View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Repository@USM

NEW STRUCTURAL EVOLVING ALGORITHMS FOR FUZZY SYSTEMS

HISHAM HAIDER YUSEF SA'AD

UNIVERSITI SAINS MALAYSIA

2018

NEW STRUCTURAL EVOLVING ALGORITHMS

FOR FUZZY SYSTEMS

by

HISHAM HAIDER YUSEF SA'AD

Thesis submitted in fulfilment of the
requirements for the degree of
Doctor of Philosophy

September 2018

ACKNOWLEDGEMENT

All Praises be to Allah the Almighty, for delivering me the patience, the potency and the guidance to conclude this thesis fruitfully.

I owe the greatest debt to my parents, brothers, sisters and all my relatives for not only their never-ending affection, love and patience, but also their encouragement and unconditioned support to me in all my decisions. Their guidance helped me to keep my motivations high throughout my studies. I would like to share this moment of happiness and express the appreciation and love to my father (**Haider Yusef**) and mother (**Mrs. Huda Abdallah**) who encouraged me in every step in my life.

I would like to express my utmost gratitude and appreciation to my main supervisor, **Professor Dr. Nor Ashidi Mat Isa** and my co-supervisor **Dr. Md. Manjur Ahmed** for their valuable and constructive suggestions that enabled this thesis to run smoothly. They provided excellent guidance through these years with a mix of trust in my ideas and instant feedback on my questions. I am very grateful to **Assc. Prof. Dr. Junita Bt. Mohamad** for the supporting materials she has provided me during PhD**.**

I am greatly indebted to my brothers **Dr. Adnan** and **Dr. Abdulmalik Haider**, for their guidance and great source of motivation. I thank all of my lab friends **Tariq Adnan**, **Abduallah Amer**, **Mohammed Alswaitti**, **Sami Salah** and all staffs of University Sains Malaysia for their supports. Special thanks to **Mrs. Nor Hidayah Saad** for translating the abstract to Bahasa Melayu.

I would also like to thank University Sains Malaysia (USM) for their financial support by awarding me the USM Fellowship. This work is also partially supported by

the Universiti Sains Malaysia (USM) through Research University Grants (RU) (Grant no. 1001/PELECT/814205) entitled ―Development of an Intelligent Auto-Immune Diseases Diagnostic System by Classification of Hep-2 Immunofluorescence Patterns.

TABLE OF CONTENTS

	Page
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iv
LIST OF TABLES	viii
LIST OF FIGURES	x
LIST OF ABBREVIATIONS	xiii
LIST OF SYMBOLS	xvi
ABSTRAK	xviii
ABSTRACT	xx
CHAPTER ONE: INTRODUCTION	
1.1 Introduction	1
1.2 Problem Statement	4
1.3 Research Objectives	6
1.4 Research Scope	7
1.5 Thesis Outlines	8
CHAPTER TWO: LITERATURE REVIEW	
2.1 Introduction	10
2.2 Interpretability-Accuracy Trade-off	11
2.2.1 Measure of Interpretability and Accuracy	12
2.2.1.(a) Distinguishability and Simplicity	13
2.2.1.(b) Consistency, Coverage and Completeness	13
2.2.1.(c) Feature Importance Levels and Rule Length	14
2.2.1.(d) Total Number of Rules/Parameters and Average Firing Rules	14
2.2.1.(e) Rule Importance Levels and Knowledge Expansion	15

2.2.2 Overfitting and Underfitting Situation 16

2.2.3 Previous Studies on Interpretability-Accuracy Trade-off 18

2.3 Evolving Fuzzy Models 21

2.3.1 Fuzzy Clustering Methods 21

2.3.2 Non-linear Parameters-Optimization Methods 24

2.3.3 Grid and Tree Partitioning Methods (Error Reducing Methods) 27

2.3.4 Comparison among Types of Evolving Fuzzy Models 32

2.4 The Curse of High Dimensionality Issue 35

2.5 Rule Pruning 37

2.6 Consequent Parameter Learning 39

2.6.1 Gradient-Descent Method and Its Drawback 39

2.6.2 Least Square Methods 42

2.7 Summary 45

CHAPTER THREE: METHODOLOGY

3.1 Introduction 47

3.2 Enhancement of Fuzzy Term Identification 48

3.2.1 Formulation of EFTI 49

3.2.2 Splitting Technique of EFTI 51

3.2.3 Adding and Updating Membership Function and Rules of EFTI 53

3.2.4 Algorithm and Flowchart for EFTI 56

3.3 Structure Identification Method 57

3.3.1 Initial System of SIM and SEA 58

3.3.2 Structural System of SIM 59

3.3.3 Evolving System of SIM 60

3.3.4 Partitioning Technique of SIM 63

3.3.5 Static Partition-Selection Technique of SIM 65

3.3.6 Formulation of SIM 66

3.3.7 Adding and Updating Membership Function and Rules of SIM 69

3.3.8 Algorithm and Flowchart of SIM 79

3.4 Structural Evolving Approach 81

3.4.1 Structural System of SEA 82

3.4.2 Evolving System of SEA 83

3.4.3 Partitioning Technique of SEA 85

3.4.4 Dynamic Partition-Selection Technique of SEA 86

3.4.5 Formulation and Adding and Updating Membership function and Rules of SEA 90

3.4.6 Rule Reduction Mechanism of SEA 91

3.4.7 Algorithm and Flowchart of SEA 93

3.5 Data Samples and Analysis 95

3.6 Summary 102

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction 104

4.2 Results of EFTI 105

4.3 Results of SIM 113

4.3.1 Evaluation of the Concept of the Proposed SIM 114

4.3.1.(a) Evaluation of the Proposed Partitioning Technique 118

4.3.1.(b) Evaluation of the Proposed Partition-Selection Technique 119

4.3.2 Performance Comparison 120

4.3.3 The features of SIM 133

4.4 Results of SEA 135

4.4.1 Evaluation of the Proposed SEA Algorithm 135

4.4.1.(a) Evaluation of the Proposed Partitioning Technique 137

4.4.1.(b) Evaluation of the Proposed Dynamic Partition-Selection Technique 139

4.4.1.(c) Evaluation of the Proposed Rule Reduction Technique 141

4.4.2 Performance Comparison 144

4.4.3 The features of SEA 154

4.5 Comparison between EFTI, SIM and SEA 155

4.6 Summary 158

CHAPTER FIVE: CONCLUSION AND FUTURE WORK

5.1 Conclusion 160

5.2 Research Contributions 161

5.3 Recommendations for Future Research 163

REFERENCES 165

LIST OF PUBLICATIONS

LIST OF TABLES

		Page
Table 2.1	Summary of the current state-of-the-arts to assess the interpretability accuracy trade-off of fuzzy rule base from 2007 until 2017.	19
Table 2.1	Continue.	20
Table 2.2	Advantages and disadvantages of the three types of fuzzy models.	34
Table 3.1	Datasets used for validation and evaluation of the proposed EFTI, SIM and SEA methods	101
Table 3.2	Simulations and their corresponding Datasets used for evaluation of the proposed EFTI, SIM and SEA methods	102
Table 4.1	Performance comparison of the proposed EFTI in RMSE with ECSFS and FGP for Simulation 1.	106
Table 4.2	Partition points for the proposed EFTI, FGP and ECSFS for Simulation 1.	108
Table 4.3	Performance comparison of the proposed EFTI in RMSE with ECSFS, Pedrycz's method, and EOCFS for Simulation 2.	111
Table 4.4	Performance comparison of the proposed EFTI in RMSE with ECSFS for Simulation 3.	112
Table 4.5	Step by step implementation of SIM algorithm using Simulation 1.	116
Table 4.6	Performance comparison of RMSE for Simulation 4.	122
Table 4.7	Performance comparison of RMSE for Simulation 5.	123
Table 4.8	Performance comparison of RMSE for Simulation 6.	124

Table 4.9	Performance comparison of RMSE for Simulation 7.	125
Table 4.10	Performance comparison of MSE for Simulation 8.	126
Table 4.11	Performance comparison of RMSE for Simulation 9.	128
Table 4.12	Performance comparison of RMSE for Simulation 10	129
Table 4.13	Performance comparison of RMSE for Simulation 11.	130
Table 4.14	Performance comparison of RMSE for Simulation 12.	131
Table 4.15	Detailed system structure of SEA algorithm using Simulation 13.	137
Table 4.16	Evaluation of the proposed partitioning selection technique using Simulation 13 where R_{cs} =32, R_{mx}=128, б =0.25, σ =0.75.	141
Table 4.17	Parameters values to find $RMSE_{thr}$.	142
Table 4.18	RMSE of the current stage without rule (i).	142
Table 4.19	The whole possible combination of rules (2^B = 4).	143
Table 4.20	The performance before and after rule reduction for $subregion_r$.	144
Table 4.21	Performance comparison for RMSE for Simulation 13.	145
Table 4.22	Performance comparison for RMSE for Simulation 14.	147
Table 4.23	Performance comparison for RMSE for Simulation 15.	148
Table 4.24	Performance comparison for RMSE for Simulation 16.	149
Table 4.25	Performance comparison for RMSE for Simulation 17.	151
Table 4.26	Performance comparison for MSE for Simulation 18 (10 folder cross-validation, testing result).	153
Table 4.27	Performance comparison between SIM and SEA for Datasets 8 to 12.	157

LIST OF FIGURES

		Page
Figure 2.1	(a) Low interpretable fuzzy partition due to indistinguishable and overlapping fuzzy sets; (b) the same fuzzy partition after constrained-based learning phase (Lughofer, 2011).	13
Figure 2.2	An example of underfitting/overfitting situation (a) underfitting, (b) perfect compromise (c) overfitting (Mathbabe, 2012).	17
Figure 2.3	Redundancy issue based on similar membership functions produced by cluster projection (Babuška, 1999).	24
Figure 2.4	A detailed structure of a simple and typical neuro-fuzzy model of two-rule system (Babuška, 1999).	26
Figure 2.5	Tree partitioning scheme for the input space (Babuška, 1999).	28
Figure 2.6	An example of the issue of ECSFS for using the refinement to find the consequent parameters of the split point (x_{splint} = 15) .	31
Figure 2.7	Subregion creation for (a) fixed grid fuzzy systems and (b) ECSFS.	32
Figure 2.8	Gradient descent algorithm (a) initial stage with an arbitrary guess, (b) the iterative and recursive processes until reaching the minimum system error (Ahmed and Isa, 2017).	41

Figure 2.9	Determining learning rate value issue (Jha, 2017).	42
Figure 2.10	Local minimum error problem suffered by gradient descent approach (Géron, 2017).	42
Figure 3.1	Initial fuzzy system membership functions with two fuzzy terms	50
Figure 3.2	Adjusting the split point using the intersection to find the best consequent parameter and split point	52
Figure 3.3	Flowchart of the proposed EFTI.	56
Figure 3.4	Algorithm of the proposed EFTI.	57
Figure 3.5	Initial structure for (a) fixed grid fuzzy systems and (b) the proposed SIM and SEA.	59
Figure 3.6	Regular triangular membership functions with regular partitions (two fuzzy terms)	60
Figure 3.7	Regular triangular membership functions with regular partitions after one splitting (three fuzzy terms)	60
Figure 3.8	Subregion creation for (a) FGP and (b) the proposed SIM, σ and φ are the minimal and maximal value of the attribute, respectively.	62
Figure 3.9	Flowchart of the proposed SIM.	80
Figure 3.10	Algorithm of the proposed SIM.	81
Figure 3.11	Subregion creation for SEA (σ and φ are the minimal and maximal value of the attribute, respectively), indicating fuzzy rules.	84
Figure 3.12	Typical impact of accuracy & interpretability toward the system,	89

Figure 3.13	Algorithm of the proposed SEA.	94
Figure 3.14	Algorithm of the proposed SEA.	95
Figure 4.1	Models output of FGP and ECSFS approaches for Simulation 1 (Wang et al., 2010a).	109
Figure 4.2	The model output of EFTI approaches for Simulation 1.	109
Figure 4.3	Sample error of the selected subregion.	119
Figure 4.4	Summation of MAD on the two subregions in each sample.	119
Figure 4.5	Error distribution values of the training samples within the selected subregion for existing works and the proposed SEA.	138
Figure 4.6	The error contribution of each training sample in the selected subregion.	139
Figure 4.7	The absolute subtraction of the red and blue line in Figure 4.6.	139
Figure 4.8	Impact of accuracy and interpretability toward the system using Simulation 13.	140

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
CL	Closure
Clas	Classification
CONS	Consistency
CPU	Relative Central Processing Unit
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System
D-FNN	Dynamic Fuzzy Neural Networks
DPFNN	Dynamic Parsimonious Fuzzy Neural Network
ECSFS	Evolving Construction Scheme for Fuzzy Systems
EER	Error-Evolving Rate
EFS	Evolving Fuzzy Systems
EFTI	Enhancement of Fuzzy Term Identification
EFuNNs	Evolving Fuzzy Neural Networks
EGE	Evolving Granule Error
ELM	Extreme Learning Machine
eTS	Evolving Takagi-Sugeno
FCM	Fuzzy C-Means
FGP	Fixed Grid Partitioning
FRBSs	Fuzzy Rule Based Systems
GA	Genetic Algorithm
GAE	Global Average Error
GD-FNNs	Generalized Dynamic Fuzzy Neural Networks
GS-EFS	Generalized smart evolving fuzzy systems

GSETSK	Generic Self-Evolving TSK
KNN	K-Nearest Neighbors
LEOA	Local Error Optimization Approach
LFM	Linguistic Fuzzy Modelling
LOLIMOT	Local Linear Model Trees
LSM	Least Square Method
MAD	Mean Absolute Deviation
MF	Membership Function
MISO	Multi Input Single Output
MSE	Mean Square Error
NA	Not Applied
NC	Number of Conditions
NFEAT	Number of Features
NFIRED	Number of Fired Rules
NFS	Neuro Fuzzy Systems
NMF	Number of Membership Functions
NR	Number of Rules
OSAMNN	Online Self-Adaptive Modular Neural Network
PANFIS	Parsimonious Network Based On Fuzzy Inference System
PFM	Precise Fuzzy Modelling
POPFNN	Pseudo Outer-Product Based Fuzzy Neural Network
PRP	Published Relative Performance
RANFIS	Randomized Adaptive Neuro-Fuzzy Inference System
Reg	Regression
R-ELANFIS	Regularized Extreme Learning Adaptive Neuro-Fuzzy Inference System

RMSE	Root Mean Square Error
SIM	Structure Identification Method
RSPOP	Rough Set–Based Pseudo Outer-Product
SAFIS	Sequential Adaptive Fuzzy Inference System
SE	Square Error
SEA	Structural Evolving Approach
SELM	Structure Evolving Learning Method
SISO	Single Input Single Output
SOFMLS	Self-Organizing Fuzzy Modified Least-Squares Network
SOFNN	Self-Organizing Fuzzy Neural Networks
SP	Split
SSE	Sum Square Error
SSEM	Simplified Structure Evolving Method

LIST OF SYMBOLS

B	The number of possible rules to be excluded without having a significant loss of the system accuracy
C_i	The number of membership functions in the attribute i
e	The sample error
E	The average error of the subregion
g	The index of the current evolving stage
LAE	Local average error
n	The number of input attributes
n_i	The number of attributes of subregion i
N	The number of training samples
Q	The consequent parameters
$Q_r^{q_1 q_2 \cdots q_n}$	Consequent part of the $subregion_r$
r	The index of the selected subregion or subrange
R	The number of rules of the subregion
$R_{cs}(g)$	The number of rules for the current evolving stage with g index
R_{mx}	The maximum number of rules
$RMSE(g)$	The root mean square error of the fuzzy system in the evolving stage g
$RMSE_{cmb}(L,H)$	The RMSE of the combination of rules of (L,H) after training
$RMSE_{ref}(L,H)$	The reference weight of each combination
$RMSE_{thr}$	The rule weight threshold
Ř,	The number of subregion

$Я$	The desired number of subregion
$subregion_r$	The selected subregion
S	The accumulated local error of the subregion
t	The target of sample i
T	The antecedent part
$T_r^{q_1 q_2 \cdots q_n}(\boldsymbol{x})$	Antecedent part of the $subregion_r$
$\boldsymbol{v}$	The system output of sample i
$\boldsymbol{x}$ $(x_1\ x_2\ \ldots x_n)$	A training input sample
x_s	S represents the selected attribute
x_{sp}	The splitting point
x_{spl}^{int}	The initial splitting point of EFTI
x_{spl}^{opt}	The optimal splitting point of EFTI
$\hat{\mu}$	Membership functions
β	Predefined threshold
η	Number of subrange
$\acute{\eta}$	Desired number of subrange
α_i	The number of conditions of subregion i
ς	The influence of the accuracy part
б	The influence of the interpretability part
σ,φ	The minimal and maximal value of the input variable x
Φ	The total number of rules of $subregion_r$ after training

ALGORITMA PERKEMBANGAN STRUKTUR BAHARU UNTUK SISTEM KABUR

ABSTRAK

Pada masa kini, isu kompromi antara kejituan dan penafsiran semakin mendapat perhatian dalam merekabentuk sistem kabur yang baharu. Dalam tesis ini, tiga model kabur berkembang iaitu peningkatan pengenalan istilah kabur (EFTI), kaedah pengenalan struktur (SIM) dan pendekatan perkembangan struktur (SEA) dicadangkan untuk menangani isu kompromi antara kejituan dan penafsiran. EFTI, SIM dan SEA direkabentuk berdasarkan kaedah-kaedah pengurangan ralat. EFTI dibangunkan untuk disesuaikan dengan masalah-masalah masukan tunggal keluaran tunggal (SISO) (iaitu satu dimensi), manakala SIM dan SEA dibangunkan untuk disesuaikan dengan masukan berbilang keluaran tunggal (MISO) (iaitu dimensi sederhana dan tinggi). EFTI bermula dengan struktur kabur mudah yang terdiri daripada dua istilah kabur dalam ruang masukan. Kemudian, EFTI terus berkembang dengan mengenal pasti titik-titik pemisahan pada ruang masukan yang serasi dengan parameter-parameter yang dihasilkan. Sebaliknya, SIM dan SEA bermula dengan satu peraturan kabur yang tidak mempunyai istilah-istilah kabur dalam ruang masukan tanpa mengira tahap dimensi masukan. Kemudian kedua-dua kaedah berkembang berdasarkan proses penutupan atau pemisahan untuk sifat masukan yang terpilih pada subkawasan yang dipilih. Sekiranya sifat yang terpilih tidak mempunyai istilah kabur, penutupan dilakukan, tetapi jika berlaku sebaliknya, pemisahan dilaksanakan. Proses perkembangan berlanjutan sehingga kejituan yang memuaskan dipenuhi atau bilangan subkawasan maksimum dicapai. Teknik pemetakan berdasarkan ciri persamaan dan teknik pemilihan-pemetakan statik dibangunkan untuk SIM. Manakala, teknik

pemetakan berdasarkan pemisahan subkawasan yang terpilih kepada dua subkawasan dengan ralat purata maksimum dan minimum dan teknik pemilihan pemetakan yang dinamik dibangunkan untuk SEA. Selain itu, teknik pemangkasan berdasarkan tahap kepentingan peraturan kabur dicadangkan untuk mengecilkan asas peraturan SEA. Berbanding dengan model SISO dan dengan menggunakan tiga set data, EFTI menghasilkan RMSE terendah dengan bilangan peraturan yang paling rendah. Bagi model MISO pula dan dengan menggunakan sembilan set data penanda aras, SIM mencapai RMSE terendah dengan saiz terkecil sistem asas-peraturan. Demikian juga untuk model-model terkini MISO dan dengan menggunakan enam set data penanda aras, SEA juga menghasilkan RMSE terendah dengan saiz terkecil sistem asas-peraturan. Sebagai kesimpulan, keputusan yang diperolehi membuktikan bahawa EFTI, SIM dan SEA dapat menghasilkan kompromi yang ketara antara kejituan dan penafsiran.

NEW STRUCTURAL EVOLVING ALGORITHMS FOR FUZZY SYSTEMS

ABSTRACT

Recently, the issue of accuracy and interpretability trade-off has been getting more attention when designing new fuzzy systems. In this thesis, three evolving fuzzy models, namely enhancement of fuzzy term identification (EFTI), structure identification method (SIM) and structural evolving approach (SEA) are proposed to spot the best trade-off between accuracy and interpretability. EFTI, SIM and SEA are designed based on error reducing methods. EFTI is developed to fit with single input single output (SISO) problems (i.e. one dimension), while SIM and SEA are developed to fit with multi input single output (MISO) (medium and high dimension). EFTI begins with a simple fuzzy structure that is composed of two fuzzy terms in the input space. Then EFTI continues evolving by identifying splitting points of the input space that are compatible with the consequent parameters. On the other hand, SIM and SEA start with one fuzzy rule that has no fuzzy term in the input space regardless of the degree level of input dimension. Then they evolve on the basis of either closure or split processes for the selected input attribute of the selected subregion. If the selected attribute has no fuzzy terms, closure is performed, otherwise split is done. The evolving continues until a satisfactory accuracy is fulfilled or maximum number of subregion is reached. A partitioning technique based on the similarity feature and a static partition-selection technique are developed for SIM. While, a partitioning technique based on splitting the selected subregion into two subregions with maximum and minimum average error and a dynamic partition-selection technique are developed for SEA. Furthermore, a pruning technique based on the importance level of the fuzzy rules is proposed to shrink the rule-base of SEA. Compared with SISO models and

using three datasets, EFTI produces the lowest RMSE with lowest number of rules. For MISO models and using nine benchmark datasets, SIM achieves the lowest RMSE with the smallest size of rule-base systems. Similarly, for MISO state-of-the-art models and using six benchmark datasets, SEA also produces the lowest RMSE with the smallest size of rule-base systems. In conclusion, the results proved that EFTI, SIM and SEA are able to produce a significant trade-off between accuracy and interpretability.

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Fuzzy modelling is considered one of the main techniques used in computational intelligence. It is widely known that it can represent systems with semantic description. Fuzzy systems are designed to produce a rule-base composed of many fuzzy rules (i.e. IF THEN). Natural language is used to express the terms involved in these rules. In fact, the reasoning form of fuzzy rules expressed by human language offers a significant feature that helps users, who are in charge to make crucial decisions, understand how the systems' outputs are concluded. From users view, this feature (i.e. interpretability) which is provided by fuzzy set theory, grants any created systems with more reliability.

Fuzzy rules of any fuzzy system are mainly generated from two different types, namely designed by human expert or by data. Fuzzy systems designed by human experts were popular in the early approaches. These approaches exploit the knowledge and experience of the human experts to form the IF-THEN fuzzy rules. The lack and difficulty of knowledge acquisition has led the researchers to move to design fuzzy systems using input-output (I/O) data by applying some machine learning techniques. The fuzzy rules generated from numerical data result a better performance than the ones generated by human experts (Alonso et al., 2015). However, these data-driven models suffer from lack of interpretability that the models, built by human expert, have. Subsequently, an issue of accuracy and interpretability trade-off has emerged.

As a result, fuzzy systems have been divided on the basis of accuracy and interpretability trade-off into two different tracks as follow:

Linguistic fuzzy modelling (LFM) (Ahmed and Isa, 2017): the main goal of this type is to build fuzzy rule based systems (FRBSs) with high interpretability using linguistic fuzzy rules. Mamdani structure is usually utilized to build LFM models due to the use of linguistic variables in both the antecedent and consequent parameters (Gacto et al., 2011).

Precise fuzzy modelling (PFM) (Ahmed and Isa, 2017): the main goal of this type is to build fuzzy rule based systems (FRBSs) with high accuracy. PFM models are mainly designed based on Takagi–Sugeno structure which build approximate FRBSs that use non-linguistic fuzzy sets for the antecedent and consequent parameters (Gacto et al., 2011).

In this work, the main focus is to find the best trade-off between accuracy and interpretability. These two characteristics have a conflict relation. They are contradicting each other. Therefore, identifying the best trade-off between accuracy and interpretability, which means to produce systems that have low RMSE with small and high interpretable rule-base, is considered a real challenge.

Many fuzzy systems have been proposed regarding the issue of accuracy and interpretability trade-off. These fuzzy systems can be categorized into three types namely, fuzzy clustering, nonlinear parameters optimization and grid and tree partitioning methods based on error reduction mechanism (i.e. error reducing methods).