Study on the Application of Computer Vision Technology in Defect Detection

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Abstract: As an important production link, industrial product quality testing would determine the quality of the products produced and affects its market competitiveness. At present, in most product lines, product testing often relies on labor, which would not only cause high cost due to human input, but also often fail to ensure the accuracy of product testing. The development of computer vision technology has broken through the bottleneck of industrial product quality inspection. Therefore, in this paper, we propose a computer vision-assisted defect detection regression model, which can determine whether the industrial product is defective by extracting the image defect feature vector and performing regression fitting. The experimental results show that this method has high accuracy and has the value of popularization and application.

1. Introduction

Computer vision technology is the use of computer to process captured images or videos. Its greatest advantage is that it has no contact with the observed objects and can realize the non-destructive detection of objects. Moreover, computers can run for a long time, or they can be masterpieces in harsh environments, which is beyond the reach of the human eye. Surface detection based on computer vision is developed around the image or video of the object being tested, including the process of acquisition, storage, processing, analysis and understanding of the image or video. Using computer vision to detect surface defects can improve product quality and reduce product cost. At present, the surface defect detection of many objects usually adopts manual detection method. However, human eyes have individual differences in resolution and are prone to fatigue, which can easily lead to false detection and missed detection. Therefore, the surface defect detection method based on computer vision proposed in this paper is proved to have research and application value.

2. Image Preprocessing

In the original image of industrial products acquired by image acquisition equipment, there are often some noises that interfere with image analysis, so it is necessary to pre-process the image firstly, before analyzing the defect by model algorithm. In this paper, for the application of surface defect detection of industrial products, image denoising and image enhancement are applied to the original image respectively [1].

2.1. Image Denoising

In the process of image acquisition, noise usually exists in the original image due to the interference of surrounding environment and equipment. According to the type and characteristics of noise, choosing the appropriate filter can help to remove the noise in the image. In this paper, an improved median filter is used to denoise speckle noise and impulse noise in image. This filter algorithm scans the pixels in the image through a membrane, and the size of membrane center corresponds to its pixel size. As shown in Figure 1, this is a median filter with a size of 3 x 3.

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w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Figure 1. 3 x 3 median filter.

In Figure 1, $w = median\{w_i\} \quad i = 1,2,\ldots,9$.
The denoising effect diagram of median filter is shown in Figure 2.

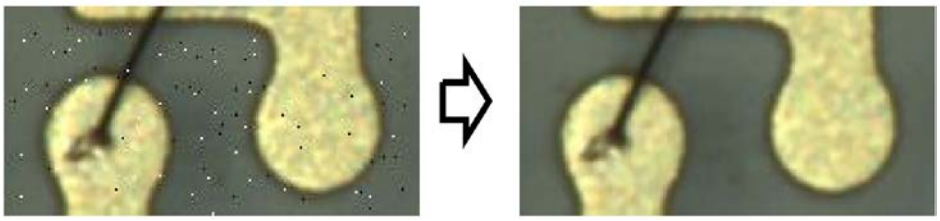


Figure 2. Denoising effect diagram of median filter.

2.2. Image Enhancement

In the process of image acquisition, due to the influence of camera, light and other conditions, some details of the image are often lost. So image enhancement is to make some important details more prominent in the image, while weakening the important information. Its goal is to improve the image quality and make it more suitable for some specific image analysis work. In this paper, a piecewise linear gray transformation method is used to realize image enhancement [2].

Piecewise linear gray scale transformation enlarges the gradient between different gray values to improve the detail contrast of the image, so as to realize image enhancement. The formula of piecewise linear gray level transformation method is as follows:

$$g(x,y) = \begin{cases} \dfrac{d-c}{b-a}[f(x,y)-a]+c & a \le f(x,y) < b \\ \dfrac{c}{a}f(x,y) & 0 \le f(x,y) \le a \\ \dfrac{M_g-d}{M_f-b}[f(x,y)-b]+d & b \le f(x,y) \le M_f \end{cases}$$

In the formula, $f(x,y)$ represents the original function image, while $g(x,y)$ represents the function image after piecewise linear transformation. Their gray scale ranges are $[0, M_f]$ and $[0, M_g]$ respectively. The transformed gray-scale image is shown in Figure 3.

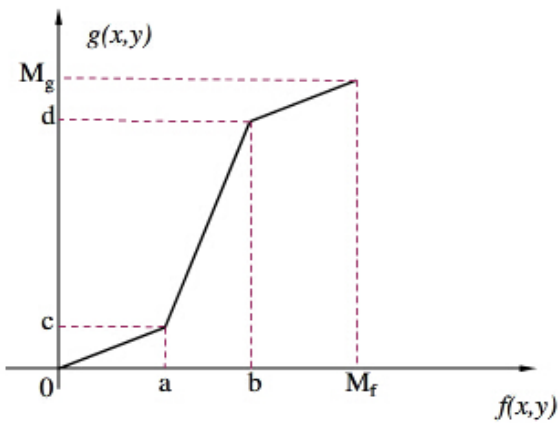


Figure 3. Gray level change of piecewise linear transform image.

It can be seen from the gray scale transformation graph that, the gray scale of each segment can be compressed or stretched by changing the position of the connecting points of the three segments or adjusting the slope of the segments. By adjusting the slope of the line segment between a and B to be greater than 1, the gray range of the partition is increased, and the gray value of the range is compressed, thus the purpose of image enhancement is realized [3].

3. Defect Detection Model Based on Computer Vision

Firstly, input a certain number of defective images and normal images, and divide them into several sub-images according to the same rules, then extract features to analyze the gray difference of these sub-images [4]. In addition, if the original size of the image is too large, in order to ensure the efficiency of the model algorithm, it is necessary to further extract the low-dimensional features from the gray difference features of the sub-image.

At the same time of reducing image feature dimension, in this paper, we also used a simple and effective regression learning model to perform defect analysis on the obtained image feature samples.

First of all, we build an S function as follow:

$$S(x) = \frac{1}{1 + e^{-x}}$$

The function $S(x)$ is monotonically increasing, and the function value increases from 0 to 1. A function value less than 0.5 indicates a defect image, and a function value greater than 0.5 indicates a normal image. By converting the defect feature vector of the image into an independent variable *x* input function, the output function value can be used to determine whether the image has a curve. The defect feature vector conversion weighting formula is as follows:

$$x = w_0 + w_1 n_1 + w_2 n_2 + \cdots w_t n_t = W^T N, \qquad \mathrm{N} = \{n_i | i = 1,2,\cdots,t\}$$

In the formula, w_i is weight coefficient. As long as the weight coefficient is determined, it is possible to analyze whether or not the image is defective after inputting any image. In this paper, a gradient ascending algorithm is used, and the logistic regression model is fitted with the determined defect image and normal image feature vector parameters, so as to obtain the weight coefficient w_i, and then analyze whether the input image is defective.

The gradient rise algorithm uses the obtained feature vector to iteratively iterate until it converges, thus obtaining the final privilege coefficient W, as follow:

$$W := W + \alpha \nabla f_w(W)$$

In the formula, α represents the speed of the iteration, ie the step size. The gradient formula of $f(x, y)$ is as follows:

$$\nabla f(x, y) = \left[\frac{\partial f(x, y)}{\partial x}, \frac{\partial f(x, y)}{\partial y}\right]$$

In the calculation process, in order to ensure the final convergence of the weight coefficients, it should be repeated multiple times. After calculating the weight coefficient W, the sample defect feature vector can be fitted by the regression model. The fitting method is as follows:

$$f_w(N) = S(W^T N) = \frac{1}{1 + e^{-W^T N}}$$

The overall process of defect detection is: firstly, split the target image is into several sub-images, and the analyze gradation difference of the sub-image separately; then, calculate the defect feature vectors and input these feature vectors into the regression model; finally, determine whether the image has defects by the value of the model output. The defect detection flow is shown in Figure 4.

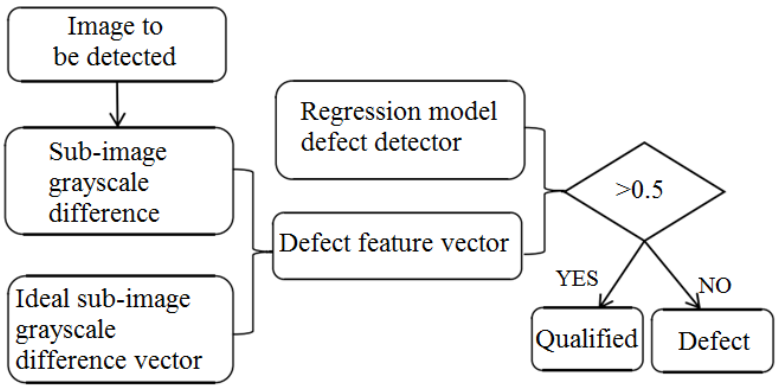
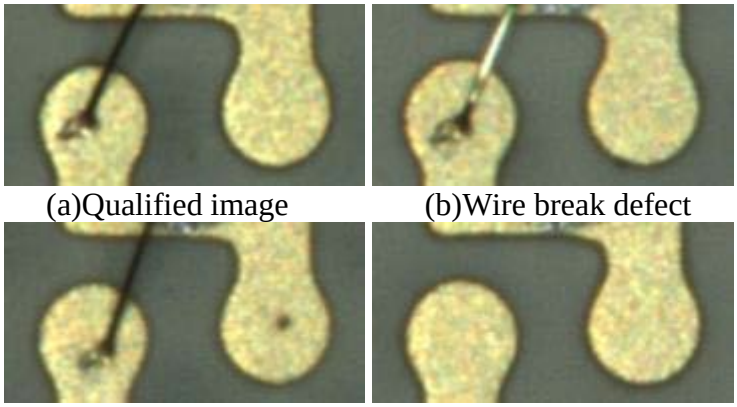


Figure 4. Defect detection flow.

4. Detection Result Analysis

Using the above defect detection model based on computer vision technology, and set the appropriate parameters such as number of iterations, step size and so on, and then enter specific sample data for training [5]. After the training is completed, the target image is input, and the system would quantitatively output the defect detection result in the form of a numerical value. In addition, we also use the support vector machine (SVM) classification algorithm for simulation under the same conditions， so as to verify the accuracy of the regression model algorithm by comparing the both test results. Although the method in this paper can effectively analyze whether the image has defects, it cannot accurately find the defective part in the image. We use a chip sample as the detection object, to detect whether there are defects such as broken wires, stains, and fewer wires on the surface of the chip, as shown in Figure 5.



(a)Qualified image (b)Wire break defect

(c)Stain defect (d)Missing wire defect

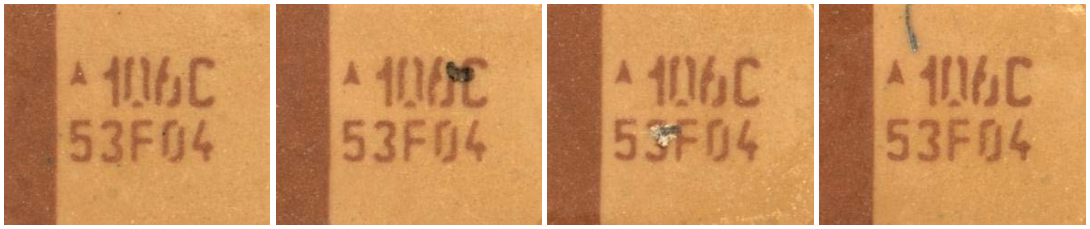
Figure 5. Contrast of chip surface qualified image and defect image.

We use 80 qualified chip images and 60 defective images as training samples for the model, and set the number of iterations to 1200 and the step size to 0.15. Defect detection was performed using the regression model and the SVM classification model, respectively, and the test results are shown in Table 1.

Table 1. Chip surface defect detection result.

–	Number of samples	Qualified sample number		Defect sample Accuracy		Accuracy	
		Regression model	SVM	Regression model	SVM	Regression model	SVM
Qualified sample	80	73	71	7	9	91%	89%
Defect sample	60	55	54	5	6		

Then, we selected some capacitor patches for testing, focusing on detecting defects such as stains, scratches, and damage on the patch, as shown in Figure 6.



(a)Qualified image (b)Stain defect (c)Damage defect (d)Scratch defect

Figure 6. Contrast of capacitor patch qualified image and defect image.

We use 75 qualified capacitor patch images and 50 defective images as training samples for the model, and set the number of iterations to 1200 and the step size to 0.15. Defect detection was performed using the regression model and the SVM classification model, respectively, and the test results are shown in Table 2.

Table 2. Capacitor patc defect detection result.

–	Number of samples	Qualified sample number		Defect sample Accuracy		Accuracy	
		Regression model	SVM	Regression model	SVM	Regression model	SVM
Qualified sample	75	70	69	5	6	93%	92%
Defect sample	50	51	49	9	11		

It can be seen from the test results that, the regression model after sample training has a high accuracy rate for industrial product surface defect detection, and even more accurate than the more complex SVM classification model. It indicates that the reversion model algorithm of this paper has a good application effect in defect detection, which can meet the high standards of defect detection of industrial products.

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