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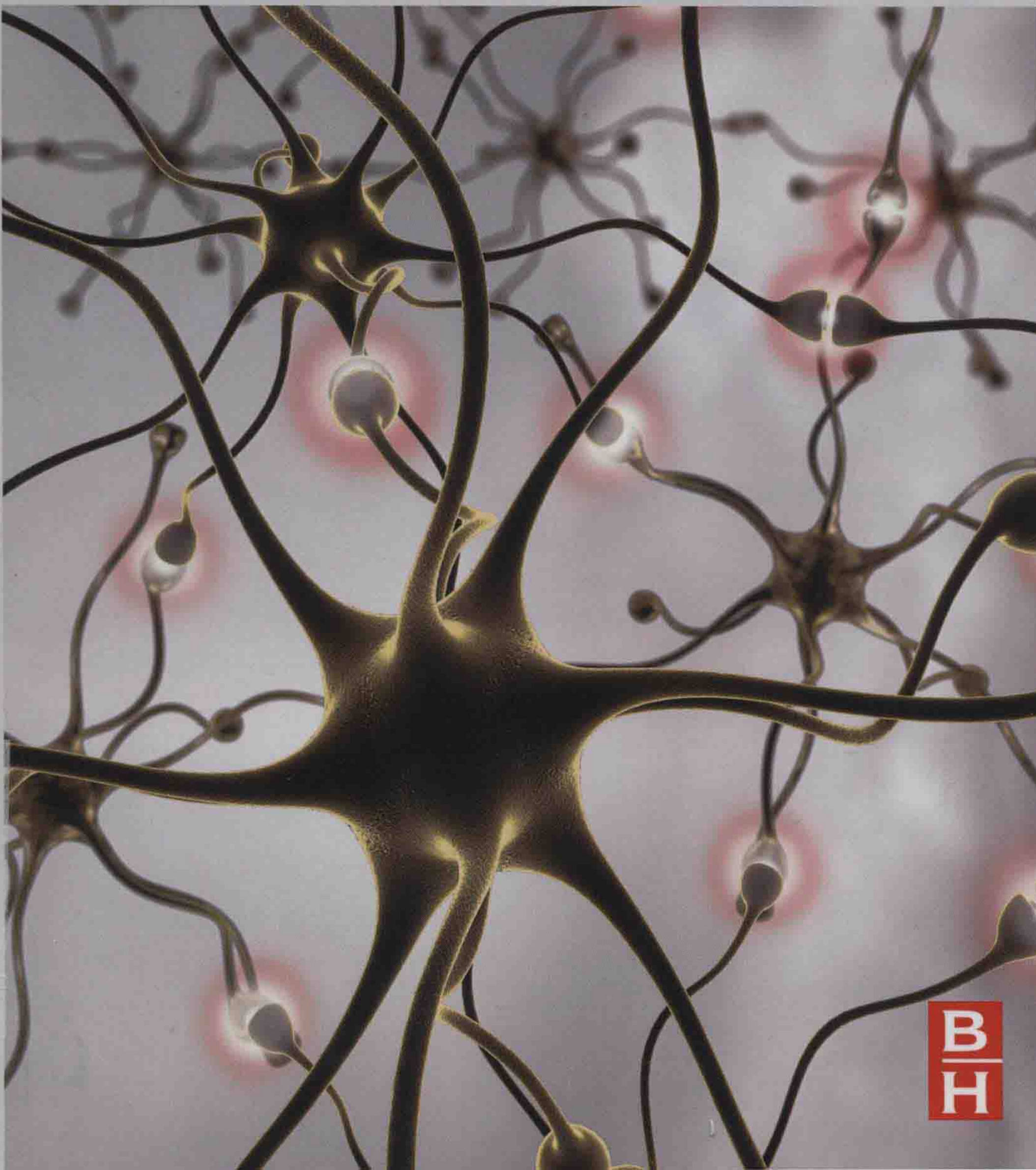
CONCEPTS, MODELING AND ALGORITHMS FOR FAST LEARNING

ERDAL KAYACAN & MOJTABA AHMADIEH KHANESAR

WITH FOREWORD BY JERRY M. MENDEL



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DEDICATION

To Omar Khayyám (1048–1131)
who played with mathematics
not only in science but also in his poems.

FOREWORD

When Nilesh Karnik and I developed type-2 fuzzy logic systems (T2FLSs) in the late 1990s we required the following *fundamental design requirement* [1]: When all sources of (membership function) uncertainty disappear a T2FLS must reduce to a type-1 (T1)FLS. The biggest problem we faced was how to go from a type-2 fuzzy set (T2FS) to a number—the defuzzified output of the T2FLS. Our approach was to do this in two steps [2]: (1) type reduction (TR), in which a T2FS is projected into a T1FS, and (2) defuzzification of that T1FS. Unfortunately, type reduction cannot be performed using closed-form formulas; it is done using iterative algorithms, e.g., enhanced KM Algorithms [3]. Iterative TR may not be a good thing to do in a real-time T2FLS, especially for fuzzy logic control, because of its inherent time delays, and not having closed-form formulas means no mathematical analyses of the T2FLS can be performed, something that is abhorred by those who like to do analyses.

Beginning in 2001 some courageous researchers proposed T2FLSs that bypassed TR and went directly to a defuzzified output for the T2FLS. All of their T2FLSs satisfied the above fundamental design requirement. I call these researchers "courageous" because they had the courage to challenge what we had done, and this is what research should be about.

Hongwei Wu and Mendel [4] were the first ones to do this when they developed minimax uncertainty bounds (WM UBs) for the end points of the type-reduced set. These results became the starting architecture for some of the applications of Hani Hagras and his students [5]. Next came Nie and Tan [6] (NT) who took the union of the fired-rule output sets and computed the output of the resulting T2FLS as the center of gravity of the average of its lower and upper membership functions (MFs). Biglarbegian et al. [7] (BMM) proposed three simplified architectures each of which combined the left and right ends of the firing intervals in different ways. In one of these architectures the output of the T2FLS is a weighted combination of two very simple T1FLSs, one associated with the left-end values of the firing intervals and the other with the right-end values of the firing intervals (this is sometimes called an *m*-*n* or BMM architecture) and, in another of these architectures the T2FLS is assumed to be a weighted average of the average of the lower and upper firing intervals, where the weights are the respective consequents of TSK rules. The latter is analogous to the NT architecture when it is applied directly to the firing intervals and could be called the BMM-NT architecture.

All of these direct defuzzification approaches bypassed type reduction; however, the WM UB architecture was too complicated to be used in analyses of T2FLS, whereas the NT, BMM, and BMM-NT architectures are simple enough so that they can be used in analyses. Biglarbegian et al. already did this in [7–9] for the BMM architecture. The authors of the present book have done it for the BMM-NT architecture, and are to be congratulated for demonstrating many kinds of rigorous analyses that can be performed for it.

Optimizing T2MF parameters by using some training data is very important. When Qilian Liang and I were doing this for IT2FLSs that included type reduction, around 2000 [10], we focused on gradient-based optimization algorithms (e.g., steepest descent). Computing partial derivatives for such T2FLSs is fraught with difficulties [11] because the two switch points that are associated with the type-reduced set change from one time point to the next and the EKM Algorithms that are used to compute those switch points require a reordering of a set of numbers in an increasing order, after which the original ordering must be restored so that correct derivatives are computed. During the past decade (or longer) T2 researchers have focused on all kinds of alternatives to using derivative-based optimization algorithms, many of which are biologically inspired [12]. ACO, PSO, QPSO, and GA are some examples. Another benefit to using such algorithms is that (in theory) they will not get trapped in local extrema, whereas a gradient-based algorithm will.

When type reduction is not in the architecture of a T2FLS computing partial derivatives is quite simple because there no longer are switch points that change from one time to the next and there is no reordering of any set of numbers. The authors of this book have recognized this and have provided both some derivative-based and derivative-free optimization algorithms. They are able to perform some very serious convergence/stability analysis for all of them, for some parameters in their BMM-NT architecture. They are to be congratulated for demonstrating that serious analyses can indeed be performed for a T2FLS.

In summary, this book will be of great value to those who believe it is important to simplify T2FLSs and to use modern optimization algorithms to tune the MF parameters of such systems.

Jerry M. Mendel
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PREFACE

This book presents the basics of FNNs, in particular T2FNNs, for the identification and learning control of real-time systems. In addition to conventional parameter tuning methods, e.g., GD, SMC theory-based learning algorithms, which are simple and have closed forms, their stability analysis are also introduced. This book has been prepared in a way that can be easily understood by those who are both experienced and inexperienced in this field. Readers can benefit from the computer source codes for both identification and control purposes that are given at the end of the book.

There are number of books in the area of FLSs and FNNs. However, this book is more specific in several aspects. First of all, whereas so many books focus on the theory of type-1 and type-2 FLCs, we give more details on the parameter update algorithms of FNNs and their stability analysis. Second, the emphasis here is on the SMC theory-based learning algorithms for the training of FNNs, because we think these algorithms are the simplest and most efficient methods when compared to other algorithms, e.g., the GD algorithm. Last but not least, this book is prepared from the view of the identification and control of real-time systems, which makes it more practical.

The fuzzy logic principles were used to control a steam engine by Ebraham Mamdani of University of London in 1974. It was the first milestone for the fuzzy logic theory. The first industrial application was a cement kiln built in Denmark in 1975. In the 1980s, Fuji Electric applied fuzzy logic theory to the control a water purification process. As a challenging engineering project, in 1987, the Sendai Railway system that had automatic train operation FLCs since from 1987, not many books are available in the market as a reference for real-time systems. This book aims at filling this gap.

In Chapter 1, we summarize the basic mathematical preliminaries for a better understanding of the consecutive chapters. The given materials include the notations, definitions and related equations.

In Chapter 2, we introduce the concepts of type-1 fuzzy sets and T1FLCs. While Boolean logic results are restricted to 0 and 1, fuzzy logic results are between 0 and 1. In other words, fuzzy logic defines some intermediate values between sharp evaluations like absolute true and absolute false. That means fuzzy sets can handle concepts we commonly meet in daily life, like *very old*, *old*, *young*, and *very young*. Fuzzy logic is more like human thinking because it is based on degrees of truth and uses linguistic variables.

In Chapter 3, we introduce the basics of type-2 fuzzy sets, type-2 fuzzy MFs, and T2FLCs. There are two different approaches to FLSs design: T1FLSs and T2FLSs. The latter is proposed as an extension of the former with the intention of being able to model the uncertainties that invariably exist in the rule base of the system. In type-1 fuzzy sets, MFs are totally certain, whereas in type-2 fuzzy sets MFs are themselves fuzzy. The latter case results in the fact that the antecedents and consequents of the rules are uncertain.

In Chapter 4, type-1 and type-2 TSK fuzzy logic models are introduced. The two most common artificial intelligence techniques, fuzzy logic and ANNs, can be used in the same structure simultaneously, namely *FNNs*. The advantages of ANNs such as learning capability from input-output data, generalization capability and robustness and the advantages of fuzzy logic theory such as using expert knowledge are harmonized in FNNs. Instead of using fuzzy sets in the consequent part (like in Mamdani models), the TSK model uses a function of the input variables. The order of the function determines the order of the model, e.g., zeroth-order TSK model, first-order TSK model, etc.

In Chapter 5, we briefly discuss a multivariate optimization technique, namely the GD algorithm, to optimize a nonlinear unconstrained problem. In particular, the referred optimization problem is a cost function of a FNN, either type-1 or type-2. The main features, drawbacks and stability conditions of these algorithms are elaborated. Given an initial point, if an algorithm tries to follow the negative of the gradient of the function at the current point to be able to reach a local minimum, we face the most common iterative method to optimize a nonlinear function: the GD method.

In Chapter 6, the EKF algorithm is introduced to optimize the parameters of T2FNNs. The basic version of KF is an optimal linear estimator when the system is linear and is subject to white uncorrelated noise. However, it is possible to use Taylor expansion to extend its applications to nonlinear cases. Finally, the decoupled version of the EKF is also discussed, which is computationally more efficient than EKF to tune the parameters of T2FNNs.

In Chapter 7, in order to deal with nonlinearities, lack of modeling, several uncertainties and noise in both identification and control problems, SMC theory-based learning algorithms are designed to tune both the premise and consequent parts of T2FNNs. Furthermore, the stability of the learning algorithms for control and identification purposes are proved by using appropriate Lyapunov functions. In addition to its well-known feature of being robust, the most significant advantage of the proposed learning algorithm for the identification case is that the algorithm has a closed form, and thus it is easier to implement in real-time when compared to the other existing methods.

In Chapter 8, a novel hybrid training method based on continuous version of PSO and SMC theory-based training method for T2FNNs is proposed. The approach uses PSO for the training of the antecedent part of T2FNNs, which appear nonlinearly in the output of T2FNNs, and SMC theory-based training method for the training of the parameters of their consequent part. The use of PSO makes it possible to lessen the probability of entrapment of the parameters in a local minima while proposing simple adaptation laws for the parameters of the antecedent part of T2FNNs when compared to the most popular approaches like GD, LM and EKF. The stability of the proposed hybrid training method is proved by using an appropriate Lyapunov function.

In Chapter 9, an attempt is made to show the effect of input noise in the rule base numerically in a general way. There exist number of papers in literature claiming that the performance of T2FLSs is better than their type-1 counterparts under noisy conditions. They attempt to justify this claim by simulation studies only for some specific systems. However, in this chapter, such an analysis is done independent of the system to be controlled. For such an analysis, a novel type-2 fuzzy MF (elliptic MF) is proposed. This type-2 MF has certain values on both ends of the support and the kernel and some uncertain values for the other values of the support. The findings of the general analysis in this chapter and the aforementioned studies published in literature are coherent.

In Chapter 10, the learning algorithms proposed in the previous chapters (GD-based, SMC theory-based, EKF and hybrid PSO-based learning algorithms) are used to identify and predict two nonlinear systems, namely Mackey-Glass and a second-order nonlinear time-varying plant. Several comparisons are done, and it has been shown that the proposed SMC theory-based algorithm has faster convergence speed than the existing methods such as the GD-based and swarm intelligence-based methods. Moreover, the proposed learning algorithm has an explicit form, and it is easier to implement than other existing methods. However, for offline algorithms for which computation time is not an issue, the hybrid training method based on PSO and SMC theory may be a preferable choice.

In Chapter 11, three real-world control problems, namely anesthesia, magnetic rigid spacecraft and tractor-implement system, are studied by using SMC theory-based learning algorithms for T2FNNs. For all the systems, the FEL scheme is preferred in which a conventional controller (PD, etc.) works in parallel with an intelligent structure (T1FNNs, T2FNN, etc.). The proposed learning algorithms have been shown to be able to control these real-world example problems with a satisfactory performance. Note that the proposed control algorithms do not need a priori knowledge of the system to be controlled.

Potential readers of this book are expected to be undergraduate and graduate students, engineers, mathematicians and computer scientists. Not only can this book be used as a reference source for a scientist who is interested in FNNs and their real-time implementation but also as a course book on FNNs or artificial intelligence in master or doctorate university studies. We hope this book will serve its main purpose successfully.

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