Neurocontroller Design Via Supervised and Unsupervised Learning

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Abstract. In this paper we study the role of supervised and unsupervised neural learning schemes in the adaptive control of nonlinear dynamic systems. We suggest and demonstrate that the teacher's knowledge in the supervised learning mode includes a-priori plant structural knowledge which may be employed in the design of exploratory schedules during learning that results in an unsupervised learning scheme. We further demonstrate that neurocontrollers may realize both linear and nonlinear control laws that are given explicitly in an automated teacher or implicitly through a human operator and that their robustness may be superior to that of a model based controller. Examples of both learning schemes are provided in the adaptive control of robot manipulators and a cart-pole system.

Key words. Nonlinear control, neurocomputing, global linearization, supervised learning, unsupervised learning, robot control, manual tracking.

1. Introduction

The recent revival in neuroengineering research, which started in 1982, has focused mainly in the field of pattern recognition and signal processing. Only a few efforts have dealt with applications to control engineering.

The massive parallelism, natural fault tolerance and implicit programming of neural network computing architectures suggest that they may be good candidates for implementing real-time adaptive controllers for large-scale nonlinear dynamic systems.

Several neural network models and neural learning schemes were applied to system controller design during the last three decades. Widrow and Smith (1964) utilized the ADALINE (Adaptive LInear Neuron) and MADALINE (Many ADALINES) architectures and the Widrow–Hoff (LMS) algorithm to provide a ‘bang-bang’ (control where the applied force is constant in the + or − direction) type of control through duplication of a known switching surface, for the linearized dynamics of a cart-pole system. Barto, Anderson and Sutton (1983) developed the ASE (Adaptive Search Element) to perform unsupervised learning and ‘bang-bang’ control of a cart-pole system. The dynamics were assumed to be totally unknown. Psaltis, Sideris and Yamamura (1987) proposed using the Back Error Propagation algorithm (BEP) (see Rumelhart et al. (1986)) and ‘specialized learning’ to reduce the total error of the controlled process in specific regions of interest. Kawato, Furukawa and Suzuki

In all of the works cited above, the learning schemes were totally independent from the control task. We believe that some, however small, a-priori knowledge of the plant dynamics is always available. We expect that utilizing the a-priori knowledge in the learning phase will improve the neurocontroller performance.

In this paper, we report preliminary results in neurocontroller design which we found encouraging. In Section 2, we describe how a-priori structural knowledge of robot dynamics may be employed in an unsupervised learning routine for the automated design of a nonlinear robot controller. In Section 3, we employ supervised learning with various teaching modes and teacher models, and compare the neurocontroller robustness to that of a model based controller. Section 4 provides a discussion and conclusion.

2. Unsupervised Learning of Control

In supervised learning, we assume the existence of some teacher that is capable of demonstrating the required control performance. That is, in order to train a neurocontroller to control some dynamic system, we must have a controller already capable of controlling the system (see Psaltis et al; 1987; Widrow, 1987; Guez and Selinsky, 1988). This is not a detriment in the case of a human trained controller as it can be used to automate a previously human controlled process. In the case of automated linear and nonlinear teachers, the dynamics of the controlled system must be known a-priori for the design of the teacher. We now present the preliminary results of a neurocontroller learning to control a dynamic system where only a general knowledge of the dynamic's structure is known and no external teacher is available. The system under consideration is a robot manipulator. This problem is of particular interest as the full dynamics of a robot are rarely known. Furthermore, the advent of new direct drive robots requires a controller capable of compensating for all of the nonlinearities of the robot.

2.1. ROBOT DYNAMICS

For a robotic manipulator consisting of an open kinematic chain of rigid links the dynamics can be described by

\[ I(q, t)\ddot{q}(t) + H(q, \dot{q}, t) + B\dot{q}(t) + G(q, t) = T(t), \]  

(1)