AN EDGE DETECTION ALGORITHM FOR REMOTE SENSING IMAGE

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ABSTRACT:

An edge detection algorithm for multispectral remote sensing image is proposed in this paper. According to the uncertainty of the objects in the RS image and the characters of multispectral image, we extend the one-dimensional cloud-space mapping model to the multi-dimensional model. The object-cloud will have the multi-dimensional digital characteristics to describe the fuzziness and randomicity of spatial objects. According to the cloud operation, multi-dimensional boundary-cloud and its digital characteristics can be obtained and the membership matrix of transition region for each dimension can be constructed. By maximum fuzzy entropy principle, edge detection can be accomplished in the membership matrix of transition region. Integrated the results of all dimensions by matrix superposition, the ultimate edge map can be obtained.

1. INTRODUCTION

At present, the multispectral remote sensing image is the main spatial data source and the integrated reflection of spectral and geometrical character of spatial objects. It is not only the representation of feature of chroma and brightness, but also has complex spectral features and structure features[1]. To produce a multi-dimensional image must sampling at two spatial coordinates and the spectrum of each point in optical image, so, the gray level of multispectral image is the function of two spatial variables and wavelength of multi-ray[2,3]. There is a much difference between normal image, single spectral and multispectral remote sensing image.

The edge detection of multispectral remote sensing image is the important method to obtain the remote sensing information and the base of understanding of remote sensing image. The most of current edge detection algorithms cannot get perfect effects in multispectral RS image. First, these algorithms are using for normal images disposal. As for multispectral remote sensing image, which possess the spectral features and structure features, the theory architecture of algorithm needs to be improved. Second, the common fuzzy edge detection algorithm base on fuzzy sets for solving the problems of fuzziness and non-randomicity of image. However, remote sensing image can be seen a variable of randomicity to some extend, the accuracy of detect result is affected[4]; Third, remote sensing data is very complex and mass, the efficiency of algorithm need to be improved. The paper performs a plentiful research of the theory architecture and algorithms of fuzzy edge detection based on fuzzy sets theory and cloud theory. An edge detection algorithm for multispectral RS image (MRED) is proposed based on the detailed analysis of the characters of multispectral remote sensing image.

2. THE MULTI-DIMENSIONAL CLOUD-SPACE MAPPING MODEL

The multispectral remote sensing image possesses the spectral information features and data features. There are plentiful repetitious information and redundant data between the bands, the relativity between the bands is not conducive to the statistic and analysis of multispectral image[5-8]. So, it needs to transform the image with eigenvector firstly, mostly image information can be centralized in few component and the relativity between the bands can be eliminated at the same time. This method can reduce the calculation spending, it make a sufficient preparative for the edge detection which be performed latter[9,10].

The cloud-space mapping model based on pixel level feature is proposed in literature[11]. Through this model the one-dimensional or two-dimensional cloud-space can be obtained, but the object that it acts on is not the multispectral image but the single band image. So, if you want to execute the cloud-based disposal to multispectral RS image, the multi-dimensional cloud-space mapping model should be established. The two-dimensional digital image is considered a function of gray level of two spatial variables, whereas, the multispectral image is generally considered as combination of a series of two-dimensional digital images that with compact correlation. For a RS image with m bands, the sample sets $X = \{x_1, x_2, ..., x_n\}$ is corresponding to a finite data set in m -dimensional character space R^m . Expression $x_k = f\left(t_k, c_k\right)$ expresses the multi-dimensional character value for the point NO. k , it is a multi-dimensional vector. Suppose there are m sub-space in universe of discourse, the m -dimensional normal cloud can be expressed with $3m$ digital characters, just as following:

$\left(Ex_1, En_1, He_1, Ex_2, En_2, He_2, ..., Ex_m, En_m, He_m\right)$. Expression $Ex_1, Ex_2, ..., Ex_m$ is expected value, $En_1, En_2, ..., En_m$ is entropy and $He_1, He_2, ..., He_m$ is super-entropy. The mathematical expected hyper surface-MEHS of m -dimensional normal cloud is defined as following[12]:

$$MEHS_A\left(x_1, x_2, ..., x_m\right) = \exp\left[-\frac{1}{2}\sum_{i=1}^{m}\frac{\left(x_i - Ex_i\right)^2}{En_i^2}\right] \quad (1)$$

The case discussed here expresses the m -dimensional normal cloud which irrelevant of dimensions. Whereas, it need to put forward the covariance matrix if there is compact correlation between dimensions. Express the variables and expected value in m -dimensional universe of discourse as matrix as following:

$$Z = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \qquad E = \begin{bmatrix} Ex_1 \\ Ex_2 \\ \vdots \\ Ex_m \end{bmatrix} \quad (2)$$

The mathematical expected hyper surface-MEHS of multi-dimensional correlative normal cloud is defined as following:

$$MES_A = (x_1, x_2, ..., x_m) = \exp\left[-\frac{1}{2}(Z - E)^T D^{-1}(Z - E)\right] \quad (3)$$

Because the multi-characters conversion to image has executed before the multi-dimensional cloud-space, the relativity between the bands have eliminated on the whole. So we only discuss the multi-dimensional cloud-space mapping model which irrelevant between the bands here. Suppose image C is a multispectral image which with m bands $C_1, C_2, ..., C_m$. In multi-dimensional character space, after the pretreatment and the multi-characters conversion for the image C , the relativity between the bands have eliminated, so, we can dispose the multispectral image C as m single-band images. Each sub-space correspond to a component of C after conversion that is a one-dimensional cloud-space. Because of fuzziness of cloud space object, an object can be divided to two parts, “actual part” and “fuzzy part ”. “Actual part” is the collection of inner pixels which membership of this object is 1. “Fuzzy part” is the pixel sets, which is except for “actual part” to edge, the membership of this object is less than 1 and has the rule that the farther to the object center, the smaller membership is. Obtain the ”actual part ” $R_k\left(k = 1, 2, ..., m\right)$ of object in band k through region increasing algorithm, there are N_{R_k} pixels in it. Suppose $f_k\left(i, j\right)$ is the pixel level at point $\left(i, j\right)$ in “actual part” of band k , The average gray level of “actual part” can be obtained by following function:

$$\overline{x}_{R_k} = \frac{1}{N_{R_k}}\sum_{(i,j)\in R_k} f_k\left(i, j\right) \quad (4)$$

Set the average gray level of “actual part” as expected value, then $Ex_k = \overline{x}_{R_k}$. Suppose “fuzzy part” $B_k\left(k = i, 2, ..., m\right)$ has N_{B_k} pixels in total, $f_k^{'}\left(i, j\right)$ is the gray level of pixel, set μ_k as membership of every pixel of “fuzzy part” ascribe to average gray level of “actual part”. Then

$$\mu_{ik} = 1 - \left|\frac{f_k^{/}(i, j) - \overline{x}_{R_k}}{255}\right|$$
$$(k = 1,2,...,m, i = 1,2,..., N_{B_k}) \quad (5)$$

Average gray level $\overline{x}_{B_k}$ of “fuzzy part” and standard deviation σ_{B_k} are:

$$\overline{x}_{B_k} = \frac{1}{N_{B_k}}\sum_{(i,j)\in B} f_k^{/}(i, j)$$
$$\sigma_{B_k} = \sqrt{\frac{1}{N_{B_k}}\sum_{(i,j)\in B}[f_k^{/}(i, j) - \overline{x}_{B_k}]^2} \quad (6)$$

Calculate parameter

$$En_{ik}^{'} = \sqrt{\frac{-\left(f_k^{'}\left(i, j\right) - \overline{x}_{R_k}\right)^2}{2\ln\left(\mu_{ik}\right)}}(k = 1, 2, ..., m) \quad (7)$$

Set $En_k = stdev\left(f_k^{'}\left(i, j\right)\right) = \sigma_{B_k}$,

$He_k = stdev\left(En_{ik}^{'}\right)$.

Now we have $3m$ digital characters of object cloud as $\left(Ex_1, En_1, He_1, Ex_2, En_2, He_2, ..., Ex_m, En_m, He_m\right)$, based on the parameters, cloud drops can be achieved by the X-cloud generator. The normal stochastic numbers $\left(En_{1j}^{'}, En_{2j}^{'}, ..., En_{mj}^{'}\right)$ which expected value is $\left(En_1, En_2, ..., En_m\right)$ and standard deviation is $\left(He_1, He_2, ..., He_m\right)$ can be obtained by formula8.

$$\left(En_{1j}^{'}, En_{2j}^{'}, ..., En_{mj}^{'}\right) = G\left(En_1, He_1, ..., En_m, He_m\right) \quad (8)$$

By formula9 we can calculate parameter μ_{kj} , and set $\left[f_k^{'}\left(i, j\right), \mu_{kj}\right]$ as cloud dripping.

$$\mu_{kj} = \exp\left[-\frac{\left(f_k^{'}\left(i, j\right) - Ex_k\right)^2}{2En_{kj}^{'2}}\right] \quad (9)$$

This object-cloud is the multi-dimensional cloud that integrates the information of different band, to a discretionary object, it can be expressed as following form:

$C(C_1(Ex_1, En_1, He_1), C_2(Ex_2, En_2, He_2), ...,$

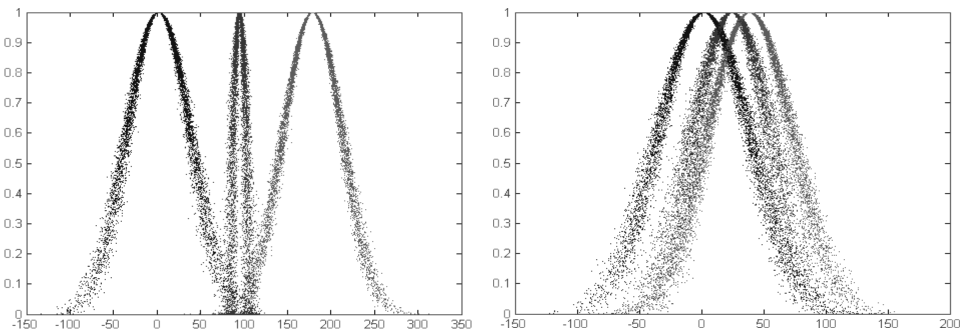
$$C_k(Ex_k, En_k, He_k))k = 1,2,...,m \qquad (10)$$

In this expression, $C_k\left(Ex_k, En_k, He_k\right)$ are three digital characters of object-cloud, which procreated in band k. So, the each dimension of multi-dimensional cloud can form a one-dimensional cloud-space by one-dimensional cloud-space mapping model.

3. Extraction of multi-dimensional edge cloud and transitional region

3.1 Extraction of multi-dimensional edge cloud

The object in image turn into multi-dimensional cloud in cloud-space though mapping model, the contiguous cloud present a intersectant state because of the uncertainty of edge pixel and influence of super-entropy[11].The edge cloud is an especial cloud which expected value is the average gray level of edge pixels, the membership of cloud drops to this cloud is the degree of every pixel of transitional region close to this average gray level. Figure1 shows two edge clouds with different digital characters.



a) Ex = 95, En = 7.3, He = 5.3 b) Ex = 24.6, En = 30.7, He = 5.3

Figure1 Edge cloud with different digital characters

The method to extract the one-dimensional edge cloud is discussed in literature[11]. Because multispectral image corresponding to a multi-dimensional space, so, the extraction of the edge cloud in multi-dimensional space must be performed in every sub-space. Suppose a multispectral image with m bands, a multi-dimensional cloud-space R^m is created though the mapping model. Two contiguous objects in image space are corresponding to two multi-dimensional clouds $A[Ex_{A1}, En_{A1}, He_{A1}, Ex_{A2}, En_{A2}, He_{A2}, ..., Ex_{Am}, En_{Am}, He_{Am}]$ and $B[Ex_{B1}, En_{B1}, He_{B1}, Ex_{B2}, En_{B2}, He_{B2}, ..., Ex_{Bm}, En_{Bm}, He_{Bm}]$. The Boolean calculation between object-cloud with corresponding dimensional in A and B can be implemented.

$$\left.\begin{aligned} Ex_{Ck} &\cong \frac{1}{2}\left|(Ex_{Ak} - 3En_{Ak} - He_{Ak}) + (Ex_{Bk} + 3En_{Bk} + He_{Bk})\right| \\ En_{Ck} &\cong \frac{1}{6}\left|(Ex_{Bk} + 3En_{Bk} + He_{Bk}) - (Ex_{Ak} - 3En_{Ak} - He_{Ak})\right| \\ He_{Ck} &= \max(He_{Ak}, He_{Bk}) \end{aligned}\right\}\left(k = 1,2,...,m\right) \qquad (11)$$

In this expression, Ex_{Ck} 、 En_{Ck} and He_{Ck} are the digital characters of edge cloud in dimension k.

The edge cloud of left and right intersectant clouds can be obtained through above algorithm. First, the expected values are achieved by its adjacent region calculation. So, the relativity of these pixels of image has been considered completely. Second, the calculate process is a smooth process similarly, so, the influence of noise is weakened to some extent. Third, the entropy and hyper entropy is obtained by calculation, the relationship with the entropy value and hyper entropy of left and right object cloud is close. And it represents the influence of random elements of image to the edge cloud expectation and standard deviation. So, logical range of transitional region can be deduced by the result.

3.2 Extraction algorithm of edge transitional region

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 the objective gray level value and background gray level value [13]. So, transition region is expressed a region which is covered by some cloud drops except for cloud core of intersectant cloud. Suppose A and B are adjacent objects in image I, 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 by mapping mode. By formula11 edge cloud $C(L_C(i,j), Ex_C, En_C, He_C)$ and three digital characters 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

$$a = Ex_C - 3\sigma - He_C = Ex_C - 3En_C - He_C$$
$$b = Ex_C + 3\sigma + He_C = Ex_C + 3En_C + He_C \quad (12)$$

Transitional region is defined as the two-dimensional pixels sets that covered by edge cloud. That is

$$TR = \{(i,j)\in I \mid a \le f(i,j) \le b \mid\} = \{(i,j)\in I \mid Ex_c - 3En_c - He_c \le f(i,j) \le Ex_c + 3En_c + He_c \mid\} \quad (13)$$

This algorithm has some advantage compared to traditional algorithm. First, the algorithm obtains the digital characteristics of edge cloud and two threshold of transition region by Boolean calculation between intersectant clouds, so, the situation of low extremum is bigger than high extremum can be prevented. Second, the algorithm doesn't refer complex algebraic operation, it is simple, fast and operating cost is small. The last, algorithm according to the image gray level forms object cloud, replace microcosmic pixel to macroscopical cloud object, In the process of cloud building , the operation which is similar to smooth algorithm can weaken the influence of noise to extracted result.

4. THE EDGE DETECTION IN TRANSITIONAL REGION.

4.1 Stochastic fuzzy feature plane and its characteristics

A two-dimensional image can be seen as a fuzzy matrix. Every element of matrix has has the membership function μ_{ij} which relative to a given gray level. The plane which formed with All $\mu_{ij}\left(i=1,2,...,M;\ j=1,2,...,N\right)$ is named image fuzzy feature plane[14], it is the base of fuzzy edge detection algorithm. In this feature plane, each pixel is corresponding to an element in matrix, the randomicity of image is not considered. This method cannot solve the problem of uncertainty of spatial object by representing adjacent degree of a fuzzy object to another object by an exact membership.

For the membership of every element to cloud core of edge cloud in transitional region changed from one to multi under the influence of super entropy, so, the corresponding element in fuzzy matrix to any pixel in transitional region is not a value but a sets of membership, the stochastic fuzzy feature plane is proposed. The three digital characters (Ex_C, En_C, He_C) of edge cloud can be obtained by calculation and the membership of each pixel can be retro-inferred by the algorithm of normal cloud generator[12]. Assume $f\left(x\right)$ is pixel gray level in transitional region, according to the mode $En_k^{'} = G\left(En_C, He_C\right)$ to build the normal stochastic data $En_k^{'}$ which expected value is En_C and standard deviation is $En_k^{'}$. The membership of each pixel can be calculated by formula14.

$$\mu_k = \exp\left[-\frac{\left(f\left(x\right)-Ex_C\right)^2}{2En_k^{'2}}\right] \quad (14)$$

Where Ex_C, En_C, He_C denote three digital characteristics of edge cloud.

By the above calculation, we can get $\mu_{ij}\left(x\right)=\left\{\mu_k\right\}$, so, fuzzy feature plane can be expressed with following forms:

$$X_{ij} = \begin{bmatrix} \{\mu_k\}_{11} & \{\mu_k\}_{12} & \cdots & \{\mu_k\}_{1N} \\ \{\mu_k\}_{21} & \{\mu_k\}_{22} & \cdots & \{\mu_k\}_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \{\mu_k\}_{M1} & \{\mu_k\}_{M2} & \cdots & \{\mu_k\}_{MN} \end{bmatrix} \begin{pmatrix} i=1,2,...,N; \\ j=1,2,...,M; k=1,2,... \end{pmatrix} \quad (15)$$

Every element in stochastic fuzzy feature plane is a aggregate of membership, it indicates that under the influence of uncertainty of spatial object, the membership of each pixel belong to another object is not a exact value but a probability distribution.

4.2 Edge detection based on maximal fuzzy entropy

The gradient image G can be obtained by the gradient operating in transition region image I that with L gray level, its histogram is $h_r, r=1,2,...,L-1$. Suppose G is divided to strong edge region $\tilde{R}e$ and transitional region $\tilde{R}s$, set $\left\{\mu_k\right\}, k=1,2,...,n$ is the probability of each pixel of G to divided to $\tilde{R}e$, $1-\left\{\mu_k\right\}$ is the probability of each pixel to divided to $\tilde{R}s$. Build fuzzy partition aggregate $Q_i = \left\{g(i,j)=r\right\}, r=0,1,...,L-1$, $g(i,j)$ is the gray value in $\left(i,j\right)$ of gradient image G. Apparently, $Q=\left\{Q_0,Q_2,...,Q_{L-1}\right\}$ is a fuzzy division of G. Though the condition entropy of fuzzy division, the condition entropy of natural fuzzy division Q under $\tilde{R}e$ is

$$H\left(Q\middle|\tilde{R}e\right) = -\sum_{r=0}^{L-1}\frac{p\left(Q_r\tilde{R}e\right)}{p\left(\tilde{R}e\right)}\log\frac{p\left(Q_r\tilde{R}e\right)}{p\left(\tilde{R}e\right)} = -\sum_{r=0}^{L-1}\frac{\mu_k h_r}{p\left(\tilde{R}e\right)}\log\frac{\mu_k h_r}{p\left(\tilde{R}e\right)} \quad (16)$$

$$p\left(\tilde{R}e\right)=\sum_{r=0}^{L-1}\mu_k h_r$$

Similarly, the condition entropy of natural fuzzy division Q under $\tilde{R}s$ is

$$H\left(Q\middle|\tilde{R}s\right)=-\sum_{r=0}^{L-1}\frac{p\left(Q_r\tilde{R}s\right)}{p\left(\tilde{R}s\right)}\log\frac{p\left(Q_r\tilde{R}s\right)}{p\left(\tilde{R}s\right)}=-\sum_{r=0}^{L-1}\frac{\left(1-\mu_k\right)h_r}{p\left(\tilde{R}s\right)}\log\frac{\left(1-\mu_k\right)h_r}{p\left(\tilde{R}s\right)} \tag{17}$$

$$p\left(\tilde{R}s\right)=\sum_{r=0}^{L-1}\left(1-\mu_k\right)h_r$$

The entropy of fuzzy division P can be obtained by formula18

$$\begin{aligned}H\left(P\right)&=H\left(Q\middle|\tilde{R}e\right)+H\left(Q\middle|\tilde{R}s\right)\\&\approx-\sum_{r=0}^{L-1}\left[\frac{\mu_k h_r}{p\left(\tilde{R}e\right)}\log\frac{\mu_k h_r}{p\left(\tilde{R}e\right)}+\frac{\left(1-\mu_k\right)h_r}{p\left(\tilde{R}s\right)}\log\frac{\left(1-\mu_k\right)h_r}{p\left(\tilde{R}s\right)}\right]\end{aligned} \tag{18}$$

According to the max fuzzy entropy theory[15], for obtain the best expression of edge curves of gradient images, need to find the best membership μ_k. The maximal fuzzy entropy principle must satisfy the following condition:

$$H\left(\mu_k\right)=\max_{r=0,1,2,\ldots,L-1}\left[H\left(\mu_k\right)\right] \tag{19}$$

Set the best membership is $\tilde{\mu}$, then, the best fuzzy feature plane $\tilde{X}_{ij}$ can be obtained by formula20.

$$\tilde{X}_{ij}=\begin{bmatrix}\tilde{\mu}_{11} & \tilde{\mu}_{12} & \cdots & \tilde{\mu}_{1N}\\ \tilde{\mu}_{21} & \tilde{\mu}_{22} & \cdots & \tilde{\mu}_{2N}\\ \vdots & \vdots & \vdots & \vdots\\ \tilde{\mu}_{M1} & \tilde{\mu}_{M2} & \cdots & \tilde{\mu}_{MN}\end{bmatrix}\left(i=1,2,\ldots,N;\ j=1,2,\ldots,M\right) \tag{20}$$

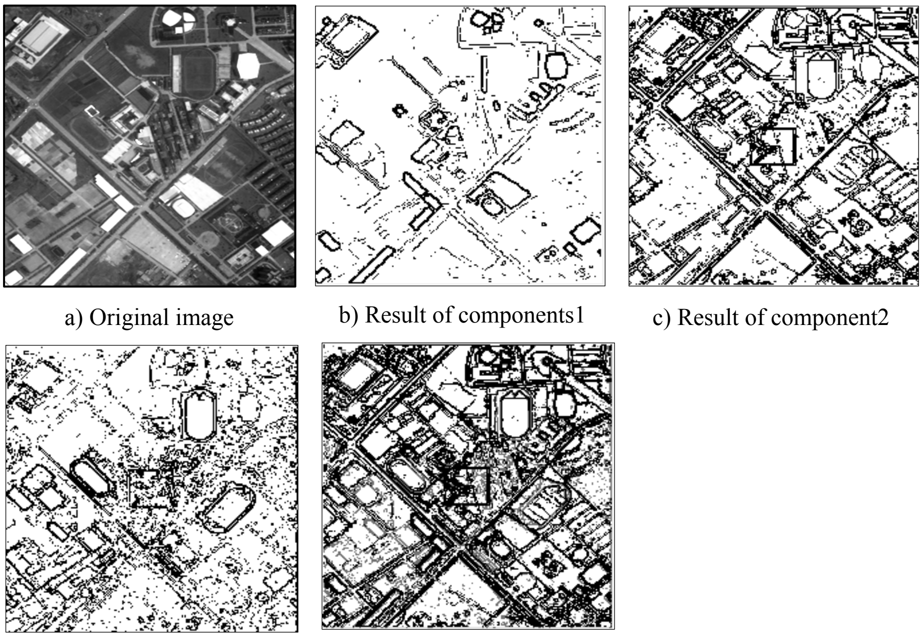
Set $\tilde{\mu}$ is the probability of each pixel divided to $\tilde{R}e$, $1-\tilde{\mu}$ is the probability of each pixel divided to $\tilde{R}s$. Calculate the entropy H of fuzzy division by formula16 to20. The best membership $\tilde{\mu}'$ can be obtained if $H\geq H_{\max}$, then, $H_{\max}=H$ and set $T=\tilde{\mu}'$ as the divided threshold.

4.3 Integration for edge maps of all dimensions

Different spatial object has different radiant capability, even a same object in different spectrum the radiant capability is possibly different. These differences lead to the number of the cloud in cloud-space corresponding to different bands unequally, so, the detailed degree of edge map that obtained by edge cloud is discordantly. For using the information of multispectral remote sensing image adequately, we need to integrate the different edge map of all components to obtain the edge information of spatial object in multispectral RS image.

The method of matrix superposition is used to integrate the edge information of all components. Suppose there are m component of multispectral RS image after the eigenvector transform, the result of edge detection of each component is expressed as $I_{Ek},\left(k=1,2,\ldots,m\right)$, element 1 in matrix is the edge and 0 is the background. Set the edge matrix of a certain component as the bottom matrix, add up the result of edge extract of each component pixel by pixel, if the accumulative total of a element is bigger than 1 or equal to 1, then set the value of this matrix element is 1, whereas is 0. To search the image thoroughly until every pixel is disposed. The method can preserving the map information in farthest, the probability of missing detect can be weakened.

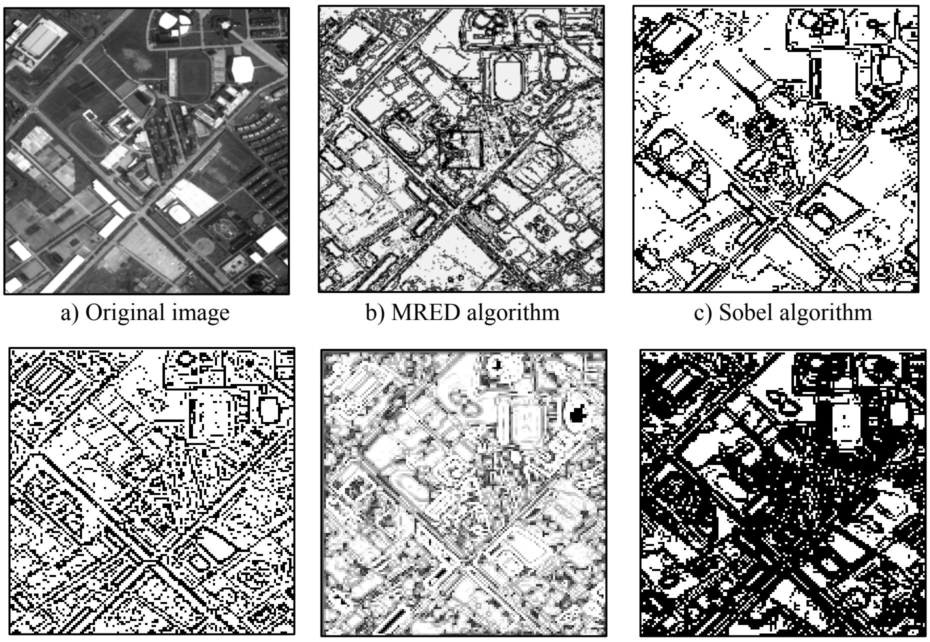
Execute edge detection for components1-3 of multispectral image respectively, the edge image can be obtained by integrate the edge information of all component, the result as figure2:



a) Original image b) Result of components1 c) Result of component2

d) Result of component3 e) Result of integration

Figure2 Edge detection result of each component and the integration result



a) Original image b) MRED algorithm c) Sobel algorithm

d) Pal.King algorithm e) FGED algorithm f) WFCE algorithm

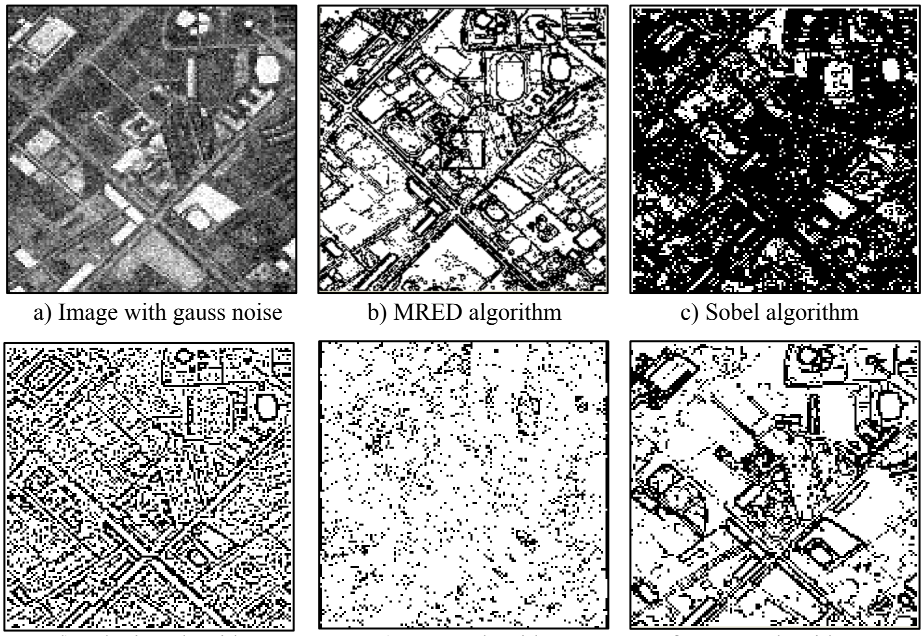
Figure3 Contrastive test of five algorithms

5. EXPERIMENTAL RESULTS OF ALGORITHM

The MRED algorithm we develop is demonstrated by applying it to some images. Multispectral RS image is selected for experiment. Fig.3.a is original image, and Fig.3.b,c,d,e,f is the edge detection result of MRED algorithm, Sobel algorithm, Pal. King algorithm, fuzzy gradient edge detection algorithm (FGED) and wavelets multi-scale fuzzy competitive edge detection algorithm (WFCE).

It can be found that in multispectral image detection, MRED algorithm have a good effect, the missing detect of Sobel algorithm is frequently. WFCE algorithm appears over detection phenomenon, the edge of object is cannot distinguished clearly. The detect result of FGED algorithm is badly and the effect of Pal.King algorithm is affected by noise obviously.

Figure4a is the image which added 10% gauss noise, the contrastive detection result with five algorithms in different noise conditions show in figure4.



a) Image with gauss noise　b) MRED algorithm　c) Sobel algorithm

d) Pal.King algorithm　e) FGED algorithm　f) WFCE algorithm

Figure4 Contrastive test of five algorithms in 10% gauss noise

Compare the detect result, we find that the MRFD algorithm have an obviously relatively superiority of antinoise capability in edge detection of multispectral image.

An edge detection algorithm for multispectral RS image (MRED) is proposed based on the detailed analysis of the characters of multispectral image. Through the multi-dimensional cloud-space mapping model the objects in image can be mapped to the cloud-space, the fuzzy feature matrix that covered by multi-dimensional edge cloud is extracted by Boolean calculation between intersectant clouds. Calculating image fuzzy division entropy by fuzzy feature matrix of each sub-cloud space, bring stochastic influence of image into solution of entropy and use fuzzy division entropy repeatedly to find the best result in membership. The edge map with preferable precision can be obtain by integrate the detect result of every sub-cloud space. MRED algorithm considering fuzzy features of remote sensing image and discussing the connatural stochastic of image at the same time, the contrastive test is proved that this algorithm is more effective than contrastive algorithm on detection quality and antinoise.

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