APPROXIMATE REASONING BY AGENTS IN DISTRIBUTED ENVIRONMENTS

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Solving complex problems by multi-agent systems in distributed environments requires new approximate reasoning methods based on new computing paradigms. One such recently emerging computing paradigm is Granular Computing. Granular computations are performed on information granules representing vague and complex concepts delivered by agents engaged in tasks such as knowledge representation, communication with other agents, and reasoning. In this paper, we present an outline of foundations for information granule calculi and methods for inducing relevant information granule constructions from data and background knowledge. These constructions can be interpreted as approximate reasoning schemes. The proposed methodology of approximate reasoning has been developed for solving complex problems in areas such as identification of objects by autonomous systems, web mining or sensor fusion.

1 Introduction

Information processing in intelligent systems, in particular in multi-agent systems, needs new soft-computing paradigms. The solutions derived by such systems should satisfy a given specification not necessarily exactly but up to a satisfactory degree. One can expect that due to such more relaxed specification constraints the robust solutions for complex problems can be derived efficiently by methods based on these new paradigms.

One of such recently emerging paradigm is Granular Computing based on rough set and rough mereological approaches (see, e.g., Zadeh and Kacprzyk [33], Zhong *et al* [35], Lin [9], Polkowski and Skowron [22,25,26], Skowron and Stepaniuk [29], Nguyen *et al* [11], Skowron [27]) as a way to achieve Computing with Words (see, e.g., Zadeh [32,34], Zadeh and Kacprzyk [33]). Granular computations are performed on information granules representing vague and complex concepts delivered by agents engaged in, for example, knowledge representation, communication with other agents, and reasoning. Our approach is related to logical aspects of perception (see, e.g., Zadeh [34]).

Specifications of complex tasks are often formulated in words, phrases or more complex texts of a natural language. Hence, the following main problem arises: if and how can an information granule, in a sense, sufficiently close to the target information granule G_t representing the task specification, be constructed from input information granules (e.g., representing sensor measurements).

One of the important problems is related to the construction of an interface allowing knowledge acquisition agents (KA-agents) to acquire knowledge from customer-agents (CA-agents), who specify a task. The aim is to induce a satisfactory approximation G_k of the target information granule G_t in the language of KA-agents, i.e., an information granule G_k sufficiently close to (or included in) the target information granule G_t. Hence, some tools for expressing inclusion and proximity (closeness) of information granules measured by the degree of proximity are needed. For this purpose we use rough sets (see, e.g., Pawlak [14], Komorowski *et al* [7]) and rough mereology (see, e.g., Polkowski and Skowron [18,20,22]). The interface construction should be supported by background knowledge (in particular, by ontology of concepts) and experimental data.

An information granule G sufficiently close to the information granule G_k delivered by KA-agents should be constructed from input information granules (representing, e.g., sensor measurements). In the search for granule G, relevant operations and inclusion (closeness) measures on information granules should be discovered and used. The granule G is constructed from basic components defined by information granule calculi. Any such calculus consists of components such as (i) elementary input information granules, (ii) operations on information granules, (iii) relations of inclusion and proximity measured by the proximity degree between information granules, and (iv) schemes of information granule construction which can be treated as approximate reasoning schemes (AR-schemes, for short) on information granules.

Elementary information granules together with inclusion and proximity relations between such granules are primitive constructs in granule construction. Higher level constructs, like information granules and related inclusion (closeness) relations, can be defined from previously constructed lower level constructs using relevant operations.

Fusion operations are important operations on information granules. They are based on negotiation schemes for resolving conflicts between agents, delivering arguments of operations. More complex operations are defined by robust AR-schemes. Such schemes are obtained by approximate reasoning rules and methods for their composition, dependent on available data and background knowledge. The robustness of AR-schemes means that the closeness (inclusion) of constructed granules is preserved in a satisfactory degree under small deviations of input granules (or operation parameters used for the granule construction). The robustness of the target construction can be deduced from the robustness of their sub-constructions, if some constraints for composition are satisfied. The robust AR-schemes should be extracted from experimental (e.g., sensory) data or/and background knowledge rather than from classical deduction mechanisms.

The AR-schemes are parameterized. Relevant information granules are constructed by tuning AR-scheme parameters. There are several kinds of parameters tuned in the process of searching for relevant information granules. Some of them come from approximation spaces of agents that make it possible to obtain a proper generalization degree of the granule constructed in the inductive reasoning. Other parameters are related to agent teams and are used to tune measures of inclusion (closeness) between information granules and to tune propagation mechanisms of the inclusion (closeness) degrees along the AR-schemes. The AR-schemes in multi-agent systems can be treated as higher order neural networks, called rough neural networks, performing operations on information granules instead of numbers. One of the main problems of a new Rough Neurocomputing paradigm is to develop methods for inducing rough neural networks.

In this paper, we outline an approach to the above mentioned problems. Our approach is based on the foundations of a calculus on information granules developed by means of rough set and rough mereological approaches. Its aim is to create a methodology and tools for solving a wide class of complex problems ranging from the identification of road traffic situations by an unmanned aerial vehicle (see, e.g., www page of WITAS project [31]) to problems of text data mining in the Internet (see, e.g., Skowron [27], Kargupta and Chan [6]).

2 Information Granule Systems

In this section, we present a basic notion for our approach, i.e., information granule system. Any such system S consists of a set of elementary granules E together with an operation $\{\cdot\}$ making collections of granules from finite sets of granules. A finite subset of the set generated from elementary granules using this operation is fixed. This subset is extended by means of other operations on information granules producing new information granules. Moreover, a family of relations with the intended meaning *to be a part to a degree* between information granules is distinguished. Degrees of inclusion are also treated as information granules. The degree structure is described by a relation *to be an exact part.* More formally, an information granule system is any tuple

$$S = (E, \{E\}, H, O, \nu, \{\nu_p\}_{p\in H}) \tag{1}$$

where

1. E is a finite set of elementary granules;

2. $\{E\}$ is a finite subset of $P_\omega(E) = E \cup P(E) \cup P(E \cup P(E)) \cup$ ... where $P(X)$ denotes the powerset of X;

3. H is a finite set of granule inclusion degrees with a binary relation $\nu \subseteq H \times H$ *to be an (exact) part*; ν defines on H a structure used to compare the degrees by assuming, e.g., $p < q$ if and only if $\nu(q,p)$;

4. O is a set of (partial) operations used to construct new granules from $\{E\}$; by means of operations from O, the set $\{E\}$ is extended to the set $G(S) \subseteq P_\omega(E)$ of granules generated from $\{E\}$ using operations from O;

5. $\nu_p \subseteq G(S) \times G(S)$ is a binary relation *to be a part to a degree at least* p between information granules from $G(S)$.

One can consider the following examples of the set E of elementary granules: (i) a set of descriptors of the form (a, v) where $a \in A$ and $v \in V_a$ for some finite attribute set A and value sets V_a, and (ii) a set of descriptor conjunctions. The set $\{E\}$ consists of granules constructed by means of an operation $\{\cdot\}$ making collections from already constructed granules. Examples of such granules are tolerance granules created by means of similarity (tolerance) relation between elementary granules, decision rules, sets of decision rules, sets of decision rules with guards, information systems or decision tables (see, e.g., Polkowski and Skowron [22], Skowron and Stepaniuk [29], Skowron [27]). The most interesting class of information granules create information granules specified in natural language and their approximations by means of experimental data tables and background knowledge.

One can consider as an example of the set H of granule inclusion degrees the set of binary sequences of a fixed length with the relation ν to be a part defined by the lexicographical order. This degree structure can be used to measure the inclusion degree between granule sequences or to measure the matching degree between granules representing classified objects and granules describing the left hand sides of decision rules in simple classifiers (see, e.g., Polkowski and Skowron [25]). However, one can consider more complex degree granules by taking as degree of inclusion of granule g_1 in granule g_2 the granule being a collection of common parts of these two granules g_1 and g_2. The relation ν satisfies some additional axioms adopted from mereology (Polkowski and Skowron [18]).

Operations from O are important for constructing an extension of $\{E\}$. One can consider, as operations on information granules set theoretical operations (defined by propositional connectives). However, there are other operations widely used in machine learning or pattern recognition (Michell [10]) for construction of classifiers. These are the $Match$ and $Conflict\_res$ operations

(Polkowski and Skowron [25]). The *Match* operation is used to construct a granule describing the matching result of elementary granules describing classified objects by granules representing the left hand sides of decision rules. The $Conflict\_res$ is an operation producing from this matching granule the resulting granule, e.g., identifying a relevant decision class for classifying object. It is worthwhile mentioning yet another important class of operations, namely, operations defined by data tables called decision tables (Skowron and Stepaniuk [29]). From these decision tables, decision rules specifying operations can be induced. More complex operations on information granules are so called transducers (Doherty *et al* [3]). They have been introduced to use background knowledge (not necessarily in the form of data tables) in construction of new granules. One can consider theories or their clusters as information granules. Reasoning schemes in natural language define the most important class of operations on information granules to be investigated. One of the basic problems for such operations and schemes of reasoning is how to approximate them by available information granules, e.g., constructed from sensor measurements.

In an information granule system, the relation to be a part to a degree has a special role. It satisfies some additional axioms of rough mereology (Polkowski and Skowron [18]). It can be shown that the rough mereological approach built on the basis of the relation to be a part to a degree generalizes the rough set and fuzzy set approaches. Moreover, such relations can be used to define other basic concepts like closeness of information granules, their semantics, indiscernibiliy and discernibility of objects, information granule approximation and approximation spaces, perception structure of information granules as well as the notion of ontology approximation. One can observe that the relation to be a part to a degree can be used to define operations on information granules corresponding to generalization of already defined information granules.

Let us finally note that new information granule systems can be defined using already constructed information granule systems. This leads to a hierarchy of information granule systems.

3 Multi-Agent System Based on Information Granules

In this section, we outline how our approach can be used in approximate reasoning by agents (Huhns [5]) in a distributed environment.

We assume each agent $ag \in Ag$ is equipped with a system of information granules $S(ag)$. Using such a system, the agent ag creates a representation for all its components. The reader can find some details of such a representation, e.g., in papers by Polkowski and Skowron [20,22]. Agents are able to extract local approximate reasoning schemes called productions from such representations. Algorithmic methods for extracting such productions from data are discussed in papers by Polkowski and Skowron [19], Skowron [27], Skowron and Stepaniuk [30]. The left hand side of each production (in the simplest case) is of the form

$$\left(st_1\,(ag)\,,\left(\epsilon_1^{(1)},\cdots,\epsilon_r^{(1)}\right)\right),\cdots,\left(st_k\,(ag)\,,\left(\epsilon_1^{(k)},\cdots,\epsilon_r^{(k)}\right)\right) \tag{2}$$

and the right hand side is of the form

$$\left(st\,(ag)\,,(\epsilon_1,\cdots,\epsilon_r)\right) \tag{3}$$

for some positive integers k, r.

Such a production (see Figure 1) represents information about an operation o that can be performed by an agent ag. In the production, k denotes the arity of operation. The operation o represented by the production is transforming standard (prototype) input information granules $st_1(ag),\cdots,st_k(ag)$ into the standard (prototype) information granule $st(ag)$. Moreover, if input information granules $g_1,\cdots,g_k$ are included (close) to $st_1(ag),\cdots,st_k(ag)$ to degrees $\epsilon_j^{(1)},\cdots,\epsilon_j^{(k)}$, then the result of the operation o on information granules $g_1,\cdots,g_k$ is included (close) to the standard $st(ag)$ to a degree at least ϵ_j where $1 \leq j \leq k$ (see Figure 1). Standard (prototype) granules can be interpreted in different ways. In particular, they can correspond to concept names in natural language.

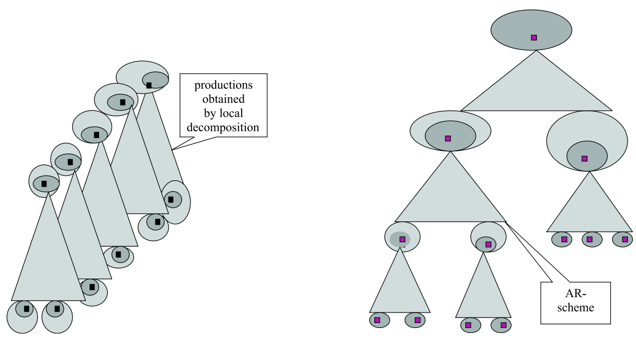

Figure 1. Productions and AR-schemes

The sample productions in Figure 1 are basic components of a reasoning system related to the agent set Ag. An important property of such productions is that they are expected to be discovered from available experimental data and background knowledge. Let us observe also that the degree structure is not necessarily restricted to positive reals from the interval $[0,1]$. The inclusion degrees can be complex information granules used to represent the degree of inclusion. It is worthwhile to mention that the productions can be also interpreted as a constructive description of some operations on fuzzy sets. The methods for such constructive description is based on rough sets and Boolean reasoning (see, e.g., Komorowski *et al* [7], Pawlak [14]).

Reasoning in multi-agent system can be represented as a construction process of information granules. This process is not restricted to internal operations performed by agents. The agents can communicate. In this process they exchange some information granules. It is important to note that any agent possesses her/his own information granule system. Hence, a granule received by one agent from another agent can not be in general understood precisely by the receiving agent. We assume that to j-th argument of any operation o performed by an agent ag there is associated an approximation space $AS(ag)^j$ (see, e.g., Skowron and Stepaniuk [29], Polkowski and Skowron [25]) making it possible to construct relevant approximations of the received information granules used next as operation arguments. The result of approximation is an information granule in the information granule system of the agent ag. In some cases, the approximation can be induced using rough set methods (see, e.g. Skowron and Stepaniuk [29]). In general, constructing information granule approximations is a complex process because, for instance, a high quality approximation of concepts can be often obtained only through dialog (including negotiations, conflict resolution, and cooperation) among agents. In this process, the approximation can be constructed gradually when dialog is progressing.

The approximation spaces are usually parameterized. It means that it is necessary to tune their parameters to find (sub-) optimal approximations of the information granules. This observation was a starting point for Rough Neurocomputing paradigm (see Skowron *et al* [28], Polkowski and Skowron [25], Pal *et al* [13], Skowron and Stepaniuk [29], Skowron [27]).

In general, the inputs of rough neurons are derived from information granules instead of real numbers and the parameterized approximation spaces correspond to real weights in the classical neuron. The result of an operation o depends on the chosen parameters of approximation spaces. The process of tuning parameters of such approximation spaces corresponds to the process of weight tuning of classical neurons.

Now, we are able to discuss one of the main concepts of our approach, i.e., approximate reasoning schemes (AR-schemes). They can be treated as some derivations obtained by using the productions of different agents. Assume for simplicity of considerations that agents are working using the same system of information granules, i.e., they do not use approximation spaces to approximate granules received from other agents. The approach can be extended to the more general case. The relevant derivations defining AR-schemes satisfy a so called robustness (or stability) condition (see Figure 1). That is, at any node of derivation the inclusion (or closeness) degree of a constructed granule (to a given standard) is higher than required by the production to which the result should be sent. This makes it possible obtain a sufficient robustness condition for the whole derivation. For details the reader is referred to papers by Polkowski and Skowron [20,22,23,24,26]. In the general case, i.e., when it is necessary to use approximation spaces, the AR-schemes can be interpreted as rough neural networks. In the case where standards are interpreted as concept names in natural language and there is given a reasoning scheme in natural language over such standards, the corresponding rough neural network represents a cluster of reasoning constructions approximately following (in other information granule systems) the reasoning given in natural language.

Let us observe that AR schemes are not classical proofs defined by means of deductive systems. They are approximate reasoning schemes discovered from data and background knowledge. The notion of classical proof is substituted by means of derivations defining AR-schemes, i.e., derivations satisfying some constraints. The deductive systems are substituted by productions systems of agents linked by approximation spaces, communication strategies and mechanism of derivation of AR-schemes. This revision of classical logical notions seems to be important for solving complex problems in multi-agent systems.

4 Conclusions and Some Directions for Further Research

We have outlined a methodology for approximate reasoning in distributed multi-agent systems. It is based on rough mereology.

Several research directions are related to the discussed AR-schemes and rough neural networks. We enclose a list of such directions together with examples of problems.

1. *Developing foundations for information granule systems.*
   Certainly, still more work is needed to develop solid foundations for synthesis and analysis of information granule systems. In particular, methods for construction of hierarchical information granule systems, and methods for representation of such systems should be developed.

2. *Algorithmic methods for inducing parameterized productions.*
Some methods have already been reported such as discovery of rough mereological connectives from data (see, e.g., Polkowski and Skowron [19]) or methods based on decomposition (see, e.g., Polkowski and Skowron [20], Skowron [27], Skowron and Stepaniuk [30], Peters *et al* [16]). However, these are only initial steps toward algorithmic methods for inducing of parameterized productions from data. One interesting problem is to determine how such productions can be extracted from data and background knowledge. A method in this direction has been proposed in a paper by Doherty *et al.* [3]

3. *Algorithmic methods for synthesis of AR-schemes.*
It was observed (see, e.g., Skowron and Polkowski [20,25]) that problems of negotiations and conflict resolutions are of great importance for synthesis of AR-schemes. The problem arises, e.g., when we are searching in a given set of agents for a granule sufficiently included or close to a given one. These agents, often working with different systems of information granules, can derive different granules and their fusion will be necessary to obtain the relevant output granule. In the fusion process, the negotiations and conflict resolutions are necessary. Much more work should be done in this direction by using the existing results on negotiations and conflict resolution. In particular, Boolean reasoning methods seem to be promising (Polkowski and Skowron [20]). Another problem is related to the size of production sets. These sets can be of large size and it is important to develop learning methods for extracting *small* candidate production sets in the process of extension of temporary derivations out of huge production sets. For solving this kind o problems methods for clustering of productions should be developed to reduce the size of production sets. Moreover, dialog and cooperation strategies between agents can help to reduce the search space for necessary extension of temporary derivations.

4. *Algorithmic methods for learning in rough neural networks.*
A basic problem in rough neural networks is related to selecting relevant approximation spaces and to parameter tuning. One can also look up to what extent the existing methods for classical neural methods can be used for learning in rough neural networks. However, it seems that new approach and methods for learning of rough neural networks should be developed to deal with real-life applications. In particular, it is due to the fact that high quality approximations of concepts can be often obtained only through dialog and negotiations processes among agents in which gradually the concept approximation is constructed. Hence, for

rough neural networks learning methods based on dialog, negotiations and conflict resolutions should be developed. In some cases, one can use directly rough set and Boolean reasoning methods (see, e.g., Skowron and Stepaniuk [29]). However, more advanced cases need new methods. In particular, hybrid methods based on rough and fuzzy approaches can bring new results (Pal and Skowron [12]).

5. *Fusion methods in rough neural neurons.*
   A basic problem in rough neurons is fusion of the inputs (information) derived from information granules. This fusion makes it possible to contribute to the construction of new granules. In the case where the granule constructed by a rough neuron consists of characteristic signal values made by relevant sensors, a step in the direction of solving the fusion problem can be found in Pawlak *et al.* [17]

6. *Adaptive methods.*
   Certainly, adaptive methods for discovery of productions, for learning of AR-schemes and rough neural networks should be developed (Koza [8]).

7. *Discovery of multi-agent systems relevant for given problems.*
   Quite often, the agents and communication methods among them are not given a priori with the problem specification and a challenge is to develop methods for discovery of relevant for given problems multi-agent system structures, in particular methods for discovery of relevant communication protocols.

8. *Construction of multi-agent systems for complex real-life problems.*
   The challenging problems are related to applying the presented methodology to real life problems like control of autonomous systems (see, e.g., www page of WITAS project [31]), web mining problems (see, e.g., Kargupta and Chan [6], Skowron [27]), sensor fusion (see, e.g., Brooks *et al* [1], Peters *et al* [15,17]) or spatial reasoning (see, e.g., Escrig [2], Düntsch [4]).

9. *Evolutionary methods.*
   For all of the above methods it is necessary to develop evolutionary searching methods for (semi-) optimal solutions (Koza [8]).

10. *Parallel algorithms.*
    The discussed problems are of high computational complexity. Parallel algorithms searching for AR-schemes and methods for their hardware implementation belong to one important research directions.

Acknowledgements. I would like to thank to Professor Lech Polkowski for the years of close cooperation on rough mereology, to Professor Jarosław Stepaniuk for the cooperation on information granule models and to Professor James F. Peters for cooperation on sensor fusion methods, insightful comments and a number of clarifying discussions on the presented paper.

The research has been supported by the State Committee for Scientific Research of the Republic of Poland (KBN) research grant 8 T11C 025 19 and by the Wallenberg Foundation grant.

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