

**HYBRID COMPUTATIONAL INTELLIGENCE MODELS
WITH SYMBOLIC RULE EXTRACTION FOR
PATTERN CLASSIFICATION**

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**HYBRID COMPUTATIONAL INTELLIGENCE MODELS WITH
SYMBOLIC RULE EXTRACTION FOR PATTERN CLASSIFICATION**

by

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	viii
LIST OF FIGURES	xi
LIST OF ABBREVIATION	xiv
LIST OF PUBLICATIONS	xvi
ABSTRAK	xviii
ABSTRACT	xix
CHAPTER 1	
INTRODUCTION	
1.1 Background.....	1
1.2 Computational Intelligence.....	4
1.3 Problems and Motivations.....	7
1.4 Research Objectives, Scope, and Approach.....	13
1.5 Research Methodology	15
1.6 Thesis Outline.....	17
CHAPTER 2	
LITERATURE REVIEW ON HYBRID COMPUTATIONAL INTELLIGENCE SYSTEMS	
2.1 Introduction	20
2.2 Computational Intelligence Paradigms.....	20
2.3 Hybrid Computational Intelligence Models.....	23
2.3.1 Hybrid CI Models for Pattern Classification.....	24

2.3.1.1	Artificial Neural Network-Based Hybrid CI Models.....	24
2.3.1.2	Fuzzy System-Based Hybrid CI Models.....	27
2.3.1.3	Remarks.....	29
2.3.1.4	Genetic Algorithm-Based Hybrid CI Models.....	30
2.3.2	Hybrid CI Models For Rule Extraction.....	31
2.3.2.1	Genetic Algorithm-Based Rule Extraction.....	34
2.3.2.2	Remarks.....	38
2.4	Summary.....	39

CHAPTER 3
ENHANCING THE FUZZY MIN-MAX NEURAL NETWORK

3.1	Introduction.....	41
3.2	Review of Fuzzy Min-Max Neural Networks.....	41
3.3	Dynamics of the Fuzzy Min-Max Network.....	45
3.3.1	Learning in FMM.....	49
3.3.2	A Numerical Example.....	50
3.4	The Modified Fuzzy Min-Max Networks.....	53
3.4.1	Pruning and Rule Extraction from FMM Networks.....	55
3.4.2	Hyperbox Selection using Euclidean Distance and Membership Function.....	57
3.5	Performance Measure and Bootstrap Method.....	59
3.5.1	Bootstrap Mean and Confidence Interval Estimation	61
3.5.2	Bootstrap Hypothesis Test.....	61
3.6	Benchmark Studies.....	62
3.6.1	PID Data Set.....	63

3.6.2	WBC Data Set.....	66
3.6.3	IRIS Data Set.....	70
3.6.4	Remarks.....	72
3.7	Summary.....	74
CHAPTER 4		
INTEGRATING FUZZY MIN-MAX NEURAL NETWORKS WITH THE GENETIC ALGORITHM		
4.1	Introduction.....	76
4.2	The Genetic Algorithm.....	76
4.2.1	Rule Extraction Using the Genetic Algorithm.....	78
4.3	A Two-Stage Pattern Classification and Rule Extraction Model.....	81
4.3.1	Stage One: The FMM-Based Pattern Classifier.....	81
4.3.2	Stage Two: The GA-Based Rule Extractor.....	82
4.3.2.1	Generating Open Hyperboxes.....	82
4.3.2.2	Evolving the Hyperboxes.....	84
4.4	Benchmark Studies.....	87
4.4.1	PID Data Set.....	88
4.4.2	Wine Data Set.....	97
4.4.3	Waveform Data Set.....	104
4.4.4	Scalability of the GA-Based FMM Networks.....	112
4.4.5	Remarks.....	114
4.5	Summary.....	115

CHAPTER 5

DEVELOPING A MULTI-AGENT CLASSIFIER SYSTEM WITH BAYESIAN FORMALISM

5.1	Introduction.....	117
5.2	Multi-Agent Systems.....	119
5.2.1	Architectures and Reasoning Models of Multi-Agent Systems.....	119
5.2.2	Remarks.....	123
5.3	Multi-Agent Classifier System.....	124
5.3.1	Bayesian Formalism for Trust Measurement.....	127
5.3.2	Modifications to the FMM-based Networks.....	131
5.4	Benchmark Studies.....	135
5.4.1	PID data set.....	136
5.4.2	WBC Data Set.....	141
5.4.3	Multi Oil Flow Data Set	145
5.4.4	Remarks.....	150
5.5	Summary.....	150

CHAPTER 6

APPLYING THE MULTI-AGENT CLASSIFIER SYSTEM TO INDUSTRIAL PROBLEMS

6.1	Introduction.....	152
6.2	Case Study I: Oil Flow Regime Classification.....	153

6.2.1	Experiments, Results, and Discussion	155
6.3	Case Study II: Fault Detection and Diagnosis.....	162
6.3.1	Experiments, Results, and Discussion	165
6.4	Summary.....	171
CHAPTER 7		
APPLYING THE MULTI-AGENT CLASSIFIER SYSTEM TO MEDICAL PROBLEMS		
7.1	Introduction.....	173
7.2	Performance Indicators.....	172
7.3	Case Study I: Acute Stroke.....	175
7.3.1	Experiments, Results, and Discussion	177
7.4	Case Study II: Acute Coronary Syndrome.....	182
7.4.1	Experiments, Results, and Discussion	183
7.5	Case Study III: Myocardial Infarction.....	188
7.5.1	Experiments, Results, and Discussion.....	189
7.6	Summary.....	194
CHAPTER 8		
CONCLUSIONS AND FURTHER WORK		
8.1	Summary of the Research.....	195
8.2	Contributions of the Research.....	197
8.3	Suggestions for Further Work.....	200
	REFERENCES.....	202

LIST OF TABLES

Table 3.1	Input features of the PID data set.....	63
Table 3.2	Rules extracted from the PID data set.....	65
Table 3.3	Test accuracy rates of different methods for the PID data set.....	66
Table 3.4	Input features of the WBC data set	67
Table 3.5	Rules extracted from the WBC data set.....	69
Table 3.6	Test accuracy rates of different methods for the WBC data set.....	70
Table 3.7	Rules extracted from the IRIS data set.....	72
Table 3.6	Test accuracy rates of different methods for the IRIS data set ..	73
Table 4.1	Terms related to the Genetic Algorithm.....	77
Table 4.2	The original and open hyperboxes in a three-dimensional input space.....	84
Table 4.3	The difference in the test accuracy rates in the second region for the PID data set.....	90
Table 4.4	Results of different networks with different hyperbox sizes for the PID data set.....	91
Table 4.5	Hypothesis tests between FMM-based networks with and without the GA for the PID data set.....	93
Table 4.6	Test accuracy rates of different classifiers published in Carpenter & Tan (1995) along with the proposed networks for the PID data set.....	94
Table 4.7	Rules extracted from MFMM1 and MFMM1-GA for the PID data set.....	95
Table 4.8	Input features for the Wine data set.....	97
Table 4.9	The difference of the test accuracy rates in the second region for the Wine data set.....	99
Table 4.10	Test accuracy rates of different hyperbox sizes for the Wine data set.....	100

Table 4.11	Hypothesis tests for FMM-based networks with and without the GA for the Wine data set.....	101
Table 4.12	Classification results for the Wine data set.....	102
Table 4.13	Rules extracted from MFMM1 and MFMM1-GA for the Wine data set.....	103
Table 4.14	The difference of the test accuracy rates in the second region for the Waveform data set.....	106
Table 4.15	Test accuracy rates with different hyperbox sizes for the Waveform data set.....	107
Table 4.16	Hypothesis tests for FMM-based networks with and without the GA for the Waveform data set.....	108
Table 4.17	Classification results for the Waveform and noise data set.....	109
Table 4.18	Rules extracted from MFMM1 and MFMM1-GA for the Waveform data set.....	110
Table 4.19	Comparison of computational times between Stage one and Stage two.....	114
Table 5.1	Hypothesis tests between the MACS and its team agents for the PID data set.....	139
Table 5.2	Test accuracy rates of different methods for the PID data set.....	140
Table 5.3	Rules extracted from the PID data set.....	141
Table 5.4	Hypothesis tests between the MACS and its team agents for the WBC data set.....	143
Table 5.5	Test accuracy rates of different methods for the WBC data set.....	144
Table 5.6	Rules extracted from the WBC data set.....	144
Table 5.7	Hypothesis tests between the MACS and its team agents for the oil flow data set.....	147
Table 5.8	Test accuracy rates of different methods for the oil flow data set.....	148
Table 5.9	Rules extracted from the oil-flow data set.....	149

Table 6.1	Average time used by FMM-GA agents to classify different data sets.....	159
Table 6.2	Rules extracted from the MACS for the oil flow regimes data set.....	160
Table 6.3	List of sensor parameters used in the experiments.....	164
Table 6.4	Hypothesis tests of the MACS and FMM-based networks for the HTC and BD tasks.....	168
Table 6.5	Rules extracted from the MACS for the HTC task.....	170
Table 6.6	Rules extracted from the MACS for the BD task.....	171
Table 7.1	Input features of the Stroke data set.....	175
Table 7.2	Rankin scale of patient upon discharge.....	176
Table 7.3	Hypothesis tests of ACC between the MACS and FMM-based networks for the RS study.....	180
Table 7.4	Performance comparison of the RS study.....	181
Table 7.5	Rules extracted from the MACS for the RS study	181
Table 7.6	Input features of the ACS data set.....	183
Table 7.7	Performance comparison of different classifiers for the ACS study.....	187
Table 7.8	Rules extracted from the MACS for the ACS study.....	187
Table 7.9	Input features of the MI study.....	189
Table 7.10	Performance comparison of different classifiers for the MI study.....	192
Table 7.11	Rules extracted from the MACS for the MI study.....	193

LIST OF FIGURES

Figure 1.1	A pattern recognition system comprises a feature extractor and a pattern classifier.....	2
Figure 1.2	The methodology followed in this research	17
Figure 3.1	An example of FMM hyperboxes placed along the decision boundary of a two-class problem.....	46
Figure 3.2	A three-dimensional hyperbox	46
Figure 3.3	A three-layer FMM network.....	48
Figure 3.4	An example illustrating the learning algorithm of FMM for a two-class problem.....	52
Figure 3.5	The classification process of an input pattern using the Euclidean distance.....	59
Figure 3.6	Test accuracy rates of the PID problem.....	64
Figure 3.7	Average number of hyperboxes for the PID problem.....	64
Figure 3.8	Test accuracy rates of the WBC problem.....	68
Figure 3.9	Average number of hyperboxes of the WBC problem.....	68
Figure 3.8	Test accuracy rates of the IRIS problem.....	71
Figure 3.9	Average number of hyperboxes of the IRIS problem.....	72
Figure 4.1	A typical GA procedure.....	78
Figure 4.2	The procedure of the proposed system.....	87
Figure 4.3	A flow chart of the proposed system.....	87
Figure 4.4	Test accuracy rates of the PID data set.....	89
Figure 4.5	Test accuracy rates of the Wine data set.....	98
Figure 4.6	Three classes of waveform patterns, each one is a combination of two triangular waveforms.....	105
Figure 4.7	Test accuracy rates of the Waveform data set.....	106
Figure 5.1	The decision ladder model (adapted from Sioutis <i>et al.</i> , 2004)..	120

Figure 5.2	The MAS architecture proposed by Fazlollahi & Vahidov (2000).....	122
Figure 5.3	The Trust-Negotiation-Communication model.....	123
Figure 5.4	The proposed MACS model.....	125
Figure 5.5	Steps involved in calculating trust.....	132
Figure 5.6	Test accuracy rates of the PID data set.....	137
Figure 5.7	Percentages of patterns classified by each team in the MACS for the PID data set.....	139
Figure 5.8	Test accuracy rates of the WBC data set.....	142
Figure 5.9	Percentages of patterns classified by each team in the MACS for the WBC data set.....	143
Figure 5.10	Test accuracy rates of the oil flow data set.....	146
Figure 5.11	Percentages of patterns classified by each team in the MACS for the oil flow data set.....	147
Figure 6.1	A schematic diagram of the flow regimes.....	153
Figure 6.2	The components of an ECT system.....	154
Figure 6.3	A schematic diagram of a twelve-electrode ECT system.....	154
Figure 6.4	Test accuracy rates of r the oil flow regime classification.....	157
Figure 6.5	Percentages of patterns classified by each team in the MACS for the oil flow regimes study.....	158
Figure 6.6	The Circulating Water (CW) system.....	164
Figure 6.7 (A)	Test accuracy rates of the MACS and its team agents for the HTC task.....	167
Figure 6.7 (B)	Test accuracy rates of the MACS and its team agents for the BD task.....	167
Figure 6.8 (A)	Percentages of patterns classified by each team in the MACS for the HTC task.....	168
Figure 6.8 (B)	Percentages of patterns classified by each team in the MACS for the HD task.....	168

Figure 7.1	The ACC results of the RS study.....	178
Figure 7.2	The SENS and SPEC results of the RS study.....	179
Figure 7.3	Percentages of patterns classified by each FMM-based team in the MACS for the RS study.....	180
Figure 7.4	The ACC results of the ACS study.....	184
Figure 7.5	The SENS and SPEC results of the ACS study.....	185
Figure 7.6	Percentages of patterns classified by each team in the MACS for the ACS case.....	186
Figure 7.7	The ACC results of the MI study.....	190
Figure 7.8	The SENS and SPEC results of the MI study.....	191
Figure 7.9	Percentages of patterns classified by each team in the MACS for the MI study.....	192

LIST OF ABBREVIATIONS

ACC	Accuracy
ACS	Acute Coronary Syndrome
AI	Artificial Intelligence
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial Neural Network
ARA	Attribute Reasoning Agents
ARC	Adaptive Resolution Classifier
ART	Adaptive Resonance Theory
ART-EMAP	Adaptive Resonance Theory Evidence MAPping
ARTMAP	Adaptive Resonance Theory MAPping
BD	Block Detection
BDI	Belief, Desire, and Intention
CI	Computational Intelligence
COD	Condition on Discharge
COMMAS	COndition Monitoring Multi-Agent System
CSCA	Cross Sensor Corroboration Agents
CW	Circulating Water
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System
EA	Evolutionary Algorithms
ECT	Electrical Capacitance Tomography
ES	Evolutionary Strategies
FAM	Fuzzy ARTMAP
FDHECNN	HyperEllipsoidal Composite Neural Network
FL	Fuzzy Logic
FMCN	FMM classifier with Compensatory Neurons
FMM	Fuzzy Min-Max
FMM-GA	original FMM with GA
FNN	Fuzzy Neural Network
FS	Fuzzy System
GA	Genetic Algorithm
GFMM	General Fuzzy Min-Max

GP	Genetic Programming
HNFB	Hierarchical Neuro-Fuzzy Binary Space Partitioning Model
HNFB ⁻¹	Inverted Hierarchical Neuro-Fuzzy BSP system
HTC	Heat Transfer Conditions
LCS	Learning Classifier Systems
MACS	Multi-Agent Classifier System
MAS	Multi-Agent Systems
MFMM	Modified FMM
MFMM1-GA	MFMM1 with GA
MFMM2-GA	MFMM2 with GA
MI	Myocardial Infarction
MKRA	Meta Knowledge Reasoning Agents
MLP	Multi-Layer Perceptron
NEFCLASS	NEural Fuzzy CLASSification
PARC	Pruned adaptive Resolution Classifier
PID	Pima Indian Diabetes
RBF	Radial Basis Function
REAP	Rule Extraction Activation Projection
RS	Rankin Scale
SENS	Sensitivity
SPEC	Specificity
TNC	Trust, Negotiation, and Communication
WBC	Wisconsin Breast Cancer

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**MODEL KECERDIKAN BERKOMPUTER HIBRID DENGAN
PENGEKSTRAKAN PERATURAN SIMBOLIK BAGI PENGELASAN
CORAK**

ABSTRAK

Tesis ini adalah berkenaan dengan pembangunan model kecerdikan berkomputer hibrid bagi menangani masalah pengelasan corak. Penyelidikan tertumpu kepada hibridisasi model rangkaian neural buatan dan algoritma genetik bagi pembelajaran dan pengestrakan peraturan berdasarkan data. Di samping itu, satu sistem pengelas pelbagai ejen yang baru telah digubal untuk menggabungkan model kecerdikan berkomputer hibrid menjadi satu kerangka kerja sepunya bagi pengelasan corak.

Rangkaian Fuzi Min-Max (FMM) digunakan sebagai tulang belakang bagi membangunkan model kecerdikan berkomputer hibrid dalam penyelidikan ini. Dua pengubahsuaian baru telah dicadangkan untuk memperbaiki prestasi FMM dan mengekstrak peraturan simbolik jika-maka daripada pangkalan pengetahuan. Pengubahsuaian pertama bertujuan mengurangkan bilangan kotak-hiper dalam FMM dan meningkatkan prestasinya. Pengubahsuaian kedua menggabungkan algoritma genetik untuk mengekstrak peraturan jika-maka kabur daripada rangkaian FMM.

Untuk memperbaiki ketegapan dan prestasi rangkaian FMM bagi pengelasan corak, satu sistem pengelas pelbagai ejen yang baru, yangdibangunkan berdasarkan model alasan kepercayaan-rundingan-komunikasi daripada sistem pelbagai ejen, telah diperkenalkan. Satu kaedah pengukuran kepercayaan baru, berdasarkan teori keputusan Bayesian telah diformulasi. Prestasi sistem pengelas pelbagai ejen telah dinilai dengan set data bandingan serta masalah industri dan perubatan yang sebenar, dan kaedah *bootstrap* digunakan untuk menilai prestasi sistem secara statistik. Keputusan yang diperolehi membuktikan keberkesanan sistem pengelas pelbagai ejen dalam menyelesaikan pengelasan corak, dengan peraturan jika-maka yang senang difahami dalam menerangkan ramalannya kepada pengguna.

HYBRID COMPUTATIONAL INTELLIGENCE MODELS WITH SYMBOLIC RULE EXTRACTION FOR PATTERN CLASSIFICATION

ABSTRACT

This thesis is concerned with the development of hybrid Computational Intelligence (CI) models for tackling pattern classification problems. The research focuses on hybridization of the Artificial Neural Network (ANN) and Genetic Algorithm (GA) models for data-based learning and rule extraction. In addition, a novel Multi-Agent Classifier System (MACS) is devised to combine the hybrid CI models into a common framework for pattern classification.

The Fuzzy Min-Max (FMM) network is employed as the backbone for developing the hybrid CI models in this research. Two novel modifications are proposed to improve the performance of FMM and to extract symbolic if-then rules from its knowledge base. The first modification aims to reduce the number of hyperboxes formed in FMM and to enhance its performance. The second modification incorporates the GA to extract fuzzy if-then rules from FMM-based networks.

To further improve the robustness and performance of FMM-based networks for pattern classification, a new MACS, developed based on the Trust-Negotiation-Communication (TNC) reasoning model of multi-agent systems, is introduced. A novel trust measurement method based on the Bayesian decision theory is formulated. The performances of the MACS are evaluated using benchmark as well as real industrial and medical problems, and the bootstrap method is used to quantify the performances statistically. The results ascertain the effectiveness of employing the MACS model for undertaking pattern classification tasks, along with comprehensible if-then rules for explaining their predictions to domain users.

CHAPTER 1

INTRODUCTION

1.1 Background

Pattern recognition is an activity that humans carry out daily without much conscious effort. Humans receive patterns via sensing organs, whereby the patterns acquired is processed by the brain to form useful information, and subsequently a decision for action to be taken for the patterns is made (Duda, Hart & Strok, 2002). However, this task is not a trivial one for computerized systems. To tackle pattern recognition problems, it is necessary for computerized systems to have techniques and algorithms that are able to process and recognize patterns from data and/or information supplied to the systems. Indeed, research in pattern recognition has inspired researchers from many disciplines owing to its cross-fertilization nature, which include engineering, computer science, physics, mathematics, and cognitive science.

In general, the task of pattern recognition can be divided into two stages, as shown in Figure 1.1 (Fu, 1968; Tou & Gonzalez, 1974; Young & Calvert, 1974; Duda *et al.*, 2002):

- (i) *feature extraction* – finding and extracting significant features from an input pattern, and then transforming the input features by using some arbitrary function so as to provide informative measurements for the input pattern;
- (ii) *classification* – designing a procedure for categorising the measurements taken from the extracted features, and then assigning the input pattern to one of the target classes by applying some decision rule

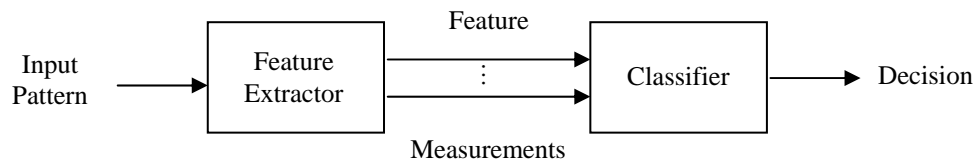


Figure 1.1 A pattern recognition system comprises a feature extractor and a pattern classifier

This research is focused on the second stage of the recognition process, i.e., pattern classification. Over the years, a number of approaches have been developed for pattern classification. Perhaps statistical approaches are among the early methods used for pattern classification. The classical method of linear discrimination proposed by Fisher (1936) and Roa (1948) is one of the earliest statistical approaches for pattern classification. Another popular statistical approach for pattern classification is the Bayesian decision approach (Devijver & Kittler, 1982; Duda *et al.*, 2002). However, statistical approaches are inefficient in handling contextual or structural information in patterns (Pal & Pal, 2002). To solve this problem, researchers have turned to the theory of formal languages (Hopcroft & Ullman, 1979), which led to the use of syntactic approaches for pattern classification. In syntactic approaches, patterns that are classified are not represented as arrays of numbers. Rather, they are described in terms of very simple sub-elements, called primitives, and of certain rules called syntactical rules. These approaches work fine for idealized patterns. But, they are inefficient in tackling noisy, distorted patterns (Pal & Pal, 2002).

Another approach for pattern classification is classification trees (Breiman, Friedman, Stone & Olshen, 1984). Classification trees are symbolic systems that assign symbolic decisions to examples, and are built upon attributes of the patterns

that are symbolic in nature, or at least discretized if they are not symbolic to begin with. The tree classifiers, however, face the same inefficiency problem as syntactic approaches in dealing with noisy, distorted patterns (Pal & Pal, 2002).

Another useful approach to pattern classification is based on the Computational Intelligence (CI) models. As pointed out in Marks (1993), Bezdek (1994), Fogel (1995), Poole, Mackworth & Goebel (1998), Pedrycz (1999), the main CI models comprise three paradigms, i.e., Artificial Neural Networks (ANNs), Fuzzy Systems (FSs), and Evolutionary Algorithms (EAs). In addition to ANNs, FSs, and EAs, other researchers have included intelligent agents as one of the CI paradigms (Poole *et al.*, 1998, Chen, 2000). These paradigms are indeed powerful methods for pattern classification, as evidenced by the many successful applications (Ishibuchi, Yamamoto & Nakashima, 2005; Gonçalves, Vellasco, Pacheco & de-Souza, 2006; Nandedkar & Biswas, 2007; Hu, 2008).

Recent advancement has resulted in the development of hybrid CI models. While each CI paradigm has its own advantages and disadvantages, hybrid CI paradigms attempt to combine the advantages of each CI paradigm and, at the same time, to avoid its shortcomings. Motivated by this line of work, the focus of this research is on the development of hybrid CI models for pattern classification and rule extraction. The hybrid models are based on the combination of ANNs, FSs, EAs, and Multi-Agent Systems (MAS), with the aim to harness the advantages of each CI paradigm and to form an effective and efficient pattern classification system. In particular, the Fuzzy Min-Max (FMM) neural network, which is a hybrid neural-fuzzy model, is adopted as the backbone of this research. Novel modifications are

introduced and incorporated into FMM in order to improve its robustness. To allow FMM to explain its predictions, a Genetic Algorithm (GA)-based rule extractor is introduced to extract fuzzy if-then rules from FMM. The extracted rules have “don’t care” antecedents, which make the rules compact and easy to comprehend. On the other hand, researchers have established a classifier ensemble results in improved performance in pattern classification. As such, the MAS framework is adopted as a platform for combining a number of FMM-based networks to form a Multi-Agent Classifier System (MACS) for tackling pattern classification tasks.

In the following sections, an introduction to CI, which includes its definition, is first given. The motivations for developing hybrid CI systems and for combining a number of hybrid CI classifiers in an MACS framework are presented. The research objectives, scope, and approach are then explained. An overview of the organization of this thesis is also presented.

1.2 Computational Intelligence

The way humans think, socialise, and reason has inspired researchers to develop CI systems that are capable of imitating such behaviors. The applications of CI systems can also be found in many areas including medical (Munakata, 1994), financial (Su & Chang, 1998), industrial (West & West, 2000), as well as management (Meesad & Yen, 2003).

One of the earliest definitions of CI was provided by Bezdek (1994), i.e.,

“a system is computationally intelligent when it deals only with numerical (low-level) data, has a pattern recognition component, and does not use knowledge in the artificial intelligence (AI) sense”.

A few other definitions of CI are also provided by other researchers. Fogel (1995) defined CI as

“these technologies of neural, fuzzy, and evolutionary systems were brought together under the rubric of computational intelligence, a relatively new trend offered to generally describe methods of computation that can be used to adapt solutions to new problems and do not rely on explicit human knowledge”.

Poole, Mackworth and Goebel (1998) extended the CI component systems to include

“the study of the design of intelligent agents” and elaborated the definition as *“the central scientific goal of computational intelligence is to understand the principles that make intelligent behavior possible, in natural or artificial systems”.*

In addition, hybrid CI systems, which are formed by integrating the individual CI component systems of neural, fuzzy, and evolutionary models, have been established. To understand how hybrid CI systems operate, an introduction to each CI model, i.e., ANNs, FSs, and EAs, is first provided, as follows.

Research in ANNs stems from the operation of the nervous system in the brain. McCulloch and Pitts (McCulloch & Pitts, 1943, Pitts & McCulloch, 1947) were the

pioneers who initiated mathematical modeling of neurons. To date, some of the popular ANNs models include the Multi-Layer Perceptron (MLP) networks (Rumelhart & Zipser, 1986; Bishop, 1995; Reed & Marks, 1998; Bortoletti, Di Fiore, Fanelli & Zellini, 2003), Hopfield network (Hopfield, 1982, 1984; Wang, Tang & Cao, 2004), Radial Basis Function (RBF) network (Broomhead & Lowe, 1988; Moody & Darken, 1989; Oyang, Hwang, Ou, Chen & Chen, 2005).

FSs are based on the theory of Fuzzy Logic (FL) introduced by Zadeh (1965). Fuzzy set theory (Zadeh, 1965) presents a methodology for representing and computing uncertain and imprecise data and/or information. It provides an inference mechanism using a set of *if-then* rules for reasoning. Examples of FSs used for pattern classification include Bellman, Kalaba and Zadeh (1966), Backer (1978), and Kamat (2004).

EAs are introduced as solutions for problems that require search and optimization. They are adaptive, robust algorithms based on the principle of evolution, heredity, and natural selection (Holland, 1986, Koza, 1992). They are population-based algorithms for which any communication and interaction are carried out within the population. There are five major branches of EAs, *viz.*, Genetic Algorithms (GA) (Holland, 1962), Evolutionary Algorithms (EA) (Fogel, Owens & Walsh, 1966), Evolutionary Strategies (ES) (Rechenberg, 1965; Schwefel, 1981; Rechenberg, 1994), Genetic Programming (GP) (Koza, 1992), and Learning Classifier Systems (LCS) (Holland, 1986). These EA models are introduced in Chapter 2.

1.3 Problems and Motivations

ANNs are popular approaches for tackling pattern classification problems. They have the ability to handle non-linear as well as noisy data collected from real environments. However, popular ANN models, such as MLP and RBF, suffer from the “catastrophic forgetting” problem when dealing with new information in an incremental manner (Polikar, Upda, Upda & Honavar, 2000, 2001). This occurs when the ANN “forgets” previously acquired information while attempting to learn new information incrementally. The “catastrophic forgetting” problem is also known as the stability-plasticity dilemma (Carpenter & Grossberg, 1987a, 1988). The dilemma aims to undertake a number of issues associated with learning systems. The fundamental questions posed by the stability-plasticity dilemma include “how can a learning system remain plastic or adaptive in response to significant events, and yet remain stable in response to irrelevant events?” and “how can a system adapt to new information without corrupting or forgetting previously learned information?” (Carpenter & Grossberg, 1987a, 1988). This is a crucial issue when the ANN operates in real environments, in which the number of data samples increases with time, and the ANN has to learn these samples in an autonomous and incremental manner.

In response to the stability-plasticity dilemma, Carpenter, Grossberg, and co-workers proposed the family of Adaptive Resonance Theory (ART) neural networks. There are a variety of ART models for unsupervised as well as supervised learning. Unsupervised ART models include ART1 (Carpenter & Grossberg, 1987a), ART2 (Carpenter & Grossberg, 1987b), ART3 (Carpenter & Grossberg, 1990), Fuzzy ART (Carpenter, Grossberg & Rosen, 1991), and supervised ART models include

ARTMAP (Carpenter, Grossberg & Reynolds, 1991), Fuzzy ARTMAP (Carpenter, Grossberg, Markuzon, Reynolds & Rosen, 1992), and ART-EMAP (Carpenter & Ross, 1995). The ART networks are examples of incremental learning systems which self-organize and self-stabilize in response to an arbitrary sequence of data samples in stationary (time-invariant) and non-stationary (time-varying) environments. They overcome the stability-plasticity dilemma by adapting knowledge (coded as prototypes) in the network structure only when a new input sample is sufficiently similar (measured against a user-defined threshold) to one of its existing prototypes. The input sample and the stored prototype are said to “resonate” when they are sufficiently similar. When an input sample is not sufficiently similar to any existing prototype, a new prototype is created with the input sample coded as the new prototype.

Among the variants of ART networks, Fuzzy ARTMAP (FAM) is one of the most widely investigated and used models for various applications, as reported in Ten-Ho & Von-Wun (1997); Lim & Harrison (2003); Tan & Lim (2004), and Vigdor & Lerner (2006). Although FAM has a number of appealing properties, such as the ability to tackle the stability-plasticity dilemma, the ability to deal with analog as well as binary input patterns, it has a number of limitations too, as pointed out by Simpson (1992). One of the important limitations highlighted by Simpson (1992) is that FAM allows overlapping of hyperboxes (prototypes) in its structure. This means that one input sample can have full membership in more than one prototype. This situation significantly weakens the notion of fuzzy sets. As such, the use of non-overlapping hyperboxes is more appropriate, which guarantees that an input sample

has full membership in only one hyperbox, unless it is a point along the boundary between two abutting hyperboxes (Simpson, 1992).

To overcome the limitations in FAM, Simpson proposed two FMM ANNs; one for pattern classification (Simpson, 1992) and another for pattern clustering (Simpson, 1993). The pattern classification FMM network is a supervised learning model which utilizes FL and ANN as the fundamental computing elements. On the other hand, the pattern clustering FMM network is an unsupervised learning model which creates and refines pattern clusters in a fashion similar to Fuzzy ART. In this thesis, the FMM network refers to the pattern classification FMM model introduced by Simpson (1992).

As explained in Simpson (1992), the FMM network possesses a number of important and useful properties for handling pattern classification problems:

- *Online Learning*: FMM learns and adapts new classes and refines existing classes quickly and without forgetting old class information. This property is important to tackle the stability-plasticity dilemma.
- *Nonlinear Separability*: FMM is able to build decision boundaries that separate classes of any shape and size.
- *Overlapping Classes*: FMM creates decision boundaries to minimize the misclassification for all overlapping classes. In other words, there is no overlap between hyperboxes of different classes.
- *Training Time*: FMM needs only one pass to learn and refine its decision boundaries.

- *Soft and Hard Decisions*: FMM has the ability to produce either hard decisions (either 0 or 1) or soft decisions (describe the degree to which an input sample fits within a predicted output class).

The above properties make FMM an attractive pattern classifier. However, FMM is not free from limitations. As the topology of a class usually is complex and is incompatible with the convex topology of hyperboxes, a smaller hyperbox size is needed to represent a particular output class (Bargiela, Pedrycz & Tanaka, 2003). As such, the performance of FMM is affected by the expansion coefficient (or the hyperbox size). A network with small hyperboxes performs better than one with larger hyperboxes. However, small hyperboxes increase the network complexity. On the other hand, similar to any other incremental learning systems, the performance of FMM is affected by the sequence of the training samples (Nandedkar & Biswas, 2007). Thus, it is worthwhile to investigate how to maintain, or even improve, the classification performance of FMM when large hyperboxes are formed in its structure, and how to mitigate the effect of training sample sequences in FMM learning.

Another shortcoming of FMM, which is a limitation suffered by most ANNs, is the inability to explain its predictions. That is why most ANNs (including FMM) are called “black-boxes” (Benitez, Castro & Requena, 1997, Kolman & Margaliot, 2005). To explain the predictions of ANNs, researchers have introduced a number of rule extraction techniques for ANNs. According to Sato and Tsukimoto (2002), rule extraction methods can be grouped into three categories, i.e., the type of input variables (continuous or discrete), the type of extracted rules (production rule, n -of- m

rule or n -of- m tree), and the approach to rule searching (pedagogical or decompositional).

Regardless of the rule extraction categories, there are two silent properties that a rule extraction method should have, i.e., prediction accuracy and rule comprehensibility (Taylor & Darrah, 2005). In this aspect, rule comprehensibility faces a serious issue, i.e., the “curse of dimensionality” where the number of rules increases exponentially with the increase of the input features or dimensions (Nelles, Fischer & Muller, 1996, Mastsushita, Furuhashi & Tsutsui, 1998, Nii, Ogino, Sakabe, Sakagami & Takahshi, 2002, Xiuju & Lipo, 2002). A number of solutions are proposed for overcoming this problem. One possible solution is to deploy a dimensionality reduction technique (Xiuju & Lipo, 2002) before network training i.e., the ANN is trained using a number of selected features only. Another solution, proposed by Hasegawa, Horikawa and Furuhashi (1992) is to use a hierarchical approach in which sub-fuzzy models are constructed hierarchically, and the number of rules in each sub-model is made very small.

On the other hand, researchers have proposed using EAs to select a compact rule sets to curb the “curse of dimensionality” problem (Nelles *et al.*, 1996, Dorado, Rabunal, Rivero, Santos & Pazos, 2002). However, one of the problems faced is the number of antecedents in the extracted rules normally is equal to the number of features. Indeed, a large number of antecedents may not be appropriate in practice, as this complicates the comprehensibility of the rules. In other words, for a rule extraction technique to be useful, only the important antecedents (features) should be retained in the extracted rules. Therefore, it is important to investigate how to extract

a compact rule set from FMM that contains only a few important antecedents and that yields a high classification performance.

In pattern classification, improved performance can be obtained by using an ensemble or committee of classifiers. Most ensemble methods assume that the member classifiers are both diverse and accurate (Hashem, Schmeiser & Yih, 1994). These assumptions mean that each classifier has to make independent classification errors, so that the overall classification accuracy is improved when all the predictions are combined. Indeed, both theoretical (Hansen, Liisberg & Salamon, 1992, Krogh & Vedelsby, 1995) and empirical (Hashem *et al.*, 1994, Maclin & Shavlik, 1995) investigations have shown that a good ANN ensemble is one where the individual networks are both accurate and make errors on different parts of the input space.

As mentioned earlier, intelligent agents are considered as one of the CI paradigms. Multi-Agent Systems (MAS) are widely used in different applications, e.g. in decision support (Fazlollahi, Vahidov & Aliev, 2000), industrial steel processing (Gao, Zeng, Xu & Sun, 2003), robot navigation (Ambastha, Busquets, Màntaras & Sierra, 2005), and power systems (Baxevanos & Labridis, 2007). In this thesis, MAS is investigated as a method to form an ensemble of FMM networks, whereby, each FMM is modelled as an agent, and the MAS framework combines all the FMM predictions, in an attempt to devise a classification system with high performances.

In the domain of MASs, a number of reasoning models are available to describe the relations between agents. These include the Belief, Desire, and Intention (BDI)

model proposed by Bratman (1987), and the decision ladder model proposed by Rasmussen, Pejtersen & Goodstein (1994). In this thesis, the Trust, Negotiation, and Communication (TNC) model proposed by Haider, Tweedale, Urlings, and Jain (2006), and Tweedale and Cutler, (2006) is investigated for modelling an MAS. In the TNC model, the core element is the trust measurement. As trust is a subjective quantity, it is worthwhile to investigate methods for trust calculations, making it an objective quantity.

1.4 Research Objectives, Scope, and Approach

The main aim of this research is to design and develop hybrid CI systems that capitalise the advantages of each CI model (ANN, FS, and EA) and, at the same time, avoid their limitations. Based on the rationale of classifier ensembles, the MAS methodology is used to devise a Multi-Agent Classifier System (MACS) that combines different classifiers into a unified framework. The main thrust of work is geared towards devising FMM-based classifiers, incorporating the GA rule extractor into the resulting FMM classifiers for explaining the predictions, as well as integrating different FMM classifiers as an MACS model for tackling pattern classification tasks.

The research objectives are as follows:

- (1) to enhance the existing FMM network with useful modifications for achieving improved classification performance with less complicated network structures,
- (2) to develop a hybrid system that integrates the FMM and GA models for pattern classification and rule extraction,

- (3) to devise an MACS model with a novel Bayesian trust measurement method for combining different FMM-based classifiers,
- (4) to evaluate the performances of the hybrid CI models by using benchmark problems, and to compare the results between the proposed models and those from other machine learning systems statistically by the bootstrap method, and
- (5) to assess the effectiveness of the resulting hybrid CI models to real industrial and medical applications.

A step-by-step approach is taken in this research to achieve the above objectives. First, the supervised FMM network is studied systematically. As stated earlier, FMM performs better when its hyperbox size is smaller. However, the trade-off is that a small hyperbox size leads to a complex network structure with many hyperboxes. Network complexity becomes an important issue when it comes to rule extraction. Since each hyperbox is translated into a fuzzy if-then rule, a complex network with a lot of hyperboxes produces a large number of rules. Therefore, useful modifications to FMM are first proposed to enhance the FMM performance in situations when large hyperboxes are formed in its structure.

As explained earlier, one limitation of the existing rule extraction methods is that the number of antecedents of the extracted rules normally is equal to the number of input features. A large number of antecedents in a rule makes it difficult for humans to comprehend the rule. As such, the GA is used to inject “don’t care” antecedents into the extracted rules so that the number of antecedents is minimized. To further improve the robustness and performance, the MAS methodology is

adopted to devise an MACS model for combining an ensemble of FMM-based models for undertaking pattern classification tasks.

During the course of achieving the objectives, extensive empirical studies are conducted using benchmark as well as real data sets to evaluate the hybrid CI systems developed in this research. The benchmark data sets are taken from public domain repositories so that performance comparison with other classification methods can be conducted. The bootstrap method is employed to quantify and compare the results statistically. Besides, a number of real data sets from industrial and medical domains are used to demonstrate the applicability of the proposed hybrid CI systems in real environments.

1.5 Research Methodology

As mentioned in the previous section, the aim of this research is to devise a CI-based hybrid system that is capable of tackling pattern classification problems with rule extraction facility. In the process of designing the hybrid CI-based pattern classification system, the following steps are followed:

1. Proposing two modified FMM networks that are able to achieve improved performances when large hyperboxes are formed. The modification is implemented by using the Euclidian distance for determining the winning hyperbox in the prediction phase. Two MFMM (modified FMM) networks are developed. To determine the winning hyperbox for a given pattern, the first modified FMM network (MFMM1) uses both the membership function and the Euclidian distance to determine the winning hyperbox, while the

second (MFMM2) uses only the Euclidian distance. The performances of both MFMM1 and MFMM2 are tested using benchmark data sets, and the results are compared with those published in the literature.

2. Developing a two-stage pattern classification system by hybridizing FMM-based networks and the GA. In the first stage, the FMM-based networks are trained, and then pruned using a user defined threshold. In the second stage, open hyperboxes are generated and fed to GA. The GA aims to improve the performance of the FMM-based networks and to extract compact rule sets with “don’t care” antecedents. Again, the two-stage pattern classification system is tested using benchmark data sets, and the results are compared with those published in the literature.
3. Designing a Multi-Agent Classifier System (MACS) based on the Multi-Agent System (MAS) framework for pattern classification. First, an ensemble of FMM-based networks, each trained with different sequences of training samples to establish different knowledge bases for prediction, is established. Then, the Trust-Negotiation-Communication (TNC) reasoning model is applied to form the MACS.
4. Devising a novel trust measurement method for the TNC model. The Bayesian decision theorem is adopted for trust measurement in the TNC model. Novel modifications are incorporated in the FMM-based networks such that the Bayesian trust measurement approach can be incorporated into the MACS effectively.
5. Applying the MACS to tackling real-world pattern classification problems. The MACS is first tested using benchmark data sets, and the results are compared with those published in the literature. Then, real industrial and

medical pattern classification problems are used. . The results are analyzed using the bootstrap method to quantify the performances of the MACS statistically.

Figure 1.2 shows an overview of the research methodology adopted to achieve the objectives set out in this research.

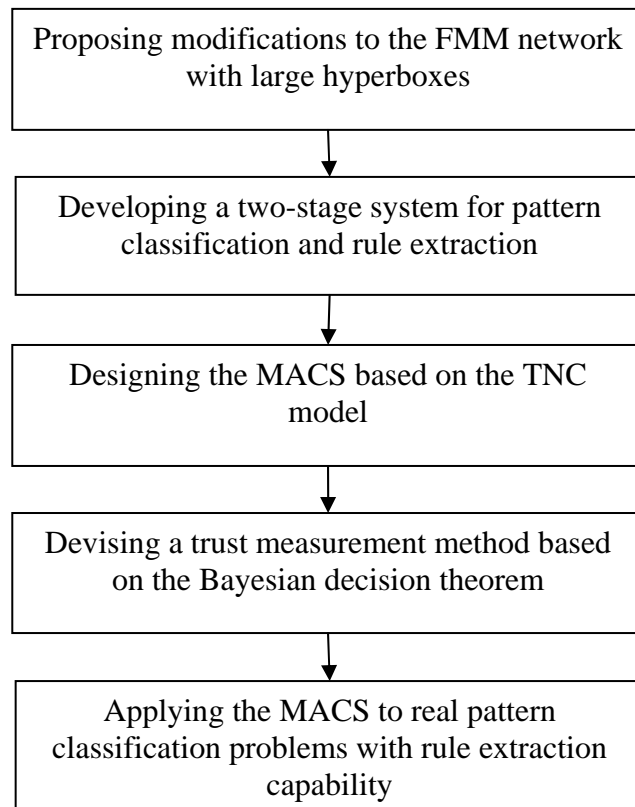


Figure 1.2 The methodology followed in this research

1.6 Thesis Outline

This thesis is organised in accordance with the objectives mentioned above. After the introduction is introduced in Chapter 1, a general review on hybrid CI models is given in Chapter 2. The review first covers the CI paradigms, then hybrid CI models for pattern classification. In particular, hybrid CI models based on ANNs, FSs, and

GAs for patterns classification are introduced. In addition, hybrid CI models for rule extraction are discussed and reviewed.

The FMM network is introduced in Chapter 3. First, a review on the latest innovations on FMM is presented, followed by a detailed description and a numerical example on the FMM learning operation. The novel modifications proposed on the prediction stage of FMM are then introduced. The modifications yielded two modified FMM networks which are MFMM1 and MFMM2. Several simulations are conducted using benchmark classification tasks and the results are compared with those obtained from other approaches.

Chapter 4 introduced two-stage pattern classification systems based on the networks introduced in Chapter 3. The proposed classification systems, have a GA module embedded in stage-2, which aims to extract comprehensive fuzzy *if-then* rules with “don’t care” as part of their antecedents. In addition, the GA module enhances the performance accuracy of the system. Again, the performances of the proposed two-stage classifier systems are evaluated using some benchmark data sets and the results are compared with other classification algorithms.

Chapter 5 introduces MASs and several models used for them. The proposed MACS is formed using the TNC model, which is introduced in this chapter. The core element of the TNC model is the trust calculation method which is then presented. A number of modifications are incorporated in the FMM based networks so that the proposed trust calculation method can be applied on them. The

effectiveness of the MACS is tested with some bench mark data sets, and the results are compared with those of other classification systems.

To demonstrate the applicability of the MACS devised in Chapter 5, and the two-stage networks proposed in Chapter 4 as decision support tools, two real-world industrial case studies are considered in Chapter 6, and three real-world medical diagnosis comprising real patient records from several hospitals in the United Kingdom and Malaysia are considered in Chapter 7. The results are compared with those obtained from different classification methods.

Finally, conclusions are drawn and contributions of this research are set out in Chapter 8. A number of areas to be pursued as further work are suggested at the end of this thesis.

CHAPTER 2

LITERATURE REVIEW ON HYBRID COMPUTATIONAL INTELLIGENCE SYSTEMS

2.1 Introduction

As explained in Chapter 1, the main focus of this research is on the use of hybrid CI models for pattern classification and rule extraction. As such, in the following section, the three main CI paradigms, namely ANNs, FSs, and EAs, are first introduced. Then, hybrid CI systems that are developed for pattern classification as well as for rule extraction are surveyed. A summary is presented at the end of this chapter.

2.2 Computational Intelligence Paradigms

ANNs are some kind of massively parallel computing systems with a large number of interconnected simple processors that are able to adapt themselves to data samples. ANNs have several advantages that make them reliable tools for pattern classification. ANNs are data driven self-adaptive methods in which they can adjust themselves to the data samples without any explicit specification of functional or distributional form for the underlying model (Zhang, 2000). They are nonlinear models, which makes them flexible in modeling real-world complex relations (Zhang, 2000). Some ANN models, e.g. MLP and RBF, are universal functional approximators (Hornik, 1991, Hornik, Stinchcombe and White, 1989), and have the ability to estimate the posterior probabilities (Richard and Lippmann, 1991).

On the other hand, FSs are designed to process ambiguous, imprecise information using fuzzy set theory. The fuzziness feature makes FSs suitable for many real-world applications, whereby it is difficult to decide if something can be categorized exactly into a specific class or not. Fuzzy set theory provides a mechanism for representing linguistic constructs such as “many”, “often”, “few”, and “sometimes”. This allows the degree of which a data sample is present or absent to be measured.

FSs generally comprise three components: a knowledge base that is formed by a group of fuzzy if-then rules; a database that includes all membership functions used in the fuzzy rules; and a reasoning mechanism that conducts an inference procedure by using rules and known facts to reach a conclusion (Jain, Tan and Lim, 2008). Each fuzzy rule is an explicit description between inputs (i.e., antecedents) and output (i.e., consequence). Such a relationship indicates the behavioral link between the antecedents and the consequence locally. Mitra and Hayashi (2000) argued that FSs can be broadly categorized into two families. The first include linguistic models based on collection of if-then rules, whose antecedents and consequence utilize fuzzy values. The second category is based on the Sugeno-type systems (Takagi and Sugeno, 1985), which uses a rule structure that has fuzzy antecedent and functional consequent parts.

EAs are a collection of algorithms based on the principles of evolution, heredity, and natural selection in living populations. There are five major EAs (Jain *et al.*, 2008), *viz.*, Genetic Algorithm (GA), Evolutionary Programming (EP), Evolution Strategy (ES), Genetic Programming (GP), and Learning Classifier System

(LCS). GA will be utilized in this thesis as the EA tool; however, the five EA types are introduced as follows.

GA proposed by Holland (1962) is the most popular EA technique for solving optimisation problems. GA is based on finding the population in a search space that fits the fitness function. Three main search operators used in GAs are selection, crossover, and mutation. The selection operator is responsible for choosing a subset group of candidate solutions (from a population) that are subsequently used to generate new candidate solutions with the crossover and mutation operators. The crossover operator is applied to combine genetic information of the existing candidate solutions whereas the mutation operator is used to create variations of a single candidate solution (Holland, 1962).

EP on the other hand focuses on the development of behaviour models while GA is concerned with genetic models. EP is based on simulation of adaptive behaviour in evolution. It was introduced a few years after GA by Fogel *et al.* (1966), EP used finite-state machines to simulate intelligent behaviour. In EP, candidate solutions to a problem are considered as a population of finite-state machines. New candidate solutions (offspring) are generated from the existing candidate solutions (parents) through mutation. All candidate solutions are assessed by a fitness function. In EP, the crossover operator is not used. Only the mutation operator is employed to provide variations in the population of candidate solutions.

ES was proposed by Rechenberg (1965), initially it was developed to optimise parameters for aero-technology devices. However the concept of evolution of

evolution was proposed by Schwefel (1981) as a development of ES. ES deals with each candidate solution in the population as a genetic building block and a set of strategy parameters, and this candidate models the behaviour as a candidate solution in its environment (Rechenberg, 1994).

GP on the other hand was proposed by Koza (1992), GP was targeted at using the computer to solve problems without being explicitly programmed to do so. The development of GP came as an extension to GA, but the difference between the two is that the GP represents individuals as executable programs such as a tree, while GA uses a string for its representation.

An interesting EA is the LCS (Holland, 1986), this algorithm tackles the machine learning process from a different angle, where it deals with it as an evolutionary rule discovery. Fuzzy *if-then* rules represent the knowledge of LCSs. Rules are encoded as binary strings where each rule is a single binary string, and is considered a classifier by itself.

2.3 Hybrid Computational Intelligence Models

Hybrid CI models are concerned with any effective combination of intelligent techniques that perform superiorly or in a competitive way to single intelligent technique (Tsakonas and Dounias, 2002). Although each CI constituent has its strength, researchers have found that combining (hybridisation) of CI constituents yields improved models. In the following sub-sections, a review on hybrid CI

models for pattern classification is first given then a survey on hybrid CI models for rule extraction is also presented.

2.3.1 Hybrid CI Models for Pattern Classification

Chapter 1 introduced the FMM network as the backbone of this thesis. The theory of FMM is built on ANNs and FSs. Hence, the scope of review for pattern classification focused on the hybridisation of these two CI paradigms. In general, hybrid CI models for pattern classification based on ANNs and FSs can be divided into two categories: ANN-based and FS-based hybrid methods. Examples of hybrid CI models based on these two methods are reviewed, as follows.

2.3.1.1 Artificial Neural Network-Based Hybrid CI models

Incorporating fuzzy logic into an ANN generates an FS-based ANN or fuzzy neural network (FNN) (Lin and Lee, 1996). By injecting fuzzy principles into ANN structures, a system with a higher degree of flexibility is attained. Fuzziness in this case means more flexibility in the boundaries of the system, which can be described as vaguely rather than crispy. In FNNs, the numerical control parameters in the neuron and the connection weights can be replaced by fuzzy parameters. Thus, FNNs have a higher degree of representation and training speed, and are more robust than conventional ANNs (Lin and Lee, 1996). As FNNs are simply fuzzified ANN models, they inherit all the advantages of ANNs.

Perhaps the first attempt to fuzzify an ANN was based on a single-layer perceptron network (Keller and Hunt, 1985). The fuzzification of the single-layer