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Research on Defect Detection Method of Painting Parts Based on Machine Vision

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Abstract: - The technology is used to study and analyze the appearance defect characteristics of sprayed auto parts. The corresponding recognition method is developed by using MATLAB and Halcon software. Firstly, the causes of background noise and uneven brightness are described from the hardware and theory, and the specific treatment methods are given from the two perspectives of eliminating background noise and balancing illumination. A variety of frequency domain low-pass filters are constructed to eliminate background noise. The image preprocessing algorithm based on homomorphic filter is studied to achieve the expected preprocessing effect. The image segmentation method of local features is adopted, and the binary processing is carried out. Corresponding recognition algorithms are designed for different defect features. The on-line monitoring system of spraying quality is established and field test is carried out to verify the effectiveness of the system and realize the rapid and accurate identification of spraying quality. The single recognition time is 320 milliseconds, and the recognition accuracy is 97%. Compared with manual identification, it is improved by about 40% and meets the needs of industry applications.

Keywords:Machine Vision; Camera Calibration; Coating Parts; Defect Detection; Contour Feature.

I. INTRODUCTION

China's manufacturing industry has achieved amazing results in just a few years. The improvement of the production process level has not only promoted the production process of the manufacturing industry, but also changed the previous manual inspection methods and accelerated the classification and positioning of goods. This can greatly improve the productivity of enterprises, reduce the production cost of products, and improve the working conditions of workers [1]. At present, the manufacturing industry is facing the severe test of the transformation of the new production mode, and the original large-scale and simple production mode can no longer adapt to the growing small batch and personalized customization needs. The existing intelligent product testing methods based on pipeline are difficult to meet the requirements of classifying different categories of products.

It is a convenient and reliable method to inspect the surface quality of coated parts by using computer vision method[2]. Many experts of the coating parts sample surface quality detection, there is no a set of relatively perfect technical and theoretical articles. At present, the method based on directional chain coding tracking has been used to obtain the contour features of defects, and the defects are refined, but their noise resistance is weak. Some scholars put forward the mobile phone defect detection technology based on the combination of subtraction and gray projection. Some scholars use the modified maximum intra-class variation to detect track surface defects, but its accuracy needs to be further improved. Some researchers have introduced the surface defect detection technology of high-speed railway based on background differentiation into practice, but it is impossible to detect it effectively [3]. At present, a track damage identification method based on reverse P-M method has been proposed, but the method has a large number of control parameters, and it is difficult to use reverse P-M method to quickly identify track defects. It has been proposed to use gray-scale map to quickly divide trajectory surfaces, but its adaptive ability is not strong. Some scholars suggest using adaptive threshold surfaces to achieve binary image segmentation. Previous studies have shown that Hough transform can efficiently detect all kinds of Mura damage under non-uniform lighting conditions, but it is greatly affected by lighting conditions, difficult to deal with complex actual production scenes, and has poor adaptive ability. Some scholars have proposed a method based on local maximum variance to achieve efficient segmentation of cell blocks and recognition of gate breaks. Some researchers have compared the grayscale, grayscale gradient and shape of images on the surface of small magnetic tiles. It has been proposed that the eight-directional anisotropic Gaussian directional differential filter is used in the convolution filter to detect the defects of the handset shell by normalization. However, it is not suitable for surface defect identification of coated parts. Researchers have studied the elastic deformation of printed boards and the noise of the background spot, and studied the detection method of the convex spot fault of

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printed circuit boards [4]. By introducing the shape coefficient of the surface, the line contour obtained by preprocessing is segmented to get the protruding area. Some scholars have suggested that the new algorithm has good resistance to the background noise of the plate when resisting the elastic deformation of the plate, but the image quality obtained by it is very poor. Some scholars plan to use local Markov mode (LMP) for target detection. By analyzing the histogram characteristics of each line segment, the seed point set on each line segment is determined, and the defects on each line segment are initially inspected. Then according to the number of defects size to judge the defects on each line segment. The error rate is high. Therefore, this project intends to introduce mechanical vision into the flexible assembly line, adopt the improved template matching algorithm to realize automatic product identification, and obtain specific characteristic parameters through the visual test system built, so as to achieve accurate identification and matching of different categories and personalized products, so as to improve the production efficiency of products.

II. OVERVIEW OF MACHINE VISION

The general definition of machine vision in academia is: "The use of optical devices and sensors as the main parts, through the independent acceptance and automatic processing of the scenery in the real world, so as to obtain information and robot actions." After the above research, it can be seen that the machine vision system uses the relevant devices and software to process and analyze the images taken by the camera [5]. It is precisely because of this advantage that in the large-scale industrial manufacturing process, through the detection of its defects, real-time detection and improvement of product defects can be achieved. Among them, the most representative are: product appearance defects and cleanliness detection, circuit board line error detection. This method has greater flexibility, and can carry out non-destructive testing of the workpiece without contacting the tested object, and has good accuracy and fast test performance. Machine vision technology detects and analyzes goods through the images generated by the camera, and determines whether there are quality problems with the goods, and a device can inspect a variety of goods, thereby saving a lot of money and improving the overall economic benefits of manufacturing enterprises [6]. The research results of this project can provide a new method for automated and intelligent commodity inspection, so as to improve the accuracy and effectiveness of product inspection. A representative computer image acquisition system is shown in Figure 1.

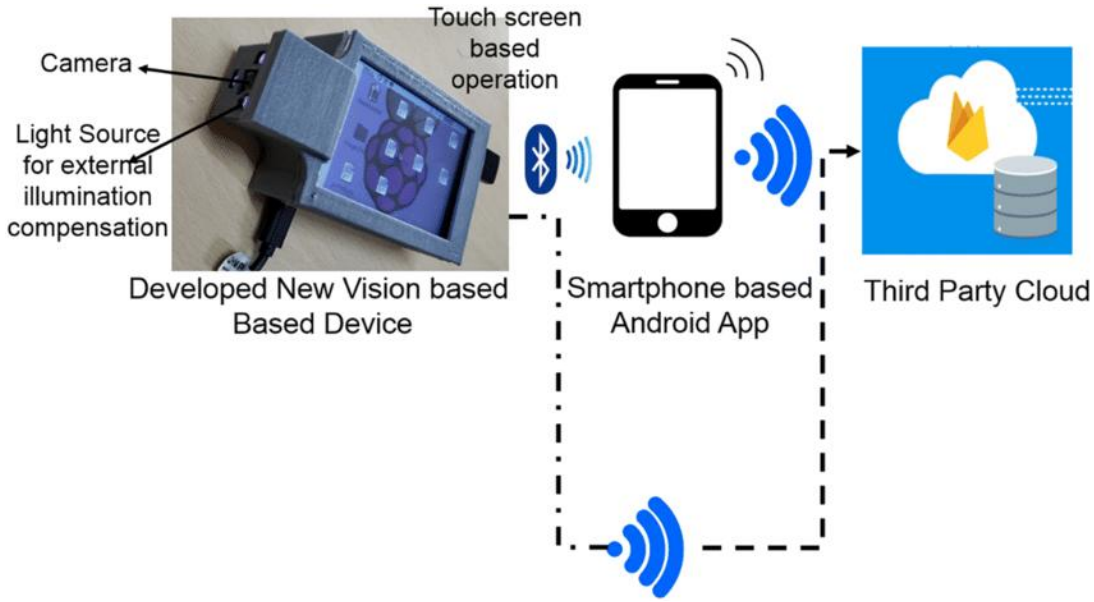

Fig.1 A typical vision acquisition system

III. FLEXIBLE PRODUCTION LINE AUTO PARTS DEFECT DETECTION BASED ON MACHINE VISION

Because this company has a large production scale, it is equipped with corresponding paint production lines for models of different shapes and sizes. However, due to the constraints of the production process and field production environment, most paint defects will appear on the surface of plate parts such as the outer end cover plate of the engine and the outer end cover plate of the transmission. Such defects will not only cause external sensory defects, but also lead to external sensory defects. It can also lead to reduced service life and reliability of components [7]. To this end, in accordance with the needs of enterprises and the market, the surface quality of paint products for body parts should be inspected, and strict inspection should be carried out to ensure the high

quality of paint products. By the combined action of a variety of factors, plate parts in the spray processing will produce flow hanging, scratches, spots, gumming and other different types of different types of surface defects, and with the arrival of intelligent manufacturing, the demand for the production line has also changed significantly, especially the flexibility of the production line put forward a higher demand.

A. System Architecture

At present, the visual defect detection system should be composed of four basic parts: image acquisition, data processing, mechanical transmission and electrical control. The system consists of two parts, including the construction of hardware test platform and the implementation of software control test algorithm [8]. Among them, in the construction of the hardware platform, including the structure of the conveyor, the overall frame, and other image acquisition parts such as cameras, lenses, light sources, as well as the construction of electrical control platforms such as PLC, PC, sensors. In the aspect of software, the realization of image preprocessing and fault identification algorithm, and the programming of logic control algorithm of the lower computer of the whole platform are mainly completed. the system is composed of hardware and software to realize non-destructive testing of vehicle parts (Figure 2 is quoted in Deep learning for the quality control of thermoforming food packages).

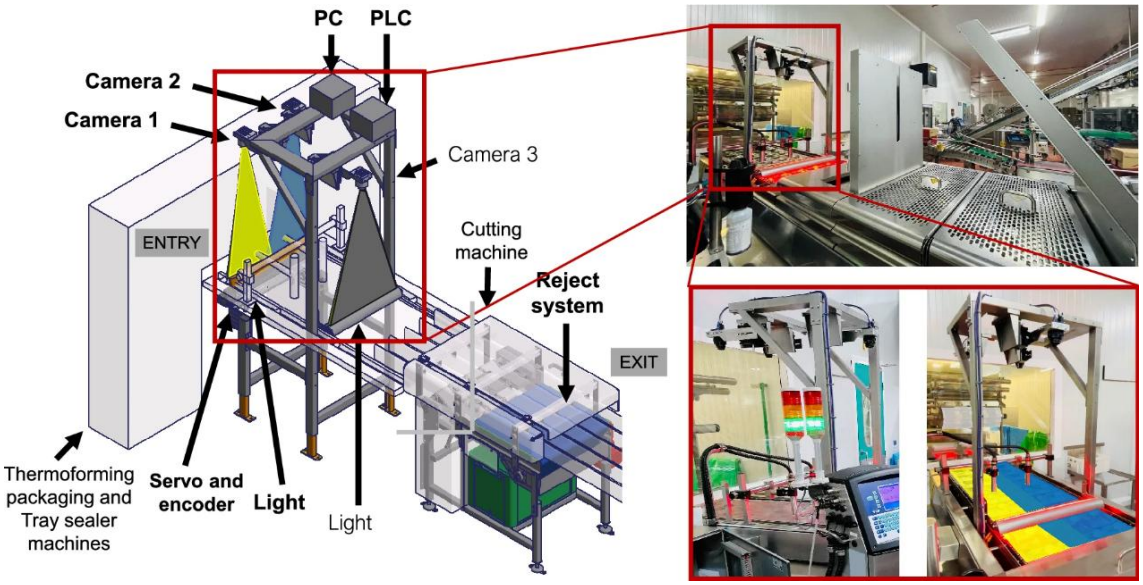

Fig.2 Three-dimensional diagram of the whole system

The test system uses PLC as the total controller to detect the defects of the coating surface image of the workpiece collected. Its composition principle and overall working flow are shown in Figure 3 (the picture is quoted in Computer Vision-Based Structural Deformation Monitoring in Field Environments). First of all, the system turns on the camera, light source and computer, completes the initialization of the system, and then begins to transmit to the material, so that the coating parts enter the detection area in order, after the light sensor in the detection area detects these information, the camera can complete the relevant image acquisition work, and then the obtained image is transmitted to the computer [9]. The image is preprocessed and defects are detected and analyzed. If no defects are found in the coated workpiece, the conveyor belt can proceed to the next step; If the corresponding defect is found, the robot arm will classify the non-conforming product into the non-conforming product area, and after the entire batch of testing is completed, the non-conforming product is re-sprayed by hand to ensure that the product is flawless.

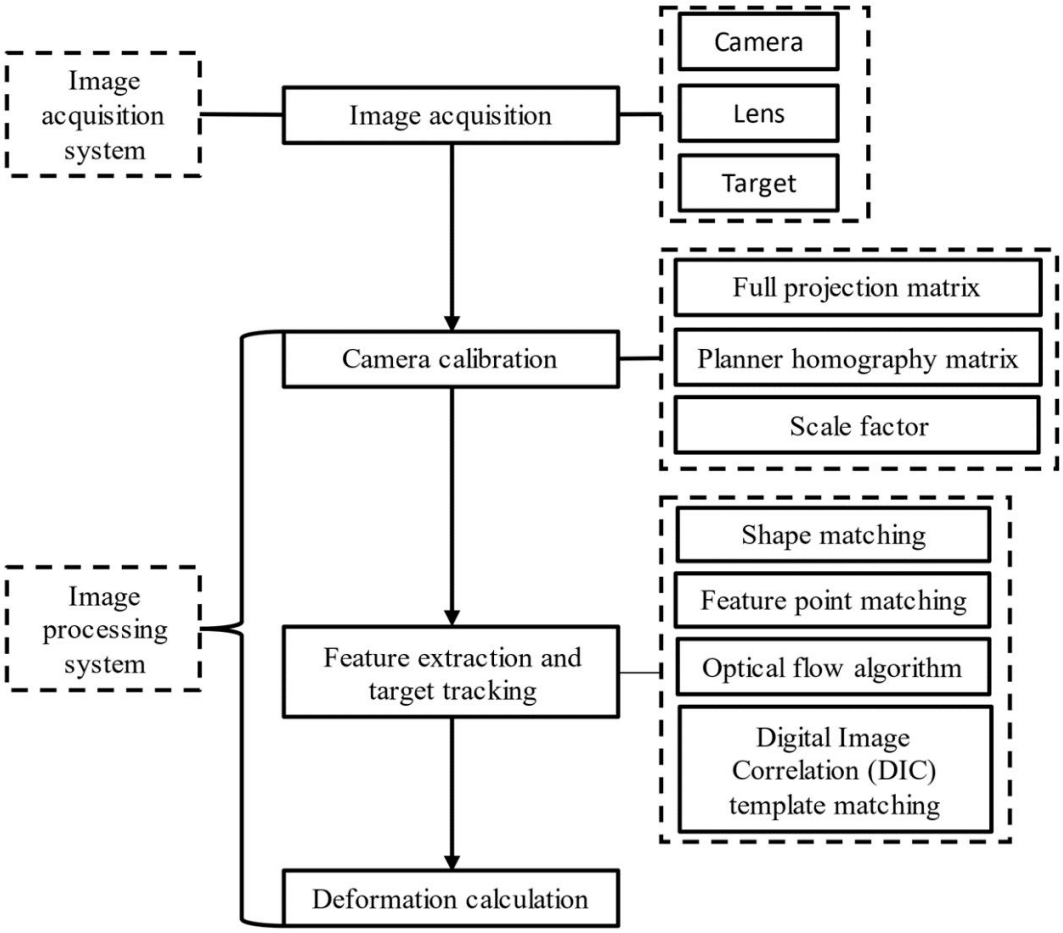

Fig.3 Schematic diagram of the overall system workflow

B. Design of image acquisition system

In the image acquisition system, lighting is a very key link, a good lighting can show the defect characteristics of the coated parts to the maximum extent, and can clearly distinguish the front and back scenes in the image, thus reducing the interference of the background on the foreground. For example, the lighting on the top of the workshop and unrelated light such as the surrounding incandescent lamps reduce the impact on image acquisition. In addition, high-quality lighting materials usually have a high degree of uniformity, can efficiently transmit light at the same time, to ensure sufficient lighting brightness, so as to reduce the impact of noise and shadows on image imaging, lay a solid theoretical and technical foundation for subsequent image processing, thereby reducing the complexity and difficulty of image processing and defect identification, and enhance the robustness and responsiveness of the algorithm. Finally, considering the practical application and manufacturing costs, under the premise of reducing the price, the light source should also have high stability and long-term working life to ensure the relative stability of long-term testing [10]. The coating defect detection system is mainly based on the vehicle parts coated with black paint as the research object. Due to the high light absorption rate of black and the high reflectivity of the coating material, the contrast between the front and back scenes is enhanced by increasing the lighting brightness of the light source, making it more convenient. A method of extracting spray parts based on black and white color is proposed.

Since most of the coated parts studied are black, a black and white camera was selected under the premise of the same resolution and manufacturing costs. The resolution of the camera is the distance between the two pixels on the camera plane after the subject is processed by the optical system. If the resolution of the camera is very low, the two pixels obtained will be merged into one pixel, and the whole picture will become very fuzzy. If the resolution of the camera is very high, then the spacing of the two pixels will be closer to the real distance of the target [11]. The whole image will be more clear, and the shooting of some details will be more clear, so a high-precision camera should be used as much as possible. Because in the industrial assembly line, the reliability and stability of the camera put forward high requirements, in the premise of ensuring the processing speed, but also must be able to collect higher quality images. Compared with CCD photosensitive chip, CMOS photosensitive

chip has lower energy consumption, faster information transmission and lower cost, but in the actual production inspection, there is a high demand for the image quality and processing speed obtained by the camera, so people use the CCD camera as the camera of the visual defect detection system. In addition, the scanning method of the camera is also a big deciding factor. The current industrial cameras can be divided into two types: linear array and planar array. Linear scanning camera uses unit light intensity to continuously scan the target, only one row of one-dimensional images can be obtained at a time, and serial motion is used to achieve the acquisition of the target. Therefore, the image obtained by linear scanning camera has high accuracy and is suitable for the acquisition of a large range of targets, but its acquisition effect is not good, and it is suitable for high-speed and high-precision scenes. The area array camera is an image obtained by using multiple photoelectric elements to obtain the 3D information of the measured workpiece synchronously [12]. The tiny photoelectric devices in the camera represent one or more pixels on the real image according to certain design criteria, and the image effect is much better than that of linear cameras, however, the image quality obtained by cheap array cameras is not good, and can not reflect the image details. Finally, the camera interface has a great impact on the field transmission distance, transmission speed, etc., and the camera interface also plays the role of power supply, so according to the various camera interfaces listed in the table, GigE was finally selected as the camera interface.

C. Development of automatic control device

Modern and efficient production requires the power automation system to conduct a comprehensive adjustment of each link, the system uses the trust PLC and related control devices to ensure the smooth progress of the detection process, and as the whole monitoring system of the PC, is by the industrial computer to complete the data collection and communication interaction with the host computer. The electronic control principle of the System is shown in Figure 4 (the picture is quoted in the Design and Analysis of a Floor Radiant Heating System Based on Energy Substitution Technology).

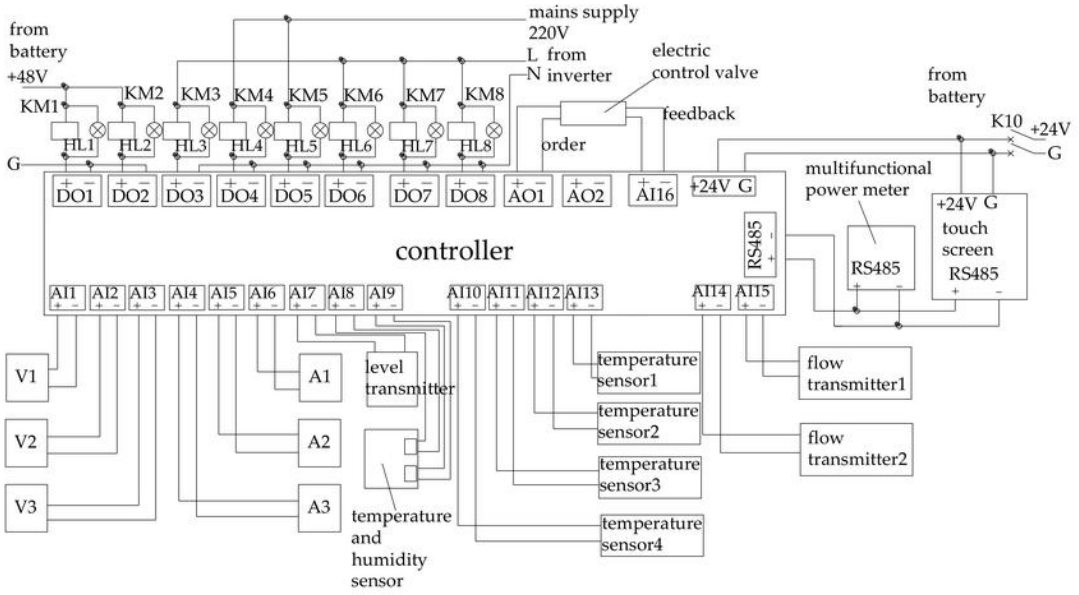

Fig.4 Electrical control diagram of the system

From the end, the coordination control between the motor servo driver, infrared sensor, light source controller, camera lens, robot arm and other components is completed [13]. When the machine starts, the PLC will send a number based on the preset conveyor belt speed to the PC, the PC will comprehensively adjust the conveyor belt speed, when the inspected goods enter the detection range, the infrared sensor detects the corresponding position, and transmits a detection signal to the PLC. PLC opens the lighting and adjusts the brightness of the lighting according to the setting, opens the camera to collect the appearance information of the paint parts, and transmits the collected image data to the industrial computer, and then the software in the computer detects the surface of the workpiece according to the image processing algorithm written in advance, and then transmits the measurement results to the PLC. The PLC controls the sorting robot arm or the pneumatic suction cup to distinguish between genuine and residual goods, and finally realizes a complete control process.

D. Machine vision correction of vehicle component cameras

In order to achieve high precision mechanical vision detection, it is necessary to ensure the authenticity and reliability of the acquired images. However, in real life, there are some distortion problems due to the different quality of the cameras used. Every point on the object surface is a point in real space, and the coordinates of the image surface formed by this point are also corresponding to it. Therefore, it is necessary to correct the distorted image, so that it is necessary to find the position relationship between the two coordinate systems related to the geometric model of the camera image, the position of this point is obtained after field testing and calibration, so that to ensure the accuracy of the calibration, it will not interfere with the subsequent work [14]. When the camera is used to shoot a physical object, the subject is in the image has coordinates, and the reality of the subject is also a coordinate value, so to analyze the relationship between the two, this process is called calibration, also known as the calculation of the projection matrix.

E. Auto parts coating defect detection algorithm

The paper selects 40 rings, 100 pixels for 100 pixels as sampling points, to study the role of these rays in the imaging process. The procedure goes like this:

(1) The $W_{gray}(i,j)$ of the three color components in the region according to equation (1).

$$W_{gray}(i,j)=\frac{1}{3}[R(i,j)+G(i,j)+B(i,j)] \tag{1}$$

The grayscale value of the target region was obtained through the get_gray_val operator in Halcon, and the R,G,B three channel separation was achieved through the decompose operator, thus obtaining the value of various color components in the target region.

(2) Illumination effectiveness ζ is calculated according to formula (2).

$$\zeta=\frac{\sum_{i=0}^{100}\sum_{j=0}^{100}W_{gray}(i,j)}{\varepsilon_i\varepsilon_j} \tag{2}$$

Where $\varepsilon_i\varepsilon_j$ is the number of pixel points. As can be seen from Figure 5, under the four different lighting methods, the lighting efficiency is above 0.2. The experimental results show that the illumination efficiency of the ring light source is about 0.55, and the brightness fluctuation of each band is very different, so there is a certain error in the acquisition of image characteristics. The lighting efficiency of the strip light source in the main lighting area is very high, up to about 0.6, while the acquisition degree of the surrounding area is only 0.25. Among them, the flat panel lighting effect is good, about 0.65, and the imaging area is evenly distributed; The coaxial lighting system can obtain good acquisition effect in different regions, but its total utilization rate is only 0.2%, which is still at a low level on the whole. A method based on the surface light source is used to obtain the image.

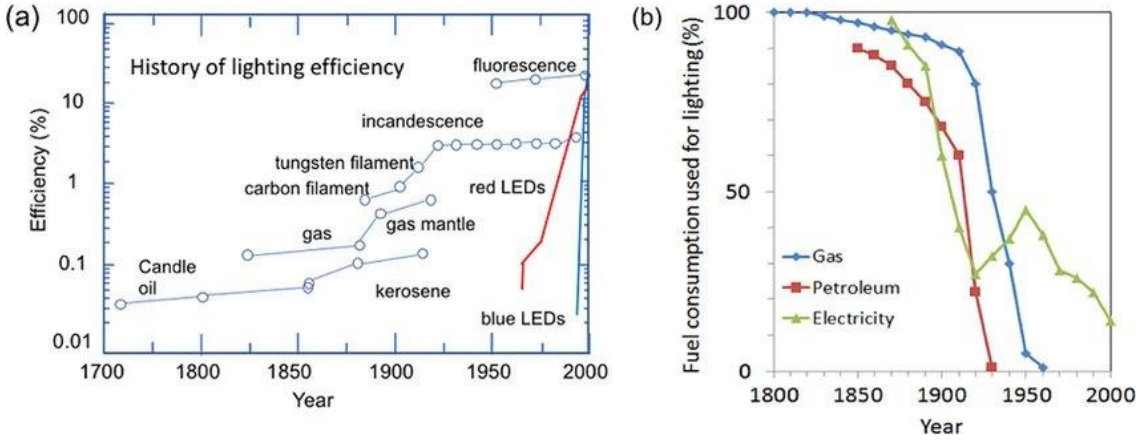

Fig.5 Illumination effectiveness of different light sources

The light efficiency of the four light sources is above 0.2, among which the average light efficiency of the planar light source is the highest, and the light efficiency of the coaxial light source is the lowest. The

illumination efficiency of the ring light source is distributed around 0.55 on average, and the fluctuation of the illumination parts in different regions is large [15]. For the acquisition of image features, there may be some cases of leakage or under-mining, so it is not suitable for defect detection under this condition. The light efficiency of the strip light source in the main irradiation area is higher around 0.6, but the acquisition performance of the nearby area is poor only 0.25, and its fluctuation difference is large, which is greatly affected by the surface quality of the parts, and it is not suitable for use. The illumination efficiency of the surface light source is around 0.65, and the acquisition of the image region is relatively average. Although the coaxial light source has good acquisition performance in each area, the efficiency is only 0.25, and the quality of image acquisition can not be guaranteed accordingly. Therefore, in order to obtain better image acquisition effect, vertical lighting of surface light source is selected as the main lighting scheme for image acquisition.

By processing the boundary information of the ring, the algorithm obtains the contour information of different parts of the measured target, which lays a good foundation for the accurate location of the ring and the identification of defects. Using Sobel operator and Canny operator for boundary detection, the boundary and skeleton of the detected object can be detected more accurately. Let the first-order horizontal and vertical 2 × 2 convolution template R_u, R_v be:

$$R_u = \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} R_v = \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix} \tag{3}$$

Convolution of image pixels using matrix:

$$\begin{cases} \Xi_u = g(u,v)R_u(u,v) \\ \Xi_v = g(u,v)R_v(u,v) \end{cases} \tag{4}$$

Ξ_u, Ξ_v is the gradient of the horizontal and vertical directions of the pixel, and its amplitude $\Xi(u,v)$ and direction ζ are respectively:

$$\Xi(u,v) = \sqrt{\Xi_u^2(u,v) + \Xi_v^2(u,v)} \tag{5}$$

$$\zeta = \arctan\left[\frac{\Xi_v(u,v)}{\Xi_u(u,v)}\right] \tag{6}$$

The Sobel operator obtains the global gradient by superimposing the weight of the vertical gradient and the lateral gradient. However, Canny operator in a given direction, through the other gradients are not maximized, so that a single boundary can get a better effect, so as to better realize the effective extraction of image boundary information. It is necessary to preprocess the image obtained by CCD camera because of various interference, which leads to the degradation of image quality and is not convenient for the later workpiece detection [16]. The method commonly used in practical applications is to filter the signal. Gaussian filter is a more common method, in which the Gaussian filter has the effect of smoothing the image and suppressing the noise. The Gaussian filter calculates the average gray level of each pixel in each window, and the weight of each pixel is determined by the following formula

$$w(i,j) = \frac{1}{2\pi\varepsilon^2} e^{-\frac{i^2+j^2}{2\varepsilon^2}} \tag{7}$$

Where, i and j represent the position of the surrounding pixel points in the window, ε represents the variance of the Gaussian distribution, and $w(i,j)$ represents the weight of the pixel point at (i,j) in the window during the smoothing process. A method based on logarithmic conversion is proposed to improve product quality [17]. Logarithmic conversion is to extend the lower gray level of the image and compress the higher gray level, so as to improve the contrast of the image. The transformation works like this:

$$t = c\log(1+s) \tag{8}$$

Where, c is the scale proportionality constant, s is the gray value of the original image, and t is the gray value of the target after transformation. A method for automatic crack identification in screen plate is presented. The algorithm Detection process is shown in Figure 6 (The picture is quoted in A Lightweight One-Stage Defect Detection Network for Small Object Based on Dual Attention Mechanism) and PAFPN).

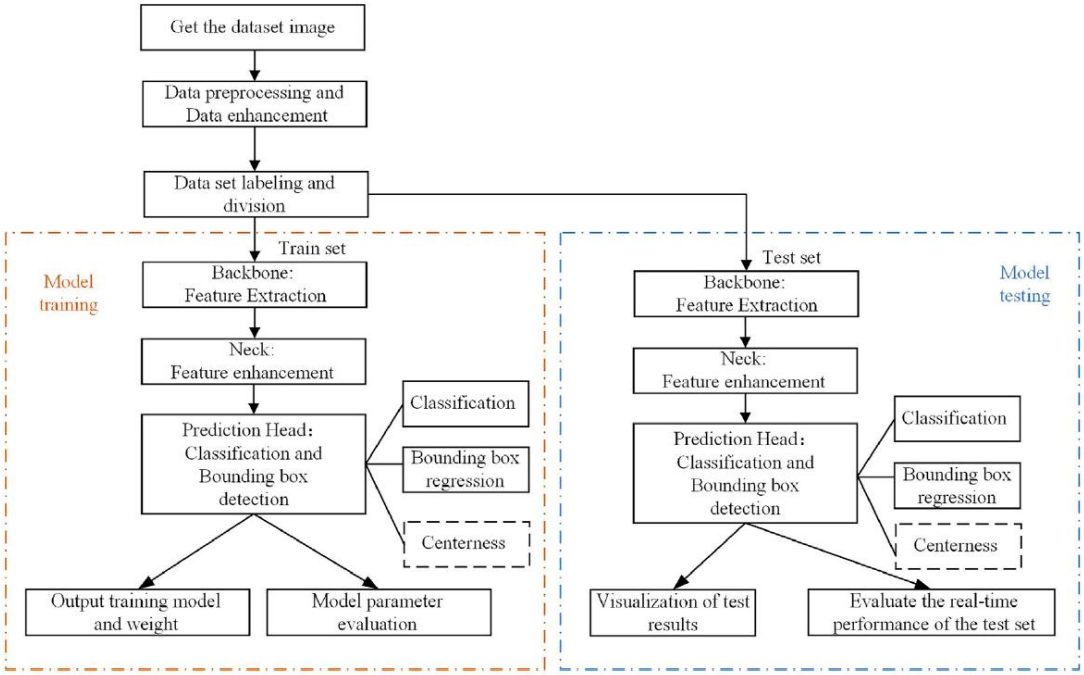

Fig.6 Flow chart of algorithm for detecting edge fracture defects of parts

Firstly, the obtained image is preprocessed, and then the black edge is located by using the pyramid algorithm based on gray level matching and the gray level matching method based on NCC. The gray peak value of the image is obtained by gray-scale processing [18]. Standardized correlation (NCC) function matching method is based on gray level information, using the similarity method, according to the correlation between the gray level between two images, to determine the coincidence between two images, and find the coincidence place. The standardized calculation formula is as follows:

$$NCC(u,v)=\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[W(u+i,v+j)-\bar{W}(u,v)]-[R(i,j)-\bar{R}]}{\sqrt{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[W(u+i,v+j)-\bar{W}(u,v)]^2-\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[R(i,j)-\bar{R}]^2}} \tag{9}$$

The pixel size of image W to be matched is $M\times N$, the pixel size of template R is $m\times n$, and the coordinate of the upper left corner image point of W subgraph $W_{u,v}, W_{u,v}$ with pixel size $m\times n$ is (u,v) in image W, and the coordinate range is $0\le u\le M-m, 0\le v\le N-n$. From the above calculation results, it can be seen that the larger the value of $NCC(u,v)$, the higher the matching degree of the detected image position, the closer it is to the template image.

IV. Experimental results and analysis

In order to verify the application of this method in flexible pipeline, a simulation test will be carried out in this paper. Considering the size and time of the experiment, the experiment will be carried out in the laboratory. The camera must be adjusted before the test is officially launched. Mount the camera on a flat surface using common type screws and use a scale to level the camera. The camera was positioned 1.3 meters above the ground. This height facilitates both manual processing and image acquisition. The system uses 12 V DC power supply to realize the network connection between the laboratory computer and the camera. The parts are obtained directly under the camera, and a black rubber pad is placed on the measuring pad under the part. This rubber pad is tested flat to ensure that the workpiece is the same in the horizontal direction of the camera. In order to ensure the acquisition of experimental images, it is necessary to deal with the problem of uneven illumination in the laboratory [19]. The test is to distribute light to the sample, use a new white paper to block the distance between the camera and the workpiece, gradually increase the exposure time, until a good image of the test sample is obtained, the exposure can be terminated, and the image can meet the requirements. This new imaging method can solve the problem of low imaging quality caused by the reflection of the light source or the workpiece itself.

A. Comparison of errors detected by various test methods in samples

Simulation experiments were carried out with 3 samples of automobile parts collected by camera, and the effect of camera calibration, noise reduction of defect image and part defect recognition were compared. A new fault diagnosis technique of flexible production line based on elastic element is presented. As can be seen from the test results in FIG. 7, the characteristics of the components of the car ring of sample 1 are extracted more completely, the important characteristics are more obvious, and the calibration of the ring is more accurate by using this research method. Sample 2 is a work piece composed of cracks. It can be seen that the image obtained by this algorithm has medium contrast, small image noise and high image quality, which indicates that the processing result by Gaussian filtering method is better [20]. Using the conventional test method, its test effect is discontinuous, and there is a significant problem of information loss, which can not highlight its important characteristics. In contrast, using mechanical vision technology to conduct non-destructive testing on the whole, the damage obtained has better shape and characteristics. Finally, the two methods are compared to verify the feasibility of using machine vision to diagnose defects.

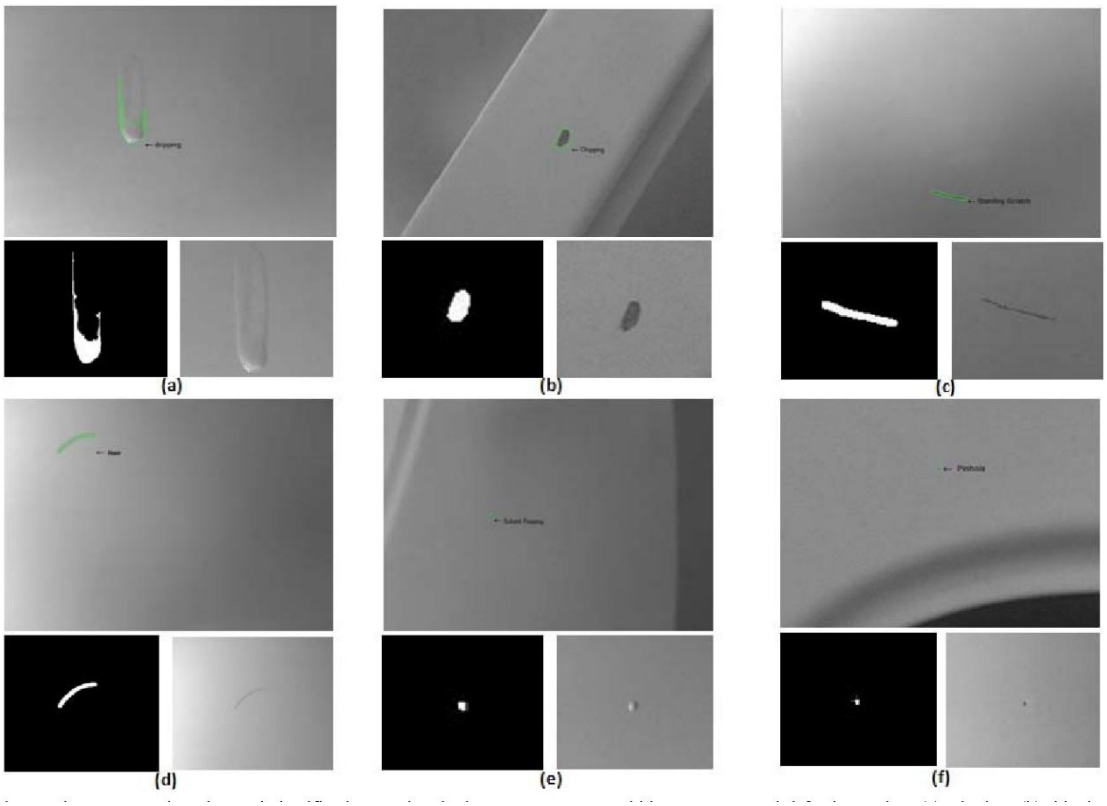

Fig.7 Comparison of camera mark effects from Sample 1 to Sample 3

B. Comparison of energy consumption of flexible production lines with different methods

In order to further test the practical application effect of this method, this project as the control group, and the research method is the experimental group. With the number of motor vehicle parts as the test dependent variable, 1000-10000 parts of the vehicle were tested. Compared with conventional methods, this method has great advantages, which can accelerate and improve the detection speed of products, improve the detection efficiency, and effectively identify the quality of various products in the flexible assembly line, and reduce energy consumption. When there are 10,000 parts, its energy consumption is 500 kilowatts. Under the same component consumption conditions, 550-700 kW of energy consumption can be obtained using conventional processes, showing the value of this technology in industry (Figure 8).

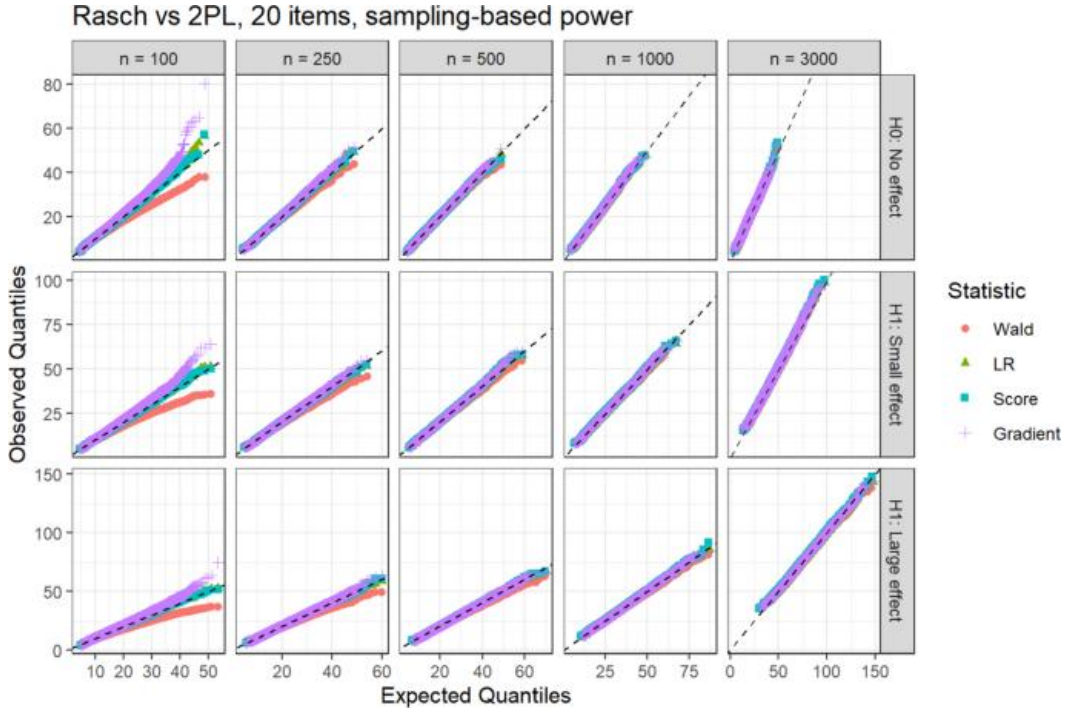

Fig.8 Comparison of energy consumption of flexible production lines under different methods

V. CLOSING REMARKS

In order to solve the problem of poor image quality and high false positive rate in the existing defect diagnosis technology, this project intends to apply machine vision technology to the defect detection, improve the image quality by correcting the camera image, and establish the polygon feature extraction model of single frame image, so as to realize the online nondestructive testing of auto parts. It changes the model of manual testing in the past. It has the characteristics of greater flexibility, more accurate and faster. On the flexible production line, various specifications of products can be imported into the test system in advance, so that various types of products can be inspected more easily, thus saving a lot of costs and improving the overall economic benefits of manufacturing enterprises.

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REFERENCES

[1] Liu, L., Lu, S., Zhong, R., Wu, B., Yao, Y., Zhang, Q., & Shi, W. (2020). Computing systems for autonomous driving: State of the art and challenges. IEEE Internet of Things Journal, 8(8), 6469-6486.

[2] Ren, Z., Fang, F., Yan, N., & Wu, Y. (2022). State of the art in defect detection based on machine vision. International Journal of Precision Engineering and Manufacturing-Green Technology, 9(2), 661-691.

[3] Dibaei, M., Zheng, X., Xia, Y., Xu, X., Jolfaei, A., Bashir, A. K., ... & Vasilakos, A. V. (2021). Investigating the prospect of leveraging blockchain and machine learning to secure vehicular networks: A survey. IEEE Transactions on Intelligent Transportation Systems, 23(2), 683-700.

[4] Marques, L. S., Gresse von Wangenheim, C., & Hauck, J. C. (2020). Teaching machine learning in school: A systematic mapping of the state of the art. Informatics in Education, 19(2), 283-321.

[5] Alexopoulos, K., Nikolakis, N., & Chryssolouris, G. (2020). Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. International Journal of Computer Integrated Manufacturing, 33(5), 429-439.

[6] Khan, A. A., Laghari, A. A., & Awan, S. A. (2021). Machine learning in computer vision: a review. EAI Endorsed Transactions on Scalable Information Systems, 8(32), e4-e4.

[7] Sun, W., Dai, G., Zhang, X., He, X., & Chen, X. (2021). TBE-Net: A three-branch embedding network with part-aware ability and feature complementary learning for vehicle re-identification. IEEE Transactions on Intelligent Transportation Systems, 23(9), 14557-14569.

[8] Waldschmidt, C., Hasch, J., & Menzel, W. (2021). Automotive radar—From first efforts to future systems. IEEE Journal of Microwaves, 1(1), 135-148.

[9] Xie, Y., Ebad Sichani, M., Padgett, J. E., & DesRoches, R. (2020). The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. Earthquake Spectra, 36(4), 1769-1801.

[10] Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2020). Integrating physics-based modeling with machine learning: A survey. arXiv preprint arXiv:2003.04919, 1(1), 1-34.

[11] Li, Y., & Ibanez-Guzman, J. (2020). Lidar for autonomous driving: The principles, challenges, and trends for automotive lidar and perception systems. IEEE Signal Processing Magazine, 37(4), 50-61.

[12] Yan, Y., Borhani, T. N., Subraveti, S. G., Pai, K. N., Prasad, V., Rajendran, A., ... & Clough, P. T. (2021). Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS)–a state-of-the-art review. Energy & Environmental Science, 14(12), 6122-6157.

[13] Malekloo, A., Ozer, E., AlHamaydeh, M., & Girolami, M. (2022). Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Structural Health Monitoring, 21(4), 1906-1955.

[14] Gheibi, O., Weyns, D., & Quin, F. (2021). Applying machine learning in self-adaptive systems: A systematic literature review. ACM Transactions on Autonomous and Adaptive Systems (TAAS), 15(3), 1-37.

[15] Fernandes, M., Corchado, J. M., & Marreiros, G. (2022). Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review. Applied Intelligence, 52(12), 14246-14280.

[16] Dong, C. Z., & Catbas, F. N. (2021). A review of computer vision–based structural health monitoring at local and global levels. Structural Health Monitoring, 20(2), 692-743.

[17] Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2022). Integrating scientific knowledge with machine learning for engineering and environmental systems. ACM Computing Surveys, 55(4), 1-37.

[18] Brunton, S. L., Nathan Kutz, J., Manohar, K., Aravkin, A. Y., Morgansen, K., Klemisch, J., ... & McDonald, D. (2021). Data-driven aerospace engineering: reframing the industry with machine learning. AIAA Journal, 59(8), 2820-2847.

[19] Machado, G. R., Silva, E., & Goldschmidt, R. R. (2021). Adversarial machine learning in image classification: A survey toward the defender's perspective. ACM Computing Surveys (CSUR), 55(1), 1-38.

[20] Yang, J., Wang, C., Jiang, B., Song, H., & Meng, Q. (2020). Visual perception enabled industry intelligence: state of the art, challenges and prospects. IEEE Transactions on Industrial Informatics, 17(3), 2204-2219.