Multi-agent modeling of the physical/biological coupling — A case study in marine biology

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Abstract. Within the framework of a pluridisciplinar research project gathering biologists, mathematicians, and computer scientists, we propose a multi-agent modeling of an ecosystem. We justify the use of a multi-agent modeling for the study of the behavior for such a system which can not be suitably modeled analytically to guarantee its relevancy. Such a modeling focusses on the behavior of the living being rather than on emergent properties of the dynamics of the system. By the way, we present the concepts (such as Petri networks [11], perception og agents, simulation of concurrent living processes) and the platform that we have developed in a generic way, using the application in biology as a case study.

1 Introduction

The main objective of this work is to identify the behavioral rules of a small crustacean, part of the family of zooplanktons named "copepod" (see Fig. 1). A keypoint in this modelling is the study of the influence of the environment on its behavior: our assumption is that the copepod has an active behavior of search for food (phytoplanktons). By "active", we mean that the copepod has an individual behavior rather than being merely transported as a particule by the turbulences of water. (At its millimetric scale, the oceans are extremely turbulent.) We aim at showing that the fact that the behavior of the copepod is active implies important consequences on its viability and its success for survival, and reproduction. Being a very important link within the food chain in oceans, a more accurate knowledge of the copepod will finally bring us a more accurate and sounder understanding of the way the marine eco-system works, as well as its dynamics. To that purpose, the project develops itself along three complementary directions that are continuously interacting with each others: *in* *vivo* observations, analytical models, and modeling of the individual behavior of copepods using agents. Our research has shown that the distribution of phytoplankton is strongly heterogeneous in the environment of the copepod [10]. Current results show that this heterogeneity influences the energy assessment of the copepod. By measuring the quantity of nitrogen absorption during nutrition, the observations show that the output of the behavior of the copepod (the ratio of the energy that is spent and the energy that is ingested) varies according to the type of distribution of food. For example, a turbulent environment, favourable to an overall mixing, increases the rate of meeting of the copepod with the particles of phytoplankton and thus increases the energetic ratio. It now remains to study the influence of the behavior of the copepod in such situations. The study of this behavior is incompatible with an analytical approach, as we will see it. So, we use a multi-agent system (MAS) approach [4].

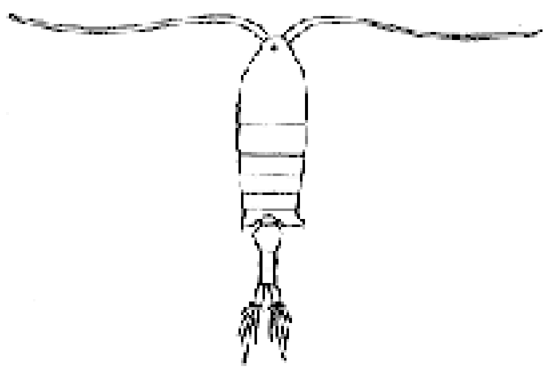

Fig. 1. Copepode *Centropages hamatus*

Using a MAS approach is a considerable change in the mode of thinking in biology which relies on models using equations, statements, and statistical analyses [5]. The researcher, in our case the biologist, has to formulate the studied individual behavior and its interactions with its environment. In section (2), we state the problem (just to give its flavor!). Section (3) is devoted to the presentation of our modeling tool. We show how the dynamics of agents is formalized with Petri nets, as well as the modelling of agents' perception of their environment. Some results are then presented in section (4).

2 The system under study

At present, the copepod is represented by models either of the type "black box" (see Fig. 2), or analytical models [1]. These models seek to describe in terms of input flow, output flow and transfer function each "process" of the organism.

Let us describe the process of ingestion of preys in the case of the phytoplankton (see Fig. 2). The copepod captures a prey (a particle of phytoplankton). After

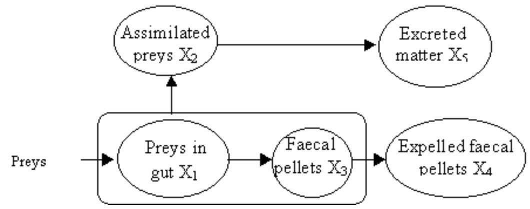

Fig. 2. Model of the process of ingestion

a handling time, the prey is stored in the gut and enters the process of digestion. The gut transforms its contents in usable energy (comparable preys) which one expresses out of nitrogen, or wastes (fecal balls). This transformation is continuous: within each Δt, a quantity Δq of caught preys is processed (this quantity is proportional to the quantity stored in the gut). Usable energy is either consumed (metabolism, digestion, or stroke), or stored (egg production for females, for example). As for wastes, it is expelled.

There are analytical models which have the ambition to represent, as well as possible, the biological processes which govern the copepods. [1] proposes a model synthesizing the various models developed until now. It captures the activities of capture and ingestion using five coupled differential equations.

This model suits for the process of capture. However, from our point of view, the contribution of the behavior is partially neglected. Indeed, one can put into equations the fact that the activity of nutrition of copepod as a function of the density of preys, the level of turbulence of the environment, the mode of hunting and the quantity of food in the gut; however, it is much more difficult to take into account various factors within the behavior such as the way copepods perceive their environment, the size of preys, and the speed of stroke of copepod relatively with that of its prey.

3 The multi-agent modeling

The system under study is composed of a mass of water in which "patches" of phytoplankton and copepods are immersed. Each agent is located and has its properties among which its behavior. The patches of phytoplanktons have a certain size and are subject to currents and turbulence. The copepod has various characteristics (its "weigth" expressed in nitrogen, the volume of its gut, its speed of stroke...). Its behavior, object of the study for the biologist, is defined by a Petri network to allow the description of sophisticated behaviors with a standard and simple tool. Agents are reactive which means that their behavior is governed by their perception and their current internal state, which, in turn, eventually induces an action and a new internal state (see Fig. 3).

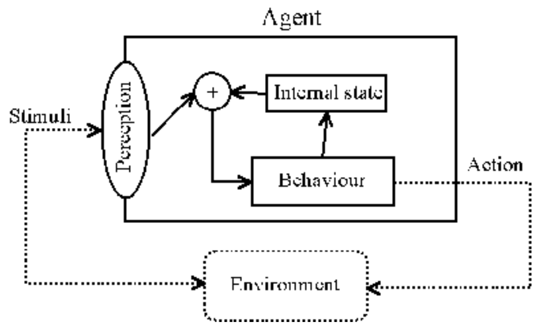

Fig. 3. Reactive agent

3.1 Modeling tool

There is a large number of modeling tools more or less general (Swarm [9], Manta [8]...). In the majority of the cases, they are platforms either adapted to one or a family of problems, or generic. To our knowledge, the generics involves, in all the cases, a dependence with respect to a data-processing environment or of a language of development but especially these platforms is containing reusable primitives and thus should be written code ! All these reasons pushed us to design a new tool of modeling and simulation of reactive, perceptive and located agents.

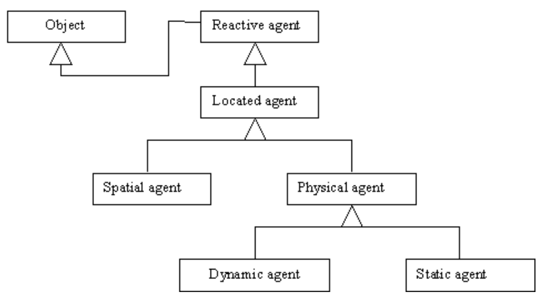

Fig. 4. Hierarchy of agent familly

We use an object language (Java) in which we find all the concepts of the paradigm object as well as a set of advanced classes (thread, stream...). These classes enabled us to define our classes of agents. Initially, these classes of agents were accessible by a language with which one can describe a category of agents via their behavior, their properties and their means of communication. A second language makes possible the description of the environment. These two languages composes a platform where one can describe the agents, to create them and activate them. At present, these two languages are encapsulated in a graphic interface written in Java (thus portable and accessible on Internet - http://www-lil.univ-littoral.fr/ ramat) and are accompanied by tools for the definition of the environment, tools for the representation of moves of located agents and layout of the variations of the properties of the agents.

Dynamics. The dynamics of agents is modeled using Petri networks. Each agent can have several Petri networks and each net perform, in parallel with others, a process. The Petri networks can model process including changes of states, moves, message exchanges... Basically, Petri networks specifies the states within which an agent can be, the possible transitions between states, and the conditions to fulfill for each transition to occur. To each state is associated a set of actions performed by the agent when the state is activated; actions may be a displacement in the space, an update of its internal state, perceiving its environment... The state is activated when it is first reached. A transition actually occurs when its condition is fulfilled.

In the simulation of real processes, it is crucial to take its duration into account. Hence, each transition is assigned a duration which is either constant and deterministic, or stochastic.The introduction of the time allows to construct dynamically a schedule. At every time t, each active Petri net checks if it has activable transitions. If it is the case then they are occur. Two cases of figure are then to consider : either the crossed transitions are not temporized or they are it. In the second case, the activation of following states put in the schedule. This mechanism supposes that all active Petri nets reach either a temporized transition or a state from which no transition can be activated.

Perception. By analogy with biological entities, any agent is endowed senses more or less developed. In our model, an agent has several senses and each one of them is defined by three parameters: the type of perceived agents, the sector (according to the orientation of the agent), and the distance within which the perceivable agents are actually perceived. By this way, one can test different scenarios according to possible models of perception of the copepod. Moreover, one agent can perceive only a part of the characteristics of another agent. One specifies in this case the perceived characteristics. Furthermore, an agent perception of a certain feature of an other agent may not be a carbon copy of the perceived agent actual feature but somehow blurred by some perception bias, or some environmental effect (turbulence...). An agent can also have several senses. The sense to be used as a certain stage of the behavior of the agent has to be specified.

In this approach, senses are at the base of the network of knowledge of the agents. Dynamically, the agent builds its neighborhood according to its position in space, and to its senses.

3.2 The model

We started from the assumption that the copepod adopts two distinct behaviors: a stroke directed in the search of food and random jumps. These behaviors have a direct influence on the process of ingestion of the cell of phytoplankton. Thus, we focus exclusively on this process and we leave aside the digestion which is not to disregard to obtain a complete model.

General information. The system is composed of three entities: a mass of water, cells of phytoplankton and copepods. Initially, we consider only one copepod at a time since the aim of this study is the hunting behavior of copepods. The mass of water constitutes the environment in which evolves and moves the other entities. The size of the copepod (1 mm) is used as the basic length for the discretization of this environment. For the moment, the environment is considered as two dimensional and split into chunks of $1mm_2$. Each chunk is dealt with by spatial agent. The cells of phytoplankton are very numerous (from 10 cells per liter to 10^8 cells per liter which yields a maximum of 10^2 cells per chunk). Thus, it is not conceivable to model each cell with one agent. The solution which was adopted consists in defining a property "Number of cells" at the level of spatial agents. One delegates the management of food to the spatial agents, that is to the environment. As the copepod, the environment is represented by a dynamic agent which behavior is described in the subsequent part.

The unit of time of simulation is noted u.t. It is fixed by the duration corresponding to the time necessary to perform the quickest action, i.e. the handling of a cell of phytoplankton by the copepod, 1/20 s.

The dynamics of the copepod. The Petri network that models the dynamics of displacements of the copepod is divided into four parts:

- as soon as a cycle of $t1$ u.t., for example 75 u. t., is elapsed, the copepod carries out a jump without considering what surrounds it,
- during $t2$ u.t. (time to cross a chunk of the environment), the copepod explores the place where it is and if food is available there; within each unit of time, it can capture a cell of phytoplankton,
- on the other hand, if there is no food, it continues to swim to reach the next chunk,
- at the end of the $t2$ u.t. necessary to cross a chunk, the copepod "chooses" a new chunk to be explored and proceeds there.

Let us take a closer look at the active phase dealing with the capture of food. With the exception of the random jumps, the copepod strokes and traverses a chunk at each $t2$ u.t. When this time amount of time has elapsed, the copepod changes its location. This change is a function of the copepod behavioral strategy. In the case of our present work, the probability that a chunk is chosen is proportional to the amount of food it holds: the more food, the more likely the copepod will move to it.

Locally, the copepod captures the cells of phytoplankton if it has not yet eaten too much within the last u.t. Indeed, the copepod decreases the quantity of food which it absorbs according to its level of satiety, itself directly bounded, for the moment, with the number of cells of phytoplankton present in the gut. The function of satiety is:

$$C_g = 1 - \frac{V_{prey}X_1}{\frac{2}{3}V_{gut}} \quad (1)$$

where $V_{prey}X_1$ represents the volume of the not-yet-digested preys and V_{gut} the volume of the gut of the copepod. It captures the cell according to a certain probability and, if it does not, the cell disappears from its field of vision.

4 Experimental Results

We define two types of copepods according to their strategy of stroke: random or directed towards food. The environment is composed of a 2D grid of 1024 square chunks (32x32). Each chunk is a spatial agent and is connected to its 8 neighbors. The cells of phytoplankton are distributed either by patches (see Fig. 5 and Fig. 6 - the distribution is multifractal [10]), or uniformly. In both cases, the total density is identical (2 cells by chunk). For patches, various densities of phytoplankton are used (represented by different levels of gray).

Using the variables defining the internal state of copepod agents, we measure within each step of simulation: the energy, expressed in pg of nitrogen, contained in the gut, its usable energy, the number of captured cells of phytoplankton and two variables of the analytical model (X_3 and X_4, see Fig. 2).

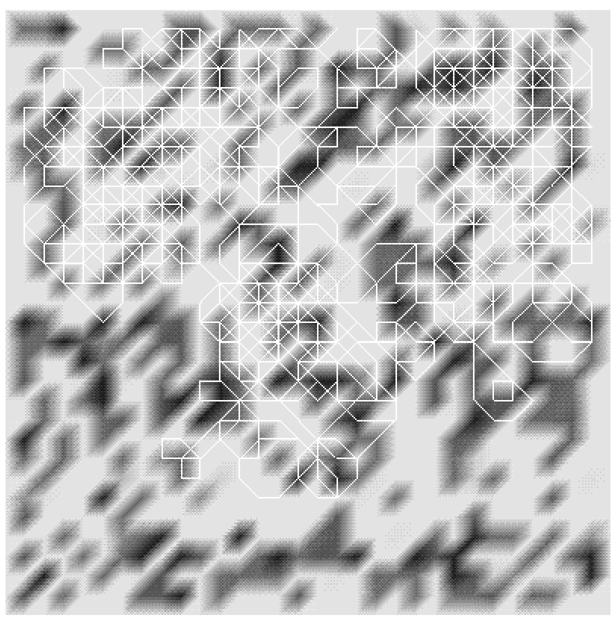

Fig. 5. Path of the copepod swimming at random

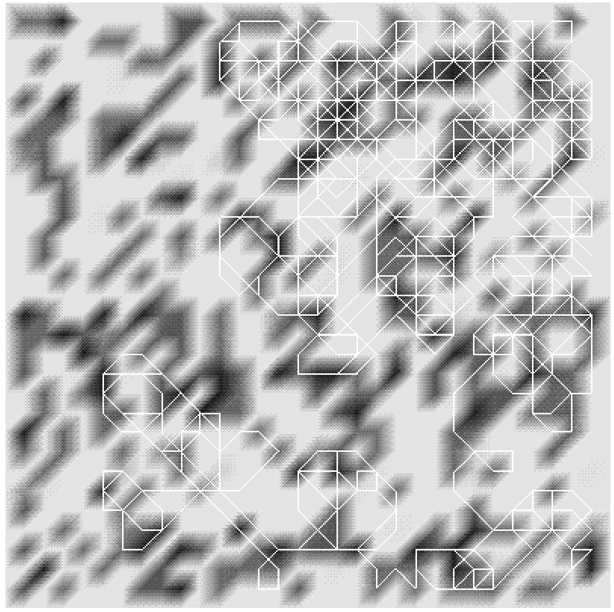

Fig. 6. Path of the copepod swimming towards food

We use a graphical tool to visualize the paths followed by copepods. By superimposing the path of the studied copepod and the distribution of cells of phytoplankton, one shows that in the case of a non homogeneous distribution of the cells of phytoplankton, the strategy of the directed stroke is more effective.

If one compares the curves representing the quantity of food in the gut of the copepod along the time (see Fig. 7), according to the distribution of the cells of phytoplankton and the strategy of stroke, it appears clearly that the directed stroke is favorable to the feeding of the copepod from the point of view of energy.

If the copepod is located inside a homogeneous field of phytoplankton, the strategy of stroke does not have any influence on the feeding since it is able to find food in all directions in same quantity. On the other hand, in a heterogeneous field, the random strategy leads the copepod to find food at random, and especially to leave chunks with food without seeking to benefit from it. Therefore this strategy is less effective.

In conclusion, we find the principal results stated in [1] for a uniform configuration of field and random stroke. It remains to carry out comparisons in vivo with results of experiments. However, these in vivo remain difficult to realize for the moment. The only points of possible comparison relates to the aspect of the paths according to the density of food [3].

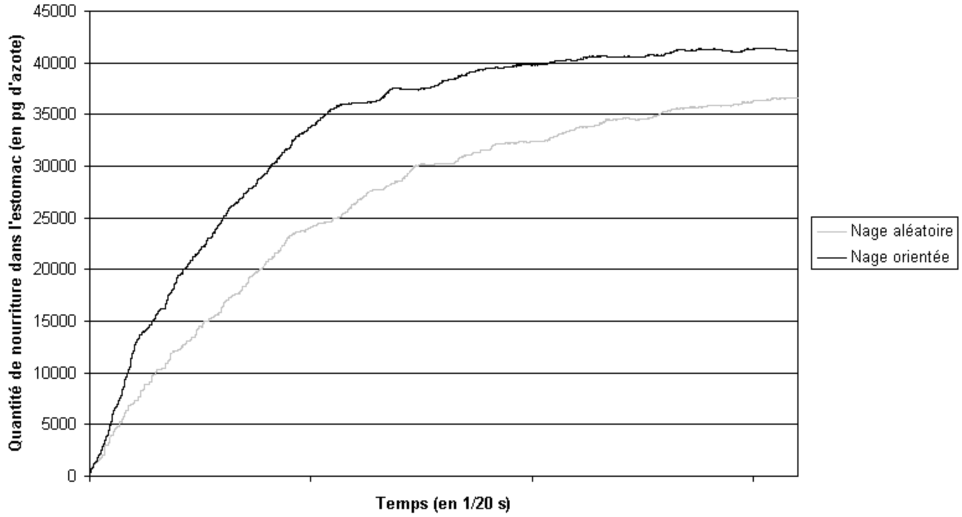

Fig. 7. Quantity of food (pg of nitrogen) in the gut of the copepod against time

5 Conclusion

As part of a joint project gathering biologists, mathematicians, and computer scientists, we have presented the modeling of the behavior of an animal pertaining to the family of zooplanktons, namely the copepod. The goal of our work is to study the coupling between the behavior of the animal and its environment. We use multi-agent systems to obtain an executable model with which a wide variety of behavioral dynamics can be expressed. Using MAS, we are also able to make the behavior of agents evolved during time, and co-adapts to its changing environment. We obtain results of simulation that are compatible with *in vivo* observations and which are based on a model of the behavior of the copepod rather than an analytical description using abstract quantities and parameters. Owing to this behavioral model, we are able to assess many assumptions about it, something which does not seem to be able to be done within the usual analytical framework.

Basically, the model presented in this paper is a translation of the analytical model into algorithm. Thus, we end-up with averaged measures resulting from assessments and random processes, such as that of satiety. The same remark is valid for the digestion part. The only new element is taking into account the behavior at the level of the stroke. We emphasize that the definition of the agents is definitely simpler and uses a reduced number of parameters compared to the analytical model.

We are now interested into breaking up the "enigmatic" processes, such as the random jumps, and the speed of constant stroke. It is obvious that these actions hides complex processes. For example, the observation shows that the speed of stroke is not constant and that these variations are due to interactions with the environment. It remains to imagine them and subsequently specify them precisely.

In addition, if one is interested in the rules of decision regarding the capture of a cell of phytoplankton, one can wonder whether elements such as the physiological state of the copepod does not come into play. For example, a female, carrying eggs, has significantly more requirements in food than a male. Furthermore, it is obvious that a copepod did not behave in the same way on its own, or within a colony of its kind.

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