SWARM INTELLIGENCE ENGINEERING FOR SPATIAL ORGANIZATION MODELLING

Rawan Ghnemat, Cyrille Bertelle

LITIS - University of Le Havre
25 rue Philippe Lebon - BP 540
76058 Le Havre cedex, France

Gérard H.E. Duchamp

LIPN - University of Paris XIII
99 avenue Jean-Baptiste Clément
93430 Villetaneuse, France

ABSTRACT

In this paper, we propose a swarm intelligence algorithm to deal with dynamical and spatial organization emergence. The goal is to model and simulate the developement of spatial centers using multi-criteria. We combine a decentralized approach based on emergent clustering mixed with spatial constraints or attractions. We propose an extension of the ant nest building algorithm with multi-center and adaptive process. Typically, this model is suitable to analyse and simulate urban dynamics like gentrification or the dynamics of the cultural equipment in urban area.

Index Terms— swarm intelligence, complex systems, self-organization, ant systems, spatial organization

1. INTRODUCTION

Many natural and artificial systems have emergent properties based on spatial development. This spatial development is both the result of some mecanisms from the system behavior and the actor of the system formation by morphogenetic feedback. Natural ecosystems or social organizations in urban dynamics are typically such emergent spatial organizations. The goal of this paper is to study some computable mecanisms and algorithms able to model such spatial self-organization processes, taking into account the complexity of the phenomena.

In section 2, complex system concepts are defined and their applications to urban dynamics understanding are described. Section 3 presents swarm intelligence algorithms as methodologies to implement the complex systems concepts, using distributed computations. Section 4 proposes some specific swarm intelligence methods based on ant systems in order to model the spatial organizations emergence. Ant clustering is presented as the basis of the self-organization process. An algorithm based on the usage of pheromon template is proposed as an extension of this self-organization process, allowing to control some spatial constraints during the self-organization phenomenon. Using multi-template, we propose a general methodology to model multi-criteria spatial self-organization. Experiments are given, using repast agent platform mixed with a geographical information system.

2. MODELLING SPATIAL COMPLEXITY

2.1. Complex System Concepts

2.1.1. From Entities to Systems

Complex system theory [11] is based on the fact that for many applicative domains, we can find similar processes linking emergent global behavior and interaction network of constituents. The global behavior is generally not accessible using classical analytical methods.

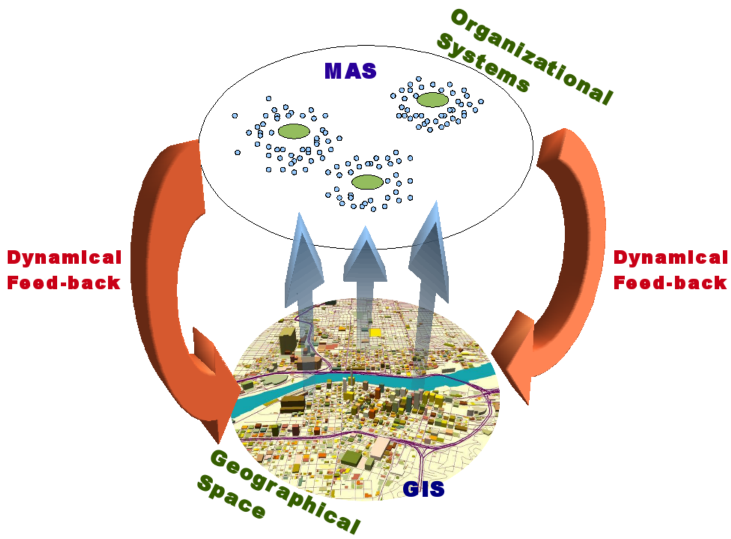
In classical analytical methods, the global behavior of the system is the description of the equations. Simulations from these formulations, consist in obtaining the trajectories of the behavior predefined in the equation formulation.

In complex systems modelling, we have to model the constituents of the system and the interaction network or system which link these constiuents, using a decentralized approach. So the global behavior of the system cannot be understood by the description of each constituent. In complex system modelling, the global behavior is an emergent property from the interaction network or systems between its constituents and lead to the creation of an dynamical organization of these constituents

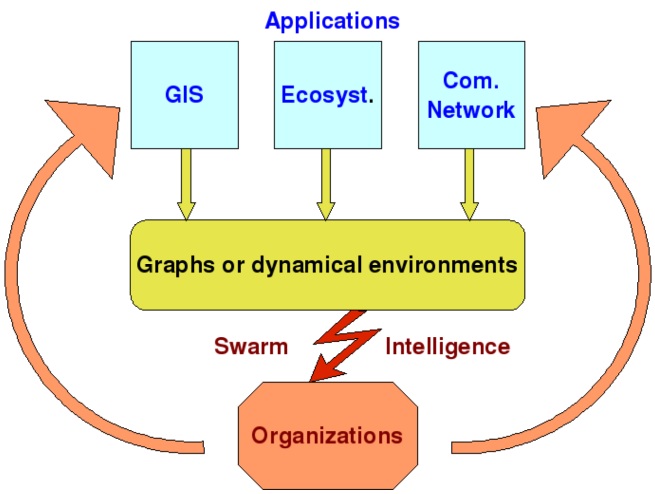
This dynamical and emergent organization retro-acts on its own components. Two kinds of feedback allow to describe these phenomenon. The positive feedback means that the emergence increases the organization constitution. the negative feedback means that the emergence has regulator properties which finally stop the increasing organization constitution and allow the system stabilization.

2.1.2. Spatial emergence from system and environment interaction

Another major aspect of complex systems is that they can be considered as open systems. This means that they are crossed by energetical fluxes that make them evolve in a



(a) Complexity of geographical space with respect of emergent organizations



(b) Modelling the organization detection using swarm intelligence over dynamical environments

Figure 1. Spatial organizations Complexity Description and the Conceptual Generic Model Based on Swarm Intelligence

continuous way. From these energetical fluxes, complex systems can evolve through critical states, using bifurcation schema and attractors behaviors. One of the major vector or support of these energetical fluxes is the environment itself where the complex systems and their entities evolve. In many natural and artificial systems, the environement has some spatial effects which interact on the whole complexity of the phenomenon. This spatial environment can be modified by the system but he can also be the catalyst of its own evolution. Understanding and modelling the deep structural effect of the interaction between the systems and its spatial environment is the goal of the study presented in the sequel.

2.2. Application to urban dynamics

Social and human developments are typical complex systems. Urban development and dynamics are the perfect illustration of systems where spatial emergence, self-organization and structural interaction between the system and its components occur. In figure 1, we concentrate on the emergence of organizational systems from geographical systems. The continuous dynamic development of the organization feed-back on the geographical system which contains the organization components and their environment. The lower part of this figure explains our analysis methodology. It consists to describe many applicatives problems by dynamical graphs or environments in order to detect organizations over these dynamical environment. For the organization detection, we use swarm intelligence processes. We model the feed-back process of this emergent organization on the system constituents and its environment. To analyse or simulate urban dynamics, nowadays, we can use the great amount of geographical databases directly available for computational treatment within Geographical Information Systems. On the organizational level description, the new development of multiagent systems (MAS) allows nowadays to develop suitable models and efficient simulations.

The applications we focuss on in the models that we will propose in the following concerns specifically the multicenter (or multi-organizational) phenomona inside urban development. As an artificial ecosystems, the city development has to deal with many challenges, specifically for sustainable development, mixing economical, social and environmental aspects. The decentralized methodology proposed in the following allows to deal with multi-criteria problems, leading to propose a decision making assistance, based on simulation analysis.

Gentrification phenomena can be modelled using such methodology. It is typically a multi-criteria self-organization processes where appears emergent coming of new population inside urban or territorial areas. This new population firstly attracted by some criteria, brings some other charateristics which are able to modify and feedback over the environment.

Cultural dynamics processes in urban areas are also such complex systems where multi-criteria must be taken into account. A modelling of these dynamics is presented latter in this paper.

3. SWARM INTELLIGENCE AND SPATIAL ENVIRONMENT

Decentralized algorithms have been implemented for many years for various purposes. In this algorithm category, multi-agent systems can be considered as generic methods [15]. Agent-based programming deals with two main categories of agent concepts: cognitive agents and reactive agents. The first category concerns sophisticated entities able to integrate, for example, knowledge basis or communications systems. Generally, efficient computations, based on these cognitive architectures, implement few agents. The second category of agents, based on reactive architecture, is expected to be used inside numerous entity-based systems. The aim of programs using such architectures, is to deal with emergent organizations using specific algorithms called emergent computing algorithms. Swarm Intelligence is the terminology used to point out such reactive agent-based methods where each entity is built with the same basis of behavior, but reacts in autonoumous way. Swarm Optimization methods concern the problems of optimization where the computation of a function extremum is based on the concept of swarm intelligence.

Ant Colony Optimization (ACO) methods [5] is a bioinpired method family where the basic entities are virtual ants which cooperate to find the solution of graph-based problems, like network routing problems, for example. Using indirect communications, based on pheromon deposites over the environment (here a graph), the virtual ants react in elementary way by a probabilistic choice of path weighted with two coefficients, one comes from the problem heuristic and the other represent the pheromon rate deposit by all the ants until now. The feed-back process of the whole system over the entities is modelled by the pheromon action on the ants themselves.

Particule Swarm Optimization (PSO) is a metaheuristic method initially proposed by J. Kennedy and R. Ebenhart [10].This method is initialized with a virtual particle set which can move over the space of solutions corresponding to a specific optimization problem. The method can be considered as an extension of a bird flocking model, like the BOIDS simulation from C.W. Reynolds [13]. In PSO algorithm, each virtual particle moves according to its current velocity, its best previous position and the best position obtained from the particles of its neighborhood. The feed-back process of the whole system over the entities is modelled by the storage of this two best positions as the result of communications between the system entities.

Other swarm optimization methods have been developped like Artificial Immune Systems [6] which is based on the metaphor of immune system as a collective intelligence process. F. Schweitzer proposes also a generic method based on distributed agents, using approaches of statistical many-particle physics [14].

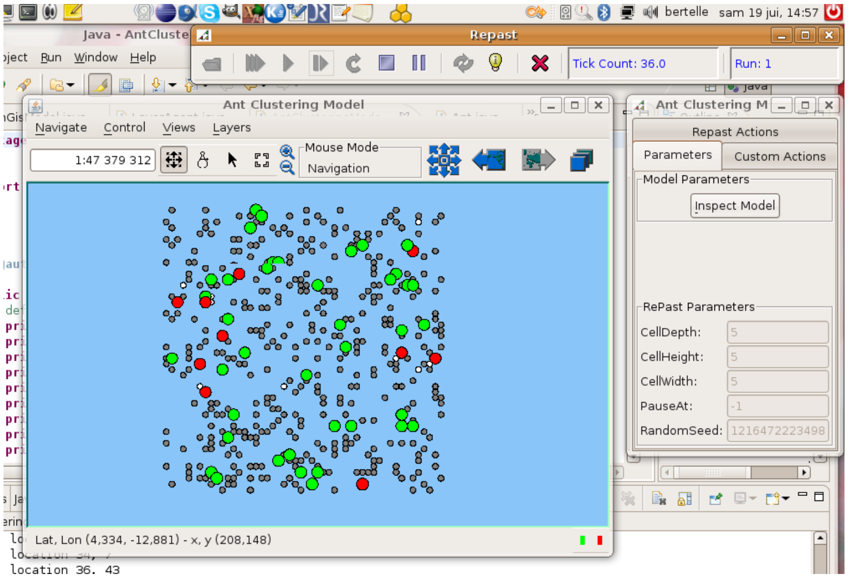
The method proposed in this paper is based on Ant Clustering and Ant Nest Building, allowing to deal with self-organization processes emerging from spatial constraints and attractive areas.

4. EMERGENT SPATIAL ORGANIZATIONS OVER COMPLEX BEHAVIORAL CLUSTERING

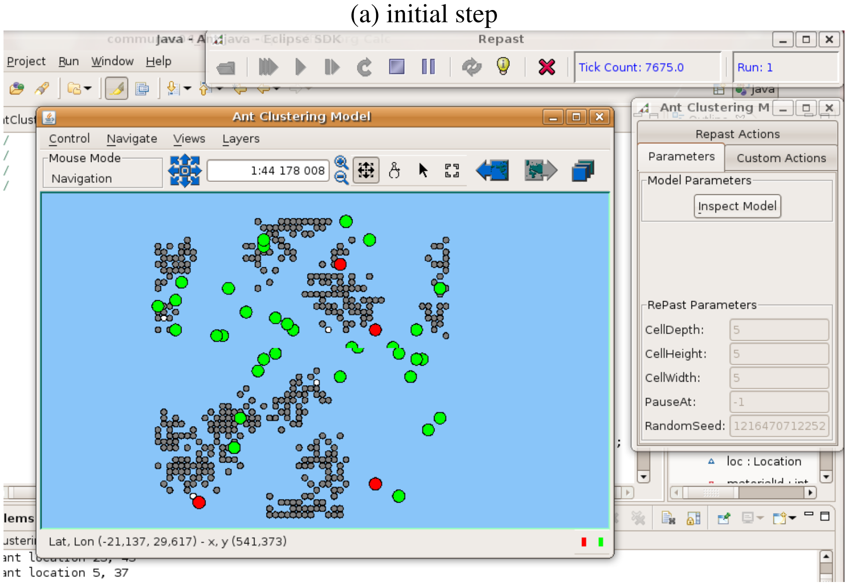
We will describe in this section, the general algorithm which is proposed to model emergent spatial organizations. This algorithm is based on the ant clustering. We introduce pheromon template to spatially control the clustering from local attraction. This method is a decentralized approach which allows to combinate multi-center and multi-criteria problem and we will show how we can apply it to model cultural dynamics in urban areas. We conclude this section with the description of an adaptive process which lead to model the feedback of the emergent system on its own mecanisms.

4.1. Ant clustering

Ant clustering algorithms are inspired by the corposes or larvea classification and aggregation that the ants colony are able to do in the real life. The ants are moving inside a closed area and are able to move some material which are randomly put on this area. After a while, and without any kind of centralized coordonation, the ants success to create some material clusters.



(a) initial step



(b) intermediate step

Figure 2. Ant Clustering Simulation using Repast on OpenMap

The algorithm is based on the following and very simple behavioral rules that each ant implements :

- When an ant is moving without carrying yet material and find some material, the ant will take the material respecting the probability number :

$$P_p = \left(\frac{k_1}{k_1 + f}\right)^2 \qquad (1)$$

where f is the material density that the ant perceives locally around itself and k_1 is the treshold. It is easy to check that if $f << k_1$ then P_p is near the value 1 and if $f >> k_1$ then P_p is near the value 0.

- When an ant is moving when carrying some material, the probability to deposite it is computed by :

$$P_d = \left(\frac{f}{k_2 + f}\right)^2 \qquad (2)$$

where f is still the material density that the ant perceives locally around itself and k_2 is another treshold. It is easy to check that if $f << k_2$ then P_d is near the value 0 and if $f >> k_2$ then P_d is near the value 1.

In figure 2, we show an implementation of this algorithm using the multi-agent platform called Repast [12]. The java version of this platform includes some packages allowing to interface with geographical database and geographical information systems (GIS). In figure 2, the graphical output windows is made under OpenMap which is a

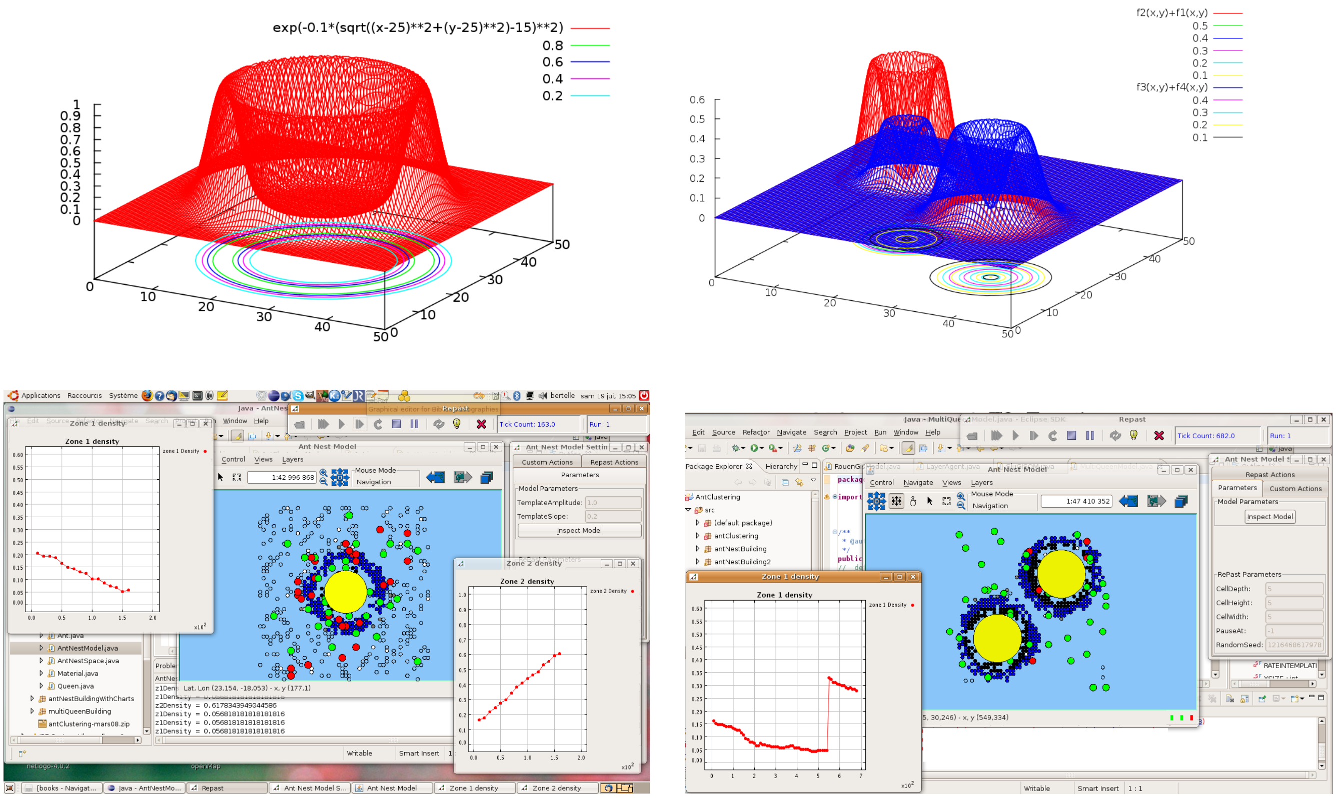


Figure 3. Templates and associated Ant Nest Building Simulation. On the left, with one queen. On the right with two queen

GIS developped in Java. In figure, the materials moved by the ants are the small grey circles, the ant moving without material are the green circles and the ant carrying material are the red circles.

4.2. Spatial constraints using template

The ant clustering shows some spatial self-organizations but has the specificity to generate clusters at random places. According to the first random moves that the ants start to do in the beginning of the algorithm, some material will initiate aggregation and the clustering processus will complete this aggregation from these initial random first aggregations. To simulate some urban dynamics, we need to introduce specific location with respect to city center for example or cultural equipments. The clustering here will represent the people usage of these centers or equipments and we need to introduce an attractive effect by using a pheromon template. This method follow the algorithm known as Ant Nest Building [5]. In ant colonies, the center corresponds to the position of the queen which needs to build the nest and the ant colony moves around it to protect the nest by various material taken on the ground. The queen emits a pheromon which allows to attract the ants during their building. The ant has to deposite the material carried only if the pheromon quantity perceived belongs to a specific range. We use an attractive fonction called P_t, corresponding to a pheromon template and represented by the left top part of the figure 3.

Using this template function, we remplace in the clustering algorithm, the two provious probabilities defined in equation (1) and equation (2) by

$$P'_p = P_p(1 - P_t) \tag{3}$$

$$P'_d = P_d P_t \tag{4}$$

4.3. Multi-template modelling

The previous subsection describes one local attractive process characterized by the queen and its pheromon template emission. The advantage of this method is to be able to combine the solutions of multi-center and multi-criteria problems, using interactive processes, each one is represented by a queen and its pheromon template.

On the figure (3), we can see on the left part, a single queen simulation and in the right part, a simulation with two queens and two pheromon templates. It is possible also for each queen to emit many different kinds of pheromons : we called them colored pheromons. Each colored pheromon will attract only the ants associated to its color.

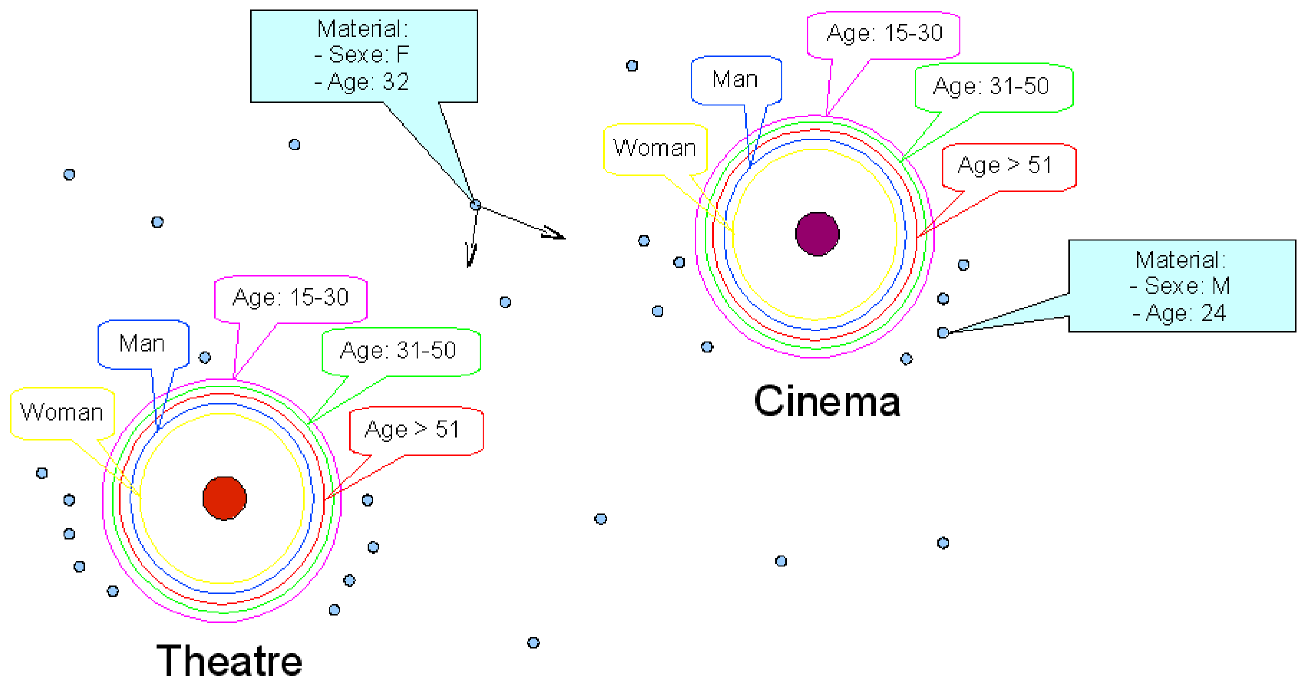


Figure 4. Cultural Equipment Dynamics Modelling

4.4. Application to cultural equipment dynamics

The multi-template modelling can be used to model cultural equipment dynamics as described in the figure (4). On this figure, we associate to each cultural center (cinema, theatre, ...) a queen. Each queen will emit many pheromon templates, each template is associated to a specific criterium (according to age, sex, ...). Initially, we put the material in the residential place. Each material has some characteristics, corresponding to the people living in this residential area. The simulation shows the self-organization processus as the result of the set of the attractive effect of all the center and all the templates.

4.5. Adaptive Spatial Organization Feedback Implementation

As explained in the section 2, complex systems deal not only with emergent organization processus from the interaction of its own entities, but also with the feedback processus of the organization over its own components. In the proposed model, we can take into account such feedback process and we present in figure 5, an adaptive processus which makes the queen (which describes the organization itself) modify the environment and the clustering processus itself. Following the template function, the queen locally defines around it two zones. The first zone is near itself and it is expected not to find material there. The second zone corresponds to the template maximum and it is expected to find a great concentration of material there. In the simulation, we count in a dynamical way the number of materials in these two zones and when these numbers reach some tresholds, we make evolve the queen by increasing its own size and so increasing the 2 associated zones. After this evolution, the ants have to move some material following the new template function attraction. The low part of the figure shows the evolution of the queen which has evolved 6 times since the simulation beginning. On this figure, we can see the red curves counting the zones density. Each gap in these density curves correspond to an evolution of the queen.

5. CONCLUSION AND PERSPECTIVES

The paper develops some specific swarm intelligence algorithms based on ant colonies processes. Using such decentralized methods, we can model complex multi-center and multi-criteria self-organizations. Urban dynamics are one of the most relevent problems where these approaches can be efficient. These studies are supported by a french regional project (Haute-Normandie) dealing with the study of cultural dynamics over urban area.

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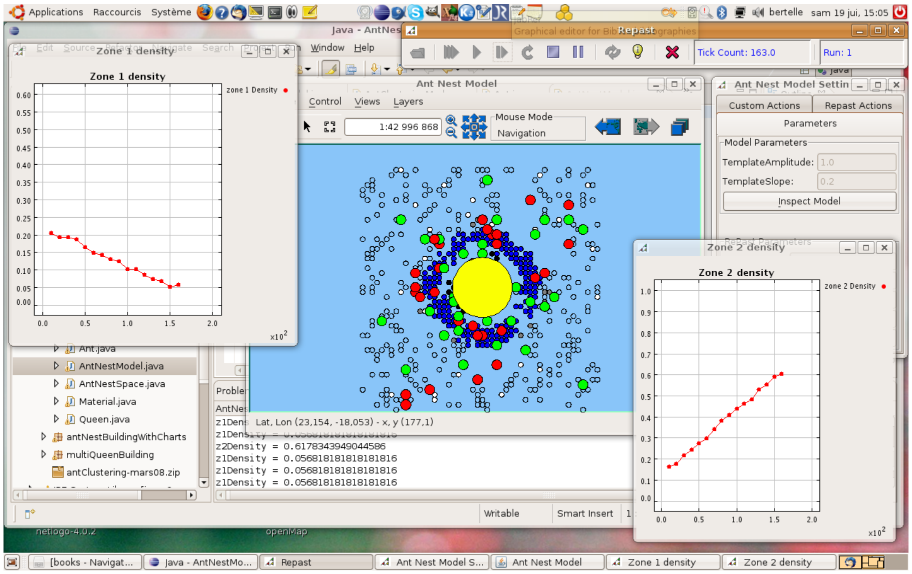
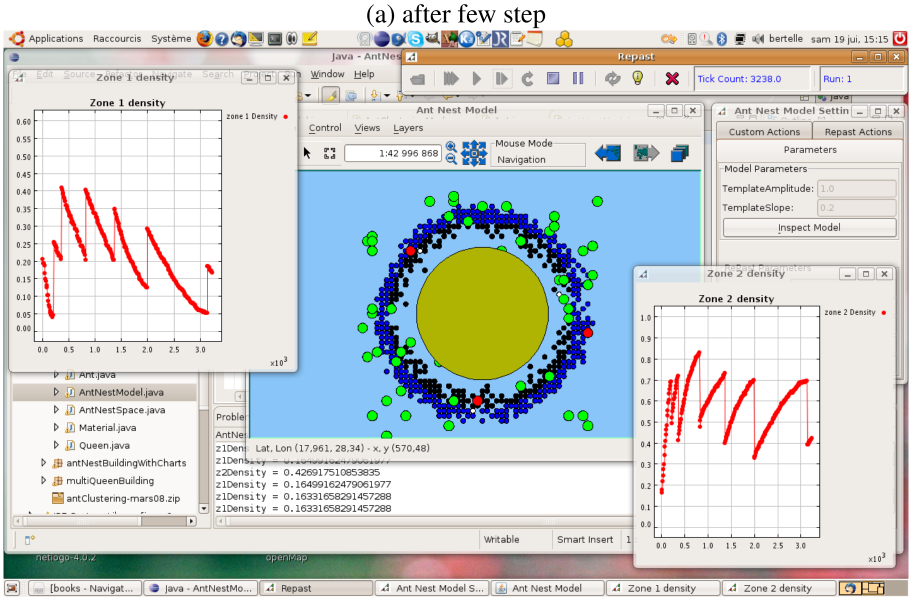


(a) after few step



(b) after queen adaptive development

Figure 5. Adaptive queen behavior modelling: according to its surround material spatial perception, the queen evolves

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