SELF LEARNING NEURO-FUZZY MODELING USING HYBRID GENETIC PROBABILISTIC APPROACH FOR ENGINE AIR/FUEL RATIO PREDICTION

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DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2017

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Abstrak

Pembelajaran Mesin merupakan pembinaan model yang boleh mempelajari dan membuat ramalan berasaskan data. Pengekstrakan peraturan dari dunia data sebenar, kebiasaannya dicemari oleh bunyi, kekaburan dan ketidakpastian. Sistem Neuro-Kabur (NFS) yang diketahui dalam meramal prestasi, mempunyai kesukaran dalam menentukan bilangan peraturan yang sesuai dan bilangan fungsi keahlian bagi setiap peraturan. Penambahbaikan hibrid Algoritma Genetik Pengkelasan Bayesian Kabur (GA-FBC) dicadangkan untuk membantu NFS dalam mengekstrak peraturan. Pemilihan ciri dilakukan di dalam tahap peraturan bagi menyelesaikan masalah FBC yang bergantung pada kekerapam ciri yang terarah pada pengabaian corak kelas kecil. Dalam keadaan dunia sebenar masalah multi-objektif seperti ramalan nisbah Udara / Minyak (AFR) telah diguna pakai. GA-FBC menggunakan maklumat bersama entropi, yang mengambilkira perkaitan di antara sifat-sifat ciri dan sifat-sifat kelas. Fungsi kecergasan adalah dicadangkan untuk menangani masalah pelbagai objektif tanpa pemberat dengan menggunakan kaedah komposisi baru. Model ini telah dibuat perbandingan dengan algoritma pembelajaran yang lain seperti algoritma Pengelompokan Kabur C-Min, (FCM) dan algoritma Pecahan Grid. Ketepatan ramalan dan kerumitan dalam Sistem Kabur Berasaskan Peraturan (FRBS) termasuk bilangan peraturan dan bilangan syarat pada setiap peraturan telah diambilkira sebagai syarat penilaian. Perbandingkan juga dibuat dengan GA-FBC yang asal bergantung kepada kekerapan yang tiada dalam Maklumat Bersama (MI). Keputusan pengujian menggunakan set data AFR menunjukkan bahawa model baharu ini dapat membawa kepada penurunan bilangan atribut dalam peraturan dan boleh meningkatkan prestasi berbanding model lain. Kajian ini membolehkan berlakunya penjanaan sendiri FRBS daripada data sebenar. GA-FBC boleh digunakan sebagai satu arah baru dalam penyelidikan pembelajaran mesin. Kajian ini menyumbang dalam mengawal pelepasan asap kenderaan bagi membantu mengurangkan punca pencemaran untuk menghasilkan persekitaran yang lebih hijau.

Kata kunci: Algoritma Genetik, Pengkelasan Bayesian Kabur, Pemilihan ciri, Pengekstrakan peraturan, Maklumat Bersama Entropi

Abstract

Machine Learning is concerned in constructing models which can learn and make predictions based on data. Rule extraction from real world data that are usually tainted with noise, ambiguity, and uncertainty, automatically requires feature selection. Neuro-Fuzzy system (NFS) which is known with its prediction performance has the difficulty in determining the proper number of rules and the number of membership functions for each rule. An enhanced hybrid Genetic Algorithm based Fuzzy Bayesian classifier (GA-FBC) was proposed to help the NFS in the rule extraction. Feature selection was performed in the rule level overcoming the problems of the FBC which depends on the frequency of the features leading to ignore the patterns of small classes. As dealing with a real world problem such as the Air/Fuel Ratio (AFR) prediction, a multi-objective problem is adopted. The GA-FBC uses mutual information entropy, which considers the relevance between feature attributes and class attributes. A fitness function is proposed to deal with multi-objective problem without weight using a new composition method. The model was compared to other learning algorithms for NFS such as Fuzzy c-means (FCM) and grid partition algorithm. Predictive accuracy and the complexity of the Fuzzy Rule Base System (FRBS) including number of rules and number of terms in each rule were taken as terms of evaluation. It was also compared to the original GA-FBC depending on the frequency not on Mutual Information (MI). Experimental results using Air/Fuel Ratio (AFR) data sets show that the new model participates in decreasing the average number of attributes in the rule and sometimes in increasing the average performance compared to other models. This work facilitates in achieving a self-generating FRBS from real data. The GA-FBC can be used as a new direction in machine learning research. This research contributes in controlling automobile emissions in helping the reduction of one of the most causes of pollution to produce greener environment.

Keywords: Genetic Algorithms, Fuzzy Bayesian classifier, Rule extraction, Feature selection, Mutual Information Entropy.

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Acknowledgement

First of all I have to express my thanks and gratitude to Allah who gives me the ability to achieve this imperfect work and without his blessing and support nothing can be done.

I would like to express my sincerest thanks and deepest gratitude to my supervisors Assoc. Prof. Dr. Azman Yasin and Prof. Dr. Horizon Gitano for their excellent guidance, caring, patience, encouragement and sharing of all their research experiences throughout these challenging years.

To my father, without his encouragement, advice, and sacrifice – none of this would have been possible. I hope he is proud of me. To my mother, who gave me life and prayed for me all the time, may Allah continuously bless her with good health. To my two brothers and sister, thanks for their love and support. To my husband Azher and my beautiful children Mustafa and Fatima, thank you for being there for me, without them my goal would not have been achieved. I dedicate this work to my family.

I thank all the workers in the UUM University and School of Computing to offer all support and facilities to complete this simple work.

Last but not least, thanks to all those who have been directly and indirectly involved in helping me complete this research.

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List of Abbreviations

AFR	Air/Fuel Ratio
ANFIS	Adaptive Network – based Fuzzy Inference System
BC	Bayesian Classifier
BN	Bayesian Network
CLT	Coolant Engine Temperature
DB	Data Base
DTGA	Decision Tree and Genetic Algorithm
ECU	Engine Control unit
FBC	Fuzzy Bayesian Classifier
FCM	Fuzzy c-means
FIS	Fuzzy Inference System
FRBS	Fuzzy Rule Base System
FS	Fuzzy Systems
GA	Genetic Algorithms
GA-FBC	Genetic Algorithm based Fuzzy Bayesian Classifier
GFS	Genetic fuzzy System
IRL	Iterative Rule Learning
KB	Knowledge Base
KNN	K-Nearest Neighbour
LDC	Linear Discriminant Classifier
MAP	Manifold Air Pressure
MAT	Manifold Air Temperature
MF	Membership Function
MIFS	Mutual Information Feature Selection
MOEA	Multi-objective Evolutionary Algorithm
MOEFS	Multi-objective Evolutionary Fuzzy System
MI	Mutual Information
MIM	Mutual Information Maximisation
MLP	Multi-Layer Perceptron
NFS	Neuro-Fuzzy System
NN	Neural Network
PW	Pulse Width – Injection Opening Time
QDC	Quadratic Discriminant Classifier
RB	Rule Base
RBFN	Radial Basis Function Network
RMSE	Root Mean Square Error
RPM	Revolution per Minute - Engine Speed
TPS	Throttle Position

CHAPTER ONE
INTRODUCTION

Developing systems or computer programs with self-learning capabilities is one of the most difficult feats in the field of computer science. Machine learning focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data.

Machine learning is not only based on algorithms which enable programs or machines to analyse data and learn from it but is also influenced by the representation of knowledge obtained in the learning process. A learning system is usually capable of informing its user of the learning it has acquired. Therefore, a user, in addition to learning about the problem of interest, can also ascertain if the representation of knowledge within the learning system is accurate and credible.

Induction is a frequently used methodology for learning systems. This implies that a learning algorithm processes samples that can lead to an accurate output for any set of input data. Learning algorithm samples that are based on real life data are generally corrupted with noise, indistinctness, imprecision, uncertainty, incompleteness, or vagueness.

Many a time, it is necessary that the learning model is readable by humans. Rule sets are one of the most understandable kinds of models in this regard. In this thesis, the different learning models in the form of rule sets are discussed.

Linguistic rules or fuzzy rules are defined as ―if-then” rules that use linguistic expressions (for example, ―if x is small, then y is approximately zero”). Fuzzy

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