Ma et al., J Remote Sens GIS 2019, 8:1
DOI: 10.4172/2469-4134.1000259

Journal of Remote Sensing & GIS

ISSN: 2469-4134

Research Article

Open Access

Cloud Detection Based on Convolutional Neural Network using Different Bands Information for Landsat 8 OLI

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Rec date: March 20, 2019; **Acc date:** March 27, 2019; **Pub date:** April 3, 2019

Abstract

The existence of clouds has seriously affected the application of remote sensing data. Therefore, accurate cloud detection is of great significance in remote sensing image processing and application. Traditional cloud detection methods are complex to operate and often require the additional ancillary information. An automatic cloud detection method based on convolutional neural network (CNN) is proposed in this study. The method utilizes a convolutional network structure to classify training samples for cloud and non-cloud. In order to make full use of image information, images of different band numbers are applied to evaluate the influence of the spectrum on cloud detection. Experiments and verification on Landsat 8 images show that the proposed method based on CNN can comprehensively and automatically detect different types of clouds on different surface types, and the cloud detection result using 7 bands is the optimal. The algorithm takes full advantage of image information and does not rely on thermal infrared information, which has practical application value for improving image utilization and subsequent retrieval of remote sensing parameters.

Keywords: Cloud detection; CNN; Landsat 8 OLI; Multiple bands

Introduction

Landsat data provides unprecedented opportunity to study land cover change and human influences on the land surface [1]. However, much of the imagery is contaminated with cloud causing the information in a cloud covered region lost or blurred [2]. Therefore, the accurate detection of cloud pixels is of great significance to the efficient popularization and application of Landsat-8 OLI data.

Cloud detection methods are divided into three categories: threshold method, statistical analysis method and artificial neural network method. Threshold method is the main algorithm used in cloud detection in the early stage. Due to its simple operation and high precision, it is widely used in the cloud detection of remote sensing images. Typical threshold methods include APOLLO (AVHRR Processing scheme Over clouds, Land, and Ocean) algorithm, CLAVR (Clouds from the AVHRR) algorithm, ISCCP (International Satellite Cloud Climatology Project) algorithm, and MODIS cloud mask (The Modis Cloud Mask algorithm) [3-6]. The threshold method is subjective in the selection of the threshold and relies on specific sensor.

The cloud detection method based on statistics utilizes morphological, texture features, etc. to derive in general from the features. Bayesian method, discriminant analysis methods and support vector machines have been successfully applied to cloud detection [7-9]. However, the above-mentioned methods only use local information and low-level features, and the complexity of remote sensing images determines that these do not have good adaptability.

The artificial neural network method initially performs cloud detection through a classifier using simple neural network training data. With the continuous development of deep learning, the powerful self-learning ability and data analysis ability of neural networks with different structures have opened up new ways for cloud detection in remote sensing image processing. CNN that can mine advanced features from images is one of the deep learning methods. Shi et al. showed a method based on CNN and SLIC algorithm to segment an image into super pixels to detect clouds with precise boundaries [10]. However, this method only utilizes the three bands of information of the image. For multi-spectral images, this may cause the loss of information affecting cloud detection.

To make the best use of the spatial and spectral information in images, a cloud detection algorithm based on CNN is proposed in the study. First, the cloud pixels and non-cloud pixels are extracted to construct a high-quality training samples, and then the CNN is used for training to obtain the cloud detection result. Considering the full use of spectral information, images with different bands is used for training and cloud detection. The verification results show that the method using 7 bands performs best in cloud detection. The algorithm achieves comprehensive and automatic cloud detection with multiple bands.

Principle and Methodology

CNN is a special artificial neural network. It can extract more advanced features owing to the powerful self-learning and data analysis capabilities, which is significant for classification, target detection, and object recognition. The CNN typically includes an input layer, convolutional layer, activation function, pooling layer, and fully connected layer. The convolutional layer is used for extracting valid information through convolution operations to learn the characteristic representation of the input data, especially for spatial features. The pooling layer is another important structure of CNN. The main function of pooling layer is to reduce the dimension of the input

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feature map. Max-pooling and average pooling are the two most common pooling operations. Functions such as sigmoid, tanh, and relu are commonly used nonlinear activation functions in CNN, Relu is often used for convolutional layers [11]. The fully connected layer connects all the features and sends the output values to the classifier. Softmax is a commonly used classifier in CNN. The cloud detection algorithm based on CNN mainly includes two stages: constructing training sample database and network training and cloud detection stage. The working flow chart is shown in Figure 1.

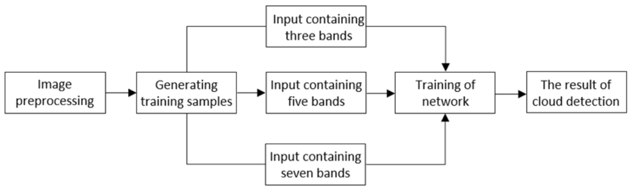

Figure 1: Cloud detection structure.

Experimental data and training set

Landsat-8 OLI can play an important role in monitoring the surface ecological environment and become one of the most valuable data sources for studying land cover change and human impact on the surface. The OLI (Operational Land Imager) carried on Landsat-8 includes nine bands with a spatial resolution of 30 meters, including a 15-meter panchromatic band. OLI includes all bands of ETM + sensor, and some bands are adjusted. For example, OLI Band 5 (0.845-0.885 μm) excludes the absorption wavelength of water vapor at 0.825 μm, shortens the band range of Band 8 in OLI panchromatic band, and can better distinguish vegetation from non-vegetation features in panchromatic images. In addition, two new bands are added: blue band (0.433-0.453 μm) for coastal zone monitoring and short-wave infrared band (1.360-1.390 μm) for improving the accuracy of cloud detection.

The plentiful training samples are the prerequisite for the neural network to continuously learn and analyze the data, hence the establishment of the database is the first step for cloud detection. At present, datasets for cloud detection are not available, so it is necessary to obtain training labels by interpreting the cloud regions in the image. However, manual interpretation requires a lot of manpower and time, and there are manual errors. In order to ensure the reliability of the training samples and establish high-quality datasets, the pixels and neighborhoods in the cloud and non-cloud regions in the image are extracted to construct the sample library, which greatly avoids the interference of the uncertain pixels on the network to improve the learning of network. Considering the richness and complexity of the sample, different types of clouds over different surface types were selected. The size of the extracted neighborhood needs to be determined according to the actual situation. In this study, it is set to 11 × 11.

Network establishment and training

The CNNs in this study can be regard as a binary class classifier (cloud and non-cloud). Figure 2 shows the overall architecture of the CNNs, which consists of two convolutional layers, two pooled layers, and three fully connected layers. The size of the network input is 11 × 11 × L, where L represents the number of bands. In this study, 3 (band 2,3,4), 5(band 2, 3, 4, 5, 9), and 7 (band 2, 3, 4, 5, 7, 8, 9) bands are used to train and compare the influence of multi-spectral information on cloud detection.

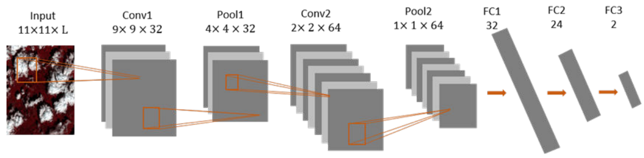

Figure 2: The architecture of CNNs.

In the convolutional layer, a two-dimensional convolution kernel which can extract spatial feature is employed. Its expression is (1) [11]:

$$v_{ij}^{xy} = f\left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} w_{ijm}^{pq}\, v_{(i-1)m}^{(x+p)(y+q)}\right) \quad (1)$$

where m represents the feature map in layer i-1 connected to the current jth feature map, Pi and Qi are the height and width of the space convolution kernel respectively, Ri is the depth of the convolution kernel in the spectral dimension, w_{ijm}^{pq} is the weight at (p, q) connected to the mth feature map, and bij is the bias of the jth feature map at the ith layer.

The pool layer is also called the sampling layer, including max-pooling and average-pooling. Max-pooling is applied to the network in this study. The rectified linear unit (ReLU) is a useful nonlinear operation and it is used for activation function in convolutional layers. It is defined as (2) [12]:

$f(x)=max(0,x)$ (2)

Where x is the input data. Dropout strategy is introduced to handle over-fitting. In the training of the network, the adaptive moment estimation (Adam) is selected as optimizer, and the learning rate is 0.001. Other parameter in the network are shown in Table 1.

Layer	Kernel	Stride	Paddin g	Output Size	Feature Volumes	Dropout
Input	--	--	--	11 × 11 × L	--	--
C1	(3,3)	(1,1)	0	9 × 9 × 32	32	--
P1	(2,2)	(1,1)	0	4 × 4 × 32	32	--
C2	(2,2)	(1,1)	0	2 × 2 × 64	64	--
P2	(3,3)	(1,1)	0	1 × 1 × 64	64	--
F1	--	--	--	32	--	50%
F2	--	--	--	24	--	25%
F3	--	--	--	2	--	--

Table 1: Parameters of CNNs.

Experimental Results and Discussion

Twenty Landsat 8 images containing different type clouds over different land surface were selected for experimentation and verification. These images are from USGS. A training sample library

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was constructed by extracting image blocks. Taking full account of the spectral information, 3, 5 and 7 bands were used to train and compare cloud detection results. The size of the network input is 11 × 11 × L (L=3, 5, 7). 10% of the samples were used for training and 90% were used for verification. Finally, the final cloud detection result was obtained through network training and tuning optimization. Furthermore, CR (cloud right rate) and ER (error rate) were used to evaluate the algorithms quantitatively using different bands. Right rate (CR) is defined as [13].

$$CR = \frac{CC}{CN} \qquad (3)$$

Where CC is the number of pixels correctly detected as cloud and CN is the number of cloud pixels in truth reference.

Error rate (ER) is defined as

$$ER = \frac{CN + NC}{TN} \qquad (4)$$

Where CN is the number of cloud pixels detected as sky pixels (non-cloud) and NC is the number of non-cloud pixels identified as cloud pixels, and TN is the total pixels in the input.

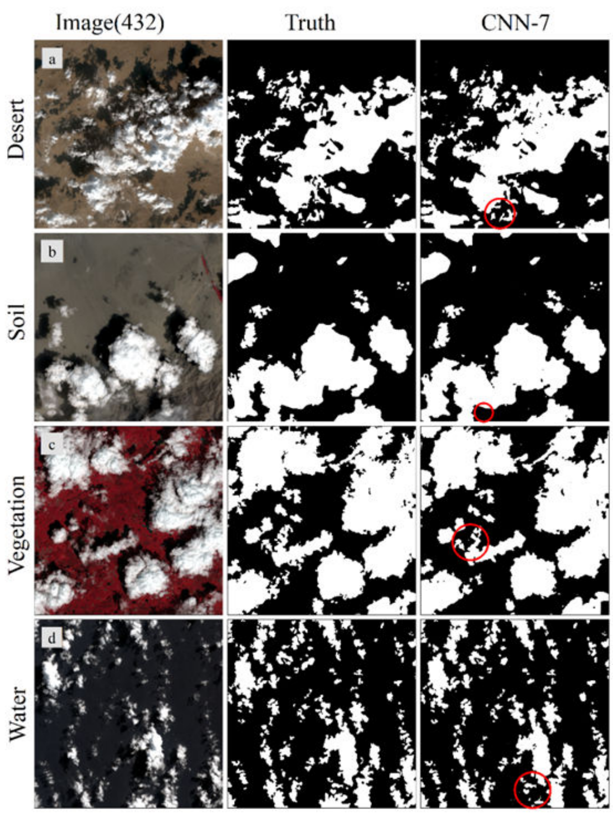

Figure 3: Results of cloud detection based on CNN using 7 bands (a) desert (b) soil (c) vegetation (d) water.

Visual comparisons

Figure 3 shows the cloud detection results of the proposed algorithm using 7 bands on different land types. (a, b, c, d) represent deserts, soil, vegetation and water bodies respectively. In Figure 3, the first column is the false color image (RGB: 432), the second column is the true value reference, and the third column is the cloud detection results of the algorithm.

Compared with false color image and reference, the cloud detection results using seven bands (band 2, 3, 4, 5, 7, 8, 9) are highly consistent with the image and the true value reference, while achieve accurate cloud boundary, suggesting that high detection precision is obtained. The detection of thin clouds and broken clouds is also comprehensive, despite the appearance of small omissions (marked by red circles).

Quantitative evaluation

CR, ER is used to quantitatively evaluate the performance of the algorithm using different bands. Table 2 shows the CR and ER of the algorithm for 3, 5, and 7 bands over different surface types. The CR of the algorithm using 7 bands reached 96.45% and has lowest error rate of 3.66%. Therefore, the algorithm using 7 bands has better performance in cloud detection.

Land types	Three bands		Five bands		Seven bands	
	CR%	ER%	CR%	ER%	CR%	ER%
Desert	95.95	4.05	96.16	4.25	96.21	3.79
Soil	95.96	4.04	96.06	3.94	96.78	3.22
Vegetation	95.91	4.09	96.15	3.85	96.22	3.78
Water	95.54	4.46	95.75	4.25	96.59	3.87
Average	95.84	4.16	96.03	4.07	96.45	3.66

Table 2: CR, ER of the algorithm using different bands over different land types.

Conclusion

A cloud detection method based on CNN is proposed to make full use of image information. In order to make better use of spectral information, contrast training and detection are carried out using different bands. The verification results show that the algorithm using 7 bands has the best cloud detection effect. The accuracy of 96.45% indicates that the algorithm can comprehensively and effectively detect clouds and obtain more accurate cloud boundaries. The algorithm has better applicability since not relying on thermal infrared information and provides a new direction for multi-spectral image processing.

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