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# Automatic Busbar Detection in Substation: Using Directional Gaussian Filter, Gradient Density, Hough Transform and Adaptive Dynamic K-means Clustering

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**Abstract:** As the power system developing towards the extra-high-voltage (EHV), ultra-high-voltage (UHV), and large capacity direction in China, online monitoring becomes much more vital for power equipment to ensure the safe operation of power system. The computer vision-based Equipment Map State Detection technique can capture the abnormal status of power device. The busbar, as a intermediate link at all levels of voltage distribution device, is vital in system safety and stability operation. In this paper, we propose an automatic busbar detection method in an image for substation using directional Gaussian filter to strengthen horizontal linear target in an image, gradient density to generate a busbar confidence map, Hough Transform to detect straight lines and adaptive dynamic K-means clustering to get closed lines for optimizing. Then, the busbar can be marked in image and it can be used for further checking whether there are foreign things hanging on the busbar. Experiments on some images taken in several substations demonstrate that our method is effective.

**Key Words:** Busbar Detection, Directional Gaussian Filter, Gradient Density, Hough Transform, Adaptive Dynamic K-means Clustering

## 1 Introduction

As the power system developing towards the extra-high-voltage (EHV), ultra-high-voltage (UHV), and large capacity direction in China, blackout accident brings more and more influence in industrial production as well as human life. Hence, ensuring the safe operation of power equipment becomes very important. So it is urgent to monitor the state of power equipment online or at regular time [1, 2] . Not only can online monitoring identify the fault or hidden trouble in time, but also ensure the normal and safe operation of power system.

Recently, computer vision has been widely used in power system [3–9]. The hidden trouble of power equipment can be directly reflected in the image (through the optical scanning system, i.e. camera) using the computer vision-based Equipment Map State Detection technique in certain application scenarios. Having corresponding decision criteria, we can capture the abnormal status of power device using some techniques, such as computer vision, image processing and fault diagnosis expert system etc. Then the warning signal will be sent out to remind one to repair or maintain in advance. Thus the fault of equipment will be avoided or decreased.

In power substation, the busbar, as a kind of primary equipment, is a conductor that connect engine and transformer to various electrical equipments. It is the intermediate link at all levels of voltage distribution device. Busbar protection is vital in system safety and stability operation [10]. Before power transmission, the substation staff need to patrol to check whether there are foreign things hanging on the busbar. Otherwise it will result in cascading failures affecting the normal operation in substation.

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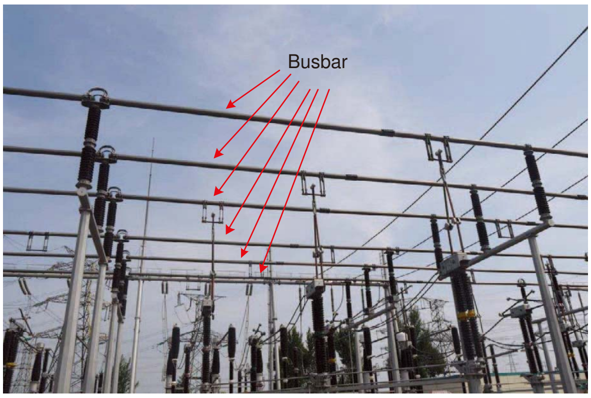


Fig. 1: An image of busbar in substation from the lateral view.

Based on the understanding of busbar in an image, this paper proposes an automatic busbar detection method in substation using directional Gaussian filter, gradient density, Hough Transform (HT) [11] and adaptive dynamic K-means clustering (ADKC). The horizontal or approximately horizontal linear target in image will be strengthened using the directional filter operator. After that, generate a busbar confidence map based on the gradient density of image. Then we use morphology operation to obtain the closed busbar region where a line segment set could be achieved through the Hough Transform. Finally, the adaptive dynamic K-means clustering method is employed to cluster line segments to get closed lines for optimizing. Thus, busbar can be marked in image. Experiments on some images taken in several substations demonstrate that our method is effective.

The structure of the rest of this paper is arranged as follows. In Section 2, the characteristics of busbar in an image are shown. Section 3 shows the details of our proposed method for busbar detection. The experimental results are

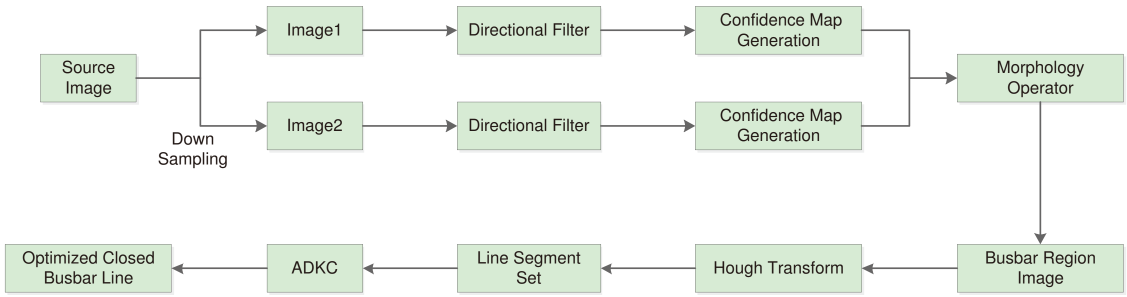


Fig. 2: The flowchart of the proposed method.

given in Section 4. Finally, conclusions are given in Section 5.

## 2 Characteristics of Busbar in Image

Based on our observation, the characteristics of busbar in image are as follows:

- The busbar has linear structure and low intensity feature in an image;
- The spatial distribution of busbar is approximately horizontal and they are approximately parallel to each other;
- A busbar has uniform width and usually has long length.

These characteristics are the prior knowledge for guiding busbar detection method.

## 3 Proposed Method

It is effective for extracting straight lines using Hough Transform in images. Hence, it is a natural choice for automatic busbar detection. In real substation scene, there are a lots of irrelevant linear structure that increase the computational cost of the HT. In this paper, we make full use of the characteristics of busbar in images, and propose a method for detecting busbar in substation.

The flow chart of proposed method is shown in Fig. 2. The input source image is re-scaled to form a image pyramid with tow level using nearest neighbor interpolation. Then fusing two scale of confidence map to form a final busbar region image. The specific method are shown as follows.

### 3.1 Directional Filter for horizontal Linear Region Enhancement

It is well known that the conventional Gaussian function is isotropic. It is considered as the optimal operator for denoising in image smoothing. The Gaussian operator template is determined through the Gaussian function as

$$G(x,y,\sigma)=\frac{1}{\sqrt{2\pi}\sigma}e^{-(\frac{x^2+y^2}{2\sigma^2})} \tag{1}$$

where the value at position $(x, y)$ is controlled by the scale factor $\sigma$.

Generally, the Equation. (1) is rewritten as

$$G(x,y,\sigma)=\frac{1}{\sqrt{2\pi}\sigma}e^{-(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2})} \tag{2}$$

where the value at position $(x, y)$ is controlled by the scale factor $\sigma_x$ and $\sigma_y$. The Equation. (1) equals to Equation. (2) when $\sigma_x = \sigma_y$. If $\sigma_x \neq \sigma_y$, it is non-isotropic and changes to a directional Gaussian filter operator through controlling the values of $\sigma_x$ and $\sigma_y$.

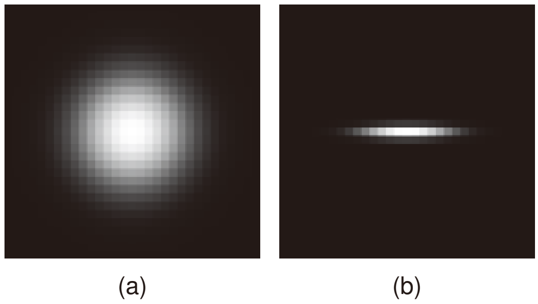


Fig. 3: Isotropic Gaussian and directional Gaussian filter operator with temple size $N = 31$, $\sigma_x = 0.81$ and $\sigma_y = 5.6$.

The busbar has the characteristics of linear structure and low intensity feature in an image. Besides, the spatial distribution of busbar is approximately horizontal. So we use the directional Gaussian filter operator (Equation. (2)) to strengthen the horizontal linear region, meanwhile, the regions or targets in other direction are restrained. It is shown in Fig. 3.

### 3.2 Busbar Confidence Map Generation

A busbar in image has uniform width and usually has long length. After using directional Gaussian filter to strengthen horizontal linear region, we generate a busbar confidence map based on gradient strength density (also called gradient density) of image inspired by text detection [12]. The busbar region can be highlighted in the busbar confidence map. Firstly, We extract the gradient strength $f_{gm}$ of image using Prewitt operator.

Define $f_{gmt}$ as

$$f_{gmt}(x,y) = \begin{cases} f_{gm}(x,y), & f_{gm}(x,y) > t_0 \\ 0, & others \end{cases} \tag{3}$$

Then define gradient strength density as

$$f_{gmd}(p_c) = \sum_{p\in\delta(p_c)} f_{gmt}(p) \tag{4}$$

where $p = (x, y)$ is the pixel coordinate in image, $\delta(p)$ is a small window whose center is $p_c$. Through the statistics, we can obtain the probability density curve of the gradient density which can be fitted using a Gaussian function on some sample data points (shown in Fig. 4). Thus, the gradient den-

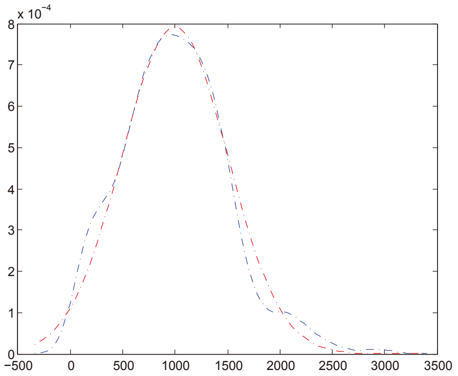


Fig. 4: The statistic distribution of gradient strength density. The blue dash line denotes the original statistic result, and the red dash line is the Gaussian fit result.

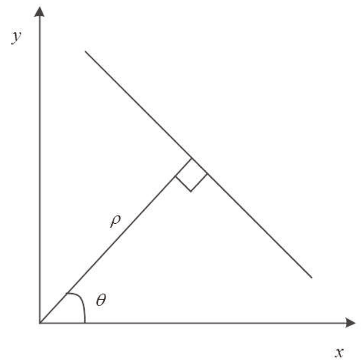


Fig. 5: The polar coordinate of a straight line.

sity as the probability density:

$$p_{gmd}(f_{gmd}(p_c)) = e^{-\frac{(f_{gmd}(p_c)-\mu)^2}{2\sigma^2}} \tag{5}$$

Then the probability density $p_{gmd}(f_{gmd}(p_c))$ is re-scaled to [0,1] to declare the probability of each pixel belonging to the busbar region. We set a threshold $t_1$ to classify whether a pixel in busbar confidence map $f_{bcm}$ belongs to busbar region. The busbar region image is

$$f_{bb}(p_c) \quad = \quad \begin{cases} 1, & f_{bcm}(p_c) > t_1 \\ 0, & others \end{cases} \tag{6}$$

After that, fusing two scale of busbar region image to form a fusion busbar image $f_{bb} = f_{bb}^{s1} \& f_{bb}^{s2}$. Finally, we use morphology operation in $f_{bb}(p_c)$, and obtain the closed busbar region $f_{cbb}(p_c)$ where a line segment set could be achieved through some straight line detection algorithms.

### 3.3 Hough Transform for Straight Line Detection

The Hough Transform (HT) is a feature extraction technique in image processing. It can be used to detect the object with specific shape, such as a straight line, circle and ellipse etc. The straight line or curve with specific shape in one coordinate space can be mapped to another coordinate space using HT. Through looking for the local maximum value in accumulator results, the task for detecting arbitrary shape is transformed into the problem of peak statistics.

The busbar has linear structure and the busbars are approximately parallel to each in an image. Hence we use the standard Hough Transform to detection the straight lines. A line in 2-dimensional space using the parametric representation is as follow

$$\rho = x \cdot cos\theta + y \cdot sin\theta \tag{7}$$

where the variable $\rho$ is the perpendicular distance of the origin to the line along a perpendicular vector. $\theta$ is the angle between this vector and the positive $x$ axis (shown in Fig. 5).

Thus, the Hough Transform provides a mapping function $(x, y) \rightarrow (\rho, \theta)$. Then the Hough Transform generates a parameter space matrix whose rows and columns correspond to $\rho$ and $\theta$ values, respectively.

### 3.4 Adaptive Dynamic K-means Clustering (ADKC)

In clustering problem, the sample set is denoted as $S = \{x^{(1)}, x^{(2)}, \cdots, x^{(m)}\}$, $x^{(i)} \in \mathbf{R}^n$. K-means is one of the simplest clustering algorithm [13]. It minimize the error sum squares of each sample to the mean value of corresponding class. The conventional K-means is described as

- Randomly select $k(k > 0)$ cluster centroids as $\mu_1, \mu_2, \cdots, \mu_k \in \mathbf{R}^n$.
- Repeat this process until convergence {
  For each sample $x^{(i)}$, compute corresponding category $c^{(i)} := \mathrm{argmin}_j \parallel x^{(i)} - \mu_j \parallel^2$
  For each category $j$, recompute the centroid $\mu_j := \frac{\sum_{i=1}^{m} \mathbf{1}\{c^{(i)}=j\}x^{(i)}}{\sum_{i=1}^{m} \mathbf{1}\{c^{(i)}=j\}}$ }
  where $k$ is the number of cluster given in advance, and $c^{(i)} \in \{1, 2, \cdots, k\}$.

where the value of indicator function $\mathbf{1}\{\cdot\}$ is 1 if its argument is true, and 0 otherwise ($\mathbf{1}\{true\} = 1, \mathbf{1}\{false\} = 0$). It is very important to choose the cluster number and the initial cluster centroid in K-means. Unfortunately, we can not know the number of cluster and the cluster centroid in advance for any given sample set when using K-means.

For line segment clustering, we propose an adaptive dynamic K-means clustering algorithm. The line segment set is denoted as $S = \{x^{(1)}, x^{(2)}, \cdots, x^{(m)}\}$. The equation of the line $x^{(i)}$ is $y = m^{(i)}x + b^{(i)}$. Rewrite $x^{(i)}$ into a 2-D vector $x^{(i)} = (m^{(i)}, b^{(i)})^T$. Define $dist(x^{(i)}, x^{(j)}) = |m^{(i)} - m^{(j)}| + |b^{(i)} - b^{(j)}|$. And $length(x^{(i)})$ is the length of line segment $x^{(i)}$.

Before introducing ADKC, we first define some notations. Let $A = \{a^{(1)}, a^{(2)}, \cdots, a^{(m)}\}$ and $B = \{b^{(1)}, b^{(2)}, \cdots, b^{(m)}\}$.

- Define $sum(A) = \sum_{i=1}^{m} a_i$
- Define $mean(A) = \sum_{i=1}^{m} a_i/m$
- Define $normweight(A) = \{\frac{a^{(1)}}{sum(A)}, \frac{a^{(2)}}{sum(A)}, \cdots, \frac{a^{(m)}}{sum(A)}\}$
- Define $A \bigotimes B = \{a_1 \cdot b_1, a_2 \cdot b_2, \cdots, a_m \cdot b_m\}$

Then the ADKC algorithm for line segment clustering could be identified with Algorithm 1.

Finally, we can achieve the optimized closed long lines using ADKC. Then, the busbar can be marked by straight line in image.

**Algorithm 1** Adaptive Dynamic K-means Clustering

**Input:** $S_1 = \{x^{(1)}\}$,$\mu_1 = x^{(1)}$,$k = 1$,$W_1 = \{length(x^{(1)})\}, \lambda > 0$,
$\mathbf{D} = (d_{ij})_{m\times m}, d_{ii} = 0$.
**Output:** line segment cluster centroids $\{\mu_1, \mu_2, \cdots, \mu_k, k > 0\}$.

$d_{ij} \leftarrow dist(x^{(i)}, x^{(j)})(i \neq j)$
$\mu \leftarrow \frac{\sum_{i=1}^{m}\sum_{i=j}^{m} \mathbf{1}\{i\neq j\} d_{ij}}{m(m-1)}, \sigma^2 \leftarrow \frac{\sum_{i=1}^{m}\sum_{i=j}^{m} \mathbf{1}\{i\neq j\}(d_{ij}-\mu)^2}{m(m-1)}$
$\xi \leftarrow max(|\frac{\mu}{2} - \sigma|, \lambda)$
**for** $i : 2 \rightarrow m$
  $len^{(i)} \leftarrow length(x^{(i)})$
  **for** $j : 1 \rightarrow k$
    $d^{(i)} \leftarrow dist(x^{(i)}, \mu_j)^2$
  **end**
    $j_{min} \leftarrow \text{argmin}_j\{d^{(1)}, d^{(2)}, \cdots, d^{(k)}\}$, $(j = 1, 2, \cdots, k)$
  **if** $d^{(j_{mid})} < \xi$
    $S_{j_{min}} \leftarrow S_{j_{min}} \cup \{x^{(i)}\}$
    $W_{j_{min}} \leftarrow W_{j_{min}} \cup \{len^{(i)}\}$
  **then**
    $k \leftarrow k + 1$
    $S_k \leftarrow \{x^{(i)}\}$
    $W_k \leftarrow \{len^{(i)}\}$
  **end**
  **for** $l : 1 \rightarrow k$
    $\mu_l \leftarrow mean(S_l)$
  **end**
**end**
**for** $l : 1 \rightarrow k$
  $W_l = normweight(W_l)$
  $\mu_l = sum(S_l \bigotimes W_l)$
**end**

## 4 Experimental Results

In order to verify the validity of the proposed method, we collect some images from Yantong and Yangquan substation in Shanxi China. The images are taken from the lateral view of the busbar.

The whole processing procedure of proposed method is shown in Fig. 6. The source image taken in substation is shown in Fig. 6(a). Fig. 6(b) is the image filtered by directional Gaussian operator. Fig. 6(c) is the gradient strength of the source image and Fig. 6(b) using the Prewitt operator. We can obviously see that horizontal (or approximately horizontal) targets have been strengthened, meanwhile the regions or targets in other direction are restrained. Fig. 6(e) and Fig. 6(f) are the busbar confidence map of different scales. The final busbar region image is given in Fig. 6(g) where the while ones represent the busbar region. Fig. 6(h) shows the line segments detected by Hough Transform. And Fig. 6(i) is the final result using the adaptive dynamic K-means clustering algorithm. In addition, some other tested images results are given in Fig. 7. From those result images, we can find that the proposed method is effective for automatic extracting busbar in image for substation.

## 5 Conclusions

To our knowledge, there are little literatures dealing with busbar detection for substation in an image with complex background. With the development of computer vision, we believe that Equipment Map State Detection technique will be popular in power system. This paper proposes an automatic busbar detection method for substation based on directional Gaussian filter, confidence map generation using gradient density, Hough Transform and adaptive dynamic K-means clustering. Then, the busbar region will be detected in an image, and marked by straight lines. Experiments on some images demonstrate that our method is effective. The proposed method has important practical value for identifying whether there are foreign things hanging on the busbar and detecting other equipments.

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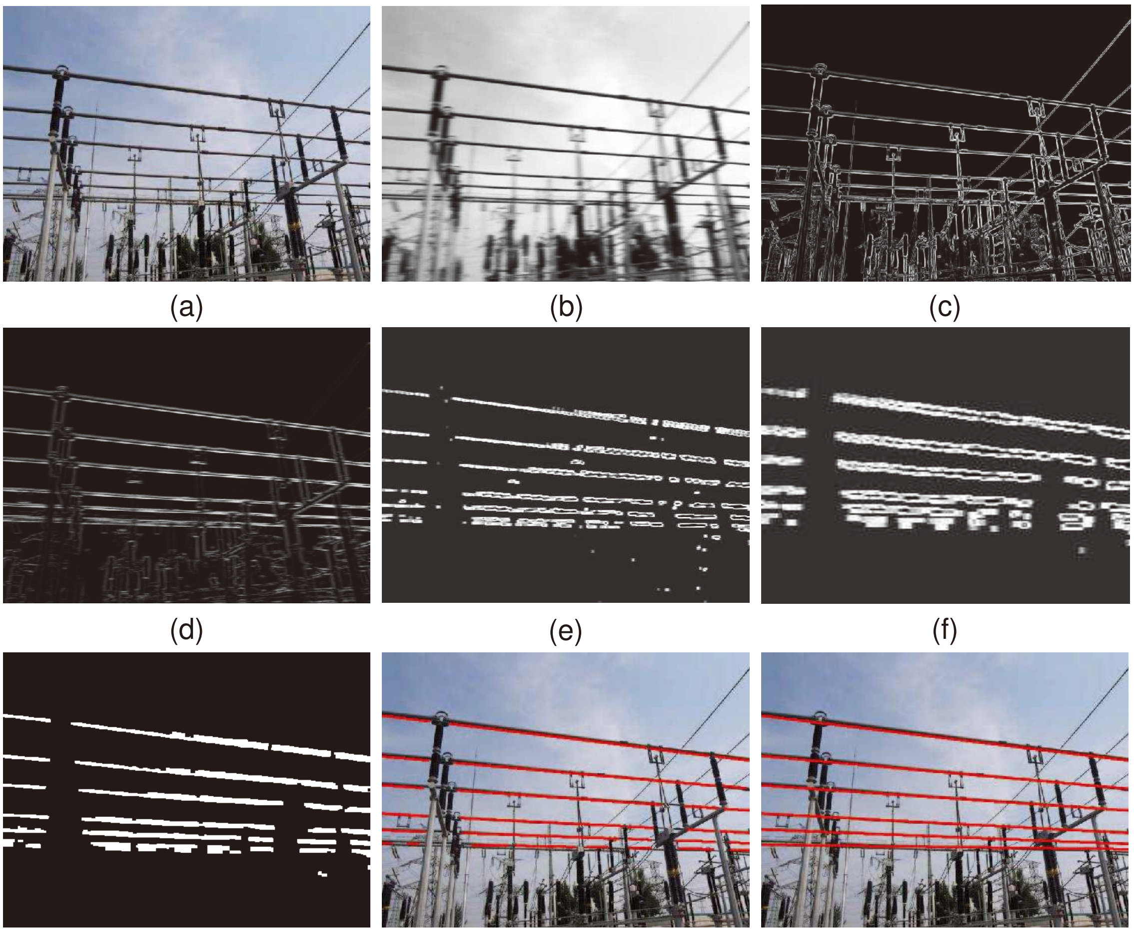
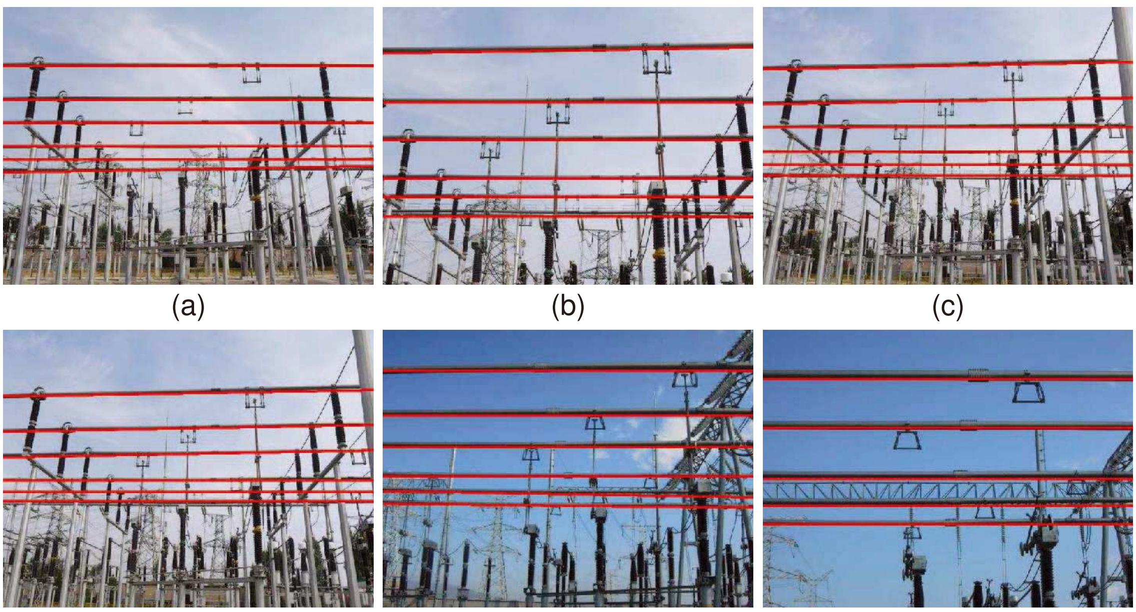


(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 6: The processing procedure of the proposed method.



(a) (b) (c) (d) (e) (f)

Fig. 7: Some other experimental results using proposed method.