Chapter 2

Artificial Higher Order Neural Networks for Modeling MIMO Discrete-Time Nonlinear System

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ABSTRACT

In this chapter, a Recurrent Higher Order Neural Network (RHONN) is used to identify the plant model of discrete time nonlinear systems, under the assumption that all the state is available for measurement. Then the Extended Kalman Filter (EKF) is used to train the RHONN. The applicability of this scheme is illustrated by identification for an electrically driven nonholonomic mobile robot. Traditionally, modeling of mobile robots only considers its kinematics. It has been well known that the actuator dynamics is an important part of the design of the complete robot dynamics. However, most of the reported results in literature do not consider all parametric uncertainties for mobile robots at the actuator level. This is due to the modeling problem becoming extremely difficult as the complexity of the system dynamics increases, and the mobile robot model includes the uncertainties of the actuator dynamics as well as the uncertainties of the robot kinematics and dynamics.

INTRODUCTION

In control theory, it is widely known how to control linear systems, but it still has difficulties in controlling nonlinear systems. Extensive knowledge about the behavior of the dynamics control system is usually needed to control them. This knowledge is represented in terms of differential or difference equations, and this mathematical description of system dynamics modeling is called mathematical model or simply model (Khalil, 1996). The advantage of these models is that they have a physical interpretation of its parameters and
variables involved in the system’s behavior. These models are complicated to build in many cases.

Operating conditions or climatic and other environmental factors can cause either system wear or degradation of its components. It is so extremely difficult to consider all the physical laws involved in the behavior of the system (Viuela & Galvn, 2004).

Additionally, current technological advances have generated an enormous variety of new problems and applications, and it is necessary to use new tools to model its dynamics with greater accuracy and robustness. A field of study that has held the attention of researchers for several years is system identification. This is to determine the mathematical model when some or all of the dynamics of the system are not known (Talebi, Abdollahi, Patel, & Khorasani, 2010).

Neural networks have grown to be a well-established methodology, which allows for solving very difficult problems in engineering, as exemplified by their applications to identification and control of general nonlinear and complex systems. In particular, the use of recurrent neural networks for modeling and learning has rapidly increased in recent years (Sanchez & Ricalde, 2003; and references therein).

There exist different training algorithms for neural networks, which normally encounter some technical problems such as local minima, slow learning, and high sensitivity to initial conditions, among others. As a viable alternative, new training algorithms, e.g., those based on Kalman filtering, have been proposed (Grover & Hwang, 1992; Haykin, 2001; Singhal & Wu, 1989). Due to the fact that training a neural network typically results in a nonlinear problem, the Extended Kalman Filter (EKF) is a common tool to use, instead of a linear Kalman filter (Haykin, 2001).

It is well known (Sanchez & Ricalde, 2003) that Recurrent Higher Order Neural Networks (RHONN) offer many advantages for the modeling of complex nonlinear systems. On the other hand, EKF training for neural networks reduces the epoch size and the number of required neurons (Haykin, 2001). Considering these two facts, we propose the use of the EKF training for RHONN in order to model complex nonlinear systems.

The best-known training approach for Recurrent Neural Networks (RNN) is the back propagation through time learning (Singhal & Wu, 1989). However, it is a first order gradient descent method, and hence, its learning speed can be very slow (Singhal & Wu, 1989). Recently, the Extended Kalman Filter (EKF)-based algorithms have been introduced to train neural networks, in order to improve the learning convergence (Singhal & Wu, 1989). The EKF training of neural networks, both feed-forward and recurrent ones, has proven to be reliable and practical for many applications over the past ten years (Singhal & Wu, 1989).

In this chapter, a Recurrent High Order Neural Network (RHONN) is first used to identify the plant model, under the assumption that all the state is available for measurement. Then the RHONN is used to design an adaptive recurrent neural identifier for nonlinear systems, whose mathematical model is assumed to be unknown. The learning algorithm for the RHONN is implemented using an Extended Kalman Filter (EKF). The applicability of this scheme is illustrated by identification for an electrically driven nonholonomic mobile robot. Traditionally, modeling of mobile robots only considers its kinematics. It has been well known that the actuator dynamics are an important part of the design of the complete robot dynamics. However, most of the reported results in literature do not consider all parametric uncertainties for mobile robots at the actuator level. This is due to the modeling problem becoming extremely difficult as the complexity of the system dynamics increases, and the mobile robot model includes the uncertainties of the actuator dynamics as well as the uncertainties of the robot kinematics and dynamics.
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