

Edge Detection of Images based on Cloud Model Cellular Automata

ZHANG Ke, YUAN Jin-sha, YANG Xue-ming

Department of Electronic and Communication Engineering, North China Electric Power University, Hebei Baoding, 071003, China

E-mail: zhangke41616@126.com

Abstract: In order to resolve the problems of edge detection algorithm of images based on fuzzy seasoning or cellular automata, a new improved edge detection algorithm of images based on cloud model cellular automata is presented. This method uses direction information and edge order information as edge characteristic information, uses cloud model to inference these information, then gives accurate feedback information got from inference results to direction information measure and direction edge order measure, and detects edge by automatic evolution of cellular automata. Finally, experiments are put forward, this algorithm has powerful ability in exiguous edge detection, and it is a promising and applied image processing algorithm.

Key Words: Edge Detection; Cloud Model; Cellular Automata; Multi-information Fusion; Cloud Reasoning

1. Introduction

Edge is the most basic characteristic of an image, which mainly refers to the gathering of the pixel that have strong changes. It contains the useful information of identifying. So it is the major method for the edge detection to analyze the images and identify the mode. At present, the typical method of edge detection mainly contains Roberts、Prewitt、Sobel[1],Canny[2]and so on. As study of wavelet is approaching, there are more edge detection based on the wavelet[3]. But these arithmetic not only have some problems such as operator and filtering scale selecting, but also ignore the neighbors around the edge point. In order to solve these problems, the author of references[4] raises an edge detection Cellular Automata (CA) mode, which leads the computer itself to search a suitable scale. But this kind of method just takes the characteristic of edge directivity into consideration and needs to frame threshold by human beings.

In the field of image processing, it is generally considered that the image itself has fuzziness, as well as the describing and explanation of the image processing. So the fuzzy theory is feasibility in image processing, and starts to have attention[5,6]. But the uncertainty of knowledge is composed of fuzziness and randomness[7], the uncertainty of images is composed of fuzziness and randomness too. Fuzzy theory uses membership to quantificationally describe the double-sided property of objective things, however, it ignores the uncertainty of membership itself. Cloud model[8] combines fuzziness and randomness, and realizes natural transformation between the qualitative linguistic value and the quantitative numerical value.

Combining cloud model and cell automata theory, this paper raises a new edge detection method of images

based on cloud cell automata(CCA), which uses direction information and edge order information of images to make cloud reasoning and then makes evolution of CA according to relations of adjacent pixels. This method doesn't only consider uncertainty of image processing, but also uses the relations of adjacent pixels.

2. Fuzzy cellular automata

CA[9] is a dynamical system in which time and space are discrete. The cells are arranged in the form of a regular lattice structure and each must have a finite number of states. These states are updated synchronously according to a specified local rule of interaction. The most elementary composing parts of CA are cells, cell space neighborhoods and rules. The formula is $G = (S, N, R)$. G refers to the state of the system. S is the state of cells. N is the relationship between neighbor and R is the rules of evolvement. The following state of each objective cell is based on the present state and evolvement rules of its neighbor cells.

Nowadays, CA has been used widely in sociology, biology, ecology, information science, computer science, physics, mathematics and many other scientific research fields. But it is still the underway step to put CA into image processing.

3. Introduction of cloud theory

3.1. Cloud model

Cloud model[10] is an uncertainty transformation model between a qualitative conception $\tilde{A}$ represented by natural linguistic value and the quantitative representation. U is an universe of discourse (one-dimension or multi-dimension) represented by

exact numerical values. The qualitative conception $\tilde{A}$ relative to any element x of U has a random number $y = \mu_{\tilde{A}}(x)$, which has steady trend. Y is the certainty

degree of x relative to $\tilde{A}$. The distribution of x in U is called cloud model, or cloud for short. Cloud consists of lots of cloud droplets, every droplet is a concrete realization of the qualitative conception in numerical domain, and this realization has the uncertainty.

The numerical characteristics of cloud consists of expectation(Ex), entropy(En) and hyper entropy(He). It combines fuzziness and randomness of linguistic value, and makes up of the mapping between qualitative conception and quantitative numerical value. Ex is the center of gravity of all cloud droplets in numerical domain, and reflects the coordinate in numerical domain, of which best represents the qualitative conception. En is a variable which describes the double-sided property of qualitative conception, reflects the range of numerical domain which can be accepted by the linguistic value, and reflects the probability that the points of numerical domain can represent the linguistic value. He is the discrete degree of En , called the entropy of entropy; it reflects condensation degree of every numerical value representing the linguistic value, as well as the condensation degree of cloud droplets.

3.2. Normal cloud generator

The every branch of social science and natural science has proved the universality of normal distribution[11]. Therefore, normal cloud becomes the most basal cloud; it is the most useful to represent basic linguistic value(linguistic atom) of natural language. In this paper all clouds adopted are normal cloud.

Cloud generator(CG) is the model which can generate cloud; its kinds contain normal cloud generator, backward cloud generator, X condition cloud generator and Y condition cloud generator[12].

When the three numerical characteristics and the number N of droplets are fixed, a cloud can be generated by CG. For example, $Ex=0, En=1, He=0.05, N=2000$, a cloud can be seen on Figure 1.

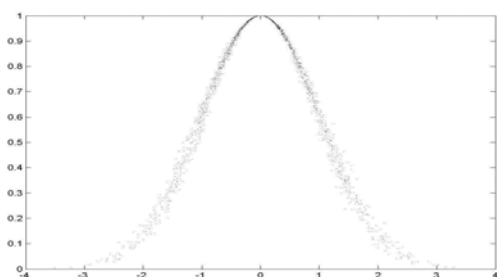


Figure.1 Cloud of CG(0,1,0.05)

When the three numerical characteristics are fixed and $x = x_0$, the cloud droplets(x_0, y_i) are called X condition cloud. When the three numerical characteristics are fixed and $y = \mu_0$, the cloud

droplets(x_i, μ_0) are called Y condition cloud. The CG which can generates X cloud or Y cloud is called X-CG or Y-CG.

4. Multi-information fusion

There are many edge characteristics information used edge detection of images, everyone has excellences itself. So how to fuse these information should be discussed. In this paper, a method fusing direction information and edge order information is put forward.

4.1. Direction information measure

The author in reference[13] put out a method to divide image pixel that based on direction information measure. This method can be taken into edge detection of images. It is supposed that the coordinate of current pixel point is (i, j) , pixel matrix is $I(i, j)$. $N(i, j)$ refers to the Moore neighborhood[11]. l_θ is a direct line which cross the centre point and has a angle θ . This line divide $N(i, j)$ into two parts: $S_{\theta 1}$ and $S_{\theta 2}$. So the definition of Direction Information Measure $M(i, j)$ is as following:

$$M_{i,j} = d_{\theta \max} - d_{\theta \min} \quad (1)$$

There into:

$$d_{\theta \max} = \max_{0^\circ \leq \theta \leq 180^\circ} (d_\theta) \quad (2)$$

$$d_{\theta \min} = \min_{0^\circ \leq \theta \leq 180^\circ} (d_\theta) \quad (3)$$

$$d_\theta = |f_{S_{\theta 1}} - f_{S_{\theta 2}}| \quad (4)$$

$$f_{S_{\theta 1}} = \sum_{(i,j) \in S_{\theta 1}} a_{i,j} \quad (5)$$

$$f_{S_{\theta 2}} = \sum_{(i,j) \in S_{\theta 2}} a_{i,j} \quad (6)$$

At last a direction information measure matrix which takes matrix $M(i, j)$ as matrix I can be gotten. When the current point direction information measure is large, it can show that there is an edge which goes across in the neighborhood. Contrarily, there isn't.

4.2. Edge order measure

The edge of the image not only has the characteristic of gray scale mutation but also shows some order characteristic of its neighborhood. Actually, edge has the neighborhood characteristic, just as follows:

1) There is a gray scale mutation on the edge. 2) Edge is not only a boundary between attributive(gray scale) area. 3) Edge area has a width. 4) Edge has its directivity. 5) Edge has its continuity. A single point can

not be called the edge.

So when chose an edge point, not only to consider the directivity, but also need to care the orderliness of its neighbor. The author of reference[14] has offered two parameters about the edge order measure:

1. The neighbor edge intensity is defined as follows:

$$E_g = \frac{|g_1 - g_2|}{|g_{\max} - g_{\min}|} \quad (7)$$

The maximum and minimum gray scale in the whole image are respectively expressed by $g_{\max}$ 、 $g_{\min}$. The two neighbors' average gray scale are respectively expressed by g_1 、 g_2 . A larger neighbor edge intensity E_g shows a greater full change of the neighbor gray scale, as well as a better orderliness, and all of these may lead to a possibility to be the edge.

2. The width of the neighbor edge isolation is defined as follows:

$$E_d = \frac{E_{d0}}{n+1} \quad (8)$$

$$E_{d0} = \|P_1 - P_2\| = \sqrt{(P_{1x} - P_{2x})^2 + (P_{1y} - P_{2y})^2} \quad (9)$$

Here P_1 & P_2 respectively refers to the two geometrical centers in two neighbors. A larger neighbor edge width E_d shows a greater possibility in different gray scale area, as well as a better orderliness, and all of these may lead to a possibility to be the edge.

In an ideal edge condition, here it takes a $(4+1) \times (4+1)$ rectangle neighbor, so $n=2$. Before measurement, it is necessary to calculate the neighbor edge intensity matrix: $E_{g(i,j)}$ and the width of the neighbor edge isolation matrix: $E_{d(i,j)}$.

5. Edge detection based on CCA

5.1. Cloudization of numerical variable

The cloudization of numerical variable is a process. According to the definition of cloud, for a numerical variable in the universe of discourse U , process P constructs set $\tilde{A}$ of the qualitative conception in U , every conception is depicted by one cloud. Process P describes clouds, which represents qualitative conception. The description of cloud is to describe the figure of cloud and (Ex, En, He) . The process P is called process of cloudization.

1. This method contains three input variables: direction information, neighbor edge intensity and width of the neighbor edge isolation. Every input variable has two qualitative conceptions {Large, Small} called linguistic value, there are six linguistic values in all. Multi-dimension cloud can realize cloudization of several linguistic values, and can be composed of some one-dimension clouds. So it's very convenient to use

one-dimension cloud as basic model. To different systems, the design of cloudization process is different. In this paper, we adopt semi-normal extended cloud to actualize cloudization:

1). Cloudization of direction information

The cloud which shows "Large" has numerical characteristics $(Ex1, En1, He)$, its figure is lower semi-normal spread, here $Ex1 = T_2$, $En1 = (T_2 - T_1)/3$; The cloud which shows "Small" has numerical characteristics $(Ex2, En2, He)$, its figure is upper semi-normal spread, here $Ex2 = T_1$, $En2 = (T_2 - T_1)/3$. Two clouds can be seen on Figure 2.

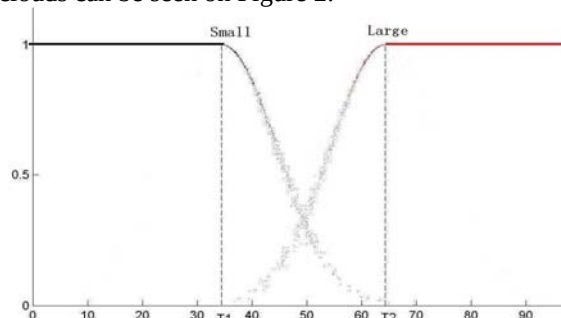


Figure.2 Cloud of direction information measure

The numerical value of T_1 、 T_2 has a direct effect of the correctness of the edge choosing. Here a gauss fits method is adopted to decide the threshold automatically. Figure 3 is a result of gauss fits of direction information measure of 136×151 image lena without noise. $T_1 = \mu + \sigma$, $T_2 = \mu + 2\sigma$, μ is expectation, σ is standard deviation, $\mu = 4.7$, $\sigma = 29.8$, $T_1 = 34.5$, $T_2 = 64.3$.

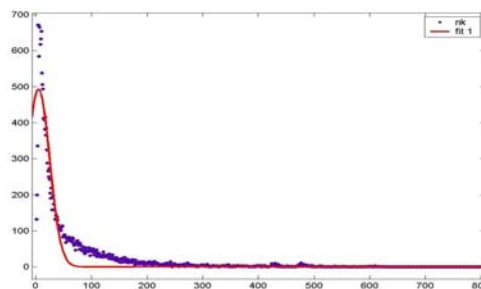


Figure.3 Direction information measure histogram gauss fits

2). Cloudization of neighbor edge intensity

The cloud which shows "Large" has numerical characteristics $(Ex3, En3, He)$, its figure is lower semi-normal spread, here $Ex3 = T_3$, $En3 = T_3/3$; The cloud which shows "Small" has numerical characteristics $(Ex4, En4, He)$, its figure is upper semi-normal spread, here $Ex4 = 0$, $En4 = T_3/3$. Usually $T_3 = 1/3$.

3). Cloudization of width of the neighbor edge isolation

The cloud which shows "Large" has numerical characteristics $(Ex5, En5, He)$, its figure is lower semi-normal spread, here $Ex5 = T_4$, $En5 = T_4/3$; The cloud

which shows ‘Small’ has numerical characteristics(Ex6,En6,He), its figure is upper semi-normal spread, here $Ex6=0, En6=T_4/3$. Usually

$$T_4 = \frac{2\sqrt{2}}{3}.$$

2. This method contains three outputs, which respectively represent the feedback to direction information and edge order information.

Cloud for direction information has numerical characteristics(Ex7,En7,He), its figure is lower semi-normal spread, here $Ex7=\sigma/2, En7=\sigma/6$.

Cloud for neighbor edge intensity has numerical characteristics(Ex8,En8,He), its figure is lower semi-normal spread, here $Ex8=T_3/2, En8=T_3/6$.

Cloud for width of the neighbor edge isolation has numerical characteristics(Ex9,En9,He), its figure is lower semi-normal spread, here $Ex9=T_4/2, En9=T_4/6$.

5.2. Cloud reasoning

The rules of cloud reasoning are: if three inputs are “Large”, the output is “yes”, otherwise it’s “no”.

IF A11 and A21 and A31 THEN B1

IF A12 and A21 and A31 THEN B2

... ..

IF A12 and A22 and A32 THEN B2

A11 and A12 represent “Large” and “Small” of direction information; A21 and A22 represent “Large” and “Small” of neighbor edge intensity; A31 and A32 represent “Large” and “Small” of width of the neighbor edge isolation; B1 represents edge, B2 represents non-edge.

This paper adopts logical operation of cloud to realize multi-condition and multi-rule reasoning. Figure 4 is the model diagram of multi-condition and multi-rule cloud model controller. The number of rules is 9; the number of antecedent of reasoning is 3. Here we use several one-dimension clouds to realize a multi-dimension cloud by multiplier(MF)[15] composed of soft “AND”. CG_{Aij} ($i=1,2,3; j=1,2$) in figure represents X condition cloud generator of linguistic value A_{ij} in rules; the first rule is relative to Y condition cloud generator CG_{B1i} ($i=1,2,3$) of linguistic B_1 . The process of reasoning is as following: When a given input vector X(direction information, neighbor edge intensity and width of the neighbor edge isolation of one pixel) stimulates three-dimension clouds composed of CG_{Aij} by MP to generate random numbers μ_{Am} ($m=1,2,\dots,9$), which can reflect the degree of activation of the relative rule. The maximal μ_{max} is selected by Rules selector(RS), it indicates that the relative qualitative rule is selected. If the first rule is selected, it indicates that this point is an edge point; and then μ_{max} will control CG_{B1i} ($i=1,2,3$) to generate

three cloud droplets Drop $(y_{1i}, \mu_{max}) (i=1,2,3)$. On the whole, cloud controller generates cloud clusters composed of many cloud droplets, so the outputs should be the mean-values $E(y_{1i}) (i=1,2,3)$.

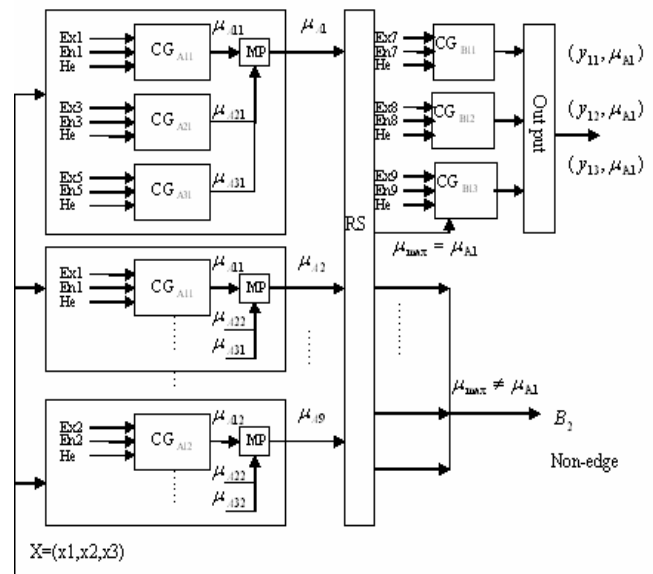


Figure.4 Cloud model controller of edge detection

The edge points judged by cloud reasoning are not all edge points. The author in reference[4] put forward the hypo-neighbor detection method to look for the edge point by considering the edge orderliness principle. But this method takes the size-up hypo-neighbor point as the edge point forcibly, which doesn't take fuzziness into account. So errors of judgment easily come out. Based on these, a new method based on Y condition cloud is used to feed back the matrix M of direction information measure, the matrix E_g of neighbor edge intensity and the matrix E_d of width of the neighbor edge isolation. Its theory is that: to decide the edge point by cloud reasoning; for all of the edge points, the Moore neighborhood which takes those as the centre point is taking into consideration, if its neighborhood accords with the edge structure[16], an edge point in the hypo-neighborhood of the neighborhood edge point may be existed, the hypo-neighbor of the maximal μ_{A1} (the degree of activation of the first rule) is to be found among each neighborhood edge point; There is no hurry to take this point as the edge point directly, but to give increment feedback to the direction information and edge order information, at the next moment, another cloud reasoning of the new direction information and edge order information should be taken to decide the edge point. This increment is got from $E(y_{1i})$ by cloud reasoning.

5.3. Rules of CCA

First, taking cell space to correspond to the gray-value matrix I.

Second, calculating the direction information

measure matrix M , the neighbor edge intensity matrix E_g and the width of the neighbor edge isolation matrix E_d of matrix I .

Third, using part regulation to judge the edge point and noise point. The requirement for one centre cell(i,j) needs to meet the following part regulation:

1. Using M , E_g and E_d as inputs to make cloud reasoning, and then set up a marker matrix $B(b_{i,j})$ and take the point whose corresponding result of cloud reasoning is an edge as 1, and the less one as 0, which refers to the non-edge point.

2. If $b_{i,j} = 1$. Observe and study its Moore neighborhood. If its neighborhood accords to the edge structure, then find out the location of the neighborhood cell whose estate is 1. t and sign the corresponding place on the matrices M , E_g and E_d . Find out the cell whose μ_{A1} is the biggest in its hypo-neighborhood for each founded neighbor cell. Make sure that the following state information measure value, neighbor edge intensity value and width value of the neighbor edge isolation are the sum of the present values and the output values of cloud reasoning. The feed point will not be feedback again.

3. If $b_{i,j} = 1$. If its neighborhood doesn't accord to

the edge structure, that is to say, it is not the edge point and its next state will be 0.

4. If $b_{i,j} = 0$. If its neighborhood accords with any edge structure, it shows that itself is an edge point too. And its following state will be 1.

5. CA begins to evolve, until a stable state ($B^t = B^{t+1}$).

6. Experiment

Take the above method into the noiseless image lena to detect its edge. The result can be seen on Figure 5. Figure 5-b and Figure 5-c are edge images by cloud reasoning, the first one $He=0$, the second one $He=0.1$. When $He=0$, cloud reasoning becomes fuzzy seasoning. Comparing the two edges, the latter one is more subtle. That is to say, the result of edge detection based on cloud reasoning is more rational than fuzzy reasoning.

Figure 5-d is the edge image by evolution based on CCA. From the images, it is clean that its orientation is more exact and its disposal of the details is better. Take the top of the hat as an example. On the whole it is joint together.

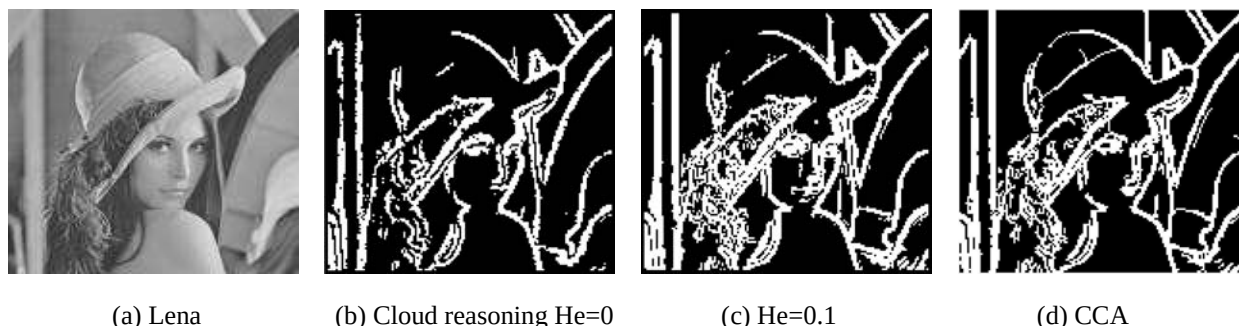


Figure.5 Test result of lena graph

Figure 6-a, figure 6-b, figure 6-c and figure 6-d are the edge images by Roberts, Prewitt, Sobel and Canny. It compares the four methods with method of this paper, Canny has a better effect than Roberts, Prewitt and

Sobel, continuity of edge is strong, CCA (Figure 6-e) has a better contour outline of edge, in particular have good detection effects for top of the hat.



Figure.6 Test result of lena graph

Figure 7 is the result of adding $N(0,20)$ Gauss noise on the image lena to detect the edge. The edge image in Figure 7-b and Figure 7-c are the edge images by Sobel and Canny. Figure 7-c has a better effect than Figure 7-b,

but it has a little distortion. The result of CCA is showed in Figure 7-d. The most effective edge can be left, but there is a little noise too.

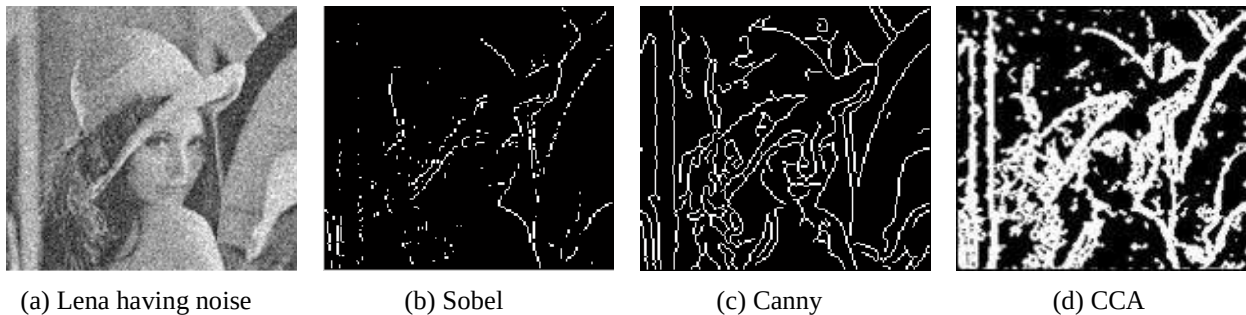


Figure.7 Test result of lena graph with noise

7. Conclusion

The edge detection algorithm of images based on CCA takes uncertainty of images composed of fuzziness and randomness into account. It fuses direction information and edge order information to make cloud seasoning, then gives feedback to input information, and realizes auto evolution detection by CA. This experiment tests noiseless image and noise image, and contrasts several edge detection method. The results of the test indicate that the algorithm of edge detection has good effect in the details and high accuracy; and it has certain effect in restraining noise, but this method still needs to be improved.

References

- [1] Zhang Yu-jin. Images processing and analysis. Tsinghua University Press, Bei Jing, 1999.
- [2] Canny J. A Computational Approach to Edge Detection. IEEE T-PAMI, Vol.8, No.6, pp.679-698, Jun.2003.
- [3] Mallat S, Huang W L. Singularity Detection and Processing with Wavelets. IEEE T-PAMI, Vol.38, No.2, pp.617-643, Feb.1992.
- [4] Chang Chun-ling, Zhang Yun-jif, Gdong Yun-yin. Cellular automata for edge detection of images. Proceedings of the Third International Conference on Machine Learning and Cybernetics, Shang Hai, pp.26-29, Aug.2004.
- [5] Zong Xiao-ping, Xu Yan, Dong Jiang-tao, Fuzzy edge detection technique using multi-information fusion algorithm, Vol.55, No.7, pp.3323-3328, Jul.2006.
- [6] Sun Wei, Xia Liang-zheng, Pan Hong, A new edge detection algorithm based on fuzzy partition. Journal of Image and Graphics, Vol.9, No.1, pp.18-22, Jan.2004.
- [7] Li De-yi. Uncertainty in knowledge representation. Engineering Science, Vol.2, No.10, pp.73-79, Oct.2000.
- [8] Li De-yi, Meng Hai-jun, Shi Xue-mei. Membership clouds and membership cloud generators. Journal of Computer Research and Development, Vol.32, No.6, pp.15-20, Jun.1995.
- [9] Zhou Cheng-hu, Sun Zhan-li, Xie Yi-chun. Research of Geography Cellular Automata. Science Press, Bei Jing, 1999.
- [10] Li De-yi, Cheung David, Ng V, et al. Uncertainty reasoning based on cloud models in controllers. Computers and Mathematics with Application Elsevier Science, Vol.35, No.3, pp.99-123, Mar.1998.
- [11] Li De-yi, Liu Chang-yu. Study on the universality of normal cloud model. Engineering Science, Vol.6, No.8, pp.28-34, Aug.2004.
- [12] Li De-yi, Yang Yi. Uncertainty artificial intelligence. National Defence Industry Press, Bei Jing, 2005.
- [13] Yang Xuan, Liang De-qun. Multiscale edge detection based on direction information. Journal of Xiadian University, Vol.24, No.4, pp.524-530, Apr.1997.
- [14] Ji Hong, Yang Yuan, Xie Wei-xin. Multiscale edge detection based on fuzzy measure in neighborhood. Journal of China Institute of Communications, No.S1, pp.37-41, Dec.1999.
- [15] Chai Ri-fa, Zeng Wen-hua. Clouds representation of qualitative rules. Computer Engineering, Vol.28, No.7, pp.161-164, Jul.2002.
- [16] Hui-jie, Cao Qing-nian, Sun Yu-qing, Bian Zheng-zhong. Edge labeling based on probability relaxation. Pattern Recognition and Artificial Intelligence, Vol.12, No.2, pp.178-183, Feb.1999.