STUDIA UNIV. BABEŞ–BOLYAI, INFORMATICA, Volume **LXII**, Number 1, 2017
DOI: 10.24193/subbi.2017.1.01

THE USE OF SIMPLE CELLULAR AUTOMATA IN IMAGE PROCESSING

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Abstract. Cellular Automata have been considered for a series of applications among which several image processing tasks. The goal of this paper is to investigate such existing methods, supporting the broader goal of identifying Cellular Automata rules able to automatically segment images. With the same broader goal in mind as future work, a detailed description of evaluation metrics used for image segmentation is also given in this paper.

1. Introduction

The one-dimensional binary-state Cellular Automata (CA) capable of performing computational tasks has been extensively studied in the literature [13, 34, 19, 23, 4]. Usually, a one-dimensional lattice of N two-state cells is used for representing the CA. The state of each cell changes according to a function depending on the current states in the neighbourhood. The neighbourhood of a cell is given by the cell itself and its r neighbours on both sides of the cell, where r represents the radius of the CA. The initial configuration of cell states (0s and 1s) for the lattice evolves in discrete time steps updating cells simultaneously according to the CA rule.

CAs have been considered for a series of applications like computer processors, cryptography, physical reality modelling, image processing and many others. Three-dimensional CAs have mainly been used within the framework of chemical systems for tasks like percolation description, dissociation of organic acid in solutions, bond interactions, simulation of diffusion controlled reaction kinetics, dissolution and many others [16].

In image processing for example, two-dimensional CAs are usually involved. The pixels of the image represent cells of the CA and they update their state

Received by the editors: November 5, 2016.

2010 *Mathematics Subject Classification.* 68Q80, 94A08.

1998 *CR Categories and Descriptors.* A.1 [**General Literature**]: INTRODUCTORY AND SURVEY; F.1.1 [**Theory of Computation**]: COMPUTATION BY ABSTRACT DEVICES – *Models of computation.*

Key words and phrases. cellular automata, image processing.

based on the states of the neighbouring cells (pixels). Multiple states of CA cells allow the processing of greyscale images or colour images. Identifying the rules that apply to cells in order to answer a certain request in image processing is nevertheless a nontrivial task.

Cellular Automata have been used for various image processing tasks among which: geometric transformations, noise filtering, feature detection, edge detection. Image segmentation was also approached by the means of Cellular Automata, but there are only few attempts in the literature.

Incorporating cellular automata into image segmentation brings several advantages:

- ease of implementation;
- parallel implementation;
- the number of classes does not need to be specified before segmentation is performed (both two-label and multi-label image segmentations are possible);
- extensibility (to various features extracted from images): currently, pixel intensity values have been used as state transition rules, but other image features such as texture or edges could be easily incorporated into the update mechanism;
- possibility to work with images of any dimension (the computational complexity of the segmentation process is not directly influenced by the image size or the number of image features).

The simplest use of CA for image processing is given by the application of specific rules for different tasks, for example totalistic rule [6, 8, 25], majority rule [38] or linear rule [20, 21].

Seed-based CAs represent another category of CA applied for image processing. One of the most popular approaches found in the literature in this sense is the GrowCut algorithm [37]. In [14] the authors show that the seeded GrowCut proposed by Vezhnevets[37] is essentially no different from the Ford-Bellman algorithm that computes shortest paths from a cell to all the other cells in the CA. An unsupervised version of GrowCut is proposed in [11]. Another version of GrowCut, that improves its ability to correctly detect the edges, is proposed in [1]. Other variants of GrowCut are proposed in [17, 12]. In [26] the authors propose an enhancement of GrowCut with automatic seed selection. In [2] the image noise is reduced (and therefore the GrowCut algorithm improved) by adding an anisotropic diffusion filter.

Another class of CAs applied to image processing involves methods for finding the optimal rule for a given task. A deterministic method based on a Hill-Climbing approach is proposed in [27]. There are also many heuristic methods based on Genetic Algorithms [35, 24, 32, 33, 15], Particle Swarm Optimization [9], Genetic Programming [31, 30].

A CA based Level Set approach was proposed in [3], and continuous CAs have been applied for image processing tasks in [29, 28].

Due to the fact that beyond the goal of this paper, our final goal is to identify CA rules that are able to successfully segment images, we intend to study the application of CA rules for image processing tasks which are close to image segmentation, like edge detection. On this purpose, the aim of this paper is to describe in detail the first class of CAs applied for image processing, namely CAs that are using specific given rules, the class of so-called 'Simple CA'. From the same perspective of a final goal, a detailed description of the most popular performance measures used for evaluating the segmentation results is also given in this paper.

2. Simple Cellular Automata for Image Processing

2.1. **Totalistic rule.** A CA very similar to the Conway's Game of Life [10] is used in [6] in order to detect the edges of an object in an image. The authors of [6] apply this method for ultrasound kidney images. The greyscale images are binarized prior to the application of the CA based method. A black cell is called 'alive' and will have the value 1, while a white cell is called 'dead' and will have the value 0. The Moore neighbourhood gives the neighbours of a cell; therefore a cell has 9 neighbours, including the cell itself. In order to apply the rule, one has to compute first the sum of the neighbours values (including the cell itself) of each cell. The rule specifies those cells with 3 alive neighbours or less will die of loneliness, while cells with 7 neighbors or more will die of overpopulation. The cells with 5 neighbours will revive and the cells with 4 or 6 will keep their previous state. After one iteration of rule application, the boundaries are detected.

The same metaphor of the Game of Life can also be found in [8]. The authors work on binarized greyscale images, use the Moore neighbourhood and have the same cell state meaning similar to [6]. They apply different 'survival' rules and find, experimentally, that the best rule is given by the survival or the revival of the cells having 3, 4, 5, 6 and 7 alive neighbours. The results are presented for 3 real world images, the performance of the proposed method being only visually analyzed.

2.2. **Linear rule.** Due to the fact that the rule search space is significantly large (2^{2^9} possible rules for Moore neighbourhood) and an exhaustive search is therefore out of question, there are researchers that focused their investigation on linear rules. The linear rules are those that can be realized by EX-OR operation only, the search space being thus reduced to 512 rules. A detailed presentation of theory and application of two-dimensional, null boundary, nine-neighbourhood cellular automata linear rules in given in [5]. There are 9 fundamental rules (1, 2, 4, 8, 16, 32, 64, 128, 256 - powers of 2), which are arranged in a certain order inside a 3x3 grid which resembles a Moore neighbourhood. Each of this 9 fundamental rules specifies which neighbour is considered when changing the state of the current cell, based on EX-OR operations. Adding these powers of 2 gives us other rule numbers that again represent the neighbours that contribute to the state of the current cell at the next iteration.

In [5] the 9 fundamental linear rules are applied for solving several image transformation tasks like translation, generation of multiples copies, zooming, thickening and thinning of symmetric images.

The authors of [25] apply all 512 linear rules to edge detection in one image only and identify three groups of rules: no edge detection rules, strong edge detection rules and weak edge detection rules. However, there is no strong evidence of the significance of these groups of rules since only one image has been used for testing purposes. Moreover, it is not clear how do the authors apply the linear rules for greyscale images, since supporting theory of linear rules deals only with binary images.

In [20], the authors show that there are 4 rules among the 512 linear rules described above that obtain best results for edge detection. Only two images are used in order to show the performance of these 4 rules, and one more image is used in order to provide comparisons with other existing methods for edge detection. However, the results are not conclusive since only 3 images are being used and only visual evidence of the rules performance is given. Moreover, the images are first binarized because these rules cannot be directly applied to greyscale images.

The linear rules described above are extended to a 25 neighbourhood (extended Moore neighbourhood) in [22]. Among all resulted linear rules, the authors find some optimal rules that can be applied to edge detection. These optimal rules are applied to 2 images (a priori binarized) and the results are only visually compared to the results obtained by other methods of edge detection. Moreover, no details of the method used for identifying the optimal rules are given in this paper.

3. Evaluation measures

In image segmentation, it is very important to establish how we define similar regions or segmentations. Segmented regions and their boundaries can be compact, discontinuous, smooth, etc. One of the most popular evaluation

		real segments	
		interest segment	background segment
computed	interest segment	TP	FN
segments	background segment	FN	TN

Table 1. Confusion Matrix

metrics (but not very reliable) is the **Dice coefficient** [7]. Dice computes the overlap between regions, quantifying the similarity of two segmentations.

Given two segmentations:

- reference segmentation (gold standard) S_r
- machine segmentation S_m

Each image point (pixel) can be classified as:

- true positive (TP): $S_r(x, y)$ is 1 $\wedge$ $S_m(x, y)$ is 1
- false positive (FP): $S_r(x, y)$ is 0 $\wedge$ $S_m(x, y)$ is 1
- true negative (TN): $S_r(x, y)$ is 0 $\wedge$ $S_m(x, y)$ is 0
- false negative (FN): $S_r(x, y)$ is 1 $\wedge$ $S_m(x, y)$ is 0

The Dice similarity coefficient is computed as the ratio between the number of pixels belonging to the intersection (of two possible segmentations) and the average of their sizes:

$$\text{Coeff}_{\text{Dice}}(S_m, S_r) = \frac{2\,|S_r \cap S_m|}{|S_r| + |S_m|} = \frac{2TP}{2TP + FP + FN} \tag{1}$$

For increased reliability, one has to also look at how the values of each pixel in the segmented image compare against some gold standard or ground truth.[1] The four basic cardinalities of the so–called *confusion matrix*, namely the true positives (TP), the false positives (FP), the true negatives (TN), and the false negatives (FN) are defined as follows:

Let $I(x, y) : R^2 \to R$ be a two-dimensional image and $S(I(x, y)) : R^2 \to \Omega$, $\Omega = \{0, 1, 2, \ldots, k-1\}$, be a k-ry decision segmentation of the image $I(x, y)$.

Each of these segmentations are composed by k segments, or regions, or classes (e.g. if $k = 2$, then the two segments are represented by the class of interest and the background; if $k = 3$, then two classes of interest and the background will represent possible segments). In the case of $k = 2$ segments, the confusion matrix can be represented as shown in Table 1.

[1] In order to call the reference segmentation *ground truth* we have to be certain that it is so. Manual reference segmentations drawn by experts normally approximate ground truth, in which case it can be used as gold standard, but not as the ground truth itself.

An alternative evaluation measure can be expressed as a percentage and its values range between 0 (no overlap) and 1 (perfect agreement) using the above values.

$$\mathrm{F}_\beta = \frac{(\beta^2 + 1) * \text{Precision} * \text{Recall}}{\beta^2 * \text{Precision} + \text{Recall}} \tag{2}$$

It is also called the *overlap index* and makes it possible to quantify reproducibility. An equivalent of the Dice coefficient is, therefore, the F_β measure with $\beta = 1$.

Precision is another measure that can be used to evaluate the quality of segmentation.

$$\frac{TP}{TP + FP} \tag{3}$$

Recall is computed as the ratio between the number of positive pixels in the reference image and the number of pixels identified as positive in the segmented image.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

In conjunction with Precision, Recall is used in order to compute the F– measure.

Specificity is computed as the ration between the number of negative pixels in the reference image and the number of pixels identified as negative in the segmented image.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

Recall and Specificity depend on the size of segments.

There are two other measures that are related to these metrics, namely **Fallout** and the **false negative rate** (FNR). They are defined by:

$$\text{Fallout} = \frac{FP}{FP + TN} = 1 - \text{Specificity} \tag{6}$$

$$\text{FNR} = \frac{FN}{FN + TP} = 1 - \text{Recall} \tag{7}$$

Since the last two measures are equivalent to Specificity and Recall, only one pair ((Recall, Specificity) or (Fallout, False Negative rate)) should be used to evaluate the performance of segmentation.

Recall is also called Sensitivity or True Positive Rate. Specificity is also called True Negative Rate (TNR). Fallout is also called the false positive rate (FPR).

Another frequently used evaluation measure is the **Global Consistency Error** (GCE) [18]. An error-based measure is the complement to similarity measures, in that two segmentations are identical if an error–based measure is 0.

This measure is computed as an average over the error of pixels belonging to two segmentations. It compares partitions of the same image and it is tolerant to one partition refining the other (e.g. by splitting or merging regions). For an image I of n pixels ($n = |I|$) and a segmented region S, we denote the set of all neighbour pixels to pixel p which belong to the same segmentation region S by $R(S, p)$. For two segmentations, one computed S_c and one reference segmentation S_r, the asymmetric Local Refinement Error in [18] at pixel p, $\mathrm{LRE}(S_c, S_r, p)$ is defined as

$$\mathrm{LRE}(S_c, S_r, p) = \frac{|R(S_c, p) - R(S_r, p)|}{|R(S_c, p)|} \tag{8}$$

The GCE between segmentations can be defined as a mean over the error of all points (pixels):

$$\mathrm{GCE}(S_1, S_2) = \frac{1}{|I|} \min \left\{ \sum_{i=1}^{|I|} LRE(S_1, S_2, p), \sum_{i=1}^{|I|} LRE(S_2, S_1, p) \right\} \tag{9}$$

By using the cardinalities previously introduced, GCE can be expressed as follows:

$$GCE(S_c, S_r) = \frac{1}{|I|} \min \left\{ \frac{FN(FN + 2TP)}{TP + FN} + \frac{FP(FP + 2TN)}{TN + FP}, \frac{FP(FP + 2TP)}{TP + FP} + \frac{FN(FN + 2TN)}{TN + FN} \right\} \tag{10}$$

This measure is able to quantify the consistency between image segmentations of differing granularities. It has the advantage of being tolerant to (label) refinement. It makes most sense to use this measure when the two segmentations being compared have comparable numbers of segments [36].

4. Conclusions

This paper presents in detail a class of CAs applied for image processing tasks that are related to image segmentation, as well as a detailed description of the most popular performance measures used for evaluating the segmentation results. As further work, an exhaustive description of CA based methods for image processing will be performed, followed by the proposal of competitive CA based methods for the task of image segmentation.

Acknowledgment

This work was supported by a grant of the Romanian National Authority for Scientific Research and Innovation, CNCS - UEFISCDI, project number PN-II-RU-TE-2014-4-1130.

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