On-line Defect Detection and Classification of Latex Gloves

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Abstract. At present, the detection of latex glove is mainly done manually. In order to realize the online detection of latex glove, this paper presents a method of defect detection and classification of latex glove based on multi-feature extraction to achieve online detection and classification of latex glove. Firstly, the target pixel and the background pixel were segmented using the OTSU method. Secondly, the image was pre-processed using median filtering, edge extraction and morphological closed arithmetic processing, and then the defect was framed using the minimum circumscribed rectangular frame selection method. Finally, the characteristics of three kinds of defects were proposed by analysis. Feature vectors were extracted using texture features and HOG features. The classification model selects SVM support vector machine to train the classifier to realize the classification of defects. When training the classifier, the Gaussian radial basis function was used as the kernel function. In view of the characteristics of the types of defects in latex glove, first classify the defects in a “one-to-one” manner, and then implement multi-classification. The experimental results show that the online defect detection and classification of latex glove based on multi-feature extraction has achieved good results.

1. Introduction
With the increase of the annual production of latex glove, the testing of latex glove is mainly done manually, which will directly affect the efficiency and cost of production. In order to solve this problem, a machine vision-based inspection method is used instead of manually realizing online detection of defects in latex glove. At the same time, the defects are classified to provide data support for improving product quality and improving processes. In view of the above problems in production, this paper uses machine vision to realize on-line defect detection and classification of latex glove, which has the characteristics of accurate defect detection and clear classification screening results. This method can solve the problems of manual testing, eliminate the waste of resources, improve the speed of product detection and reduce the rate of defective products missed detection, which has high practical value and application prospect in the field of latex glove production.

2. Image Acquisition Device and System Model
According to the needs of real-time detection and classification of latex glove, the image acquisition device is composed of these four parts, which include the ONTOP camera, parallel light source, PC and photoelectric switch. The conveyor belt transports the latex glove placed on the mold, triggers the photoelectric switch low level to become high level, and the camera starts acquiring images. After the image information is collected, the host computer sends a signal to the PLC, the conveyor belt moves, and the next round of latex glove detection is carried out. Different from the traditional defect classification and recognition method, this paper first extracts the latex glove area, then preprocesses the image and extracts multiple features from it. The training model is used to train the classification
model, and the test sample is used to judge the prediction result of the model. Figure 1 shows the specific model diagram.

Figure 1. Classification system model

### 3. Image Processing and Analysis

#### 3.1. Latex Glove Area Extraction

Since the background of the production workshop contains many messy objects, which has a great influence on the subsequent algorithm processing of the latex glove, the latex glove need to be partially extracted for the next defect detection. In this paper, the OTSU method is used to perform dynamic threshold segmentation, and the initial extraction is performed for the detection of latex glove[1]. As shown in the figure, the picture a is the photo collected by the image acquisition part, and the picture b is the latex glove area extracted by the OTSU method[2].

![Image Acquisition and OTSU Extraction](image)

(a) Image acquisition  (b) Extracted image

Figure 2. Area extraction process

#### 3.2. Extraction of Defective Areas of Latex Glove

Transform the initial extracted target area of latex glove into grayscale images. It is found that there is noise, and most of the pretzel noise brings a lot of difficulties to image processing, which has a direct effect on the subsequent defect marking, feature vector extraction and so on. So the median filter is used to remove salt and pepper noise. Because there are some holes in the defect area and the contour line is broken, the morphological closed operation, the expansion operation and the corrosion operation are selected to fit the defect area to smooth the contour and prepare for the subsequent defect extraction. The formula for closed operations is as follows:(⊕,⊙) indicate expansion and corrosion.

\[
A \bullet B = (A \oplus B) \ominus B
\]  

The closed operation processed image is shown in figure 3. Use the contour to extract and remove the edges of the outer ring of the glove and circle the defects using a minimum external rectangle, as shown in figure 4.
3.3. Feature Extraction

As shown in figure 5, the main defect glue marks, glue particles, stains of latex glove. In this paper, the texture feature grayscale symbiosis matrix and HOG feature are used to extract the image feature vector together, and the extracted feature vector is combined with svm for classification training.

![](image1.png)  ![](image2.png)

**Figure 5.** Type of defects

3.3.1 HOG feature

The HOG feature of the latex glove is extracted, which effectively describes the deformed feature of the defect, and at the same time better solves the effect of the factory environment and the change of light on the image.

Firstly, the defective image turns gray. Secondly, the most commonly used gamma correction method is to normalize the color space of the defective image of the latex glove (normalization) to change the contrast of the image and reduce the interference of the environmental factor on the image (illumination change). At the same time, it can reduce noise interference and is more conducive to feature extraction. Then calculate the gradient size and direction of each pixel of the defect image; mainly to obtain the contour information, and once again reduce the interference of lighting. The gradient size formula is:

\[
G_x(x,y) = H(x + 1,y) - H(x - 1,y) 
\]

\[
G_y(x,y) = H(x,y + 1) - H(x,y - 1) 
\]

In the formula, \(G_x(x,y), G_y(x,y), H(x,y)\) respectively represent the horizontal gradient, vertical gradient and pixel value of the pixel in the input image. The gradient value and gradient direction of the pixel are:

\[
G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} 
\]

\[
\alpha(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) 
\]
Thirdly, the defect image is divided into each small cell, and each several cells form a block, and the feature descriptors of all cells in a block are connected in series to obtain the HOG feature descriptor of the block. Finally, the HOG feature descriptors of all blocks in the defective image are connected to obtain the defective HOG feature descriptors.

3.3.2 Texture feature
In this paper, the gray level co-occurrence matrix is used to describe the local texture features of the image. The gray level co-occurrence matrix can extract 14 texture features, among which the four features of energy, inverse moment, contrast and entropy are applied to this paper, which not only improves the calculation speed, but also ensures a certain accuracy[3-5].

1) Angular Second Moment: It reflects the uniformity of graphic distribution and the thickness of image texture. The high ASM shows a more uniform and regular texture pattern.

\[ ASM = \sum_{i} \sum_{j} P(i, j)^2 \] (6)

2) Inverse Differential Moment: Reflect the uniformity of image texture and measure the local change of image texture. A high value means that there is no change between the different areas of the image texture, and the part is very uniform.

\[ IDM = \sum_{i} \sum_{j} \frac{P(i, j)}{1 + (i - j)^2} \] (7)

3) Contrast: directly reflect the brightness of a given pixel value and its domain pixel value.

\[ CON = \sum_{i} \sum_{j} (i - j)^2 P(i, j) \] (8)

4) Entropy: It is a measure of the amount of information in an image and represents the complexity of texture in the image.

\[ ENT = \sum_{i} \sum_{j} P(i, j) \log P(i, j) \] (9)

In this paper, according to the characteristic of the defect of latex glove, 4 directions are taken in the experiment. 0°—135°the gray level symbiosis matrix of the four equal points, maintain the characteristic index separately, calculate its value and carry on the cycle normalization, then specify the average value and variance as the final extracted feature.

3.4. Classification Model
Since the three types of defect samples are limited and belong to non-linear separable problems, it is relatively reasonable to select SVM as the classification model[6-8]. Different choices of kernel function will generate different classification models.

There are four kinds of commonly used kernel functions:

1) Linear kernel function:

\[ k(x_i, x_j) = x_i^T x_j \] (10)

2) Polynomial kernel functions:

\[ k(x_i, x_j) = (\gamma x_i^T x_j + r)^\gamma, \gamma > 0 \] (11)

3) Two-layer neural network kernel function:

\[ k(x_i, x_j) = \tanh(\gamma x_i^T x_j + r) \] (12)
(4) Radial basis function:

\[ k(x_i, x_j) = e^{-\gamma|x_i-x_j|^2}, \quad \gamma > 0 \]  

In this paper, the most commonly used Gaussian radial basis functions are used as kernel functions\[9\]. SVM support vector machines are widely used in binary classification problems, so support vector machines use different methods to achieve multi-class classification\[10\]. At present, the multi-class classification methods of support vector machines are mainly divided into two types: one is "one-to-one" and the other is "one-to-many". Compared with the three shortcomings proposed in this paper, the first method requires fewer samples per sub-SVM and has higher accuracy and speed. Therefore, the "one-to-one" method was chosen. Perform 3 sub-classifiers for classification. Finally, the classification of categories is determined by voting.

4. Experimental Results and Performance Analysis

For detection classification, two parts of training samples and test samples need to be prepared. Use the training sample to train your own classification model, and then use the test sample to adjust the parameters to meet the expected goal, so as to obtain a satisfactory classification model. Table 1 shows the target sample data used in the experiment.

| Defect type      | Number of training samples | Number of test samples |
|------------------|---------------------------|------------------------|
| Flow glue        | 160                       | 20                     |
| Colloidal particles | 160                      | 20                     |
| Stains           | 160                       | 20                     |
| Total            | 480                       | 60                     |

In this paper, a total of 540 images of defects in latex glove were collected, and the test samples and training samples were divided 1:8. Table 2 shows the recognition accuracy.

| Defect type      | Stains       | Flow glue    | Colloidal particles |
|------------------|--------------|--------------|---------------------|
| Accuracy rate    | 95.3%        | 94.6%        | 90.5%               |

In order to detect and classify several possible defects on the surface of latex glove, the multi-feature support vector machine defect identification and classification method used in the experiment obtained an average accuracy rate of 93.46% and an average recognition time of 261 ms. The expected results were achieved in the laboratory environment.

5. Conclusion

In this paper, the online defect detection and classification methods of latex glove are studied. Firstly, the OTSU threshold segmentation is performed on the images collected by the latex glove to extract the target area. Secondly, the median filtering, edge extraction and morphological closed arithmetic processing algorithms are used to achieve image preprocessing. Finally, the smallest circumscribed rectangle is used to select the defect frame; by observing and analyzing the characteristics of the defect and the changing characteristics of the on-site lighting environment, the HOG features and texture features of the defect are extracted as the input of the classification model, and the classification model selects the support vector machine to realize the classification. The accuracy rate reached 93.46%. Meet the expected goal. This method is not only applicable to the detection and classification of latex glove, but can also propose new ideas for the detection and classification of other machine vision by modifying the algorithm and parameters and related thresholds.
6. References

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