SOCIAL INSECTS AS THE MULTI-AGENT SYSTEMS

1) General introduction into application domain

Colonies of social insects – ants, bees, wasps, and termites – can be viewed as highly parallel, distributed systems for solving the problems intrinsic to colony survival and reproduction. Colonies are highly parallel in that large numbers of individual colony members are interchangeable: the system is composed of redundant individuals behav- ing according to a stereotyped set of rules. Although the workers of many species exhibit a behavioral flexibility that allows them to perform more than one job in the course of their lives, all of the individuals engaged in any one job, such as foraging for food or feeding the brood, seem to follow essentially the same set of behavioral rules. Further- more, all workers follow the same set of rules governing when they perform a given job, and when they switch to another one. In those species in which workers are morphologi- cally and behaviorally specialized to the performance of a single task, workers of a given specialization behave in the same way, making the colony as a whole highly parallel. Colonies are distributed in that they function without hierarchical organization. Information is not integrated in a command center that directs the colony's activities. Instead, information remains dispersed throughout the colony, distributed across all workers and their immediate environments. Individual workers respond to local environmental cues and to interactions with each other – not to signals from central command – and this distributed process achieves the colony's coordination and execution of work. (Hirsh 2001, p.1)

Multiagent systems used in the AI community are typically knowledge based, consisting of heterogeneous unembodied agents carrying out explicitly assigned tasks, and communicating via symbols. In contrast, many extremely competent natural collective systems of multiple agents (e.g. social insects) are not knowledge based, and are predominantly homogeneous and embodied; agents have no explicit task assignment, and do not communicate symbolically. A common method of control used in such collective systems is stigmergy, the production of a certain behaviour in agents as a consequence of the effects produced in the local environment by previous behaviour. The stigmergy is used successfully in a collective robot system modelled on ants. (O.E Holland 2016, p.57)

2) Research papers about your application domain and the multi-agent systems

2.1) Concept of stigmergy

The subject of stigmergy is best approached by considering the ways in which embodied agents (call them robots) can interact. At any instant, a robot can affect another robot directly and immediately in three main ways:

- by affecting the other robot's sensors: for example, by being sensed as an obstacle
- by applying force to the other robot, actively or passively (possibly through the environment): for example, by colliding with it
- by communicating with the other robot

A robot can also affect another robot indirectly, and with a delay, by changing a part of the environment which the other robot may subsequently encounter. The changes may influence the other robot in the following ways when it arrives at the altered location:

¯ by affecting its sensors, and consequently its choice of behaviour

¯ by altering the effect of its actions (for example, if the environmental change is the laying down of a film of oil, the effect may be to cause the robot to lose traction and therefore to follow a different trajectory than it would have without the change)

The effects of these indirect interactions constitute stigmergy (Grass6, 1959). Active stigmergy (Holland Beckers 1996) occurs when the effect is to influence the choice of behaviour of the second robot through sensory input.

(O.E Holland 2016, p.58)

2.2) Swarm Intelligence and wasp behavior

Swarm Intelligence,

a term coined by Beni and Wang in 1989, describes the collective emergent behavior resulting from decentralized and self-organized systems. Its roots are the studies of self-organized social insects, such as ants, wasps or termites. In a colony of such insects, there is no central entity or mechanism controlling or even defining objectives, yet these creatures with strict sensory and cognitive limitations manage to perform complex tasks such as food foraging, brood clustering, nest maintenance and nest construction. As a result, the mechanisms underlying their complex behavior as a whole became subject of great interest and study, resulting in a great wealth of models inspired by Nature.

The particular relevance of such models for our work is based from the fact that most problems dealt within a colony, particularly in the case of wasps, are analogous to the scheduling and logistic engineering problems raised when considering unit production for real-time strategy games.

Wasp Behavior,

From their studies of the wasps, Theraulaz and colleagues created a model of dynamic task allocation that successfully emulates the self-organized behavior of wasps.

The model consists in a wasp hive in which there are two possible tasks: foraging and brood care. Individuals decide which task to do according to their response threshold and stimulus emitted by the brood. The system has the following main features:

– Tasks have the capacity of emitting stimuli that affects the individuals task selection decisions (stimulus);

– Individuals possess response thresholds that represent their predisposition to perform certain tasks (response thresholds);

– Each individual has a force that is taken into account during dominance contests to determine the winner. Dominance contests form a hierarchy within the colony (force);

– When an individual performs a task, the respective response threshold is decreased while the other response thresholds associated with other tasks are increased. This means that the more an individual performs a task the more likely he is to do it again, creating task specialists in the society (specialization).

These four features guide the model towards both performance and flexibility. The capacity of specialization of each individual leads self-organization towards optimal performance, allowing the whole work force to dynamically adapt to the constantly changing external environment as well as the intrinsic needs of the colony resulting, for instance, from loss of individual, etc. Such characteristics are of importance when considering the production scheduling in RTS games. (Antunes, Pinto 2011, p.72)

2.3) The computationality complete ant colony

When McCulloch and Pitts introduced neural networks as models for studying the central nervous system, their first analytical step was to investigate the máximum potential sophistication of information processing by such networks. They were able to show that neural networks are, in principle, computationally complete. That is, such a network can be constructed to solve any problem accessible to a finite digital computer. Lachmann and Sella have recently applied the same methodology to information processing in social insects, addressing the following question. Is the parallel distributed organization of an ant colony capable, in principle, of processing information with the same sophistication as any computer, or is the ant colony limited in its maximum potential sophistication?

The specific aspect of colony organization investigated by Lachmann and Sella is task allocation, the colony's distribution of workers to different jobs in dynamic response to the shifting state of the environment and the needs of the colony. For a schematic mathematical depiction of this process, they adopt a generalization of a model originally set forth by Pacala.

Based upon this very schematic description of colony dynamics, Lachmann and Sella build a constructive proof of computational completeness.

(Hirsh 2001, p.3)

2.4) Foraging concept

Foraging consists in searching and collecting items in an environment and move them to storage point(s). Ostergaard et al. (2001) define the foraging as a two-step task known as searching and homing, where robots have to find as quick as posible items in the environment and return them to a goal region. While Winfield (2009) defines the foraging with a four state machine (searching, grabbing, homing and depositing), many variations can be derived from this basic point of view to define some special cases like dealing with energy limitations. However, most of the literature that works on foraging consider the two tasks searching and homing, since the two others are more related to robot design. As scalability is an important factor in nowadays applications, we believe that cooperation (over communication) is an important factor to consider in the conception of a foraging system. Therefore, we define foraging as the conjunction of the two tasks (searching and homing) with consideration of communication:
- Searching Robots inspect the search space for targets (or food). While the random walk is the most adopted strategy of search in unknown environments, several other search strategies can be used according to the environment structure and the amount of information provided to robots.
- Homing Robots have to return home with the collected food by using prior information and/or onboard sensors, following a pheromone trail or even exploiting specific tools (e.g. compass).
- Communication The cooperation between robots either in searching or in homing tasks can improve the group performance by accelerating the search when avoiding already visited regions or in homing when exploiting together found food. In several other problems

cooperation can be achieved without communication, as in Feinerman et al. (2012). However, communication routine is necessary to share and receive information between agents in the swarm directly via transmitting messages or indirectly via the environment.
(Zedadra et al. Complex Adapts Syst Model 2017, p.3)

<u>3) Projects or research teams which are interested in the same application domain and their results</u>

3.1) RTS games. WAIST: R-Wasp (Warcraft III)

Based on the properties of the natural model created by Theraulaz and colleagues, Cicirello and colleagues proposed an algorithm for dynamic task allocation that later was adapted to Morley's factory problem from General Motors, denominated as Routing-Wasp or R-Wasp.
(Cicirello 2001, p.473) (Morley 1996, p.53)

WAIST, an algorithm inspired in the social intelligence of wasps for scheduling unit production in real-time strategy games and evaluated its performance with a set of five scenario variants developed as a modification of the game Warcraft III The Frozen Throne. The variants accounted for factors such as: the rate and distribution of the requests issued over the scenario, the number of available factories, and environment changes such as the destruction and construction of factories during the scenario.
The performance of WAIST in each scenario variants was compared to three other approaches: random attribution; distance-based attribution, and global attribution, which considers all the information available at the moment from the game environment.
Overall, WAIST performed comparably to the global attribution algorithm (and better than the other), an encouraging result considering WAIST is a decentralized algorithm that relies on local information while the latter has full global knowledge. As such, we believe WAIST to be an efficient and reliable alternative for real time scheduling in real time strategy games.
While WAIST experiences some limitations when dealing with low amounts of requests, it demonstrated good performance in situations of higher congestion of requests, and when setting up from one production type to another has a cost that cannot be ignored.
(Antunes, Pinto 2011, p.81)

3.2) A robotic model of a social insect system "Cementeries"

In order to study the possible use of social insect control techniques in collective robotics, a system was designed around a very simple ant behaviour - corpse gathering. The dead ants from a colony are sometimes found placed together in heaps ('cemeteries') some distance from the nest. The development of these heaps was studied by Deneubourg and his colleagues (Deneubourg et al. 1991) who showered 4000 dead ants onto a nest, and recorded the outcome. Ants from the nest would occasionally pick up a dead ant, carry it for a while, apparently aimlessly, and then drop it, apparently at random. However, after a few hours, the dead ants were seen to be arranged in many small piles. As time went by, these small piles were succeeded by a smaller number of much larger piles, and eventually the characteristic cemetery arrangement appeared. In a computer simulation, Deneubourg showed that the qualitative aspects of this sequence of events could be reproduced by a very simple model in which individual ants wandered at random, picking up dead ants with a probability that decreased, and dropping them with a probability that increased, with the sensed local density of dead ants. The stigmergic links were thus the change in the probability of picking up or dropping a dead ant as a function of the number of dead ants having been picked up or dropped in that area previously.
(O.E Holland 2016, p.59)

4)Research directions into the future

Even if there exists a collection of foraging algorithms evaluated with real robots, the need for using them on real applications or outdoor environments is important to validate them. The most challenging issue right now, is how to implement real foraging robots. Future directions or issues might include:

- The design of the robot should inspire from the real individuals (e.g. ants). If we imitate the collective intelligent behavior of ants for example, we need to deeply study the design of ants in order to produce an Ant-like-Robot (material, shape, actuator,...) that could produce the same behavior in real world.
- For Brooks (Brooks 1990), interactions over the real world are more difficult tan reasoning in the symbolic world. Thus, it is time to start deploying the proposed foraging robots in real world in order to test their applicability and efficiency.
- In designing micro-robots, energy and transport efficiency are of paramount importance.
- Decentralized lightweight data mining algorithms could be fruitfully exploited to support the MAF system.

(Zedadra et al. Complex Adapts Syst Model 2017, p.21)

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