Detection Method of Smart Meter Carrier Module Pin Based on Blob Analysis

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Detection Method of Smart Meter Carrier Module Pin
Based on Blob Analysis

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Abstract

In order to achieve automatic detection of pin defects in smart meter carrier module, a machine vision detection method based on Blob analysis is proposed in this paper. Firstly, the interface region of carrier module is segmented using the maximum class variance method combined with perspective transformation. Secondly, a two-stage identification strategy based on Blob analysis is proposed to complete the rough positioning of the pins, which takes the distribution rules of the pins as constraint conditions. The spot is extracted by adaptive binarization strategy. Finally, the centroid method was used to calculate the spot center of the pin, which is registered with the template point set. The defect detection of the pin was completed according to the offset of each pin.

Key Words: Machine Vision; Blob analysis; Electric meter pin; Power grid equipment

1 Introduction

In recent years, with the construction of intelligent power grid in China, the resource scheduling capability, safety level and intelligence degree of the power grid have been comprehensively improved [1]. As one of the key equipments for the construction of the intelligent power grid, the smart meter realizes remote meter reading and control functions through its internal carrier module, which facilitates power supply companies to read users' electricity consumption data. The carrier module adopts a modular design and has a standard appearance and interface, using pins to connect with the electric meter base. When the pin in the module interface is missing or tilted beyond a certain angle, the carrier module will not work properly. Therefore, it is indispensable to carry out quality inspection on the carrier module pins before leaving the factory. Traditional carrier module pin detection is mostly completed by manual visual inspection, with low detection efficiency and prone to omissions and false alarms. With the development of machine vision technology, using machine vision technology for automatic defect detection has become the mainstream detection method in the industry. Therefore, designing a fast and accurate carrier module pin detection algorithm is of great significance.

Currently, there have been relevant researches on pin detection methods both domestically and abroad. Stroppa et al. used pyramid template matching algorithm to identify pins in electrical connectors and added multi-template strategy to deal with changes in pin types, shapes, colors, and surface smoothness [2]; Guo et al. used template matching algorithm to identify the pins in electrical connectors and called different template matching methods according to different connector types [3]; Zhao et al. used a combination of deep neural networks and template matching strategies to achieve fast positioning of pins in electrical connectors [4]; Zhang et al. used k-means clustering to cluster the pins in hyperspectral images and detected problematic pins by comparing them with standard templates [5]; Fan Liangyu et al. identified the centroid coordinates of pins in connectors using Blob algorithm and compared them with standard templates to detect the regularity of pins [6]; Xu Peng et al. addressed the problem that threshold segmentation cannot be applied due to the differences in gray scale values of pins by using dynamic threshold segmentation and then selected features to locate the pin area. Finally, they obtained the center coordinates of the pin area by fitting a circle [7]; Li Huipeng et al. performed sub-pixel edge detection of the bright spots of the pins using Zezike moments and used the center of the ellipse fitted by the edge points as the position feature point of the pin [8]; Zhang Yuan et al. used laser triangulation to obtain point clouds of connectors, clustered the point clouds according to the number of pins, and finally fitted the coplanarity plane by RANSAC algorithm to the centroid of each cluster. The qualification of the product was judged based on the distance between various points and the fitted plane [9]; Fang Jianlong et al. used Canny algorithm to detect the outer contour of the connector terminal and
filtered out interference points by bubble sort to reduce system error[10].

Although there have been certain researches on pin detection methods both domestically and abroad, these studies are focused on specific types of pins and connectors due to the wide variety of connector types that can contain pins. Therefore, corresponding researches for carrier module pin detection are currently lacking. In this regard, this paper proposes a carrier module pin detection method based on Blob analysis to achieve fast and accurate detection of the pins in the carrier module.

2 System Framework

The process of the carrier module pin detection algorithm proposed in this paper mainly includes: image preprocessing, interface segmentation, pin positioning and recognition, pin center point positioning, and defect detection. The flowchart of the algorithm is shown in Figure 1.

Fig. 1 Flow chart of needle detection algorithm

(1) First, preprocess the back image of the carrier module, remove the image noise by using median filtering, then use the maximum class variance method (OTSU) to obtain the optimal segmentation threshold to segment the image, locate the interface according to the area and aspect ratio of the connected domain in the binary image, and combine perspective transformation to segment the interface.

(2) Use the arrangement rule of pins as a constraint condition to complete the identification of pins. First, use Blob analysis to complete the preliminary recognition of the pins in the interface. Based on this, align with the two-dimensional coordinate template of the pins to obtain the positions of unidentified pins, and perform secondary recognition in the neighborhood of these positions.

(3) After completing the coarse positioning of each pin, determine a rectangular area centered on these position coordinates, extract the pin spot by using an adaptive binarization strategy in this area, and use the gray centroid method to extract the centroid of the spot for each pin.

(4) Align the measured pin coordinate set with the template coordinate set, and judge whether the pins exist defects based on the position information and quantity information of all pins.

3 Interface Segmentation.

For a back image of the carrier module, there exists a problem that the proportion of pins in the image is too small. Moreover, since a module has two interfaces and the pins are located inside these two interfaces, in order to facilitate pin recognition and reduce useless computation while excluding the influence of irrelevant regions, the interface area in the image is segmented first. The segmentation process is as follows: (1) First, use the maximum class variance method to obtain the optimal segmentation threshold, binarize the image, and then bisect the binary image according to the height. The two interfaces are separated based on their position relationships. Then, extract all connected domains' contours in both images, sort the contours by descending order of contour areas, and remove the contours with small areas. (2) Perform polygon fitting on the remaining contours to obtain fitting contours with four vertexes and the shape of convex quadrilaterals, which are the interface contours. (3) Obtain the four vertices of the minimum bounding rectangle of the interface contour and use perspective
transformation to complete the interface segmentation. The principle of the maximum class variance method [11] is to find a threshold $T$ that maximizes the inter-class variance between the background and the object after threshold segmentation. The inter-class variance can be defined as:

$$\sigma^2 = w_0(m_0 - m_T)^2 + w_1(m_1 - m_T)^2$$  \(1\)

where, $m_0, m_1$ is the gray mean of each part after the image is segmented into two parts with threshold value, $m_T$ is the global mean, and $w_0, w_1$ is the proportion of the two parts. The threshold values $T$ are successively set within the gray level $[0, L - 1]$ so that the gray value $\sigma^2$ is the optimal threshold.

In the process of interface segmentation described above, perspective transformation both segments the interface and corrects its skew. The general formula for perspective transformation is:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

among them, $\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$ is the transformation matrix, $\begin{bmatrix} x \\ y \\ z \end{bmatrix}$ is the source point matrix, $\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$ is the target point matrix.

In this paper, the coordinates of the four vertices of the interface obtained by rectangle fitting $(x_0,y_0), (x_1,y_1), (x_2,y_2), (x_3,y_3)$ are used as the source points to convert to the target points $(0,0), (W,0), (0,H), (W,H)$ where $W$ and $H$ are respectively the width and height of the minimum enclosing rectangle of the interface. The segmentation effect is shown in Figure 2.

![Fig. 2 Interface segmentation](image)

**4 Pin recognition and positioning**

After segmenting the interface, the main issue is how to accurately extract the position feature points of the pins. To this end, we developed a Blob analysis strategy based on prior knowledge alignment for coarse positioning of pins and designed an adaptive binarization strategy combined with centroid
calculation to extract the position feature points of the pins.

4.1 The pin recognition strategy based on Blob analysis

Under ideal conditions, pins located in the same interface should have similar features, such as brightness. Therefore, pins can be found based on the commonality of their features. However, during the actual detection process in industrial scenarios, modules may be tilted at a certain angle during shooting, or the quality and installation position of the pins themselves may result in diversity in the sharpness features of the pins. This is shown in Table 1.

<table>
<thead>
<tr>
<th>Influence factor</th>
<th>Advanced features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process quality (Shown in the red box)</td>
<td>![Image]</td>
</tr>
<tr>
<td>Installation position</td>
<td>![Image]</td>
</tr>
<tr>
<td>Shooting Angle / Same module</td>
<td>![Image]</td>
</tr>
</tbody>
</table>

Table 1 Diversity of pin tip features

To fully utilize the feature information of pins and achieve accurate recognition, this paper proposes a two-stage recognition strategy based on arrangement rules constraints. Based on Blob analysis, the strategy utilizes the brightness, shape, area, and position relationship of pins to complete their recognition.

The Blob is a connected area with similar characteristics. In this paper, the area composed of similar gray scale is regarded as a Blob, and the pin insertion area is located by filtering through gray scale, shape and other characteristics. The steps of identification using Blob analysis are as follows:

1. First, set two thresholds, \( \text{minTh} \) and \( \text{maxTh} \), and set the step size \( S \). Within the threshold range, the image is divided into several binary images according to the step size.

2. The central coordinates and the features such as area, radius and circularity of the connected domain in each binary image were obtained. According to the conditions, the connected domain satisfying the conditions is obtained.

3. The distance between the connected domains in different binary images is calculated. If the distance is less than threshold \( d \), it is considered to be the connected domain at the same location, and the number of times that the connected domain at the same location appears in all binary images is counted. If the distance is less than threshold \( r \), the connected domain is ignored.

4. The connected domains at the same location are combined to obtain their location centers.
Finally, all connected domain centers are counted and output.

In general, in order to reduce background interference, the lower threshold limit (minTh) and minimum area (minArea) of connected domains cannot be set too small. Otherwise, some darker speckles in the background may also be retained. However, setting these conditions too high will bring new problems. Due to oxidation, processing, and other reasons, the reflectivity of some pins may deteriorate, causing their brightness to decrease. Setting the threshold too high will result in these pins, as well as some small-area pins, being mistaken for background and not being recognized. Therefore, a win-win solution is needed that ensures the recognition of darker and smaller-area pins while also avoiding misrecognition of speckles in the background.

As the pin positions and structures in the same type of carrier module are fixed and do not undergo excessive deformation, this paper uses the distribution rule of pins as prior information and binds it to the corresponding type of carrier module. Knowing the distribution rule of the pins, the two-dimensional coordinate template for this type of carrier module can be constructed in advance. This template can be used to label the recognized pins for supplementary recognition of new pins and final positional accuracy detection. The flowchart of the algorithm is shown in Figure 3. The improved recognition algorithm consists of two steps: primary recognition and supplementary recognition. The overall steps are:

1. Firstly, Blob analysis was used to identify the pins.
2. The coordinate point set of the initially identified pin and the template point set were registered, so that the pin in the image was matched with the template one by one. When no suitable target point was matched with the point in the template, it meant that there was an unidentified pin at the position or the pin was missing at the position.
3. Then, a rectangular area is expanded with this location \((p_x, p_y)\) as the center. Conditions such as minTh and minimum area of threshold are reduced in this area, and Blob analysis method is used again for secondary identification. The size of the rectangular area can be described as:

\[
(a_x^i, a_y^i) = (p_x^i - \frac{p_x^{i+1} - p_x^i}{\alpha_x}, p_y^i - \frac{p_y^{i+k} - p_y^i}{\alpha_y})
\]

Where, \((a_x^i, a_y^i)\) is the upper-left coordinate of the rectangular region, \(\alpha_x\) and \(\alpha_y\) is used to control the cutoff ratio in the x and y directions, where 1/2 and 1/3 are taken, and the parameter \(k\) is used to take the y-coordinate of a point in the previous row.

According to the Closest Point set, the Closest Point set and the template Point set were registered using the Interative Closest Point (ICP) algorithm. The registration process can be seen as using a transformation matrix to transform the source Point set X so that the global deviation between the transformed X and the standard Point set P is minimal. The process can be expressed as:
\[
(R, T) = \arg \min \left\{ \frac{1}{N} \sum_{i=1}^{N} ||P_i - (RX_i + T)||^2 \right\} \tag{3}
\]

One-stage Blob recognition algorithm and two-stage Blob recognition algorithm are respectively used for the same image, and the experimental results are shown in Figure 4.

(a) First-stage identification  
(b) Two-stage identification

Fig. 4 Identification results based on Blob analysis

4.2 Pin center point positioning

Before performing center point extraction, the image needs to be converted to a binary image. However, traditional binarization methods cannot achieve complete segmentation of pin features due to their diversity. In order to accurately represent the positions of the pins, this article proposes an adaptive binarization strategy based on area and structural constraints to solve the problem that traditional binarization methods cannot effectively segment pins.

On the identified result point set \( X \), a rectangular region is determined with \((x', y') \in X\) as the center, and subsequent binarization operations are carried out in this region. The size of the rectangular region is:

\[
(w', h') = (\alpha w', \beta h') \tag{4}
\]

Where, \((w', h')\) are the width and height of the rectangle, \( w' \) and \( h' \) are the width and height of the segmented interface, and \( \alpha, \beta \) are used to control the size of the rectangle area (\( \alpha = 0.06, \beta = 0.027 \) in this paper).

In the initial stage of the algorithm, the initial segmentation threshold is determined based on the percentage of pixel intensity in the region. Considering the low brightness of pin spots with poor reflectivity, the initial threshold is sometimes relatively low. In addition, in the process of iteration, the pin spot characteristics are evaluated, and the evaluation criteria are composed of aspect ratio \( a \) of boundary rectangle, aspect ratio \( b \) of the smallest enclosing rectangle, area \( S \), and roundness \( e \), as shown in the equation.

\[
Q(a, b, S, e) = \frac{a_1 b_1 + a_1 + b_1 + \frac{a_1}{b_1}}{S} + e \tag{5}
\]
The process of adaptive binarization algorithm can be described as follows:

(1) For a rectangular region with N pixels, an appropriate initial threshold $t = g_0$ is selected according to the intensity of pixels in the region.

(2) $t$ was used to binarize the rectangular region, and then all the connected domains in the region were marked to obtain the contour $c'_i$ of each connected domain, calculate the area $S_i$ of the connected domain, and eliminate the $S_i < \mu N$ meeting the conditions. Then calculate the circularity $e_i$ of the remaining connected domain, the aspect ratio $a_i$ of the boundary rectangle, the length to width ratio $b_i$ of the smallest enclosing rectangle, and record the score $Q_i$.

(3) Make $t = t + \tau$, repeat step (2) until $t \geq 255$ or $Q_i > M$ (M is the evaluation threshold) and $S_i > \sigma N$ end ($0 < \sigma < 0.05$). I get $t$ and $c'_i$ that maximize $Q_i$.

The effect of adaptive binarization for different pin characteristics is shown in Fig. 5, with the optimal threshold in the red box.

Fig. 5: Binarization effect of different pin features

After the pin spot is obtained, the centroid of the contour is obtained by using the image moment as the feature point of the pin position. Moment is an operator describing image features, and the calculation formula of image moment is as follows:

$$m_{ij} = \sum_{x,y} f(x, y) * x^i * y^j$$  \hspace{1cm} (6)

Where, $f(x, y)$ is the pixel value at point $(x, y)$. The centroid of the image can be obtained by using the zero-order moment $m_{00}$ and the first-order moment $m_{10}, m_{01}$ and the calculation formula of the centroid is shown in Equation (8).
\[
\bar{x} = \frac{m_{10}}{m_{00}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i f(x_i, y_i)}{\sum_{i=1}^{n} \sum_{j=1}^{n} f(x_i, y_i)}, \quad \bar{y} = \frac{m_{01}}{m_{00}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} y_i f(x_i, y_i)}{\sum_{i=1}^{n} \sum_{j=1}^{n} f(x_i, y_i)}
\]

(7)

The result of using moment to calculate mass center is shown in Fig. 6

---

5 Defect judgement

Because the pin center coordinates are obtained with reference to the upper left corner of the interface, the errors generated during interface segregation will directly affect the judgment of the pin position. Moreover, if there is no reference benchmark, the defect judgment of the pin will depend more on the positional relationship between the pins, but the result obtained in this way will have a large error and cannot meet the measurement accuracy. Therefore, this paper still need to rely on the two-dimensional coordinate template used in the recognition stage and use a set of registration algorithms to complete the registration between the measurement point set X and the template point set P, obtaining a new registered point set \( \hat{X} \). In this article, the ICP algorithm is still used for registration.

Ideally, after several iterations, the sum of the distance between the two points reaches the minimum, that is, the distance between the corresponding points reaches the minimum. However, due to the small number of points involved in registration, when the tilt of the pin occurs, the corresponding position center of the pin will also be offset. In this case, the point can be regarded as an outlier relative to other normal points. Due to the small number of points participating in registration, when outliers also participate in registration, other points with normal positions will share the offset of outliers. As a result, the distance between corresponding points does not reach the minimum after iteration, which is easy to cause greater deviation and lead to false detection. Therefore, in the process of each iteration in this paper, once the Euclidean distance between a point in the template point set P and the nearest point exceeds the set threshold \( T_d \), points at the corresponding positions in the template point set P and the measurement point set X will be removed at the same time, and the iteration will be carried out again, so as to solve the influence of outliers on the registration effect. Where, the size of the filtering threshold \( T_d \) is the median distance between all corresponding points. The effect after registration is shown in Figure 7.
After the registration of the measuring point set and the template point set is completed, the judgment can be made according to the relationship between the two sets of point sets. The judgment rule of pin defects is as follows:

(1) Pin missing detection. After the registration of the template point set and the measurement point set is completed, each point in the measurement point set is paired with a point in the template point set. Therefore, when there is an unpaired point in the template point set, the corresponding pin of the point is considered missing, and the location number of the missing pin can be obtained.

(2) Detection of pin positivity. After registration of the measured point set $X$, a new point set $\hat{X}$ was obtained. The Euclidean distance between each point in $\hat{X}$ and the corresponding point in the template point set $P$ was calculated and compared with the tolerance threshold to determine whether there was a pin tilt. The formula for calculating Euclidean distance is as follows:

$$D_i = \|\hat{X}(i) - P(i)\|_2 \quad (8)$$

A sample result of algorithm detection is shown in Figure 8. The two different interfaces (12 pins and 4 pins) in the figure are the same module. The pins marked with green rectangular box in Figure 8 (a) are normal, the pins marked with red rectangular box in Figure 8 (b) are tilted, and the pins marked with red rectangular box in Figure 8 (c) are missing.
6 Experimental results and analysis

In order to verify the effectiveness of pin detection method and the accuracy of measurement, this paper prepared three data sets:

(1) Dataset i : This dataset will be used to verify the effectiveness of the recognition algorithm in this paper. 500 images on the back of the carrier module were collected (some images had pin defects). In order to exclude the influence of other irrelevant factors on the experiment, the two interfaces were segmented in advance, so there were a total of 1000 interface images, which covered different types of pin tip features.

(2) Data set ii : This data set is the back image of carrier module collected in actual operation. There are 4000 carrier modules in some images with horizontal displacement and tilt to a certain extent, including 400 unqualified module images.

Data set i is used to test the pin recognition algorithm. Table 2 compares the four pin recognition methods. Method 1 uses global threshold segmentation and selects the area and shape of connected domain to complete recognition. Methods 2 and 3 use single template and multiple template respectively for template matching, and use the six matching methods listed in this paper. The matching results are the maximum of the six matching methods. Method 4 Uses deep learning method and the Faster-RCNN target detection network to identify pins. There are 1134 interface images in the dataset, and all pins in the images are labeled. The iterations of FTL-RCNN and RPN in the training process are 8000 and 12000 respectively. Method 5 is proposed in this paper.

<table>
<thead>
<tr>
<th>Table 2 Comparison of pin identification methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Methods</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Recognition rate</td>
</tr>
</tbody>
</table>

As can be seen from Table 2, the pin recognition algorithm proposed in this paper can well complete the pin recognition task, with the recognition rate reaching 99.6% on dataset i. The recognition rate of the thresholding segmentation method is only 58.20%, the reason is still that the selected threshold is not universal, and the fixed threshold can not adapt to different images. Using template matching algorithm, which can identify both use the single template or a template Settings need to consider the matching degree. In addition, the selection of the template image is also the key factors influencing the effect of matching, the use of template still cannot fully cover the diversity characteristics of pin, and the number of templates increases with the multiplication of computation. And because of the small pin in the target images, and the characteristics of relatively drab, and pin remains in the background and spot light similar when using depth study is relatively easy to produce false identification, and this strategy makes full use of the characteristics of the tip of the pin, and connecting with the pin arrangement rule, to darker, or the brightness of background such as reflective of pin also completed properly identify, And you don't have to go through a lot of sample training. After analysis, the main factors causing the algorithm to identify the error are blurred image, module shooting tilt Angle is too large.

Data set ii is used for the overall test of the algorithm in this paper. We will verify the algorithm by
mean time $T$, accuracy $AR$, false detection rate $ER$ and missed detection rate $MR$. Table 3 shows the experimental results, in which the accuracy rate, false detection rate and missed detection rate are defined as:

$$AR = \frac{n_0}{N_0}$$  \hspace{1cm} (10)

$$ER = 1 - \frac{n_0}{N_1}$$ \hspace{1cm} (11)

$$MR = 1 - \frac{n_2}{N_2}$$ \hspace{1cm} (12)

In the formula, $N_0$, $N_1$ and $N_2$ respectively represent the total number of samples, the number of qualified samples and the number of unqualified samples; $n_0$, $n_1$ and $n_2$ respectively represent the number of correct samples detected, the number of qualified samples detected and the number of unqualified samples detected.

<table>
<thead>
<tr>
<th>Module type</th>
<th>$N_0$</th>
<th>$N_1$</th>
<th>$N_2$</th>
<th>$t$</th>
<th>AR</th>
<th>ER</th>
<th>MR</th>
</tr>
</thead>
<tbody>
<tr>
<td>TXHX13-GD31001</td>
<td>4000</td>
<td>3600</td>
<td>400</td>
<td>0.087s</td>
<td>99.53%</td>
<td>0.53%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

As can be seen from Table 3, the algorithm in this paper still has a high recognition rate of 99.53% for complex and changeable images, and can achieve 100% recognition rate for defective modules, which further proves the stability and robustness of the algorithm. The reason for the false detection of the algorithm to a certain extent is mainly reflected in the large angle tilt and deviation of some images in the data set, which leads to the missing identification in the first step of pin identification. As the detection result is closely related to the correct identification of pin, the false detection is caused. And the large angle tilt of the module will lead to the registration algorithm can not work well, which will affect the judgment of the result.

7 Conclusion

In order to realize automatic detection of pin defects in smart meter carrier module and solve the problem that traditional machine vision detection methods cannot adapt to complex and variable images taken in industrial sites, this paper proposes a pin detection method based on Blob analysis. Compared with traditional detection methods, this method has stronger robustness and accuracy, and can effectively complete the identification and detection of communication module pins. Aiming at the complex characteristics of the needle tip, the arrangement rules of the needle were taken as constraints, and the needle was identified based on Blob analysis. In addition, an adaptive binarization strategy is used to extract the feature points of the needle position to solve the problem that the traditional binarization method can not effectively extract the feature of the needle tip. Compared with some existing detection methods, the method proposed in this paper has higher accuracy in the identification of pins, which also
reflects the robustness of the proposed method.

**Statements and Declarations**

All authors disclosed no relevant relationships.

**Database availability statement**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Reference**


