Joint MAS-PDE Modeling of Forest Pest Insect Dynamics: Analysis of the Bark Beetle's Behavior

David Picard, Aymeric Histace and Marie-Charlotte Desseroit

ETIS UMR 8051, ENSEA, University of Cergy-Pontoise, CNRS, Cergy-Pontoise, France

Abstract. This article deals with the social behavior modeling of a particular forest pest insect: the bark beetle. This ant-like insect has been responsible for the devastation of acres of pines trees in North America since 2005. Any tactic of forest pest management requiring prediction of pest population change over time and/or space, a realistic modeling of beetle colonies behavior would be a real benefit. The originality of this work is to propose a reactive Multi-Agent-System integrating physical diffusion phenomena. The main idea is to take into account the natural vanishing of the trail markers emitted both by decomposing trees (ethanol) and the agents that have found a source of food (pheromone). The proposed experiments show, on the one hand, that the MAS-PDE modeling leads to a realistic global behavior of the colony when considering a usual foraging scenario and, on the other hand, that, when compared with a simple reactive agent, the proposed model has a faster convergence to the asymptotic usual expected "S-shape" behavior of the agents' colony.

1 Introduction

Modeling population dynamics is the essential part of both research and management of forest pest insects. Any tactic of forest pest management requires prediction of pest population change over time and/or space. However, the scope of prediction depends on management objectives. An example of complex objective is to minimize the impact of pest population on forest ecosystems during several years. These kind of complex objectives require prediction of population changes over long time intervals and over large areas. Of course, it is impossible to predict pest abundance at specific location ten years ahead, but it may be possible to predict the change in average pest population density as a result of some change in environment.

Formerly, to tackle this objective, mathematical modeling was the major tool for predicting population dynamics and the reader could refer to Berryman and Millstein [1] for a complete overview of some of the most known models that are mainly based on modifications of discrete-time analog of the logistic model. The main advantage of such methods is that parameters of these models can be adjusted to fit available data.

Nowadays, mathematical modeling based approaches tend to be replaced by Multi-agent Modeling (MAM) that has constituted an important research and development area for the past two decades [2]. A MAM is formed of two elements, a Multi-agent System (MAS), and an environment in which the MAS evolves. When designing a Multi-agent model (MAM), the modeler has control over the multi-agent system behavior and

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development and the environment. The latter is especially important in evolutionary models as it determines the direction of the adaptation.

Fundamentally, a MAS is a system composed of multiple interacting agents within an environment. The most simple MAS, called “reactive MAS” [3], assumes the behavior of the agents can be modeled by a simple state machine (*e.g.* “resting”, “foraging”, *etc*). These behavioral states often involve the modification of the environment (for instance the deposit of a pheromone) or interacting with other agents. Such agents do not have have any memory capability, nor any decision making process. Thus, the switch from one behavior to another is performed in reaction to some changes of the environment or due to some interactions with other agents. However, the collective behavior of the MAS, emerging from the interactions of the agents with the environment, can often be far more complex than that of the agents alone. Ant colonies are a good starting example for such MAS: Although the local behavior of a single ant does not seem to be controlled centrally, nor any explicit coordination between ants is observable, the superorganism “ant colony” is able to construct complex nest architectures or adapt its distribution of foragers to food sources in an efficient way [4].

Cognitive MAS, based on a cognitive architecture, allows more complex behavior modeling. A cognitive architecture can be defined as the organizational structure of functional processes and knowledge representations that enable the modeling of cognitive phenomena like memory [5]. Nevertheless, such MAS needs to have a very deep knowledge about the individual behavior of each single agent of the colony, which is not always easy to model when too few parametric data are available from the expert (entomologists for instance).

Considering now the “environment” of the Multiagent Model [6], the related dynamic is usually considered as a static phenomenon. It means that a food source will only be modified (location, quantity) by the interacting agents of the MAS but not by possible underlying external physical phenomena (like diffusion for example). This could be considered as a limitation since the environment has a strong influence onto the global behavior of the agents.

The aim of this article is to propose a MAM based on a simple reactive MAS and the taking into account of evolution physical laws related to the corresponding environment. More precisely, we want to show that by integrating the way the resources and the trail markers could naturally vanish (steered by a diffusive phenomenon parametrically described using the spatio-temporal heat equation), we can obtain a more realistic modeling of the global behavior of the MAS dynamics.

Practically speaking, we focus our attention on the behavior modeling of an social pest insect: the “Bark beetle”. Bark beetles are ecologically and economically significant [7] since outbreak species help to renew the forest by killing older trees and other species aid in the decomposition of dead wood. However, several outbreak-prone species are known as notorious pests that can cause tremendous damage to pine tree forests for instance [8]. As a consequence, a better understanding of the social behavior of this beetle would definitely be of some precious help to limit its damage capability.

This article is organized as follows: We first introduce the bark beetle species with a focus on the entomological data. Second, we introduce the proposed MAM that permits to model the social behavior of the bark beetle with a taking into account of the physical law steering the inner evolution of the available resources in a given environment. We then propose an experimental section in which the behavior of the model is shown. Finally, the obtained modeling results are discussed and concluded.

2 A Social Pest Insect: The Bark Beetles

2.1 Bark Beetles Description

Bark beetles are so-named because the best known species reproduce in the inner bark (living and dead phloem tissues) of trees. Some species, such as the mountain pine beetle (*Dendroctonus ponderosae*), attack and kill live trees. Most, however, live in dead, weakened, or dying hosts. Once beetles find a suitable host tree, they release aggregating pheromones to attract other beetles enabling a “mass attack” that can overwhelm even a healthy tree defenses [7]. Along with releasing pheromones, the attacking beetles introduce a staining fungus that infects and blocks the sapwood further weakening the tree. Aggregating pheromones plus a pathogenic fungus infection help make relatively healthy trees a quick meal for bark beetles.

Most bark beetles look the same to the casual observer. Bark beetles are usually less than 5mm long, shiny brown to black, cylindrical, with hard wing covers. Basically, they look like everyday beetles, only smaller (see Fig. 1(a) for illustration). Beetles spend almost their entire life beneath tree bark. After mating, an “egg gallery” is excavated by the female beetle, sometimes with help from a male friend. Eggs, laid along the sides of the gallery, hatch within a few weeks. The larvae feed on the nutritious inner bark of the tree, pupate, and then emerge as an adult. The adult beetle only spends a few days outside the bark flying to relocate to a new host.

(a) A typical bark beetle

(b) Colony galleries on a dead tree

Fig. 1.

Bark beetles excavate egg galleries like tiny tunnels in the live inner bark (Fig. 1(b)). Engraver beetles score the sapwood, too. Larvae excavate “larval mines”. Bark beetle galleries weaken the host tree and eventually kill it by girdling. Water and nutrient transport in the live inner bark and in the outer edge of the sapwood are effectively disrupted.

2.2 Ecological Role

Bark beetles and forests evolved together. In balanced forests, beetles have many beneficial roles. The most important are:

- Beetles “thin” naturally overstocked forests. Beetle-induced thinning is often irregular and patchy contributing to forest diversity. Gaps encourage changes in vegetation and forest structure beneficial to wildlife.
- Beetles help recycle old forests. Beetles introduce wood decay fungi through the bark where adults burrow into trees. Decay fungi help to rapidly decompose wood and hasten nutrient recycling back into the soil.
- Beetle killed trees are a food source important to birds and other insect predators. Snags provide roosting and nesting habitat.

However, due to peculiar warm climatic conditions, some deregulation could appear in the natural balance between forests and bark beetle population growing. As a consequence, massive outbreaks of a specific species of bark beetles (the mountain pine beetles) in western North America in 2005 have killed millions of acres of forest from New Mexico to British Columbia threatening increases in mudslides, forest fires and other adverse effects. A similarly aggressive species in Europe is the *spruce ips typographus*. Another tiny bark beetle, the coffee berry borer, *Hypothenemus hampei* is a major pest on coffee plantations around the world.

3 Modeling of Bark Beetles Behavior

In this section we explain the notations used in the paper, along with the physical quantities we model.

3.1 Hypotheses and Notations

Bark beetles are social insects and consequently, the global behavior of a nest can be modeled by a simple reactive MAS based on simple interaction among the different agents. Three main hypothesis will steer the behavior of each agent : (i) They look for food sources (pine trees for example) ; (ii) Once a food source is detected the agent emit a particular pheromone that will strengthen the related path (the “trail markers”), and (iii) food sources emit on their surroundings an attractor element (trees in decomposition emit ethanol that naturally attract xylophagus insects).

For the experiments, we consider a 2D area of evolution. Each site of this area are located using their cartesian coordinates (x, y). The following related notations are used to characterize resources and agents:

Resources

Let $s(x, y)$ denotes a food source (trees):

- the corresponding evolution law of the available resources is noted $R_s(t)$,
- the corresponding evolution law of the ethanol emission is noted $E_s(t)$,
- and $E(x, y, t)$ denotes the quantity of ethanol at the coordinates (x, y) and for a given instant t.

Agents

Let $a(x, y)$ denotes an agent at the location (x, y) of the area

- $n_s(t)$ denotes the number of agents on a given site s,
- $q_a(t)$, the probability for a given agent a to quit the colony, at instant t,
- and $p_a(x, y, t)$ the probability of an agent to move to location (x, y), at instant t.

Moreover, agents are mobile only if they are not on a resources site.

4 Experiments

For all the following experiments, we will consider a closed homogenous SMA. Only beetles will interact (no other types of agents) and that the total amount of agents will stay the same (50 agents) all along the different experiments (no phenomenon like “birth” or “death” of agents will be taken into account).

For all experiments, we use the usual logistic law to model the evolution of the resources on a site:

$$R_s(t + 1) = R_s(t) - \alpha n_s(t) \tag{1}$$

with α a given value representing the mean consumption rate of an agent between two iterations of the evolving process. This non-linear choice is motivated by the fact that numbers of agents related to a resource is not a fixed value all along the process.

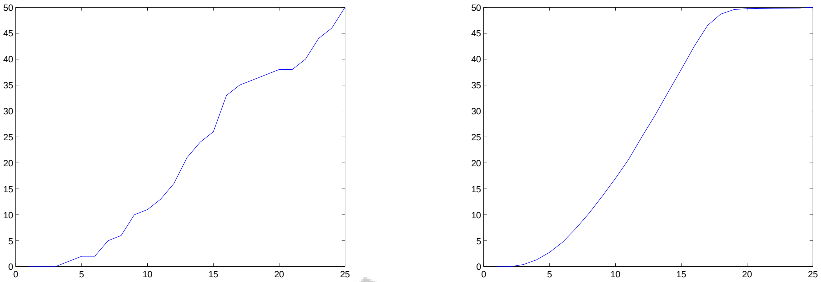
4.1 Agents Departure Modeling

In this first scenario, only one resource is considered and 50 agents are located on it. We want to test the effect of resources exhaustion on the mobility of the agents. We propose to model the probability of departure of an agent by the ration of available resources at time t:

$$q_a(t) = 1 - \frac{R_s(t)}{R_s(0)} \tag{2}$$

No emission of ethanol is taken into account (i.e. $E_s(t) = 0$) nor emission of pheromone. Fig. 2.(a) shows the number of agents that turns to a “mobile” state against the number of iterations.

A usual “S-phenomenon” [9] characterizes this evolution law. For a better illustration, Fig.2.(b) shows the smoothed evolution law computed as a mean of the phenomenon on 50 realizations. This first experiment shows the viability of our model considering simple conditions of evolution. Let us know enrich the model.



(a) (b)

Fig. 2. Illustration of the "S-phenomenon" related to the number of "mobile" agents function of the iteration number of the process for a unique resource site where all agents (50) are located at $t = 0$: (a) for one realization of the experiment, (b) averaging on 50 realizations of the experiments.

4.2 Resource Attraction and Aggregating Behavior Modeling

We now want to model the resources attraction phenomenon and the aggregating behavior of the agents. We consider the agents are randomly located all over the area of evolution and that ethanol and pheromones are emitted respectively by the resource sites and the agents which have found a resource site. The corresponding emission laws are Gaussian functions such as:

$$E(x,y,t) = \sum_s E_s(t) e^{-\gamma[(x-x_s)^2+(y-y_s)^2]} \ , \tag{3}$$

for ethanol emission ($E_s(t) = \mu R_s(t)$, μ being a positive value lesser than one), and

$$Ph(x,y,t) = \sum_s Ph_s(t) e^{-\gamma[(x-x_s)^2+(y-y_s)^2]} \ , \tag{4}$$

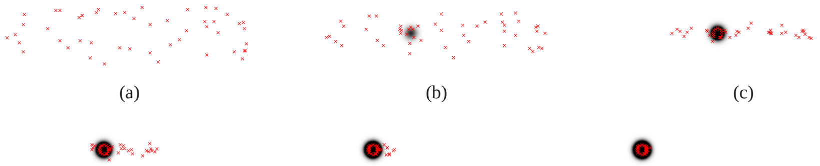
for pheromone emission ($Ph_s(t) = \nu n_s(t)$, ν being a positive value lesser than one).

We propose to model the probability of movement by the quantity of attracting markers in the neighborhood of the agents. Let us define the quantity of attracting markers $A(x,y,t)$ as a coupling between ethanol and pheromones at location (x,y) and time t:

$$A(x,y,t) = \eta Ph(x,y,t) + (1-\eta) E_(x,y,t) \ , \tag{5}$$

with $0 \leq \eta \leq 1$ being the coupling term. The probability to move to location $(x^\star, y^\star)$ for agent a is then:

$$p_a(x^\star, y^\star) = \frac{A(x^\star, y^\star, t)}{\sum\limits_{(x,y)\in N(a)} A(x,y,t)} \ , \tag{6}$$



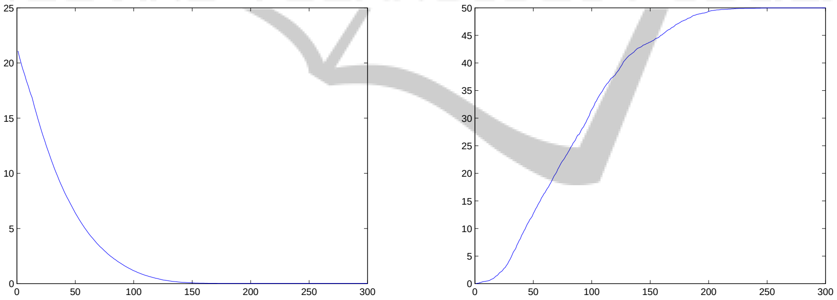
(a) (b) (c)

(d) (e) (f)

Fig. 3. Illustration of Experiment 2: 50 agents are randomly dispatched all over the evolution area (red stars) where a unique source of food is present. Evolution of the agents' position is shown for (a) iteration 0 of the process, (b) iteration 20, (c) iteration 60, (d) iteration 100, (e) iteration 140 and finally (f) iteration 180. The dark disk that progressively appears in the center of the area highlights the position of the source of food, the gray level intensity is related to the level of emitted pheromone: the more black, the more pheromone.

with $N(a)$ being the neighborhood of agent a. In all our experiments, we consider 8-connexity neighborhoods. Whenever an agent arrives on a resources site, it stops moving and starts emitting pheromones and consuming resources.

In Fig.3, we show the evolution of agents location as well as the pheromone levels over time for a single run. As we can see, the agents are attracted to the resources site.



(a) (b)

Fig. 4. (a) Mean distance of the agents to the source of food function of the iteration number of the process with $\eta = 0.7$. (b) Amount of agents on the source of food function of the iteration number of the process (averaging on 50 realizations of the experiment)

In Fig. 4, we show (a) the mean distance of the bark beetles to the source of food with $\eta = 0.7$ (more importance is given to pheromone emission than ethanol emission), and (b) the amount of agents on the source of food over time t.

As we can see on Fig. 4.(a), the proposed model for ethanol and pheromone emission is compatible with a realistic modeling of the behavior of the beetles' colony: for a sufficient number of iterations (approximately 140) all the agents have converged to the source of food. The exponential decreasing of the plot shows a two-step process: in a first fast step, agents which are close from the resource site are attracted by the ethanol emission of decomposing tree. Once they are on the resource site they then begin to emit pheromone, attracting more and more agents. In a second step, due to the decreasing of the resource, there's a deceleration of the process since less and less ethanol is emitted. Moreover, Fig. 4 .(b) shows the expected “S-phenomenon” related to that kind of behavior.

Nevertheless, one limitation of this behavioral model is the insufficient taken into account of the underlying physical phenomenon related to pheromone and ethanol emissions. More precisely, if the Gaussian laws of Eqs. (3) and (4) are realistic, they do not integrate any temporal dynamics highlighting for instance a natural diffusion process. And yet, this diffusion scheme will interact with the attraction process by modifying the expected p_a probability. We now propose to integrate such a diffusive property within the model.

5 Joint SMA-PDE Modeling

We now propose to consider that ethanol and pheromones are naturally dissipated within the atmosphere at each iteration of the evolving process characterizing the colony of beetles. For this, the simple isotropic diffusion process is considered. This physical phenomenon is simple but as so, remains easy to control on the contrary of more complex anisotropic processes. This natural phenomenon is mathematically defined by the usual PDE of Eq. (7) also known as the “heat-equation”:

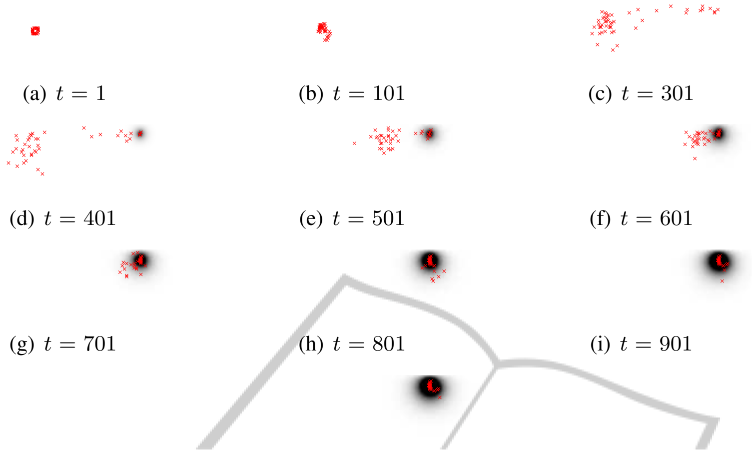
$$\frac{\partial Ph(x,y,t)}{\partial t} = \triangle Ph(x,y,t) = \frac{\partial^2 Ph(x,y,t)}{\partial x^2} + \frac{\partial^2 Ph(x,y,t)}{\partial y^2} \tag{7}$$

with $\triangle$, the Laplacian operator. If in Eq. (7), pheromone emission is considered, a similar equation is related to natural diffusion of ethanol. Consequently, for each iteration of the experiment, the initial distributions of pheromone and ethanol of Eqs. (3) and (4) are naturally vanishing. Practically speaking, for each iteration t, Eqs. (3) and (4) are convolved with a bidimensionnal Gaussian filter with standard deviation σ that controls the speed of the isotropic diffusion. Iteration after iteration, the maximal amplitude of the pheromone emission is decreasing whereas the global spreading is made over a larger surface of the area of simulation.

For the experiments, we set 2 different resources sites. At the beginning, all agents are located on the first site, which has limited resources. On the contrary, the second site has a near infinite quantity of resources. We expect the agents to quickly leave the first site (as in section 4.1), and converge to the second site (as in section 4.2).

Fig. 5 shows the behavior of the beetles for different iteration of the process. As it can be noticed, after a significant lapse of time corresponding to the random research for food, the agents that are near the second site are attracted by the ethanol. Once these agents find the resource site, the emission-diffusion of pheromone makes possible a fast convergence of all agents to the corresponding site.

Fig. 6 shows the average distance of the agents from the initial point (x_0, y_0), function of the iteration number of the evolving process. The global behavior of the colony is characterized by a double “S-phenomenon”. The first “S” corresponds to the small pool of agents attracted by the ethanol at first, while the second “S” corresponds to the remaining agents attracted by the pheromones. Compared to previous experiments, the phenomenon is slower due to the initial location of the agents. Agents first exhaust the food on their initial location, before they randomly move in the neighborhood. A



(a) $t = 1$ (b) $t = 101$ (c) $t = 301$

(d) $t = 401$ (e) $t = 501$ (f) $t = 601$

(g) $t = 701$ (h) $t = 801$ (i) $t = 901$

(j) $t = 951$

Fig. 5. Beetles' behavior corresponding to the joint SMA-PDA modeling proposed. σ is arbitrarily set to 1.

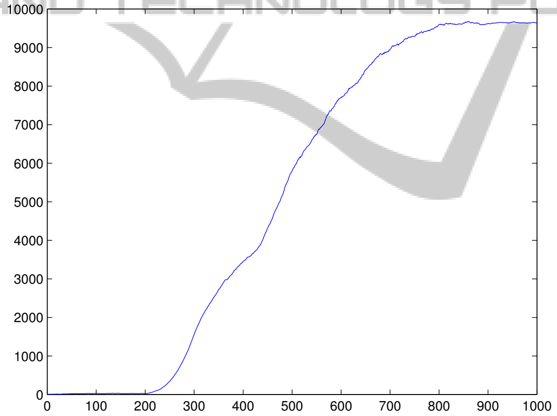


Fig. 6. Average distance of the agents from the initial site they were localized at $t = 0$, function of the iteration number of the process. Contrary to other experiments, this curve was obtained with only one realization of the evolving process.

necessary significant lapse of time is needed for few agents to find the second source thanks to the ethanol diffusion. Nevertheless, as soon as an agent is located on the new resource site, the emission/diffusion of pheromone produces an acceleration of the convergence when compared with experiment of section 4.2. Moreover, it is important to notice that the "S-shape" of Fig. 6 was obtained with only one realization of the experiment, whereas for Experiment 1 and 2, it was necessary to average the results over 50 realizations to obtain similar results. This shows the benefit of integrating the underlying physical phenomenon that steers the natural evolution of pheromone/ethanol diffusion, once emitted by agents.

6 Conclusions and Perspectives

In this article, a joint MAS-PDE for the modeling of the behavior of the bark beetle's colonies is presented. The main originality of the proposed approach is to integrate within a simple reactive MAS some possible physical phenomena that steers the diffusion of emitted substances like pheromone or ethanol. The prospective experiments of this work show that such a joint model could lead to more realistic simulations of the global behavior of the colony, with no need for multiple realizations of the process. If this study is focused on the bark beetle, clearly identified since 2005 as a pest insect, extensions to ant-like insects are straight forward. The next experiments will consist in (i) improving the MAS by a managing of the "birth" and "death" of the beetles, but also of the funding of new colonies by females, and(ii), in considering the possibility to integrate more complex diffusion processes, like anisotropic ones, in order to take into account the structure of the bark beetle's nest within trees (galleries), and natural perturbations like wind.

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