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MODEL AND SIMULATION OF MULTI-LEVEL EMERGENCE

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Abstract

This work propose a model of multiple emergence phenomenon, which is based on a reactive multi-agent system. Each agent is defined as a minimal living-like entitie exchanging information for aggregation with others. This model is evaluated from several simulations implemented on the MadKit platform. Thus we can show and analyze different interesting properties of emergent structures such as robustness and adaptability. Finally, this study is positioned in a larger objective of understanding and designing artificial and natural complex systems.

Key-words: Emergence, Multi-Agent Systems, Reactive Agents, Simulation, Autopoiesis.

1. INTRODUCTION

The understanding of emergence is capital in the study of complex systems whether they are biological, physical, informational, software, etc. In artificial ones this phenomenon must be controlled to better design intelligent systems.

In nature, emergence exists generally in the form of *multi-level emergent structures* (also called multiple emergence) [1]. It is the production of emergence in a system composed of subsystems which are themselves the product of passed emergences.

We propose a computer model of this type of emergence based on Artificial Life approach [2], [3]. It consists in defining agents as live-based forms (architectures and organization). For example, ant societies have been copied to build self-organized systems [4].

Several works have been done to define emergent phenomena (as mathematical [5], [6] or biological [7] models). In this paper we adopt a multi-agent definition, which covers different domains (such as philosophy, cognitive sciences and economy). It is a positive, temporal and constructive definition of emergence (from [5] and [8]).

A phenomenon is said *emergent* if:
- there is a set of agents in interaction via the environment whose dynamics is not expressed in the terms of the phenomenon to produce but in a vocabulary or a theory *D*.
- these interactions produce a global phenomenon which can be a *stable structure*, a *trace of execution* or any static or dynamic invariant.
- this global phenomenon is observed either by an external observer or by the agents, in terms distinct of the subjacent dynamic, i.e. in a vocabulary or a theory ***D'***.

Note this definition implies that the global phenomenon can be *observed* only through:
- a *trace* in the *environment* for example
- an *interpretation* in a vocabulary D**'** distinct from D.

When the general dynamic of the system is not the juxtaposition of each individual dynamics but a retroaction of the whole to all parts, it is the *emergence in the strong sense*.

This paper aims to explore the functioning of emergence by defining a reactive multi-agent system. Then we propose a MAS model, based on minimal entities and minimal interactions that can ensure:
- the multiple emergence of complex structures,
- the resistance and the adaptation to perturbations (i.e. an autopoïetic system),
- a clear characterization of the interactions.

Section 2 presents the mathematical model of multiple emergence. In section 3 the multi-agent simulation of this model is briefly presented. Several simulations of the model are developed in section 4 and show different interesting properties. Finally we give some perspectives and a conclusion on this work in section 5.

2. MODEL

The mathematical model of multiple emergence is a Multi-Agent System (MAS) model [9]. Consider a set of agents evolving and interacting in a discrete environment with a discrete time.

2.1 Environment and Information

The environment is a discrete rectangular surface representing a torric world. The environment acts primarily as an interaction gradient between agents. Each square (the space unit) contains data about quantity and type of information emitted by the agents.

The management of information is based on a biological approach (as insect pheromones). The agents emit and perceive information called "Interaction Pheromones" which are propagated in the environment via a ***diffusion*** model. The Pheromone quantity in a square fluctuates each turn according to the import of information from the 8-neighbors squares, the export of information towards these squares, the evaporation of the Pheromones and the drop of information on the square by the agents (see figure 1).

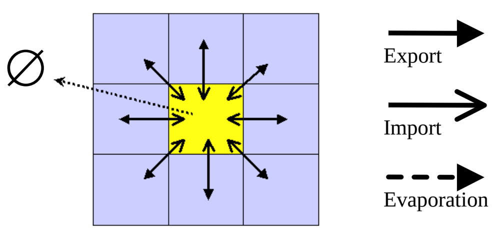

Figure 1 : Diffusion Model

The diffusion model has been chosen to conserve a permanent dynamic in the system in order to create a favorable framework to produce emergence[10].

An Interaction Pheromone has three properties: its type, a diffusion coefficient and an evaporation rate. Agents can emit Pheromones taken from three groups labeled: **Presence (*Pr*), Attractive (*Att*), Repulsive (*Rep*)**.

- The Presence Pheromones gives information about the population of agents in the environment,
- The Attractive and Repulsive Pheromones can respectively attract and repulse agents.

These groups of Pheromones were chosen to provide the agents an interaction framework allowing formations of emergent structures by **aggregation**.

The type of each possible Pheromone is the concatenation of his group label with an integer (the Pheromone level), which represents the state of the information emitter (e.g. Rep_2). We will present the emitter agent state later.

The two other Pheromones properties represent the diffusion model parameters in connection with export, import and evaporation of Pheromones in the environment. The diffusion coefficient is constant for any Pheromone.

The evaporation rate depends on the Pheromone level. This rate can be calculated recursively from the initial level of Pheromones (level 0) with a function called $\boldsymbol{f}$.

Let be Rep_i a Presence Pheromone:

$$Rep_{i+1} = f\left(Rep_i\right) \quad \text{and} \quad Rep_i = f^{-1}\left(Rep_{i+1}\right)$$

2.2 Agents

Agents are reactive entities that interact via emission and perception of Pheromones in the environment. The agents behavior consists in 4 distinct stages: **Perception, Emission, Mutation** and **Move**.

Each agent has a state which is an integer equal to or higher than 0. This state is fundamental for the multi-level emergence production, because it modifies the agent perception and emission abilities and limits interactions between specific agents.

Every turn each agent only perceives some types of Pheromones depending on its current state. In the same way, each agent only emits certain types of Pheromones. This is represented by an "exchange table" in the figure below:

$$a_i \overset{Behave}{\Longleftarrow\!\!\Longrightarrow} \begin{pmatrix} Pr_{i-1} & \varnothing & \varnothing & \varnothing & \varnothing & \varnothing \\ Pr_i & \varnothing & \varnothing & Pr_i & Att_i & Rep_i \\ Pr_{i+1} & Att_{i+1} & Rep_{i+1} & \varnothing & \varnothing & \varnothing \end{pmatrix}$$

Figure 2 : Emission and Perception of information for an i-state agent

Explanation: An agent that is in a state ***i*** **perceives** only attractive and repulsive Pheromones emitted by agents in a state ***i+1***, so it is only attracted or repulsed by directly higher agents. It also **perceives** *Presence Pheromones* emitted by agents in state ***i-1***, ***i*** and ***i+1*** (see Pr indices).

At the same time, an agent **emits** continually Pheromones of each group (***Pr***, ***Att***, ***Rep***) with a level equal to its state. This behavior outlines the most important characteristic of the implemented system: the organization is structured by interactions between agents in adjacent states.

The **mutation** ability allows an agent to change its state to a higher or lower state. This mechanism depends on the perception of Presence Pheromones emitted by other agents. If an ***i***-state agent (agent in state ***i***) is surrounded by numerous ***i***-state agents and by few ***i+1***-state agents, it tries to switch its state from ***i*** to ***i+1***. Conversely, if there are not enough ***i-1***-state agents, it tries to switch for the lower state. Agents manage this mechanism with predetermined coefficents.

The emergence of new structures is based on the density of agents in close states. An agent tries "unconsciously" to switch its state, hence increasing the probability to produce emergence.

The last behavior is rather simple. Any agent **moves** once each turn towards one of the 8-neighbors squares. To do so, it chooses the most attractive square which is the one with the highest quantity of attractive Pheromone it perceives. Otherwise it avoids repulsive squares which are the ones where the quantity of repulsive Pheromone is higher than the quantity of attractive Pheromone.

Moreover, slight modifications have been made to this phase to ensure that the agents are continuously moving. If there were no movement, agents could not interact and aggregate. Thus emergence could not happen.

We proved [11] that this behavior is recursive. In fact, the mutation stage is an application **H** of the recursive function ***f*** on all possible Pheromones perceived and emitted by agents. The moving phase is the same for every agent of the system. Thus we can write:

Let α_i be an ***i***-agent,

$$a_{i+1} = H(a_i) \quad \text{and} \quad a_i = H^{-1}(a_{i+1})$$

3. EXPERIMENTATIONS

3.1 Platform and model adaptation

The multi-level emergence model has been implemented on the MAS platform Madkit [12], [13] with the TurtleKit plug in. TurtleKit is a simulation engine inspired by StarLogo software which provides tools for exploiting multi-agent simulations based on agents who evolve in a discretized world. TurtleKit also provides tools for information diffusion management.

The diffusion model has been parameterized to produce cellular-like structured emergence[14]. An *i+1*-state agent attracts around it ***i***-state agents which are organized in circle around it. This structure has been chosen for multiple reasons. It provides a simulation testbed for an Artificial Life approach of multiple emergence. Plus, it makes possible to delimit two distinct zones: outside and inside the structure. It allows a clearer quantitative and qualitative visibility of the interactions between agents.

The simulations have been made in a torric environment with a population rating between 250 and 2000 agents. All agents have been initialized with state 0 (*i=0*).

We now present the main results of the simulations: multi-level emergence, complexity analysis and autopoietic behavior.

3.2 Multi-level emergence

Simulations highlight the formation of emergent circular organisations. Figure 3 shows a level-*1* emergent structure.

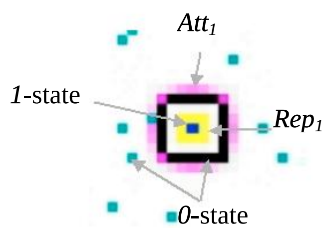

Figure 3 : level-*1* emergent Structure

An *1*-state agent (the dark gray one in the center of the structure), attracts - and repulses - ***0***-state agents (the black ones). Repulsive level-*1* Pheromones – emitted by the core agent and perceived by ***0***-state agents – are visualized in the center of the circular structure with the lightest gray. Outside the structure Attractive level-*1* Pheromones are visualized (in light gray). They attract ***0***-state agents and cause a circular organization. Some ***0***-state agents (in gray) are wandering in the environment.

Figure 4 shows a result of a multi-level emergence (level-*2* structure) obtained after about 140 turns.

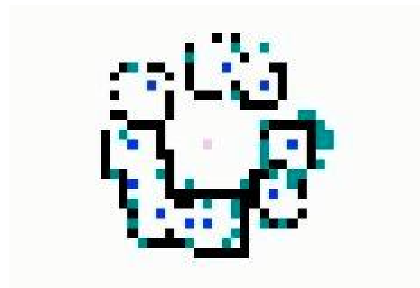

Figure 4 : level-*2* emergent Structure

In the center of figure 4 the ***2***-state agent (in the lightest gray) attracts ***1***-state agents (in dark gray). These ***1***-state agents attract ***0***-state agents (in black). A circular structure composed by lower-level circular structures is thus created.

The highest level of emergence reached in simulations was the third level. We demonstrated [11] that this limit was induced by physical resources (CPU, memory…).

Another limit for emergence in a general framework comes from the nature of the agents behavior and thus from the inherent nature of emergence. In the formed structures the ratio between core agents (*i+1*-state agents) and peripheral agents (*i*-state agents) is always the same whatever the level of emergence. We proved [11] that we can calculate the maximal emergence level of such a system if we know this ratio – the structural ratio.

Let be $\Delta_\alpha = \frac{\textit{number of } a_i}{\textit{number of } a_{i+1}} = 13 \pm 2$ this ratio and Na_0 the initial number of agent in the environment. It is easy to deduce the maximum level of emergence n:

$$n = \frac{log(N\alpha_0)}{log(\Delta_a)}$$

3.3 Complexity Measure

Successive emergences within the system produce a complexity increase [15]. We shall now present two aspects of this phenomenon: the structural complexity and the spatial complexity.

Structural Complexity

Many measurements were taken on agents organization within the emergent structures [16]. The figure 5 depicts a typical case of simulation. It shows the amount of organization as a function of time for the first level and the second level of structures.

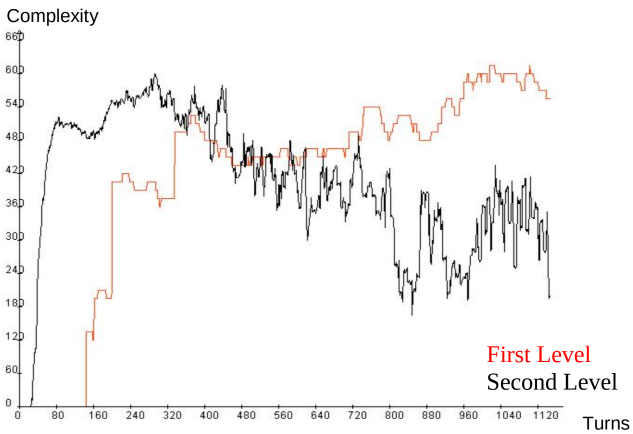

Figure 5: Structural Complexity measurement

The birth and the organization of emergent structures are fast phenomena. Whatever the emergent level of the structure is, a maximum of complexity is quickly reached (complexity is computed from the amount of agents in formed structures). Then, the lower level structures (level-*1*) become less organized for the benefit of organization of higher level structures. This can be simply explained:

During the emergence of level-*i+1* structures, level-*i* structures migrate in their direction. It induces at first disorganization due to their movement, then an increase in the concentration of information around the newly formed structures. This high concentration produces instability and thus a decrease in organizational complexity. At the same time, level-*i+1* emergences are structuring and their complexity increases.

Spatial complexity

Another aspect of the increase in complexity comes from the nature of emergence structuring. The agents are organized by aggregation. During the execution of the simulations, it produces a concentration of activity in small areas.

This phenomenon can be seen on figure 6:

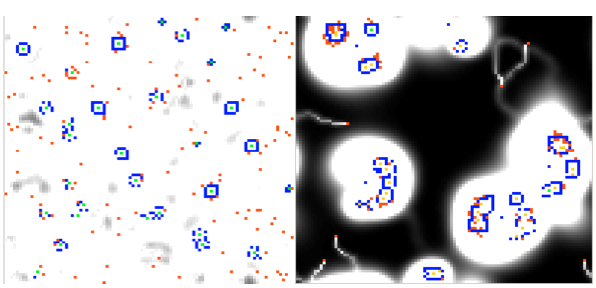

Figure 6 : Spatial Complexity

White areas represent the amount of information – i.e. the quantity of Pheromones. The other squares (in gray) are agents.

The first snapshot was obtained at the early time of a typical simulation. Numerous level-*1* structures have emerged and the environment is saturated with information.

The second snapshot shows a more mature system. Second level structures are emerging. All agents and most of the information emitted by them are concentrated in isolated patches. In "old" simulations, these patches become most of time a single zone in which all the interactions between agents occur.

The surface covered by information and agents in the environment tends to be increasingly small until the formation of the single zone. In the same way, the complexity within these zones increases gradually until reaching its maximum in the single zone.

This system behavior outlines the second significant aspect of the system: the autopoiesis.

3.4 Autopoiesis

The implemented system presents an autopoietic behavior. We shall now present it with the purpose of exhibit interesting properties for Multi-Agent System design.

Autopoiesis is a concept that was initiated by Humberto Maturana and Fransisco Varela in the middle of the seventies to describe life characteristics [17], [18]. Autopoiesis is defined as follow [19]:

An autopoietic system is a dynamic system that is defined as a composite unity as a network of productions of components that, a) through their interactions recursively regenerate the network of production that produces them, and b) realize this network as a unity in the space in which they exist by constituting and specifying its boundaries as surfaces of cleavage from the background trough their preferential interactions within the network.

The b) notion is clearly expressed in the system. It has been shown in the study of its spatial complexity. In information patches created during simulations, agents interact preferentially, building "artificial" boundaries with external medium.

The a) notion is more difficult to apprehend. Two examples will be shown to explain it: disturbances resistance and emergence regeneration.

Disturbances resistance

Many simulations were made to test the resistance of the system. In figure 7, one of them is given.

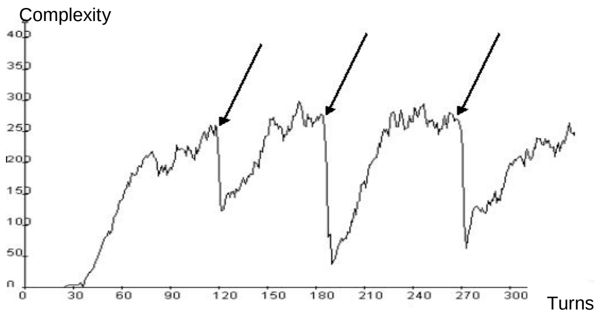

Figure 7 : Robustness test

It represents the amount of organization in the system as a function of time. Three disturbances were made during this typical simulation (arrows). A disturbance consists in moving agents in a random direction for 10 turns. For each disturbance, a very strong reduction of organization follows and the system complexity reaches quickly a minimum. Then there is a reorganization of the system that comes back to his previous complexity level. Many measurements on simulations and graphs have shown us that this reorganization is faster than the birth of the structures - for a same starting complexity.

Emergence regeneration

The second example that confirms the system autopoietic nature is rather amazing. The nature of agents mutation induces versatility. In relation to instabilities or deadlock situations agents can mute to reach a higher or lower level and then produce new system behaviors. It is the case in the following example:

When a level-*2* structure is formed, we shown that instabilities appear – induced by high quantities of information. The amount of complexity for level-*1* structures also decreases (see Figure 5). Due to the high concentration in Repulsive Pheromones, it produces a more or less important expulsion of *0*-state agents in the environment.

In less stable systems, it only increases the pool of *0*-state agents wandering in the environment.

In more unstable systems, numerous agents are expulsed out of the emergent structures. The concentration of *0*-state agents becomes important, causing some of them to mutate towards the state 1. These *1*-state agents attract around them *0*-state agents to create new level-*1* structures. These structures are then attracted by the level-*2* structure, making it more stable.

This example aims to explain the aupoietic nature of the system. From a emergentist point of view, standard autopoietic systems regenerate the production network in a fixed level [20] (the level 0). As for it, the present system regenerates the elements necessary for the emergence and maintenance of higher level structures. The system is its own driving force in terms of emergence and complexity increase.

4. DISCUSSION

The described system aims to be a general framework for the study of multi-level and recursive emergence. The developped model offers a great flexibility. Many experimentations (all not presented here) have been made using different parameters and produced this varied results:

- Modifications on diffusion model produce new emergence structuring like a snake-shaped organization (i.e. agents organized as a snake body),
- Modifications on agents perception and emission alter the robustness quality against disturbances,
- Modifications of the agents mutation coefficients influence the autopoietic behavior of the system…

These experimental results show us functionalities that exceed the restrictive framework of multi-level emergence. Now the objective is to handle and to use these functionalities to design multi-agent systems:

- On one hand the great flexibility and versatility of agents behavior should permit to resolve tasks in heterogeneous and open systems. Moreover, autopoietic characteristics are an interesting way to ensure robustness and adaptability of a system. In particular we intend to study our approach for nano-technology systems where numerous “simple” agents interact to produce structures and functions with a great robustness and suppleness,
- On the other hand in a more theoretical framework, this system can be useful for the study and understanding of complex and self-organizing systems. The model can be modified at will to become an emergence and complex systems testbed.

5. CONCLUSION

In this paper we presented a reactive model of an emergent system which can produce multi-level emergence. Some experimentation have been analysed in order to present some of the system properties such as autopoiesis and complexity increase behavior. These properties are now better understood and can be managed.

This work on emergence is at its first-stage, but the presented preliminary results are very promising. We now plan to analyse every system elements to define their role in order to understand and predict the emergence and structuration processes. We hope to apply these results for synthesizing and analysing complex systems based on nanotechnology, collective robotics or biological entities.

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