A new swarm mechanism based on social spiders colonies: from web weaving to region detection

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Abstract:

In multi-agent systems, the reactive approach emphasizes on the individual simplicity in comparison to the collective complexity of the task being performed. However, to apply such an approach to solve a problem, the components of the multi-agent system have to be designed such as the society is able to fulfill its requirements with a reasonable efficiency. Taking inspiration from natural swarm systems is a way to solve this conception issue.

This article presents a new swarm mechanism inspired by the simulation of the collective weaving in social spiders. The main difference with existing mechanisms is the possibility in the spider model to integrate non-local information in local processing. In this paper, we describe the simulation model and its transposition to a specific application case: the extraction of regions in an image. Some experiments conducted on real gray level images are detailed together with studies about the influence of the different algorithm parameters on its performance.

Keywords:
Reactive multi-agent system, swarm intelligence, self-organization, region detection.

1. Introduction

Reactive multi-agent systems are systems made of simple behaving units with decentralized control. Agents are situated in a dynamic environment through which they interact. They are characterized by limited (possibly no) representation of themselves, of the others and of the environment. Their behaviors are based upon stimulus-response rules, decision-making is based on limited information about the environment and on limited internal states and it does not refer to explicit deliberation. In such systems, the individuals do not have an explicit representation of the collective task to be achieved because of their simplicity. Therefore, the solution of the problem is the consequence of successive interactions between agents through environment.

In such systems, the regulation of activities can be achieved by self-organization. Camazine et al [6] define self-organization as "*a process in which pattern at the global level emerges solely* *from numerous interactions among lower-lever components of the systems*". Self-organized mechanisms are robust, decentralized, and can resist to perturbations.

Applying a self-organized approach to solve a given problem requires designing the environment, the agent behaviors and the dynamics of the whole such as the society is able to fulfill its requirements with a reasonable efficiency. The difficulty is proportional to the distance between the simplicity of individuals and the complexity of the collective property. Furthermore, links between individual behaviors and collective properties are not obvious since they are expressed at two separate levels of abstraction.

Taking inspiration from self-organized phenomena in biology is a way to tackle this engineering problem. However, the domain lacks of theories to describe the swarm mechanisms, of methodologies for encoding the problems in a way in relation with the swarm mechanism and for decoding collective results as exploitable solution in the problem domain. Despite these drawbacks, biologically inspired approaches have proven their interests in some cases. For example, model inspired by ants colonies have lead to new approaches for solving optimization problems[3].

We investigate a new swarm mechanism based on collective weaving activity in social spiders. As knowledge about this mechanism was not well stated, we first worked with biologists to know the individual mechanisms that enable the collective weaving. Biological assumptions needed to be formulated and validated. For this purpose, multi-agent models can help by providing concepts and tools to describe individual behaviors and simulate their collective effect. As soon as the swarm mechanism has been established, we transposed it. The transposition corresponds to encode the problem such as to be an input for the swarm mechanism; to adapt the swarm mechanism to the specificities of the problem, if necessary to improve it for efficiency purpose; and then to interpret the collective result of the swarm mechanism as a solution of the problem.

This paper presents how we found out an original swarm mechanism and how we transpose it to region detection. It is structured as follow. Section 2 presents related work and provides elements to argue the originality of our work. In section 3, we describe the biological background about the social spiders, the assumptions about the collective weaving, and provide some insights about the model we built. Section 4 presents how such a model has been transposed for region detection in gray level images. In the next section, we describe experiments and their results. Sections 6 and 7 discuss our work in terms of application and swarm mechanism. Section 8 draws some conclusions and future work.

2. Related work

Reactive approaches [16][5][13][26] emphasize on the simplicity of individuals compared to the properties observed at a collective level. Their inherent properties make them suitable for two main streams of use: the simulation of collective phenomenon and the collective problem solving.

Reactive multi-agent models provide concepts to describe a system as a set of simple entities (agents) that act and interact in a shared environment[28]. They enlighten the relationships between individual behaviors and collective observed phenomena[16]. This is a reason why recently multi-agent simulations (also called individual-based simulations) have been undertaken in biology to capture the global effect as a consequence of the behavior and interaction of simple individuals.

For example, the aim of some simulations was to test hypothesis about the way social structures can emerge, such as a division of labor in the case of ants in the MANTA project[7], or about fishes population dynamics[21]. Multi-agent models have also been used to investigate activities in colonies of honey bee [33], or of termites[23]. Numerous applications of such models on several collective phenomena (fishes, birds, etc) can be found in [30].

The inherent properties of reactive systems make them convenient to collectively solve problems. Their simplicity allows the solving of oversized problems, previously unreachable by "classical" methods (see [12] for an application to the N-Puzzle problem). These systems can easily be adapted to new constraints at run-time [1][14][25].

Reactive approaches have been applied to many problems such as cartographic generalization[1], distributed air traffic control[36], workload management[25], assignment problems[14], optimization problems[10][11], etc. Behavioral models can be based on a satisfaction principle: [12] used situated agents trying to achieve satisfaction in an environment that represents the problem domain. The satisfaction achievement is based on action in their environment; such as "moving". An acting agent may attack another: Ferber based Eco problem solving paradigm on such behaviors[16]. An adaptation of this model has been used for quadratic assignment problems[14]. In other cases, agents can perceive and react to force-fields defined in their environment; these force-fields are, in return, built upon the previous actions of the agents as in [1][25][34][36]. [3][10][11] replicated stigmergic principle from ants behavior to derive algorithms applied either to static or dynamic combinatorial optimization problems with applications on many problems like the traveling salesman problem. [24] inspires from ants too and derives a new search algorithm.

As we can see from these examples, existing self-organized systems like those observed in physics or biology are a source of inspiration to help the design of systems. Biological inspiration is one of the most used approaches. The principles underlying this approach is that the complex collective behavior exhibited by societies of animals such as wolves, ants, termites, wasps, and so on; can be viewed as a response to some environmental problem faced by the society.

One of the most common metaphors is that of ants. The knowledge about interaction mechanisms through pheromones in ant societies [8][9] has been a source of inspiration for new methods for reactive problem solving. Especially, the ant colony optimization (ACO) meta-heuristic has proven to provide very good results[11].

Except the ants metaphor, equilibrium between ecosystems is the metaphor from which the Eco problem solving[16] is derived. Fish and bird social models in biology have been sources of inspiration to implement flocking[29][35].

Social phenomena exist also in the case of spiders. In spiders' species, any status from fully solitary to social exists. Furthermore, as opposite to social insects, there is no cast in the society[20]. Therefore the studies of colonies of spiders could lead to an interesting and original model towards the collective intelligence perspective[31]. As far as we know, there is very little work on the modeling of spiders from a multi-agent perspective except [32] about collective decision process and [15] about the coordination during prey capture, both with *A. Eximius* species.

We applied a swarm mechanism inspired by social spiders for an image-processing problem. In this domain, the multi-agent paradigm has been used in two different ways. In the first case, the multi-agent approach is used as a framework to integrate and coordinate image-processing components ([2] for example). Such systems are not self-organized; agents are cognitive and interact through message communication. In the second case, the image is envisaged as an environment in which agents evolve: [27] was inspired by ant behavior to detect outlines and [22] uses cellular automata to extract regions.

3. Biological background on spiders

Among the thousands of spider species in the world, only about fifteen species can be qualified as social spiders. *Anelosimus eximius* which can be found in French Guiana is one of them. The individuals live together, share the same web and cooperate in various activities such as brood care, web weaving, hunting, ... On the web, spiders are gathered in small clusters under the vegetal sheets included in the web and are distributed on the whole silky structure. Figure 1 shows such a society and its web.

Despite their apparent individual simplicity, these spiders are exhibiting interesting collective behavior during prey capture and web weaving.

A. eximius are small arthropods (5 mm), able to collectively build silky structures bigger than ten m^3 that always respect architectural properties whatever the biological environment is. Webs are not geometrical but twofold: an horizontal hammock and an aerial network of silk lines.

Figure 1 : a spider colony and its web.

We cooperated with biologists to find out the underlying mechanisms. We proposed a multi-agent model[4] in which the environment is modeled as a square grid, each case being associated with a stake. Stakes can be of different heights to model the environmental diversity of the vegetation. They can be connected by silk dragline(s) fixed on top of them (see Figure 2).

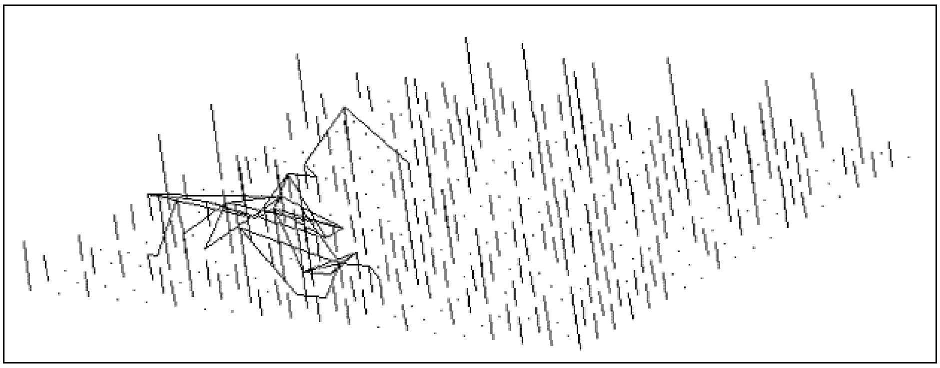


Figure 2 : view of modeled environment.

Agents are always situated on top of the stakes. The web weaving activity needs two behavioral items: movement and silk fixing. Items are independent i.e., an agent can fire these 2 actions in the same simulation cycle: to *move* to a close stake and to *fix* a silk dragline. Furthermore, items are fired stochastically according to a constant or contextual probability.

When fixed; the dragline provides a new path (the shortest one) between the current stake and the last on which silk was fixed (whatever the spider moves were). The probability to fix the silk (called *Psilk*) is constant over time.

Since silk draglines are fixed between stakes, they offer new directions of movement. The spider has to choose whether to follow a dragline or to move to one of the 8 adjacent stakes. This choice is influenced by the silk attraction tendency and reflects the propensity of spiders to follow a silk dragline instead of moving to an adjacent stake. The mechanism that underlies the movement can be expressed as a stigmergic process. Stigmergy was initially proposed by Grassé[18] in the case of termites and can be summarized as follow: "*the result of the activity of an individual triggers and focuses the activity of itself and of others*". The probability for a spider to move to a given stake is dependent on the type of access. In the neighborhood, the probability is constant.

When following a silk dragline, the probability is proportional to the number of silk draglines and to the silk attraction.

The simulation model is detailed in Table 1 and 2.

We implemented this model and conducted experiments. Under some range of parameters, we showed that it is possible to simulate collective weaving from simple individual behaviors (as shown in Figure 3). Results were validated from the biological point of view. Studies demonstrated the key role of the silk attraction: when too low, no web is built and all available space is used; when too strong, spiders are trapped in their own silk and no collective weaving occurred; when well chosen, we showed that the web size is related to the attraction: the higher the attraction, the smaller the covered surface[4].

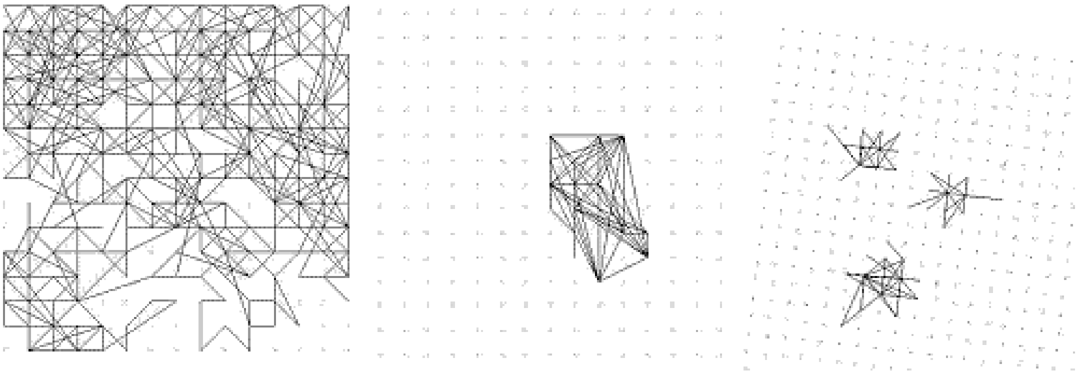


Figure 3 : Webs obtained with different attraction for silk (left: null attraction; center: medium attraction; right: strong attraction).

The individual model is very simple. Each individual is characterized by a small number of actions (2 behavioral items), by a limited perception (the neighbor positions and the draglines fixed on the current position), by very limited internal states, and by no representation of others.

The environment model is three-dimensional (two are used in the behavioral model; the last is used for visualization and for statistics purposes) and serves as an external memory. Interactions are indirect and take place through the environment. They are based on stigmergy: the presence of silk influences the choice of movement according to an attraction factor towards the silk.

From the computer science point of view, the behavior can be interpreted as a collective mechanism for space exploration which is characterized by limited perception and indirect coordination. The size of the explored space (the size of the web) is related to the silk attraction factor.

4. Transposition to region detection

4.1. Description of the problem

The problem is to extract various regions from an image[19]. Segmenting an image A consists in providing a partition of pixels (a set of regions R_i) such as $\forall i, R_i = 0$, $\forall i,j R_i \cap R_j = 0$ and $\cup_i R_i = A$. Moreover, regions must share some properties: they must be connected sets of pixels with homogeneous radiometric characteristics. In our case, all the pixels of a region should have the same gray level, more or less a given tolerance. Generally it can be expected that the regions correspond to features in the image that will be later interpreted as meaningful objects. Thus, relevance of extracted regions is, in general, task dependent. There is no general solution to this problem since many equivalent partitions can be found.

This problem shows some similarities with the collective weaving. It requires an exploration of a space that has to be restricted to a subset of its elements (the pixels of the region).

Furthermore, such an application enables visual assessment. In our case, it makes the development of the application easier by allowing fast interpretation of the results.

First, our model will have to produce, from a given picture, an intermediate structure constituted by the webs that have been woven. Future works will consist to extract sets of labeled pixels from this structure, each set representing an extracted region.

4.2. Generalities about the approach

Initially, the environment corresponds to an image. Basically, all spiders are put in it and are in charge of detecting one region. The agents will explore the image and lay down draglines on some pixels: those that are "interesting". Silk fixing is then a way to ensure pixel selection. Each agent is described by the same behavior and provided with parameters, which characterize the region it has to detect. Finally, the environment contains collective webs that will be interpreted to deduce regions by considering the pixels on which the web is fixed.

This mechanism derives directly from the simulation model but the extraction is limited to one region. To enable the detection of several regions simultaneously, the spiders are distributed among groups; each group has its own set of parameters and behaves according to the previous mechanism.

More precisely, we had to adapt each component of the simulation model to the problem to solve. The environment represents the input of the system, a gray level image, in which agents will evolve; stakes correspond now to pixels, the height corresponds to the gray level of the pixel. The transposition of agents consists in the transposition of their behavioral items. The movement remains unchanged and silk fixing now depends on the context and, thus, is related to the gray level of the region to detect. The interaction principle is based on stigmergy as in the simulation model.

With such a system, the spiders could build a web on pixels that share the same gray level but the set of woven pixels is not necessarily connected. In such case, this result does not correspond to a region. This is the reason why a third behavioral item was added to make an agent probabilistically return back to its web when it doesn't fix silk on the current pixel, thus restricting exploration to pixels in the neighborhood of the already selected ones.

The next sections detail such a model. A summary of the whole model is provided in Tables 1 and 2.

4.3. Description of the model

a) Environment

The environment corresponds to a gray level image. It is represented by a two dimensional array whose elements are the pixels of the image. Each pixel (p) is featured by its gray level and by the list of draglines (denoted Dl_p) already fixed on it. Initially, the environment contains no dragline, the agents will add draglines during runtime.

Each dragline d of a given Dl_p conventionally starts from p and is characterized by its end pixel end_d. When several regions are simultaneously detected, the dragline is labeled by the group of spider $spiderg_d$ that created it.

Such components can be formally defined as:

- *Environment* = array [NxM] of pixel.
- *Pixel=[gray: 0..255, D:List of Dragline]* // conventionally each element of D starts from the pixel.
- *Dragline = [end, spiderg].*

b) Agents

As mentioned above, an agent behaves according to three behavioral items; **movement**, **silk fixing** and **return to web**; which are cyclically checked. A behavioral item fires stochastically according to the local environment characteristics and to the agent features.

The agents can be distributed into sets. In this case, the agents belonging to the same set are focusing on the same region and will share the same parameters. A distinction between the silk fixed by members of a group and the silk fixed by members of other groups is made.

We provide first a global view of the agent model that is valid for both the single region detection case and for several regions detection case. The differences will then be detailed when describing the **movement** item.

(1) Agent features

The features of an agent correspond to the parameters conditioning its behavior and to its internal state. Parameters are fixed for an execution and internal state evolves according to the performed actions.

We can consider two main sets of parameters.

The first set characterizes the exploration behavior of the agent and is linked to the **movement** and **return** items. The concerned parameters are the perception radius of the agent (called *R*); its tendency to return back on web (called *BackProbability*); and its attraction for the silk. We implemented the attraction in two ways according to the number of regions to detect. These parameters could then be *Pdragline* in the single region case, or *AttractSelf* and *AttractOther* otherwise.

The second set characterizes the way the silk is fixed and will condition the pixel selection made by the agent (through the **silk fixing** item). It is composed of the gray value of the region to be searched (*RefLevel*) and the tolerance of selection (*Selectivity*).

Internal state is described by the position of the agent, called the current pixel (*CurrentP*), and by the last pixel on which it has fixed a dragline (*LastFixed*).

(2) Perceptions

Perceptions provide the locally available information in the environment on the basis of which the decision is made.

We define three functions: $Neigh_p$, $Scuts_p$ and $Access_p$ that respectively provide the list of neighbor pixels, the list of pixels that can be reached by following a dragline and the union of both. Each set corresponds to a set of pixels that are accessible in one system cycle by applying the **movement** item.

If we suppose *i* is a pixel:

$Neigh_i=\{p\in P / Dist(p,i)\leq R \text{ and } p\neq i\}$ where *P* is the set of the pixels of the image.

$Scuts_i=\{p\in P / \exists l\in Dl_i, p=end_l\}$ and

$Access_i=Neigh_i\cup Scuts_i$.

We define Number(a,b), with *a* and *b* being two pixels, as the number of draglines that start on *a* and end on *b*. Number(a,b,spg) is the same restricted to the draglines labeled by the *spg* group of agents. These values will be used to make the choice of movement dependent on the silk attraction.

$Number(a,b)=CardNb(\{l\in Dl_a / end_l=b\})$

and $Number(a,b,sg)=CardNb(\{l\in Dl_a / end_l=b \text{ and } spiderg_l=sg\})$

with CardNb being the cardinal number.

(3) Basic behavior cycle

The basic cycle of an agent is described by three successive behavioral items, each one consisting in a probabilistic decision and the possible performance of the action:

1. **Movement**: choose a pixel *p* from accessible ones according to a probability distribution; then carry out the movement to the selected pixel;
2. **Fixing silk**: choose to fix according to a contextual probability (the lower the distance between the gray level of the current pixel and the *RefLevel*, the higher the probability) if the decision is made, carry out the silk fixing and exit basic cycle;
3. Otherwise **Return to web**: choose to return to the web according to *BackProbability*, if the decision is made, return to the last fixed pixel.

The section 4.4 details each item.

c) System dynamics

The system dynamics describes the way interactions take place and is responsible for the scale change from individual behavior to global phenomenon. It is related to the control of the system and defines the way actions are selected to perform the global task.

In the spider model, it is based on stigmergy. This is a way to achieve coordination without any explicit reference to the task being performed: the past actions put traces (inscriptions) in the environment; and these traces favor in return some actions among others. In our case, the modifications are the apparition of silk draglines. It provides new possibilities for movement and they are favored by silk attraction.

An execution starts initially with an environment empty of silk representing an image. Each agent or set of agents is initialized with parameters characterizing the region to detect through the *Reflevel* and the S*electivity* values. All the agents have the same *Backprobability* and attraction for the silk.

The system evolves by cycles. In each one, every agent is successively active and applies its basic cycle according to the local environment. The execution ends after a user-fixed number of cycles.

d) Interpreting the results: from web to region

Biological simulations aimed to answer how a collective web can be built from interacting individuals. An assessment of the result of simulations was carried out (visual aspect and some statistics -size, average height- which have to correspond to real data). Improvement of the individual behavior model leads to a better correspondence between the real and the experimental results.

Here the goal of system is to solve the problem of extracting regions. Since the agents have no explicit representation of the global task that has to be accomplished, we must face the issue of interpreting the global result of the model, which was not asked (and thus not answered) in simulation. We have to deduce regions from the available information in the environment. This information is the set of silk draglines dropped on pixels.

From a local point of view, the pixel perspective, a list of draglines is associated to each pixel. Each dragline is labeled by the group of agents that has laid it down. From a global point of view, each group of agent is dedicated to the detection of a given region (through the S*electivity*, *Reflevel* and *BackProbability* values).

By gathering all the pixels a group *spg* has woven on, we obtain a rough region (RR_{spg}), that is, pixels are put together without consideration of the number of times the group has woven on them. Formally, $RR_{spg}=\{i \in P / Number(i,*,spg)>0\}$ where * corresponds to any pixel in the image.

To avoid selection of low ranked pixels in a region we propose to restrict the pixel set composing the region to those whose number of draglines is above a given threshold $R_{spg}=\{i\in P / Number(i,*,spg)\geq Threshold\}$.

We define the degree of belonging of each pixel to a region as the number of draglines that the group associated to the region wove on the pixel. $\forall i\in R_{spg}$, $Bdeg(i,R_{spg})= Number(i,*,spg)$.

With such a method, a pixel belongs to a given region with a certain degree. This additional information can be used to improve global results when an ambiguous pixel simultaneously belongs to several overlapping regions.

4.4. Detail of behavioral items

The behavioral items detail how the agents interact with their environment. The firing of a behavioral item is context dependent. Basically, we first compute a probability of performing action from the parameters and from the features of the current position, or simpler, we use a constant probability. Then, according to this probability, the behavioral item is fired and the action performed or not.

The following details the computing of the probability and the effect of the action upon the environment and upon the internal state.

a) Movement

As mentioned previously, silk is attractive and influences the movement of spiders: spiders have the tendency to follow silk draglines rather than moving to adjacent position. We had to implement such a principle.

The way we implemented the attraction for silk consisted in associating each accessible position with a weight according to the way to access it (Figure 4):

i) Neighbor positions ($p\in Neigh_{CurrentP}$) have the same weight;

ii) Positions accessible by one or more dragline ($p\in Neigh_{CurrentP}$) are weighted according to the number of draglines linking them to the current position and according to the silk attraction factor.

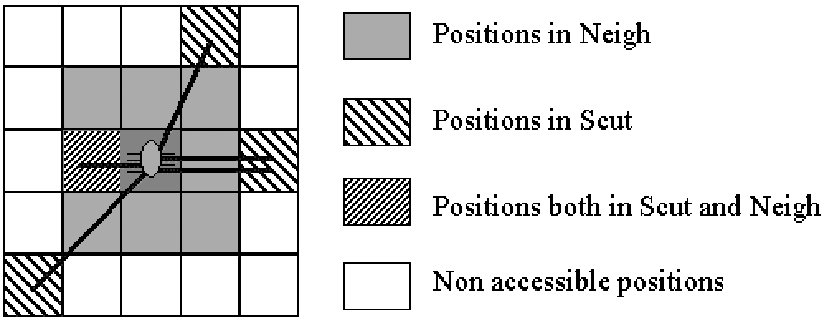


Figure 4 : agent-centered illustration of the different accessible positions (perception radius R is supposed to be equal to 1).

By normalizing the weights, we obtain a distribution of probabilities over the accessible positions. It must be noticed that a pixel might be accessible simultaneously by both ways. In such a case, its weight is the sum of the two described weights.

We implemented two ways of computing this distribution of probabilities according to the number of regions to be searched.

The first one corresponds to a situation in which agents cooperate to detect a single region: labels on draglines are not taken into account. This model derives directly from the simulation model. In this case, we consider only one set of agents and make no distinction in silk. The choice of movement is not dependent on the number of draglines observed and the decision can be divided into two steps. First, the agent faces an alternative: will it follow a silk dragline or not? *Pdragline* is the probability for the agent to move this way. If the agent prefers to follow draglines, it randomly chooses a dragline and reaches the pixel at its end. Thus, the more draglines leading to p belonging to $Scuts_{CurrentP}$, the more likely the agent is to reach p. Otherwise, it moves randomly to a pixel belonging to $Neigh_{CurrentP}$.

Formally:

i) $\Pr oba(move(p)) = \dfrac{1 - Pdragline}{CardNb(Neigh_{CurrentP})}$ if $p \in Neigh_{CurrentP}$

ii) $\Pr oba(move(p)) = \dfrac{Pdragline * Number(CurrentP, p)}{CardNb(Dl_{CurrentP})}$ if $p \in Scuts_{CurrentP}$

The second implementation takes place in a perspective of competition between agents to detect several regions. In this case, we distinguish the silk according to the set of agents that wove it.

Assessing the probability to reach a pixel consists in giving a constant weight to each reachable one in $Neigh_{CurrentP}$ and a weight linked to the number of draglines between this pixel and the location of the agent. The choice of following a dragline is then dependent on the number of draglines present on the considered pixel and on the kind of silk.

We distinguish two kinds of attractions for silk according to the labels of draglines. *AttractSelf* describes the attraction of an agent for its own silk and for the silk of members of its group; *AttractOther* describes the attraction for the silk of agents of the other groups. From this, we compute two contributions to the weight of a pixel that are combined.

Formally:

$$\Pr oba(move(p)) = \frac{w(p)}{\sum_{a \in Access_{CurrentP}} w(a)} \text{ where}$$

i) w(p) = constant if $p \in Neigh_{CurrentP}$

ii) w(p)= AttractSelf*F(Number(CurrentP,p,Mygroup)))
+AttractOther*
F((Number(CurrentP,p)) - Number(CurrentP,p,Mygroup))) if $p \in Scuts_{CurrentP}$

F is a function expressing how the number of draglines in the path influences the weight until a given saturation. In our experiments, we used *F(x)= min(x, SaturationValue); SaturationValue* corresponds to a limit from which the number of draglines does not any longer influence the result.

Once the decision is made, carrying out movement consists in updating the current pixel value: *CurrentP* $\leftarrow$ *p.*

b) Silk fixing

The decision is made according to the probability to fix a dragline on the current pixel. It is computed from a Gaussian distribution whose mean is *RefLevel* and whose standard deviation is *1/Selectivity*.

Fixing a dragline consists in adding one dragline in the environment; this is made by updating the dragline list of the current pixel $Dl_{Currentp} \leftarrow Dl_{Currentp} \cup \{(CurrentP; LastFixed)\}$ and the dragline list of the LastFixed pixel $Dl_{LastFixed} \leftarrow Dl_{LastFixed} \cup \{(LastFixed; CurrentP)\}$; and updating internal state of the agent *LastFixed* $\leftarrow$ *CurrentP*.

c) Return to web

The decision probability is constant (*BackProbability*) and the performance of the action consists in updating the location of agent: $CurrentP \leftarrow LastFixed$.

5. Empirical assessment of the approach

This part highlights the main advantages of this approach from empirical results. After presenting general results obtained with the approach (such as the coverage of the image and the homogeneity of extracted regions), we will focus on the flexibility of the process to assess its potential.

5.1. Expected properties

Two main properties are generally expected for extracting regions in pictures: coverage and homogeneity.

An efficient extraction algorithm is first characterized by a good coverage of the extracted regions. When it determines a region, we expect it to extract the entire region and not to forget some of its parts. In our case, this coverage is the global consequence of the exploration process of the agents.

Moreover, the extracted regions must be relevant. First, the extracted region must be constituted by pixels of homogeneous radiometric properties. Furthermore, we do not want the apparition of artificial boundaries due to small variations of light intensity in a single region. This characteristic will be the consequence of the silk-fixing item or, in other words, the selection process.

The results of the execution of such an algorithm are quite difficult to analyze mathematically because they refer to a semantic content. Therefore we have first focused on qualitative rather that quantitative results to assess the properties of our approach. Moreover, the aim of those experiments was not to assess accurately the results observed but to validate our approach for the task of extracting regions and to verify its flexibility and adaptability proper to reactive approaches.

5.2. Experimental setup

The tests presented in this paper have been carried out with two real images: the first shows a calibration grid and the second is Alain (see Figure 5). The resolution of those pictures is 256*256. They are obtained from a CCD camera and have not been preprocessed (no histogram stretching, no contrast enhancement, etc.).

Figure 5 : grid and Alain images used for experiments.

An experiment consists first in creating the environment corresponding to the considered picture. Then the user manually drops agents in the environment depending on the region to extract. The *Reflevel* of agents are assigned according to their initial position and the user defines for each agent its other parameters.

In this paper, we present results obtained when extracting a single region. Agents have a cooperative behavior and share the same features. The attraction for silk of the agents is thus ruled by the *Pdragline* probability.

The exhibited results will be of two kinds. Some will correspond to the web built by agents: all the draglines are shown even if they are woven above a non-pertinent zone. It explains why some pixels are not visible as they are hidden by draglines woven onto other pixels. Others show the belonging degree of each pixel. The brighter the pixel is represented, the higher the belonging degree of the pixel for the considered region.

Ultimately, it must be noted that two kinds of experiments have been conducted: the first ones are displayed in the next part and consisted in extracting a region from the images, their aim was to show the results our approach could obtain. The goal of the others was to exhibit the inherent flexibility and to confirm the relevancy of our approach. They will be presented in the following part.

5.3. Raw results

As the following pictures bring to light, our approach gives satisfying results when parameters of the spider-model have been accurately and empirically tuned by trials and errors.

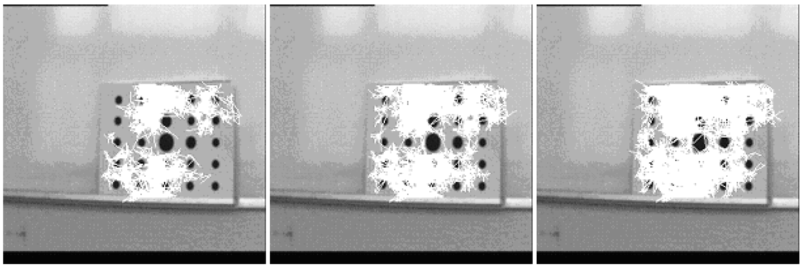


Figure 6 : Web (in white) resulting from the extraction of the grid (*5 agents each one defined by RefLevel 175, Selecty1, Backprobability 0.2,Pdragline 0.5*) after 5000,10000, 20000 cycles.

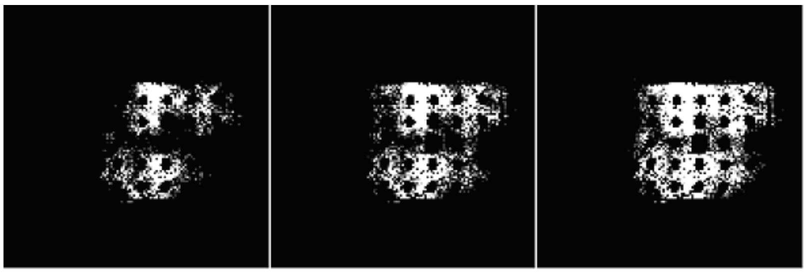


Figure 7 : Degree of belonging of pixels resulting from the extraction presented in Figure 6.

Although the grid is not well “detached” in the environment the algorithm provides good results even if the region is not fully covered (Figures 6 and 7), it must be noticed that Alain’s hair is also well extracted (Figures 8 and 9). Figure 10 shows different regions our approach is able to extract from Alain’s image.

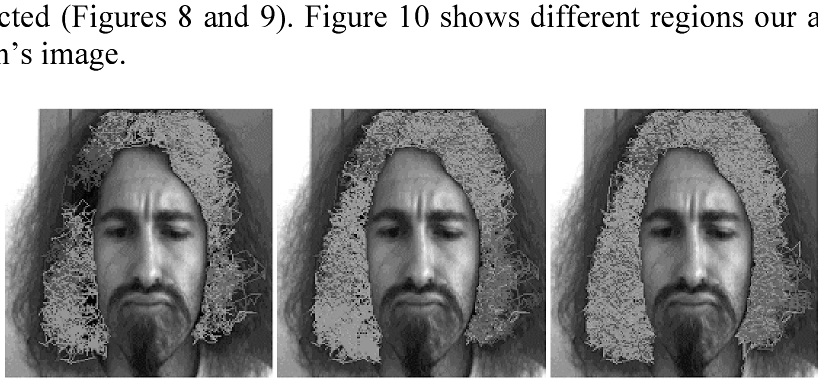


Figure 8: Web resulting from the extraction of Alain’s hair (*5 agents each one defined by RefLevel 16, Selectivity 0.1, Backprobability 0.2,Pdragline 0.1*) after 5000, 10000 and 20000 cycles.

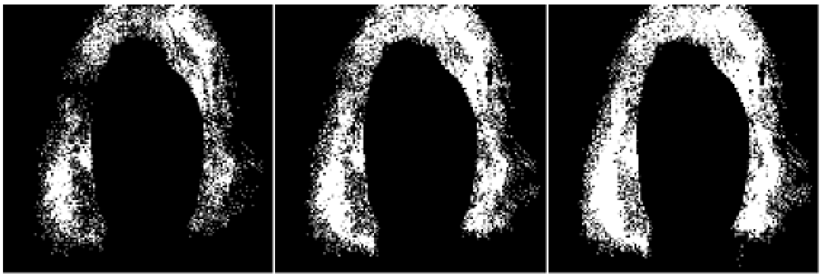


Figure 9 : Degree of belonging of pixels resulting from the extraction presented in Figure 8.

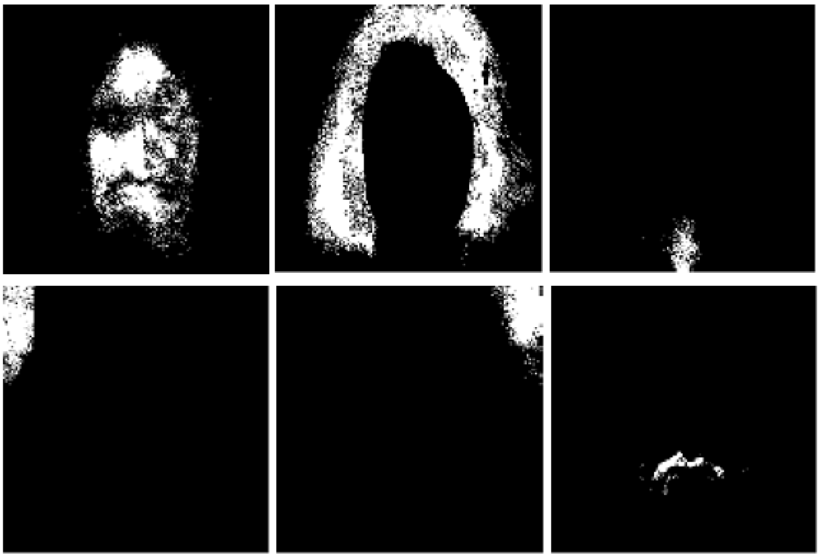


Figure 10 : Example of extracted regions in Alain's picture : Face, Hair, Beard, Background and Moustache.

A first conclusion is that results confirm the relevancy of our approach since it is able to extract properly various kinds of regions from real images. One of its major advantages is that the same simple behavior is used, and only the individual parameters determine the extracted region.

In the next part, we will focus on the relationships between individual parameters and properties of collective webs and then the quality of the results.

5.4. Studies of the process

In this part, we will link initial individual parameters with final collective results in order to find heuristics to estimate parameters needed to extract a specific region.

To do this, we will center on the relation between parameters of the model and the observed results. If we consider that all agents have the same features, a model is described by four parameters: the values of *Pdragline*, *Backprobability*, *Reflevel* and S*electivity*.

The first two parameters govern the movements of the agents and thus the exploration process. The two last ones are related to the selection of pixels thus determining the relevancy of the extracted regions.

Of course, because the process is based on the stigmergy ensured by the silk draglines laid down in the environment, selection and movement are tied, but we could at first try to specify the influence of each aspect.

a) *Influence of the exploration process*

The importance of *Backprobability* is illustrated by Figures 11 and 12. The return behavioural item prevents agents from building a web linking two non-connected regions. Indeed, the inverse of this probability corresponds to the mean length of the path before returning to the web.

If the probability is not high enough, the agents could reach another non-connected region from a web and then weave draglines linking those two regions. It is the case in Figure 11 in which a web has been woven in the beard, eyes and eyebrows of Alain. However, the *Backprobability* must not be too high, especially if the agent is highly selective, because a low *Backprobability* allows the agents to cross small noisy zones to carry on selection processes afield.

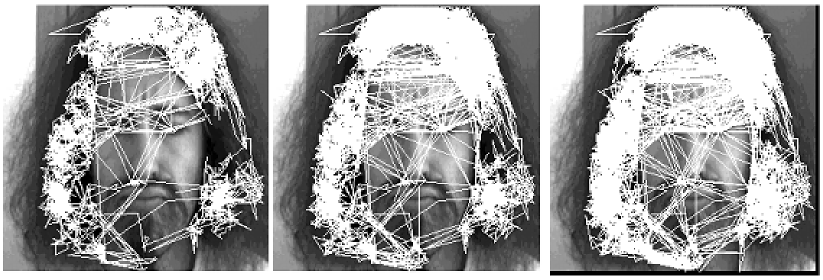


Figure 11 : Web built with a null *Backprobability* (parameters of the 5 agents : *Reflevel 16, Selectivity 0.1, Backprobability 0 Pdragline 0.5*) after 5000, 10000 and 20000 cycles.

Figure 12 : Degree of belonging of pixels resulting from the extraction presented in Figure 11.

A non-null *backprobability* is then required to obtain regions of totally connected pixels. However, as the Figure 13 shows, it has for consequence a restriction of the surface covered by the agents. Moreover, the Figure 13 shows that when the *backprobability* is non-null, the corresponding curve presents an exponential profile. It must be noticed that a non-null *backprobability* improves the number of woven pixels in the beginning of the experiments. It can be explained by an amplification effect. When *backprobability* is non-null, the spiders will return back to their web in the neighborhood of already selected pixels. Thus they will stay in an interesting region and the fixing of new draglines will then be favored.

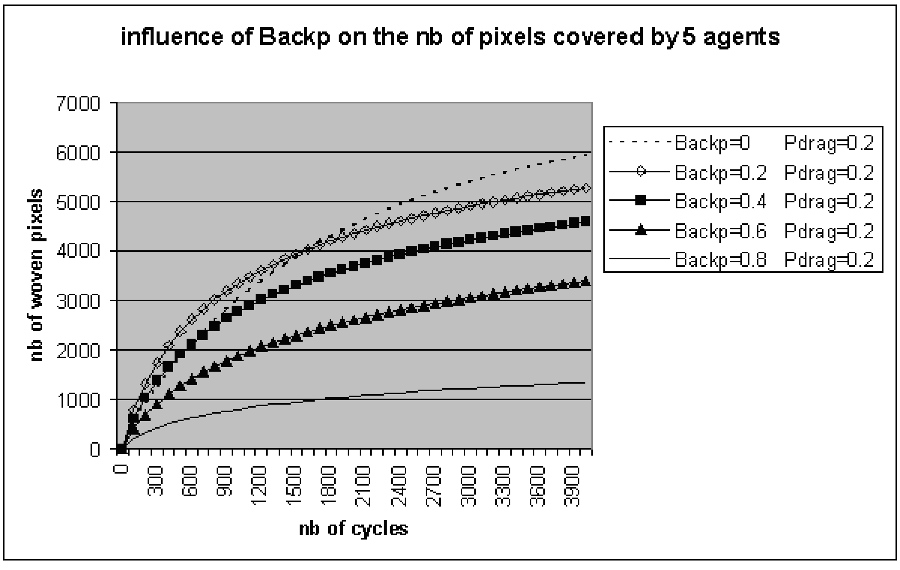
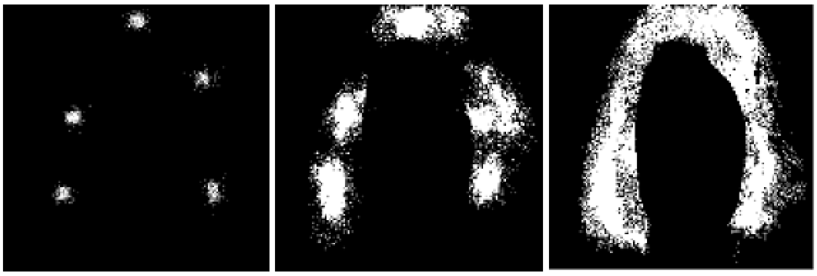


Figure 13 : experiments conducted with different values of backprobability (*backp*) parameter.
The spiders are always put at the same places with same parameters except backprobability. A curve consists in the mean number of woven pixels during 100 identical experiments.

In order to study the importance of the silk attraction, the three following experiments, shown in Figures 14 and 15, have been conducted under the same conditions except that the value of *Pdragline* was not the same.

a) b) c)

Figure 14 : Impact of *Pdragline* on webs after 20000 cycles (same parameters for 5 agents : *Reflevel 16, Selectivity 0.1, Backprobability 0.2, Pdragline is for a)0.8, for b)0.5 for c)0.2*).



a) b) c)

Figure 15 : Degree of belonging of pixels resulting from the extraction presented in Figure 14.

These extraction results are representative of the influence of the attraction for silk parameter: in Figure 14a, this parameter was set high. The web that the agents have constructed captures them and they do not explore the entire region (the surface covered by the web is small). In Figure 14b, this parameter is medium and the region explored by agents is bigger but some part of the region is still unexplored. Ultimately, when the parameter is low as in Figure 14c, agents are urged to explore their environment and the region covered is larger.

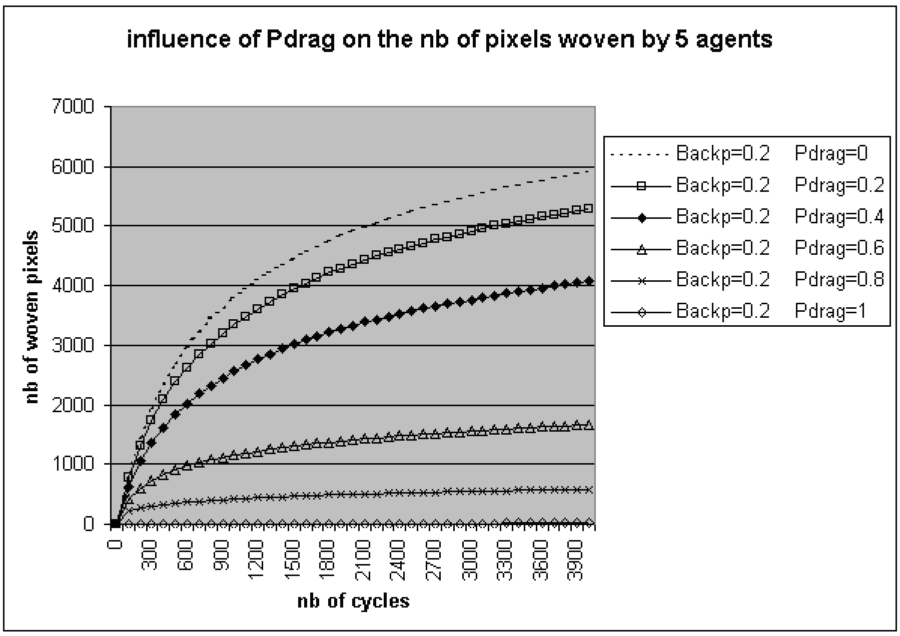


Figure 16 : experiments conducted with different *pdragline* parameters.
The spiders are always put at the same place with same parameters except *pdragline*. A curve consists in the mean number of woven pixels during 100 identical experiments.

Thus, if attraction is strong (Figure 14a) the size of the surface covered by an agent would be small (Figure 16 presents qualitative results). Obtaining a good coverage would require dropping a lot of agents in the environment. The product of the number of agents by the mean size of the covered surface must correspond to the size of the region we wish to extract. On the contrary, if silk attraction is weak (Figure 14c), it requires fewer agents, but the density of draglines might be not significant enough to lead to relevant results.

b) Influence of selection process

The *Selectivity* parameter is directly linked to the desired homogeneity of the gray level of the region to detect. Figures 17 and 18 present zones whose borderlines do not correspond to the desired results because of a too high *Selectivity*.

Figure 17 : Extraction with high *Selectivity* (parameters for 5 agents : *Reflevel 16, Selectivity 1, Backprobability 0.2 and Pdragline 0.5*) after 5000, 10000 and 20000 cycles.

Figure 18 : Degree of belonging of pixels resulting from the extraction presented in Figure 17.

In most cases, *Selectivity* has to be accurately tuned. Indeed, the agents' selection must tolerate small light intensity fluctuations without allowing the selection of pixels of borderlines and of other regions. If the region we want to extract is well separated from the rest of the image, *Selectivity* should be low to consider small fluctuations of gray level in the region. On the contrary, if the region is not well detached from the image (like the grid), *selectivity* must be set high to extract expected borderlines. However, from now on, small fluctuations of light intensity in searched regions might hinder the extraction process.

c) Heuristics for setting parameters

The experiments cast a new light on the process: even if parameters are empirically tuned, a few heuristics enabling their determination can be mentioned.

Relating to the exploration process, the value of the attraction is highly dependent on the number of agents we put into the environment. If we drop a lot of spiders, a high attraction would be interesting: spiders will weave small webs with high density and the region will be the result of the fusion of those small webs. On the contrary, if agents are fewer, to ensure a wider exploration of the environment, a low attraction is required but agents are then prone to go astray.

Concerning the selection, if the region to be extracted has radiometric properties close to the rest of the picture, a high *selectivity* is required.

These hypotheses applied to extract the Alain's beard lead to the results of Figure 19. Since, the region is not very big, few agents will be sufficient; the *Backprobability* coefficient and

Pdragline parameter will be set high. Because the region is well detached, *Selectivity* might be not accurately tuned.

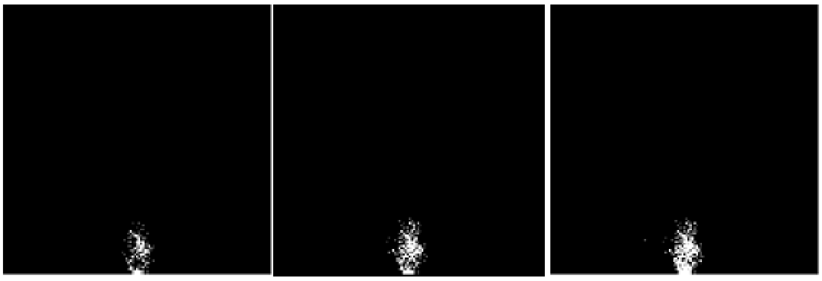


Figure 19 : Extraction of beard with heuristics (parameters for 2 agents :
***Reflevel 16, Selectivity 1, Backprobability 0.2 and Pdragline 0.5*) after 1000, 2000 and 3000 cycles.**

6. Discussion about the application

As shown by the results, our application currently enables the partial detection of region and all the ingredients are available in our approach for detecting various regions if the required parameters are well assessed. However, a major drawback has to be solved in order to produce a real application: parameters are until now empirically adjusted. [22] faced the same issue but we also have to determine the number of agents and their initial position. Once this stage is over, we could undertake automatic region detection and compare our approach to the algorithms that already exist. This work demonstrates that a new technique inspired from biology can lead to a potential application. Current experiments have to be seen as an initial study.

It is also possible to detect simultaneously several regions (Figure 20) by the use of the second implementation of the movement behavior and by gathering the agents with the same initial parameters into groups. To do so, it is sufficient to set the *Attractother* coefficient to null. In this case, the global process consists in several processes without competition that ignore each other. A positive value of *Attractother* introduces competition between groups: webs built by a group might be attractive for other groups, which will possibly compete for the selection of the same pixels.

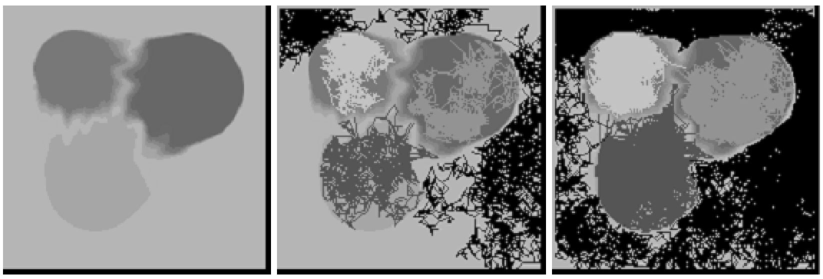


Figure 20 : Webs resulting of simultaneous extractions of 4 regions
with 4 groups after 0, 5000 and 10000 cycles.

Until now, even if few heuristics have been made clear, these parameters require information about the region that one wishes to extract. It can be bypassed if we envisage images in semi-structured environment (like inside a building) that provide some regularities we can rely on. For example to extract walls in a corridor image (see Figure 21), because walls are at each side of image, it may be sufficient to drop spiders near the left and right borders of the image.


Figure 21 : Example of semi-structured environment.

We can also focus on online specialization and self-organization to dynamically adjust parameters. Indeed, the silk laid down in the environment contains a lot of information that can be used. For example, if draglines are not present on pixels, it might mean that no agent is searching this gray level and that a region might be present but will not be detected. Then, if the agent meets a lot of pixels with the same gray level without any dragline fixed on them; it could decide to extract the region corresponding to this gray level.

In the same application domain, the approach we propose could be extended to similar tasks. It could be adapted to detect regions according to their textures. In this case, the adaptation would consist in the modification of the silk fixing item by expressing a condition the pixel neighborhood has to fulfill in terms of texture. The same kind of adaptation could be envisaged to detect outlines. In this case, the silk fixing item would select pixels such as the gray level of their neighborhood is significantly different. Our approach could also be adapted to detect region in color images with similar principle. The selection process would be expressed with a distance measurement computed between the three values corresponding to the desired color and a reference level expressed as three values.

7. Review of the swarm mechanism

We proposed a new swarm mechanism: the spider model. Swarm mechanism consists in a process, which enables a collection of simple agents interacting locally with their environment to collectively produce a complex pattern. Implementing such a mechanism requires specifying the environment, the agents and their behavior, and the dynamic of the whole.

The Tables 1 and 2 summarize the implementations of the spider swarm mechanism. The same core principles have been used in the cases of the simulation and of the region detection application.

By comparing simulation model and application model, it can be noticed that the internal state, the effect of behavioral items and the dynamic principle remain the same.

Table 1 presents the features of the environment and of the agents. In both cases, the environment is an array. Each element of the array corresponds to a stake or to a pixel; and silk draglines can be put between two elements.

An agent has only two variables as internal state: its current position and the last position on which it wove.

Behavioral items correspond to stimulus-response rules. Items are examined successively and are not exclusive: several can be fired in the same basic cycle (Table 3). Table 2 focuses on the effect of behavioral items and on the computing of their firing probabilities. Basically, the global behavior of the agents is based on two processes that are coupled through the environment: the movement to an accessible position and the fixing of silk on some positions.

The dynamic of the system is stigmergic: past actions put traces in the environment (silk dragline in our case) that influence the choice of the current action. Stigmergy occurs thanks to the silk and to its attraction during spiders' movements.

A stigmergic principle is also used in the case of ants. Basically, during their movements the ants leave pheromones that in return influence their choice of direction. What fundamentally differs between these two “implementations” of stigmergy is the use of silk instead of pheromones. Silk draglines make non-local elements accessible during movement. Therefore, it is a way to introduce non-local information into the processing.

Nevertheless, some differences between the simulation and the application model must be noticed. As we mentioned, applying the simulation model mainly needs some modifications of the model: i) to encode the problem such as to be the environment of the swarm mechanism; ii) to adapt the swarm mechanism by providing some application-specific parameters and by specifying the context of firing of items; iii) and to interpret the collective result so as to determine region.

The environment has been slightly modified from simulation model to application one so as to represent an image. The collective webs have to be interpreted in application case. We need to process the webs to extract features (belonging degree of pixels) that are significant in the application domain. Noteworthy modifications are made in the probability under which items can fire to make some of them sensible to application domain: silk fixing is contextual and a new behavioral item (return to web) has been introduced to fulfill application requirements.

8. Concluding remarks and future work

The work presented in this article takes place in the perspective of building reactive multi-agent systems by taking inspiration from collective phenomena in biology. It presents a new swarm mechanism inspired from an original social model: the social spiders; and illustrates how it can be applied in a region detection problem.

The approach we followed consisted first to work with biologists to exhibit the individual behavior of spiders that lead to collective weaving; and in a second step, to transpose the simulation model to an application.

This work extends the current repertoire of swarm approaches by providing a new collective mechanism based on silk. The main difference with existing mechanisms is the possibility in the spider model to integrate non-local information in local processing.

The experiments we undertook in region detection have to be considered as an initial study. However, they demonstrate the potential of the spider approach for collective problem solving. They show that such a mechanism can provide all the ingredients necessary to detecting various regions and underline that the next step is to determine accurately the parameters with respect to the task to be accomplished.

Future works can be considered with several perspectives. One, as mentioned, concerns its improvement for region detection. Other concerns the mechanism in itself. Even if we quoted some properties about this particular swarm mechanism, it remains a lot of work to precisely identify the link between the parameters and the results obtained. The impact of adding a negative feedback (deterioration of the draglines for example) in the environment is still to be analyzed. The last work deals with the extension of its field of application.

9. Acknowledgments

The ideas exposed here wouldn’t be without the cooperation of biologists Professor Bertrand Krafft, Alexandre Bernard; and without the support of the CNRS which funded part of this work in the case of the GIS Sciences de la Cognition.

The authors wish to thank Anne Chevreux for the first implementation of the model and Alain.

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11. Tables

	Environment	Results	Agent	
			Parameters	**Internal state**
Simulation	Grid of stakes Dragline= [end].	Web	*Pdragline* attraction for silk *Psilk*: probability to fix silk *R= 1* perception radius (constant)	CurrentP LastFixed
Region detection	P = array [NxM] of Pixels Dragline= [end, spiderg].	Region	*BackProbability* *RefLevel* *Selectivity* *R* perception radius *Silk attraction* *i)* Pdragline *ii)* AttractSelf AttractOther	

Table1 : instantiation of swarm mechanism

Behavioral items		Movement	Silk-fixing	Return to web
Effects	On Environment		$Dl_{CurrentP} \leftarrow Dl_{CurrentP} \cup \{(CurrentP, LastFixed)\}$ $Dl_{LastFixed} \leftarrow Dl_{LastFixed} \cup \{(LastFixed, Current,)\}$	
	On Agent	$CurrentP \leftarrow p$	$LastFixed \leftarrow CurrentP$	$CurrentP \leftarrow LastFixed$
Probability according to the application	Simulation of collective weaving	$\mathrm{Pr}oba(move(p)) = \frac{1 - Pdragline}{CardNb(Neigh_{CurrentP})}$ if $p \in Neigh_{CurrentP}$ $\mathrm{Pr}oba(move(p)) = \frac{Pdragline * Number(CurrentP, p)}{CardNb(Dl_{CurrentP})}$ if $p \in SCuts_{CurrentP}$	*Psilk* Constant	Constant Null (item not used)
	For single region detection-	$\mathrm{Pr}oba(move(p)) = \frac{1 - Pdragline}{CardNb(Neigh_{CurrentP})}$ if $p \in Neigh_{CurrentP}$ $\mathrm{Pr}oba(move(p)) = \frac{Pdragline * Number(CurrentP, p)}{CardNb(Dl_{CurrentP})}$ if $p \in SCuts_{CurrentP}$	Context dependent: Gaussian distribution whose mean is *RefLevel* and whose standard deviation is $1/Selectivity$.	Constant: *BackProbability*
	For several regions detection-	$\mathrm{Pr}oba(move(p)) = \frac{w(p)}{\sum_{a \in Access_{CurrentP}} w(a)}$ • w(p) = constant if $p \in Neigh_{CurrentP}$ • w(p)=*AttractSelf**F(#(CurrentP,p,MyGroup))) + *AttractOther**F((#(CurrentP,p)) - #(CurrentP,p, MyGroup)))if $p \in$ Scuts		

Table 2: behavioral items instantiation of swarm mechanism

Functioning of the system	Basic cycle of an agent

Repeat
  Foreach agent
    Execute its basic cycle
Until a fixed number of times is reached
	Foreach behavioral item
	    Compute its firing probability (Fp)
	    According to Fp, perform the action part

Table 3: functioning of the system and agent basic cycle.