# Adaptive Control of Nonlinear Systems Using Neural Networks

by

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### Abstract

In contrast to linear adaptive control, adaptive design techniques for nonlinear systems have yet to be established for a general class of nonlinear structure. Most of the current approaches to nonlinear adaptive control, such as sliding control, input-output linearisation and the popular feedback linearisation, primarily deal with systems where the uncertainty is due to unknown parameters which appear linearly with respect to the known nonlinearities. Artificial neural networks have offered an alternative approach to solve a more general class of nonlinear problems. In particular, it is their ability to form an arbitrarily close approximation of any continuous nonlinear function and their inherent adaptivity, that has generated much of the research into the use of neural networks for the identification and control of nonlinear systems.

This thesis is concerned with the development of a stable neural network based adaptive control scheme for discrete-time nonlinear systems. The scheme is based on the model reference adaptive control design methodology with a multi-layered neural network generating the model reference control. The neural adaptive control framework is developed for arguably the least analytically tractable nonlinear system, namely general multi-input multi-output non-affine discrete-time dynamic systems with unknown structure. The relative degree and order of the system and the maximum lag in the plant input and plant output terms are the only a priori knowledge assumed.

Critical to any model reference adaptive control approach is the convergence of the tracking error and the stability of the closed-loop system. Therefore, an enhancement is proposed to the model reference neural adaptive control scheme which enables the derivation of sufficient conditions to guarantee the convergence of the tracking error between the controlled output and the desired response. Lyapunov theory is used to

guarantee the stability of the closed-loop system.

Simulation studies undertaken demonstrate the effectiveness of the proposed scheme in controlling discrete-time nonlinear systems which may consist of non-idealities such as nonminimum phase or marginally stable behaviour, as well as dynamic, sensor or load disturbances. The robustness of the new neural adaptive control scheme to dynamic variations and uncertainties is also demonstrated. The practical feasibility of the new approach is investigated through its application to an automobile anti-skid brake system. Despite the highly nonlinear and time-varying dynamics of the vehicle/brake system, the simulation study results indicate that the proposed neural network based anti-skid brake system can provide effective braking performance even under severe variations in environmental conditions.

From the research presented in the thesis, it is concluded that the use of artificial neural networks in the adaptive control of nonlinear systems indicates much promise for the future. Furthermore, the results of the work provide a basis for the development of practical neural adaptive controllers.