The Earth Environment Change Detection Method Based on the Variable Weight Markov Random Field Combined with the Space Gravity Model

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Abstract. For the traditional earth environment change detection algorithm based on remote sensing image, only the band information of the image is utilized, and it is difficult to obtain the defect of the complete change detection result. Based on the spectral information of the image, the change detection method based on Markov random field model introduces the spatial correlation of pixels, which improves the accuracy of change detection to some extent. However, due to the over-use of spatial correlation in the process of introducing pixel spatial information, these methods have the disadvantage of poor detection results due to the fixed weight parameters in the modelling process. Aiming at the limitations of these methods, this paper proposes the environment of earth change detection method based on the variable weight markov random field combined with the space gravity model. Using the space gravitation model, the use of pixel spatial information is more reasonable, and the idea of variable weight is introduced to improve the defect that the change detection result is too smooth due to the fixed weight parameter. Experiments on real high-resolution remote sensing image datasets verify the effectiveness and feasibility of the proposed method.

1. Introduction

Remote sensing interpretation is an important means to analyse the environment of earth, in which the change detection method of high-resolution remote sensing image plays an important role. High resolution remote sensing image change detection refers to the processing and analysis of two remote sensing images in the same area with different imaging time, so as to judge whether the ground feature attributes in the region of interest have changed. It has been widely used in land survey, urban expansion analysis, resource exploration, ecological environment monitoring, natural disaster monitoring and evaluation, military reconnaissance and other fields.

In recent years, researchers continue to study new change detection algorithms to further improve the accuracy and accuracy of multi temporal high-resolution remote sensing image change detection results. However, at present, there is not a universal algorithm which can be applied to simultaneous interpreting two high resolution remote sensing images with different sensors, different shooting situations and different shooting environments. Random field modelling theory can express the spatial information of the pixels in the image, and has the advantages of suppressing the noise and enhancing the regional consistency, so it has been widely used in remote sensing image classification and change detection.
Zhou et al. Proposed the idea of introducing conditional random field (CRF) into the image spot area, which is more robust to noise than traditional methods [1]. Wei lifei et al. Fused the feature vectors of multiple images through CRF, synthesized the change information of multiple image features, and overcame the shortage of using single feature for change detection [2]. LV et al. Proposed the mixed conditional random field model (HCRF), which solved the problem of excessive smoothing in homogeneous regions [3]. Cao et al. Proposed a change detection algorithm combining CRF and fuzzy C-means (FCM). By adding fuzzy membership information into CRF, the integrity of change detection results is stronger, and the noise is suppressed [4]. Markov random field model (MRF) is a probability statistical model, which takes into account the interaction and distribution characteristics of the pixels in the image, effectively provides the spatial information of the pixels, so it is widely used to improve the accuracy of high-resolution image classification and remote sensing image change detection in different imaging time [5]. It extracts spatial background information through the dependency between adjacent pixels. Although MRF can usually obtain better classification results than pixel classification, it is difficult to obtain the spatial weight coefficient to determine the contribution of neighbouring pixels to the central pixel [6]. In the traditional MRF, the adjacent pixels on the center pixel are treated equally, so the classification accuracy is improved in the uniform region, and a large amount of noise often appears in the boundary region where important details are lost, resulting in a high error rate in the detection results [48]. Tso and Olsen introduced multi-scale blur lines into MRF to limit over segmentation, and estimated MRF model parameters through probability histogram analysis of edge pixels [49]. Tara balka et al. integrated the fuzzy edge free / edge function into the spatial energy function to obtain a new energy function, so as to achieve the purpose of preserving the boundary pixels in the detection results [50]. Zhang et al. Introduced the relative homogeneity index (RHI) to obtain the appropriate spatial weight [51]. But these edge detection algorithms and RHI algorithm have poor ability to suppress the noise in the image. In addition, the spatial weight is determined according to the distance between the adjacent pixel and the center pixel. No matter what the local image statistics are, only the influence of the distance between pixels is considered. Therefore, more effective methods are needed to deal with the boundary pixel and spatial weight estimation problem.

To sum up, these methods effectively combine the spectral information and pixel spatial information in the image, and improve the transformation detection accuracy of high-resolution remote sensing images with different imaging time. However, the low utilization or overuse of spatial information will lead to the low accuracy of the final change detection results. In order to solve the above problems, this paper proposes a variable weight MRF high-resolution remote sensing image change detection method considering the spatial relationship, and compares with the existing classical algorithms to prove the effectiveness and feasibility of the proposed method.

2. Methodology
The flow chart of the proposed method is shown in Figure 1, and a change detection algorithm of variable weight Markov random field based on Spatial Gravity model is proposed. Firstly, the difference image is obtained by CVA. Secondly, the fuzzy c-means algorithm is used to obtain the initial change detection results. Then, the improved Potts model of Spatial Gravity model is used to build the marker field, and the Gaussian mixture model is used to build the feature field based on the pixels of the difference image. Finally, in the Bayesian framework, conditional iterative model (ICM) is used to obtain the optimal solution of map, which is to obtain the final image change detection results.

2.1 Image differential method
In order to fuse the information of each band in high-resolution remote sensing image, It is necessary to gray the remote sensing image after pre-processing to get two single band gray images. Then, the pixel gray levels of the two single band images are subtracted one by one to obtain the difference image.

\[
D(i, j) = X^1_{(i, j)} - X^2_{(i, j)}
\]  
(1)
$D(i,j)$ represents the gray value of the difference image, $X^1_{(i,j)}$ and $X^2_{(i,j)}$ represents the high-resolution remote sensing images of two different periods. In the difference image, the larger the $D(i,j)$ gray value is, the more likely the pixel will change. The smaller the gray value is, the less likely the pixel will change. In order to ensure that the pixel gray value in the differential image $D(i,j)$ is not negative, the differential image $D(i,j)$ is usually specified, and the value range of pixel gray value is specified to 0 to 255.

![Flowchart of the proposed approach](image)

2.2 Variable weight MRF random field modelling

The gray information of each pixel in the difference image is taken as the observation data, and the initial change detection result of the difference image is obtained by FCM clustering. The feature field model is established by analysing the distribution characteristics of each class of labelled pixels. It is usually assumed that the distribution is Gaussian distribution, and the optimal segmentation is carried out under the Bayesian framework. Suppose the size of the difference image to be segmented is $m \times n$.

Assign the label $Y = \{Y_1, Y_2, \ldots, Y_I\}$, $I$ is the number of labelled species, and the labelling field is established with the improved Potts model. The feature vector of each pixel position of the image $X = \{X_1, X_2, \ldots, X_s; s = m \times n\}$. The characteristic field model is established by Gaussian mixture model. According to Bayes criterion, the image segmentation is expressed as follows

$$P(Y = y|X = x) = \frac{P(X = x|Y = y)P(Y = y)}{P(X = x)} \quad (2)$$

The maximum $P(Y = y|X = x)$ obtained by map is the best change detection result.

$$\hat{Y} = \arg \max_{Y} P(Y = y|X = x) \quad (3)$$

Because the feature field $x$ is the feature vector of each position in the image and does not change with the change of the label field $Y$, the influence of $P(X = x)$ is not considered. The optimal change detection result obtained from image segmentation can be expressed as follows:

$$\hat{Y} \propto \arg \max_{X} P(X = x|Y = y)P(Y = y) \quad (4)$$

2.2.1 Characteristic field modelling

The gray value of the difference image obtained by image different method is used as the observation feature, and the FCM clustering method is applied to the difference image to obtain the initial change detection results.
Assuming that in the initial change detection results obtained by FCM, different types of observation features are independent of each other, the probability distribution of the difference image can be expressed as:

\[ P(X = x | Y = y) = \prod_{y = y_i} P(x_i | y_i) \]  

Then assume that each pixel in the difference image is independent of each other and obeys Gaussian distribution. Gaussian mixture model (GMM) is used to describe the observation data of each category of difference image.

\[ P(x_i | y_i) = \frac{1}{\sqrt{2\pi} \sum y_i} e^{-\frac{1}{2}(x-u_m)(\sum y_i)^{-1}(x-u_m)} \]  

The final expression can be obtained from formula (5) and (6).

\[ P(X = x | Y = y) = \prod_{y = y_i} \prod_{x = x_i} \frac{1}{\sqrt{2\pi} \sum y_i} e^{-\frac{1}{2}(x-u_m)(\sum y_i)^{-1}(x-u_m)} \]  

Where \( x \) is the feature vector of each position of the image, \( u_m \) is the mean value, \( \sum y_i \) is variance.

### 2.2.2 Space gravity model

In order to make good use of the spatial correlation between pixels. The membership degree obtained by FCM method represents the spatial relationship of pixels [5], which is convenient to define the spatial correlation between pixels more accurately in the neighbourhood system of MRF model. The spatial attraction between pixels is defined by the following formula:

\[ w_{ij} = z(p_i) \times z(p_j) \times \frac{1}{R_{ij}^2} \]  

Where I is in the second-order neighbourhood system with 3 x 3 window size, \( y_i \) is the center pixel, as shown in Figure 2(a). \( p_i \) and \( p_j \) represents the membership information of pixel and pixel belonging to category Z respectively. \( R_{ij} \) is the center pixel \( y_i \) and other pixels \( y_j \) in the neighbourhood system, as shown in Figure 2(b). In order to make better use of the spatial relationship between pixels.

| \( N_{i,1} \) | \( N_{i,2} \) | \( N_{i,3} \) | \( 1/\sqrt{2} \) | 1 | 1/\sqrt{2} |
| \( N_{i,4} \) | \( i \) | \( N_{i,5} \) | 1 | \( i \) | 1 |
| \( N_{i,6} \) | \( N_{i,7} \) | \( N_{i,8} \) | 1/\sqrt{2} | 1 | 1/\sqrt{2} |

a. Neighborhood \( N_i \) of center pixel \( x_i \)
b. The distance between the center pixel \( x_i \) and its neighborhood \( N_i \)

Figure 2. Spatial neighbourhood of central pixel \( x_i \)
2.2.3 Label field modelling

The label field is represented by the MRF of the second-order neighbourhood system. The second-order
neighbourhood system and its binary potential clique type. Hammersley-Clifford theory links the global
probability with the local probability, making the MRF model with local property equivalent to the
global Gibbs random field (GRF) model, so the prior probability obeys the Gibbs distribution[12][14].

\[ P(Y) = \frac{1}{Z} e^{-U(Y)} \]  

Where \( U(Y) \) is the energy function; \( Z \) is the normalized constant, also known as the partition function,
t is the temperature, usually set to 1.

\[ Z = \sum_{y \in Y} -U(Y) \]  

\( V \) is the group potential function. In this paper, we use the Potts model improved by the space gravity
model to define the binary potential function [5].

\[ V(i, j) = \begin{cases} 0, & y_i \neq y_j \\ w_{ij}, & y_i = y_j \end{cases} \]  

2.2.4 Model parameter estimation

Under the condition of given feature field and label field, based on map, the global optimal estimation
of image segmentation can be expressed as:

\[ P(Y) = \frac{e^{-\beta N(y)}}{\sum_{y \in Y} e^{-\beta N(y)}} \]  

In the calculation of the total energy function of the image, the idea of variable weight is added to
increase the selection range of the potential function. Let the energy of feature field, label field and total
energy of image be \( Ef \), \( El \) and \( Ea \) respectively. The expression of each energy is as follows:

\[ Ef = \ln \left( \sqrt{\frac{2\pi|\Sigma_r|}{2}} + \frac{1}{2} (x - u_m)(\Sigma_r)^{-1}(x - u_m) \right) \]  

\[ El = \beta N_i(y_i) \]  

\[ Ea = Ef + El \]  

The variable weight value is introduced into the total energy function \( \tau(t) \), Then the energy function
of the image can be expressed as:

\[ \tau(t) = c/(t + 1) + 1/L \]  

It can be seen from the above formula that it is a decreasing function of the number of iterations \( t \).
Where \( c \) is a constant, the meaning of this parameter is to control the influence time and intensity of the
feature field on the image segmentation process. \( L \) is the number of image classification, which is set to
2 in the change detection of high-resolution remote sensing image, that is, change region and no change
region. The conditional iterative model (ICM) algorithm is used to find the condition that makes the
energy minimum, and the optimal labelling field \( y \) is updated iteratively .The best result of image
change detection is obtained.

3. Results & Discussion

3.1 Dataset description

Experiments were carried out on two groups of quick bird 0.6m high-resolution remote sensing image
data. The original image data was located in a certain area of Chongqing, and was captured by
simultaneous interpreting of different sensors at different time periods.

In Experiment 1, the change type of the two images was industrial land. Many new buildings can be
seen in the two images of Experiment 2. In Experiment 1 and Experiment 2, the change types were
different. The two images used in the experiment have been registered. As shown in the Figure3:
3.2 result analysis

In order to verify the feasibility and effectiveness of the proposed method, five change detection methods are compared with the proposed method. The four methods are EM, K-means, MRF and Otsu. All the algorithms are programmed on MATLAB 2014b and run in Intel (R) core (TM) i5-4200 2.30 GHz processor with 4 GB ram. As shown in Figure.4 and Figure.5, they are EM, K-means, MRF, Otsu, the method in this paper and the real reference change results drawn manually.

Figures 4 (e) and 5 (e) are the results of our method. The model of MRF $\beta$. The value is set to 1. It is an empirical value to control the energy produced by the marker field. As shown in Figure. 4(a-b) and Figure. 5 (a-b), the change detection results of K-means and EM algorithms are close to the real reference results. However, due to the lack of consideration of the spatial pixel correlation of the difference image, there are many salt and pepper noises in the no change area of the image, which reduces the accuracy of the change detection results. Otsu method obtains the change detection result by calculating the best threshold between the change pixel and the no change pixel, which has poor noise suppression ability. Although the MRF method in Figures.4 (c) and Figure.5 (c) considers the spatial information of pixels, there is the problem of excessive use of spatial information. In the process of MRF modelling, because the weight parameters are fixed, the detection results are too smooth. The false alarm pixels of the detection results are more than those of the proposed method. As shown in Figure4.(e) and Figure5.(e), the proposed method has good robustness under the influence of noise, and the homogeneous region obtained is more complete.
Table 1-2 shows the quantitative evaluation results of the five methods, showing the differences between EM, K-means, MRF, OTSU and the proposed methods. The accuracy of the proposed method is evaluated by the number of false alarm pixels, missed pixels and total error pixels. Compared with other methods, for the first group of data, the total error rate of this method is reduced by 6.93%, 6.45%, 3.33% and 4.83% respectively. The number of error pixels is reduced by more than 30000. For the second data, compared with MRF, the total error rate of this method increases by 0.55%, but the false alarm rate decreases by 7.66%. Compared with other methods, the number of error pixels is reduced by 3.16%, 1.22% and 4.26% respectively, and the total number of error pixels is reduced by more than 8600. The change detection method based on variable weight Markov random field combined with spatial gravity model makes reasonable use of the spatial correlation between pixels. Compared with the existing change detection methods, this method overcomes the shortcomings of overuse of spatial information in high-resolution remote sensing images, effectively reduces the false alarm rate, missing detection rate.
and total error of change detection results, and improves the accuracy and accuracy of change detection in high-resolution remote sensing images.

Table 1. Quantitative change detection results for the Experiment 1.

| Method | False alarms | Misdetection | Total errors |
|--------|--------------|--------------|--------------|
|        | Pixels       | $P_f$(%)     | Pixels       | $P_m$(%)     | Pixels       | $P_t$(%)     |
| EM     | 126123       | 22.66        | 47037        | 40.75        | 173160       | 25.77        |
| k-means| 119886       | 21.54        | 50058        | 43.37        | 169944       | 25.29        |
| MRF    | 99088        | 17.8         | 49894        | 43.23        | 148982       | 22.17        |
| OTSU   | 98490        | 17.7         | 60543        | 52.45        | 159033       | 23.67        |
| Proposed| 60768       | 10.92        | 65809        | 57.01        | 126577       | 18.84        |

Table 2. Quantitative change detection results for the Experiment 2.

| Method | False alarms | Misdetection | Total errors |
|--------|--------------|--------------|--------------|
|        | Pixels       | $P_f$(%)     | Pixels       | $P_m$(%)     | Pixels       | $P_t$(%)     |
| EM     | 71281        | 14.5         | 40437        | 19           | 111718       | 15.86        |
| k-means| 23957        | 4.87         | 74113        | 34.83        | 98070        | 13.92        |
| MRF    | 38082        | 7.74         | 47509        | 22.33        | 85591        | 12.15        |
| OTSU   | 24504        | 4.98         | 94997        | 44.64        | 119501       | 16.96        |
| Proposed| 34265       | 6.97         | 55201        | 25.94        | 89466        | 12.70        |

4. Conclusions
In this paper, the change detection method based on variable weight Markov random field combined with spatial gravity model is proposed. Compared with EM, K-means, MRF, Otsu change detection algorithm, the regional consistency of change detection results obtained by this method is better, and the detection accuracy and accuracy are further improved. The Potts model is improved by the Spatial Gravity Model to solve the problem that the change detection results are too passivated due to the excessive use of spatial correlation features in the traditional marker field modelling. Because the potential function is fixed when building MRF model, the idea of variable weight is introduced to increase the range of potential function value selection, which improves the defect that the change detection result is too smooth due to the fixed weight parameter in traditional MRF. Experiments on two high-resolution remote sensing image datasets show the effectiveness and feasibility of the proposed method.

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