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Nonlinear systems parameters estimation using radial basis function network

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Abstract

In this paper, a new on-line scheme for the state and parameter estimation of a large class of nonlinear systems is presented. This scheme uses a radial basis function neuronal predictor with the on-line learning of weights. The algorithms developed are potentially useful for adjusting the controller parameters of variable speed drives. The other interesting feature of the proposed method is its application to failure and fault detection. The parameter identification scheme is an algebraic method combined with state estimation. The asymptotic convergence of the estimates to their nominal values is achieved using the Lyapunov's arguments. The simulation results and the real-time estimation of both rotor resistance and speed of an induction motor based on this approach, show rapidly converging estimates in spite of the measurements noise, discretization effects, parameters uncertainties (e.g. inaccuracies on motor inductance values) and modeling inaccuracies. The other applications of the proposed method include the on-line estimation of the parameters of a synchronous generator.

Keywords: State/parameter estimation; Time-varying parameter; High-gain observer; Radial basis function; Learning algorithms; Induction motors; Real-time implementation; Fault detection

1. Introduction

This paper is devoted to on-line state and parameter identification for a reasonably large class of nonlinear systems. In linear systems context and in particular some nonlinear cases, parameter estimation is often achieved using the least-square method (Walter and Pronzato, 1994; Landau, 1998). The application of the least-square algorithm in the nonlinear systems context, usually requires the nonlinear model outputs to be expressed linearly in terms of the unknown parameters. Unfortunately, some non-linear plants cannot be parameterized linearly. The identification of nonlinear systems parameters is also often studied using the least-square technique and the passivity approach (Landau et al., 2000). But in the latter approach, the linearization of the non-linear model around an equilibrium point is required. Therefore, this method may not provide successful results for a wide range of operating points of the plant.

Several contributions exist in the context of nonlinear systems parameter estimation using the variable structure theories (Xu and Hashimoto, 1993; Niethammer et al., 2001; Floret, 2002; Ahmed-Ali et al., 2004). But in the artificial neural network application area, most contributions deal with nonlinear system states identification or approximation of unknown functions from discrete measurements in the discrete time-domain (Narendra and Parthasarathy, 1990; Chen and Billings,

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1992; Sadegh, 1993; Chen and Chen, 1993; Kuschewski et al., 1993; Abido and Abdel-Magid, 1997; Liu et al., 1999; Schilling et al., 2001). In this paper, a continuous-time formulation rather than a discrete one is used because nonlinear physical systems are usually continuous in nature and are hard to meaningfully discretize (Slotine and Li, 1991). Furthermore, digital control systems may be treated as continuous-time systems in analysis and design if high sampling rates are used. Moreover, the availability of cheap computation now allows high sampling rates and thus continuous-time models to be used.

In this article, we describe and evaluate a recently proposed method (Kenné et al., 2003, 2004; Kenné, 2003) for the estimation of the states and parameters of a large class of nonlinear systems. Most of the time, parameters of plants encountered in practice are unknown and time varying. This is the case of the rotor resistance of an induction motor (IM) which may vary up to 100% of its nominal value due to rotor heating and this variation can be hardly recovered using a thermal model combined with temperature sensors (Marino et al., 2000). Control algorithms exploiting this type of parameter need to be updated on-line in order to increase its performance.

In this paper, we also focus on time-varying parameter estimation. Our approach is to combine state identification with parameter estimation using artificial neural network (ANN) and in a further investigation, compare both variable structure and ANN approaches. This ANN approach is based on the inversibility of the nonlinear system with respect to time-varying parameters. The asymptotic convergence of the proposed neural identifier is achieved using the Lyapunov'arguments. This is motivated by the fact that, certain techniques employed in the neural network context have long been developed by the control engineering community. For example, the backpropagation algorithm is a simple version of the smoothed stochastic gradient algorithm (Chen and Billings, 1992).

We use a radial basis function (RBF) neural network to estimate the non-measurable states. This choice is motivated by the fact that RBF networks approximate nonlinear systems with outputs that are linear combinations of the network weights. Therefore, it is relatively easier to derive the learning algorithm of the weights with a higher rate of convergence in the RBF networks than in the multi-layered perceptron (MLP) structure for some problems. Furthermore, it has been acknowledged in Gorinevsky (1995) and Abido and Abdel-Magid (1997) that in many problems, approximation properties of RBF networks are advantageous as compared to other methods including MLP networks. Comparative studies can be found in (Chen and Billings, 1992; Ortiz-Gómez et al., 2003).

The proposed RBF neuronal identifier combined with high-gain observer has been applied to estimate the rotor resistance and speed of an induction motor. Simulations and experimental results show that this algorithm works well. The other applications of the proposed method include on-line estimation of the parameters of a synchronous generator, diagnostics and fault detection.

The remainder of the paper is organized as follows. The neural network identifier is presented in Section 2 and the parameter estimation law is derived. In Section 3, we apply this algorithm to the estimation of the rotor resistance and speed of an IM with two cases studied. In the first case, the rotor speed is assumed to be measured, while the simultaneous identification of both rotor resistance and rotor speed is treated in the second case. Both schemes use stator currents and voltages measurements and are easily implementable in real time. Computer simulations and real-time implementation results are presented in Sections 4 and 5, respectively. These results show the robustness of this approach with respect to time-varying parameters, measurements noise, discretization effects, parameters uncertainties and modeling inaccuracies. Finally, in Section 6, the main conclusions of the paper are given.

2. Design of the neural identifier

2.1. Problem setting

Let us consider the following class of nonlinear system:

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

where f is a uniformly continuous function on a compact $\Omega_f \subset \mathbf{R}$; $\mathbf{x} \in \mathbf{R}^n$ is the state vector; $\mathbf{u} \in \mathbf{R}^m$, $m \leqslant n$ is the vector of the measurable inputs and $\boldsymbol{\theta}(t) \in \mathbf{R}^p$, $1 \leqslant p \leqslant n$ is the vector of the unknown time-varying parameters which can be expressed as follows:

$$\boldsymbol{\theta}_i(t) = \boldsymbol{\theta}_{in} + \Delta\boldsymbol{\theta}_i(t) \text{ with } |\Delta\boldsymbol{\theta}_i(t)| \leqslant \mu_i, \quad i = 1, \ldots, p. \tag{2}$$

In (2), $\boldsymbol{\theta}_{in}$ is the nominal value of $\boldsymbol{\theta}_i(t)$ and μ_i is a known positive constant.

The following assumptions will be made until further notice.

(i) The components of the state vector $\mathbf{x}$ are measurable or can be estimated,
(ii) $\boldsymbol{\theta}(t) \in \Omega_\theta$ which is a compact set of $\mathbf{R}^p$,
(iii) the system described by (1) is inversible in terms of the unknown parameters $\boldsymbol{\theta}(t)$ in the sense of the work of Lecourtier et al. (1987).

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

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