From Self-Organized Systems to Collective Problem Solving

Chevrier Vincent

LORIA UMR 7503,BP 239, F-54506 Vandoeuvre cedex
chevrier@loria.fr

Abstract. The reactive multi-agent approach emphasizes individual simplicity over the collective complexity of the task being performed. However, to apply such an approach to a problem, the components of the multi-agent system have to be designed in such a way that the society be able to fulfill its requirements with a reasonable efficiency. Inspiration from natural self-organized systems is a way to solve this conception issue.

This article illustrates two cases of how natural self-organized systems can be transposed to engineer societies of agents that collectively solve problems. It presents two original self organized models conceived in cooperation with biologists and details how transposition principles have been used to design collective problem solving systems.

1 Introduction

This article concerns the design of multi-agent systems that collectively solve a problem. It focuses on reactive systems made up of simply behaving agents with decentralized control that despite their individual simplicity are able to collectively solve problems whose complexity is beyond the scope of individuals: "'intelligence"' of the system can be envisaged as a collective property.

One of the difficulties in the design of reactive multi-agent systems is to specify simple interactions between agents and between them and their environment so as to make the society be able to fulfill its requirements with a reasonable efficiency. This difficulty is proportional to the distance between the simplicity of individuals and the complexity of the collective property.

Taking inspiration from self-organized phenomena in biology is a way to tackle this engineering problem. This article describes two original models, transposed from collective behavior in biology, to engineer societies of agents that collectively solve problems.

2 Context of the Work

Reactive multi-agent systems [1] are systems made up of simply behaving units with decentralized control. Agents are situated in a dynamic environment through

M.-P. Gleizes, A. Omicini, and F. Zambonelli (Eds.): ESAW 2004, LNAI 3451, pp. 222–230, 2005.

which they interact. They are characterized by limited (possibly no) representation of themselves, of the others and of the environment. Their behaviors are based on stimulus-response rules. Decision-making is based on limited information about the environment and on limited internal states and does not refer to explicit deliberation. The individuals do not have an explicit representation of the collective task to be achieved because of their simplicity. Therefore, the solution of the problem is a consequence of successive interactions between agents and the environment. In such systems, the regulation of activities can be achieved by self-organization.

Camazine et al [2] define self-organization as a process in which pattern at the global level emerges solely from numerous interactions among lower-lever components of the systems. Self-organized mechanisms are robust, decentralized, and can resist to perturbations. Reactive multi-agent systems can be viewed as artificial self organized ones. Their characteristics enable them to adapt dynamically their function or structure to changing conditions without external intervention. This is one of the reasons why their applications are becoming more and more attractive: from scene animation in movies [1] to optimization problems [3, 4]; or flood forecast [5]. A lot of examples of transposition of natural self-organized systems for problem solving can be found in [6].

Applying a self-organized approach to solve a given problem requires designing a system as three components: the environment, the agent behaviors and the dynamics of the whole such that the agent society is able to fulfill its requirements with a reasonable efficiency. The difficulty is proportional to the distance between the simplicity of individuals and the complexity of the collective property.

Designing such systems can be achieved by applying some guidelines or methodologies such as [7, 8, 1] or using some formal framework [9].

Another approach can be the transposition of natural self-organized systems. Social models in biology can be a source of inspiration for designing reactive multi-agent systems. Several collective phenomena exist in nature and knowledge about the organization of animal societies can be transposed into multi-agent systems as collective problem solving methods, or at least used as a metaphor in view of designing these systems.

In this article, we detail how two original self organized models built in cooperation with biologists have been transposed to collective problem solving. The first is inspired from the collective weaving in social spiders and it has been transposed to region detection in grey scale images; the second models specialization among a group of rats and it has been transposed to allocation problem.

3 Principles for Transposition

The key idea of transposition is to reuse a collective mechanism that exists in a biological self organized system. The hypothesis underlying this approach is that

[1] MASSIVE: Multiple Agent Simulation System In Virtual Environment, http://www.massivesoftware.com

the complex collective behavior exhibited by societies of animals is a response to some environmental problem faced by the society.

In our case, a self-organized system that collectively solve a problem is described as:

- An environment that is a representation of the problem (its initial conditions and constraints);
- A collective pattern that is interpreted as a solution of the problem at macro level;
- Individual behaviors at micro level that generates the pattern from the environmental constraints.

Transposition consists of adapting each of these elements found in a biological system to the context of the problem concerned, and in preserving the collective response. Concretely, it needs to encode the problem and relating it to swarm mechanism and to interpret the collective results as an exploitable solution in the problem domain:

- the pattern in problem domain is the same as in natural systems; the dynamics principles that enable it are unchanged,
- the environment is modified to model the problem,
- agents' behavior is adapted to make the link between the environment and the system dynamics
- For efficiency purposes, some new behaviors can be added.

The next sections describe two natural self organized systems and detail how we applied these transposition principles.

4 From Web Weaving to Region Detection

This section presents a collective phenomena in social spiders and its transposition to region detection in gray level images. Details about the simulation model and the problem solving can be found in [10].

4.1 Biological Considerations

Among the thousands of spider species in the world, only about fifteen species can be qualified as social spiders. *Anelosimus eximius* is a species of social spider which can be found in French Guiana. The individuals live together, share the same web and cooperate in various activities such as brood care, web weaving, hunting, ...

Despite their apparent individual simplicity, these spiders are exhibit interesting collective behavior such as web weaving. *A. eximius* are small animals (5 mm) and yet they are able to collectively build silky structures bigger than ten m^3 that always respect architectural properties whatever be the biological environment. Webs are not geometrical but twofold: an horizontal hammock and an aerial network of silk lines.

4.2 Simulation Model

We built a multi-agent model to reproduce the collective behavior of web weaving. It is a reactive model characterized by the absence of social reference and by simple individual behavioral items.

In our proposal, the environment models the natural vegetation and the web being built. It is implemented as a square grid in which each position corresponds to a stake characterized by its height. The web is constituted by the set of silk drag lines whose extremities are fixed on the top of two stakes. The set of agents is composed of spiders. They are always located on the top of a stake and behave according to two independent items:

1. a **movement** item which consists of the spider moving to a reachable stake : one of the 8 adjacent stakes or one linked by (at least) one silk drag line;
2. a **silk fixing** item which consists of the spider dropping a silk drag line on the top of the current stake.

All behavioral items are stochastic: the silk fixing is ruled by a constant probability and the movements are determined by a contextual probability distribution which depends on the silk attraction factor.

Interactions are mediated by the silk drag lines. As spiders move, they construct silky structures in the environment which offer new paths for their movements. Spiders are attracted by silk drag lines and are likely to follow a drag line instead of moving to an adjacent stake. By this way, past actions put traces in the environment which in turn favor some actions over others. This kind of coordination is called stigmergy[11].

The simulation of this activity starts with an environment empty of silk and consists, during a fixed number of cycles, of making the spiders execute successively their two behavioral items. These simulations show that the silk attraction factor plays a key role in the building: when it is too low, the silk is fixed everywhere in the available space, when it is about average, a collective web is built; and when its is too high, spiders are trapped in their own web and separate webs are built.

4.3 Transposed Model

The problem we chose was of extracting various regions from an image. Segmenting an image A consists of providing a partition of pixels (a set of regions) that share some properties: mainly they must be a connected set of pixels of homogeneous radiometric characteristics, in our case the gray level; their intersection has to be empty.

This problem shows some similarities to collective weaving. It requires an exploration of a space that has to be restricted to a subset of its elements (the pixels of the region). Furthermore, such an application enables visual assessment.

Initially, the *environment* corresponds to an image. Basically, all spiders are put in it and are in charge of detecting one region. The agents will explore the image and lay down drag lines on some pixels: those that are interesting.

Silk fixing is then a way to ensure pixel selection. Each agent is described by the same behavior and provided with parameters, which characterize the region it has to detect. Finally, the environment contains collective webs that will be interpreted to deduce regions by considering the pixels on which the web is fixed. The environment corresponds to a gray level image and is represented by a two dimensions array whose elements are the pixels of the image, the gray level correspond to height of stakes. Silk drag lines are put between pixels.

Agents are characterized by three items executed sequentially:

1. the movement item that is the same as in the simulation model;
2. the silk fixing item is now contextual: the probability to fix the silk is proportional to the distance between the gray level of the pixel and the gray level the spider has to detect
3. otherwise the 'Return to web' item that makes the spider to return to the web according to constant probability.

The last item is a new one. It is needed to ensure the spider does not build a web on pixels that share the same gray level but that are not necessarily connected and do not correspond to a region. This item restricts the exploration to pixels in the neighborhood of the already selected ones.

The interaction is still based on stigmergy as it was in the simulation model and therefore the dynamics of the system is the same as in simulation.

By gathering all the pixels an agent has woven on, we obtain a region; that is, pixels are put together without a consideration of the number of times the agent has woven on them. By applying a threshold on the number of fixed drag lines, we can restrict the pixels that belong to a region.

4.4 Comments

All the ingredients for detecting various regions are available in our approach if the required parameters are well assessed. It is also possible to detect simultaneously several regions by gathering agents with the same initial parameters into groups. However, a drawback has to be solved in order to produce a real application: parameters have to be empirically adjusted and we have to determine the number of agents and their initial position.

5 From Specialization to Task Allocation

This part presents a reactive model that enables the reproduction of the specialization that is observed in groups of rats confronted by an increasing difficulty to reach food. Details of the simulation model and especially its adaptive properties can be found in [12].

5.1 Biological Considerations

The self-organized phenomenon in biology, modeled in this section, is social differentiation in a group of rats in a diving-for-food situation. This situation is a complex social task in which, for a group of 6 rats, the food accessibility is made difficult by progressive immersion in water of the only path of access to the food source (the feeder). This experimental schedule leads to the emergence of a specialization in the group of rats, in two stable profiles: supplier and non-carrier rat. The non-carrier (a) animals never dive, but get food only by stealing it from the suppliers by fighting for it. The supplier (b) rats dive, bring the food back to the cage and cannot defend the food they carried. So, putting groups of rats in a situation in which they have an increasing difficulty to reach food, leads to the emergence of a social structure.

5.2 Simulation Model: Hamelin

We propose a reactive model to reproduce this phenomenon in which agents don't have cognitive abilities (even if rats do have).

In this model, the environment corresponds to the feeder and the water-submerged path.

All rats are reactive agents characterized by 4 internal states and 3 behavioral items. The states are:

- The strength of the agent s, which stands for its ability to win when it is involved in a fight.
- Its anxiety (or fear) for the water θ corresponding to its reluctance to dive into water.
- Its hunger h which embodies the need for food and constitutes the motivation for the agent.
- The possessed amount of food $Food$ implemented as the size of the owned pellet.

The behavior of the agent is a combination of items: to dive, to attack (and fight) and to eat. Each of them is stochastically triggered or carried out. The associated probability is computed according to the internal state of the rat and biological observations.

The dive action is modeled as a response threshold [13]. Fight is modeled as a dominance relationship [14]. We reused these existing models and coupled them. When the action is effectively performed a reinforcement alters the internal state of the agents allowing them to learn and modify their behaviors according to their past actions.

This model prove to be sufficient to reproduce the collective phenomenon and to exhibit adaptive properties both at collective and individual levels.

5.3 Transposed Model

The general framework to transpose the Hamelin model consists of a dynamic task allocation problem among machines, connected together in a network. Initially the tasks are available on a central server. The machines can acquire the data by accessing directly the server or by 'attacking' each other. As some policies are put on the server in order to avoid crashes, some agents can easily access the server while others not so easily(and the more an agent can connect, the easier it is for it to access).

We use this toy example to assess the transposition principles we expressed in case of the Hamelin model; and in that context proposed a first transposed model. The expected pattern is a specialization of agents according to their access mode to the server.

The *environment* corresponds to the server and the network between machines. Environment is characterized by such features as the maximum number of connections, the data size, etc.

The machines are the *agents* of the system. Their internal states are transposed as follow:

– The strength has the same meaning as in the simulation model.
– The anxiety characterizes the difficulty to connect to the server.
– The hunger corresponds to the available space to store data.
– The amount of food represents the data stored.

The transposition of behavioral items was made as follow. Diving corresponds to accessing directly the data on the server, fighting is unchanged and is ruled by the same principles as in simulation. Eating is now associated to the processing of the data.

The *dynamics* of the system is, as in the simulation model, based on the coupling of the diving and fighting items.

We ran experiments with this transposed model and the results are encouraging. They show that specialization appears in the set of machines and that there is a gain in processing time when using the specialization model with respect to a system with no specialization.

However, they are obtained on specific instances of problem and we need more experiments to have a better assessment of the transposed model, especially, by applying the model to a wider range of problem instances.

6 Concluding Remarks

This article described how self-organized models in biology can be transposed to engineer societies of agents that collectively solve problems.

It focused on two original self organized models established in cooperation with biologists and detailed how transposition principles have been instantiated in those cases.

The first model concerned the web weaving activity of social spiders. This model extends the repertoire of biologically inspired systems by providing a new collective mechanism of stigmergy based on silk. The main difference with existing mechanisms is that there is the possibility in the spider model to integrate non-local information in local processing. The second model deals with social differentiation in group of rats. It proposes a reactive model with no social cognition nor global stimulus that produces a social structure.

This article also pointed out that the development and analysis of these transposed system requires experiments[15, 16] to find the relevant value of parameters that enable efficient solving of the problem. This is the reason why our current direction of work is the development of a platform for the analysis of artificial self-organized systems[17].

Acknowledgment

The author would like to acknowledge Christine Bourjot for her valuable comments on this text.

Part of the work presented here was partially funded by the Région Lorraine in the Pôle de Recherche Scientifique et Technologique "Intelligence Logicielle".

References

1. Parunak, H.V.D.: Go to the ant. Engineering Principles from Natural Agent Systems. Annals of Operations Research **5** (1997) 69–101
2. Camazine, S., Deneubourg, J.L., Franks, N., Sneyd, J., Theraulaz, G., Bonabeau, E.: Self-Organization in Biological Systems. Princeton University Press. (2001)
3. Bonabeau, E., Dorigo, M., Theraulaz, G.: Swarm Intelligence. Oxford University Press. (1999)
4. Dury, A., Le Ber, F., Chevrier, V.: A reactive approach for solving constraint satisfaction problems. In: Proceedings of the 5th International Workshop on Intelligent Agents V, Agent Theories, Architectures, and Languages, LNAI 1555, Springer-Verlag (1999) 397–412
5. Georgé, J.P., Gleizes, M.P., Glize, P., Regis, C.: Real-time simulation for flood forecast: an adaptive multi-agent system S. In: Proceedings of the AISB'03 symposium on Adaptive Agents and Multi-Agent Systems, University of Wales, Aberystwyth, 7-11 April. (2003)
6. Di Marzo Serugendo, G., Foukia, N., Hassas, S., Karageorgos, A., Mostéfaoui, S.K., Rana, O.F., Ulieru, M., Valckenaers, P., van Aart, C.: Self-organization: paradigms and applications. In: Engineering Self-Organising Systems: Nature-Inspired Approaches to Software Engineering LNAI 2977, Springer-Verlag (2004) 1 – 19
7. Bernon, C., Camps, V., Gleizes, M.P., Picard, G.: Designing agents behaviours within the framework of ADELFE methodology. In: Proceedings of Engineering Societies in the Agents World, ESAW 03, LNAI 3071, Springer Verlag (2004) 311 – 32
8. Muller, J.P.: Emergence of collective behavior and problem solving. In: Proceedings of Engineering Societies in the Agents World, ESAW 03, LNAI 3071., Springer Verlag (2004) 1 – 21
9. Kazadi, S., Chung, M., Lee, B., Cho, R.: On the dynamics of puck clustering systems. Robotics and Autonomous Systems **46(1)** (2004) 1–27
10. Bourjot, C., Chevrier, V., Thomas, V.: A new swarm mechanism based on social spiders colonies : from web weaving to region detection. Web Intelligence and Agent Systems : An International Journal - WIAS **1** (2003) 47–64

11. Grassé, P.P.: La reconstruction du nid et les coordinations interindividuelles chez bellicositermes natalensis et cubitermes sp., la théorie de la stigmergie : essais d'interprétation du comportement des termites constructeurs. Ins. Soc. **6** (1959) 41–84
12. Thomas, V., Bourjot, C., Chevrier, V., Desor, D.: Hamelin: A model for collective adaptation based on internal stimuli. In: From animals to animats 8 - Eighth International Conference on the Simulation of Adaptive Behaviour - SAB'04, Los Angeles, USA. (2004) 425–434
13. Theraulaz, G., Bonabeau, E., Deneubourg, J.L.: Response threshold reinforcement and division of labour in insect societies. Proc. Roy. Soc. London B 265 (1998) 327–332
14. Hemelrijk, C.K.: Dominance interactions, spatial dynamics and emergent reciprocity in a virtual world. In: Proceedings of the fourth international conference on simulation of adaptive behavior. (1996) 545–552
15. Edmonds, B.: Using the experimental method to produce reliable self-organised systems. In: Proceedings of the 2nd International Workshop on Engineering Self-Organising Applications (ESOA 2004) at 3rd AAMAS, New York. (2004)
16. Edmonds, B., Bryson, J.: The insufficiency of formal design methods the necessity of an experimental approach for the understanding and control of complex mas. In: Proceedings of the 3rd Internation Joint Conference on Autonomous Agents and Multi Agent Systems (AAMAS'04), New York, ACM (2004) 936–943
17. Bourjot, C., Chevrier, V.: A platform for the analysis of artificial self-organized systems. In: Proceedings of Advances in Intelligent Systems - Theory and Applications AISTA 2004. Luxembourg. (2004)