

A low-cost 2.5D robotic guidance system for depalletization of enameled iron-cast pots in a high-mix production line

Djordje Milojevic^{1,2*}, Marija Savkovic², Nikola Komatina², Arso Vukicevic², Marko Djapan², Marko Miletic¹, Ivan Macuzic²

¹ The Academy of Applied Studies Polytechnic, Belgrade, Serbia

² University of Kragujevac, Faculty of Engineering, Kragujevac, Serbia

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* Correspondence: djmilojevic@politehnika.edu.rs

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ABSTRACT

Robotic depalletization in high-mix manufacturing environments presents significant challenges due to variations in product geometry, irregular object positioning, and strict production cycle-time requirements. Conventional vision-guided robotic systems often rely on predefined object locations or expensive three-dimensional sensing technologies, limiting their applicability in cost-sensitive industrial environments. This paper presents the development and industrial validation of a low-cost 2.5D robotic guidance system for the automatic depalletization of enameled iron-cast pots in an existing enameling production line. The proposed system integrates a six-axis industrial robot, an industrial vision camera, a laser distance sensor, and a custom-designed end-of-arm tool developed through three iterative design stages. A novel zone-based inspection strategy is introduced, in which the pallet is divided into overlapping inspection regions, enabling reliable object localization despite positional deviations caused by manual palletizing and transportation. The laser distance sensor provides height compensation, while the optimized vacuum gripping system improves handling reliability for products of different masses and intermediate cardboard separators. Experimental validation was performed across 210 depalletization cycles under real industrial operating conditions, with 100 cycles dedicated to the final system. The proposed system achieves an average cycle time of 7.6 ± 0.4 s, and achieves the grasping/object localization success rate of 98%.

KEYWORDS

Robotic depalletization, 2.5D vision, Machine vision, Industrial robotics, High-mix manufacturing, Sensor fusion, End-of-arm tooling, Material handling.

1. INTRODUCTION

Industrial automation has become an essential component of modern manufacturing systems, driven by the increasing demand for higher productivity, improved product quality, and reduced dependence on manual labor. Among the numerous material-handling operations performed in manufacturing environments, palletizing and depalletizing remain particularly challenging due to the variability of product arrangements, object positioning uncertainties, and the need to maintain short production cycle times. While robotic depalletization has become common in highly standardized production environments, its implementation in high-mix manufacturing remains considerably more complex because conventional robot programming assumes fixed object locations and repeatable operating conditions.

The application of machine vision significantly improves the flexibility of robotic depalletization systems by enabling automatic object localization prior to grasping. Depending on the application requirements, robotic guidance systems typically employ either two-dimensional (2D) vision, three-dimensional (3D) sensing, or hybrid approaches. Although 3D vision systems provide accurate spatial information, they are often associated with high acquisition costs, increased computational complexity, and more demanding integration requirements. In contrast, low-cost solutions combining conventional industrial cameras with complementary distance sensors can provide sufficient spatial information for many industrial applications while maintaining lower implementation costs. Such systems are commonly referred to as 2.5D vision systems, where two-dimensional image information is supplemented with depth measurements obtained from an independent sensor.

There are several challenges that limit the applicability of conventional vision-guided robotic solutions in industrial process. Iron-cast pots are manually palletized, resulting in significant variations in object position and orientation between pallets. Additional positioning errors are introduced during pallet transportation, while reusable cardboard separators of varying thickness generate uncertainties in the vertical position of each pallet layer. Furthermore, the production operates under high-mix, low-volume conditions involving six different pot geometries, eighteen size variants, and approximately 150 product configurations. At the same time, the robotic system must satisfy a production cycle time of 9 ± 1 s without modifying the existing enameling line.

To address these challenges, this paper proposes a low-cost 2.5D robotic guidance system for automatic depalletization of enameled iron-cast pots. The proposed system combines a six-axis industrial robot, an industrial camera, a laser distance sensor, and a custom-designed end-of-arm tool developed through several design iterations. In contrast to conventional approaches relying on predefined object locations, the proposed method introduces a zone-based inspection strategy, in which the pallet is divided into overlapping inspection regions that enable reliable object localization despite significant positional deviations. Laser-based height validation is integrated with vision-based localization to compensate for variations in pallet height while maintaining low hardware complexity and industrially acceptable cycle times.

The proposed solution was implemented and experimentally validated in an operating enameling production line. Three successive End-of-arm-tooling (EOAT) design iterations were evaluated with respect to cycle time, localization robustness, Z-axis validation, and gripping reliability. Experimental results demonstrate that the final system satisfies the industrial cycle-time requirements while providing reliable depalletization under the positional variability characteristic of high-mix manufacturing environments.

The remainder of this paper is organized as follows. Section 2 provides a literature review in this area. In section 3, the research methodology is given. Also, Section 3 presents the architecture of the proposed robotic guidance system together with the iterative development of the end-of-arm tooling and the proposed zone-based localization strategy. Section 4 presents the experimental results, while section 5 gives conclusions and discusses future research directions.

2. LITERATURE REVIEW

This section reviews the state of the art in robotic depalletization. Subsection 2.1 covers industrial automation and HMLV production; Subsection 2.2 examines vision-guided depalletization approaches and their trade-offs; Subsection 2.3 identifies the research gap addressed here.

2.1. Industrial automation and robotic depalletization

The continuous demand for higher productivity, improved product quality, and increased manufacturing flexibility has accelerated the adoption of industrial robotics across a wide range of production sectors.

Material handling operations, including palletizing and depalletizing, represent a significant portion of repetitive manual labor in manufacturing environments and are therefore among the first candidates for automation [1],[2]. Besides improving production efficiency, robotic depalletization contributes to enhanced workplace safety by reducing repetitive physical tasks and minimizing operators' exposure to ergonomically demanding working conditions [3], [4].

Although robotic depalletization has become a mature technology for standardized products, its implementation remains challenging in manufacturing environments characterized by frequent product changes, irregular object placement, and variable packaging configurations. Such conditions are particularly common in high-mix, low-volume (HMLV) production, where conventional robot programming based on predefined pick positions is often insufficient to ensure reliable operation [5]. Under these conditions, conventional robot programs based on predefined pick positions become increasingly unreliable, requiring adaptive perception algorithms capable of handling positional uncertainty and product variability.

Traditional robotic depalletization systems typically rely on predefined pallet layouts and fixed robot trajectories, making them highly effective in mass production environments where product placement remains consistent. However, such approaches exhibit limited robustness when applied to production systems characterized by irregular object placement, varying product geometries, and frequent product changeovers.

The emergence of Industry 4.0 has accelerated the adoption of intelligent automation technologies capable of increasing manufacturing flexibility, productivity, and resource efficiency [6]. Modern production systems increasingly rely on the integration of industrial robots, machine vision, smart sensors, and real-time data acquisition to enable autonomous decision-making and adaptive process control. While large-scale manufacturing has widely adopted highly automated production systems, small and medium-sized enterprises often face significant challenges associated with the cost and complexity of implementing advanced robotic solutions. Consequently, there is growing interest in low-cost, easily deployable robotic systems that can be integrated into existing production lines without extensive modifications while maintaining the flexibility required by high-mix manufacturing environments.

Several recent studies have addressed robotic manipulation in flexible manufacturing environments using machine learning, deep neural networks, and AI-based object detection methods [7], [8], [9]. While these approaches have demonstrated promising localization performance, they generally require extensive training datasets, high computational resources, and specialized hardware, making industrial deployment more demanding.

2.2. Machine vision guidance

To improve operational flexibility, recent research has focused on integrating machine vision into robotic depalletization systems. Vision-guided robots are capable of locating workpieces directly on the pallet, thereby reducing the dependence on precise pallet positioning and improving adaptability to production variations [10]. Conventional 2D vision systems are widely used due to their relatively low cost and ease of integration; however, they generally require accurately controlled object positioning and provide limited information about object height. Consequently, their applicability decreases when products exhibit significant positional deviations or when pallet height varies during the depalletization process [11]. Nevertheless, they provide only planar information and therefore require additional methods for estimating object height or compensating for variations in pallet layers [12].

To overcome these limitations, many researchers have adopted three-dimensional sensing technologies, including structured-light cameras, stereo vision systems, and laser scanners. Such approaches provide accurate spatial information that enables reliable pose estimation even under complex object arrangements. Nevertheless, 3D vision systems often involve considerably higher hardware costs, increased computational requirements, and more demanding calibration procedures, which may limit their applicability in small and medium-sized manufacturing companies or when retrofitting existing production lines [13], [14]. More recently, deep learning and artificial intelligence techniques have been successfully applied to robotic grasp planning and object detection [15]. Convolutional neural networks and transformer-based vision models have demonstrated remarkable robustness against object occlusions and varying illumination conditions. However, these approaches typically require large annotated datasets, powerful computing hardware, and extensive model training before deployment, making their implementation difficult in industrial environments where production changes frequently and commissioning time is limited [16].

Consequently, recent research has increasingly focused on hybrid vision solutions that combine multiple sensing modalities. By integrating conventional industrial cameras with complementary depth sensors, these systems offer a compromise between the simplicity and low cost of 2D vision and the improved spatial awareness of full 3D sensing. Such approaches have demonstrated promising results in industrial pick-and-place applications while maintaining relatively simple system architectures and short processing times [17], [18], [19]. Sensor fusion between industrial cameras and laser distance sensors has proven particularly effective in robotic handling applications where accurate height estimation is required but complete three-dimensional scene reconstruction is unnecessary. Such approaches reduce hardware costs while maintaining sufficient positioning accuracy for industrial manipulation tasks [20].

2.3. Research gap

Despite the considerable progress reported in the literature, relatively few studies address robotic depalletization under high-mix, low-volume production conditions where multiple product geometries, manually palletized objects, reusable packaging materials, and strict production cycle times must be handled simultaneously. Existing solutions frequently assume predefined object arrangements, rely on expensive 3D sensing technologies, or require computationally intensive vision algorithms that are difficult to integrate into existing industrial production lines.

Furthermore, limited attention has been devoted to low-cost robotic guidance systems capable of compensating simultaneously for horizontal object displacement, vertical positioning uncertainty caused by varying pallet layer heights, and gripping variability introduced by different product geometries and packaging conditions. These challenges become particularly significant when retrofitting robotic systems into existing manufacturing processes, where production interruptions and hardware modifications must be minimized.

3. METHODOLOGY

The objective of this paper was to integrate an industrial robotic manipulator into an existing iron-cast pot enameling production line, replacing the manual depalletization process previously performed by a human operator. The robot was required to unload enameled iron-cast pots from pallets measuring $1200 \times 800 \times 2000$ mm (length $\times$ width $\times$ height) and place them onto an intermediate conveyor buffer supplying the enameling machine. Since the production line was already operational, the robotic system had to be integrated without modifying the existing manufacturing process or reducing its throughput.

A major design constraint was the required production cycle time, which ranged between 9 ± 1 s depending on the dimensions of the pot. Smaller pots required shorter enameling times and therefore imposed the most demanding cycle-time requirement of approximately 8 s per pick-and-place operation. Consequently, the robotic depalletization system had to perform object detection, height estimation, grasp planning, and material handling within the available production time while maintaining reliable operation. An additional challenge originated from the high-mix manufacturing environment. Different pot geometries, varying product masses, cardboard separators between pallet layers, and unavoidable positional deviations caused by manual pallet loading prevented the use of conventional fixed-position robotic programs. Therefore, the proposed system required a robust guidance strategy capable of reliably locating and handling products despite significant variations in their position and geometry.

Figure 1 illustrates the proposed research methodology adopted in this study. The research process begins with the analysis of the industrial problem and the definition of the system requirements imposed by the existing enameling production line. Based on the identified challenges, a low-cost 2.5D robotic guidance system was designed by integrating an industrial robot, a industrial camera, a laser distance sensor, and a custom-developed end-of-arm tool. The system was refined through three iterative development stages, where each iteration addressed the limitations identified during experimental evaluation. Finally, the proposed solution was validated under real industrial operating conditions by evaluating cycle time, object localization reliability, Z-axis compensation, and gripping performance, demonstrating its suitability for high-mix manufacturing environments.

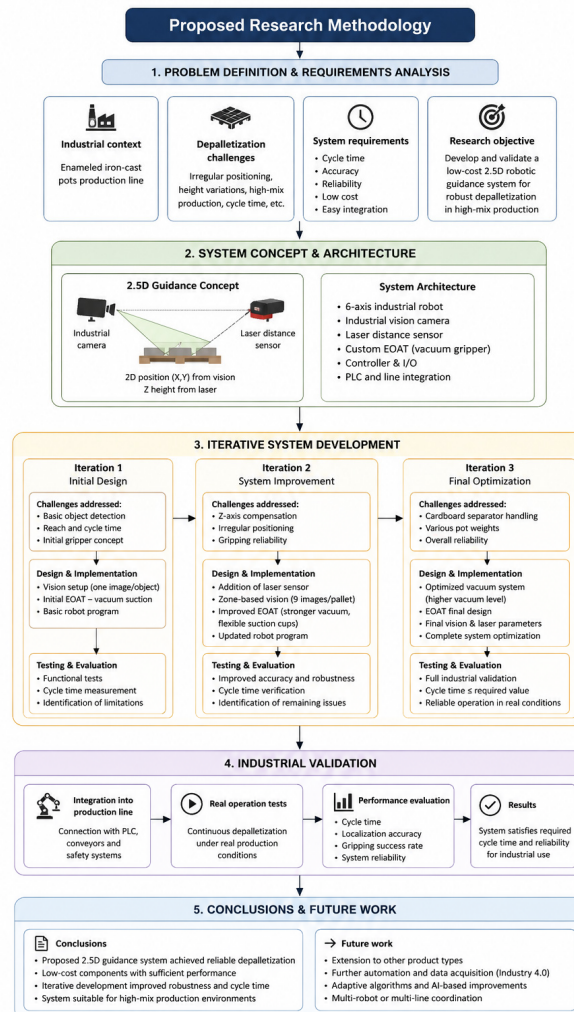


Figure 1: Research methodology adopted for the development and validation of the proposed 2.5D robotic depalletization system

3.1. Challenges of the Depalletization Process

The integration of a robotic depalletization system into the existing enameling production line introduced several technical challenges that influenced both the mechanical design of the end-effector and the development of the robot guidance strategy.

3.1.1. Robot Reach

The working envelope of the industrial robot did not allow access to the entire pallet without repositioning the pallet itself. Consequently, pallet replacement operations were required after the accessible portion had been emptied, increasing the overall lead time. To minimize production interruptions, the conveyor buffer was designed to temporarily store up to six pots, providing approximately 40–60 s for pallet replacement without stopping the enameling process. Depending on the product dimensions and the corresponding production rate, pallet replacement intervals ranged from approximately 10 min to 1 h.

3.1.2. Pallet Packing Strategy

Originally, pots were palletized manually in alternating upright and inverted orientations without a predefined arrangement (Figure 2.).



Figure 2: Worker manually depalletizing pots

Such an arrangement was unsuitable for reliable robotic handling and therefore required modification. A standardized palletizing strategy was introduced in which pots were stacked according to predefined layouts and separated by cardboard sheets measuring approximately 1150×750 mm with thicknesses ranging from 3 to 6.5 mm. While this significantly simplified robot operation, it introduced additional challenges related to cardboard handling and height compensation.

3.1.3. Positioning Uncertainty

One of the most significant challenges was the variability in pot positioning. Since palletizing was performed manually, the position of individual pots varied from pallet to pallet (Figure 3.a). Additional positional deviations were introduced during pallet transportation through the production facility. Furthermore, repeated reuse of cardboard separators caused permanent deformation, resulting in lateral displacement of pots as well as variations in stack height. Consequently, the nominal robot positions could not guarantee successful grasping, making adaptive vision-based localization and laser-assisted height estimation essential.

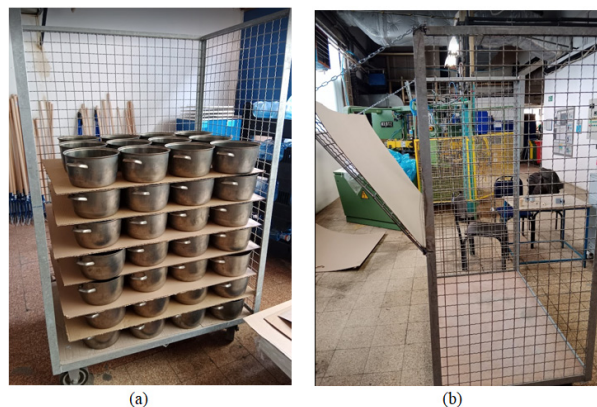


Figure 3: Pallet packing arrangement(a), and cardboard disposal add-on(b)

3.1.4. Cardboard Handling

After completing the depalletization of each pallet layer, the intermediate cardboard separator had to be removed before processing the next layer. Due to its large dimensions and limited stiffness, reliable manipulation of the cardboard within the confined pallet space proved impractical. To simplify this operation, the rear side of the pallet was modified with a dedicated opening that allowed the robot to push and dispose of the cardboard sheets without complex manipulation (Figure 3.b).

3.1.5. High-Mix, Low-Volume Production

The production line operates under high-mix, low-volume manufacturing conditions. The robotic system was therefore required to handle six different pot geometries and eighteen size variants, corresponding to approximately 150 individual product types. This large product diversity significantly increased the complexity of the vision system, gripping strategy, and robot programming, requiring a flexible guidance approach capable of adapting to varying object dimensions and positions without mechanical reconfiguration.

To address these challenges, this paper proposes a low-cost 2.5D robotic guidance system for automatic depalletization of enameled iron-cast pots in a high-mix manufacturing environment. The proposed solution combines a six-axis industrial robot, an industrial vision camera, a laser distance sensor, and a custom-designed end-of-arm tool developed through three iterative design stages.

3.2. System Architecture

The proposed robotic depalletization system consists of a Mitsubishi RV-7FLL six-axis industrial robot equipped with a custom-designed EOAT, a SICK Inspector83x camera, and a SICK DT20 laser distance sensor. The EOAT incorporates four vacuum suction cups used for handling both enameled iron-cast pots and intermediate cardboard separators placed between pallet layers. The EOAT was developed through several design iterations aimed at improving positioning accuracy, reducing cycle time, and increasing operational robustness under high-mix production conditions. Each iteration addressed limitations identified during experimental deployment.

3.2.1. Initial EOAT Design

The initial EOAT design relied on predefined nominal pot locations stored in the robot program. During each pick cycle, the robot first approached the expected pot position, where the industrial camera performed object localization. Since the camera was mounted perpendicular to the tool flange, the robot was required to rotate the tool by approximately 10° about the tool Y-axis to obtain an appropriate viewing angle (Figure 4). After image acquisition and pose estimation, the robot returned to its original orientation before executing the pick-and-place operation.

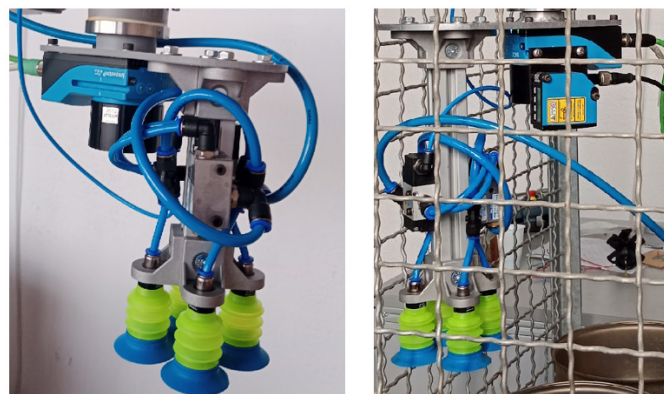


Figure 4: Initial EOAT Design: Extended EOAT Dual-Vacuum + Camera+ laser distance sensor

Although this approach enabled successful object localization, the additional rotational motion increased the overall cycle time beyond the allowable limit required to synchronize with the enameling production line. Height compensation between pallet layers was performed using a laser distance sensor mounted at an inclined angle. In practice, the sensor occasionally measured the side wall or edge of the pot rather than its bottom surface, producing underestimated or invalid distance measurements. Consequently, incorrect Z-axis offsets were calculated, preventing the suction cups from establishing reliable contact with the workpiece.

The vacuum system consisted of two vacuum generators supplied through a single 8 mm pneumatic hose, with each generator serving two 6 mm suction cups. While this configuration was adequate for lighter products, it provided insufficient holding force for heavier pot variants and low-quality cardboard separators. Furthermore, larger deviations between the expected and actual pot positions occasionally exceeded the search range of the vision algorithm, causing object localization failures and requiring manual operator intervention.

3.2.2. Improved EOAT Design

In the second design iteration, the original solid aluminum EOAT body was replaced with a modular structure constructed from aluminum extrusion profiles (Figure 5). This modification reduced the overall weight of the EOAT while providing greater flexibility for mechanical adjustments and future upgrades.



Figure 5: Improved EOAT Design: Quadruple-Vacuum + laser distance sensor + Angled Camera

The camera was mounted at a predefined inclination, eliminating the need for the additional wrist rotation previously required for object localization. As a result, the object detection procedure was simplified and the overall pick-and-place cycle time was significantly reduced.

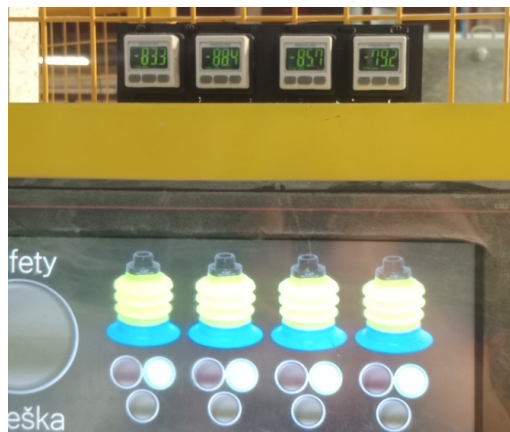


Figure 6: Pressure sensors with graphical representation on an HMI

The laser distance sensor was repositioned to the geometric center of the EOAT. This configuration increased the probability that the laser beam intersected the bottom surface of the pot or the intermediate cardboard separator rather than the pot edge, resulting in more reliable distance measurements and improved Z-axis offset estimation.

The vacuum system was also redesigned by doubling the number of vacuum generators, allowing each suction cup to operate with an independent vacuum source. This modification substantially increased the available gripping force, enabling reliable handling of heavier cast-iron pots and low-quality or deformed cardboard separators. Furthermore, pressure sensors were integrated into the pneumatic system to continuously monitor vacuum quality. These sensors enabled the detection of suction loss caused by worn suction cups, unsuccessful pick-and-place operations, or vacuum generator malfunction, thereby improving the overall reliability of the system (Figure 6).

Despite these improvements, a significant limitation remained. In cases where the displacement of a pot from its nominal pallet position exceeded the field of view (FOV) of the camera, the object could not be detected, preventing successful grasp planning. Several software-based approaches were evaluated to mitigate this issue, including lowering the template matching score threshold and enabling partial feature matching. Although these methods increased the detection range, they also substantially increased the occurrence of false-positive detections. In several cases, false object localization resulted in incorrect robot trajectories, leading to collisions between the EOAT and either the pallet structure or the pot itself. Consequently, these approaches were deemed unsuitable for reliable industrial operation.

3.2.3. Proposed Zone-Based 2.5D Guidance System

In the final EOAT iteration, the standard suction cups were replaced with compliant rubber suction cups equipped with spring-loaded extensions. This modification introduced passive vertical compliance, allowing the robot to compensate for small inaccuracies in height estimation by moving several additional millimeters along the Z-axis without compromising the grasping process.

Although the previous mechanical and pneumatic improvements significantly increased the reliability of the system, the vision-based object localization method remained insufficiently robust for industrial operation. The template matching algorithm relied on searching for objects within predefined regions around their nominal pallet positions. When the displacement of a pot exceeded the camera field of view, object localization failed, preventing successful grasp planning.

To overcome this limitation, a novel zone-based 2.5D guidance strategy was developed (Figure 7). Instead of performing object localization only at predefined pick locations, the pallet surface was partitioned into nine partially overlapping inspection zones. For each zone, the robot positioned the camera at the corresponding inspection point, where all visible pots within that region were detected simultaneously.



Figure 7: Proposed Zone-Based 2.5D Guidance System: Flat sideways camera, suction cups with movement compensation, new scanning method

The inspection zones were intentionally designed with overlapping fields of view. Consequently, any pot located near the boundary of one zone remained visible within at least one adjacent zone, ensuring complete coverage of the pallet despite positioning deviations. Figure 8 illustrates the spatial arrangement of the nine inspection zones together with their corresponding inspection centers.

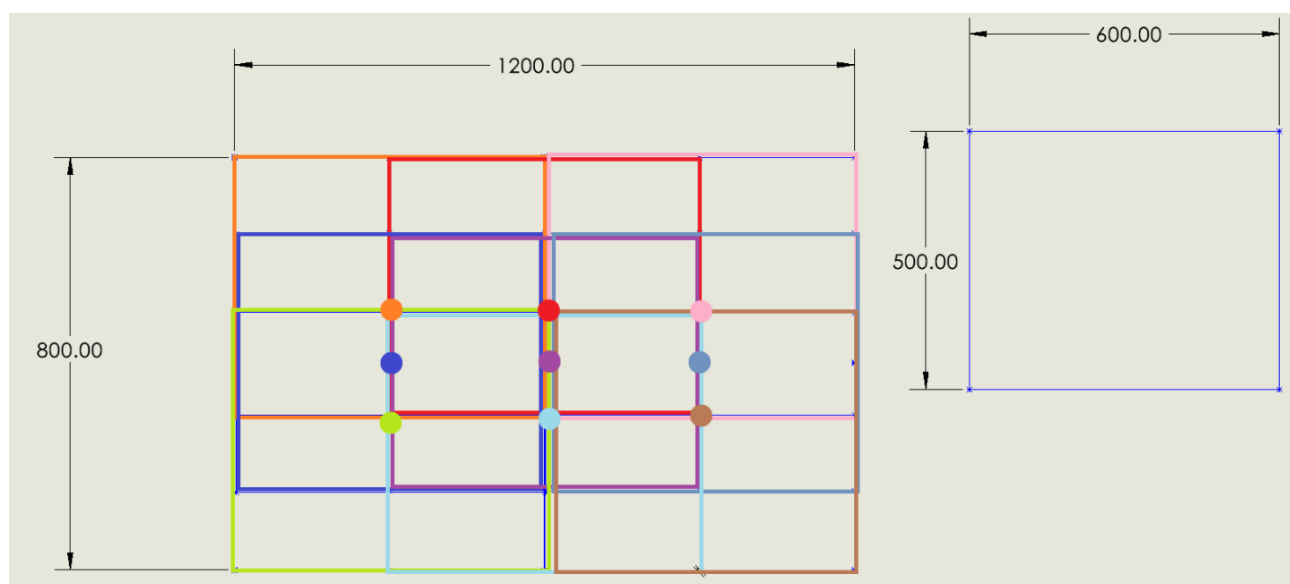


Figure 8: Demonstrations on zone positioning and coverage

The increased camera working distance required to capture the larger inspection areas inevitably reduced the effective depth resolution of the vision system, resulting in the loss of one measurable height layer. This limitation was

compensated by integrating laser-based height measurements, allowing accurate estimation of the remaining Z-axis offset while preserving complete pallet coverage.

Table 1. summarizes the main technical challenges identified during the integration of the robotic depalletization system into the existing enameling production line, together with the engineering solutions implemented to address them. Rather than representing isolated design modifications, these solutions constitute complementary components of the proposed low-cost 2.5D robotic guidance system. The iterative development process enabled each identified limitation to be systematically addressed, resulting in improvements in system robustness, positioning accuracy, gripping reliability, and compliance with the required industrial cycle time.

Table 1. Identified challenges and implemented solutions in the proposed robotic depalletization system

Challenge	Proposed solution
Position uncertainty	Zone-based 2.5D vision guidance
Height variation	Laser-based Z-axis validation
Heavy products	Redesigned EOAT and independent vacuum generators
Cardboard handling	Compliant suction cups and pallet modification
High-mix production	Adaptive vision templates and configurable robot program

Performance evaluation criteria:

The performance of the proposed robotic depalletization system was evaluated using five key performance indicators (KPIs): cycle time, gripping failure rate, localization failure rate, amount of Z-axis compensation failure, and amount of manual interference. These criteria were selected because they directly reflect the industrial requirements of the enameling production line and represent the main technical challenges encountered during system development. Together, they provide a comprehensive assessment of the efficiency, reliability, and robustness of the proposed 2.5D robotic guidance system.

Cycle time was adopted as one of the key performance indicators (KPIs) for evaluating the proposed robotic guidance system. The duration of each pick-and-place cycle was measured from the moment the robot initiated the object localization procedure until the successfully handled pot was placed onto the conveyor buffer. The measured cycle time therefore included robot positioning, image acquisition, object localization, Z-axis validation, grasp execution, and placement operations. The obtained values were compared with the production requirements of the enameling line, enabling quantitative assessment of the effectiveness of each EOAT design iteration and the proposed zone-based guidance strategy.

One of the primary design constraints of the proposed robotic depalletization system was compliance with the production cycle time of the existing enameling line. Since the robot was integrated into an already operating manufacturing process, its operation had to be synchronized with the throughput of the enameling machine without introducing production bottlenecks. Depending on the dimensions of the iron-cast pots, the required cycle time ranged about 9 ± 1 s per pick-and-place operation, with smaller products imposing the most demanding requirement due to their shorter enameling time.

To satisfy this constraint, every stage of the depalletization process was analyzed and optimized, including robot motion planning, image acquisition, object localization, height validation, grasp execution, and object placement. During each design iteration, the influence of mechanical modifications and sensing strategies on the overall cycle time was experimentally evaluated. Consequently, cycle time served not only as a performance indicator but also as one of the principal optimization criteria throughout the iterative development of the proposed system.

Vacuum grasping reliability was evaluated to determine the ability of the proposed EOAT to consistently handle iron-cast pots and intermediate cardboard separators throughout the depalletization process. Reliable gripping is particularly important in high-mix production, where products differ in geometry, mass, and surface characteristics. In addition, the repeated use of cardboard separators and gradual wear of the suction cups may adversely affect vacuum quality. Therefore, the proposed system incorporates independent vacuum generators and pressure sensors for each suction cup, enabling continuous monitoring of the gripping process and early detection of vacuum loss or unsuccessful pick-and-place operations. Gripping reliability was assessed based on the successful completion of the pick-and-place cycle without product slippage, object loss, or manual intervention.

Accurate estimation of the Z-axis position is essential for reliable grasping because the height of each pallet layer changes continuously during depalletization. Furthermore, variations in cardboard thickness and deformation caused by repeated reuse introduce additional height uncertainties that cannot be compensated using predefined robot positions alone. To address this issue, the proposed system employs a laser distance sensor to measure the distance between the EOAT and the pallet surface prior to each grasping operation. The measured values are used to calculate the required Z-axis offset, allowing the robot to compensate for height variations and ensuring consistent

contact between the suction cups and the handled object. The effectiveness of the Z-axis compensation strategy was evaluated by its ability to maintain successful grasping despite variations in pallet layer height.

Robust object localization represents one of the key performance criteria of the proposed robotic guidance system. Due to manual palletizing, transportation-induced shifts, and product variability, the actual positions of the pots frequently deviate from their nominal locations. Conventional vision approaches based on predefined search positions may therefore fail when the displacement exceeds the camera field of view. To overcome this limitation, the proposed methodology introduces a zone-based inspection strategy in which the pallet is divided into overlapping acquisition zones. This approach enables complete pallet coverage while ensuring that objects located near the boundaries of one inspection zone remain visible within adjacent zones. Localization robustness was evaluated according to the system's ability to consistently detect pots across the entire pallet without requiring manual intervention or producing false-positive detections.

4. RESULTS AND DISCUSSION

The proposed robotic depalletization system was experimentally validated under real industrial operating conditions in an enameling production line. The evaluation focused on evaluating average cycle time, the failure rate of both object localization and picking systems, Z-axis compensation failures, and the total number of required manual interventions during the whole testing. These indicators were selected because they directly reflect the operational requirements of the enameling production line and provide a comprehensive assessment of the effectiveness and robustness of the proposed robotic depalletization system.

Table 2. summarizes the performance improvements achieved through the three successive EOAT design iterations. Each iteration addressed specific limitations identified during experimental evaluation, resulting in gradual improvements in both mechanical reliability and vision-guided object localization.

Table 2. Performance comparison of the three EOAT design iterations

Performance metric	Initial EOAT	Second Iteration EOAT	Proposed system
Number of tested cycles (N)	50	60	100
Average cycle time[s]	10.5 ± 1.5	8.5 ± 0.6	7.6 ± 0.4
Grasping failure (%)	40%	25%	2%
Localization failure (%)	20%	20%	2%
Z-axis compensation failure (N)	12	3	0
No. of manual interventions (N)	27	15	2

The results demonstrate a continuous improvement in system performance throughout the iterative development process. The average cycle time decreased from 10.5 ± 1.5 s for the initial EOAT design to 8.5 ± 0.6 s after the second iteration, reaching 7.6 ± 0.4 s for the proposed system. This reduction confirms that the implemented mechanical modifications and optimization of the vision-guided localization strategy successfully satisfied the industrial cycle-time requirement while improving the repeatability of the robotic operation. Relocating the laser sensor to the center of the EOAT improved the repeatability of height measurements and increased the accuracy of Z-axis compensation, which in turn, reduced the failure rates of both grasping and localization. The redesigned vacuum system, with one vacuum generator assigned to each suction cup and integrated pressure sensors, significantly improved gripping reliability while enabling automatic detection of suction failures and component degradation. Nevertheless, object localization failures still occurred when the displacement of a pot exceeded the field of view of the camera.

A similar trend can be observed for grasping and localization performance. The grasping failure rate decreased from 40% in the initial configuration to 25% in the improved EOAT design and finally reached 2% failure in the proposed system. Object localization remained 20%, ultimately achieving 2% after introducing the proposed zone-based 2.5D guidance strategy. These results indicate that the iterative improvements in the EOAT design, vision system configuration, and localization methodology substantially increased the reliability of autonomous depalletization. The effectiveness of the proposed laser-assisted height estimation is reflected in the number of unsuccessful Z-axis compensations. While the initial EOAT design resulted in 12 failed Z-axis corrections, this number was reduced to three in the second iteration and completely eliminated in the final implementation. Furthermore, the number of manual interventions required during system operation decreased from 27 to 2, demonstrating a considerable improvement in operational autonomy and overall system robustness.

Proposed Zone-Based 2.5D Guidance System addressed this limitation by introducing the proposed zone-based scanning strategy. Instead of acquiring an image at every individual pick location, the pallet was inspected using nine overlapping acquisition zones, each covering multiple potential object positions. This reduced the total number of image acquisitions from one image per object to only nine images for the entire pallet. Consequently, the overall

depalletization cycle time decreased below the 9 ± 1 s range achieved in the previous iteration while maintaining reliable object localization across the complete pallet area. The addition of compliant rubber suction cups with spring-loaded compensators further increased grasping robustness by accommodating small errors in height estimation. Unlike the rigid suction cups used in previous iterations, the compliant design tolerated minor Z-axis deviations without compromising vacuum sealing, resulting in more reliable pick-and-place operations under industrial conditions.

As summarized in Table 2, the proposed solution satisfied all evaluation criteria, including a cycle time below 8 s, reliable vacuum gripping, accurate Z-axis validation, and consistent object localization. These improvements demonstrate that the developed low-cost robotic guidance system is suitable for deployment in high-mix industrial depalletization applications. Compared with the initial EOAT design, the proposed system reduced the average cycle time by approximately 28%, decreased the grasping error rate by 95%, decreased object localization error by 90%, completely eliminated unsuccessful Z-axis compensations, and reduced the number of required manual interventions by approximately 92%.

5. CONCLUSION

This paper presented the development and industrial validation of a low-cost 2.5D robotic guidance system for the automatic depalletization of enameled iron-cast pots in a high-mix production environment. The proposed system integrates a Mitsubishi six-axis industrial robot, an industrial camera, a laser distance sensor, and a custom-designed end-of-arm tool developed through three iterative design stages. The objective was to replace manual depalletization while satisfying the strict cycle-time requirements of an existing enameling production line without introducing expensive sensing technologies or major modifications to the manufacturing process.

The iterative development process demonstrated that both the mechanical design of the EOAT and the perception strategy have a significant influence on the overall system performance. Successive improvements in camera placement, laser sensor positioning, vacuum generation, and suction cup design increased the reliability of object handling and Z-axis compensation while reducing the pick-and-place cycle time. The remaining limitation associated with pre-defined object localization was substantially reduced through the proposed zone-based inspection strategy, which enables reliable detection of pots despite positional deviations caused by manual palletizing and transportation.

Experimental validation confirmed that the final system achieved the required industrial cycle time while providing reliable object localization, robust vacuum gripping, and accurate height compensation for different pallet layers. Furthermore, the proposed solution demonstrated stable operation under high-mix manufacturing conditions involving multiple product geometries and significant variations in object positioning. These results indicate that low-cost sensor fusion based on an industrial camera and a laser distance sensor represents a practical alternative to considerably more expensive 3D vision systems for industrial depalletization tasks.

The developed robotic guidance system has been successfully integrated into an existing production line and has contributed to reducing manual labor while maintaining production throughput and operational reliability. Owing to its modular architecture, the proposed approach can be adapted to similar material-handling applications requiring flexible robotic depalletization under variable production conditions.

Experimental evaluation demonstrates that the proposed approach satisfies the required industrial cycle time while improving localization robustness, Z-axis compensation accuracy, and gripping reliability. The proposed solution provides a practical and cost-effective alternative to more expensive 3D vision systems for robotic depalletization in high-mix manufacturing environments. However, the system has some residual failures where localization fails due to inadequate overhead light levels which are caused due to external roof lightning. This can be fixed in future by enclosing the work area completely and implementing ceiling lightning closer to the pallet scanning area. The wear of the pneumatic components can also cause grasping failure over time. In this case, in between the vacuum system and the EOAT, filters are placed in order to protect the more expensive vacuum generators from residual dust or grease left on pots.

Future work will focus on further improving system autonomy by incorporating adaptive vision algorithms capable of automatically generating inspection zones for new product layouts, as well as investigating the integration of machine-learning-based object detection methods to increase robustness under more complex pallet configurations. Future research will address automatic pallet recognition and dynamic optimization of robot trajectories to further reduce cycle time and improve system efficiency.

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