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Surface Defect Detection Method for Welding Robot Workpiece Based on Machine Vision Technology

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With the development of welding technology and the improvement of automation level, welding robots are playing an increasingly important role in industrial production. However, during the welding process, due to factors such as material characteristics, welding parameters, or improper processes, defects may appear on the surface of the workpiece, which may reduce the quality and service life of the workpiece. In order to solve this problem, this article used frequency domain feature extraction and nearest neighbor classifier in workpiece detection algorithms under machine vision technology to extract and classify surface defect images of workpiece, and studied the detection method of welding robot workpiece surface defects. The research results indicated that, under the same other conditions, the accuracy of machine vision technology was over 90% for all five different defect types, while the accuracy of traditional technology was between 75.5% and 84%. The performance of machine vision technology was far superior to traditional technology, indicating that machine vision technology could improve the accuracy of welding robot workpiece surface defect detection methods.

Keywords: surface defect detection, machine vision technology, welding robot, accuracy rate, detection and response time

1 Introduction

With the continuous development of welding technology, welding robots have gradually replaced traditional manual welding methods and become important equipment in the modern welding field. However, in the application process of welding robots, the detection of surface defects on workpiece has always been a challenging problem. Traditional visual inspection methods require a large amount of manual involvement, are time-consuming and laborious, and prone to errors, It cannot meet the requirements of efficient and accurate detection. Machine vision technology can achieve automatic detection and classification of surface defects in welded workpiece through the use of image processing and pattern recognition, and has the advantages of high efficiency and precision. This can not only improve the quality and efficiency of welding processes, but also reduce labor costs and achieve intelligent production and manufacturing.

In the welding production process, the detection of surface defects on workpiece is an important and complex task, so there have been many research results on it. Among them, in order to solve the problem of low accuracy in identifying surface defects of small-sized metal workpiece, Wang Yi combined attention mechanism with Ghost convolution on the basis of the network and proposed a surface defect recognition algorithm based on neural networks. The research results showed that the average accuracy of the improved network was 0.9978, which was 7.07 percentage points higher than the original network. This indicated that the network significantly improved the accuracy of metal workpiece surface defect detection [1]. The detection of workpiece surface defects is an indispensable part of modern industry. The use of convolutional neural networks can effectively improve the detection efficiency. However, due to the existence of subtle defects on the workpiece surface, the characteristics of defect parts are easily covered by the characteristics of other parts, reducing the detection accuracy. To this end, Wang Yiming proposed a three-level visual attention network, which combined three convolutional modules at each level with a visual attention module. By weighting the skeleton features constructed by the convolutional module, the features of the defect area were enhanced, and the features of the background area were suppressed to improve the recognition accuracy of the defect area. Research found that in areas prone to errors, the weight of soft attention templates was higher; adding a visual attention module could improve the accuracy of defect recognition from 90.9% to 98.1% [2]. Li Zhihui took circular metal workpiece as the research object, and designed corresponding orthogonal experimental schemes by adjusting the brightness of the light source and the angle between the workpiece and the camera, as well as the angle between the workpiece and the camera. The surface image of the workpiece was processed to determine the characteristics of defects, and the experimental results were analyzed. The experimental results showed that obtaining the optimal placement position among these three factors through orthogonal experiments could better determine the surface defects of metal workpiece. This provided a fast and practical method for achieving the placement of light sources, cameras, and inspected workpiece in machine vision based automatic workpiece grinding technology [3]. However, the above detection methods require a large amount of manual involvement, are time-consuming and laborious, and prone to errors. These cannot meet the needs of efficient and accurate detection.

The development of machine vision technology has provided new solutions for surface defect detection of welding robot workpiece, and more and more scholars have combined and analyzed the two, resulting in a large number of research results. Among them, the detection of surface defects is an important measure to prevent defective products from entering the market. Using machine vision technology to detect them is both efficient and economical, and is the main trend of future development. Zhao Langyue provided a detailed description of 30 typical industrial defect samples and evaluated their performance; finally, the existing problems in current research on defect recognition technology were identified, and future research directions were proposed [4]. In response to the problems of low defect localization accuracy, low recognition rate, and low classification accuracy in existing metal surface quality detection technologies, Zhou Shente constructed a sheet metal surface quality detection system based on machine vision and used the least squares feature transformation algorithm to extract defect feature points. He combined BP (Back Propagation) neural networks with support vector machine and constructed a surface quality detection method for sheet metal based on the combination of BP neural networks and support vector machine. Through experiments, it could be found that the defect detection rate of the defect detection system reached 92.68%, and the detection time for a single frame image was only 498 ms. This indicated that the system could effectively extract and identify defects on the surface of metal plates, meeting the online detection requirements of metal plate surfaces [5]. The above research provides a theoretical basis for combining machine vision technology with welding robot workpiece surface defect detection methods.

This article aimed to study the detection method of surface defects in welding robot workpiece based on machine vision technology. By analyzing and processing welding workpiece images, automatic detection and classification of workpiece surface defects could be achieved. This article used machine vision technology and traditional technology to conduct experiments on detecting surface defects of workpiece using two types of welding robots. By comparing accuracy, average detection time, average response time, and ease of use, it was proved that machine vision technology could significantly improve the effectiveness of welding robot workpiece surface defect detection methods, and could provide a new solution for workpiece surface defect detection problems in the field of welding robots, promoting the development and application of welding technology. In practical production, this method was expected to reduce the cost and risk of manual inspection, improve the quality and efficiency of welding processes, and contribute to the development of industrial manufacturing.

2 Materials and Methods

2.1 Collection, preprocessing, and workpiece detection algorithms for surface defects of workpiece

Surface defects of welding robot workpiece refer to various surface defects that occur during the welding process, including uneven welding seams, pores, slag inclusions, cracks, etc. [6,7]. These defects have a direct impact on the welding quality, which may lead to issues such as reduced strength of the workpiece, decreased sealing performance, and poor corrosion resistance. Surface defects in welded workpiece have a direct impact on welding quality. In response to these defects, strict control of parameters, appropriate welding processes and materials, and necessary quality inspection and repair work are required during the welding process to ensure the quality and reliability of welded joints [8,9].

In order to better detect surface defects of workpiece, image acquisition of workpiece is the foundation of the entire detection and recognition. Therefore, selecting image transmitters and light sources is particularly important. At the same time, an image acquisition platform was constructed and an image acquisition software was written to achieve the collection of workpiece images [10,11].

(1) Image sensor

The image sensor is the core component of a camera, which converts optical signals into corresponding electrical signals. The performance of the sensor has a significant impact on the quality of the collected surface defect images of the workpiece. Therefore, the selection of image sensors is very important [12,13].

With the continuous improvement of CMOS (Complementary Metal Oxide Semiconductor) technology, people have developed various types and performance indicators of CMOS image sensors.

The portable digital microscope selected in this paper adopts USB (Universal Serial Bus) direct insertion and direct use mode. According to the size of the object to be detected, the size of the detection field is determined. The distance between the camera and the object to be detected is adjusted, and then the magnification of the portable digital microscope is adjusted, so that the surface defects of the workpiece can get a complete imaging effect [14,15]. CMOS sensor and portable digital microscope are shown in Table 1:

Tab. 1 *Basic information of CMOS sensor and portable digital microscope*

CMOS image sensor	sensitivity	High
	Signal-to-noise ratio	Good
	Integration degree	High
	Processing technology	Currency
	Reliability	High
	Dynamic range	Small
	Maximum frame rate	1000fps
	Cost	Low small
	Volume	Low (one tenth of Charge Coupled Device)
	Power dissipation	Fast (parallel read)
	Read pixel data speed	High
Portable Digital microscope	Activity	1280*10242pixels
	Pixel	8um*2.8um*
	Like element	1.0V/lux-sec
	Size	71.0 dB
	Sensitivity	44.0 dB
	Dynamic range	5.0MM ---∞
	Signal-to-noise ratio	1---40X; 240X
	Working distance	17fps@1280*1024
	Magnification factor	170 mW
	Frame power consumption	1280*10242

(2) Selection of light sources

Appropriate light sources and lighting methods are selected to make the light of the tested object shine on the tested object, highlighting its features and enhancing its feature contrast; choosing a suitable light source can effectively reduce the influence of external factors on feature values. The purpose of image acquisition is to obtain a clear background and object boundaries, as well as an image with consistent overall brightness values, thereby reducing subsequent processing work. The light source of LED (Light Emitting Diode) lamps is a cold light source, which would not cause deformation of objects due to excessive heating in visual inspection lighting. LED light sources have advantages such as fast adjustability, even automatic adjustability, energy conservation, and environmental protection, and LED point light sources are easy to achieve uniform lighting. Therefore, this article chooses LED white light sources to provide lighting. The basic situation is shown in Table 2:

Tab. 2 *Basic information of LED*

Type	LED
Colour	Many
Brightness	Centre
Life	Greater than 100000
Stability	High
Adjustable	Yes
Environment protection	Yes
Characteristic	Stable output, cheap price, small area

(3) Implementation of image acquisition

After selecting the LED ring light source and forward lighting method, this article constructed an experimental platform for image acquisition. Using Visual C++6.0 platform programming, the image acquisition of the electronic eyepiece curved packaging shell was completed.

2.1.1 Preprocessing of workpiece images

In general, the collected workpiece image is an RGB (Red Green Blue) tricolor image, and noise interference cannot be avoided in the image under on-site collection conditions. Image processing requires that the detected object's image be clear and have clear features, which requires appropriate image preprocessing. The selection and design of image preprocessing processes are largely determined by the feature selection and classification algorithm of the detected object.

The image preprocessing used in this article includes operations such as graying, filtering and denoising, and image enhancement. These preprocessing methods are different, but their purpose is the same, which is to maximize the completeness and clarity of image information. Fig. 1 shows the image preprocessing flowchart.

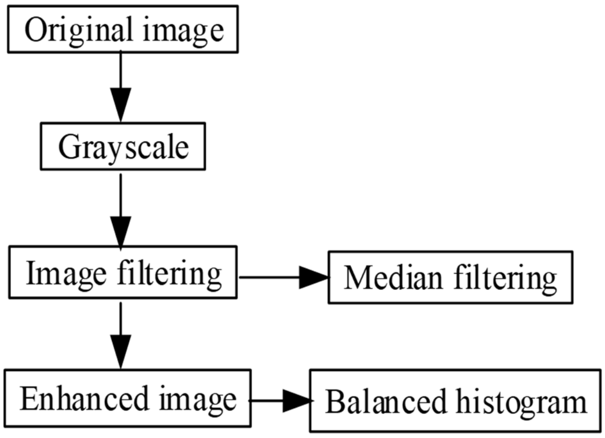


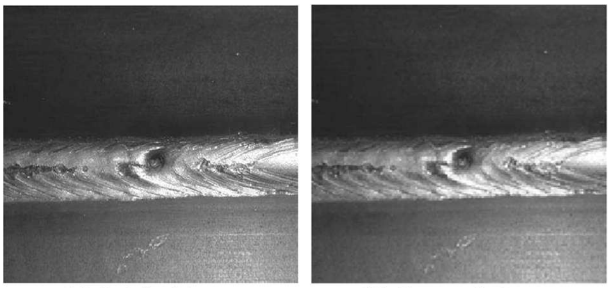
Fig. 1 *Image preprocessing flowchart*

In the pretreatment process of this paper, the original image is grayed first. The median filter is used to denoise it, and finally the histogram equalization method is used to achieve image enhancement, so as to increase the contrast between the defective and non defective areas of the image.

(1) Image grayscale

The obtained images are generally color images with complex information and three channels of information. The grayed image only has grayscale values, and simplifying the image information is beneficial for further processing. Meanwhile, the grayed image does not affect the main information such as image contours.

This article would use the weight weighting method for image graying, which uses RGB weights of 0.299, 0.587, and 0.114, respectively. The weight weighting method balances the impact of the pixel values of R, G, and B colors on grayscale in color images. The grayscale image is shown in Fig. 2:



(a) Original image (b) Grayscale image

Fig. 2 *Grayscale image*

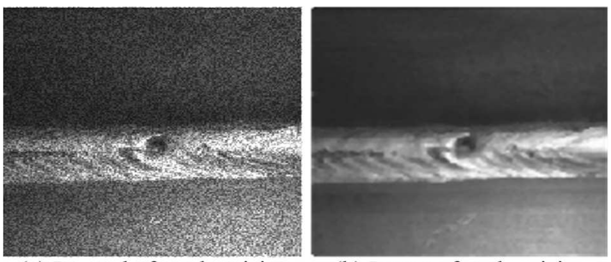
The calculation of grayscale is as follows:

$$J(a,b) = 0.299*R(a,b) + 0.587*G(a,b) + 0.114*B(a,b) \tag{1}$$

In Formula (1), $J(a,b)$ represents the grayscale value of the grayscale image at the point (a,b). $R(a,b)$, $G(a,b)$, and $B(a,b)$ represent the color information values of red, green, and blue in the color image at point (a,b), respectively.

(2) Median filtering

During the process of imaging and digitization, the original image would be affected by many types of external noise, which can reduce the quality of the image; In image processing technology, filtering is often used to filter out noise. The energy in the image is mainly distributed in the low frequency range, but the feature information in the high frequency range is often masked by noise. Different images need to be processed using different methods. When choosing a method, two points should be noted: Firstly, the filtering process should not affect the edges and other information of the image; secondly, the visual effect after filtering must be better than before. The median filter counts pixels one by one, which is a nonlinear filter; it has satisfactory noise removal ability for a variety of random noises, and has a good suppression effect on impulse interference and salt-and-pepper noise. Therefore, the median filtering method is used for image filtering in this paper. The results after denoising are shown in Fig. 3:



(a) Image before denoising (b) Image after denoising

Fig. 3 *Image median filtering denoising image*

(3) Image enhancement

Image enhancement refers to the enhancement of certain specific features in an image, such as edges and contours. Histogram equalization is a method of changing the distribution of image gray values. After stretching, the image gray values become evenly distributed. For the case that the image is too bright and too dim, the histogram equalization is very effective, so this paper adopts the histogram equalization method to achieve image enhancement. The enhanced image is shown in Fig. 4:

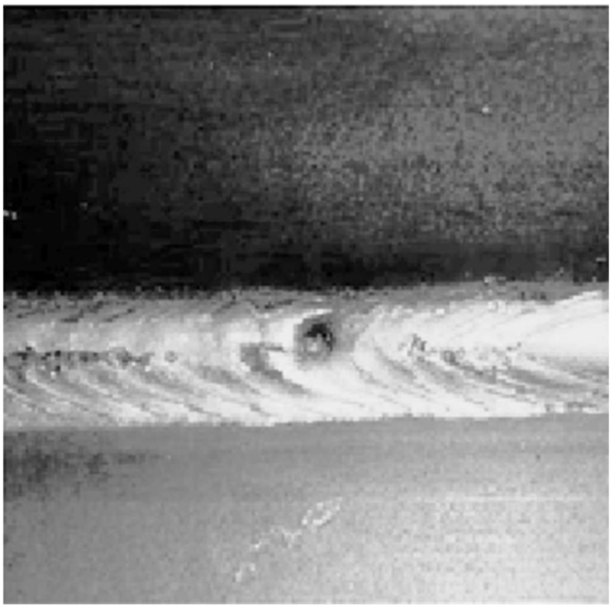


Fig. 4 *Enhanced image*

Comparing the histograms of the image before and after enhancement, it can be clearly observed that the histogram distribution of the enhanced image is more uniform, and the contrast of various regions in the image becomes more pronounced, achieving the effect of image enhancement.

2.1.2 Workpiece detection algorithm under machine vision technology

(1) Frequency domain feature extraction

In the frequency domain space, the Gabor transform in wavelet transform is used to construct a 5*8 Gabor filter.

Feature extraction:

Gabor filter banks perform convolution operations on workpiece images to obtain multi-scale and multi-directional filtered images. The grayscale mean and variance are used to form feature vectors to classify workpiece. It is assumed the given Gabor wavelet filter bank is as follows:

$$\rho = (\mu_{m1}, \mu_{m2}, \ldots, \mu_{mM}) \tag{2}$$

Gabor filters and image convolution operations are as follows:

$$H(O) = (\theta_{m1}, \theta_{m2}, \ldots, \theta_{mM}) \tag{3}$$

$$\begin{cases} \theta_{mo}(a,b) \iint O(a,b)\mu_{mo}(a\text{-}a_o)(b\text{-}b_o)fa_o fb_o \\ \quad m = (g, \vartheta, v_a, v_b) \end{cases} \tag{4}$$

$O(a,b)$ represents a Grayscale, and the average value φ_{mo} and variance τ_{mo} of the filtered image are taken to form the Gabor feature vector.

$$\varphi_{mo} = \iint |\theta_{mo}(a,b)| fafb \tag{5}$$

$$\tau_{mo} = \sqrt{\iint |\theta_{mo}(a,b)\text{-}\varphi_{mo}|^2 fafb} \tag{6}$$

$$g = [\varphi_{01}, \varphi_{02}, \ldots, \varphi_{40}, \tau_{01}, \tau_{02}, \ldots, \tau_{40}] \tag{7}$$

(2) Nearest neighbor classifier

The nearest neighbor distance classifier is the type of classifier with the least computational complexity among various classifiers. It only needs to calculate the distance between the feature values of the object to be detected and the feature vectors of the standard type, and then determine the type by the minimum distance between them and each type. This article chooses to calculate the Mahalanobis distance between the detected object and the known defect set to determine the type of defect.

Mahalanobis distance and Euclidean distance are the two most commonly used discriminative criteria using distance. Euclidean distance represents the actual distance between two points. Given points $a = (a_1, a_2, \ldots, a_q)$ and $b = (b_1, b_2, \ldots, b_q)$, their Euclidean distances in a q dimensional space are as follows:

$$f^2(a,b) = (a_1\text{-}b_1)^2 + \ldots + (a_q\text{-}b_q)^2 \tag{8}$$

When conducting multivariate data analysis, Euclidean distance shows its shortcomings. Firstly, the calculation process of Euclidean distance does not consider the impact of overall changes on distance. Secondly, the calculation of Euclidean distance is dimensional, which is unfavorable for multivariate data processing. Mahalanobis distance is a useful method for measuring similarity between samples, and it is not affected by dimensionality.

The mean vector of n dimensional population H is $\varphi = (\varphi_1, \varphi_2, \ldots, \varphi_n)$, and the covariance matrix of $\sum(\tau_{ok})$ is H. The Mahalanobis distance between sample $A = (a_1, a_2, \ldots, a_n)$ and population H is as follows:

$$f^2(A, H) = (A\text{-}\varphi)'\Sigma^{-1}(A\text{-}\varphi) \quad (9)$$

3 Discussion of results

3.1 Welding robot workpiece surface defect detection experiment

In order to verify the effectiveness and real-time performance of relevant image processing algorithms based on machine vision, this article conducted welding robot workpiece surface defect detection experiments and analyzed the experimental results.

3.1.1 Experimental design

This article aimed to develop an effective method for detecting surface defects in welding robot workpiece based on machine vision technology. In order to achieve this goal, this article designed a series of experiments and conducted a detailed analysis of the experimental results. This article selected suitable welding robots and related machine vision equipment, determined appropriate welding parameters, and ensured the stability and consistency of the welding process. At the same time, a certain number of welding workpiece were selected as experimental samples, and different types of defects were artificially introduced during the welding process, such as scratches, spot marks, inclusions, cracks, pits, etc.

In order to evaluate the accuracy and robustness of the welding robot workpiece surface defect detection method under machine vision technology, this method was compared with traditional welding robot workpiece surface defect detection methods, and accuracy, average detection time, and average response time were selected as performance evaluation indicators to measure the accuracy and comprehensiveness of the welding defect detection method.

3.1.2 Identification and classification effect evaluation

(1) Accuracy

This article prepared 200 sample images for collection, divided the images into 5 sample sets, and constructed a nearest neighbor classifier. This article projected the feature values to be classified onto the principal component feature matrix, and calculated the Mahalanobis distance between the sample and the mean of the feature set in Matlab (matrix&laboratory). The accuracy of the two methods for scratches, point marks, inclusions, cracks, and pits was calculated. For the rigor of the experiment, this article would repeat the above steps 10 times, and the recognition results for each time are shown in Fig. 5:

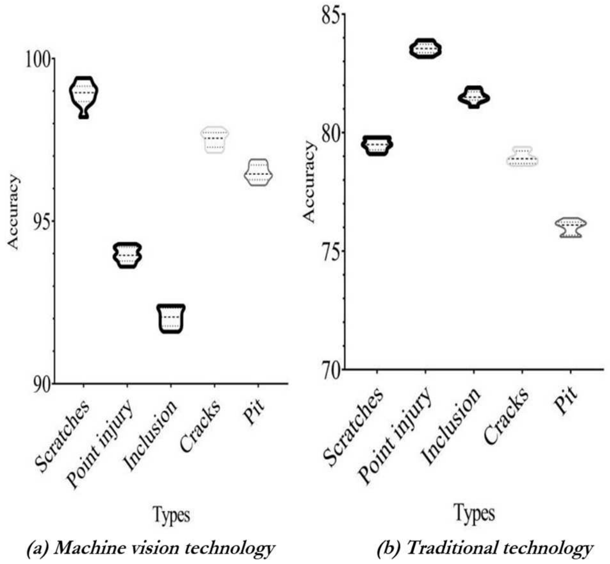


Fig. 5 *Accuracy of surface defect detection methods for welding robot workpiece under two technologies*

From Fig. 5 (a), it could be seen that for scratches, the maximum and minimum accuracy values were 99.4 and 98.2%, respectively. For point scratches, the maximum and minimum accuracy values were 94.3 and 93.6, respectively. For inclusions, the maximum and minimum accuracy values were 92.4 and 91.6%, respectively. For cracks, the maximum and minimum accuracy values were 97.9 and 97.1%, respectively. For pits, the maximum and minimum accuracy values were 96.9 and 96.1%, respectively; from Fig. 5 (b), it could be seen that for scratches, the maximum and minimum accuracy values were 79.8 and 79.1%, respectively. For point scratches, the maximum and minimum accuracy values were 83.9 and 83.2%, respectively. For inclusions, the maximum and minimum accuracy values were 81.9 and 81.1%, respectively. For cracks, the maximum and minimum accuracy values were 79.4% and 78.6%, respectively. For pits, the maximum and minimum accuracy values were 76.4 and 75.6%, respectively; from Fig. 5, it could be seen that for the five different types of defects, the accuracy of machine vision technology was above 90%, while the accuracy of traditional technology was between 75.5-84%, indicating that machine vision technology could improve the detection and classification effect of welding robots on surface defects of workpiece.

(2) Average detection time

The detection time refers to the time from the input image to the output of defect detection results. Its length can better reflect the relationship between machine vision technology and high welding robot workpiece surface defect detection methods. Therefore, this article calculated the detection time and the average detection time, as shown in Fig. 6:

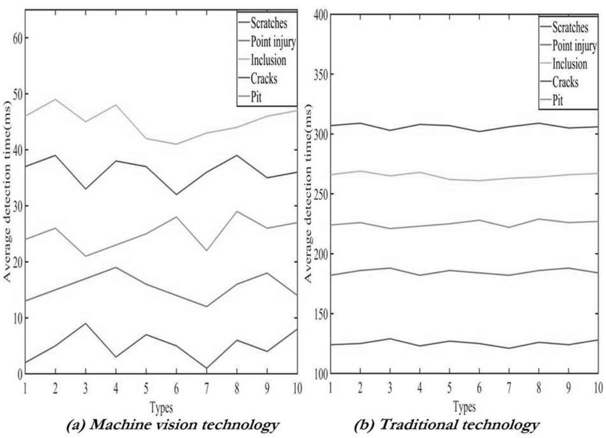


Fig. 6 *Average detection time of surface defect detection methods for welding robot workpiece under two different technologies*

From Fig. 6 (a), it could be seen that for scratches, the average detection time was below 10ms. For point wounds, the average detection time was between 11ms and 20ms. For inclusions, the average detection time was between 40ms and 50ms. For cracks, the average detection time was between 31ms and 40ms. For pits, the average detection time was between 20ms and 30ms; from Fig. 6 (b), it could be seen that for scratches, the average detection time was between 120ms-130ms. For point wounds, the average detection time was between 181ms-189ms. For inclusions, the average detection time was between 260ms-270ms. For cracks, the average detection time was between 301ms-310ms. For pits, the average detection time was between 220ms-230ms; from Fig. 6, it could be seen that for five different defect types, the average detection time of machine vision technology was below 50ms, while the average detection time of traditional technology was between 120ms-310ms, indicating that machine vision technology could improve the efficiency of welding robot surface defect detection of workpiece.

(3) Average response time

The response time of workpiece detection methods is influenced by multiple factors and is also related to hardware devices and software environments. When ensuring that these influencing factors are the same, only comparing the response time under machine vision technology and traditional technology can better reflect the quality of that technology. Therefore, this article recorded the average time under the two technologies, and the results are shown in Fig. 7.

From Fig. 7, it could be seen that under machine vision technology, the average response time of welding robots was between 5ms and 15ms. Under traditional technology, the average response time of welding robots was between 25ms and 35ms. Combining it with Fig. 6 could demonstrate that machine vision technology could enable welding robots to respond to input in a timely manner and quickly complete the task of detecting surface defects on workpiece.

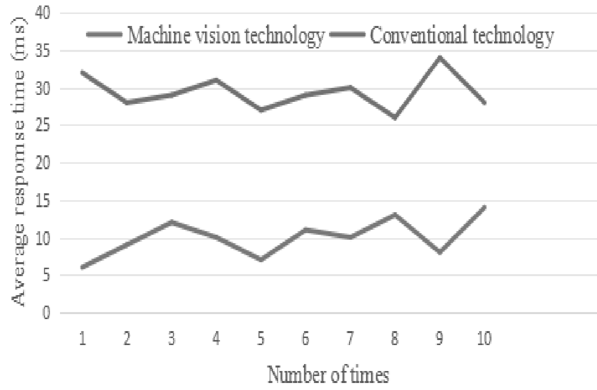


Fig. 7 *Average response time of surface defect detection methods for welding robot workpiece under two different technologies*

3.1.3 Evaluation of actual application effects

Usability refers to the degree to which a product or system is easy to operate, easy to understand, low in learning costs, and able to meet user needs for users. It is an important criterion for evaluating whether a product or system is easy to use. Here are some common usability indicators:

Learning curve: The learning time and effort required to use the technology or product are evaluated. Easy to use technology should have a low Learning curve, so that users can quickly start and master basic operations.

User interface design: The comprehensibility and intuitiveness of the user interface are evaluated. An easy-to-use interface should be concise and clear, providing clear navigation and operation guidance to avoid users getting lost or confused.

Interaction process: The smoothness of user interaction with technology or products is evaluated. Easy to use technology should provide a natural and consistent way of interaction, reducing users' cognitive burden and operational difficulty.

Error handling and feedback: The handling of user errors by technology or products is evaluated. Easy to use technology should provide clear error prompts and helpful information, guide users to correct errors, and provide immediate feedback.

Customizability: Whether the technology or product can meet the personalized needs of users is evaluated. Easy to use technology should have flexible configuration options and personalized settings, so that users can customize according to their preferences and needs.

Documentation and support: Technical or product documentation, help documentation, and user support resources are evaluated. Easy to use technology should provide clear and comprehensive documentation and support to help users solve problems and obtain necessary information.

These indicators can help evaluate the usability of technology or products and provide users with a better user experience. In practical applications, further evaluations and adjustments can be made based on specific scenarios and user needs.

Usability refers to the degree to which users can easily use a product or system and achieve expected goals by providing a clear, simple, and intuitive user experience. It focuses on user needs, user behavior, and user experience, and considers them as important considerations in the design and development process. Therefore, this article invited 20 experts in the field of welding robots to rate the usability of welding robots under two technologies to ensure good results in practical applications. The scores were divided into 10 levels (1-10 points), and the scores of each expert were counted. The higher the score, the better the usability. The average scores of each indicator are shown in Tab. 3:

Tab. 3 *The usability evaluation results of welding robots under two different technologies*

	Machine vision technology	**Conventional technology**
Learning curve	9.2	6.5
User interface design	9.4	6.1
Interactive process	9.1	6.9
Error handling and feedback	9.7	6.3
Customizability	9.5	6.7
Documentation and support	9.3	6.2
Total average score	9.4	6.5

According to Tab. 3, the rating of welding robots under machine vision technology was above 9 points, with a total average score of 9.4 points. However, under conventional technology, the rating of welding robots was between 6-7 points, with a total average score of 6.5 points. These data indicated that welding robots under machine vision technology had good usability, could meet customer needs in practical applications, and could demonstrate good application effects.

4 Conclusions

This paper would take the welding robot workpiece surface defect detection technology as the core, introduce the committed step of workpiece image acquisition and pre-processing, time-domain feature extraction and nearest neighbor classifier, and analyze a defect detection method based on machine vision technology. Comparing it with traditional technologies, it could be seen that machine vision technology could achieve automated detection and recognition of surface defects in welded workpiece, improve recognition accuracy, and reduce detection and response time. The research results demonstrated that the surface defect detection method of welding robot workpiece based on machine vision technology had great application prospects and practical value; by introducing this method, the quality control ability in the welding production process could be improved. Labor costs could be reduced, and production efficiency and product quality could be improved, bringing new opportunities and challenges to the development of the welding industry.

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