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Development of a Vision-Guided Supervisory Control Framework for QR Code-Based Industrial Sorting Systems

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ABSTRACT: *This paper presents the development of an automated sorting system integrating a three-degree-of-freedom (3-DOF) robotic manipulator with a QR code-based machine vision framework. The proposed architecture utilizes an industrial-grade imaging sensor for data acquisition, while the vision processing and decoding tasks are executed via LabVIEW in conjunction with the NI Vision Development Module. Control logic is implemented through a Siemens S7-1200 Programmable Logic Controller (PLC), which coordinates the precision movement of the robotic arm's stepper motors for the pick-and-place sequence. Experimental validation indicates that the system achieves a QR code recognition accuracy exceeding 98%, demonstrating robust performance under simulated production conditions. The results confirm the effectiveness of the LabVIEW-PLC integration as a feasible solution for enhancing automation efficiency in small-to-medium-scale industrial applications.*
Keywords: 3-DOF robotic arm, QR code, image processing, LabVIEW, PLC S7-1200.

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I. INTRODUCTION

In the era of Industry 4.0, the automation and digital transformation of manufacturing systems have become indispensable in order to enhance production efficiency, product quality, and traceability. Among various automation tasks, the classification and sorting of goods based on identification information represent a critical challenge in modern industrial environments. In this context, Quick Response (QR) codes have been widely adopted due to their high information density, low implementation cost, and reliable readability using machine vision techniques [1], [2].

Traditional industrial sorting systems typically depend on photoelectric sensors, color sensors, or one-dimensional barcode readers. While these solutions are effective in simple applications, they exhibit limitations in flexibility, scalability, and information capacity, particularly when dealing with diverse product types or dynamic production requirements [8], [10]. By contrast, the integration of image processing techniques with robotic manipulators enables more accurate object identification and classification, while significantly improving system adaptability and intelligence.

Recent research has demonstrated the effectiveness of LabVIEW as a powerful platform for image processing, human–machine interfaces, and robotic control, especially when combined with industrial automation hardware [1], [2], [10]. In parallel, programmable logic controllers (PLCs), such as Siemens S7-1200, continue to play a crucial role in real-time control due to their reliability, deterministic performance, and ease of integration with industrial networks [5]–[7]. However, existing studies primarily focus on individual aspects such as vision-based recognition, robot motion control, or PLC-based automation, with relatively limited attention given to fully integrated systems that combine all these components.

Specifically, research addressing the coordinated integration of a three-degree-of-freedom (3-DOF) robotic arm, QR code recognition based on image processing, and real-time control implemented on a Siemens S7-1200 PLC remains scarce in the current literature [3], [6], [7]. To address this research gap, this paper proposes an automated goods sorting system that integrates a 3-DOF robotic arm with QR code–based image processing implemented in LabVIEW, while the overall system control and synchronization are executed by a Siemens S7-1200 PLC. The proposed approach aims to improve sorting accuracy, system flexibility, and industrial applicability, thereby contributing to the development of intelligent and scalable automation solutions in smart manufacturing environments.

II. EXPERIMENTAL SETUP

Numerous studies have demonstrated the effectiveness of machine vision techniques in controlling robotic pick-and-place operations within industrial environments. Several researchers have employed LabVIEW as an integrated platform for image acquisition, processing, and robotic motion control to implement product sorting systems based on visual features such as color and geometric shape [1], [2], [10]. In addition, product sorting solutions utilizing barcode and QR code identification have been widely investigated and applied in smart manufacturing lines, owing to their reliability and suitability for automation systems [8].

In the domestic research context, most studies have primarily focused on product sorting models based either on image processing implemented in LabVIEW or on conveyor-based systems controlled by programmable logic controllers (PLCs) [5], [6]. Although these approaches have shown promising results in specific applications, reports on comprehensive systems that integrate QR code–based image processing, Siemens S7-1200 PLC control, and multi-degree-of-freedom robotic arms remain limited [6], [7]. This research gap highlights both the novelty and the practical significance of the proposed study, which aims to achieve a unified integration of machine vision, PLC-based control, and robotic manipulation for automated goods sorting

III. RESULTS AND DISCUSSION

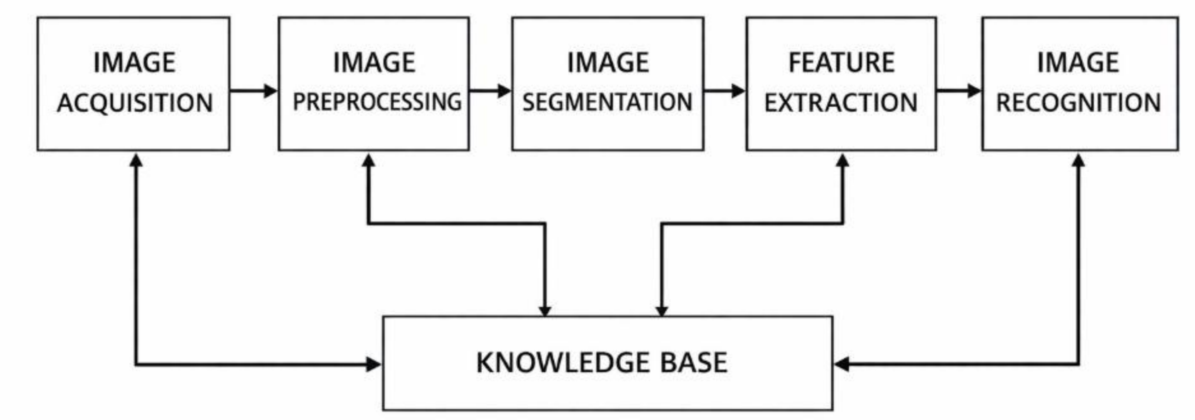

Fig.1 Block diagram of the basic steps in image processing

Fig.1 illustrates the overall workflow of the proposed QR code–based product sorting system, which consists of six main stages: image acquisition, image preprocessing, image segmentation, feature extraction, image recognition, and a knowledge base. This structured pipeline enables reliable product identification and supports real-time control of the robotic sorting system.

a. Image Acquisition

Image acquisition is the first and most critical stage in the image processing pipeline, as it directly affects the accuracy of subsequent processing steps. In the proposed system, images of products are captured using an industrial camera installed at a fixed position above the conveyor belt. The camera continuously acquires images as products move through the inspection area.

Image quality is influenced by camera resolution, illumination conditions, conveyor speed, and mechanical stability. To ensure reliable QR code recognition, the acquisition process is designed to minimize motion blur, vibration, and noise. The captured image data are transmitted directly to the LabVIEW platform for further processing [1], [2], [10].

b. Image Preprocessing

Image preprocessing aims to enhance the quality of the acquired images and prepare them for robust segmentation and recognition. The primary objectives of this stage are noise reduction, illumination normalization, and contrast enhancement.

In this system, preprocessing operations include grayscale conversion to reduce computational complexity, illumination and contrast normalization to compensate for uneven lighting, noise filtering to suppress disturbances, image smoothing to improve boundary continuity, and binarization to facilitate object–background separation. These operations improve the robustness of subsequent segmentation and recognition stages [1], [8].

c. Image Segmentation

Image segmentation divides the preprocessed image into meaningful regions corresponding to individual products and their regions of interest (ROIs). The purpose of this stage is to isolate areas containing relevant identification information, such as QR codes, while suppressing background elements.

Segmentation techniques employed in the system include intensity thresholding, edge detection using the Canny algorithm, and region partitioning based on predefined geometric constraints. The segmentation results significantly reduce computational load and improve recognition accuracy by focusing analysis on relevant regions only [2], [10].

d. Feature Extraction

After segmentation, quantitative features are extracted from each ROI to form a numerical representation of the detected objects. This stage converts visual information into feature vectors suitable for recognition and decision making.

Extracted features include region area, shape characteristics, relative position on the product, number of detected objects, and average intensity or brightness. These features provide a compact and effective description of the product characteristics and serve as the basis for comparison with reference data stored in the knowledge base [1], [2].

e. . Image Recognition and Control Integration

Image recognition is performed by comparing the extracted feature vectors with reference templates stored in the knowledge base. Based on this comparison, the system determines the product type and evaluates whether it meets predefined classification criteria.

The recognition results are transmitted to the Siemens S7-1200 PLC, which executes real-time control commands for the conveyor belt, sorting actuators, and robotic arm. This integration enables coordinated operation between image processing, industrial control, and robotic manipulation, ensuring reliable and fully automated sorting performance [5]–[7].

f. Knowledge Base

The knowledge base stores reference images, feature templates, and decision thresholds used during the recognition process. Acting as a comparison memory, it supports accurate classification and decision making for each product.

Moreover, the knowledge base enhances system flexibility and scalability. New product types can be accommodated by updating reference data without modifying the core processing algorithm, making the proposed system suitable for practical industrial applications [4], [9].

g. Discussion

Experimental results confirm that the proposed image processing pipeline provides stable QR code recognition under controlled lighting and conveyor speed conditions. The modular structure shown in Fig. 1 facilitates seamless integration with the PLC and robotic arm, improving system reliability and adaptability. Compared with conventional sensor-based sorting methods, the proposed approach offers higher flexibility and information capacity, making it well suited for smart manufacturing environments [1], [8], [10].

IV. SYSTEM SOFTWARE ARCHITECTURE AND COMMUNICATIONINTERFACE

1. LabVIEW-Based Graphical Programming Interface

LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench), developed by National Instruments (USA), is a graphical programming environment widely applied in industrial automation, measurement, and control systems. Unlike conventional text-based programming languages such as C or Pascal, LabVIEW follows a dataflow programming paradigm, in which execution is determined by the availability of data. This characteristic makes LabVIEW particularly suitable for real-time image acquisition, image processing, and human–machine interface (HMI) development [1], [2], [6].

Fig. 2 LabVIEW software interface

Fig. 2 illustrates the LabVIEW software interface employed in the proposed system. The interface integrates image acquisition, image processing, system monitoring, and communication with the PLC, providing an intuitive and flexible platform for system operation and supervision.

a. Image Acquisition Module

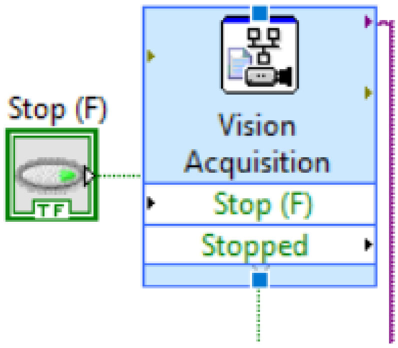

Fig. 3 Vision Acquisition block for image capture

The image acquisition module, shown in Fig. 3, is implemented using the NI Vision Acquisition Express block available in the VISION/VISION EXPRESS TOOLBOX. This module is responsible for capturing images from the industrial camera installed above the conveyor belt.

The Vision Acquisition Express block allows selection of the acquisition source and configuration of different acquisition modes, including single-image capture, continuous acquisition, and fixed-number acquisition. In addition, camera parameters such as resolution, brightness, contrast, white balance, and image orientation can be adjusted to ensure stable image quality under industrial operating conditions. Control and indicator elements are integrated into the interface to support real-time monitoring of the acquisition process.

b. Image Processing Module

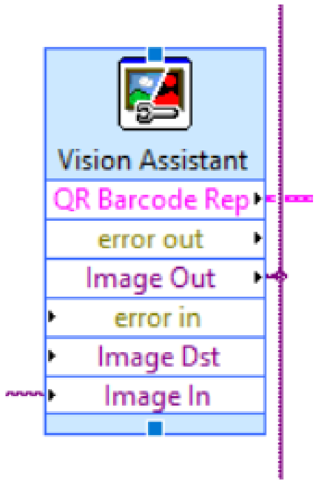

Fig. 4 Vision Assistant image processing block

The image processing module is implemented using the Vision Assistant block, as shown in Fig. 4. This module provides a comprehensive set of image processing tools, including filtering operations, geometric analysis, color processing, mathematical functions, and region-of-interest (ROI) selection.

In the proposed system, the Vision Assistant block is used to perform essential preprocessing and analysis tasks such as noise reduction, image smoothing, ROI extraction, and feature analysis. The modular and graphical nature of this block enables rapid development and easy modification of processing algorithms, thereby improving system flexibility and maintainability [1], [8], [10].

2. OPC COMMUNICATION

OPC (OLE for Process Control) is a standardized data communication framework based on the client–server architecture, widely used in industrial automation to enable interoperable and flexible data exchange among heterogeneous systems. OPC allows control, monitoring, and visualization software to communicate seamlessly with industrial devices supplied by different manufacturers [5], [6], [9].

Fig. 5 KEPServerEX software interface

Fig. 5 presents the interface of KEPServerEX, which is employed as the OPC middleware in the proposed system. Developed by Kepware Technologies, KEPServerEX functions as an OPC gateway that connects industrial hardware devices—such as the Siemens S7-1200 PLC—to higher-level software platforms, including SCADA, HMI, and custom applications such as LabVIEW.

In this study, KEPServerEX is used to establish real-time communication between the LabVIEW-based image processing platform and the Siemens S7-1200 PLC. PLC variables are mapped to OPC tags within the server, allowing LabVIEW to read process data and transmit control commands. This communication mechanism ensures synchronized operation between vision processing, decision making, and PLC-based control actions.

KEPServerEX 6, the latest major version of the platform, offers enhanced performance, improved security, and expanded protocol support compared with earlier releases. These features contribute to reliable and scalable operation in modern industrial automation systems that integrate machine vision, robotic control, and PLC-based supervision [6], [7], [9].

V. DYNAMIC AND KINEMATIC MODEL OF A THREE-DEGREE-OF-FREEDOM ROBOTIC ARM

1. Robot Structure and Modeling Assumptions

The robotic manipulator considered in this study is a serial three-degree-of-freedom (3-DOF) arm with a revolute–revolute–revolute (RRR) joint configuration. The robot is a custom-built model designed to perform pick-and-place operations in an automated product sorting system, where high positioning accuracy and moderate speed are required.

For kinematic and dynamic modeling purposes, the robot links are assumed to be rigid bodies, while the effects of link elasticity, joint friction, and backlash are neglected. These assumptions are commonly adopted in robot modeling and control studies to simplify the mathematical formulation and reduce computational complexity, especially in light-payload industrial applications [3], [10]. Under these conditions, the resulting model is sufficiently accurate for motion simulation, trajectory planning, and controller design in vision-based robotic systems [1], [4].

2. Forward Kinematics

Forward kinematics (FK) is concerned with determining the position and orientation of the robot end-effector with respect to the base coordinate frame when the joint variables are known. FK analysis constitutes the theoretical basis for robot motion simulation, trajectory generation, and control algorithm development [3].

In this study, the Denavit–Hartenberg (D–H) convention is employed to systematically describe the geometric relationships between consecutive robot links. This method provides a standardized framework for assigning coordinate frames and deriving homogeneous transformation matrices, thereby enabling consistent kinematic modeling of serial manipulators [3], [10]. By multiplying the individual transformation matrices, the overall transformation from the base frame to the end-effector frame is obtained, allowing analytical computation of the end-effector pose as a function of joint angles.

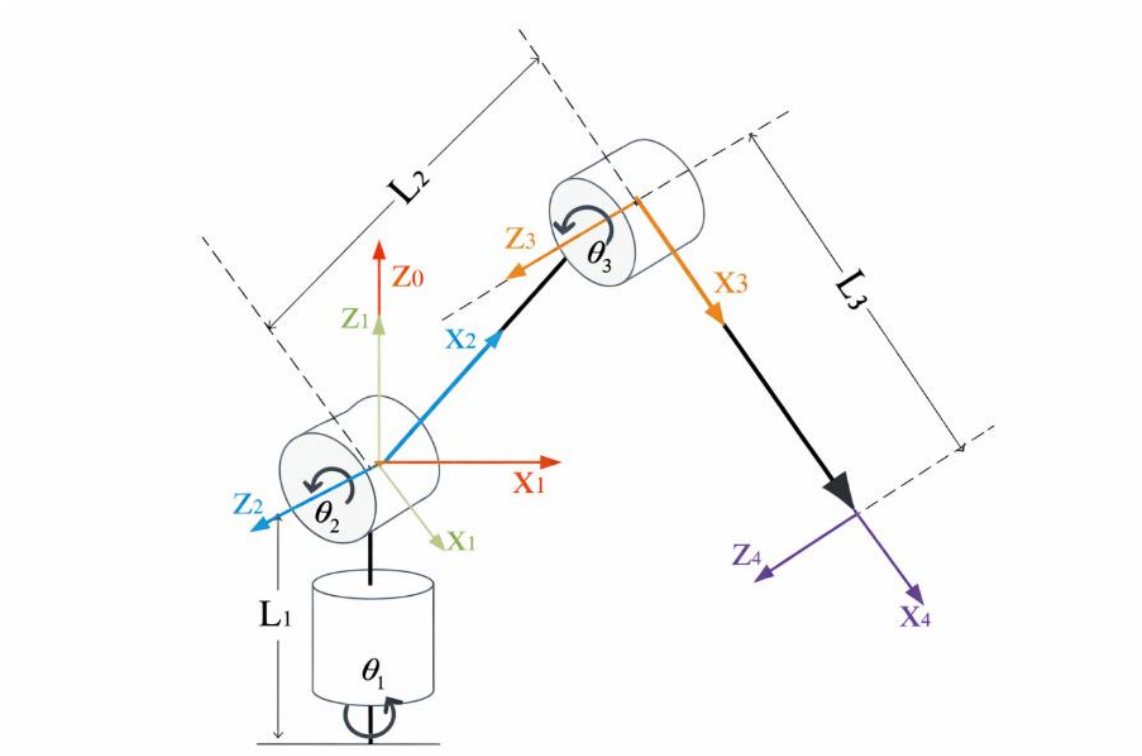

Fig. 6 Robot kinematics in three-dimensional space (3D kinematic diagram)

Based on Fig. 6 and following the standard Denavit–Hartenberg (D–H) convention, coordinate frames are assigned to each link such that the Zi axis aligns with the axis of motion of the i-th joint. The geometric parameters of the robot are summarized in Table 1.

Table 1: Denavit–Hartenberg Parameters of the Robot

Joint i	a_{i-1}	α_{i-1}	d_i	θ_i
1	0	0	0	θ_1
2	0	90°	0	θ_2
3	L_2	0	0	θ_3
4	L_3	0	0	0

In there:

- i: It denotes the sequential index of the robot joint.
- a_{i-1}: It is the distance between two consecutive joint axes. Z_i với Z_{i+1} Along the axis X_i.
- α_{i-1}: It is the angle formed between two consecutive joint axes. Z_i with Z_{i+1} Measured from X_i.
- d_i: It is the offset distance along the joint axis. X_{i-1} với X_i Along the axis Z_i.
- θ_i: It is the angle between two consecutive axes. X_{i-1} với X_i Measured from Z_i.
- L_i: Length of the robot links.
- 1.2. Forward Kinematics Matrix.

The homogeneous transformation matrix between two consecutive coordinate frames, (i-1) and i, is defined by the general expression:

$$T_i^{i-1} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 & a_{i-1} \\ \cos\alpha_{i-1}\sin\theta_i & \cos\alpha_{i-1}\cos\theta_i & -\sin\alpha_{i-1} & -d_i\sin\alpha_{i-1} \\ \sin\alpha_{i-1}\sin\theta_i & \sin\alpha_{i-1}\cos\theta_i & \cos\alpha_{i-1} & d_i\cos\alpha_{i-1} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

The overall forward kinematics matrix from the base frame to the end-effector is determined by the product of the individual transformation matrices:

$$T_0^4 = T_1^0 T_2^1 T_3^2 T_4^3 = \begin{bmatrix} R_{EE} & P_{EE} \\ 0 & 1 \end{bmatrix} \quad (2)$$

3. Inverse Kinematics

Inverse kinematics (IK) addresses the problem of determining the joint variables that enable a robotic manipulator to reach a specified position and orientation of its end-effector. Unlike forward kinematics, which yields a unique solution for a given set of joint variables, the inverse kinematic problem may admit multiple solutions or, in some cases, no feasible solution depending on the robot configuration and workspace constraints [3].

In this study, the inverse kinematics of the 3-DOF RRR robotic arm is solved using algebraic methods. By exploiting the geometric structure of the manipulator and the analytical expressions derived from the forward kinematic model, closed-form solutions for the joint angles are obtained. This approach offers low computational complexity and is well suited for real-time implementation in motion planning and control applications [3], [10].

The analytical inverse kinematic solution provides the joint angle commands required for pick-and-place operations and serves as a fundamental component for trajectory generation and coordinated control of the robotic arm within the proposed vision-based sorting system [1], [4].

a. Determination of Joint Angle θ_1:

- Transformation Matrix T_0^4 is obtained as:

$$\begin{bmatrix} R_{EE} & P_{EE} \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & P_x \\ r_{21} & r_{22} & r_{23} & P_y \\ r_{31} & r_{32} & r_{33} & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

- Multiply the transformation matrix by:

$$(T_1^0)^{-1} T_0^4 = {}^{IK}T_4^1 = \begin{bmatrix} r_{11}c_1 + r_{21}s_1 & r_{12}c_1 + r_{22}s_1 & r_{13}c_1 + r_{23}s_1 & P_xc_1 + P_ys_1 \\ r_{21}c_1 - r_{11}s_1 & r_{22}c_1 - r_{12}s_1 & r_{23}c_1 - r_{13}s_1 & P_yc_1 - P_xs_1 \\ r_{31} & r_{32} & r_{33} & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

- Meanwhile, according to forward kinematics:

$${}^{FK}T_4^1 = T_2^1 T_3^2 T_4^3 = \begin{bmatrix} c_{23} & -s_{23} & 0 & L_3c_{23} + L_2c_2 \\ 0 & 0 & -1 & 0 \\ s_{23} & c_{23} & 0 & L_3s_{23} + L_2s_2 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

- From the position components of the forward kinematics matrix, the following equations are obtained:

$$\begin{cases} P_xc_1 + P_ys_1 = L_3c_{23} + L_2c_2 \\ P_yc_1 - P_xs_1 = 0 \\ P_z = L_3s_{23} + L_2s_2 \end{cases} \quad (7)$$

- Thus, the solution for θ_1 is determined by:

$$\theta_1 = \begin{cases} \operatorname{atan2d}(P_y, P_x) \\ \operatorname{atan2d}(-P_y, -P_x) \end{cases} \quad (8)$$

b. Determination of Joint Angle θ_3:

- By using the system of equations:

$$\begin{cases} P_x c_1 + P_y s_1 = L_3 c_{23} + L_2 c_2 \\ P_z = L_3 s_{23} + L_2 s_2 \end{cases} \tag{9}$$

$$L_2^2 + L_3^2 + 2L_2L_3c_3 = \left(P_x c_1 + P_y s_1\right)^2 + P_z^2 \tag{10}$$

- After squaring and summing the coordinate equations to eliminate θ_2, the resulting system of equations is:

$$\begin{cases} c_3 = \dfrac{\left(P_x c_1 + P_y s_1\right)^2 + P_z^2 - L_2^2 - L_3^2}{2L_2L_3} \\ s_3 = \pm\sqrt{1 - c_3^2} \end{cases} \tag{11}$$

- From this, the solution for θ_3 is determined as follows:

$$\theta_3 = \begin{cases} \operatorname{atan2}\left(s_3, c_3\right) \\ \operatorname{atan2}\left(-s_3, c_3\right) \end{cases} \tag{12}$$

c. Determination of Joint Angle θ_2:

- Transform the system of equations into matrix form:

$$\begin{cases} P_x c_1 + P_y s_1 = \left(L_3 c_3 + L_2\right) c_2 - \left(L_3 s_3\right) s_2 \\ P_z = \left(L_3 s_3\right) c_2 + \left(L_3 c_3 + L_2\right) s_2 \end{cases} \tag{13}$$

- Using Cramer's method:

$$D = \begin{bmatrix} L_3 c_3 + L_2 & -L_3 s_3 \\ L_3 s_3 & L_3 c_3 + L_2 \end{bmatrix} \tag{14}$$

$$D_c = \begin{bmatrix} P_x c_1 + P_y s_1 & -L_3 s_3 \\ P_z & L_3 c_3 + L_2 \end{bmatrix}$$

$$D_s = \begin{bmatrix} L_3 c_3 + L_2 & P_x c_1 + P_y s_1 \\ L_3 s_3 & P_z \end{bmatrix}$$

- From this, it follows that:

$$\begin{cases} c_2 = \dfrac{\det\left(D_c\right)}{\det\left(D\right)} \\ s_2 = \dfrac{\det\left(D_s\right)}{\det\left(D\right)} \end{cases} \tag{15}$$

- After applying Cramer's method and determining θ1 and θ3, the joint angle θ2 can be calculated using a linear equation in terms of sinθ2 and cosθ2. We have:

$$\theta_2 = \operatorname{atan2}\left(s_2, c_2\right) \tag{16}$$

With: $c_i = \cos\theta_i,\quad s_i = \sin\theta_i,\quad c_{23} = \cos\left(\theta_2 + \theta_3\right),\quad s_{23} = \sin\left(\theta_2 + \theta_3\right)$

4. Robot Force Kinematic

Dynamic modeling plays a crucial role in the analysis and control of robotic manipulators, particularly in applications involving precise motion execution such as automated sorting and pick-and-place tasks. In recent years, several studies have demonstrated the effectiveness of integrating robot dynamics with control and monitoring platforms based on LabVIEW and PLC systems, highlighting the importance of accurate force and motion modeling [1]–[4].

In this study, the dynamic behavior of the three-degree-of-freedom (3-DOF) serial robotic arm is formulated using the Lagrangian approach, which is well suited for multi-link robotic systems and has been widely adopted in industrial and research-oriented robot applications [3], [4]. The modeling assumes rigid links and neglects frictional and elastic effects, consistent with previous works focusing on lightweight robotic manipulators for industrial automation [2], [8].

By expressing the system dynamics in terms of kinetic and potential energy, the resulting equations of motion can be represented in a standard matrix form involving inertia, Coriolis–centrifugal, and gravitational components. This formulation provides a solid foundation for controller design, simulation, and integration with PLC-based automation and OPC communication frameworks, as reported in related LabVIEW- and OPC-based industrial systems [5]–[10].

Calculation of Total Kinetic Energy

$$K\left(\theta,\dot{\theta}\right)=\sum_{i=1}^{n}\left(\frac{1}{2}m_i v_{Ci}^T v_{Ci}+\frac{1}{2}\omega_i^T I_i \omega_i\right) \tag{17}$$

Calculation of Total potential energy:

$$U\left(\theta\right)=\sum_{i=1}^{n}\left(-m_i g^T P_{Ci}+U_{ref_i}\right) \tag{18}$$

Using the Lagrange equation:

$$L\left(\theta,\dot{\theta}\right)=K\left(\theta,\dot{\theta}\right)-U\left(\theta\right) \tag{19}$$

Using the Lagrange differential equation:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}}\right)-\frac{\partial L}{\partial \theta}=\tau \tag{20}$$

Using the general Dynamic equation to Compute the Three Matrices M, C, and G:

$$M\left(q\right)\ddot{q}+C\left(q,\dot{q}\right)\dot{q}+G\left(q\right)=\tau \tag{21}$$

Where:

- q: Joint coordinate vector
- $\dot{q}$: Joint velocity vector
- $\ddot{q}$: Joint acceleration vector
- τ: Torque applied to the robot
- M: Inertia matrix
- C: Coriolis and centrifugal forces
- G: Gravitational torque

VI. DESIGN AND EXPERIMENTATION

1. QR Code Image Processing Algorithm in LabVIEW

The QR code image processing algorithm is designed to ensure reliable product identification in an automated sorting environment. The processing sequence includes image acquisition, grayscale conversion, noise filtering, contrast enhancement, QR code region detection, and information decoding.

Image data are captured by an industrial camera and processed in the LabVIEW environment. The NI Vision library provides built-in QR code detection and decoding functions, allowing direct extraction of encoded information without the need for custom decoding algorithms. Similar LabVIEW-based vision systems have demonstrated high recognition accuracy and real-time performance in industrial sorting and automation applications [1], [2], [8].

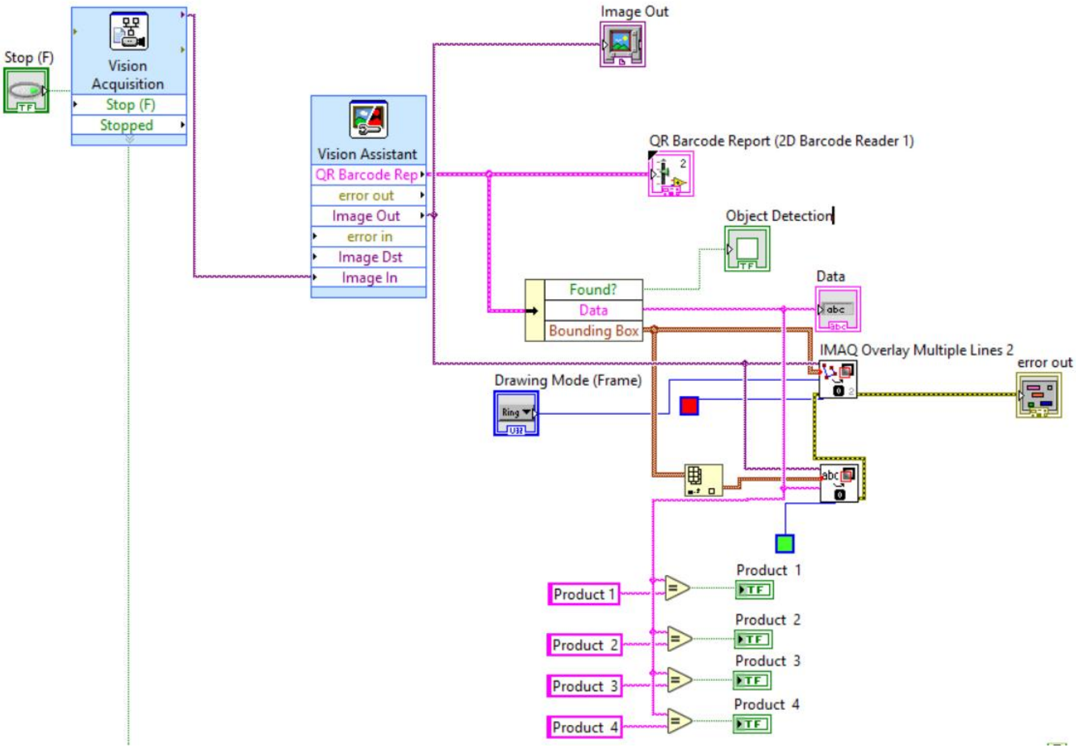

Fig. 7 Illustrates the block diagram of the QR code scanning and product sorting system.

2. PLC S7-1200 and Robot Control

The Siemens S7-1200 PLC is programmed using TIA Portal to receive sorting information transmitted from LabVIEW via OPC communication. Based on the decoded QR code data, the PLC generates control signals to drive the servo motors of the robotic arm through pulse train output (PTO) channels.

The PLC program is organized using modular function blocks, which improves scalability and simplifies system maintenance. This PLC–LabVIEW integration approach has been widely applied in industrial automation and monitoring systems using OPC-based communication frameworks [5], [6], [7], [9]. The layout of the automated product sorting system is shown in Fig. 7.

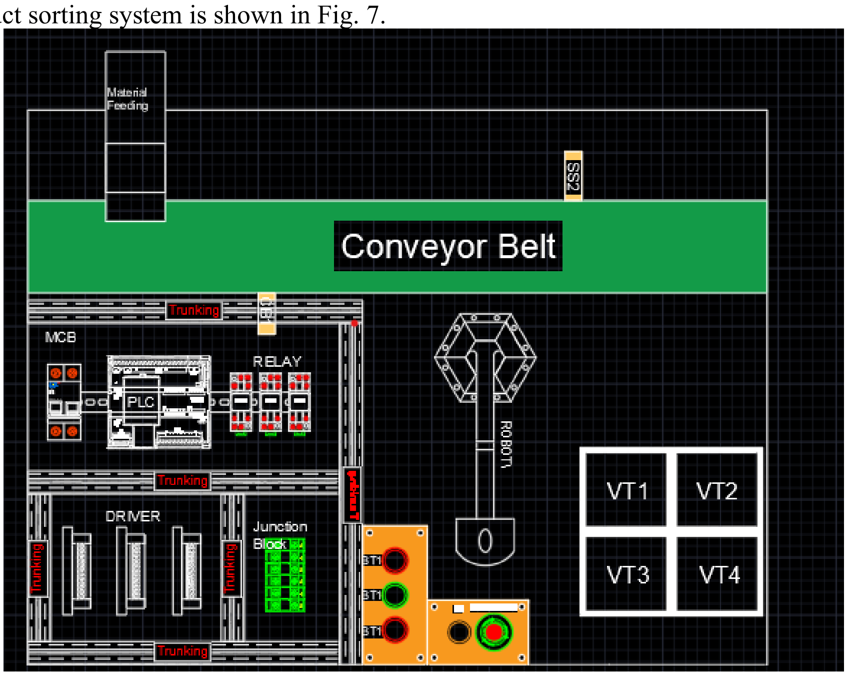

Fig. 8 Layout diagram of the automated product sorting system

3. Experimental Results

Experimental tests were conducted under typical industrial lighting conditions to evaluate system performance. The results indicate that the proposed system can accurately recognize QR codes with an average processing time of less than 0.5 s per product. The classification accuracy exceeds 98%, and the robotic arm demonstrates stable operation with good positioning repeatability.

These results are consistent with previous studies on LabVIEW-based robotic sorting and industrial automation systems, confirming the practicality and effectiveness of the proposed approach [2], [4], [8], [10]. An overview of the system after experimental implementation is presented in Fig. 8.

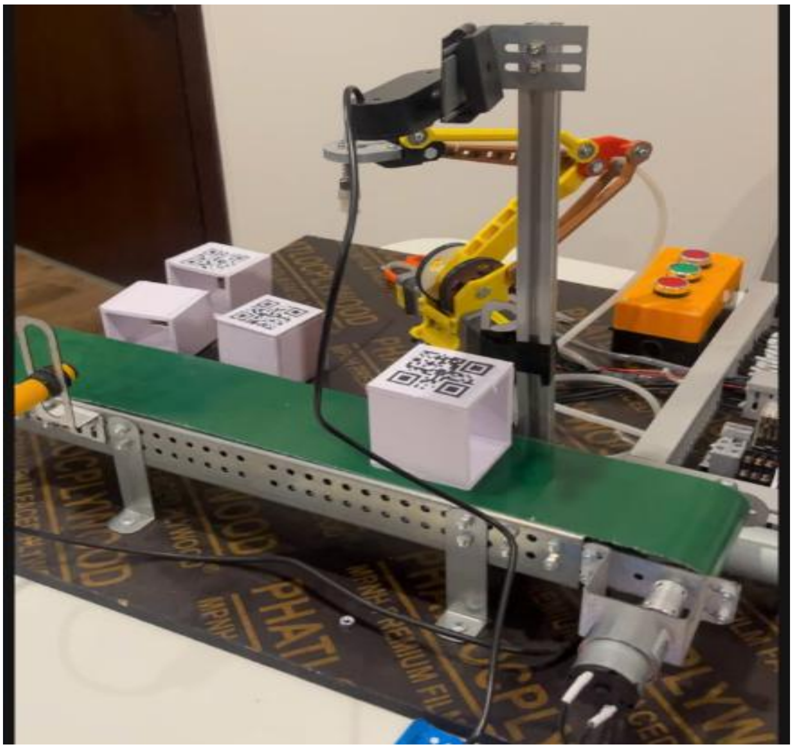

Fig. 9 Overview of the Model After Experimental Implementation

VIII. CONCLUSION

This research has successfully developed and validated an automated sorting architecture that synthesizes a three-degree-of-freedom (3-DOF) robotic manipulator with a robust machine vision framework. By leveraging the computational capabilities of the LabVIEW-based NI Vision Development Module for QR code decoding and the deterministic control of a Siemens S7-1200 Programmable Logic Controller (PLC), the system achieves a seamless hardware-in-the-loop integration. Empirical evaluations demonstrate that the proposed system exhibits high operational reliability and precise trajectory execution, yielding a classification accuracy suitable for the throughput requirements of small-to-medium-scale automated production environments.

Moving forward, the research will be extended to incorporate deep learning-based object detection algorithms to enhance recognition robustness under non-ideal lighting and occluded conditions. Furthermore, the system architecture is designed to be scalable; subsequent iterations will involve the integration of 6-DOF robotic manipulators and the implementation of advanced motion planning algorithms to facilitate more complex pick-and-place operations in high-density industrial settings.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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