Label Detection Method Based on Label Design Documents

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Abstract

In the manufacturing industry, labeling is one of the core processes before product delivery. Product label is an important way for customers to understand products. Therefore, it is an important part to ensure the quality of commodities to check the labeling quality and ensure the product labeling is correct. Therefore, testing the labeling quality and ensuring that the product is labeled correctly is an important part of ensuring product quality. For the production line with frequent product changes, the existing label detection algorithm is not applicable, a label detection method based on the label design document is proposed. This method can automatically generate classification rules, classify them through label design files, and obtain unique features, so as to accurately identify whether labels are mislabeled or not.

Keywords

Label detection, Frequent product changes, Classification.

1. Introduction

With the development of machine vision and artificial intelligence, more and more intelligent detection methods are applied to industrial production. Research related to label detection automation has also gradually become the main research direction in this field.

[1] proposed a detection method using image area, center of gravity, and second-order moment direction as label features. The correctness of the label is detected by calculating the feature similarity between the detection image and the template image. However, this method requires constant illumination and target position. To ensure that all changes in the image is the label. Therefore, template images need to be reacquired after product change. As a result, this method cannot be used in a production line where products are frequently changed. [2] proposed a deep learning model based on principal component analysis(PCA). This method uses SVM to identify whether the label is qualified. However, it needs a lot of positive and negative samples to train the model and cannot meet the convenience requirements.

The above labeling detection algorithms are all based on the fixed image acquisition environment, the product size is small and the number of the same label is large. However, there is no research on the labeling detection of products with large volume and multiple labels. Therefore, in view of this situation, this paper proposes a label detection method for dynamic image acquisition by robot end camera. Because dynamic image acquisition cannot achieve a fixed image acquisition quality, the changes in the image are not only labels, and there are more than 100,000 kinds of labels, some of which are very similar, so the traditional label detection algorithm is not fully applicable to the requirements of this paper. At the same time, facing the production situation where product labeling location and content often change, the label detection algorithm through deep learning is also not applicable. Therefore, this paper proposes a method to detect the label by extracting the label features from the label design documents. Next, we introduce the label design document in Chapter 2, in preparation for introducing the label detection method in Chapter 3.

2. Label Design Document

2.1 SVG File

The original label design document format is CDR format, but because the CDR format is a non-open source file format, special software (Coreldraw) is required for processing. Therefore, it can be converted to the open source W3C standard SVG file format for processing.

SVG is a language for describing two-dimensional graphics using XML. It can be used to describe two-dimensional vectors and vector/raster graphics[3].The SVG image will not lose its graphic quality when it is enlarged or resized, so it can retain the content of the CDR design document without losing during the conversion process. SVG files converted from CDR files have two main attributes: border/fill attributes and shape attributes. Border/fill attributes is used to determine the border thickness and color of the shape or the fill color and type of the shape. Shape attributes is used to determine the position, size and outline information of the shape. At the same time, it also contains the index of the border/fill attribute data name that needs to be used when rendering.

In order to get the label design draft, the label design document must be parsed and rendered first. The specific process is as follows:

Step1 Read the contents of the SVG file and parse the statements of the two attributes into corresponding data structures.

Step2 Traverse the shape attribute data sequentially and read the corresponding border/fill attribute data.

Step3 Render all shapes in order with corresponding border/fill attributes.

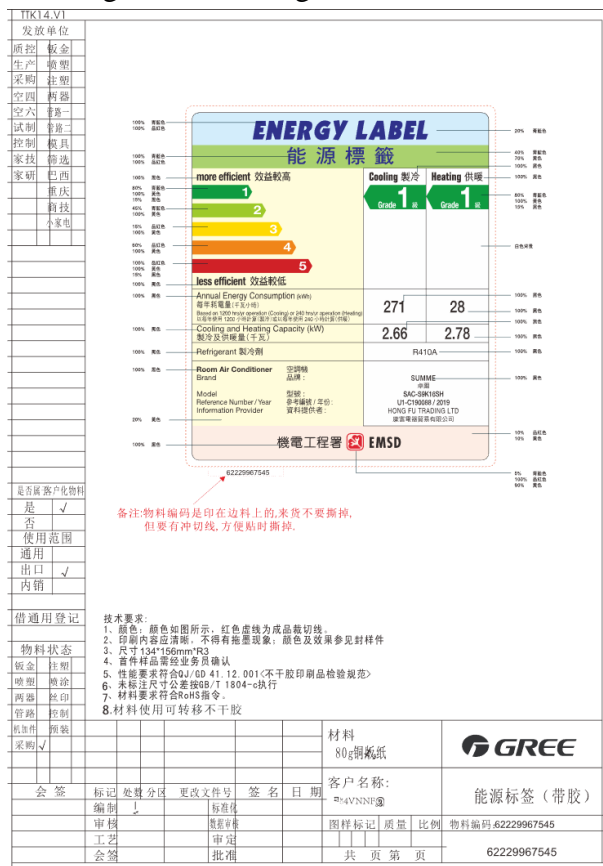The result of parsing and rendering the label design document is shown in Figure 1.

Fig. 1 Label design document

2.2 Label Design Draft Extraction

The label design document contains not only the label design draft, but also the description for the design draft and the label production information. Part of the information will obscure the content of

the label design draft. Therefore, this paper proposes a design draft extraction method combining shape data and design document image.

By analyzing the design documents, the three characteristics of the design documents are as follows: First, the design document has two standard formats, and the overall size of the design document can be used to determine the format of the design document. For one format, the main content of the design document is in the same place. Second, analyzing the outline of the main content, we can see that the outline with the largest area is the outline of the label. Third, there are two forms of description of the outer border of the label in the SVG file. One is to use only one shape to form the border. In this case, to get the border position, you only need to locate the shape with the largest bounding rectangle. The second is to form a border with multiple shapes that appear consecutively, and these shapes will be in the same combination. In this case, to get the border position, you need to locate the shape group with the largest bounding rectangle. According to the above three characteristics, the extraction of the design draft consists of the following three steps:

Step1 Determine the format of the design file by its overall size, and then get the main content.

Step2 Extract the outline of all shapes in the main content and find the largest contour. Take its border rectangle as the ROI for precise positioning in the next step.

Step3 Read all shapes in the ROI and extract the label design draft accurately using the method shown in Figure 2. The final result is shown in Figure 3.
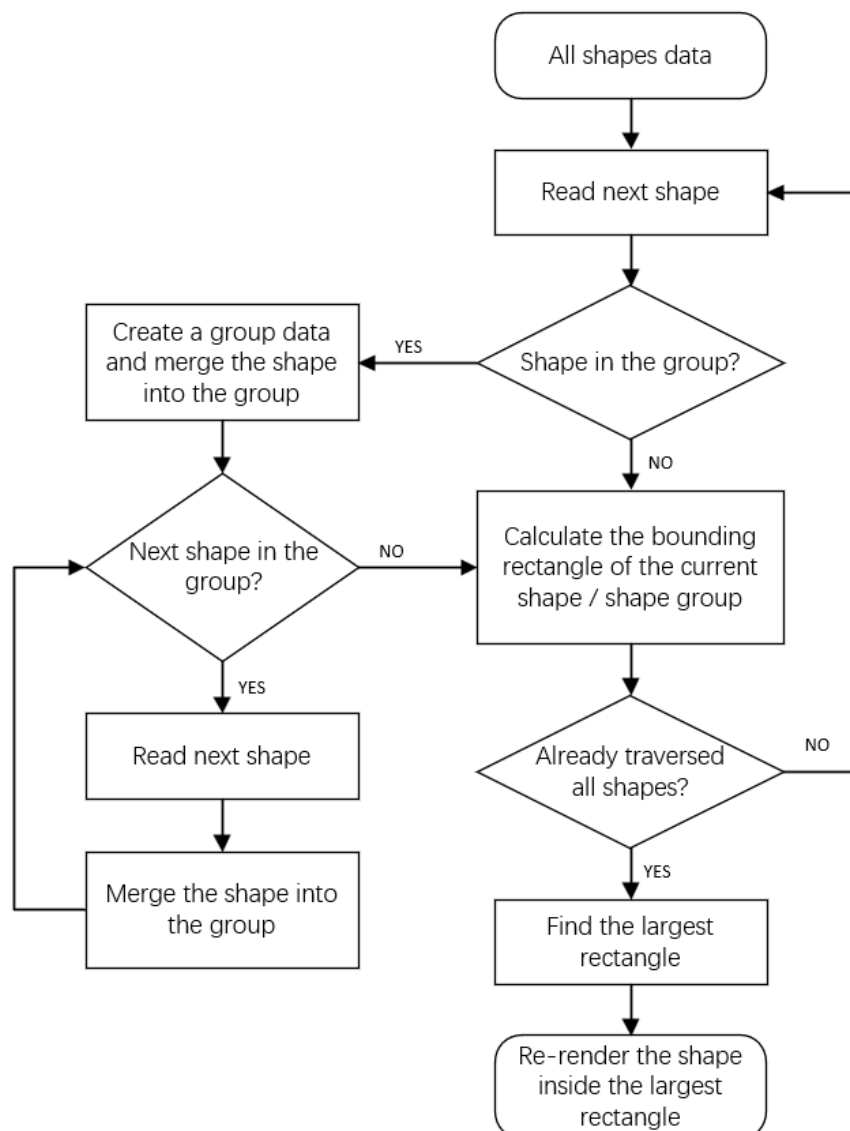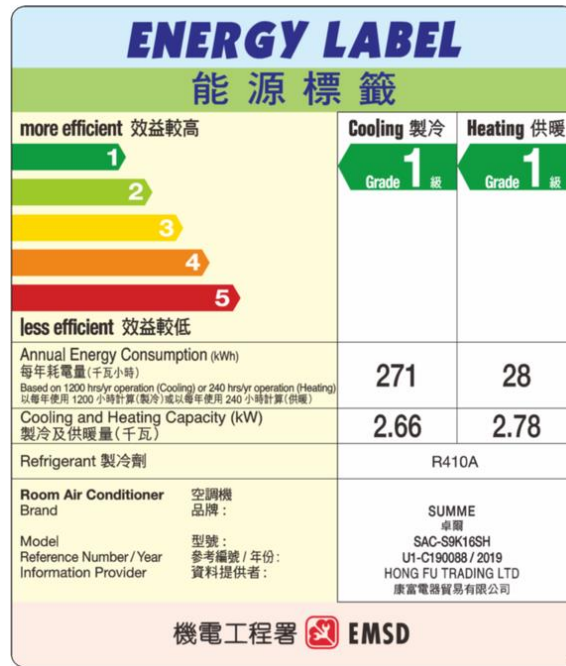

Fig. 2 Method flow

Fig. 3 Label design draft

3. Label Detection Method

The core idea of this method is to obtain the label features which can be used to detect the label correctness by analyzing the label design draft automatically. So as to solve the problem of labeling inspection for the production line with frequent product changes. A novel label detection method is proposed.

The whole method can be divided into two parts: one is to analyze the design document to get the label features, and the other is to compare the label features with the features of the collected images. These two parts happen asynchronously. The overall structure of the method is shown in Figure 4.
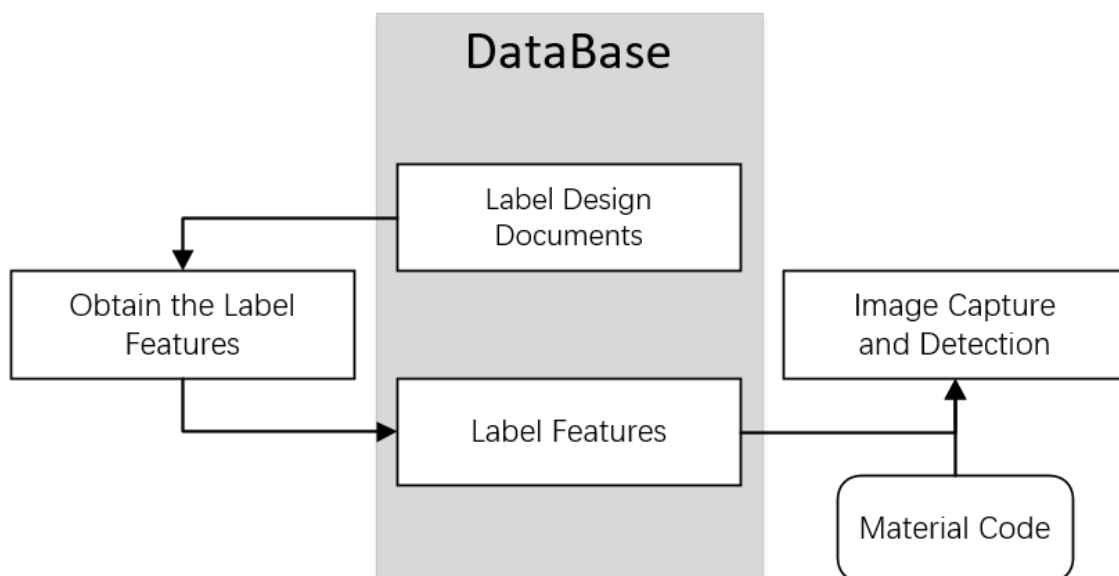

Fig. 4 Method structure

The "Obtain the Label Features" section can analyze all label design documents at any time, and obtain label identification features and store them in the database. The "Image Capture and Detection" part is responsible for loading label features from the database based on the material code entered by the operator, and determining whether the labeling is correct in the captured image. "Material code" is the unique ID of the label in the production system.

3.1 Label Classification

After analyzing the sample labels, we found that some labels have obvious features that can be used for identification and detection, such as QR code, barcode, and material code features. Some labels are mainly shapes, which have less shapes but the shapes and their combinations have distinct characteristics. Therefore, classifying labels and designing different feature extraction methods and detection strategies will help improve detection efficiency. This paper divides labels into four types, which are barcode/QR code labels, shape labels, material code labels and general labels. Examples of these four types of labels are shown in Figure 5.

(a)barcode/QR code label   (b) shape labels   (c) material code labels   (d) general labels

Fig. 5 The label samples

The scheme of label classification is as follows. First, detect whether the label contains a barcode or QR code, and if so, a barcode/QR code label. Otherwise, the number of contours of the sub-shape of the label is calculated. If the number of contours of the label is ≤40, it is a shape label. Otherwise, check whether the label contains the material code, and if so, judge it as the material code label. Otherwise it is judged as a general label.

For the four types of labels, this paper proposes four different detection methods. The four methods differ mainly in the features used for detection and the rules for feature extraction. Next, the feature extraction methods and detection methods for these four types of labels will be introduced.

3.2 Obtain the Label Features

3.2.1 Barcode/QR Code Label Features

QR codes and barcodes are selected as the label recognition feature because barcodes and QR codes are fast, flexible, and highly accurate[4]. The most important reason is that the barcode and QR code on the label have unique code values, which can be used to accurately identify the label.

The technology for identifying barcodes and QR codes is now relatively mature. There are many commercial and shareware programs that can read different types of barcodes and QR codes. However, among the open source barcode and QR code readers, only the Zbar library can meet the high performance, stable and robust requirements, and it is small in size and very easy to integrate. Therefore, the Zbar library was selected to identify the barcode and QR code of the label.

Finally, the feature extraction method for this type of label is to use the zbar library to identify the barcode/QR code of the label design draft, and then store the code value and location into the label feature database.

3.2.2 Shape Label Features

Aiming at the characteristics of shape labels, this paper proposes to identify this type of labels through shape-based matching methods. Considering that the label is not fixed at a certain position in the image during detection, it is necessary to locate the label. However, since most shape labels have no obvious outer border, it is necessary to select shape features with translation, rotation, and scale invariance, and then obtain the overall position of the label by matching and positioning the features. The hu moments just meet the requirements of translation, rotation and scale invariance[5]. Hence, the hu moments of each sub-shape of the label are selected as the label features. In order to improve

the recognition accuracy, the overall geometric ratio of the label is used as a feature. The feature extraction method for this type of label is as follows:

Step1 Sub-shapes are segmented from the label design draft, and contour extraction is performed according to the rules of simultaneously extracting internal and external contours.

Step2 Determine if the total number of contours is greater than 20, if yes, keep the outer contours, otherwise keep the inner and outer contours.

Step3 Calculate the Hu moment and aspect ratio of the contours and the overall aspect ratio of the label, and then store them into the label feature database.

3.2.3 Material Code Label Features

The material code is the unique ID of the label, and some labels place their material code in the corner of the label. Therefore, the material code value and the relative position of the material code in the label are set as the main features of the label. At the same time, considering the perspective distortion that may affect the identification of the material code during detection, this paper uses perspective transformation to project the four vertices of the label in the image into a rectangle with the same aspect ratio as the original label for correction. Therefore, it is necessary to save the aspect ratio of the label as a feature.

Because the material code is composed of numeric characters, the aspect ratio of each character must be greater than 0.5 and less than 3. Because the material code is an independent string of lines, and in order to avoid the case where the morphological expansion of the label text is too small, it will be stuck by other lines. This article uses the method of extending the line from the area position to merge the areas.

The feature extraction method for this type of label is as follows:

Step1 Binarize the design draft to extract all the outer contours.

Step2 Cut out the contour of the bounding rectangle whose aspect ratio is less than 0.5 or greater than 3, and the remaining contour area is the text candidate area.

Step3 Merging text candidate regions to obtain candidate character lines.

Step4 Material code recognition is performed on all candidate character lines, and then the material code area is determined.

Step5 Save material code, area location, and aspect ratio of the label to the label feature database.

The printed number-recognition neural network used in this paper is an 18-layer convolutional neural network[6], and the training data has a sufficient variety of printing fonts. At the same time, the original characters are also processed by ±5 and 15 degrees of rotation and slight expansion. The training accuracy is 98.66% and the verification accuracy is 98.14%. Because the font size of the material code printed on the label is relatively neat and small, the recognition rate can reach 99.99% when the network is actually used.

3.2.4 General Label Features

Analysis of the general labels in the sample found that the size and layout of the labels in the same region or the same manufacturer were roughly the same, the difference was only in the parameter text or graphic symbols. On the other hand, the labels of different regions or manufacturers are quite different.

Due to the noise, distortion, and blurry edges of the picture during the detection, the picture will be a slightly different from the design draft. At the same time, because the labels belong to the same region or manufacturer, the discrimination is very small. Therefore, the detection method using template matching is difficult to determine the threshold when distinguishing labels belonging to the same region or manufacturer.

In view of the differences and similarities between labels, this paper takes the layout and size of labels as the basis to cluster similar labels first. Then calculate the difference area between labels in the same category. The image in the difference area is used as individual distinguishing feature. The

layout is represented by the horizontal and vertical projection histograms of the binarized labels. Size is expressed using the aspect ratio of the label. The classification method is as follows. First select the categories with the same aspect ratio, and then calculate the EMD distance[7] of the histogram. If the EMD distance of the horizontal and vertical histograms are less than 10, the type can be determined. Otherwise create a new category and set the current label as the "main label" for the new category. On the other hand, the method for extracting distinguishing features within a class is as follows. First perform a difference operation with the "main label" and then use the morphological open operation to remove interference like contour edge shadow. The non-zero area in the image is the difference area, and the image in the difference area is the distinguishing feature.

Compared to the four distance measurement methods: Correlation method, Chi-square method, Intersection method, and Bhattacharyya distance method, EMD has the advantage of being insensitive to histogram translation[8]. At the same time, this paper uses horizontal and vertical projection histograms to represent layout of the label, so EMD is selected as the basis for judging whether the layout characteristics of the labels are similar.

The feature extraction method is as follows:

Step1 Calculate the aspect ratio of the label.

Step2 Use dynamic threshold binarization to highlight graphic lines and text content in the label.

Step3 Calculate the horizontal and vertical projection histogram of the label. Then find the category of the label based on the aspect ratio and histogram.

Step4 Calculate distinguishing features within a class. Then store the aspect ratio, histogram and distinguishing features within the class into the label feature database.

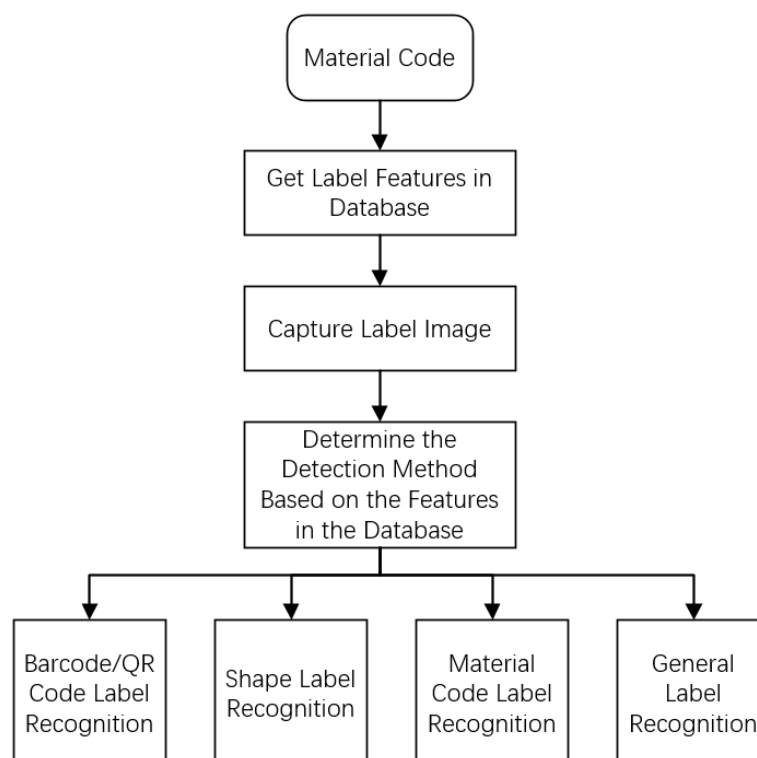### 3.3 Detection of Labeling Correctness

Fig. 6 Detection process

As shown in Figure 6, the template features and label types are first read from the database according to the "Material code", and then the label image are captured. Finally, the detection method is selected according to the label type and the detection result is output.

Identification of barcode/QR code labels is relatively simple. Use the Zbar library to identify the image. If the template is a QR code, identify the QR code, and if it is a barcode, identify the barcode.

The recognition result is compared with the template code value. If the characters are equal, the labeling is correct.

The main problem of shape label recognition is interference caused by contours that do not belong to the label, as shown in Figure 7. First, candidate contours are obtained according to the aspect ratio of each sub-shape, then the hu moment distance between the template contour and the candidate contour is calculated, and finally the contour with the smallest hu moment distance is taken as the best matching contour. The best matching contours of all template contours are obtained according to the above rules, and the overall aspect ratio is calculated to determine whether the labeling is correct. The acceptable range of aspect ratio is 80% ~ 120%.

Fig. 7 Shape image with interference

The formula for calculating the hu moment distance is as follows:

$$D(A,B) = \sum_{i=0}^{6} \left| \frac{1}{H_i^B} - \frac{1}{H_i^A} \right| \tag{1}$$

$D(A,B)$ is the distance between the contours A and B, and H_i^A and H_i^B are the result of logarithmic transformation of the i−th number of hu moment of contour A and B.

For material code labels, because the position of the material code is relative to the front view of the label, it is necessary to transform the label to the front view by perspective transformation, and then extract the image of the material code area for character recognition. First, the four sides of the label are obtained by fitting a straight line, then the corners of the label are obtained by finding the intersection of the line, and finally the label is projected into a rectangle created by the template aspect ratio and the label width. The results are shown in Figure 8. According to the location of material code in the feature database, the image of detection area is segmented from the transformed image. In order to cope with text sticking, blurring or too thin and thick, the detection area image is segmented using dynamic threshold binarization. Then use the trained printed digital recognition neural network for character recognition. Finally, check whether the recognition result is the same as the template label material code. If they are the same, the labeling is correct.

(a) Fitting a straight line   (b) Result of transformation

Fig. 8 Perspective transform

For general labels, first determine whether the aspect ratio of the label is within the error range of 80% to 120% of the template aspect ratio, and if so, convert it to a front view. The method is the same as

in the material code label detection. Otherwise, judge it as labeling error. Next, calculate the horizontal and vertical projection of the transformed label, and then calculate the EMD distance between the projection of the transformed label and the projection of the template label. If the EMD distance of the horizontal and vertical projection is less than 15, labels are considered similar and can be judged in the next step. Otherwise, labels are judged to be wrong. The final step is the detection of the difference area. The location and image of the difference area of the label are stored in the database. First, the difference area image is extracted from the label according to the location of the area, and then template matching is used to judge. If the matching result is greater than 0.7, the content of the difference area is determined to be correct.

4. Conclusion

This paper proposes a label detection method based on label design files. This method can analyze all the labels that may be used for production in advance, and only need to enter the label material code to complete the detection. Because the method's template feature extraction and detection process is performed asynchronously, this greatly saves the time to create a template when switching products. Compared with other detection methods, this method is not only suitable for production lines that frequently change products, but also for dynamically collected label images. Moreover, the method in this paper can be applied to multiple types of labels at the same time, and can meet the production needs of large factories.

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