



Automatic Cloud Segmentation Based on Fused Fully Convolutional Networks

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Abstract. Cloud detection and segmentation of remote sensing images is a pivotal task in the area of weather forecast. Many meteorologic applications such as precipitation forecast, extreme weather forecast, etc., depend on the results of the cloud detection. In this paper, based on the satellite remote sensing image dataset, we propose an image segmentation model to address the cloud detection problem. Our model is derived from the fully convolutional neural network, which achieves pixel-level cloud segmentation results on high resolution, large scale, multi-channel satellite images. We introduce Deep Feature Aggregation and Model Fuse strategies to improve the cloud segmentation results. Compared with the traditional methods, our proposed algorithm has the advantages that is independent of the expert knowledge, totally data motivated, and more robust in hard cases. The testing results show that the proposed model can satisfy the requirements of the weather forecast, thus has a strong potential to be put into business usage.

Keywords: Remote sensing images · Semantic segmentation · FCN · Deep learning · Cloud detection

1 Introduction

There is no need to say more about the crucial role that the remote sensing data has played in people's daily life of contemporary society. As the development of the high-precision sensors, a growing amount of high-resolution remote sensing data is collected every second, raising an increasing demanding on new effective techniques to handle such vast amounts of data of extremely high dimensionality. Among which, meteorological satellite remote sensing data is the satellite images collected by meteorological satellites for weather forecasting missions. Every day, tons of this kind of satellite images are generated by the meteorological satellites in orbit. Since the detection of meteorological satellite remote sensing image is the preliminary of meteorological forecasting, it becomes an important and attractive topic to researchers (Fig. 1).

Concisely, the cloud detection task for meteorological satellite images is to identify the type of each pixel of the image, i.e., cloudy, probably cloudy, clear and probably clear. Or on the other hand, one can treat it as a four-classes semantic segmentation task based on remote sensing data.

Traditionally, cloud detection is treated with the thresholds-based models [1, 16]. The quality of the acquired thresholds depends on the sensor accuracy and the experts' understanding of the physical meaning of the collected signals in addition with the careful statistical analysis. Being simple and reliable, the physical models for cloud segmentation have already been employed in commercial products, e.g., the MODIS cloud product [16]. Such advantages, however, come with price. The reliance on the experts' accumulated experience causes the model too costly to obtain and almost impossible to transfer to other similar datasets. More importantly, threshold methods are unusual sensitive to the data noise. Thus, researchers are looking for effective machine learning models learned purely from the collected data, which are known for robustness.

approach helps, it still cannot achieve good pixel-level cloud detection performance [15]. suggests to use FCN [14] for cloud detection. However, they have not carefully designed the network structure for cloud detection task. Also, they model is limited into small input data and it cannot solve the challenge of the exceeding of GPU memory when taking the extremely high-resolution remote sensing data as input.

As far as we know, there is no literature studying the cloud detection on extremely high resolution (5500×5500) and multiple channels (16 channels) meteorological satellite remote sensing images.

To bridge the gap, we propose a novel FCN-based model for the cloud detection task on such extremely high resolution and multiple channels images. We use Deep Feature Aggregation (FA) to improve cloud segmentation results by adopting multi-scale features. Moreover, we fused the segmentation results by two structurally-distinct models based on FCN and hereby achieve state-of-the-art performance. Our proposed model is able to obtain pixel-level cloud detection results, i.e., to assign each pixel belonging the image a label of cloud, probably cloud, clear or probably clear. Experiments on practical datasets show that our method outperforms state-of-the-art FCN networks in terms of accuracy, precision, recall, F1 and IoU, while it is also efficient enough to support real-time weather forecasting.

2 Methodology

2.1 Datasets and Cloud Detection

The concerned cloud remote sensing images are collected by Himawari-8 satellite¹, which collects data for the Earth every ten minutes. The original data has 16 spectrum channels (6 visible channels and 10 infrared light channels), and 5500×5500 pixels per image. The data is open for downloading. We choose one-month data as the training set, and four-day data from another month as the test set.

To obtain the annotation of the images, we use the expert-corrected label from commercial MODIS [16] cloud product. In our annotation, every pixel of data is labeled as either *cloudy*, *probably cloudy*, *clear* or *probably clear*. Thus, the issue of cloud detection could be viewed as a four categories semantic segmentation problem. And our model is expected to output a label for each pixel. The major challenge of cloud detection is, due to the extremely high resolution and multiple channels of the input data and limited by the hardware resources, one cannot directly apply semantic segmentation strategies to address the problem.

2.2 The Segmentation Model for Remote Sensing Images

Overview of Our Framework. We design a novel FCN based framework to handle the segmentation tasks on extremely high resolution and multiple channels remote sensing images. As shown in Fig. 2, our framework consists of three parts:

¹ http://www.data.jma.go.jp/mscweb/en/himawari89/cloud_service/cloud_service.html.

Stitch of Patch Predictions. After we have the prediction of each patches, we need to fuse them into the original size to make the model valid for evaluation and usage. The fusion process is by combining the patched prediction into whole, and vote the results of the shared boundary pixels of the patches. Figure 3 illustrates this process.

3 Experimental Results

3.1 Settings

In this section we describe the detailed model training and evaluation procedures. As stated before, during training, we use randomly sampled $256 \times 256 \times$

3.2 Results Comparison

We measure the performance of our results in multiple indicators, including IoU, accuracy, precision, recall and F1. The IoU of the class i is computed as

$$IoU_i := \frac{Prediction_i \cap Groundtruth_i}{Prediction_i \cup Groundtruth_i}.$$

And mean IoU is the mean of IoU of each class.

To fully compare our model with others, we report the above indicators in two cases: the cloudy/non-cloudy two classes segmentation and the cloudy/probably cloudy/clear/probably clear four classes segmentation.

As illustrated in Table 1, our proposed model outperforms the result by the Vanilla FCN network structure in literature and FCN [14] coupled with feature aggregation operator only. Meanwhile, our algorithm could simulate the segmentation results of commercial software like MODIS [16] cloud product. What is more, driven by data, our approach is more robust in extreme cases, compared with MODIS [16] cloud product. Last but not least, since our method does not rely on expert knowledge, it could be easily transferred into other similar detection tasks on remote sensing data.

Table 1. Testing results of the proposed algorithm. **FA** denotes Feature Aggregation, **Att** represents Attention Skip.

Metrics	IoU	Accuracy	Precision	Recall	F1 value
FCN Class#2	0.8826	0.9376	0.9382	0.9358	0.9368
FCN+FA Class#2	0.8857	0.9394	0.9389	0.9386	0.9387
FCN+FA+Att Class#2	0.8879	0.9406	0.9407	0.9393	0.9400
FCN Class#4	0.7862	0.9402	0.7964	0.7665	0.7787
FCN+FA Class#4	0.7873	0.9405	0.8002	0.7633	0.7787
FCN+FA+Att Class#4	0.7938	0.9425	0.8053	0.7741	0.7871

3.3 Correcting the Wrong Annotation

Surprisingly, we find that our algorithm could even correct the wrong annotation of MODIS [16] cloud product in some extreme cases. Figure 4 shows some scenarios where our predictions are better similar to expert's prediction, than the results of MODIS [16] cloud product. This indicates the commercial potential of our model (Fig. 5).

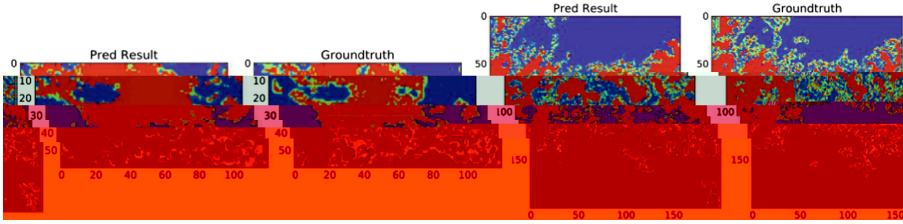


Fig. 4. Our model can improve the results of the MODIS cloud production. As left two image shows, the ground truth image has an artifact that a straight line in the middle of the image. Such an issue is also shown in the right figure.

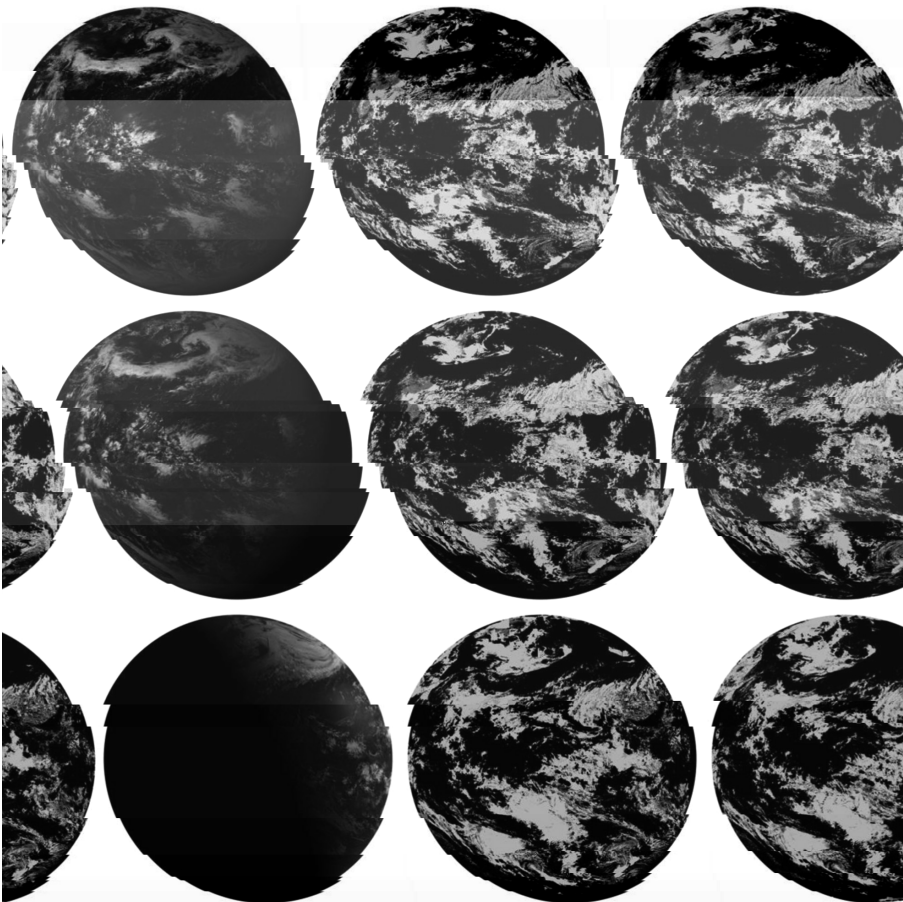


Fig. 5. Four class prediction results. The left images are the input image. The middle images are four class prediction results. The right images are four class ground truth.

4 Conclusion

The cloud detection task based on meteorological satellite remote sensing data is the key for many follow-up applications. In this work, based on FCN [14], we come up with a novel framework for the cloud detection of extremely large remote sensing images. Specifically, the original image is first split into small patches. Then, the segmentation network outputs the prediction of the small patches. Last, we mosaic the prediction of the small patches along their shared boundaries, hence obtaining the segmentation of the extremely large remote sensing images. As a result, our approach can achieve the state-of-the-art performance in cloudy/non-cloudy two classes segmentation task and cloudy/probably cloudy/clear/probably clear four classes segmentation task. Thanks to the data driven properties, our method does not rely on expert knowledge, and could be easily to extend into other similar problems. Experiments indicates our model has strong commercial potential in business usage.

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