IMAGES SEGMENTATION BASED CONTOUR USING EVCA APPROACH, EVOLUTIONARY CELLULAR AUTOMATA

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ABSTRACT

We use an evolutionary process to seek a specialized powerful rule of Cellular Automata (CA) among a set of best rules for extracting edges in a given black-white image. This best set of local rules determines the future state of CA in an asynchronous way. The Genetic Algorithm (GA) is applied to search the best CA rules that can realize better the edge detection.

Index Terms — Genetics Algorithms, Evolutionary Cellular Automaton, Edge Detection.

1 INTRODUCTION

A complex system is rudely defined as being constructed by a big number of simple parts, interacting mutually, capable to exchange some stimuli with their environment and capable also to adapt their internal structure as a consequence of such interaction. These interactions can provoke complex, coherent, emergent behaviour and cannot be assigned to the separated simple subsystems but rather to a collective effect [1].

Most of these systems are not susceptible of mathematical, analytic discussion and can only be explored by the means "of the numeric experiences."

To simulate the behaviour of a complex system, a powerful mathematical model has been developed. Named the cellular automaton (CA) [2][3].

It has the advantage to be easy to understand and to implement. If we want to exploit the whole power of this model (CA), we should understand the phenomenon of the emergence, and therefore of the complex systems. This phenomenon is the direct consequence of the complexity of the interactions inside the system.

The resolution of problems by emergence consists in discovering the local rules of the interaction between the elements of the complex system represented by simple units that will be able to emerge a solution forward a global problem that the system takes faces. This concept is known as Inverse Problem [2].

More clearly, we aim to recover the local rules to the level of every unit of the system that will have a certain expected and adequate global behaviour to solve a given problem [4] [2]. The space of research will be the space of the local rules of interaction and research will be guided by a calculated quality criteria in the global level that reflect the adequacy of the system to the proposed problem.

The possibility to solve the "Inverse Problem" is to use a stochastic research strategy, in order to optimize the gotten result.

In this paper, we are using Genetic Algorithms (GAs) in order to evolve CA to perform computations that require global coordination [5]. Indeed, we are interested into CA [2, 3] and the edge detection [6]. Among a variety of researchers having investigated the proprieties of CA, we can't miss to cite the works of John von Neumann [7], Stephen Wolfram [8], and John Conway [9]. CA can be interpreted like a set of rules which through an Evolutionary CA (EvCA), we can find one or several appropriate rules for a definite problem. The idea of using one packet of rules in edge detection and filtering are in the merit of Rosin [3]. Indeed, it is used in restoration of black-white images. Moreover, Rosin [3] studied these best rules in details and showed the interest of each one. The result of its study showed that a single rule can remove isolated pixels in a noise black-white image.

In this paper, we use a GA to find a single powerful rule for extracting efficiency edges in a given black-white image. Indeed, an EvCA is applied in order to determine the best local rules of the CA, using a GA on a population of CA candidates [5]. After this introduction, Section 2 presents the EvCA-ED approach. Experimental results are reported in Section 3. Conclusions are drawn in the last section.

2 THE EVCA FOR EDGE DETECTION (EVCA-ED)

The proposed approach takes advantage of the calculating faculties of the CA, to transform the initial configurations defined by a numerical image lattice as discrete input data in order to find its edges.

The CA unit is represented by a rectangle of 9 cells. In particular case of bi-colour image, the problem is to find the best CA patterns or rules for edge detection among 2^{51} possible patterns or rules.

A simple rule is not able itself only to represent all configurations possible of pixels patches in the image. The idea is to regroup the rules in packets [3] [4].

The execution of a simple packet of CA local rules evolved using evolutionary process [3, 4] produces an emergent phenomenon. In this paper, the GA is applied to search the desirable CA rules that can realize better the edge detection. In order to cover the space of research, let us setting up some problematic as:

1. Useless rules and packets puts the following difficulties

   1.1. How does the convergence progress? Generally it will be slow and very elevated time is consumed on sequential machines (Simulation).

   1.2. Global effect of the rules during the process of segmentation.

2. The redundancy of a (rules/packets) during the process of evolution lead us to the first problem.

3. The training can be assured by a pool of practice of images or by the evolutionary concept of the GA [10], therefore an excessive use of resources, which comes back to the problematic of convergence in 1.1.

In our study, we must avoid the redundancy of a (rules/packets) during the process of evolution and the contradictory rules in the same packet (2 patches with different transition).

The packet with best fitness will be the dedicated base packet for image edge segmentation.

The following code describes the GA process to determine the best packet of transition rules that able to achieve the edge detection of colour images.

2.1 Algorithm

1. The input data: Input Image.

2. Initialization of the GA: Construction at random of rule packets extracted from the neighbourhood model figured on the whole of the image (see Figure 2).

   - Edge detection method: For each CA, the process: First, searches; among the current packets; the similar rule according to its neighbourhood. Second, modifies the central pixel according to the defined transition.

   - Evaluation of the edge detection result: We compute the distance between the edge detection result and the ideal one considered to assess the approach. We can also evaluate the error of miss-classed pixels.

3. Reproduction: Generate a new population by applying selection, crossover and mutation. We use the edge detection described above in the evaluation process.

4. The process iterates until there is no improvement in the objective function for a given stall limit consecutive generations, or for a fixed maximum of iterations [10].

5. The result: optimal packet of rules.

2.2 Rules format

We represent the transition rule of a CA by the concatenation of the cells states of the immediate cell neighbourhood to update. Then we add the future cell state after update [3]. This rule (pattern) is transformed as a chromosome (linear) (see Figure 1).

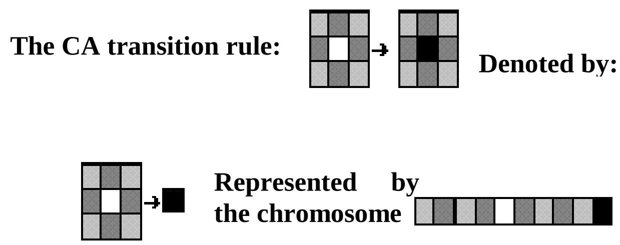

Figure 1: CA rule notation and the chromosome representation the CA rule.

The rule is applied when its part neighbourhood coincides with a patch of the same dimension on the image. Then, we replace the central pixel of the patch by the value of the future state in the rule.

The correspondence between the part neighbourhood of the rule and a patch of the image is reduced according to the rotational operators (rotation to 0°, 90°, 180° and 270°, reversal horizontal and vertical"flip-flop"). The rules are therefore symmetrical.

Each individual population is represented by a chromosome which is a transition vector according to a neighbourhood model (see Figure 2). We report that for the case of the black (0) and white (1) images, the numbers of the possible combinations to construct of the research space will be decreased contrary to the general case. To make the CA deterministic, we must take in consideration the constraints listed above.

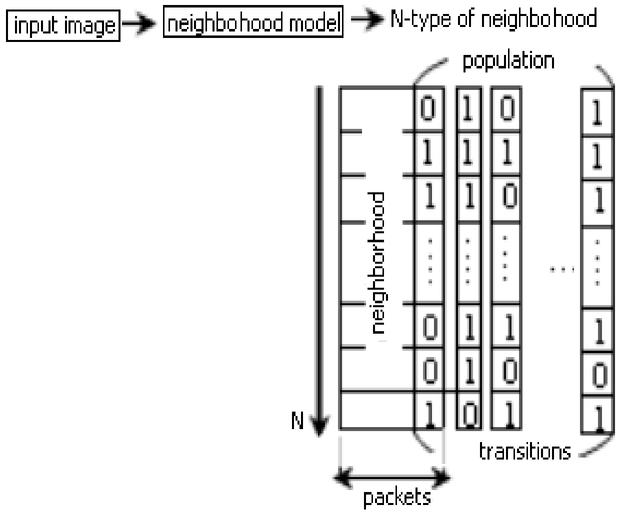

Figure 2: Construction of the neighbourhood model from an input image

2.3 The crossover operator

For giving the possibility to explore a vast surface of the research space, the chromosomes representation can be presented by two types of crossing, a horizontal and vertical crossing.

According to the neighbourhood model, we use the horizontal crossing operator. We take two vectors of transitions fathers and we form two children transition vectors by interchanging the future state of the central cell.

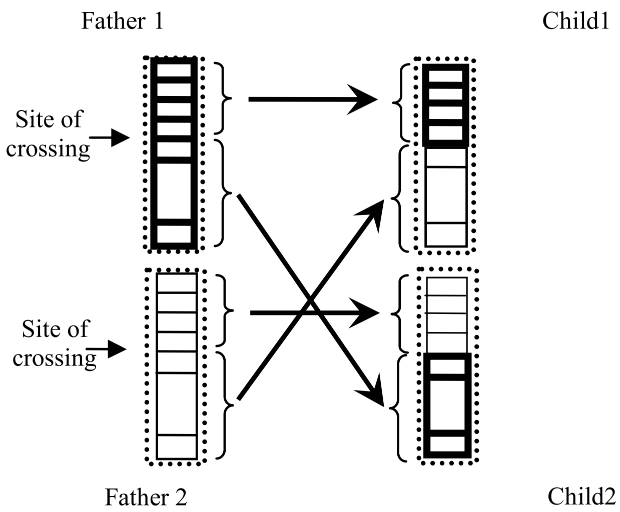

Figure 3: Horizontal crossover operator

It permits to combine the best rules to get better individuals. This strategy preserves a form of cohesion and stability of the crossing operator.

2.4 The mutation operator

Applying a mutation to a transition can be marked by changing the state of any cell in any transition (Figure 4). This change (mutation) is achieved according to a certain probability. Very sure some precautions are taken to keep the integrity of the packet of rules (the redundancy and the contradiction). The rules must be always valid and executable.

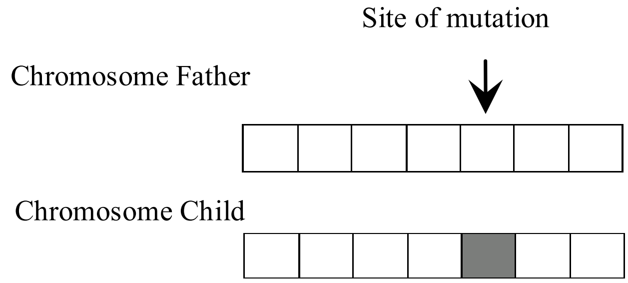

Figure 4: Mutation operator

The selection process based on the edge detection assessment in EvCA represents an interdisciplinary process. Let *Err=nbr of pixels where* (ImageED ≠ImageIdealED), which *Err* and *nbr* are the abbreviation of error and number respectively.

The fitness function used to assess the edge detection is given by:

F=1–(Err/L×H) where L and H represent the image width and height. The *Err* function computes the number of the points finds non equal in the two images: the resulted image and the ideal one.

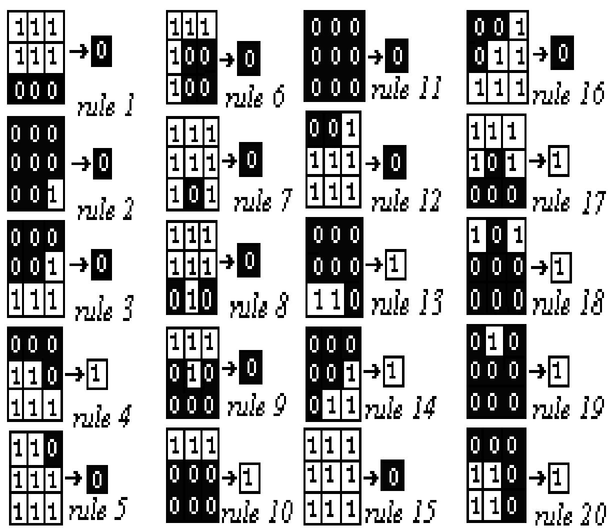

Figure 5: A best packet of CA rules find by GA

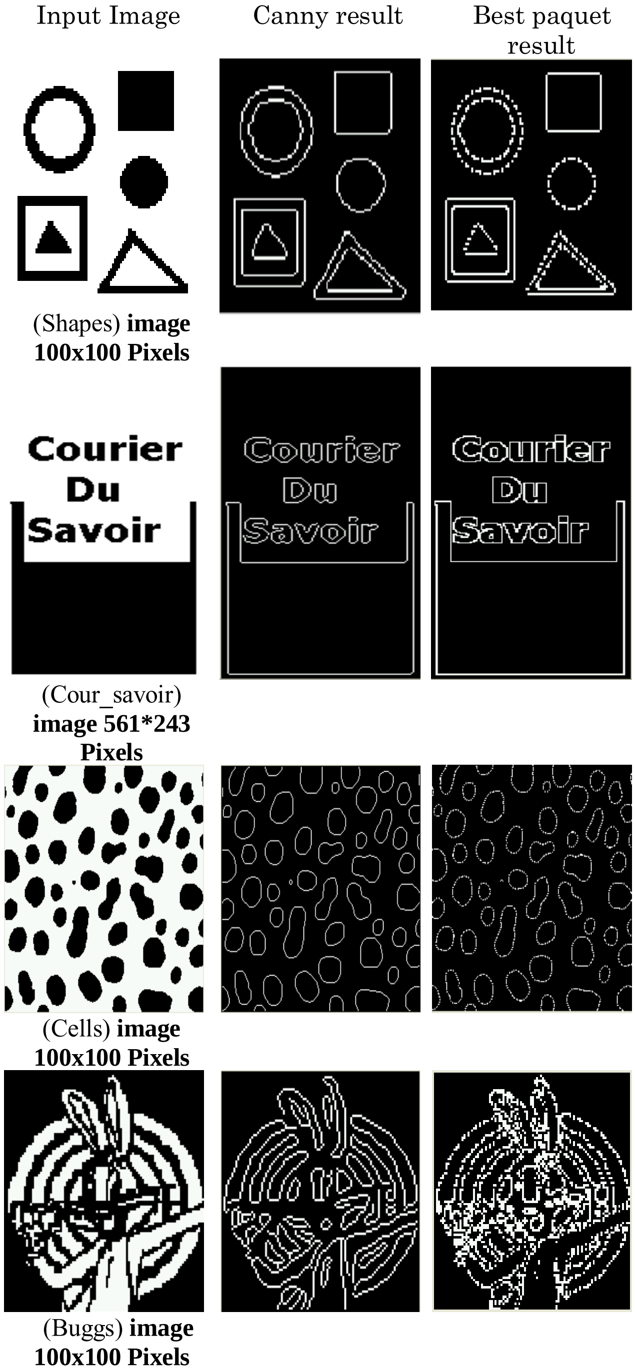

Figure 6: Edge detection of images "Shapes", "Cour_savoir", "Cells" and "Buggs"

3 EXPERIMENTAL RESULTS

We present both synthetic and real results (see Figure 6) of the EvCA-ED compared to Canny edge detector [6]. These following experiments are performed by using MATLAB on a Pentium 4, CPU 1:70 GHz with 256 MB.

The EvCA-ED uses the powerful rule number 15 extracts better the edges in all the experimental results performed on a class of binary images (see Figure 8). Consequently, for an edge detection of a binary images class, only one powerful rule is able to give better results, what of the substantial gains give in the cost and in the qualities. We have distinguished the powerful rule number 15 (0000000001) (see Figure 5) for edge detection.

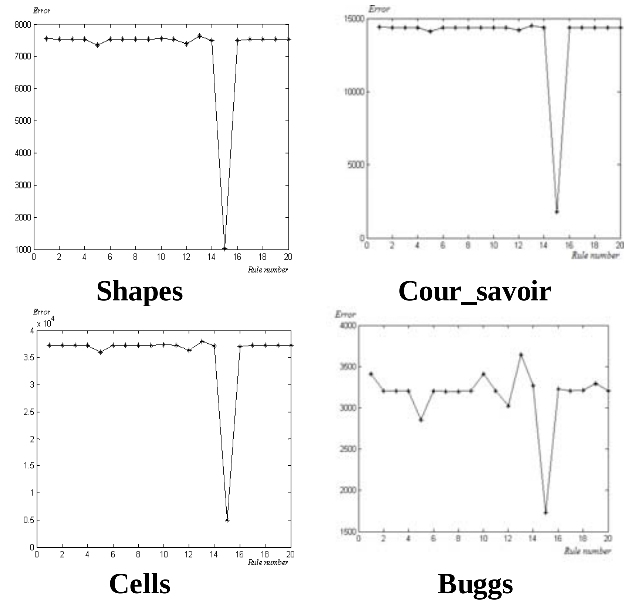

Figure 7: The error obtained rule by rule of images "Shapes", "Cour_savoir", "Cells" and "Buggs"

The precedent pictures represent the results of the segmentation by the optimal packet found by EvCA-ED.

Each graph of figure 8 presents the error evaluation of the EvCA-ED of the experiments presented in 6 respectively. For each rule, we get the fitness value of the its result. These graphs show clearly that the rule number 15 gives the better fitness result. These results and robustness of this rule compared to the others still the same in different experiments made on black-white images.

The first image (see figure 6."shapes") shows six shapes It can be seen that different edges of shapes are better extracted by the powerful rule number 15 than by Canny edge detector (see Figure 9). The same result is presented in an edge detection of two words 'cour' and 'savoir' (see Figure 8."cour_savoir"). In figure 8."cells", we use a synthetic image containing different geometric cells. It can be seen that different edges are better extracted by EvCA-ED using the powerful rule number 15 than the Canny edge detector [6] despite the interference of some cells. The EvCA-ED results using the rule number 15 is the adequate one comparably to the others (see figure 8, 6 and figure 7) and better than the Canny results.

Table 1: Evaluation values of the experiments reported in Figure.6.

	Shapes image 128x186 Pixels		**Cour_savoir** image 238x238 Pixels		**Cells** image 100x101 Pixels		**Buggs** image 100x100 Pixels	
Best packet	Fitness	T(S)	Fitness	T(S)	Fitness	T(S)	Fitness	T(S)
	0.809	22.893	0.841	69.450	0.822	188.46	0.745	28.000

Table 2: Evaluation values of the experiments reported in Figure 9

	Cour_savoir image 128x186 Pixels		**Cells** image 238x238 Pixels		**Shapes** image 100x101 Pixels		**Buggs** image 100x100 Pixels	
Rule number	Fitness	T(S)	Fitness	T(S)	Fitness	T(S)	Fitness	T(S)
Rule 1	0.3351	7.3900	0.3417	16.324	0.2434	2.8340	0.6586	2.8240
Rule 2	0.3423	6.6290	0.3415	14.891	0.2463	2.9950	0.6794	2.7840
Rule 3	0.3423	6.8300	0.3415	16.673	0.2463	3.5150	0.6794	2.7340
Rule 4	0.3423	7.5710	0.3415	15.973	0.2463	3.2040	0.6794	2.7240
Rule 5	0.3532	7.0200	0.3643	16.614	0.2651	2.9240	0.7146	2.9850
Rule 6	0.3423	6.8500	0.3415	15.602	0.2463	2.6840	0.6794	2.9540
Rule 7	0.3440	6.5600	0.3416	15.513	0.2463	2.9540	0.6797	3.0750
Rule 8	0.3428	7.0700	0.3415	15.572	0.2463	2.9240	0.6797	3.0440
Rule 9	0.3422	6.9000	0.3415	15.533	0.2463	3.1150	0.6792	2.9440
Rule 10	0.3419	6.6800	0.3410	15.171	0.2436	2.6940	0.6588	2.7330
Rule 11	0.3423	6.3390	0.3415	13.138	0.2463	2.5340	0.6794	2.0930
Rule 12	0.3466	7.7110	0.3586	16.173	0.2600	2.8340	0.6977	2.7740
Rule 13	0.3375	7.3310	0.3308	15.853	0.2352	2.7640	0.6357	2.7240
Rule 14	0.3422	6.6200	0.3444	17.094	0.2503	2.7740	0.6727	2.7640
Rule 15	**0.9330**	**3.9150**	**0.9126**	**10.535**	**0.8971**	**1.7330**	**0.8272**	**2.4840**
Rule 16	0.3417	6.6800	0.3460	16.464	0.2508	2.9540	0.6773	2.8740
Rule 17	0.3423	7.5310	0.3416	15.412	0.2463	5.0980	0.6795	2.7940
Rule 18	0.3418	7.4610	0.3414	17.766	0.2463	3.2750	0.6786	2.7840
Rule 19	0.3422	6.7090	0.3415	15.322	0.2461	2.7040	0.6709	2.8640
Rule 20	0.3423	6.2790	0.3415	15.432	0.2463	5.3180	0.6794	2.8440
Best packet	0.8413	69.450	0.822	188.46	0.809	22.893	0.745	28.000

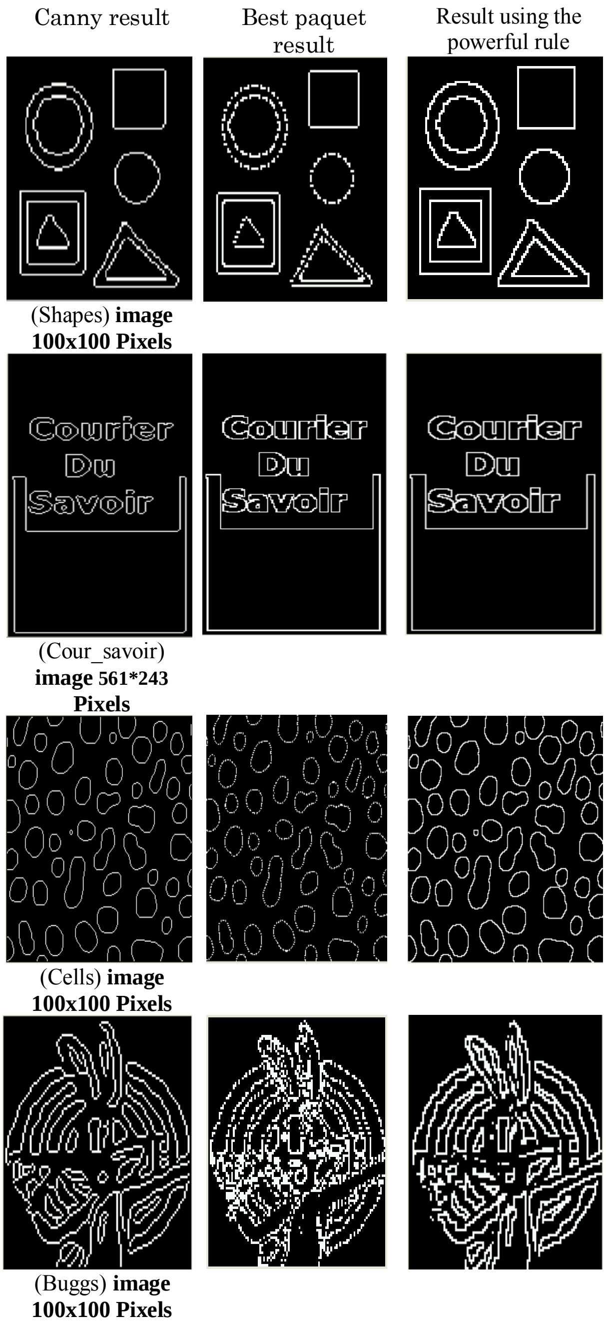

Figure 8: Compare edge detection of images "shapes", "cour_savoir", "cells" and "Buggs"

4 CONCLUSION

In this paper, our proposed model of CA applied in edge detection provides insights on how evolutionary processes can be used to discover local patterns that give rise to optimal edge detection of a given binary image. Indeed, one of such local structural properties were identified via the GA allowed us to analyze the evolutionary emergence of sophisticated computation.

In this paper, we have demonstrated that the edge detection can be interpreted like an evolutionary phenomenon of a set of CA, controlled by a best packets or a single powerful rule of CA applied on a category of image. Indeed, the image can be modelled by a CA which we can implement easily.

The EvCA-ED shows the degree of specialization aspect of CA of edge detection. Indeed, the robustness of the powerful rule number 15 shows that each rule has its fitness value. Thus, we can say that for a given global computation task, the GA evolve a best packet of rules which each one has its robustness value.

The emergence phenomenon is clearly appeared in the fact that one rule is able to detect edges in a given class of image this result illustrates that in a given task each rule has a degree of adaptation.

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