Preface

Aim of the book. The main goal of this book is to present recent results in the area of feedback linearisation using empirical models based on dynamic neural networks and to provide the reader with methods for analysing, designing and implementing these techniques.

Background. Many common control problems involve controlled systems that exhibit nonlinear behaviour in that the relationships between controlled and manipulated variables depend on the operating conditions. If the nonlinearities are mild or the operating conditions do not change much, then the effect of nonlinearities may not be severe, and linear control techniques are applicable.

However, many industrial systems exhibit highly nonlinear behaviour and they may be required to operate over a wide range of operating conditions. When conventional linear controllers are used to control highly nonlinear processes, the controllers must be tuned in a conservative manner in order to avoid unstable behaviour. However, this can result in a serious deterioration of control performance. Thus, more sophisticated control techniques are required that use information about the nonlinearities of the controlled system.

The last few decades have witnessed a tremendous development in nonlinear control theory. One important nonlinear control technique is known as feedback linearisation. This technique was developed in the 1970s and consists of transforming a nonlinear system into a controllable linear system by means of static state feedback and nonlinear transformations. Undoubtedly, one of the main reasons to study the feedback linearisation problem lies in its potential use in applications. Once a system is feedback linearised, it admits a standard linear controller design. Moreover, systems with multiple inputs and multiple outputs can be linearised and decoupled, allowing an efficient use of single loops with linear controllers.

The information about the nonlinear dynamic behaviour of a system is encapsulated in a dynamic model that often takes the form of a set of nonlinear differential equations. Many nonlinear control techniques are model-based in that they require the use of this type of dynamic model, including the feedback linearisation approach. The direct way of obtaining a nonlinear model of the plant is to derive a physically based model from principles such as mass and energy balances. These models provide a rich physical insight into the process and are applicable over a wide range of operating conditions. However, physical models are often not available due to the engineering effort and cost associated with their development and maintenance. An alternative way to obtain the required model is to identify it using measured input–output data. The development of techniques of system identification has made possible the synthesis of empirical dynamic models using data measured from the system. In recent years, there has been considerable interest in developing nonlinear dynamic models from input–output data and a variety of model structures and techniques are available.

The predominant family of structures for obtaining nonlinear empirical models is known as artificial neural networks, or simply neural networks, which are inspired by the connections of biological neurons. These models consist of a set of interconnected processing units or artificial neurons and are regarded as structures capable of approximating generic nonlinear input–output maps. Inherent capabilities of neural models such as generalisation, parallel distributed processing and nonlinear dynamic approximation make them a promising tool for nonlinear system identification.

The field of neural computations has evolved from neurological roots when the first artificial neural models were proposed to today's solid mathematical formulations. Neural networks can be divided into static and dynamic networks. A static neural model is described by an algebraic equation while a dynamic neural network is represented by a difference or differential equation depending on whether it is based on a discrete or continuous domain, respectively. One of the most common architectures for static neural networks is the multilayer feedforward network or multilayer perceptron. For the purpose of the nonlinear system identification for control, perhaps the most relevant architectures are the ones offering a state space model such as the Hopfield networks and their variations.

A dynamic recurrent neural network, or simply a dynamic neural network, is a collection of dynamic neurons partially interconnected to a function of their own output. Such networks can be represented by a nonlinear state space model. Dynamic recurrent neural networks can approximate a wide range of nonlinear dynamic behaviours and can be considered as generic nonlinear dynamic systems approximators.

Intended readership. This book has been written to serve a wide range of individuals. In order to achieve this, we have attempted to present a balanced view of the theoretical and practical issues. Thus we hope that the book will be of interest both to practising control engineers with an interest in nonlinear control techniques and also to academic researchers in control theory. Case studies are presented to illustrate design and application issues; relevant mathematical proofs are also included. We have made an effort to present intuitive explanations and illustrative examples of the main results discussed in the book. The very nature of nonlinear systems requires the use of some advanced mathematical tools, which are introduced when necessary. We have assumed that the readers have a working knowledge of engineering mathematics and that they have had some exposure to basic linear control theory, including linear state space methods.

Outline of the book. Chapter 1 provides a general outline of the control techniques introduced in the book within the context of nonlinear identification and control theory. Chapter 2 introduces fundamental analytical concepts that will be used later in the book. Chapter 3 presents an introduction to feedback linearisation, including to feedback linearising-decoupling techniques for dynamic systems with multiple inputs and multiple outputs. Chapter 4 presents a general description dynamic neural networks, which are further analysed in terms of their stability. Training methods relevant to system identification and structure selection techniques are also discussed. Chapter 5 presents theories of approximation relevant to static and dynamic neural networks. Chapter 6 provides a description of the design and implementation of the feedback linearising strategy employing dynamic neural networks. The final control scheme is built up within a multiloop proportional+integral (PI) structure. Chapter 7 provides case studies based on laboratory experiments and simulations and compares the performance of the techniques presented in this book with more conventional control strategies.

Resources. Additional supporting material for this book can be found at the following URL: `http://www.rdg.ac.uk/~shs99vmb/strategies`.

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