A classification algorithm based on Cloude decomposition model for fully polarimetric SAR image

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Abstract. Remote sensing is an important technology for monitoring coastal zone, but it is difficult to get effective optical data in cloudy or rainy weather. SAR is an important data source for monitoring the coastal zone because it cannot be restricted in all-weather. Fully polarimetric SAR data is more abundant than single polarization and multi-polarization SAR data. The experiment selected the fully polarimetric SAR image of Radarsat-2, which covered the Yellow River Estuary. In view of the features of the study area, we carried out the H/α unsupervised classification, the H/α-Wishart unsupervised classification and the H/α-Wishart unsupervised classification based on the results of Cloude decomposition. A new classification method is proposed which used the Wishart supervised classification based on the result of H/α-Wishart unsupervised classification. The experimental results showed that the new method effectively overcome the shortcoming of unsupervised classification and improved the classification accuracy significantly. It was also shown that the classification result of SAR image had the similar precision with that of Landsat-7 image by the same classification method, SAR image had a better precision of water classification due to its sensitivity for water, and Landsat-7 image had a better precision of vegetation types.

Key words: polarimetric MAR; Cloude decomposition; coastal zone; classification

1. Introduction
Coastal zone is the area between the sea and land. It is rich in natural resources and has always been in the center of people's attention. Remote sensing technology has always been playing an important role on coastal zone research. However, the climate of coastal zone is cloudy and rainy, optical data is difficult to obtain in this area so that inconvenience comes to extraction and supervision. SAR is a kind of active microwave remote sensing sensor and it can work all-weather and all-day. Therefore, SAR data can be an effective data to replace optical data in the coastal zone.

With the development of SAR technology, the working mode of SAR has been gradually turned into the multi-polar, multi-band imaging mode with more information. Applications of SAR are more extensive, including military, agriculture etc. Image classification is an important application of SAR data[1]. Foreign research about SAR image classification has achieved remarkable results. Fukuda(2001) proposed the SVM classification method[2]. Lee(2004) proposed a classification method
based on Freeman decomposition and Wishart classifier. Singh (2011) used PCA to analyse spatial texture, and extracted the most effective texture feature for SAR image classification. Ataollah(2011) combined ANN and genetic algorithm for PolSAR image classification, and achieved higher classification accuracy than MLC and Wishart method. Kayabol(2012) proposed an unsupervised classification algorithm based on hierarchical clustering and statistical expectation maximization for high resolution SAR images.

SAR technology started late in China, the present study focuses on the improvement of foreign advanced algorithm. Chen Jin-song(2004) proposed a NN classification method based on the target decomposition for full polarization SAR image. Liu Xiu-qing(2004) proposed an iterative classification method based on unsupervised classification. Zhang Xiang(2013) combined different decomposition methods to extract classification features, then through SVM classification experiment concluded that information of coherent and non-coherent decomposition are complementary. Chen Jun(2014) proposed a supervision classification method based on the Pauli decomposition and SVM. This paper chose a Radarsat-2 image that covers Yellow River estuary area to research on classification method of SAR image with characteristics' information of coastal zone features. We performed four kinds of classification methods on Cloude decomposition result image, including the H/α classification, H/α-Wishart classification, H/A/α-Wishart classification, and a new Wishart classification which based on the H/A/α-Wishart classification result, and evaluated these methods. We also classified a Landsat-7 image covering the same region to analyse the respective advantages and causes of optical and SAR images.

2. Data and Pretreatment

2.1. Data
Radarsat-2 data is used in this study. The work mode is fine full polarization mode, and the working band is C band, while the incident angle is from 25.79°~27.62° with the distance to the resolution of 12 meters, azimuth resolution to 8 meters. The data type is single look complex data (SLC) with the range of 37.59°N~37.88°N and 118.92°E~121.79°E, imaging time on July 3, 2009.

2.2. Data Pretreatment

2.2.1 Filtering processing
The existence of speckle noise is the most basic feature of SAR image, which is the inevitable principle defect of SAR system. The existence of noise seriously affects the quality of the image and causes difficulties on image interpretation, so this article chosen enhance Lee method of "3 * 3" window to filter the SAR image.

2.2.2 Polarization target decomposition
The features of PolSAR data is mainly random scatterer, so incoherent polarization target decomposition has a wider application, so this article used Cloude decomposition (incoherent decomposition) method for the SAR image after filtering processing to get three components - entropy, scattering angle and anti-entropy, which showed as in figure 1.
From figure 1 (a), it can be seen that the scattering entropy of water body and water body-related features is small, and the scattering entropy of different vegetation types is larger. From the physical meaning of scattering entropy, it can be concluded that the water body can be regarded as a point target. The scattering process is more stable and the scattering type is single, while the different types of vegetation can be regarded as random scatterers. The scattering process consists of many pure target linear combinations and more chaotic, scattering type is more complex. From figure1 (b), it can be seen that the average scattering angle of different types of vegetation is larger, and the average scattering angle of water body and water body-related feature type is smaller. This is mainly because the scattering type of the water body is isotropic surface scattering, and the scattering type of vegetation is body scattering or even scattering. From figure1 (c), it can be seen that the entropy of water body and water body-related features is relatively large, while the anti-entropy of different types of vegetation is small.

3. Experiment

SAR image feature classification can be divided into two categories - supervised classification and unsupervised classification. Supervised classification is mainly anthropogenic selection of object categories and unsupervised classification is mainly clustering categories or specific types of scattering. At present, the mainstream polarization SAR remote sensing classification method is based on the classification of polarization target decomposition. In this paper, H / α -Wishart classification and H / A / α -Wishart classification are used to classify Cloude decomposing images based on H / A / α -Wishart classification. Unsupervised classification results were then subjected to Wishart supervised classification. And then by visual interpretation and quantitative evaluation to compare the advantages and disadvantages of these four different classification methods. Finally, in order to compare the advantages and disadvantages of SAR image and optical image in feature extraction, this paper chooses an optical image to classify and contrast the experiment.

3.1. Unsupervised classification based on Cloude decomposition image

(1) H/α unsupervised classification

The experimental data were subjected to H / α unsupervised classification. The classification results are shown in Figure 2.
Figure 2. H / \( \alpha \) unsupervised classification images

Figure 2 (b) (c) is the distribution of the features in the H / \( \alpha \) plane and the coloring of the images in the classification. From Figure 2 (b), it can be seen that the features of this area are mainly concentrated in low scattering entropy and medium scattering entropy. From the classification results in Figure 2 (a), the overall classification of this classification method is not effective, and the obvious obscuration phenomenon is found in the seawater, river, pond, tidal flat mud and Suaeda salsa. Other vegetation is simply divided into two categories. The classification result is determined by the classification principle of H / \( \alpha \) unsupervised classification. The H / \( \alpha \) plane classification is classified according to the target scattering mechanism. The backward scatter characteristics of the water bodies such as seawater and rivers are similar in this area, and the wetland of Suaeda salsa is characterized by high water content in the soil and water Characteristics, and therefore also be divided into this category. The other vegetation types had similar scattering characteristics. The reed marshes were classified as one species because of their high plant height and scattering type, which were distinguished from the dwarf plant species such as arable land.

2) H/\( \alpha \)-Wishart unsupervised classification

The H / \( \alpha \)-Wishart unsupervised classification of the test data is shown in Figure 3. It can be seen from Figure 3 ming area is clearer. However, it is still not good to classify the types of water bodies, such as sea water, rivers, ponds and aquaculture areas, which are closely related to water bodies.

3) H/A/\( \alpha \)-Wishart unsupervised classification

The H / A / \( \alpha \) -Wishart unsupervised classification of the test data is shown in Figure 4.
It can be seen from Figure 4 that different types of vegetation have serious misclassification phenomenon. The introduction of anti-entropy A scattering component makes the information increase, resulting in information redundancy, and the types of ground objects are divided into too many types. Water, rivers, aquaculture areas and other water-related features or is divided into a class. Suaeda salsa can be clearly separated from adjacent seawater and ponds.

3.2. Supervised classification on unsupervised classification result

Three kinds of unsupervised classification above are all based on the scattering characteristics of ground features, prone to produce erroneous classification phenomenon. To solve this problem, this paper improved classification methods above, proposed a Wishart supervised classification method that based on the H/A/α-Wishart unsupervised classification result. The main idea of this method is to perform the Wishart supervised classification on the H/A/α-Wishart unsupervised classification result, combining it with the prior knowledge. The classification results are as shown in Figure 1, in which nine kinds of ground feature have better classified effect.
3.3. Classification of Landsat7 image

In the optical contrast experiment, a Landsat7 image of August 31, 2009 was selected. The imaging data is similar to the SAR data imaging time, and the variation of the surface features is small, and the water level of the Yellow River Estuary is high. The classification result is comparatively high. Because of the vegetation coverage in the study area, the 4, 3, 2-band combination of vegetation sensitivity was selected in the Landsat7 image, and the Wishart monitoring based on the H / A / α - Wishart unsupervised classification. The classification results are shown in figure 6.

![Figure 6. Landsat7 image SVM supervised classification result](image)

Results and analysis

It can be seen from Figure 6 that 4, 2, 2-band pseudo-color synthetic images of the overall classification results are better, reed marsh, Suaeda wetlands, cultivated land, breeding and other objects have been more accurately divided. However, there is still some misclassification in the ground surface. Part of the sap was broken up into tidal flat mud, and some seawater and river were mistakenly divided into ponds.

4. Results and analysis

4.1. Comparison and analysis of SAR image classification results

For the three unsupervised classification methods, the H/ α -Wishart classification was significantly improved compared to the H / α classification. The different types of vegetation were well classified. The advantage of this method over the former was vegetation type and the Wishart measure is more sensitive to vegetation. The overall effect of H/A/ α -Wishart classification is between H / α classification and H / α -Wishart classification. The biggest advantage of this method is that the classification effect of Suaeda salsa is improved.

On the whole, the supervised classification based on unsupervised classification results can effectively overcome the shortcomings of the above three kinds of unsupervised classification, and the nine types of objects are well classified. According to the classification accuracy (Table 1), it can be seen that the accuracy of classification of other landform types is more than 90%, and the cultivated land is more than 85%. The average precision and accuracy are more than 97%, which fully demonstrates the validity of Wishart supervised classification method based on H / A / α -Wishart unsupervised classification results.
Table 1. SAR image classification result (Wishart classification based on H/A/α-Wishart classification).

| object                  | Accuracy(%) | average accuracy(%) | weighted accuracy(%) |
|-------------------------|-------------|---------------------|----------------------|
| Sea Water               | 95.79       |                     |                      |
| River                   | 99.74       |                     |                      |
| Intertidal Mudflats     | 96.71       |                     |                      |
| Suaeda Heteroptera      | 100.00      |                     |                      |
| Farmland                | 87.52       |                     |                      |
| Reed                    | 100.00      |                     |                      |
| Salsa wetland           | 99.67       |                     |                      |
| Reservoir               | 100.00      |                     |                      |
| Aquiculture Area        | 99.22       | 97.63               | 97.13                |

4.2. Comparison and analysis of SAR image and optical image classification results

Both of optical image and SAR images have achieved good classification results. According to the classification results (Table 2), we can found the classification accuracy of all classes reached more than 90%, and the average accuracy and weighted accuracy reached more than 96%. Comparing with the classification accuracy of SAR image and optical image, we can see there points.

(1) For water-related objects’ classification, SAR image is better than optical image, such as Sea Water, River, Reservoir, Intertidal Mudflats, Suaeda Heteroptera.

(2) For vegetation objects’ classification, optical image is better than SAR image, such as Aquiculture Area, Suaeda Wetland, Reed, Farmland.

(3) The average accuracy and weighted accuracy of SAR image reached more than 97%, the average accuracy and weighted accuracy of optical image reached more than 96%, both of them have achieved satisfactory classification accuracy.

Table 2. optical image classification result.

| object                  | Accuracy(%) | average accuracy(%) | weighted accuracy(%) |
|-------------------------|-------------|---------------------|----------------------|
| Sea Water               | 90.54       |                     |                      |
| River                   | 93.73       |                     |                      |
| Intertidal Mudflats     | 90.23       |                     |                      |
| Suaeda Heteroptera      | 100.00      |                     |                      |
| Farmland                | 95.64       |                     |                      |
| Reed                    | 97.13       |                     |                      |
| Salsa wetland           | 100.00      |                     |                      |
| Reservoir               | 99.84       |                     |                      |
| Aquiculture Area        | 99.74       | 96.32%              | 96.22%               |

5. Conclusions

(1) Four types of Radarsat-2 fully polarized images have been classified by Cloude decomposition using four different methods, including H / α classification, H / α-Wishart classification and H / A / α-Wishart classification. Unsupervised classification method, and a Wishart supervised classification based on H / A / α-Wishart unsupervised classification results. Among them, Wishart supervised classification accuracy based on H / A / α-Wishart unsupervised classification is more than 97%, which is the best classification method.

(2) By comparing the effects of polarimetric SAR images and optical images on the classification of coastal landforms, it is found that the classification accuracy of the two types of images is similar, but the SAR images are more accurate for classification of water-related features Optical images are more accurate for vegetation classification. This is because SAR images are sensitive to water and can be
used to classify water-related features. And the optical image uses 4,3,2 band combination, and it can highlight the performance of vegetation characteristics, therefore, it has more accurate classification of vegetation types.

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