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Information granularity model for evolving context-based fuzzy system

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ABSTRACT

An information granule has to be translated into significant frameworks of granular computing to realize interpretability–accuracy tradeoff. These two objectives are in conflict and constitute an open problem. A new operational framework to form the evolving information granule (EIG) is developed in this paper, which ensures a compromise between interpretability and reasonable accuracy. The evolving information granule is initiated with the first information granule by translating the knowledge of the entire output domain. The initial information granule is considered an underfitting state with a high approximation error. Then, the EIG starts evolving in the information granule by partitioning the output domain and uses a dynamic constraint to maintain semantic interpretability in the output-contexts. The important criterion in the EIG is to determine the prominent distinction (output-context) in the output domain and realize the distinct information granule that depicts the semantics at the fuzzy partition level. The EIG tends to evolve toward the lower error region and realizes the effective rulebase by avoiding overfitting. The outcome on the synthetic and real-world data using the EIG shows the effectiveness of the proposed system, which outperforms state-of-the art methods.

1. Introduction

Information granules are presented as a certain conceptual framework of basic entities [1]. A level of abstraction that is conceived by global knowledge implies interpretability and hence, information granules. Granular computing, which is a unified conceptual and computing framework by the information granules, exhibits the descriptive and functional representation of the global concept [2,3].

Conditional or context-based fuzzy granular model was proposed by Pedrycz [3–6], in which conditional fuzzy *C*-means was considered [6]. The main objective was to define the output context partition and then cluster the corresponding inputs. The number of contexts and clusters per context are predefined and fixed [6]; hence, a computational model of the fuzzy system is manually designed by human experts [7,8]. In addition, the number of output-context and its corresponding input clusters are based on the distinct nature of the data and considered locally distributed. The result is often highly prejudiced and uncertain because prior knowledge of humans to design the fuzzy model is limited. Without considering the input space, the partition on the output domain may cause underfitting or overfitting phenomena that could lead to inaccurate performance. The input space for avoiding the imbalance partition of the output domain needs to be considered when partitioning the output domain because data are unevenly distributed in the input space. This imbalance partition of the output domain maybe referred to as overfitting condition.

Error-reducing evolving methods are described in the simplified structure evolving method (SSEM) [9] and evolving-construction scheme for fuzzy system (ECSFS) [10]. In both studies, the structure of the fuzzy rulebase system evolved and errors to fit the changes were reduced within the given system. These evolving processes continued to achieve the desired threshold accuracy. In addition, extremum and inflexion points were computed by using least square method (LSM) to obtain the best accuracy. Learning methods employed in [9,10] are based on global and localized learning for the rule consequent and the rule antecedent parameters, respectively. Without considering the antecedent part, the lack of localized learning in the consequent part may cause an imbalanced partition of the output domain. Self-adaptive fuzzy inference network (SaFIN), self-constructing neural fuzzy inference network (SONFIN), and evolving neural-fuzzy semantic memory (eFSM) were proposed by Tung et al. [11], Juang and Lin [7], and Tung

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Table 1
Summary of related work to assess the interpretability–accuracy tradeoff of fuzzy rule base.

Authors	Refs.	Year	Type	NR	Acc.	CM	$C_{ONST.}$	CBC	O/U Condition
Pedrycz and Kwak	[6]	2006	$R_{EG.}$	√	√	FCM		√	
Liu et al.	[14]	2007	$R_{EG.}$	√	√	HL & SM			
Pulkkinen and Koivisto	[13]	2010	$R_{EG.}$	√	√	GFS	√		
Mencar et al.	[8,15]	2011	$C_{LAS.}$	√	√	FCM			
Tung et al.	[11]	2011	$C_{LAS.}$ and $R_{EG.}$	√	√	SM	√		
Tung and Quek	[12]	2012	$R_{EG.}$	√	√	SM	√		
Wang et al.	[9,10]	2010, 2013	$R_{EG.}$	√	√	LSM	√	√	√
Solis and Panoutsos	[20]	2013	$R_{EG.}$	√	√	DS	UE		
Sanchez et al.	[16,17,19]	2013, 2013, 2014	$C_{LAS.}$ and $R_{EG.}$	√	√	DS, HCD	FOU		
Fazzolari et al.	[18]	2014	$C_{LAS.}$	√	√	MOEA	FD		
Lu et al.	[25]	2014	$R_{EG.}$	√	√	TW	√		

NR = number of rules, CBC = condition-based clustering, CM = clustering method, $C_{ONST.}$ = constraint, Acc. = accuracy, O/U = overfitting/underfitting, FCM = Fuzzy *c*-means, $R_{EG.}$ = regression, $C_{LAS.}$ = classification, GFS = genetic Fuzzy system, HL = Hebbian learning, SM = similarity measure, LSM = least square mean, DS = distance similarity, UE = uncertainty estimation, FOU = footprint of uncertainty, HCD = hybrid centroid density, MOEA = multi-objective evolutionary algorithm, FD = Fuzzy discretization, TW = time window.

and Quek [12], respectively. These fuzzy systems have attempted to design a consistent and compact fuzzy rulebase system to ensure a clear semantic meaning of fuzzy partitions with reasonable accuracy. Self-adaptation in these fuzzy systems [7,11,12] is applied at the consequent and antecedent parts independently; therefore, structure learning includes pruning inconsistent or identical rules and deleting orphaned rules. Hence, an operational framework for granular computing is needed to synchronize the self-adaptation in both consequent and antecedent parts, and the formation of the distinct information granule is required to consider the aforementioned limitations of the existing methods.

Interpretability and accuracy are two contradictory requirements for the fuzzy information granule [4,6–12]. Interpretability is the ability to explain the behavior of an application system in an understandable way. Accuracy is the capability to represent the similarity between the real test data and the proposed fuzzy model. Mean square error (MSE) or root MSE (RMSE) measures the accuracy of how reasonable the model is with respect to the real test data. Nevertheless, interpretability is a subjective property, and its measure remains an open problem [29]. Most researchers use the following aspects for interpretability measure: fewer rules, fuzzy linguistic terms that have semantic property, and rule premises [29]. Table 1 summarizes the works that consider interpretability–accuracy tradeoff for fuzzy models grouped by publication year. Information granule should be specific in a way that well-defined semantics are experienced. Therefore, interpretability constraint can be significantly considered for granular computing to provide a descriptive representation of the experimental evidence. Various models consider the interpretability constraint, which is depicted in the eighth column of Table 1. Consequently, various clustering approaches are considered to apply the interpretability constraint (seventh column of Table 1). Nevertheless, few studies considered the context or condition-based approach and overfitting or underfitting situation while the evolving granulation process continues.

Furthermore, the concept of justifiable granularity and allocation of information granularity [16,17,20,21,25] consist of the fundamental blocks of granular computing. The optimal allocation of information granularity [21,48] can be employed to group decision making problems [22–24] in which the initial preferences from the decision maker can be adapted to reach higher agreement [48]. Nevertheless, the initial preferences are often arbitrarily decided, and the designed model might not be able to achieve a desirable performance because the granularity depends on the distribution of the application problem. Therefore, granular computing with sequential decision making was proposed in [26,27] where finer granulation level with more detailed information is considered. A relationship between progressive computing and granular computing was proposed in SSEM [9], ECSFS [10], and top-down progressive computing [28]. Progressive computing in these models realizes an evolving granule system from coarser information granulation to finer information granulation. SSEM and ECSFS are used as overfitting and underfitting criteria to continue progressive computing as depicted in Table 1.

Models to overcome the interpretability–accuracy tradeoff are well documented in literature. Numerous algorithms to represent fuzzy granular models, adaptive neural fuzzy systems, and evolving fuzzy systems have been developed. Motivated by the aforementioned existing models and Table 1, the following concerns are significant when considering a computing framework for fuzzy information granule: (1) evolving granule process from bloated granularity (coarser partition) to higher granularity (fine partition), (2) interpretability constraint for granular computing, (3) overfitting and underfitting situations in the evolving process, and (4) the stability–plasticity tradeoff.

First, the information granule evolves from coarser to fine partition, which consequently provides the oblique decision boundaries [8,31]; thus, the evolving process and its decision boundaries allow us to achieve low model error. For example, ECSFS [11] and SSEM [10] models are error-reducing evolving methods, and boundary constraints are used in the evolving method. Consequently, many studies on fuzzy granular approach focus on the improvement of interpretability constraints (or decision boarders) to achieve a low model error [16,17,20,21,25]; this is a second significant consideration for granular computing. Therefore, evolving granule approach and interpretability constraint are important to coexist concurrently. Hence, this computing framework can be a tradeoff between interpretability and accuracy.

The third important consideration is the overfitting and underfitting situations in the evolving granule approach. Underfitting occurs when information granule is too coarse to fit data, thereby resulting in poor testing accuracy. Furthermore, some evolving stages cannot properly represent the data when the evolving granule process continues, which results in an unbalanced state. Therefore, this unbalanced state leads to fuzzy system overfitting (i.e., the data fit is close because of the small and unbalanced information granule), thereby resulting in poor testing accuracy. Hence, evolving granule approach should consider the underfitting and overfitting state of each evolving stage. Moreover, the realization of these unbalanced states can enhance the system performance if stability–plasticity tradeoff is considered. The stability–plasticity tradeoff is the fourth significant consideration to design a granular framework, combines the past and any future knowledge from the training data, and achieves a current and up-to-date system for modeling the application environment [11,12]. Therefore, the stability–plasticity tradeoff is important