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Information transfer, behavior of vessels and fishing efficiency: an individual-based simulation approach

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Abstract – A simulator dedicated to the modeling of individual search behaviors of fishing vessels has been built using multi-agents systems methodology. The harvesting activity of a virtual fleet is simulated and applied to a static virtual fish population, distributed in a bi-dimensional spatially explicit environment. The resource population can differ depending on different degrees of aggregation. Each vessel of the fleet is modeled as a singular and autonomous agent of the fishery system. The model focuses on the representation of information transfer among vessels, which results in an orientation of search effort. The informative search behavior is compared to a stochastic search, in order to estimate efficiency gains allowed by information transfers. Results show a strong dependence of the fleet's efficiency towards the level of aggregation of the resource. For higher levels of aggregation the informative behavior results in important gains in efficiency. Conversely, a misleading effect of information appears in the weakest aggregations. The informative behavior leads to the progressive convergence and the gathering of the agents. When the aggregation is strong, this "pack effect" is stable in time and enables the vessels to make quick catches. For the weakest aggregation levels, the "pack effect" is unstable and leads the ships to a perpetual pursuit state, without catches. Thus, the size of existing networks appears as a key parameter of vessel behaviors. This approach, using an individual-based simulator, seems quite appropriate to connect individual behaviors to the dynamics of the fishing efficiency, which are generally studied in an aggregated manner. It allows to quantify the effects of the exchange of information among vessels, which is commonly considered as a qualitative phenomenon. Such an approach should be enlarged to a more global modeling of all of the components of the individual search behaviors of vessels.

Key words: Fishing behavior / Fishing efficiency / Fish aggregation / Individual-based model / Multi-agent systems / Simulation

Résumé – Transfert de l'information, comportement des navires et efficience de pêche : une approche par simulation individus-centrée. Les méthodes de modélisation des systèmes multi-agents sont utilisées pour simuler les comportement individuels de navires de pêche. On modélise ainsi l'activité de recherche d'une flottille virtuelle exploitant une population de poissons. La ressource est distribuée de manière statique dans un environnement bi-dimensionnel spatialement explicite et peut présenter différent degrés d'agrégation. Chaque navire est modélisé comme un agent autonome. Le modèle s'attache en particulier à la représentation du transfert de l'information entre navires, et à ses conséquences sur l'orientation de l'effort de recherche des poissons. Le comportement de recherche dit « informatif » est comparé à une recherche aléatoire, afin d'estimer les gains d'efficacité de pêche induits par le transfert d'information. Lorsque la ressource est fortement agrégée, le comportement informatif permet des gains d'efficacité de pêche très importants. A contrario, un effet trompeur de l'information est mis en évidence pour les faibles agrégations. Le comportement informatif conduit également à un regroupement des navires. Lorsque l'agrégation est forte, cet « effet de meute » est stable dans le temps et permet aux navires de réaliser des captures rapidement. Pour les faibles agrégation, l'effet de meute est instable et conduit les navires à une situation de perpétuelle poursuite, sans capture. La taille des réseaux d'information constitue ainsi un élément-clé du comportement des navires. Une telle approche, basée sur une simulation individu-centrée, apparaît comme la méthode appropriée pour relier les comportement individuels des navires à la dynamique de l'efficacité de pêche, qui est généralement analysée à partir de données agrégées. Elle permet de quantifier les effets de l'échange d'information entre navires, alors que ce phénomène est généralement considéré de manière qualitative. Au travers d'un modèle plus global, une telle approche devra être élargie à toutes les composantes du comportement individuel des navires de pêche.

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1 Introduction

In the context of overexploitation of a great part of the world's marine resources, the question of the efficiency of the fishing vessels, and by extension that of the subjacent behaviors of fishing, cannot be ignored. Particularly, detailed analyses on fishing behaviors have become a necessity in order to understand potential changes in fishing pressure (Hilborn 1985; Hilborn and Walters 1987). The fishing efficiency is here defined as the capacity of fishermen to find available fish and is a key component of the global fishing power of vessels (Robson 1966; Laurec 1977). This last parameter takes into account all contributing factors related to the fishermen and to the vessel so that, for a given stock, a unit of nominal fishing effort results in catches (Gascuel 1995). Many studies, dealing with different fisheries, have shown the amplitude of the variations of the fishing power, whose effect on the exploited resources can be very significant (Hilborn and Ledbetter 1985; Gascuel et al. 1993; Millischer et al. 1999). However, an important problem in the measure of the real efficiency of the fishing activity lies in the fact that many qualitative factors are involved in its constitution, such as experience (Abrahams and Healey 1990), knowledge and learning ability of fishermen (Dreyfus-Leon 1999; Salthaug 2001; Xiao 2004), competition or cooperation phenomenon within a fleet (Vignaux 1996; Gillis and Peterman 1998; Swain and Wade 2003), and information exchanges among vessels (Allen and McGlade 1986), which determine the desirability of a particular fishing zone (Hilborn and Walters 1992). An associate problem is the fact that these qualitative factors operate at an individual scale (Thorlindsson 1998; Squires and Kirkley 1999), making an analytical approach even more difficult.

In addition, some recent works observed the variety and the strategic importance of the interactions between vessels and, more generally, of the individual fishing behaviors (Dorn 1998; Powell et al. 2003; Salthaug and Aanes 2003). In particular, the existence of information exchanges between vessels and its importance on the organization and the efficiency of the search strategies were underlined (Hilborn 1985; Hancock et al. 1995; Gaertner et al. 1999), without being studied in detail or quantified. The objective of this study is to highlight such a relation between efficiency and behavior, focusing on the impact of information exchanges on the fishing efficiency of vessels. Actually, such a study is limited by the lack of quantitative data sets about the way these exchanges occur. Thus, a modeling approach using virtual simulation practice appears quite suitable, as an exploratory tool, in order to propose and to test the relevance and the consequences of a theoretical model (Dreyfus-Leon and Kleiber 2001) of information exchanges among vessels.

Previous models for fishery simulation (Hilborn and Walters 1987; Allen 1991; Gillis and Peterman 1998) dealt with fleets composed of interchangeable individuals, only characterized by a global state. They do not directly take into account individual interactions and decision-making processes. Individual-based simulation models, using the Multi-Agent Systems (MAS) methodology, allow such a direct modeling of location and individual scaled processes, in a bottom-up modeling approach (Coquillard and Hill 1997). This methodology is based on a discrete representation of a system in space and time, by individual elements in interaction, the "agents" of the system, which form this system (Ferber 1995). Each agent is defined by its methods, or functions, which lead to actions in and on the environment, and by its attributes, which allow him/her to carry out these actions. Thus, an agent appears as an autonomous computer process, able to perceive and react to its environment's variations. One of the main qualities of multi-agent systems is the easy combination of both quantitative and qualitative assumptions in the model implemented (Ferber 1997). The representation of individual choices, and their determinism, can't avoid qualitative assumptions on the structure and social organization of a fleet (Hilborn 1985). In particular, the representation of information exchanges between individuals must take into account the decisions taken on the supposed quality of information.

Several anthropological and sociological works could enlighten some qualitative elements showing that information is generally exchanged between fishermen connected by economic, ethnic or friendship links (Breton 1981; Bouju 1995). Thus, a fleet is structured by acquaintance networks, in which fishermen, pertaining to the same network, exchange some information which tends to be more accurate when there is a strong link between agents (Pichon 1992). We propose a synthetic model of information exchanges among vessels based on these two points: existence of networks, and variation of accuracy of the information exchanged. This model is implemented, using the object-oriented language JAVA, into a generic multi-agent simulator, dedicated to the modeling of individual search behaviors of fishing vessels. This simulator leads us to experiment with different scenarios of the information transfer process among a virtual fleet, explicitly modeled by its individual components. The goal of the simulations is to test and compare the relative efficiency of different kinds of informative behavior. Thus, the simulator enables us to analyze the consequences, in terms of efficiency and spatial behavior of vessels, of the different modes of cognitive and informative behavior taken into account in the model.

2 Material and methods

The harvesting activity of a fleet is simulated and applied to a virtual fish population, in a bi-dimensional spatially explicit environment. Each vessel of the fleet is modeled as a single and autonomous agent of the fishery system. The agents are able to travel, to fish, and to search for the resource. The aim of the experiment is to measure and analyze the effects of information on the search efficiency. Thus, the model of information transfer is compared to a random search model, in order to estimate the efficiency gain allowed by the exchange of information.

2.1 The fishery simulator

The fishing area

The fishing area is represented as a squared grid 81×81, made up of an 8-neighboring cells network (each cell is directly neighbored by eight cells). This spatial representation

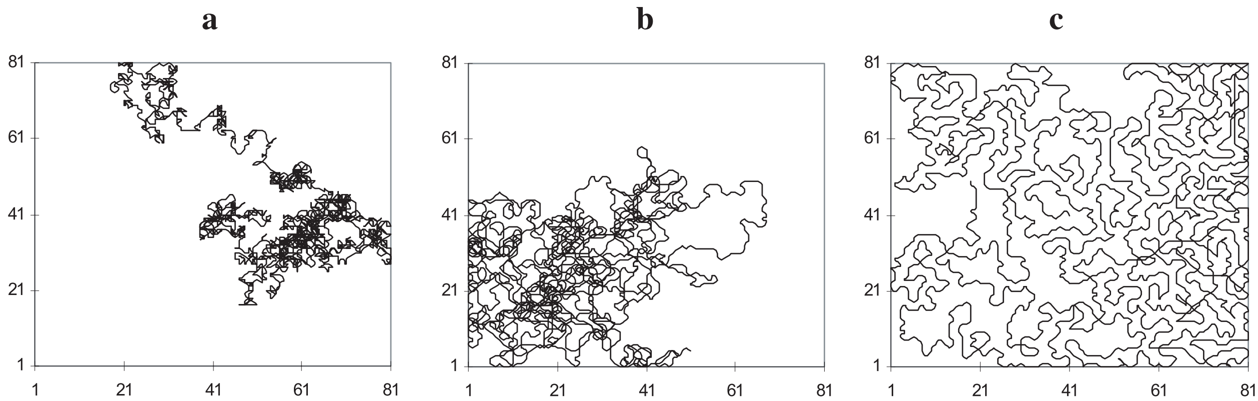

Fig. 1. Trajectories of a virtual vessel in the 81 × 81 squared grill, simulated over 2000 hours of search (null resource over the whole fishing zone). (a) Purely random movement (Brownian movement); (b) random search (stochastic behavior), with memory = 1 (the vessel chooses a cell not explored at the previous time step); (c) random search (stochastic behavior), with memory = *t* (the present time step).

simulates an isotropic circular space, centered on the cell (41, 41). The chosen dimensions allow an isotropic division of the whole zone into 9 sub-zones (27×27), or 81 sub-zones (9×9). Such a division defined an agents' representation of space, and is used in the behavioral model of agents (see Structure of informative exchanges). The squared structure necessitates a non-euclidian calculation of the distance between two cells. In this case, the distance is equal to the minimal number of cells to reach from one cell to the other.

The resource is represented as a collection of "schools", distributed into the fishing area. Here, a school is defined as a resource unit located in one cell and which can be a catch in one time step. The schools form a "cluster" of the resource when they are aggregated.

The agents "vessel"

At each time step, the agents location is given by their cartesian coordinates in the spatial grid. The agents have a local perception of the cell corresponding to their location (x, y) and of the 8-neighboring cells of (x, y). Thus, they can locate the presence of a school in their immediate environment at any moment. The fishing area is delimited. So the agents perceives only 5-neighboring cells if they are on a border, and 3-neighboring cells if they are on a corner.

The basic behavior of an agent is divided into two types of activity: fishing within the present cell, or moving to a neighboring cell in the spatial grid. When fishing, the agent catches the whole school located in the present cell. For the moving behavior, two situations can occur. If there is at least one neighboring cell with a school, the agent moves to it. If there are several, the agent chooses randomly among them. If there is no school in the neighborhood, the agent chooses a neighboring cell, according to its search method. This method depends on the search model. The random search model defines a basic reference agent, so called "stochastic" agent, unable to exchange information with other agents. In that case, the neighboring cell is chosen randomly among the cells where the agent hasn't moved to before. The information transfer model defines the way the agents, so called "informative" agents, exchange and use their information to conduct their search. In that case, the agent chooses a direction of search, and the neighboring cell is chosen according to that direction. If the informative agent does not receive any interesting information, the neighboring cell is chosen according to the random search model.

These two models define two separate types of agents. The stochastic agents have only one search method, which corresponds to the random search model. Whereas the informative agents have two methods: they use the informative search method first, but can eventually adopt a random search if information they receive is non-informative.

2.2 Random search model

To define the stochastic behavior, a distinction is to be made between random movement and random searching of ships. In the random movement, or "random walk", the agent chooses randomly one of the eight neighboring cells and moves to it at each time step (Fig. 1a). This movement is comparable to the Brownian movement of molecules, and is clearly too simple to represent a realistic random search of vessels. It leads to a very strong inefficiency of the search, and thus artificially accentuates the efficiency gains allowed by information exchanges.

In the random search model, the agent chooses randomly and moves to one of the neighboring cells that it has not explored since a delimited number of time steps. This number, so called the "*memory*" parameter, corresponds to the number of previous positions that the agent keeps in memory at each time step of the simulation. For each agent position, nine cells are explored simultaneously: the cell corresponding to the agent position, and the eight neighboring cells that the agent perceives. A memory equal to 1 makes the agent choose randomly among the three or five neighboring cells that it has not explored at the previous time step (Fig. 1b). With an infinite memory (*memory* = *t*, with *t* the present time step), the agent keeps in memory every previous position, and thus, it never comes back to the areas already explored. When every neighboring cell has been already explored during the *memory* previous time steps, the agent calculates the position of the nearest cell that has not been explored, and moves to the neighboring cell that is in the direction of this nearest cell. If there are several equidistant cells, the agent chooses one of them randomly.

This behavioral model allows a realistic representation of the real random search of the vessels, which consists in the systematic exploration of new fishing areas that the fisherman chooses randomly (Allen and McGlade 1986). Although this type of search is random, it brings in a deliberation from the fisherman. The rules of the model give a realistic representation of such a deliberation.

The agents exploring capacity increases very largely by taking into account such random search behavior. The limiting parameter is the value of the memory of the agents, for which an increase induces an improving of the search quality (Figs. 1b and 1c). The simulations retained for the experiment are successively led with the two extreme values *memory* = 1 and *memory* = *t* (with *t*, the present time step).

2.3 Information transfer model

The model of information transfer within the fleet synthesizes the representation of information exchanges around two issues: the structure of informative exchanges, which depends on accuracy and dissemination capacity of information, and the decision-making procedure of agents.

Structure of informative exchanges

Information is related to the catches and location of agents at each time step of the simulation. Information is transmitted according to an acquaintance list, in which each informative agent can consult the fishing results and the location of its partners, belonging to the same acquaintance network. Thus, the virtual fleet is structured by several networks, in which agents can exchange information about their activity.

Three kinds of information, corresponding to three levels of accuracy, so called High, Middle, and Low, can be exchanged among vessels. The accuracy level depends on the location of transmitting agent, which can be given as a cell location (High level of accuracy), as a sub-zone location with a division of the whole fishing zone into 81 sub-zones (Middle), or as a sub-zone location with a division into 9 sub-zones (Low).

The diffusion capacity of information depends on two parameters. First, the size of the acquaintanceship networks determines the number of agents interacting between each other. Second, the type of networks of acquaintanceship leads to different structures of informative exchanges. Two types of networks are considered. The first type corresponds to closed networks, in which agents provide mutual informative exchanges. In this case, no information can be forwarded from a group of agents towards another. The informative relationships (transmission and reception of messages) between agents are exclusive and reciprocal. The second type defines open networks of agents, in which the relationships are not reciprocal. This allows some diffusion of information from a group of agents towards another one, and leads to an asymmetric structuring of the fleet (Fig. 2). The exchange by open networks is quite a realistic representation of the phenomena of espionage between vessels, which consists in a non-reciprocal information

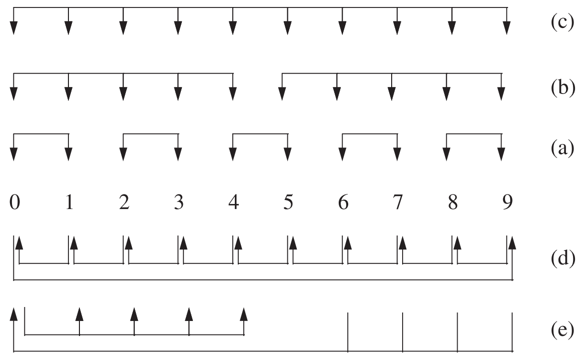

Fig. 2. Schematization of the various structuring induced by the various types and sizes of acquaintanceship networks, in the case of a fleet of ten agents. The numbers correspond to the ten agents of the fleet; the arrows indicate the agents to which each agent transmits information. At the top, closed networks (a) size = 2 (five groups of two agents); (b) size = 5 (two groups of five agents); (c) size = 10 (one group of ten agents). At the bottom, open networks (d) size = 2 (ten groups of three agents, having non-reciprocal-relationships; for example, agent 0 receives information from 1 and sends information to 9); (e): size = 5 (ten groups of nine agents having non-reciprocal exchanges; for example, agent 0 receives information from agents 6, 7, 8, 9, and transmits to agents 1, 2, 3, 4). The last case figure (e) shows only the information exchanges of agent 0.

transmission. This phenomenon can be compared to a passive form of information, which does not require acquaintanceship. In real conditions, this passive type of information is added to an active transmission, that the closed networks can represent.

Thus, the structure of informative exchanges among the agents depends on three synthetic parameters which define several types of informative behaviors: accuracy of information (High, Middle or Low); size of networks (2, 5 or 10); type of network (closed or open). Each one of these parameters is tested in the simulation experiment.

Decision procedure of agents

The key element of the information transfer model is the decision-making procedure, which defines the way the agent uses the information it receives. In other terms, it determines what information the agent would consider as a useful one to guide its search. In real fisheries, this kind of judgment results from a subjective decision-making process, and depends on the fisherman's own history. Each fisherman has a representation of what is a "good" catch, "good" information, or a "good" zone in term of desirability, which may differ according to the time step and the fisherman. Thus, the decision-making procedure depends on the agent's past results during the simulation and on the distance of transmission of each information.

For the receiving agent, the data processing is done in two stages. Firstly, it scans the available information, and keeps in memory the most useful information. Secondly, it compares this information to its own spatial position and its own catch successes. This comparison will decide whether the agent heads for the transmitter's location or not. These two processes are based on a calculation of the expected performance, expressed in catches per unit of time, in relation to each piece of information. This calculation must take into account the cost of travel time during which the receiving agent assumes that it won't fish. This cost is equal to the distance of the shortest route between the receiver's location cell and the transmitter's location (cell for the High level of accuracy, or sub-zone center for Middle and Low levels).

Furthermore, information can be regarded as a skewed estimator of local abundance. In real fisheries, a transmitting fisherman tells what he caught in the past, and the receiver has to deduce, upon this information, what he will be able to catch in the future. Thus, the resource local depletion leads to an unavoidable bias in any transmitted information. In order to take this bias into account in the model, the calculation of the transmitter's performances depends also on the distance of transmission. The more distant a transmitter is, the more its last catches have to reflect the presence of a cluster that would still be valued by the receiver. That is, that the transmitter's catches must be positive on a great number of time steps. In the model, this number is equal to the distance.

Let us consider an agent k at step t, located in cell (x, y) of sub-zone z, which receives an information from agent k' located in cell (x', y') of sub-zone z', at the time step t. Agent k is able to calculate the distance $d_{k,k'}$ of the shortest course from (x, y), to (x', y') if information accuracy is High, or to the center cell of z' if information accuracy is Middle or Low. This distance is calculated in number of cells, which is equivalent to a number of steps of travel time. Thus, the performance of k', noted $U_{k'}$, is equal to its CPUE (Catch Per Unit of Effort) on the $d_{k,k'}$ last time steps:

$$U_{k'}[t] = \frac{\sum_{i=1}^{d_{k,k'}[t]} C_{k'}[t-i]}{d_{k,k'}[t]} \tag{1}$$

with: i = the time step index; t = the actual time step; $C_{k'}[i]$ = the catch of k' at each time step i.

The expected performance of k, related to the k' performance, and noted $\Pi_{k'}$, is calculated for the n next time steps, with: $n = 2 \times d_{k,k'}$. The first $d_{k,k'}$ time steps corresponds to the moving towards k' location, during which we assume that k won't have any positive catch. The next $d_{k,k'}$ time steps corresponds to the fishing stage, during which we assume that the performance of $k$would be equal to $U_{k'}$. Thus, $\Pi_{k'}$ is calculated as:

$$\Pi_{k'}[t] = \frac{U_{k'}[t]}{2}\cdot \tag{2}$$

If k has N network partnerships, with which it exchanges information, it compares each expected performance related to each transmitting agent k', and chooses the best one, denoted Ω_k, which corresponds to the transmitting agent $k_{\max}$ located at $d_{\max}$ from k:

$$\Omega_k[t] = \mathrm{Max}_{k'=1 \to N}(\Pi_{k'}) = \frac{\sum_{i=1}^{d_{\max}[t]} C_{k_{\max}}[t-i]}{2 \times d_{\max}[t]}\cdot \tag{3}$$

Then, the agent k compares Ω_k to its own results. The point is that agent k would follow the information given by $k_{\max}$ unless it has better results in the $n_{\max}$ past steps, with $n_{\max} = 2 \times d_{\max}$. The results of k are thus analyzed on the J time steps before t, from $J = 1$ (catch realized by k at t-1) to $J = n_{\max}$ (mean CPUE on the $n_{\max}$ time steps before t). This leads to the calculation of a vector of $n_{\max}$ values of CPUE for k, each CPUE being calculated on the J time steps before t. The best value, denoted Φ_k, is then considered as the best past result of k during the $n_{\max}$ steps before t:

$$\Phi_k[t] = \mathrm{Max}_{J=1 \to 2 \cdot d_{\max}[t]}\left(\frac{\sum_{i=1}^{J} C_k[t-i]}{J}\right)\cdot \tag{4}$$

The calculation of Φ_k and Ω_k is done at each time step t, for each receiving agent k , in relation with the information available at t. For a receiving agent k, the decision to follow an information is taken under two conditions: k is in search state (no resource in its own location cell and its neighborhood); and $\Omega_k[t] > \Phi_k[t]$.

If $\Omega_k[t] \leq \Phi_k[t]$, the receiving agent adopts the random search behavior. During the moving phase towards the transmitter's location, the discovery of a school or the reception of better information is taken into account. At any moment, the agents can modify their decision. For the Middle or Low accuracy level of information, the receiving agent goes toward the center cell of the sub-zone location of agent $k_{\max}$ selected. As soon as k has reached a cell of the concerned sub-zone, it adopts the random search.

For each agent of the acquaintance network, these calculations take into account the costs of travel time, and the probabilities of local depletion of the resource, related to the long haul information. At each time step, the update of the indices Ω and Φ allows a very controlled use of information, and avoids too risky choices. The decision-making process remains the same one whatever the situation that an agent may encounter (short or long-haul information, small or large amounts of simultaneous information). Thus, the model constitutes a synthetic and generic representation of information exchanges within a fishing fleet.

2.4 Distribution of schools

The comparison of stochastic and informative behaviors is done in controlled conditions of the environment. Thus, the simulations are carried out with a single non-renewable and static resource, which can represent a species, a cohort or a category. This resource is only characterized by its level of aggregation, measured by an aggregation coefficient, noted Ca. An initial number of 656 schools (10% of the cells are occupied by a school) is distributed among the cells of the spatial grid, and aggregated until it presents a chosen level of aggregation.

Five levels of reference have been retained, noted from 0 to 4: random distribution of schools ($Ca = 0$); random distribution of numerous and little clusters ($Ca = 1$); slight heterogeneity in clusters size, and number of clusters is divided by 2 ($Ca = 2$); strong heterogeneity in clusters size, and, consequently, few clusters ($Ca = 3$); a unique cluster ($Ca = 4$). Furthermore, in order to minimize the simulations variability, only one series of resource distribution is used (Fig. 3).

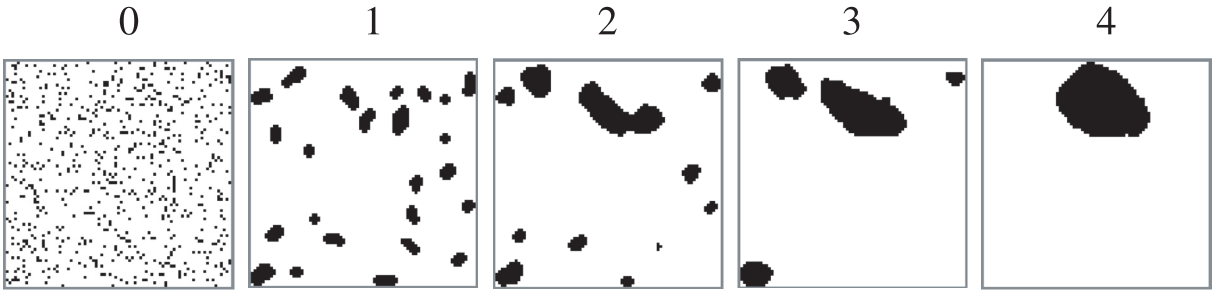

Fig. 3. Cartography of resource distribution successively used for simulations. It corresponds to five reference levels (noted from 0 to 4) of the resource aggregation coefficient *Ca* (intensity of the "clustering").

Table 1. Parameters used in simulations.

Parameters	Values tested	Unit	Use
Aggregation level (Ca)	0; 1; 2; 3; 4	–	Schools distribution
Size of networks	2; 5; 10	Number of agents	Information transfer model
Accuracy level	High; Middle; Low	–	Information transfer model
Type of networks	Closed; Open	–	Information transfer model
Memory	∞ (maximum); 1 (minimal)	Number of time steps	Random search model
Initiate period (Pi)	30 (default value); 5; 80	Number of time steps	Sensitivity analysis
Objective of catch	30 (default value); 50	Number of schools	Sensitivity analysis

2.5 The simulation experiment

All the simulations are carried out with a fleet formed by ten identical agents, having the same search behavior. During one simulation, the agents differ only by their spatial location and their own "history" (spatial trajectory; series of catches).

At the beginning of a simulation, all the agents start their activity at the center cell of the fishing area, located in (41, 41). This choice has been made to have isotropic conditions of simulation. In the case of informative agents, the information exchanges occur only after an initiate period, noted P_i, of 30 time steps, during which agents search the resource with the random search model. This initial period avoids a situation where information exchanges occur, at the beginning, while all the agents are in the same situation.

For each simulation, every agent has an objective of catch, equal to 30 schools. Once this objective is reached, the agents stop their activity, and come out of the fleet. The simulation ends when the ten agents have reached their objective. Hence, the nominal effort used to reach this objective, i.e. the time of activity, can be considered as an inverse measure of the fishing efficiency of the vessels. The average T and the standard deviation σ of the individual time of activity are calculated. The efficiency index of the fleet is given by the reverse of T, and σ gives the dispersion of individual efficiency within the fleet. The efficiency index is compared to the results of a stochastic fleet, fishing under the same conditions of simulation. Thus, the relative efficiency gain Ψ, related to the informative search behavior, is given by:

$$\Psi = \frac{T_{\text{stochastic}}}{T_{\text{informative}}} - 1.$$

The aim of the experiment is to test the influence of every parameter of the random search model and the information transfer model on the efficiency, according to the distribution of schools. For each parameter value, and for every aggregation level, a sample of 30 simulations is carried out. The resultant T and σ are averaged for this sample. Then, the relative efficiency gain Ψ is calculated as an average using a sample of 30 simulations based on informative agents, and 30 different simulations based on stochastic agents, both under the same conditions. Furthermore, sensitivity test are undertaken to measure the influence of the initiate period value and the catch objective value on the results (Table 1).

3 Results

The results are first given for a maximum memory of the agents. The effect on efficiency of the size of information networks, accuracy of information and type of networks is analyzed. Then a comparison with the minimal value of memory is examined. Finally, we describe the agents spatial behavior related to the informative behavior.

3.1 Effect of size and accuracy

Whatever the accuracy of transmitters' location contained in the information, the utility of the exchange of information between agents increases with the aggregation of the resource. Thus, the three sizes of network become successively more efficient than random search (Fig. 4 top). For every level of aggregation, a network of size 2 (fleet structured by five networks of 2 agents) is at least as efficient as a random search. For sizes 5 (two networks of 5 agents) and 10 (a unique network of 10 agents), there is a misleading effect of information for the lowest levels of aggregation (Ca = 0 and Ca = 1), which results in a fall of efficiency comparing to a pure stochastic search.

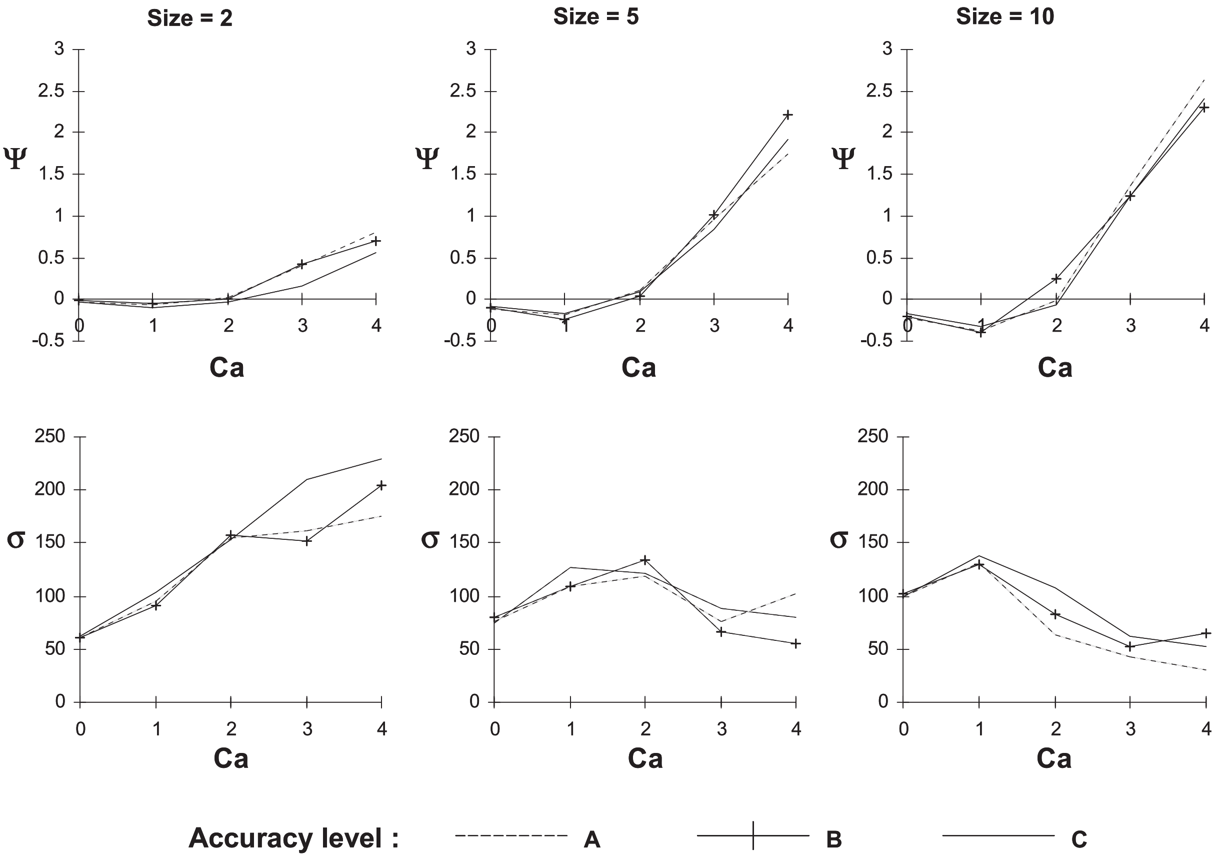

Fig. 4. Comparison of the gains of efficiency Ψ (at the top) and of the standard deviation σ of the individual performances (at the bottom), related to an informative fleet according to the aggregation level of the resource *Ca*, for the three degrees of accuracy of information used in simulations and for three size of closed networks. (A) Highest level of accuracy; (B) intermediate level of accuracy; (C) lowest level of accuracy. Size = 2: the fleet is framed by five networks of two agents. Size = 5: two networks of five agents. Size = 10: one network of ten agents. All the networks are closed. The memory of agents is maximum.

As information is used to locate aggregates, it becomes misleading in case where is none or few aggregates. This misleading effect is accentuated when aggregation corresponds to a random distribution of clusters of comparable and lower size (Ca = 1). In this case, the catches of the transmitting agents are sufficiently significant so that the receiving agents often follow information related to positive catches. But the low size of the clusters leads quickly to a local depletion because of the fishing activity of the transmitting agents, making the receiving agents movement useless. Thus, information only becomes useful when aggregation has grown over a threshold level. This threshold corresponds to the appearance of strong heterogeneity in the size and the distribution of clusters (Ca = 2).

Finally, the existence of information transfers within the fleet allows strong gains of relative efficiency. The maximum increase is nearly 300% in the case of a single network, for a maximum level of aggregation: in this case, such a gain indicates that an informative agent is, on average, four times more efficient than a stochastic agent. Even a slightly informative search (size of network = 2) always increases the efficiency of the fleet, but in a relatively smaller proportion (up to 70% of maximum gain of efficiency). On the contrary, the increase in the intensity of the information exchange allows very significant gains for strong aggregations, but with the risk of a misleading effect of information for weak aggregations. All in all, the three degrees of accuracy of information allow similar gains of efficiency. Thus, the major parameter, in terms of efficiency gain, is much more the size of the acquaintanceship network than the accuracy of transmitted information.

Scattering of individual results increases with the aggregation of the resource in the case of a slightly informative search (size = 2). On the contrary, the existence of large size networks lowers the variation, while improving the global efficiency of the fleet (Fig. 4 bottom).

Only slight differences between the three degrees of accuracy are detectable. Thus, although the tendencies are similar, standard deviation related to the less accurate location appears slightly higher than others. This location increases the risk of a small misleading effect of information for the receiving agents.

3.2 Effect of type of network

With equal sizes of networks, a fleet structured by open type informative networks is found to be systematically more efficient than a fleet having closed networks (Fig. 5). The correlation between increase of efficiency and *Ca* is similar to the case of closed networks, with the same misleading effect of information for lower aggregation levels. Up to the threshold

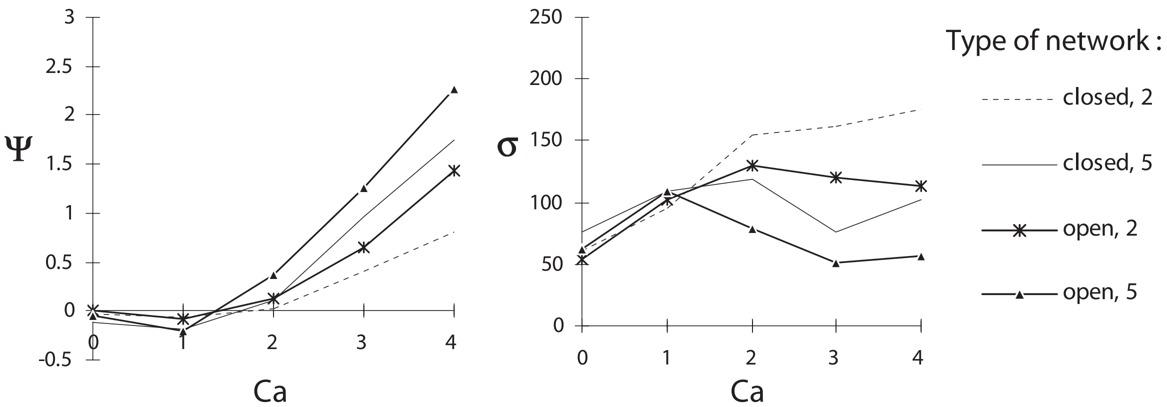

Fig. 5. Comparison of the efficiency gain Ψ related to closed and open networks of size 2 and 5, according to the aggregation level of the resource *Ca*, with a maximum degree of accuracy (A). Closed, 2: closed networks of size 2; Closed, 5: closed networks of size five; Open, 2: open networks of size 2; Open, 5: open networks of size 5. The memory of agents is maximum.

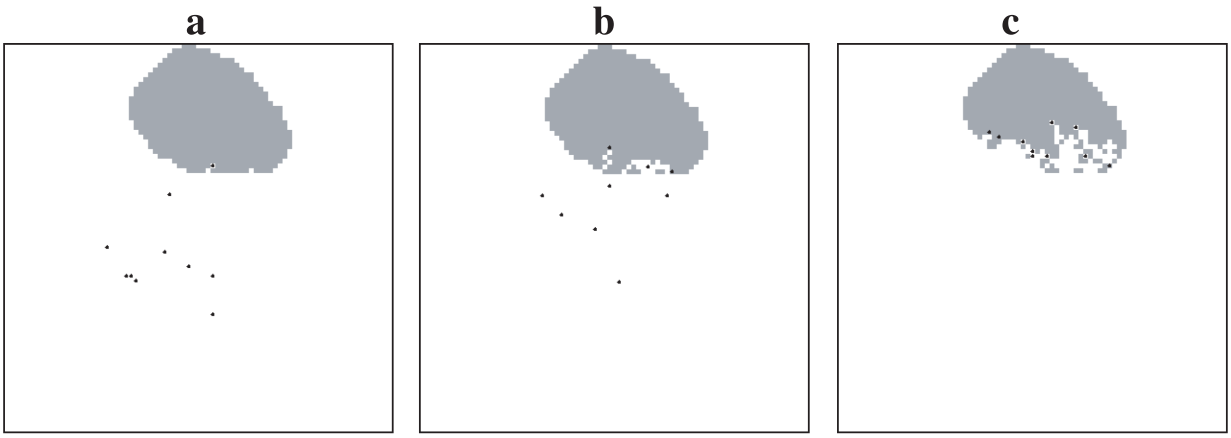

Fig. 6. Illustration of the increased dissemination of information by the use of open networks. The example presented relates to an informative fleet of maximum memory, structured by open networks of size 5, evolving in a landscape of resource characterized by a maximum initial aggregation (Ca = 4). (a) Location by a vessel of a cluster of resource, and emission of information towards four vessels; (b) the receiving agents move towards the cluster, and inform in their turn four other vessels; (c) as a result, the cluster is located and exploited by the whole fleet, besides the size of networks is only 5.

value of real utility of information (Ca = 2), the open networks are always more efficient than the closed networks. For lower values of *Ca*, both network types give similar results. In the same way, up to the threshold Ca = 2, the standard deviation of individual performances is notably reduced by the use of opened networks, for all the degrees of accuracy of the information taken into account.

The opening of the networks allows a greater dissemination of information among the agents. It makes the fleet more connected than in the case of closed networks. Thus, maximum connectivity, with a size 10 for the closed networks, can be approximated with a size of open network equal to 5.

Furthermore, this threshold value corresponds to the appearance of a strong heterogeneity in the size and a reduction of the number of clusters. Then, information allows a rapid exploitation of the clusters discovered by an agent, but with a risk of misleading effect of information if the cluster is not of sufficient size. From this threshold value, information becomes useful, but risky. The opening of the networks makes it possible to limit the consequences of this risk, by delaying the diffusion of information within the fleet.

For example, in the case of open networks of size 5, if agent 0 is the first to find a cluster, it acquaints agents 1, 2, 3 and 4 about its catches (Fig. 6a). As soon as the latter obtain catches in their turn, they inform the other agents of the fleet, not necessarily having been acquainted by agent 0 (Fig. 6b). For instance, if agent 3 is the second agent exploiting the cluster, it informs agents 4, 5, 6 and 7. The first information spread from a network to another, with a delay related to the travel time of each agent towards the cluster. All the agents can be informed, but only under the condition that the first receiving agents achieve large catches (Fig. 6c). The existence of a delay in the diffusion of information within the fleet generates a buffer effect, which limits the risk of misleading effect of information.

Thus, the opening of networks increases the dissemination of information, i.e. its ability to be exchanged among a great number of agents, and, at the same time, decreases its rapidity of dissemination, by the delay effect in the information process. Both mechanisms induce an indirect increase of the fleet connectivity, which improves the performance and the adaptation capacity of agents.

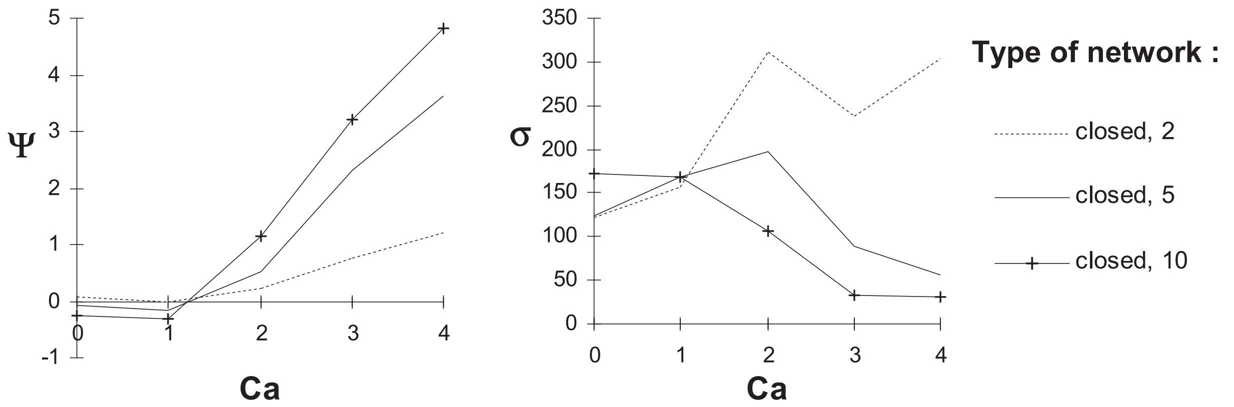

Fig. 7. Comparison of the efficiency gain Ψ and standard deviation of the individual performances σ related to an informative fleet with a memory at minimum level (*memory* = 1), according to the aggregation level of the resource *Ca*. The networks are closed, with size 2, 5 or 10. The accuracy level is High.

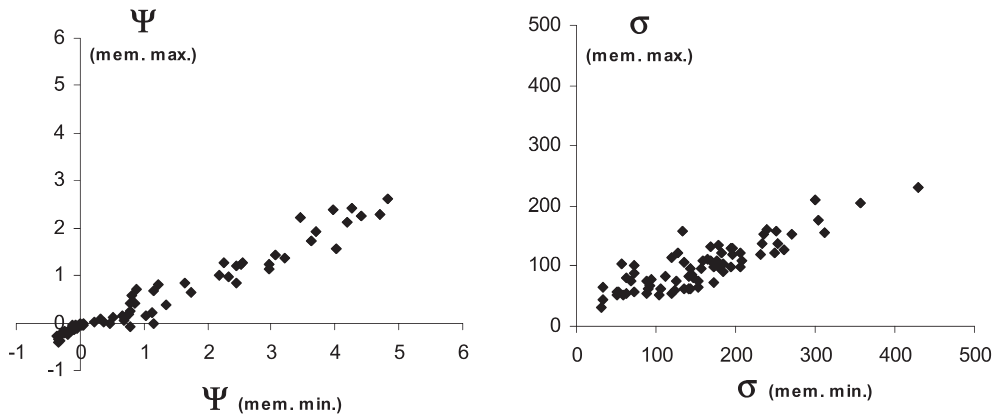

Fig. 8. Relation between results related to minimum and maximum memory of agents. Left: efficiency gains; right: standard deviation of individual performances. Each point corresponds to the results (average on 30 simulations) obtained for a given value of the parameters *Ca*, size, accuracy and type, in the cases of minimal (abscissa) and maximum (ordinate) values of memory.

3.3 Effect of memory

The results obtained with a minimal level of agents' memory are qualitatively similar to the previous ones. The vessels fishing efficiency increases with the aggregation and the size of the information networks, while the dispersion of individual performances decreases (Fig. 7). One finds the existence of a misleading effect of information for the weakest aggregations, for which there is no real heterogeneity of the resource (*Ca* = 0: random distribution of schools, and *Ca* = 1: random distribution of clusters of low and similar size).

From a quantitative point of view, the decrease of the agents' memory induces a global increase of the efficiency gain allowed by the exchange of information, and of the dispersion of individual performances. This quantitative increase appears for every type, size and accuracy level of information transfers (Fig. 8). The maximum profit, which corresponds to a maximum aggregation and a single network, is in this case of 500%. A slightly informative search (five networks of two agents) is always as efficient as a purely stochastic search, and allows profits of efficiency of 100% for strong aggregations.

A significant implication of that increase is the shifting of the threshold of real utility of information towards the weakest aggregations. Indeed, the misleading effect of information is slightly diminished for *Ca* = 1, since the two situations *Ca* = 0 and *Ca* = 1 are more or less equivalent. Furthermore, the Ψ values for *Ca* = 2 are largely positive, whereas they were quite null in the maximum memory case. The reasoning of their random search allows the vessels to quickly locate aggregates, whatever their size. Thus, for the maximum value of agents' memory, the informative behavior only becomes really more efficient when there are strong differences between the aggregates, and a very strong concentration of the resource. Thus, the increase in memory makes the efficiency of search more dependent on the degree of aggregation of the schools.

A large memory implies a significant orientation of random search, and provides the agents with the capacity to quickly explore randomly the fishing zone. Thus, it decreases the risks of searching in virgin areas. This is why it is all the more interesting to use information exchange to orientate the search when the agents memory is weak.

3.4 Spatial behavior of the fleet

The informative behavior of agents is characterized by a "pack effect", which results in a systematic convergence and gathering of agents pertaining to the same acquaintanceship

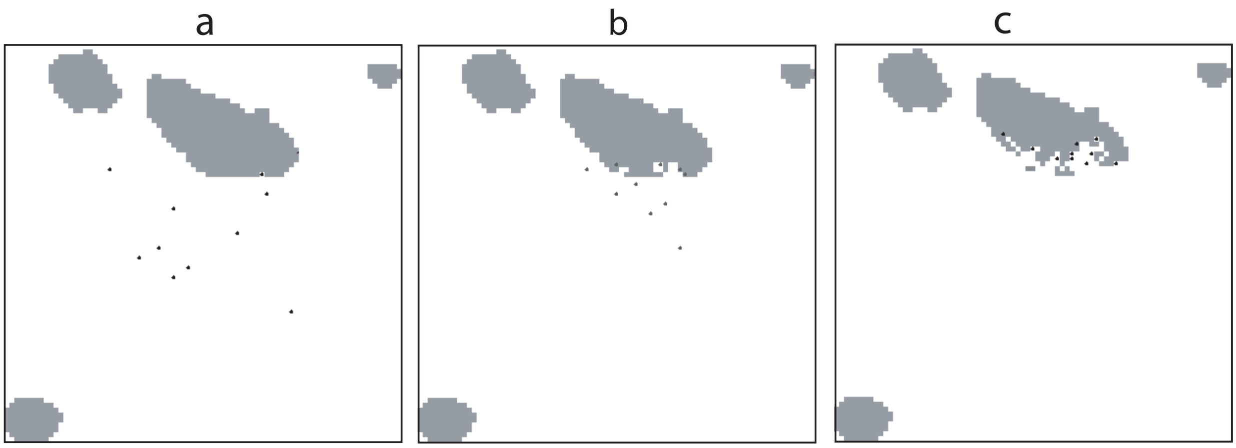

Fig. 9. Illustration of the pack effect induced by a diffusion of information within the fleet, in the case of an initial aggregation $Ca = 3$, and a maximum connectivity of agents (one unique closed network of ten agents). Strong connectivity induces a convergence around the same cluster (significant grouping). (a) Location of the cluster by a vessel; (b) grouping of the fleet around the same cluster; (c) exploitation of the cluster by the gathered fleet.

network. The intensity and stability of this grouping depend on the connectivity of the fleet, i.e. on the size and type of networks, and on the aggregation level of the resource. A strong connectivity induces a convergence around the same cluster. If the aggregation is significant, the convergence of the vessels results in the formation of a significant fishing group which is stable in time, as the size of the exploited cluster is sufficient to avoid the misleading effect of information and to reduce the local competition between vessels (Fig. 9). If not, the low size and random spatial distribution of the clusters make the consequences of the local competition even more significant. It leads to a misleading effect of information, and prevents the formation of stable fishing groups (Fig. 10). In this case, each agent is in perpetual pursuit state, unless it finds itself a cluster. Thus, the fleet exploits successively the resource clusters, with an alternation of search in significant packs, resulting in the succession of oriented groupings, and the breaking down of the groups due to intermediate random search.

For an intermediate connectivity of the fleet, the exploitation is led by several groups of vessels. In each group, the previous phenomenon occurs. Thus, the efficiency of this type of search depends on the equilibrium between connectivity, which determines the number of potential groups of vessels, and level of resource aggregation, which determines the size of clusters and, by consequence, the risk of local competition between vessels.

4 Discussion

The results of this simulation work highlights several phenomenon. First of all, the dissemination of information within the fleet induces a pack effect, i.e. a systematic grouping of the vessels belonging to the same acquaintance network. The efficiency of the search is then strongly dependent on the degree of initial aggregation of the resource schools. For weak aggregations, a misleading effect of information appears. This one is related to an insufficient spatial heterogeneity of the resource, resulting in a very significant local competition, leading finally to a misleading convergence of the vessels, on overfished grounds.

The local competition of the vessels is inherent to the pack effect. It has variable consequences according to the number and the size of the resource clusters. This competition appears because the size of the exploited cluster is sufficient to create a grouping of vessels, but insufficient to sustain an exploitation by the whole group or the whole fleet. A local overexploitation of the resource occurs quickly, due to the rapid concentration of vessels. Then, information becomes more or less misleading, depending on whether the probability of finding a cluster close to the cluster already exploited. The local overfishing, due to an informative cooperation between vessels, is a very realistic phenomenon, which is notably observed in purse seine and long line tuna fisheries (Fonteneau et al. 1998). Such a combination of cooperation and local overfishing is very likely responsible of the non-linearity of the relation between CPUE and fishing effort (Maury et al. 1998).

When aggregation exceeds a threshold value, corresponding to the appearance of heterogeneity in the size and the distribution of the clusters, the pack effect leads to an optimal exploitation of the resource and the formation of stable fishing groups, with some local competition, but without significant misleading effect. The allowed efficiency gains are then very significant, up to between 300 and 500% in the simulations. Compared to reality, these very important efficiency gains could appear quite exaggerated, because of the mechanistic representation of agent's behavior in the model used for simulations. However, they aren't unrealistic. In effect, some great variations in efficiency could be observed in different fisheries (Gascuel et al. 1993; Millischer et al. 1999; Salthaug and Aanes 2003). Such variations have great consequences for the analysis of the fishing activities real impact on the resource. They can result in important bias in fishery assessment when they aren't entirely taken into account (Hilborn and Walters 1992).

The pack effect phenomenon is well known and observed in many pelagic (Fonteneau et al. 1998) or demersal (Pichon 1992; Vignaux 1996) fisheries. These results show the various

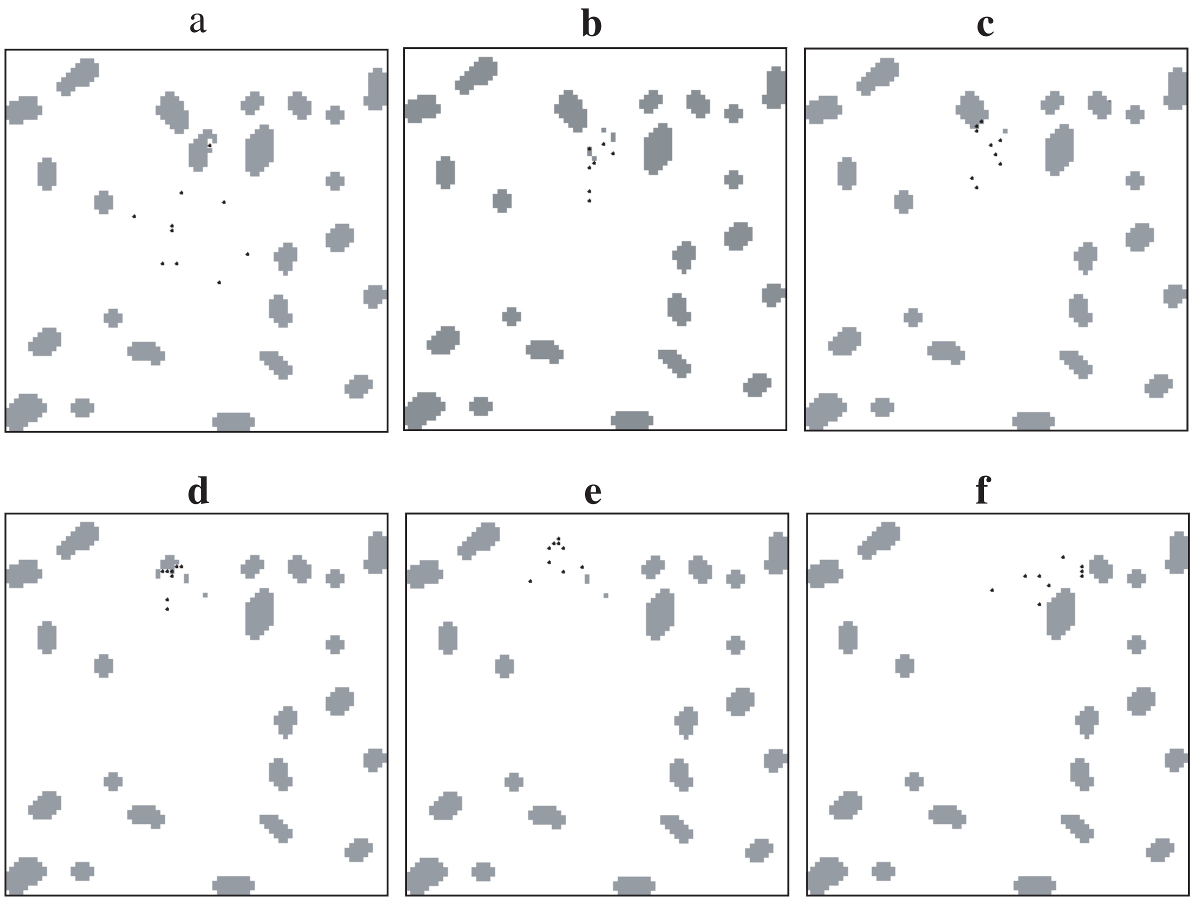

Fig. 10. Illustration of the pack effect produced by a diffusion of information within the fleet, in the case of an initial aggregation $Ca = 1$, and a maximum connectivity of the fleet (one unique closed network of ten agents). (a) Location of a cluster by a vessel; (b) pack effect of the whole fleet, converging towards the source of information; as the cluster is of low size, a local competition between the first vessels, and a misleading effect for the last arrived on spot, appear; (c) discovering of a new cluster, whereas the last arrived agents are still to seek schools of the first cluster; (d) the fleet converges on the second cluster, and again local competition and misleading effect of information appear; (e) and (f) the alternation phenomenon reoccurs.

impacts on efficiency this pack effect can have, according to the importance of the initial resource aggregation and the connectivity of the fleet. Thus, they make it possible to highlight the potential consequences of behaviors actually observed in the real fisheries. The central result is the very significant fishing power gains that such behaviors can induce.

However, a grouping of the vessels can also be observed in reality without active exchange of information, but by the simple observation of the other vessels of the fleet (Hancock et al. 1995; Vignaux 1996). Actually, this type of behavior is in fact very close to the current model. It can be interpreted as a passive form of information, which doesn't require acquaintanceships. This is a very degraded information, which consists in the direct observation of the fishing behavior of neighboring ship. From that observation, the observing vessel deduces the presence of some resource, in the same way that, in the simulator, the informative agents interpret a value of catches as a local abundance index. By its own immobility, the vessel being observed "transmits" some information, which reflects for the other vessels probable catches.

An important consequence of the simulation results is the identification of the main factors that determine the efficiency of the informative behavior. Thus, the preponderant factors are much more the size and type of acquaintanceship networks, which describe the networks structure, than the information accuracy itself. The point is that the local competition diminishes the utility of a high level of accuracy. On the contrary, it proves all the more interesting to have significant information transfers, i.e. a strong connectivity of the fleet, when the initial aggregation of the resource is significant. So the spatial dimension of the utility of information is dependent on the scale of heterogeneity.

The opening of the networks is an important factor, as it allows an indirect increase of connectivity, by the mechanisms of increase in the dissemination of information and a buffer effect related to the delay of information. These results show how the partial opening of the networks of information makes it possible to improve the efficiency of the information exchange. Such a phenomenon is a priori realistic. Actually, the structure of real information networks is the result of many different kinds of relationship among fishermen: economics, ethnics, kinship, friendship, acquaintanceship (Breton 1981; Bousquet 1994; Bouju 1995). Thus, the social structure of a fleet is undoubtedly made up of a complex network of reciprocal and nonreciprocal exchanges, in which different heterogeneous groups of fishermen are involved. In real fleets, in which the same fisherman can (but not necessarily) belong to several groups, the open type of network could be added to the closed groups.

Furthermore, espionage constitutes another important source of information for fishermen (Vignaux 1996). An exchange by open networks can represent the phenomena of espionage between vessels in a very realistic way, as a non reciprocal transmission of information. This phenomenon can be compared to a passive transmission of information, which doesn't require links of dealings. Such a phenomenon is also added to an active transmission, that the closed networks can represent.

The multi-agent simulator presented in this work is dedicated to the modeling of individual search behaviors of fishing vessels. It integrates not only the informative behavior aspects of search behavior, but also different kinds of fishermen knowledge. The individual knowledge is an important aspect of individual fishing behavior in real fisheries (Thorlindsson 1988; Dreyfus-Leon 1999; Xiao 2004) and is as such just as important as information transfer in influencing the orientation of search effort. Thanks to this simulator, a study and a comparison of cognitive and informative aspects of individual search has been proposed (Millischer 2000). Such a simulation study features the relation that can exist between efficiency, spatial behaviors and individual exploitation strategies, defined by informative and cognitive individual behaviors.

5 Conclusion

This multi-agent individual-based simulator focuses on individual, qualitative and spatial aspects of fishing exploitation, generally neglected by traditional fishery models (Hilborn and Walters 1992; Dreyfus-Leon 1999). Individual-based models make it possible to articulate a local representation of the processes with a synthetic vision at a global level. They constitute a tool where behavioral and analytical approaches of individual processes are related to synthetic population dynamics (Lomnicki 1999). In our case, the individual-based approach made it possible to connect the dynamics of the fishing efficiency of a fleet, generally studied in an aggregated manner, with the existence of individual search behaviors of vessels. If the use of individual-based models generates many discussions in fields such as ecology or population biology (De Angelis and Gross 1992; Grimm 1999), it is justified rather naturally to represent the fishing activity. The impact of the interaction between vessels on the global efficiency of the fleet has been referred to for a long time (Hilborn 1985; Allen and McGlade 1986; Gillis and Peterman 1998), without being directly formalized nor quantified. Our approach made it possible to confirm and quantify the importance of individual informative behaviors in the analysis and the measurement of the activity of fleets.

The model suggested here enables the integration of the qualitative aspects of the decision-making process of individual fishermen within a basically quantitative step. This integration is of high interest for the modeling of fishery systems, in which the concepts of interaction and behavior are central. The understanding of these interactions methods and these individual behaviors is necessarily achieved through a quantification of the subjacent qualitative processes. The simulator gives a framework for the quantification.

The use of multi-agents systems for an individual-based modeling allows a spatial approach of individual processes. The spatial component is of great importance in the interactions between resource and fishing activity. In particular, the non-linearity of the relation between CPUE and abundance, which skews the use of CPUE as abundance index (Clark and Mangel 1979) results from both the heterogeneity of the space distribution of abundance, and the adaptation of the vessels to this heterogeneity (Gauthiez 1996; Poulard and Leauté 2002). This study has enabled us to demonstrate the potential impact of the spatial adaptation of fishing vessels, on the overall fishing efficiency.

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