Automatic Geometric Correction of Complex Sea Condition Remote Sensing Image Based on Decision Tree Classification

Li Hua¹, Haigang Sui², Wei Ding², Hongbo Fu²

¹ College of Resources and Environment, Huazhong Agricultural University, Wuhan, China
² State Key Laboratory of Information Engineering in Surveying Mapping and Remote Sensing, Wuhan University, Wuhan, China
E-mail: fuhongbowhu@163.com

Abstract. The geometric correction of ocean remote sensing image is a prerequisite for its data application. In this paper, to solve the problem that the sea island is sparse, cloud interference is severe, the control point is difficult to obtain, an automatic correction technique based on decision tree classification is proposed. In this paper, the image is processed by the method of super-pixel segmentation first. Then, the spectral and texture features in the superpixels are selected, including the energy value, the entropy and the correlation value of the gray level co-occurrence matrix and the normalized water index. Finally, the tree image classification model is used to classify the image superpixels, and the clear sky area which will be matched directly with the reference image can be extracted. Through the template matching and polynomial geometric model, the geometric correction of the remote sensing image is automatically corrected. Through the experiment of Landset8 OLI_TIRS image, compared with the classification results of the other two classification methods, the final precision is better than the other two methods. Therefore, the technical process proposed in this paper can be applied to the geometric correction of complex sea condition remote sensing images.

1. Introduction

With the continuous development of earth observation technology, the application of remote sensing is more and more widely, of which ocean remote sensing is widely used in waterway, fishery, meteorological and other fields. The geometric correction of remote sensing image is a prerequisite for its application. And a large number of remote sensing images are constantly updated, the match method that the control points are selected manually has been unable to meet the needs of data production. Automatic remote sensing image geometric correction technology can solve such problems. The traditional method of automatic correction of remote sensing images by using the rich feature points on land has good effect. However, in the ocean environment, due to the large area of seawater, the island is sparse, cloud interference is great, resulting in match point can not be obtained, fine correction can not be completed automatically.

Geometric correction requires the more obvious control points in remote sensing images. In order to get control points in cloudy and less island images, it is first necessary to eliminate cloud interference. Second, islands or coastline which have obvious features need to be searched. Finally, by using the feature-specific islands and coastline, the images are matched with the reference images to complete a remote sensing image correction. In order to eliminate cloud interference, Chen uses the tree-like structure to extract the characteristics of the sub-block image. The second moments and the first order difference of the block image are calculated and the cloud and the object are separated. But the tree
structure is fixed, only applies to the removal of cloud interference in a particular remote sensing image. And the block division results in a large difference in pixel characteristics between each block, which has a greater effect on the accuracy of the subsequent classification results. The equal size segmentation method results in a large difference in the characteristics of each block pixel, which has a great influence on the accuracy of the classification result. Liu Pengyu [2] used the gray-level co-occurrence matrix and Gabor filter to extract the texture features of the image, and comprehensively describes the contents of the image, so that the cloud, land and water were classified. Chen [3] used the decision tree to classify the remote sensing images, and concluded that the decision tree method is simple and intuitive, and the overall classification accuracy is 90.65%. However, for ocean with less islands in remote sensing images, islands are often difficult to classify, and broken clouds and small island reefs are prone to misclassification.

In this paper, first, the image are divided into sub-regions by superpixel image segmentation. The pixels in each sub-region are similar under the measure of brightness and texture. Based on the characteristics of the brightness and texture of ocean remote sensing images, use the image super pixel block to train to get the decision tree model. From the classification results, the super-pixel blocks of test image whose island or coastline characteristics is obvious are obtained, which can be matched with reference image. Then a series of control points after the template matching, and the geometric correction of the test image is carried out by using the polynomial model. Thus the automatic geometric correction process is completed. This paper is based on the OLI_TIRS image of Landset8 in Ryukyu Islands.

2. Geometric correction process
Through the analysis of ocean remote sensing images, The following four types exist in the image.

![Figure 1](image1.png)

**Figure 1.** (a) Clear sky ocean, (b) Clear sky island, (c) Sparse cloud, (d) Sparse cloud.

The clear sky island images can match the benchmark image well, because this situation that the cloud interference is small, coastline characteristics is obvious is similar to the reference image.

So it is necessary to automatically extract the range of the clear sky in a remote sensing image. This process requires the segmentation and classification of the images. For the adaptive segmentation method, this paper adopts the super-pixel segmentation. For the classification method, the decision tree is used to adapt the classification.

2.1. Superpixel image segmentation
In a remote sensing image automatically extract the scope of clear sky islands. This process requires the image to be segmented and sorted. For the adaptive segmentation method, this paper adopts the super-pixel segmentation. For the classification method, the decision tree is used to adapt the classification.

The super-pixel segmentation method is a simple linear iterative clustering method. The advantages of this method are computationally fast, the edge tracking effect is better[4], the input parameters are few, only one parameter k, which represents the estimated number of super-pixel segmentation. The simple linear iterative clustering algorithm is as follows:

1. Convert the RGB image to CIELab color space. Given the number of super-pixels to be segmented, the number k is 2000 and the image size is 4237 × 4205 pixels, denoted as N, then the seed points step distance S is calculated according to the following formula.

$$S = \sqrt{\frac{N}{k}}$$
The seed points are evenly distributed over the image in steps.

Step 2: Perturb the seed point: Select the point with the smallest gradient change as the new seed point in the neighborhood of the $3 \times 3$ pixel of the seed point to prevent interference from the noise. Each seed point is a cluster center.

$$C_k = [l_k, a_k, b_k, x_k, y_k]^T$$

The $l_k$ is the brightness of the seed point, the $a_k$ is the red and green axis value, the $b_k$ is the yellow blue axis value, and $x_k, y_k$ is the spatial coordinate of the seed point.

Step 3: Traverse all cluster centers $C_i$, then traverse the pixels $i$ with a size range of $2S$ centered around the seed points, calculate the distance measure of spatial characteristics of the pixels and the color characteristic:

The characteristic of space distance:

$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$

The characteristic of color distance:

$$d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$

Set the factor $m$ to represent the maximum value of the color distance. Integrated distance measure $D'$:

$$D' = \sqrt{\left(\frac{d_s}{S}\right)^2 + \left(\frac{d_c}{m}\right)^2}$$

Compare each pixel point to the surrounding cluster center, labeling the smallest distance of the superpixel.

2.2. Classification characteristics selection

There is a large gap between the ocean and the land in spectral characteristics. In order to highlight the characteristics of the water, the differential water index (NDWI) is selected as the spectral classification characteristics.

$$NDWI = \frac{(Band2 - Band4)}{(Band2 + Band4)}$$

In this paper, the gray level co-occurrence matrix (GLCM) is used, which is defined as the probability that two pixels whose distances is $d$ and the direction is $x$ appears in the image. Because the image of the image is characterized by the texture of the cloud. Through the $(d, \theta)$ value, a lot of GLCM can be combined to analyze the spatial distribution pattern of image gray level. In this paper, the three measures are selected as energy, entropy and correlation.

Energy is the measure of image uniformity, the more uniform the image, the larger the value:

$$Energy = \sum_{a,b} G_{\theta,d}(a,b)$$

Entropy is the measure of the amount of image information, the image is close to random or the noise is large, entropy will be larger:

$$Entropy = \sum_{a,b} [(ab)G_{\theta,d}^2(a,b)] - \mu_x \mu_y$$

Where $\mu$ is the mean and $x$ is the standard deviation.

$$\mu_x = \sum_{a} a \sum_{b} G_{\theta,d}(a,b)$$

$$\mu_y = \sum_{b} b \sum_{a} G_{\theta,d}(a,b)$$

$$\delta_x = \sum_{a} (a - \mu_x)^2 \sum_{b} G_{\theta,d}(a,b)$$

$$\delta_y = \sum_{b} (b - \mu_y)^2 \sum_{a} G_{\theta,d}(a,b)$$
2.3. Decision Tree Classification

The decision tree is a simple but widely used classifier proposed by Breiman [5] and others, and the decision tree is constructed by training data, which can efficiently classify unknown data. There are two advantages: 1) The decision tree model can be read well and descriptive, and it is helpful for manual analysis. 2) High efficiency, decision tree only needs to be constructed ones and used repeatedly. The maximum number of calculations for each forecast is not more than the depth of the decision tree.

A decision tree includes a root node (Rootnode) on behalf of the input variable, a series of internal nodes (Internal nodes) on behalf of the branch and the terminal node (Terminal nodes) on behalf of the leaves.

In this paper, the Classification and Regression Tree (CART) is used to implement the decision tree. The principle is as follows:

The \( \{x_1, x_2, \ldots, x_n\} \) represents the n attributes of a single sample, and y represents the classes. The CART algorithm divides the dimension space into a non-overlapping rectangle by recursive way. The primary judgment at the tree node is called a branch, which corresponds to dividing the training sample into subsets. The branches at the root node correspond to the total training samples. Each subsequent decision is a training subset partitioning process, so the The process of tree construction is actually a property query to generate a division rules.

The Gini indicator is commonly used to measuring impurity. Assuming the number of samples is \( C \), the Gini impurity of the node can be defined as:

\[
Gini(A) = 1 - \sum_{i=1}^{C} p_i^2
\]

The \( p_i \) represents the probability of belonging to class \( i \). Or use the Entropy Impurity:

\[
EI(A) = -\sum_{i=1}^{C} p_i \log_2 p_i
\]

If all the samples of the model are from the same class, then the impurity is zero, otherwise it is a positive value. When all the classes appear with equal probability, the entropy is max.

2.4. Template match

Use the result which is classified by decision tree to match the reference image to obtain the control points.

Because of the obvious characteristics of the remote sensing image of the clear sky, the water brightness is low, and the land brightness is higher, so the template matching can be more accurate corresponding to the pixel.

The superpixel block classified as the clear sky is matched with the reference image. The difference between the superpixel image and the reference image is measured by the correlation, the better the matching, the greater the matching value. The correlation measure is calculated as follows:

\[
d_{corr}(H_1, H_2) = \frac{\sum_i H_1'(i) \cdot H_2'(i)}{\sqrt{\sum_i H_1'^2(i) \cdot H_2'^2(i)}}
\]

The \( H_1, H_2 \) represents the superpixel block to be matched and the reference image.

After obtaining the matching point, use the quadratic polynomial model to correct the images.

3. Results and analysis

3.1. Experimental results
The experimental data are OLI_TIRS images of Landset8, and the latitude and longitude range is 128.46 °E ~ 129.75 °E 28.39 °N ~ 29.53 °N. The area is Ryukyu Islands, the islands are extremely sparse and the cloud coverage is 40%.

The image whose size is 4237 × 4205 pixel is divided into 2000 superpixels, the following figure shows the results of superpixel segmentation. As can be seen from the results, each superpixel image type is more consistent. Then, five OLI_TIRS remote sensing images near the Ryukyu Island are processed with superpixel segmentation.

![Figure 2. The result of superpixel segmentation.](image)

The average NDWI of each superpixel and the energy, entropy and correlation of the gray level co-occurrence matrix are calculated and classified with decision tree. The following model is obtained by training the data.

![Figure 3. The decision tree classification model.](image)

According to the model obtained by training, the results are tested with the data as follows:
Figure 4. The result of classification.

Obtain the superpixel of the island as follows:

Figure 5. Superpixel of the island.

The model is used to match the blue sky island super pixel with the reference image, and the four islands are used as the matching control points, leaving one island as the precision test point.

3.2. Accuracy evaluation

The classification model of the decision tree is compared with the Naive Bayesian classification method and the K-means clustering method. The evaluation criterion is the amount of the super-pixels of clear sky and wrong classification. The evaluation of the island extraction is the NASA Coastline vector data.

The following are the results of the Naive Bayesian model and the Kmeans classification method.

Table 1. The result of classification.

|                      | Decision Tree | Bayesian Belief | k-Means |
|----------------------|---------------|-----------------|---------|
| Count of island super pixels | 17            | 26              | 4       |
| Count of misclassification   | 2             | 13              | 1       |

The number of clear sky islands classified with Bayesian classification are more, but most of them are covered the cloud, so the template matching method to match these superpixel will occur, k-Means method to get the number of clear blue islands, resulting in The number of control points is small, can not cover the entire image, the final geometric precision correction accuracy.

In this paper, 5 pair of test points of 5 images are randomly selected to verify the corrected image geometric accuracy. The following is the correction accuracy.
Table 2. The result of geometric accuracy.

| Test point number | Basemap test point Longitude | Basemap test point Latitude | Corrected image Longitude | Corrected image Latitude | Relative error (m) |
|-------------------|------------------------------|-----------------------------|---------------------------|--------------------------|--------------------|
| 1                 | 110.5953676                 | 20.1104276                 | 110.5945106              | 20.11199656              | 208.0614727       |
| 2                 | 117.8379696                 | 15.1216538                | 117.8378905              | 15.12349789              | 211.4951584       |
| 3                 | 96.14830704                 | 40.8165308                | 96.1408869               | 40.84352397              | 870.3646871       |
| 4                 | 120.1254373                 | 40.07711525               | 120.1266489              | 40.08135823              | 629.4872926       |
| 5                 | 126.5537363                 | 35.70248423               | 126.5559381              | 35.70852891              | 860.6281058       |
| Average           |                              |                            |                           |                          | 556.0073433       |

4. Conclusion

Through the research and experimentation, this paper proposes the use of decision tree classification to extract the superpixel blocks of ocean islands with large cloud cover. This method has the ability to search the area of the image that can match the reference image to a great extent and to achieve automatic geometric correction of the sparse island images.

At the same time, the superpixel segmentation is used to make the initial clustering of the region with similar internal features and spatial features, which is beneficial to the improvement of the accuracy of the classification result, which has a great advantage compared with the traditional block segmentation. The spectral and texture features of the islands are also full used. The decision tree model is analyzed intuitively. The island image has more texture information than the cloud and the ocean, and the internal correlation is strong and the brightness distribution is not uniform.

However, there are some problems need to be solved in the next step. The adaptability of the template matching is poor, and it is susceptible to cloud interference. The island matching method needs to be improved. Non-uniform control points can not guarantee the geometric accuracy of the whole image, the quadratic polynomial model may not be able to meet the situation of non-uniform control points, and the geometric adjustment model needs to be improved.

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