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Agent Decision using Granular Computing in Traffic System

Yasser F. Hassan, Marwa Abdeen and Mustafa Fahmy

***Abstract*—**In recent years multi-agent systems have emerged as one of the interesting architectures facilitating distributed collaboration and distributed problem solving. Each node (agent) of the network might pursue its own agenda, exploit its environment, develop its own problem solving strategy and establish required communication strategies. Within each node of the network, one could encounter a diversity of problem-solving approaches. Quite commonly the agents can realize their processing at the level of information granules that is the most suitable from their local points of view. Information granules can come at various levels of granularity. Each agent could exploit a certain formalism of information granulation engaging a machinery of fuzzy sets, interval analysis, rough sets, just to name a few dominant technologies of granular computing. Having this in mind, arises a fundamental issue of forming effective interaction linkages between the agents so that they fully broadcast their findings and benefit from interacting with others.

***Keywords*—**Granular computing, Rough sets, Agents, Traffic system.

I. Introduction

THERE has been a growing interest in agent systems and their collaborative structures of multi-agent topologies. There is a great deal of methodological and algorithmic pursuits as well a wave of application-oriented developments cf. [1][3] [4][6][14][15]

Given the nature of the problem tackled by such systems where we commonly encounter nodes (agents) operating quite independently at various levels of specificity, it is very likely that the effectiveness of the overall system depends directly upon a way in which the agents collaborate and exchange their findings. In this study, we are interested in the development of schemes of interaction (communication) in multi-agent systems where exchange of findings obtained locally (at the level of individual agents) are represented as information granules [7][8][9] [10][11][12][13][16] rather than plain numeric entities (which might not be feasible or very much limited in terms of knowledge representation). There are a number of important and practically relevant issues dealing with various ways of expressing incoming evidence available to an individual agent which expresses findings in the format available to all other agents in the network.

Authors are with the Department of Mathematics and Computer Science, Faculty of Science, Alexandria University, Egypt, (corresponding author e-mail: y.fouad@alex-sci.edu.eg).

II. Granular Agents and Multi-agent Systems: Architectural and Functional Insights

In a nutshell, by a granular agent we mean a processing module which realizes processing carried out at the level of information granules (no matter what formalism of information granulation is being used there). The module comes with substantial processing capabilities, is able to carry out some learning and enhancements on a basis of locally available experimental evidence. It communicates its findings to other agents and engages into some collaborative pursuits. Each agent operates at its own level of information granularity

A general scheme of a multi-agent system can be schematically outlined in Figure 1. Note that the communication layer of each agent (which comes in the form of a certain stratum) plays a pivotal role in establishing a sound and effective collaborative interaction which becomes essential when building distributed models, forming distributed control strategies and constructing distributed classification architectures, just to name the most representative categories of tasks.

The communication scheme in which an agent accepts some result of processing offered by some other agent has to deal with an issue of representation of the incoming evidence in the setting of the information granules.

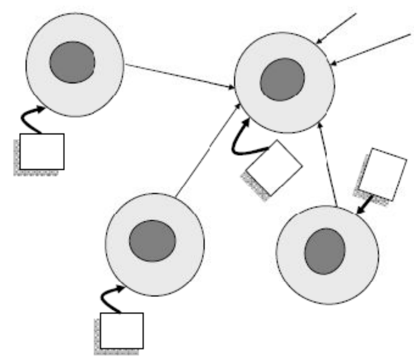

Fig. 1 An overview of a multi-agent system

III. Agent Communication: Internal Representation of Incoming Evidence

Agent accepts findings coming from other agents and expresses them in the format which is pertinent to its own processing. We can view this process as translating an input evidence X with the aid of a vocabulary of information granules {A1, A2, …, Ac} pertinent to the agent under discussion. Both X and Ai could exhibit a significant diversity in terms of their underlying formalism of information granulation. In spite of this possible diversity, some general representation guidelines can be envisioned. First, we can describe X by considering an extent to which X and Ai overlap considering that this concept is reflective of the notion of closeness (resemblance) between these two information granules. Anticipating that such a quantification might not be able to capture the entire matching process, we consider X and Ai in the context of an extent to which X is included in Ai. The predicate of inclusion itself could be gradual viz. returning a certain numeric quantification with values confined to the unit interval. Denote the results of this representation by λi and μi, respectively

$$\lambda_i = \tau(X \cap A_i) \quad (1)$$

$$\lambda_i = \tau(X \subset A_i) \quad (2)$$

where the operation τ is used here to schematically capture the realization of the operations of overlap and inclusion. Overall, the scheme realized above is graphically represented in Figure 2.

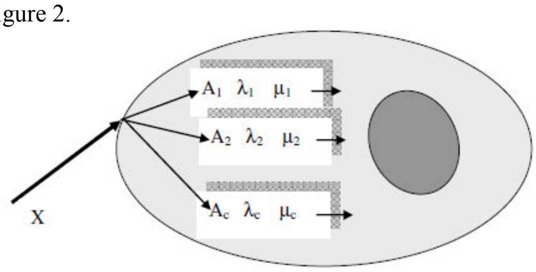

Fig. 2 The representation of incoming evidence through the operations of overlap and inclusion

IV. Communicating Granular Findings

The results of granular processing carried out within the bounds of a certain agent are next broadcasted to other agents existing in the system. To do so, the agent realizes its findings in the form of a certain information granule. Typically, for the agent we encounter a collection of information granules in some input space (say, some receptor space) and a family of information granules in the output space (e.g., a space of actions, decisions, etc.). There could be a fairly advanced web of connections between them which could be either "hardwired" or it may exhibit some level of plasticity which is essential in supporting learning capabilities. Rule-based architectures such as e.g., fuzzy rule-based models are examples of such granular architectures. The result of processing are expressed via degrees of overlap and inclusion pertaining to the individual information granules in the output space.

Referring to the way in which the input evidence has been captured, the internal processing realized by the agent returns a vector of degrees of overlap γ (=[γ_1 γ_2 … γ_m]) and degrees of inclusion □ (=[$□_1$ $□_2$ … $□_m$]) . Those need to be translated into some information granule where in this construct we engage the corresponding information granules B_j. Being more formal, we are concerned with the following inverse problem:

-for given vectors γ and □ information granules B_i and a family of constraints

$$\gamma_i = \tau(B \cap B_i) \quad \eta_i = \tau(B \subset B_i) \quad i = 1, 2, \ldots, m$$

determine B. The graphical visualization of the underlying problem is illustrated in Figure 3.

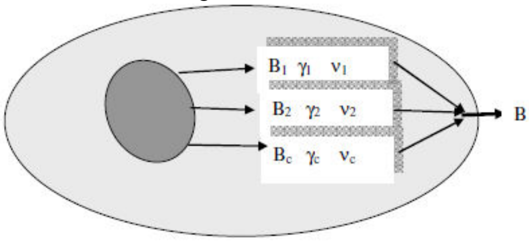

Fig. 3 The essence of communicating granular findings

V. Acceptance of Multiple Input Evidence and Its Representation

Evidence coming from different agents is expressed in terms of Ai producing the results conveyed in the format (1) – (2). As we encounter several sources of information which might be in some interaction, they need to be reconciled or aggregated [2]. Schematically we display this situation as included in Figure 4.

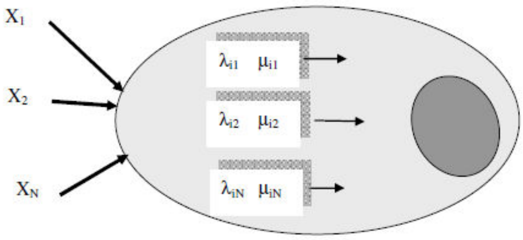

Fig. 4 Multiple source evidence and its reconciliation prior to further processing by the computing core of the agent

The crux of the construct is to reflect upon the nature of reconciled evidence which has to be taken into account when proceeding with further processing realized by the agent. Intuitively, any sound aggregation would return some quantification at the same level of granularity as the originally available evidence. For instance, from the statistical perspective, we could contemplate using average, modal or median as a meaningful descriptor of the available evidence. A more suitable approach would be the one in which we convey not only the single numeric quantity but an information granule whose role is to quantify the diversity of available sources of evidence.

In what follows, we discuss several detailed computing realizations which support the implementation of the individual communication mechanisms presented so far.

VI. The Granular Computing Implementation For Road Traffic

The traffic control systems need to respond to specified events e. g. presence of an incoming vehicle in detection area or discharging of vehicles queue. The response of traffic control system has to be as quick as possible. Thus, it is necessary to detect such events immediately after their occurrence.

The main aim of a road traffic modeling is to describe spatiotemporal characteristics of the vehicles movement. Traffic parameters are usually evaluated for a given road segment and time interval. Thus, definitions of space (road) and time granulation are necessary for data analysis using traffic models. Straightforward identification of data granules in a traffic model enables implementation of the granular computing methods for traffic parameters computations.

In many cases the data granules can be easily identified, especially for the discrete traffic models [5]. The models assume traffic lanes division into segments called agents. Each agent contains the same or different rule according to which agent states are updated in a synchronous and local manner.

The agent may be considered as a data granule in the description of a road traffic stream. In the presented study a space granulation based on the agent traffic model was proposed. Furthermore, zooming-out and zooming-in operators were defined for the proposed granulation. Zooming-out operator deals with the shift from a fine granularity to a coarse granularity. This operator discards certain details, which makes distinct road agents no longer differentiable. The zooming-in operator defines the change from a coarse granularity to a fine granularity, providing more details in traffic stream description.

The introduced granulation involves dividing the traffic lane into agents. The granule describes the segment of the traffic lane (called agent) characterized by its state.

The state of the agent defines as a value of traffic density (number of vehicles present in the agent). Thus, granulation is a set of agents {i} and configuration is a set describing current states of the agents A_L={a_(1,L),a_(2,L) ,…,a_(n(L),L) }, where L denotes level of granularity,a_(i,L) is a state of agent number i for granularity level L and n(L) is a number of agents at granularity level L.

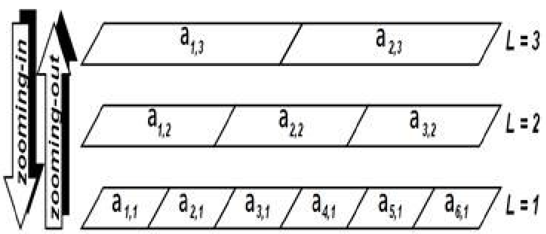

Fig. 5 Traffic lane granulation

At the lowest granularity level (L = 1) states of the agents have binary values:a_(i,1)=0 , if the agent i is empty and a_(i,1)=1 , if there is a vehicle present in the agent i. Accordingly, at higher granularity levels (L > 1) the state values of a agent denote number of vehicles present in the agent: a_(i,L)∈{0,1,…,L}.

By zooming-out operation, a subset of the cells is considered as a whole. This causes that information is lost. The zooming-out for traffic lane granulation is a mapping A_1→A_L defined by formula:

$$a_{j,L} = \sum_{i=jL-(L-1)}^{jL} a_{i,1}\,,\ j = 1, \dots, n(L),\ \ n(L) = \frac{n(1)}{L} \quad (3)$$

For granularity levels L and 2L the following equality is true:

$$a_{j,2L} = a_{2j-1,L} + a_{2j,L} \ (4)$$

Zooming in is a multi-valued mapping: $A_1 \to A_L$. By the zooming-in operation on a agents configuration AL we obtain a set of configurations {A1} that fulfill the condition given by formula (3).

The set {A1} is called the refinement of AL. E. g. refinement of the configuration A3{3,1} at third level of granularity is a set of configurations at the first level:

{A1}={{1,1,1,0,0,1},{1,1,1,0,1,0},{1,1,1,1,0,0}}.

The granulation method suggested in this section takes into account practical aspects of its application in the traffic control systems. The algorithms of traffic signals control [2][8], utilize traffic characteristics extracted for defined regions – so called detection zones. Such zones are usually situated in particular traffic lanes, at approaches of an intersection, where passing vehicles are counted, occupancy is detected or other measurements are performed (e. g. velocity).

VII. Conclusion

In this study, we elaborated on the role of effective communication mechanisms in multi-agent and showed that given various perspectives and mechanisms of computing supported individual agents there is a need to develop schemes of interaction at the level of information granules. We have formulated the main communication mechanisms by starting with conceptual aspects and offering detailed algorithmic developments.

There are several observations of a general nature that are worth spelling out:

- The communication is quantified by describing relationships between information granules in terms of their overlap and inclusion. This description emphasizes the relevance of this principle which associates well to rough sets
- Any exposure to multiple sources of evidence leads to the emergence of information granules; the principle of justifiable granularity is a compelling illustration of the way in which information granules are constructed
- The quantification of interaction between agents gives rise to information granules of higher type (say, type-2 fuzzy sets).

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