Change Detection Based on Feature Optimization in High Resolution Optical Image

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Abstract. Object-oriented change detection (CD) method can make full use of feature information of high resolution optical images. However, the feature information is redundancy in Object-oriented CD of high resolution optical image due to the fact that the image has multiple bands. Therefore, feature optimization is necessary to object-oriented CD. Aiming at the problem, a novel CD method based on feature optimization which combines improved locally linear embedding (ILLE) algorithm and object-oriented technology is proposed. Firstly, two temporal images are inverted into objects using multi-scale segmentation algorithm. Secondly, the spectral and texture features of the objects are extracted to construct the novel feature change vector. Thirdly, the improved LLE algorithm, which introduces the Geodesic distance metric, is designed to optimize the feature change vector. Finally, the CD result is obtained by FCM algorithm. Experiments construct on the real GF-1 images, and the results confirm the effectiveness of the proposed method.

1. Introduction

Change detection (CD) is a process of determining land cover changes information using remote sensing images acquired in the same geographical area at different times [1]. It plays an important role in urban planning, agricultural survey, environmental protection and disaster assessment [2], and becomes a hot topic in remote sensing application research.

In general, the CD methods can be divided into two categories: pixel-based CD and object-oriented CD. The traditional pixel-based CD technology is usually applied to low and medium resolution optical images for obtaining better CD results [3], [4], [5]. With the advancement of remote sensing technology, the image resolution is gradually improved, high resolution optical images become popular data sources for CD for the reason that it can clearly show the texture and structure information of the ground objects. However, the traditional pixel-based CD method has limitations in high resolution optical image due to hardly making full use of structure and texture feature of the pixel, it leads to salt and pepper phenomenon and the low accuracy in the CD results [6]. The Object-oriented CD method regards the object which contains enough structure and texture information as a basic unit to improve the utilization of multiple features and the smoothness of CD results. Therefore, object-oriented CD method is more suitable for high resolution remote sensing [7].

In recent years, scholars have present many object-oriented CD methods. Among that, a multi-feature fusion CD method is proposed in [8], where the objects are first obtained, and the multi-dimensional features of the object are extracted to build feature change vectors. Then the feature change vectors are imported into the support vector machine (SVM) for classifying the object into
changed class or unchanged class. However, the training time of SVM is longer owing to the large number of features. In [9], after the multiple features from objects are extracted, this method introduces change vector analysis (CVA) algorithm to calculate the changing intensity of object, so as to improve the judgment results on the changed or unchanged of ground objects. Feng et al. [10] propose a multi-scale fusion approach, where the objects are obtained from different segmentation scales, and then the final CD result was achieved by fusing the CD results of various segmentation scales. In [11], the BOW features of the object are constructed according to BOW model, and then the CD result is generated by measuring BOW feature similarity between two temporal objects. These object-oriented CD methods are focused on the utilization of multi-dimensional feature. However, they ignore the feature information redundancy in high resolution optical image. Therefore, feature optimization is an important part of the object-oriented CD.

At present, many methods are commonly used for feature optimization in the direction of remote sensing image processing, such as principal component analysis (PCA) [12], linear discriminant analysis(LDA), and so on. However, these methods only can handle data with linear relationships. As a result, they are not very ideal in the application of remote sensing image due to that the statistical properties of the remote sensing image generally obey nonlinear distribution [13]. The locally linear embedding (LLE) is a nonlinear dimension reduction algorithm based on manifold learning [14]. It both has the advantages of linear dimension reduction and nonlinear dimension reduction. Thus, the algorithm is suitable for feature optimization of CD in high resolution optical image. Unsatisfactorily, LLE algorithm still has a serious problem, it is sensitive to nearest neighbor selection. In order to obtain a better result of feature optimization, the algorithm needs further improvement.

Hence, the CD method based on feature optimization which combines improved locally linear embedding (ILLE) algorithm and object-oriented technology is presented. Firstly, the image objects are obtained by using multi-scale segmentation algorithm, and the multiple features of objects are extracted to construct the novel feature change vector. Then the improved LLE algorithm, which introduces the Geodesic distance metric to implement the adaptive selection of neighbors, is designed to optimize the feature change vector. Finally, the CD result is obtained. The method not only can overcome the limitations of traditional pixel-based CD method, but also can get as much valuable change information as possible while compressing the feature volume by introducing ILLE algorithm into the object-oriented CD. The GF-1 images are acquired as experiment data, and the CD result shows the effectiveness of the proposed method.

2. The Proposed Method

The flow chart of the proposed method is shown in figure 1, which is organized by the flowing 6 steps: 1) multi-scale image segmentation; 2) spectral and texture features extraction; 3) a novel features change vectors construction; 4) the LLE algorithm is improved by the Geodesic distance and mean Geodesic distance; 5) feature optimization by the ILLE algorithm; 6) CD result is obtained by the FCM method.

2.1. Multi-scale image segmentation

The image object is the basic unit of object-oriented CD method. Therefore, accurate extraction of the object is the premise of obtaining precise CD results. To get high-quality image objects, the multi-
scale segmentation algorithm of eCognition software is chosen to segment the images. Then the algorithm parameters of scale, shape and compactness are set appropriately, and the image objects with higher internal homogeneity are generated.

2.2. Feature extraction
1) Spectral feature: we choose the spectral mean of the object as a spectral feature; it is defined as:

\[ \text{Sp}_i = \frac{1}{m \sum_{j=1}^{m} g_j} \]

Where, \( i \) represents the object \( i (i = 1, 2, \ldots) \), \( m \) is the total number of pixels in each band of object \( i \), and \( g_j \) is the gray value of the \( j \) th pixel in each band of object \( i \).

2) Texture feature: at present, gray-level co-occurrence matrix (GLCM) is widely used in texture feature extraction due to its strong robustness [15]. So four GLCM statistics, namely, entropy, mean value, energy and contrast of each band are selected as texture feature.

2.3. Feature optimization

2.3.1 A novel feature change vector construction. In order to avoid the feature inconsistency caused by different value dimensions, the features are normalized to \([0, 1]\). The feature vector of the object \( i \) is defined as:

\[ O_i = (O_{i1}, O_{i2}, \ldots, O_{iN}) \]

Where, \( N \) is the total number of features contained in the object \( i \). Suppose \( S_b \) is the number of bands contained in the object \( i \), as we extract one spectral feature and four texture features for each band, so \( N = S_b \times 5 \). \( t \in \{1, 2\} \) represents the first phase image 1 and the second phase image 2, respectively. \( O_t^{j} \) represents the \( j \) th feature value of the object \( i \) at phase image \( t \).

In fact, the quality of the feature is uneven, not all features play an equal role in CD. So it is essential to feature optimization for characterizing the contribution of each feature. In general, the larger the standard deviation of the difference image between the two temporal images, the more valid change information [16]. Therefore, the standard deviation of the feature difference image can be calculated firstly, and then the weight of feature can be set according to the standard deviation. The change value of the \( j \) th feature in the object \( i \) can be measured by

\[ c_i^j = \frac{\sigma_i^j}{\sum_{j=1}^{N} \sigma_i^j} (\text{abs}(O_{i1}^j - O_{i2}^j)) \]

Where, \( \sigma_i^j \) is the standard deviation of the \( j \) th feature difference image, the feature change vector of the object \( i \) can be expressed as

\[ c_i = (c_i^1, c_i^2, \ldots, c_i^N)^T \]

In equation (4), \( c_i \) is the optimized change vector of spectral and texture feature from all bands of the object \( i \), which has a high dimension and information redundancy. Therefore, further feature optimization by reducing dimension is essential in the process of the object-oriented CD.

2.3.2 Improved LLE algorithm (ILLE). LLE is a nonlinear dimension reduction method; it becomes more and more popular to scholar due to its potentiality to handle multi-dimensional data and search nonlinear feature of data. The main idea of this method is to linearly reconstruct each sample by the weighted combination of its \( k \) nearest neighbors, and then to search a low-dimensional result of the sample. In order that the linear reconstruction value of sample is best saved.
The k nearest neighbors selection, which consists of distance metric and neighbor selection rule, is the first key step of the LLE algorithm. It imposes a huge influence on the final dimension reduction effect. The traditional LLE algorithm has some limitations in distance metric and neighbor selection rule: 1) the Euclidean distance is utilized to measure the distance between samples. However, it only represents the linear distance between two samples, which cannot truly reflect the spatial distribution relationship between samples [17]. 2) the rule to select neighbor is to utilize a constant k as the number of nearest neighbors for each sample. However, the low-dimensional result is sensitive to the value of k, and the optimal value of k must be set manually for many times to be determined.

Aiming at the above limitations of the traditional LLE algorithm, we choose to improve the distance metric and neighbor selection rule. Suppose \( C = [c_1, c_2, \ldots, c_m] \in \mathbb{R}^{N \times M} \) is the set of high-dimensional spatial data. \( Y = [y_1, y_2, \ldots, y_M] \in \mathbb{R}^{d \times M} \) is the low-dimensional result of C.

Improved distance metric: to overcome the limitation of Euclidean distance, we adopt the Geodesic distance to measure the distance between samples \( c_i \) and \( c_j \) for the reason that the Geodesic distance can accurately describe the complex positional relationship of nonlinear data [18]. The formula is defined as follows:

\[
d_g = \text{dijkstra}(c_i, c_j)
\]

Where, \( \text{dijkstra}(c_i, c_j) \) is the Geodesic distance between \( c_i \) and \( c_j \) calculated by Dijkstra algorithm [19].

Improved neighbor selection rule: instead of manually selecting k nearest neighbors for sample \( c_i \) in LLE method, the mean of the Geodesic distance between \( c_i \) and other samples is taken as the threshold, which is set to adaptive select the number of nearest neighbors of \( c_i \). The formula is defined as follows:

\[
T = \frac{1}{M - 1} \sum_{j} \text{dijkstra}(c_j, c_i), \ j \neq M, j \neq i
\]

In equation (6), \( M \) is the total number of samples in C, \( T \) is the threshold for nearest neighbors selection. If the Geodesic distance \( d_g \) between \( c_i \) and \( c_j \) is smaller than \( T \), \( c_j \) is the nearest neighbor of \( c_i \). The formula is as follows:

\[
c_j \text{ is the nearest neighbor of } c_i = \begin{cases} \text{true}, & d_g \leq T \\ \text{false}, & d_g > T \end{cases}
\]

Owing to that such a neighbor selection method can adaptive select the number of nearest neighbors for samples according to the density of sample distribution, the method can avoid the manual blindness selection of neighbors number \( k \). Therefore, it is reasonable to use Geodesic distance and set the threshold for adaptive selecting the nearest neighbors of the sample. By doing this, the high-quality nearest neighbors and better low-dimensional result with the most valuable information can be obtained.

2.3.3 Feature optimization by ILLE algorithm. The detailed steps of ILLE algorithm for feature optimization are as follows:

1) Adaptive selection of nearest neighbors: The nearest neighbors of \( c_i \) are calculated according to equations (5), (6) and (7), whose subscript is set as \( Q_i \).

2) The reconstruction weight calculation of sample \( c_i \): each sample is reconstructed linearly with its neighborhood sample. Suppose \( w_i = [w_{i1}, w_{i2}, \ldots, w_{im}] \) as the reconstruction weight matrix of sample \( c_i \). \( w_{ij} \) is the reconstruction weight between \( c_i \) and its nearest neighbor sample \( c_j \). In order to achieve an
accurate reconstruction of the sample $c_i$, the reconstruction error must be minimized. The minimum error function is defined as:

$$\min J(w) = \sum_{i=1}^{M} \left| y_i - \sum_{j=Q} w_{ij} c_j \right|,$$

s.t. $\sum_{j=Q} w_{ij} = 1$  \hspace{1cm} (8)

Therefore, $w_i$ can be calculated according to equation (8).

3) Low-dimensional result $y_i$ of the sample $c_i$: in low-dimensional space, keeping the $w_{ij}$ unchanged and minimizing the reconstruction error function $J(Y)$, the low-dimensional result $y_i$ of the sample $c_i$ was obtained by:

$$\min J(Y) = \sum_{i=1}^{M} \left| y_i - \sum_{j=Q} w_{ij} y_j \right|,$$

s.t. $\sum_{j=Q} y_{ij} y_j^T = I$  \hspace{1cm} (9)

Where $I$ is an M-dimensional unit matrix. Suppose $(W)_{ij} = w_{ij}$, the equation (9) can be turned into a constrained optimization problem, and then equation (9) can be converted to

$$(1-W)Y(1-W)^T = \lambda Y^T$$  \hspace{1cm} (10)

According to equation (10), the low-dimensional result $Y$ is obtained.

2.4. CD results
1) Generation of difference image: after feature optimization by ILLE algorithm, the dimension of the $c_i$ is reduced to $d$, and the changing intensity of $c_i$ is calculated as

$$Int(c_i) = \left( \sum_{j=1}^{d} \left( y_{ij}^i \right)^2 \right)^{\frac{1}{2}}$$  \hspace{1cm} (11)

Where $y_{ij}^i$ is the $j$th feature of the low-dimensional sample $y_i$.

2) Change detection: the CD result can be obtained by FCM algorithm [20].

3. Experiment Result
3.1. Experiment data
To verify the feasibility of the proposed method, the GF-1 images which are derived from Hefei city, Anhui province are selected as experiment data. The two temporal images were obtained in April 2014 and January 2015, including four bands of blue, green, red and near-infrared with the resolution of 2 meters, which are shown in Figure 2 (a), (b). The reference image is shown in (c).

Figure 2. Experiment data. (a) GF-1 image acquired in April 2014. (b) GF-1 image acquired in January 2015. (c) Reference image
3.2. Experiment results analysis

![Figure 3](image)

Figure 3. Experiment results. (a) Segmentation result of 1st image (scale 15). (b) Segmentation result of 2nd image (scale 15). (c) difference image. (d) CD result

In this experiment, the segmentation results of two temporal images are shown in figure 3(a), 3(b), respectively. In the process of feature optimization, the feature dimension \( N \) is 20. After feature optimization by ILLE method, the \( N \) is reduced to 4. Then the difference image is generated by equation (10), and the CD result is obtained by FCM, which are shown in figure 3(c), 3(d), respectively.

To verify the superiority of the proposed method compared with the traditional pixel-based CD methods, the pixel-based CVA method is introduced for comparison [11]. To prove the effectiveness of feature optimization, the object-oriented feature fusion CD (OFF) method without feature optimization is compared with the CD result of our method. It directly calculates the change of the spectral and texture features to obtain the CD result. In order to validate the availability of the LLE algorithm in the object-oriented CD, the CD based on LLE method (CD-LLE) is designed for comparison. These comparison CD results and reference image can be observed from figure 4.

![Figure 4](image)

Figure 4. CD results. (a) CVA. (b) OFF. (c) CD-LLE. (d) Proposed method. (e) Reference image

From the visual effect of the CD results in figure 4, the CVA method based on pixel performs poorly due to the obvious salt and pepper phenomenon; The OFF method is more accurate in judging the water changes than CVA method, but the CD result of bare land and plant is still not satisfactory. The CD-LLE method is good for detecting the bare ground change, whereas it performs poorly in detecting the vegetation and water. The CD result of our proposed method has fewer detection errors in the detection of vegetation, water, roads and other ground objects. In addition, the CD result is more homogeneous, and its boundary information remains better. So the CD result of our method is more consistent with the reference result. At last, to evaluate the performance of CD results quantitatively, we select the indicators of overall accuracy (OA), false rate (FR), missed rate (MR), kappa coefficient (Kappa) to analyze the accuracy of the CD results. The value of indicators are shown in Table 1.

| Method  | OA (%) | FR (%) | MR (%) | Kappa  |
|---------|--------|--------|--------|--------|
| CVA     | 79.78  | 11.52  | 8.70   | 0.4998 |
| OFF     | 82.33  | 10.10  | 7.57   | 0.5425 |
| CD-LLE  | 87.08  | 7.45   | 5.46   | 0.6631 |
| Ours    | 93.78  | 2.93   | 3.29   | 0.8325 |

It can be seen from Table 1 that the OA of our method is 93.78%, and the Kappa coefficient is about 0.83. They are significantly higher than the three comparison methods. Moreover, the FR and
the MR of our method are the smallest of these four methods. Thus it can be seen that the proposed method is more effective and feasible than the CVA, OFF and CD-LLE methods.

4. Conclusion
In this paper, a CD method based on feature optimization which combines object-oriented CD technology with ILLE algorithm is proposed. The optical image objects are segmented based on multi-scale segmentation algorithm. And the spectral feature and texture features are extracted to construct the novel feature change vector. The feature change vector is optimized by improving the LLE algorithm based on the Geodesic distance metric. Finally, the CD result is obtained by FCM algorithm. The experimental results show that the proposed method can effectively improve the OA of CD, and it has definite application value in CD of high resolution optical images.

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