Chapter 3
Neural Network-Based System Identification Schemes

3.1 Introduction

System identification is an important issue in determining a dynamical model for an unknown plant as well as in monitoring and control of system states. This field of study has been the focus of attention of researchers for several years. Online system identification to date is mostly based on recursive methods such as least squares [73].

Neural Networks have been widely employed for system identification since they can learn complex mappings from a set of examples. The mapping property, the adaptive nature and the ability of neural networks to deal with uncertainties make them viable choices for identification of nonlinear systems. There are several criteria that can be used to categorize neural network-based identifiers for nonlinear systems. For instance, one can categorize them via their input-state-output representations. There are then two basic categories: state-space representations and input-output representations. If the states of the system are available, the state-space representation allows the user to employ static neural networks. Using an input-output representation, however, needs some type of dynamic elements. Tap delay line and recurrent neural networks are commonly used to model dynamical systems.

In [74]-[77], several approaches were developed for identification and control of nonlinear systems based on stability theory. However, either some a priori knowledge about the nonlinear system is assumed or their adaptation laws are too complicated therefore in practice they are only applicable to certain classes of nonlinear systems. Such assumptions are often not valid for flexible-link manipulators such as Space Station Remote Manipulator System (SSRMS). In [78], a recurrent fuzzy neural network was presented for identification and control of dynamical systems. Mahdavi et. al. [79] experimentally verified an output feedback neural controller for DC-DC converter. However, no mathematical proof of stability was provided. On the other hand, backpropagation is widely used in classification and identification and it has been shown to give promising results, e.g. [79, 56, 55]. However, the main
The drawback of the mentioned work on backpropagation is the lack of a mathematical proof of stability.

In this chapter, the neural network designed for observer in the previous chapter is modified for identification of general MIMO nonlinear systems. Unlike many other methods, the proposed approach does not assume knowledge of the nonlinearities of the system nor that the nonlinear system is linear in its parameters. Both parallel and series-parallel models are considered. As a case study, identification of the dynamics of flexible-link manipulators are considered to demonstrate the excellent performance of the proposed schemes.

The reminder of this chapter is organized as follows. In Section 3.2, two neural network identification schemes for parallel model are proposed. At first, a linearly parameterized neural network (LPNN) is introduced in Section 3.2.1 and also a mathematical proof of stability is given. The results of Section 3.2.1 are extended to a more general model of MIMO nonlinear systems in Section 3.2.2. In this section, a nonlinear-in-parameters neural network (NLPNN) is introduced that takes advantage of the full capability of universal approximation theory. The proposed identifier then modified for series-parallel identifier model in Section 3.3. Section 3.4 presents a case study on the identification of the dynamics of a flexible-link manipulator. Section 3.5 gives some simulation results. The proposed neuro-identification scheme has been implemented on an experimental set-up consisting of a three-link macro-micro manipulator. Section 3.6 describes the test-bed and demonstrates the experimental results. Finally, Section 3.7 gives some conclusions.

3.2 A Parallel Identification Scheme

In this section, the LPNN and NLPNN introduced in the previous chapter are employed to identify the dynamics of an unknown nonlinear system given by

$$\dot{x} = f(x,u),$$

(3.1)

where $u \in \mathbb{R}^m$ is the input vector and $x \in \mathbb{R}^n$ is the state vector of the system and $f(\cdot)$ is an unknown nonlinear function. Similar to the previous chapter, it should be assumed that the open loop system (3.1) is stable.

By following along the similar steps given in the previous chapter, i.e., $Ax$ is added to and subtracted from (3.1), where $A$ is an arbitrary Hurwitz matrix, we can get

$$\dot{x} = Ax + g(x,u),$$

(3.2)

where $g(x,u) = f(x,u) - Ax$. Based on (3.2), a recurrent network model can be constructed by parameterizing the mapping $g$ by feedforward (static) neural network architectures, denoted by $N$. Therefore, the following model is considered for identification purposes.