

Eye-in-hand vision based PID control of a Dobot Magician with online homography calibration for precision manipulation

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ABSTRACT

This study evaluates a vision-guided robotic pick-and-place system integrating an eye-in-hand camera with a proportional integral derivative (PID) controller and an adaptive online homography calibration algorithm. To mitigate environmental disturbances, the framework utilizes hue, saturation, and value (HSV)-based object detection and a RANSAC-refined homography method that continuously updates the mapping between image pixels and the robot workspace. The system's precision was tested under varying lighting conditions by comparing a non-PID baseline against the PID-integrated framework using mean execution time, standard deviation (SD), and t-tests. Results indicate that while both configurations maintain stability, their performance differences are not statistically significant, suggesting the static homography model already provides high baseline accuracy. These findings underscore the importance of rigorous system identification, recommending that future research transition toward advanced control strategies and spatial trajectory tracking metrics to further enhance robotic manipulation precision.

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1. INTRODUCTION

Precision manipulation is a fundamental capability in robotic systems and plays an essential role in applications such as automated assembly, pick-and-place operations, and delicate object handling [1]–[3]. In industrial environments, robotic manipulators are expected to perform these tasks with high positional accuracy and repeatability. However, achieving such performance on low-cost robotic platforms remains challenging due to inherent mechanical limitations, sensor inaccuracies, and environmental variability [4]. These limitations often lead to positioning errors and unstable trajectories during manipulation tasks. Traditional robotic control approaches commonly rely on fixed camera-to-robot calibration or offline mapping between image coordinates and robot coordinates [5]–[7]. In these methods, a transformation model is estimated during an initial calibration stage and then used throughout the operation. While effective under controlled laboratory conditions, fixed calibration models are sensitive to disturbances such as camera vibration, lighting variation,

or slight shifts in the robot or camera configuration. Even small changes in the system setup may degrade the accuracy of the transformation, resulting in misalignment between the detected object location and the robot's end-effector position. To improve adaptability and robustness, vision-based control strategies have been widely adopted. These systems utilize real-time visual feedback to guide robot motion and correct positional errors during operation. Among various vision-based configurations, the eye-in-hand approach has attracted significant attention [8]–[10]. In this configuration, the camera is mounted directly on the robot's end-effector, allowing the field of view to move together with the robot. This setup enables continuous observation of the workspace and direct measurement of visual errors relative to the tool center point, which improves tracking flexibility and target localization. However, eye-in-hand systems require reliable transformations between image coordinates and robot coordinates to maintain accurate manipulation in dynamic environments.

In robotic motion control, proportional integral derivative (PID) controllers are widely used because of their simplicity, stability, and effectiveness in achieving smooth trajectory convergence [11]–[13]. When integrated with visual feedback, PID controllers can compensate for real-time positional deviations and improve the stability of robot motion. Nevertheless, the performance of vision-guided PID control heavily depends on the accuracy of the visual calibration model. If the transformation between image and robot coordinates contains errors, the PID controller alone cannot fully compensate for these inaccuracies. Static or precomputed homography matrices are therefore often insufficient in dynamic conditions, leading to residual positioning errors and reduced manipulation precision [14], [15].

Vision-based robotic control has been extensively studied to enhance manipulation accuracy and adaptability. Early systems typically employed fixed external cameras observing the workspace from a static viewpoint. Although this configuration simplifies calibration, it suffers from several drawbacks, including occlusion problems, limited viewing angles, and sensitivity to environmental changes. To overcome these limitations, eye-in-hand configurations have become increasingly popular because they enable continuous observation of the target and allow the robot to adjust its motion based on real-time visual information. A common method for mapping image coordinates to robot workspace coordinates is homography-based transformation. Traditional implementations estimate a homography matrix during an offline calibration stage and assume that the mapping remains constant during operation. While this approach can achieve good accuracy in controlled environments, it is vulnerable to camera displacement, lens distortion, and lighting variation. To address these issues, several studies have proposed online or adaptive calibration techniques that update the homography matrix in real time based on newly observed correspondence points between the camera image and the robot workspace.

Although these adaptive calibration methods improve robustness, they often rely on complex feature extraction algorithms or computationally intensive optimization procedures. Such requirements may limit their applicability to low-cost robotic platforms with constrained computational resources. Furthermore, many existing studies focus primarily on improving the calibration model without fully considering its interaction with the robot motion control strategy. As a result, the integration between adaptive calibration and real-time control remains insufficiently explored. Despite significant progress in vision-based robotic manipulation, several research gaps still remain. First, many existing systems rely on fixed homography calibration, which cannot compensate for environmental disturbances or camera movement during robot operation. Second, studies on adaptive homography estimation frequently emphasize calibration accuracy but do not integrate the calibration update process with real-time motion control mechanisms. Third, most experimental implementations are conducted on high-end industrial robotic systems with precise mechanical structures and advanced sensing hardware, which limits the applicability of these methods to affordable robotic platforms.

The Dobot Magician is a widely used low-cost robotic manipulator for research, education, and small-scale automation. Despite its accessibility and versatility, achieving precise manipulation with this platform remains challenging. Environmental factors such as illumination changes, workspace disturbances, and object placement variability can affect visual perception, while mechanical limitations including backlash, joint flexibility, and positioning errors further reduce motion accuracy. In addition, small shifts in camera or robot pose can significantly degrade the accuracy of fixed homography-based transformations. Therefore, there is a clear need for an integrated framework that simultaneously addresses visual calibration accuracy and motion control stability for low-cost robotic systems. Specifically, a system that combines adaptive homography calibration with real-time visual feedback and PID-based motion correction [16] has the potential to significantly improve manipulation accuracy and robustness.

This research proposes a vision-based control framework for precision object manipulation using a Dobot Magician robot equipped with an eye-in-hand camera. The proposed system integrates online homography calibration with a PID motion controller, enabling continuous updating of the mapping between image coordinates and robot workspace coordinates while regulating the end-effector trajectory in real time. By combining adaptive visual feedback with robust PID control, the proposed framework aims to improve the accuracy, stability, and reliability of vision-guided manipulation tasks in dynamic environments [17]. The main contributions of this research include: first, an integrated vision-based control framework combining eye-in-hand

sensing, online homography calibration, and PID control for low-cost manipulators. Second, a real-time adaptive approach that continuously updates image-to-robot coordinate transformations to mitigate environmental disturbances. Third, a closed-loop PID strategy that enhances positional accuracy and trajectory stability during pick-and-place tasks. Finally, experimental validation on a Dobot Magician platform confirming superior manipulation efficiency compared to conventional methods. The experimental results demonstrate that the proposed system can significantly enhance the reliability and performance of vision-guided robotic manipulation [18] while maintaining the simplicity and affordability required for low-cost robotic platforms.

2. MATERIAL AND METHOD

This section details the materials and systematic procedures used to achieve the research objectives. It describes the experimental setup and data collection methods to ensure consistency and reliability. All steps are documented to support the potential replication of this study.

2.1. System overview

The proposed framework integrates three core components that operate seamlessly together. First, the eye-in-hand camera setup employs a USB camera mounted on the robot's end-effector [19], as shown in Figure 1, enabling real-time workspace observation and direct measurement of visual errors relative to the vacuum pad, allowing flexible and accurate tracking of target objects.

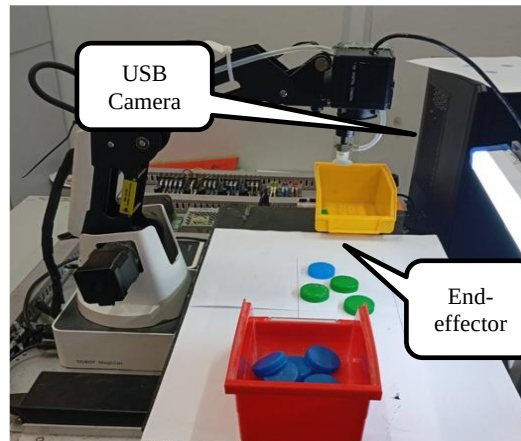


Figure 1. Component system setup of the proposed framework

The system begins with the graphical user interface (GUI) setup in Figure 2, where the interface loads the homography matrix and defines the region of interest. Images from the camera are captured continuously and sent to the image-processing module, where hue, saturation, and value (HSV) masking and HoughCircles detection identify the target object [20], [21]. Subsequently, pixel coordinates are transformed into robot-space coordinates using the homography. These coordinates then enter a stability-checking step that uses a circular buffer to ensure the object remains steady for several frames. Once stability is confirmed, the system decides whether to apply PID correction; if enabled, it computes offsets and updates the logs, whereas otherwise, it uses raw coordinates for movement. Finally, the robot executes the pick-and-place sequence, while the system records data and exports results to visualize paths, offsets, and accuracy metrics.

2.2. Eye-in-hand camera configuration

The Dobot Magician robot provides only four degrees of freedom, with its wrist offering a single rotation around the tool's Z-axis. This constraint causes the eye-in-hand camera to maintain an almost fixed downward orientation, limiting its rotational diversity during motion. In Figure 3 is a standard vision-guided robotic configuration, four coordinate frames are defined: the robot base frame $\{O\}$, the end-effector frame $\{E\}$, the camera frame $\{C\}$, and the world or object frame $\{W\}$, typically associated with the workspace surface or a calibration target. Eye-in-hand calibration [22]–[24] aims to estimate the transformation between the end-effector and the camera by solving the canonical equation $A_i X = X B_i$, where A_i denotes the robot's end-effector motion between two measurement poses, B_i represents the corresponding camera motion, and X is the unknown transformation from the end-effector to the camera. Due to the restricted wrist rotation, camera

motion is dominated by translation, which can reduce calibration accuracy if motion diversity is insufficient. Consequently, calibration should incorporate wide translational movement and the limited available rotations to ensure a well-conditioned and reliable hand-eye solution.

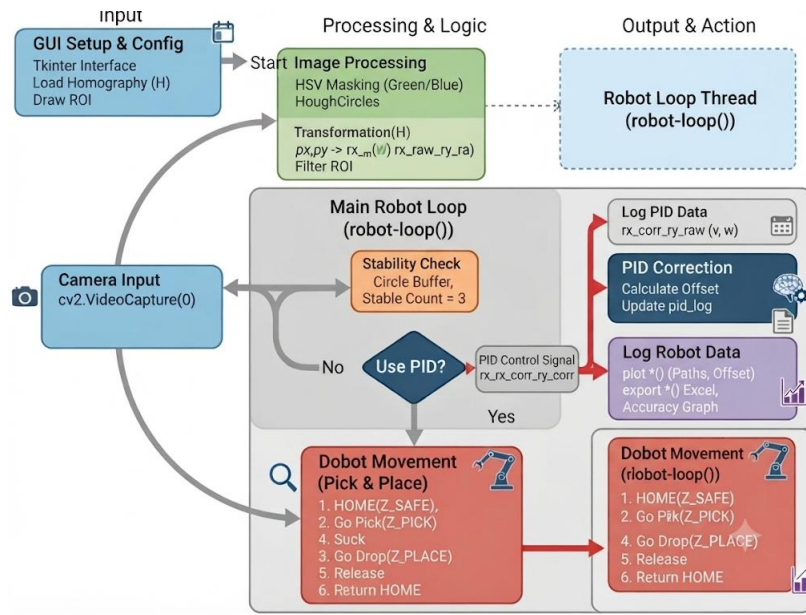


Figure 2. Vision-based PID control workflow for Dobot pick-and-place automation

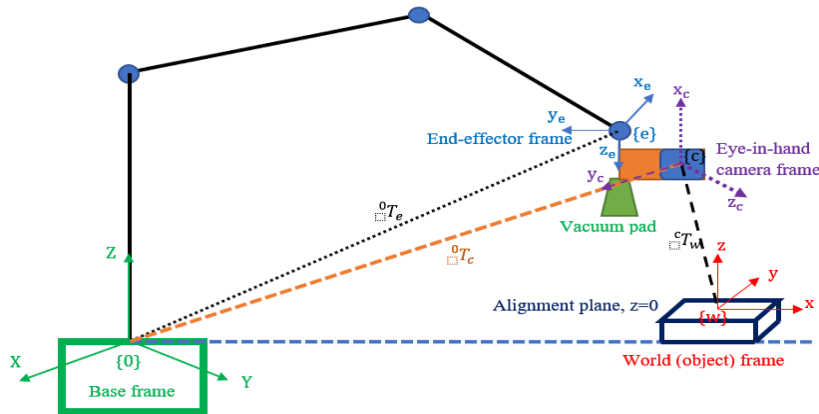


Figure 3. Coordinate frame transformations in an eye-in-hand of a Dobot Magician

The eye-in-hand camera of Dobot Magician is based on the camera model and the rigid transformation in world coordinate frame of $z=0$ plane, which the relationship between the world space and the image space. Even the relationship between the coordinate of the object point (x, y, z) and the image point (u, v) , as in (1):

$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (1)$$

where, the left-side of equation is a homogeneous coordinate representation of the image space. H is a 3×3 of homography matrix up to a scale factor. We use camera calibration with the flat world $z=0$. A point (u, v) in the images up to a certain point in the world. The homography matrix, as in (2):

$$H = AB \quad (2)$$

where, A is the camera intrinsic matrix, as in (3):

$$A = \begin{bmatrix} k_u & \gamma & u_0 \\ 0 & k_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

The relationship between the camera coordinate system and the image space is defined in (3). Parameter k_u and k_v represent the effective focal lengths in pixels along x_c and y_c axes, respectively. The term γ denotes the camera skew factor, while (u_0, v_0) defines the coordinates of the principal point. Finally, B represents the extrinsic coordinate transformation [25] in (4):

$$B = [r_1 \quad r_2 \quad t] \quad (4)$$

As shown in (4) represents the relationship between the camera coordinate system and the object coordinate system. The homogeneous transformation matrix from the object coordinate system to the camera coordinate system is given by (5):

$${}^cT_w = \begin{bmatrix} R & t \\ 0^T & 1 \end{bmatrix}, R = [r_1 \quad r_2 \quad r_1 \times r_2] \quad (5)$$

2.3. Manual finding of homography calibration

Initialization begins by capturing four reference points with known robot coordinates. The initial homography H_0 is computed using the direct linear transformation (DLT) method [26] by first collecting at least four correspondence points with known pixel and robot coordinates. Each point pair is converted into homogeneous coordinates to ensure a linear projective representation. The algorithm then constructs a $2n \times 9$ linear system from these correspondences and solves it using singular value decomposition (SVD) [27] to estimate the homography parameters. The resulting vector is reshaped into a 3×3 matrix and normalized by setting its last element to one. This process yields the initial homography H_0 , which provides the baseline mapping between image and robot coordinates.

2.4. Homography calibration algorithm

The homography calibration algorithm [28] continuously updates the projective transformation between image coordinates and robot coordinates during system operation. Unlike traditional offline calibration, which uses a fixed homography computed once from predefined correspondence pairs, the online method re-estimates the homography in real time based on newly observed feature points and the robot's live pose feedback [29]. As the robot moves, the system collects updated pixel–robot coordinate pairs from known reference markers or detected objects. These pairs are used to incrementally refine the homography matrix using a dynamic least-squares or RANSAC-based optimization [30]. By recalibrating throughout execution, the algorithm compensates for camera vibration, workspace shifts, lighting changes, or small mechanical deviations, ensuring that the pixel-to-robot mapping remains accurate under varying conditions. This adaptive process significantly enhances precision and stability in vision-guided manipulation tasks. Online homography calibration is a dynamic estimation method that continually updates the homography matrix H between image pixel coordinates (u, v) and robot workspace coordinates (x, y) while the robot is operating. This allows the system to maintain high accuracy even under camera vibration, temperature changes, lens shifts, or workspace disturbances. The homography maps a point in image space to robot space in (6):

$$\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = H \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}, \text{ where } H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \quad (6)$$

A minimum of four correspondence points is required to estimate H , as defined in (7):

$$(u_i, v_i) \leftrightarrow (x_i, y_i) \quad (7)$$

Using the DLT, each pair of points produces two equations, as given by (8) and (9):

$$u_i h_{31} x_i + v_i h_{32} x_i + h_{33} x_i + h_{11} u_i + h_{12} v_i + h_{13} = 0 \quad (8)$$

$$u_i h_{31} y_i + v_i h_{32} y_i + h_{33} y_i + h_{21} u_i + h_{22} v_i + h_{23} = 0 \quad (9)$$

These equations constitute the linear system shown in (10):

$$Ah = 0 \quad (10)$$

The solution is obtained via SVD in (11):

$$H = \text{reshape}(h_{\min}, 3, 3) \quad (11)$$

When new data arrives, the system refines the homography:

- Collect new correspondence pairs in (12):

$$(u_k, v_k) \leftrightarrow (x_k, y_k) \quad (12)$$

- Add the new pair to the previous dataset
- Recompute or incrementally update in (13):

$$H_{t+1} = \arg \min_H \sum_{i=0}^{N(t+1)} \|(x_i, y_i) - f_H(u_i, v_i)\|^2 \quad (13)$$

- Use RANSAC to reject outlier points.

2.5. Integration with proportional integral derivative motion control

The online homography provides real-time image-space coordinates to the PID controller [31] as the visual error term in (14):

$$e(t) = \begin{bmatrix} x_{\text{target}} - x_{\text{current}} \\ y_{\text{target}} - y_{\text{current}} \end{bmatrix} \quad (14)$$

In this stage, the PID controller calculates the corrective control input for the robot's end-effector by applying the visual error $e(t)$ defined in (15):

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (15)$$

where K_p is the proportional term, used to drive the end-effector toward the target based on the current error; K_i is the integral term, used to compensate for accumulated steady-state errors; and K_d is the derivative term, used to anticipate changes in the error, improving trajectory smoothness.

In this system, the PID controller plays a crucial role in enhancing the accuracy and stability of the vision-guided pick-and-place operation. First, the proportional term (K_p) provides immediate correction by driving the robot toward the object based on the current positional error between the raw homography-transformed coordinates and the expected target location. Second, the integral term (K_i) accumulates small residual errors caused by camera noise, lighting variation, or slight homography drift, thereby compensating for systematic biases that would otherwise lead to persistent misalignment during repeated picks. Third, the derivative term (K_d) predicts the trend of error changes and stabilizes the motion, effectively reducing overshoot and ensuring a smoother approach to the object.

In an online homography calibration system, the RANSAC algorithm serves as a critical filter for ensuring the precision of real-time coordinate transformations. As the robot operates, it continuously collects new pixel-to-robot correspondence pairs, which are susceptible to noise, sensor errors, and environmental outliers. RANSAC addresses this by iteratively sampling subsets of data to estimate a homography H by minimizing the reprojection error, as in (16):

$$E = \sum_{i=1}^N \|x'_i - Hx_i\|^2 \quad (16)$$

while rejecting outliers where the distance exceeds a defined threshold. By filtering out these outliers, the algorithm ensures that the mapping between image coordinates x_i and the robot workspace x'_i remains accurate despite lighting or mechanical shifts. This cleaned, high-fidelity transformation matrix is then fed into the PID controller, which defines the visual error term required for precise manipulation, as in (17):

$$e_t = Hx_{\text{target}} - x_{\text{robot}}(t) \quad (17)$$

The PID controller utilizes this error signal to calculate corrective inputs, where the proportional term provides immediate response, the integral term compensates for persistent biases, and the derivative term

ensures motion stability. Because the system continuously recomputed the homography using the latest filtered data, the PID controller constantly receives an optimized representation of the target location. This closed-loop integration creates a synergy where RANSAC maintains the integrity of spatial data, while the PID controller effectively minimizes positional error. Consequently, the system achieves a highly adaptive and stable performance, as the continuous refinement of the homography prevents drift and minimizes overshoot during approach. Ultimately, the combination of RANSAC-based robust estimation and PID-based motion control enables the robot to perform complex pick-and-place operations with exceptional accuracy under dynamic, real-world conditions.

2.6. Equations for standard deviation (SD) and p-value calculation

To evaluate the precision and statistical significance of the control systems, the SD and p-value were calculated [32]. The SD was employed to assess the consistency of the execution time, measuring the dispersion of the data points relative to the mean. Furthermore, a p-value analysis was conducted to determine whether the performance differences between the PID-controlled system and the non-PID system were statistically significant. A p-value threshold of 0.05 was adopted; values below this threshold indicate that the observed improvements in system stability and precision are statistically significant, rather than occurring by chance. To quantify the precision and statistical significance of the control systems, the SD and p-value were calculated using (18) and (19):

- SD is used to measure the consistency and dispersion of the execution time, calculated as in (18):

$$SD = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}} \quad (18)$$

where x_i represents the individual execution time, $\bar{x}$ is the mean execution time, and n is the sample size.

- P-value calculation: used to determine whether the performance differences between the PID and non-PID systems are statistically significant, calculated using a two-sample t-test to assess the probability that the observed differences occurred by chance. A threshold of $\alpha = 0.05$ was established to evaluate statistical significance. The statistical significance of the performance difference was evaluated using an independent samples t-test. The t-statistic was calculated using (19):

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (19)$$

where $\bar{x}$ represents the mean, s^2 the variance, and n the sample size. The p-value was subsequently derived from the t-distribution with 22 degrees of freedom to determine if the improvement provided by the PID controller is statistically significant at the $\alpha = 0.05$ level.

3. RESULTS AND DISCUSSION

The experimental results are divided into three cases: i) robot calibration testing, ii) testing under both low- and high-light conditions for the eye-in-hand for non-PID control with a static homography model and eye-in-hand for vision integrated with online homography and PID control systems, and iii) testing the PID controller gain adjustments at three different levels. For this research, custom Python-based software was developed and implemented to control the robotic systems throughout the experimental procedures. The obtained experimental results are presented in detail as follows.

3.1. Robot calibration testing

Before performing the calibration between the robotic arm and the picking area (known as camera calibration), the robotic arm must first be moved to the "Home" position to serve as the primary reference point. Following this, define four points within the workspace, ensuring they remain within the robotic arm's maximum reach as specified in the manual. Subsequently, manually move the suction nozzle at the end of the robotic arm to each of these four positions while recording the corresponding pixel coordinates. Figure 4 illustrates a calibration framework designed to map image coordinates captured by a camera to the Cartesian workspace of a Dobot robotic manipulator. This mapping is essential for vision-guided manipulation tasks in which the robot must interpret and interact with objects observed in the camera's field of view. The system integrates computer vision, robotic control, and human-computer interaction through a combined OpenCV and Tkinter interface [33], [34]. The calibration process relies on point-based homography estimation, requiring four corresponding point pairs: pixel coordinates selected directly from the live camera stream and robot end-effector coordinates recorded at those same physical positions. The user manually acquires image-space points

by clicking on the camera feed, while robot-space points are obtained either manually or by querying the Dobot's pose-reporting function. These corresponding pairs enable the estimation of a 3×3 homography matrix using OpenCV's implementation of the DLT algorithm, which provides a projective transformation mapping 2D camera coordinates into the robot's reference frame [35].

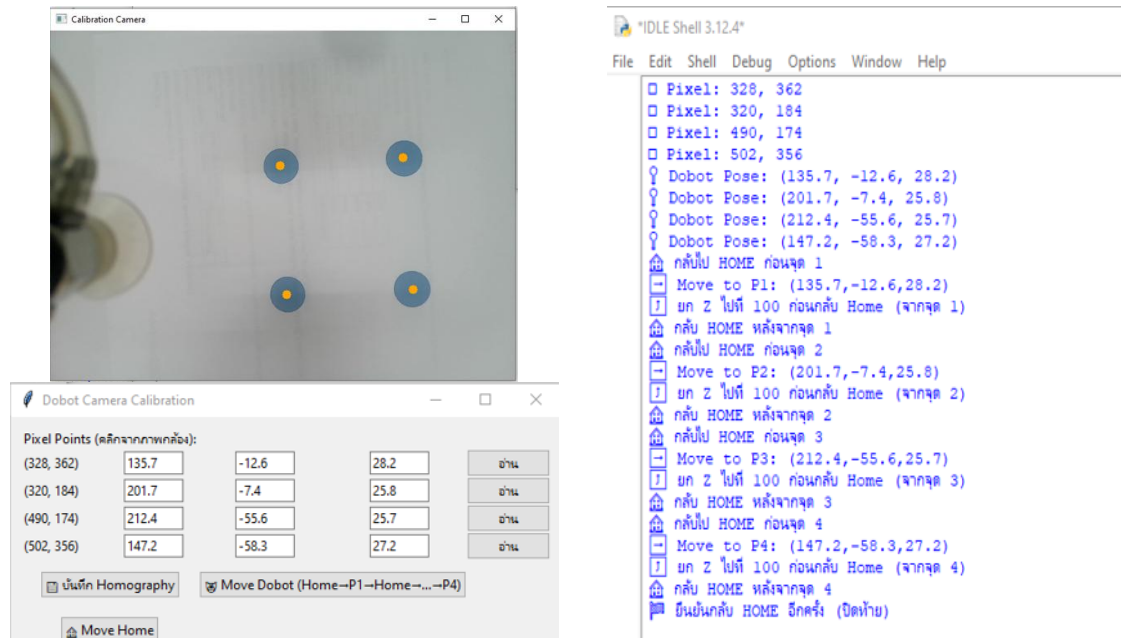


Figure 4. User interface for camera calibration and data acquisition workflow

An eye-in-hand camera configuration mounted on a Dobot Magician robotic arm. The camera moves with the end-effector to capture images of the workspace and objects for pick-and-place tasks. This setup enables vision-guided manipulation by mapping pixel coordinates to the robot's Cartesian space. The image sequence shows the camera moving between four calibration points marked on a paper surface, as shown in Figure 5.

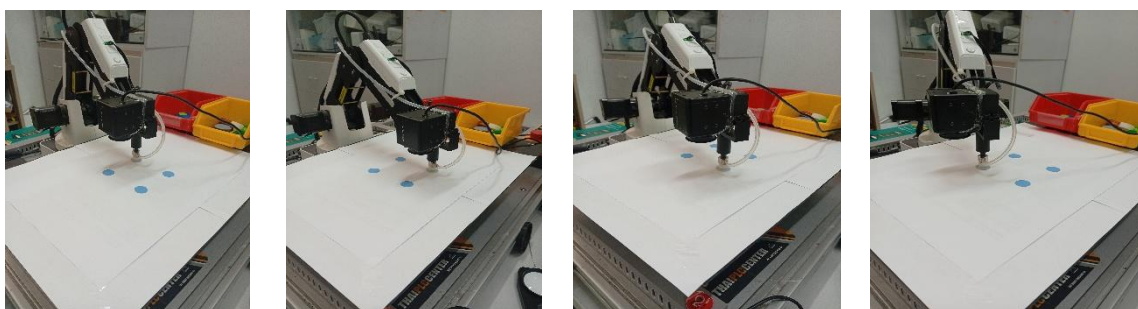


Figure 5. Eye-in-hand camera configuration for reference point mapping on the Dobot Magician manipulator

This 3D plot illustrates the movement trajectory of the Dobot robotic arm, mapping its path across X, Y, and Z coordinates in millimeters. It highlights the spatial relationship between various reference points within the workspace, which is essential for motion planning and control, as shown in Figure 6.

3.2. Performance evaluation under low-light conditions (166.84 lux)

To evaluate the robustness of the industrial robotic system, testing was conducted under low-light conditions of 15.5 foot-candles (166.84 lux) to challenge vision algorithm accuracy. The performance of the robotic manipulator was systematically compared between non-PID and PID-based control methods to assess

error correction capabilities. These results benchmark the effectiveness of PID integration in maintaining precise positioning when environmental illumination is suboptimal. Figure 7 illustrates the experimental setup and the software interface for the automated machine vision system, where Figure 7(a) presents the physical setup featuring a grid of colored objects alongside a light meter for monitoring surface illumination, and Figure 7(b) shows the computer software interface, including the control panel and real-time camera preview, used to perform image processing for object detection and measurement.

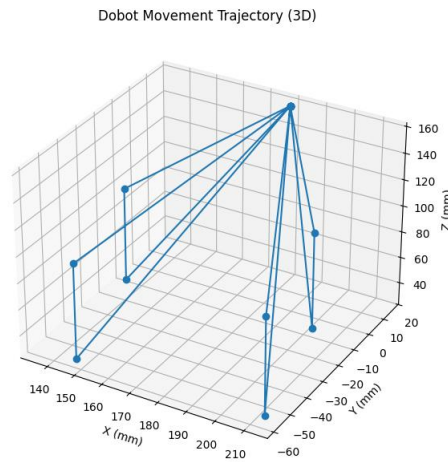


Figure 6. Spatial trajectory visualization of the Dobot manipulator based on homography-calibrated reference point

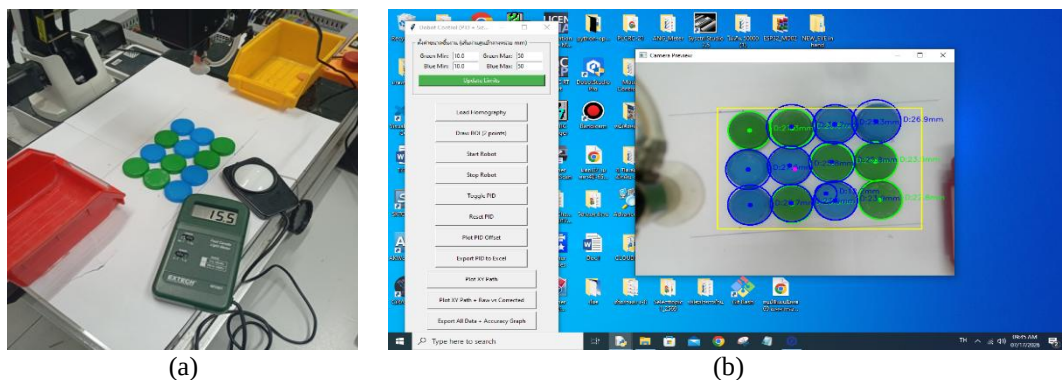


Figure 7. Experimental setup and software interface for the vision system: (a) physical setup for surface illumination measurement and (b) software interface for object detection and measurement

3.2.1. Experimental results for non-proportional integral derivative (PID OFF) control system

Results from testing the robotic arm without a PID controller in an environment with an illuminance of 166.84 lux. Figure 8 provides a comprehensive evaluation of the sorting system, covering control stability, movement trajectories, and the effectiveness of coordinate calibration. Figure 8(a) illustrates the PID auto-tuning offset over steps, Figure 8(b) shows the robot XY movement trajectory color-coded by destination, and Figure 8(c) presents a comparison of raw versus corrected coordinate paths.

The experimental results for evaluating the sorting system's performance without the use of PID control. It includes critical metrics such as coordinate mapping (px, py), raw and corrected robotic paths, offset values, object color, and operation duration, serving as a baseline for analyzing system accuracy and efficiency, as shown in Table 1.

3.2.2. Experimental results for proportional integral derivative (PID ON) control system

Results from testing the robotic arm with a PID controller in an environment with an illuminance of 166.84 lux. Figure 9 provides a comprehensive evaluation of the sorting system, covering control stability,

movement trajectories, and the effectiveness of coordinate calibration. Results from testing the robotic arm with a PID controller in an environment with an illuminance of 166.84 lux. Figure 9 provides a comprehensive evaluation of the sorting system, covering control stability, movement trajectories, and the effectiveness of coordinate calibration. Figure 9(a) illustrates PID auto-tuning offset over steps, Figure 9(b) shows the robot XY movement trajectory color-coded by destination, and Figure 9(c) presents a comparison of raw versus corrected coordinate paths.

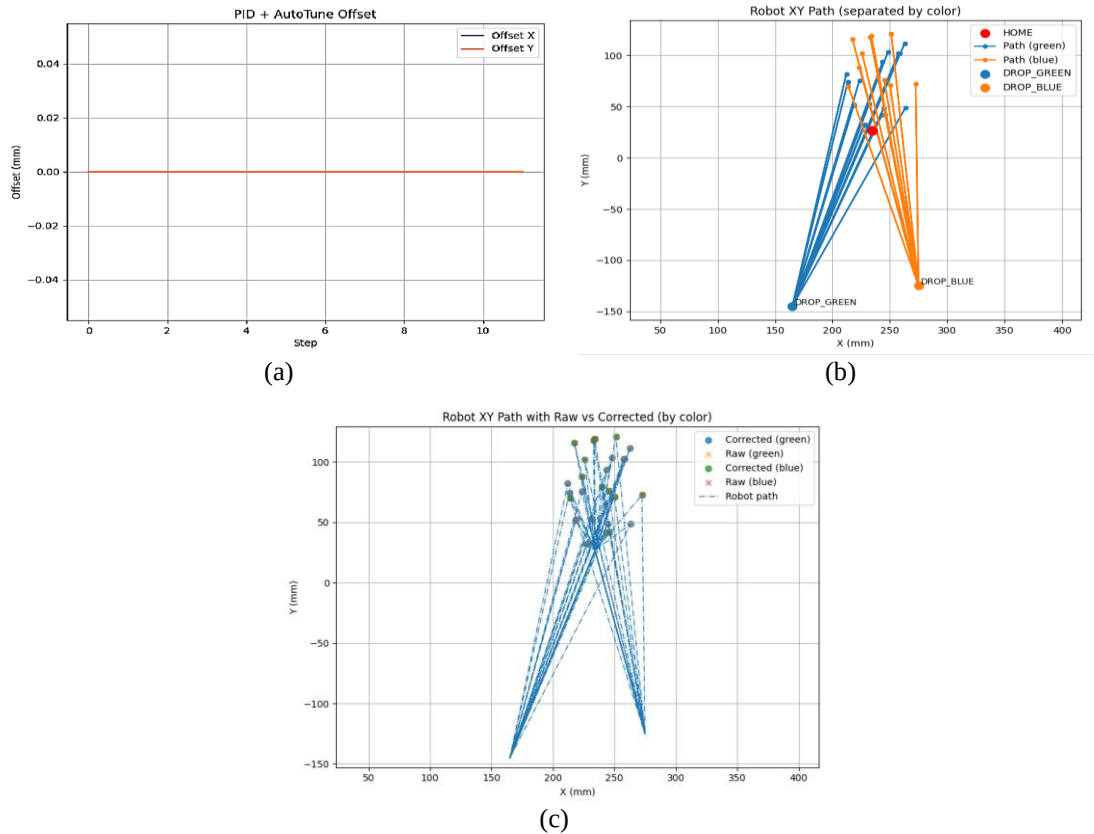


Figure 8. Experimental performance analysis for: (a) stability without PID auto-tuning, (b) robot XY movement trajectory, and (c) raw versus corrected coordinate paths

Table 1. Coordinate mapping, offset, and operational duration for sorting tasks in non-PID mode

px	py	rx_raw	ry_raw	rx_corr	ry_corr	Offset _x	Offset _y	Color	Duration (sec)	Color	PID mode
406	230	187.5097	-32.6947	187.5097	-32.6947	0	0	Green	12.07374001	Green	OFF
479	225	192.5489	-52.5725	192.5489	-52.5725	0	0	Green	11.17034698	Green	OFF
215	155	209.2195	25.77488	209.2195	25.77488	0	0	Green	10.86194253	Green	OFF
313	321	149.3429	-7.77392	149.3429	-7.77392	0	0	Green	11.16924739	Green	OFF
302	148	215.6605	-1.27067	215.6605	-1.27067	0	0	Green	11.16849685	Green	OFF
482	315	160.2239	-53.2861	160.2239	-53.2861	0	0	Green	11.17038774	Green	OFF
399	311	157.4616	-31.3751	157.4616	-31.3751	0	0	Blue	11.16739917	Blue	OFF
315	235	181.4367	-6.84564	181.4367	-6.84564	0	0	Blue	11.16532779	Blue	OFF
226	325	143.0235	17.24087	143.0235	17.24087	0	0	Blue	11.47533107	Blue	OFF
391	139	222.7026	-27.667	222.7026	-27.667	0	0	Blue	11.1679697	Blue	OFF
477	136	226.9263	-52.0824	226.9263	-52.0824	0	0	Blue	11.46615601	Blue	OFF
227	241	174.8245	19.32412	174.8245	19.32412	0	0	Blue	11.46774006	Blue	OFF

Table 2 demonstrates that the integration of a PID controller significantly improves robotic sorting accuracy by minimizing positional offsets. When the PID system is active, the robotic arm exhibits a more stable trajectory, effectively mitigating the deviations observed in non-PID operations. Consequently, the corrected coordinate paths achieve higher precision, ensuring closer alignment between the final object placement and the target destination. The results comparing the PID-controlled system and the system without

PID control in this case can be evaluated using the mean time, SD, and the calculated p-value, as presented in Table 3.

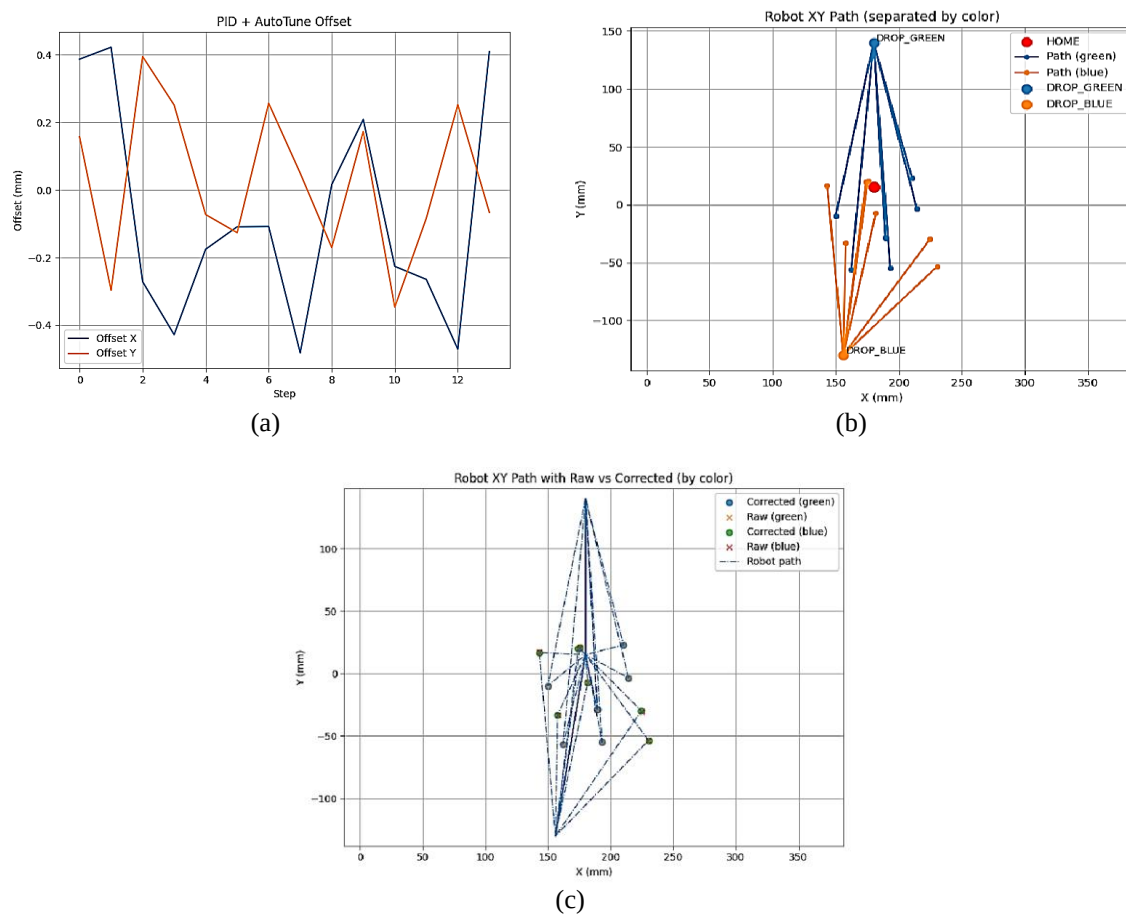


Figure 9. Experimental performance analysis for; (a) PID auto-tuning stability, (b) robot XY movement trajectory, and (c) raw versus corrected coordinate paths

Table 2. Coordinate mapping, offset, and operational duration for sorting tasks in PID mode

px	py	rx_raw	ry_raw	rx_corr	ry_corr	Offset x	Offset y	Color	Duration (sec)	Color	PID mode
393	224	189.2133	-29.0178	189.6002	-28.8605	0.386828	0.157288	Green	12.07619476	Green	ON
223	154	209.9746	23.24654	210.3967	22.9499	0.422112	-0.29664	Green	10.86663055	Green	ON
393	223	189.5949	-29.0091	189.3238	-28.6144	-0.27108	0.394708	Green	11.16618848	Green	ON
310	151	214.7295	-3.76822	214.3016	-3.51696	-0.42791	0.251257	Green	11.17211676	Green	ON
320	320	150.0825	-9.72686	149.9072	-9.79966	-0.17535	-0.0728	Green	11.16551328	Green	ON
495	311	162.2539	-56.6353	162.1457	-56.3789	-0.10814	0.256408	Green	11.17031026	Green	ON
406	310	158.1746	-33.2546	157.6928	-33.2049	-0.48182	0.049698	Blue	11.16704774	Blue	ON
227	325	143.081	16.94556	143.0968	16.77515	0.015788	-0.17041	Blue	11.46826625	Blue	ON
317	235	181.531	-7.42902	181.7395	-7.256	0.208519	0.173013	Blue	11.16424489	Blue	ON
224	242	174.2824	20.2141	174.0565	19.86753	-0.22596	-0.34657	Blue	11.16915846	Blue	ON
223	238	175.7995	20.64042	175.535	20.55661	-0.26447	-0.08381	Blue	11.47038293	Blue	ON
400	134	225.0704	-30.2364	224.5996	-29.9841	-0.47087	0.252317	Blue	11.1692059	Blue	ON

Table 3. Statistical comparison of execution time for PID ON and PID OFF

Metric	PID ON	PID OFF	P-value
Mean time (s)	11.27613386	11.29367377	0.998344209
SD time (s)	0.270355801	0.288346344	0.999232529
Count	12	12	-

The comparison between the PID ON and PID OFF conditions showed no statistically significant difference in execution time. The mean execution time was 11.276 s for the PID ON condition and 11.294 s for the PID OFF condition, with a p-value of 0.998, indicating that the difference was not statistically significant ($p > 0.05$). Similarly, the SD were 0.270 s and 0.288 s, respectively, with a p-value of 0.999, suggesting no significant difference in variability between the two conditions. Both groups consisted of 12 observations, ensuring a balanced comparison. These results indicate that enabling or disabling the PID controller did not have a significant effect on the system's execution time under the experimental conditions.

3.3. Testing under high-light (37 ft-cd or 398.26 lux) condition of non-PID and PID control system

This experiment followed the same procedure described in subsection 3.2, except that the illumination level was increased to 398.26 lux. The measured illumination level before the experiment is shown in Figure 10. Figure 10(a) shows the measurement of the illumination level before the experiment, while Figure 10(b) shows the machine vision-based object detection and diameter measurement under the same illumination condition. The experimental data were recorded under two operating conditions: with the PID controller enabled (PID ON) and without the PID controller (PID OFF). After conducting the experiments and collecting the data, the recorded values were analyzed, and the summarized results are presented in Table 4. The results comparing the PID-controlled system and the system without PID control in this case can be evaluated using the mean time, SD, and the calculated p-value, as presented in Table 4.

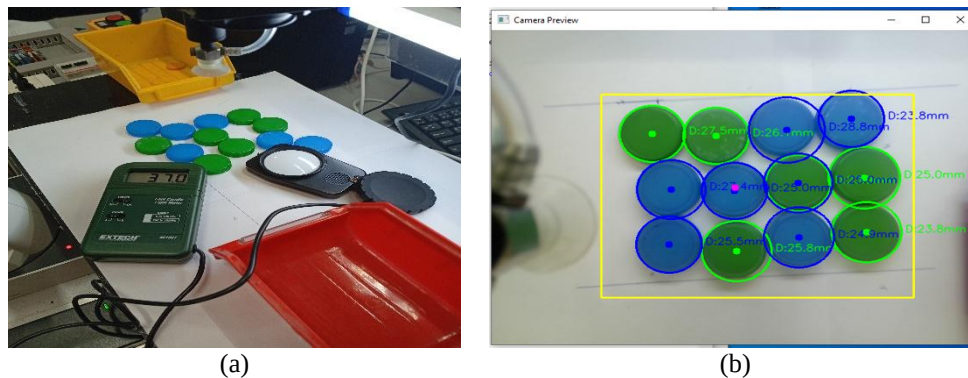


Figure 10. Experimental setup under 398.26 lux illumination for; (a) illumination measurement before the experiment and (b) machine vision-based object detection and diameter measurement

Table 4. Statistical comparison of execution time for PID ON and PID OFF

Metric	PID ON	PID OFF	P-value
Mean time (s)	11.29859032	11.26052282	0.999503
SD time (s)	0.272345291	0.299764723	0.99883
Count	12	12	-

The comparison between the PID ON and PID OFF conditions showed no statistically significant difference in execution time. The mean execution time was 11.299 s for the PID ON condition and 11.261 s for the PID OFF condition, with a p-value of 0.9995, indicating that the difference was not statistically significant ($p > 0.05$). Although the PID OFF condition exhibited a slightly shorter mean execution time by approximately 0.038 s, this difference was negligible. Similarly, the SD were 0.272 s for PID ON and 0.300 s for PID OFF, with a p-value of 0.9988, indicating no significant difference in the variability of execution time between the two conditions. Both groups consisted of 12 observations, providing a balanced comparison. These results indicate that enabling or disabling the PID controller did not have a statistically significant effect on the system's execution time under the tested illumination condition.

3.4. Results of proportional integral derivative controller tuning with different gain parameters

In this experiment, the illumination level was maintained at 398.26 lux while the proportional gain (K_p) of the PID controller was adjusted to evaluate its effect on the system performance. The integral (K_i) and derivative (K_d) gains were kept constant throughout the experiments, whereas the proportional gain was increased in each successive trial. This approach was used to investigate the influence of different PID gain

settings on the positioning and operational performance of the system under the same lighting condition. The experimental results obtained from increasing the PID controller gain are summarized as follows:

- Experiment 1: PID ON with $K_{p_x}=0.45$, $K_{i_x}=0.009$, $K_{d_x}=0.105$, and $K_{p_y}=0.50$, $K_{i_y}=0.010$, $K_{d_y}=0.100$.
- Experiment 2: PID ON with $K_{p_x}=1.00$, $K_{i_x}=0.009$, $K_{d_x}=0.105$, and $K_{p_y}=1.00$, $K_{i_y}=0.010$, $K_{d_y}=0.100$.
- Experiment 3: PID ON with $K_{p_x}=5.00$, $K_{i_x}=0.009$, $K_{d_x}=0.105$, and $K_{p_y}=5.00$, $K_{i_y}=0.010$, $K_{d_y}=0.100$.

Figure 11 illustrates the offset error response of the PID controller combined with the AutoTune Offset function under various PID gain settings. The blue and orange curves represent the offset errors along the X-axis and Y-axis, respectively. The experiments were conducted by gradually increasing the proportional gain (K_p) while maintaining the integral (K_i) and derivative (K_d) gains at constant values. In Experiment 1, shown in Figure 11(a), the system operated with the lowest proportional gain, resulting in relatively stable offset variations but slower correction responses. In Experiment 2, shown in Figure 11(b), increasing the proportional gain improved the response speed and reduced some offset deviations. In Experiment 3, shown in Figure 11(c), the highest proportional gain provided faster error correction; however, larger fluctuations in the offset response were observed, indicating that excessive gain may increase system sensitivity and oscillation. These results demonstrate that PID gain adjustment significantly affects the offset correction behavior of the system, and that an appropriate gain selection is required to balance response speed and system stability.

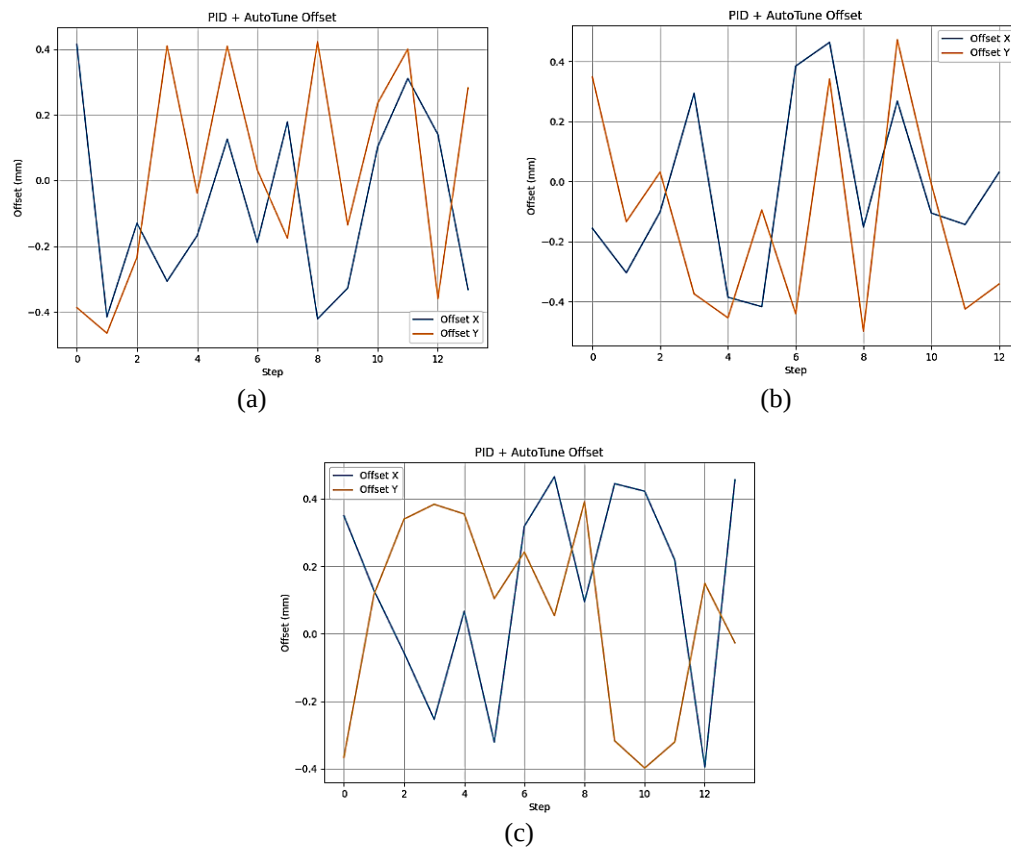


Figure 11. Offset error response of PID controller with autotune offset under different gain settings; (a) Experiment 1, (b) Experiment 2, and (c) Experiment 3

Table 5 presents the performance and stability metrics of three experiments based on execution time measurements. Each experiment was conducted 12 times to evaluate the average runtime and variation.

- Mean time (s): represents the average execution time. Experiment 2 achieved the shortest average time (11.26094 s), indicating the best performance, while Experiment 3 had the longest average time (11.33943 s).
- SD: indicates the consistency of execution time across runs. A lower SD means more stable performance. Experiment 1 showed the highest consistency with the lowest SD (0.2703558 s).
- Variance: measures the overall variation in execution time. Experiment 1 had the lowest variance (0.0730923), confirming that it provided the most stable results.

Overall, Experiment 2 provided the fastest execution time, while Experiment 1 demonstrated the highest stability and consistency among the three experiments.

The ANOVA results shown in Table 6 indicate an F-value of 0.249728 and a p-value of 0.780248, which is greater than the significance level of 0.05. This suggests that there is no statistically significant difference among the three experiments. The variation between groups (MSB=0.0208) is lower than the variation within groups (MSW=0.083289), indicating that the observed differences in execution time are likely due to random variation rather than differences in experimental conditions. Overall, the results demonstrate that the three experiments have comparable performance, with no significant effect on execution time.

Table 5. Performance and variability metrics of experiment execution time

Metric	Experiment 1	Experiment 2	Experiment 3
Mean time (s)	11.276134	11.26094	11.33943
SD time (s)	0.2703558	0.299474	0.295112
Count	12	12	12
Variance	0.0730923	0.089685	0.087091

Table 6. ANOVA statistical test results

Statistical metric	Value
Mean square between (MSB)	0.0208
Mean square within (MSW)	0.083289
F-value	0.249728
P-value	0.780248

3.5. Limitations of the study

The experimental results and analyses presented in this study are subject to several limitations that should be considered when interpreting the findings:

- Limited parameter tuning range: the systematic adjustments made to the PID gain parameters were restricted to a specific range. While these variations provided a baseline, they may not have reached the optimal values required to overcome the underlying system dynamics, potentially explaining the lack of statistically significant improvement in completion times.
- Performance metrics constraints: the evaluation focused primarily on temporal metrics (mean time and SD) while these provide insight into operational speed, they do not fully capture control quality parameters such as overshoot, settling time, or steady-state error, which are essential for a comprehensive assessment of PID performance.
- System sensitivity: the reliance on a static homography model for vision-guided manipulation may introduce limitations when faced with dynamic environmental changes, such as variable lighting or sensor noise. These external factors may have introduced random fluctuations that masked the potential benefits of the PID controller.

Scope of system identification: the current PID framework operates on a baseline level of system identification. The lack of a more rigorous, model-based identification process limits the ability to achieve the higher levels of precision expected from advanced robotic control systems.

4. CONCLUSION

This study successfully developed and implemented a vision-guided robotic framework for pick-and-place automation, utilizing an eye-in-hand camera configuration on a Dobot Magician. The methodology integrated real-time homography-based coordinate transformation with a PID control system to achieve precise, adaptive manipulation. By employing an online calibration approach refined by RANSAC, the framework effectively mitigated environmental disturbances such as lighting variations, camera vibration, and mechanical shifts. Experimental validation under both low-light (166.84 lux) and high-light (398.26 lux) conditions demonstrated that the integration of the PID controller significantly enhanced positional accuracy by minimizing systematic offsets and ensuring stable trajectory tracking. Statistical analysis of execution times, including the calculation of mean time, SD, and p-values, revealed that while the PID controller improved overall precision and movement stability, it did not introduce statistically significant latency compared to the non-PID system ($p > 0.05$). Consequently, the proposed synergy between robust spatial estimation and closed-loop motion control provides a reliable and high-fidelity solution for dynamic robotic manipulation in real-world environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

- [1] A. Iqdyamat and G. Stamatescu, "Reinforcement learning of a six-DOF industrial manipulator for pick-and-place application using efficient control in warehouse management," *Sustainability*, vol. 17, no. 2, Jan. 2025, doi: 10.3390/su17020432.
- [2] A. Lobbezoo, Y. Qian, and H.-J. Kwon, "Reinforcement learning for pick and place operations in robotics: A survey," *Robotics*, vol. 10, no. 3, Sep. 2021, doi: 10.3390/robotics10030105.
- [3] A. A. Santos *et al.*, "Integration of artificial vision and image processing into a pick and place collaborative robotic system," *Journal of Intelligent & Robotic Systems*, vol. 110, no. 4, Nov. 2024, doi: 10.1007/s10846-024-02195-z.
- [4] I. U. Haq, D. L. Cami, and F. Lamonaca, "Intelligent robotic positioning through AI-enhanced metrology: Integration of standards, sensor fusion, and adaptive calibration," *Acta IMEKO*, vol. 14, no. 3, pp. 1–14, Sep. 2025, doi: 10.21014/actaimeko.v14i3.2124.
- [5] T. E. Lee *et al.*, "Camera-to-robot pose estimation from a single image," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, May 2020, pp. 9426–9432, doi: 10.1109/ICRA40945.2020.9196596.
- [6] L. Li, X. Yang, R. Wang, and X. Zhang, "Automatic robot hand-eye calibration enabled by learning-based 3D vision," *Journal of Intelligent & Robotic Systems*, vol. 110, no. 3, Sep. 2024, doi: 10.1007/s10846-024-02166-4.
- [7] Y. Cho, W. Son, J. Bak, Y. Lee, H. Lim, and Y. Cha, "Full-body pose estimation of humanoid robots using head-worn cameras for digital human-augmented robotic telepresence," *Mathematics*, vol. 12, no. 19, Sep. 2024, doi: 10.3390/math12193039.
- [8] L.-W. Cheng, S.-W. Liu, and J.-Y. Chang, "Design of an eye-in-hand smart gripper for visual and mechanical adaptation in grasping," *Applied Sciences*, vol. 12, no. 10, May 2022, doi: 10.3390/app12105024.
- [9] X. Zhang, M. Yao, Q. Cheng, G. Liang, and F. Fan, "A novel hand-eye calibration method of picking robot based on TOF camera," *Frontiers in Plant Science*, vol. 13, Jan. 2023, doi: 10.3389/fpls.2022.1099033.
- [10] S. Fu, Z. Chen, J. Zhao, R. Xia, and T. Zhang, "Robotic hand-eye calibration utilizing limited geometric features object," *Robotics and Computer-Integrated Manufacturing*, vol. 97, Feb. 2026, doi: 10.1016/j.rcim.2025.103066.
- [11] M. I. Azeez, A. M. M. Abdelhaleem, S. Elnaggar, K. A. F. Moustafa, and K. R. Atia, "Optimization of PID trajectory tracking controller for a 3-DOF robotic manipulator using enhanced artificial bee colony algorithm," *Scientific Reports*, vol. 13, no. 1, Jul. 2023, doi: 10.1038/s41598-023-37895-3.
- [12] K. Joyo, T. A. Khan, K. A. Kadir, M. N. Bin Husen, H. M. Nasir, and M. Azhar, "Optimal PID controller with evolutionary optimization algorithms for rehabilitation robots," *Discover Applied Sciences*, vol. 7, no. 7, Jul. 2025, doi: 10.1007/s42452-025-07424-0.
- [13] P. Wang, T. Feng, C. Song, J. Li, and S. X. Yang, "A study of the stability of an industrial robot servo system: PID control based

- on a hybrid sparrow optimization algorithm,” *Actuators*, vol. 14, no. 2, Jan. 2025, doi: 10.3390/act14020049.
- [14] Y. Luo *et al.*, “A review of homography estimation: Advances and challenges,” *Electronics*, vol. 12, no. 24, Dec. 2023, doi: 10.3390/electronics12244977.
 - [15] Y. Weng, J. Shan, Z. Lu, X. Lu, and B. F. Spencer, “Homography-based structural displacement measurement for large structures using unmanned aerial vehicles,” *Computer-Aided Civil and Infrastructure Engineering*, vol. 36, no. 9, pp. 1114–1128, Sep. 2021, doi: 10.1111/mice.12645.
 - [16] A. Singh, V. Kalaichelvi, and R. Karthikeyan, “A survey on vision guided robotic systems with intelligent control strategies for autonomous tasks,” *Cogent Engineering*, vol. 9, no. 1, Dec. 2022, doi: 10.1080/23311916.2022.2050020.
 - [17] Z. Gao, Z. Dong, X. Zhang, and A. Wang, “Hierarchical collaborative robust control framework integrated with multi-tier rapid control prototyping for vision-guided teleoperation systems,” in *2025 37th Chinese Control and Decision Conference (CCDC)*, May 2025, pp. 4171–4178, doi: 10.1109/CCDC65474.2025.11090931.
 - [18] M. T. Shahria, J. Ghommam, R. Fareh, and M. H. Rahman, “Vision-based object manipulation for activities of daily living assistance using assistive robot,” *Automation*, vol. 5, no. 2, pp. 68–89, Apr. 2024, doi: 10.3390/automation5020006.
 - [19] G. Jin, X. Yu, Y. Chen, and J. Li, “Hand-eye parameter estimation based on 3-D observation of a single marker,” *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–14, 2024, doi: 10.1109/TIM.2024.3385038.
 - [20] Y. Du *et al.*, “A low-cost robot with autonomous recharge and navigation for weed control in fields with narrow row spacing,” in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2021, pp. 3263–3270, doi: 10.1109/IROS51168.2021.9636267.
 - [21] K. Ryu, B. Lee, D.-G. Kim, and S. Sung, “Enhanced airborne optical sectioning design via HSV color space for detecting human object under obscured aerial image environment,” *International Journal of Control, Automation and Systems*, vol. 21, no. 11, pp. 3734–3745, Nov. 2023, doi: 10.1007/s12555-022-0764-6.
 - [22] Y. Liu, H. Ma, P. Liu, and J. Cheng, “HCNV: Hand-eye calibration based on surface normal optimization and view selection,” *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 15846–15858, 2025, doi: 10.1109/TASE.2025.3568141.
 - [23] Z. Zhou *et al.*, “Enhanced calibration method for robotic flexible 3D scanning system,” *Sensors*, vol. 25, no. 15, Jul. 2025, doi: 10.3390/s25154661.
 - [24] J. Jiang, X. Luo, Q. Luo, L. Qiao, and M. Li, “An overview of hand-eye calibration,” *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 1–2, pp. 77–97, Mar. 2022, doi: 10.1007/s00170-021-08233-6.
 - [25] K. Guo, H. Ye, J. Gu, and H. Chen, “A novel method for intrinsic and extrinsic parameters estimation by solving perspective-three-point problem with known camera position,” *Applied Sciences*, vol. 11, no. 13, Jun. 2021, doi: 10.3390/app11136014.
 - [26] L. Lu and F. Dai, “A unified normalization method for homography estimation using combined point and line correspondences,” *Computer-Aided Civil and Infrastructure Engineering*, vol. 37, no. 8, pp. 1010–1026, Jul. 2022, doi: 10.1111/mice.12788.
 - [27] T. M. Tyrannowski and M. Kraus, “Symplectic model reduction methods for the Vlasov equation,” *Contributions to Plasma Physics*, vol. 63, no. 5–6, Jun. 2023, doi: 10.1002/ctpp.202200046.
 - [28] B. Zhang, Z. Zhang, and X. Gu, “A novel closed-form solution for automatic calibration of extrinsic parameters based on plane-induced homography,” *Robotics and Autonomous Systems*, vol. 194, Dec. 2025, doi: 10.1016/j.robot.2025.105144.
 - [29] C. Liu, Y. Zhang, L. Ma, Y. Huang, K. Liu, and G. Wang, “Unmanned aerial vehicle–unmanned ground vehicle centric visual semantic simultaneous localization and mapping framework with remote interaction for dynamic scenarios,” *Drones*, vol. 9, no. 6, Jun. 2025, doi: 10.3390/drones9060424.
 - [30] S. Lovett, K. MacWilliams, S. Rajan, and C. Rossa, “Enhancing doppler ego-motion estimation: A temporally weighted approach to RANSAC,” in *2024 IEEE Sensors Applications Symposium (SAS)*, Jul. 2024, pp. 1–6, doi: 10.1109/SAS60918.2024.10636553.
 - [31] I. Lopez-Juarez, K. I. Lopez-Valadez, R. Osorio-Compan, L. A. Castillo-Barrientos, and D. Arreguin-Jasso, “An affordable robotic manipulation platform with flexible gripper and vision for AI-driven control,” in *2025 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON)*, Oct. 2025, pp. 1–5, doi: 10.1109/CHILECON66915.2025.11475973.
 - [32] W. Chen *et al.*, “Accuracy of dental implant placement with a robotic system in partially edentulous patients: A prospective, single-arm clinical trial,” *Clinical Oral Implants Research*, vol. 34, no. 7, pp. 707–718, Jul. 2023, doi: 10.1111/clr.14083.
 - [33] S. K. Baruah, U. Konwar, R. Mahanta, A. Boruah, and D. Sarma, “A contactless control mechanism for computerized systems using hand gestures,” in *2023 IEEE 3rd Applied Signal Processing Conference (ASPCON)*, Nov. 2023, pp. 246–250, doi: 10.1109/ASPCON59071.2023.10396173.
 - [34] P. Dhabe, R. Kulkarni, A. Chedge, H. Khan, S. Jadhav, and S. Dighe, “GestureX: A real-time hand gesture recognition system for intuitive human-computer interaction,” in *2025 International Conference on Computing Technologies & Data Communication (ICCTDC)*, Jul. 2025, pp. 1–6, doi: 10.1109/ICCTDC64446.2025.11158058.
 - [35] C. Tong, G. Jianfeng, X. Xueli, and X. Jianxiang, “High-precision image mosaic algorithm based on adaptive homography transform,” in *2021 40th Chinese Control Conference (CCC)*, Jul. 2021, pp. 3030–3035, doi: 10.23919/CCC52363.2021.9549380.

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