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Article

Research on Optimization of Assembly Quality Inspection System of Industrial Robot Based on Machine Vision and Improvement of Enterprise Benefit

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Abstract: In the process of Industry 4.0 and industrial intelligence, industrial machine vision plays a crucial role in the quality inspection of workpiece assembly. It can effectively address production and manufacturing issues caused by workpiece quality problems during assembly, thereby significantly improving production quality and efficiency. This paper optimizes traditional industrial robot assembly quality inspection methods by adopting machine vision technology, combining hardware and algorithms to enhance the machine vision system. The TMS320C6711 digital signal processor serves as the core for image information processing, integrated with the EMIF interface, DMA, and interrupt mechanisms to achieve high-speed data transmission and real-time image processing capabilities. A multi-module collaborative solution based on SAA7111, CPLD, and MCU is adopted to optimize the image acquisition module, further enhancing system stability and flexibility. Additionally, an intelligent lighting optimization method combining PWM control algorithms with neural network scene recognition is employed to effectively address the issue of low assembly quality detection accuracy under varying lighting conditions, ensuring reliable performance in complex lighting environments. Results show that compared to traditional machine vision systems, the newly optimized system offers higher accuracy and classification accuracy, with detection accuracy improving from 92.77% to 94.15%, representing an 11.38% increase. Additionally, compared to traditional detection methods, the system significantly reduces detection time, enhancing the operational efficiency of industrial robots. It provides a reliable basis for assembly quality inspection in industrial robots and offers valuable insights for the application of machine vision in industrial fields.

Keywords: machine vision; industrial robots; assembly quality inspection; DSP platform; deep learning

1. Introduction

1.1. Research Background

In the context of the rapid development of Industry 4.0 and smart manufacturing, industrial robots—a key technology in modern manufacturing—are increasingly gaining attention, particularly in the field of assembly quality inspection. Machine vision, serving as the “eyes” of industrial robots in assembly processes, plays a crucial role in quality inspection [1]. With its advantages of high precision, efficiency, and automation, machine vision technology enables rapid and accurate identification and classification of defects during the assembly process, thereby enhancing production quality and efficiency to a certain extent [2-3]. As the quality requirements in the manufacturing sector continue to rise, traditional visual inspection methods and inspection systems based on conventional machine vision often fail to achieve efficient and precise detection results. How to improve the performance and detection efficiency of assembly quality inspection systems has become a key issue facing the manufacturing sector today [4-6].

Chauhan et al. [7] used Fanuc robots, artificial intelligence, and computer vision to film the assembly site and transport materials, classify assemblies as acceptable or unacceptable, and locate assembly defects, thereby integrating and constructing an automated assembly inspection system to reduce defect rates, improve product quality, and reduce costs. Genta et al. [8] established an appropriate defect generation model based on operator assembly defect rates and assembly process complexity to predict the probability of defects occurring, and established an assembly quality inspection procedure for short production cycles to control the assembly process. Mosca et al. [9] proposed a multimodal sensing mode using a 3D snapshot sensor and a color camera in a computer vision system to detect geometric and surface defects in aircraft manufacturing assembly. In addition, Magalhaes and Ferreira [10] designed an integrated industrial vision system based on collaborative robots for industrial automation quality inspection. This method not only reduced quality issues in the production process but also lowered production costs, thereby enhancing the profitability of manufacturing enterprises. In 2020, Frustaci et al. [11] reported a machine vision system for online inspection of catalytic converter assembly, which incorporated image segmentation programs and combined geometric models to detect potential geometric defects in exhaust system interfaces. This assembly inspection system features high flexibility, high precision, and low cost. In 2022, Frustaci et al. [12] combined hardware and software collaborative methods, using a computer vision system built on a heterogeneous multi-processor system-on-chip to perform automatic quality inspection of the welding process during assembly. This approach strictly controlled temporal and spatial properties, achieving performance 23 times higher than pure software solutions.

Currently, in existing machine vision inspection systems, due to the limitations of traditional hardware platforms, the system is often composed of a cascade transmission structure involving image acquisition cards, PCs, and terminal control units, resulting in issues such as low real-time performance, high costs, and poor reliability. In complex industrial environments, especially those with significant changes in lighting conditions or unstable environmental conditions, unstable image acquisition quality can affect system detection accuracy. These issues can be addressed by improving the hardware platform, integrating advanced image acquisition and transmission platforms, and introducing intelligent lighting control systems to ensure stable image acquisition quality [13-14]. With the successful application of deep learning image processing technology, deep learning technology centered on convolutional neural networks (CNNs) will become the core algorithm for visual systems.

Singh and Desai [15] applied CNN and ResNet-101 for automated surface defect detection in a grinding process of manufacturing production, combining multiple support vector machines for surface image classification. Basamakis et al. [16] utilized CNN to construct a deep learning object detection framework for assembly operations, adaptable to various manufacturing systems, enabling automated, non-destructive, and efficient detection of objects such as correct, misaligned, and missing parts in complex assembly production environments. Shaloo et al. [17] created a low-cost and real-time automatic optical inspection system using the YOLO algorithm (You Only Look Once) in CNN and a camera, and equipped the system with the andl TIA Portal v17 to control the quality of the assembly process, achieving a detection accuracy of 98%. Lin et al. [18] utilized region-based CNN, transfer learning, the AlexNet model to build a visual inspection system for detecting assembly defects in similar manual tool products.

Deep learning can automatically learn features in complex environments, accurately identify assembly defects, and further improve the accuracy and efficiency of machine vision system recognition and detection [19-20]. Combining PWM control algorithms with neural network scene recognition can dynamically optimize lighting while improving image acquisition quality, thereby enhancing detection accuracy and effectively addressing the challenge of accurately detecting defects under complex lighting conditions in traditional visual systems [21].

This paper proposes optimization schemes for the hardware, software algorithms, and control technology of the proposed machine vision industrial robot assembly quality detection system based on the DSP platform to improve the overall performance of the designed detection system. In terms of hardware, the TMS320C6711 digital signal processor is utilized, employing the EMIF interface and DMA technology to optimize data transmission and image processing, thereby enhancing data transmission and image processing rates. In terms of software algorithm optimization, two convolutional neural networks—AlexNet and FasterR-CNN—were combined to optimize the identification and classification of assembled parts. Regarding lighting, to address the impact of lighting on detection during the assembly process, the lighting was controlled via PWM and combined with neural network scene recognition technology to further optimize the detection system's accuracy. The performance optimization of this detection system has further improved detection efficiency, generating economic benefits for enterprises.

1.2. Innovative Aspects of This Study

This paper proposes a DSP-based machine vision system upgrade solution to overcome the technical challenges faced by industrial robots in terms of low real-time performance in quality inspection, insufficient accuracy in quality inspection, and low system inspection efficiency. It breaks through the hardware architecture bottlenecks of traditional computer-based machine vision processing systems, particularly the sequential chain architecture of "image acquisition card-PC-terminal control device." The TMS320C6711 digital signal processor is selected as the system's core processor, and the EMIF interface is utilized to expand external data storage capacity. This enables the simultaneous use of interrupt and DMA technologies for data transmission, significantly improving transmission speed. To further enhance the system's flexibility, dynamism, and practicality, this paper adopts an SAA7111+CPLD+MCU design structure in the system design process, replacing the traditional I2C controller with an I2C bus-controlled SAA7111. Further optimizing the performance of the signal transmission process enhances the system's safety and reliability. To effectively assess quality issues in assembled components (such as precision errors), this paper proposes the application of the AlexNet pre-classification + Faster R-CNN recognition algorithm, based on deep learning technology, to achieve deep image feature extraction of assembled components using a dual convolutional neural network.

Additionally, to address the limitations of complex and variable light intensity changes in industrial environments, the author proposes a light source optimization control algorithm based on PWM control algorithms and neural network scene recognition. This combines a light intensity calculation model under mixed lighting conditions to precisely control light intensity and utilizes a neural network scene recognition algorithm for real-time analysis and adaptive adjustment of scene lighting. This fundamentally addresses the issues caused by unstable lighting, effectively ensuring the detection accuracy and stability of the system in industrial environments with varying lighting conditions, thereby enhancing production efficiency and assembly quality for enterprises.

2. Research Methods

2.1. Hardware Optimization

This paper proposes a novel design and implementation method for a machine vision system based on the TMS320C6711 digital signal processor. The paper finds that optimizing the traditional small-system hardware architecture can effectively address data transmission redundancy issues in conventional DSP systems. Extensive work has been done to expand external storage resources, using the EMIF interface to extend external memory and form an efficient storage structure. For image acquisition and data transmission, a combination of interrupts and DMA is employed, while power and clock circuits are processed with multi-level filtering [22]. In the final PCB board design, the system's interference resistance was considered, and a multi-layer PCB board design was adopted to minimize external interference in the system. This paper employs a combination of SAA7111, CPLD, and MCU in the system's image acquisition section. The SAA7111 is controlled using a microcontroller to simulate the I2C bus, which reduces costs while increasing system flexibility. The specific system parameter settings are detailed in Table 1.

Table 1. Parameters of the image processing system on the DSP platform.

Parameter item	Parameter value
Image resolution	640×480 pixels
LLC clock frequency	27 MHz
LLC2 clock frequency	13.5 MHz
Pixel count per row	640 points
The number of sampling rows in the odd field	Line 240 (Lines 47-286)
The number of rows of even field sampling	Line 240 (Lines 360-599)
DMA transmission word length	Programmable
Transmission count value	0X00012C00
Source address value	0X17200000
Destination address value	0X80000000

By optimizing the DMA controller functionality through the above adjustments, the data transfer method can be configured to support flexible data block transfer modes under various conditions. Each data block can consist of multiple data frames, and the address generation method as well as the data transfer word length can be dynamically and flexibly configured to meet real-time requirements. After laboratory testing, this system meets the requirements. Compared to traditional PC-based vision systems, the data processing rate is approximately 2.5 times faster, and the startup time is reduced by 25 seconds. The improved processing rate directly impacts production inspection efficiency. Additionally, its simpler structure offers significant potential for reducing manufacturing costs, providing industrial enterprises with a more cost-effective vision inspection solution. During laboratory testing, it was found that the system operates normally during image acquisition and processing, with significantly reduced latency. The optimization of the DSP-based hardware architecture enables it to meet the requirements of real-world industrial robot assembly quality inspection, and future upgrades are also relatively easy to implement to meet evolving needs.

2.2. Algorithm Optimization

This paper adopts a multi-pronged approach to improve the detection accuracy and efficiency of quality inspection in industrial robot assembly, focusing on optimizing autofocus algorithms, image processing algorithms, and deep learning algorithms. In the optimization of autofocus algorithms, a combination of hill-climbing search algorithms and equidistant search algorithms is proposed. Based on a hybrid autofocus method, equidistant search replaces the coarse focus in traditional algorithms to locate the approximate focus range. Subsequently, an improved hill-climbing search algorithm is used for fine focusing to achieve precise focus adjustment. The hill-climbing search algorithm is prone to getting stuck in local optima during fine focusing. However, the optimized hill-climbing search algorithm balances both the detection accuracy of the focal length and effectively reduces the time required for focal length detection using the hill-climbing search algorithm [23].

The optimized image processing scheme primarily employs adaptive median filtering based on the Sobel operator. Traditional median filtering achieves good noise reduction, but the filtering process often results in the loss of edge information [24]. The adaptive median filtering used in this paper can adjust the filter window in real-time based on the characteristics of different images. Combined with the Sobel operator, it effectively preserves boundary information, ensuring image detail.

In terms of deep learning algorithms, the study proposes a dual CNN network structure based on AlexNet+FasterR-CNN. AlexNet performs coarse segmentation of the assembly parts, while FasterR-CNN is used for precise defect detection. This improves detection accuracy and, by reducing the FasterR-CNN computation area, enables faster information processing. The basic workflow of the algorithm is as follows:

$$F(X) = \max(0, X * W + b) \tag{1}$$

In this context, x represents the input feature map, w denotes the convolution kernel weights, and b represents the bias term. To further enhance the effectiveness of feature extraction, the pooling layer employs an improved max pooling operation, specifically:

$$P(X) = \max_{subregion}(X)_{4^1} \tag{2}$$

2.3. Software Optimization

In terms of software, the industrial robot assembly quality inspection system uses a combination of Visual Studio 2010 and Halcon function library programming. Based on the many problems encountered in actual production, an image capture module based on a multi-level data caching mechanism is proposed, which solves the problem of real-time visual information collection and allows switching between software and hardware trigger modes as needed. For this problem, the intelligent trigger algorithm based on area judgment is expressed as:

$$T(x, y) = \begin{cases} 1, & \text{if}\,(x, y) \in R_{target} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In the formula, $T(x, y)$ represents the trigger state, and R_{target} denotes the predefined target area. In response to the complex and variable lighting conditions in industrial environments, we propose an adaptive threshold image enhancement algorithm, namely:

$$I_{enhanced}(x, y) = \alpha \cdot I_{original}(x, y) + \beta \cdot G(x, y) \tag{4}$$

In the equation, $I_{enhanced}$ and $I_{original}$ represent the enhanced and original images, respectively,

$G(x, y)$ is the Gaussian smoothing kernel, and α and β are adaptive weight coefficients.

In terms of robot state information collection and processing, this system establishes a state vector s containing key parameters such as speed, displacement, and mass for real-time monitoring, as follows:

$$S = [v_x, v_y, v_z, p_x, p_y, p_z, m, \theta]^T \tag{5}$$

In the equation, v is the velocity component, p is the position coordinate, m represents the mass of the workpiece, and θ is the joint angle.

2.4. System Integration

In this study, after completing the optimization of each module, we conducted system integration research. Based on the actual conditions of industrial robot assembly production lines, we focused on in-depth analysis of key aspects such as hardware integration, software fusion, and algorithm coordination. At the hardware level, we adopted a data bus structure centered on the TMS320C6711 digital signal processor, supplemented by an EMIF bus to connect external storage devices and image acquisition modules. Considering the complex electromagnetic interference issues in industrial environments, the integration process incorporated multi-level power filtering and signal isolation technologies. The overall system architecture can be mathematically modeled as:

$$S_{total} = \{H_{DSP}, H_{Image}, H_{Light}\} \cup \{S_{Control}, S_{Process}\} \cup \{A_{Focus}, A_{CNN}\} \tag{6}$$

To ensure real-time and stable data processing, a double-buffering mechanism is used for data interaction between functional modules, and a data flow model is established, namely:

$$D_{flow} = \begin{cases} D_{in} \to B_1 \to P_{current} \\ D_{in} \to B_2 \to P_{next} \end{cases} \tag{7}$$

In the equation, D_{in} represents the input data stream, B_1 and B_2 are double buffers, and P denotes the processing flow. At the software level, the event-driven task scheduling system we developed enables automated coordination among various functional modules, with its core algorithm expressed as:

$$T_{schedule} = \arg\min_t \sum_{i=1}^{n} w_i \cdot t_{i_\psi} \tag{8}$$

Here, w_i represents the task weight, and t_i represents the task execution time. At the algorithm level, by establishing a unified feature descriptor and decision-making mechanism, multiple algorithms can complement each other's strengths. The decision fusion model can be expressed as:

$$R_{final} = \sum_{i=1}^{m} \alpha_i \cdot R_{i_\psi} \tag{9}$$

3. Optimization Analysis

3.1. Optimization Background and Objectives

3.1.1. Optimization Background

With the development of Industry 4.0 and smart manufacturing, the widespread adoption of assembly automation has made robots the primary execution devices on assembly production lines. However, the current limitations of traditional assembly inspection systems—such as slow response times, poor recognition accuracy, and weak adaptability to lighting conditions—no longer meet the demands of modern production lines for inspection cycle times. To address this, this paper leverages DSP platform-based hardware and software co-optimization design, integrating deep learning algorithms and intelligent lighting control strategies to comprehensively optimize the assembly quality inspection system, thereby enhancing the system's intelligence, detection accuracy, and corporate efficiency.

3.1.2. Core Optimization Content

(1) Hardware structure design. The TMS320C6711 DSP is used to connect to external storage space via the EMIF interface for data transmission, and DMA acceleration is employed to enhance data transfer speed. An interrupt mechanism enables parallel execution of image processing and data transmission, fundamentally improving system response time and real-time performance.

(2) Image preprocessing. The image acquisition module is optimized by introducing an adaptive median filtering algorithm to improve the accuracy of edge extraction. Additionally, the system is trained using images of multiple industrial components to enhance its ability to recognize complex assembled parts.

(3) Improved CNN network model. Utilizing an object detection network model based on AlexNet and FasterR-CNN, precise detection and classification of various installation components are achieved. Training samples include common installation defect samples to enhance the model's generalization performance for similar installation defects. A smart lighting system combining neural network background scene recognition with PWM is proposed, which adjusts lighting intensity in real-time based on the background scene to ensure clear and stable captured images, eliminating the degradation of detection performance caused by background lighting differences.

3.2. System Performance Comparison Analysis

3.2.1. Comparison of System Optimization Before and After

To demonstrate the effectiveness of the method described in this paper in optimizing the performance of assembly quality inspection systems based on industrial robots, we conducted a comparative analysis of the performance indicators of the optimized system, collected data on various performance indicators, and compared the changes in various indicators before and after optimization. Table 2 shows a comparison of the performance indicators of the system before and after optimization.

Through experimental research and practical application, the assembly quality inspection system has been proven to be stable and has been successfully applied to a certain automotive parts production line. The number of inspection workers has been reduced by 40%, product inspection efficiency has reached 91.97%, the classification pass rate is 94.60%, and the average inspection time per piece does not exceed 180 milliseconds. After continuous operation for 72 hours, the failure rate is less than 0.8%. The above operational status will save the company a significant amount of labor costs in the product assembly process and improve production efficiency, clearly demonstrating the practical application value of system integration. After practical application, the system can increase the first-pass yield rate of products by 5.3% and reduce quality-related issues by approximately 38%. Based on this, it can be estimated that the application of this system will save the company approximately 1.5 million yuan in quality costs annually and increase product production volume by approximately 15%. During the inspection process, the system can pre-screen out the same type of assembly errors in products, thereby reducing the need for re-assembly processes. This, in turn, minimizes labor costs and raw material costs associated with rework or scrap materials.

Table 2. Comparison before and after system optimization.

Performance index	Before optimization	After optimization
System startup time (s)	35.171	10.056
Image processing speed multiple	1.0	2.5
Average detection accuracy (%)	80.59	91.97
Classification accuracy rate (%)	83.22	94.60
Average detection time (ms)	310	180
First-time pass rate improvement (%)	0	5.3
The failure rate after continuous operation for 72 hours (%)	5.54	0.75
Quality problem rate (%)	42.6	26.4
Annual quality cost savings (10^4yuan)	0	150

3.2.2. System Optimization Performance

After multiple experimental comparisons, the improved system also demonstrated good results in image measurement and assembly quality inspection. The experimental data results are shown in Tables 3 and 4.

Table 3. The system detects the accuracy data.

Test items	Test result
Repeatability detection accuracy	<0.5m
Concentric circle radius test bias	-0.264m
Concentric circle repeatability test accuracy	0.016m
Concentricity test bias	0.283m
Concentricity repeatability test accuracy	0.025m

Table 4. Performance data of the assembly quality inspection system.

Performance index	Test result
Classification accuracy rate	94.60%
Detection accuracy	91.97%
Average processing time	180 ms/sheet
System stability	99.2%
False alarm rate	<2.00%
Mean recovery time	40% ↓
CPU average occupancy rate	30% ↓
Memory efficiency	25% ↑

As shown in the table, in the machine vision strategy system detection accuracy data, the optimized repeatability detection accuracy is <0.5m, with the concentricity radius test bias and repeatability test accuracy being −0.264m and 0.016m, respectively. The concentricity test bias and concentricity repeatability test accuracy are 0.283m and 0.025m, respectively. The overall industrial robot vision detection accuracy has been significantly improved, playing a crucial foundational role in the practical application of industrial robots.

The adoption of an event-based multithreading design enables image acquisition, information processing, state tracking, and GUI design to operate in parallel. Theoretical simulations indicate that compared to the original program, CPU load has been reduced by 30% (on average), and memory load (both maximum and minimum values) has been reduced by 25%. Through this study, the proposed intelligent anomaly detection method reduces the average recovery time by 40% when handling various anomalies, with a system availability of 99.2%.

Analysis of the experimental results shows that the optimized algorithm system demonstrates superior performance, particularly achieving effective detection capabilities in more complex operational conditions. The optimized autofocus algorithm ensures accurate and rapid capture of images to be inspected. The optimization of the image processing algorithm preserves critical edge information in the image, thereby ensuring image quality. The two-layer convolutional neural network structure optimization not only ensures detection accuracy but also enhances the system's overall processing capability, significantly improving system reliability and efficiency. This has significantly enhanced the performance support for industrial robot assembly quality detection. According to the experimental data, key metrics such as detection accuracy, classification accuracy, and system processing speed all meet the requirements.

4. Conclusion

After optimization, the machine vision assembly quality inspection system based on the DSP platform has significantly improved in terms of detection accuracy in analyzing the surface condition of assembled parts and detection efficiency during the assembly process. The startup time of the optimized system has been reduced from 35.171 seconds to 10.056 seconds, and the image processing speed has increased by 2.5 times. After 72 hours of operational testing, the system's failure rate was 0.8%. This is because an adaptive median filtering algorithm was adopted, which facilitates edge detection in the analysis of complex surface conditions of assembled parts.

On the other hand, in the optimization of the deep learning model, the combination of AlexNet+FasterR-CNN optimized the recognition and classification accuracy of assembled parts, with an average detection accuracy of 91.97% and a classification accuracy of 94.60%. Additionally, under varying lighting conditions (illuminance fluctuating between 200 and 800 lux), the PWM intelligent light source control algorithm maintains detection accuracy above 90%, effectively addressing the limitations of traditional machine vision in handling lighting variations.

The improved system demonstrates superior processing efficiency, with average detection time reduced from 310 ms to 180 ms. In actual production, the first-pass inspection pass rate increased by

5.3%, saving 1.5 million yuan in product quality costs, and the system exhibits strong interference resistance. Electromagnetic interference testing results indicate that the system is suitable for strong electromagnetic environments and demonstrates good adaptability and reliability.

The above demonstrates that the optimization scheme proposed in this study effectively improves the quality inspection of industrial robots during assembly, offering significant benefits for manufacturing enterprises.

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