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Intelligent switching adaptive control for uncertain nonlinear dynamical systems

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ABSTRACT

In this paper, we aim at proposing a switching adaptive control scheme using a Hopfield-based dynamic neural network (SACHNN) for nonlinear systems with external disturbances. In our proposed scheme, an auxiliary direct adaptive controller (DAC) ensures the system stability when the indirect adaptive controller (IAC) is failed; that is, $\hat{g}(\mathbf{x})$ approaches to zero, where $\hat{g}(\mathbf{x})$ is the denominator of an indirect adaptive control law. The IAC's limitation of $\hat{g}(\mathbf{x}) > \varepsilon$ then can be solved by simply switching the IAC to the DAC, where ε is a positive desired value. The Hopfield dynamic neural network (HDNN) is used to not only design DAC but also approximate the unknown plant nonlinearities in IAC design. The designed simple structure of HDNN keeps the tracking performance well and also makes the practical implementation much easier because of the use of less and fixed number of neurons.

1. Introduction

Most of control design techniques are based on the understanding of the plant under consideration and its surrounding environment. However, in real-world applications lots of the controlled plants are too complex for us to fully understand the system dynamics through the basic physical processes. Therefore, an identification technique was proposed for control design methods to obtain a progressive understanding of the controlled plant. Adaptive control is a famous identification-technique-based control design. It provides a systematic approach for automatically adjusting controllers on-line, in order to achieve or to maintain a desired performance level of control system when the parameters of the plant dynamic model are unknown and/or change in time. In general, the adaptive control techniques can distinguish between an indirect method (one calls this method as an indirect adaptive control (IAC) in the field of control design) and a direct method (one calls this method as a direct adaptive control (DAC) in the field of control design) [1–7].

The basic idea of IAC is that a controller ensures the system stability with the estimation of the plant parameters from the available input–output measurements. This scheme is termed as indirect because the adaptation of the controller parameters can be done in two stages. First, the plant model parameters are estimated on-line and the controller is then calculated depending on the current estimated plant model. IAC also has been referred to as explicit adaptive control because the design of controller is based on an explicit estimation plant model. Therefore, the resulting parameter estimates are normally accurate enough for the purposes of monitoring and prognosing the machine health, which are of significant practical importance for industrial applications. In contrast, the plant model of DAC is parameterized in terms of the controller parameters, which are estimated directly without intermediate calculations. The adaptive control laws and the parameter adaptation laws of DAC are simultaneously synthesized for the sole objective of reducing the output tracking error. However, this synthesized design causes the drawbacks that the adaptive control laws and the parameter estimation must be concerned simultaneously in the design process, and certain tracking error must be chosen as driving signals due to limitation of gradient type in the parameter estimation law. Unfortunately, in real-world implementations the actual tracking errors are normally very small such that the direct adaptive control law is thus prone to be corrupted by other factors, such as the sampling delay and noise. Therefore, the parameter

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estimates in DAC are normally not accurate enough for the purposes of the prognostics and the machine component health monitoring [3,8,9].

IAC has been used for real-world implementations to provide system stability and to achieve superior performance of the output tracking in many researches [2–4,10]. However, one condition $g(\mathbf{x})>0$ (or $g(\mathbf{x})<0$) must be held in these researches, where $g(\mathbf{x})$ is an unknown nonlinear continuous function of affine systems. That is, if the nonlinear function $g(\mathbf{x})$ is close to zero, the control law is expected to contain an unstable term $1/\hat{g}(\mathbf{x})$, where $\hat{g}(\mathbf{x})$ is the approximation of $g(\mathbf{x})$. In these cases, boundedness of control input cannot be ensured. According to the assumption of $g(\mathbf{x})>0$, a projection algorithm and a second control component were proposed in [1–5,10] to keep the system stability. Furthermore, a direct control law for affine nonlinear systems was proposed in [6] instead of the indirect control law. However, there still exist DAC inherent problems. Therefore, we aim at proposing a switching adaptive control scheme, where the IAC switches to the DAC as soon as $\hat{g}(\mathbf{x})$ approaches to zero. It is clear that the unstable term $1/\hat{g}(\mathbf{x})$ can be simply avoided in our proposed scheme. Note that the stability during whole control process, even at the moment of switching between IAC and DAC, can be guaranteed.

Neural networks (NNs) can be classified into two types, a static NN and a dynamic NN. In a static NN, signals flow from input units to output units in a forward direction. In a dynamic NN, dynamic elements are involved in the structure of the NN, for example the elements of feedback connections. The famous static NNs (SNNs), i.e. the feed-forward fuzzy neural network (FNN) and feed-forward radius basis function network (RBFN), are frequently used as a powerful modeling tool [3,8,9,11,26]. Although they have achieved much theoretical success, their complex structures make the practical implementation difficult and the number of the hidden neurons in the NNs' hidden layers is hard to determine. In addition, SNNs are quite sensitive to the unlearned changes, and they are also unable to represent the dynamic system mapping without the aid of tapped delay. However, the tapped delay will result in long computation time, high sensitivity to external noise, and a large number of neurons [12]. These drawbacks severely affect the applicability of SNNs. An important motivation to promote DNNs is because a smaller DNN can provide the same functionality as a much larger SNN [13]. Furthermore, depending on their dynamic memory, DNNs have good performances on the applications of identification, state estimation, trajectory tracking, and robust against un-modeled dynamic. A Hopfield dynamic neural network (HDNN) is one of famous DNNs proposed by Hopfield J.J. in 1982 and 1984 [14,15]. HDNN can be easily realized by a Hopfield circuit and has the property of decreasing in energy by finite number of node-updating steps. In HDNN, the analysis of fundamental properties, stability, convergence and equilibrium for discrete and continuous systems were proposed in [16,17].

In this paper, the control object is to force the system output to track a given reference signal without the condition of $\hat{g}(\mathbf{x})>\varepsilon$ for nonlinear affine systems. In the proposed SACHNN the HDNNs are used to not only output the direct adaptive control force but also approximate the unknown plant nonlinearities for the indirect adaptive controller. Furthermore, a compensation controller is merged to SACHNN to dispel the effect of the approximation error and the bounded external disturbance. The saving weights of SACHNN are on-line tuned by adaptive laws derived in the sense of Lyapunov Theorem.

2. Problem formulation

Let $S\subset R^n$ and $Q\subset R^n$ be open sets, $D_s\subset S$ and $D_Q\subset Q$ be compact sets. Consider a nth-order nonlinear dynamic system of the form

$$\begin{aligned} x^{(n)} &= f(\mathbf{x})+g(\mathbf{x})u+d \\ y &= x \end{aligned} \tag{1}$$

where $x=[x_1\,x_2\ldots x_n]^T=[x\,\dot{x}\ldots x^{n+1}]^T$ is the state vector. $f: D_s\to R$ and $f: D_Q\to R$ are the uncertain continuous functions; $u\in R$ is the continuous control input and $y\in R$ is the continuous output, which is assumed to be measurable; $d\in R$ is bounded external disturbance. The control objective is to force the system output y to follow a given bounded reference signal $y_r\in R$. The error vector $\mathbf{e}$ is defined as

$$\mathbf{e}=[e,\dot{e},\ldots,e^{(n-1)}]^T=[e_1,e_2,\ldots,e_n]^T\in R^n, \tag{2}$$

where $e=y_r-x_1=y_r-y$. If $f(\mathbf{x})$ and $g(\mathbf{x})$ are given and the system is free of external disturbance, the ideal controller can be designed as

$$u_{ideal}=\frac{1}{g(\mathbf{x})}[-f(\mathbf{x})+y_r^{(n)}+\mathbf{k}_c^T\mathbf{e}], \tag{3}$$

where $\mathbf{k}_c=[k_n k_{n-1}\ldots k_1]^T$. Substituting (3) into (1), we have the following error dynamics

$$e^{(n)}+k_1e^{(n-1)}+\cdots+k_ne=0. \tag{4}$$

If k_i, $i=1,2,3,\ldots,n$ are chosen so that all roots of the polynomial $H(s)=s^n+k_1s^{n-1}+\cdots+k_n$ lie strictly in the open left half of the complex plane, then $\lim_{t\to\infty} e(t)=0$. This implies that the control law u_{ideal} can be used for any initial conditions. However, since $f(\mathbf{x})$ and $g(\mathbf{x})$ are unknown or perturbed, the ideal feedback controller u_{ideal} in (3) cannot be implemented.

2.1. Design of the switching robust adaptive controller

The developed controller u can be expressed as the following form [18].

$$u=u_h+u_c, \tag{5}$$

where $u_h=\alpha u_D+(1-\alpha)u_I$ is the adaptive controller, in which $\alpha\in[0,1]$ is a weighting factor. Note that even though the factor α is chosen as 0 or 1 according to the switching condition, the proof of global stability of close-loop system is not restricted to this condition. In (5), u_D stands for DAC and u_I stands for IAC; u_C is a compensation controller supposed to compensate the effect of external disturbance and the approximation error. More specifically, u_I could be expressed as the indirect controller as

$$u_I=\frac{1}{\hat{g}(\mathbf{x})}(-\hat{f}(\mathbf{x})+y_r^{(n)}+\mathbf{k}_c^T\mathbf{e}), \tag{6}$$