

A Vision-Based Error Compensation Method for Accurate Robotic Positioning in Automated Marking

Olzhas Olzhayev¹, Akhanseri Ikramov², Sayat Ibrayev³

Joldasbekov Institute of Mechanics and Engineering, Almaty, Kazakhstan^{1, 2, 3}

International Information Technology University, Almaty, Kazakhstan¹

Al-Farabi Kazakh National University, Almaty, Kazakhstan²

Abstract—Accurate robotic positioning is essential in automated marking because residual pose error directly shifts the permanent mark. This study presents a one-step vision-based residual error compensation method that measures the displacement between the target and the marking-tool position after the initial robot motion, transforms that displacement into the robot base frame, and applies it as a translational Tool Center Point (TCP) correction. The platform combines an AR4-MK3 six-degree-of-freedom manipulator, a fixed Intel RealSense D455 RGB-D camera, and a 50 W electromagnetic marking device. At five spatially distinct target points, the mean Euclidean positioning error decreased from 7.40 ± 1.35 mm to 2.14 ± 0.36 mm. The mean paired decrease was 5.26 mm (95% confidence interval: 4.04–6.48 mm), and all five points improved by 70.7%–71.4%. An exploratory point-level paired test gave $t(4) = 11.92$ and $p < 0.001$. The result supports the feasibility of inserting a local visual correction immediately before marking without changing the nominal robot kinematic model. The evaluation is a five-point pilot rather than a repeatability or full workspace study; raw repeated-trial, orientation-error, timing, robustness, and quantitative mark-quality measurements were not available. The conclusions are therefore limited to translational positioning under the tested camera and workcell configuration.

Keywords—Vision-based error compensation; robotic positioning; automated marking; RGB-D camera; tool center point; industrial robotics; positioning accuracy

I. INTRODUCTION

Industrial robots support welding, assembly, machining, inspection, material handling, and surface-processing operations because they combine programmable motion with high repeatability [1]. Repeatability, however, is not equivalent to absolute accuracy. Kinematic parameter errors, joint clearances, compliance, assembly tolerances, thermal effects, and environmental disturbances can displace the end-effector from a commanded Cartesian target [2]. These errors are important in marking because the final tool position determines the location of a permanent identifier.

Robot calibration and error compensation improve absolute positioning by identifying differences between nominal and actual robot behavior [3]. Kinematic calibration can reduce systematic geometric error, but non-kinematic effects such as compliance, thermal drift, payload, and base deformation may remain [4]. High-accuracy calibration also commonly uses laser trackers, coordinate-measuring machines, or photogrammetric systems, which improve traceability but increase workcell cost and integration effort [5].

Machine vision provides a complementary route because it observes the current relationship among the target, tool, and workpiece [6]. Vision-guided correction has been applied to machining, drilling, grinding, assembly, and navigation tasks [7]. In contrast to a purely global calibration model, a local measurement made after the initial robot motion can capture the net residual error produced by several upstream sources.

Prior work includes vision-guided robot localization [8], neural-network prediction of positioning error [9], and models that incorporate non-kinematic and weak rigid-base effects [10]. Hand-eye vision has also been used for indirect compensation [11], while photogrammetric calibration has improved camera-guided robot accuracy [12]. Recent studies additionally address uncertainty in TCP calibration [13], stereo-vision closed-loop measurement [14], and high-precision tool-path generation for engraving [15]. These approaches establish the value of external sensing, but many require global calibration, extensive data collection, iterative control, or specialized metrology.

Vision-based residual correction is well suited to automated marking. Even after the target is transformed into the robot coordinate system, the executed tool position can still contain errors from target localization, camera calibration, camera-to-robot registration, TCP definition, and manipulator mechanics. Because these errors accumulate along the measurement and positioning chain, the initially calculated TCP pose should not be treated as an error-free final command.

The proposed workflow inserts a single visual correction after the initial positioning motion and before tool activation. The camera measures the target-to-tool displacement; the displacement is expressed in the robot base frame, and the corresponding translational offset is added to the TCP command. The method does not replace robot or camera calibration; it compensates for the residual displacement that remains after those procedures.

The research gap is therefore application-specific rather than a claim that visual correction is new in itself. Existing studies mainly evaluate calibration, machining, drilling, assembly, or trajectory control. Automated marking requires target localization, frame transformation, residual error measurement, correction, and permanent mark execution to operate as one ordered sequence. A practical question is whether a simple pre-marking correction can improve a low-cost workcell without retraining a model or changing the nominal robot kinematics.

This study makes three contributions: 1) a marking-specific sense-correct-execute workflow that uses the same fixed RGB-D camera for initial localization and residual measurement; 2) an explicit frame-consistent formulation that transforms camera-space displacement before TCP correction; and 3) a transparent five-point pilot analysis that reports point-level dispersion, confidence intervals, and an exploratory paired comparison. The scope is translational correction under a fixed camera and fixed tool orientation. The study does not claim full six-degree-of-freedom compensation, industrial robustness, or metrological equivalence to a laser tracker.

II. RELATED WORK

Industrial robot accuracy enhancement is commonly divided into kinematic calibration, extended error modeling, data-driven compensation, and external-sensor feedback. Kinematic methods identify geometric parameters from measured poses [16], whereas extended models incorporate compliance, backlash, base deformation, thermal effects, and load-dependent behavior [17]. Model-free methods learn commanded-to-measured error mappings [18], including neural, radial-basis, Gaussian-process, and other regression models [19]. Deep models can represent nonlinear workspace error [20], and similarity or incremental-learning strategies can reduce calibration effort [21]. These gains depend on the coverage and stability of the training data.

External metrology provides traceable end-effector measurements. Laser trackers are widely used for calibration and accuracy assessment [22], and real-time trajectory compensation can reduce path error [23]. Such systems offer higher accuracy than commodity RGB-D cameras but require line of sight, careful setup, and additional capital equipment. Visual guidance offers a lower-cost alternative for local correction. Examples include visually guided pose improvement in robotic machining [24], online visual correction for robotic drilling [25], and integrated machine-vision compensation architectures [26].

A reproducible visual correction chain requires both camera calibration and frame registration. Intrinsic calibration relates pixels and depth to camera-frame coordinates and is commonly estimated from multiple views of a calibration pattern [27]. Camera-to-robot registration is the hand-eye problem. Foundational solutions include the Tsai-Lenz method [28], separable rotation-translation estimation [29], Lie-group formulations of $AX = XB$ [30], and dual-quaternion estimation [31]. Later work optimized pose selection [32], solved robot-world/hand-eye calibration jointly [33], and minimized reprojection error directly [34]. Reviews and comparative evaluations show that calibration accuracy depends on pose diversity, image localization error, and the selected solver [35]-[37].

The proposed correction is also related to image-based and position-based visual servoing. Classical visual servo control uses image or reconstructed pose error to generate motion commands [38]-[40], and modern robot-vision treatments emphasize explicit coordinate-frame conventions and stability assumptions [41], [42]. In multi-sensor systems, temporal and

spatial calibration must be considered together when measurements and robot states are not synchronized [43]. Three-dimensional hand-eye calibration with line laser sensors [44] and learning-based vision for small and medium-sized production cells [45] further demonstrate the range of sensing and integration choices.

The Intel RealSense D455 is an active-stereo RGB-D device whose manufacturer specifies depth resolution up to 1280 x 720 and depth accuracy below 2% at 4 m under the stated test conditions [46]. Independent close-range characterization confirms that D455 performance varies with distance, surface geometry, and device-specific effects [47]. Evaluation under indoor mapping conditions also shows that measurement noise depends on range and surface inclination [48]. Consequently, a D455 cannot be treated as a substitute for a traceable metrology system, and its uncertainty forms part of the residual error reported in this study.

Published compensation results are not directly rankable because robots, workspaces, sensors, metrics, and test protocols differ. Accuracy and repeatability also change between offline and online robot-programming environments [49]. A laser-tracker and neural-network method reduced mean positioning error from 0.8497 to 0.0490 mm [50], while an offline deep-belief-network method reduced error from 0.469 to 0.084 mm [51]. Laser-tracker calibration has likewise demonstrated submillimeter improvement on industrial robots [52]. ISO 9283 provides standardized concepts for pose accuracy and repeatability [53], but the present pilot does not implement the complete standard protocol. Its contribution is the marking-specific local correction sequence, not superior absolute accuracy over these differently instrumented systems.

III. MATERIALS AND METHODS

A. Experimental Vision-Guided Robotic Marking System

The experimental platform comprises an AR4-MK3 six-degree-of-freedom manipulator, a fixed Intel RealSense D455 RGB-D camera, a 50 W electromagnetic marking device, and a computer-based controller. The marking device is rigidly mounted on the robot end-effector. The camera observes the workpiece and tool from above in an eye-to-hand configuration. The camera was not moved during the reported five-point experiment.

The system uses two positioning stages. First, the target is localized from aligned color and depth data and transformed into the robot base frame to generate an initial TCP position. The robot then moves the marking tool to that command and comes to rest. Second, the vision system estimates the remaining target-to-tool displacement. After transforming the displacement into the base frame, the controller issues one corrected TCP command before activating the marking tool.

The controller performs image acquisition, target and tool localization, depth association, camera-to-base transformation, residual-error calculation, and robot command transmission. Fig. 1 identifies the interface view (left), the fixed camera and observed workpiece region (upper right), and the robot-mounted electromagnetic marking tool (lower right).

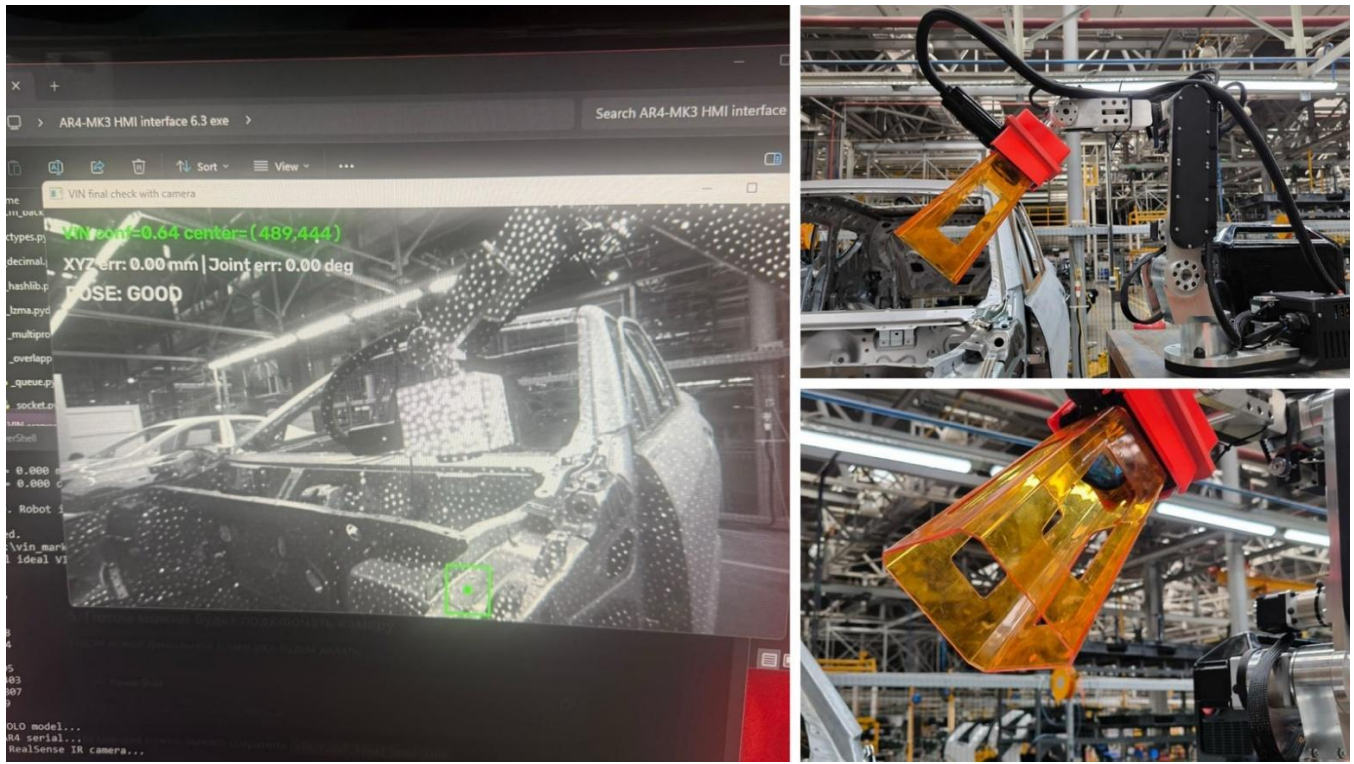


Fig. 1. Experimental vision-guided marking cell: camera and detection interface (left), fixed RGB-D camera and observed workpiece region (upper right), and AR4-MK3 manipulator with the electromagnetic marking tool (lower right).

B. Camera Calibration and Coordinate Frames

Four frames are used: the camera frame $\{C\}$, robot base frame $\{B\}$, TCP frame $\{T\}$, and workpiece/target frame $\{W\}$. The camera is fixed relative to the robot base. A camera-frame point p^c is mapped to the base frame by the homogeneous transformation $p^b = T_{BC} p^c$, where T_{BC} contains the rotation R_{BC} and translation t_{BC} . The target and measured tool points are transformed independently before their difference is used for correction.

The intrinsic model deprojects an aligned pixel-depth observation according to $p^c = z K^{-1} [u, v, 1]^T$, where K is the camera intrinsic matrix and z is the depth associated with the detected image location. Target and tool image regions are localized by the workcell detector; the center of each detected region defines (u, v) , and valid depth samples around that center are aggregated to suppress isolated depth outliers. This definition makes the visual measurement reproducible at the algorithmic level, although the detector version, exact acquisition resolution, calibration residuals, and per-frame raw observations were not retained in the experimental record.

The fixed eye-to-hand transformation T_{BC} was determined before the positioning experiment from paired camera-frame and robot-base observations and then held constant. The transformation must be validated in the actual work volume because intrinsic calibration error, target localization error, depth bias, and registration error propagate into the compensation vector. The original study did not archive an independent traceable uncertainty budget; consequently, the reported post-compensation error represents

the combined robot-and-vision result rather than robot error alone.

C. Vision-Based Positioning Error Estimation

After the initial robot positioning, the camera observes the desired target and the marking-tool reference within the same scene. Let P_t and P_m denote their three-dimensional positions after deprojection and transformation into a common coordinate frame. The component-wise residual and Euclidean distance are defined in Eq. (1)-(7). In implementation, displacement E in $\{C\}$ is rotated into $\{B\}$ by R_{BC} ; the translation t_{BC} cancels because E is a difference between two points.

Let the desired target position be defined as:

$$P_t = (x_t, y_t, z_t) \quad (1)$$

and the actual position of the marking tool after the initial robot movement as:

$$P_m = (x_m, y_m, z_m) \quad (2)$$

The positioning error along each coordinate axis is calculated as:

$$e_x = x_t - x_m \quad (3)$$

$$e_y = y_t - y_m \quad (4)$$

$$e_z = z_t - z_m \quad (5)$$

The resulting error vector is expressed as:

$$E = [e_x; e_y; e_z] \quad (6)$$

while the total positioning error is calculated using the Euclidean distance:

$$e = \sqrt{e_x^2 + e_y^2 + e_z^2} \quad (7)$$

The vector therefore represents both the magnitude and direction of the residual translation. Frame consistency is essential: a displacement measured in {C} cannot be added directly to a TCP position in {B}. Only the residual after rotation into {B} is passed to the compensation stage.

D. Proposed Error Compensation Method

The proposed method applies one translational correction after the initial motion. The initial TCP position is expressed in the robot base frame. The compensation offset is obtained from the camera-space residual through the rotation R_{BC} , and the corrected TCP position is transmitted as a second point-to-point command.

The initial TCP position is represented as:

$$P_{TCP} = [x_{TCP}; y_{TCP}; z_{TCP}] \quad (8)$$

Using the residual expressed in {C}, the base-frame compensation offset is defined as:

$$\Delta P^B = R_{BC} E^C \quad (9)$$

The corrected base-frame TCP position is then calculated as:

$$P_{TCP}^{corr} = P_{TCP} + \Delta P \quad (10)$$

or, in expanded base-frame form:

$$P_{TCP,corr}^B = [x_{TCP} + \Delta x^B, y_{TCP} + \Delta y^B, z_{TCP} + \Delta z^B]^T \quad (11)$$

The corrected position is transmitted to the robot controller only after the initial motion has settled. The tool orientation is held at the taught marking orientation and is not changed by the compensation algorithm. This design is appropriate for the planar workpiece used in the pilot, but it does not compensate for rotational error. Orientation error can change contact angle, normal force, and mark geometry and must be measured in a full six-degree-of-freedom extension.

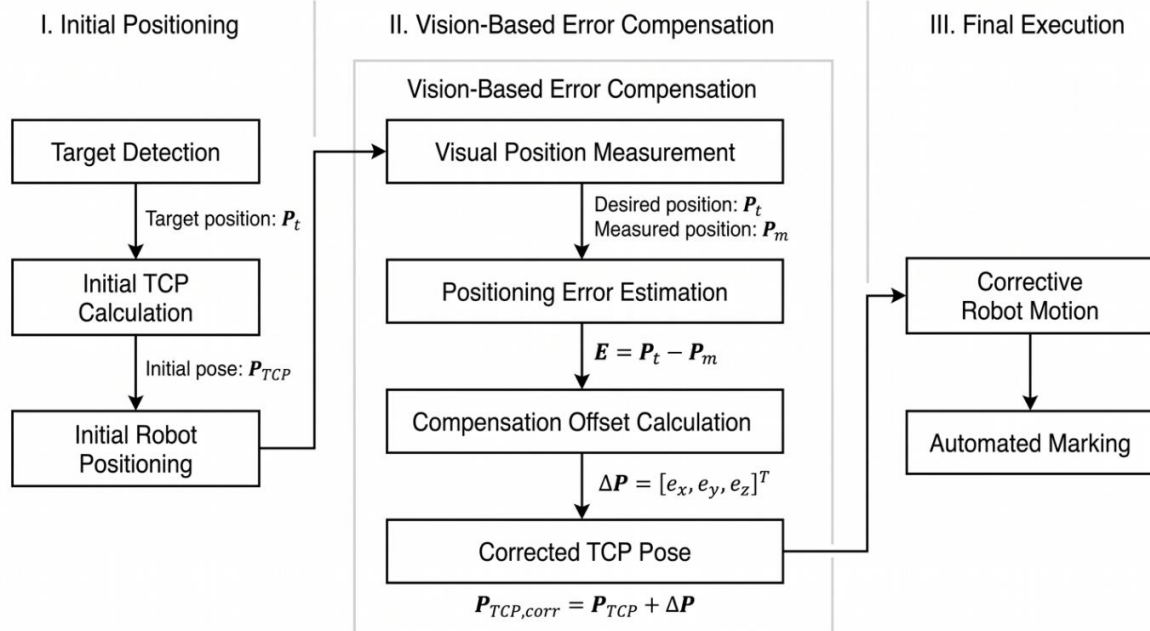


Fig. 2. Proposed vision-based error compensation framework for robotic positioning and automated marking.

Fig. 2 summarizes the marking-specific sequence. In the schematic, ΔP denotes the frame-consistent offset defined formally in Eq. (9). The first command uses the transformed target position, and the second uses the residual displacement measured after the robot has settled. The technical distinction from global calibration and learned workspace compensation is that the proposed offset is local, task-timed, and calculated immediately before permanent marking. The approach still depends on valid camera calibration and does not remove the need for metrological validation.

E. Experimental Procedure

The method was evaluated at five distinct target locations, P1-P5, within the accessible marking area. At each location, the robot executed the initial target command, stopped, and

was observed by the D455. The Euclidean tool-to-target distance was recorded before compensation. The base-frame correction was then applied, the robot stopped again, and the final distance was recorded. The retained dataset contains one before-and-after pair for each spatial target point. Although preliminary workcell operation involved repeated positioning, trial-level raw measurements and exact base-frame coordinates for P1-P5 were not preserved; the manuscript therefore treats the five sites, not repeated trials, as the experimental units and does not claim ISO 9283 repeatability.

The primary outcome was Euclidean positioning error in millimeters. Secondary descriptive outcomes were the absolute paired decrease and percentage reduction at each point. The uncompensated first command serves as the within-point open-

loop baseline. No independent calibrated-positioning baseline, orientation-error series, cycle-time log, or robustness series for illumination, camera displacement, vibration, and workpiece rotation was available. These omissions are stated explicitly so that the pilot is not interpreted as a full industrial qualification study.

F. Statistical Analysis

Means, sample standard deviations, and two-sided 95% t confidence intervals were calculated across the five target points. A paired t-test compared the before- and after-compensation errors at the same spatial points, and Cohen's dz was calculated as the mean paired decrease divided by the standard deviation of the paired decreases. Because $n = 5$ and no repeated-trial data were retained, the inferential statistics are exploratory and characterize consistency across sampled locations rather than production repeatability.

IV. RESULTS

Table I reports the five paired point-level observations. The uncompensated errors ranged from 5.8 to 9.1 mm, and the compensated errors ranged from 1.7 to 2.6 mm. Every target point improved, with percentage reductions between 70.7% and 71.4%. Fig. 3 illustrates the physical before-and-after correction sequence; the images are illustrative, whereas the numerical evaluation is based on the measurements in Tables I and II.

Fig. 3(a) shows the marking tool after the initial positioning command, and Fig. 3(b) shows the tool after the correction command. The corresponding dataset-level mean displacement decreased from 7.40 mm before compensation to 2.14 mm after compensation. Individual P1-P5 values are reported in Table I rather than overlaid on the photographs because the photographs do not provide a traceable scale for independent measurement.

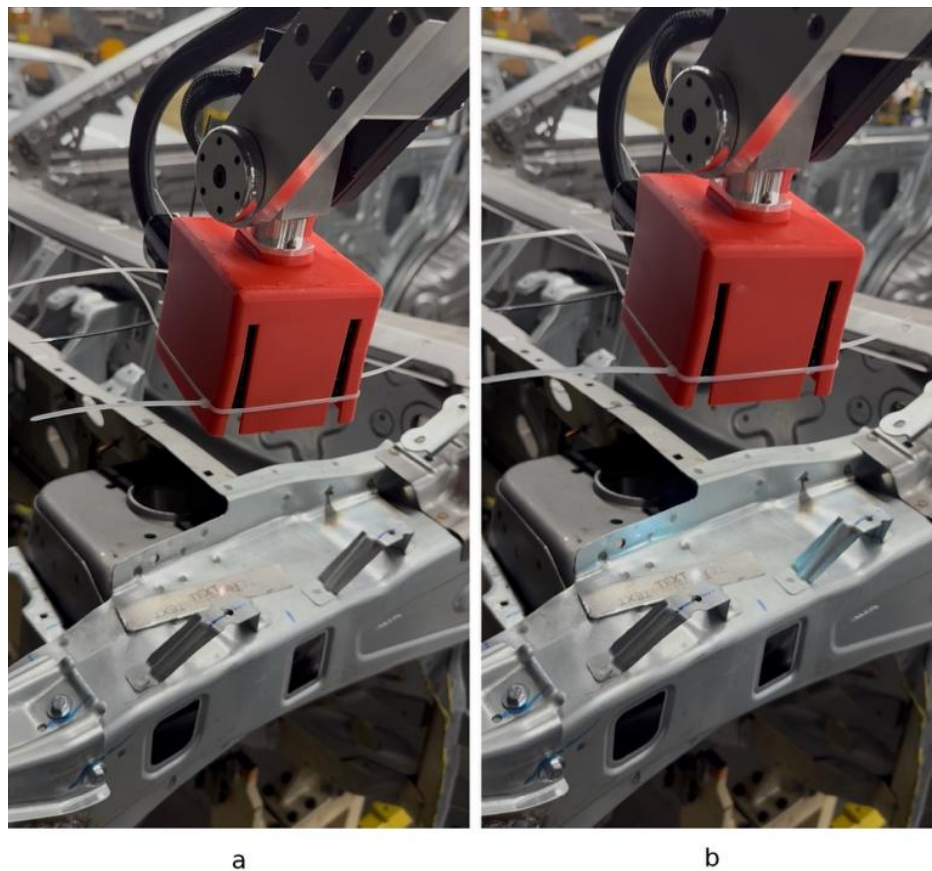


Fig. 3. Execution of the visual correction: (a) tool position after the initial command and (b) tool position after the correction command. Across P1-P5, the mean measured error decreased from 7.40 to 2.14 mm.

For target point i , percentage error reduction was calculated as:

$$R = \left(\frac{e_{\text{(before)}} - e_{\text{(after)}}}{e_{\text{(before)}}} \right) * 100\%$$

where, $e_{\text{before},i}$ and $e_{\text{after},i}$ are the Euclidean errors measured before and after compensation at the same target point. Table I preserves the individual observations.

The mean error was 7.40 ± 1.35 mm before compensation and 2.14 ± 0.36 mm after compensation. The mean paired decrease was 5.26 ± 0.99 mm, with a 95% confidence interval of 4.04-6.48 mm. The exploratory paired test yielded $t(4) = 11.92$, $p = 0.0003$, and Cohen's $dz = 5.33$. These statistics indicate a consistent reduction across the five sampled locations, but they do not substitute for repeated trials at each point.

TABLE I. POINT-LEVEL POSITIONING ERROR BEFORE AND AFTER VISUAL COMPENSATION

Target point	Before compensation (mm)	After compensation (mm)	Error reduction (%)
P1	7.2	2.1	70.8
P2	5.8	1.7	70.7
P3	8.4	2.4	71.4
P4	6.5	1.9	70.8
P5	9.1	2.6	71.4
Mean	7.4	2.14	71.0

TABLE II. DESCRIPTIVE AND EXPLORATORY POINT-LEVEL STATISTICS ACROSS FIVE TARGET LOCATIONS

Quantity	Estimate	95% CI
Before compensation	7.40 $\pm$ 1.35 mm	5.72-9.08 mm
After compensation	2.14 $\pm$ 0.36 mm	1.69-2.59 mm
Paired decrease	5.26 $\pm$ 0.99 mm	4.04-6.48 mm
Paired test	t(4) = 11.92	p = 0.0003
Effect size	Cohen's dz = 5.33	Point-level

After correction, the electromagnetic tool was activated. The photograph below shows one resulting mark and demonstrates process feasibility. It is not a quantitative mark-quality test: the retained experiment does not include independent measurements of mark-center deviation, character dimensions, depth, edge quality, or repeatability (Fig. 4). Accordingly, marking quality is not used as evidence for the positioning claim.

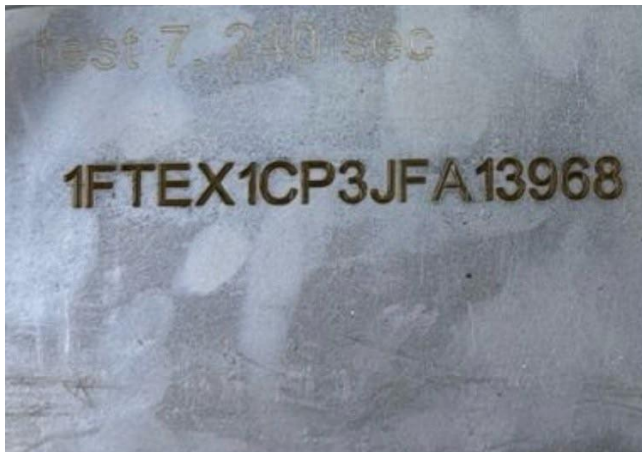


Fig. 4. Example mark produced after visual correction. The image demonstrates execution feasibility only; mark geometry was not measured quantitatively.

The available evidence therefore supports a narrow conclusion: one local translational correction reduced measured tool-to-target error at each of five tested sites. It does not establish orientation accuracy, camera-only measurement uncertainty, mark-quality repeatability, cycle-time overhead, or robustness to environmental changes.

V. DISCUSSION

Across the five target sites, compensation reduced mean error from 7.40 to 2.14 mm and produced a mean paired decrease of 5.26 mm. The narrow range of percentage reductions indicates similar relative behavior at the sampled sites. The point-level confidence interval excludes zero, and the exploratory paired test is consistent with a large reduction. Because only five site-level pairs were retained, these results should be interpreted as pilot evidence rather than an estimate of trial-to-trial repeatability.

The improvement is attributable to measuring the net residual displacement after the initial command. This timing allows one correction to incorporate the combined effect of localization, transformation, TCP, and manipulator errors present at that moment. The revised formulation also makes clear that camera-space displacement is rotated into the robot base frame before it is added to the TCP position. Direct addition without this transformation would be valid only if the camera and base axes were already coincident.

The approach reuses the camera already present in the marking cell, but this does not make the measurement metrologically independent. Published D455 characterizations show that depth error depends on range, surface inclination, and device behavior [47], [48]. The final 2.14 mm value therefore includes camera and registration uncertainty. The method should be described as low-cost visual compensation rather than as a replacement for traceable external metrology.

Table III positions the result against selected calibration and compensation studies. The numerical values are contextual because the studies use different robots, sensors, workspaces, and error definitions. Laser-tracker and learned models achieve smaller residuals but require calibration datasets and high-accuracy reference instruments. The proposed method uses one local RGB-D correction and addresses a less demanding marking setup. Its novelty is the integrated pre-marking sequence and explicit frame-consistent offset, not state-of-the-art absolute positioning accuracy.

TABLE III. CONTEXTUAL COMPARISON WITH SELECTED COMPENSATION METHODS

Study	Sensing and method	Reported result	Comparison notes
Ma et al. [10]	Laser tracker; non-kinematic and base-error model	Trajectory error - 1.3231 to -0.1297 mm	Robotic milling; signed axis error
Jiang et al. [50]	Laser tracker; optimized neural network	Mean 0.8497 to 0.0490 mm	Global calibration and learning
Tao et al. [51]	Laser tracker; DE-DBN offline compensation	0.469 to 0.084 mm; 82.14%	Training data and traceable metrology
Li et al. [26]	Industrial camera, PLC, iterative correction	Accuracy within 0.231 mm	Different robot and repeated grasping task
Present pilot	D455 RGB-D; one local TCP correction	7.40 to 2.14 mm; 71.0%	Five marking sites; no trial-level repeats

The study has six principal limitations. First, the retained dataset contains only five spatial observations and no trial-level repetition series. Second, exact base-frame coordinates and robot joint configurations for P1-P5 were not archived, which limits workspace reproducibility. Third, the work uses one camera, robot, tool, and controlled workcell. Fourth, illumination, camera displacement, workpiece rotation, vibration, and larger workspace changes were not tested independently. Fifth, only translation was corrected; orientation and contact-normal error were not measured. Sixth, image-processing time, error-estimation time, correction-motion time, total added cycle time, and quantitative mark quality were not instrumented. These constraints preclude broad industrial generalization. A follow-up study should use an ISO 9283-informed repeated-point protocol, publish raw trials and target coordinates, validate camera and hand-eye uncertainty, add calibrated and alternative vision baselines, measure timing and mark geometry, and test environmental perturbations.

VI. CONCLUSION

This study presented a marking-specific, vision-based residual error correction for an AR4-MK3 robot. The method measures the target-to-tool displacement after the initial command, rotates that displacement from the camera frame into the robot base frame, and applies one translational TCP correction before marking. Across five target sites, mean error decreased from 7.40 ± 1.35 mm to 2.14 ± 0.36 mm. The mean paired decrease was 5.26 mm (95% confidence interval: 4.04-6.48 mm), and all sites improved by approximately 71%.

The result demonstrates feasibility under the tested configuration, not complete industrial validation. The study does not establish repeated-trial precision, rotational accuracy, camera metrological uncertainty, mark-quality repeatability, processing time, or robustness to environmental changes. Future work should report raw repeated measurements at documented workspace coordinates, compare calibrated and alternative vision baselines, quantify the full camera-to-robot uncertainty chain, measure orientation and mark geometry, and evaluate cycle time and robustness before broader deployment claims are made.

ACKNOWLEDGMENT

This study was funded by the research project “BR24992947 - Development of Robots, Scientific, Technical, and Software for Flexible Robotization and Industrial Automation (RPA) in Automotive Industrial Enterprises in Kazakhstan Using Artificial Intelligence”.

REFERENCES

- [1] Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, opportunities and future directions of smart manufacturing: a state of the art review. *Sustainable Futures*, 2, 100023.
- [2] Wu, J., & Tao, Y. (2020). Review on the research status of positioning accuracy reliability of industrial robots. *China Mechanical Engineering*, 31(18), 2180-2188.
- [3] Li, Z., Li, S., & Luo, X. (2021). An overview of calibration technology of industrial robots. *IEEE/CAA Journal of Automatica Sinica*, 8(1), 23-36.
- [4] Liao, W. H., Tian, W., Li, B., Li, P. C., Zhang, W., & Li, Y. F. (2022). Error compensation technology and its application progress of an industrial robot. *Acta Aeronautica et Astronautica Sinica*, 43(5), 627142.
- [5] Santolaria, J., Conte, J., & Ginés, M. (2013). Laser tracker-based kinematic parameter calibration of industrial robots by improved CPA method and active retroreflector. *The International Journal of Advanced Manufacturing Technology*, 66(9), 2087-2106.
- [6] Bai, Y., Zhang, B., Xu, N., Zhou, J., Shi, J., & Diao, Z. (2023). Vision-based navigation and guidance for agricultural autonomous vehicles and robots: A review. *Computers and Electronics in Agriculture*, 205, 107584.
- [7] Ding, T., Ouyang, P., Zhang, H., Feng, X., Hua, L., & Zhu, D. (2025). 3D vision-guided robotic grinding framework for repairing random defects. *IEEE Transactions on Automation Science and Engineering*, 22, 15819-15831.
- [8] Olzhayev, O., Tursynova, A., & Ibrayev, S. (2026). A Coordinate Transformation Framework for Vision-Guided Robotic Positioning in Automated Vehicle Body Marking. *International Journal of Advanced Computer Science & Applications*, 17(8), 568.
- [9] Hu, J., Hua, F., & Tian, W. (2020, March). Robot positioning error compensation method based on deep neural network. In *Journal of Physics: Conference Series* (Vol. 1487, No. 1, p. 012045). IOP Publishing.
- [10] Ma, S., Deng, K., Lu, Y., & Xu, X. (2023). Error compensation method of industrial robots considering non-kinematic and weak rigid base errors. *Precision Engineering*, 82, 304-315.
- [11] Olzhayev, O., Imanbayeva, N., Mamikov, S., & Baibek, B. (2025). A Novel YOLO-Like Multi-Branch Architecture for Accurate Apple Detection and Segmentation Under Orchard Constraints. *International Journal of Advanced Computer Science and Applications*, 16(11).
- [12] Ulrich, M., Steger, C., Butsch, F., & Liebe, M. (2024). Vision-guided robot calibration using photogrammetric methods. *ISPRS Journal of Photogrammetry and Remote Sensing*, 218, 645-662.
- [13] Li, Y., Li, B., Zhao, X., Cheng, S., Zhang, W., & Tian, W. (2023). Error similarity analysis and error compensation of industrial robots with uncertainties of TCP calibration. *Applied Sciences*, 13(4), 2722.
- [14] Zhang, S., & Qiao, Z. (2025). An autonomous calibration method for end-effector positioning error in robots using stereo vision closed-loop measurement. *The International Journal of Advanced Manufacturing Technology*, 139(7), 3511-3523.
- [15] Adamik, M., Babinec, A., Dekan, M., & Kovariková, Z. (2025, October). 6 DoF Robot Tool Path Generator for the Purpose of High-Precision Engraving of Unknown Surfaces. In *International Symposium on Measurements and Control in Robotics* (pp. 3-16). Cham: Springer Nature Switzerland.
- [16] Chen, T., Yang, W., Li, S., & Luo, X. (2025). Data-driven calibration of industrial robots: A comprehensive survey. *IEEE/CAA Journal of Automatica Sinica*, 12(8), 1544-1567.
- [17] Saleh, R. A., Nasser, S. F., & Abdullah, T. S. (2025, August). Advances in error compensation for robotic manipulators: a systematic review from geometric calibration to AI-driven hybrid control. In *2025 5th International Conference on Emerging Smart Technologies and Applications (eSmarTA)* (pp. 1-10). IEEE.
- [18] Wang, Z., Chen, J., San, H., Gong, M., Zhang, X., & Chen, W. (2025). Kinematic calibration of delta robots via model-free PSO-RBF prediction and compensation. *Measurement*, 118828.
- [19] Romano, G., Bilancia, P., Locatelli, A., Mucciarini, M., Iori, M., & Pellicciari, M. (2026). A machine learning-based tool for enhancing position accuracy in industrial robots with a reduced dataset. *Robotics and Computer-Integrated Manufacturing*, 101, 103289.
- [20] Che, C., Liu, B., Li, S., Huang, J., & Hu, H. (2023). Deep learning for precise robot position prediction in logistics. *Journal of Theory and Practice of Engineering Science*, 3(10), 36-41.
- [21] Raghunath, M. P., Deshmukh, S., Chaudhari, P., Bangare, S. L., Kasat, K., Awasthy, M., ... & Waghulde, R. R. (2025). PCA- and PSO-based optimized support vector machine for efficient intrusion detection in the Internet of Things. *Measurement: Sensors*, 37, 101806.
- [22] Wang, S., Yang, J., & Sang, X. (2026). Laser-Tracker-Based Robot Pose Measurement Using PSD Spot Sensing and Multi-Sensor Fusion with Simulation Validation. *Micromachines*, 17(3), 290.
- [23] Omarov, B., Omarov, B., Rakhymzhanov, A., Niyazov, A., Sultan, D., & Baikuekov, M. (2024). Development of an artificial intelligence-

- enabled non-invasive digital stethoscope for monitoring the heart condition of athletes in real-time. *Retos*, 60, 1169-1180.
- [24] Momynkulov, Z., Tursynova, A., Olzhayev, O., Ikramov, A., Ibrayev, S., & Omarov, B. (2025). Three-dimensional trajectory planning for robotic manipulators using model predictive control and point cloud optimization. *Computer Modeling in Engineering & Sciences*, 145(1), 891-918.
- [25] Maghami, A., & Khoshdarregi, M. (2024). Vision-based target localization and online error correction for high-precision robotic drilling. *Robotica*, 42(9), 3019-3043.
- [26] Li, Y., Lai, P., Yang, T., & Li, Z. (2026). Design and development of a machine-vision-based positioning compensation system for industrial robots. *Discover Applied Sciences*, 8, 174. <https://doi.org/10.1007/s42452-025-08196-3>
- [27] Zhang, Z. (2000). A flexible new technique for camera calibration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(11), 1330-1334. <https://doi.org/10.1109/34.888718>
- [28] Tsai, R. Y., & Lenz, R. K. (1989). A new technique for fully autonomous and efficient 3D robotics hand/eye calibration. *IEEE Transactions on Robotics and Automation*, 5(3), 345-358. <https://doi.org/10.1109/70.34770>
- [29] Horaud, R., & Dornaika, F. (1995). Hand-eye calibration. *The International Journal of Robotics Research*, 14(3), 195-210. <https://doi.org/10.1177/027836499501400301>
- [30] Park, F. C., & Martin, B. J. (1994). Robot sensor calibration: Solving $AX = XB$ on the Euclidean group. *IEEE Transactions on Robotics and Automation*, 10(5), 717-721. <https://doi.org/10.1109/70.326576>
- [31] Daniilidis, K. (1999). Hand-eye calibration using dual quaternions. *The International Journal of Robotics Research*, 18(3), 286-298. <https://doi.org/10.1177/02783649922066213>
- [32] Strobl, K. H., & Hirzinger, G. (2006). Optimal hand-eye calibration. In 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 4647-4653). IEEE. <https://doi.org/10.1109/IROS.2006.282250>
- [33] Jegadeesan, R., Beno, A., Manikandan, S. P., Rao, D. N. M., Narukullapati, B. K., Kumar, T. R., ... & Batu, A. (2022). Stable Route Selection for Adaptive Packet Transmission in 5G-Based Mobile Communications. *Wireless Communications and Mobile Computing*, 2022(1), 8009105.
- [34] Koide, K., & Menegatti, E. (2019). General hand-eye calibration based on reprojection error minimization. *IEEE Robotics and Automation Letters*, 4(2), 1021-1028. <https://doi.org/10.1109/LRA.2019.2893612>
- [35] Omarov, B. (2025). Deep learning in biomedical image and signal processing: a survey. *Computers, Materials & Continua*, 85(2), 2195-2253.
- [36] Jiang, J., Luo, X., Luo, Q., Qiao, L., & Li, M. (2022). An overview of hand-eye calibration. *The International Journal of Advanced Manufacturing Technology*, 119, 77-97. <https://doi.org/10.1007/s00170-021-08070-1>
- [37] Eneuse, I., Foo, M., Ibrahim, B. S. K. K., Ahmed, H., Supmak, F., & Eyobu, O. S. (2022). Accuracy evaluation of hand-eye calibration techniques for vision-guided robots. *PLOS ONE*, 17(10), e0273261. <https://doi.org/10.1371/journal.pone.0273261>
- [38] Hutchinson, S., Hager, G. D., & Corke, P. I. (1996). A tutorial on visual servo control. *IEEE Transactions on Robotics and Automation*, 12(5), 651-670. <https://doi.org/10.1109/70.538972>
- [39] Omarov, B., Baikukekov, M., Momynkulov, Z., Kassenkhan, A., Nuralkyzy, S., & Iglukova, M. (2023). Convolutional LSTM network for heart disease diagnosis on electrocardiograms. *Computers, Materials & Continua*, 76(3), 3745-3761.
- [40] Ibrayev, S., Omarov, B., Amanov, B., & Momynkulov, Z. (2024). Development of a deep learning-enhanced lower-limb exoskeleton using electromyography data for post-neurovascular rehabilitation. *Engineered Science*, 31, 1269.
- [41] Corke, P. (2017). *Robotics, Vision and Control: Fundamental Algorithms in MATLAB* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-319-54413-7>
- [42] Hartley, R., & Zisserman, A. (2004). *Multiple View Geometry in Computer Vision* (2nd ed.). Cambridge University Press. <https://doi.org/10.1017/CBO9780511811685>
- [43] Furgale, P., Rehder, J., & Siegwart, R. (2013). Unified temporal and spatial calibration for multi-sensor systems. In 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 1280-1286). IEEE. <https://doi.org/10.1109/IROS.2013.6696514>
- [44] Li, M., Du, Z., Ma, X., Dong, W., & Gao, Y. (2021). A robot hand-eye calibration method of line laser sensor based on 3D reconstruction. *Robotics and Computer-Integrated Manufacturing*, 71, 102136. <https://doi.org/10.1016/j.rcim.2021.102136>
- [45] Yang, X., Zhou, Z., Sorensen, J. H., Christensen, C. B., Unalan, M., & Zhang, X. (2023). Automation of SME production with a cobot system powered by learning-based vision. *Robotics and Computer-Integrated Manufacturing*, 83, 102564. <https://doi.org/10.1016/j.rcim.2023.102564>
- [46] Intel RealSense. (2024). Intel RealSense Camera D400 Series Product Family Datasheet (Revision 019). Intel Corporation.
- [47] Servi, M., Mussi, E., Profili, A., Furferi, R., Volpe, Y., Governi, L., & Buonamici, F. (2021). Metrological characterization and comparison of D415, D455, and L515 RealSense devices in the close range. *Sensors*, 21(22), 7770. <https://doi.org/10.3390/s21227770>
- [48] Hubner, P., Hou, J., & Iwaszczuk, D. (2023). Evaluation of Intel RealSense D455 camera depth estimation for indoor SLAM applications. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-1/W2-2023, 1207-1214. <https://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-1207-2023>
- [49] Placzek, M., & Piszczek, L. (2018). Testing of an industrial robot's accuracy and repeatability in off- and online environments. *Eksplotacja i Niezawodność - Maintenance and Reliability*, 20(3), 455-464. <https://doi.org/10.17531/ein.2018.3.15>
- [50] Jiang, Y., Yu, L., Jia, H., Zhao, H., & Xia, H. (2020). Absolute positioning accuracy improvement in an industrial robot. *Sensors*, 20(16), 4354. <https://doi.org/10.3390/s20164354>
- [51] Tao, Y., Liu, H., Chen, S., Lan, J., Qi, Q., & Xiao, W. (2023). An off-line error compensation method for absolute positioning accuracy of industrial robots based on differential evolution and deep belief networks. *Electronics*, 12(17), 3718. <https://doi.org/10.3390/electronics12173718>
- [52] Nubiola, A., & Bonev, I. A. (2013). Absolute calibration of an ABB IRB 1600 robot using a laser tracker. *Robotics and Computer-Integrated Manufacturing*, 29(1), 236-245. <https://doi.org/10.1016/j.rcim.2012.06.004>
- [53] International Organization for Standardization. (1998). ISO 9283:1998 Manipulating industrial robots - Performance criteria and related test methods. ISO.