Deep Learning based Discharge Information Extraction for Ultraviolet Image of Electrical Equipment

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Abstract. Convolutional networks are powerful visual models that transform images into more effective representations. To make full use of this technique, we propose a new method based on deep learning and convolutional network to effectively get the discharge information of an ultraviolet (UV) image. We firstly segment the equipment region and the UV spot region separately by using the DeepLab network, and then several properties which can show the discharge information are extracted on the basis of the segmentation. The use of the DeepLab network helps to get a reliable segmentation result, and more accurate discharge information. We take 5000 UV images to test our network, and use the concept mean IOU to evaluate its performance. The results show the advantage of the method, and it can meet the demands of further fault diagnosis.

1. Introduction
The condition of electrical equipment is important for the safety of the whole grid. The UV imaging detection is one of the most popular ways to detect the discharge around or inside the equipment. The way for an ultraviolet imager to save data is through image. The image is created by two channels: the visible-light image channel and the UV image channel. As shown in Figure 1(a), several white spots are generated by the UV image channel. Meanwhile, the visible-light image channel shows what kind of equipment and where the spot occurs captured by the imager.

For a single UV image, the key way to determine whether there is a fault is through image processing techniques. To estimate the number of photon, we need to segment the UV spot region [1-2]. Besides, to treat the UV images intelligently and make the fault diagnosis accurate, the image process result and analyze information should be extracted more reliable. Obviously, it is hard to achieve with traditional image process methods.

Recently, deep learning based methods have been explored and widely used in many computer vision and image processing areas, including image classification, object detection, semantic image segmentation [3, 4], etc. Under the motivation of the successful applications of the deep learning methods, we explore the application of deep learning method on automatic diagnose of an UV image for electrical equipment.

Therefore, we here propose a deep learning method based discharge information extraction for UV image of electrical equipment. It makes full use of the advantage of the deep learning method, and locates the equipment and the UV spot regions accurately. The method can extract the discharge information on the basis of the segmentation result and make the result to be more reliable.
2. Proposed method

2.1. Data Preparation

The ultraviolet images treated here are mostly captured from the CoroCam series ultraviolet imager. The ground truth images are labelled into three classes: the first class is the background (labelled with \( l = 0 \)), the second class is the equipment where the discharge occurs (labelled with \( l = 1 \)), and the third one is the ultraviolet spot region (labelled with \( l = 2 \)). As shown in Figure 1(b), we use black color to represent \( l = 0 \), the grey color is the equipment region, and the white color is the spot region. The area of the UV spot region can show the photon number, therefore here we only focus on the strongest UV spot region which is also the biggest region. Other tiny spot regions are omitted. Similarly, only the equipment which occurs the discharge will be labelled.

![Figure 1. A sample image and its labelled segmentation image.](image)

2.2. Segmentation Network

The segmentation network is based on the DeepLab network proposed by [4]. DeepLab is based on VGG-16 convolutional network, which is targeted for image classification. As shown in Figure 2, the architecture is mainly combined by three stages: the Convolutions stage, the ASPP stage and the upsample stage. The focus of our treatment is to locate the equipment and the UV spot region, and it does not require a refined segmentation result. Therefore, the CRF (Fully-Connected Conditional Random Fields) is not adopted here to get a more accurate result.

![Figure 2. An overview of the proposed network architecture.](image)
The main approach of DeepLab is to turn the fully connected layer into convolutional layer, so it can produce coarse score map, instead of a single score as in classification task.

The first feature of the network is the use of atrous convolution. The concept of atrous convolution comes from the computation in wavelet transform [5], in which the motivation was to achieve efficient computation. In DeepLab, the main contribution of atrous convolution is to enhance resolution, which can achieve a larger field of view in convolution. Large field of view brings larger context information, and is helpful for extracting more representative features for segmentation.

Take one-dimensional atrous convolution for an example. Assumed the input signal is $x[n]$, with the filter $w[k]$, the output $y[n]$ is as follows:

$$y[n] = \sum_{k=1}^{K} x[n + r \cdot k] w[k]$$

(1)

The second feature of the network is the atrous spatial pyramid pooling (ASPP) technique. Different rates of atrous convolution extract features at different scales. Therefore, a combination of atrous convolution layers at different atrous rates is more likely to extract multi-scale information, and is beneficial to segmenting objects at different scales. In specific, multiple parallel atrous convolutional layers with different sampling rates are employed. The features extracted from different sampling rates are further processed separately, and the corresponding score maps are fused to generate the final coarse score map.

The detailed architecture is shown in Figure 3. We can find that the atrous convolution is used in Conv5 layers in the Convolutions stage. Furthermore, four filters are used in the ASPP stage with rate 6, 12, 18, 24, respectively. The feature maps generated from the four fc8 layers and the fusion result with input image Figure 1(a) for the labelled three classes are shown in Figure 4. After obtaining the coarse score map, an interpolation treated is adopted to get a upsampling score map, which provide a dense prediction for the whole image.

\[ \text{Figure 3. The detailed architecture of the proposed network.} \]
2.3. Discharge Information Extraction

For an input UV image $I_0$, its segmented result is represented as $I_B$. As discussed in Section 2.1, the value range of all pixels in $I_B$ is $[0, 2]$, where 1 is the equipment region and 2 is the UV spot region. According to our label strategy, only one equipment region and one spot region are segmented. Take $R^1$ to represent the equipment region, and the spot region is $R^2$.

For $R^1$, we aim to get its minimum enclosing rectangle, and find its height $H$, width $W$ and four vertexes. With the four vertexes, the parameters of the four boundary lines can be calculated. As shown in Figure 5. The two shorter lines are written as $l1 = [a_1, b_1], l2 = [a_2, b_2]$, and two longer lines are $l3 = [a_2, b_3], l4 = [a_2, b_4]$. Here, $a$ and $b$ are the slope and intercept.

For $R^2$, we get the following information by the binary region statistic:

- a. the UV spot region area, represented as $A$
- b. the UV spot region perimeter, represented as $P$
- c. the UV spot region solidity, represented as $S$
- d. the coordinates of the UV spot region centre, represented as $X0 = [x_0, y_0]$
- e. the UV spot region location, calculate the cross points between lines go through $X0$ and perpendicular to $l1, l2, l3, l4$, which are $X1, X2, X3, X4$ in Figure 5. The location information can be represented as $[d_H, d_W]$. 

\[
\begin{align*}
    d_H &= \sqrt{\frac{(x_1 - x_0)^2 + (y_1 - y_0)^2}{(x_i - x_j)^2 + (y_i - y_j)^2}} \\
    d_W &= \sqrt{\frac{(x_1 - x_0)^2 + (y_1 - y_0)^2}{(x_i - x_j)^2 + (y_i - y_j)^2}}
\end{align*}
\]

Here, $[x_i, y_i], i = 1, 2, 3, 4$ are the coordinates of $X1, X2, X3, X4$, respectively.
Figure 5. Sample for getting the UV spot region location.

Therefore, for an input UV image, after the extraction of different regions and the information statistic, the final discharge information can be written as \([A, P, S, d_H, d_W]\), which can represent the size, regulation and the location of a UV spot region.

3. Experiments

The extraction process in Section 2.3 is a direct way with no error occurs. Therefore, in the experiments section, we mainly focus on the performance of the segmentation process.

3.1. Parameters Setting

The experiments are implemented within Caffe[6], a popular deep learning framework. To reduce the convergence time of the network, the model weights are initiated with the Imagenet-pretrained VGG-16 model weights. As shown in Figure 3, the number of output in all the score layers are 3. These layers are initiated with zero-centered gaussian random numbers. The initial learning rate is set to \(10^{-3}\), with a "Poly" learning policy to gradually decrease the learning rate. The mini-batch size is 2, and the max iteration size is 20000. We optimize the loss function with respect to the network weights following the custom SGD procedure, the relationship between loss and iteration is shown in Figure 6. The whole training process is on a single GTX-1080 GPU.

Figure 6. Relationship between train loss and iteration.

3.2. Experimental Results

5000 UV images captured by the CoroCam series ultraviolet imager are collected here for experiments. The resolution is not restricted in our network. The images are labelled into 3 classes as discussed in Section 2.1 to get the groundtruth. The performance of segmentation is measured by mean IOU(intersection over union).
\[ IOU = A / (A \cup B) \]  

Figure 7. Evaluate Criterion.

Like the evaluate criterion marked in Figure 7, assumed the region A is the segmented equipment region, and B is the groudtruth equipment region. Then the IOU of the equipment region of an UV image is calculated according to equation (3). So is the calculation of the UV spot region.

We here take 4000 images for training and 1000 images for test, the mean IOU of the equipment region and UV spot region is 92.01% and 85.67%, respectively. The result can fully meet our discharge information extraction demands, which can then be used to justify whether there is a fault occurs.

4. Conclusion

In this paper, we have proposed a novel method to treat the UV image. It can extract the UV image discharge information for electrical equipment. The DeepLab network is adopted to locate the equipment and UV spot region through semantic image segmentation. With a binary region statistic, the discharge information can be extracted through a 5 dimension feature. With the structured information, the automatic fault diagnosis can be processed. The experiment shows that the method can achieve a reliable result, and provide more intelligent information to get a further discharge fault diagnosis for electrical equipment.

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