How Social Spiders Inspired An Approach To Region Detection.(Id 353)

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ABSTRACT

Reactive problem solving is a way to propose systems composed of simple interacting agents that collectively solve problems outside the scope of individual perceptions. In this domain, natural social systems are sources of inspiration for simple mechanisms.

This article presents an approach for region detection inspired by social spiders. Based on a behavioral model determined by the simulation of collective weaving, we describe how we transposed it to obtain an approach for region detection in gray level images.

Categories and Subject Descriptors

I.2.11 [**Artificial intelligence**]: Distributed Artificial Intelligence – *Multi-agent systems.*

General Terms

Algorithms, Experimentation.

Keywords

Reactive multi-agent system, biological inspiration, region detection

1. INTRODUCTION

This article presents how social simulation in biology has been used to propose an approach for region detection in gray level images.

Reactive approaches emphasize systems of simple behaving units with decentralized control. In such approaches, "intelligence" is observed at collective level, but is not necessarily present at agent level. One of the difficulties in the design of reactive multi-agent systems is to specify simple interactions between agents and between them and their environment so as to observe complex collective properties. This difficulty is proportional to the distance between the simplicity of individuals and the complexity of the collective property. Furthermore, links between individual behaviours and collective properties are not obvious since they are expressed at two separate levels of abstraction.

Social models in biology are a way to tackle such a problem by providing decentralized models with simple and robust mechanisms. Knowledge about the organization of animal societies can be transposed into multi-agent systems and applied in collective problem solving, or at least used as a metaphor in view of designing these systems.

The article is constructed as follows : the first part focuses on reactive systems and their application to problem solving. The second part provides a general background about the original biological model, the social spiders model, and the simulation we carried out. The third part presents how such a model can be transposed for region detection in gray level images. The following section provides an experimental assessment of the approach before we conclude and propose further works.

2. RELATED WORKS

In this part, we mention works connected to ours in terms of reactive models for problem solving and applications of multi-agent systems to image processing.

Reactive approaches [11,5,9] for problem solving place emphasis on the simplicity of individuals in comparison to the properties observed at a collective level. In such systems, 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. Furthermore, the decision making process is mainly based on stimulus-response rules and does not refer to explicit deliberation. Therefore, problem solving is the consequence of interactions between agents through environment. Such an approach has been applied in various domains such as cartographic generalization [1], distributed air traffic control [21], workload management [14], assignment problems [10], ...

One of the major issues is to determine the environment, the individual behaviors, and the dynamics of the whole so as to solve a given problem with reasonable efficiency. Social models in biology can be a source of inspiration for designing reactive multi-agent systems [15] since the observed animal societies show collective behavior to solve an issue faced by the colony with limited individual capacities.

One of the most common metaphors is that of ants. The knowledge about interaction mechanisms through pheromones in ant societies [6,7] has been a source of inspiration for new methods for reactive problem solving [19,8,3] with applications on many problems like the traveling salesman problem. Fish and bird social models in biology have been sources of inspiration to implement flocking [17,20].

In our case, we applied our approach to images. In the image processing 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]. In the second case, the image is envisaged as an environment in which agents evolve: [16] Ramos et al were inspired by ant behavior to detect outlines and [13]Liu by cellular automata to extract regions.

3. BACKGROUND ON THE BIOLOGICAL MODEL

The model we built is inspired by work undertaken to simulate the collective web building activity of social spiders [4].

In this study, we applied a multi-agent model for the simulation of collective weaving in a social spider species in order to check biologists' assumptions that i) social spiders as well as social insects can exhibit stigmergic coordination [18] and ii) the sociality can be achieved only with making "lone spiders" ignore each others. Stigmergy [12] is a way to achieve coordination without any explicit reference to the tasks being performed by any spider of the colony: past actions leave traces in the environment; and these traces favor in return some actions among others. In the case of spiders, stigmergy is put into practice through the silk.

We proposed a model that can reproduce the collective behavior and that was characterized by the absence of social reference and by simple individual behavioral items.

In our proposal, the environment modeled the natural vegetation and was implemented as a square grid in which each position corresponded to a stake. Spiders behaved according to two independent items: a movement item which consists in the spider moving to a reachable stake; and a fixing item which consists in the spider dropping a silk dragline on the top of the current stake. As spiders move, they construct silky structures in the environment which offer new paths for their movements. Spiders are attracted by silk draglines and are likely to follow a dragline instead of moving to an adjacent stake.

All behavioral items are stochastic : silk fixing is ruled by a constant probability and movements of the spiders are determined by a contextual probability distribution which depends on silk attraction.

Stigmergy occurs in the dynamics of the system through the silk attraction factor : when attraction is null, silk is not taken into account during movement and no satisfying web is built; when attraction is medium, it allows collective web building, when it is too strong, collective building is impossible, each spider being trapped in its own silk.

4. APPROACH FOR REGIONS DETECTION

We first describe the problem to be solved, then provide a brief overview of the approach and make the link with the simulation model. In a third section, we detail the components of the transposed model and, in the final section, we describe how it is possible to interpret the structures produced by the system to obtain regions.

4.1 Description of the problem

The goal of our model is to extract various regions from an image. A region is defined as a set of contiguous pixels whose radiometric properties are homogeneous.

This definition is voluntarily not explicit. Two different criteria: the distance between pixels and the homogeneity of the gray level of the considered pixels have to be taken into account and a compromise might be required.

Indeed, due to the presence of noise in images, the two criteria must be loosened. The region, even if it corresponds to an object, is not characterized by a single gray level but small fluctuations must be allowed. Moreover, aberrant pixels might appear on a real image, like, for example, a gray pixel in a black region, that could create artificial borderlines and split a region into two parts.

Our model will have to produce, from a given picture, sets of labelled pixels, each label representing a region extracted.

4.2 Generalities about the approach

Before providing a precise description of the multi-agent model, this part gives a general overview of the principles underlying it.

The approach is built upon the same components as the simulation model: the environment, the agents and the dynamics of the whole.

The transposition of the simulation model consists in modifying the environment so as to make it represent the input of the system, a gray level image, in which agents will evolve; stakes are now associated with pixels. As agents evolve in the environment, they will fix silk draglines between pixels that will allow them to move on new paths. Finally, the environment will contain collective webs that will be interpreted to deduce regions.

Agents are ruled by the same basic behaviors but silk fixing now depends on the context and is related to the gray level of the pixel of the current agent location. Agents lay down draglines on some pixels: those that are "interesting". Silk fixing is then a way to ensure pixel selection and each agent is provided with parameters which describe the region it has to detect.

For sake of efficiency, we add a third behavioral item that makes an agent probabilistically return back to its web when no pixel is selected, thus avoiding the exploration of the whole image and restricting selection of pixel to the neighborhood of the already built web.

The dynamics of the system is still stigmergic: past actions in the environment will favor some actions among others and focus activity of the agents.

4.3 Description of the model

In this part, we will use the following notations : If X is a kind of object to be defined, $X=[char_1, char_2, ..., char_n]$ specifies the characteristics of X as being $char_1$, etc; and the use of $char_X$ will denote the access to the *char* characteristic of an instance *x* of X.

4.3.1 Environment

The environment of the system corresponds to a gray level image and is represented by a two dimension array whose elements are the pixels of the image. Each pixel (*p*) is indexed by its coordinates (x and y) in the image and is featured by its gray level and by the list of draglines Dl_p already fixed on it. Initially, the environment contains no draglines. Draglines will be added by the agents during runtime.

Each dragline *d* of a given Dl_p conventionally starts from p, is characterized by its end pixel, and is labeled by the spider that created it.

Environment :

P = array [NxM] of pixel. Pixel=[gray,Dl].

Dragline = [end, spider].

4.3.2 Agents

4.3.2.1 Agent features

Features of an agent correspond to parameters conditioning its behavior and to its internal state. Parameters are fixed for an execution (there is no online specialization) and internal state evolves according to performed actions.

A first set of parameters characterizes the region the considered agent will have to focus on and will condition the pixel selection made by the agent : *RefLev* $\in$[0..255] which is the gray value of the region to be searched and *Selectivity*, that reflects tolerance of selection.

A second set of parameters characterizes the exploratory behavior of the agents. This set is made of *BackProbability* which is the probability for the agent to return to the last fixed pixel when no silk is fixed on the current one, its perception radius *R* and the parameters that determine the attraction for silk. We implemented it in two ways that will be subsequently described. Parameters could then be *Pdragline* or *AttractSelf* and *AttractOther* coefficients.

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*.

4.3.2.2 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 corresponding to the accessible pixels in one move.

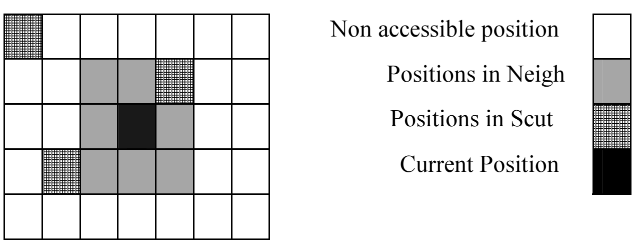


Figure 1. illustration of the different accessible pixels (perception radius R is supposed to be equal to 1).

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,sp) is the same restricted to the draglines labeled by considered agent sp.

If we suppose i is a pixel: $Neigh_i = \{p \in P / Dist(p,i) \le R \text{ and } p \ne i\}$; $Scuts_i = \{p \in P / p=end_l\ \forall l \in Dl_i\}$ *and* $Access_i = Neigh_i\ U\ Scuts_i$.

$Number(a,b) = cardnb(\{l \in DL_a / end_l = b\})$. *and* $Number(a,b,sp) = cardnb(\{l \in DL_a / end_l=b \text{ and } spider_l=sp\})$ *with cardnb being the cardinal number.*

4.3.2.3 Basic cycle

The basic cycle of an agent can be described in 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 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 **Returning to web**: choose to return to the web according to *BackProbability*, if the decision is made, return to the last fixed pixel.

4.3.2.4 Detail of behavioral items

Movement

Probability to move to an accessible pixel (called *p*) depends on the way to access it (Figure 1): *i)* by moving to a neighbor pixel ($p \in Neigh_{CurrentP}$) or *ii)* by following a dragline ($p \in Scuts_{CurrentP}$). It must be noticed that a pixel might belong to the two sets.

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 where agents cooperate to detect one single region: labels on draglines are not taken into account.

Proba (move(p))=

i) $(1\text{-}Pdragline)/(cardnb(Neigh_{CurrentP}))$ if $p \in Neigh_{CurrentP}$

ii) $Pdragline * Number(Current_p, p)/cardnb(Dl_{currentp})$ if $p \in SCuts_{Currentp}$

The choice of the kind 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 not to follow draglines, it moves randomly to a pixel belonging to $Neigh_{CurrentP}$. Otherwise, it randomly chooses a dragline and reaches the pixel belonging to Scuts at its end. Thus, the more draglines leading to p, the more likely the agent is to reach p.

The second implementation takes place in a perspective of competition between agents to detect several regions. We distinguish two kinds of attractions for silk according to the labels of draglines.

$$Proba\ (move(p)) = w(p) / \sum_{a \in Access_{CurrentP}} w(a)$$

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

ii) w(p)= AttractSelf*F(Number(CurrentP,p,Me))) + AttractOther*F((Number(CurrentP,p)) - Number(CurrentP,p,Me))) if p ∈ Scuts

AttractSelf describes attraction for its own silk, *AttactOther* describes attraction for silk of other agents. 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).

This procedure consists in giving a constant weight to each reachable pixel if the considered pixel belongs to $Neigh_{currentP}$ or a weight linked to the number of draglines linking this pixel to the location of the agent. The choice of following a dragline is then dependent on the numbers of draglines present on the considered pixel and of the kind of silk.

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

Silk Fixing

The decision is made according to a probability to fix a dragline on the current pixel which 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 $\boxed{Dl_{CurrentP} \leftarrow Dl_{CurrentP} U\{(CurrentP, LastFixed)\}}$ and the dragline list of LastFixed Pixel $\boxed{Dl_{LastFixed} \leftarrow Dl_{LastFixed}\ U\{(LastFixed,\ Current,)\}}$; and updating internal state of the agent $\boxed{LastFixed \leftarrow CurrentP}$.

Returning to web

Decision probability is constant and performance of action consists in updating the location of agent $\boxed{CurrentP \leftarrow LastFixed}$.

4.3.3 System dynamics

Dynamics rules how the system evolves through the interactions of agents and is based on the stigmergy principle. Agents perform actions that modify the environment which, in return, constrains the set of future possible actions. In our case, modifications are the apparition of silk draglines. Silk attraction implements in the agents' behavior the influence of the silky structure: new possibilities for movement appear and are favored by silk draglines.

An execution starts initially with an environment empty of silk representing an image. Each agent is initialized with parameters describing the region to detect through the R*eflevel* and the S*electivity* values. The system evolves by cycles. In each one, every agent is successively active and applies its "decision" process according to the local environment.

Execution ends after a user-fixed number of cycles.

4.4 System outputs: from web to regions

Biological simulations aimed to answer how a collective web can be built from interacting individuals. A qualitative assessment of the result of simulations was carried out (visual aspect and some statistics –size, approximate surface, average height- which have to correspond to real data). Improvement of the individual behavior model leads to better matching between real and experimental results. In no case, did the simulation focus on the efficiency in the process in terms of growth speed, average density, ...

Here the goal of system is to solve a given problem and, because agents have no representation of the global task that has to be accomplished, we must face the issue of interpreting global results of the model, which was not asked (and thus not answered) in simulation. We have to deduce regions from sets of pixels and silk draglines which are the available information dropped in the environment.

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

By gathering all the pixels an agent has woven on, we obtain a rough region, that is, pixels are put together without consideration of the number of times the agent has woven on them. Thus, we define the degree of belonging of each pixel to a region as the number of draglines which an agent extracting the region wove on it. To avoid selection of low ranked pixels in a region we propose to restrict the pixel set composing a region to those whose belonging degree is above a given threshold.

With such a method, a pixel belongs to a given region with a certain degree. Thus we define a region as

R= {i ∈ P/ Number(i,_,Spider) > Threshold }

and ∀ i ∈ R Number(i,AnyPixel,AgivenSpider) is the belonging degree of i to the region R associated to AgivenSpider.

This additional information can be used to improve global results when an ambiguous pixel simultaneously belongs to several overlapping regions.

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 coverage of the image and 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 characterised 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 consequence of the exploratory behaviour of the system as a whole related to the exploration ability of our agents.

Moreover, extracted regions must be relevant. First, the region extracted 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 decision process or, in other words, the selection process.

The results of the execution of such an algorithm are quite difficult to analyse mathematically because they refer to a semantic content : indeed, we consider that an extracted region is relevant if it corresponds to a region a human would have detected. 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 sets

The tests presented in this paper have been made with two real images taken by cameras : the first shows a calibration grid in front of a wall and the second is Alain. The resolution of those pictures is 256*256.

Figure 2. Images grid and Alain used for experiments

An experiment consists first in creating the environment corresponding to the considered picture. Then the user 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. Because we have limited ourselves for these experiments to extract a single region, all agents have the same features.

We ran experiments with both cooperative and competitive behaviours. For the extraction of a single region, results were qualitatively equivalent. In this paper, we present only results concerning the first way the moves of the agents were implemented. Attraction for silk of Agents is thus ruled by a *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 ther 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 regions from 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 satifying results when parameters of the spider-model have been accurately and empirically tuned by trials and errors.

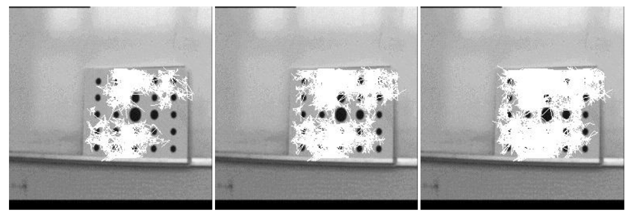


Figure 3. Web (in white) resulting from the extraction of the grid (Parameters of the experiment : *5 agents each one defined by RefLevel 175*, *Selectivity1, Backprobability 0.2,Pdragline 0.5*) after 5000,10000 and 20000 cycles

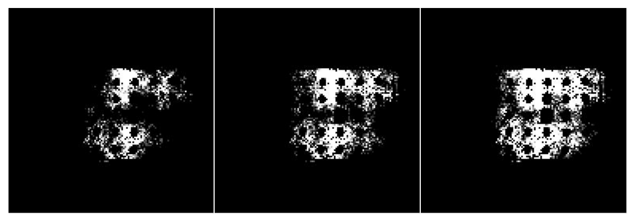


Figure 4. Degree of belonging of pixels for the same extraction

Although the grid is not well "detached" in the environment the algorithm provides good results even if the region is not fully covered (figure 3 and 4), it must be noticed that Alain's hair is also well extracted (figure 5 and 6).

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

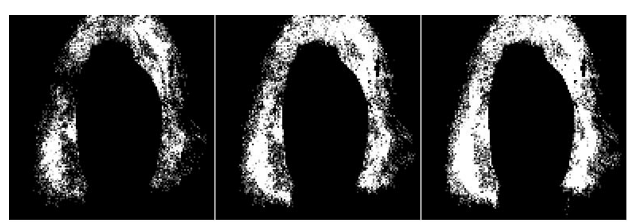


Figure 6. degree of belonging of pixels for the same extraction

Figure 7 shows different regions our approach is able to extract from Alain's image.

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

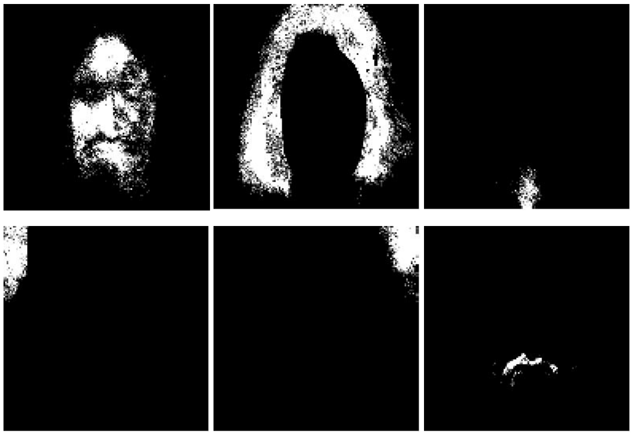


Figure 7. Example of extracted regions in Alain's picture : Face, Hair, Beard, Background and Moustache

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 Discussion about 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 *Pdragline* of the agents, their B*ackprobability*, their *Reflevel* and their S*electivity* values.

The first two parameters govern the moves of the agents and thus the exploratory behaviour of the system. The two last ones are related to the selection of pixels thus determining the relevancy of the extracted regions.

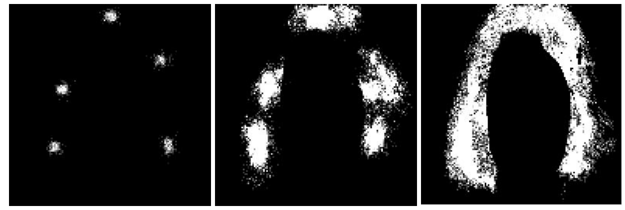
Of course, because the process is based on the stigmergy ensured by the silk draglines laid down in the environment, selection and movement are tied, but we could at first try to specify the influence of each aspect.

5.4.1 Influence of moves

The three following experiments, shown in figures 8a), 8b), 8c) and 9a) 9b) 9c), have been conducted under the same conditions except that the value of *Pdragline* was not the same.

a) b) c)

Figure 8. Impact of *Pdragline* on webs after 20000 cycles (experiments done with the same parameters for 5 agents : *Reflevel 16, Selectivity 0.1, Backprobability 0.2* but *Pdragline is for 0.8 a), for 0.5 b) and 0.2 for c)*).



a) b) c)

Figure 9. Degree of belonging of fig 8.

These extraction results are representative of the influence of the attraction for silk parameter : in figure 8a), this parameter was set high. Agents are captured by the web they have constructed and do not explore the entire region (the surface covered by the web is small). In Figure 8b), 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 8c), agents are urged to explore their environment and the region covered is larger.

Thus, if attraction is strong (figure 8a)) the size of the surface covered by an agent would be small. Obtaining a good coverage would require to drop 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 8c)), it requires fewer agents, but the density of draglines might be not significant enough to lead to relevant results.

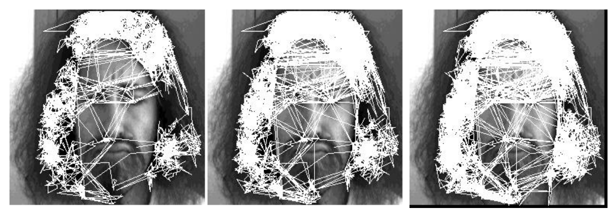


Figure 10. Web (in white) built with a null *Backprobability* (parameters of the 5 agents : *Reflevel 16, Selectivity 0.1, Backprobability 0* but *Pdragline is for 0.5*) after 5000, 10000 and 20000 cycles.

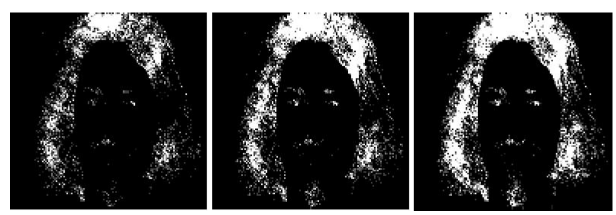


Figure 11. Degree of belonging of fig 10

The importance of *Backprobability* is illustrated by figures 10 and 11. The return behavioural item prevents agents from building a web linking two non contiguous 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 contiguous region from a web and then weave draglines linking those two regions. It is the case in Figure 10 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 low

Backprobability allows the agents to cross small noisy zones to carry on selection processes afield.

5.4.2 Influence of selection of pixels

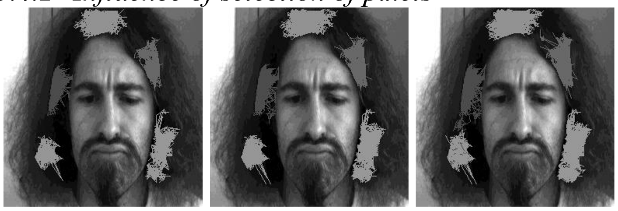


Figure 12. Extraction with high *Selectivity* (parameters for 5 agents : *Reflevel 16, Selectivity 1, Backprobability 0.2 and Pdragline 0.5*) after 5000, 10000 and 20000 cycles.

Figure 13. Degree of belonging of fig 12.

Selectivity is directly linked to the homogeneity of the gray level of woven pixels due to the selection process. Figures 12 and 13 present zones whose borderlines do not correspond to the desired results because of a too high *Selectivity*.

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, S*electivity* 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.

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

These hypothesis applied to the task of extracting the Alain's beard lead to the results of figure 14. Since, the region is not very big, few agents will be sufficient and the *Backprobability* coefficient and *Pdragline* parameter will be set high. Because the region is well detached, *selectivity* might be not accurately tuned.

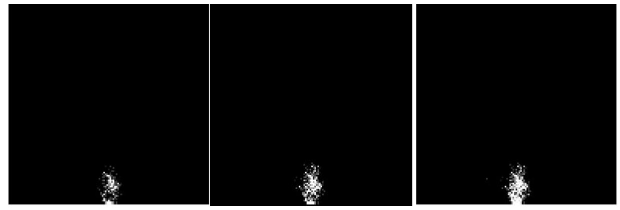


Figure 14. Extraction of beard with heuristics (parameters for 2 agents : *Reflevel 16, Selectivity 1, Backprobability 0.2 and Pdragline 0.5*) after 1000, 2000 and 3000 cycles.

5.5 Conclusion of these experiments

As shown by our results, all the ingredients are available in our approach for detecting different regions if the required parameters are well assessed. It is also possible to detect simultaneously several regions (figure 15) by the use of the second implementation of movement behaviour and by gathering 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 which 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.

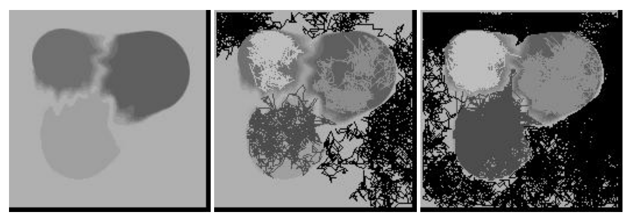


Figure 15. Webs resulting of simultaneous extractions of 4 regions with 4 groups after 0, 5000 and 10000 cycles.

However, a major drawback has to be solved in order to produce a real application : parameters are empirically adjusted. Liu [13] 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.

Until now, even if few heuristics have been made clear, these parameters require information about the region that one wishes to extract. In some applications, such information might be available but we can focus also on online specialisation and auto-organization. Indeed, 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 this gray level is not searched by agents and that a region which will not be detected might be present. 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.

6. CONCLUDING REMARKS AND FUTURE WORK

We have presented in this article an approach for region detection inspired by an original social model: the social spiders.

The transposition of this model provides a reactive multi-agent system in which agent behavior is ruled by 3 simple items, and relies on very limited information and memory. Furthermore, agents don't have any explicit representation of the global task being performed and coordinate themselves by silk draglines through environment.

This approach gives very encouraging results. The individual model is simple and allows flexibility of the system which can be adapted to various contexts: without any optimisation of the system it is able to extract different kinds of regions in real images by simply modifying some parameters.

Currently two drawbacks must be mentioned: assessment of the approach is qualitative and initial parameters have to be estimated before runtime, this prevents automatic extraction of all the significant regions of an image.

Further work will focus on parameter adaptation by adopting a perspective of self organized systems and by considering natural abilities of biological systems.

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