Chapter 1

Towards Granular Multi-Agent Systems

1.1 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, 1999; Zhong *et al*, 1999; Lin, 1998, Polkowski and Skowron, 1999a, 2001a, 2001b; Skowron and Stepaniuk, 2001a; Nguyen *et al*, 2001; Skowron, 2001) as a way to achieve Computing with Words (see, e.g., Zadeh, 1996, 2001; Zadeh and Kacprzyk, 1999). 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, 2001).

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, 1991; Komorowski *et al*, 1998) and rough mereology (see, e.g., Polkowski and Skowron, 1996a, 1996b, 1998a, 1999a). 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-Neuro Computing 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 address of WITAS project in the bibliography) to problems of text data mining in the Internet (see, e.g., Skowron, 2001; Kargupta and Chan, 2001).

1.2 Information Granule Systems and Parameterized Approximation Spaces

In this section, we present a basic notion for our approach, i.e., information granule system. Any information granule system is any tuple

$$S = (G, R, Sem) \tag{1.1}$$

where

(1) G is a finite set of parameterized constructs (e.g., formulas) called information granules;

(2) R is a finite (parameterized) relational structure;
(3) Sem is a semantics of G in R.

For any information granule system two more components are given:

(1) A finite set H of granule inclusion degrees with a partial order relation $<$ which defines on H a structure used to compare the inclusion degrees; we assume that H consists of the lowest degree 0 and the largest degree 1;
(2) A binary relation $\nu_p \subseteq G \times G$ *to be a part to a degree at least* $p \in H$ between information granules from G, called *rough inclusion.* (Instead of $\nu_p(g, g')$ we also write $\nu(g, g') \geq p$.)

Components of an information granules system are parameterized. This means that we deal with parameterized formulas and a parameterized relational system. The parameters are tuned to make it possible to construct finally relevant information granules, i.e., granules satisfying a given specification or/ and some optimization criteria.

There are two kinds of computations on information granules. These are computations on information granule systems and computations on information granules in such systems, respectively. The purpose of the first type of computation is the relevant information granule systems defining parameterized approximation spaces for concept approximations used on different levels of target information granule constructions and the purpose of the second types of computation is to construct information granules over such information granule systems to obtain target information granules, e.g., satisfying a given specification (at least to a satisfactory degree).

Examples of complex 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, 1999a; Skowron and Stepaniuk, 2001a; Skowron, 2001). The most interesting class of information granules are information granules approximating concepts specified in natural language 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, 2001a). 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.

New information granules can be defined by means of operations performed on already constructed information granules. Examples of such operations are set theoretical operations (defined by propositional connectives). However, there are other operations widely used in machine learning or pattern recognition for construction of classifiers (Mitchell, 1997). These are the $Match$ and $Conflict\_res$ operations (Polkowski and Skowron, 2001a). We will discuss such operations in one of the following sections. It is worthwhile mentioning yet another important class of operations, namely, operations defined by data tables called decision tables (skowron and Stepaniuk, 2001a). From these decision tables, decision rules specifying operations can be induced. More complex operations on information granules are so called transducers (Doherty *et al*, 2002). 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 ν_p to be a part to a degree at least p has a special role. It satisfies some additional natural axioms and additionally some axioms of mereology (Polkowski and Skowron, 1996a). 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, indiscernibility 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. For details the reader is referred to the book (Pal *et al*, 2002).

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.

1.3 Granular Multi-Agent System

In this section, we outline how our approach can be used in approximate reasoning by agents (Huhns and Singh, 1998) 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 (see, e.g., Polkowski and Skowron, 1998a, 1999a). 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 (Polkowski and Skowron, 1996b; Skowron, 2001; Skowron and Stepaniuk, 2001a). The left hand side of each production (in the simplest case) is of the form

$$\left(st_1\left(ag\right),\left(\varepsilon_1^{(1)},\ldots,\varepsilon_r^{(1)}\right)\right),\ldots,\left(st_k\left(ag\right),\left(\varepsilon_1^{(k)},\ldots,\varepsilon_r^{(k)}\right)\right) \tag{1.2}$$

and the right hand side is of the form

$$\left(st\left(ag\right),\left(\varepsilon_1,\ldots,\varepsilon_r\right)\right) \tag{1.3}$$

for some positive integers k, r.

Such a production 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 $st_1(ag), \ldots, st_k(ag)$ into the standard (prototype) information granule $st(ag)$. Moreover, if input information granules $g_1, \ldots, g_k$ are included (close) to $st_1(ag), \ldots, st_k(ag)$ to degrees $\varepsilon_j^{(1)}, \ldots, \varepsilon_j^{(k)}$ at least, then the result of the operation o on information granules $g_1, \ldots, g_k$ is included (close) to the standard $st(ag)$ to a degree at least ε_j where $1 \leq j \leq r$ (see Figure 1.1). Standard (prototype) granules can be interpreted in different ways. In particular, they can correspond to concept names in natural language.

The sample productions in Figure 1.1 are basic components of a reasoning system related to the agent set Ag. An important property of such

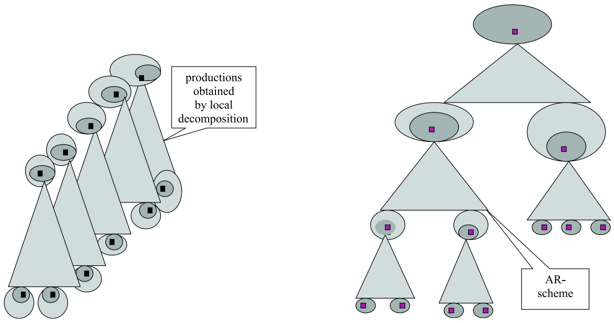

Fig. 1.1 Productions and AR-schemes

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*, 1998; Pawlak, 1991).

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, 2001; Polkowski and Skowron, 2000) 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, 2001a). 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-Neuro Computing paradigm (see Skowron *et al*, 1999; Polkowski and Skowron, 2001a, Pal *et al*, 2001, 2002; Skowron and Stepaniuk, 2001a, Skowron, 2001).

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 1.1). 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 (Polkowski and Skowron, 1998a, 1999a, 1999b, 2000, 2001b). 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.

1.4 Classifiers as Information Granules

An important class of information granules create classifiers. One can observe that sets of decision rules generated from a given decision table $DT = (U, A, d)$ can be interpreted as information granules (see, e.g., Skowron, 2001). The classifier construction from DT can be described as follows:

(1) First, one can construct granules G_j corresponding to each particular decision $j = 1, \ldots, r$ by taking a collection $\{g_{ij} : i = 1, \ldots, k_j\}$ of left hand sides of decision rules for a given decision.

(2) Let E be a set of elementary granules (e.g., defined by conjunction of descriptors) over $IS = (U, A)$. We can now consider a granule denoted by

$$Match(e, G_1, \ldots, G_r)$$

for any $e \in E$ being a collection of coefficients ε_{ij} where $\varepsilon_{ij} = 1$ if the set of objects defined by e in IS is included in the meaning of g_{ij} in IS, i.e., $Sem_{IS}(e) \subseteq Sem_{IS}(g_{ij})$; and 0, otherwise. Hence, the coefficient ε_{ij} is equal to 1 if and only if the granule e matches in IS the granule g_{ij}.

(3) Let us now denote by $Conflict\_res$ an operation (resolving conflict between decision rules recognising elementary granules) defined on granules of the form $Match(e, G_1, \ldots, G_r)$ with values in the set of possible decisions $1, \ldots, r$. Hence,

$$Conflict\_res(Match(e, G_1, \ldots, G_r))$$

is equal to the decision predicted by the classifier

$$Conflict\_res(Match(\bullet, G_1, \ldots, G_r))$$

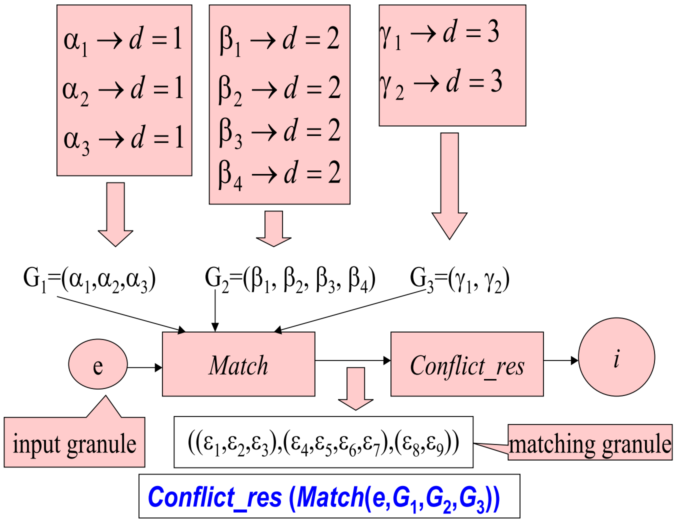

Fig. 1.2 Classifiers as Information Granules

on the input granule e.

Hence, classifiers are special cases of information granules. Parameters to be tuned are voting strategies, matching strategies of objects against rules as well as other parameters like closeness of granules in the target granule.

The classifier construction is illustrated in Fig. 1.2 where three sets of decision rules are presented for the decision values $1, 2, 3$, respectively. Hence, we have $r = 3$. In figure to omit too many indices we write α_i instead of g_{i1}, β_i instead of g_{i2}, and γ_i instead of g_{i3}, respectively. Moreover, $\varepsilon_1, \varepsilon_2, \varepsilon_3$, denote $\varepsilon_{1,1}, \varepsilon_{2,1}, \varepsilon_{3,1}$; $\varepsilon_4, \varepsilon_5, \varepsilon_6, \varepsilon_7$ denote $\varepsilon_{1,2}, \varepsilon_{2,2}, \varepsilon_{3,2}, \varepsilon_{4,2}$; and $\varepsilon_8, \varepsilon_9$ denote $\varepsilon_{1,3}, \varepsilon_{2,3}$, respectively.

The reader can now easily describe more complex classifiers by means of information granules. For example, one can consider soft instead of crisp inclusion between elementary information granules representing classified objects and the left hand sides of decision rules or soft matching between recognized objects and left hand sides of decision rules.

1.5 Approximation Spaces in Rough-Neuro Computing

In this section we would like to look more deeply on the structure of approximation spaces in the framework of information granule systems.

Such information granule systems are satisfying some conditions related to their information granules, relational structure as well as semantics. These conditions are the following ones:

(1) Semantics consists of two parts, namely relational structure R and its extension R^*.
(2) Different types of information granules can be identified: (i) object granules (denoted by x), (ii) neighborhood granules (denoted by n with subscripts), (iii) pattern granules (denoted by pat), and (iv) decision class granules (denoted by c).
(3) There are decision class granules $c_1, \ldots, c_r$ with semantics in R^* defined by a partition of object granules into r decision classes. However, only the restrictions of these collections to the object granules from R are given.
(4) For any object granule x there is a uniquely defined neighborhood granule n_x.
(5) For any class granule c there is constructed a collection granule $\{(pat, p) : \nu_p^R(pat, c)\}$ of pattern granules labeled by maximal degrees to which pat is included in c (in R).
(6) For any neighborhood granule n_x there is distinguished a collection granule $\{(pat, p) : \nu_p^R(n_x, pat)\}$ of pattern granules labeled by maximal degrees to which n_x is at least included in pat (in R).
(7) There is a class of $Classifier$ functions transforming collection granules (corresponding to a given object x) described in two previous steps into the power set of $\{1, \ldots, r\}$. One can assume object granules to be the only arguments of $Classifier$ functions if other arguments are fixed.

The classification problem is to find a $Classifier$ function defining a partition of object granules in R^* as close as possible to the partition defined by decision classes.

Any such $Classifier$ defines the lower and the upper approximations of union of decision classes c_i over $i \in I$ where I is a nonempty subset of $\{1, \ldots, r\}$ by

$$\underline{Classifier}(\{c_i\}_{i\in I}) = \{x \in \bigcup_{i\in I} c_i : \emptyset \neq Classifier(x) \subseteq I\}$$

$$\overline{Classifier}(\{c_i\}_{i\in I}) = \{x \in U^* : Classifier(x) \cap I \neq \emptyset\}.$$

The positive region of $Classifier$ is defined by

$$POS\,(Classifier) = \underline{Classifier}(\{c_1\}) \cup \ldots \cup \underline{Classifier}(\{c_r\}).$$

The closeness of the partition defined by the constructed $Classifier$ and the partition in R^* defined by decision classes can be measured, e.g., using ratio of the positive region size of $Classifier$ to the size of the object universe. The quality of $Classifier$ can be defined taking, as usual, only into account objects from $U^* - U$:

$$quality(Classifier) = \frac{card(POS\,(Classifier) \cap (U^* - U))}{card((U^* - U))}.$$

One can see that approximation spaces have many parameters to be tuned in order to construct the approximation of high quality class granules.

One more interesting issue is the direct connection between descriptions using classifier-based granules and the characterisation in terms of the Dempster-Shafer theory of evidence. This inter-connection derives from the relationships that exist between rough set theory and evidence theory as described in e.g., (Skowron and Grzymala–Busse, 1994). We may introduce belief and plausibility functions that characterise granules defined by classifiers in the following way (with previous notation):

$$Bel_{Classifier}(I) = \frac{|\{x \in U^* : Classifier(x) \subseteq I\}|}{|U^*|}$$

$$= \frac{|\{\underline{Classifier}(\{c_i\}_{i\in I})|}{|U^*|}$$

$$Pl_{Classifier}(I) = \frac{|\{x \in U^* : Classifier(x) \cap I \neq \emptyset\}|}{|U^*|}$$

$$= \frac{|\{\overline{Classifier}(\{c_i\}_{i \in I})|}{|U^*|}$$

More detailed information about the classifier quality given by $Bel_{Classifier}$ and $PL_{Classifier}$ can be used to tune $Classifier$.

1.6 Standards, Productions, and *AR*-schemes

AR-schemes have been proposed as schemes of approximate reasoning in rough-neuro computing (see, e.g., Pal *et al*, 2002; Skowron, 2001). The main idea is that the deviation of objects from some distinguished information granules, called standards or prototypes, can be controlled in appropriately tuned approximate reasoning. Several possible standard types can be chosen. Some of them are discussed in the literature (see, e.g., Pal *et al*, 2002). We propose to use standards defined by classifiers. Such standards correspond to lower approximations of decision classes or (definable parts of) boundary regions between them.

Rules for approximate reasoning, called productions, are extracted from data (for details see Skowron, 2001a). Any production has some premises and conclusion. In the considered case each premise and each conclusion consists of a triple $(classifier, standard, deviation)$. This idea in hybridization with rough-fuzzy information granules (see, e.g., Skowron, 2001a) seems to be especially interesting. The main reasons are:

- standards are values of classifiers defining approximations of cut differences and boundary regions between cuts (Skowron, 2001a),
- there is a natural linear order on such standards defined by classifiers.

To explain the meaning of productions let us consider the following example of a production with two premises:

$$\textbf{if} \ \ (C_1, stand_1, \varepsilon_1) \ \textbf{and} \ \ (C_2, stand_2, \varepsilon_2) \ \textbf{then} \ (C, stand, \varepsilon)$$

In the production classifiers C_1, C_2, C are labeled by standards $stand_1$, $stand_2$, $stand$ and deviations ε_1, ε_2, ε. The deviation ε is showing the range in which (in the considered linear order) can the deviation move the standard *stand*. The intended meaning of such production is that if the deviation of input from standards $stand_1$, $stand_2$ are respectively at most ε_1, ε_2 then the conclusion deviates from *stand* to degree at most ε.

From production extracted from data *AR*-schemes can be derived (see, e.g., Skowron, 2001a).

One more important step that can be performed in order to bring this framework closer to the idea of pure computing with words is by substituting the degrees of closeness (deviations $\varepsilon, \varepsilon_1, \varepsilon_2$ in our case) by linguistic variables. What we want to make possible is the formulation of granule production in a purely linguistic way, for example:

if similarity between C_1 and standard $stand_1$ is *high*
and similarity between C_2 and standard $stand_2$ is *low*
then similarity between C and standard *stand* is *medium*

To achieve this task we have to define partitions for the ranges of deviation as the deviation is used to measure similarity between classifier and corresponding standards. Let us consider the deviation ε for the classifier C and standard *stand*. It is quite natural to assume that the subsets of ε range are ordered linearly. Also, their layout should be fuzzy-like. We may e.g. take three such sets stating represented as $\{low, medium, high\}$. As these sets may (and in fact should) overlap, in turn we get more possible linguistic values e.g. $\{low, low\, or\, medium, medium, medium\, or\, high, high\}$.

The retrieval of proper sets for deviation ranges should be devised as an interactive data-driven process. By analysis of standards and classifiers and matching them against the training data we attempt to establish an initial layout for deviations. This layout (the choice and setting of subsets) is then verified and possibly modified in order to achieve high compliance with the underlying data sets. The choice of proper parameters for the sets of deviation ranges may be based on various known techniques in data analysis such as clustering, statistical analysis, density analysis etc.

1.7 Conclusions and Some Directions for Further Research

We have outlined a methodology for approximate reasoning in distributed multi-agent systems. Developing such methodology is very important for making progress in complex, real-life projects, like control of autonomous vehicles. Among research directions related to the discussed *AR*-schemes and rough neural networks are: (i) developing foundations for information granule systems, (ii) algorithmic methods for inducing parameterized productions and AR-schemes, (iii) algorithmic (adaptive) methods for learning in rough neural networks, in particular, fusion methods in rough neural neurons, (v) developing of multi-agent systems based on approximate reasoning for complex real-life problems, (vi) parallel algorithms searching for AR-schemes and methods for their hardware implementation.

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