Efficient Region Segmentation of PV Module in Infrared Imagery using Segnet

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Abstract. As renewable energy, solar energy resources are a major focus. The flaw detection of the PV production system is an important guarantee for the stable operation of the system. Hotspot detection is a key step. It is very important to extract the efficient region in the infrared image of the photovoltaic module in advance to improve the hot spot detection precision. In this paper, we propose an effective region segmentation method for infrared image of photovoltaic module based on SegNet, which greatly improves the calculation efficiency and detection accuracy. We use mask processing to hide the irrelevant background area in the original image and label the image data with labelme software. We trained and validated the model using infrared images of photovoltaic modules captured by the portable infrared imager provided by the electric company, and we assessed the model. This paper is the first attempt to use deep learning technology to solve the engineering problem of effective region segmentation of photovoltaic module infrared image. The experimental results show that the segmentation effect of our proposed methodology is remarkable in practical technical applications.

1. Introduction
As the economy and population grow rapidly, global demand for electricity continues to grow. On the one hand, traditional fuels, such as oil and coal, have become less and less stored. On the other hand, traditional fuels emit a large quantity of carbon dioxide, causing severe atmospheric pollution [1]. Currently, the global energy industry is promoting clean manufacturing. As an environmentally responsible renewable energy, solar energy is widely used around the world to meet the concept of sustainable development [2]. To ensure the long-term stable operation of the photovoltaic power generation system, fault detection is necessary. The hotspot effect is one of the most important problems to detect. It may result in a loss of power and degradation of the photovoltaic system [3][4][5]. In the field of photovoltaic power generation, the recognition of hotspot defects mainly uses image processing algorithm to detect the infrared image of photovoltaic modules. In practical engineering applications, the infrared image of photovoltaic module usually contains the interference background information of thermal imager, land, people and so on. Therefore, it is very important to extract the efficient region in the infrared picture of the photovoltaic module in advance to improve the accuracy of hot spot detection.

Figure 1 is an infrared image of a PV module captured by a portable thermal imager. The grid lines on the PV module panel interfere with the detection when using the conventional image processing algorithm, which will affect the segmentation effect. Furthermore, the conventional image processing algorithm cannot achieve pixel level accuracy.
Figure 1. Infrared image captured by hand held infrared imager.

In order to get more accurate detection, we propose an efficient method of region segmentation for the infrared image of photovoltaic module based on segnet.

The main contributions of this work are:
- This is the first time in the photovoltaic system, we are trying to apply deep learning technology to the efficient extraction of the infrared picture region of the photovoltaic module. And we obtained a high accuracy rate of pixel level.
- This method is better than most conventional methods as it emphasizes the target as much as possible and excludes other irrelevant information.

The structure of this paper is organized as follows. Section 2 presents primarily the development history of the semantic segmentation algorithm of the image and the extraction of the effective region. Section 3 focuses on the semantic segmentation algorithm and algorithm evaluation criteria. The results of the experiments are presented in section 4. Lastly, results will be discussed and a conclusion reached in Section 5.

2. Related works

This research covers computer vision, photovoltaic power generation and other fields. There will be a brief discussion about the development of this technology. Section 2.1 will introduce a number of semantic image segmentation algorithms. In section 2.2 we will discuss some methods of extraction of efficient regions of photovoltaic modules.

2.1. Semantic segment algorithm of the image.

Semantic segmentation is an important research theme in the area of computational vision[6]. This is a pixel level recognition method, marking the object category for each pixel. Semantic segmentation network models based on deep learning comprise the FCN network, the u-net network, the segnet network and so on[7][8]. Segnet is a convolutional neuronal network with an encoder decode structure. It is a semantic segmentation network based on the FCN and the modified vgg-16 network[9][10]. Compared to other networks, segnet enhances boundary contour, optimizes the spatial complexity of the algorithm, and generally achieves better results in semantic segmentation[11][12]. Inspired by this, we attempt to use the segnet method to extract the area of the photovoltaic module from the short-range infrared image.
2.2. Effective region extraction of photovoltaic module

An efficient region segmentation algorithm based on local statistical features was proposed by [13] to process the infrared image of the PV generation region obtained from aerial photography. Efficient methods of extracting existing PV regions are mainly used in aerial infrared imagery, but there are few detection methods for short-range infrared imagery. In addition, the grid line of the infrared image near the PV module is very evident, which brings interferences to the actual extraction of the region.

3. Methodology

In this section, we mainly introduce efficient methods of extraction of photovoltaic modules. We will focus on acquiring and processing the data sets and the SegNet network model we use.

3.1. Acquisition and processing of datasets

3.1.1. Acquisition of datasets. Our data sets are supplied by electricity company. The training dataset includes 500 infrared images. The test dataset is made up of 150 infrared images. Figure 2 shows the original infrared image of the dataset. In order to improve the robustness of the data, we enhance the data set. Common methods for expanding data include random clipping, horizontal and vertical flipping, displacement, and rotational reflection [14]. We use mirror and flip to expand the data set.

3.1.2. processing of datasets. Figure 2 shows the infrared image provided of the electricity company. In order to reduce the interference of the identification of the instrument to training, we mask the interference area in advance, and the effect is shown in Figure 3. As segnet is a pixel level recognition algorithm, we use labelme software to tag the data.

![Figure 2. original image.](image1)

![Figure 3. Mask processed image](image2)

3.2. SegNet network model

In this paper, the segnet network model is used to segment the effected region of infrared image of the photovoltaic module. As shown in Figure 4, segnet features a network of encoders and a corresponding network of decoders. Among them, input is the original image, output is the result image of segmentation output, the blue part represents the convolution layer, the green part represents the pooling layer, the red part represents the upsampling layer, and the yellow part represents the softmax classifier. The encoder of segnet network structure is a vgg16 model composed of 13 convolution layers, and corresponds to the decoder. The encoder contains both batch standardization and activation function operation [15]. When 2 * 2 maximum pooling is performed, the corresponding maximum pooling index position is stored at the same time. At the decoder, the maximum pooled index is used for upsampling and convolution. The softmax layer uses the input features of the last decoder to sort each pixel independently [16][17][18].

Segnet is a symmetrical network structure model. The encoder network extracts high-dimensional features by convolution, and reduces the number of parameters and image size by pooling. The decoder network obtains high-dimensional feature map by deconvolution and up sampling [19]. Segnet improves the training speed by removing the full connection layer, and speeds up convergence and suppresses the over fitting by adding batch standardization operations in the convolution layer.
At the same time, only a small amount of memory is used to store index information in the training process.

3.3. evaluating indicator
In image segmentation, the IOU(Intersection-Over-Union) is generally used as the standard for assessing the algorithm. The formula (1) is the pixel accuracy, which refers to the proportion of properly marked pixels in the total pixels. The formula (2) is the mean class precision. First calculate the proportion of the correct number of pixels in each class, then take the average. The formula (3) is the intersection and union ratio of two sets of actual and forecast values. The Formula (4) is the ratio of frequency to weight, and the weight is set according to the frequency of each class. The average IU is the most commonly used evaluation standard. The average IU is usually used to evaluate the algorithm.

$$
\text{pixel accuracy} = \frac{\sum_{i=0}^{k} p_{ii}}{\sum_{i=0}^{k} \sum_{j=0}^{k} p_{ij}} \quad (1)
$$

$$
\text{mean pixel accuracy} = \frac{1}{k+1} \sum_{i=0}^{k} \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij}} \quad (2)
$$

$$
\text{Mean IU} = \frac{1}{k+1} \sum_{i=0}^{k} \frac{p_{ij}}{\sum_{j=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ji} - p_{ii}} \quad (3)
$$

$$
\text{Frequency weighted IU} = \frac{1}{\sum_{i=0}^{k} \sum_{j=0}^{k} p_{ij}} \sum_{i=0}^{k} \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ji} - p_{ii}} \quad (4)
$$

Where $k$ is the number of classifications minus 1, $P_{i}$ is the real quantity, $P_{ij}$ represents the number of pixels that are originally of class $i$ but are predicted to be of class $j$.

4. Experiment
In this section, we will show our experimental process and some parameters. The results will be displayed as images and data.

4.1. Experimental parameter setting
This experiment is done on the server of Intel (R) Xeon (R) CPU e5-2620 V4 @ 2.10 GHz. The software environment is Ubuntu 18.04 Chinese version and python version 3.6, based on tensorflow deep learning framework. The convolution layer is 3 * 3 and the pooling layer is 2 * 2. The training parameters are shown in Table 1.
Table 1. The training parameters.

| parameter    | value |
|--------------|-------|
| Epoch        | 50    |
| Batch-size   | 2     |
| Learning rate| 0.001 |

4.2. experimental results

We trained the segnet model with 500 hot spot infrared images of PV modules provided by the electricity company. The value of epoch is 50 and the training takes about 30 minutes. Figure 5 shows the change of loss value during training. Figure 6 shows the change of accuracy during training.

![Figure 5. the change of loss value during training.](image1)

![Figure 6. the change of accuracy during training](image2)

We use 150 pictures to verify the trained model. Figure 7 shows part of the prediction result images, in which the first column corresponds to the pre-processed image. The images corresponding to the second column are the prediction results. The figures show that the segnet model makes it possible to efficiently extract the PV module region from the infrared image.

![Figure 7. part of the prediction result images](image3)
Here we use the IOU evaluation criteria. The Model recognition accuracy are shown in Table 2. The mean pixel level recognition accuracy is 94.48%. The Frequency weighted IU is 92.68%.

Table 2. The recognition accuracy.

| parameter                        | value  |
|----------------------------------|--------|
| Mean IU                          | 0.9448 |
| Frequency weighted IU            | 0.9268 |

5. Discussion
In this work, we propose a method to extract the effective region of infrared image of photovoltaic module based on segnet. We use 500 infrared images for training and 150 infrared images for verification. The mean pixel accuracy can reach 94.48%. The Frequency weighted IU is 92.68%. The experimental results show that our algorithm is effective in the photovoltaic infrared image segmentation provided by the electricity company.

Acknowledgments
This work was supported by the National Key Research and Development Program of China (Grant No. 2018YFB1500800).

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