Evolutionary Cellular Automata Based-Approach for Convex Hull Detection

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Abstract— Predicting the behavior of complex systems before their spreading, will be of fundamental importance in the near future. In this context, this paper present the use of an evolutionary process to seek a specialized powerful packet of Cellular Automata among a set of best transitions rules for extracting convex hull in a given black-white image of a polygonal and curved edge. This best set of local rules determines the future state of cellular automata in an asynchronous way. The Genetic Algorithm is applied to search the best cellular automata rules that can realize better the convex hull detection.

Keywords— Genetic algorithm, Evolutionary Cellular automata, Convex hull detection.

I. Introduction

THE emergence phenomenon in complex systems is one of the key concepts that begins to be one of the solutions for solving difficult problems. We can understand the emergence of the property is a direct result of the interactions complexity into the system [1]. The actions of simple components with local information and communication give rise to coordinated global information processing. The convex hull of a set of points is a tool widely used in computer graphics and modeling [2]. The problem is to find the smallest polygon or curvature including all initial points.

The study of evolving Cellular Automata (CA) framework using evolutionary algorithms is a good example to show how evolution can create systems in which emergent computation takes place [3]. We are using Genetic Algorithms (GAs) as an optimization formalism in the search space CAs rules to perform computations that require global coordination. The convex hull of a set of points is a tool widely used in computer graphics and modeling. The problem is to find the smallest polygon or curvature including all initial points.

In this paper, we are interested into CA [4] and the convex hull detection. Among a variety of researchers having investigated the proprieties of CA, we can't miss to cite the works of John von Neumann [5], Stephen Wolfram [6], and John Conway [7]. CA are discrete dynamical systems, which are widely applied in modelling systems in areas such as pattern recognition and image processing [8], [9].

A cellular automaton consists of a regular grid of cells that can each cell take at a given time a state of a finite set. Time is also discrete and the state of a cell at time t + 1 is based on the state at time t of a finite number of cells called its neighborhood. With each unit of time, the same rules are applied simultaneously to all cells of the grid, producing a new generation of cells entirely dependent on the previous generation.

CA can be interpreted like a set of rules which through an Evolutionary CA (EvCA) [10], we can find sub-set or several appropriate rules for a definite problem. The idea of using one packet of rules in convex hull detection is in the merit of Rosin [11]. Moreover, Rosin studied these best rules in details and showed the interest of each one.

In this paper, we use a CAs to find convex hull in images of a polygonal or curved edge and we are using the GA to improve and generating the results to find a single powerful packet of rules for extracting efficiency convex hull 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. After this introduction, Section 2 presents the EvCA for convex hull detection (EvCA-CHD) approach. Experimental results are reported in Section 3. Conclusions are drawn in the last section.

II. The EvCA For Convex Hull Detection

The proposed method of EvCA-CHD takes advantage of the calculating faculties of the CA, to transform the initial configurations defined by a binary image lattice as input discrete data in order to find its convex hull. In the CAs-CHD method, we seek the best packet of transition rules for convex hull detection of a black-white image. The CA unit is represented by a rectangle of 9 cells. Indeed, the problem is to find the best CAs for convex hull detection among 251 possible rules. In this broad area of research that we analyze, we must work with the inverse problem where we seek the optimal rules that gives the best detection of convex hulls in different formats outline objects in the image. In order to explore all configurations in the space research, we grouped the rules in packets [12]. CA can be interpreted like a set of rules which through an EvCA, we can find one or several appropriate rules for a definite problem of polygonal or curved convex hull.

The idea of using a set of rules in convex hull detection is reported in the work of Rosin [11]. It can be used in generally edge of convex hull detection. Moreover, Rosin studied the bests rules in details and shows the interest of each one. The result of its study showed that a set of best rules give a best convex hull in a binary image.

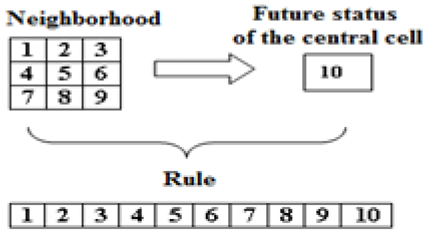

Fig. 1: CA rule notation and the chromosome representation the CA rule

In this paper, we inspirit of this fact to seek a best and powerful packet of rules for extracting efficiency convex hull in polygonal and curved edge in a given black-white image class. We represent the transition rule of a CA by the concatenation of the cells states of the current cell neighborhood to update. Then, we add the future cell state after updating. This rule is transformed as a linear chromosome (see Figure. 1) [12].

The rule is applied when its part neighborhood 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 neighborhood 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

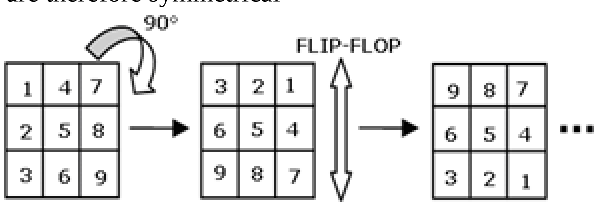

Fig. 2: Symmetrical rules using the rotational operators of rotation to 0°, 90°, 180° and 270°

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 add the following constraint, every rule of the packet must be different from the other.

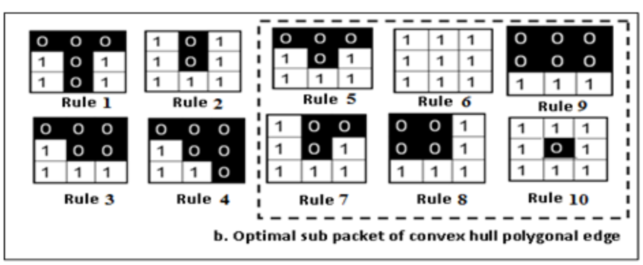

Fig. 3: A best packet of CA rules with the future state central cell of each transition given by value 1

The execution of a simple packet of CA local rules evolved using evolutionary process produces an emergent phenomenon. In this paper, the GA is applied to search the desirable CA rules that can realize better the convex hull detection. Each individual of the population is represented by a chromosome which is a transition vector.

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 patch's with different transition). In EvCA-CHD approach, We use a GA to generate to finding this best and optimal packet of rules for anyone that complex configuration convex hull found in the input image. The following code describes the GA to determine the best packet of transition rules that able to achieve the convex hull detection of binary images.

Algorithm

1. The input data: Input black-white image.
2. Initialization of the GA: Construction at random of rule packets extracted from the CAs training packet (see Fig. 3).
   (a) Convex hull detection method: For each CA, the process: First, searches; among the current packets; the similar rule according to its neighborhood. Second, modifies the central pixel according to the defined transition.
   (b) Evaluation of the convex hull detection result: We evaluate the error of miss-classed pixels between the convex hull detection result and the ideal one considered.
3. Reproduction: Generate a new population by applying selection, crossover and mutation. We use the convex hull detection described above in the evaluation process.
4. The process iterates until the error $\leq$ a given threshold or a maximum of iterations.
5. The result: optimal packet of rules.

To explore a vast set of configurations, the chromosome representation can be presented by two types of structure from the input image: the horizontal and the vertical. We use the horizontal one.

The crossover exchanges, with given probability a genetic material between two parent chromosomes corresponding to two CA transition rules for producing two offspring. The mutation is a random change of gene in a given CA transition rule (parent). The selection process based on the convex hull detection assessment in EvCA represents an interdisciplinary process. Let Err=nbr of pixels where:

$$\text{ImageCHD} \neq \text{ImageIdealCHD} \quad (1)$$

Which Err and nbr are the abbreviation of error and number respectively.

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

$$F=1-(err/L*H) \quad (2)$$

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

III. Experimental Results

These following experiments are performed by using MATLAB on a Intel Core Duo, CPU 2.00GHz with 2.00 GHz. We present both synthetic and real results (see Figures. 4, 5, 6 and 7) of the EvCA-CHD compared to ideal convex hull detector using bwconvexhull Matlab function [2].

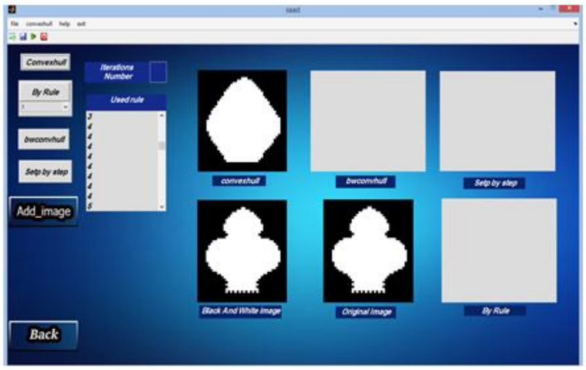

Fig. 4: The Cellular automata for convex hull detection of black white images

The proposed method using the best packet extracts better the convex hull in all type of edge in a binary image. We have distinguished two sub rules of the best packets, the first use only four rules witches are able to give better results of convex hull for polygonal edge and the second present better extracting the convex hull for curved edge of a class of binary images.

Fig. 5: Convex hull detection of concave image (98x99) . (a) input image, (b) result of the execution rule 5, (c) result of the execution rule 8, (d) result using a best packet of CA with 8 iterations and 5.4966 sec

In the figure 5, the input image represent the concave form. It can be seen that different polygonal edge in the image are reconstructed the polygonal convex hull by the execution of rules number 5 and 4 of the best packet CAs result.

In the following figure (see Figs. 6), the input images presents the different form of polygonal edges of a binary images class ie. the gray level images are translated on black white images.

Its shows three form of polygonal edges and it can be seen that different convex hull detection of polygonal edges are better extracted by using the sub optimal packet of CAs result.

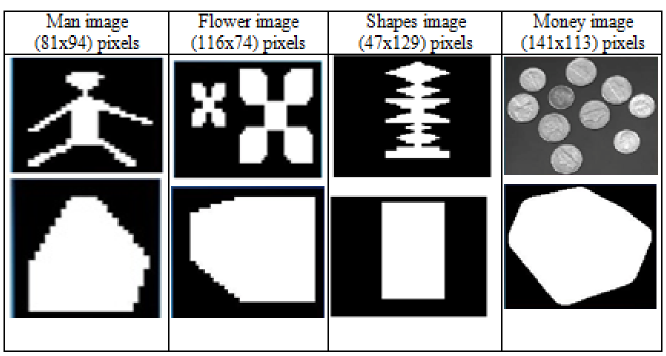

Fig. 6: Convex hull detection in the polygonal edge of input binary images, using the CAs optimal sub packet

The same result is presented in an convex hull detection of curved edge (see Fig. 7). In this figure, we use a synthetic image containing different geometric shapes. It can be seen that different convex hull in curved edges are good extracted by the best packet of CAs result.

Concerning the complexity, in spite of the implementation has made without the specialiczed hardware that are available [13].

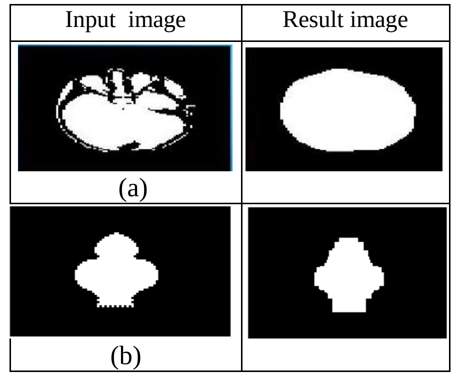

Fig. 7: Convex hull detection in the curved edge of input binary images, using the CAs optimal packet. (a) Medical image (128 x 128) pixels and (b) Curved image (96 x 94) pixels

TABLE I: EVALUATION VALUES OF THE EXPERIMENTS REPORTED IN FIGURES. 6 AND 7,
ITERAT_NUMB: ITERATION NUMBER OF RULES EXECUTION

Results using	CAs sub packet				CAs optimal packet	
Input image	Man	Flower	Shapes	Money	**Medical**	**Curved**
Temps (sec)	156.85	282.40	290.13	800.26	797.19	284,12
Iterat_Numb	7	12	6 20			24

The emergence phenomenon is clearly appeared in the fact that a smallest packet of 10 rules is able to detect convex hull in a given class of image. This result illustrates that in a given task each rule has a degree of adaptation in polygonal or curved edges for convex hull detection in a black-white image. For each image.

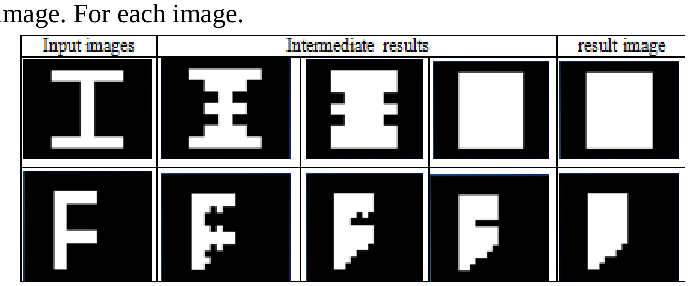

Fig. 8: Intermediate convex hull detection of images contained polygonal edge

The complexity of configuration found in the image allows to determine the number of iteration rules. thus the sequence and the execution order of the rules is varied from one image to another (see Fig.8)

TABLE II: INTERMEDIATE RESULTS OF SEQUENCE EXECUTED RULES. (A), (B) AND (C) INPUT IMAGES, RI : THE NUMBER OF RULE IN PACKET I={1..10}

Number of Iterations		1	2	3	4
The sequence of executed rules	'I' image	R8 R8 R8 R8 R9 R9	R4R4R4R4R7 R7R7R7R9R9	R5 R5 R5 R5	/
	'F' image	R8R8R8R 9R9R9R9	R3R3R3R3R4 R4R5R5R7R7 R7 R8 R8 R9	R3R4R5	R1R2R2R10

IV. CONCLUSION

In this paper, we propose a model of CA applied in convex hull detection using an evolutionary approach based on the concept of emergence for the detection of the convex hull of polygonal and curved contours in binary images. Specifically, we used the CAs as a powerful modeling tool for images. After considering the image as a CA, the main idea is to find the best local transition rules that detect points of the convex hull in a polygonal or curved edge in black-white image.

The originality of the proposed approach is based on a classification and specialization of rules best pack according to the type of edge in the black-white image for the smallest convex hull detection. The result is found in the specification of rules. Indeed, a single packet EvCAs-CHD is capable of detecting the smallest convex hull.

The emergence phenomenon is clearly appeared in the fact that one packet is able to detect convex hull in a class of given image. This result illustrates that in a given task each rule has degree of adaptation in polygonal or curved edge.

The most important advantage of EvCA-CHD is that it gives an acceptable package for synthetic images and details very low. The present numerical results of the proposed approach are promising and encourage us to extend our approach to images of low homogeneity, with texture and noise

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