Chapter 2
Granular Computing and Human-Centricity in Computational Intelligence

Witold Pedrycz
University of Alberta, Canada, and Polish Academy of Sciences, Poland

ABSTRACT

Information granules and ensuing Granular Computing offer interesting opportunities to endow processing with an important facet of human-centricity. This facet implies that the underlying processing supports non-numeric data inherently associated with the variable perception of humans. Systems that commonly become distributed and hierarchical, managing granular information in hierarchical and distributed architectures, is of growing interest, especially when invoking mechanisms of knowledge generation and knowledge sharing. The outstanding feature of human centricity of Granular Computing along with essential fuzzy set-based constructs constitutes the crux of this study. The author elaborates on some new directions of knowledge elicitation and quantification realized in the setting of fuzzy sets. With this regard, the paper concentrates on knowledge-based clustering. It is also emphasized that collaboration and reconciliation of locally available knowledge give rise to the concept of higher type information granules. Other interesting directions enhancing human centricity of computing with fuzzy sets deals with non-numeric semi-qualitative characterization of information granules, as well as inherent evolving capabilities of associated human-centric systems. The author discusses a suite of algorithms facilitating a qualitative assessment of fuzzy sets, formulates a series of associated optimization tasks guided by well-formulated performance indexes, and discusses the underlying essence of resulting solutions.

INTRODUCTION

Constructs of Computational Intelligence (CI) (Angelov et al., 2008; Crespo & Weber, 2005; Kacprzyk & Zadrozny, 2005; Kilic et al., 2007; Molina et al., 2006; Pedrycz & Gomide, 1998; Pham & Castellani, 2006; Wang et al., 2009) exhibits a surprising diversity of design methodologies. The concepts and architectures of neurofuzzy systems, evolutionary fuzzy systems are becoming more visible and widespread in the literature.

In spite of this variety, there is a single very visible development aspect that cuts across the entire field of CI and fuzzy modeling, in particular.

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In a nutshell, such constructs are built around a single data set. What also becomes more apparent nowadays is a tendency of modeling a variety of distributed systems or phenomena, in which there are separate data sets, quite often quite remote in terms of location or distant in time. The same complex phenomenon could be perceived and modeled using different data sets collected individually and usually not shared. The data might be expressed in different feature spaces as the views at the process could be secured from different perspectives. The models developed individually could be treated as a multitude of sources of knowledge. Along with the individual design of fuzzy models, it could be beneficial to share sources of knowledge (models), reconcile findings, collaborate with intent of forming a model, which might offer a global, unified, comprehensive and holistic view at the underlying phenomenon. Under these circumstances an effective way of knowledge sharing and reconciliation through a sound communication platform becomes of paramount relevance, see Figure 1.

A situation portrayed in Figure 1 is shown in a somewhat general way not moving into the details. It is essential to note that the mechanisms of collaboration and reconciliation are realized through passing information granules rather than detailed numeric entities.

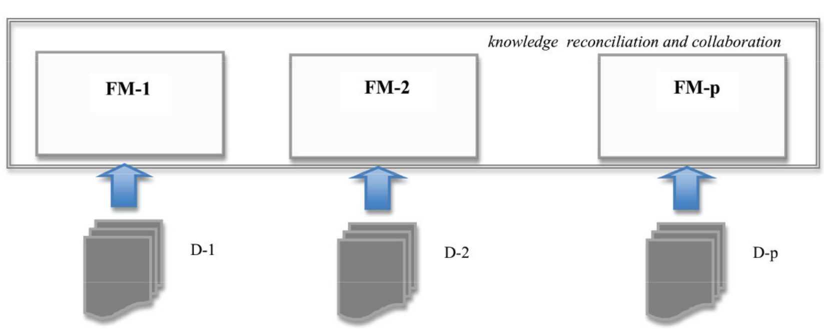
The general category of fuzzy models under investigation embrace models described as a family of pairs $<R_i, f_i>$, i=1, 2, …,c. In essence, these pairs can be sought as concise representations of rules with R_i forming the condition part of the i-th rule and f_i standing in the corresponding conclusion part. It is beneficial to emphasize that in such rules, we admit a genuine diversity of the local models formalized by f_i. From the modeling perspective, the expression $f_i(\mathbf{x},\mathbf{a}_i)$ could be literally *any* modeling construct, namely

- Fuzzy set,
- Linear or nonlinear regression function,
- Difference or differential equation,
- Finite state machine,
- Neural network

One can cast the fuzzy models in a certain perspective by noting that by determining a collection of information granules (fuzzy sets) R_i, one establishes a certain view at the system/phenomenon. Subsequently, the conclusion parts (f_i) are implied by the information granules and their detailed determination is realized once R_i have been fixed or further adjusted (refined).

In light of the discussion on knowledge reconciliation and mechanisms of collaboration, it becomes apparent that the interaction can focus on information granules R_i and communication schemes that invoke exchange of granules whereas conclusion parts can be adjusted accordingly once the collaborative development of information granules has been completed.

Figure 1. A General platform of knowledge reconciliation and collaboration in fuzzy modeling



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