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Identification of nonlinear systems with time-varying parameters using a sliding-neural network observer

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ABSTRACT

In this paper, a new method for the identification of nonlinear systems with time-varying parameters using a sliding-neural network observer is investigated. The proof of the finite-time convergence of the estimates to their true values is achieved using Lyapunov arguments and sliding mode theories. An application example illustrated the effectiveness of the approach and the obtained results show high convergence rate and very satisfactory parameter estimation accuracy. The computing results under noisy condition also demonstrate that good state and parameter estimation can be achieved despite the disturbance (noise) in the system. The reduced number of hidden units and the small transient period demonstrate that the proposed method can be easily implementable in real-time.

1. Introduction

This paper is devoted to parameter identification for a large class of nonlinear systems using a sliding mode neural observer. In many practical cases, system parameters are unknown and are time varying. In linear systems, parameter estimation is often achieved using the least square method [17]. The application of the least square algorithm to the estimation of nonlinear system parameters, usually requires the nonlinear model outputs to be expressed linearly in terms of the unknown parameters. Unfortunately, some nonlinear plants cannot be parameterized linearly. The identification of nonlinear system parameters is also often studied by using the combination of the least square technique and the passivity approach [9]. However, in the latter approach, the linearization of the nonlinear model around an equilibrium point is required. Thus, this method may not provide successful results for a wide range of operating points of the plant.

Recently, a robust identification and control algorithm with time-varying parameter perturbations has been proposed in [1]. But the application of this method requires the nonlinear model outputs to be expressed linearly in terms of the unknown parameters. This motivated our previous works [7,2] where parameter estimation methods based on the radial basis function (RBF) neuronal predictor have been introduced.

Although different approaches have been developed [3–5,8,13] for nonlinear system states estimation, only partial and quite weak results have been obtained in terms of time-varying function approximation and time-varying parameter estimation. The state of the art concerning the estimation of the nonmeasurable states using artificial neural network (ANN) has been presented in [7].

The main contribution of this paper is the extension of the works proposed in [7,2]. In the latter approaches, the asymptotic convergence was proved under some conditions. In this paper, the convergence and the robustness properties of the previous results are improved by using a sliding-neural observer and the extension of the previous works to the cases where the state vector of the nonlinear system is partially known is achieved. A new adaptive law is also used to estimate the unknown bound of the error between the neural network output and the output of the nonlinear system. The proposed method is dedicated to parameter estimation in the continuous time-domain for a large class of nonlinear systems whose model outputs can be expressed as linear or nonlinear combination of the unknown parameters. The method proposed in this paper can be viewed as a step towards the design of nonlinear systems time-varying parameter identification using sliding-neural network observer without using the assumption that the inverse dynamics of the system is known.

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The remainder of the paper is organized as follows. In Section 2, a sliding-neural observer based on the radial basis function network (RBFN) is designed and the proof of the convergence in finite time is achieved using Lyapunov and sliding modes theories. The extension of the approach to the cases where the state vector is not completely known is presented in Section 3 and an application example with some numerical simulations are reported in Section 4. Finally some concluding remarks are given in Section 5.

2. Sliding-neural observer for parameter identification

In this section, a modified version of the methods proposed in [7,2] is presented and the convergence and robustness properties are improved using a sliding-neural observer. The extension of the previous works to the cases where the state vector of the nonlinear system is partially known is also investigated.

2.1. Problem setting

Let us consider the following class of nonlinear systems:

$$\dot{x} = f(x, \theta(t), u), \tag{1}$$

where f is a continuous function on a compact $\Omega_f \in \mathbb{R}$; $x \in \mathbb{R}^n$ is the state vector; $u \in \mathbb{R}^m$, $m \leqslant n$ is the vector of the measurable inputs and $\theta(t) \in \mathbb{R}^p$ is the vector of the unknown time-varying parameters which can be expressed as follows:

$$\theta_i(t) = \theta_{i,n} + \Delta\theta_i(t) \text{ with } |\Delta\theta_i(t)| \leqslant \mu_i,\ i = 1, \ldots, p. \tag{2}$$

In (2), $\theta_{i,n}$ is the nominal value of $\theta_i(t)$ and μ_i are unknown positive constants.

The following assumptions will be made until further notice.

(i) The components of the state vector x are measurable. Therefore the state vector x is assumed to be available and can be considered as the output vector of the nonlinear system (1).
(ii) $\theta(t) \in \mathbf{\Omega}_\theta$ which is a compact set of $\mathbb{R}^p$.
(iii) the system described by (1) is invertible in terms of the unknown parameters $\theta(t)$ in the sense of the work of [10].

Remark 1. Assumption (i) is not a restriction for the method proposed in Section 2.2. It has been used to simplify the study in this section. The cases where the state vector is not completely known are discussed in Section 3.

Assumption (iii) means that, there exists a function g continuous and bounded such that

$$\theta(t) = g(x, \dot{x}, u) \quad \text{for } 1 \leqslant p \leqslant n. \tag{3}$$

In the general case, the function g contains the higher order time-derivatives of the terms $\dot{x}$ and u. Note that it is not possible to use immediately Eq. (3) to estimate the unknown parameter $\theta(t)$ since the derivative state $\dot{x}$ is not available.

By using Taylor formula, the system described by (1) can be rewritten as follows:

$$\dot{x} = f(x, \theta_n, u) + \Delta f(x, u, t), \tag{4}$$

where

$$\Delta f(x, u, t) = \int_0^1 \left.\frac{\partial f}{\partial \alpha}\right|_{(\alpha = \theta_n + \xi\Delta\theta(t))} \Delta\theta(t)\, \mathrm{d}\xi \tag{5}$$

is the uncertainty term due to the variation of the parameter $\theta(t)$. The term $f(x, \theta_n, u)$ is continuous on a compact $\mathbf{\Omega}$, thus it can be approximated by an RBF neural network [4,5]. Therefore, one can write

$$f(x, \theta_n, u) = \Psi(\chi, w^*) + e_f(\chi)$$

or

$$f(x, \theta(t), u) = \Psi(\chi, w^*) + e_f(\chi) + \Delta f(x, u, t)$$

with

$$\Psi_i(\chi, w^*) = \sum_{j=1}^{N} w^*_{ij} \phi(\|\chi - C_j\|, v_j), \tag{6}$$

where $\phi(\cdot)$ denotes a nonlinear function; C_j and $v_j, j = 1, \ldots, N$ are the center and the width of the j-th hidden unit, respectively; N is the number of the hidden nodes or RBF units; w^* is the optimal weight vector and satisfies $\|w^*\| \leqslant R_\omega$; $\chi = (x, u)^{\mathrm{T}}$ is the input vector of the RBFN; $e_f(\chi)$ is the optimal approximation error tolerance, which is unknown and bounded $\forall \chi \in \mathbf{\Omega}$.

The term $\Delta f(x, u, t)$ is time-varying and cannot be approximated by a static neural network. In the following analysis, sliding robust terms will be used in the identification scheme to compensate the effect of the uncertainty $\Delta f(x, u, t)$. The aim is to realize or to approximate the underlying dynamics $f(x, \theta(t), u)$ using ANNs assuming that the terms $e_f(\chi)$ and $\Delta f(x, u, t)$ are bounded by unknown positive constants.

2.2. Sliding-neural observer

In order to identify the time-varying parameters $\theta(t)$, let us now consider the following observer:

$$\dot{\hat{x}} = \Psi(\chi, \hat{w}) + b(x, \hat{x}, t) \tag{7}$$

or

$$\dot{\hat{x}}_i = b_i(x, \hat{x}, t) + \sum_{j=1}^{N} \hat{w}_{ij} \phi(\|\chi - C_j\|, v_j), \tag{8}$$

where the term $b_i(x, \hat{x}, t),\ i = 1, \ldots, n$ are introduced in order to improve the convergence of the neural network in the presence of the uncertainty term $\Delta f(x, u, t)$. The RBF $\phi(\cdot)$ has the following form:

$$\phi(Z, v) = \exp\left(\frac{-\|Z\|^2}{2v^2}\right).$$

The center C_j and the width v_j of the j-th hidden unit are chosen as follows [6]:

$$v_{ij} = \frac{\chi_{i_{\max}} - \chi_{i_{\min}}}{N}, \tag{9}$$

$$C_{ij} = \chi_{i_{\min}} + \frac{2j - 1}{2} v_{ij}, \tag{10}$$

where $\chi_{i_{\min}}$ and $\chi_{i_{\max}}$ are the lower and upper bounds of the i-th element of the RBF input vector χ, respectively.

Remark 2. The selection of the center C_j and the width v_j for RBFN has significant effect on the performance of the algorithm. In literature several strategies exist but one can distinguish two main categories. The first one consists in simultaneously optimizing the center C_j, the width v_j and the weights w_{ij}, by using for example the well-known backpropagation algorithm. Unfortunately, this approach may lead to the convergence of the algorithm to the local minimum due to the slowly convergence of the hidden layer (with nonlinear neurons) and the fast convergence of the output layer (with linear neurons). The second approach consists in optimizing or selecting initially the center and the width before carrying out the adjustment of the weights. Therefore, once the optimization or selection of the center and the width is achieved, the learning of the weights is completely a linear problem and is thus more easier to perform as compared to