

# A MULTI-AGENT APPROACH FOR EDGE DETECTION USING A GENETIC ALGORITHM FOR PARAMETERS' SPACE EXPLORATION

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## ABSTRACT

In this paper, an agent based approach for edge detection is presented. It uses the blackboard system as a means of communication between agents. A population of agents is deployed on a two-dimensional representation of an image. Every agent is able to decide whether the pixel on which it is situated belongs or does not belong to the homogeneous region looked for, and thus to exhibit a reactive behaviour: breeding and labelling, or diffusion, allowing the emergence of a complex phenomenon at the global level. This phenomenon is the segmentation of the image. The behaviour of agents is inspired from the natural diffusion phenomenon. The approach has been implemented with the Netlogo platform which is a very powerful agent based simulator, and since the parameters space is very huge, a genetic algorithm has been used to lessen the complexity of the problem.

**Keywords:** Complex Adaptive Systems, Agent-based Simulation, Edge Detection, Emergence, The Blackboard System, Genetic Algorithms

## 1 INTRODUCTION

A complex system is a system composed of a set of homogeneous or heterogeneous elements interacting with each others in a non linear way (retroactive interactions) which gives rise to a dynamics allowing the system to exist as a whole, different from the sum of its components [1]. So, two levels are to be distinguished:

- A micro-level, representing the components level, having the local properties of every component.
- A macro-level, representing the system as a whole, with novel properties which are not found in any individual component taken separately. Here, we talk about emergence of new properties.

In addition to natural complex systems: ant colonies, the cell, the human brain, etc., there are artificial a lot of complex systems such as artificial neuron networks, artificial immune systems, and cellular automata. These systems are made of a huge number of non linear interacting distributed entities. These entities are evolving in a dynamic environment where a centralised control is impossible to take place.

A complex adaptive system is a complex system having the ability to adapt to the changes occurring in its environment. It is characterised by its autonomy, adaptation, emergence, and self-organisation [10]. The elements of the system, agents, interact with each other according to behaviour rules and adapt as a response to the changes in their environment. Thus, the experience of the agents is explored to determine their future behaviour, and so that of the system.

The concept of emergence is very important here to describe how a non compositional phenomenon at the macro-level appears on the basis of the structure of interaction at the micro-level. The advantage of this is the possibility for the micro-level to self-adapt offering at the same time flexibility and robustness though the possible simplicity of components at the micro-level [3]. The complexity of a complex system is the unpredictable result of the emergent behaviour of the system. Marvin Minsky [2] defines the concept of emergence as follows. Emergence is the "the non predictable appearance, in a complex system, of a phenomenon which is not inherent in different parts of that system."

In such systems, the roles of the environment are multiple:

- At the micro-level: A medium of interaction because interactions may be realised in different ways: directly through sending messages or indirectly via changing the environment.
- At the macro-level: A collective memory; by saving the set of modifications made by interacting entities, the environment memorises the reproduced dynamics which will influence future interactions and canalises them. And, the control of the micro-level because, as a feedback, the environment may be modified by the observer for influencing the dynamics of the micro-level and so its global trajectory.

Multi-agent systems permit modelling heterogeneous, complex, dynamic, non linear and evolving systems, and make it possible to appear some kind of intelligence and some capacities which are different and globally superior to

those of their composing agents. This intelligence emerges from the coexistence and the cooperation of more or less autonomous agents [4]. Therefore, we can say that multi-agent systems are a powerful tool for modelling and simulating complex adaptive systems.

In the work presented in this paper, the emerging phenomenon of the system is image segmentation and more precisely edge detection. The approach is inspired from that of J. Liu [5, 10] with our introduction of the blackboard system as an indirect means of communication. A population of agents is deployed on the two-dimensional representation of the image. Every agent is able to decide whether the pixel on which it is situated belongs or does not belong to the homogeneous region looked for. Homogeneity is defined by the relative contrast, regional mean, and region standard deviation of the grey scale intensity. Agents exhibit a reactive behaviour: breeding and labelling, or diffusion, allowing the emergence of a complex phenomenon at the global level. This phenomenon is the segmentation of the image.

Initially, the agents move randomly on the image. If an agent finds a pixel which belongs to a homogeneous region searched according to predetermined criteria, it labels it, breeds a certain number of offspring entities and delivers them to the local region in different directions. Then, it updates the blackboard; that is what transmits the information to the other agents. This information represents the best direction of movement to be chosen that may lead to a more fruitful search. The reproduced agents have also the task to look for the pixels that belong to the homogeneous searched region. On the other hand, when a heterogeneous region is found, an agent will diffuse to another pixel in a certain direction within its local region.

Literally speaking, many approaches to image segmentation have been proposed. Mazouzi et al. [6] have proposed a multi-agent approach for depth image segmentation. Keshkar et al. [7] have used the hidden Markovian chain to design a multi-agent system for image segmentation. Their proposed approach is a supervised one. Djemame et al. in [8] proposed a bio-inspired multi-agent approach for image segmentation based on social spiders. In [5], Liu et al. present an adaptive approach based on reactive agents for IRM image segmentation. This approach is inspired from the natural diffusion phenomenon. Melkemi et al. in [15] propose a new distributed image segmentation algorithm structured as a multi-agent system composed of a set of segmentation agents and a coordinator agent. Starting from its own initial image, each segmentation agent performs the iterated conditional modes method, known as ICM, in applications based on Markov random fields, to obtain a sub-optimal segmented image. The coordinator agent diversifies the initial images using the genetic crossover and mutation operators along with the extremal optimization local search.

Multi-agent models have many parameters to be controlled; otherwise the search process will be a chaotic one. Regulating these parameters is a very hard task. In this work we have used a genetic algorithm to regulate these

parameters. The presented approach has been implemented using the Netlogo platform [12] which gave the possibility of well presenting the complex and adaptive nature of our system.

Consequently, this paper will be organised as follows. Section 2 describes some basic concepts about image segmentation, blackboard systems and genetic algorithms. In section 3 the proposed approach is presented. Section 4 illustrates and discusses some experimental results. Finally, a conclusion and some perspectives are drawn up in section 5.

## 2 BASIC CONCEPTS

### 2.1 Edge detection

Image segmentation is a very important step in image interpretation. It aims at isolating and classifying the image pixels into categories. There exist several methods for image segmentation, but no method is absolute or optimal. In fact, the complexity of the images to trait (texture, minute details, etc.) makes it very hard to establish a general method. In addition, it is difficult to decide whether a method is better than another in a given context. For evaluating these methods, some evaluation criteria have been put. There are two main approaches in image segmentation: the frontier approach and the region approach.

*The frontier approach:* consists of detecting the edge. An edge is a frontier between two homogeneous regions of the image. A homogeneous region is a region of the image with pixels having similar characteristics: intensity, texture, and colour. The contrast between regions should be relatively marked.

*The region approach:* in this approach, edges cannot be supposed to be found between objects to be determined; we rather search to which region of the image these objects belong. This corresponds to localise regions in the image having homogeneity characteristics. A region is a connected set of image elements (pixels) having similar properties (intensity, texture, etc.) which differentiate them from the elements of neighbouring regions.

In the field of image segmentation, there are many methods for edge detection based on different algorithms, namely, derivative methods, surface methods, morphological methods, adaptive methods and structural methods [13][14]. Structural methods are the most immediate to detect and localise variations. The edges are assimilated to the high gradient points. In surface methods, the transition between two regions is presented by a "model". Morphological methods work with the maximum and minimum of neighbourhood intensities of every pixel. In these two latter approaches, the image of intensities is considered as a surface. Structural approaches are based on the spatial nature of the image. On the basis of problems' collective solving, adaptive approaches use multi-agent systems.

## 2.2 Blackboard systems

The blackboard is a common area (a shared memory) in which agents can exchange information and knowledge:

- Agents start communicating by writing on the blackboard.
- Agents look for new information on the blackboard; they are able to filter this information.
- Agents must subscribe in a central site to get the permission to write on the blackboard.

The blackboard is a powerful paradigm for problems' distributed solving which uses the following metaphor [11]: "Imagine a group of specialist humans or agents sitting in front of a big blackboard. Specialists work in collaboration for solving a problem by using the blackboard as a workspace for developing the solution. The problem solving will start when the problem and initial data are written on the blackboard. Specialists observe the blackboard looking for an occasion to apply their expertise to develop the solution. When a specialist finds some useful information which contributes to finding the solution, he subscribes it on the blackboard. This complementary information allows other specialists to apply their expertises. This process of adding contributions will continue until the solution is found." (Fig. 1)

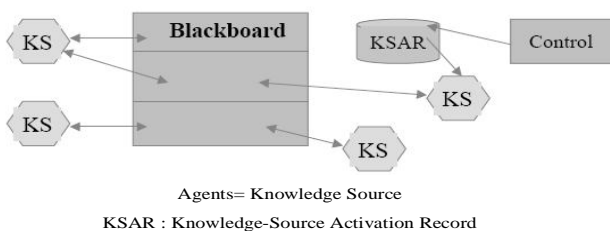


Figure 1: The blackboard system

## 2.3 Genetic Algorithms

Genetic algorithms were first introduced by John Holland in 1960: "Adaptation in Natural and Artificial Systems" [9]. These algorithms are a computing model inspired from natural evolution principle. They permit to solve many categories of problems, namely optimisation problems. In this framework, a potential solution to the problem is encoded in a linear data structure called a chromosome (a genotype). Every chromosome constitutes the genetic code of an individual of the population (phenotype).

The algorithm works on a set of individuals called a population on which some operators are applied. The population of chromosomes is chosen randomly. Every chromosome is then evaluated with a fitness function that attribute to it a value linked to the initial problem: this is to give a score to every chromosome. A selection will then take place according to the fitness of the individuals to generate a population called parent population. After this, two basic operators called crossover and mutation are applied on this population to obtain an intermediate

population. Crossover is to combine parts of individuals, whereas mutation is the random altering of a part of an individual. This operator permits to avoid a premature convergence towards a local solution. Finally, an evaluation is made for the intermediate population chromosomes, and a selection of a new solution is applied on the parent and intermediate populations in order to get a new population. A new iteration of the genetic algorithm process will then start on this population.

The general principle of the genetic algorithm can then be summarised as follows. The algorithm will repeat the following steps until a stop condition is met.

- Initialize the population with randomly generated individuals (candidate solutions).
- Evaluate every individual of the current population (compute fitness).
- Select genitors from parent population.
- Create offspring population by applying the variation operators (crossover and mutation) on genitors.
- Go back to step 2

In our approach, we consider the exploration of the parameters space as an optimisation problem. We should well specify the function to be maximised. In a multi-agent model, the choice of the fitness function is problematic for many reasons. First, it is not the result of a calculation to be evaluated, but it is the dynamics of a process. Second, some emergent phenomena can be difficult to be quantitatively characterised because they are generally related to a subjective interpretation made by a human observer.

## 3 THE PROPOSED APPROACH

A population of autonomous entities (reactive agents) is deployed on a grey scale image  $S$  which is represented by a 2 dimension array  $M$  of which every element represents a pixel. Every pixel is defined by its location  $(i,j)$  and its colour. Pixels belong to different homogeneous segments. The array  $M$  represents effectively the environment of our system which is dynamic. Every agent can perceive its neighbourhood and test whether the pixel on which it is situated belongs or does not belong to the searched homogeneous region. This allows it to exhibit some reactive behaviour as a response to the local stimulus. Two behaviours are offered: breeding and diffusion

### 3.1 Local stimulus

All the time, every autonomous entity (agent) situated on a pixel with the location  $(i,j)$  perceives its environment consisting of the set of its neighbouring pixels by evaluating the three criteria: the relative contrast, regional mean, and regional standard deviation of the grey scale intensity [5]. This evaluation permits to choose the appropriate behaviour and to execute the corresponding one. The neighbourhood of an agent is the circular region with the radius  $R$  and centre  $(i,j)$  (Fig. 2)

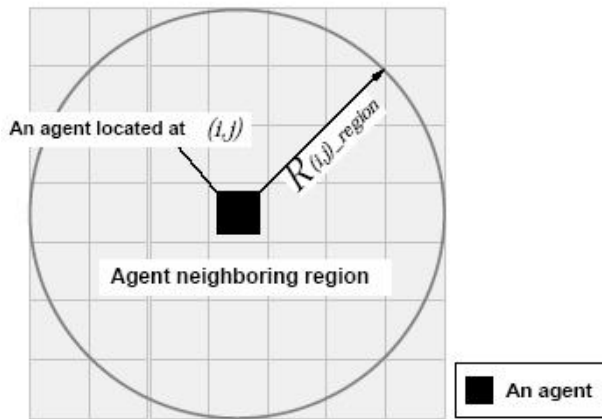


Figure 2: The neighbouring region of an agent at location (i,j) [5]

Mathematically speaking, a homogeneous region in a location with the coordinates (i,j) of the image S can be specified using the following criteria.

- contrast\_criterion  $G_{(i,j)} \in (\eta_1, \eta_2)$ .
- mean\_criterion  $Mean_{(i,j)} \in (M_1, M_2)$ .
- std\_criterion  $Std_{(i,j)} \in (D_1, D_2)$ .

Where  $\eta_1, \eta_2, M_1, M_2, D_1,$  and  $D_2$  denote pre-defined constants related to the image to be segmented.

The relative contrast criterion is defined as follows:

$$G_{(i,j)} = \sum_{\|(i,j)-(k,l)\| \leq R_{(i,j)}} p(i,j,k,l) \quad (1)$$

$$\text{Where } p(i,j,k,l) = \begin{cases} 1 & \text{if } \|I(i,j) - I(k,l)\| \leq \delta \\ 0 & \text{else} \end{cases}$$

R: the radius of agent neighbouring region centred at (i,j),

I(i,j): the gray-scale intensity value at (i,j), and

$\delta$ : a pre-defined positive threshold.

The following formula expresses the regional mean.

$$mean_{(i,j)} = \frac{1}{N} \sum_{\|(i,j)-(k,l)\| \leq R_{(i,j)}} I(k,l) \quad (2)$$

Where N is the number of pixels of a neighbouring region centred in the location (i,j).

The regional standard deviation is expressed as follows.

$$std_{(i,j)} = \sqrt{\frac{1}{N} \sum_{\|(i,j)-(k,l)\| \leq R_{(i,j)}} (I(k,l) - mean_{(i,j)})^2} \quad (3)$$

### 3.2 Agents behaviour

Initially, a population of agents is randomly deployed on the image. Every agent diffuses on the image taking a direction chosen randomly and with a predefined step; this

allows a good exploration of the search space. If an agent finds a pixel belonging to a homogeneous region, it labels this pixel, reproduces a predefined number of agents, updates the blackboard and becomes finally inactive. Updating the blackboard permits the transmission of information to the other agents to choose the best direction allowing finding a pixel belonging to a homogeneous region. The reproduced agents behave the same way as the original ones do. However, if an agent after some time does not arrive to localise a searched pixel, it consults the blackboard to choose a direction that is likely to lead to a fruitful search (Fig. 3).

Every agent has a predefined limited life span. If the agent attains it, it becomes inactive and disappears from the image. This process ends up when all the pixels of the image are labelled or when no agent is active in a given moment.

The interactions of agents at the micro-level will give rise to the emergence of a complex phenomenon at the macro-level. This phenomenon is the image segmentation

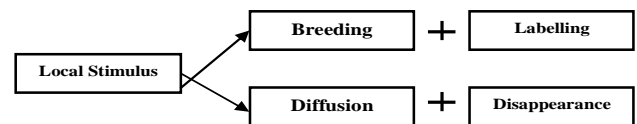


Figure 3: The Autonomous Entity's Behaviour

### 3.3 Communication

In our approach, the communication between agents is indirect. It is achieved via the blackboard as a means of exchanging information. The matrix representing the image is subdivided into 8x8 blocks. We associate with every block a vector V with the length 8 indicating the respective probabilities of the 8 possible directions (Fig. 4). Initially, the vector V contains nil values. If the agent labels a pixel belonging to a homogeneous region by following the direction d, it will transmit this information to the blackboard by updating the vector V corresponding to the block on which it is situated.

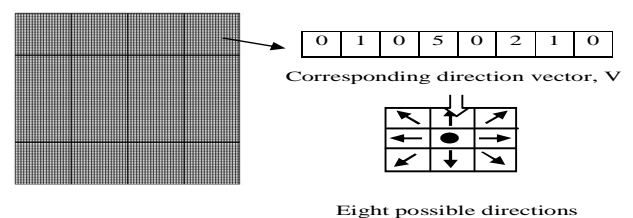


Figure 4: Communication through the Blackboard Implementation

The proposed approach is characterised of the simplicity of the local level rules that permit the emergence of a complex phenomenon at the global level, it is the image segmentation into homogeneous regions and more precisely edges detection.

We have used Netlogo platform to implement this algorithm. This framework provides portability because it is programmed in Java. The main advantage of Netlogo is that it makes it possible to simulate the behaviour of a huge number of parallel working interacting autonomous agents.

Parameters optimisation:

The most problematic issue in such an approach is the choice of the general parameters, namely:

*N*: the number of used autonomous entities (agents).

*DR*: Their life span

*R*: the radius of the neighbouring region of a pixel

*P*: the diffusion step

*NR*: the number of the reproduced agents during reproduction.

The complexity of such a task is the reason behind our choice of genetic algorithms. They are used to find the best values of the above parameters, and thus a better image segmentation. Because the random character of such a system may lead to an unacceptable solution, we should carefully choose the evaluation (fitness) function. The fitness function presents the evaluation criterion of segmentation quality realised by giving every time values for each parameter of the segmentation, and this is done by comparing the result with the previously segmented ones (the standard of comparison). A set of reference images and their corresponding segmented images are used for training. The fitness function *F* is given by formula (4).

$$F = \frac{\text{number of correctly labelled}}{\text{number of labelled pixels of the standard image}} \quad (4)$$

This function has as a maximum value equals to 1, if all the concerned pixels are labelled. Every solution to the problem is presented by a chromosome (Tab. 1).

Table 1: A chromosome representation

1	0	1	0	0	1	1	0	1	0	1	1	0
Life span DR			number of agents N			reproduced agent NR			step P		radius R	

The different values of parameters are presented by the following tables (Fig. 5).

Code	N	Code	DR	Code	NR	Code	P
000	100	0000	3	000	1	00	1
001	200	0001	4	001	2	01	2
010	300	0010	5	010	3	10	3
011	400	0011	6	011	4	11	4
100	500	....	....	100	5	Code	P
101	600	....	....	101	6	0	1
110	700	1110	17	110	7	1	2
111	800	1111	19	111	8		

Figure 5: Possible values of the optimised parameters

The length of a chromosome is 13 bits. So, there are  $2^{13}=8192$  possible combinations.

#### 4 EXPERIMENTAL RESULTS

For implementing our approach, we have used the Netlogo as a programming environment. It is a multi-agent based environment that allows the simulation of complex systems. In the following are presented some experimental results when using one class of agents for segmenting a complex image of size  $512 \times 512$  (Fig. 5). The parameters associated with this agent class are presented in table 2.

Table 2: The attribute values of the segmentation agents class

$\delta$	$\eta_1$	$\eta_2$	$M_1$	$M_2$	$D_1$	$D_2$	N	DR	NR	P	R
15	0	5	90	180	-	-	500	12	3	3	1

The total number of agents used throughout the process of segmentation is inferior to the number of pixels in the image *i.e.*  $512 \times 512 = 262144$  pixels.

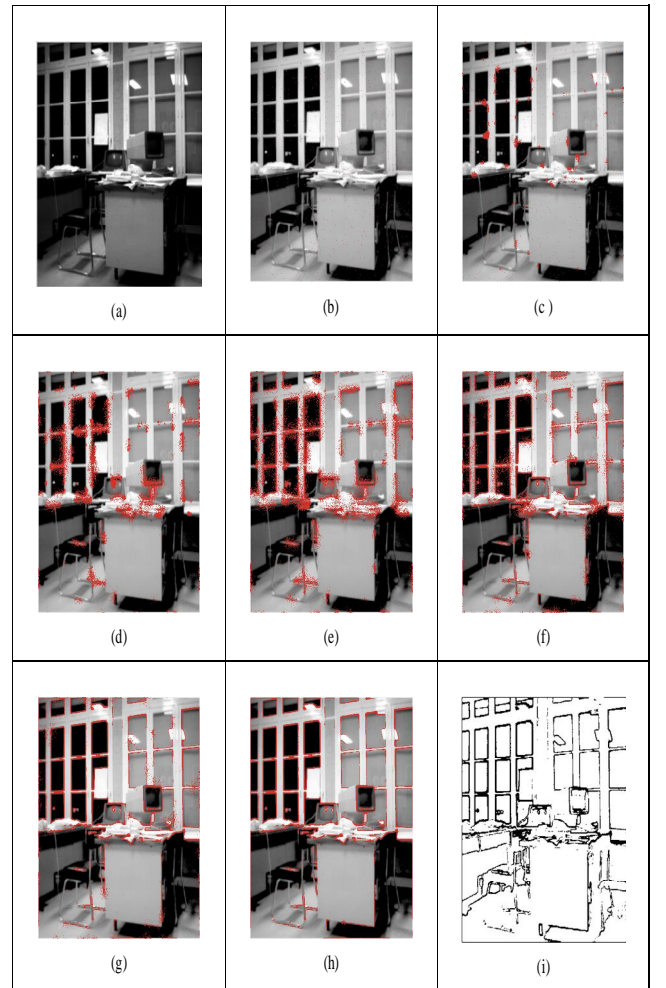


Figure 6: The edges detection steps



The values attributed to  $\delta$ ,  $\eta_1$ ,  $\eta_2$ ,  $M_1$ ,  $M_2$ ,  $D_1$ , and  $D$  depend on the image to be segmented.

For the execution of the genetic algorithm, we have a set of grey scale JPG images of size 512x512 pixels. Every image represents a natural scene associated with it an image containing its edge drawn in hand. The fitness function represents the distance between the edge hand drawn image and that resulting from our approach. We have a population of 32 individuals; every individual represents the parameters to be optimised. For realising the task of the genetic algorithm (image segmentation), the algorithm has been executed for 20 times (Fig. 7).

The best results have been found using a population of agents having between 400 and 800 agents, with a span life inferior to the average, a step of diffusion between 2 and 3. The number of reproduction represents generally the third of the span life. The neighbourhood radius is set to 1.



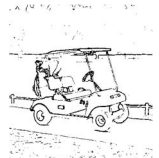

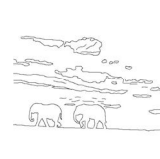
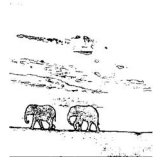


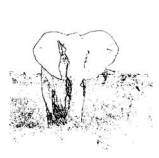

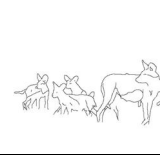
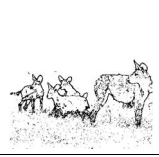

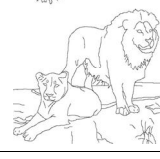


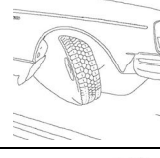
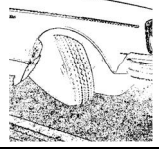

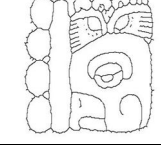

Original image 256 grey scale	Edge drawn by a human	The detected edge
		
		
		
		
		
		
		

Figure 7: Segmented Images Obtained After the Training Process

The following results have been found using N=500 agents, a life span DR= 15, Diffusion step P=2, Number of reproduced agents PR=4, and radius R=1 (Fig. 8).

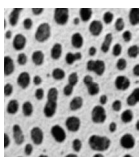








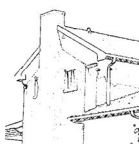


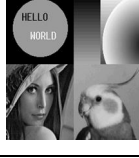








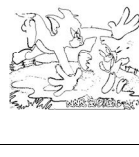

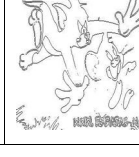
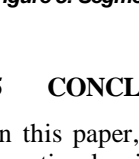
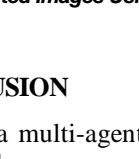
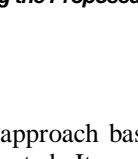
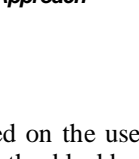
Original image	Proposed approach	Canny method	Prewitt method
			
			
			
			
			
			
			

Figure 8: Segmented Images Using the Proposed Approach

## 5 CONCLUSION

In this paper, a multi-agent approach based on the use of genetic algorithms was presented. It uses the blackboard paradigm as a means of communication between agents. Each agent, being situated on a specific pixel, explores its neighbourhood and when it finds a pixel that belongs to a searched homogeneous region, it labels it and transmits the direction to be explored to the other agents through the blackboard. This agent reproduces some copies of itself and then die. Genetic algorithms have been used to optimise the parameters related to the number of agents, the number of reproduced agents, the radius of neighbourhood, the diffusion step and the life span. The Algorithm has been tested on some reference images, known to be good model in the field of image segmentation, and has given good results. As future work, we will try to apply the proposed approach for solving other optimisation problems.

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