Hindawi Publishing Corporation
Journal of Sensors
Volume 2015, Article ID 327123, 8 pages
http://dx.doi.org/10.1155/2015/327123

Research Article

Automatic Change Detection Method of Multitemporal Remote Sensing Images Based on 2D-Otsu Algorithm Improved by Firefly Algorithm

Liang Huang,[1] Yuanmin Fang,[1] Xiaoqing Zuo,[1] and Xueqin Yu[2]

[1]*Faculty of Land Resource Engineering, Kunming University of Science and Technology, Kunming 650093, China*
[2]*Kunming Surveying and Mapping Institute, Kunming 650051, China*

Correspondence should be addressed to Liang Huang; kmhuangliang@163.com

Received 30 October 2014; Accepted 3 February 2015

Academic Editor: Xue Cheng Tai

This paper presents a new automatic change detection method of multitemporal remote sensing images based on 2D-Otsu algorithm improved by Firefly algorithm. The proposed method is designed to automatically extract the changing area between two temporal remote sensing images. First, two different temporal remote sensing images were acquired through difference value method of remote sensing images; then, the 2D-Otsu threshold segmentation principles are analyzed and the optimal threshold of 2D-Otsu threshold segmentation method is figured out by using the Firefly algorithm, where the difference images are conducted with binary classification to obtain the changing category and the nonchanging category; finally, the proposed method is used to carry out change detection experiments on the two selected areas, where a variety of methods are compared. Experimental results show that the proposed method can effectively and quickly extract the changing area between the two temporal remote sensing images; thus, it is an effective method of change detection for remote sensing images.

1. Introduction

With the development of society and technology, human activities are changing the landscape of ground surface and its utilization mode every day. The rapid population growth and frequent natural disasters have also accelerated the speed of such changes. Therefore, quickly and effectively monitoring the information of such changes and analyzing the characteristics, causes, impacts and results of the changes have great significance to the global sustainable development [1]. Emergence and development of remote sensing technology have provided technical support for quickly and effectively monitoring the information of these changes. Detection of remote sensing image changes aims to acquire the changing information of desired surface features by analyzing and processing two or multiple remote sensing images of the same area at different times [2, 3]. Currently, the change detection technology of remote sensing image has been widely used in many fields, such as disaster assessment [4], land use/coverage monitoring [5], environmental change monitoring [6], agricultural survey [7], and urban planning [8].

Currently, a number of methods have been proposed for the change detection of remote sensing image. At present, change detection mainly includes two strategies: direct comparison and postclassification comparison, of which the postclassification comparison strategy is an approach to classifying (supervised or unsupervised method) different temporal images of the same area to compare and analyze the classified results in order to obtain the location and type of changing information. The advantage of this strategy is to minimize the impact of nonfeature change factors, but the change detection accuracy through this strategy is substantially equal to the product of the two classification accuracy values, and the classification error of each temporal classification result will be amplified in the process of comparison, thus inevitably exaggerating the extent of changes. Meanwhile, it is often more complex and difficult to get high-accuracy

classification results, resulting in low-accuracy and uncertain change detection results [9]. Therefore, the strategy of direct comparison has always been highlighted in researches on change detection. Direct comparison is a strategy to obtain difference images by directly operating and alternating the pixel values of different temporal remote sensing images of the same area that have been calibrated so as to figure out the changing area by analyzing the difference images. In analyzing these difference images, it would be the most simple thing to directly use one-dimensional threshold processing methods, but the processing accuracy of threshold is not high [10, 11]. In order to improve the processing accuracy of threshold, many scholars have proposed to extend the one-dimensional threshold selection method to two dimensions (2D). Currently, a number of two-dimensional threshold selection methods have been raised, such as 2D entropy (2D maximum entropy, 2D minimum cross entropy) [12], 2D-Otsu [13], and 2D maximum fuzzy entropy [14], but it is still difficult to select the threshold values of the two-dimensional histogram, for which unremitting exploration efforts have been made by many scholars. To solve this problem, many scholars attempt to achieve fast optimization for the 2D threshold by combining 2D threshold segmentation method and optimization algorithm. Shen et al. [15], Zheng et al. [16], and Alim et al. [17] sought to figure out the optimal threshold of 2D maximum entropy, respectively, through genetic algorithm, ant colony algorithm, PSO (Particle Swarm Optimization) algorithm, and ABCO (Artificial Bee Colony Optimization). Qian used PSO algorithm to find the optimal threshold of 2D-Otsu [18]. Tian and Zeng used QPSO (Quantum-behaved Particle Swam Optimization) algorithm to carry out image threshold segmentation in combination with 2D maximum fuzzy entropy [19]. The applications of PSO algorithm, QPSO algorithm, bee colony algorithm, ant colony algorithm, and genetic algorithm have improved the speed of figuring out thresholds, but the optimization results may be inaccurate as these algorithms are prone to falling into local extremum.

The Firefly algorithm [20] is a global optimization algorithm proposed by Yang, which can overcome the problem of easily falling into local optimum. Chen et al. [21] and Alomoush et al. [22], respectively, applied the Firefly algorithm to find optimal threshold and then used for image segmentation and achieved good segmentation results. Given the fast global search capability of the Firefly algorithm and the good segmentation result of 2D-Otsu threshold segmentation method, this paper segments the thresholds of difference images by combing the Firefly algorithm and 2D-Otsu threshold method to obtain the binary change detection map.

2. Architecture of the Proposed Method and Problem Formulation

Assume $T_1 = \{T_1(i, j), 1 \le i \le M, 1 \le j \le N\}$ and $T_2 = \{T_2(i, j), 1 \le i \le M, 1 \le j \le N\}$ are the remote sensing images of the same area at different times t_1 and t_2 that underwent standard product preprocessing and coregistration; the remote sensing image sizes are $M \times N$. The ultimate aim of the proposed method is to generate the binary change map. The proposed method consists of three steps: (1) construction of difference image; (2) threshold optimization based on Firefly algorithm; and (3) generation of final binary change map.

First, it is construction of difference images. Currently, there are two methods, namely, image algebraic operation and image transformation, to construct difference images. The method based on image algebraic operation includes difference method, ratio method, and the combination of difference method and ratio method; the method based on image transformation includes principal component analysis, change vector analysis and correlation analysis. Since the image algebraic operation method requires simple algorithm but can obtain high accuracy, this paper applied the image difference method of the image algebraic operation, which can be expressed below:

$$\mathrm{DI}(x, y) = T_1(i, j) - T_2(i, j), \tag{1}$$

where $\mathrm{DI}(x, y)$ is the difference image constructed.

Second, it is optimization of Firefly threshold. After acquiring the difference images, the difference images need to be analyzed so as to obtain the binary change map. Binary classification through threshold segmentation is one of the most frequently used methods. Selecting thresholds via one-dimensional histogram is the easiest method, of which the main method is OTSU algorithm. However, as OTSU algorithm does not use local spatial data of the image, the segmentation will be ineffective when the image is subject to noise disturbance or gray scale distribution intersection. Therefore, many scholars have expanded it to two-dimensional approach, and better segmentation results have been achieved [23]. To this end, this paper used the 2D-Otsu algorithm to analyze difference images acquired. However, compared with the thresholds selected in one-dimensional histogram, 2D-Otsu algorithm requires a large amount and a long time of computation. To solve the above problem, the Firefly algorithm is introduced to optimize the threshold of 2D-Otsu algorithm.

Third, it is generation of the final binary change map. After figuring out the optimal threshold of 2D-Otsu algorithm, threshold segmentation is given to difference images to obtain the binary change detection map of the two temporal remote sensing images.

3. Change Detection Based on 2D-Otsu Algorithm Improved by Firefly Algorithm

3.1. 2D-Otsu Threshold Segmentation Method. The size of the difference image $\mathrm{DI}(x, y)$ is $M \times N$, where $1 \le x \le M$, $1 \le y \le N$, the gray scale of the image is L, and the average gray-scale of pixel neighborhood is also divided into L level. A binary group is obtained by calculating the average gray scale of its neighborhood at each pixel point, that is, the gray-scale value of the pixel point and the average gray-scale value of its neighborhood. Assume the probability of the binary group

(i, j) is f_{ij}; the corresponding joint probability density p_{ij} can be defined as [13, 24]

$$p_{ij} = \frac{f_{ij}}{(M \times N)}, \tag{2}$$

where $M \times N$ is the number of pixels of the difference image, $i, j = 1, 2, \ldots, L$, and

$$\sum_{i=1}^{L} \sum_{j=1}^{L} p_{ij} = 1. \tag{3}$$

Assume that there are two categories, namely, C_0 (changing category) and C_1 (nonchanging category) in the 2D histogram, as well as two different probability density distribution functions. Set the threshold value as (s, t); then, the probabilities of C_0 and C_1 are shown below:

$$\begin{aligned} \omega_0 &= \sum_{i=1}^{s} \sum_{j=1}^{t} p_{ij}, \\ \omega_1 &= \sum_{i=s+1}^{L} \sum_{j=t+1}^{L} p_{ij}. \end{aligned} \tag{4}$$

The corresponding mean vectors of C_0 and C_1 are

$$\overline{\mu}_0 = \left(\mu_{0i}, \mu_{0j}\right)^T = \left(\sum_{i=1}^{s} \sum_{j=1}^{t} \frac{i p_{ij}}{\omega_0}, \sum_{i=1}^{s} \sum_{j=1}^{t} \frac{j p_{ij}}{\omega_0} \right)^T, \tag{5}$$

$$\begin{aligned} \overline{\mu}_1 &= \left(\mu_{1i}, \mu_{1j}\right)^T \\ &= \left(\sum_{i=s+1}^{L} \sum_{j=t+1}^{L} \frac{i p_{ij}}{\omega_1}, \sum_{i=s+1}^{L} \sum_{j=t+1}^{L} \frac{j p_{ij}}{\omega_1} \right)^T. \end{aligned} \tag{6}$$

The total mean vector of 2D histogram is

$$\overline{\mu}_T = \left(\mu_{Ti}, \mu_{Tj}\right)^T = \left(\sum_{i=1}^{L} \sum_{j=1}^{L} i p_{ij}, \sum_{i=1}^{L} \sum_{j=1}^{L} j p_{ij} \right)^T. \tag{7}$$

Usually, the probability away from the histogram diagonal can be negligible; then, it can be assumed in the two areas: $i = s+1, \ldots, L$; $j = 1, \ldots, t$ and $i = 1, \ldots, s$; $j = t+1, \ldots, L$ have $p_{ij} \approx 0$, where

$$\omega_0 + \omega_1 \approx 1, \qquad \overline{\mu}_T = \omega_0 \overline{\mu}_0 + \omega_1 \overline{\mu}_1. \tag{8}$$

Define a between-class dispersion matrix:

$$\begin{aligned} S_B &= \omega_0 \left(\mu_{0i} - \mu_{Ti}\right) \left(\mu_{0j} - \mu_{Tj}\right) \\ &\quad + \omega_1 \left(\mu_{1i} - \mu_{Ti}\right) \left(\mu_{1j} - \mu_{Tj}\right). \end{aligned} \tag{9}$$

Use the trace of S_B as a measure of the between-class dispersion matrix; then, the 2D-Otsu function of the threshold value (s, t) corresponding to the difference image can be defined as

$$\begin{aligned} t_r \sigma_B(s, t) &= \omega_0 \left[\left(\mu_{0i} - \mu_{Ti}\right)^2 + \left(\mu_{0j} - \mu_{Tj}\right)^2 \right] \\ &\quad + \omega_1 \left[\left(\mu_{1i} - \mu_{Ti}\right)^2 + \left(\mu_{1j} - \mu_{Tj}\right)^2 \right]. \end{aligned} \tag{10}$$

By using Formula (8), it can be simplified into

$$t_r \sigma_B(s, t) = \frac{\left[\omega_0 \mu_{Ti} - \overline{\mu}_i\right]^2 + \left[\omega_0 \mu_{Tj} - \overline{\mu}_j\right]^2}{\omega_0 \left[1 - \omega_0\right]}, \tag{11}$$

where $\overline{\mu}_i = \sum_{i=1}^{s} \sum_{j=1}^{t} i p_{ij}$, $\overline{\mu}_j = \sum_{i=1}^{s} \sum_{j=1}^{t} j p_{ij}$.

The segmentation criteria corresponding to the 2D-Otsu threshold segmentation method has to maximize the 2D-Otsu function $t_r \sigma_B(s, t)$ for the purpose of obtaining the optimal threshold (s^*, t^*).

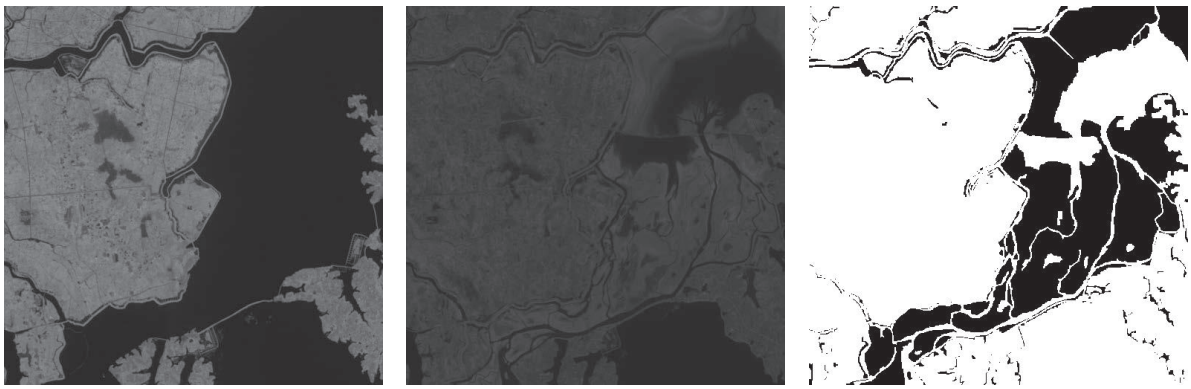
3.2. 2D-Otsu Threshold Segmentation Method Based on Firefly Algorithm. In order to solve the problem that 2D-Otsu threshold segmentation method requires a large amount and long time of computation, this paper applied the Firefly algorithm to the threshold optimization for 2D-Otsu threshold segmentation method and proposed the 2D-Otsu threshold segmentation method based on the firefly algorithm, so as to convert the threshold value selection of 2D-Otsu threshold segmentation method into the optimization of 2D-Otsu function $t_r \sigma_B(s, t)$ based on the Firefly algorithm.

The Firefly algorithm [25], proposed by Yang in the Cambridge University, is a bionic swarm intelligent optimization algorithm by simulating the natural behaviors of fireflies. The algorithm is characterized by simple parameter setting, high-accuracy optimization, and powerful global optimization [20]. The principle of Firefly algorithm is to simulate firefly individuals in nature by searching for space dots. In the optimization process, by using the phototaxis characteristics of firefly, the searching and optimization process is simulated into the attraction and movement process of firefly individuals, where the target function of the problem is measured by the merits of the position of firefly individuals. In other words, the target function of the problem is converted into the firefly seeking maximum brightness. The process of survival of the fittest among firefly individuals is also the iterative process of feasible solutions in the course of target function optimization. Therefore, the Firefly algorithm can rapidly conduct global optimization [21].

Firefly algorithm consists of two main elements: brightness and attraction, where brightness reflects the merits of the position of fireflies and determines the movement direction of firefly individuals, while attraction determines the movement distance of firefly individuals. Through the continuous updating and iteration of brightness and attraction, the optimal solution to the target function will be achieved [21, 26, 27]. In the Firefly algorithm, the relative fluorescence brightness of firefly individuals is defined as

$$I = I_0 \times e^{-\gamma r_{ij}^2}, \tag{12}$$

where I_0 is the maximum fluorescence brightness of the firefly, γ is the attraction coefficient of light intensity, which is usually set to a constant; r_{ij} is the spatial distance between Fireflies i and j, that is, $r_{ij} = \|x_i - x_j\|$, where x_i and x_j are, respectively, the spatial position of Fireflies i and j.



(a) July 15, 1989 (b) January 14, 2010 (c) Reference map of changed area

Figure 1: Multitemporal remote sensing images of Poyang Lake in Jiangxi Province.

The attraction degree of firefly is defined as

$$\beta = \beta_0 \times e^{-\gamma r_{ij}^2}, \tag{13}$$

where β_0 is the biggest attraction of the firefly.

In the case that Firefly i is attracted by Firefly j and moves towards the position of Firefly j, it can be defined in the formula below:

$$x_i = x_i + \beta \times \left(x_j - x_i\right) + \alpha \times \left(\text{rand} - \frac{1}{2}\right), \tag{14}$$

where α is the step size factor which is a constant between $[0, 1]$; rand is the uniformly distributed random factor between $[0, 1]$; $\alpha \times (\text{rand} - 1/2)$ is the random disturbance to avoid untimely falling into local optimum.

By setting the 2D-Otsu function $t_r\sigma_B(s, t)$ as the target function of the Firefly algorithm, the optimization result of the Firefly algorithm is the position $t_r\sigma_B(s^*, t^*)$ of the firefly with maximum brightness and (s^*, t^*) is the desired threshold. The implementation process is as follows:

(1) initialize the basic parameters of the Firefly algorithm. Set the number of fireflies as n, of which the maximum attraction is β_0, the light intensity attraction coefficient is γ, the step factor is α, and the maximum number of iterations is T;

(2) by randomly initializing the position of fireflies, calculate the 2D-Otsu function value $t_r\sigma_B(s_i, t_i)$ corresponding to each firefly and take the target function as their brightness to get the position of the firefly with maximum brightness;

(3) calculate the relative brightness I and attraction degree β of fireflies based on (12) and (13), and determine their movement direction according to the relative brightness;

(4) update the spatial position of fireflies based on Formula (14), and carry out random disturbance on fireflies in the best position;

(5) recalculate the brightness of fireflies based on the updated position of fireflies;

(6) when the maximum number of searches is reached, go to (6); otherwise, the number of searches should plus 1; then, go to (3) for the next search;

(7) output the position and brightness of the firefly with maximum brightness, and segment the difference images by taking (s^*, t^*) as a threshold.

4. Experiments and Results

4.1. Description of Experimental Data. In order to verify the validity and reliability of the proposed method as well as the advantages of the proposed method on the operating speed, the paper selected two groups of experimental data set, both of which were Landsat5 TM remote sensing images, with a spatial resolution of 30 m. The data set is provided by International Scientific & Technical Data Mirror Site, Computer Network Information Center, and Chinese Academy of Sciences (http://www.gscloud.cn/).

The first group of data set consists of two Landsat5 TM remote sensing images of the local area of Poyang Lake in Jiangxi Province, as shown in Figures 1(a) and 1(b). Figures 1(a) and 1(b) were, respectively, acquired on July 15, 1989, and on January 14, 2010, and the size of two remote sensing images was 510 × 510 pixels, with a gray-scale of 256; their reference changing map is shown in Figure 1(c), where the black area is the changing area, and 69,413 pixels were changed and 190,687 pixels were unchanged.

The second group of data set consists of two Landsat5 TM remote sensing images of the local area of Dongting Lake in Hunan Province, as shown in Figures 4(a) and 4(b). Figures 4(a) and 4(b) were, respectively, acquired on July 19, 1991, and on October 24, 2009, and the size of two remote sensing images was 610 × 610 pixels, with a gray-scale of 256; their reference changing map is shown in Figure 4(c), where the black area is the changing area, and 102,096 pixels were changed and 270,004 pixels were unchanged.

4.2. Change Detection Results and Analysis. The proposed method was verified by two experimental schemes.

(a) Image differencing (b) Image ratioing (c) Mixed method

Figure 2: The first set of experiments of Poyang Lake in Jiangxi Province.

Table 1: False alarms, missed alarms, and total errors for three difference methods in Poyang Lake.

Difference image acquisition methods	False alarms		Missed alarms		Total errors	
	Pixels	%	Pixels	%	Pixels	%
Difference operator	4945	2.59%	8636	12.44%	13581	5.22%
Ratio operator	10142	5.32%	7670	11.05%	17812	6.85%
IMTF operator	3204	1.68%	12499	18.01%	15703	6.04%

The first experimental scheme, respectively, applied difference method, ratio method, and the combination of difference method and ratio method to construct difference images and used the improved 2D-Otsu algorithm based on Firefly algorithm for segmentation to get the binary change map, where, after several experiments, the parameters of the Firefly algorithm were set below: the number of fireflies $n = 50$, the initial attraction degree $\beta_0 = 0.2$, light intensity coefficient $\gamma = 1$, step factor $\alpha = 0.25$, and the maximum number of iterations $T = 100$. The second experimental scheme, respectively, applied the proposed 2D-Otsu improved by Firefly algorithm, two-dimensional maximum entropy and two-dimensional maximum fuzzy entropy to process the difference images obtained from the image difference method to get the binary change map. In order to quantitatively evaluate the accuracy of the proposed method, the false detection rate, missed detection rate, and overall error rate were taken as evaluation factors [2].

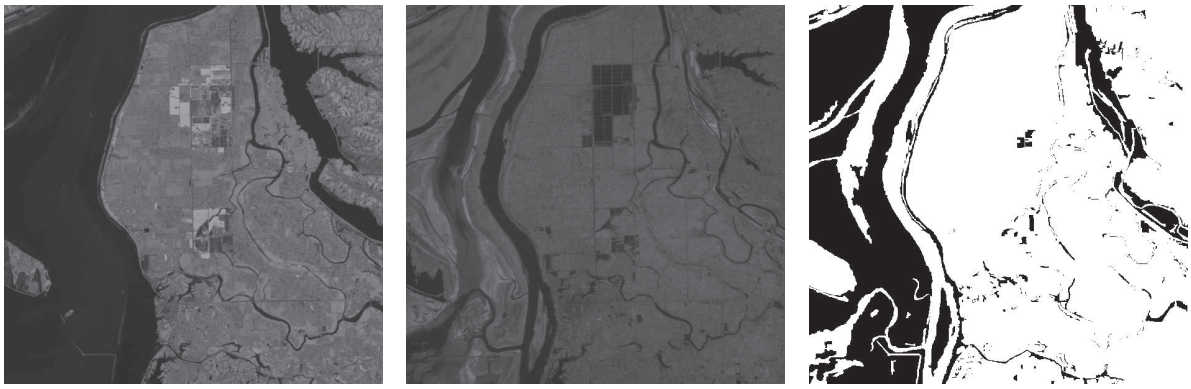
In the first experimental scheme, the 2D-Otsu algorithm improved by the proposed Firefly algorithm based on the two groups of data set, respectively, processed the difference images constructed through difference method, ratio method, and the combination of difference method and ratio method to get the binary change map, of which the detection results are shown in Figures 2 and 5, and the change detection accuracy is shown in Tables 1 and 3. As can be seen from Tables 1 and 3, the difference method led to the minimum number of pixel errors, followed by the result produced by the combination method, and the ratio method led to the maximum number of pixel errors. According to the three evaluation factors, namely, overall false detection rate, missed detection rate, and overall error rate, the difference image resulting from the image difference method can get better change detection results. In addition, as can be seen from Figure 5, the detection results from the ratio method produced a number of missed and false changed pixel elements; although the detection resulting from the combination method reduced the number of false detections, it led to a huge number of missed detections; the detection results from difference method did not produce a number of false or missed detections; thus, it was much closer to the reference map.

In the second experimental scheme, the 2D-Otsu algorithm, two-dimensional maximum entropy and two-dimensional maximum fuzzy entropy improved by the Firefly algorithm based on the two groups of data set processed the difference images obtained from the image difference method to get the binary change map, of which the detection results are shown in Figures 3 and 6, and the comparison results among the change detection accuracy based on the three methods are shown in Tables 2 and 4. As can be seen from Tables 2 and 4, although the detection results based on the two-dimensional maximum entropy and the two-dimensional maximum fuzzy entropy had a very low false detection rate, a number of changed pixel elements were missed. The missed detection rate based on the two-dimensional maximum entropy method was above 80%, while the missed detection rate based on the two-dimensional maximum fuzzy rate was between 55% and 65%. The false detection rate and the missed detection rate based on the proposed method were lower, of which the false detection rate was maintained below 3%, and the missed detection rate was maintained below 13%. As can also be seen from Figures 3 and 6, compared with the reference change map, the binary change detection results based on the two-dimensional maximum entropy and the two-dimensional fuzzy maximum entropy showed a number of changed pixel elements.

As can be seen from the two experimental schemes, the proposed method is an effective and reliable change detection method for multitemporal remote sensing images.

(a) Proposed method (b) 2D maximum entropy (c) 2D maximum fuzzy entropy

Figure 3: The second set of experiments of Poyang Lake in Jiangxi Province.



(a) July 19, 1991 (b) October 24, 2009 (c) Reference map of changed area

Figure 4: Multitemporal remote sensing images of Dongting Lake in Hunan Province.

Table 2: False alarms, missed alarms, and total errors for three change detection methods in Poyang Lake.

Change detection methods	False alarms		Missed alarms		Total errors	
	Pixels	%	Pixels	%	Pixels	%
Proposed method	4945	2.59%	8636	12.44%	13581	5.22%
2D maximum entropy	28	0.01%	58870	84.81%	58898	22.64%
2D maximum fuzzy entropy	164	0.09%	39906	57.49%	40070	15.41%

Table 3: False alarms, missed alarms, and total errors for three difference methods in Dongting Lake.

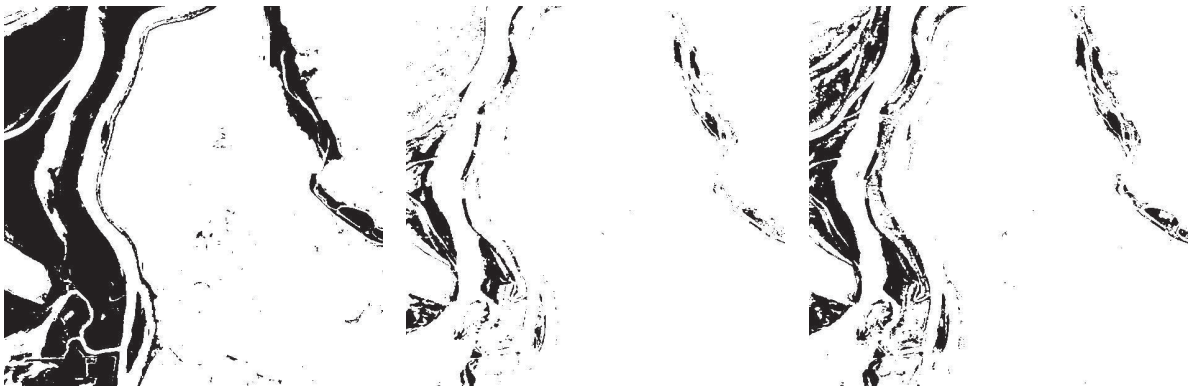
Difference image acquisition methods	False alarms		Missed alarms		Total errors	
	Pixels	%	Pixels	%	Pixels	%
Difference operator	4548	1.68%	11268	11.04%	15816	4.25%
Ratio operator	85119	31.53%	29885	29.27%	115004	30.91%
IMTF operator	1295	0.47%	36496	35.75%	37791	10.16%

5. Conclusion

Thresholding processing is an effective method to detect changes in multitemporal remote sensing images. One-dimensional thresholding can be simply implemented, but the thresholding accuracy is not high. In order to improve the accuracy of detection change, the 2D-Otsu algorithm is used for the change detection of multitemporal remote sensing images. However, the 2D-Otsu algorithm has difficult threshold selection and requires a large amount of computation; thus, the Firefly algorithm is introduced to conduct threshold optimization for 2D-Otsu algorithm, from which the automatic change detection method of multitemporal remote sensing images based on 2D-Otsu algorithm improved by Firefly algorithm has been proposed. First, this paper first applied the image difference method to construct the difference images, and conducted threshold optimization for 2D-Otsu algorithm by using Firefly algorithm; then, the 2D-Otsu algorithm was used to segment the threshold values on the difference images to get the binary change map, and finally the false detection rate, missed detection rate,

(a) Image differencing (b) Image ratioing (c) Mixed method

Figure 5: The first set of experiments of Dongting Lake in Hunan Province.



(a) Proposed method (b) 2D maximum entropy (c) 2D maximum fuzzy entropy

Figure 6: The second set of experiments of Dongting Lake in Hunan Province.

Table 4: False alarms, missed alarms, and total errors for three change detection methods in Dongting Lake.

Change detection methods	False alarms		Missed alarms		Total errors	
	Pixels	%	Pixels	%	Pixels	%
Proposed method	4548	1.68%	11268	11.04%	15816	4.25%
2D maximum entropy	27	0.01%	83949	82.23%	83976	22.57%
2D maximum fuzzy entropy	183	0.07%	63810	62.50%	63993	17.20%

and overall error rate were separately used to evaluate the accuracy of detection results.

In order to verify the effectiveness, reliability, and operating speed advantages of the proposed method, several change detection experiments were made to the two groups of data set, and the results were compared with the change detection methods based on the two-dimensional maximum entropy and the two-dimensional maximum fuzzy entropy. Experimental results showed that the change detection accuracy (overall error rate) of the proposed method averaged 4.74%, better than the detection accuracies based on the two-dimensional maximum entropy method (22.61%) and the two-dimensional maximum fuzzy entropy method (16.31%). Therefore, the proposed method can efficiently and accurately identify the changing area of multitemporal remote sensing images. Of course, further researches are still required in terms of how to set the initial parameters of fireflies so as to reduce the impacts of nonoptimal initial parameters on threshold optimization.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This research work was supported by the National Natural Science Foundation of China (no. 41161071), the Department of Education Research Fund of Yunnan Province (no. 2013J062), and Scholarship Award for Excellent Doctoral Student granted by Yunnan Province. The authors would like to express their thanks to the anonymous reviewer for the constructive comments.

References

[1] J. Q. Zhong, *Change Detection Based on Multitemporal Remote Sensing Image*, Graduate School of National University of Defense Technology, Hunan, China, 2005.

[2] F. Bovolo and L. Bruzzone, "A detail-preserving scale-driven approach to change detection in multitemporal SAR images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 12, pp. 2963–2972, 2005.

[3] N. S. Mishra, S. Ghosh, and A. Ghosh, "Fuzzy clustering algorithms incorporating local information for change detection in remotely sensed images," *Applied Soft Computing Journal*, vol. 12, no. 8, pp. 2683–2692, 2012.

[4] X. Tong, Z. Hong, S. Liu et al., "Building-damage detection using pre- and post-seismic high-resolution satellite stereo imagery: a case study of the May 2008 Wenchuan earthquake," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 68, no. 3, pp. 13–27, 2012.

[5] R. S. Lunetta, J. F. Knight, J. Ediriwickrema, J. G. Lyon, and L. D. Worthy, "Land-cover change detection using multi-temporal MODIS NDVI data," *Remote Sensing of Environment*, vol. 105, no. 2, pp. 142–154, 2006.

[6] J. O. Odindi and P. Mhangara, "Green spaces trends in the city of Port Elizabeth from 1990 to 2000 using remote sensing," *International Journal of Environmental Research*, vol. 6, no. 3, pp. 653–662, 2012.

[7] H. J. Tang, W. B. Wu, P. Yang, Q. B. Zhou, and Z. X. Chen, "Recent progresses in monitoring crop spatial patterns by using remote sensing," *Scientia Agricultura Sinica*, vol. 43, no. 14, pp. 2879–2888, 2010.

[8] Y. Q. Tang, X. Huang, and L. Zhang, "Fault-tolerant building change detection from urban high-resolution remote sensing imagery," *IEEE Geoscience and Remote Sensing Letters*, vol. 10, no. 5, pp. 1060–1064, 2013.

[9] H. S. Zhang, *The Research of Object-Based Remote Sensing Change Detection for Coastal Surface*, Zhejiang University, Hangzhou, China, 2010.

[10] W. B. Sun, H. X. Chen, H. Y. Tang, and G. Yu, "Unsupervised image change detection based on 2D fuzzy entropy," *Journal of Jilin University: Engineering and Technology*, vol. 41, no. 5, pp. 1461–1467, 2011.

[11] P. A. Rogerson, "Change detection thresholds for remotely sensed images," *Journal of Geographical Systems*, vol. 4, no. 1, pp. 85–97, 2002.

[12] A. D. Brink, "Thresholding of digital images using two-dimensional entropies," *Pattern Recognition*, vol. 25, no. 8, pp. 803–808, 1992.

[13] J. Liu and W. Li, "Automatic thresholding of gray-level pictures via two-dimensional OTSU method," *Acta Automatica Sinica*, vol. 19, no. 1, pp. 101–105, 1993.

[14] M. L. F. Velloso, T. A. Carneiro, and F. J. de Souza, "Unsupervised change detection using fuzzy entropy principle," in *Proceedings of the IEEE International Symposium on Geoscience and Remote Sensing*, vol. 4, pp. 2550–2553, September 2004.

[15] X. Shen, Y. zhag, and F. Li, "An improved two-dimensional entropic thresholding method based on ant colony genetic algorithm," in *Proceedings of the WRI Global Congress on Intelligent Systems (GCIS '09)*, pp. 163–167, May 2009.

[16] L. Zheng, G. Li, and Y. Bao, "Improvement of grayscale image 2D maximum entropy threshold segmentation method," in *Proceedings of the International Conference on Logistics Systems and Intelligent Management (ICLSIM '10)*, vol. 1, pp. 324–328, IEEE, Harbin, China, January 2010.

[17] S. Alim, P. J. Du, and S. C. Liu, "Maximum 2D entropy image segmentation based on artificial bee colony optimization," *Computer Engineering*, vol. 38, no. 9, pp. 223–225, 2012.

[18] X. J. Qian, "Application of PSO algorithm in 2D Otsu image segmentation," *Computer Simulation*, vol. 27, no. 12, pp. 279–281, 2010.

[19] J. Tian and J. C. Zeng, "2D fuzzy maximum entropy image threshold segmentation method based on QPSO," *Computer Engineering*, vol. 35, no. 3, pp. 230–232, 2009.

[20] X.-S. Yang, "Firefly algorithms for multimodal optimization," in *Stochastic Algorithms: Foundations and Applications*, vol. 5792 of *Lecture Notes in Computer Science*, pp. 169–178, Springer, Berlin, Germany, 2009.

[21] K. Chen, F. Chen, M. Dai, Z.-S. Zhang, and J.-F. Shi, "Fast image segmentation with multilevel threshold of two-dimensional entropy based on firefly algorithm," *Optics and Precision Engineering*, vol. 22, no. 2, pp. 517–523, 2014.

[22] W. K. Alomoush, S. N. H. S. Abdullah, S. Sahran, and R. I. Hussain, "Segmentation of MRI brain images using FCM improved by firefly algorithms," *Journal of Applied Sciences*, vol. 14, no. 1, pp. 66–71, 2014.

[23] X.-M. Zhang, Y.-J. Sun, and Y.-B. Zheng, "Precise two-dimensional Otsu's image segmentation and its fast recursive realization," *Acta Electronica Sinica*, vol. 39, no. 8, pp. 1778–1784, 2011.

[24] Q. Chen, L. Zhao, J. Lu, G. Kuang, N. Wang, and Y. Jiang, "Modified two-dimensional Otsu image segmentation algorithm and fast realisation," *IET Image Processing*, vol. 6, no. 4, pp. 426–433, 2012.

[25] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*, Luniver Press, Beckington, UK, 2008.

[26] X. G. Du, J. W. Dang, Y. P. Wang, X. G. Liu, and S. Li, "Mutual information medical image registration based on firefly algorithm," *Computer Science*, vol. 40, no. 7, pp. 273–276, 2013.

[27] C. P. Liu and C. M. Ye, "Novel bioinspired swarm intelligence optimization algorithm: firefly algorithm," *Application Research of Computers*, vol. 28, no. 9, pp. 3295–3297, 2011.