Chapter 5
Robust Adaptive Control Using Higher Order Neural Networks and Projection

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ABSTRACT
By using dynamic higher order neural networks, we present a novel robust adaptive approach for a class of unknown nonlinear systems. Firstly, the neural networks are designed to identify the nonlinear systems. Dead-zone and projection techniques are applied to weights training, in order to avoid singular cases. Secondly, a linearization controller is proposed based on the neuro identifier. Since the approximation capability of the neural networks is limited, four types of compensators are addressed. We also proposed a robust neuro-observer, which has an extended Luenberger structure. Its weights are learned on-line by a new adaptive gradient-like technique. The control scheme is based on the proposed neuro-observer. The final structure is composed by two parts: the neuro-observer and the tracking controller. The simulations of a two-link robot show the effectiveness of the proposed algorithm.

1 INTRODUCTION
Feedback control of the nonlinear systems is a big challenge for engineer, especially when we have no complete model information. A reasonable solution is to identify the nonlinear, then a adaptive feedback controller can be designed based on the identifier. Neural network technique seems to be a very effective tool to identify complex nonlinear systems when we have no complete model information or, even, consider controlled plants as “black box”.

Neuro identifier could be classified as static (feedforward) or as dynamic (recurrent) ones (Narendra & Parthasarathy, 1990). Most of publications in nonlinear system identification use static networks, for example Multilayer Perceptrons, which are implemented for the approximation of nonlinear function

DOI: 10.4018/978-1-61520-711-4.ch005
in the right side-hand of dynamic model equations (Jagannathan & Lewis, 1996). The main drawback of these networks is that the weight updating utilize information on the local data structures (local optima) and the function approximation is sensitive to the training dates (Haykin, 1994). Dynamic neural networks can successfully overcome this disadvantage as well as present adequate behavior in presence of unmodeled dynamics, because their structure incorporate feedback (Kosmatopoulos, Polycarpou, Christodoulou, & Ioannou, 1995; Rovithakis & Christodoulou, 1994; Yu & Li, 2001).

Neurocontrol seems to be a very useful tool for unknown systems, because it is model-free control, i.e., this controller is not depend on the plant. Many kinds of neurocontrol were proposed in recent years, for example, Supervised Neuro Control (Hunt & Sbarbaro, 1991) is able to clone the human actions. The neural network inputs correspond to sensory information perceived by the human, and the outputs correspond to the human control actions. Direct Inverse Control (Grant & Zhang, 1989) uses an inverse model of the plant cascaded with the plant, so the composed system results in an identity map between the desired response and the plant one, but the absence of feedback dismisses its robustness; Internal Model Neuro Control (Narendra & Parthasarathy, 1990) used forward and inverse model are within the feedback loop. Adaptive Neuro Control has two kinds of structure: indirect and direct adaptive control. Direct neuro adaptive may realize the neurocontrol by neural network directly (Hunt & Sbarbaro, 1991). The indirect method is the combination of the neural network identifier and adaptive control, the controller is derived from the on-line identification (Narendra & Parthasarathy, 1990). Resent results show that discrete-time neural networks are also convenient for real applications (Jagannathan, 2006; Alanis, Sanchez & Loukianov, 2007; Yang, Ge, Chai, & Lee, 2008).

In this chapter we extend our previous results (Poznyak, Yu, Sanchez & Perez, 1999; Yu & Poznyak, 1999). The neuro control was derived by gradient principal, so the neural control is local optimal (Poznyak, Yu, Sanchez & Perez, 1999). No any restrictions of weights are needed, because the controller did not include the inverse of the weights. We assume the inverse of the weights exist, so the learning law was normal (Yu & Poznyak, 1999). The main contributions of this chapter are: 1) A special weights updating law for the higher order neural networks is proposed to assure the existence of neurocontrol. 2) Four different robust compensators are proposed. By means of a Lyapunov-like analysis we derive stability conditions for the neuro identifier and the adaptive controller. We show that the neuro identifier-based adaptive control is effective for a large classes of unknown nonlinear systems.

2 NEURO IDENTIFIER

The controlled nonlinear plant is given as:

\[ \dot{x}_i = f(x_i, u_i, t), \quad x_i \in \mathbb{R}^n, \quad u_i \in \mathbb{R}^n \quad (1) \]

where \( f(x_i) \) is unknown vector function. In order to realize indirect neural control, a parallel neural identifier is used (Poznyak, Yu, Sanchez & Perez, 1999; Yu & Poznyak, 1999):

\[ \frac{d}{dt} \hat{x}_i = A\hat{x}_i + W_{1,i} \sigma(\hat{x}_i) + W_{2,i} \varphi(\hat{x}_i) \gamma(u_i) \quad (2) \]