Performances Analysis in Collective Systems

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1. Introduction

The multi-agent approach has been used for several years to study complex systems and to give new techniques of resolution both in artificial life to simulate and to analyse insect societies [2][4][5][6], and in robotics to solve problems such as the collecting or the sorting out of elements in a dynamical environment [1][3][5]. The reactive agent architecture is based on a simple process of action-reaction often extended with capabilities of adaptation and learning.

However, studies that have been carried out on these systems suffer from a lack of formalism, in particular when performances are evaluated. The experimental approach, based on a direct observation (of real or simulated systems) does not allow for quantitative analysis. Mathematical models have been proposed to analyse the behaviour of action-selection [3][7], agent specialization [6] and collective work among insects [2][4][5]. But these studies give better results on individual agents behaviour than on global collective performances.

The aim of this study is to propose a method to compute the global performances of collective systems given the behaviour of agents, the environment and the kind of events that can happen.

Difficulties lie in the fact that these processes contain a lot random events. Therefore, the problem consists in modelling the system with the right level of description. Thus we will not study issues that are based on emerging phenomenae because, as M. Mataric [8] emphasizes it, it is impossible to determine them without testing the system.

2. Principle

The performance of a collective system is assessed as a function of time, because duration is an essential characteristic of the efficiency of an artificial system which carries out specific tasks. As events are unpredictable, duration is computed by means of statistics. We assume the following hypotheses which simplify the modelling of agents: agents are independent (the problem of avoidance is neglected) and move with a steady speed, time is considered as discrete, agents behaviour is known to us (algorithms), agents consume energy, tasks consists in searching and moving samples, and tasks can be performed independently.

Because difficulties on modelling depend directly on the complexity of the task, we will start by modelling *simple and representative situations* first and then move on to more general, and therefore complex, situations.

If the origin location and the destination location of the task are known, computation of the average working time is easily deduced from the behaviour algorithms of the agents (the average number of elementary movements).

Phases of exploration are more tricky to evaluate. During such phases, agents perform simple research algorithms analysing their nearby environment. The first stage consist in choosing *an elementary process representing the behaviour of an agent trying to achieve an exploration task ($task_i$).* If the average duration of the elementary process as well as the probability of success for $task_i$ are known, we can deduce the average time to get to success.

More formally, let us note $\mathbf{P_0}$ the elementary process, $\mathbf{T_0}$ the average duration of P_0 (computed from the behaviour algorithms), $\mathbf{p_0}$ the probability that the searched-object was discovered during each process P_0 and $\mathbf{T_{be}}$ the average duration of P_0 when the element is detected (route base-element).

P_0 is a binomial process. If n_s is the rank of success, an isolated agent discovers the element with the approximate $(n_s - 1)T_0 + T_{be}$ duration.

The average duration of exploration is equal to the mathematical expectation :

$$\sum_{N=1}^{\infty}((N-1).T_0+T_{be})(1-p_0)^{(N-1)}.p_0$$

$$Thus,\ we\ obtain\quad \left(\frac{1}{p_0}-1\right)T_0+T_{be} \qquad (1)$$

Now we compute the probability $p_{0(N)}$ for a set of N agents to find a sample during P_0. Agents are independent and try to perform the same task. The probability that no agent find a sample is $(1-p_0)^N$. As a consequence, the probability for one of them to succeed is $p_{0(N)} = 1-(1-p_0)^N$

To get the average time of search for N agents, we use formula (1) with $p_{0(N)}$ instead of p_0.

If the environment contains several elements, we can apply the formula (1) with the new probability p_0 which is the average value of $\frac{S(w)}{S}$ for all possible paths (S is the surface of the environment and $S(w)$ is the detected surface during the process P_0 for the path w).

3. Collector robots

We have applied this principle for the collecting robots example. This classical problem can be stated as follows : we suppose there are several mobile robots starting from a fixed base and exploring an unknown space. Their goal is to discover and to transport samples of ore back to the base. The problem statement can be extended by substituting the phase of discovery with more general processes.

In the studied issue the environment holds only one element of ore, searched by N agents which work either independently or cooperatively (teams of agents) [9][10]. We have determined the average duration of the transportation, recruitment and research tasks (T_0, T_{be}) where P_0 *is an exploratory sweep.*

With a single sample in the environment it is easy to compute the probability to find it with one agent during a P_0 process (see [10]). We have obtained complex formulae which depend on three kind of parameters : agent capacity, cardinality and environment definitions. We have studied the influence of each parameter by plotting different curves. Thus we have demonstrated how the most efficient technique depends on the initial parameters values.

4. Empirical results

We have decided to compare our theoretical results with simulated values to evaluate the quality of the model. Thus, we have simulated the collector robots issue and obtained an average duration from a set of simulations. Results show a short difference between theoretical values and empirical results (error 2%). But there are significative differences when we have been driven to make approximations in the probability calculations (error 20%).

5. Conclusion

Our method permits an assessment of the average duration of simple reactive MAS, and it is confirmed by experimental measures. We have tried to extend this model to more complex issues such as the presence of many obstacles, the loss of agents, the presence of several samples and the communication between agents. In general, it is mathematicaly difficult to evaluate the probability of events and the possible behaviours. However, we think that our approach is a promising stage to mathematically model more realistic collective systems.

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