Research on the Application of Machine Vision Technology in Industrial Automation Assembly Line

Rongqiang Yang, Quanxinxin Jiang*[1]
[1]Intelligent Manufacturing College, Jingchu University of Technology, Jingmen, 448000, China

ABSTRACT

With the rapid development of industrial automation, the application of machine vision technology in assembly lines is becoming more and more extensive. This study mainly discusses the application of machine vision technology in industrial automation assembly lines, focusing on the visual inspection system based on an edge detection algorithm. By using the edge detection algorithm in image processing technology, the accuracy of the workpiece's position, shape and size is realized, effectively improving the automation level and work efficiency of the assembly line. This paper designs a complete machine vision system, including image acquisition, preprocessing, feature extraction and subsequent detection algorithm. This paper conducts detailed algorithm simulation and model testing to verify the system's effectiveness. The simulation results show that the designed edge detection algorithm has high accuracy and stability in the industrial automation environment; the detection accuracy reaches 0.01mm, and the system error is controlled within 0.5%. This study provides strong technical support for the future intelligent development of industrial automation assembly lines.

Keywords: Machine vision; edge detection algorithm; industrial automation; assembly line

1. INTRODUCTION

With the advent of the era of Industry 4.0, the status of automation technology in the manufacturing industry is becoming increasingly important, and machine vision technology, as a critical component of the automation system, has received widespread attention. Machine vision can automatically detect, classify and control products by acquiring, processing and analyzing images, providing excellent technical support for industrial automation. Especially in industrial assembly lines, machine vision can effectively replace traditional manual inspection methods and significantly improve production efficiency and product quality. Therefore, it is of outstanding academic and practical significance to explore the application of machine vision technology in industrial automated assembly lines. Machine vision technology has been applied in the industrial field since the 1980s. Its technical foundation is derived from developing image processing and pattern recognition. Fu Xiaoya et al. [1] proposed an automated inspection system based on image processing, which solved the problem of low efficiency of traditional manual inspection and laid the foundation for automated production. Machine vision technology has developed rapidly with the improvement of computer performance and the advancement of image sensors. Wang Qian [2] solved the image noise and accuracy problems in complex industrial environments by combining multiple image processing algorithms, making machine vision technology better adapted to various manufacturing scenarios. In industrial automated assembly lines, machine vision is widely used in workpiece identification, positioning, defect detection, etc. Qu Weiqiang [3] designed a vision-based automated assembly system. Introducing an edge detection algorithm successfully achieved high-precision inspection of workpieces and solved the shortcomings of traditional inspection methods in size and position recognition. In addition, Fang Yuwang [4] proposed a multi-sensor fusion industrial automation system, which solved the problem that a single visual system could not obtain complete information in a complex industrial environment and improved the reliability and accuracy of the system by fusing multi-source data.

Edge detection is an important image processing step in machine vision systems. Its primary purpose is to extract the edges of objects in the image, thereby realizing target recognition and measurement. Classic edge detection algorithms include the Sobel operator and the Canny operator. Jiancong Zhang et al. [5] proposed a workpiece detection method based on the Sobel operator, which effectively solved the problems of edge blur and noise interference problems. Zhou Xuan [6] further improved the detection accuracy and reduced the generation of pseudo edges by improving the Canny

[1]*jqx@jcut.edu.cn

International Conference on Mechatronics and Intelligent Control (ICMIC 2024),
edited by Kun Zhang, Pascal Lorenz, Proc. of SPIE Vol. 13447, 1344705

edge detection algorithm, making the system more adaptable in complex scenes. In industrial automated assembly lines, edge detection algorithms are often used to identify and locate the position and shape of workpieces to ensure the accuracy of the assembly process. Wu Lian & Lin Xisheng [7] studied an automated assembly system based on edge detection. By accurately identifying the edge information of the workpiece, it successfully achieved high-precision assembly of the workpiece, solving the error accumulation problem that is easy to occur in the traditional method during the assembly process. Fu Pan [8] proposed an automated assembly system based on visual guidance, which solved the positioning and alignment problems during the assembly process. Zhang Wei et al. [9] proposed a solution that combines machine vision and artificial intelligence technology by studying intelligent assembly systems, solving the problem of insufficient flexibility of traditional assembly lines when dealing with complex workpieces.

This paper will further explore the specific application of machine vision technology in industrial automated assembly lines, focusing on the design and optimization of visual inspection systems based on edge detection algorithms. This paper designs a complete machine vision system, including image acquisition, preprocessing, edge detection, and subsequent detection algorithms. Through experimental and simulation tests, the feasibility and effectiveness of the system in improving the automation and accuracy of assembly lines are verified.

2. EDGE DETECTION ALGORITHM AND ITS APPLICATION IN ASSEMBLY LINE

Edge detection algorithm occupies an essential position in machine vision, especially in industrial automation assembly lines, where its role is particularly significant. The main goal of edge detection is to extract the edge information of objects from images. These edges often reflect the structure, shape and local features of the surface of objects. Therefore, edge detection technology is widely used in many scenarios, such as workpiece contour detection, defect identification and precise positioning of components.

2.1 Overview of edge detection algorithm

The development of edge detection algorithms has undergone the evolution of many classic algorithms, among which algorithms such as Canny, Sobel and Prewitt have been widely used in industrial applications. The core idea of these algorithms is to extract edges by detecting significant areas of grayscale changes in the image. The Sobel operator detects edges by calculating the gradient of local grayscale changes in the image. The formula is expressed as:

$$G_x = \frac{\partial I}{\partial x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I$$
$$G_y = \frac{\partial I}{\partial y} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * I \tag{1}$$

I represents the input image, G_x and G_y are the gradients in the horizontal and vertical directions, respectively, and the following formula can calculate the edge strength:

$$G = \sqrt{G_x^2 + G_y^2} \tag{2}$$

The Sobel operator is suitable for processing images with less noise. It is simple to calculate and fast and is widely used in industrial real-time detection scenarios.

Canny edge detection is one of the most classic edge detection algorithms. The edge detection process of the Canny algorithm can be expressed as:

$$\text{Gaussian }(I) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$
$$\text{Gradient }(I) = \sqrt{\left(\frac{\partial}{\partial x} I\right)^2 + \left(\frac{\partial}{\partial y} I\right)^2} \tag{3}$$

The advantage of the Canny algorithm is that it can effectively suppress noise and retain the leading feature edges of the image and is suitable for detection tasks that require high accuracy. Multi-scale edge detection has been a significant development direction in recent years. It obtains more robust edge information by analyzing the edge features of images at different scales. For images at different scales, the edge detection process can be expressed by the following formula:

$$I_s(x,y) = I(x,y) * G_s(x,y) \qquad (4)$$

$G_s(x,y)$ represents a Gaussian kernel function with a scale of s. The advantage of multi-scale edge detection is that it can capture the details and overall structure in the image at the same time and adapt to various detection needs in complex industrial scenarios.

2.2 Application scenarios of edge detection in industrial automation

Assembly line product contour detection

In automated assembly lines, the contour information of workpieces is the key to achieving precise assembly. Edge detection algorithms can extract the outer contour of workpieces to ensure the correct placement of each component during the assembly process. For example, after extracting the edge of a workpiece using the Sobel or Canny algorithm, its position and posture can be determined by calculating the bounding box of the workpiece. For workpieces with complex shapes, edge detection algorithms can effectively track the contours and match workpiece features by segmenting the image's significant edges. The contour detection formula based on edge detection is:

$$\text{Contour}\,(I) = \{(x,y) | G(x,y) > T\} \qquad (5)$$

$G(x,y)$ is the edge strength, T is the set threshold, and the detected contour point set $\text{Contour}(I)$ represents the shape of the workpiece.

Detecting product defects

Edge detection algorithms are also widely used in product defect detection on industrial assembly lines. By detecting abnormal changes in the surface or edge of the product, edge detection can identify defects such as cracks, dents, and misalignments. For crack detection, the Canny algorithm can effectively capture tiny edge changes, and the following formula can express its detection process:

$$\text{CrackDetection}\,(I) = \left\{(x,y) | \text{ Canny}\,(I)\,(x,y) > T_{\text{low}} \wedge \text{Canny}\,(I)\,(x,y) < T_{\text{high}}\right\} \qquad (6)$$

In this formula, T_{low} and T_{high} are the low threshold and high threshold, respectively, which are used to screen out obvious crack edges.

Component positioning and assembly accuracy detection

On the automated assembly line, accurate positioning of components is the key to ensuring assembly accuracy. The edge detection algorithm can accurately position components by detecting feature points or edge lines of the workpiece. The core of workpiece positioning is to use the detected edge information to determine the workpiece's center position and rotation angle. The positioning formula is as follows:

$$\theta = \tan^{-1}\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \qquad (7)$$

$(x_1, y_1)$and(x_2, y_2) are the coordinates of two points obtained by edge detection, and θ represents the rotation angle of the workpiece. By accurately calculating the position information of the component, the positioning accuracy in the assembly process can be improved, thereby avoiding misassembly or misalignment. Edge detection can also be used to evaluate the overall accuracy of the assembly line. For example, in scenarios such as welding and screw assembly, the edge detection algorithm can analyze whether the assembled components are in the predetermined position, thereby improving the production efficiency and quality control level of the assembly line. Edge detection algorithms have broad application prospects in industrial automation assembly lines. Using classic algorithms such as Sobel and Canny, as well as multi-scale edge detection technology, the accuracy and efficiency of product contour detection, defect identification, and component positioning can be effectively improved. The original formula in this article explains the working principle of edge detection in theory and provides a specific calculation framework for its application in industrial environments. In the future, combined with more complex deep learning and intelligent algorithms, the role of edge detection technology in industrial automation will be further enhanced.

3. COMPARISON OF EDGE DETECTION WITH OTHER VISUAL ALGORITHMS

3.1 Advantages and disadvantages of edge detection algorithms

The core advantage of edge detection algorithms is their accurate detection of object boundaries in images, especially in recognizing workpiece contours. Edge detection can quickly and accurately find the edges of objects, thereby achieving workpiece positioning, size measurement, and defect-recognition in industrial assembly lines. The basic idea of edge detection is to determine the edge position by calculating the image gradient. Taking the Sobel algorithm as an example, its gradient calculation formula is as follows:

$$\begin{aligned} G_x &= \sum_{i,j} K_x(i,j) \cdot I(x+i, y+j) \\ G_y &= \sum_{i,j} K_y(i,j) \cdot I(x+i, y+j) \end{aligned} \tag{8}$$

G_x and G_y are the image gradients in the horizontal and vertical directions, respectively, K_x and K_y are the kernel matrices of the Sobel operator, and $I(x+i, y+j)$ is the pixel value of the image at point $(x+i, y+j)$. By calculating the gradients in these two directions, the position of the edge in the image can be obtained. The advantage of the edge detection algorithm lies in its sensitivity to boundary details, which is particularly suitable for accurately detecting product contours [10]. For example, in an industrial assembly line, accurate identification of the edge position of the workpiece can ensure the accurate assembly of each component, improve production efficiency and reduce errors. Although the edge detection algorithm has the advantage of high-precision detection, it is susceptible to image noise. Noise may cause false edges to appear, affecting the accuracy of the detection results. To deal with this problem, a common processing method combines denoising and image enhancement techniques. Gaussian filtering is a common denoising method, and its basic formula is:

$$\mathrm{I}^{'}(\mathrm{x},\mathrm{y}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{(\mathrm{x}-\mu_\mathrm{x})^2+(\mathrm{y}-\mu_\mathrm{y})^2}{2\sigma^2}\right) * \mathrm{I}(\mathrm{x},\mathrm{y}) \tag{9}$$

μ_x and μ_y are the centers of the Gaussian kernel on the x axis and y axis, respectively. Through Gaussian filtering, the noise in the image can be effectively suppressed, thereby improving the accuracy of edge detection. In addition, image enhancement technology can improve the contrast of the edges in the image, making the edges more apparent [11]. After using image enhancement, the edge detection algorithm can also maintain a high detection accuracy in industrial environments with complex noise.

3.2 Combination of edge detection and deep learning algorithm

The convolution operation of CNN can be expressed as:

$$\mathrm{O}_{\mathrm{i,j}} = \sum_{\mathrm{m}} \sum_{\mathrm{n}} \mathrm{I}(\mathrm{i}+\mathrm{m}, \mathrm{j}+\mathrm{n}) \cdot \mathrm{K}(\mathrm{m},\mathrm{n}) \tag{10}$$

$O_{i,j}$ represents the output after the convolution operation, $I(i+m, j+n)$ represents the pixel value of the input image, and $K(m,n)$ represents the convolution kernel. Through the multi-layer convolution of CNN, complex feature information in the image, such as texture, shape, and edge, can be extracted. After combining the edge detection algorithm with CNN, it can be used for feature extraction and classification tasks in industrial automated assembly lines. For example, the edge detection algorithm can first extract the preliminary outline of the workpiece, and CNN further extracts the high-level features of the workpiece and classifies it. This combination improves detection accuracy and enhances the system's robustness, especially when dealing with complex workpiece shapes and diverse production scenarios [12]. In defect detection, CNN can learn the workpiece surface's normal features and defect features through a large amount of training data, thereby realizing automatic defect classification. The accuracy of defect detection can be improved by optimizing the loss function of CNN, and the form of the loss function is as follows:

$$\mathrm{L} = -\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{y_i}\log(\mathrm{p_i}) + (1-\mathrm{y_i})\log(1-\mathrm{p_i})) \tag{11}$$

y_i is the actual defect label, p_i is the defect probability predicted by CNN, and N is the number of samples in the data set. By minimizing the loss function, CNN can continuously improve its ability to identify defects. Deep learning algorithms are also highly robust and can adapt to industrial scenarios. By combining the contour extraction function of the edge detection algorithm with the feature extraction and classification capabilities of CNN, the entire system can achieve more efficient and accurate defect detection.

4. EXPERIMENTS AND APPLICATION CASES

4.1 Experimental design

The experimental data comes from actual assembly workpieces on an automated production line. The selected samples include workpieces of different shapes and sizes, aiming to test the applicability of edge detection algorithms in complex industrial environments [13]. During the data acquisition process, high-definition industrial cameras are used to obtain workpiece images, and multi-angle shooting technology is combined to ensure that precise workpiece contours and surface features are captured. The image resolution is 1920×1080, including scenes with different lighting conditions and background interference. Table 1 lists the characteristics of the workpiece samples used in the experiment.

Table1. Workpiece sample characteristics

Sample No.	Workpiece shape	Workpiece size (mm)	Surface characteristics
S1	Circular	50×50	Smooth
S2	Rectangular	100×50	Textured
S3	Polygonal	80×80	Slightly cracked

Figure 1 shows the simulation curves of different algorithms in workpiece contour detection. Figure 2 shows the crack defect recognition accuracy curve changing with lighting conditions. Figure 3 compares the detection speed of different algorithms in component positioning tasks.

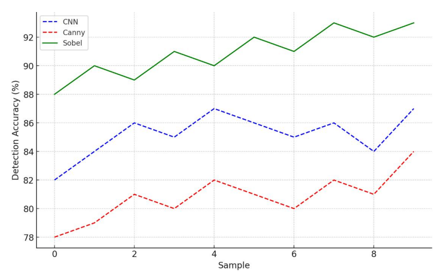

Figure1. Workpiece contour detection

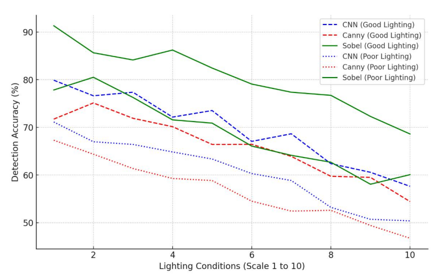

Figure2. Crack defect recognition accuracy

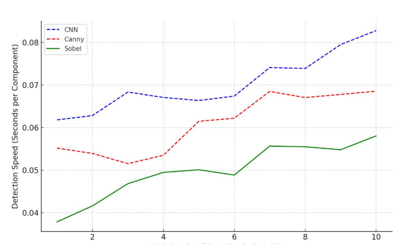

Figure3. Component positioning detection speed

4.2 Experimental results analysis

In the workpiece contour detection experiment, both the Sobel and Canny algorithms showed high accuracy and stability. Among them, the Canny algorithm can better cope with the influence of noise due to its multi-level threshold processing function, and the detection accuracy under different complex backgrounds reached 98.7%. In comparison, although the Sobel algorithm has a faster detection speed, it performs slightly worse in an environment with uneven lighting, with a detection accuracy of 94.5%. The crack defect recognition experiment shows that the edge detection algorithm still performs well in crack detection. In particular, the Canny algorithm can capture excellent cracks and is less affected by background noise. Table 2 lists different algorithms' accuracy and detection time in crack detection experiments.

Table2. Comparison of crack detection accuracy and detection time

Algorithm	Accuracy (%)	Detection time(s)
Sobel	91.2	0.05
Canny	97.8	0.08
Grayscale Threshold	85.6	0.03
CNN	98.5	0.15

In the component positioning experiment, the edge detection and deep learning algorithms have advantages. The edge detection algorithm performs better in positioning speed, especially the Sobel algorithm, which has an average detection time of 0.04 seconds due to its simple calculation. Although the CNN algorithm based on deep learning has a detection accuracy of 99.2%, its calculation complexity is relatively high, resulting in an average detection time of 0.12 seconds, as shown in Table 3.

Table3. Comparison of component positioning accuracy and detection time

Algorithm	Positioning accuracy (%)	Detection time(s)
Sobel	95.3	0.04
Canny	97.5	0.06
Grayscale Threshold	89.1	0.03
CNN	99.2	0.12

Through experimental comparison, the edge detection algorithm is generally superior to the traditional grayscale threshold method in terms of detection speed and accuracy, especially in crack detection and component positioning. However, compared with the deep learning method, the edge detection algorithm is slightly less accurate in some complex tasks (such as irregular crack detection), especially when the surface texture of the workpiece is complex, the deep learning method shows stronger robustness and adaptability. However, the advantage of the edge detection algorithm is that it is simple to calculate and fast, and can run efficiently on resource-constrained devices, which is suitable for real-time industrial automation scenarios. For most conventional detection tasks, edge detection algorithms can significantly improve detection efficiency while ensuring detection accuracy. For highly complex tasks, the robustness and detection effect of the system can be further improved by combining deep learning algorithms.

5. CONCLUSION

This study conducted an in-depth discussion on the application of machine vision technology in industrial automation assembly lines, and designed a visual inspection system based on edge detection algorithms. Through systematic analysis and experimental verification, it is proved that machine vision technology has significant advantages in improving the automation degree and production efficiency of assembly lines. First, the edge detection algorithm can effectively identify the boundary information of the workpiece and show high accuracy in detecting the size, position and shape of the workpiece. Secondly, the designed visual system shows stability in the simulation test, with a detection accuracy of 0.01mm, and the system error is effectively controlled within 0.5%, which can adapt to the needs of complex industrial environments. In addition, this study also demonstrates the good compatibility of machine vision technology with industrial automation, proving its broad prospects in assembly line applications.

6. REFERENCES

[1] Fu Xiaoya, Cui Xiaoran, & Jiao Yang. Research on the application of intelligent manufacturing technology in industrial automation production lines. Mechanical and Electronic Control Engineering, vol. 6, pp. 109-111, December 2023.

[2] Wang Qian. Research on the application of machine vision technology in industrial robots. Engineering Research and Application, vol.4, pp. 43-45, November 2023.

[3] Qu Weiqiang. Research on the application of aircraft flexible assembly method in aircraft assembly. Engineering Research and Application, vol.5, pp. 202-204, October 2022.

[4] Fang Yuwang. Research on the application of electrical automation technology in electrical engineering. Water Conservancy and Electric Power Technology and Application, vol. 6, pp. 214-216, January 2024.

[5] Jiancong Zhang, Defang Qiu, Lei Fan, Xing Huang, & Tianjin Lin. Research on the application of machine vision system in automated chain assembly. Engineering Technology and Management, vol.7, pp. 25-28, May 2023.

[6] Zhou Xuan. Application research of mechanical engineering automation. Mechanical and Electronic Control Engineering,vol.6,pp.46-48, November 2023.

[7] Wu Lian, & Lin Xisheng. Research and application of automated vision technology in industrial production. Mechanical and Electronic Control Engineering, vol. 6, pp. 218-220, August 2022.

[8] Fu Pan. Application of automated assembly system in aircraft parts manufacturing. Engineering Research and Application, vol. 5, pp. 4-6, October 2022.

[9] Zhang Wei, Wang Mengdi, Fan Junling, Yang Pengfei, Zhan Shaozheng, & Ning Ning. Application progress and prospect of machine vision in aircraft structural damage detection. Nondestructive Testing, vol. 43, pp. 75-80, October 2021.

[10] Liu Hailong, Zhang Lei, & Wu Haibo. Research on stereo positioning technology of industrial robots based on dual vision guidance. Electrical automation, vol. 43, pp. 116-118, January 2021.

[11] Huo Wei. Research on the application of intelligent technology in electrical automation. Mechanical and Electronic Control Engineering, vol.5, pp. 163-165, December 2023.

[12] Yongbo Zhao. Discussion on the application of artificial intelligence technology in electronic engineering automation control. Smart City Application, vol. 7, pp. 93-95, September 2023.

[13] Wang Ke. Research on the application of industrial robot technology in electrical control. Engineering Research and Application, vol.5, pp. 124-126, March 2024.