Infrared-Visual Image Fusion and CNN Model in Electrical Faults Diagnosis

Lei Su\textsuperscript{1}, Qi Ni\textsuperscript{1}, Qiao Jin\textsuperscript{1}, Boyuan Cao\textsuperscript{1}, Zhaohong Xu\textsuperscript{2}, Xiao Yu\textsuperscript{2}, Dai Wang\textsuperscript{2*}
\textsuperscript{1}State Grid Shanghai Electric Power Company, Shanghai 200122, China
\textsuperscript{2}Institute of Science and Technology for Brain-Inspired Intelligence, Fudan University, Shanghai 200433, China
\textsuperscript{*}Corresponding author’s email: wang_dai@fudan.edu.cn

Abstract. In this paper, we proposed a new faults diagnosis method based on the fusion of visible and infrared images of electrical equipment. Firstly, the discrete wavelet transform method is used to fuse the visible and infrared images, which enables the accurate location of the electrical equipment. Then, a deep convolution neural network (CNN) model is employed to identify faults in electrical equipment. Three parameters of CNN including connection weight, convolution layer parameters and pooling layer strategy are designed in this paper. The inputs of CNN are the fused reconstructed images and the outputs are the classifications of faults. Finally, simulation experiments and analysis show that the algorithm proposed in this paper can effectively improve the contrast and clarity of the fused images. It can reduce noise interference, and improve the location accuracy of electrical equipment. More specifically, the faults diagnosis rate is improved by 2-6\% with the proposed method.

1. Introduction
The safety and reliability of the substation is an important issue, which affects the stable operation and safety of the power system. The traditional faults detection of substation relies heavily on humans. However, due to the large number of substation equipment, many professionals are needed, which is quite time-consuming and costly. In recent years, the application of infrared thermal imaging on power equipment fault diagnosis has become more and more popular. Compared to traditional method, infrared thermal imaging detection (ITID) has the advantages of non-contact, non-power failure, and non-destruction. More importantly, it can predict the failures of equipment and detect overheating in real time. Despite with the help of the substation inspection robot with ITID equipment, the collection of infrared images becomes easier. It remains a challenging problem that many human resources are still needed to inspect collected images, which is quite inefficient. Besides, the accurate location of device is unavailable.

There are many studies on the feature extraction of infrared image and further recognition of faults. Guo et al. uses Zernike moments, which is characterized by rotation and scaling invariance, as the features of the equipment and further conduct classification and recognition based on Relevance Vector Machine (RVM) \cite{1}. Inspired by the complement system in the immune system, Bai et al. proposed to establish power device template image libraries, and further determine the contour and position of target region by matching the template with the image, and finally extract the regions of interest by k-means \cite{2}. However, the features used in these methods are manually designed, which are very subjective and
vulnerable to perturbation. Furthermore, the large background noise will decrease the performance of the improved Maximally Stable Extremal Region (MSTR) proposed by Feng et al. [3]

With the rapid development of deep learning, it has been widely applied to extract features of images automatically, classify and identify target objects under various environment [9-13]. Specifically, the improved convolutional neural network (CNN) algorithms, Faster RCNN, is used to recognize transformer equipment at substation [5-6] and electrical devices in UAV [7-8]. For the infrared image of electronic equipment at substation, GoogLeNet CNN based on double supervised signal [4] and PCNN with threshold exhibit higher accuracy rate for recognition [14], compared to traditional segmentation approach.

Although the infrared image can use thermal radiation to capture the temperature characteristics of electrical equipment, it still loses some information and are easily affected by environment. Benefiting from the development of multi-source sensor technology, multi-source image fusion makes great contribution to military [15] and industrial [17] research. Due to the characteristics of intuitively reflecting the visual characteristics of the actual scene of the visible light image, the combination between visible and infrared image allows reliable and robust target tracking [16,19-21] and accurate power equipment fault detection [18], which adapts to complex real environment better. Besides, compared with other fusion methods for the infrared and color visible images, discrete wavelet transform has good performance in preserving image information [22, 23, 25] while preserving less computational complexity [24], thus being applied extensively.

Therefore, previous researches on fault diagnosis of infrared images of power equipment have some disadvantages, such as low accuracy and poor generalization of the model. With the development of artificial intelligence and deep learning, object detection based on visible light images has been well developed and widely used. However, few studies have focused on the fault recognition based on fused visible light and infrared images. To solve the problem of low position accuracy, we propose to fuse visible light images and infrared images, which allows more precise location. Then an improved CNN model is designed to perform fault diagnosis. The simulation results suggest that our method can effectively improve the contrast and recognition accuracy of power equipment images. The fused image has richer features, and the defect recognition rate is significantly improved.

2. The dual-spectrum fusion based on discrete wavelet transform

The essence of dual-spectrum image fusion based on wavelet transform is the feature decomposition and reconstruction of visible light image and infrared image. Fig.1 presents the flow chart of fusion process.

![Image of flow chart](image)

Fig.1 The flow chart for the fusion of visible light image and infrared image based on discrete wavelet transform.

The equation that describes the fusion process can be written as

$$ D = \Psi^{-1} \left[ LH_{F,N} \left( \Psi \{ f_i \} \right) \right]. $$  \hspace{1cm} (1)
Here, $f_i$ is $i$th image as input. $D$ represents the reconstructed image after fusion. $\Psi$ and $\Psi^{-1}$ are operator and inverse operator of wavelet transform, respectively. $LH_{F,N}$ is fusion operator.

2.1. Discrete Wavelet Transform (DWT)

The continuous form of wavelet transform $f(t)$ can be written as:

$$WT(a, b) = \frac{1}{\sqrt{a}} \int_\infty^{-\infty} \Psi\left(\frac{t-b}{a}\right)f(t)dt,$$

where $a$ is the scaling factor, $b$ is the translation parameter.

By discretizing $a$ and $b$ as $a = d_0^m$ and $b = nd_0^m$, where $m, n \in Z, d_0 > 1$, we can obtain the corresponding discrete wavelet function $\Psi_{m,n}(t)$:

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{d_0^m}} \Psi\left(\frac{t-nd_0^m}{d_0^m}\right)$$

The coefficient for transformation is

$$DWT_f (m, n) = \int_\infty^{-\infty} f(t)\Psi_{m,n}(t)dt = \langle f, \Psi_{m,n} \rangle.$$  

Finally, the discrete form of wavelet transform can be written as:

$$f(t) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \langle f, \Psi_{m,n} \rangle \Psi_{m,n}(t).$$

2.2. The fusion of low-frequency image

In this paper, the weighted average method is used to fuse the low frequency components of visible light images $L_{1,N}(a, b)$ and infrared light images $L_{2,N}(a, b)$. The coefficient of fusion can be represented as

$$L_{F,N}(a, b) = a_1L_{1,N}(a, b) + a_2L_{2,N}(a, b),$$

where $a_1$ and $a_2$ are weighting coefficient, satisfying $a_1 + a_2 = 1$.

2.3. The fusion of high-frequency image

We employ the local variance method to fuse the high frequency components of the visible light images $H_{1,N}(a, b)$ and the infrared light images $H_{2,N}(a, b)$. The local variance is

$$Diff = \frac{1}{W_1 \times W_2} \sum_{i=1}^{2} \left[ H_{i,N}(a, b) - \mu \right]^2,$$

where $H(a, b)$ is the high-frequency component and $\mu$ is the mean of variances.

$$\begin{align*}
W_1 &= \frac{D_{1,N}(a, b)}{D_{1,N}(a, b) + D_{2,N}(a, b)} \\
W_2 &= \frac{D_{2,N}(a, b)}{D_{1,N}(a, b) + D_{2,N}(a, b)}
\end{align*}$$

where $D_{1,N}(a, b)$ and $D_{2,N}(a, b)$ are the local variance of visible and infrared images in all directions, respectively.
3. The fault diagnosis based on deep convolutional neural network (CNN)

Depending on the extent of overheating, the thermal fault defects of substation equipment can be divided into three levels: general, severe, and urgent defect. However, due to the limitation of the accuracy of infrared temperature measurement, the recognition of faults is of low accuracy and calculation efficiency. Therefore, in this work, we employ a trained CNN model to identify faults for real time.

CNN is a multi-layer feedforward artificial neural network, and each layer contains many feature maps corresponding to the abstract layer. Each unit or coefficient in the feature map can be treated a neuron. Linear convolution, nonlinear activation and spatial pooling are used to realize the connection of feature maps at different stages. The process of feature extraction and defect recognition based on CNN is shown in Fig.2.

![Image](image_url)

Fig.2 The structure of the CNN

The CNN model consists of one input layer, two convolution-pooling layers and one output layer. The input is the fused image of visible light image and infrared image and the output is the result of faults of equipment. The first convolutional layer of CNN can detect low-order features while the second convolutional layer detect more complex features. The pooling layer between two convolutional layers is used to compress the size of image and reduce the number of training parameters while retains important information. The detailed design of CNN are as follows.

3.1. Weight

The connection weight between input layer and the first convolutional layer, and weight between pooling layer and the second convolutional layer are determined by Gaussian probability distribution:

$$P \in R^{(r\times r) \times N} = [\tilde{p}^1, \tilde{p}^2, \ldots, \tilde{p}^N],$$

where $\tilde{p}^i$, $1 \leq i \leq N$ is a $r \times r$ matrix representing convolutional kernel and $N$ is the number of kernels.

3.2. Convolutional layer

By convoluting the feature map of previous layer and the convolutional kernel, convolutional layer can extract the feature of the image. The convolution result at the point $(x, y)$ in the $i$th feature map is determined by

$$C_{x,y,i}(\Theta) = \sum_{m=1}^{r} \sum_{n=1}^{r} \Theta_{x+m-1,y+n-1} \cdot P_{m,n},$$

where $\Theta$ is the input image after fusion and $P$ is the connection weight matrix.

3.3. Pooling layer

The pooling layer usually appears periodically between two adjacent convolutional layers. The common pooling strategies mainly include average pooling and maximum pooling. However, by averaging the points in each pooling neighborhood, the average pooling will weaken the strong activation point. The maximum pooling often overfit the training set, affecting the generalization performance. Therefore, we propose a root mean square pooling method.

The root mean square pooling strategy has inherent frequency selectivity and translation invariance, which enables the CNN model nonlinearity and translation invariance. The pooling result of point $(x, y)$ at the $j$th map is:
where $e$ is the radius of pooling.

4. Results

4.1. The fusion of images

Fig.3(a)(b)(c) are visible light image of power equipment taken by a robot at a substation, infrared image and dual-spectrum fused image based on the wavelet transform proposed in this paper, respectively. Fig.3 shows that the fused image contains more information with more clear characteristics of power equipment, especially faults feature.

![Fig.3](image_url)

Fig.3 (a) The visible light image; (b) The infrared image; (c) The fused image of (a) and (b).

4.2. Faults Diagnosis of CNN before and after fusion

To examine the performance of our method, we test its accuracy and efficiency at dataset and compared with other methods. The results are shown in Table 1.

| Methods                        | Accuracy  | Efficiency |
|--------------------------------|-----------|------------|
| CNN based on fused image       | 98.48%    | 1.98s      |
| CNN based on infrared image    | 96.91%    | 1.98s      |
| SVM based on infrared image    | 92.72%    | 4.59s      |
Table 1 shows that the performance of method proposed in this paper, the fault diagnosis of CNN based on the fused image of visible light and infrared images is better than other methods with higher accuracy 98.48% and faster calculation efficiency 1.98s.

5. Conclusion
Aiming at the problem of faults diagnosis of the electrical equipment at substation, a new method is proposed in this paper. Firstly, the visible light and infrared images of equipment are fused based on discrete wavelet transform. Then, we obtained an improved CNN model to identify the faults in the fused image by designing the connection weight, the calculation of the convolutional layer, and the pooling strategy. The simulation results show that compared with other methods, the CNN fault recognition method of the fused image has higher accuracy and faster calculation efficiency. The method presented in this paper are of great effectiveness and can be applied to real environment.

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