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Gray Level Image Edge Detection Using a Hybrid Model of Cellular Learning Automata and Stochastic Cellular Automata

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Abstract

The mathematical model that aims at determining points in an image at which the image brightness suddenly changes is called edge detection. This study aims to propose a new hybrid method for edge detection. This method is based on cellular learning automata (CLA) and stochastic cellular automata (SCA). In the first part of the proposed method, statistic features of the input image are hired to have primary edge detection. In the next step CLA and SCA are employed to amplify pixels situated on edge and castrate those pixels which are part of the image background. The simulation results are conducted to prove proposed method performance and these results suggest that the proposed method is more efficient in finding edges and outperforms the existing edge detection algorithms.

Keywords

Cellular Learning Automata, Stochastic Cellular Automata, Edge Detection, Image Processing, Statistic Feature

Subject Areas: **Artificial Intelligence, Image Processing**

1. Introduction

The various applications in image processing, such as medical, military and engineering science, cause to promote techniques in feature extraction of image [1]. Derivation feature of digital image makes it easy to analyse image characteristics. Edge detection of digital image is one of the significant features, which is quite meaningful. Nowadays, numerous methods are considered for edge detection in image processing and machine vision, such as Sobel method [2], gradient operator [3] [4], edge detection with wavelet transform [5]-[8], cellular au-

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tomata (CA), cellular learning automata (CLA) and fuzzy cellular automata (FCA) [9]-[12]. Several well-known methods use first-order derivatives to estimate edge orientation [2] [13]. The main weakness of these methods is remaining the huge numbers of waste pixel in the input image after applying the algorithm, which causes the problem for detection real edges. Chang *et al*. [9] applied cellular automata for edge detection. This method worked based on some standard rule which was defined by authors. The problem of the mentioned method is the type of rules where all of them are constant with different sample images. Therefore, this deficiency makes algorithm dependent on input image. Most of these methods present in the past have a major deficiency; these are parametric for different edges dependent on a particular parameter. This parameter represents accuracy of edges. Although a number of algorithms have been developed for edge detection, it is still a challenging task to extract proper edges with desirable performance.

To have high quality edge detection method, an algorithm with four stages is employed. In the first stage standard deviation is calculated using Moore neighborhood [14]. Those edges which are extracted in this stage contain many waste pixels that should be removed. Then in the second step, an optimum function is employed to amplify the edge pixels and castrate those non edge pixels. The problem of this optimum function is that it keeps the same power for all pixels which makes some pixels blur. This defect will be solved in Stage 3 and Stage 4 where Stochastic Cellular Automata (SCA) and CLA are used, respectively. In fact, SCA are CA whose updating rule is a stochastic one, which means that the new entities' states are chosen according to some probability distributions. It is a discrete-time random dynamical system [15] [16]. The CLA are the systems which have simple component, and behavior of each component is in the base of neighbor's behavior and last experience of it [17] [18].

This paper is divided into five parts. In Section 2, basic concepts of CLA and SCA and their structures are introduced. Section 3 discusses the proposed model and all details of the algorithm. The simulation results and comparison are presented in Section 4. Finally, the conclusion is derived in Section 5.

2. Preliminaries

In this section preliminaries information about learning automata (LA) and SCA will be defined.

2.1. Learning Automata

Narendra *et al*. [19] first introduced learning automata, which have been successfully employed in various applications. A learning automaton can be considered a decision-making unit situated in a stochastic environment that learns the optimal action through frequent interactions with the surrounding environment. An automaton is simply a set of a finite number of actions, where an action is randomly selected based on a specific probability distribution and applied to the environment. A reinforcement signal is sent back to the automaton based on evaluating the impact of the selected action. The automaton learning mechanism employs this feedback to update the existing action probability distributions. Repeating this action increases the probability distribution of better actions, and the most favorable or optimal action is eventually determined. **Figure 1** presents the interaction process of automata and their environment.

Learning automata are represented by a four-tuple $\{\alpha,\beta,p,T\}$, where $\alpha=\{\alpha_1,\alpha_2,\cdots,\alpha_r\}$ is a set of actions, $\beta=\{\beta_1,\beta_2,\cdots,\beta_r\}$ denotes a set of input actions, $p=\{p_1,p_2,\cdots,p_r\}$ is a state probability vector and T is a learning algorithm used to update the state probability vector:

$$p(n+1)=T\left[\alpha(n),\beta(n),p(n)\right]$$

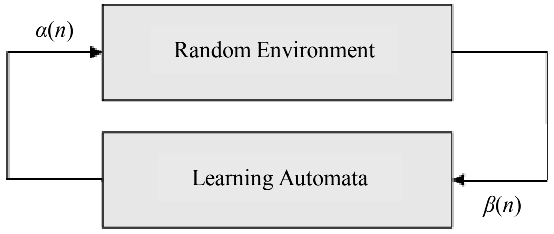


Figure 1. Interactions of learning automata and their environment.

After an automaton receives the reinforcement signal, it updates the state probability vector, applying Equation (1) for favorable response and Equation (2) otherwise.

$$\begin{aligned} &P_i(n+1) = P_i(n) + \alpha\left[1 - P_i(n)\right], \\ &P_j(n+1) = (1-\alpha) P_i(n), \qquad \forall j,\ j \neq i. \end{aligned} \tag{1}$$

$$\begin{aligned} &P_i(n+1) = (1-b) P_i(n), \\ &P_i(n+1) = \frac{b}{r-1} + (1-b) P_j(n), \qquad \forall j,\ j \neq i. \end{aligned} \tag{2}$$

where r, a and b are the number of automaton actions, reward parameter and penalty parameter, respectively. An overview of the varieties of learning automata is presented by Thathachar and Sastry [20].

2.2. Stochastic Cellular Automata

Stochastic cellular automata locally interacting Markov chains [21] are an important extension of cellular automaton. Cellular automata are a discrete-time dynamical system of interacting entities, whose state is discrete. The state of the collection of entities is updated at each discrete time according to some simple homogenous rule. All entities' states are updated in parallel or synchronously. Stochastic Cellular Automata are CA whose updating rule is a stochastic one, which means the new entities' states are chosen according to some probability distributions. It is a discrete-time random dynamical system. From the spatial interaction between the entities, despite the simplicity of the updating rules, complex behaviour may emerge like self-organization. As mathematical object, it may be considered in the framework of stochastic processes as an interacting particle system in discrete-time.

3. Proposed Method

There are few edges in a uniform image, like image of the sea and there are many edges in image including many different objects. From statistical point of view it means standard deviation in image with the low number of edges is low and vice versa. The number of edges in each image can be determined with the help of this feature.

The proposed method is divided in to 3 main steps as follows:

Step 1: At first for each pixel, standard deviation is calculated using Moore neighborhood. This value is placed instead of pixel. This procedure is repeated for all pixels of image.

Step 2: After applying standard deviation, all detected edges have good quality; however the main weakness of this method is disability to remove the waste pixels from the background of image. To solve this problem, an optimum function is defined in Equation (3) to makes edges pixel stronger and background pixels weaker.

$$F(i,j) = \sqrt{I(i,j)^{\beta}} \qquad \beta > 2 \tag{3}$$

where $I(i,j)$ denotes the pixel in column i and row j.

Normally, the value of β is constant for all pixels in an image. This constant value causes all edges pixel going to be stronger with same impact and also all no edges pixels become weaker with same impact. In many cases this trend can lead the algorithm to the excellent result.

Step 3: To improve the optimum function (Equation (3)) performance, value of β is adjusted by using SCA. In this method, SCA has investigated each pixel conditions. By considering to probability of belonging each pixel to edge or not and also considering to following rules, SCA has determined appropriate value to β.

Before defining rules, we assume that variable *Similarity_Count* save numbers of pixel in Moore neighborhood of each pixel which have same gray level with the central pixel. Mentioned rules are represented in **Table 1**. Third column shows the probability of belonging a pixel to edge.

Table 1. SCA rules.

	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6	Rule 7	Rule 8	Rule 9
Similarity_Count	0	1	2	3	4	5	6	7	8
Edge_Probability (%)	0	85	95	85	80	55	40	20	5

To determine the value of β for each pixel Equation (4) is used.

$$\beta = 2 + \text{Edge}_{\text{Probability}} \times \beta_{\text{old}} \tag{4}$$

where β_{old} is equal to 2.

Step 4: In the last step of the proposed method our aim is to reinforce the edges pixel and remove the pixels which are belong to background. To obtain the mentioned goal a learning automaton with following rules is employed.

1) Dedicate a learning automaton with two actions (edge, non edge) to each pixel.

2) Each action initial probability is measured using Equation (5).

$$\text{Edge} = \frac{\dfrac{\text{Pixel}(i,j)}{\sum_{i=1}^{\text{Column}}\sum_{j=1}^{\text{Row}}\text{Pixel}(i,j)}}{\text{Maximum}\left(\dfrac{\text{Pixel}(i,j)\ \forall i=1,\cdots,\text{Column}\ \text{ and }\ j=1,\cdots,\text{Row}}{\sum_{i=1}^{\text{Column}}\sum_{j=1}^{\text{Row}}\text{Pixel}(i,j)}\right)} \tag{5}$$

$$\text{Non Edge} = 1 - \text{Edge}$$

3) Action edge in each automaton will be awarded and action non edge will be punished if two rules were satisfied simultaneously:

a) Numbers of automaton in the Moore neighborhood of mentioned automaton which choose action edge are between 2 and 4.

b) Mentioned automaton chooses action edge.

In rest of states action edge will be punished and action non edge will be awarded.

4) The proposed method will be terminated if the entropy of two sequential stages is lower than the ε.

5) Now, each automaton has its final action and if the action is edge the corresponding pixel is the part of edge and vice versa.

4. Experimental Results

In the current section, various experiments have been tested to identify and validate the proposed method's performance.

4.1. Experimental Setup

A MATLAB 7 platform on a PC with an Intel Core i7, 2.3 GHz CPU, 8 GB memory and 500 GB hard disk with a Windows 7 Professional operating system is utilized to perform the introduced method. In this research all images are gray level with dimensions 256×256 and 512×512.

4.2. Testing Output of the Proposed Method

In the first experiment, the proposed method is applied on three images with dimension 256×256. Lena, Peppers and House images are chosen as the test images and are shown in **Figure 2(a)**. Standard deviation of each image is calculated based on Step 2 and output images are depicted in **Figure 2(b)**. As can be seen, waste pixels in background are still remained in the images. In the next step Equation (3) has applied in **Figure 3(b)** with the respect to Step 3. This step's results are presented in **Figure 2(c)** and finally in Step 4, learning automata is employed to enhance the image's edges and results are depicted in **Figure 2(d)**.

4.3. Effect of β Coefficient

In the second experiment, the effect of parameter β on Equation (3) is measured. To do so, House image is chosen as the text image where is shown in **Figure 3(a)**. **Figure 3(b)** is the result when standard deviation is applied in **Figure 3(a)**. Then after value of β manually is set to 3 and then Step 4 is run by employing **Figure 3(b)** as the input image. The output image is presented in **Figure 3(c)**. In second part of this experiment proposed algorithm is applied in **Figure 3(b)** and the result is depicted in **Figure 3(d)**. This test clearly shows the advantage of determining value of β base on SCA.

4.4. Computational Time

In this experiment computational time of the four well-known edge detection methods are represented in Table 1. The results in Table 1 show the Sobel and Robet computational time are better than our proposed SCA-CLA method while SCA-CLA beat CNN-PSO in case of computational time. All the time in Table 2 is measured in millisecond (ms).

4.5. Comparison

To compare our proposed method with two basis edge detection methods namely Robert and Sobel [1], the Peppers image is chosen as a test image where shows in Figure 4(a). Robert and Sobel edge detection methods are tested in Figure 4(a) and results are shown in Figure 4(b) and Figure 4(c), respectively. Figure 4(d) is the result when proposed method applied in Figure 4(a). The result clearly prove the superiority of our proposed method rather others well-known methods.

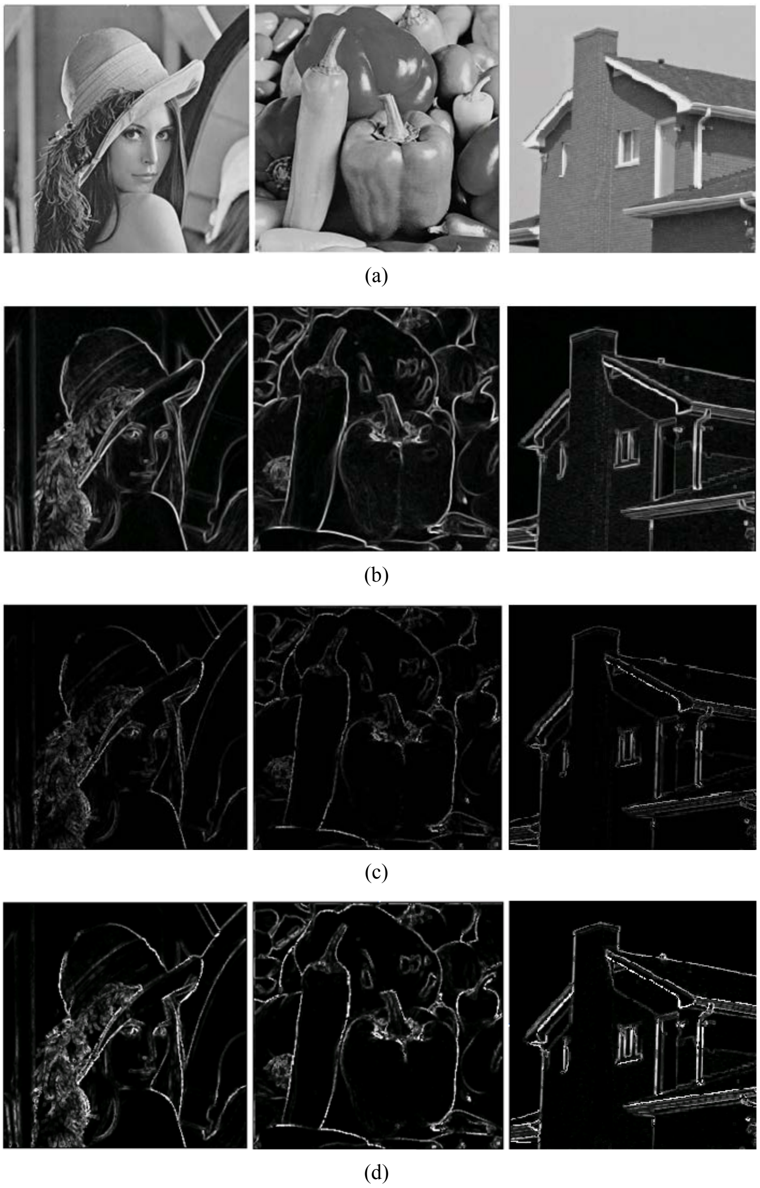
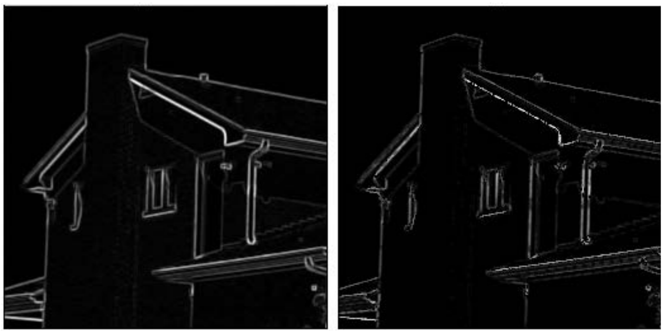


Figure 2. (a) Original images; (b) Standard deviation of images in the first row; (c) Apply SCA in images in row 2; (d) Apply CLA on images in row 3.

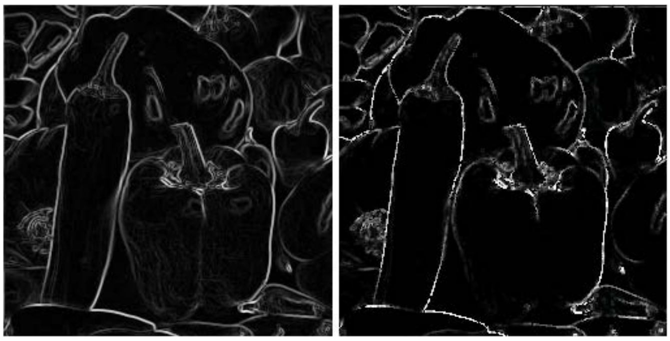
(a) (b)



(c) (d)

Figure 3. (a) Original image; (b) Standard deviation of original image; (c) Result image when $\beta = 3$; (d) Result image by proposed algorithm.

(a) (b)



(c) (d)

Figure 4. (a) Original image; (b) Robert edge detection; (c) Sobel edge detection; (d) Proposed method edge detection.

Table 2. Comparing the proposed method with others methods.

	Sobel	Robert	CNN-PSO	SCA-CLA
128×128	16 (ms)	27 (ms)	194 (ms)	92 (ms)
256×256	53 (ms)	92 (ms)	569 (ms)	348 (ms)
512×512	174 (ms)	341 (ms)	1994 (ms)	1274 (ms)

5. Conclusion

This paper conducted to present a new method for edge detection based on a hybrid model of cellular learning automata (CLA) and fuzzy cellular automata (FCA). In the first part of algorithm, standard deviation is applied to obtain the initial edges. Although in the second step an optimum function with the constant power is used to improve the edges quality, this power is constant for all the pixels and causes those non edge pixels to blur. To solve this problem, a hybrid model of SCA and CLA is used. The main advantage of the proposed method is using SCA and CLA for adjusting optimum function to reinforce edge pixels and castrate those non edge pixels. The numerical experiments and comparisons with the well-known existing methods justify the superior performance and efficiency of our proposed method.

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