Preface

Machine intelligence refers back to 1936, when Alan M Turing proposed the idea of a universal mathematics machine, a theoretical concept in the mathematical theory of computability. The desire for intelligent machines remained just an elusive dream until the first computer was developed. When the first computer appeared in the early fifties, we admired it as an artificial brain, and we thought that we are successful in creating a low level decision making cognitive machine. Researchers coined the term Artificial Intelligence (AI) and waited for many potential applications to evolve. Research in AI is directed toward building "thinking" machines and improving our understanding of intelligence. As evident, the ultimate achievement in this field would be to mimic or exceed human cognitive capabilities including reasoning, recognition, creativity, emotions, understanding, learning and so on. Even though we are a long way from achieving this, some success has been achieved in mimicking specific areas of human mental activity.

Recent research into AI together with other branches of computer science has resulted in the development of several useful intelligent paradigms, which forms the basis of this volume. This volume is focused on some of the recent theoretical developments and its practical applications in engineering, science, business and commerce. The intelligent paradigms can be roughly divided among knowledge-based systems, computational intelligence and hybrid combinations.

Knowledge-based systems include expert and rule-based systems, intelligent agents and techniques for handling uncertainty (e.g., fuzzy logic). Computational intelligence includes neural networks, fuzzy inference systems, evolutionary computation and other optimization algorithms, rough sets, probabilistic reasoning and so on. The integration of different learning and adaptation techniques, to overcome individual limitations and achieve synergetic effects through hybridization or fusion of these techniques, has in recent years contributed to a large number of new hybrid system designs.

This volume is a rare collection of 18 chapters compiling the latest developments in the state-of-the-art research in intelligent paradigms and some of its practical interesting applications. The chapters are authored by world leading well-established experts in the field. Each chapter focuses on different aspects of intelligent paradigms and is complete by itself.

The volume is divided into two parts: "Theory" (Chapters 1-9) and "Applications" (Chapters 10-18). However, this does not intend to strictly divide the chapters. The theoretic chapters are not limited to theory only; they also illustrate the theory with examples or real-world applications. The chapters in the second part do not only give applications, but treat the underlying theory as well. The division merely indicates the main focus of the chapters contained in the respective parts.

The volume is further organized as follows:

Chapter 1 begins with an introduction to Support Vector Machines and some of the few computationally cheaper alternative formulations that have been developed in recent years. Further, the Multi-category Proximal Support Vector Machine (MPSVM) is presented in detail. The authors use a linear MPSVM formulation in an iterative manner to identify the outliers in the data set and eliminate (reducing) them. A k-nearest neighbor classifier is able to classify points using this reduced data set without significant loss of accuracy. The proposed theoretical frameworks are validated on a few publicly available OCR data sets.

Chapter 2 presents Bayesian Control of Dynamic Systems. Bayesian networks for the static as well as for the dynamic case have gained an enormous interest in the research community of machine learning and pattern recognition. Although the parallels between dynamic Bayesian networks and description of dynamic systems by Kalman filters and difference equations are well known since many years, Bayesian networks have not been applied to problems in the area of adaptive control of dynamic systems. To show how a Bayesian network can control a dynamic system authors exploit the similarities with Kalman Filters to calculate an analytical state space model. The performance of this analytical model is compared with the state space model after training with the EM algorithm and a model whose structure is deduced using difference equations. The experiments show that the analytical model as well as the trained model is suitable for control purposes, which leads to the idea of a Bayesian controller.

Chapter 3 introduces "AppART": a hybrid neural network based on adaptive resonance theory for universal function approximation. AppART is an Adaptive Resonance Theory (ART) low-parameterized neural model that incrementally approximates continuous-valued multidimensional functions from noisy data using biologically plausible processes. AppART performs a higher order Nadaraya-Watson regression and can be interpreted as a fuzzy logic standard addictive model. Authors present AppART dynamics/training and its theoretical foundations as a function approximation method. Three benchmark problems are solved in order to study AppART from an application point of view and to compare its results with the ones obtained with other models. Finally, two modifications of the original AppART formulation aimed at improving AppART efficiency are proposed and tested.

The authors of Chapter 4 present an algorithmic approach to the main concepts of rough set theory. The rough set theory is a mathematical formalism for representing uncertainty, which can be considered as an extension of the classical set theory. It has been used in many different research areas, including those related to inductive machine learning and reduction of knowledge-based systems. This chapter is focused on the main concepts of rough set theory and presents a family of algorithms for implementing them.

An automated case generation from databases using similarity-based rough approximation is presented in Chapter 5. Knowledge acquisition for a case-based reasoning system from domain experts is a bottleneck in the system development process. It would be useful to derive representative cases automatically from larger, available databases rather than acquiring them from domain experts. Case generation is a branch of data mining that aims at choosing representative cases from large data sets for future case-based reasoning tasks. This Chapter presents two algorithms using similarity based rough set theory to derive cases automatically from available databases. The first algorithm, *SRS1*, requires the user to choose the similarity thresholds for the objects in a database, while the second algorithm, *SRS2*, can automatically select proper similarity thresholds. These algorithms can handle noise and inconsistent data in the database and select a reasonable number of the representative cases from the database. Also these algorithms are easily scalable. The algorithms were implemented and the experimental results showed that their classification accuracy was similar to that of well-known machine learning systems, such as rule induction systems and neural networks.

Chapter 6 introduces a new version of a machine-learning algorithm, FDM, based on a new notion of the fuzzy derivative. The main idea is to describe the influence of the change of one parameter on another. In this algorithm sets of classification rules are generated and a coefficient of significance for every single rule is defined. A new example is classified into a class for which its total degree of membership is maximal. In this way, the effect of a single non-informative rule having occurred by chance is decreased due to the coefficient of significance. The fuzzy derivative method is mainly used to study systems with qualitative features, but it can also be used for systems with quantitative features. The algorithm is applied to classification problems and comparisons made with other techniques.

In Chapter 7, the author explains the model and fixpoint semantics for fuzzy disjunctive programs with weak similarity. In such knowledge representation and commonsense reasoning, we should be able to handle incomplete and uncertain information. In recent years, disjunctive and multivalued, annotated logic programming have been recognized as powerful tools for maintenance of such knowledge's. This chapter presents a declarative model, and fixed-point semantics for fuzzy disjunctive programs with weak similarity – sets of graded strong literal disjunctions. Fuzzy disjunctive programs may contain the binary predicate symbol ~ for weak similarity, which is the fuzzy counterpart of the classical equality. In the end, the mutual coincidence of the proposed semantics will be reached.

Chapter 8 proposes an automated report generation tool for the data-understanding phase. To be able to successfully prepare and model data, the data miner needs to be aware of the properties of the data manifold. The outline of a tool for automatically generating data survey reports for this purpose is described in this chapter. Such report is used as a starting point for data understanding, acts as a documentation of the data, and can be redone if necessary. The main focus is on describing the cluster structure and the contents of the clusters. The described system combines linguistic descriptions (rules) and statistical measures with visualizations. Whereas rules and mathematical measures give quantitative information, the visualizations give qualitative information of the data sets, and help the user to form a mental model of the data based on the suggested rules and other characterizations.

In Chapter 9, the authors propose a framework for a grammar-guided genetic programming system called Tree-Adjunct Grammar Guided Genetic Programming (TAG3P), which uses tree-adjunct grammars along with a context-free grammar to set language bias in genetic programming. The use of tree-adjunct grammars can be seen as a process of building context-free grammar guided programs in the two dimensional space. Authors show some results of TAG3P on the trigonometric identity discovery problems.

The main contribution of Chapter 10 is the development of a framework to determine both agent's behavior and cooperation allowing to express (1) cooperation, (2) adaptability, (3) mobility, and (4) transparency. In a multi-agent environment, each agent could be working at common goals with globally cooperative behaviors. In order to construct a model integrating agent's behavior and cooperation among agents, authors present two approaches for agent collaboration. As for the first approach, a social agency model for constructing a prototype system for guide activities in a laboratory is introduced. The interaction between autonomous agents is then formalized. As for the second approach, an autonomous agent's architecture in social agency aimed at communicating with other agents in knowledge-level is presented.

Chapter 11 presents two frameworks, an action control framework and a safety verification framework for intelligent information systems based on paraconsistent logic program called EVALPSN. Two examples for EVALPSN based intelligent information systems, an intelligent robot action control system and an automated safety verification system for railway interlocking are presented.

Chapter 12 deals with the different neuro-fuzzy paradigms for intelligent energy management. Fusion of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) have attracted the growing interest of researchers in various scientific and engineering areas due to the growing need of adaptive intelligent systems to solve the real world problems. This chapter presents a fuzzy neural network for developing an accurate short term forecast for hourly power demand and a Mamdani and Takagi Sugeno fuzzy inference system learned using neural network learning technique for controlling the reactive power of a manufacturing plant. Performance of the developed models is compared with neural networks and other connectionist paradigms.

In Chapter 13, the authors use a real-coded genetic algorithm for information space optimization for Inductive Learning. This chapter begins with a presentation of new feature construction methods. The methods are based on the idea that a *smooth* feature space facilitates inductive learning thus it is desirable for data mining. The methods, Category-guided Adaptive Modeling (CAM) and Smoothness-driven Adaptive Modeling (SAM), are originally developed to model human perception of still images, where an image is perceived in a space of index colors. CAM is tested for a classification problem and SAM is tested for a Kansei scale value (the amount of the impression) prediction problem. Both algorithms have been proved to be useful as preprocess steps for inductive learning through the experiments. Authors have also evaluated CAM and SAM using datasets from the UCI repository and the empirical results has been promising.

In Chapter 14, the authors present a hybrid detection and classification system for human motion analysis (moving pedestrians in a video sequence). The technique comprises two sub-systems: an active contour model for detecting and tracking moving objects in the visual field, and an MLP neural network for classifying the moving objects being tracked as 'human' or 'non-human'. The axis crossover vector method is used for translating the active contour into a scale-, location-, resolution-, and rotation-invariant vector suited for input to a neural network according to the most appropriate level of detail for encoding human shape information. Experiments measuring the neural network's accuracy at classifying unseen computer generated and real moving objects are presented, along with potential applications of the technology.

Chapter 15 discusses two applications of the theory of fuzzy sets in investigating and evaluating human learning abilities and cognitive processes. They are an integral part of the Interactivist-Expectative Theory on Agency and Learning (IETAL) and its multiagent expansion known as Multi-Agent Systems Interactive Virtual Environments (MASIVE). In the first application presented, a fuzzy set is defined to ease and automate the process of detection of negative variation in filtered brain waves during the Dynamic Cognitive Negative Variation (CNV) experiment. The automatic detection of brain waveforms that are contingent of negative variation is a crucial part of the experiment that measures individual human learning parameters. By eliminating the direct influence of the human expert, a level of objectivity is being maintained over the duration of the whole experiment. The decision process is significantly shorter, which contributes to more accurate measuring, as is the case in numerous experiments involving human subjects and learning. In the second application, fuzzy sets serve as tools in the process of grading, which are a highly cognitive, but ill-defined problems. The fuzzy evaluation framework that is given is very general, and straightforwardly applicable in any evaluation process when the evaluator is expected to quantize one or several aspects of a given artifact.

In Chapter 16, the authors present a full explanation facility that has been developed for any standard Multi-Layered Perceptron (MLP) network with binary input neurons that performs a classification task. The interpretation of any input case is represented by a non-linear ranked data relationship of key inputs, in both text and graphical forms. The knowledge that the MLP has learned is represented by average ranked class profiles or as a set of rules induced from all training cases. The full explanation facility discovers the MLP knowledge bounds as the hidden layer decision regions containing classified training examples. Novel inputs are detected when the input case is positioned in a decision region outside the knowledge bounds. Results using the facility are presented for a *48*-dimensional real-world MLP that classifies low-back-pain patients. Using the full explanation facility, it is shown that the MLP preserves the continuity of the classifications in separate contiguous threads of decision regions across the *48*-dimensional input space thereby demonstrating the consistency and predictability of the classifications within the knowledge bounds.

Chapter 17 presents a detailed survey of the automatic translation or autocoding systems used in translating unstructured natural language texts or verbatims produced by health care professionals to categories defined by a controlled vocabulary. In the medical domain, over the centuries several controlled vocabularies have emerged with the goal of mapping semantically equivalent terms such as *fever, pyrexia, hyperthermia*, and *febrile* on the same (numerical) value. Translating unstructured natural language texts or verbatims produced by healthcare professionals to categories defined by a controlled vocabulary is a hard problem, mostly solved by employing human coders trained both in medicine and in the details of the classification system. These techniques could also be applied to other problem domains.

The final chapter presents a genetic programming approach for the Induction of a natural language parser. When we try to deal with Natural Language Processing (NLP) we have to start with the grammar of a natural language. But the grammars described in linguistic literature have an informal form and many exceptions. Thus, they are not useful to create final formal models of grammars, which make machine processing of sentences possible. These grammars can be a starting point for the attempts to create basic models of natural language grammar at the most. However, it requires expert knowledge. Machine learning based on a set of sample sentences can be the better way to find the grammar rules. This kind of learning (grammatical inference) allows avoiding the preparation of knowledge about the language for the NLP system. The examples of correct and incorrect sentences allow the NLP systems with the self-evolutionary parser to try to find the right grammar. This self-evolutionary parser can be improved on the basis of new examples. Thus, the knowledge acquired in this way is flexible and easily modifiable. Authors proposed theoretical bases for the use of two classes of evolutionary computation that support-automated inference of fuzzy automaton-driven parser of natural language. This chapter examines the use of edge encoding, a genetic programming approach for induction of parser based on a fuzzy automaton.

Acknowledgments

We are grateful to the authors of this volume and Greg Huang (Massachusetts Institute of Technology, USA), Pavel Osmera (Brno University of Technology, Czech Republic), Jose Mira (The Universidad Nacional de Educación a Distancia, Spain), Xiao-Zhi Gao (Helsinki University of Technology, Finland), Paulo Jose ad Costa Branco (Institute Superior Technical, DEEC, Portugal), Janos Abonyi, (University of Veszprém, Hungary), José Manuel Benítez (University of Granada, Spain), and Eulalia Schmidt (Polish Academy of Sciences, Poland) for the tremendous service by critically reviewing the chapters within the stipulated deadline. The editors are deeply grateful to Clarence W. de Silva (University of British Columbia) for the encouraging comments on the volume. The editors would like to thank Springer-Verlag, Germany for the editorial assistance and excellent cooperative

collaboration to produce this important scientific work. Last but not the least, we would like to express our gratitude to our colleagues from the School of Business Systems, Monash University, Australia and Knowledge-Based Intelligent Engineering Systems Centre, University of South Australia, Australia for supporting us to produce this volume. We hope that the reader will share our excitement to present this volume on "*Innovations in Intelligent Systems and Applications*" and will find this very useful.

Ajith Abraham, Lakhmi Jain, Berend Jan van der Zwaag
April 2003

Volume Editors

Ajith Abraham, Ph.D.
Computer Science Department
Oklahoma State University
700 N Greenwood Avenue
Tulsa, OK 74106, USA
Tel.: +1-918-5948188, Fax: +1-918-5948281, eFax: +1 (509) 691-2851
E-mail: ajith.abraham@ieee.org
Web: http://ajith.softcomputing.net

Lakhmi Jain, Ph.D.
Knowledge-Based Intelligent Engineering Systems Centre (KES)
University of South Australia, Adelaide
Mawson Lakes, South Australia, 5095, Australia
Phone: +61 8 8302 3315, Fax: +61 8 8302 3384
E-mail: L.Jain@unisa.edu.au
Web: http://www.kes.unisa.edu.au

Berend Jan van der Zwaag, M.Sc. (assoc. editor)
Department of Electrical Engineering
University of Twente
P.O.Box 217, 7500AE Enschede, The Netherlands
Tel.: +31 53 489 2842, Fax: +31 53 489 1060
E-mail: b.j.vanderzwaag@utwente.nl
Web: http://www.sas.el.utwente.nl