PCANet Based Digital Recognition for Electrical Equipment Infrared Images

Ying Lin¹, Jiafeng Qin¹, Weiwei Zhang¹, Hao Zhang¹, Demeng Bai¹ and Ran Xu¹

¹ State Grid Shandong Electric Power Research Institute, Jinan, 250012, China

Corresponding author: lysiwork@163.com

Abstract. In this paper, a digital recognition method for electrical equipment infrared images based on PCANet is proposed. The main purpose of this paper is to recognize the displayed digits which can recover the temperature matrix of the whole infrared image. We use the PCANet deep learning network to identify the printed digital quickly, and then reconstruct the temperature matrix of the thermal image. The PCANet architecture here includes two PAC stages and one output stage. We discuss the related parameters among the whole procedure, including the number of the PCA stages, the number of filters, and the block overlap ratio. Besides, we compare the proposed digital recognize method with the traditional HOG+SVM method. It can be found that the proposed one has a higher accuracy. We also define a criterion to evaluate the performance of the combined temperature value recovery. The criterion contains the recognized and groundtruth temperature range which can reflect the effect of error recognition. The experimental results show that the algorithm has high accuracy and robustness. With the recovered temperature matrix, a further fault analysis can be proceeded for electrical equipment infrared images. Furthermore, deep learning architectures can be chosen to get intelligent infrared image fault diagnosis for electrical equipment.

1. Introduction

Infrared detection technology is the main method of live detection for electrical equipment. With the development of artificial intelligent, more and more methods aim on automatic infrared image analysis for electrical equipment.

Most of the automatic infrared image analysis method is based on traditional image processing technology [1-4]. [1] uses priori knowledge and pooling method for insulator detection, [2] aims on arrester segmentation with watershed algorithm. These methods are relative simple and have low robustness. Different from traditional machine learning algorithm, people turn to deep learning method for electric equipment segmentation, detection and diagnosis [5, 6]. [6] takes current transformer as an example, using RCNN to identify the object with overheated area, and then determine the fault type.

It can be found that above methods mainly focus on image processing technology, but neglect the acquisition of the temperature matrix, and this is what we focus on in this paper. This article is proposed for infrared images which have lost the temperature information, and use PCANet to identify the digit and symbol. With the known pseudo-color palette, the temperature information of the infrared image can be reconstructed. Furthermore, the intelligent infrared image analysis can be easily processed.

2. Proposed Algorithm
2.1. Temperature matrix and pseudo-color infrared image Transformation

The infrared image saved by an infrared thermography as shown in Figure 1. It is generated from the original temperature matrix, and then changed into a pseudo-color image by selected palette and maximum and minimum temperature. It can be seen in figure 1, an infrared detection image is composed of two parts: the equipment detection area which is presented in green frame and temperature display area in red frame.

The color palette is an indexed set of color denoted by a $l_c \times 3$ matrix, $l_c$ is the number of colors in the palette. Each row of the matrix is a RGB color denoted as $[r^i, g^i, b^i]$, $i$ represents the color index of the palette.

![Figure 1. An Infrared image with iron red palette.](image)

Assume the temperature matrix is $T$, the temperature range is $[t_{\text{min}}, t_{\text{max}}]$. For each temperature value of the temperature matrix $t(i, j)$, its corresponding color index is $k(i, j)$ as calculated in (1).

Here, the value range of $k$ is $[1, l_c]$.

$$k(i, j) = \begin{cases} \lfloor l_c \rfloor, & t(i, j) \geq t_{\text{max}} \\ \frac{(t(i, j) - t_{\text{min}})}{(t_{\text{max}} - t_{\text{min}})} \times l_c + 1, & \text{Others} \\ 1, & t(i, j) < t_{\text{min}} \end{cases}$$

Here, $\lfloor \rfloor$ means round down. $(i, j)$ represents the coordinate of the $i$-th row and $j$-th column in the temperature matrix. When getting $k(i, j)$, we set the pseudo-color value of $(i, j)$ as $[r^i, g^i, b^i]$, so the pseudo-color infrared image can be easily generated.

Similarly, when the temperature matrix is unknown and temperature range and palette are known like the situation in our paper, the global temperature matrix can be recovered as shown in (2).

$$t(i, j) = t_{\text{min}} + (t_{\text{max}} - t_{\text{min}}) \times \arg \min_k d_c(i, j, k) / l_c$$

Here, $d_c$ is the distance between the color of $(i, j)$ pixel in the infrared image and the color index in the color palette.

$$d_c = \sqrt{(r^i - r(i, j))^2 + (g^i - g(i, j))^2 + (b^i - b(i, j))^2}$$

By traversing $k$ to get minimum value of the distance, we can get the color index which is nearest to the pixel, and then calculate the temperature corresponding to the pixel.

2.2. PCANet Architecture

Different from other image recognition problem, the digital recognition for infrared image temperature matrix recovery is only a tiny part for electrical equipment infrared image analysis. If the complexity
of the algorithm is high, it will affect the efficiency of the whole analysis procedure. As a result, it is crucial for us to choose a relative simple, high-efficiency and accurate deep learning method.

In this paper, we use PCANet to identify the printing digit in infrared images which is a cascaded linear network [7]. By using binary hashing and block histograms, PCANet is extremely easy and efficient.

Figure 2 display the structure of a typical two-layer PCA filter. The input sample firstly go through the two-layer PCA for patch-mean removal and convolution, then the sample go into the output layer. Through hashing code and block histogram, the final feature is obtained. Details of the method can be shown in [7].

![Figure 2. The Architecture of PCANet.](image)

2.2.1. The first stage: PCA. We resize the input images to $m \times m$, the filter size is denoted as $k_i \times k_i$, and the number of filters is $L_i$. One single sample $I$ will turns to $L_i$ outputs, denoted as $I_i^L$, $i = 1, 2, \cdots, n$, $l_i = 1, 2, \cdots, L_i$.

2.2.2. The second stage: PCA. In the second stage, the filter size is $k_2 \times k_2$, the number of filters is $L_2$. Through the operation of the second stage, Each $I_i^L$ turn into $L_2$ samples: $O_i^L, l_2 = 1, 2, \cdots, L_2$, which means $I$ turns into $L_1 \times L_2$ outputs.

For some complex recognition problem, we can repeat more PCA stages which means a more deeper and complex network. If there are $k$ PCA stages in the network, supposing number of filters in each layer are $L_1, L_2, \ldots, L_k$, then $I$ will turns into $L_1 \times L_2 \times \cdots \times L_k$ samples.

2.2.3. Output stage: Hashing and Block Histogram. Each $O_i^L$ is binarized by a Heaviside step(like) function $H(\bullet)$:

$$H(x) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases}$$

(4)

Then the $L_2$ binary images belonging to $I_i^L$ are combined into one gray image $T_i^L$.

$$T_i^L = \sum_{l_2=1}^{L_2} 2^{l_2-1} H(O_i^{L_2})$$

(5)

Through this procedure, all pixels in $T_i^L$ are distributed in the range $[0, 2^{l_2} - 1]$.

We compute the histogram for each $T_i^L$, the size of block is $B_s \times B_s$, and the block overlap ratio is $B_o, s = B_s \times B_o$ is the step of histogram. Finally, we get $L_H$ histogram:

$$L_H = \left\lfloor \frac{m -(B_s - s)}{s} \right\rfloor \times \left\lfloor \frac{m -(B_s - s)}{s} \right\rfloor$$

(6)
The floor here means round down. All histograms are concatenated and then combine into one vector, each feature dimension of the input sample is \( L_s \times L_w \times 2^c \).

### 3. Experiments

We collect 6000 infrared images of several kinds of electrical equipment to verify the accuracy of the proposed algorithm. We have selected 10000 samples including 12 classes which are number ‘0’ to ‘9’, decimal point ‘.’ and negative sign ‘-‘. We take 7000 samples for training and 3000 samples for testing, the size of the sample is 28×28.

#### 3.1. Impact of Parameters

In this section, we mainly discuss how to set the network parameter for better recognition result.

##### 3.1.1. The number of the PCA stages and the filters

We first set the number of stage as 1(denoted as PCANet-1), and then change \( L_1 \) from 2 to 12, the recognition accuracy is shown in figure 3(a). It can be found when the value exceeds 6, the accuracy turns to stable. Furthermore, we set the number of stage of the stage to 2(denoted as PCANet-2) and \( L_2 \) to 8, and then change \( L_1 \) from 4 to 24(as shown in figure 3(b)). Namely, when \( L_1 \) is larger than 8, the accuracy becomes stable. The filter size of \( k_1, k_2 \) is both 7, the block size \( B_s \) is 7, and the overlap ratio \( B_w \) is 0.6.

![Figure 3](image)

**Figure 3.** The recognition accuracy of different number of stages and filters. (a) is result of PCANet-1, (b) is result of PCANet-2.

##### 3.1.2. The block overlap ratio

Change the value of \( B_w \) from 0.1 to 0.7 and set \( L_1, L_2 \) to 8, the error rate is shown in Table 1, it can be found that the reliable value of \( B_w \) is 0.5 or 0.6.

| \( B_w \) | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 |
|---|---|---|---|---|---|---|---|
| PCANet-1 | 0.48 | 0.48 | 0.53 | 0.40 | 0.42 | 0.37 | 0.38 |
| PCANet-2 | 0.42 | 0.42 | 0.38 | 0.3 | 0.3 | 0.3 | 0.3 |

Therefore, we choose the PCANet-2 architecture, the parameters \( L_1, L_2 \) is 8, \( k_1, k_2 \) is 7, \( B_s \) is 7, and \( B_w \) is 0.6.

##### 3.2. Feature Analysis

With parameters determined in 3.1, the PCA filters learned in each stage is shown in figure 4. The output feature after each stage is shown in figure 5. After multi patch-mean removal and convolution process, one single sample becomes \( L_s \) hashing coded gray images, and then the block-wise histogram will be computed.
3.3 Algorithm Performance Comparison

To verify the accuracy of the method we proposed in this paper, we compare our method with the traditional HOG+SVM [8] method which is one of the most effective method for object recognition before deep learning. The recognition result is shown in Table 2. HOG4_4 means the size of the HOG cell is 4×4, block size is 8×8, HOG8_8 means the size of the HOG cell is 8×8, block size is 16×16. Other parameters overlap ratio is 50%, the number of orientation bins for gradient is 9. We can find that, PCANet gets a much better performance without any complex settings.

**Table 2. Comparison of precision rates (%) of PCANet-2 and HOG+SVM**

| Algorithm     | PCANet-2 | HOG4_4+SVM | HOG8_8+SVM |
|---------------|----------|------------|------------|
| Accuracy (%)  | 99.7     | 87.3       | 97.2       |

3.4. Global analysis of the algorithm

To test the global accuracy of the whole procedure for temperature matrix recovery, we compare the result between human labelling and our method. The goal for digital recognition is to recover the temperature matrix through temperature range, and the temperature value is combined by several digits or symbols. A error recognition of a single digit would lead to a large difference from the original temperature value.

Therefore the difference between the recognized and true temperature range is our way for evaluate the whole algorithm:

\[
p = (1 - \frac{t_{\text{min}} - t'_{\text{min}}}{t_{\text{min}}}) \times (1 - \frac{t'_{\text{max}} - t_{\text{max}}}{t_{\text{max}}})
\]

(7)

\(t_{\text{min}}, t'_{\text{min}}\) is the maximum and minimum value of the true temperature range, and \(t'_{\text{max}}, t_{\text{max}}\) is the recognized temperature value, \(p\) is the accuracy we defined.

Figure 6 shows the temperature distribution of infrared images after temperature value recognition. After 3000 infrared images testing, the average accuracy of the algorithm is 92.61%.
Figure 6. Temperature distribution results. (a) are infrared images with labeled temperature value. (b) are the temperature distribution of its temperature matrix from the recognized temperature value.

4. Conclusion
In this paper, we proposed a method to recover the temperature matrix by digital recognition for electrical equipment infrared images using PCANet algorithm. The PCANet was adopted to recognize the digit or symbol, and then combined the complete temperature range. In the experimental section, we discussed the parameter settings of the network, and then evaluate the performance of the algorithm, the results proved the effective of this paper. Next, we will aim at designing an end-to-end deep learning architecture to get more reliable result for electrical equipment infrared image fault analysis.

References
[1] Z. Zhao, G. Xu, Y. Qi et al 2016 Representation of binary feature pooling for detection of insulator strings in infrared images IEEE Transactions on Dielectrics and Electrical Insulation, 23(5) pp 2858-2866
[2] C. A. L. Almeida, A. P. Braga, S. Nascimento, et al 2009 Intelligent thermalgraphic diagnostic applied to surge arresters: A new approach IEEE Transactions on Power Delivery, 24(2) pp 751-757
[3] H. Zou and F. Huang 2015 A novel intelligent fault diagnosis method for electrical equipment using infrared thermography Infrared Physics & Technology, 73 pp 29-35
[4] Jadin M S, Taib S 2012 Infrared Image Enhancement and Segmentation for Extracting the Thermal Anomalies in Electrical Equipment Electronics & Electrical Engineering, 120(4) pp 107-112
[5] Lin Y, Su J, Li C, et al 2016 Deep Learning for Intelligent Substation Device Infrared Fault Image Analysis MATEC Web of Conferences, 55
[6] Lin Y, Guo Z, Chen Y 2015 Convolutional-recursive network based current transformer infrared fault image diagnosis Power System Protection and Control,16 pp 87-94
[7] Chan T H, Jia K, Gao S, et al 2015 PCANet: A Simple Deep Learning Baseline for Image Classification? IEEE Transactions on Image Processing, 24(12) 5017
[8] DALAL H N, TRIGGS B 2005 Histograms of oriented gradients for human detection IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1 pp 886-893