Cloud detection of multi-feature remote sensing images based on deep learning

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Abstract. Satellite remote sensing technology provides massive image data for meteorological field, which can accurately extract the spatial distribution of cloud, and can be used to analyze the spatial and temporal changes of cloud. Aiming at the problems that the traditional algorithm is sensitive to noise and has poor recognition effect on broken clouds, a multi-feature remote sensing image cloud detection algorithm based on neural network structure is proposed, which has a good recognition effect on all types of clouds. The experimental results show that the accuracy of cloud detection in this paper reaches 92%, which is about 6% higher than the traditional algorithm, and avoids the disadvantage of the traditional algorithm which is sensitive to noise.

1. Introduction

With the rapid development of satellite remote sensing technology, massive data need deeper data mining, and cloud is an important element in meteorological field [1,2]. Achieving high-precision cloud detection in remote sensing images plays an important role in the study of cloud-aerosol interaction, atmospheric - surface interaction and other fields [3,4]. Traditional algorithms extract targets according to the similarity between pixels in the region, but these algorithms are very sensitive to the noise, and high-resolution remote sensing images will have certain noise, so these algorithms have certain limitations in remote sensing image cloud detection[5]. Reference [6] uses cloud-containing images to make cloud labels and training models, and uses convolutional neural networks to realize cloud detection, and proposes an adaptive pooling model according to the characteristics of clouds, but it does not judge whether the hierarchical structure and parameter settings of convolutional neural networks are optimal, and the accuracy of cloud detection still needs to be further improved. Reference [7] realizes remote sensing image cloud detection based on improved full convolution neural network. Compared with full convolution neural network, this method improves training speed, cloud detection accuracy and convergence effect, but there are also cases where snow is mistaken for cloud. Reference [8, 9] uses neural network SegNet to detect ZY-3 image cloud, which improves the sensitivity of traditional
algorithm to noise. However, thin clouds and broken clouds have missed detection to a certain extent, which needs to be further improved. Reference [10, 11] combined U-Net and residual module, realized FY-4 A image cloud detection, and improved the recognition accuracy of thin and broken clouds. However, by adjusting the parameters, the recognition accuracy can still be further improved.

Aiming at the problems that the classical algorithm is sensitive to noise and has low edge retention rate, a multi-feature remote sensing image cloud detection algorithm based on neural network structure is proposed and improved in these two aspects. Firstly, using U-Net to extract image features and train a cloud detection model, the preliminary cloud detection of the image to be detected is realized. Secondly, the multi-band information of remote sensing image is input into the cloud detection model. Finally, the average value of the feature map output by each feature is used as the final cloud detection result.

2. Materials and Methods

Remote sensing images have abundant spectral features. Taking ZY-3 image as an example, the products have panchromatic, multispectral, blue band, green band, infrared band, near infrared band and other image characteristics. Clouds is significantly different from other ground objects in infrared band. Compared with the traditional algorithm using only one band, using multi-band data can undoubtedly mine the deep features of remote sensing images and achieve higher precision cloud detection. The neural network trains the model by extracting typical features from the training set, and after several rounds of training model tests, it stops training when reaching saturation or higher accuracy. Among them, the size and quantity of the training set and whether it covers the typical features of different kinds of ground objects have a certain influence on the training results. Generally speaking, images need to be preprocessed, including data annotation, image segmentation and data enhancement.

The algorithm flow of this manuscript is as shown in Fig.1: firstly, the improved neural network u-net is trained by the preprocessed data set; Secondly, the multi-band remote sensing images are sent to the cloud detection model in sequence. Then, the cloud detection feature map of each band are generated in sequence. Finally, the average value of each cloud detection feature map is used as the final result of cloud detection.

![Figure 1. Flow chart of this manuscript](image)

U-Net is a network structure proposed in [11], 2015, which has the advantages of simple structure, and can train good results only by applying fewer data sets. As is shown in Fig.2, U-Net is a contraction-expansion structure.

1)Convolution layer. The convolution of the input image and the weight matrix is obtained by moving the convolution kernel on the input image, which is stored as a feature matrix. The function of convolution layer is to continuously dig deep features of cloud, obtain more complex details, and transfer features through iterative updating and sharing weights.

2)Pooling layer. In the process of down-sampling data processing, the size of acquired features is reduced by simple nonlinear operation, the number of learning parameters required by the model is reduced, the receptive field is increased, and the efficiency is improved.

3)Upsampling layer. The feature map is restored to the original image size, and the extracted typical features are enlarged.

4)Characteristic map. The probability that each pixel on the image is judged as cloud and background is called feature map. The innovation of U-Net is that it not only obtains the typical features of the image by first shrinking and then expanding the feature map, but also directly obtains the feature map of the symmetrical part of the U-shaped structure (the horizontal line in the middle of the U-shaped map) in
each part. This way of fusing multiple feature maps preserves the category features of the cloud to the greatest extent.

5) Soft-max layer. According to the random gradient descent method, the training of neural network is evaluated. Generally, the algorithm of soft-max and cross entropy is adopted in the last layer to realize pixel classification.

![Figure 2. Structure of U-Net](image)

### 3. Results & Discussion

As shown in Figure 3. From left to right, there are ZY-3 original image, OTSU cloud detection results and cloud detection results of this method. For high-resolution remote sensing images, the image itself has certain white noise, while traditional algorithms such as OTSU algorithm are sensitive to noise. For example, the red boxes in Figure 3 (b) and (h) mistake a lot of white noises for noise. Compared with this, U-Net has higher extraction accuracy, avoids this shortcoming, and keeps the broken cloud contour well. When the land in the experimental area is complex and the color difference is large, traditional algorithms such as OTSU can't make the optimal solution for cloud when seeking the optimal threshold, so Figure 3(e) will identify the red box and building area as cloud in a large scale. The algorithm avoids the shortcomings of traditional algorithms, and the overall accuracy of cloud detection is 92%, which is about 6% higher than that of classical cloud detection algorithm.
4. Conclusions
This manuscript realizes cloud detection of ZY-3 image by multi-feature U-Net method. Through quantitative evaluation, the accuracy rate of cloud detection reaches 92%, which is about 6% higher than the traditional algorithm, and avoids the shortcoming that the classical algorithm is sensitive to the noise of high-resolution remote sensing images. The method proposed in this paper has higher accuracy of cloud detection, better edge retention, and is more in line with people's subjective feelings.

Satellite remote sensing technology provides data support for meteorology and environment. After introducing deep learning, it will definitely establish a deeper connection between data and models.

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