Automated Hanging and Mounting System for Batches of Electroplated Components based on YOLO Machine Vision Technology

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Abstract*—This study presents an innovative industrial electroplating automated hanging system aimed at addressing critical challenges prevalent in traditional manufacturing processes, such as labor shortages and high employee turnover. The system integrates TensorFlow and Keras deep learning frameworks, employing the YOLO (You Only Look Once) machine vision recognition model alongside existing image processing techniques. This integration signifies a significant reduction in reliance on manual labor and introduces automation through the incorporation of robotic arms, marking a pivotal advancement in the field of intelligent machinery. Following extensive training and testing on a dataset of 512 target images, the system achieved impressive results: an average precision rate of 97.05%, a recall rate of 100%, an F1 score of 1.00, and an average precision mean average precision of 97.05%. The deployment of a custom C# control interface further enhances operational efficiency and strengthens user interaction, facilitating seamless coordination between software and mechanical systems. Despite a slightly lower production efficiency compared to manual operation, with a throughput of 14 items per minute, the automated assembly system boasts continuous 24-hour operation capability and offers a potential solution to Taiwan's widespread labor shortage issue. The system is projected to recoup its investment within approximately six months if operated continuously for 24 hours a day. Despite its relatively lower production efficiency, the system's continuous operation and economic benefits underscore its significant value. This research not only highlights the potential of the YOLO algorithm in industrial automation but also elucidates the profound impact of deep learning technologies in overcoming labor dependency challenges in traditional industrial environments. Furthermore, the study emphasizes the importance of advanced technologies such as machine learning and robotics in modern industrial processes, offering opportunities for the realization of more sustainable, efficient, and cost-effective manufacturing solutions.

***Keywords*—deep learning, YOLO algorithm, machine vision, electroplated components, intelligent machinery**

I. INTRODUCTION

In an increasingly demanding and competitive market, various industries are striving to create high-end products that meet the strictest sustainability and efficiency requirements. With the promotion and development of industrial automation concepts, the integration of heterogeneous electromechanical systems such as artificial intelligence [1–3], optoelectronic sensors [4], and computer vision recognition [5] is one of the most critical research projects for future fully automated systems. As technology continues to advance, AI technology has spread in recent years to fields such as defense industries [6], autonomous vehicles [7–9], semiconductor manufacturing [10], Smart manufacturing [11, 12], and medical rehabilitation [13]. In traditional mechanical industries where there is a significant demand for labor, combining automation with robotic arms and computer vision assistance to replace manual labor for complex, hazardous, or labor-intensive tasks can greatly accelerate work efficiency, reduce task durations, and address the aforementioned challenges. Utilizing computer vision for "recognition and positioning" in conjunction with robotic arms for "grasping and positioning" can enhance the efficiency of traditional industries while reducing cost requirements.

Based on vision, robot guidance is a rapidly developing field in the robotics and automation sectors. Robots use computer vision algorithms to perceive their surroundings, identify objects [14, 15], and navigate in complex environments. This technology plays a crucial role in various applications, including industrial automation, autonomous vehicles, and service robots [16, 17]. By adopting cameras and advanced image processing techniques, vision-guided robots can obtain real-time data from their environment, enabling them to make informed decisions and execute tasks with higher precision and efficiency. In recent years, deep learning algorithms, including Convolutional Neural Networks (CNNs) [18, 19], have significantly improved the performance of vision-based robot guidance systems. These algorithms empower robots to recognize and track objects, estimate their positions and orientations accurately, and perform tasks such as grasping, picking, and placing with high precision [20].

In traditional industrial production, manual labor for assembly and transportation is common but inefficient. Quick, high-quality production is crucial in competitive industries, yet manual processes are slow and rely on skilled workers. Nowadays, many industries use computer vision-assisted robotic arms for handling electroplated parts, a key element in automated production lines. These robotic arms, essential in many traditional industries, pick and position parts precisely. Our system, utilizing computer vision for object recognition, captures and processes images of these parts. It identifies their characteristics, differentiates features, and guides the robotic arms to accurately place the parts. This system greatly improves speed and efficiency on the production line.

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II. System Architecture

The system architecture presented in this research emphasizes the application of artificial intelligence visual recognition technologies in the handling of electroplating components. This system integrates the YOLO object detection algorithm with robotic arms and automated devices, achieving highly precise and rapid processing of electroplated assemblies, as illustrated in Fig. 1. Through accurate visual identification and automated physical manipulation, the system effectively suspends electroplated components onto carriers, significantly enhancing production efficiency and product consistency. Additionally, the system employs self-trained data to optimize the YOLO algorithm, thereby improving its capability to identify various electroplated components. By combining deep learning with advanced image processing techniques, the accuracy of identification and detection is further enhanced. This integration of technologies not only increases operational efficiency but also addresses challenges encountered in the production process, such as labor shortages and quality control, bringing new possibilities for automation and intelligence in traditional industries.

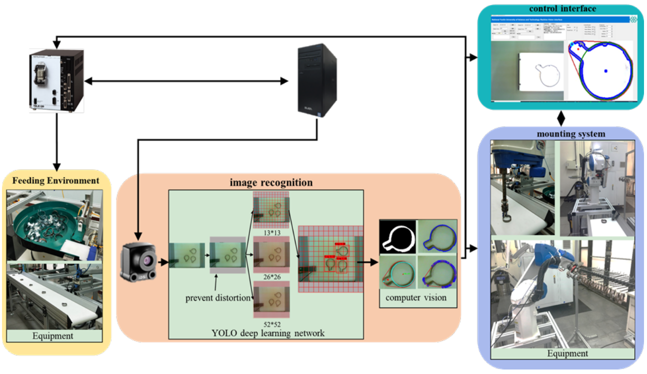

Fig. 1. Automated mounting system architecture for electroplating components with AI visual technology.

In this research, we employed the YOLO (You Only Look Once) target detection algorithm from the realm of deep learning to train the system for identifying electroplated components on the production line in our experimental setup. The main aim of this study was to swiftly and accurately extract areas of interest from images. To fulfill this objective, we initially transformed RGB images into grayscale and applied filtering techniques for noise reduction. Subsequently, by performing image binarization, dilation, and erosion operations, and utilizing the find contours function, we were able to effectively extract contour information from the images. Ultimately, using the ConvexHull convex hull function and the Hough Circle algorithm, we precisely determined the gripping positions for the robotic arms. This led to the realization of highly efficient and accurate automated operations. The following sections will provide a detailed explanation of this process. The study utilized YOLOv3 running on a specific software-hardware platform. The software component employed Python 3.6, TensorFlow 1.15.2, and Keras 2.3.1 for model development. TensorFlow and Keras are acknowledged as among the most comprehensive model foundations across all deep learning frameworks. All experiments were conducted on a computer equipped with the Windows 10 operating system, featuring an Intel Core i7-12700H processor (2.3GHz), 32GB of RAM, a 1TB solid-state drive, and an NVIDIA GeForce RTX4060 graphics card.

III. Research Methods

A. Image Acquisition

In this experiment, we utilized the uEye XS2 industrial camera for image acquisition. This compact camera is equipped with an autofocus feature and has a frame rate of 15.0fps, with a high resolution of 2592×1944 pixels. For image processing, we employed the Emgucv 4.3.0.3890 software. In this experiment, image capture was conducted using a conveyor belt, and actual shots were taken on a vibration alignment machine, resulting in the acquisition of an image dataset, as illustrated in Fig. 2.

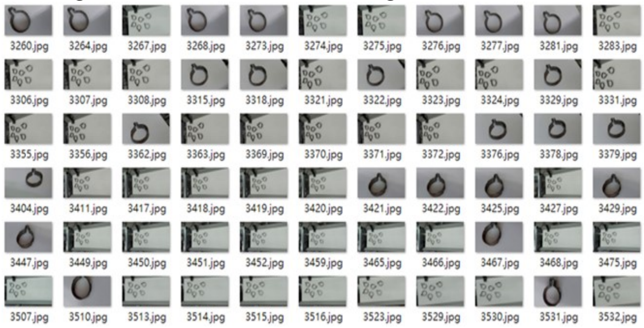

Fig. 2. Component image capture dataset.

B. YOLO Deep Learning Object Detection

In traditional machine vision applications, the process typically involves analyzing the entire image and then extracting the Region of Interest (ROI) through methods such as binarization, morphological transformations, and the findcontours function. This often includes locating the contours of the workpiece and drawing a bounding rectangle around these contours. Subsequently, conditions such as contour area and perimeter are used to filter out non-ROI areas and segment the selected regions. However, this method is only effective in stable and simple environments. In complex environments, it becomes inadequate. Therefore, in this study, we have employed the deep learning YOLOv3 algorithm to extract the image ROI, allowing us to process only the ROI area. This significantly reduces the processing time.

In this research, a total of 521 images captured in-house were used. From these, 10% (52 images) were randomly selected to form the test set, while the remaining 90% (468 images) were divided into a training set consisting of 90% (421 images) and a validation set comprising 10% (47 images). Since our study focused on a single category of annotation, the YOLOv3 network model was employed to train the model for identifying electroplated components. We utilized the yolo_weights.h5 as the pre-trained weight file, provided officially by YOLO, and set the training to run for 100 epochs. The training was halted prematurely at the 64th epoch, as the loss had plateaued, indicating no further improvement, with the training loss converging to 5.33 and the validation loss to 4.45. This study presents the YOLO model's predictions, displaying four electroplated components at random angles in (a) and three electroplated components at random angles in (b), as depicted in Fig. 3.

To evaluate the performance of the trained weights, we utilized metrics such as recall rate, F1-score, and Mean Average Precision (mAP). A set of 90 prepared images was used as the test set to assess the model's capability in accurately counting electroplated components. Accuracy and recall are direct indicators of the model's ability to differentiate samples, with higher values indicating stronger recognition capabilities. The results of this study demonstrated that the model achieved an average precision of 97.05%, a recall rate of 100%, an F1-score of 1.00, and a mAP of 97.05%.

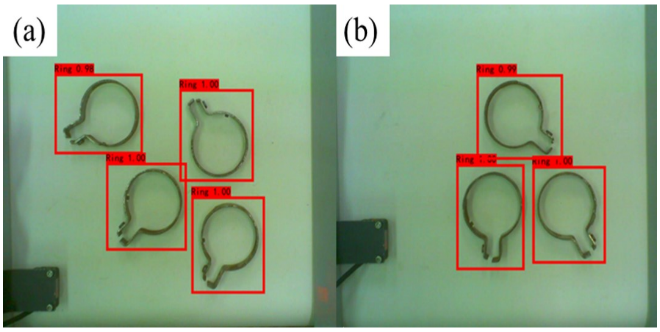

Fig. 3. Displays the YOLO model's predictions, depicting four electroplated components at random angles in (a) and three electroplated components at random angles in (b).

C. Machine Vision

In order to rapidly extract the gripping points of electroplated components, this study employed computer vision algorithms, including binarization, morphological processing, contour detection, convex hull analysis, and Hough circle transform. Firstly, binarization is a rapid segmentation algorithm that divides the image into foreground (objects) and background based on pixel grayscale differences. This process significantly reduced the data volume in the image, making the contours of the electroplated components more pronounced. For example, as shown in Fig. 4(a), the input image was binarized to separate the conveyor belt as the background and the electroplated components as the foreground, as depicted in Fig. 4(b).

However, after binarization, it was observed that there were small gaps within the objects. To fill these gaps, this study applied a dilation operation. Nevertheless, dilation could lead to distortion of the object's shape, as illustrated in Fig. 4(c). Therefore, after dilation, an erosion operation was performed to ensure image clarity and successfully segment the electroplated components within the foreground, as shown in Fig. 4(d). Following these image processing steps, the features of the electroplated components became highly distinct.

To prevent the inclusion of other components that resemble the ones in this study during the recognition process, the FindContours algorithm was employed to detect the contours of the electroplated components. Subsequently, their arc length and area were calculated, as depicted in Fig. 4(e). The electroplated components in this study exhibit a prominent convex feature, making them well-suited for detection using convex hull analysis, as illustrated in Fig. 4(f), where the blue portions represent convex hull points, and the red portions indicate the connections between these points.

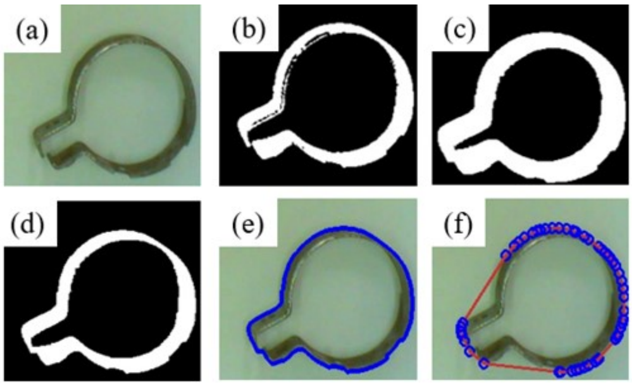

Fig. 4. (a)Input image, (b)Binary output image, (c)Image dilated, (d)Image eroded, (e)Image contours, (f)Convex hull detection.

Since this study only requires the convex hull points on prominent features, we utilized the Hough Circle algorithm to determine the circle's center and radius. The Hough circle radius served as a filtering criterion for selecting convex hull points. When the distance from the Hough circle center to a convex hull point was greater than the radius, it was retained; otherwise, it was filtered out, as shown in Fig. 5(a).

Subsequently, we took the average of the filtered convex hull points to identify the point P3, farthest from the center, as depicted in Fig. 5(b). Once we knew the position of point P3, we could calculate the angle compensation by connecting point P3 with the center, enabling the robotic arm to determine the rotation angle, as illustrated in Fig. 5(c). Point P4 represents the gripping point of the arm.

Finally, by subtracting half of the Hough radius from P3 (P3 point minus half of the protrusion distance), we could determine half of the protrusion distance. We then calculated the X-coordinate of point P4 by subtracting half of the protrusion distance from the X-coordinate of P3, multiplied by Cosθ. Similarly, we computed the Y-coordinate of point P4 by subtracting half of the protrusion distance from the Y-coordinate of P3, multiplied by Sinθ, as shown in Fig. 5(d).

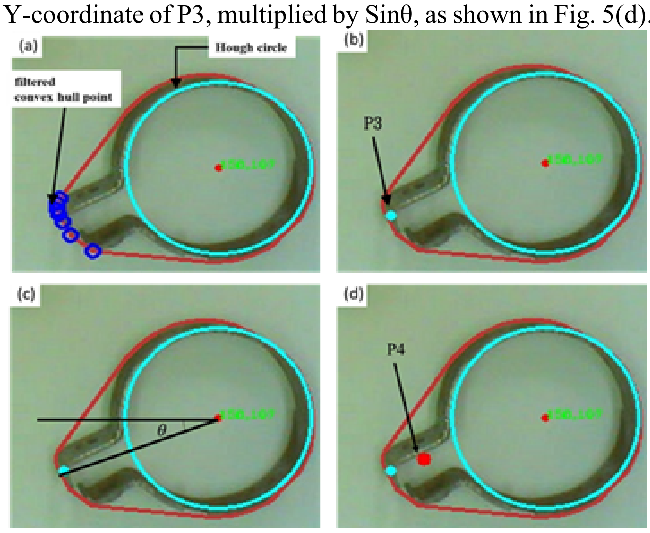

Fig. 5. Hough circle and convex hull point illustration.

IV. Conclusion

This research has developed an AI-based visual recognition system tailored for electroplated components, integrating YOLO object detection and image processing techniques. The system offers real-time recognition and precise positioning of electroplated components on a production line. With extensive training, it achieved an average precision of 97.00%. Deep learning and image augmentation techniques were employed to enhance performance and reliability, reducing the need for manual intervention and addressing challenges such as labor shortages and quality control. These innovative technologies have the potential to significantly enhance production efficiency and quality, opening up new opportunities in industrial automation and smart manufacturing. The system enables rapid classification of electroplated components, replacing traditional sorting methods, with a maximum speed of 14 items per minute, and it can further increase throughput.

The automated assembly system developed in this study is capable of processing 14 items per minute, resulting in a total production capacity of 6,720 items within an uninterrupted 8-hour operational window. In contrast, a manual operator can assemble 26 items per minute, considering a 15% buffer for operational comfort, resulting in an average daily output of 10,608 items. Consequently, when operating over identical time frames, the output from this automated mechanism constitutes merely 60% of the yield attainable via manual labor. Despite its relatively lower production efficiency compared to manual operation, the system presents significant advantages, including continuous 24-hour operation capability and the potential to mitigate Taiwan's widespread labor shortage issue. The investment for this system is expected to be recouped within approximately six months if the system operates continuously for 24 hours a day. For future recommendations, further optimization of the system's operational workflow could be pursued, along with enhancements in machine vision recognition accuracy and identification speed. These improvements would effectively shorten the system's operational time while achieving higher levels of production efficiency and economic benefits.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

C.-H. Lee worked on conceptualization, formal analysis, writing, investigation, drawing & editing; P.-H. Huang and M.-C. Chiu worked on supervision & proofreading; all authors had approved the final version.

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