RPCA Based Temperature Digit Extraction for Electrical Equipment Infrared Images

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Abstract. Infrared thermography technology is one of the most important ways to diagnosis the status of electrical equipment. The data we get is thousands of infrared images. In order to meet the demands of massive electrical equipment infrared images automatic diagnosis and provide reliable analysis basis, in this paper, a temperature digit extraction method based on RPCA is proposed. The assumption of this paper is that the infrared images have lost their temperature information during data circulating. In this case, to analyze the infrared images quantitatively, the most important thing is to recover the temperature matrix by digit recognition. The first step is to get the temperature region and then separate each single digit area. In order to achieve this goal, we first take advantage of RPCA to get the temperature area and then use histogram statistics to get a single number or symbol area. We take 6000 sample images including transmission and transformation equipment to evaluate the performance of the temperature region extraction method. The experimental results show that the algorithm can extract the digits with high accuracy which could provide data foundation for quantitative infrared image fault analysis. Furthermore, we will aim at finding a more flexible algorithm to get the digit rapidly and reliably.

1. Introduction

In the past few years, with wide application of infrared thermography technology (IRT), plenty of infrared images have been created. Different from traditional electrical live detection ways, detect data of IRT is save in the form of images and each infrared image contain large quantity of information. Take State Grid Shandong Electric Company for example, about 100 thousand infrared images are collected every month. Therefore, it is impossible for people to analyse these images manually. To analyse these infrared images intelligent for electrical equipment, many algorithms have been proposed[1-3].

Meanwhile, to manage these infrared images effectively, many instrument companies design their own save format to save extra detection information within the image file, such as the original temperature matrix, the detection time, the detection emissivity and so on. These information are the foundation for analyze the infrared image. Unfortunately, these information would be lost during the traditional long term data circulation.

As a matter of fact, the shown infrared images are generated from the original temperature matrix by known palette and unrecognized temperature range. The temperature matrix is the most important data for electrical infrared analysis. Therefore, by recognize the temperature range, we can recover the temperature matrix.
The first step for digit recognition is to separate each single digit in a temperature value sign, which is the main content of our paper. Further process such as the traditional digit recognition will be successfully carried out by many traditional object recognition algorithms [4-6].

2. Digit Area Extraction based on RPCA

2.1. Temperature digit region extraction

Infrared images generated by different infrared thermal imager have different font, size and position temperature digit marking as shown in figure 1, so it cannot be segmented by fixed area. However, the position of the whole temperature display area containing temperature marking and color palette is relative constant, so we can cut the temperature display area and treat this part of area separately.

![Infrared images from different infrared thermal imager](image1)

**Figure 1.** Infrared images from different infrared thermal imager

We solve the problem by taking advantage of RPCA method [7]. The infrared image can be considered as combination of an ideal low-rank image and external noise denoted as \( I = I^0 + E \). Here \( I \) represent the original infrared image, \( I^0 \) represent the ideal low-rank image, and \( E \) is the noise image.

In this section, we take the right 20% area of the image as the temperature display area, the temperature marking can be considered as the extra noise \( E \) relative to the ideal image. Different from traditional goal to find the ideal image, we aim at finding the noise image \( E \) here.

The optimization problem is:

\[
\min_{I^0, E} \| I^0 \|_* + \lambda \| E \|_1 \quad \text{s.t.} \quad I = I^0 + E
\]

Here, \( \| I^0 \|_* \) is the nuclear norm of \( I^0 \), and \( \| E \|_1 \) is the \( l_1 \) norm of \( E \).

The optimized result is shown in figure 2. Through optimizing and calculating, the noise \( E \) which is different from color palette and background is extracted.

![The result of RPCA for figure 1(a)](image2)

**Figure 2.** The result of RPCA for figure 1(a). (a) is a gray image of the selected temperature display area, (b) is the ideal image, and (c) is our target containing the temperature marking.
Then we expansion $E$ and form several connected area (as shown in figure 3(a)). Several properties can be obtained through statistics for each region $R_i$:

a. The centre of region $[x_i, y_i]$ : the central point of the region.

b. The bounding box $[w_i, h_i]$ : the length and width of the region’s bounding box.

c. The area $A_i$ : the number of pixels within the region.

d. The regularity $S_i$ : calculated from $A_i$ and area of the bounding box

$$S_i = A_i / (w_i \times h_i)$$

(2)

![Figure 3](image)

**Figure 3.** Results of temperature digit area extraction. (a) is the result of the expansion of $E$. (b) is the extracted region, marked with a red box.

We set the weight of each $R_i$ as $W_i = A_i \times S_i$. Find two connected region with biggest weight, and compare row coordinate of the two areas. Area with smaller coordinate is the temperature upper bound region, and area with bigger coordinate is the lower bound region. We denote the upper bound region as $R_{\text{max}}$, the lower bound region as $R_{\text{min}}$. The extraction result is shown as figure 3(b).

2.2. Single digit or symbol segmentation

We binarize $E$ after expansion, and get the binary image $D$. Here the binary threshold is determined by Otsu. Each single digit or symbol can be segmented by following steps:

a. Calculate the sum of each column in $D$: $C = \text{sum}(D)$, the size of $C$ is $1 \times n_d$, $n_d$ is the number of column of $D$;

b. Search continuous non-zero areas of $C$ and get the coordinate

$$id_x = \text{find}(C > 0)$$

$$L = id_x(2 : \text{end}) - id_x(1 : \text{end} - 1)$$

$$id_y = \text{find}(L > 1)$$

$$id_{x_k} = id_x(id_y)$$

$$id_{x_{k+1}} = id_x(id_y + 1)$$

(3)

c. Segment the region of single digit and symbol according to the obtained coordinate.
\[ d(1) = D(:,1: id_{g}(1)) \]
\[ \text{for } i = 1: \text{length}(id_{g}) - 1 \]
\[ d(i+1) = D(:, id_{g}(i) : id_{g}(i+1)) \]
\[ \text{end} \]
\[ d(\text{end}) = D(:, id_{g}(\text{end}) : id_{g}(\text{end})) \]

Take the extracted upper bound ‘38.1’ in figure 3(b) for example, the procedure of the segmentation is shown in figure 4.

After each single digit or symbol is segmented, the following step is to recognize them separately and then combine together. The printed digit even the handwritten digit recognition problem is a relative mature one, which have many effective algorithms to solve as we mentioned in introduction. With the recognized temperature, a quantitative analysis for massive electrical equipment infrared image becomes reality.

Figure 4. Single digit or symbol segmentation process. (a) is the binarized image \( D \) with its column sum \( C \), the height of the bar in the lower image is the sum value of its corresponding column. (b) is the segmented results.

3. Experiments
We collect 6000 infrared detection images of all kinds of transmission and transformation equipment to evaluate the performance of the propose method. Some sample infrared image results are shown in figure 5.
Figure 5. The whole procedure of sample infrared images. (a) are the input infrared images, (b) are the RPCA optimized results, (c) are the temperature region extraction results, (d) are the single digit or symbol segmentation results.

The digit extraction method based on RPCA is the fundamental of the digit recognition, section 2.1 is the extraction of the temperature region, and section 2.2 is the segmentation of single digit or symbol area. Digits and symbols are printed with relative fixed distance and location among each other within the same infrared image. Therefore, there is rarely error occurred in section 2.2, we here only discuss the performance of the temperature region extraction.

Here, we use the concept IoU(Intersection over Union) to judge the accuracy. As shown in figure 6, the green frame is the manually labeled ground-truth temperature region denote as $R^*$, and the red frame is the region extracted by proposed algorithm denote as $R'$. The IoU value is the overlapping ratio between $R$ and $R'$, which is defined as follows:

$$O(R, R') = \frac{|R \cap R'|}{|R \cup R'|}$$  \hspace{1cm} (5)

Figure 6. The IoU concept explanation

We calculate the IoU value of each image among the 6000 infrared images, and then compute the mean value of these IoU values which is the mean IoU of the propose algorithm. The mean IoU considers both the overlap and intersection region of the two regions, therefore, it can truly reflect the accuracy of the algorithm.

After computation, the average IoU is 83.37%. This evaluation criterion focus on the temperature region of the first part, the accuracy here can fully satisfied the requirement of the PCA input and won’t influence the accuracy of recognition.

But in some situations, the optimization method in this paper cannot handle the problem, as shown in figure 7.
Among the part images of each failed case, the first three images are the result of RPCA similar with figure 2., the fourth image is the result of E expansion, and the fifth one is the extracted temperature region.

We can find from the images that the main reason of failure is the chaotic background leading to the failure of RPCA noise extraction. Figure 7(a) has many extra marking information and cause big noise region to select; too many tiny lines occurred in figure 7(b) and then the minus symbol failed to be extracted. But in figure(c), although the background is noisy, the contrast between the temperature marking and background is big enough, the extraction results still keep right.

4. Conclusion
In this paper, we proposed a method which can extract temperature digit for electrical equipment infrared images based on RPCA. The main case we treated in this paper is the temperature information loss of the infrared image which makes it impossible for further fault analysis. Through RPCA optimization and location statistic, we extracted the marked temperature range region and then segmented each single digit and symbol separately. According to the experimental results, the method we proposed can handle most cases for temperature digit extraction from electrical equipment infrared images.

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