RESEARCH ON THE EDGES OF IMAGE BASED ON CLOUD MODEL

WANG Zuo-cheng [a, c *], XUE Li-xia [b] Zhang Xi-ping[a]

[a]Software Institute, ChongQing University of Posts and Telecommunications, ChongQing,China-cs_wangzc@hotmail.com [b]College of Computer Science and Technology, ChongQing University of Posts and Telecommunications, ChongQing,China-xuelx@cqupt.edu.cn [c]Institute of Remote Sensing and Geography Information System, Peking University, China

Commission PS-2: WgS II/1

KEY WORDS: Image, Edge, Model, Spectral, Fuzzy Logic, Cloud model

ABSTRACT:

To extract rules for detecting edges, it is helpful to have some familiarity with different kinds of edges in order to construct a suitable characterization. Typically, researchers have characterized edges as a step function or as a slope between two flat regions. In reality however, edges may deviate from these cases in any number of manners, such as gradual in transition, between areas of non-uniform intensity, between areas of similar intensity, noisy, or any combination of these problems. Furthermore, effective edge detection must go beyond local shape characteristics to reflect structural constraints. Edges appear not only as a local phenomenon, but as part of larger structures which can also be characterized heuristically. Again, we argue that it is possible to express structural constraints heuristically in a systematic way. We employ fuzzy reasoning for these tasks because the nature of the data is indeterminate at a low-level stage of processing. This paper presents a new method applied to edge modeling based on cloud model. According to the characteristics of section plane of edge, three types edge can be classified, ladder, pulse and fastigium. According to the edge digital characteristics, we can extend the normal cloud model to multi-distributing cloud models, Γ cloud, triangle cloud, trapezoid cloud, etc.. The new edge models can represent the digital characteristics perfectly. The method has three steps: 1) Edge transitional region extracting, which formed by part of the pixels between the objective and background of image. 2) Cloud-core generating by digital characteristics of image. 3) Edge vector cloud generating by backward cloud generator. The edge cloud is not normal distributing cloud in most cases. Γ distributing, triangle distributing and trapezoid distributing or others are more popular in edge cloud. The method we develop is demonstrated by applying it to the problem of edge modeling, various performance studies testify that the method is both efficient and effective.

1. INTRODUCTION

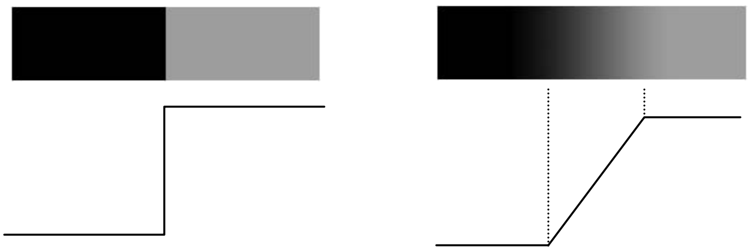
In the past several decades, many effective algorithms of edge detection have been presented[1-4]. However, most of them are not effective in edge detection because of randomness and fuzziness of image. It is helpful to have some familiarity with different kinds of edges in order to construct a suitable characterization. Edges are formed from pixels with derivative values that exceed a preset threshold. Thus, the idea of an edge is a “local” concept that is based on a measure of gray-level discontinuity at a point[5]. It is possible to link edge points into edge segments, and some times these segments are linked in such a way that corresponds to boundaries. A reasonable definition of “edge” requires the ability to measure gray-level transitions in a meaningful way. Many researches study the edge of image and propose many edge detection algorithms[6]. Three type edges are proposed, ladder, pulse and roof[7]. However, the edges have fuzzy characteristics obviously. Many edges can not belong to any of the three types exactly. Aiming at the fuzziness and randomness of edges of image, especially RS image, fuzzy set, rough set and other fuzzy theories, random field models have been adopted. Fuzzy-sets provide a helpful method to transacting the fuzzy and random edges. The most commonly used method of uncertainty reasoning is based on fuzzy set theory [8-11]. By using fuzzy rules of the form “ If A then B”, where “A” and “B” are linguistic terms, fuzzy reasoning is accomplished by fuzzy operations, such as “Min” and “Max” operations on membership functions[12-14].

The basis of fuzzy set theory is the membership function. Traditionally, the membership function of a fuzzy set is a one-point to one-point mapping from a space U to the unit interval [0, 1] [12]. After the mapping the uncertainty of an element belonging to the fuzzy concept becomes certain to that degree, a precise number. The uncertain characteristics of the original concept are not passed on to the next step of processing at all. This is the intrinsic shortcoming of the fuzzy set model, which was often criticized by probabilists and experts in relevant fields. Consequently, conventional fuzzy reasoning methods have the shortcoming in that they generate certain results and can not really mimic human being’s fuzzy thinking[15].

In order to overcome the intrinsic shortcoming of the fuzzy set model, Dr. Deyi Li proposed the cloud model[16]. And now, cloud model have been extended to two and multidimensional ones and explored the applications of cloud models in spatial data mining and knowledge discovery[16-19]. We have explored the applications of cloud models in image processing[20-23]**.** We consider that the cloud model can be adopted to accomplish vagueness and randomness handling of edges in RS image. In the following section, we will study the vagueness and randomness of the edges of image, and propose the fuzzy edge model based on cloud model.

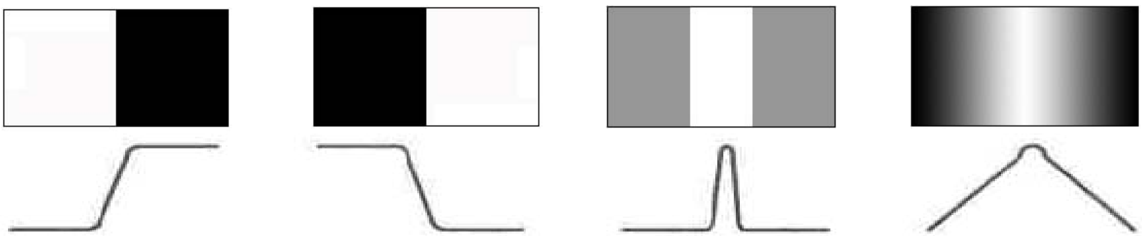
2. THE FYZZY EDGES CHARACTERISTIC

Edge can be modeled intuitively. This will lead us to a formalism in which "meaningful" transitions in gray levels can be measured. Intuitively, an ideal edge has the properities of the model shown in Figure.1(a). An ideal edge according to this model is a set of connected pixels (in the vertical direction here), each of which is located at an orthogonal step transition in gray level (as shown by the horizontal profile in the figure).
In practice, optics, sampling, and other image acquisition imperfections yield edges that are blurred, with the degree of blurring being determined by factors such as the quality of the image acquisition system, the sampling rate, and illumination conditions under which the image is acquired. As a result, edges are more closely modeled as having a "ramplike" profile[7], such as the one shown in Figure.1(b). The slope of the ramp is inversely proportional to the degree of blurring in the edge. In this model, we no longer have a thin (one pixel thick) path. Instead, an edge point now is any point contained in the ramp, and an edge would then be a set of such points that are connected. The "thickness" of the edge is determined by the length of the ramp, as it transitions from an initial to a final gray level. This length is determined by the slope, which, in turn, is determined by the degree of blurring. This makes sense: Blurred edges tend to be thick and sharp edges tend to be thin.



(a) (b)

Figure 1. Model of digital edge



(a) (b) (c) (d)

Figure 2. Image and profile

The first and second derivatives of the edge gray-level have been accomplished. Results show that the first derivative is positive at the points of transition into and out of the ramp as we move from left to right along the profile. It is constant for points in the ramp, and is zero in areas of constant gray level. The second derivative is positive at the transition associated with the dark side of the edge, negative at the transition associated with the light side of the edge and zero along the ramp and in areas of constant gray level. Some researches conclude from these observations that the magnitude of the first derivative can be used to detect the presence of an edge at a point in an image (i.e., to determine if a point is on a ramp). Similarly, the sign of the second derivative can be used to determine whether an edge pixel lies on the dark or light side of an edge.

We conclude from these observations that the magnitude of the edges can be classified three types: ladder,Figure.2(a,b), pulse, Figure.2(c) and roof, Figure.2(d). Ladder edge exists between different gray level regions of adjacent. Pulse edge corresponds to narrow transitions in gray levels. Roof edge has thick transitions in gray levels.

The edges shown in Figure.2 are free of noise. In fact, there are not edges like the ideal edges in image, especially in remote sensing image. So many factors influence the image. It leads to randomness and fuzziness in remote sensing image. Fuzzy reasoning, as outlined by Zadeh[12], with the power to model and respond usefully to approximate situations, is ideally suited to these problems. However, conventional fuzzy reasoning methods have the shortcoming in that they generate certain results and could not really mimic human being's fuzzy thinking. Therefore, many fuzzy edge models could not express the fuzziness and random of edge of image perfectly. Cloud model proposes a new method to represent the fuzzy edges.

3. CLOUD MODEL

Cloud model, which is a new uncertain theory derived from traditional Fuzzy set and Probability statistics theory, is a model of the uncertain transition between a linguistic term of a qualitative concept and its numerical representation. In short, it is a model of the uncertain transition between qualitatives and quantitatives[16,17].

Let U be the set $U = \{u\}$, as the universe of discourse, and T a linguistic term associated with U. The membership degree of u in U to the linguistic term T, $C_T(u)$, is a random number with a stable tendency. $C_T(u)$ takes the values in [0,1]. A membership cloud, or compatibility cloud, is a mapping from the universe of discourse U to the unit interval [0,1]. That is

$$C_T(u) : U \to [0,1]$$
$$\forall u \in U \quad u \to C_T(\mathrm{u}). \qquad (1)$$

The geometry of the compatibility cloud is a great aid in understanding the uncertainty of the transition between a linguistic term and its numerical representation. A normal cloud is defined with three digital characteristics[14,15], expected value *Ex*, entropy *En* and hyper entropy *He* (Figure.3). The expected value *Ex* is the position at *U* corresponding to the center of gravity of the cloud. In other words, the element *Ex* in the universe of discourse is fully compatible with the linguistic term. The entropy *En* is a measure of the coverage of the concept within the universe of discourse. It can be also considered as a measure of fuzziness of the concept. *En* is defined by the bandwidth of the mathematical expected curve (*MEC*) of the normal cloud showing how many elements in the universe of discourse could be accepted to the linguistic term. The *MEC* of the normal cloud to a linguistic term may be considered as its membership function from the fuzzy set theory point of view. The hyper entropy *He* is the entropy of the entropy *En*. It is a measure of dispersion of the cloud drops.

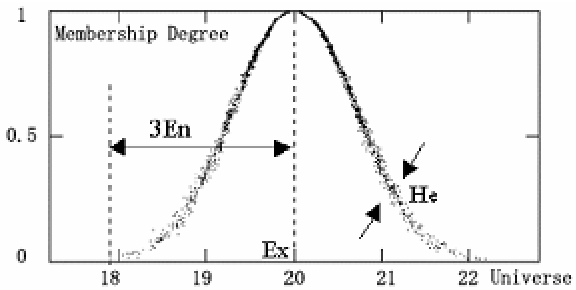


Figure 3. Illustration of the three digital characteristics of a normal cloud

If we only have some cloud drops $(x_1,u_1),(x_2,u_2),...,(x_n,u_n)$, we can construct a whole cloud by least square fitting, this cloud is called geometric cloud. That is, solve the following non-linear equation group, we can get the three parameters of the geometric cloud.

$$\sum_{i=1}^{n}\left(u_i - \exp\left[\frac{-(x_i-Ex)^2}{2En^2}\right]\right)^2 = \min \qquad (2)$$

If there are only two cloud drops $(x_1,u_1),(x_2,u_2)$, the expected value and entropy of the geometric cloud can be calculated directly by the following formulas.

$$Ex = \frac{x_1\sqrt{-2\ln(u_2)} + x_2\sqrt{-2\ln(u_1)}}{\sqrt{-2\ln(u_1)} + \sqrt{-2\ln(u_2)}}$$
$$En = \frac{x_2 - x_1}{\sqrt{-2\ln(u_1)} + \sqrt{-2\ln(u_2)}} \qquad (3)$$

The geometric cloud method is used in uncertainty reasoning when several rules are activated simultaneously.

4. CLOUD MODEL EXTENDING FOR FUZZY EDGES

The edge cloud is not normal distributing cloud in most cases. Γ distributing, triangle distributing and trapezoid distributing or others are more popular in edge cloud, so we extend the cloud model[15].

Γ membership function is one of the most popular fuzzy set function. Half-descending and half-ascending membership function are:

$$\mu(x) = \begin{cases} 0 & (0 \le x \le a) \\ e^{-k(x-a)} & (x > a) \end{cases}$$
$$\mu(x) = \begin{cases} 0 & (0 \le x \le a) \\ 1 - e^{-k(x-a)} & (x > a) \end{cases} \qquad (4)$$

Because of expect and standard deviation of exponent distributing $e(k)$ are $1/k$. Γ cloud can be achieved by Γ generator algorithm. First, k can be gotten according to digital characteristics (Ex, En, He), then the random numbers can be achieved.

Γ cloud generating algorithm is shown as the following:

(1) Calculating $a = Ex, k = 1/En$, $k_H = 1/He$.

(2) Generating exponent random numbers by the parameter k, $x_i^{/} = E(k_H)$, calculating $x_i = a \pm x_i^{/}$, $\pm$ is random.

(3) Generating exponent random numbers by the parameter k_H, $k_i^{/} = E(k_H)$, calculating $k_i^{//} = k_i^{/} - He + k$.

(4) Calculating $u_i = \begin{cases} \exp[k_i^{//}(x_i - a)] & (0 \le x \le a) \\ \exp[-k_i^{//}(x_i - a)] & x > a \end{cases}$, (x_i, u_i) is cloud drop.

Half-descending and half-ascending cloud can be generated like this, Figure.4 shows Γ cloud.

Triangle membership function is a kind of predigestion of normal membership function. The triangle membership function is:

$$\mu(x) = \begin{cases} \dfrac{x-a}{m-a}, & a < x \le m \\ \dfrac{b-x}{b-m}, & m < x \le b \\ 0, & other \end{cases} \qquad (5)$$

Trapezoid cloud is composed of uniform distribution, half-increasing and half-decreasing normal cloud. For the sake of simplicity, uniform distribution, half-increasing and half-decreasing triangle cloud can construct the trapezoid cloud too.

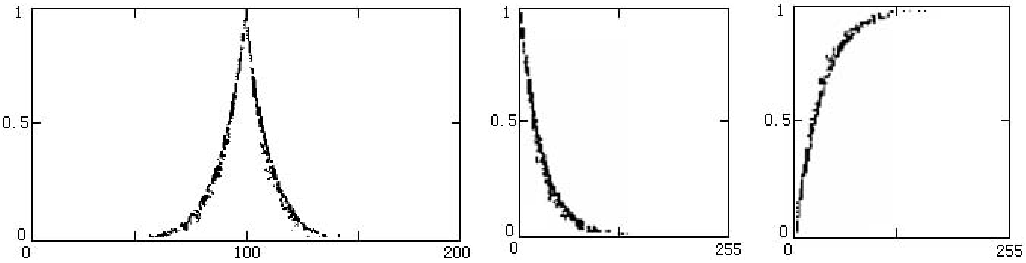


Figure 4. Γ cloud, half-descending and half-ascending cloud

Besides the three parameters, Ex, En, He, trapezoid cloud has 4-th parameter, w, denotes the width of uniform distributing.

5. CONSTRUCTING EDGE CLOUD

Based on the edge transitional region, edge clouds can be constructed according to cloud generator.

5.1 Edge transitional region extracting and cloud-core generating

Transitional region is formed by part of the pixels between the objective and background of image. These pixels locate between objective and background, gray level distributing is also between objective gray level value and background gray level value[24]. In traditional algorithm of transitional region extraction, extreme value L_{high} and L_{low} are needed to be confirmed. Some extreme instances such as $L_{low} > L_{high}$ would be happened because of the complexity of image. It always conduces the later division process can not perform. In addition, the noise influences the value of L_{high} and L_{low} obviously, and leads to transitional region excursion.

In fact, if an object is regarded as formed with real part and imaginary part, so, the transitional region between two adjacent objects should be formed with these two objects fuzzy part in common. The imaginary part of adjacent objects is expressed a region which is covered by some cloud drops except for cloud core of intersectant cloud. Based on the above understanding of transitional region, a transitional region definition and extraction algorithm is proposed.

Suppose A and B are adjacent objects in image I, according to object representation algorithm based on cloud model[22], two intersectant clouds $A=(P_A(i,j), Ex_A, En_A, He_A)$ and $B=(P_B(i,j), Ex_B, En_B, He_B)$ in cloud space can be obtained through mapping mode. According to formula9, edge cloud $C(L_C(i,j), Ex_C, En_C, He_C)$ and three digital characteristics can be obtained at the same time. Ex_C is the gray level expected value of the core of edge cloud, En_C is entropy which is express the gray level scope of edge cloud. Set a and b as the left and right threshold of transition region, then

$$\begin{aligned} a &= Ex_C - 3\sigma - He_C = Ex_C - 3En_C - He_C \\ b &= Ex_C + 3\sigma + He_C = Ex_C + 3En_C + He_C \end{aligned} \tag{6}$$

In fact, if an object is regarded as formed with real part and imaginary part, so, the transitional region between two adjacent objects should be formed with these two objects fuzzy part in common. The imaginary part of adjacent objects is expressed a region which is covered by some cloud drops except for cloud core of intersectant cloud. Based on the above understanding of transitional region, a transitional region definition and extraction algorithm is proposed. Transitional region is defined as the two-dimension pixels sets which covered by edge cloud in cloud space. That is

$$\begin{aligned} TR &= \{(i,j) \in I \,|\, a \le f(i,j) \le b\} = \\ &\{(i,j) \in I \,|\, Ex_C - 3En_C - He_C \le f(i,j) \le Ex_C + 3En_C + He_C\} \end{aligned} \tag{7}$$

5.2 Generating of edge vector cloud

Based on transitional region, the mean gray level can be used to represent the cloud-core. We can get the digital feature of cloud-core. Given a limited set of pixels from cloud-core [15], $pixel_i(u, C_x)$, as samples of a compatibility cloud, the three digital characteristics *Ex*, *En* and *He* could be produced by the following algorithms. We call this algorithm and its hardware implement a backward cloud generator (Figure. 5).

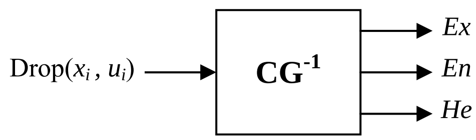


Figure 5. A backward cloud generator

(1) $Ex = mean(x_i)$

(2) $En = stdev(x_i)$

(3) $En'_i = \sqrt{\dfrac{-(x_i - Ex)^2}{2\ln(u_i)}}$, $He = stdev(En'_i)$

The $mean(x)$ denote function of mean of x, $stdev(x)$ denote function of root mean square.

According to the algorithm, we can get many clouds from the image according to the gradient. We call them "object-clouds". One "object-cloud" expresses a spatial object in image.

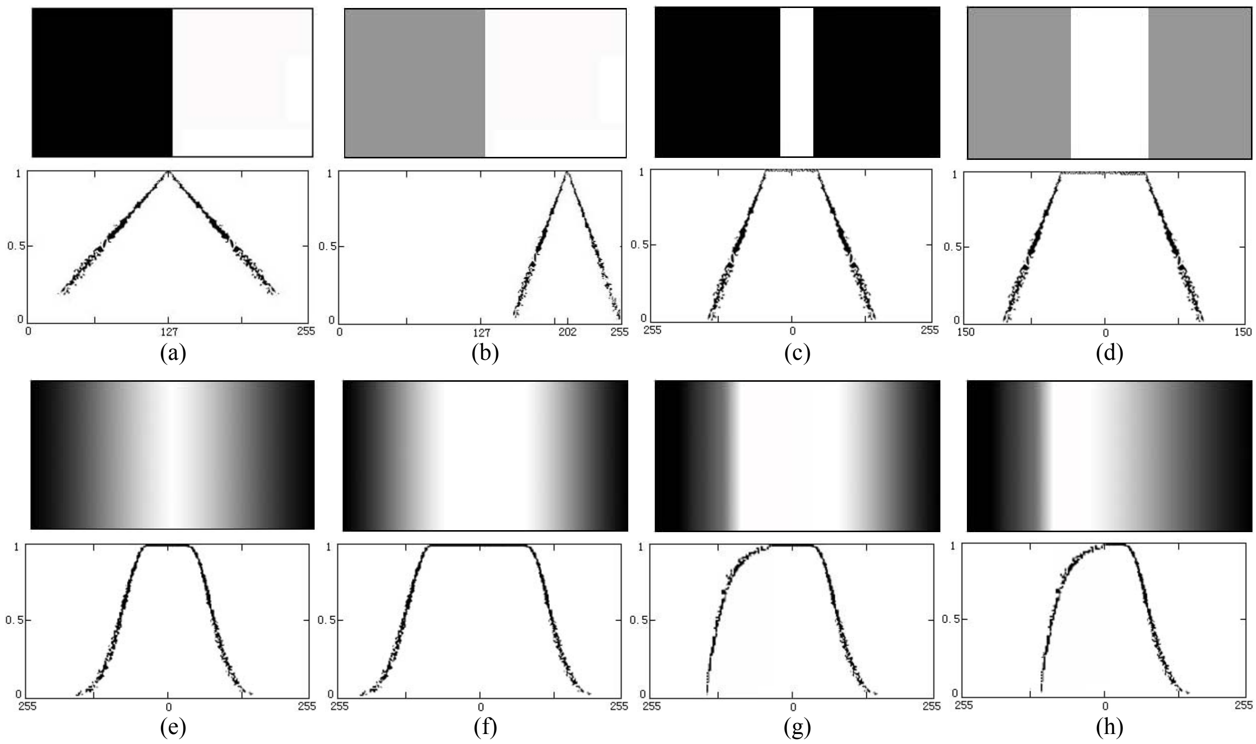


Figure 6. Edge image and edge vector cloud

6. EXPERIMENTS

Representing the different fuzzy edge by edge vector cloud is demonstrated using the three types of edge. Because so many factors influence the image, the edges present many different types. We select some representative edges and construct the edge vector cloud (Figure.6).

Figure.(a) and Figure.(b) show edges free of noise, triangle cloud can represent them. Figure.(c) and Figure.(d) are the other types edge free of noise, trapezoid cloud can be used. Figure.(e) and Figure.(f) are symmetrical edges, normal cloud and trapezoid cloud can represent them perfectly. Figure.(e) and Figure.(f) are antisymmetric edges because of noise. Normal cloud, trapezoid and Γ cloud are combined.

7. CONCLUSIONS

In this paper, we have addressed edge representation, which is an important issue in image processing areas. A new method for representing the edge of images has been described, which is based on the fuzzy characteristics of edges and the performances of cloud fuzzy algorithms. This algorithm can meet the needs of fuzzy edge representing, and is very useful and feasible in the processing of edge detecting by cloud operation algorithms or virtual cloud operations. Cloud theory gives the symmetrical cloud operation algorithm, such as normal cloud. However, many edge vector clouds are antisymmetric clouds, so how to accomplish symmetrical clouds operation is what we should do next.

ACKNOWLEDGMENTS

The work is supported by Chongqing Nature Science Fund (CSTC 2007BB2392).

REFERENCES

1. Q. Wang, H. Ruan. “Fast Fuzzy Edge-detection Algorithm”. Journal of Image and Graphics, 2001,6A(I):92-95.

2. Wang Z.C. Xue L.X. Li Y.SH. Wang L.L. “A new Edge Detection Algorithm”, The 14th International Conference on Geoinformatics[C]. Wuhan,2006,(11): P6419-37.

3. W. Hong, W. Chen. “An Improved GFO Algorithm for High Quality Edge-detection of Images”. Journal of Image and Graphics, 1999,4A (2):143-146.

4. J. H. Liu, J. X. Tang, T. J. Long. “An improved fast edge detection algorithm based on fuzzy sets” J. Syst. Sim. 2003,15(2): 273-274(297).

5. JD. Foley, Avan Dam, SK. Feiner, JF. Hughes. Computer Graphics: Principles and Practice, Second Edition[M]. Boston,MA,USA:Addison-Wesley, 1990.

6. Zhang,Y.J. Image Segmentation. Beijing: Science Press,2001.

7. Rafael C. Gonzalez, Richard E. Woods. Digital Image Processing Second Edition[M]. Pearson Education Inc.,2002.

8. Pal S K, King R A. “On edge detection of X-ray images using fuzzy sets”, IEEE-PAM1,1983,5(1):69-77.

9. Menbardt W, Imme M. “Contour detection using fuzzy sets”, Signal Process :Theories and Applications, 1998,1633-1636.

10. Huang L K, Wang M J. “Image thresholding by minimizing the measure of fuzziness”, Pattern Recognition, 1995,28(1):41-51.

11. Ye,X.Q, Gu,W.K, Xiao,Q. "Fast fuzzy segmentation Algorithm", Pattern Recognition and Artificial Intelligence. 1996,9(1):66-70.

12. Zadeh, L.A. "The concept of linguistic variable and its application to approximate reasoning", Information Science, 1975, 8(1): 199-249.

13. Zadeh, L.A. "Fuzzy logic = computing with words", IEEE Trans. on Fuzzy systems, 1996,4(2):103-111.

14. He, X.G. Fuzzy theories and fuzzy techniques in knowledge processing (2nd ed), Beijing: National Defence Industry Press. 1998.

15. Di, K.C. Spatial Data Mining and Knowledge Discovery. Wuhan:Wuhan University Press,2001.

16. Li, D.R., Di, K.C., Li, D.Y. "Knowledge representation and uncertainty reasoning in GIS based on cloud models", The 9th International Symposium on Spatial Data Handling,Beijing,2000(8):1-12.

17. Di, K.C., Li, D.Y., Li, D.R. "Knowledge representation and discovery in spatial databases based on cloud theory", International Archives of Photogrammetry and Remote Sensing, 32(3/1), July, 1998, Columbus, Ohio, 1998a:544-551.

18. Di, K.C., Li, D.R., Li D.Y. "Intelligent query in spatial databases based on cloud model", In Li, D.R. etal. (eds.), Spatial Information Science, Technology and Its Applications, Wuhan : WTUSM Press, SIST'98, Dec., 1998b.

19. Di, K.C., Li, D.Y., Li, D.R. "Cloud theory and its applications in spatial data mining and knowledge discovery", Journal of Image and Graphics,1999a, 4(11).

20. Xue L.X. Wang Z.C. Li Y.SH. Wang L.L. "Fuzzy Edge Detection Based on Cloud Model", Journal of Southwest Jiaotong University,2006,41(1):85-90.

21. Wang Z.C. Xue L.X. Li Y.SH. Wang L.L. "A new Edge Detection Algorithm", The 14th International Conference on Geoinformatics[C]. Wuhan,2006,(11): P6419-37.

22. Wang Z.C. Xue L.X. Xiao Y.P. "Spatial uncertain region representation based on cloud model", The 2-nd International conference on space information technology[C]. Wuhan, 2007,(11): 679573-1~6.

23. Wang Z.C. Li Y.SH. Xue L.X. Wang L.L. "Image Texture Segmentation Based on Cloud Fuzzy Theory", Journal of Southwest Jiaotong University, 2007,29(7):163-167.

24. Y. J. Zhang and J. J. Gerbrands. Transition region determination based thresholding. Pattern Recognition Letters, 1991,12:13-23