Machine Vision Based on Pipe Joint Surface Defect Detection and Identification

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Abstract. In the production process, pipe joints often have surface defects such as cracks, pits, bumps, etc., and the manual detection efficiency is low and the cost is high. This paper presents a machine vision based method for detecting surface defects of pipe joints. The preprocessing algorithm, image initial detection algorithm, image segmentation algorithm and feature extraction algorithm of tube joint surface defect image are studied and BP neural network classifier is designed. Finally, the designed classifier was tested by 300 samples of cracks, pits and bump defects on the surface of the pipe joint. The experimental results show that the recognition rate of the classifier reaches 95.5\%, which can better meet the surface of the pipe joint. Defect detection requirements.

Keywords. Pipe joint defects; machine vision; defect segmentation; feature extraction; BP neural network.

1. Introduction
The pipe joint is influenced by the forging processing technology, the related forging equipment and so on in the processing process, the surface often has the crack, the bruise, the pit and so on quality flaw. The inspection of surface defects of pipe joints in China adopts manual inspection, which mainly relies on the human eye to distinguish the defects, and the manual inspection has great limitations in practical application: (1) the long-term work of the human eye is easy to produce visual fatigue, resulting in missed inspection and false inspection; (2) the working environment of the pipe joint production workshop is poor, and the long-term work will cause harm to the body; (3) the real-time inspection of the product cannot be realized on-line, which will affect the production efficiency of the product\textsuperscript{[1]}.

The labor intensity of the manual inspection is high and the cost of the inspection is high. It can only be judged whether a certain part is defective or not\textsuperscript{[2]}. The detection of minor defects and complex background defects is not sensitive to the complete detection of product defects. Therefore, a more advanced method is needed instead of manual surface defect detection.

In recent years, with the rapid development of scientific information technology, the software and hardware technology of machine vision has also been developed rapidly, which provides the best scheme for the detection of surface defects of products. There are many advantages of using machine vision for surface defect detection: (1) Machine vision system can realize on-line detection, and continuously carry out high-speed and high-efficiency detection\textsuperscript{[3]}; (2) Standardization of product inspection results are not influenced by subjective factors; (3) recording and preserving relevant data in real time is helpful to find out the causes of defects and to carry out process control and adjustment\textsuperscript{[4]} help enterprises to reduce their manpower expenditure and save production cost. Therefore, the research
and development of visual detection algorithm for surface defects of pipe joints cannot only improve the automation level of forging enterprise production line, but also bring great economic and social benefits.

2. Design of Test Platform for 1 Tube Joint Testing
The hardware system of tube joint surface defect detection plays a decisive role in the detection results. The hardware mainly includes lens, camera, light source and industrial control computer. The hardware system completes the collection of high quality tube joint defect image under the action of light source and transmits it to industrial PC for related image processing operation. The article selects the Mako G-507C model camera from Allied Vision, Germany, the Computer M3520-MPW2 model lens from Daheng, and the industrial PC and LED light source from Yanhua. The experimental platform for pipe joint detection is shown in figure 1.

![Figure 1](image1.png)

**Figure 1.** Test platform for pipe joint: 1-light source; 2-dark box; 3-camera; 4-lens; 5-small forgings; 6-industrial PC; 7-computer.

3. Defect Image Preprocessing and Image Segmentation

3.1. Image Preprocessing
Due to the noise of illumination, air impurity and dust, photoelectric converter and camera device, the image surface defect image of the pipe joint is often presented as isolated pixel point or pixel block which causes strong vision, so the original image cannot be segmented and recognized directly, so some image preprocessing algorithms are needed to improve the image quality [5]. Three defect-free images, crack images, bruise images, and pit images were selected from the collected tube joint surface defect images, and then the median filter, mean filter, gaussian filter, adaptive median filter denoising and calculating the average values of their PSNR, MSE and SSIM were carried out respectively. the results are shown in table 1, and the denoising effect of adaptive median filtering is better. the adaptive median filtered image is shown in figure 2.

![Figure 2](image2.png)

**Figure 2.** Adaptive median filter.

| Filter                | PSNR   | MSE    | SSIM  |
|-----------------------|--------|--------|-------|
| Mean filter           | 32.0705| 41.1719| 0.9336|
| Median filtering      | 37.7016| 11.8364| 0.9577|
| Gauss filter          | 34.4625| 23.8636| 0.9507|
| Adaptive median filter | 38.3192| 11.1938| 0.9605|

3.2. Initial Image Inspection
95% The pipe joints produced by the enterprise are all non-defect forgings, only a small number of parts have defects on them, the purpose of the initial inspection of the image is to detect the defective small forgings for subsequent processing, and remove the images without defects. It is helpful to shorten the detection time and improve the real-time performance of the system. This paper determines whether the image is defective or not.

**Table 1.** Filtered PSNR, MSE and SSIM values.
The differential shadow image is obtained mainly by subtracting the template image and the preprocessed image. When there is no defect in the image, the gray value of all points of the difference image is 0, and if there is a defect, the gray value of the difference image is not 0 pixels. The basic ideas are as follows:

Firstly, the difference image between the tube joint template image and the current image is calculated, and a threshold is set to binarize the difference image. When the pixel point of the tube joint difference image is larger than that value, it is proved that there is a defect in the collected image, otherwise, there is no defect on the surface of the tube joint, and the image is deleted. The formula is expressed as follows:

\[
g(x, y) = \begin{cases} 
1 & k(x, y) \geq T \\
0 & k(x, y) < T 
\end{cases}
\]  

(1)

Poor shadow detection algorithm is simple and practical. It is helpful to improve the real-time performance. Therefore, this paper chooses the differential shadow algorithm for the initial inspection of the defect image of the pipe joint.

3.3. Image Segmentation
Defect segmentation is a key step in image processing and image recognition. The effect of segmentation directly affects image recognition and even determines the success or failure. The surface defect image of the pipe joint consists of two parts: background and defect area. In order to identify and analyze the defect, it is necessary to use the corresponding algorithm to extract the defect area of interest.

The surface defect can be divided into “contrast defect” and “pattern defect” from the point of view of the defect. There are obvious differences in the defect area and background of the defect, but the defect area and background of the pattern defect are not different in color and gray, but the texture and pattern are different [6]. A threshold-based segmentation algorithm is used for contrast defects. In this paper, by designing the experimental illumination scheme, the surface defect image of the pipe joint is a contrast type defect image, so the defect area is segmented mainly by the threshold pair.

The OTSU algorithm, also called the maximum inter-class variance method, is considered to be the best algorithm in the image threshold segmentation algorithm because it is simple and independent of the brightness and contrast of the image [7]. In this paper, the defect area of the OTSU segmentation tube joint is selected, and the image segmentation results are shown in figure 3. The basic principles of OTSU are as follows:

Suppose the total number of pixels of the input image is N, the gray level is \([0, L - 1]\), \(n_i\) represents the number of pixels of the gray level is \(i\), and the probability of each gray level is:

\[
p_i = \frac{n_i}{N}
\]  

(2)
\[ \sum_{i=0}^{L-1} p_i = 1, \quad p_i \geq 0 \]  

Assuming that the threshold value \( T(k) = k \) is selected, \( 0 \leq k \leq L-1 \), and the image is divided into \( C_1 \) and \( C_2 \) categories, the gray scale range of \( C_1 \) is \([0,k]\), and the gray scale range of \( C_2 \) is \([k+1,L-1]\), the probability of the occurrence of class \( C_1, C_2 \) is as follows:

\[ P_1(k) = \sum_{i=0}^{k} P_i \]  

\[ P_2(k) = \sum_{i=k+1}^{L-1} P_i = 1 - P_1(k) \]  

And the average gray value of the whole image is \( C_1, C_2 \) as follows:

\[ m_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^{k} iP_i \]  

\[ m_2(k) = \frac{1}{P_2(k)} \sum_{i=k+1}^{L-1} iP_i \]  

\[ m_G = \sum_{i=0}^{L-1} iP_i \]  

The inter-class variance is defined as follows:

\[ \sigma^2 = \frac{(m_G P_1 - m)^2}{P_1 (1 - P_1)} \]  

Let \( k \) traverse the whole gray level at \([0,L-1]\), and get the maximum \( k \) value of \( \sigma^2 \) is the optimal segmentation threshold.

![Figure 3. OTSU segmentation.](image)

3.4. Target Segmentation Location in Defect Area

The defect area of the tube joint image only accounts for a small part of the whole image, and after image preprocessing and image segmentation, the defect area needs to be located. Based on horizontal and vertical projection, the defect region image of the surface defect region of the binarized pipe joint is located, that is, the minimum rectangular region of the defect region of the pipe joint is located [8]. The steps are as follows:

(1) The vertical and horizontal projection of the surface defect image of the pipe joint after binarization is carried out, and the statistical diagram of the projection bright spots in two directions is obtained. The formula is as follows:

Level:
\[ H(y) = \sum_{x=0}^{M} g(x, y) \quad (y = 0, 1, 2, \ldots, M - 1) \]  
(10)

Vertical:

\[ H(x) = \sum_{y=0}^{N} g(x, y) \quad (y = 0, 1, 2, \ldots, N - 1) \]  
(11)

(2) According to the horizontal and vertical projection statistics of the defect area, the coordinate range of horizontal and vertical direction in the defect image of the pipe joint is determined, and the location of the defect area is realized.

According to the above method, the defect area of the crack, pit and bruise defect of the pipe joint is located, and the results are as follows.

The location results of the crack defects are shown in figure 4.

![Figure 4. Location of crack defect area.](image)

The area positioning results of the pit defects are shown in figure 5.

![Figure 5. Location of pit defect area.](image)

The result of the area localization of the bruise defect is shown in figure 6.

![Figure 6. Location of bruising defect area.](image)

4. Selection and Identification of Defect Area Feature Extraction

4.1. Defect Feature Extraction

(1) Geometric characteristics. Geometric features are the basic features of the target area of the image. In this paper, we mainly extract the geometric features of the defect area of the pipe joint, such as circumference, area, aspect ratio, rectangle, circularity and so on.
Suppose \( f(x, y) \) represents the input image, \((x, y)\) represents the coordinates of pixel points, the maximum value of coordinates is \( x_{\text{max}} \) and \( y_{\text{max}} \), the minimum value is \( x_{\text{min}} \) and \( y_{\text{min}} \), the set of edge points in the defect area is \( R_b \), and the set of target area points in the defect area is \( R_d \). The following geometric features are extracted from the defect area of pipe joint:

(a) Area \( S \) of the defect area refers to the total number of pixels in the defect area [9].

\[
S = \sum_{(x, y) \in R_d} 1
\]  

(b) The circumference of a defect area, the total number of pixels at the edge of the defect area [10].

\[
L = \sum_{(x, y) \in R_b} 1
\]

(c) The ratio of height to width of the defect area to the slenderness of the defect area refers to the ratio of vertical height to horizontal width of the rectangle cut out of the defect area [11].

\[
l = \frac{H}{W}
\]

(d) The ratio of the area of the defect area to the area of the outer-cut rectangle [12].

\[
R = \frac{S}{H \times W}
\]

(e) The extent to which the defect is nearly circular refers to the ratio of the square of the defect area circumference to the area of the defect area [13].

\[
C = \frac{L^2}{4\pi S}
\]

(2) Grayscale features. Usually, the gray features of the defect area are described by the statistical features of the defect area histogram, which represents the gray distribution of the defect area on the surface of the pipe joint, and contains the necessary feature information for the defect classification. The definition of the first-order gray histogram of the image with gray level \( K \) is shown in the following formula:

\[
P(k) = \frac{N(k)}{M} \quad (k = 0, 1, 2, \ldots, L - 1) \]

In the above equation, \( M \) represents the total number of pixels in the image region, and \( N(k) \) represents the number of pixels with a gray level of \( K \).

In this paper, the gray histogram of the defect area of the pipe joint is obtained, and the following gray features are extracted:

(a) Gray average

\[
\bar{k} = \sum_{k=0}^{L-1} kP(k)
\]

(b) Gray variance \( \sigma^2 \)
\[ \sigma^2 = \sum_{k=0}^{L-1} (k - \bar{k})^2 P(k) \]  

(19)

(c) Energy \( H_p \)

\[ H_p = \sum_{k=0}^{L-1} P(b)^2 \]  

(20)

(e) Entropy \( H_E \)

\[ H_E = \sum_{k=0}^{L-1} P(b) \log_2 (P(b)) \]  

(21)

(f) Minimum gray value \( \min G \)

\[ \min G = \min \{ f(i, j) \} \]  

(22)

(3) Texture features

The texture feature reflects a regional feature, which is related to the size, shape, direction and position of the object, and has the characteristics of strong noise resistance and rotation invariance. Different defects on the surface of the pipe joint have their own unique texture characteristics. In this paper, the related texture features of the surface defects of the pipe joints are extracted by the gray level symbiosis matrix. Extract the following texture features for the surface defect area of the pipe joint:

(a) Contrast \( \text{Con} \)

\[ \text{Con} = \sum_i \sum_j (i - j)^2 P(i, j) \]  

(23)

(b) Second-order angular moment \( \text{Asm} \)

\[ \text{Asm} = \sum_i \sum_j P(i, j)^2 \]  

(24)

(c) Texture Entropy \( \text{Ent} \)

\[ \text{Ent} = -\sum_i \sum_j P(i, j) \log P(i, j) \]  

(25)

(d) Relevance \( \text{Corr} \)

\[ \text{Corr} = \left[ \frac{\sum_i \sum_j ((ij)P(i, j) - u_x u_y)}{\sigma_x \sigma_y} \right] \]  

(26)

In the upper form

\[ u_x = \sum_i \sum_j i P(i, j) \]  

(27)

\[ u_y = \sum_i \sum_j j P(i, j) \]  

(28)
\[ \sigma_x = \sqrt{\sum_i \sum_j (i-u_x)^2 P(i, j)} \]  
\[ \sigma_y = \sqrt{\sum_i \sum_j (j-u_y)^2 P(i, j)} \]  

(29)  
(30)

4.2. Experiment of Feature Extraction in Defect Area of Pipe Joint

Get the defect area segmentation and grayscale map of the defect image of the pipe joint. The geometric features of the defect area are extracted by the binarized image of the pipe joint, and the grayscale and texture features of the defect area are obtained by the grayscale image of the defect area. In this paper, the 14 feature values of the defect area of the pipe joint are extracted in Table 2. The binarization and grayscale of the defect area of the sample of the pipe joint are shown in Figure 7.

| Category         | Crack 1 | Crack 2 | Crack 3 | Pit 1 | Pit 2 | Pit 3 | Touch 1 | Touch 2 | Touch 3 |
|------------------|---------|---------|---------|-------|-------|-------|---------|---------|---------|
| Area             | 9.5     | 27      | 13      | 21.5  | 45    | 47.5  | 61.5    | 115     | 87.5    |
| perimeter        | 23.071  | 35.313  | 25.313  | 25.5563| 26.142| 30.727| 61.556  | 93.539  | 69.213  |
| aspect ratio     | 5       | 4.9474  | 4.4667  | 1.6735 | 1     | 1.8445| 6.1017  | 10.142  | 5.8873  |
| Rectangular      | 0.475   | 0.5594  | 0.4786  | 0.438775| 0.7438| 0.6359| 0.4640  | 0.6138  | 0.5167  |
| Circular         | 4.4609  | 3.6773  | 3.9244  | 2.4186 | 1.2091| 1.5826| 4.9054  | 6.0571  | 4.3589  |
| Mean value       | 65.727  | 70.833  | 59.659  | 97.3485| 99.160| 123.51| 79.345  | 80.748  | 74.578  |
| Variance         | 20.612  | 18.093  | 15.146  | 5.3157 | 4.3684| 21.955| 18.118  | 27.708  | 17.473  |
| Energy           | 0.2061  | 0.3286  | 0.1862  | 0.2469 | 0.3032| 0.1917| 0.3666  | 0.3075  | 0.1820  |
| Entropy          | 10.528  | 11.023  | 13.242  | 12.2387| 11.084| 12.679| 10.640  | 10.998  | 13.178  |
| Minimum gray value| 27      | 32      | 42      | 87     | 56    | 62    | 19      | 24      | 38      |
| Contrast         | 175.20  | 46.16   | 263.83  | 387.99 | 167.57| 237.00| 226.60  | 123.80  | 208.50  |
| Second-order angular moment | 0.0004  | 0.0005  | 0.0004  | 0.00014| 0.00015| 0.0001| 0.0007  | 0.0006  | 0.0008  |
| Texture Entropy  | 0.2158  | 0.3338  | 0.2469  | 0.6836 | 0.5535| 0.4861| 0.1728  | 0.2234  | 0.1785  |
| Relevance        | 0.7746  | 3.0133  | 1.4003  | 0.2639 | 2.3815| 0.099 | 1.4386  | 1.188   | 1.8080  |
It can be seen from the above table that the aspect ratio of cracks and bruises, the circularity is larger, the aspect ratio of pits is relatively small, and the circumference and area of bruises are relatively large. The mean gray value, the minimum gray value of the pit defect is larger than that of the crack and the bruise, the angle second moment of the bruise is the largest, and the texture entropy of the pit is larger.

4.3. Classifier Design

The pipe joint surface defect detection system studied in this paper converts the categories of three defects: \([0,0,1]\) represents crack, \([0,1,0]\) represents pit, and \([1,0,0]\) represents bump. The same category of defects are input together in the training process. The design process of BP neural network is described in detail below.

The number of neurons in the input layer, the hidden layer and the output layer are firstly determined when designing the pipe joint defect classifier. The number of input layers is related to the number of extracted features. In this paper, 14 feature values are extracted, so the number of neurons in the input layer is 14. The number of neurons in the output layer is the number of training samples of pipe joint, and the number of output layer is 3. Hidden layer has a multilayer structure and single layer structure, the calculation of multilayer structure is complex, high operation speed, in this paper, the choice of a single layer, the number of hidden layer neurons number according to the related empirical formula obtained range between 5-15, the number of neurons in hidden layer in this experiment the initial value is set to 5, and then gradually increased to 15, respectively, experiments, choose the number of neurons with high recognition rate in final and the number of neurons in the hidden layer. The learning rate is between 0.01 and 0.8. The initial weight is usually a random number between -1 and 1. The network is shown in table 3.

After the parameters of the classifier were determined, 70 samples of each defect were selected to train the classifier. After 24 times of training, the designed BP neural network classifier reached the target error of the design, and the prediction accuracy of the designed classifier was 0.9998. The results of BP neural network classifier are shown in figure 8. After the BP neural network was trained,
90 test samples (30 for each crack, pit and bump) were used to test the classifier. The test results are shown in table 4.

| Training methods | Number of neurons in input layer | Number of hidden layer neurons | Number of neurons in output layer | Maximum number of training | Error accuracy | Learning rate |
|------------------|---------------------------------|-------------------------------|----------------------------------|----------------------------|----------------|--------------|
| Train            | 14                              | 14                            | 3                                | 500                        | $10^{-4}$       | 0.1          |

![Figure 8. Training results of BP neural network classifier for pipe joint.](image)

**Table 3. BP neural network related parameters.**

| Type of identification | Test samples | Correct number | Misjudgment | Recognition rate |
|------------------------|--------------|----------------|-------------|------------------|
| Cracks                 | 300          | 287            | 13          | 95.7%            |
| Pits                   | 300          | 288            | 12          | 96.0%            |
| Touch                  | 300          | 282            | 18          | 94.0%            |
| Total                  | 900          | 857            | 43          | 95.2%            |

From table 4, it can be seen that the accuracy of classification and identification of surface defects of pipe joints based on bp neural network is over 95%, which can better realize the classification and identification of surface defects of pipe joints.

**5. Conclusion**

In this paper, an experimental platform for detecting the surface defects of pipe joints is designed to study the surface defects image preprocessing, initial image detection, image segmentation, feature extraction and defect recognition technology of pipe joints able to meet the inspection requirements in production. The successful rate of surface defect classification in BP neural network is over 95%.

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