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Development of a Vision-Guided SCARA Robot System Based on a Refurbished Mechanical Platform for Automated Pick-and-Place Applications

This study presents the development of a vision-guided 4-DOF SCARA robotic arm based on a refurbished mechanical platform for automated pick-and-place applications. The existing mechanical structure was retained, while a new electrical and control system was developed. The proposed system integrates motor control, point-to-point (PTP) motion control, and a human-machine interface (HMI) for robot operation and monitoring. A machine vision module was also integrated to detect objects and determine their positions, enabling automatic pick-and-place operations. The developed system coordinates image-based object localization with robot motion commands. Experimental tests were conducted to evaluate the positioning and image-based coordinate calculation performance of the system. The average robot positioning errors were 0.81 mm along the X-axis and 0.51 mm along the Y-axis. The results demonstrate the feasibility of reusing an obsolete SCARA mechanical platform to develop an integrated and functional robotic system for automated pick-and-place applications.

Keywords: SCARA robot, machine vision, pick-and-place, low-cost robotics, refurbished robot.

1. INTRODUCTION

Industrial robots play an important role in modern manufacturing by improving productivity, repeatability, and automation in repetitive tasks such as assembly, sorting, material handling, and pick-and-place operations [1-3]. Among industrial manipulators, Selective Compliance Assembly Robot Arm (SCARA) robots are particularly suitable for planar pick-and-place applications because of their compact structure, high-speed motion, and relatively simple kinematic configuration [4,5]. The integration of machine vision further increases the flexibility of SCARA-based systems by allowing robots to detect objects, determine their positions and orientations, and generate motion commands according to the detected target pose. Vision-guided robotic systems have therefore become an important approach for flexible automation and automated material handling [6-8].

Several studies have investigated the integration of SCARA robots and machine vision for automated manipulation. Hema et al. [9] developed a stereo vision system for an Adept SCARA robot to perform bin-picking operations. Their system segmented partially occluded objects and calculated grasping points using stereo vision, demonstrating the feasibility of vision-

only object localization for robotic bin picking. Hu et al. [10] developed a low-cost 4-DOF SCARA system for spanner fetching and placement. Their vision system consisted of image calibration, color-based image recognition, and object localization, from which the center, length, slope, and tool information of the spanner were obtained for robot control. In the same period, Nerakae et al. [11] developed a flexible automatic assembly system integrating machine vision with a SCARA robot. Image calibration was used to determine the shape and orientation of assembly spaces, and the resulting coordinate information was used to control the SCARA robot during pick-and-place operations. More recently, Kapusi et al. [12] investigated the application of deep learning to an industrial SCARA system for real-time object detection, demonstrating the potential of neural-network-based perception for robotic applications. Nguyen et al. [13] developed a SCARA robot for palletizing applications based on computer vision and proposed a method for calculating 3D object coordinates from camera images while simplifying the camera calibration process. In 2025, Phuc and Son [14] further integrated computer vision, deep learning, and a 4-DOF SCARA robot to develop an autonomous chess robot. Their system used deep learning for chess-piece recognition and position detection, demonstrating the increasing integration of AI-based perception with SCARA robotic systems [15]. The approaches of these studies and the limitations relevant to the present work are summarized in Table 1.

Although these studies demonstrate the effectiveness of vision-guided SCARA robots, several limitations

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remain. Most reported systems focus on newly designed or dedicated robotic platforms, while less attention has been given to the refurbishment and functional reuse of obsolete SCARA mechanical platforms. This is an important practical issue because rapid technological development can make industrial robots obsolete while their mechanical structures remain usable. In particular, outdated components, compatibility problems, and difficulties in obtaining spare parts can create significant challenges for continued operation and remanufacturing. Research on remanufactured industrial robots has highlighted these issues and identified remanufacturing as a potential alternative to complete replacement. In addition, existing vision-based studies generally focus on object detection and localization for specific applications, such as bin picking, spanner handling, assembly, palletizing, or chess-piece manipulation. Many conventional approaches rely on application-specific image processing, calibration, or coordinate relationships. More recent deep-learning-based approaches can improve visual recognition capabilities, but they generally introduce additional requirements for training data and computational resources. Consequently, a complete system that integrates camera calibration, image-based object localization, coordinate transformation between the camera and robot coordinate systems, and robot motion control on a refurbished SCARA platform remains less explored. Such integration is particularly important because the camera coordinate system does not generally coincide with the robot coordinate system.

To address these limitations, this study develops a vision-guided 4-DOF SCARA robot system based on a refurbished mechanical platform for automated pick-and-place applications. The existing mechanical structure is retained, while a new electrical and control system is developed and integrated with hybrid stepper motors, a microcontroller, motor drivers, an HMI, and a machine vision module. The proposed vision system performs camera calibration, image processing, object detection, centroid and orientation estimation, and coordinate transformation from the image/camera coordinate system to the robot coordinate system. The resulting target position and orientation are then transmitted to the robot controller for automated pick-and-place operation. The system is experimentally evaluated through robot positioning tests and image-based coordinate calculation tests using rectangular and circular objects. This study focuses on the development and experi-

mental validation of an integrated vision-guided robotic system that demonstrates the practical reuse of an obsolete SCARA mechanical platform while providing the required object localization and positioning capability for automated pick-and-place applications. The developed system targets applications in which a planar, high-repeatability manipulator must locate randomly placed parts: (i) sorting and feeding of small parts in small and medium-sized enterprises, where purchasing a new industrial robot with a vision package is not economically justified; (ii) teaching and research laboratories, where an open and fully accessible controller and vision pipeline is more valuable than a closed commercial one; and (iii) the remanufacturing of aging industrial robots, which extends the service life of existing assets and supports circular-economy and sustainability goals. The scientific and engineering merit of this work is a complete, reproducible methodology for converting a mechanically sound but electronically obsolete SCARA arm into a vision-guided robot, covering motor retrofitting, kinematics, camera calibration, camera-to-robot coordinate mapping, and experimental verification.

The main contributions of this study are summarized as follows:

- Refurbishment of an obsolete SCARA platform. The original links, harmonic gearboxes, ball screw, and belt drives were retained, and the original motors were replaced by hybrid stepper motors with encoders, with new motor brackets and transmission components designed to fit the existing structure.
- New electrical and control system. An ESP32-based controller, motor drivers, and a Nextion HMI (Kinematic, Teaching, and Image Processing modes) were developed, together with forward and inverse kinematic models and a workspace analysis of the refurbished robot.
- Vision-based object localization. A machine vision module was developed and integrated with the robot controller to detect objects, determine their position and orientation, and provide the target coordinates for automated pick-and-place operation.
- Experimental validation. The average positioning errors were 0.81 mm (X) and 0.51 mm (Y), and the image-based coordinate errors did not exceed 2.2 mm and 2.0°, which is sufficient for pick-and-place operations.

Table 1. Summary of related vision-guided SCARA studies and their limitations

References	Application	Approach	Limitation
[9]	Bin picking	Stereo vision, segmentation of occluded objects	Vision-only localization; no treatment of an aging or refurbished robot or of a camera-to-robot mapping procedure
[10]	Spanner fetching and placement	Color-based recognition after image calibration	Recognition tied to a specific tool and color; new platform built
[11]	Flexible assembly	Image calibration of assembly spaces	Application-specific calibration; new hardware
[12]	Real-time object detection	Deep learning on an industrial SCARA	Needs training data and computing resources; no refurbishment aspect
[13]	Palletizing	3D coordinates from images, simplified calibration	Designed for palletizing on a new robot; not based on a retrofit
[14]	Chess robot	Deep learning for piece recognition	Highly application-specific; relies on neural networks

The remainder of this paper is organized as follows: Section 2 presents the mechanical and electrical design of the refurbished SCARA robot system, including the robot control and HMI. Section 3 describes the forward and inverse kinematic models and the robot workspace. Section 4 introduces the computer vision system, including camera calibration, image processing, and coordinate transformation. Section 5 presents the experimental setup and discusses the robot positioning and image-based coordinate calculation results. Finally, Section 6 concludes the paper and outlines directions for future development.

2. DEVELOPMENT OF THE SCARA ROBOT

2.1 Mechanical Design and Robot Refurbishment

The SCARA robot was reconstructed from an existing mechanical platform to reduce the need for complete mechanical fabrication. As shown in Figure 1, the main links and robot base recovered from the original SCARA robot were retained as the primary structural components. The original transmission mechanisms, including harmonic gearboxes, a ball screw mechanism, and timing belt transmissions, were also reused. The transmission ratios of the four joints are 80:1, 50:1, 54:20, and 35:20, respectively.

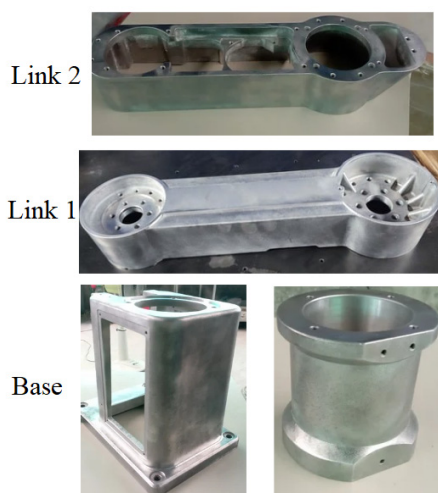


Figure 1. Recovered mechanical components from the original SCARA robot

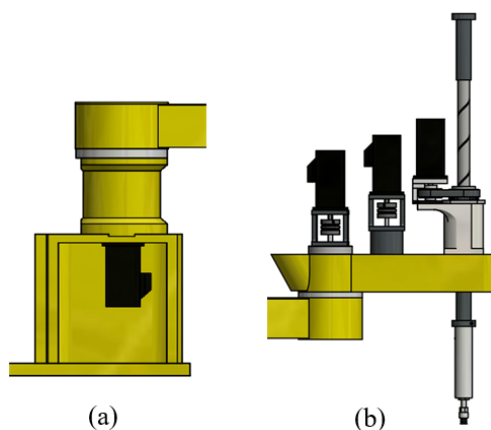


Figure 2. Motor mounting assembly in 3D: (a) motor 1; (b) motor 2-3-4

To integrate the new control system, the original motors were replaced with hybrid stepper motors equipped with encoders for position feedback. The selected motors were based on the power and torque specifications of the original motors. Because the new motors required different mounting arrangements, new motor brackets and transmission components were designed and fabricated. The resulting mechanical configuration is illustrated in Figure 2, where the new motor mounting structure is integrated with the existing transmission system.

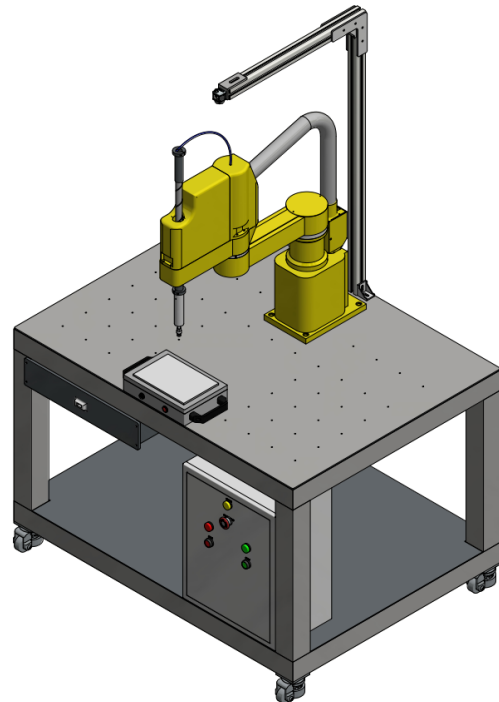


Figure 3. Complete robot model designed in 3D

Several additional components were designed using 3D CAD and fabricated to complete the reconstructed robot. A working table was developed using box steel and steel plates to provide a rigid workspace for robot operation. In addition, a two-piece PETG protective cover was fabricated using 3D printing to protect the motors from dust and moisture. A vision system was also developed and integrated with the reconstructed robot to support object localization and vision-based pick-and-place operations. The overall reconstructed robot system is shown in Figure 3.

2.2 Electrical System Design

The electrical system was developed to integrate the power supply, motor drive, control, HMI, and vision processing units, as illustrated in Figure 4. The system is organized into four main blocks: the power supply, control block, power circuit, and image processing blocks. The main input is 220 VAC, which is protected by an MCB and passed through a contactor and EMI filters before being converted into the required DC voltages. A 48 VDC supply is used for the motor drivers, while 5 VDC is provided for the ESP32 controller and HMI. A separate 12 VDC supply is used for the vacuum pump, while the relay supply is isolated from the ESP32 power supply to reduce electrical interference.

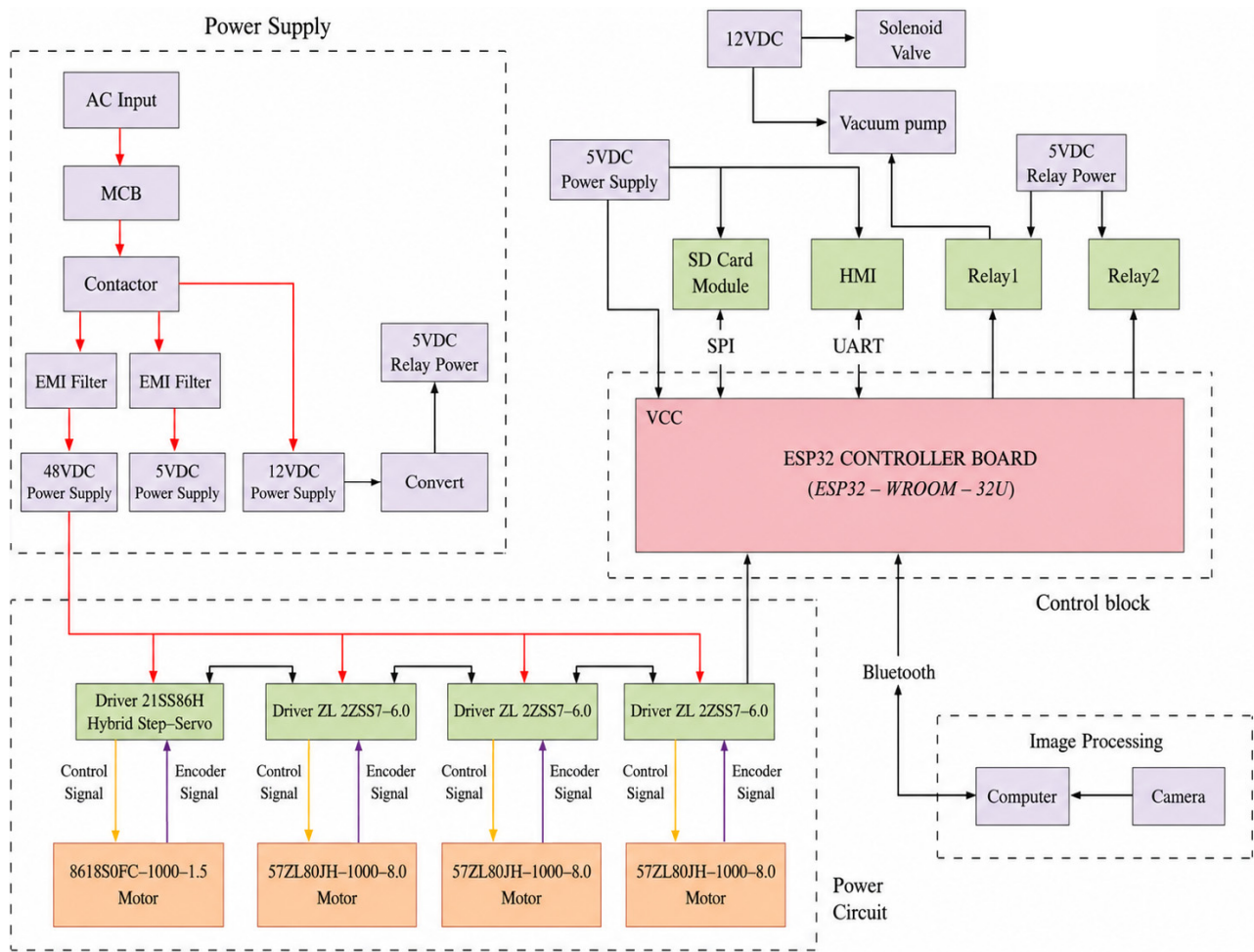


Figure 4. General schematic of the electrical design

The motor drive block consists of the hybrid stepper motors and their corresponding drivers. The drivers receive PUL (Pulse) and DIR (Direction) signals from the ESP32 to control motor motion and also process the encoder feedback signals. The control block uses an ESP32 as the main microcontroller for robot operation and communication with peripheral devices. Meanwhile, the vision processing block consists of a computer and camera, where image processing and object localization are performed. The resulting control data are transmitted from the computer to the ESP32 through Bluetooth.

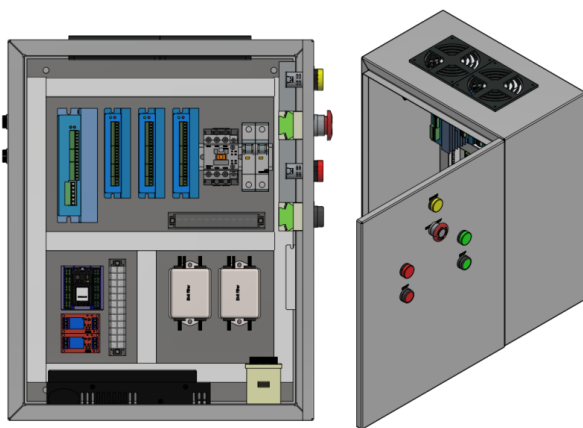


Figure 5. Electrical cabinet design in 3D

The electrical cabinet was also designed using a 3D CAD model to arrange the main electrical components and optimize the internal layout. The 3D design of the electrical cabinet is presented in Figure 5, providing an overview of the component arrangement and wiring space before fabrication and assembly.

2.3 Robot Control and HMI

The robot control system was developed using an ESP32 as the main controller. The control program was implemented in C++ and Python, with the ESP32 responsible for initializing the GPIO pins, serial communication, SPI communication, and Bluetooth before entering the main control loop. The controller continuously monitors the HMI commands and executes the corresponding robot control functions according to the selected operating mode. The overall control flow is illustrated in Figure 6.

An HMI based on the Nextion Enhanced NX8048 K070_011C was developed to provide an interactive interface for robot operation. The HMI uses a 7-inch display with 32 MB Flash and 8192 B RAM. It includes five main functional pages: Kinematic, Teaching Mode, Image Processing, Operation Guide, and About of Project. The main HMI interface is shown in Figure 7.

The Kinematic page allows the user to control individual joints using sliders or by directly entering the desired joint values.

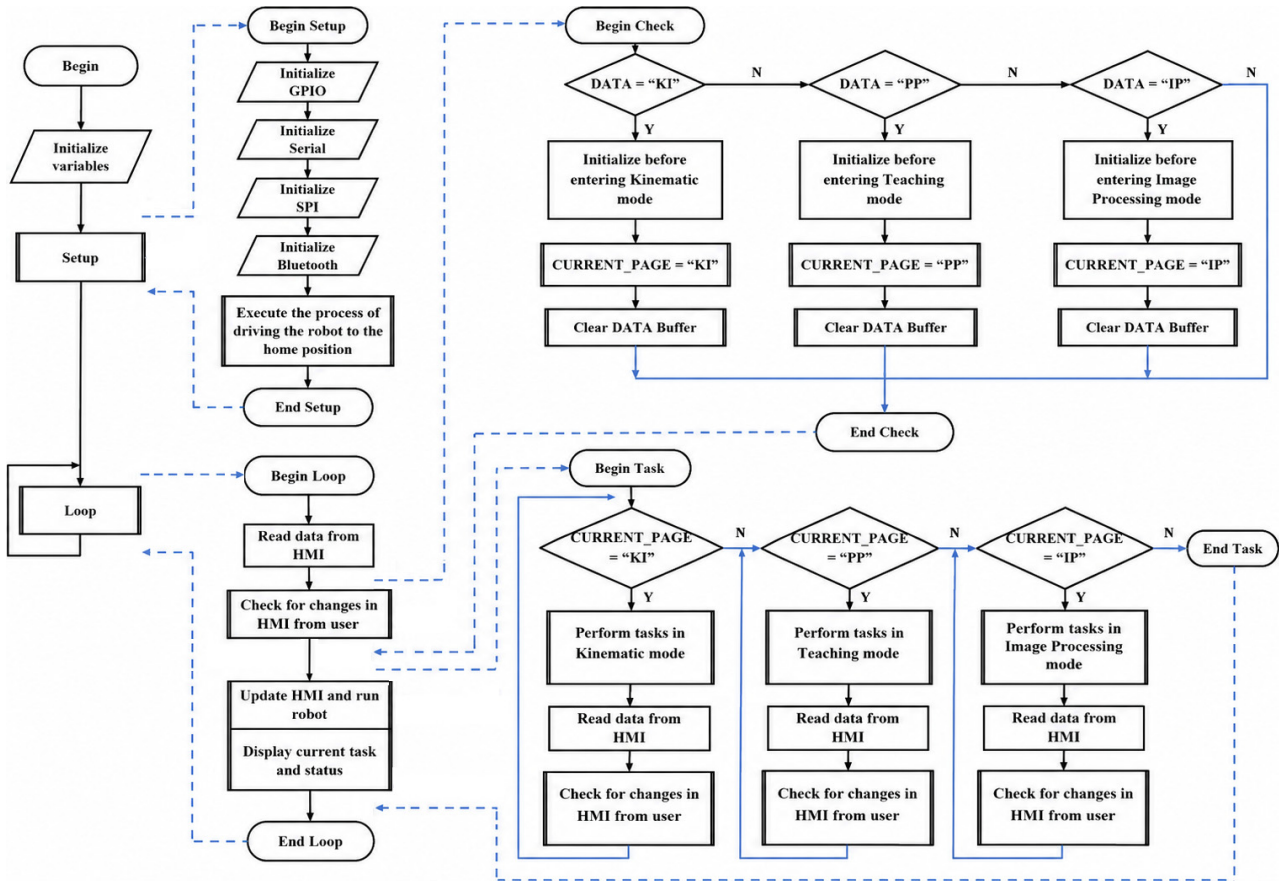


Figure 6. Control flow of the SCARA robot



Figure 7. HMI interface for SCARA robot control

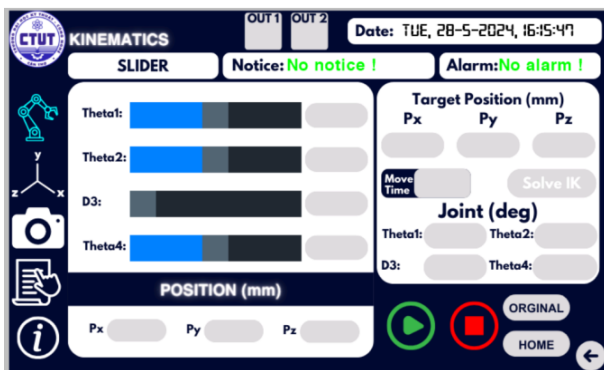


Figure 8. Kinematic control interface

The user can also specify the desired Cartesian position and motion time, after which the ESP32 performs inverse kinematic calculations and returns the corresponding joint values to the HMI. The robot can then be commanded to execute the calculated motion. The Kinematic interface is shown in Figure 8.

The Image Processing page displays the position and orientation data obtained from the vision system, while the Operation Guide and About of Project pages provide operating instructions and project information, respectively.

The Image Processing interface is presented in Figure 10.



Figure 9. Teaching Mode interface for recording and executing robot positions

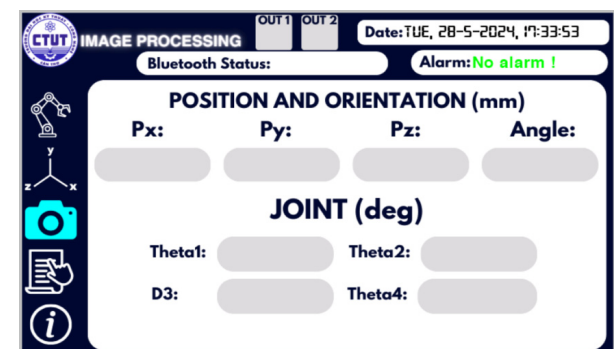


Figure 10. Image Processing interface for vision-based robot operation

The Teaching Mode interface is shown in Figure 9. The Teaching Mode provides a method for recording and executing predefined robot positions. After moving the robot to a desired position, the position can be saved together with the motion time, waiting time, and relay states. The stored positions can subsequently be executed using the RUN/STOP function, while existing positions can be edited or cleared when required.

3. THE ROBOT KINEMATIC EQUATION

3.1 Forward Kinematics

The forward kinematic model of the SCARA robot was established using the Denavit–Hartenberg (D-H) convention. The coordinate frames were assigned according to the mechanical structure of the robot, as shown in Figure 11.

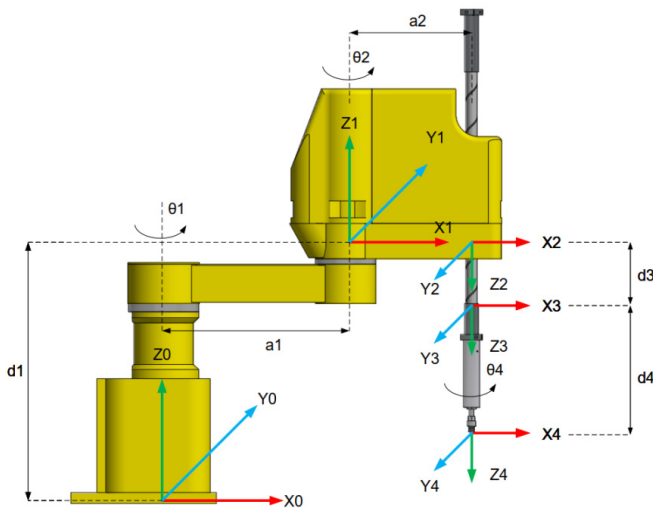


Figure 11. D-H coordinate frame assignment of the SCARA robot

Based on the assigned coordinate frames, the geometric parameters and joint variables are defined according to the D-H convention. The corresponding parameters used to establish the kinematic model are summarized in Table 2.

Table 2. D-H parameters of the SCARA robot

Link	a_i	α_i	a_i	a_i	variable
1	a_1	0°	d_1	θ_1	θ_1
2	a_2	180°	0	θ_2	θ_2
3	0	0°	d_3	0	d_3
4	0	0°	d_4	θ_4	θ_4

Using the D-H parameters in Table 2, the homogeneous transformation matrices between consecutive coordinate frames are obtained as:

$$H_1^0 = \begin{bmatrix} \cos \theta_1 & -\sin \theta_1 & 0 & a_1 \cos \theta_1 \\ \sin \theta_1 & \cos \theta_1 & 0 & a_1 \sin \theta_1 \\ 0 & 0 & 1 & d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

For the second joint, the transformation matrix is:

$$H_2^1 = \begin{bmatrix} \cos \theta_2 & \sin \theta_2 & 0 & a_2 \cos \theta_2 \\ \sin \theta_2 & -\cos \theta_2 & 0 & a_2 \sin \theta_2 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

The transformation associated with the third, prismatic joint is:

$$H_3^2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & d_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

For the fourth revolute joint, the transformation matrix is:

$$H_4^3 = \begin{bmatrix} \cos \theta_4 & -\sin \theta_4 & 0 & 0 \\ \sin \theta_4 & \cos \theta_4 & 0 & 0 \\ 0 & 0 & 1 & d_3 + d_4 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

The overall transformation matrix from the robot base frame to the end effector frame is calculated by:

$$H_4^0 = H_1^0 H_2^1 H_3^2 H_4^3 \quad (5)$$

From the resulting transformation matrix, the Cartesian coordinates of the end effector are obtained as:

$$\begin{aligned} P_x &= a_1 \cos(\theta_1) + a_2 \cos(\theta_1 + \theta_2) \\ P_y &= a_1 \sin(\theta_1) + a_2 \sin(\theta_1 + \theta_2) \\ P_z &= d_1 - d_3 - d_4 \end{aligned} \quad (6)$$

These equations establish the relationship between the joint variables and the position and orientation of the end effector. The resulting forward kinematic model is used as the basis for the subsequent inverse kinematic formulation and robot motion control.

3.2 Inverse Kinematics

The inverse kinematic model was developed to determine the joint variables from the desired Cartesian position and orientation of the end effector. Based on the forward kinematic equations, the planar position is given by:

$$\begin{aligned} P_x &= a_1 \cos(\theta_1) + a_2 \cos(\theta_1 + \theta_2) \\ P_y &= a_1 \sin(\theta_1) + a_2 \sin(\theta_1 + \theta_2) \end{aligned} \quad (7)$$

From equations (7), the second joint angle can be determined as:

$$\cos \theta_2 = \frac{P_x^2 + P_y^2 - a_1^2 - a_2^2}{2a_1a_2} \quad (8)$$

Let

$$M = \frac{P_x^2 + P_y^2 - a_1^2 - a_2^2}{2a_1a_2}, N = \pm \sqrt{1 - M^2} \quad (9)$$

The second joint angle is then obtained from:

$$\theta_2 = a \tan 2(N, M) \quad (10)$$

The first joint angle is calculated as:

$$\theta_1 = a \tan 2((a_2 M + a_1)P_y - a_2 NP_x, a_2 NP_y + (a_2 M + a_1)P_x) \quad (11)$$

The orientation of the end effector is represented by α , where α is the angular deviation of the end effector relative to the robot base coordinate frame. The fourth joint angle is therefore obtained from:

$$\theta_4 = \alpha - (\theta_1 + \theta_2) \quad (12)$$

Finally, the displacement of the prismatic joint is obtained from the vertical position relationship:

$$d_3 = d_1 - d_4 - P_z \quad (13)$$

3.3 Robot Workspace

The workspace of the reconstructed SCARA robot was evaluated based on the joint limits and geometric dimensions of the mechanism. The allowable joint ranges are $\theta_1 \in [-90^\circ, 90^\circ]$, $\theta_2 \in [-135^\circ, 135^\circ]$, $d_3 \in [0, 200]$ mm, and $\theta_4 \in [-360^\circ, 360^\circ]$. The main link dimensions are $a_1 = 325$ mm, $a_2 = 225$ mm, $d_1 = 450$ mm, and $d_4 = 250$ mm.

Based on the forward kinematic model, these parameters were implemented in MATLAB to evaluate the reachable workspace of the robot. The resulting workspace is shown in Figure 12, illustrating the reachable region obtained from the allowable joint motions.

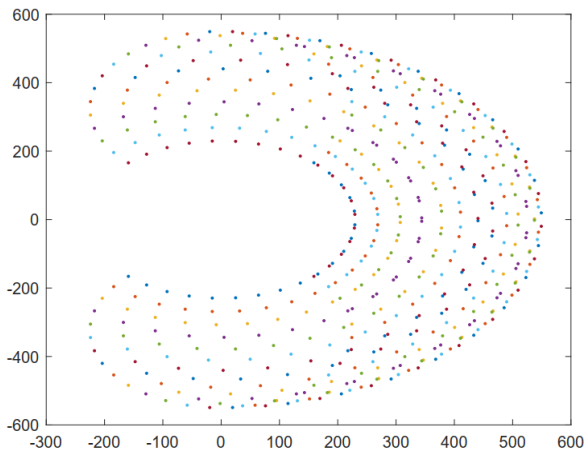


Figure 12. Workspace of the SCARA robot

The workspace analysis provides a geometric reference for defining the robot operating region and selecting feasible Cartesian target positions for subsequent motion control and pick-and-place experiments.

4. COMPUTER VISION SYSTEM

4.1 Camera Calibration

Camera calibration was performed to determine the intrinsic and extrinsic parameters required for mapping image coordinates to real-world coordinates. An A4

checkerboard with 10×7 squares and a square size of 25 mm was used as the calibration target. A total of 32 images were captured from different orientations while keeping the camera fixed and stable. The calibration images are presented in Figure 13.

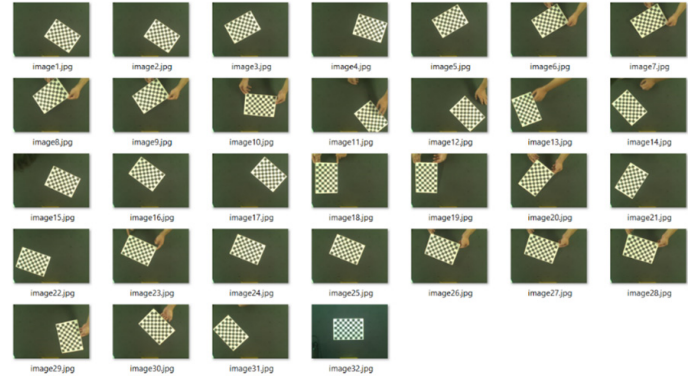


Figure 13. Checkerboard images for camera calibration

The calibration was performed using the Camera Calibrator Toolbox in MATLAB 2019b. The resulting intrinsic matrix is:

$$K = \begin{bmatrix} 4.8111 \times 10^3 & -0.0038 \times 10^3 & 1.8638 \times 10^3 \\ 0 & 4.8157 \times 10^3 & 1.2920 \times 10^3 \\ 0 & 0 & 1 \end{bmatrix} \quad (14)$$

The extrinsic rotation matrix and translation vector are given by:

$$R = \begin{bmatrix} -0.9999 & 0.0101 & 1.8638 \times 10^3 \\ -0.0102 & 4.8157 \times 10^3 & 1.2920 \times 10^3 \\ 0.0030 & -0.0209 & 0.9998 \end{bmatrix} \quad (15)$$

$$T = \begin{bmatrix} 126.3833 \\ 937.3041 \\ 937.3041 \end{bmatrix} \quad (16)$$

For a pixel coordinate:

$$m_p = [x \quad y \quad 1]^T \quad (17)$$

the corresponding real-world coordinate is calculated as:

$$M_w = R^{-1} (K^{-1} Z m_p - T) \quad (18)$$

where Z denotes the camera height relative to the reference plane.

4.2 Image Processing

The vision-based localization method was developed to determine the position and orientation of the objects within the robot workspace. The processing pipeline is illustrated in Figure 14. The input image is converted from BGR to grayscale, followed by Gaussian filtering and Otsu thresholding to obtain a binary image. Object contours are then extracted from the binary image using findContours function.

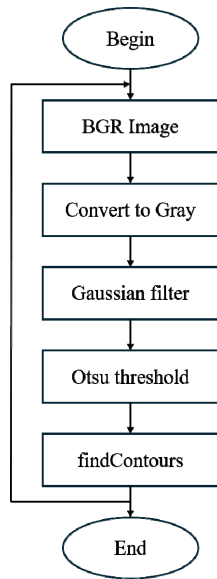


Figure 14. Image processing flowchart

The extracted contour is used to determine the centroid coordinates (x, y) and orientation angle α of each object. This approach was applied to both rectangular and circular objects, with the object detection results shown in Figure 15. The obtained centroid and orientation represent the object pose in the image coordinate system and are used as the input for the subsequent coordinate transformation.

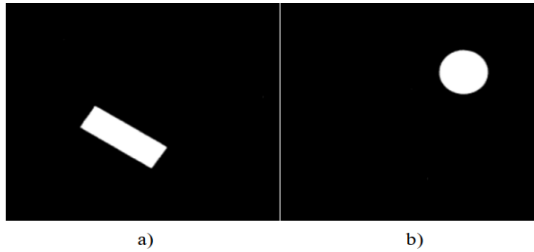


Figure 15. Image-Based object detection results: (a) rectangular object; (b) circular object.

The image coordinates are first transformed into real-world coordinates using the calibrated camera model and are then mapped to the robot coordinate system. The resulting position and orientation are transmitted to the robot controller, allowing the end effector to reach the detected object with the required orientation for the pick and place operation.

4.3 Coordinate Transformation

The real-world coordinate system obtained from camera calibration does not coincide with the robot coordinate system. Therefore, a coordinate transformation was established to map the object position from the real-world coordinate system to the robot workspace. The transformation is represented by:

$$\begin{bmatrix} X \\ Y \end{bmatrix} = R \begin{bmatrix} x \\ y \end{bmatrix} + T \quad (19)$$

$$\begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} \quad (20)$$

where (x, y) denotes the real-world coordinates and (X, Y) denotes the corresponding robot coordinates. The matrix R represents the rotation between the two coordinate systems, while T represents their translational offset.

To determine R and T , three reference points were selected. For each point, (x_i, y_i) represents its coordinates in the real-world coordinate system and (X_i, Y_i) represents the corresponding robot coordinates. Substituting the three corresponding points into (20) yields a linear system with six unknown parameters:

$$\begin{aligned} X_1 &= a_{11}x_1 + a_{12}y_1 + T_1 \\ Y_1 &= a_{21}x_1 + a_{22}y_1 + T_2 \\ X_2 &= a_{11}x_2 + a_{12}y_2 + T_1 \\ Y_2 &= a_{21}x_2 + a_{22}y_2 + T_2 \\ X_3 &= a_{11}x_3 + a_{12}y_3 + T_1 \\ Y_3 &= a_{21}x_3 + a_{22}y_3 + T_2 \end{aligned} \quad (21)$$

The system is rewritten in matrix form as:

$$A = BI \quad (22)$$

where

$$I = \begin{bmatrix} a_{11} & a_{12} & a_{21} & a_{22} & T_1 & T_2 \end{bmatrix}^T \quad (23)$$

The transformation parameters are then obtained from:

$$I = B^{-1}A \quad (24)$$

Using the reference coordinates obtained in the experiment, the resulting rotation matrix and translation vector are:

$$R = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} 0.0053 & 0.9954 \\ 0.9946 & -0.0074 \end{bmatrix} \quad (25)$$

$$T = \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} = \begin{bmatrix} 307.3240 \\ -121.8669 \end{bmatrix} \quad (26)$$

The obtained R and T are subsequently applied to the real-world coordinates calculated from the vision system, thereby providing the corresponding target coordinates in the robot coordinate system.

5. RESULTS AND DISCUSSION

Based on the available mechanical components, the SCARA robot was first designed in a 3D environment to determine the mechanical configuration and arrangement of the components. In addition to the main robot components, several supporting structures and equipment were designed, such as the camera mounting structure and working table.

Table 3. Overall dimensions of the developed SCARA robot

Parameter	Value
Length	895 mm
Width	1200 mm
Height	1865 mm
Mass	Approximately 150 kg

Based on the 3D design on Inventor software, the robot was subsequently assembled into a physical prototype, as shown in Figure 16. The overall dimensions and mass of the developed prototype are summarized in Table 3. The prototype has an overall length, width, and height of 895, 1200, and 1865 mm, respectively, with an approximate mass of 150 kg. The completed hardware provides the experimental platform for implementing and evaluating the proposed robot control and vision-based system.

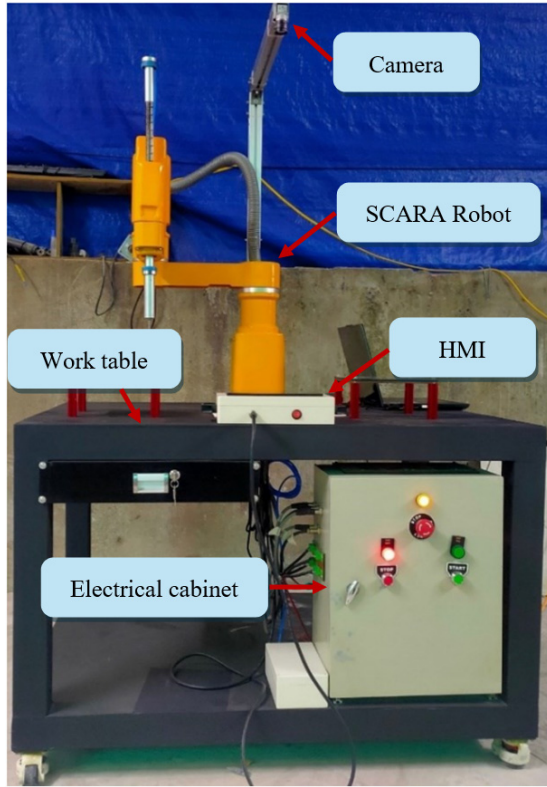


Figure 16. The experiment robot system

The positioning error of the developed SCARA robot was experimentally evaluated by comparing the commanded and actual end-effector positions. A checkerboard consisting of 10×7 squares, with each square measuring 50 mm, was used as a reference for position measurement. The checkerboard was aligned with the robot coordinate system at the initial position of $X = 550$ mm and $Y = 0$ mm, as shown in Figure 17.

The robot was then commanded to move to ten different positions, and the actual displacement along the X and Y axes was measured using a caliper. The commanded positions, actual positions, and corresponding positioning errors are presented in Table 4. The

average positioning errors were 0.81 mm along the X-axis and 0.51 mm along the Y-axis.

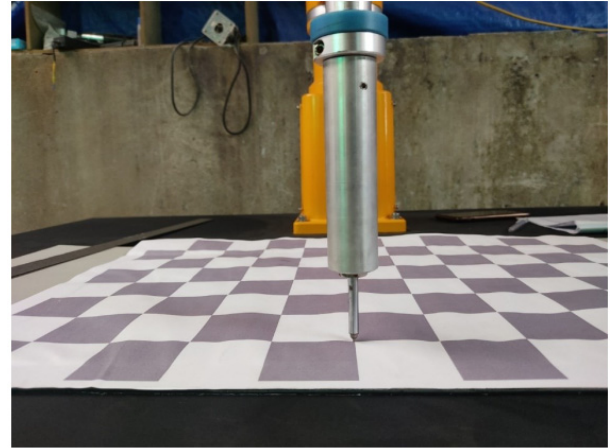


Figure 17. Experimental setup for positioning error verification

The image processing results are presented in Figure 18, where the object position and orientation are detected from the captured images. For both objects, Gaussian filtering and Otsu thresholding separate the object from the background, and the extracted contour coincides with the object boundary. The centroid and orientation angle computed from this contour are overlaid on the image for visual observation and are used as the object pose in the subsequent coordinate calculation. The detected image coordinates are then transformed into the camera coordinate system and subsequently mapped to the robot coordinate system. For the rectangular object, the centroid at $(u,v) = (1275.7, 884.3)$ pixels corresponds to $(242.7, 145.3)$ mm in the camera coordinate system and to $(453.3, 118.4)$ mm in the robot coordinate system, compared with the measured position of $(455, 120)$ mm. For the circular object, the calculated position of $(330.0, 17.2)$ mm is compared with the measured position of $(332, 15)$ mm. The orientation angle β measured in the image is converted to the robot orientation angle θ by $\theta = \beta + 180^\circ$, which corresponds to the orientation convention of the robot controller. For both objects, the calculated orientation agrees closely with the measured orientation. The corresponding coordinate calculation errors obtained using the image-based method are summarized in Table 5. For the rectangular object, the X-axis, Y-axis, and orientation errors are 1.7 mm, 1.6 mm, and 2.0° , respectively. For the circular object, the corresponding errors are 2.0 mm, 2.2 mm, and 1.0° , respectively.

Table 4. Experimental results of robot positioning error

Trial	Commanded X (mm)	Commanded Y (mm)	Actual X (mm)	Actual Y (mm)	X Positioning Error (mm)	Y Positioning Error (mm)
1	500.00	-50.00	499.63	-50.08	0.37	0.08
2	450.00	-50.00	449.70	-49.72	0.30	0.28
3	400.00	100.00	401.35	99.49	1.35	0.51
4	450.00	50.00	450.60	49.61	0.60	0.39
5	500.00	50.00	500.50	49.61	0.50	0.39
6	450.00	-100.00	448.90	-99.02	1.10	0.98
7	500.00	-100.00	499.49	-99.73	0.51	0.27

8	420.00	55.00	421.40	54.48	1.40	0.52
9	520.00	30.00	519.56	29.11	0.44	0.89
10	475.00	65.00	476.48	65.78	1.48	0.78
Average					0.81	0.51

Table 5. Image-based coordinate calculation error

	Rectangular object	Circular object
Image coordinate (u, v, β)	(1275.7, 884.3, -32°)	(1795.6, 1523.2, -71°)
Camera pose (X, Y, θ)	(242.7mm, 145.3mm, -32°)	(139.9mm, 22.3mm, -71°)
Robot pose (X, Y, θ)	(453.3mm, 118.4mm, 148°)	(330.0mm, 17.2mm, 109°)
Actual pose (X, Y, θ)	(455mm, 120mm, 150°)	(332mm, 15mm, 110°)
X-axis error	1.7mm	2.0mm
Y-axis error	1.6mm	2.2mm
Angle error	2.0°	1.0°

These errors are larger than the robot positioning errors in Table 4 (0.81 mm and 0.51 mm) because they combine several sources: camera calibration and lens distortion, the pixel resolution of the extracted contour, the coordinate transformation, which is determined by exactly three reference points and cannot average out their measurement errors, and the positioning error of the robot itself. The accuracy could be improved by using more reference points with a least-squares estimate of the transformation. These results demonstrate that the proposed vision-based coordinate transformation method can provide sufficiently accurate position and orientation information for robot pick-and-place operations.

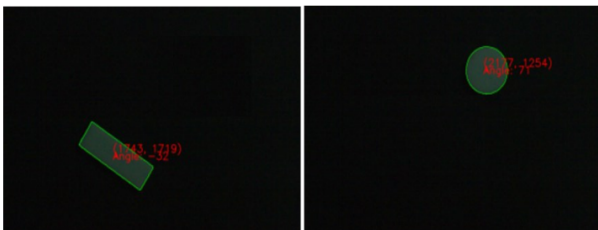


Figure 18. Image processing results

6. CONCLUSION

This study presented a vision-guided 4-DOF SCARA robot system developed from a refurbished mechanical platform for automated pick-and-place applications. A new electrical and control system was integrated with the robot, together with kinematic models, HMI, and a machine vision system for object localization and robot positioning. The proposed vision system successfully detected the position and orientation of both rectangular and circular objects and transformed their coordinates into the robot coordinate system.

The image-processing software was developed by the authors in Python using the OpenCV library. It integrates camera calibration and image processing and outputs target coordinates directly to the robot controller, without training data. Although the individual operators are standard, the originality of the software lies in linking calibration, object detection, coordinate transformation, and robot communication into one program that converts a camera image into robot target coordinates. The complexity of the work lies in coor-

inating four driven axes, a vision computer, a microcontroller, and an HMI across four coordinate frames, and its novelty is the experimentally validated reuse of an obsolete SCARA platform as a complete vision-guided robot.

Experimental results showed average robot positioning errors of 0.81 mm along the X-axis and 0.51 mm along the Y-axis. The image-based coordinate calculation errors were 1.7 mm and 1.6 mm in X and Y, respectively, with an orientation error of 2.0° for the rectangular object. For the circular object, the corresponding errors were 2.0 mm, 2.2 mm, and 1.0°. These results demonstrate the feasibility of the developed system for vision-based automated pick-and-place applications.

Future work will focus on integrating artificial intelligence into the vision system to improve object detection and recognition, enabling the robot to handle a wider range of objects and achieve more flexible and intelligent pick-and-place operations.

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NOMENCLATURE

a_1, a_2	Lengths of link 1 and link 2
d_1, d_2, d_3	Base height, prismatic-joint displacement, tool length
$\theta_1, \theta_2, \theta_3$	Joint angles of revolute joints 1, 2, 4
α	Orientation of the end effector
H_{i-1}^i	Homogeneous transformation matrix
P_x, P_y, P_z	End-effector coordinates in the robot base frame
M, N	Auxiliary variables of the inverse kinematics
K	Camera intrinsic matrix
R, T	Camera extrinsic rotation matrix and translation vector
m_p	Pixel coordinate vector
M_w	Real-world coordinate vector
Z	Camera height relative to the reference plane
(x, y)	Real-world coordinates of a point on the reference plane

(X, Y)	Coordinates of the same point in the robot frame
A, B, I	Vectors/matrix of the linear system

ACRONYMS AND ABBREVIATIONS

AI	Artificial intelligence
BGR	Blue-green-red color order
CAD	Computer-aided design
D-H	Denavit–Hartenberg
DIR	Direction (signal)
DOF	Degrees of freedom
EMI	Electromagnetic interference
GPIO	General-purpose input/output
HMI	Human-machine interface
MCB	Miniature circuit breaker
PETG	Polyethylene terephthalate glycol
PTP	Point-to-point
PUL	Pulse (signal)
SCARA	Selective Compliance Assembly Robot Arm
SPI	Serial peripheral interface
UART	Universal asynchronous receiver-transmitter
VAC/VDC	Volts, alternating/direct current

РАЗВОЈ SCARA РОБОТСКОГ СИСТЕМА СА ВИЗУЕЛНИМ НАВОЂЕЊЕМ ЗАСНОВАНОГ НА РЕПАРИРАНОЈ МЕХАНИЧКОЈ ПЛАТФОРМИ ЗА АУТОМАТИЗОВАНЕ ОПЕРАЦИЈЕ ПРЕМЕШТАЊА ПРЕДМЕТА (PICK-AND-PLACE)

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Овај рад представља развој SCARA роботске руке са четири степена слобде и визуелним навођењем, засноване на репарираној механичкој платформи, намењене за аутоматизоване операције премештања предмета. Задржана је постојећа механичка структура, док су развијени нови електро-систем и систем управљања. Предложени систем обједињује управљање моторима, управљање кретањем од тачке до тачке (PTP) и интерфејс човек-машина (HMI) за руковање роботом и праћење његовог рада. Такође је интегрисан модул машинског вида за детекцију предмета и одређивање њихових позиција, чиме се омогућавају аутоматизоване операције премештања. Развијени систем усклађује локализацију предмета на основу слике са командама за кретање робота. Сprovedена су експериментална испитивања ради процене перформанси система у погледу позиционирања и израчунавања координата на основу слике. Просечне грешке у позиционирању робота износиле су 0,81 mm дуж X-осе и 0,51 mm дуж Y-осе. Резултати потврђују изводљивост поновног коришћења застареле SCARA механичке платформе за развој интегрисаног и функционалног роботског система намењеног аутоматизованим операцијама премештања предмета.