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System Design of Workpiece Automatic Cleaning Device based on YOLOv5

Ru-Tao Wang* , Yue-Ling Zhao, Yi-Yang Li, Dong Guo

School of Electrical Engineering, Liaoning University of Technology, Jinzhou 121001, Liaoning, China

**Author to whom correspondence should be addressed.*

Abstract: The recognition and positioning of material baskets are key links in the automatic workpiece cleaning device. Aiming at the problems of low recognition accuracy and poor precision of traditional visual methods for material basket recognition, a control system of automatic workpiece cleaning device based on YOLOv5 was designed. The YOLOv5 detection algorithm was improved by introducing the attention mechanism and optimizing the loss function, which enhanced the attention to the target area and improved the accuracy of feature extraction, thus realizing the position recognition and coordinate acquisition of workpiece material baskets. In addition, a cleaning system with Siemens S7-1200 PLC as the control core was designed. By controlling servo motors to drive the gantry and adjust the operation of the crane, the automatic grabbing and handling of material baskets were realized, and the automatic control of the cleaning process was achieved. Meanwhile, a human-computer interaction (HMI) and monitoring interface was designed, which could intuitively display the operating status of material baskets and improve the interaction capability of the automatic workpiece cleaning device.

Keywords: Machine vision; Automatic cleaning device; YOLOv5; PLC; HMI

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1. Introduction

With the rapid development of industrial automation and intelligent manufacturing technologies, workpiece cleaning, as a key link in the mechanical processing process, its cleaning quality directly affects the processing accuracy, service life and overall performance of products. However, traditional workpiece cleaning methods mainly rely on manual operation, which not only has low efficiency and high labor intensity, but also the cleaning quality is greatly affected by human factors, making it difficult to ensure consistency [1]. In addition, manual cleaning also has certain potential safety hazards. Especially in cases involving high temperature, high pressure or chemical cleaning fluids, operators may face occupational health and safety risks [2]. Therefore, in order to improve production efficiency, reduce labor costs and ensure the stability of cleaning quality, designing workpiece cleaning devices based on automated and intelligent control has become an important research direction in the modern manufacturing industry [3].

Basket recognition and positioning is an important part of the cleaning device. This device uses a PLC (Programmable Logic Controller) as the core of the system control, uses an industrial camera to collect basket image information and send it to the PC terminal. Then, based on the basket position coordinates identified by the YOLOv5 object detection algorithm, it further controls the servo motor to drive the gantry and the traveling crane to move, so as to realize the automatic grabbing and handling of the basket.

2. Composition of the cleaning device

The structure of the automatic workpiece cleaning device is designed to meet the requirements of efficient and stable workpiece cleaning. Every aspect, from the overall architecture to the tiny components, has been carefully considered [4]. In terms of overall layout, the modular design concept is adopted, dividing the entire device into three major functional modules: loading, cleaning, and unloading. Each module is relatively independent yet closely cooperative, ensuring the smoothness and efficiency of the cleaning process. Specifically, the cleaning device consists of key components such as a structural chassis, a transport gantry, a transport crane, a material basket, a loading table, an unloading table, and an industrial camera. Among these, the main function of the industrial camera is to acquire image information of the material basket. The automatic workpiece cleaning device is shown in **Figure 1**.

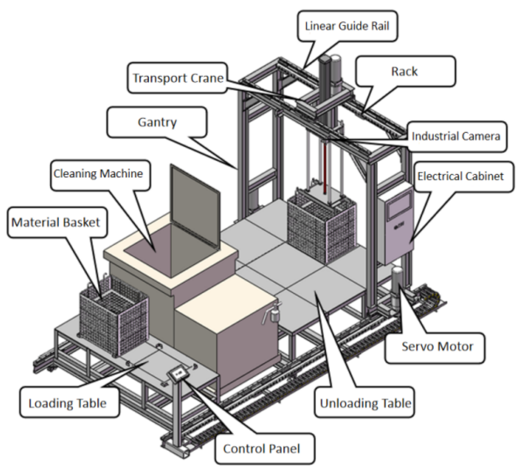

Figure 1. Automatic workpiece cleaning device.

Among these components, the transport crane is a crucial core part of the entire system, with a servo motor, reducer, drive gear, and electric cylinder mounted on its upper part. The servo motor, relying on its speed control capability and fast response characteristics, provides stable and precise support for the operation of the transport crane. The matching reducer can reasonably adjust the output speed of the servo motor through the gear transmission ratio, while realizing torque amplification to meet the power demands under different working conditions. Driven by the reducer, the drive gear meshes with the rack on the linear guide rail of the gantry; when the drive gear rotates, the transport crane can achieve smooth and accurate horizontal linear movement along the linear guide rail slider installed at its lower part. The transport crane is shown in **Figure 2**.

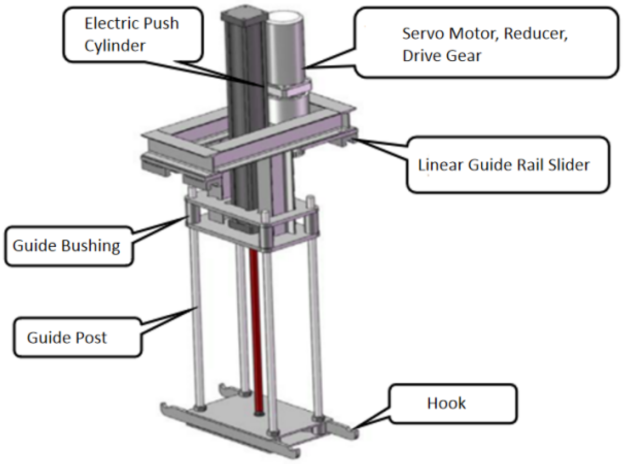

Figure 2. Transport crane.

The industrial camera installed on the gantry is mainly responsible for capturing images of material baskets in the loading area and unloading area. The YOLOv5 model performs object detection on the captured images to obtain the position coordinates of the material baskets in the loading table and the coordinates of empty positions in the unloading table. Based on the coordinate information, the PLC controls the transport crane to accurately grab the material baskets and cooperates with the gantry to transport the material baskets, thus completing the loading, cleaning, and unloading processes.

3. Improvement of material basket position recognition based on YOLOv5

3.1. YOLOv5-based visual recognition algorithm

Due to the complex environment of cleaning workshops, the existing YOLOv5 algorithm shows insufficient accuracy in identifying material baskets during real-world operation [5,6]. To address this problem, this study improves YOLOv5 in two key ways: integrating the CBAM (Convolutional Block Attention Module) and refining the loss function. The inclusion of CBAM strengthens the model's capacity to focus on relevant target regions and enhances the precision of feature extraction, while the redesigned loss function improves the reliability and accuracy of both localization and classification. Together, these enhancements provide a stronger and more stable detection framework for practical application scenarios.

3.1.1. Introduction of the attention mechanism CBAM

CBAM is a simple yet effective attention module for feedforward convolutional neural networks (it is a plug-and-play module that can be added at multiple positions. The performance of adding the CBAM module at different positions varies across different datasets) [7]. When the attention mechanism is introduced into the YOLOv5 network structure (by adding the CBAM module to the CBL module), the two are integrated to form a hybrid structure of "Conv+BN+LeakyReLU+attention". Through attention integration, the YOLOv5 model's ability to extract locally important features of material baskets is enhanced. The structure of the YOLOv5 + CBAM module is shown in **Figure 3**.

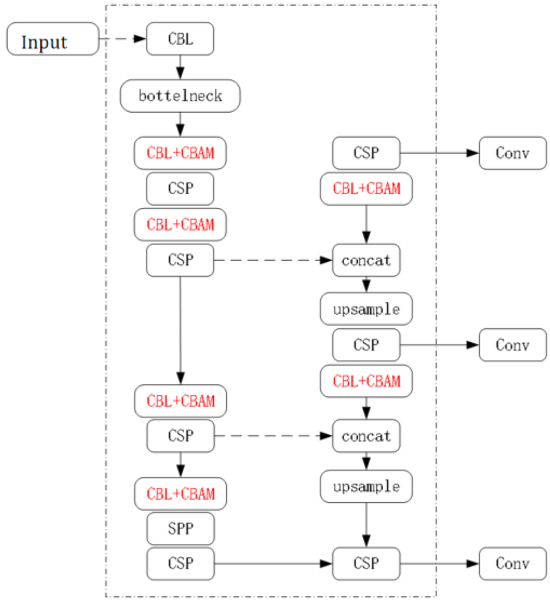

Figure 3. Structure diagram of the YOLOv5 + CBAM module.

3.1.2. Optimization of the loss function

The CIOU loss function used in YOLOv5 performs well in the target bounding box regression task. However, it only considers the geometric overlap between the predicted boxes and ground-truth boxes, while ignoring the adaptability to target shapes and specific tasks [8,9]. To further improve the accuracy of material basket recognition, this design optimizes the loss function of YOLOv5 to enhance its detection capability.

EIoU Loss is an improvement over CIoU Loss. It enhances the fitting capability for target boxes by more effectively balancing the center point offset of bounding boxes and aspect ratio alignment. Its calculation formula is as follows (1):

$$L_{EIOU} = L_{IOU} + L_{dis} + L_{asp} = 1 - IOU + \frac{\rho^2(b,b^*)}{c^2} + \frac{\rho^2(\omega,\omega^*)}{\omega_c^2} + \frac{\rho^2(h,h^*)}{h_c^2} \tag{1}$$

Among them, IOU is the Intersection over Union (IoU) between the predicted box and the ground-truth box; $\rho\ (b,b^*)$ is the Euclidean distance between the center points of the predicted box and the ground-truth box; c is the length of the diagonal of the minimum enclosing box, which is used to normalize the center offset distance; ω and h are the width and height of the predicted box; ω^* and h^* are the width and height of the ground-truth box; ω_c and h_c are the maximum ranges of width and height.

Focal loss is a loss function applied to classification tasks, mainly solving the problem of class imbalance between positive and negative samples. It reduces the impact of a large number of anchor boxes (with low overlap with the target box) on bounding box regression optimization, thereby making the regression process focus more on high-quality anchor boxes. In this design, Focal Loss is combined with the EIoU Loss function to form an improved loss function Focal-EIoU Loss, whose calculation formula is as follows (2):

$$L_{Focal-EIOU} = IOU^{\gamma} L_{EIOU} \tag{2}$$

By combining the dynamic weight mechanism of Focal loss and the bounding box regression optimization of EIoU, Focal-EIoU Loss can effectively address the problems of class imbalance between positive and negative samples and bounding box misalignment in material basket detection, thereby improving the overall detection accuracy.

3.2. Material basket recognition experiment

To further evaluate the independent effects and combined effects of the attention mechanism and optimized loss function on the YOLOv5 model in the material basket detection task, this study designed four groups of experiments as outlined:

(1) Experiment 1: Without introducing the attention mechanism or optimizing the loss function, to verify the original YOLOv5 algorithm;

(2) Experiment 2: Only introducing the attention mechanism, i.e., YOLOv5 + CBAM;

(3) Experiment 3: Only optimizing the loss function, i.e., YOLOv5 + Focal-EIoU Loss;

(4) Experiment 4: Introducing both the attention mechanism and the optimized loss function, i.e., YOLOv5 + CBAM + Focal-EIoU Loss.

This study comprehensively evaluated the YOLOv5 model before and after improvement from three key performance metrics: mean Average Precision (mAP), Precision, and Recall. The goal was to objectively measure the improvement effect of introducing the CBAM attention mechanism and Focal-EIoU loss function on the model's detection performance.

The mAP of the initial YOLOv5 model in Experiment 1 was 0.905. In Experiment 2, by introducing the attention mechanism to focus on the spatial and channel information of images, the performance was effectively improved, with the mAP increasing by 0.024. In Experiment 3, optimizing the loss function improved the overall detection accuracy, leading to an mAP increase of 0.032. In Experiment 4, after introducing both the attention mechanism and the optimized loss function, the mAP reached 0.965, which effectively enhanced the model's detection performance for target regions, with the mAP increasing by 0.06 and achieving the best effect. The experimental data results are shown in **Table 1**.

Table 1. Experimental data results

Experiment	mAP	Precision	Recall
Experiment 1	0.905	0.820	0.898
Experiment 2	0.929	0.935	0.857
Experiment 3	0.937	0.818	0.926
Experiment 4	0.965	0.766	0.939

Verification was conducted using the initial YOLOv5 model and the improved YOLOv5 + CBAM + Focal-EIoU Loss model. This improved model can not only quickly identify the position of the material basket but also achieve a significant improvement in recognition accuracy, exhibiting good detection performance.

4. Control system design

4.1. I/O point assignment

In a Programmable Logic Controller (PLC), I/O points are electrical ports connected to industrial on-site equipment via terminals. The PLC performs signal transmission and control with on-site equipment through these ports [10]. The I/O address assignment is shown in **Table 2**.

Table 2. I/O address assignment

Input/output	Description	Input/output	Description
I0.0	Start	Q0.0	Gantry forward
I0.1	Stop	Q0.1	Gantry backward
I0.2	Emergency stop	Q0.2	Transport crane move left
I0.3	Automatic	Q0.3	Transport crane move right
I0.4	Manual	Q0.4	Lift material basket
I0.5	Stroke switch of loading area	Q0.5	Lower material basket
I0.6	Stroke switch of cleaning area	Q0.6	Cleaning tank cover open
I0.7	Stroke switch of unloading area	Q0.7	Cleaning tank cover close
IW20	Temperature detection	Q1.0	Cleaning control
IW22	Liquid level detection	Q1.1	Heating control
IW23	Turbidity detection	Q1.2	Fluid replenishment control
IW34	Vision detection	Q1.3	Filtration control

4.2. PLC wiring diagram design

The CPU 1215C serves as the central control unit of the PLC. On the left side are input quantities, including sensor detection signals and control buttons; on the right side are output quantities, which control the operation process and achieve the output effect. Among them, the PLC controls the on-off of AC relays to realize functions such as cleaning, heating, fluid replenishment and filtration of the ultrasonic cleaning machine. The PLC wiring diagram is shown in **Figure 4**.

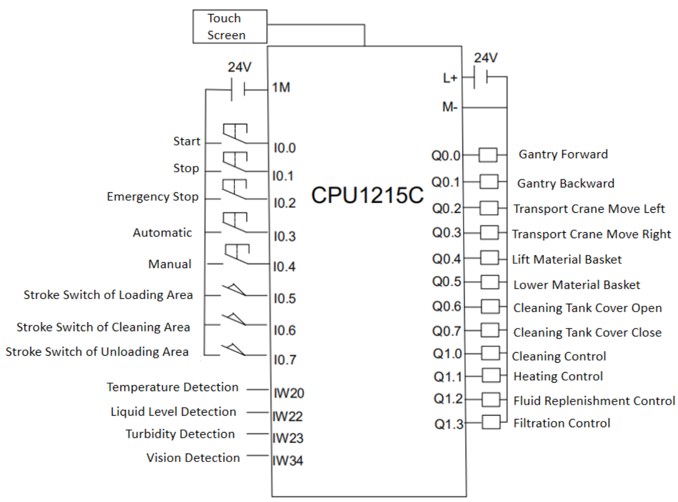

Figure 4. PLC wiring diagram.

4.3. System simulation screen design

The automatic workpiece cleaning device is simulated using TIA Portal V16 Software. The structure in the red box area of the simulation screen simulates the material basket grabbing process of the actual gantry and transfer crane.

When the simulation starts, the PLC (Programmable Logic Controller) controls the gantry and transfer crane to operate, grab the material basket, and transport it to the cleaning area. After the material basket is transported to the cleaning area, the transfer crane is controlled to move according to the preset position of the cleaning tank, and the material basket is lowered into the cleaning tank for cleaning. Once the cleaning is completed, the material basket is lifted out of the cleaning tank. The PLC then controls the gantry to move. The cleaning simulation screen is shown in **Figure 5**, and the HMI (Human-Machine Interface) monitoring screen is shown in **Figure 6**.

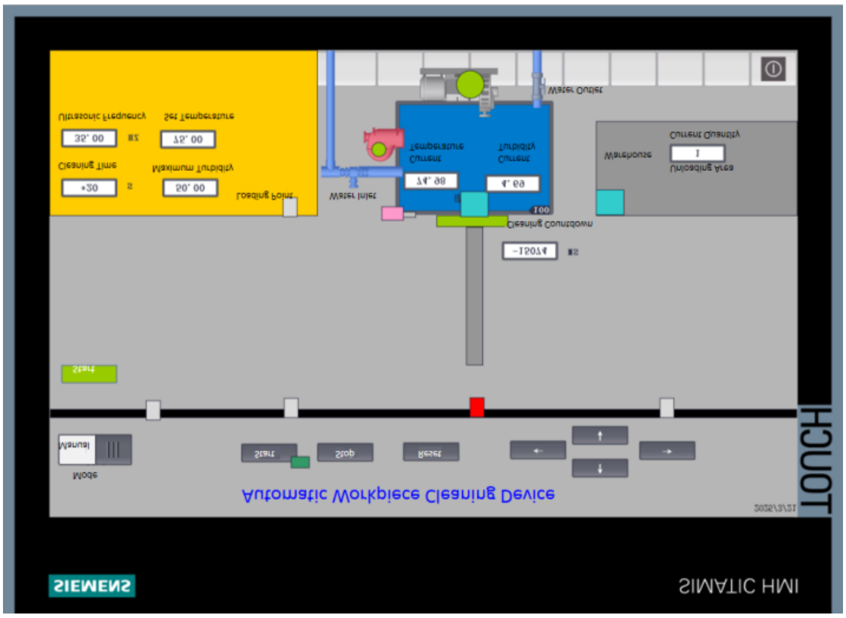

Figure 5. Simulation screen of the cleaning process.

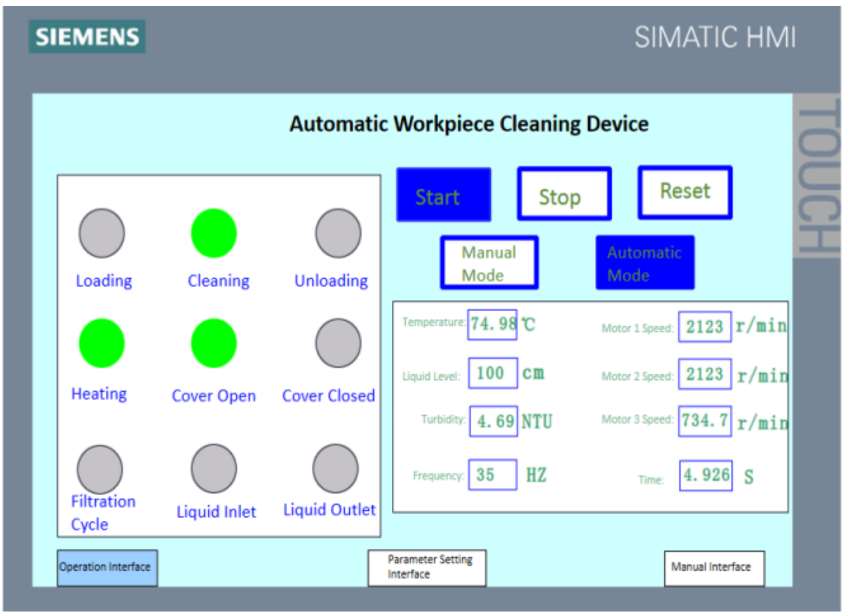

Figure 6. Monitoring screen of the cleaning process.

System simulation of the automatic workpiece cleaning device was conducted using the TIA Portal V16 platform, verifying the feasibility and reliability of the equipment's design scheme and control logic. Simulation results show that the improved YOLOv5 algorithm achieves the expected effect in terms of recognition accuracy for material baskets. It can quickly identify the position of material baskets and target placement areas, thereby realizing the stable operation of the process in all links, including feeding, cleaning, and unloading.

5. Conclusion

The automatic workpiece cleaning device based on YOLOv5 designed in this paper improves the accuracy and robustness of target detection by introducing the CBAM attention mechanism into the YOLOv5 algorithm and optimizing the loss function, providing a reliable visual foundation for the intelligent control of the device. With PLC as the control unit, the device realizes the accurate grabbing and handling of material baskets, and completes the automatic management of processes such as feeding, cleaning, and unloading, which effectively improves the cleaning efficiency and quality. The program design and simulation experiments for the feeding, cleaning, and unloading processes have all verified the feasibility of the system's control logic and the stability of its overall operation.

Disclosure statement

The authors declare no conflict of interest.

References

[1] Yin H, 2024, Design of Full-Automatic Robotic Arm Pipetting System and Analysis of Visual Recognition and Positioning. Electronic Technology, 53(6): 228–229.

[2] Chen D, Liu Q, 2024, Design of Automatic Car Cleaning System Using PLC Technology. Industrial Control Computer, 37(8): 175–176.

[3] Xia X, 2024, Design of Manipulator Sorting Material Control System Based on S7-1200 PLC. Industrial Control Computer, 37(11): 138–140.

[4] Yin Z, Sun R, 2016, Design of Automatic Workpiece Cleaning Device Based on PLC. Automation & Instrumentation, 2016(7): 235–237.

[5] Wang X, 2024, Control System Design of Single-Lane Stereo Garage Based on S7-1200 PLC and Machine Vision. Automation & Instrumentation, 39(10): 18–23.

[6] Chen J, Diao G, Tang M, et al., 2025, Research and Design of Riding Helmet Wearing Monitoring Based on YOLOv5. Internet of Things Technology, 15(7): 32–35.

[7] Devi M, Rajkumar T, 2025, A Novel Attention Based Deep Learning Model for Software Defect Prediction with Bidirectional Word Embedding System. Soft Computing, 29(4): 1–18.

[8] Zhao X, Ma M, Wang L, et al., 2024, Lightweight Apple Leaf Disease Detection Based on YOLOv5. Automation Application, 65(18): 146–148.

[9] Zhang Y, Gao M, 2025, Floating Garbage Target Detection Algorithm Based on Improved YOLOv5s. Computer Engineering and Design, 46(3): 910–917.

[10] Lü D, Li J, 2025, Design of Stepper Motor Control System Based on PLC. Automation Application, 66(1): 6–8.