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Research on Transmission Line Image Defogging Method with Improved Dehazenet Algorithm

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Abstract. Intelligent detection methods are gradually being integrated into power grid inspection work. There are many weather factors in the process of intelligent inspection, which can affect data acquisition. In order to address the problems of distortion and imbalanced contrast in images obtained in foggy weather, this paper proposes an improved DehazeNet algorithm. The algorithm introduces parallel convolutional layers conv_a and divides reshape_a to improve feature extraction effectiveness and retain corresponding features while increasing receptive field. Multi-scale image feature extraction is achieved through four convolutional layers of different sizes using the parallel convolutional structure. The bilateral linear rectification unit is used as the activation function to effectively estimate the transmission rate. Experimental results show that the improved DehazeNet algorithm has a 5.5% increase in PSNR, 0.02% increase in SSIM, and 6% increase in information entropy. The algorithm in this paper has better haze removal effect compared to the DehazeNet algorithm.

Keywords: Power grid, Multi-scale, DehazeNet, PSNR

1. Introduction

With the emergence and development of the concept of smart grid, the tasks of acquiring and processing image information are also increasing. In the face of foggy weather, the camera (signal receiver) obtains both the target image information and the fog noise, which hinders target analysis and reduces the acquisition of image features [1].

The goal of image enhancement is to remove fog noise as much as possible, improve contrast, and obtain a clear image with significant contrast, but these methods often suffer from the problem of loss of image details. Image restoration [2] is based on a series of algorithms using atmospheric degradation models, and traditional dehazing algorithms mostly rely on image restoration. The Multi-Scale Retinex with Color Restoration (MSRCR) [3] method adjusts the relationship between the RGB color channels in the original image proportionally to highlight relatively dark areas and eliminate color distortion in the image. However, this algorithm is relatively complex

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and requires lightweight processing. He [4] et al. found that in images without haze signals, there are some pixels in local regions that have low brightness values in the color channels. For single images, direct dehazing is not possible, so Tang used a random forest algorithm combined with feature estimation for atmospheric transmission. In outdoor heavy fog environments, simple linear processing methods cannot easily extract features. Due to the excellent performance of convolutional neural networks (CNN) in image recognition and processing, the convolutional layers of CNN can efficiently remove noise and interference by extracting features from images using filters. The pooling layers of CNN can reduce the size of the output feature map, reduce computational complexity, and effectively prevent overfitting. The Multi-Scale Convolutional Neural Network (MSCNN)[5] combines features of different scales and has excellent performance in removing strong haze from images.

2. DehazeNet Design Model Diagram

In 2016, CAI [6] proposed the "DehazeNet[7]" network, which is a trainable end-to-end system used for transmission estimation to directly estimate the mapping relationship between hazy images and transmission rates. Hazy images with fog interference are taken as input, and the network outputs the transmission map. Then, by using the atmospheric scattering physical model and image restoration, the hazy image is restored to a state close to the original image. The DehazeNet algorithm incorporates a Maxout network in the feature extraction layer. The BReLU function is applied to ensure both local linearity and bilateral constraints, resulting in scalar output values. Fig 1 is the network diagram of DehazeNet.

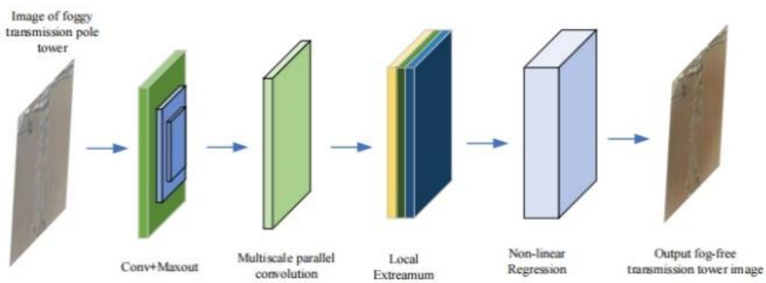

Fig 1 DehazeNet network diagram

The convolutional layer adopts the Conv+Maxout structure, which is designed to reflect the established hypothesis/prior theory of image deblurring processing. The Maxout units in the layer are used for feature extraction. The non-linear activation function (Bilateral Rectified Linear Unit, BreLU[8])is utilized to extend the rectified linear unit and reduce the search space with bilateral constraints, thereby improving the quality of restoration. When filtering with 16 convolutions using the Maxout network, with 4 convolution inputs per image, if the output image is 3×16×16, the output will be 16×12×12. The utilization of multiple scale features in the Inception model is beneficial for dehazing. The network adopts 16 convolution kernels of size 7×7, 16 convolution kernels of size 5×5, and 16 convolution kernels of size 3×3, each corresponding to 16 feature maps. After the output becomes 48×10×10, maximum pooling is applied to the multiple scales, which is sensitive to local extrema data and maintains local invariance of the transmission rate.

3. Implementation of Improved DehazeNet Algorithm

The convolutional layer conv_a and the reshape layer reshape_a are used to extract the basic features of the image. Then, a max pooling layer pool_a is used to obtain the atmospheric light constant of the image. Finally, the bilateral linear rectification unit is still used to accelerate convergence. Fig 2 is the network structure diagram of the improved DehazeNet.

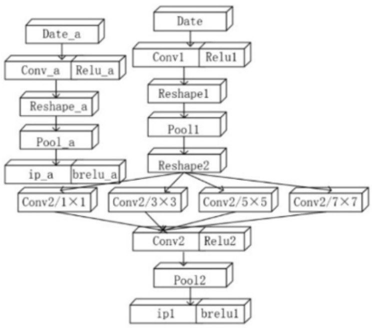

Fig 2. Improved DehazeNet network diagram

The improved DehazeNet network adds a new convolutional layer conv_a and a reshape layer reshape_a to the original DehazeNet network. The conv_a layer is parallel to the convolutional layer conv1 in the DehazeNet network. The reshape_a layer is partitioned from the original reshape1 layer in the DehazeNet network. The conv_a layer and the reshape_a layer are used to extract the basic features of the image, and the max pooling layer pool_a is used to extract the atmospheric light constant of the sampled image. The conv1 layer and the reshape1 layer are used to extract the basic features of the image, and the pooling layer pool_1 is used to further extract the atmospheric transmission rate of the image. A reshape2 layer is added after the pooling layer pool_1.

To reduce the computational complexity during the final image processing, a parallel convolutional layer conv2/1x1 with a size of 1×1 is introduced in the multi-scale mapping section. Correspondingly, in the reshape layer, a new dimension reshape_a is created, and in the subsequent convolutional concatenation layer, a new bottom structure is added to incorporate this smaller convolution kernel conv2/1x1 into the overall network architecture. Considering the limited size of the existing training set and the known weights of the existing network, fine-tuning training is used. The weight initialization method is employed to make the output variances of each layer in the neural network as equal as possible, ensuring better information flow in the network. The first part of the network consists of the convolutional layer conv1 and the reshape layer reshape1. The convolutional layer is used for filtering, and the reshape layer provides the appropriate data input format for the subsequent pooling layer. A pooling layer pool1 is added for further feature extraction.

4. Experimental Analysis

Different depths of field in images will affect the atmospheric transmission rate. In this experiment, images of power transmission lines with different scene depths are taken. Close-range images of towers are obtained using tower cameras and distant images of power transmission lines are obtained using drones (capturing the features of tower bodies). In this experiment, 500 samples of insulator images, 200 samples of tower images, and 500 samples of images with other foreign objects are manually selected as the original samples. Data augmentation is performed using the OpenCV framework, and the images with added noise and blurring can be expanded 11 times. Then, fog is added to the images using OpenCV, resulting in a training set of 13,200 hazy images. Table 1 shows the software and hardware configurations of the experimental environment.

Table 1. Experimental environment parameters

CPU	RA	GPU	system	framework	language
Intel(R) Core (TM) i7-12700H 2.30GHz	64G	GeForce GTX3050	Windows 11	Pytorch Gpu 1.13.1	Python 3.9.1

Figures 3 and 4 demonstrate the defogging effects of different depths of field and different algorithms.

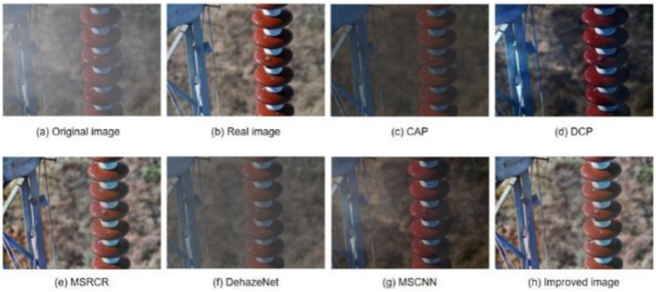

Fig 3. Comparison of insulator images obtained by camera

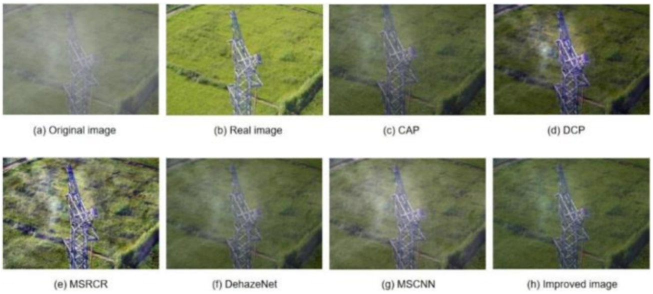

Fig 4. Comparison of transmission tower images obtained by UAV

4.1 Experimental Performance Evaluation

The performance evaluation of this experiment is measured using three technical indicators: Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Information Entropy. Additionally, a comparison is made with other deep learning network-based algorithms.

Table 2 showcases the performance indicators of selected images for data comparison.

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Image	Method	PSNR	SSIM	Comentropy
Fg.3	CAP	13.15	0.64	5.74
	DCP	13.64	0.77	5.66
	MSRCR	19.74	0.73	5.87
	DehazeNet	18.29	0.92	5.88
	MSCNN	21.28	0.94	6.05
	Improved	23.54	0.94	6.57
Fg.4	CAP	14.74	0.69	6.70
	DCP	15.19	0.75	6.67
	MSRCR	17.30	0.45	7.55
	DehazeNet	17.03	0.85	6.73
	MSCNN	20.64	0.86	7.02
	Improved	22.98	0.87	7.32

4.2 Qualitative Analysis of Experimental Results

Through comparative experiments, the CAP algorithm loses some original colors and shows average results with relatively low contrast. The images generated by the DCP algorithm have a darker tone and less information, with significant color differences compared to the original images. The MSCRCR algorithm enhances the local features of the image but suffers from color distortion. The DehazeNet algorithm, designed for distant scene images, has lower information presentation compared to MSCRCR. For close-range image processing, both algorithms have similar information entropy, but the DehazeNet algorithm retains the color and contrast of the images. The MSCNN algorithm, utilizing deep learning, further improves the defogging effect and enhances the edge features compared to traditional algorithms. The improved algorithm in this study aims to enhance the defogging effect of the DehazeNet algorithm by combining traditional image enhancement methods, making the features more prominent, and using image enhancement to make the colors more vibrant.

5. Conclusion

In this study, the DehazeNet algorithm was improved to address the oversaturation and skyline blurring issues present in traditional single-image defogging methods. The improvements include: 1) incorporating a new network structure to enhance feature extraction efficiency; 2) rearranging the data dimensions through the division and reshaping layers within the original DehazeNet network to simplify network processing; 3) introducing parallel convolution layers conv2/1 with a size of 1x1 in the multi-scale mapping section, improving speed and feature extraction In foggy environments where certain features have similar colors to the background, the performance may be suboptimal, and this can be further improved through preprocessing and training modifications.

Acknowledgments

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