Cloud detection of GF-7 satellite laser footprint image

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Abstract
In November 2019, the GaoFen-7(GF-7) satellite was equipped with China’s first laser altimeter with full waveform recording capability, which obtains high-precision long-range three-dimensional coordinates. The influence of clouds is noticeable for laser transmission, and a footprint camera is used to determine laser pointing and to image the ground. However, the cloud inevitably appears in the laser footprint image. In this study, the authors propose a cloud detection scheme for footprint images based on deep learning. First, an adaptive pooling model is proposed according to the characteristics of the cloud region. Next, model fusion was performed based on the SegNet and U-Net training results. Finally, test time augmentation was used to enhance the data and to improve cloud detection accuracy. The experimental results show that the fusion result of the model was approximately 5% better than that of the traditional cloud detection algorithm, which improved the shortcomings of the traditional algorithm, such as poor detection effect for thin clouds and complex underlying cloud surfaces. The related conclusions have certain reference significance for GF-7 data processing and related research on footprint images.

1 INTRODUCTION
Satellite laser altimetry technology actively emits laser pulses with certain energy and spectral characteristics to the detected target through a light source and obtains information, such as the distance and composition of the detected target by measuring the intensity of the scattered echo; its accuracy can reach the sub-meter or centimetre level, gradually making it an important technical means of new earth observation [1]. In November 2019, China successfully launched the GaoFen-7 (GF-7) satellite, which was equipped with China’s first geoscience laser altimeter system [2] that was used to obtain generalised elevation control points and to assist optical cameras in performing stereo mapping. The laser subsystem of the GF-7 satellite includes the laser footprint camera (LFC) and a laser altimeter. The LFC and the laser receiver share a telescope, which is primarily used to capture the laser spot and panchromatic image of ground objects at a single laser emission time. A laser footprint image (LFI) helps the LFC intuitively judge if the laser is affected by clouds or the topography where the laser spot is located, providing the most intuitive evaluation criteria for laser data quality control. Clouds have a noticeable influence on laser altimetry data [3], and the atmospheric scattering deviation can reach several metres; thus, cloud detection based on a footprint image is very important.

Traditional cloud detection algorithms for optical remote sensing images can be divided into two categories according to classification criteria: 1) based on spectral characteristics and 2) based on texture features. The method based on spectral features is used to extract clouds according to the difference between visible light and near-infrared band clouds and other surrounding ground objects [4,5]; however, these methods are not applicable to remote sensing images with a limited band range. Therefore, we primarily analysed cloud detection methods based on texture features [6,7] and adjacent pixels [8,9]. The classical image segmentation algorithm based on texture features has also achieved good results in cloud detection. OTSU [10], region seed growing [11], and simple linear iterative...
cluster [12] extract the target based on the similarity between pixels in the area. However, these algorithms are very sensitive to noise and target size, and high-resolution remote sensing images contain white noise; therefore, these algorithms have limitations in the cloud detection of remote sensing images. The gradient-based watershed [13], Laplace transform, and other algorithms are used for image segmentation according to the peak change of gradient at the edge of the region but are sensitive to gradients and prone to over-segmentation. Supervised classification algorithms, such as K-means [14], support vector machine, and convolutional neural networks (CNNs) [15,16] achieve high cloud detection accuracy by selecting regions with common characteristics and summarising them as segmentation criteria; however, further optimisation in cloud detection accuracy and detection efficiency is possible.

However, with the continuous improvement of the spatial resolution of remote sensing images, the spectral differences within the same type of ground objects increase, the spectral differences between classes decrease, and the phenomena of the same object and spectral foreign matter are more common. With the continuous improvement of the spatial resolution of remote sensing images, texture spatial information becomes more complex, a challenge that traditional algorithms based on spectral features and texture features solve with difficulty [1]. Chen et al. [15] used cloud area images to create cloud labels and training models and used CNNs to realise cloud detection. However, the hierarchical structure and parameter settings of CNNs have not been optimally determined, and the accuracy of cloud detection must be further improved. Pei et al. [17] realised remote sensing image cloud detection based on an improved fully convolutional network (FCN). Compared with the FCN, this method improves the training speed, cloud detection accuracy, and convergence effect; however, snow is occasionally misjudged as clouds. Yao et al. [18] realised ZY-3 image cloud detection using a neural network SegNet, which improved the sensitivity of the traditional algorithm to noise. However, missing detection for thin clouds and broken clouds needs further improvement. Zhang et al. [19] realised FY-4A image cloud detection combined with U-Net and a residual module, which improved the recognition accuracy of thin and broken clouds. However, adjusting the structure and parameter settings allows for further improvement in cloud detection accuracy.

Compared with other remote sensing images, footprint images lack rich band features and present a smaller image range; thus, the traditional algorithm is not applicable, and the cloud detection effect is poor. In this study, the authors propose a cloud detection scheme for footprint images based on a deep learning algorithm. First, an adaptive pooling model is proposed according to the characteristics of the cloud, which improves the disadvantage of the poor cloud feature extraction effect of traditional pooling. Second, the image to be detected was enhanced based on test time augmentation (TTA). Finally, based on the fusion results of the SegNet and U-Net models, higher accuracy cloud detection and cloud area contour recognition was performed. According to the footprint image characteristics, we proposed a set of practical operational algorithm flows, which provide quality control for the follow-up optical and laser data products of GF-7 and have reference significance for related research.

2 | INTRODUCTION OF GF-7 FOOTPRINT IMAGE DATA

GF-7 is the first earth observation satellite in China equipped with a laser altimeter, and the LFI is a part of the laser system. The LFC and the laser receiver share a telescope, which is primarily used to capture the laser spot and ground object image at a single laser emission time. The footprint image helps the LFC intuitively judge if the laser is affected by the cloud as well as the location of the laser spot. The GF-7 satellite laser altimeter has synchronous and asynchronous data acquisition modes. As is shown in Figure 1, under different working modes, the LFI adopts different imaging mechanisms: 1) synchronisation: when the emitted laser hits the charge-coupled device (CCD) array camera, the CCD camera simultaneously exposes the ground; and 2) asynchronous: exposure is performed by the CCD camera at three time points: 15 ms before laser emission, 0.15 ms when the laser hits the CCD camera after laser emission, and 2 ms after on-orbit laser spot imaging is completed. The laser completes one emission and two exposures to the ground in 17.15 ms. The image size of the synchronous mode for LFI is 550 × 550 pixels, and that of asynchronous mode is 84 × 84 pixels.

The LFI plays an important role as an auxiliary equipment in a laser system by: 1) estimating the terrain of the laser point position and intuitively judging if the laser is affected by clouds; 2) extracting laser spot centroid coordinates, analysing the change in the laser pointing angle, establishing a long-period spot centroid monitoring system module; and 3) assisting optical images to classify ground objects. The related parameters of LFI are shown in Table 1.
| Project | Parameter                  |
|---------|----------------------------|
| Image type | Panchromatic               |
| Image size | 550 × 550                  |
| Spatial resolution | 3.2 m                     |
| Operating spectral range | 400–800 nm and 1064 nm    |
| Instantaneous field of view | 6.4 μrad              |
| System focal length | 2578.125 mm                |
| Image quantisation bit number | 14 bits                |

3 | EXPERIMENTAL PRINCIPLE

Semantic segmentation is a concept proposed to solve multi-classification segmentation in the field of image segmentation, which aims to extract the contours of multiple objects with high precision through deep learning. The semantic segmentation neural network trains the model by extracting typical features from the training set and stops training when it reaches saturation or higher precision after several rounds of training model tests that determine the size and quantity of the training set and if it covers the typical features of different types of ground objects that influence the training results. The images generally must be pre-processed.

The algorithm flow of this study is shown in Figure 2. First, the improved cloud detection neural networks, U-Net and SegNet, are trained by using the pre-processed datasets. Second, the image to be predicted is enhanced by TTA; the enhanced data are sent to the fusion model for cloud detection. Finally, based on the LFI results, the cloud detection results in the spot are extracted.

3.1 | Data pre-processing

Pre-processing is primarily divided into the following parts: data annotation, image segmentation, and data augmentation.

3.1.1 | Data annotation

The primary purpose of data annotation is to classify each pixel on the image to be trained. Taking cloud region extraction as an example, data annotation software, such as Labelme [20], is used to outline the cloud region on a remote sensing image. In the generated label file, the pixels of the cloud region are assigned a “1”, as shown in the red area in Figure 3; Other regions are divided into background pixels and assigned a “0”, as shown in the black regions in Figure 3.

3.1.2 | Image segmentation

Image segmentation facilitates neural network training. The size to be divided depends on the configuration of the graphics processing unit and the setting of the neural network. Generally, the values are 64, 128, 512, and 1024.

3.1.3 | Data augmentation

Data augmentation trains the number of sets and facilitates extraction of the main features by the neural network. By rotating and adding salt-and-pepper noise and morphological transformation, the order of magnitude of the training set is increased to a larger base. The footprint image size is 550 × 550. Several 256 × 256 image blocks are randomly selected from each image, and the training set images are increased to 20,000 by data augmentation.

3.2 | U-Net

U-Net is a network structure proposed in 2015 [21], which has an advantageous simple structure and can train good results only by applying fewer datasets. U-Net is largely a contraction–expansion structure, and the previous contraction process adopts an FCN structure [22], which is composed of a convolution layer and a pooling layer and is primarily used to extract typical image features. The expansion process is composed of a...
convolution layer and a de-convolution layer (upsampling layer). In the image segmentation field, a feature fusion method (skips connection in the middle of the figure) is proposed for the first time and uses the recovered feature map of the de-convolution layer to splice with the original copied and cut feature map (see Figure 4).

3.2.1 | 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 the convolution layer is to continuously dig deep features of the cloud, to obtain more complex details, and to transfer features through iterative updating and sharing weights.

3.2.2 | Pooling layer

During downsampling data processing, the size of the acquired features is reduced by a simple nonlinear operation, the number of learning parameters required by the model is reduced, the receptive field is increased, and the efficiency is improved.

3.2.3 | Upsampling layer

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

3.2.4 | Characteristic map

The probability that each pixel on the image is judged as a cloud and the background is called a feature map. The innovation of U-Net is that it obtains the typical features of the image by shrinking and expanding the feature map and directly obtains the feature map of the symmetrical part of the U-shaped structure (the skipped connection in the middle of the U-shaped map) in each part. This method of fusing multiple feature maps preserves the category features of the cloud to the greatest extent.

3.2.5 | Softmax layer

According to the stochastic gradient descent method, neural network training was evaluated. Generally, the Softmax and cross entropy algorithms are adopted in the last layer to perform pixel classification. The last layer adopts the Softmax regression model and cross entropy methods

\[
\text{Softmax} : S_j = \frac{e^{a_j}}{\sum_{k=1}^{T} e^{a_k}}.
\]

The input value of Softmax is the weight value \(W_x\). Softmax is a binary classification problem; thus, \(W_x\) is a \(2 \times 1\) vector, \(T\) is the number of categories, \(\alpha_j \in \{1, 2\}\), represents the element in the vector, and \(\alpha_k\) represents the sum of elements in \(W_x\). The output value \(s\) of Softmax is the probability of samples in each class, and \(s\) is a \(2 \times 1\) vector

\[
\text{crossentropy} : E = -\sum_{j=1}^{T} y_j \log p_j.
\]

The input \(p_j\) of cross entropy is the \(j\)th element in the output value \(s\) of the Softmax model, and \(y_j\) is a vector of \(1 \times T\), in which only one element has a value of 1, and the other \((T - 1)\) elements have a value of 0. The cross entropy function is the loss function of the Softmax model, which can measure the training results. Accuracy is the probability percentage of identifying image samples, which can also measure the degree of model training. Therefore, loss and accuracy are used to observe the training process, to adjust the parameters, and to modify the training process.

3.3 | SegNet

SegNet is a network structure proposed in 2017 [23], which has the advantages of a simple network structure and fast training. SegNet has generally an encoder–decoder structure; the former encoder is the network structure of VGG-16 [24] and is composed of a convolution layer and a pooling layer, whereas the decoder is basically symmetrical with the encoding process and is composed of a convolution layer, a pooling layer, a upsampling layer, and a Softmax layer (see Figure 5). The concepts of these layers are described in Section 3.2. SegNet is often used for semantic segmentation of remote sensing images and has achieved good results in many image recognition and image semantic segmentation competitions [21]. Compared with the latest network structure, SegNet is widely used and relatively mature.

3.4 | TTA

TTA, a widely used technology in machine learning [24], is a post-processing algorithm that aims to improve the segmentation effect by enhancing the back-end data without changing the model. The images are input to be detected after cutting,
rotating, mapping, and compressing to enhance their typical features to improve recognition accuracy. After multiple rounds of training and iterations, however, the cloud detection model gradually converges, and the accuracy tends to be saturated. Because only the images to be detected are input into the model, the cloud region may miss detection owing to the local generalisation of typical features; thus, TTA processing of the images is necessary. Figure 6 shows the TTA algorithm flow as follows: 1) the image to be detected is processed by rotation and colour mapping to obtain eight enhanced data, which are sequentially input into the cloud detection model along with the original image; 2) the inverse transformation of the geometric operation in step 1) is performed on the characteristic probability map output by the cloud detection model, and the image plane coordinates of the image to be detected is restored; and 3) the sum and average the nine feature probability maps are obtained, and the cloud pixel probability map is output.

FIGURE 5 Schematic diagram of SegNet structure

FIGURE 6 Schematic diagram of TTA

3.5 | Adaptive pooling model

Unlike other ground objects in remote sensing images, the cloud region does not have abundant texture information; therefore, the traditional pooling model cannot extract the cloud region features well [15]. The convolution layer and the pooling layer are connected by an activation function. The most common are the maximum pooling and average pooling models.

The feature graph matrix obtained by the convolution layer is $C_{ij}$, the size of the pooling area is $c \times c$, $b$ is the offset, and the pooling step is $c$. The maximum pooling model and the average pooling model can be expressed as

$$F_{ij}^{\text{max}} = \max \left( \sum_{i=1}^{c} \sum_{j=1}^{c} C_{ij} \right) + b \quad (3)$$
$$F_{ij}^{\text{avg}} = \frac{1}{c^2} \left( \sum_{i=1}^{c} \sum_{j=1}^{c} C_{ij} \right) + b. \quad (4)$$

Figure 7 shows that the maximum value of the feature matrix of the four regions in Figure 7(a) was used as the cloud feature when the maximum pooling model was adopted; however, the laser spot in area A and the high-reflectivity ground objects in areas C and D affected the extraction result, weakened the cloud feature, and increased the false detection rate. The mean value of the feature matrix of the four regions in Figure 7(b) was used as the cloud feature when the average pooling model was adopted. If the step size was too large or too small, the complex ground objects or large blanks on the underlying surface of the cloud affected the extraction results.

To extract and retain the most cloud pixel features and to avoid possible errors caused by traditional pooling models, an adaptive pooling model is proposed based on the average and maximum pooling models. In the complex pooling area, the model adaptively adjusts the pooling process through the pooling weight coefficient $\mu$; the expression is as follows:

$$F_{ij} = \mu \max \left( \sum_{i=1}^{c} \sum_{j=1}^{c} C_{ij} \right) + \frac{1-\mu}{c^2} \left( \sum_{i=1}^{c} \sum_{j=1}^{c} C_{ij} \right) + b. \quad (5)$$
Figure 8 shows (from left to right) the footprint image, the OTSU cloud detection results, and SegNet cloud detection results. Red represents the area identified as cloud pixels, and black represents the pixels of other ground objects. Table 2 shows the results of the cloud amount statistics from two experiments; the cloud amount is defined as the ratio of pixels identified as clouds by the algorithm to total pixels. To objectively evaluate the cloud amount detected by the two algorithms, the cloud amount was calculated by artificially sketching the cloud outline as an evaluation standard.

Figure 8(a) and (d) shows footprint images almost completely covered by thick clouds. Figure 8(b) and (e) and the very poor OTSU detection results show cloud amounts that were almost 40% different from that of the standard; SegNet detection results were between 1% and 2%, because the OTSU is a method for analysing the optimal threshold through the statistical histogram of the image grey level, which is not suitable for cloud detection of footprint images when the grey level of most pixels in the image is close. Compared with the SegNet cloud detection algorithm, OTSU maintained high cloud detection accuracy.

The pooling weight coefficient $\mu$ dynamically adjusts the weight ratio of the two models according to different pooling areas

$$
\mu = \frac{C_{\text{ave}} - C_{\text{min}}}{C_{\text{max}} - C_{\text{min}}}
$$

where $C_{\text{ave}}$ is the average value of elements other than the maximum and minimum values in $C_{ij}$, $C_{\text{max}}$ is the maximum value of elements in $C_{ij}$, and $C_{\text{min}}$ is the minimum value of elements in $C_{ij}$.

4 | EXPERIMENTAL ANALYSIS

4.1 | Comparison with the traditional cloud detection algorithm

Figure 8 shows (from left to right) the footprint image, the OTSU cloud detection results, and SegNet cloud detection results. Red represents the area identified as cloud pixels, and black represents the pixels of other ground objects. Table 2 shows the results of the cloud amount statistics from two experiments; the cloud amount is defined as the ratio of pixels identified as clouds by the algorithm to total pixels. To objectively evaluate the cloud amount detected by the two algorithms, the cloud amount was calculated by artificially sketching the cloud outline as an evaluation standard.

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Cloud detection was performed based on SegNet and U-Net, respectively. U-Net had fast training speed, a small model, and finer cloud area edge; however, the cloud detection results were noisier. SegNet detection results had higher overall accuracy (OA)—approximately 2% higher than that of U-Net—and avoided the interference of small holes and noise. However, the disadvantage lies in the low accuracy of the identified cloud edge contour, which is inconsistent with subjective intuition. The nature of SegNet as a binary classification problem yielded a slight difference in overall classification accuracy. Model fusion is similar to TTA technology, which obtains multiple feature maps through a single input and judges the category of each pixel through voting. This modification has little improvement on the OA of the cloud detection of footprint images but can partially eliminate stitching traces and improve the subjective effect of cloud detection. This method is necessary for large images or images with multiple classification problems. However, for the challenges discussed in this study, detection accuracy reached 90%, and auxiliary method improvements were limited. After multiple tests, 7/3 was selected as the optimal fusion weight ratio of the SegNet/U-Net model, to maintain the best fusion effect, to remove small noise and holes, and to improve the subjective effect of cloud detection.
FIGURE 9  Comparison of cloud detection results. (a) and (e) Laser footprint image. (b) and (f) SegNet cloud detection result. (c) and (g) U-Net cloud detection result. (d) and (h) Model fusion cloud detection result

FIGURE 10  Comparison of cloud detection results

referred to image segmentation quality evaluation indexes, such as OA, Hausdorff_Dist, Jaccard distance, Avg_PerpenDist, consistency coefficients, segmentation accuracy, and other common indexes, for image segmentation quality [25]. Among the six evaluation indexes, OA and precision are two relatively intuitive quantitative indexes that reflect the quality of the segmentation results. For cloud detection, the accuracy of classical algorithms was low because of sensitive noise and small edge retention. Indexes, such as the Jaccard_Index, Hausdorff_Dist, and Avg_PerpenDist, measure the influence of sensitive noise and consider factors, such as the cloud detection contour. For smaller Hausdorff distance values, the Jaccard coefficient and average distance coefficient were larger, and the cloud detection result accuracy was higher.

According to various indexes, the cloud detection accuracy of the deep learning cloud detection algorithm was approximately 5% higher than that of the traditional algorithm, and the cloud detection accuracy of the model fusion results was approximately 2% higher than that of SegNet and U-Net. Combined with the Jaccard_Index and Hausdorff_Dist, U-Net extracts cloud contoured approximately 2–3% better than SegNet, which had an overall cloud detection accuracy of approximately 1–2% better than that of U-Net; the model fusion cloud detection results have the advantages of both indices. Preserving the contour of the cloud area yields higher cloud detection accuracy and avoids errors caused by small noise and gaps. The evaluation of each index on the experimental results is stored in Table 3.

| Quality evaluation | OTSU | SegNet | U-Net | SegNet+U-Net |
|--------------------|------|--------|-------|--------------|
| OA                 | 86.39| 90.43  | 89.32 | 91.84        |
| Hausdorff_Dist     | 70.97| 65.33  | 61.55 | 59.33        |
| Jaccard_Index      | 85.18| 90.43  | 92.43 | 92.43        |
| Avg_PerpenDist     | 78.22| 86.34  | 84.11 | 88.34        |
| Conformity Coefficient | 87.33| 91.54  | 90.18 | 92.54        |
| Precision          | 89.18| 93.54  | 92.43 | 94.88        |

5  CONCLUSION

The following conclusions were obtained.

1. The cloud detection of the footprint image was performed by the improved SegNet and U-Net model fusion results
by quantitative evaluations; cloud detection accuracy reached 91.84%. The cloud detection accuracy of this method was approximately 2% better than that of SegNet and approximately 5% better than that of OTSU and other classical algorithms, thereby improving the poor detection effect of classical cloud detection algorithms for thin clouds and complex underlying cloud surfaces. The method presented in this study had higher cloud detection accuracy and better edges.

2. To verify the actual accuracy of the cloud detection module, one track footprint image data were randomly selected for cloud detection, and 50 images were randomly selected for comparison with subjective human outline results. The OA was approximately 90%, except for factors, such as overexposure and high-reflectivity ground objects. The method provided cloud parameters for GF-7 standard laser altimetry products as quality control.

Semantic segmentation of remote sensing has great advantages in the field of cloud detection. Suggestions for future improvement are as follows: remote sensing images contain texture and spectral information. In this study, cloud detection was only performed by combining cloud texture features; future work will attempt to combine cloud spectral features and texture features for comprehensive cloud detection to further improve cloud detection accuracy.

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AUTHOR CONTRIBUTIONS

Jiaqi Yao: conceptualisation; data curation; methodology. Xinming Tang: data curation; methodology. Guoyuan Li: methodology. Jinquan Guo: methodology. Jiyi Chen: methodology. Xiongdan Yang: validation. Bo Ai: validation; writing—review and editing.

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