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A preliminary investigation of Anisotropic Selection in Cellular Genetic Algorithms

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Abstract. We introduce the two concepts of Fuzzy Neighborhood and Anisotropic Selection to control the exploration/exploitation tradeoff in cellular genetic algorithms.

Introduction

In this paper we deal with the exploration/exploitation tradeoff in cellular genetic algorithms (cGAs). This concept is closely related to the notions of selective pressure and diversity. We propose to use *anisotropic selection* (AS) to promote diversity and to control selective pressure in genetic search. Previous studies on cGAs selected the size and the shape of neighborhoods [1], or the shape of the grid [2–4] as basic parameters to tune the search process. Altering these structural parameters entails a deep change in the way we deal with the problem. For instance, there is no built-in mean to swap from a rectangular grid to a square grid without misshaping the neighborhood relation. One important advantage of the *anisotropic selection* scheme is that it allows to control the exploration/exploitation tradeoff without effect, neither on the grid topology, nor on the neighborhood shape; so the cellular genetic algorithm we propose can work on a square grid and a simple von Neumann neighborhood shape. The paper is divided in 5 sections. In the first one we give a brief definition of cGA and an overview of existing techniques used to control the exploration/exploitation tradeoff. Section 2 introduces the anisotropic selection concept. Section 3 studies the influence of AS on the selective pressure. In section 4 we compare anisotropic selection and rectangular grids topologies' influence on the selective pressure. Finally, in section 5 we show how AS promotes the emergence of niches.

1 Cellular Genetic Algorithms

1.1 Characterizing the CGA

Cellular Genetic Algorithms (cGAs) are a subclass of Genetic Algorithms (GAs) in which exploration and population diversity are enhanced thanks to the existence of small overlapped neighborhoods [5]. Such a kind of structured algorithms is specially well suited for complex problems [6]. We assume a two-dimensional

toroidal grid as a spatial population structure. Each grid cell contains one individual of the population. The overlapping neighborhoods provide an implicit mechanism for migration of genetic material throughout the grid. A genetic algorithm is assumed to be running simultaneously on each grid cell, continuously selecting parents from the neighborhood of that grid cell in order to produce an offspring which replaces the current individual according to a replacement method.

1.2 Takeover Time

A standard technique to study the induced selection pressure without introducing the perturbing effect of variation operators is to let selection be the only active operator, and then monitor the growth rate of the best individual in the initial population [7]. The takeover time is the time it takes for the single best individual to conquer the whole population. The grid is initialised with one cell having the best fitness and all the other having a null fitness. Since no other evolution mechanism but selection takes place, we can observe the way the best individual spreads over the grid by counting generation after generation the number of copies of this one. A shorter takeover time thus means a higher selective pressure. It has been shown that when we move from a panmictic population, as in standard GA, to a spatially structured one of the same size with synchronous updating of the cells, the global selection pressure induced on the entire population is weaker [1].

The takeover time is influenced either by the neighborhood size and shape and by the grid topology.

Neighborhood size and shape in a cGA are parameters that have some influence on the takeover time. A larger overlap of local neighborhoods of the same shape speeds up the best individual's spreading over the grid. The influence of the shape is given by Sarma and De Jong through a measure on the neighborhood which represents the spatial dispersion of a cell pattern [1]. More than the size of the neighborhood in terms of individuals, the determinant particularity of a local neighborhood is its radius. The takeover time decreases with this radius in a spatially structured population.

To measure the relation between grid topology and selective pressure, we consider rectangular grids, so-called *RG*, where the population size is fixed to 4096. We use the following grid shapes: 2×2048 ; 4×1024 ; 8×512 ; 16×256 ; 32×128 and 64×64 individuals. The selection strategy is a binary tournament. For each cell we randomly choose two individuals in its neighborhood (Von Neumann neighborhood) and the best one replaces the individual of the cell on the grid if it has a better fitness or with the probability 0.5 if the fitnesses are equal. Figure 1 shows the average on 20 independent runs of growth of best individual copies against generations, the takeover time is reached when the number of copies is equal to the size of the grid (see table 1). The average of increase rate, that is the number of new best individuals copies at each time step, of these curves for three rectangular grid shapes (64×64 , 32×128 , 16×256) is plotted figure 2. This figure helps to understand the growth of the best individual

copies. The increase rate of the best individual is the same for all grids in the first generations. Then, the spreading speeds down to reach a constant speed for the rectangular grids. This constant is $2lp_1$ where p_1 is the probability of selecting the best individuals when there is 1 copies of it in the neighborhood¹. More accurately, the spreading starts speeding down when a smallest diameter of the torus (a diameter of the smallest dimension of the grid) is filled by copies of the best individual (see figure 3(b)). Then, the speed becomes constant until the best individual has spread over a diameter of the other dimension (see figure 3(c)); this is the reason why the 64×64 grid curve has no constant period: radii in the two dimensions are filled at the same time. Finally, the increase rate of the growth curves falls down to zero as the best individual finishes to conquer the grid. The results of the experiments we conducted are in agreement with E.Alba and J.Troya observations that narrow grid shapes induce low selective pressure [2]. We will see in the next sections that quite the same behavior is observed with the anisotropic selection method.

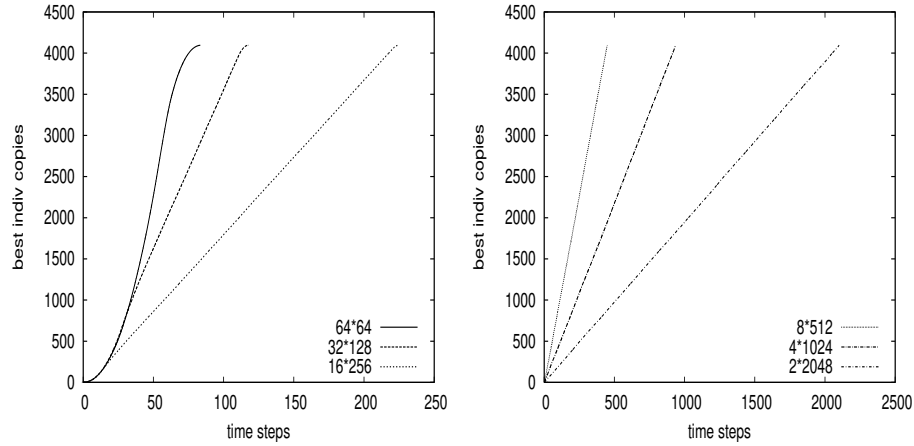


Fig. 1. Growth curves of the best individual on different grid shapes.

2 Anisotropic selection

This section introduce the Anisotropic Selection (AS) method where not all the neighbors of a cell have the same probability to be selected.

¹ As defined in [4]

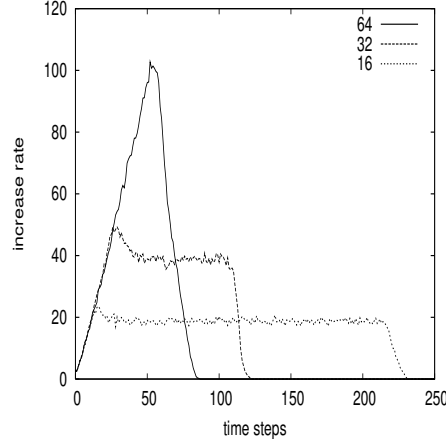


Fig. 2. Increase rate against time steps for three rectangular topologies.

Grid shape	Takeover Time		
	Avg	Min	Max
64×64	83.4 _{1.9}	79	87
32×128	117.8 _{2.4}	114	123
16×256	225.0 _{3.8}	219	232
8×512	449.7 _{6.3}	437	463
4×1024	937.1 _{9.9}	921	960
2×2048	2101.2 _{29.9}	2045	2155

Table 1. Takeover time for different rectangular grid topologies.

2.1 Von Neumann Fuzzy Neighborhood

The von Neumann neighborhood is defined as all cells reachable in a fixed axial direction (*NorthSouth* or *EastWest*). In the *von Neumann Fuzzy Neighborhood*, we assign different probabilities to choose one cell in the neighborhood according to the direction. Let p_{ns} be the probability to choose a cell in the *NS* direction and $p_{ew} = 1 - p_{ns}$ the probability to choose a cell in the *EW* direction. More, we assume the probability to stay in place is $\frac{1}{5}$ as for uniform distribution. So, the probability to reach *N* or *S* is $\frac{2}{5}p_{ns}$, and the probability to reach *E* or *W* is $\frac{2}{5}p_{ew}$.

Let $\alpha = 2(p_{ns} - 0.5)$ be the control parameter in the range $[0, 1]$; the case $\alpha = 0$ corresponds to standard von Neumann neighborhood with $p_{ns} = p_{ew} = \frac{1}{2}$, and $\alpha = 1$ is the limiting case for fuzzy neighborhood where $p_{ns} = 1$ and $p_{ew} = 0$. In this last case, there is a vertical neighborhood with three neighbors only.

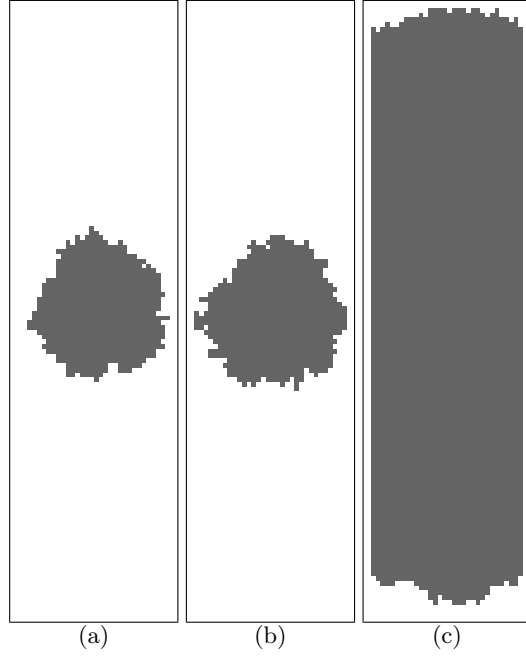


Fig. 3. Spreading of the best individual over a 32x128 grid

2.2 Definition

The Anisotropic Selection operator exploits the von Neumann Fuzzy Neighborhood; it works as follow: for each cell it selects k individuals in the cell neighborhood according to the p_{ns} probability (k stands in the range $[2, 5]$). The k individuals participate to a tournament and the winner replaces the old individual if it has a better fitness or with probability 0.5 if the fitnesses are equal. Sarma and De Jong [1] established that increasing the neighborhood size creates a larger overlap and decreases the propagation time. Hence increasing local neighborhood sizes while keeping the grid size fixed should result in corresponding increases in selection intensity reflected by higher growth rates of the best individual. The control parameter α is a measure of anisotropy: $\alpha = 0$ corresponds to standard selection, and $\alpha = 1$ is the limiting case with the utmost anisotropy. We conjecture that the selection pressure decreases while increasing anisotropy.

3 Selective pressure and Anisotropic Selection

In this section we describe the relationship between selection pressure and anisotropic selection. First we measure the takeover time for different anisotropic degrees, then we go further into the analyse with the growth curve of the best individual.

We measure the effect of different anisotropy degrees on the takeover time. In our experiments, the anisotropic selection is based on tournament selection of size $k = 2$ on the square grid of side 64. All the 4096 cells are updated synchronously, they change their states simultaneously. For each cell, individual is replaced if the selected individual have a better fitness. For each value of control parameter α , we perform 20 independent runs. When $\alpha = 0.0$, no direction is privileged and anisotropic selection is equivalent to the standard isotropic method. When $\alpha = 1.0$, only one direction is exploited, the grid can not be filled and the takeover time is not defined. The figure 4 shows the influence of anisotropic selection on the takeover time. The takeover time increases when the parameter α increases. The correlation between takeover time and the anisotropic degree is not linear ; it fast increases after the value $\alpha = 0.9$. These results are fairly consistent with our expectation that selection intensity decreases with the anisotropy degree.

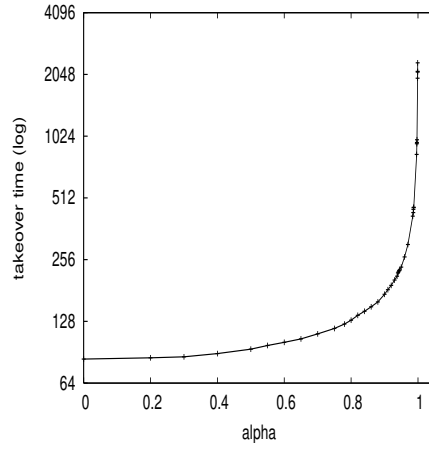


Fig. 4. Average of the takeover time as a function of the anisotropic degree α .

The figure 5 shows the average curves of the growth of best individual copies and its rate of increase as a function of time steps. The shape of the curve is decomposed in three parts: in the first one, the rate of increase is nearly proportional to the time steps; The growth curve is approximatively a parabola. In the second one, this rate becomes constant after a period of decrease; The growth curve becomes linear. In the last one, the rate decreases linearly until zero with a different slope from the first part. The higher the anisotropic degree α , the weaker the initial slope of the increase rate. In the same way in the second part, the slope of growth curve is smaller when α is higher. So, the selective pressure is lower when the anisotropic degree is higher.

The three part of the growth curve correspond to three periods in the spread of the best individual on the square grid (see figure 6). During the first one, the

best individual spreads more in the privileged direction rather than the other one. This period is finished, as describe in section 1.2, when a diameter of the torus is filled by best individual copies in the privileged direction (see figure 6(b)). During the second period, the best individual fills the second direction of the grid until it has spread over a diameter in the less privileged direction (see figure 6(c)). The best individual front is sharp at the beginning, and becomes approximatively a horizontal line later. The third time finish to fill the grid. Taking into account those three times, it would be possible to have the equation of the growth curve as in [4].

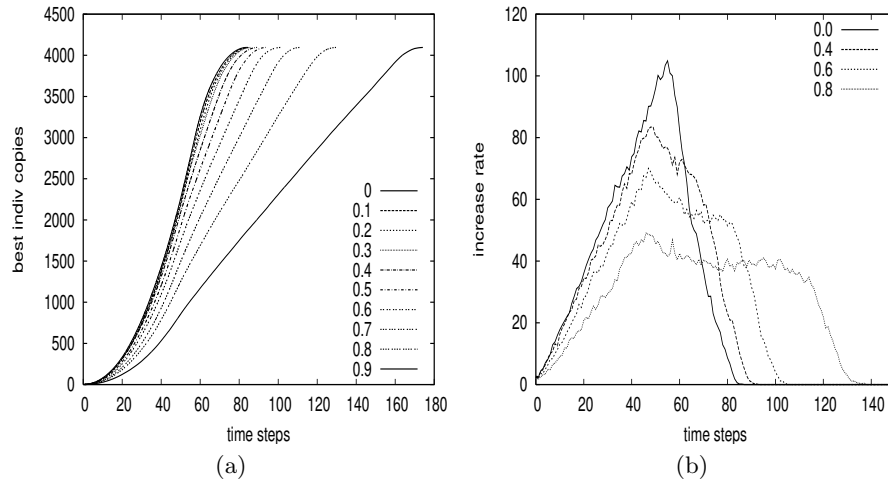


Fig. 5. Growth curves of the best individual on a square grid (a) and the rate of increase of the corresponding curves (b) for different anisotropic degree α .

4 Anisotropic Selection vs. Rectangular Grid

The modification of the rectangular grid shape and the tuning of the anisotropic degree are two methods for varying the selective pressure. This section shows in which way they can be equivalent and the difference of those methods.

4.1 Takeover time analysis

Taking the experimental results from sections 1.2 and 3, we have computed the α parameter values for which we obtained the same takeover time as for each rectangular grid shapes. In figure 7 we plot the α values as a function of the $\frac{l}{L}$ ratio and exhibit the correlation between those parameters. We can see that α is proportional to the $\frac{l}{L}$ ratio. So, it is possible to have the same selective pressure using the two methods, according to the takeover time measure, with $\alpha = 1 - \frac{l}{L}$.

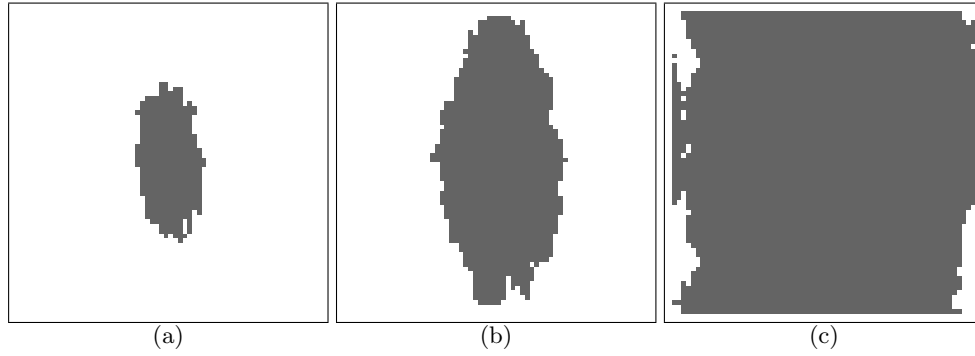


Fig. 6. Spreading of the best individual with $\alpha=0.75$

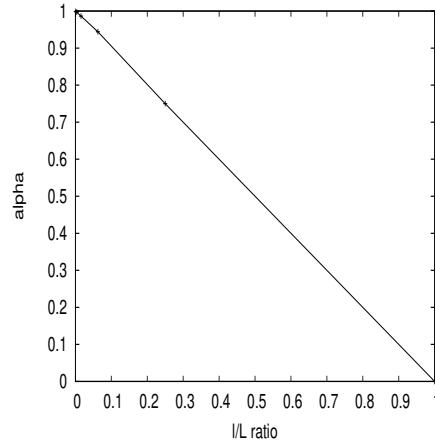


Fig. 7. Anisotropic degree α as a function of $\frac{l}{L}$ for the same takeover time.

4.2 Growth curve analysis

Figure 8 shows the mean growth curves of the best individual spreading against time steps for all grid shapes and for the corresponding square grids using anisotropic selection. Although we found the same takeover time with rectangular grid shapes and with some values of anisotropic degree, the selective pressure is exerted in a different way for the two methods during the spread of the best individual. It is weaker during the first generations in the anisotropic case then it becomes slightly stronger, and finally reaches the same takeover time.

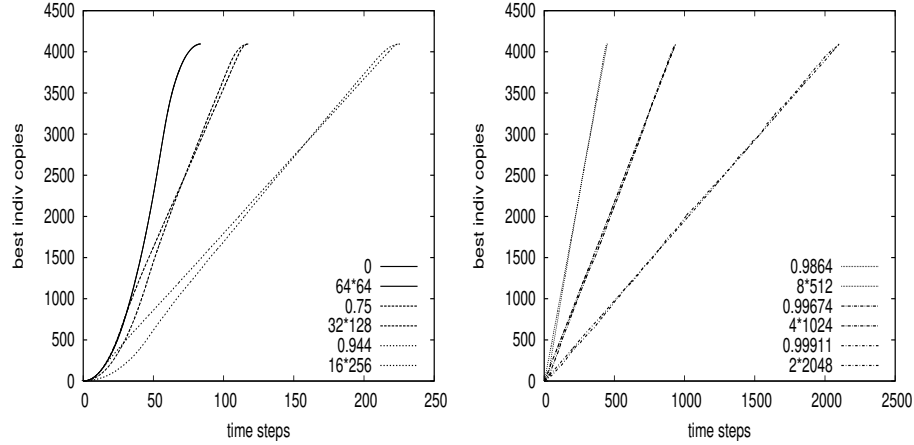


Fig. 8. Comparison between growth curves on different grid shapes and on a square grid with adapted anisotropy degree.

5 Anisotropic selection promotes niching

Many real optimization problems require the coexistence of diverse solutions during the search. In this section we show how the anisotropic selection is able to promote niching.

5.1 Niching methods

Niching methods have been proposed in the field of genetic algorithms to preserve population diversity and to allow the GA to investigate many peaks in parallel. As a side effect, niching prevents the GA from being trapped in local optima. Niching methods are inspired from nature where species specialize themselves to different ecological niches (for example food) in order to decrease the selective pressure they undergo. Niching GA's tend to achieve a natural emergence of niches in the search space. A niche is commonly referred to as an optimum of the domain, the fitness representing the resources of that niche [8]. Niching methods are used to solve multimodal problems, and in dynamic optimization too [9]. For such problems a GA must maintain a diverse population that can adapt to the changing landscape and locate better solutions dynamically. There are different niching GA for panmictic population: sharing, crowding, etc. These methods are based on the concept of distance: sharing [10] decreases the fitness according to the number of similar individuals in the population, and with crowding, replacement is performed considering the distance between solutions.

5.2 Experimental results

To show up to what extent anisotropic selection promotes niching, we have conducted experiments where two solutions with the best fitness (here 1) are placed on the grid at the initial generation. These solutions are farther from each other in the less favored direction (here oriented horizontally). We use a square grid with 64×64 individuals. Figure 9 shows some snapshots of the spreading of the two bests over generations for different anisotropic degrees. Cells in light grey (resp. dark grey) are copies of the first best (resp. the second best), and all white cells have a null fitness value. Generations grow from top to bottom, and the anisotropic parameter α increases from left to right. The left-hand row ($\alpha = 0$) represents standard binary tournament schema ; we observe that isotropic selection is not able to maintain niches, after 1000 generations the grid is a mixture of the two optima. On the other hand, as α increases, frontiers between niches emerge and cells with the same lineage seems more and more closely linked.

Conclusions and perspectives

This paper presents a new selection scheme in cellular genetic algorithms. The main objective is to control in a flexible way the exploration/exploitation trade-off. We propose to exploit the cellular GA characteristics to promote diversity during a genetic search process. Previous studies in cGA selected structural parameters, as neighborhood or grid shape, to tune the selective pressure. The main drawback of these techniques is that altering a structural parameter entails a deep change in the way we deal with the problem. The new selection scheme we propose is based on *fuzzy neighborhood* where a cell is chosen according to different probabilities. In order to favor one direction rather than the other one, *anisotropic selection* chooses individuals in fuzzy neighborhood. Experiments conducted to establish relation between the takeover time and the degree of anisotropy are consistent with our expectation that selection pressure decreases with the degree of anisotropy. Analysis of the growth curves allows to distinguish three different phases in the diffusion process. Then experimental results establish linear correlation in takeover between AS and cGA using rectangular grid. Finally we point out capabilities of AS to promote the emergence of niches.

This paper is a preliminary investigation and a more extensive analysis must be made to confirm that equilibrium between exploration and exploitation makes AS a good technique for complex problems in static or dynamic environments. Future works should address the following issues: compare AS and changes in the neighborhood shape and size, measure AS effects with cGA using mutation and crossover, change the balance of directions dynamically. This last point is an important feature: tuning the control parameter α , it would be possible to make the algorithm to self-adjust the selective pressure, depending on global or local measures of diversity. This adaptive ability have two important advantages: first, parameter α may vary in a continuous way, second, changes in this parameter

have no effect, neither on the grid topology, nor on the neighborhood shape. In general, we have to continue investigation of *Anisotropic Selection* to assess its validity and generality.

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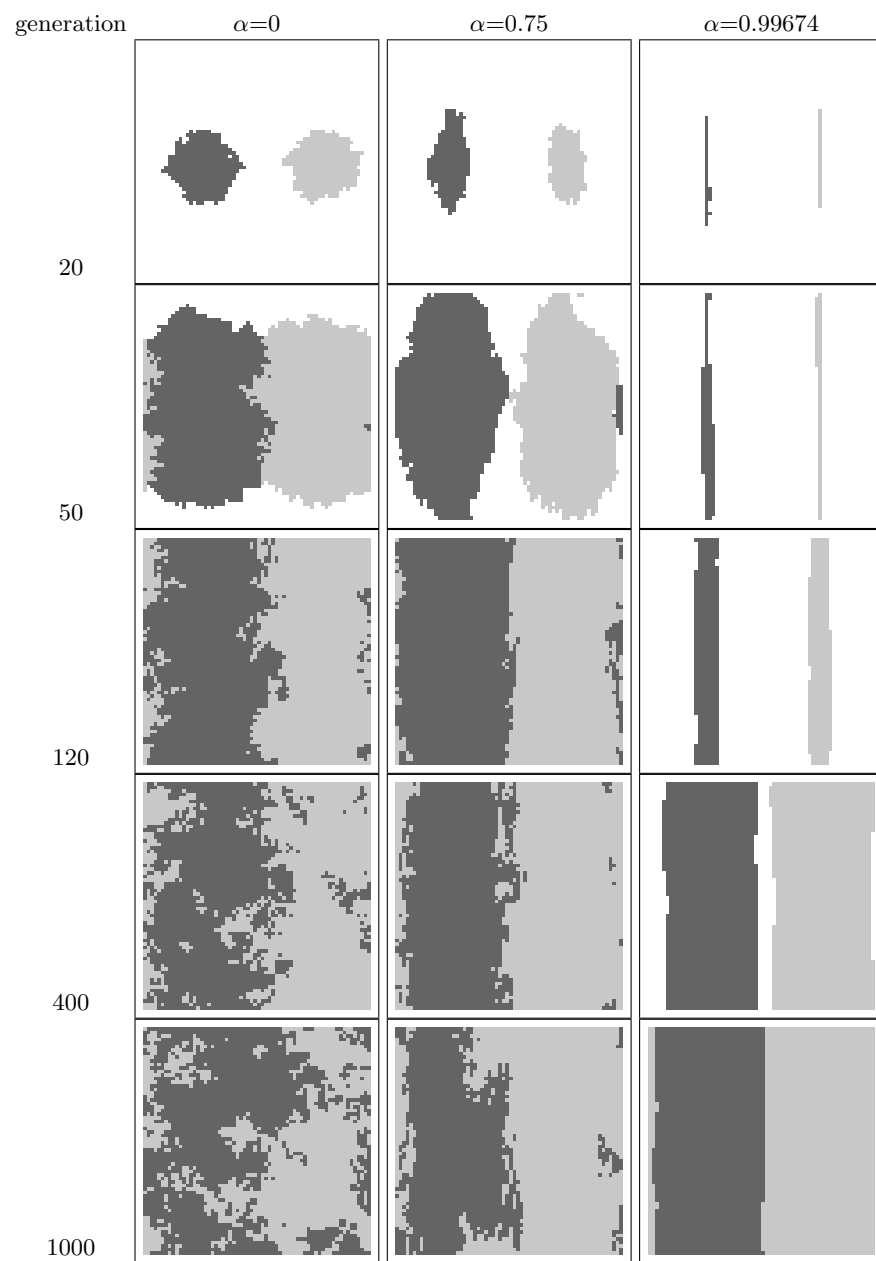


Fig. 9. Spreading of two copies of the best individual