linear controller is designed for a linear approximation model of a nonlinear plant[4]. That is able to be called a ready methodology by reason that we can use the linear control theory. It is necessary, however, to have a theoretical model of plant, and we would find inadequate performance when a trajectory of plant is widely different from of an approximation model.

In this research, we propose a new design method of model following control system using neural networks. The proposed method is based on the methodorogy of designing a linear controller for a linear approximation plant model, and we can apply it to a unknown nonlinear plant by using neural networks for identification. We introduce a additional control input to reduce a tracking error with only linear controller designed for a approximation model obtained from the identification model. We note that just one neural networks is used through the proposed method. In the following, in Section 2, we identify a nonlinear plant using the multilayer neural networks . In Section 3, the linear approximation plant model is obtained from the identification model. In Section 4, the additional control input is described. In section 5, we explain designing procedure of an optimal preview controller(OPC)[5] which is adopted as the linear controller. In Section 6, Some results of numerical simulation are shown.

2. Identification using neural networks[1]

We consider a single-input single-output continuous time nonlinear plant of the form

$$y(t)=f\left[\dot{x}(t),x(t),u(t)\right] \tag{1}$$

where $y(t)$, $x(t)$ and $u(t)$ are the output, the state and the control input at time t, respectively, $f[\cdot]$ is a nonlinear function.

We assume the discrete time nonlinear system which is equivalent to the plant exists. Namely, we have the discrete time model of plant

$$y_{k+1}=g\left[u_k,u_{k-1},\cdots,u_{k-m+1},y_k,y_{k-1},\cdots y_{k-n+1}\right] \tag{2}$$

where y_k and u_k are sampled time series of $y(t)$ and $u(t)$, respectively, that is, y_k equals $y(kT)$ and u_k equals $u(kT)$ with any integer k and sampling time T. n is the order of y_k, m is the order of u_k and $n\geq m$. $g[\cdot]$ is a nonlinear function.

In this paper, we employ the identification model called the series-parallel model, and it is explained in the following.

First, a neural networks is substituted for nonlinear function $g[\cdot]$, and the identification model using neural networks, which we name the neural-model in this paper, is described by

$$\hat{y}_{k+1}=h\left[u_k,u_{k-1},\cdots,u_{k-m+1},y_k,y_{k-1},\cdots y_{k-n+1}\right] \tag{3}$$

where $\hat{y}$ is the output of neural-model, $h[\cdot]$ is a nonlinear function represented by the neural networks, and after learning process, this model is estimated with the feedback form

$$\hat{y}_{k+1}=h\left[u_k,u_{k-1},\cdots,u_{k-m+1},\hat{y}_k,\hat{y}_{k-1},\cdots \hat{y}_{k-n+1}\right] \tag{4}$$

We apply the multilayer neural networks with the input layer of N nodes, one hidden layer of M neurons, and a single output neuron, therefore the input-output relation of neural-model is defined as follows:

$$p_k=\Psi r^{\mathsf{T}}+\beta \tag{5}$$

$$\begin{aligned} r_k &:=[r_{1,k}\ r_{2,k}\ \cdots r_{N,k}]^{\mathsf{T}} \\ &=[u_k\ u_{k-1}\cdots u_{k-m+1}\ y_{k-1}\ y_{k-2}\cdots y_{k-n+1}]^{\mathsf{T}} \end{aligned} \tag{6}$$

$$p_k:=\left[p_{1,k}\ p_{2,k}\ \cdots p_{M,k}\right]^{\mathsf{T}} \tag{7}$$

$$o_{i,k}=\xi\left(p_{i,k}\right) \tag{8}$$

$$o_k:=\left[o_{1,k}\ o_{2,k}\ \cdots o_{M,k}\right]^{\mathsf{T}} \tag{9}$$

$$\hat{y}_{k+1}=\phi^{\mathsf{T}}o_k \tag{10}$$

where r_k is the input vector to the neural-model, p_k is the input vector to the hidden layer, o_k is the output vector of the hidden layer, and $N=n+m$. Ψ is the weight matrix to the hidden