A Single Image Mosquito Streaks Removal Method of High-Speed Railway Traction Substation Using DCNN

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Abstract. With the proposal of intelligent high-speed railway, the research on remotely monitoring the intelligent traction substation becomes a key subject of high-speed railway safe operation. However, mosquitoes adhered to the glass window or camera lens can severely hamper the visibility of a background scene, and degrade images considerably. Therefore, we propose a single image mosquito streaks removal method of high-speed railway traction substation based on the deep convolutional neural network. First, we employ guided filter to split input image into smoothing image and edge-preserving image. Then, the edge-preserving image is fed into our designed convolutional neural network to obtain learning map, which solves problems of background interference and focuses the model on the structure of rain streak in images, and the clean image is finally generated through adding the input image and learning map. The experiment results on Heishan traction substation real datasets show the effectiveness of our proposed method.

1. Introduction
At the end of 2019, the mileage of China high-speed railway had achieved more than 35 thousand kilometers [1]. High-speed railway traction substation, which is shown in Figure 1, and it served as unique power supply for electric locomotives, it makes a difference to ensure the safe operation of power system. Currently, with the proposal of intelligent high-speed railway, the research on remotely monitoring the intelligent traction substation becomes a key subject of high-speed railway safe operation, which not only ensures the safety of railway, but drastically reduces the cost of human and economic resources. How to effectively monitor states of traction substation is the premise of high-speed railway management. However, mosquitoes attached to a glass window or windscreen or lens can hamper the visibility of a background scene, and degrade an image. Moreover, in most cases, the focus of the camera is on the background scene, making the appearance of mosquitoes in an image blur, and because the mosquito moves too fast, it is easy to form streaks in the image.
Figure 1. High-speed railway traction substation.

Mosquitoes attached to a glass window or windscreen or lens can hamper the visibility of a background scene, and degrade an image, especially at night. Moreover, in most cases, the focus of the camera is on the background scene, making the appearance of mosquitoes in an image blur. In this paper, we address the visibility degradation problem caused by mosquito streaks. Our goal is given an image impaired by mosquitoes, we intend to remove the mosquitoes, so that the image looks like there is no mosquito. For video-based methods, mosquito streak can be more easily identified and removed using inter-frame information, the methods work well, but are significantly aided by the temporal content of video. We consider the mosquito streaks have something in common with the rain streak, both of them produce a high frequency signal on the image.

In this paper, we instead focus on removing mosquito streak from a single image, similarly, a few methods have been proposed to tackle the rain streak detection and removal problems. Li et al. [2] proposed a method based on Gaussian mixture models in which patch-based priors are used for both a clean layer and a rain layer, in [3], Li et al. utilized Gaussian mixture model (GMM) patch priors for rain streak removal, with the ability to account for rain streaks of different orientations and scales, Jiang et al. [4] considers the discriminative feature of rain streaks and the clean video in the gradient domain, [5] utilized discriminative sparse coding to recover a clean image from a rainy image.

Inspired by these, we propose a single image mosquito streaks removal method of high-speed railway traction substation based on the deep convolutional neural network. This method can quickly and accurately locate the area of mosquito pattern, suppress the background noise, and thus transforming a mosquito streaks image into a clean image.

2. Methodology
We illustrate the overall architecture of our proposed mosquito streaks removal framework in Figure 2. First, given an input image adhered by mosquito streaks, we adopt guided filter [6] to split it into smoothing image and edge-preserving image, i.e., low-frequency base layer and high-frequency detail layer, and the radius of the guided filter for low-pass filtering is 16. It can be seen clearly from the Figure 2 that the interference of background is removed and only mosquito streaks and object structures remain in the edge-preserving image after subtracting the smoothing image.

Then, the edge-preserving image is fed into our designed convolutional neural network to obtain learning map, and the specific network structure is described in detail in section 2.1, finally, the clean image is generated through adding the input image and learning map.
2.1. Network design

We design the mosquito streaks removal convolution neural network, as shown in Figure 3. The edge-preserving image is fed into the network to obtain learning map. Since deeper architectures can better explore and model image feature, inspired by the deep residual network (ResNet) [7] that simplifies the learning process by changing the mapping form, we design a dual residual network to directly reduce the mapping range from input to output, which can train the network convergence faster.

Besides, to further improve the mosquito streaks removal result, we introduce the global context block [8] to enhance image quality via focusing on high frequency details during training, which is lightweight and can effectively removes background interference and focuses on the structure of mosquito streaks. Global context block (GC block) can benefit a wide range of visual recognition tasks, and the flexibility of the GC block allows it to be plugged into network architectures used in various computer vision problems. In this paper, we apply it to the penultimate layer and the last layer.

![Figure 3. The mosquito streaks removal convolution neural network.](image_url)

During our experiments, we set the size of all convolution filter kernel to $3 \times 3$, and set the number of dual residual block $N = 5$, and in order to alleviate gradient disappearance, speed up training process and improve performance, we adopt BatchNormalization layer after each convolution layer.

2.2. Loss function

The input of our mosquito streaks removal network is an image adhered with mosquitos $X$ and the output is an approximation to the clean image $Y$, and we denote the learning map as $X'$. Based on the previous discussion, we define the loss function of the designed network as the mean squared error between the fusion image of the input mosquito streaks image and the learning map and the clean image, the specific formula is as follows.

$$ L = \sum_{i=1}^{N} L_{\text{MSE}} ((X_i + X'_i), Y_i) $$

(1)

Where $N$ denotes the number of training images.
3. Experiments and analysis

3.1. Experimental dataset and training process
The initial dataset used in the experiments are scene maps in traction substation, which are collected by the acquisition system from Heishan traction substation in Shenyang city. To build the initial dataset, all kinds of traction substation images at night are manually selected, more than 2000 in total, and we evaluated 600 training images and 20 testing images.

The experimental environment in this paper is described as follows: Ubuntu 18.04 operation system, Intel Xeon Silver CPU, NVIDIA GeForce RTX 2080Ti GPU with 11GB memory, python 3.6.4, deep learning open-source software library Tensorflow. We use SGD algorithm with a batch size of 20 and momentum of 0.9 for the training procedure, learning rate start from 0.1.

3.2. Experiment and result
After the training, we tested the 20 images. The effect of 3 groups of images are shown in Figure 4, from which, we can see that the result is able to filter out the rain streaks. Besides, we also show the processing images as follows. In the next subsection, we will evaluate the SSIM between the original image, the result and groundtruth.

Figure 4. The visualization results in different processing stages. From left to right, there are origin image, edge-preserving image after guided filtering, learning map through the designed network, the final result and groundtruth. Among them, the red rectangle represents the mosquito streaks.

3.3. Structural similarity analysis
SSIM [9] algorithm is used to calculate the difference between two images from three aspects of image brightness, contrast, and structure. The range of structural similarity is 0 to 1. When two images are as like as two peas, the value of SSIM is equal to 1. We tested the effect on the SSIM of input image and the corresponding compared with the ground truth, and the figures of the three images mentioned in the previous section is shown in TABLE 1. It can be seen from Figure 4 and Table 1 that our proposed method removes the rain streaks while keeping background details.

TABLE 1. SSIM results of input image, the corresponding result compared with groundtruth.

| Figure | Input Image | Result |
|--------|-------------|--------|
| (a)    | 0.736       | 0.796  |
| (b)    | 0.724       | 0.812  |
| (c)    | 0.701       | 0.824  |

Meanwhile, we use the grayscale histogram to visualize the input image and the result, as is shown in Figure 5. The red dashed rectangle box represents high frequency mosquito streak is removed and the background is restored, and the mosquito streak is obtained via subtraction of the original image and the result.
Figure 5. Grayscale histogram of the input image and the result.

4. Conclusion
This paper presents a single image mosquito streaks removal method of high-speed railway traction substation based on the deep convolutional neural network. First, we employ guided filter to split input image into smoothing image and edge-preserving image. Then, the edge-preserving image is fed into our designed convolutional neural network to obtain learning map. Finally, the clean image is generated through adding the input image and learning map. Meanwhile, structural similarity (SSIM) is utilized to compare the difference between the input image and the clean image, and the experiment results on Heishan traction substation real datasets show the effectiveness of our proposed method. In the future, the research will focus on water drop and fog removal of the monitoring image of traction substation.

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