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Remote Sensing Image Enhancement Based on Relative Entropy and Fuzzy Algorithm

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Abstract: An improved maximum between-cluster variance (OTSU) algorithm was proposed to obtain the threshold adaptively in order to overcome the disadvantages of traditional Pal-King algorithm. The algorithm is able to globally enhance the remote sensing images but, for the relevance of neighboring pixel information is not taken into account in the improved algorithm, the visual effect of low contrast images is also not so good. The algorithm in this study can be used to realize the self-adaptive contrast enhancement when the relative entropy is regarded as a criterion. In order to test the enhancement effect of the proposed algorithm for remote sensing image, we choose 50 remote sensing images for test. Experimental results show that a good visual effect is obtained and the clarity, standard deviation has been improved greatly. Therefore, the algorithm is thought to be an effective ways to get better visual effects and more obvious detailed information.

Key words: Remote sensing image, fuzzy enhancement, OTSU algorithm, relative entropy

INTRODUCTION

Remote sensing image is always affected by various factors inevitably during the imaging process which will result in adverse visual, low resolution and brightness deficiencies, so that the gray of remote sensing image cannot cover the range of sensors achieved. Therefore, remote sensing image enhancement technology plays an active role in improving image contrast, highlighting some local details and other aspects. Because of the complexity of the image, uncertainty and imprecision issues may be possibly caused. Many scholars committed to apply the fuzzy theory into image processing. An image edge fuzzy enhancement algorithm proposed by Pal and King got a good application in image processing (Pal and King, 1983). However, the algorithm exists many shortcomings, such as more mistakenly enhanced, long time consuming and large difference when dealing with different images. In response to these shortcomings, some improved algorithm based on fuzzy membership function is proposed and a certain good effect is achieved (Shiwei *et al*., 2010; Zhang *et al*., 2010). Aimed at determining the threshold of fuzzy algorithm, literature (Alharbi *et al*., 2012) has compared five fuzzy threshold selection methods. Currently, fuzzy algorithm has been successfully applied to the image contrast enhancement, image edge detection, medical image enhancement, color image enhancement and other fields and achieved good results (Nair *et al*., 2011; Verma *et al*., 2013; Chaira, 2012; Khunteta and Ribhu, 2012). Meanwhile, fuzzy algorithm combined with a wavelet algorithm or the NSCT algorithm were used for image enhancement (Khehra and Pharwaha, 2012; Du *et al*., 2012; Men *et al*., 2010). Because the relevance of neighboring pixel information is not taken into account in the improved algorithm, the enhancement effect in details is limited.

In this study, an improved maximum between-cluster variance (OTSU) algorithm to obtain the threshold adaptively is proposed to make the fuzzy algorithm more reasonable. Meanwhile, we combine fuzzy algorithm with the relative entropy algorithm for the first time and propose an adaptive image locally enhancement method which is pixel-based epsilon neighborhood information. The method is based on relative entropy criteria. Thus the detailed information after image enhancement will be identified more clearly (Deng, 2009). Experimental results show that the algorithm can get a good visual effect and obtain more obvious details.

THE IMPROVED FUZZY ALGORITHM

The traditional fuzzy algorithm: In traditional fuzzy algorithms, the fuzzy membership function used by Pal and King as follows:

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$$\mu_{mn} = \psi(x_{mn}) = \left[1 + \frac{x_{max} - x_{mn}}{F_d}\right]^{-Fe} \quad (1)$$

where, x_{max} is the maximum gradation value of the image X, x_{mn} is the gradation value of pixel of the point (m, n), F_d is reciprocal fuzzy factor, F_e is exponential fuzzy factor, normally, $F_e = 2$.

Using Fuzzy enhancement for μ_{mn}, nonlinear transformation enhanced function defined by Pal-King is:

$$\mu'_{mn} = \begin{cases} 2\mu^2_{mn} & 0 \le \mu_{mn} \le 0.5 \\ 1 - 2(1 - \mu_{mn})^2 & 0.5 < \mu_{mn} \le 1 \end{cases} \quad (2)$$

And the inverse transform is defined as follows:

$$X'_{mn} = \psi^{-1}(\mu'_{mn}) \quad (3)$$

Obtained by Eq. 2, the threshold value is unreasonable to set to 0.5, selecting the appropriate threshold is very important which will directly affect the final enhancement effect. Therefore, we get the threshold adaptively by an improved OTSU algorithm.

The improved OTSU algorithm: The basic idea of OTSU algorithm is divide the image pixel into two categories C1 and C2 with threshold T according to the gray value, C1 is composed of pixels of the gray value in [0, T], C2 is composed of pixels of the gray value in [T+1, L-1], the class variable between C1 and C2 is calculated as follows:

$$O(t)^2 = W_1(t)W_2(t)[U_1(t)-U_2(t)]^2 \quad (4)$$

where, $W_1(t)$ is the number of pixels contained in C1, $W_2(t)$ is the number of pixels contained in C2, $U_1(t)$ is the average gray value of all pixels in C1, $U_2(t)$ is the average gray value of all pixels in C2. T is the value obtained in [0, L-1] sequentially, the optimal threshold value of OTSU is the T value which makes the between-class variance largest.

OTSU algorithm will appear a phenomenon that the membership required to 0 for not very different pixel-level image, losing a lot of gray information. To solve this problem, the OTSU algorithm is improved as follows:

$$P(t) = W_1(t)W_2(t)|U_1(t)-U_2(t)| \quad (5)$$

The value of T that makes P(t) to maximum is the optimal threshold improved in this study.

CONTRAST ENHANCEMENT BASED ON RELATIVE ENTROPY OF NEIGHBORHOOD INFORMATION

In the logarithmic image processing model for image enhancement, the relative entropy is used to determine the detail information of the image, the larger relative entropy of the image pixel is usually in the edges or the texture region of the image and smaller relative entropy of the image pixels is generally in the smoother areas. The LIP enhancement algorithm is performed for larger relative entropy of the image pixel in Literature (Deng, 2009), making the details of the image enhanced. However, this enhancement algorithm does not take the pixel neighborhood information into account adequate but enhance the individual pixels which is at the cost of good noise immunity and enhancements to details.

Therefore, this article uses the results of the fuzzy enhancement and adopt relative entropy-based neighborhood information to enhance the contrast.

A model of probability P is defined in the fuzzy enhanced image, in the model, the pixel entropy about x_n is defined as:

$$I_P(x_n) = -\log p_n = -\log\frac{x_n}{S} \quad (6)$$

where, S is obtained by Eq. 7:

$$S = \sum_{n=0}^{N-1} x_n \quad (7)$$

Then a pixel uniformly distributed probability model Q is defined, in the model, qn=1/N. The relative entropy definition is generated by comparing the model P and Q:

$$D(Q,P) = \sum_{n=0}^{N-1} q_n \log\frac{q_n}{p_n} = \frac{1}{N}\sum_{n=0}^{N-1}(\log A - \log x_n) = \log\frac{A}{G} \quad (8)$$

$$G = \exp\left[\frac{1}{N}\sum_{n=0}^{N-1}\log x_n\right] \quad (9)$$

where, A = (S/N) is the arithmetic mean, G is the geometric mean which is obtained by the Eq. 9.

Analysis from the Eq. 6, the smaller the relative entropy D(Q, P) is, the closer the two distributions will be. Since, the model Q is uniformly distributed, the distribution of the model P is closer to uniformly distributed and the pixels in the model P belongs to the smooth areas of the image. In contrast, the relative entropy D (Q, P) bigger means the two distributions differ greater, the pixels in the model P belongs to the edge or the texture region of the image.

In order to extract and enhance the pixel with large relative entropy, we use a negative image of the original image (which is obtained from x1 [x, y] = M-x[x, y], M is the maximum gradation value of the original image). Assumed the relative entropy of pixel of the point [x, y] in the image expressed in d0 (x, y), the pixel relative entropy of the negative image expressed in d1 (x, y), defined d (x, y) = d0 (x, y)×d1 (x, y), so that we can set a threshold on d (x, y) to enhance the image. Since, d0 is too sensitive in the noise image, d is choosed as a criterion to improve the noise immunity of the algorithm.

Algorithm implements steps:

- Normalized the image I after fuzzy enhanced
- Then expanding the boundaries of the image after fuzzy enhanced. In the experiment, we select a 3×3 window, extending up, down, right and left of the image to get Y
- Calculated each pixel relative entropy d0(x, y) of the image and relative entropy d1(x, y) of the negative image, respectively, then get d(x, y)
- Using Gaussian kernel function F (x, y) convolution with the image I to obtain neighborhood information for each pixel, obtained from the Eq. 10:

$$I_{conv}(x,\ y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(m,\ n)F(m+x, n+y) \tag{10}$$

$$F(x, y) = K\exp\left(-\frac{(x+y)^2}{c^2}\right) \tag{11}$$

$$K = \iint F(x, y)dxdy \tag{12}$$

In the Eq. 11, c is a constant, here take c = 1, K is obtained from the Eq. 12:

- Set the threshold tk, namely: d(x, y) = tk
- Enhance transformation of adaptive image (Asari *et al*., 2006). Transform the extracted pixel I (x, y) to the enhanced pixel S (x, y) by the Eq. 13:

$$S(x,\ y) = \begin{cases} 255\times I_{n,\,enh}(x,\ y)^{E(x,y)} & d(x, y) \geq t_k \\ I(x,\ y) & d(x, y) < t_k \end{cases} \tag{13}$$

$$I_{n,enh} = \frac{\ln(1+\mu In)}{\ln(1+\mu)} \tag{14}$$

$$E(x, y) = \left(\frac{I_{conv}(x, y)}{I(x, y)}\right)^P \tag{15}$$

$$P = \begin{cases} 2 & \sigma \leq 30 \\ -0.03\sigma + 29 & 30 < \sigma \leq 80 \\ 1/2 & \sigma > 80 \end{cases} \tag{16}$$

where, in, enh is a logarithmically nonlinear enhancement function in (LIP) algorithm, μ is the set parameters, the degree of contrast enhancement varies with its value. E(x,y) is obtained by the formula (15), the value of P is determined by the variance of the gray image by the Eq. 16.

EXPERIMENTAL RESULTS AND ANALYSIS

In order to test the enhancement effect of the proposed algorithm for remote sensing image, we choose 50 remote sensing images with 256 grayscale for study. In the experiment, we compare the proposed algorithm with an improved fuzzy algorithm which is based on wavelet transform and fuzzy theory and NSCT transform fuzzy theory. The NSCT transform include three decomposition layers and the corresponding direction is the numbers 4, 8, 16, respectively.

In order to evaluate the remote sensing image enhancement effect of proposed algorithm, we give enhanced images about the improved fuzzy algorithm which is based on wavelet transform and fuzzy theory and NSCT transform fuzzy theory, as shown in Fig. (1-5). It can be seen that the improved fuzzy enhancement algorithm has been greatly enhanced in brightness to the original image but the effect of details enhancement is not obvious because of a global fuzzy processing. The enhancement method based on the wavelet transform and fuzzy theory appeared a pseudo-Gibbs phenomenon. We find that it did not have pseudo-Gibbs phenomenon in the algorithm based on NSCT transform and fuzzy theory and the visual effect is also not so good.

Fig. 1: Original

Fig. 2: Fuzzy enhanced

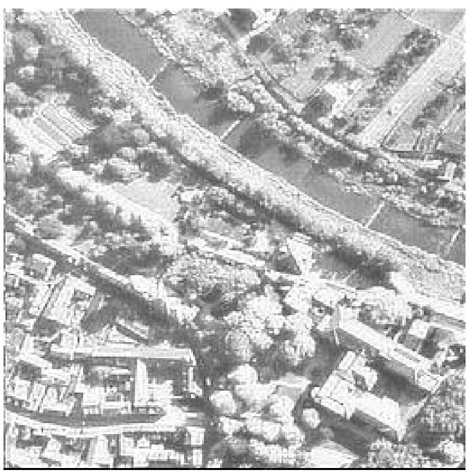

Fig. 3: Fuzzy wavelet

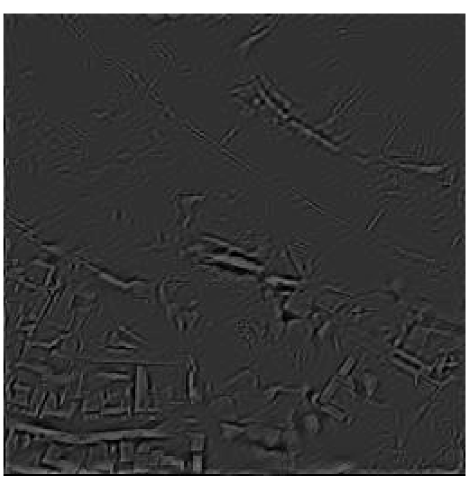

Fig. 4: Fuzzy NSCT

Fig. 5: Proposed

Table 1: Indicators of different enhanced methods

	Fig. 2	Fig. 3	Fig. 4	Fig. 5
Clarity	17.89	24.27	14.55	26.01
Entropy	6.30	6.24	5.78	6.17
Standard deviation	45.43	37.56	20.52	52.75
Contrast	0.12	0.13	0.24	0.18
Time(s)	2.04	5.86	1844.30	11.18

Then, we choose four kinds of objective evaluation indicators clarity, information entropy, standard deviation, contrast to evaluate the enhanced image.

In Table 1 we gave some information from fifty images about clarity, information entropy, standard deviation, contrast and algorithm running time based on different models including wavelet transform and fuzzy algorithm, the NSCT transform algorithm, fuzzy theory and the proposed enhanced algorithm.

It can be seen from the data in Table 1, keeping the image information entropy change small, the image clarity and standard deviation of the proposed algorithm perform much better than other algorithms. The contrast of the images used by the proposed algorithm is inferior to NSCT algorithm but the efficiency of the proposed algorithm is far superior to NSCT algorithm. So, we believe that a better objective evaluation index can be achieved in the proposed algorithms.

It is found that the proposed algorithm can offer us better visual effects and sharpness as well as more information significantly than other algorithms by the comparison of subjective visual effects and objective indicators.

CONCLUSION

Given the drawbacks existed in remote sensing images, such as overall brightness dim, low contrast, the inconspicuous distinction between target and background, the fuzzy enhancement algorithm is adopted to enhance the remote sensing image. As it is difficult to get the threshold for the traditional Pal-King algorithm, an improved OTSU algorithm is proposed to obtain the adaptive threshold. Meanwhile, since the fuzzy enhancement is a global fuzzy processing and the enhanced effect of details is not obvious, we use the relative entropy as a criterion for the first time to get the adaptive contrast of the neighborhood information enhanced. The algorithm maintains the brightness of the original image and enhance the image details at the same time. Experiments show that the algorithm can achieve good visual effects and get more obvious details.

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