Available online at www.sciencedirect.com
ScienceDirect
Fuzzy Sets and Systems 297 (2016) 1–25
FUZZY sets and systems
www.elsevier.com/locate/fss

Enhancing Fingrams to deal with precise fuzzy systems

David P. Pancho [*,1], Jose M. Alonso [1], Luis Magdalena [1]

European Centre for Soft Computing, Edificio de Investigación, C/Gonzalo Gutiérrez Quirós s/n, 33600 Mieres, Asturias, Spain

Received 22 December 2014; received in revised form 8 May 2015; accepted 9 May 2015

Available online 17 June 2015

Abstract

Interpretability is a highly valued capability of fuzzy systems that turns essential when dealing with human interaction. Precise fuzzy modeling prioritizes performance at the cost of harming interpretability. Fuzzy Inference-grams (Fingrams) permit the graphical representation of fuzzy systems facilitating their comprehension, analysis and interpretation at inference level. We enhance Fingrams to better represent and analyze precise fuzzy systems. A specific metric and new representations handle the particularities of such systems. A new visual artifact allows to discover the set of data instances not covered by a given fuzzy system. A novel visual representation allows to study in detail the elements that are involved in the inference of a single data instance. The potentials of the enhanced methodology are sketched by taking the Fuzzy Unordered Rule Induction Algorithm (FURIA) as an illustrative example of precise fuzzy system. For instance, a highly valuable representation is obtained for the stretching mechanism of FURIA, thus facilitating its comprehensibility.

Keywords: Fuzzy system models; Fuzzy inference systems; Interpretability; Comprehensibility analysis; Expert analysis; Information visualization; Social network analysis; Precise fuzzy modeling; FURIA

1. Introduction

Interpretability is a highly appreciated capability of fuzzy systems that permits the correct understanding of systems behavior [1]. Interpretability of fuzzy systems represents their ability to formalize the behavior of a real system in a human understandable way [2,3]. It takes advantage of the use of linguistic variables [4] and rules [5,6] with high semantic expressivity close to natural language. According to some authors interpretability is of subjective nature and depends on the talent and background of the end-user [7].

Abbreviations: FRBS, Fuzzy Rule-Based System; LFM, Linguistic Fuzzy Modeling; PFM, Precise Fuzzy Modeling; FURIA, Fuzzy Unordered Rule Induction Algorithm; Fingram, Fuzzy Inference-Gram.

* Corresponding author.
E-mail addresses: david.perez@softcomputing.es (D.P. Pancho), jose.alonso@softcomputing.es (J.M. Alonso), luis.magdalena@softcomputing.es (L. Magdalena).
[1] Tel.: +34 985 456 545.

http://dx.doi.org/10.1016/j.fss.2015.05.019
0165-0114/

Several factors influence in the assessment of interpretability [8] from low to high levels [9]. Mainly, they can be grouped in two main issues [7]: (1) readability (transparency) of the system description, and (2) comprehensibility of the system explanation. Notice that it only makes sense to take care about interpretable constraints [10] when there is a need of human interaction in any of the steps of the process (design, inference, improvement, ...).

Fuzzy systems are not interpretable per-se. Although the use of linguistic variables and rules favors interpretability, this does not guarantee it. A careful design is demanded to simplify their understanding and ensure their interpretability [11,12].

Fuzzy modeling [13] – system modeling with fuzzy rule-based systems (FRBSs) – can be done through two alternative approaches attending to the interpretability-accuracy trade-off: producing linguistic or precise fuzzy modeling [14]. Linguistic fuzzy modeling (LFM) prioritizes interpretability. It yields fuzzy rules composed of linguistic variables [4] taking terms with a real-world meaning [15,16]. On the contrary, precise fuzzy modeling (PFM), which has accuracy as its main objective, constructs FRBSs that lack of semantic expressivity.

An effort has been done to obtain intermediate approaches that keep a good interpretability-accuracy trade-off. On the one hand, some works propose to improve accuracy of LFM [17]. On the other hand, others introduce techniques to enhance interpretability of PFM [18].

One of the key issues in the generation of a fuzzy system with good interpretability is the comprehension of the fuzzy inference process [19]. Understanding such process becomes an arduous task when dealing with PFM even for fuzzy modeling experts. We can highlight two of the most famous FRBSs for PFM: Mamdani FRBSs [6] and Takagi–Sugeno FRBSs [20]. The former, Mamdani FRBSs are typically multi-input–single-output systems with min–max inference mechanism, widely recognized as the easiest inference mechanism to understand. The latter, Takagi–Sugeno FRBSs produce as rule outputs non-linear combinations of the inputs involved in each rule, hindering its comprehension. Some authors have made an effort in simplifying and enhancing Takagi–Sugeno FRBSs [21,22]. Anyway, in both cases the use of weighted rules, advanced defuzzification strategies, a high number of rules, variables or antecedents per rule, can make harder the understanding of the system behavior at inference level [1,2,23–25]. Moreover, when an instance fires several rules, as usual in PFM, the inferred output is hard to interpret.

There are not many publications tackling with visual analysis of the fuzzy system inference process. Probably, this is due to the well-known linguistic expressivity of LFM what gives prominence to linguistic representations. However, as mentioned before, not all fuzzy systems preserve such characteristic. Thus, visual tools would stand out in the case of PFM.

Pham et al. [26] overview the requirements to graphically represent fuzzy systems and critically review the existing methods for visualizing fuzzy data and relationships. Different alternatives support the visualization of fuzzy data, fuzzy partitions and fuzzy rules depending on the requirements the end-user may demand. A few authors [27–32] present 2D graphical representations for FRBSs. Only [31,32] represent rule interaction at inference level in terms of rule overlapping. Namely they use parallel coordinates to visualize high-dimensional fuzzy points and rules. This brief review shows that there is a lack of methods depicting the interaction among rules that, however, could strongly help in the comprehension of the rule base behavior at inference level.

Fuzzy Inference-grams [33], or Fingrams in short, have arisen as a powerful tool for visualizing and analyzing FRBSs. Fingrams give a global view of fuzzy systems, and allow us to understand its behavior at a high level of abstraction. They present fuzzy systems as social networks where rules are individuals that relate each other reflecting how they cover the input space. Different metrics and visual artifacts have been proposed to reflect the particularities of the different kinds of fuzzy systems [33,34]. It is worthy to note the capability of Fingrams to graphically depict the inference mechanism of fuzzy systems. Fingrams let us visualize how instances are covered by rules, which are the rule outputs, and so on.

This paper proposes the use of Fingrams to understand the behavior of precise fuzzy systems – fuzzy systems constructed by PFM – and its particularities. To do so, we have extended Fingrams to effectively represent the characteristics of precise fuzzy systems.

Here we propose a visual representation that allows us to uncover how the inference mechanism operates for a single instance. It shows which rules cover the instance, giving us a complementary local view of the system.

Additionally, we propose a novel graphical representation for instances that are not covered by any rule in a given FRBS. This way we can quantify the uncovered instances and act consequently. It should be noticed that uncovered instances penalize the precision of FRBSs and their early detection and correction is essential for the correct behavior of the system.