SIMILARITY REASONING-DRIVEN EVOLUTIONARY FUZZY SYSTEM FOR MONOTONIC-PRESERVING MODELS

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ACKNOWLEDGEMENTS

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Last but not least, I would like to thanks to my beloved family for their understanding, support, encouragements and endless love.
SISTEM EVOLUSI KABUR BERTERASKAN PENAAKULAN KESERUPAAN UNTUK MEMENUHI MODEL BERSIFAT MONOTONIK

ABSTRAK

ABSTRACT

(Fuzzy Inference System (FIS) is a popular computing paradigm which has been identified as a solution for various application domains, e.g. control, assessment, decision making, and approximation. However, it suffers from two major shortcomings, i.e., the "curse of dimensionality" and the "tomato classification" problem. The former suggests that the number of fuzzy rules increases in an exponential manner while the number of input increases. The later is an important fuzzy reasoning problem while a fuzzy rule base is incomplete. The focus of this thesis is on fuzzy rule base reduction techniques, fuzzy rule selection techniques, Approximate Analogical Reasoning Schema (AARS), evolutionary computation techniques and monotonicity property of an FIS, in order to overcome these two shortcomings. The main contribution of this thesis is to formulate the fuzzy rule selection problems to facilitate the AARS and FIS modeling as an optimization problem. An optimization tool, i.e., genetic algorithm (GA), is further implemented. The applicability of the proposed framework is demonstrated and evaluated with two real problems, i.e., education assessment problem and failure analysis problem. The empirical results show the effectiveness of the proposed framework in selecting fuzzy rules and reconstruct a complete rule base with the selected fuzzy rules. However, it is observed that the results obtained do not always fulfill the monotonicity property. Hence, the proposed framework is further extended, and a set of mathematical conditions are adopted as governing equation. Again, the applicability of the extended framework is demonstrated and evaluated with an education assessment problem and a failure analysis problem.
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<td>Approximate analogical reasoning schema</td>
</tr>
<tr>
<td>AR</td>
<td>Analogical reasoning</td>
</tr>
<tr>
<td>CBA</td>
<td>Computer-based assessment</td>
</tr>
<tr>
<td>CRA</td>
<td>Criterion-reference assessment</td>
</tr>
<tr>
<td>EC</td>
<td>Evolutionary computation</td>
</tr>
<tr>
<td>FATI</td>
<td>First aggregate then inference</td>
</tr>
<tr>
<td>FERI</td>
<td>Fundamental equation of rule interpolation</td>
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<td>FIS</td>
<td>Fuzzy inference system</td>
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<td>FITA</td>
<td>First inference then aggregate</td>
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<td>FMEA</td>
<td>Failure mode and effect analysis</td>
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<td>FPR</td>
<td>Fuzzy production rule</td>
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<td>FRI</td>
<td>Fuzzy rule interpolation</td>
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<td>GA</td>
<td>Genetic algorithm</td>
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<tr>
<td>HS</td>
<td>Harmony search</td>
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<tr>
<td>MOEA</td>
<td>Multi-objective evolutionary algorithm</td>
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<tr>
<td>MOI</td>
<td>Mean-of-inversion</td>
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<tr>
<td>NLP</td>
<td>Non-linear programming</td>
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<td>PSO</td>
<td>Particle swarm optimization</td>
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<td>SQP</td>
<td>Sequential quadratic programming</td>
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<tr>
<td>SR</td>
<td>Similarity Reasoning</td>
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<td>SVD</td>
<td>Singular value decomposition</td>
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Journal papers

1. Tze Ling Jee, Kai Meng Tay & Chee Khoon Ng (2011), Enhancing a fuzzy failure mode and effect analysis methodology with an analogical reasoning technique, *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 15, no. 9, pp. 1-8. (SCOPUS)


Book chapter

Conference


8. Tze Ling Jee, Kai Meng Tay & Chee Khoon Ng (2010), A fuzzy inference system based FMEA methodology with case study, ENCON 2010.


CHAPTER 1

INTRODUCTION

1.1 Background of Research

An inference technique is a method that attempts to derive answers from a knowledge base. It can be viewed as the "brain" that reasons about the information in the knowledge base for the ultimate purpose of formulating new conclusions (Russell & Norvig, 2003). From the literatures, various inference techniques have been reported, e.g. automatic logical inference (Harrison, 2009), Bayesian inference (Box & Tiao, 1992), probabilistic inference (Pearl, 1988), and fuzzy inference (Jang et al., 1997).

Fuzzy inference system (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy production rules, and fuzzy reasoning (Jang et al., 1997). It has found successful applications in a variety of problems such as control (Jang et al., 1997), decision (Kouikoglou & Phillis, 2009), selection (Broekhoven & Baets, 2008), assessment (Tay & Lim, 2008a, 2008b), and approximation (Jang et al., 1997) problems. The twofold identity of FIS is their strength (Guillaume, 2001). On one hand, they are able to handle linguistic behavior which can be understood by human. The ability to incorporate human/expert knowledge where information is described by vague and imprecise statements is one of the success key factors. Furthermore, the behaviour of an FIS is also expressed in a language that could be easily interpreted by humans. On the other hand, they play the role as universal approximator that are able to perform non-linear mappings between inputs and
outputs. The mapping is accomplished by a rule base; which consists of a number of If-Then rules, each of which describes the local behavior of the mapping. FIS is widely applied in many application domains, for example, it has been applied to calculate the resonant frequencies of rectangular microstrip antenna (MSAs) with thin and thick substrates (Guney & Sarikaya, 2009). Besides, it was applied to failure mode and effect analysis (FMEA) methodology, i.e., fuzzy FMEA methodology (Tay & Lim, 2006, 2008a, 2008b, 2010).

1.2 Problem Statements

Despite FISs' popularity, they suffer from a number of weaknesses, i.e., it is a tedious work to obtain a complete fuzzy rule base, especially for multi-input FIS models (Jang et al., 1997). With the use of grid partition, the number of fuzzy rules required increases in an exponential manner and this phenomenon is known as the "curse of dimensionality" (Jang et al., 1997). For an example, an FIS model that has three inputs and each input has five partitions, the number of fuzzy rules in the rule base is 125 (5 x 5 x 5).

Besides, some of the fuzzy rules may not be available, i.e., incomplete rule base. For an incomplete rule base, some consequents are unknown or missing. The unknown consequents are denoted as conclusion throughout this thesis, and the antecedents for unknown consequents are denoted as observations. In a conventional FIS model, it is normally assumed that the unknown consequents as zero. However, this assumption may not always be appropriate because this may lead to the "tomato classification" problem (Hsiao et al., 1998).

In order to solve the "curse of dimensionality" and "tomato classification" problem, similarity reasoning (SR) techniques, such as Approximate Analogical Reasoning Schema (AARS) (Turksen & Zhao, 1988) and Fuzzy Rule Interpolation (FRI) (Kóczy & Hirota, 1997) were developed. SR could be used to construct the conclusion of an observation with refer to
the incomplete fuzzy rules. Besides, it allows the fuzzy rules required to be reduced, and a complete fuzzy rule base reconstructed from the incomplete fuzzy rules.

Despite of the popularity of SR techniques, it is not sure how these techniques could be practically and systematically implemented in an FIS modeling problem. Thus, in this thesis, a new fuzzy rule selection approach to facilitate AARS and FIS modeling that is based on an optimization theory (i.e., genetic algorithm (GA)) is developed. The proposed GA-based fuzzy rule selection approach highlights a set of important fuzzy rules to experts for information/fuzzy rules gathering. AARS allows the unknown fuzzy rules to be reconstructed, based on the available fuzzy rules. The practicality of the proposed framework is demonstrated with two real world problems.

Another recent trend in FIS modeling is the fulfillment of the monotonicity property. Consider an FIS model, \( y = f(x_1, x_2, \ldots, x_i, \ldots, x_n) \), that satisfies the monotonicity condition between its output, \( y \), with respect to its \( i^{th} \) input, \( x_i \). Output \( y \) monotonically increases or decreases as \( x_i \) increases, i.e. \( f(x_1, x_2, \ldots, x_i, \ldots, x_n) \leq f(x_1, x_2, \ldots, x_i', \ldots, x_n) \) or \( f(x_1, x_2, \ldots, x_i', \ldots, x_n) \geq f(x_1, x_2, \ldots, x_i, \ldots, x_n) \), respectively, for \( x_i' < x_i \). The importance of this line of study has been highlighted in a number of recent publications (Broekhoven & Baets, 2009; Kouikoglou & Phillis, 2009; Seki et al., 2010; Tay & Lim, 2008a, 2008b, 2011a; Won et al., 2002). Among the important aspects include: (i) many real world systems and control problems obey the monotonicity property (Kouikoglou & Phillis, 2009; Seki et al., 2010; Won et al., 2002; Tay & Lim, 2011a; Lindskog & Ljung, 2000); (ii) the validity of the FIS output needs to be ensured for undertaking comparison, selection, and decision making problems (Kouikoglou & Phillis, 2009; Tay & Lim, 2008a, 2008b); (iii) in the case when the number of data samples is small or the fuzzy rule set is incomplete, it is important to fully exploit the available qualitative information/knowledge (Broekhoven & Baets, 2009); (iv)
taking the additional qualitative information/knowledge of the system into consideration makes the model identification process less vulnerable to noise and inconsistencies in data samples, as well as mitigates the over-fitting phenomenon (Broekhoven & Baets, 2009). However, there are only a few articles that address the issues on how to design monotonicity-preserving FIS models (Kouikoglou & Phillis, 2009).

Generally, theoretical proof of the exact monotonicity in FIS is difficult (Seki et al., 2010). However, there are some mathematical conditions that are useful to preserve monotonicity in FIS models. In Won et al. (2002), a set of mathematical conditions (i.e., the sufficient conditions) have been derived with the assumption that the first derivative of a Sugeno FIS is always greater than or equal to zero, or less than or equal to zero, for a monotonically increasing or decreasing function, respectively. The sufficient conditions suggest that two mathematical conditions (at the antecedent and consequent parts) are essential to obtain a monotonicity-preserving FIS model. For a fuzzy partition (at rule antecedent), maintaining a monotonically-ordered rule base can preserve the monotonicity property. This condition has been used and extended in (Kouikoglou & Phillis, 2009; Tay & Lim, 2008a, 2008b, 2011a). In Broekhoven and Baets (2009), it has been verified that for three basic T-norms (minimum, product, and Lukasiewicz), a monotonic input-output behavior is obtained for any monotonic rule bases. Some useful guidelines have also been proposed (Broekhoven & Baets, 2009). The relationships among the monotonicity property, monotonic rule base, and comparable fuzzy sets for single-input-rule-modules-connected FIS model are discussed in (Seki et al., 2010). Another recent enhancement in this line of studies is the development of monotonicity index for FIS models (Tay & Lim, 2011a).

As extension of this work, a new monotonicity-preserving framework which comprise of fuzzy rule selection, similarity reasoning (i.e., AARS) and evolutionary computation for FIS