Change Detection Based on IR-MAD Model for GF-5 Remote Sensing Imagery

Guibin Xu¹, Huafeng Li¹*, Yuwei Zang², Lianke Xie² and Chunxiao Bai³

¹Hubei Huazhong Electric Power Technology Development Co., Ltd, Wuhan, China
²State Grid Shandong Electric Power Research Institute, Jinan, China
³State Grid Shanxi Electric Power Research Institute, Xi’an, China

*Corresponding author e-mail: 2805336586@qq.com

Abstract. GF-5 is the domestic full spectrum satellite with the most spectral bands, and it can comprehensive observe earth and atmosphere, the data can effectively monitor the changes of ground objects. However, due to the high wave dimension and large data of the hyperspectral remote sensing image, which reduces the processing and operation speed, and brings great uncertainty to the accuracy. In order to improve the accuracy and processing speed of hyperspectral imagery change detection, a method of iterative weighted multivariate change detection based on IR-MAD is proposed. In this paper, the high-resolution remote sensing image of GF-5 is used as the data source. After geometric correction, removal of bad line and other pre-processing methods, the change detection results are obtained by the iterative weighted multivariate (IR-MAD) change detection method. The experiments show that: the algorithm in this paper is compared with change vector analysis (CVA) change detection, principal component change vector analysis (PCA-CVA) change detection method, and iterative weighted multivariate (IR-MAD) detection method without principal component extraction. The detection accuracy of this method is high, and the error rate and missed rate are also low.

1. Introduction

Due to human production activities and continuous replacement of ecosystems on earth, the ground cover also changes. Satellite remote sensing for Earth observation has the characteristics of large scope, high time efficiency, short cycle, low restriction and high economic benefit. Using multi-temporal satellite images to observe the ground multiple times for obtaining the process of changing, which is change detection, has always been the hotspot of remote sensing research [1].

Hyperspectral remote sensing images have many bands, and can obtain complete feature information. At present, the official launch of the domestic GaoFen-5 (GF-5) and the popularization of UAV hyperspectral data provide a rich data source for hyperspectral change detection studies. However, due to the large number of hyperspectral data bands, how to effectively use the rich spectrum information of hyperspectral imagery to extract the information of ground changes is the main research hotspot of current change detection. In the field of traditional multispectral change detection, Zhao Min[2] proposed an object-oriented multi-feature grading change vector analysis (CVA) method. Nielsen [3] proposed an iterative weighted multivariate based on linear transformation. In hyperspectral change detection, Wu Chen [4] used independent component analysis (ICA) to extract changes in a single feature. Recently, because the deep learning algorithm is mature, Wang [5]
introduced the algorithm of convolutional neural network (CNN) and the application of pixel unmixing to hyperspectral change detection, and all of them have obtained good results.

The above method improves the accuracy of hyperspectral remote sensing change detection to a certain extent, but there are still problems such as dimensionality disaster, slow processing speed and insufficient data usage. Aiming at the above situation, this paper proposes a method of iterative weighted multivariate change detection based on principal component analysis (PCA). In this paper, we acquired GF-5 remote sensing image data. Firstly, geometric correction, removing bad line and other pre-processing methods are carried out for the data. Then the main bands in the hyperspectral image were extracted by PCA, and the change detection results were obtained by the inverse weighted multivariate (IR-MAD) change detection method.

2. Study area and data

2.1. Study Area

The study area is located in Yancheng City, Jiangsu Province, with 34°05′ east longitude and 120°16′ north latitude. It is located in the eastern coastal area of China, in the estuary of the Yellow Sea and the Huaihe River. It belongs to the transition zone from subtropical to warm temperate zone, and the marine warm and humid monsoon climate is obvious. The climate of the study area is mild, the four seasons are distinct, the sunshine is sufficient, the cold and warm is normal, the rainfall is moderate, and the land, ocean and tidal resources are unique. It is the prefecture-level city with the longest coastline in Jiangsu Province. The reserve resources along the beach cover 44% of the beach area and the area has the largest land reserve resources in eastern China. There are China's largest coastal wetland type nature reserves in the region, which is extremely rich in biodiversity and is a typical coastal wetland ecosystem in China. However, domestic agriculture, aquaculture, salt industry, etc., the use of tidal flat reclamation by humans has led to a sharp decline in wetland area and has become the greatest threat to the protection of coastal wetlands [6].

2.2. Acquisition of Remote Sensing Data

GF-5 operates in a sun-synchronous orbit with an average orbital height of 705 km and an inclination of 98.2°. It has a launch mass of about 2800kg, a power of 1700W and a design life of 8 years. GF-5 uses visible short-wave infrared hyperspectral camera with spectral resolution of 5nm (VNIR), 10nm (SWIR), spectral range of 0.4~2.5μm, spatial resolution of 30m, ground coverage width of 60km, and it has 330 original bands (VNIR 150, SWIR 180).

In order to study the change detection, two images were obtained in the coastal areas near Yancheng city, Jiangsu Province on July 15, 2018 and November 1, 2018 when the coastline and crops changed significantly in summer, autumn and winter.

3. Methods

3.1. Remote Sensing Data Pre-processing

Although the data of the GF-5 has been basically processed, the accuracy of the change detection required in this study is high, and the original data cannot meet the experimental requirements. Firstly, select control points in the Landsat 8 image data that has been geometrically corrected and the GF-5 image data separately to realize the geometric precision correction of the GF-5 data. After geometric correction, the error is within 1 pixel, which meets the experimental requirements of change detection.

After image quality inspection, VNIR1~3, 128~132, SWIR14~22, 35~68, 90~130, 139~180 bands are affected by different degrees of water vapor and other factors, and there are different degrees of strips, bad lines, noise and etc., which will influence the result. Therefore, the problematic bands were removed and left 196 bands in the end.
3.2. Remote Sensing Image Change Detection Method

3.2.1. Principal Component Analysis. Principal Component Analysis (PCA) is a mathematical analysis method that reduces the dimensionality of multidimensional variables and extracts the main information of the data. Hyperspectral remote sensing images have the characteristics of high data dimension and more bands. PCA can extract the main feature bands in the data to facilitate subsequent processing. The main steps are as follows: Firstly, standardize the remote sensing data matrix to obtain a normalized sample matrix. Then the matrix is subjected to the covariance matrix to obtain the eigenvalues and eigenvectors of the operation, and select the main feature. And the dimensional reduced matrix is the final result [7].

3.2.2. Iterative Weighted Multivariate Detection. In view of the impact of noise errors on image data detected by traditional detection methods, Nielsen [8] found a Canonical Correlation Analysis (CCA) transformation method based on statistical analysis, referred as Multivariate Alteration Detection (MAD). It can reduce the impact of errors caused by noise through the detection of the MAD transformation method. Later, Nielsen [7] improved the algorithm, which can calculate automatically to obtaining the threshold, and it namely Iteration Re-weight Multivariate Alteration Detection (IR-MAD) algorithm. Nielsen applied it in the Hyperspectral change detection and the results were better.

The main flow of IR-MAD is as follows: First, set the weight of each pixel of the hyperspectral image for change detection to 1. After one MAD iteration, assign two images to the new weight values which are between 0 and 1. Then set the unchanging pixels to a high weight value, and finally get a matrix of the same size as the original image but with different weights. After multiple iterations, the weight value increase for each pixel is fixed, and then the mean clustering is used to segment the changed and unchanged regions.

The core of the multiplicative weighted multivariate change is MAD, and the original MAD transform can be represented by (1):

\[
\begin{bmatrix}
X \\
Y
\end{bmatrix} \rightarrow
\begin{bmatrix}
a'_pX - b'_pY \\
\vdots \\
a'_1X - b'_1Y
\end{bmatrix} \rightarrow
\begin{bmatrix}
U_p - V_p \\
\vdots \\
U_1 - V_1
\end{bmatrix} \rightarrow
\begin{bmatrix}
MAD_p \\
\vdots \\
MAD_1
\end{bmatrix}
\]

(1)

Where X, Y are the initial image data; U and V are typical variables in a typical correlation analysis; a and b are linear combination coefficients. We need to solve the (3) eigenvectors and eigenvalues of the corresponding generalized characteristic equation (2).

\[
\sum_{XY}\sum_{YY}^{-1}\sum_{XX}a = \rho^2\sum_{XX}a
\]

(2)

\[
\sum_{XY}\sum_{XX}^{-1}\sum_{YY}b = \rho^2\sum_{YY}b
\]

(3)

Because the image data satisfies the characteristics of the Gaussian distribution, according to the central limit theorem, the MAD variable also approximately obeys the Gaussian distribution. Then there is a variable \( T_i \) expressed as the sum of the squares of the normalized MAD variables, which is in accordance with the chi-square distribution with a degree of freedom p, as in (4).

\[
T_i = \sum_{p=1}^{p} \left( \frac{MAD_p}{\sigma_iMAD} \right)^2 \in \chi^2(p)
\]

(4)

The probability of the chi-squared value \( T_i \) is weighted as the mean and variance-covariance of the image CM for each iteration, as in (5).

\[
CM_j = P\{T_j > t\} = P\{x^2(p) > t\}
\]

(5)
3.3. Change Detection Process

In this study, the pre-processed hyperspectral image data is used for PCA to extract the main components, and then the iterative weighted multivariate detection is performed on the images of different phases. Then the detection results are segmented out of the changed and unchanged regions by threshold. The process is shown in Figure 1.

![Diagram of Change Detection Process]

**Figure 1.** The flow chart of PCA-IR-MAD Change detection

4. Results and Analysis

The experimental data of the two scenes is located in Yancheng, Jiangsu Province, with an east longitude of 120°20' and a north latitude of 34°5', both of which are 406*371 pixels. Figure 2 (a) (b) show the pre-processed GF5 images. Synthetic false color images of 60, 40, and 20 bands are selected. For quantitative analysis, the reference change image 1 (c) was created. Using the confusion matrix, overall accuracy, Kappa coefficient, missed detection rate and other evaluation indicators to analyze the change detection accuracy. According to the above algorithm and data processing flow, the change results of the partial change of the seaside in Yancheng City, Jiangsu Province were obtained. The white part was the change area, while the black represented the unaltered area, and the number of them are 48735 and 101891, respectively.
Figure 2. GF-5 hyperspectral images

Combined with the hyperspectral images of Yancheng in July (a) and November (b) in 2018, the following trends can be found. First, the summer crops cover the ground, while in the autumn and winter the farmland becomes bare land due to the crop harvest. Second, because of the abundant rainfall in the summer, the sea level rises, and in the autumn and winter with little rain, the seawater becomes a tidal flat, and some of the ponds also become dry. Besides, in the autumn and winter, some winter wheat is planted, so some of the free land covered with plants again.

4.1. Change Detection Accuracy Analysis

In order to verify the accuracy of the proposed algorithm and the accuracy and effectiveness of the proposed method, the original data extracted without PCA is selected, and the CVA and IR-MAD algorithms are used to detect and compare the changes. Visually, it can be found that CVA can effectively detect changing water surface, farmland and tidal flat. The IR-MAD algorithm can also accurately identify small changes in water and farmland. The two algorithms have their own advantages, but IR-MAD is slightly insufficient in the identification of building changes and road surface changes, while CVA lacks stability in terms of vegetation changes. In a word, there are a lot of missed detection in two methods.
4.2. Detection and Analysis of Changes in Different Bands of Images

Because of the high dimensionality of hyperspectral, this paper takes PCA as the main means of dimensionality reduction. In order to select the appropriate principal component band and verify the accuracy of the algorithm, different principal component bands were selected for change detection. The results are shown in Fig. 4. From the result of Fig. 4(a), it can be seen that when the number of extracted bands is small, the results are rough, and some farmland changes are not refined, and some roads and houses are not well separated from the crops. However, as the number of extracted bands increases, as shown in Figure 4(b)(c), the changes are gradually refined. When the number of suitable bands of the PCA is exceeded, as shown in Figure 4(d), the details of the change detection begin to decrease again, indicating that the first 60 bands selected in this paper are suitable, and the quantitative analysis results are shown in Table 2.

Figure 4. Change detection results of each bands

It can be seen from Fig. 5 that the effect of using the first 30 bands is not optimal when using the algorithm proposed this paper for change detection. Because the algorithm is an iterative weighting algorithm, the accuracy of detection increases significantly with the increase of the band (the first 45). The original remote sensing image used in this paper has a total of 196 bands after pre-processing. After PCA calculation, the statistical index of each band is obtained. The first 60 bands have a good principal component index. Starting from the 61st band, the PCA statistical index of the latter bands has poor quality, which means these bands have high noise. It can also be seen from Fig. 4(d) that the
accuracy of the algorithm is obviously reduced after calculating the change detection result using the first 75 bands. Therefore, choosing the appropriate number of principal component bands is especially important in change detection.

Table 2. Change detection accuracy of each of PCA bands GF-5 hyperspectral image

| Principal component band | False detection rate | Missed detection rate | Kappa | Overall accuracy |
|-------------------------|----------------------|-----------------------|-------|------------------|
| First 30                | 0.24101              | 0.1699                | 0.6211| 0.8132           |
| First 45                | 0.23112              | 0.3376                | 0.6021| 0.8341           |
| First 60                | 0.20301              | 0.1033                | 0.6887| 0.8499           |
| First 75                | 0.24865              | 0.3901                | 0.5612| 0.8167           |

Figure 5. Detection and comparison of hyperspectral image changes in principal component bands

5. Conclusion
In this paper, the hyperspectral image data of Jiangsu Yancheng GF-5 at the same position but at different times are used. The results of hyperspectral change detection are generated by IR-MAD algorithm. The results show that: (1) The use of domestic GF-5 hyperspectral imagery is effective and can meet the requirements of basic data quality. (2) The GF-5 hyperspectral imagery can use the IR-MAD change detection method to extract the change information. (3) The GF-5 hyperspectral image can obtain the change information of plants and surface features well, and can effectively detect the changes of water, which can provide effective support for ecological detection, land use and land planning.

6. Acknowledgments
This work was financially supported by Power grid environmental protection ecological data application model and environmental risk prediction and assessment technology research project and Shandong Province Environmental Sensitive Area Data Vectorization and Database Construction Project.
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