Chapter 7

High Order Neuro-Fuzzy Dynamic Regulation of General Nonlinear Multi-Variable Systems

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ABSTRACT

The direct adaptive dynamic regulation of unknown nonlinear multi variable systems is investigated in this chapter in order to address the problem of controlling non-Brunovsky and non-square systems with control inputs less than the number of states. The proposed neuro-fuzzy model acts as a universal approximator. While with the careful selection of a Lyapunov-like function, the authors prove the stability of the proposed control algorithm. Weight updating laws derived from the Lyapunov analysis assure the boundedness of the closed-loop signals incorporating the well-known modified parameter hopping. In addition, the proposed algorithm shows robustness when facing modelling errors, and therefore, the state trajectories present uniform ultimate boundedness. The proposed dynamic controller proved to control those general nonlinear systems, which are difficult or even impossible to control with other algorithms. Simulation results on well-known benchmark problems demonstrate the applicability and effectiveness of the method.

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INTRODUCTION

Nonlinear dynamical systems are generally represented by nonlinear dynamical equations of the form:

\[ \dot{x} = f(x, u) \quad (1) \]

or, after appropriate transformation if it is possible, by its equivalent affine in the control form:

\[ \dot{x} = f(x) + G(x) \cdot u \quad . \quad (2) \]

The mathematical description of the above system is required, so that we are able to control it. Unfortunately, the exact mathematical model of the plant, especially when this is highly nonlinear and complex is rarely known and thus appropriate identification schemes have to be applied in order to provide an approximate model of the plant. The problem becomes more complex when the system, apart from being “unknown,” is also time varying. Adaptive systems and consequently adaptive control is one of the active approaches in the control theory that gives answers in this kind of problems since 1950 (Aseltine, Mancini, & Sartune, 1958; Ioannou & Sun, 1996).

In this framework, adaptive control approaches rely on adequate approximates of the system parameters (indirect control approaches) or on estimates of the controller parameters incorporated to the system dynamics (direct control approaches), as they described accurately in Ioannou and Fidan (2006). Neural networks and fuzzy inference systems in their neuro-fuzzy approach, being universal approximators, are effectively used to approximate the unknown functions involved in system dynamics (Hornik, Stinchcombe, & White, 1989; Passino & Yurkovich, 1998).

However, the remarkable capabilities of neural networks to learn (identification) and control (adaptively) nonlinear dynamical systems (Narendra & Parthasarathy, 1990; Chen & Narendra, 2002; Plett, 2003; Zhan & Wan, 2006) together with the human like thinking of fuzzy logic is leading to their use for a wide class of applications. Therefore, the tracking accuracy depends mainly on neural networks structure, which should be chosen appropriately from the designer (Li, Chen, & Yuan, 2002; Kumar, Panwar, Sukavanam, Sharma, & Borm, 2011; Pedro & Dahunsi, 2011; Thammano & Ruxpakawong, 2010).

Fully connected Recurrent Neural Networks (RNN) (Tsoi & Back, 1994; Rashid, Huang, & Kechadi, 2007) contains interlink between neurons to reflect the dynamics of the nonlinear system but it suffers both by structure complexity and the poor performance accuracy (Rashid, Huang, & Kechadi, 2007). Many researchers focused in Dynamic Recurrent Neural Networks (DRNN), such as Higher Order Neural Networks (HONNs), which doesn’t contain interlink between hidden layer neurons leading in this way to the network structure complexity reduction (Pearlmutter, 1995; Rashid, Huang, & Kechadi, 2007). Thus, among neural networks, HONNs, especially in their recurrent form have been shown to be particularly effective in modelling and controlling dynamical nonlinear systems (Rovithakis & Christodoulou, 2000). In control applications, researchers often assume that the states of the system are all measurable. In practise, however, this is not always the case and one should consider state estimation first. Discrete time Recurrent Higher Order Neural Networks (RHONN) have been recently proposed (Alanis, Sanchez, Loukianov, & Perez-Cisneros, 2010; Alanis, Sanchez, Loukianov, & Perez-Cisneros, 2011; Alanis, Leon, Sanchez, & Ruiz-Velazquez, 2011), where the NN weights learning is performed using Kalman filtering discrete-time schemes. Those schemes proved to be very useful for real-time applications.

The neural and fuzzy approaches are most of the time equivalent, differing between each other mainly in the structure of the approximator chosen. In order to bridge the neural and fuzzy approaches several researchers introduce adaptive schemes
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