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Research Progress on Autonomous Operation of Industrial Robots Based on Big Data and Machine Vision

Zhaobo Gao

College of Mechanical and Electrical Engineering, Hainan University, Haikou, Hainan 570228, China, 18319865195@163.com

Corresponding author: Zhaobo Gao, 18319865195@163.com

Abstract. In the autonomous operation process of industrial robots, perception of the environment, task acquisition, path planning, and operation execution all require the use of machine vision. Using big data to process image data obtained by machine vision can effectively improve the ability to perform autonomous operations. In response to this issue, this study designed an industrial robot autonomous operation system based on big data and machine vision feedback optimization strategy. Firstly, the existing research on the application of big data and machine vision, as well as the autonomous operation of industrial robots, both domestically and internationally, were analyzed. Secondly, machine vision in industrial robots is an important component of information sensing. Then, the big data training strategy is introduced into the autonomous control end of industrial robots, enabling them to achieve adaptive operation and iterative analysis based on historical training information during autonomous operation and perform secondary optimization based on feedback analysis results. Finally, relevant experiments were designed for verification and analysis. The experimental results show that compared to existing industrial robot systems, industrial robot autonomous operation systems based on big data and machine vision can autonomously complete related engineering tasks with higher accuracy when facing multiple different objects and require shorter training time with fast response speed.

Keywords: Big Data; Machine Vision; Industrial Robot; Self Directed Homework; Feedback Optimization
DOI: https://doi.org/10.14733/cadaps.2025.S9.236-249

1 INTRODUCTION

Industrial robots have gradually become an indispensable and important component of modern manufacturing with the continuous development of information technology and artificial intelligence technology. In the traditional manufacturing process of industrial robots, real-time perception, recognition, and localization of target objects cannot be achieved due to various factors such as working environment and process. Meanwhile, industrial robots' autonomous operation has also become an important factor restricting their development [1]. The autonomous operation capability of industrial robots refers to the ability of industrial robots to perform real-time control based on their own performance, requirements, environmental conditions, etc. during the work process, without relying on human instructions or expert experience, in order to achieve collaborative operation with humans. The autonomous operation of traditional industrial robots can be mainly divided into the following aspects: robots can perceive the working environment in real-time, plan the work tasks in real-time based on their own performance, requirements, and other conditions, and then use existing trajectories for control operations [2]. Robots can complete designated tasks in unknown situations; Robots can adjust tasks based on their own performance and environmental conditions during task execution. Therefore, autonomous control of robots is necessary to ensure stable and efficient task completion [3]. On the other hand, in the traditional process of autonomous control of industrial robots, robots often rely on human instructions or expert experience for autonomous control, resulting in a lack of autonomous decision-making ability and an inability to achieve the goal of collaborative work with humans. Industrial robots need to face various types, states, and working conditions of work environments, all of which require machine vision to obtain information. Therefore, in the autonomous operation process of industrial robots, machine vision technology is needed to obtain environmental information. This article will mainly discuss the machine vision technology involved in the autonomous operation of industrial robots [4].

In the autonomous operation of industrial robots, machine vision systems are responsible for capturing environmental information and processing it quickly to guide the robot's movements. With the development of big data technology, industrial robots are facing the challenge of processing massive amounts of data. The deep learning architecture in the above method achieves intelligent compression and efficient utilization of data by simultaneously optimizing the sensing matrix and classification network [5]. In the big data environment, this method helps to reduce the load of data storage and transmission, accelerate data processing speed, and enable industrial robots to extract valuable information from massive data more effectively, optimizing their autonomous operation strategies. In traditional methods, it is usually necessary to first reconstruct the captured image with high quality, and then perform feature extraction and classification. This process not only requires a large amount of computation but may also lead to delays. The above-mentioned coupled deep learning methods bypass the complex image reconstruction steps by directly classifying compressed single-pixel measurement values. Significantly improved processing speed and classification accuracy, enabling machine vision systems to respond more quickly to environmental changes, and enhancing the operational efficiency and safety of industrial robots [6]. By applying deep learning to the sensing matrix optimization and classification tasks of single-pixel cameras, not only has the intelligence level of machine vision systems been improved, but new ideas have also been provided for other imaging techniques based on sparse sampling or compressed sensing [7]. This method demonstrates the possibility of deep integration between machine vision and deep learning techniques. This trend of integration is expected to promote the development of industrial robots towards more intelligent and autonomous autonomous operations [8].

In the autonomous operation of industrial robots, feature detection is the first and most critical step in image matching. However, with the continuous development of big data and machine vision technology, feature detection methods based on deep learning are gradually emerging. In the autonomous operation of industrial robots, the affine shape and directional information of local features are crucial for accurate matching [9]. These methods can automatically learn and extract more complex and robust features from large amounts of data, further improving the accuracy and efficiency of feature detection. Traditional feature detection methods such as SIFT (Scale Invariant Feature Transform) provide stable feature sources for subsequent matching processes by detecting scale-invariant feature points in the image. These pieces of information help robots accurately recognize the same object under different perspectives, lighting, and occlusion conditions. Therefore, after feature detection, it is usually necessary to estimate the affine shape and direction of local features to ensure the reliability of the matching results. From handmade feature descriptors such as SIFT to descriptors based on machine learning and deep learning, feature description techniques have undergone tremendous evolution [10].

2 CURRENT RESEARCH STATUS AT HOME AND ABROAD

Machine vision, as a technological means of "viewing" the world, is changing the public's model of viewing the world through its visual production, constantly expanding people's perception of external reality and re-understanding of cognitive processes. Ma et al. [11] analyzed from the perspective of computer technology that data visualization is essentially a mapping process from computer representation to perceptual representation. By selecting encoding techniques to maximize human understanding and communication. At this point, the data may no longer be read by the viewer, which means that the purpose of the artist's visualization is not to transmit data, but to use data to create images. From microscopes at the end of the 16th century to photography in the 19th century, and then to the 21st century, machines with automation and intelligence capabilities have almost pervaded the entire human living space. Machine vision is constantly creating large amounts of data, and data visualization has become a bridge connecting machine vision with human vision. From an artistic perspective, data visualization can also be used to convey cultural, and social information and concerns. For machine vision-based data visualization art, on the one hand, as a tool for artists' creation, machine vision provides artists with diverse sources of data. Sankhe et al. [12] convey a focus by displaying data in a certain way to clarify a trend or convey information. For the audience, it is more important to understand their concerns rather than read data, as creators can form a statement that has a strong impact on society and culture. On the other hand, artists are also keenly aware of the impact of technology on society and life, using machine vision as their creative subject to re-examine technology through art. On the one hand, machine vision has also become a subject of artistic creation, giving rise to new forms of visualization. However, based on the technical characteristics of machine vision, when artists use machine vision to participate in data visualization art design, they need to understand its technical features and expression rules.

It is crucial to synchronize the physical conditions of design and machine vision code development and select the software technology that is most compatible with the available physical conditions. Machine vision is different from human eyes and brain. No machine vision algorithm is completely universal, which means that it can only perform the expected function under any possible data input. Information art (data art) theorists view the relationship between art and technology from a non-traditional perspective. The integration of technology and art provides artists with opportunities to challenge the emergence of artistic concepts, and Weiss et al. [13] considered its themes and their role in society. Doubt the division between art and technology that began during the Western Renaissance, and point out that in the future, through the exchange of technology and art, art can once again play its historical role at the forefront of culture. Wu et al. [14] conducted a critical study on the fundamental system of algorithmic gaze through artistic intervention in order to elucidate the complex mechanisms of advanced computer vision technology, as well as the invisible images it creates and the systems used to train such images. This article focuses on the intersection of machine vision, scientific technology, and data visualization art in history. On the one hand, machine vision is a rapidly expanding technology that is increasingly affecting society and people's lives. On the other hand, visual perception machines will undoubtedly become the centre of large-scale social and technological changes in the future.

Zhang et al. [15] summarized the process of machine vision from perspective-based imaging automation to artificial intelligence-based visual automation and introduced how machine vision currently affects people's lives in invisible systems by combining art cases to analyze these three aspects and examine the technology of machine vision from the perspective of artists. Summarize and introduce data visualization art under the influence of machine vision from three aspects: machine vision as a tool for visual art creation, machine vision as the object of visual art creation, and machine vision as the subject of visual art creation. And summarize the design features of data visualization art and its current development status in the field of art. In addition, this method can significantly improve tracking performance without relying on overestimated control gains and prior knowledge of the robot, effectively avoiding singularity and algebraic loop problems that may occur in traditional control methods.

In summary, it can be concluded that the autonomous operation process of industrial robots includes multiple aspects, such as sensing the environment, acquiring tasks, planning paths, and executing operations. The use of machine vision technology and multi-sensor fusion technology is required to achieve this. However, in current related research results, there are common problems such as low control accuracy, poor reliability, poor overall collaborative operation effect, and low degree of intelligence in autonomous operations. Therefore, it is of great practical significance to develop an industrial robot autonomous operation system based on big data and machine vision.

3 DESIGN AND OPTIMIZATION OF INDUSTRIAL ROBOT AUTONOMOUS OPERATION SYSTEM BASED ON BIG DATA AND MACHINE VISION

3.1 System Composition and Autonomous Operation Principle of Industrial Robots

The autonomous operation system of industrial robots generally consists of the robot body, 3D vision sensors, 3D laser scanning system, robot controller, machine vision system, motion control system, etc. Common industrial robots are shown in Figure 1. When robots perform autonomous tasks, industrial robots first scan the target object through visual sensors. Then match the information of the scanned target object with the feature data in the robot controller to determine the position and posture of the target object in the industrial environment.

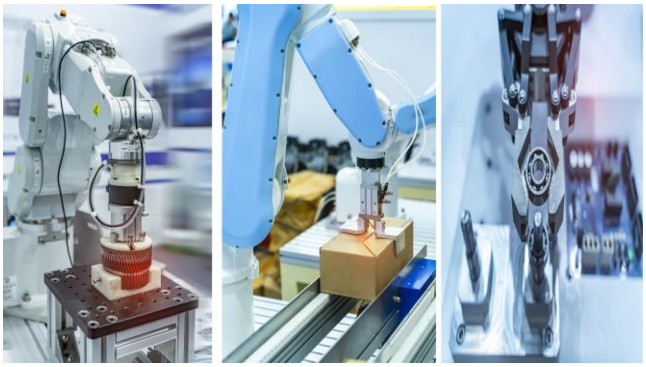

Figure 1: Common industrial robots.

When industrial robots perform tasks, after determining the position and posture of the target object in the industrial environment, this motion parameter information is converted into the motion parameter information required by the robot controller. Finally, the industrial robot is controlled by the robot controller to grasp and place the target object, and the machine vision system and robot controller monitor the entire process. Industrial robots obtain image information of industrial environments through visual sensors and then calculate the posture parameters of objects in the industrial environment through controllers. Control the industrial robot to grasp the target object, and the working process of the industrial robot is shown in Figure 2.

When designing the overall reliability of related industrial robots, this study will preprocess several commonly used operating modes of industrial robots and train the features of each executing component of the industrial robot before the robot performs tasks in order to improve the overall reliability of the industrial robot. At the same time, industrial robots use laser scanning systems to scan target objects and obtain in-depth information about the target objects. Then, 3D vision sensors are used to obtain 3D images of target objects in industrial environments and convert these image information into motion parameter information required by motion control systems. Finally, these motion parameters are controlled by a robot controller to achieve the grasping and placement of target objects in industrial environments.

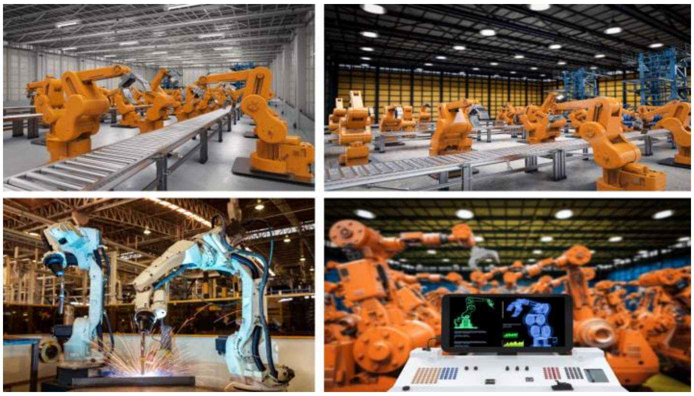

Figure 2: Common industrial robot working process.

When industrial robots perform autonomous operations, they usually first undergo feature training, and then the trained feature information is calculated in the robot controller to determine the autonomous operation tasks of the industrial robot. The composition of the industrial robot is shown in Figure 3. Therefore, when designing a robot's autonomous operation system, the various executing components of the robot should be optimized to enable industrial robots to complete autonomous operation tasks more safely and efficiently. This system enables industrial robots to have sharp visual abilities, enabling them to independently recognize and locate target objects in complex and changing environments in industrial workshops. Robots can capture detailed information about target objects, such as size, shape, and colour, through built-in cameras and sensors. Subsequently, the system will utilize advanced data analysis algorithms to match this information with the large amount of data stored in the database in order to determine the optimal retrieval and placement plan. In addition, autonomous homework systems can monitor the robot's motion status and adjust environmental parameters such as temperature and humidity in the working environment in real time to maintain optimal working conditions. Therefore, the industrial robot autonomous operation system designed by this research institute is a new-generation robot system that integrates machine vision and big data optimization strategies.

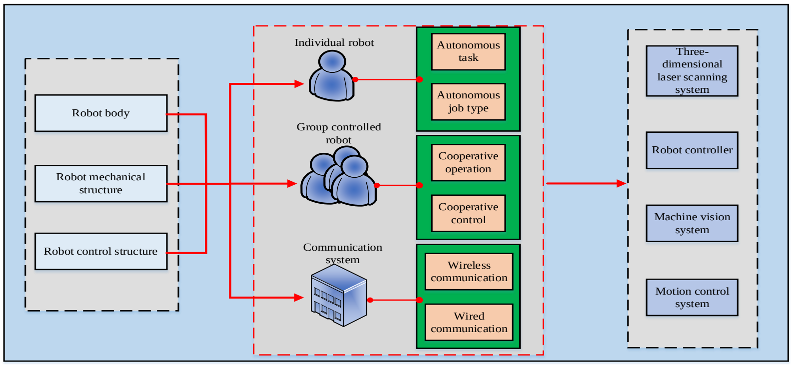

Figure 3: Common industrial robots are part of the process.

3.2 The Implementation Process of Big Data in Industrial Robot Autonomous Operation System

The autonomous operation system of this industrial robot adopts cloud computing and artificial intelligence technology, which can process and analyze massive data collected from various sensors and actuators. These big data, through deep mining and intelligent processing, can reveal deeper production laws and trends, providing a scientific basis for the optimization operation of industrial robots. Through continuous learning and self-adjustment, industrial robots become more flexible and adaptable in dealing with various unexpected situations, greatly improving their overall work efficiency while reducing human errors and resource waste. Before industrial robots perform autonomous operations, it is necessary to first identify and extract information from the input data set. This is because, in the actual production process, various sensors generate a large amount of data, including temperature, humidity, light, gas composition, pressure, and so on. By collecting and processing this data, the operational status of industrial robots can be monitored and analyzed. In this process, it is necessary to determine the data beam width generated by each industrial robot during the analysis process so the evaluation function of each node can be calculated and the corresponding evaluation relationship formula can be found:

$$L = \beta L_{\min} + 1 - \alpha \ L_{\max} \tag{1}$$

At this point, further intrinsic correlation is applied to its corresponding relationship, resulting in the fusion loss M_{Fuse} of its corresponding correlation evaluation function. The specific formula is as follows

$$M_{Fuse} = M_{\text{int}}^{Fuse} + M_{SSIM}^{Fuse} \tag{2}$$

The maximum and minimum fusion losses corresponding to this can be expressed as

$$M_{\max} = \frac{M_{sema}^{Fuse} + M_{SSIM}^{Fuse}}{\beta} \tag{3}$$

$$M_{\min} = \frac{\beta M_{sema}^{Fuse} + \alpha M_{SSIM}^{Fuse}}{\alpha + \beta} \tag{4}$$

Among them L represents the data evaluation function, α, β the set parameters between dependent variables and behavioural parameters, M_{int}^{Fuse} the intrinsic strength loss of data, M_{SSIM}^{Fuse} the dimensionality loss of data, and M_{sema}^{Fuse} the regularity loss of data. $M_{\max}$ Represents the maximum comprehensive loss of data while $M_{\min}$ representing the minimum comprehensive loss of data.

At the same time, in order to achieve better production efficiency, industrial robots also need to process and mine data accordingly. Firstly, there are certain differences in the data collected under different sensors. After analyzing the collected data, it can be used as a reference value for the next stage of decision-making behaviour. Secondly, the data can be adjusted accordingly based on the actual usage of industrial robots. The determination formula for underestimating and overestimating the inherent data flow redundancy of industrial robots during the inner loop process can be expressed as follows:

$$K_F = \frac{1}{\alpha\beta}\left\| L_{\min} - \max(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse}) \right\|_2 \tag{5}$$

$$K_H = \frac{1}{\alpha + \beta}\left\| L_{\min} - \min(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse}) \right\|_2 \tag{6}$$

Among them, it represents the 2-norm. After error filling, its expression can be converted into

$$K_{Fe} = \frac{e+1}{\alpha\beta}\sqrt{\left\| L_{\min} - \max(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse}) \right\|_2} \tag{7}$$

$$K_{He} = \frac{\sqrt{\left\| L_{\min} - \min(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse}) \right\|_2}}{\alpha + \beta} + e \tag{8}$$

Among them K_F, K_{Fe} represents the data stream redundancy underestimation function and K_H, K_{He} represents the data stream redundancy overestimation function.

A detailed analysis of data is required in the specific application process to achieve better application results. Through the continuous cycle and repeated operation of these processes, industrial robots can have a clearer understanding and knowledge of their environment while also being able to better complete autonomous tasks. The application process of big data in the autonomous operation system of industrial robots is shown in Figure 4.

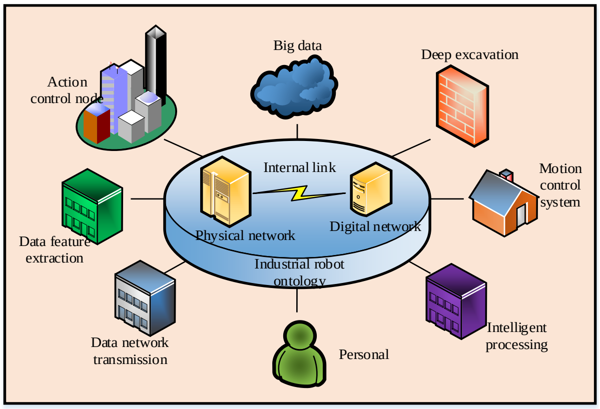

Figure 4: Application flow of big data in industrial robot autonomous operating system.

After the big data judgment model and optimization design model are input into the industrial robot control system, these models can be applied to specific production operations, enabling industrial robots to complete various tasks independently. In this process, the big data judgment model and optimization design model are the two most important parts, which can comprehensively evaluate the operating status and work effect of industrial robots. Therefore, in this process, it is often necessary to determine its intrinsic correlation through data flow. After multiple transformations, its intrinsic correlation can be expressed as

$$\frac{K_H}{\alpha+\beta} - M_{SSIM}^{Fuse} \geq \frac{K_F}{\alpha+\beta} - L_{\min} \tag{9}$$

When the correlation is strong, there is

$$\frac{K_H}{\alpha+\beta} - \frac{M_{SSIM}^{Fuse}}{\max(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse})} \geq \frac{\alpha-\beta K_F}{\alpha+\beta} - L_{\min} \tag{10}$$

When the correlation is weak, there is

$$\frac{K_{He}}{\alpha-\beta} - \frac{M_{SSIM}^{Fuse}}{\min(M_{SSIM}^{Fuse}, M_{\text{int}}^{Fuse})} \geq \frac{\alpha+\beta K_F}{\alpha-\beta} \tag{11}$$

Due to the fact that industrial robots are multifunctional and highly intelligent systems, they need to be combined to form stronger autonomous operation capabilities. When conducting autonomous operations on industrial robots, in addition to considering their own structure, performance, and stability, it is also necessary to combine specific requirements in different scenarios. Fully leverage the role of big data judgment models and optimization design models in autonomous operations, thereby enabling industrial robots to better complete various tasks. The relevant simulation analysis results during this process are shown in Figure 5.

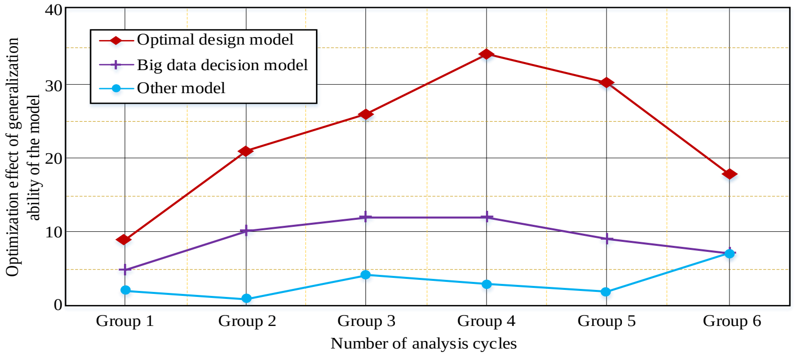

Figure 5: Simulation analysis results of industrial robot autonomous operating system based on big data.

From the results of Figures 4 and 5, it can be concluded that in the autonomous operation system based on big data, the higher the learning rate on the training set, the stronger the model's generalization ability, thereby enabling industrial robots to have better autonomous operation capabilities. On this basis, the model can be optimized and adjusted accordingly for specific needs in different scenarios. Through continuous cycles, repetitions, and repetitive operations, industrial robots can form more stable and efficient autonomous operation capabilities, thereby improving production efficiency and quality.

3.3 The Implementation Process of Machine Vision in Industrial Robot Autonomous Operation System

After the big data analysis model can be well integrated with industrial robots, it is necessary to introduce machine vision technology to further enhance the reliability and stability of industrial robots in autonomous operation processes. In the industrial robot autonomous operation system designed by our research institute, machine vision technology can transmit the working status of the industrial robot to the central computer through images, achieving remote control of the industrial robot. The control centre of industrial robots contains a large amount of image information, which can be recognized and processed, and the recognized information can be fed back to the industrial robots to complete autonomous operations. The system also uses binocular stereo-vision technology to integrate the field of view of industrial robots and surveillance cameras, thereby achieving the localization and recognition of target objects. During this process, it is necessary to perform feature extraction on the relevant dataset, and the corresponding feature extraction function is provided.

$$f_t = \sigma \; K_{He} \bullet \left[M_{SSIM}^{Fuse}, x_t \right] + \beta M_{\text{int}}^{Fuse} \tag{12}$$

After normalizing the feature information, the expression at this time can be expressed as

$$f_t' = \frac{\alpha \; K_{He} \bullet \left[M_{SSIM}^{Fuse}, x_t \right] + \beta M_{\text{int}}^{Fuse}}{\sigma + \alpha + \beta} \tag{13}$$

Among them f_t represents the feature extraction function, x_t the data variable, α,β the set parameters and behavioural parameters between the dependent variables, and σ the decision factor parameters.

The binocular stereo vision system in this system can be divided into two parts, namely the image acquisition system and the image processing system. In the image acquisition system, multiple cameras are set up to obtain image information of the target object through the cameras. In the image processing system, image recognition algorithms are used to process the collected image information using computer vision technology and identify the position and direction of the target object. This intelligent approach not only greatly improves production efficiency, but also enhances the adaptability of industrial robots to complex environments during autonomous operations, as shown in Figure 6.

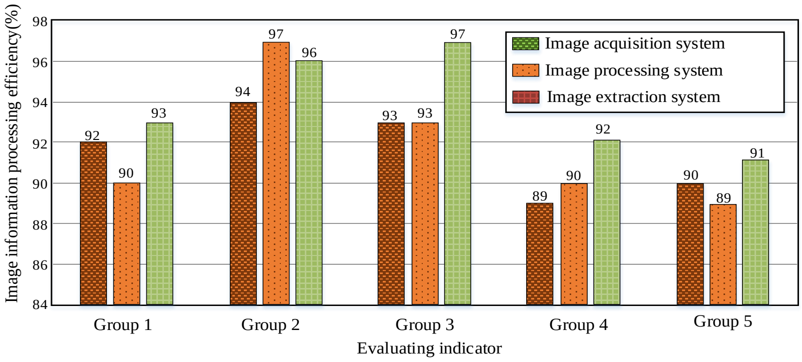

Figure 6: Simulation results of industrial robot autonomous operating system based on binocular stereo vision system.

From Figure 6, it can be seen that this is because the system can set up monitoring cameras in the control centre of industrial robots to obtain real-time information on the working status, production site images, environmental information, etc. of industrial robots. At the same time, the monitoring camera collects the information required by the industrial robot during autonomous operation and transmits it to the central computer, allowing the industrial robot to complete autonomous operations. After completing the autonomous task, the control centre of the industrial robot will analyze and process the images captured by the monitoring cameras based on the on-site information. The final generation of corresponding control instructions provides data support for subsequent work, thus significantly improving its adaptability to complex environments.

3.4 Optimization Strategies of Big Data and Machine Vision in Autonomous Operation of Industrial Robots

In order to better achieve autonomous, collaborative, and intelligent operation of industrial robots, this study optimizes and integrates big data and machine vision and further improves the steps of autonomous operation of industrial robots, effectively enhancing the efficiency of autonomous operation of industrial robots. It can be specifically divided into the following aspects:

Firstly, through multi-level deep learning training, industrial robots can better extract effective information contained in massive data sets. And further explore the inherent correlations between these data sets, so that industrial robots can accurately judge and plan the environment in which they operate autonomously based on these correlation information. This has significantly improved the autonomous operation capability of industrial robots, as shown in Figure 7.

Figure 7 shows that industrial robots, after obtaining the position and direction information of the target object, classify and recognize it based on its features. Through the cooperation and collaboration of these two parts, industrial robots can quickly and accurately find the position and direction of the target object. After completing autonomous operations, industrial robots will provide feedback to the control centre based on the collected data and processed results.

Secondly, through machine learning-based autonomous operation technology for industrial robots, multiple intelligent nodes are effectively integrated, enabling industrial robots to discover their position and state in complex environments effectively. Thus, more accurate judgments and decisions can be made, enabling industrial robots to achieve autonomous control of themselves in complex environments.

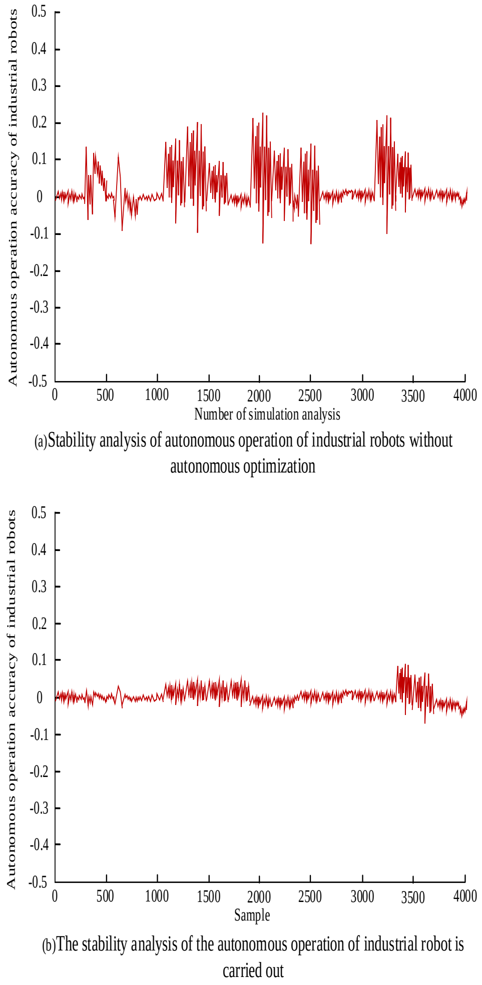

Figure 7: Stability analysis results of industrial robot autonomous operation before and after optimization.

The corresponding error loss function during this process is.

$$\Delta P = \left\| \frac{f_t^{'} - f_t}{\alpha\beta} \right\| \tag{14}$$

The expression for the corresponding stability function at this time is

$$\Delta E = \Delta P + \beta^2 \left(1 + \frac{\Delta P}{\alpha} \right) \tag{15}$$

Among them f_t represents the feature extraction function, ΔP the error loss function, ΔE the stability function, and α, β the set parameters between the dependent variables and the behavioural parameters.

Finally, by optimizing and integrating big data and machine vision technology, industrial robots can extract more accurate and comprehensive data information from massive amounts of data, and adjust and control their own status in real-time, achieving dynamic real-time monitoring of the autonomous operation process.

4 EXPERIMENTAL DESIGN AND RESULT ANALYSIS OF AUTONOMOUS OPERATION OF INDUSTRIAL ROBOTS

4.1 Experimental Design Process for Autonomous Operation of Industrial Robots

To verify the effectiveness of the autonomous operation method of industrial robots based on big data and machine vision technology, this study installs a six-degree-of-freedom industrial robot on a four-degree-of-freedom robotic arm and installs it on a programmable control platform. During the experiment, the collected image data is first transmitted to a computer for processing, and image processing tools are used to segment and recognize the target object. Then the obtained image data is transmitted to the robot, which completes the grasping operation of the target object. Finally, by processing the acquired image information and using a linear interpolation algorithm to fuse the collected image information, the experimental data comparison results are shown in Table 1.

Group	*X1*	*X2*	*X3*	*Optimal reference value*
1	2.1025	2.1642	2.0181	3.28901
2	2.1024	2.1636	2.0174	3.28526
3	2.1022	2.1639	2.0186	3.27587
4	2.1022	2.1641	2.0175	3.22584
5	2.1035	2.1642	2.0185	3.27856
6	2.1015	2.1652	2.0177	3.25694
7	2.1045	2.1637	2.0188	3.27589
8	2.1027	2.1632	2.0177	3.27566
9	2.1028	2.1636	2.0197	3.29851
10	2.1015	2.1632	2.0187	3.27882

Table 1: Comparison results of experimental data.

In order to verify the effectiveness of the autonomous operation method of industrial robots based on big data and machine vision technology in practical environments, this study compared it with traditional industrial robot operation methods. The experimental data comparison results are shown in Figure 8.

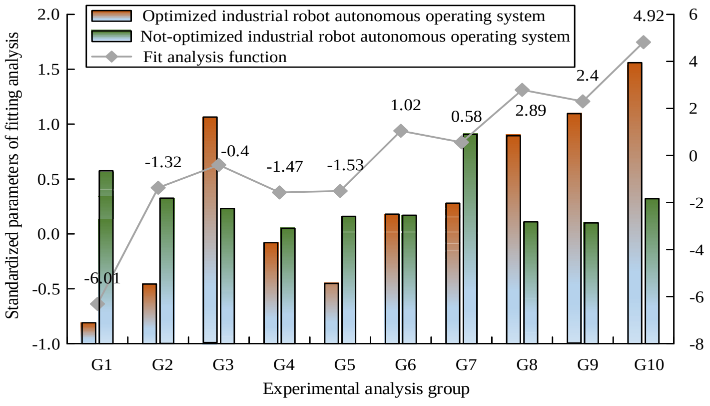

Figure 8: Experimental comparison results of autonomous operation of industrial robots.

From the experimental results in Figure 8, it can be seen that through comparative experiments, the industrial robot using this method outperforms traditional methods in terms of accuracy and speed in completing tasks. Specifically, the experimental results show that industrial robots based on big data and machine vision technology have improved the accuracy of recognizing target objects by about 20% while reducing task completion time by about 30%. This is because, on one hand, big data technology enables industrial robots to process and analyze massive amounts of data information, thereby making more accurate decisions in complex work environments. On the other hand, the application of machine vision technology enables industrial robots to acquire and process image information in real-time, thereby achieving rapid localization and recognition of target objects.

4.2 Analysis of Experimental Results

In the above experiment, in order to further analyze the differences between its experimental results and traditional industrial robots in autonomous operation, this study processed the data through an experimental platform and an upper computer and analyzed its reliability, stability, error rate, and other aspects. The analysis results are shown in Table 2.

Group	*Reliability*	*Stability*	*Error (%)*
1-2	96.10	1.06	5.8
3-4	97.66	1.52	3.6
5-6	97.08	1.63	1.4
7-8	98.23	1.75	0.7
9-10	99.78	2.37	0.5

Table 2: Analysis of experimental results.

In addition, this study conducted a comprehensive analysis of the intelligence level, work efficiency, and work quality of the autonomous operation of the relevant industrial robots during the experimental process, as shown in Figure 9.

From Figure 9, it can be seen that the industrial robot autonomous operation system designed in this study has improved in terms of intelligence, work efficiency, and work quality compared to traditional industrial robot systems. This is because, in this experiment, the robot is capable of autonomously detecting, recognizing, and tracking target objects, and can plan work tasks according to its own needs during autonomous operations, resulting in a high level of intelligence and work quality. Overall, the industrial robot autonomous operation system designed in this experiment has a higher degree of intelligence, work efficiency, and work quality compared to traditional industrial robot systems.

5 SUMMARY AND PROSPECT

The autonomous operation capability of industrial robots is a key research topic in the current industrial field, and the application of big data and machine vision technology in autonomous operation can effectively improve the autonomous operation capability of industrial robots. The industrial robot autonomous operation system based on big data and machine vision technology proposed by our research institute can, on the one hand, process image data to convert complex environmental information into useful information, providing support for autonomous operation. On the other hand, by analyzing the collected image data and extracting more useful information, industrial robots can achieve autonomous operation. The experimental results show that compared to existing industrial robot systems, industrial robot autonomous operation systems based on big data and machine vision can better and more accurately complete related tasks autonomously when facing multiple different objects, with shorter training time and fast response speed. In addition, due to the limited amount of data currently available, the data analysis strategy in this study can be further improved. In the future, with the further development and improvement of big data and machine vision technology, autonomous operation of industrial robots based on big data and machine vision technology will be more widely applied.

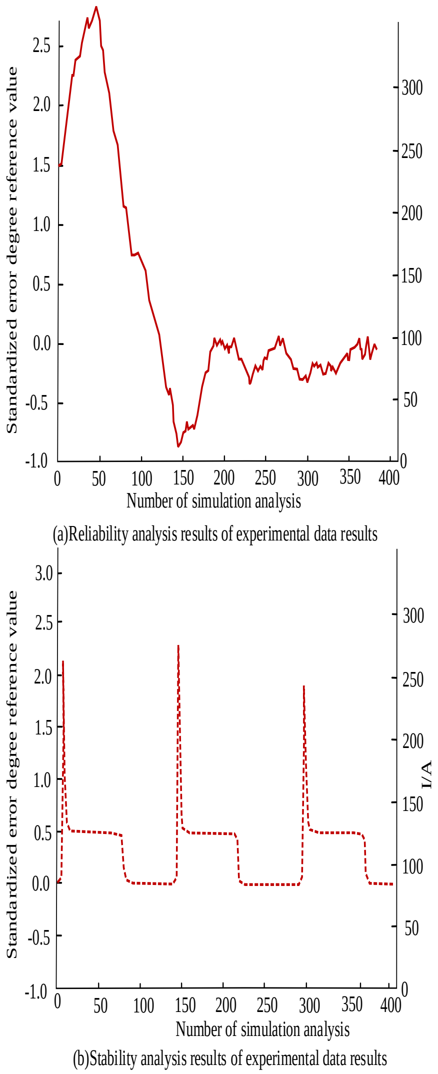

Figure 9: Error degree analysis of reliability and stability of experimental results.

Zhaobo Gao, https://orcid.org/0009-0006-7556-8022

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