Cellular Automata in Image Processing

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Abstract

Cellular automata can be successfully applied in image processing. In this paper we discuss the application of two-dimensional cellular automata to the problems of noise removal and border detection in digital images. The proposed methods are compared with some classical or recent methods. A very important feature of the proposed methods is their intrinsic parallelism, since they are implemented on well-known parallel-working machines, as cellular automata are.

KEYWORDS: cellular automaton, image processing, Gaussian filter, SUSAN method.
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1 Introduction

There is a various kind of applications in many scientific fields involving image processing.

For instance, *image enhancement* is the processing of images to improve their appearance to human viewers or to enhance the performance of other image processing system. In most applications involving images or image processing one of the most common problems is *the presence of noise*.

The objective of image enhancement (for example improving image quality, intelligibility, visual appearance) is dependent of application context. An image enhancement algorithm that performs well for one class of images may not perform as well for other classes.

Classically, image enhancement is formulated in either spatial or transform (basically *the Fourier transform*) domains. One of the most used spatial domain techniques is that of the so-called *convolution masks*. Such an example may be *the Gaussian filter* ([2]). In transform domains, perhaps the most famous technique is *the Wiener filter* ([2]).

The detection of edges is another essential task in image processing. In particular, in the processing of biological or medical images, the edges study became a very important component. There are many edge detection methodologies in the form of diverse algorithms ([1], [4], [6]). Most of them are based on the localization of regions where the pixel intensity changes. It is important that the border detection methodology to be independent of the image characteristics.

These procedures are generally based on calculations of directional derivatives that result in computationally intensive tasks or previous knowledge of the image nature. However, these last requirements limit the applicability of the process.

In this paper we propose an alternative to the above procedures for image processing by using cellular automata.

2 Cellular Automata

Cellular automata were introduced by Ulam and von Neumann ([3]). They have been progressively used to model a great variety of dynamical systems in different application domains ([5], [7]).

A cellular automaton is basically a computer algorithm that is discrete in space and time and operates on a lattice of sites (in our case, pixels).

A (*bi-dimensional, deterministic*) *cellular automaton* (CA) is a triple $\mathcal{A} = (S, N, \delta)$, where S is a nonempty set, called the *state set*, $N \subseteq \mathbb{Z}^2$ is the *neighborhood*, and $\delta : S^N \to S$ is the *local transition function (rule)*; the argument of δ indicates the states of the neighborhood cells at a given time, while its value the central cell state at the next time.

In order to define a neighborhood in a standard way we can use some norms h on $\mathbb{R}^2$ such that $N = B_h(0, r) \cap \mathbb{Z}^2$ (where $B_h(0, r)$ is the ball of radius $r \geq 1$). The most common neighborhoods are:

- von Neumann neighborhood using the norm

$$\mathbb{R}^2 \ni x \mapsto h(x) := |x|_1 = |x_1| + |x_2| \in \mathbb{R}_+, \ x = (x_1, x_2).$$

- Moore neighborhood attached to the norm

$$\mathbb{R}^2 \ni x \mapsto h(x) := |x|_\infty = \max\{|x_1|, |x_2|\} \in \mathbb{R}_+, \ x = (x_1, x_2).$$

A cellular automaton $\mathcal{A} = (S, N, \delta)$ is said to be *symmetric* if the value of the local rule is constant on symmetric inputs, i.e. $\delta(s_1, s_2, \ldots, s_{|N|}) = \delta(s_{\sigma(1)}, s_{\sigma(2)}, \ldots, s_{\sigma(|N|)})$, for every $s_1, s_2, \ldots, s_{|N|} \in S$ and $\sigma \in S_{|N|}$ (the permutation group of $|N|$ degree).

3 The CA Model for Filtering Digital Images

A digital image is a bi-dimensional array of $n \times n$ pixels. Each pixel can be characterized by the triplet (i, j, k) where (i, j) represents its position in the array and k the associated color. The image may be then considered as a particular configuration state of a cellular automaton that has as cellular space the $n \times n$ array defined by the image. Each site in the array corresponds to a pixel.

We propose a dynamical rule which hopefully will solve our problem. This rule must be such that given a noisy image as initial configuration it produces a trajectory whose final configuration corresponds to a noise-reduced version of the image. It is desirable that the dynamics be applicable to any kind of images without distinction (monochromatic, gray level or color).

The model is based on a bi-dimensional symmetric non-deterministic CA of the form $\mathcal{A} = (S, N, \delta)$ with $S = \{\#, 0, 1, \ldots, k-1\}$. A pixel color is represented by a state in $\{0, 1, \ldots, k-1\}$ ($k = 2$ for a monochromatic image; $k = 16$ for an image with 16 colors and/or gray levels; $k = 256$ for an image with 256 colors and/or gray levels), $\#$ is the quiescent state associated to the cells outside the grid, N the von Neumann neighborhood, while the local transition function δ is based on a comparison criteria of the central cell state with those of the cells from its neighborhood. Thus $\delta : S^5 \to S$ is defined by

$$\delta((s_i)_{i=1}^5) = \begin{cases} j\ (\neq \#), & \text{if } s_3 \neq \# \text{ and } |\{i \mid s_i = j\}| = \max\limits_{l=0}^{k-1} |\{s_i = l\}|, \\ \#, & \text{if } s_3 = \#. \end{cases}$$

Figure 1: a) Original image; b) Image with noise;
c) Result of the Gaussian filter; d) Result produced by CA

A cell (not being in the quiescent state) changes its state to the state of the majority of cells in the neighborhood. The cells disposed outside the lattice of $n \times n$ pixels are assumed to be in the quiescent state and the rule was defined in order to assure their remaining in the quiescent state. In Figure 1 d) we can see the results obtained by this model. A comparison with the Gaussian filter shows (see Figure 1 c) and d)) that we can obtain a better image enhancement using CA.

A very important feature of the Gaussian filter is a strong dependence of the results with a threshold value. This is not true for the filter based on a cellular automaton.

The experiments show that two-dimensional cellular automata may be used as a noise filter over arbitrary images.

4 The CA Model for Border Detection in Digital Images

In this section we present a cellular model that can be used in the process of edge detection. An edge is a boundary or a contour at which a significant change occurs in some of the physical aspects of the image. These changes manifest themselves in a variety of ways, including changes in intensity, color or texture. The significance of a particular physical change in an image depends in general on the nature of the image. For instance, an intensity change that would be classified as an edge in some applications, might not be considered an edge in other applications. In this sense it is important that the border detection methodology be independent of the characteristics of the image.

As in the previous section we propose a dynamical rule for a cellular automaton whose cellular space is the two-dimensional array defined by the image. This rule must be such that given an image as initial configuration state it is required that the cellular automaton reaches a final configuration where the only active cells correspond to the borders of the image.

The model for border detection of a digital image is based on a bi-dimensional cellular automaton $\mathcal{A} = (S, N, \delta)$ with $S = \{0, 1, \ldots, k-1\}$. The states represent the colors associated to the image pixels, N the von Neumann neighborhood, while the local transition function is $\delta : S^5 \to S$,

$$\delta(s_1, s_2, s, s_3, s_4) = \begin{cases} 0, & \text{if } |s - s_i| < \varepsilon,\ (\forall) i = \overline{1, 4}, \\ s, & \text{otherwise} \end{cases} ,$$

ε being a threshold value which is established depending on the application. The automaton cells which are not included in the image are in the state 0. As in the model presented in the previous section the digital image is a lattice of $n \times n$ pixels, each pixel being characterized by its position in the lattice and the associated color. The transition rule is based on a comparison criteria of the central cell state with those of its neighbors. If the difference between the central cell state and each of the neighborhood cells states is less than a given threshold value ε then the state of the central cell at the next time will be zero, otherwise it will remain unchanged. Thus the rule is independent of the nature of the considered image; it is indifferent if the image is black and white, gray level or color. The proposed transition rule is applied in a synchronous way.

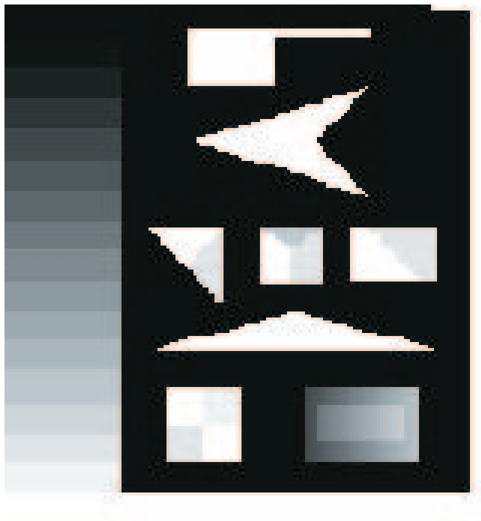

Figure 2: Original image

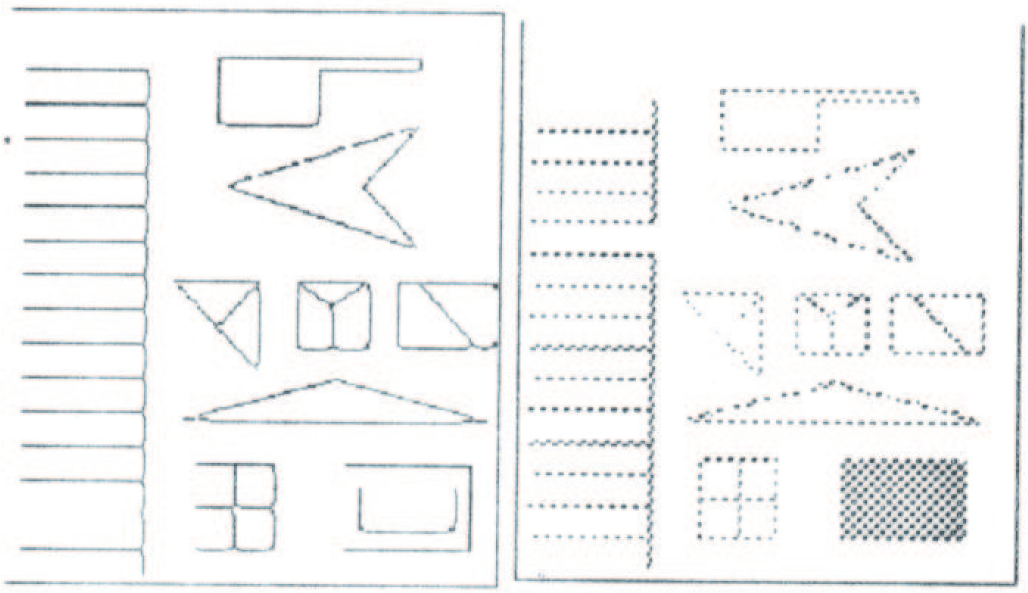

Figure 3: a) Result of SUSAN edge detector; b) Result of CA edge detector

The Figure 3 (a) and b)) shows the outputs of the SUSAN edge detector and the CA border detector for the image of Figure 2. We observe that the border produced by the CA edge detector shows:

- the edge connectivity at junctions;
- no false edge is reported;

- qualitative similarity with those produced by the SUSAN method.

By experimental comparison of different methods for border detection of a digital image we observe that the method based on the cellular model described above leads to a better performance.

In conclusion a two-dimensional cellular automaton with a very simple transition rule may be used as a very efficient border detector in digital images. The border detection method based on a cellular automaton has a general applicability to monochromatic, gray level and color images. The obtained results are very promising, the border produced by the cellular automaton border detector in digital images without noise are very satisfactory. In some cases may be comparable to those produced by the application of other edge detectors. The introduction of a threshold in the dynamical rule of the cellular automaton enhances the possibilities of the proposed method of edge detection and produces results that may be considered satisfactory. A very important feature of the proposed method is its intrinsic parallelism since it is implemented on a cellular automaton where the individual cells update in a synchronous manner and independently of each other. We can conclude that the proposed edge detector method is faster than other typical edge detector algorithms.

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