Camera Calibration as a Software V&V Strategy for Safe Autonomous Indoor Drone Navigation

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Abstract

This study investigates the impact of onboard camera calibration on the accuracy and software testability of autonomous indoor drones in industrial environments. In Cyber-Physical Systems (CPS), uncalibrated optical noise often generates non-deterministic inputs, leading to flaky tests and false failures that compromise the software validation process. By comparing factory settings against a refined approach using ChArUco patterns to correct intrinsic parameters and lens distortions, we demonstrate that proper calibration reduced the maximum positioning error in the transverse axis (X) by approximately 63% at a 3-meter distance (dropping from 1.00,m to 0.37,m), while maintaining a vertical precision of 0.02,m. These findings highlight that precise optical adjustment is a critical Verification and Validation (VV) requirement rather than a mere hardware tuning step. By isolating physical noise from software logic bugs, our approach ensures deterministic testing and enables safe, autonomous intralogistics operations in GPS-denied environments, such as those found in the Manaus Industrial Pole.

Keywords

Drones, ChArUco, Camera Calibration, Indoor Navigation, Verification and Validation (V&V)

1 Introduction

The automation of logistical processes within enclosed warehouses represents a growing challenge for Industry 4.0, primarily due to the unreliability of Global Navigation Satellite System (GNSS/GPS) signals in indoor environments. In these settings, signals are often non-existent or unstable due to attenuation and shadowing caused by metallic structures and concrete obstacles [2]. In this context, Unmanned Aerial Vehicles (UAVs) configured as Cyber-Physical Systems (CPS) emerge as viable solutions for internal inspections due to their high mobility and capacity to flexibly collect video data without geographic restriction [4]. To enable intelligent autonomous navigation, structured grid mappings based on visual anchors are employed, relying on fiducial markers (such as ArUco) to estimate the drone's pose through 2D-3D correspondences [3].

The success of this approach, however, hinges on a critical factor: the optical distortions inherent in onboard cameras. The pose estimation algorithm is directly conditioned by the geometric quality of the processed image, and factory-standard parameters often prove insufficient to ensure the reliability required in narrow industrial aisles.

When left unaddressed, errors in the lens's intrinsic matrix propagate silently through the software layers. In the physical domain, this failure in geometric perception results in horizontal drift and critical oscillations in flight control [5]. Within the scope of Software Engineering and V&V, these distortions manifest as non-deterministic behaviors and false negatives during testing routines. Developers and quality assurance analysts may expend significant resources debugging routing meshes under the assumption of logical bugs, when the root cause fundamentally lies in the imprecision of the camera's optical calibration.

1.1 Industrial Context

This report presents the results of a project conducted by the Paulo Feitoza Foundation (FPFtech) in partnership with TPV (Envision), aimed at automating intralogistics processes within the Manaus Industrial Pole (PIM). The central motivation was to replace physical inventory auditing — a traditionally slow, manual process that exposes operators to severe risks associated with working at heights — with an autonomous aerial inspection ecosystem. To address this problem, the team designed an autonomous aerial inspection ecosystem that integrates Computer Vision, Artificial Intelligence, and Digital Twin concepts. In the developed architecture, the drone navigates through warehouse aisles guided by 3D grid mapping and visual anchors based on ArUco markers.

The main contributions of this work are: (i) the quantification of the impact of camera calibration on drone localization precision in an industrial environment; (ii) the framing of calibration as a critical V&V activity for the safety of Cyber-Physical Systems; (iii) the validation of the approach in a real-world logistical scenario, utilizing high-value-added assets.

2 System Architecture and Validation Methodology

To validate the reliability of the telemetry software within the proposed logistical context, a test environment was structured to replicate the physical constraints of an industrial aisle. From a software engineering perspective, the validation methodology aimed not only to measure precision but also to ensure the determinism of the Verification and Validation (V&V) process. This was achieved by treating calibration as a testability requirement to isolate logical failures from sensing noise. The methodology was divided into four stages:

(1) **Test Environment Setup:** A physical localization grid measuring 3,0 m × 4,0 m × 2,0 m (X, Y, Z axes) was established. An ArUco marker was positioned at fixed coordinates (X = 1,24, Y = 4,0, Z = 1,11) to serve as the *ground truth* reference.
(2) **Data Collection Protocol:** The drone was operated in a hovering state at three depth distances relative to the marker: 1 m, 2 m, and 3 m. To ensure statistical significance and isolate transient hardware anomalies, the protocol consisted of 20 independent runs (trials) for each depth level, totaling 60 telemetry essays. The objective was to evaluate the amplification of pose estimation error as a function of distance, stressing the limits of the computer vision algorithm and assessing the consistency of the optical noise across multiple runs.
(3) **Software Refinement via ChArUco:** Trials were conducted comparatively. First, telemetry was extracted using factory-default calibration. Subsequently, the standard intrinsic matrix was replaced with an optimized one, calculated using **ChArUco** patterns (Figure 1). This hybrid target integrates ArUco markers with a traditional chessboard to enable corner detection with subpixel precision. The presence of markers within the grid allows for the unique identification of corner coordinates via marker IDs, which facilitates reliable intrinsic calibration even when the calibration board is only partially visible in the captured frame [1]. This stage is fundamental to avoiding false negatives in integration tests, where optical errors could be misinterpreted as bugs in the control code.
(4) **Performance Metrics:** Localization error was evaluated by measuring the maximum variation of the estimated coordinates (X, Y, Z) relative to the actual physical position. The altitude (Z) was locked by the flight controller during measurements to isolate horizontal lateral deviation (*drift*) as the primary analysis variable. This metric validates whether the control loop receives stable data, eliminating non-deterministic behaviors (*flaky behaviors*) that would hinder software certification in an industrial environment.

2.1 Hardware Implementation and Vision Module

The proof of concept was developed using a commercial DJI Mavic 3E drone. For visual anchoring, we utilized 9x9 cm printed ArUco markers (from the `DICT_4X4_1000` dictionary).

Pose estimation is performed using the `solvePnP` function from the OpenCV library, which resolves the correspondence between the 3D coordinates of the physical marker and its 2D projections onto the optical sensor plane. Supplying this function with refined intrinsic parameters, rather than factory defaults, was the core focus of this V&V validation.

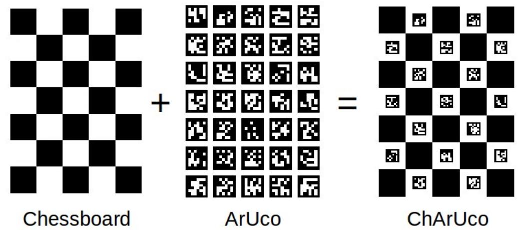

Figure 1: ChArUco Pattern: the basis for subpixel calculation of the intrinsic matrix.

2.2 Data Architecture: The Three-Dimensional Mapping (3D Grid)

To enable intelligent navigation without GPS signals, the system represents the physical warehouse as a manipulable data structure. The continuous environment is discretized into a *3D Occupancy Grid Mapping* — a spatial matrix where ArUco markers function as static *landmarks*, pre-registered at known absolute coordinates.

During runtime, the integration between visual perception and the navigation software occurs continuously. When the `solvePnP` function detects a marker, it calculates the relative translation and rotation of the camera. Subsequently, a geometric transformation converts this estimate to update the drone's absolute position within the three-dimensional matrix.

This visual update provides the positional reference for the control loop to execute routes without accumulating inertial sensor error. Consequently, the integrity of this entire logical mapping is critically dependent on the camera's mathematical precision: any unaddressed optical distortion will corrupt the coordinates calculated in the *3D Grid*, inducing the drone to navigate to the incorrect cell.

3 Results and Discussion of Software Impact

Experimental analysis demonstrated that addressing lens distortion at the software level substantially improves UAV flight stability. The results presented in Table 1 reflect the aggregated measurements from the 20 independent trials performed at each distance. Across all iterations, the post-calibration behavior exhibited high consistency, drastically reducing the data variance and eliminating the flaky behaviors previously observed in the telemetry logs. Table 1 presents a comparison of the maximum deviation on the X-axis, which is historically the most vulnerable axis to optical noise in longitudinal navigation scenarios.

Table 1: Maximum observed variation in the longitudinal X axis (m)

Actual Distance (Y)	Without Calib.	Post-Calib.	Improvement (%)
1 m	0,06	0,04	33,3
2 m	0,31	0,17	45,1
3 m	1,00	0,37	63,0

During the trials, the altitude (Z) was software-locked to isolate the impact of calibration on the horizontal navigation plane. The residual deviation on the vertical axis was only 0.02 m, which is consistent with natural motor vibration. In contrast, the precision on the X-axis revealed the direct impact of calibration: the 63% error reduction at a 3-meter distance represents the difference between a safe operation and a collision with shelving units.

With factory-default parameters, even minimal angular estimation uncertainty propagated geometrically, displacing the drone by up to 1.00 m at a distance of 3 meters from the target, a margin incompatible with the width of industrial aisles in the PIM. Correcting the coefficients reduced this error to 0.37 m, which falls within the safe operational margin.

This improvement is visually evident in the spatial dispersion of telemetry during hovering. Figure 2 illustrates the captured point cloud. At 1.2 meters (Figure 2b), the system displays a dense cluster with minimal variance. At 3 meters (Figure 2a), the uncertainty volume increases consistently, demonstrating that instability does not stem from isolated events, but rather from continuous oscillation caused by the low apparent resolution of the marker at long distances. It can be observed that while precision remains at the centimeter level at short distances, the error grows non-linearly as the marker occupies a smaller area on the optical sensor 3.

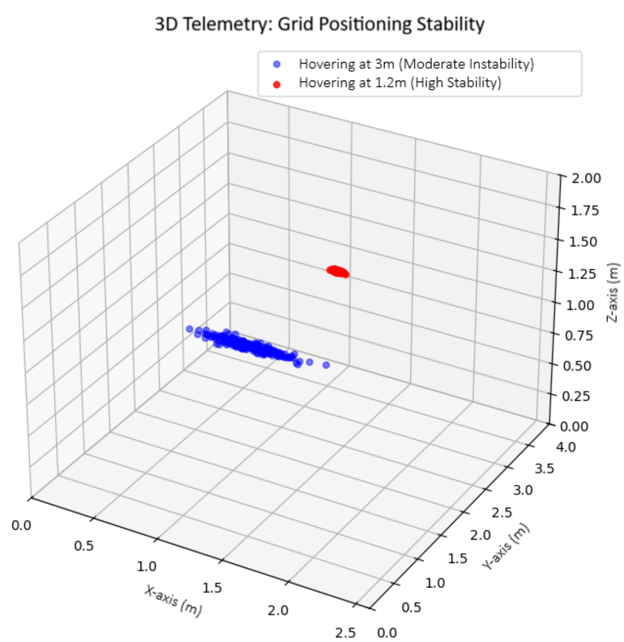

Figure 2: Stability mapping: (a) Inherent oscillation at 3 meters; (b) High cohesion and precision at 1.2 meters.

3.1 Dynamic Trajectory Evaluation in Aisles

To evaluate the feasibility of the control loop in a scenario analogous to a logistical aisle, the system underwent an autonomous movement trial. Figure 4 illustrates the telemetry recorded during the execution of a quadrangular path at a fixed altitude ($Z \approx 1{,}10$ m).

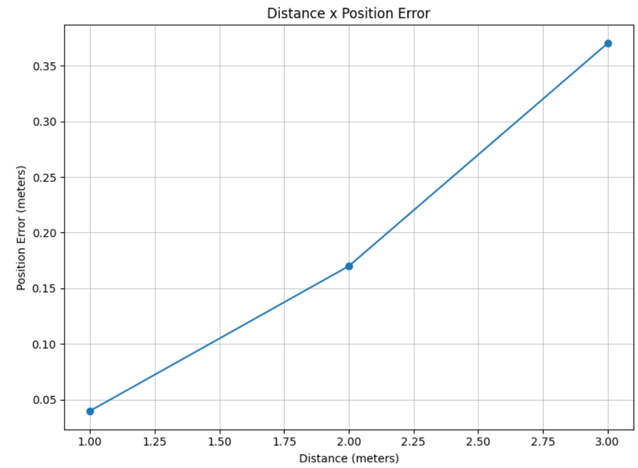

Figure 3: Non-linear growth curve of X-axis telemetry error as a function of actual distance.

The platform maintained the geometric cohesion of the circuit, recording a loop closure error of only 0,35 m, a margin compatible with the standard width of industrial aisles in the PIM.

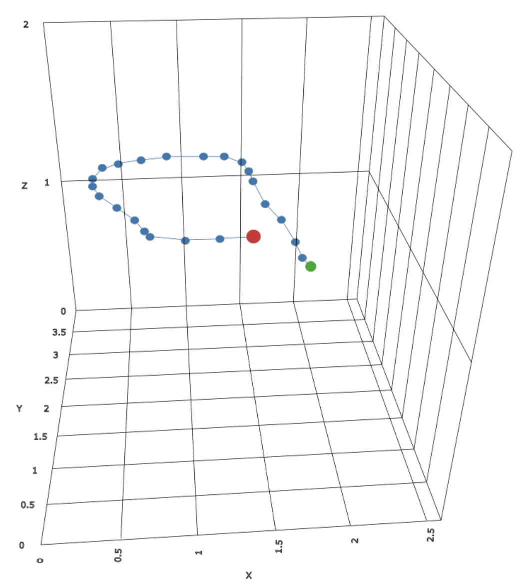

Figure 4: Estimated telemetry during a closed-circuit dynamic routing test.

3.2 Lessons Learned and Industrial Recommendations

The execution of this project in a real-world environment allowed the consolidation of practical learnings that go beyond computer vision theory, serving as a guide for other intralogistics automation initiatives:

- **Fallibility of Factory Parameters:** For high-value assets and tasks in narrow aisles, intrinsic factory parameters are insufficient. What initially appeared to be acceptable noise proved to be a concerning collision risk. Companies must treat calibration not as an optional adjustment, but as one of the primary V&V safety *gates* of the solution.
- **Lighting and Materials:** Industrial reflections on common surfaces (paper/vinyl) saturate pixels and degrade marker detection. The use of matte materials is essential to ensure pose accuracy in environments with variable lighting.
- **Periodic Calibration:** Physical impacts and thermal variations in the warehouse alter optical alignment. It is recommended to treat the revalidation of the intrinsic matrix as preventive maintenance, integrating it into the asset's health *checklist*.
- **Determinism in Software Testing:** The lack of optical calibration generates noisy pose data, resulting in inconsistent field tests (*flaky tests*). Treating calibration as a fundamental V&V step allowed the team to decouple logical code failures from physical hardware noise, drastically optimizing debugging time for the development and Quality Assurance (QA) teams.

Given that the UAVs employed in these missions are high-value corporate assets, methodological rigor in the perception layer is a business necessity. The treatment of intrinsic matrices acts as an essential data sanitization process, preventing angular errors (such as *yaw*) from propagating through the logical layers of the navigation software. Therefore, the central recommendation of this report is that the calibration methodology be formalized as a Technical Acceptance Criterion for any drone deployment in intralogistics missions, ensuring that software sophistication is not held hostage by hardware inconsistencies.

3.3 Project Outcomes and Deployment Status

Regarding the macro industrial adoption, the autonomous inspection ecosystem is currently in its final phase of deployment and homologation within the factory floor. The primary initial goal of replacing manual, high-risk inventory audits at extreme heights has proven technically viable during the current pilot phase. The system is actively being tested and validated in a designated section of an industrial aisle, and the physical infrastructure is currently being scaled up to cover the entire warehouse, with an estimated total of 8,000 fiducial markers undergoing installation.

Although the autonomous system has not yet definitively replaced the human workforce—operating under assisted validation parallel to human operators during this stage—the flight stability and deterministic behavior achieved through software-level camera calibration provided the necessary V&V safety guarantees. This validation step was the critical milestone required to safely expand the infrastructure to the remaining aisles and confidently transition to a 100% unmanned operation.

4 Conclusion and Future Work

The obtained results indicate that, in the context of Cyber-Physical Systems, optical calibration transcends simple hardware maintenance, assuming the role of a critical Verification and Validation (V&V) requirement. The absence of proper treatment for lens distortion introduces direct noise into the perception layer. Consequently, the control loop must handle positioning fluctuations and non-deterministic behaviors (*flaky behaviors*), masking real logical failures and compromising the reliability of software tests.

By applying the ChArUco pattern, a 63% reduction in pose estimation error on the X-axis was observed (from 1.00m to 0.37m). More than a metric precision gain, this improvement acted as an essential input data sanitization step that proved crucial for the real-world deployment, which is currently scaling to accommodate a warehouse-wide infrastructure of 8,000 navigational markers. With the mitigation of false detections that caused route validation to fail, debugging efforts could be assertively focused on control and navigation logic. Consequently, the pilot system achieved the necessary maturity for its current homologation phase, paving the way to entirely replace human operators in high-risk inventory tasks across the entire facility.

For the upcoming development cycles, technical effort should migrate from the isolated optimization of precision to the continuous quality assurance of the ecosystem. The *roadmap* prioritizes three fronts:

- **Continuous V&V:** Integrate calibration validation into regression testing *pipelines*, allowing the monitoring of optical deviations throughout the equipment's lifespan;
- **Sensor Fusion:** Incorporate stochastic filters (such as the Kalman Filter) to couple computer vision with inertial odometry, ensuring stable telemetry even during temporary marker occlusion;
- **Dynamic Recalibration:** Design update routines for the intrinsic matrix capable of compensating for physical impacts and natural thermal variations of daily operations on the factory floor.

Artifact Availability

Repository cannot be shared due to industrial restrictions and confidentiality constraints.

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