Computer Vision System for Dimension Control in the Prefabrication of Concrete Panels

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Abstract

This paper presents a computer vision system for dimensional quality control of concrete panel formwork. The methodology combines corner detection with photogrammetric principles to analyse overhead images of formwork assemblies, comparing detected geometries with design specifications. Validation on synthetic images demonstrates high accuracy, with mean absolute errors below 1.12 mm for dimensional and 0.02° for orientation measurements. While application to real-world factory conditions revealed challenges in corner detection requiring future improvements, the established framework provides a foundation for automated quality control in concrete prefabrication, enabling early detection of assembly errors before concrete placement.

1 Introduction

Computer vision systems are increasingly transforming industrial quality control processes, offering new possibilities for automated inspection and dimensional verification [1, 2]. In the construction sector, prefabricated concrete elements represent a crucial advancement toward more efficient, sustainable building practices. These elements accelerate construction timelines and enable circular construction approaches through component reuse, addressing challenges of affordable housing and climate change mitigation.

The success of prefabricated concrete systems depends on precise dimensional control during manufacturing, particularly when considering extended service life and component reuse. Dimensional deviations can compromise assembly efficiency, structural performance, and durability. While image-based methods have shown success in various industries [3-5], their adoption in construction has been limited by implementation complexities [6-9].

This paper presents a novel approach to dimensional control in concrete panel prefabrication, focusing on formwork verification prior to concrete casting. The methodology combines computer vision techniques with photogrammetric principles to analyse overhead images of formwork assemblies, identifying dimensional deviations when corrections are still feasible.

While existing image-based quality control systems, particularly in more digitalized industries, have shown promising results, they often require significant infrastructure investments and process modifications. Our approach prioritizes seamless integration with existing prefabrication workflows, requiring minimal additional infrastructure compared to existing quality control systems. This practical focus introduces challenges related to image quality and environmental variability, necessitating robust algorithms for reliable real-world performance.

The key contributions of this work include: a modular quality control framework for integration into existing processes, a robust algorithm combining computer vision with photogrammetric principles, and a systematic validation progressing from synthetic to real-world scenarios, demonstrating both theoretical and practical aspects of the methodology.

The remainder of this paper is organized as follows: Section 2 reviews the state of the art in computer vision applications for construction quality control. Section 3 details the proposed methodology, presenting a systematic workflow from image acquisition to deviation detection. Section 4 addresses practical implementation challenges in industrial environments, focusing on robust feature detection under real-world conditions. Section 5 presents the validation of the methodology using both synthetic and real-world images. Finally, Section 6 discusses results, limitations, and future research directions.

2 State of the Art and Related Work

The use of computer vision system for dimension control in manufacturing and industry, to measure and inspect the dimensions of products and components with high precision, is widely developed in scientific research and has already been broadly applied in some industries. They are most prevalent in industries such as Printed Circuit Board (PCB) manufacturing, for detecting solder joint defects, component misalignment, and missing components [10, 11], and the automotive Industry, for ensuring that all parts meet precise specifications to assembly the vehicle and maintain safety and performance [12, 13].

It's also important to mention that computer vision systems can perform real-time inspections. This allows to ensure products meet specified dimensions and tolerances, supporting the early identification of defects during the production process. These systems can automatically measure dimensions such as length, width, height, and angles, among other parameters, ensuring consistency and accuracy of the products. They can also inspect surface characteristics such as texture, roughness, and colour, detecting any deviations from the target specifications [14, 15].

Implementing computer vision in the construction sector clearly offers many benefits, but it also comes with several challenges, many related to the dynamic outdoor environment of a construction site [16]. In the prefabrication industry, while factory operations are possible, many issues identified on construction sites persist [17]. These include varying lighting conditions and the need for skilled personnel with expertise in both construction and computer vision.

In summary, computer vision systems enable to achieve high accuracy and enhance productivity since speed up production lines. In addition, they can also contribute to monitor safety compliance, ensuring that workers follow safety protocols. However, specific problems related to application in the construction industry exist and some have been identified; it is now up to the technical-scientific community to work on their resolution.

3 Proposed Workflow for Image-based Dimension Control

This section presents a computer vision workflow for dimensional control of concrete panel formwork. As illustrated in Fig. 1, the process consists of six main steps: overhead image acquisition, preprocessing to enhance geometric features, corner detection, comparison with projected design specifications, deviation computation, and visualization overlay. This workflow enables quick identification of assembly errors through automated geometric analysis.

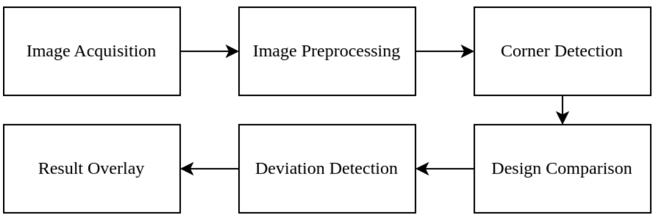

Fig. 1 Flowchart of the proposed methodology.

The methodology prioritizes robustness and practical applicability, utilizing established computer vision techniques within industrial prefabrication environments. The modular design allows independent improvements to each processing step without affecting the overall workflow.

Successful implementation of the proposed method requires well-defined quality requirement parameters for formwork assembly. As shown in Fig. 2, our industry partner's tolerances vary by component size: ±2 mm for dimensions up to 0.5 m, and ±5 mm for longer dimensions. Panel thickness has an asymmetric tolerance of + 0-2 mm due to structural requirements, while openings must maintain positions and dimensions within ±5 mm. These tolerances represent typical industry standards but may vary based on specific application requirements.

Measure		Tolerance
A & B	≤ 0.5 m	± 2 mm
A || B	> 0.5 m	± 5 mm
C		+ 0 – 2 mm
Openings: Position and Dimensions		± 5 mm

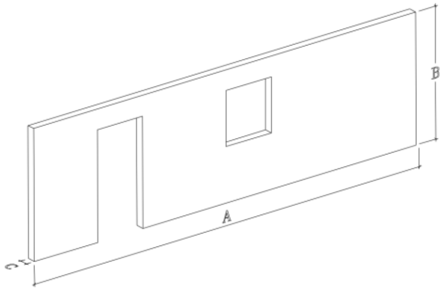

Fig. 2 Admissible tolerances for prefabricated concrete panels in our partner facility.

The computer vision system enables more precise and consistent deviation detection than traditional manual measurements. While current tolerances as shown in Table 1 reflect conventional quality control capabilities, improved measurement precision through automation could allow tighter tolerances without increasing rejection rates, ultimately leading to higher quality products with better fit accuracy and improved performance characteristics.

3.1 Image Acquisition

The presented methodology uses a straightforward image acquisition setup that integrates into existing prefabrication facilities. As shown in Fig. 3, a single camera is mounted above the production area, either fixed to the facility's roof or attached to an existing portal crane. While crane mounting offers flexible positioning, it requires accounting for camera location variability in processing. The harsh industrial environment, with concrete dust exposure, necessitates regular optical system maintenance.

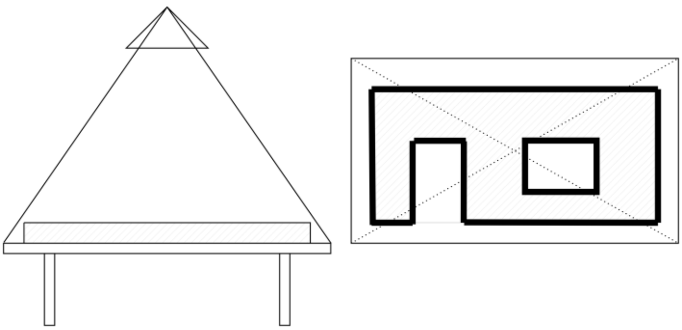

Fig. 3 Schematic of the proposed setup for image acquisition. A single camera is mounted above the production area to capture nadir images of the panels and formwork.

Accurate system calibration is crucial for dimensional measurements. This includes precise knowledge of the camera's position relative to the working area and the camera's internal parameters, particularly lens distortion characteristics. While the initial setup requires careful measurement of the camera height and position, recalibration can use reference features like table edges to adjust for position changes, or calibration boards.

The selected camera hardware must ensure sufficient spatial resolution to detect dimensional deviations at the required tolerance levels. The ground sampling distance (GSD) - the physical distance represented by each pixel in the image - must be significantly smaller than the minimum tolerance to be detected. For a given camera height and sensor parameters, the GSD can be calculated using the triangular relations between the size of a pixel on the sensor and on the surface.

As shown in Fig. 3, the camera orientation relative to the panel aligns the image's longer dimension (width) with the panel's length, maximizing the available resolution for dimensional measurements. For panels exceeding the field of view, 90-degree camera rotation and image stitching may be necessary.

Fig. 4 shows an example of a synthetic image created for the development and demonstration of the presented methodology. The image is in the recommended orientation, such that the long side of the panel aligns with the width of the image and the entire panel is contained.

Fig. 4 Example of a synthetic image created for the development of the presented methodology.

While synthetic images clearly demonstrate the methodology, real factory conditions present significant challenges, as shown in Fig. 5. Temporary installations and manual image capture introduce practical difficulties in achieving optimal viewpoints. These two images demonstrate the challenging requirements of the integration into existing fabrication processes. Due to optimized schedules and utilization of the available installations, often no dedicated area for experiments is available and the following data processing needs to accommodate for this.

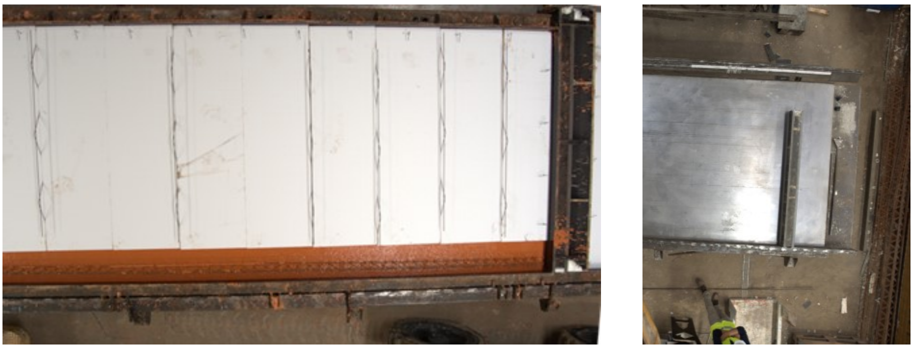

Fig. 5 Two overhead images captured during experiments at our partners factory showing the challenges of the real-world application.

3.2 Image Preprocessing

The preprocessing stage prepares the raw images for geometric analysis through several essential steps. First, geometric calibration corrects lens distortion and perspective effects using previously determined camera parameters, ensuring accurate dimensional measurements in the image space. The calibrated image is then cropped to remove any occlusions from surrounding equipment or structures that might interfere with the analysis, as can be seen in the right image of Fig. 5.

A critical step is the rotation and alignment of the image to ensure the panel edges are parallel to the image axes, simplifying subsequent geometric analysis. This alignment is typically performed using the table edges as reference features. Depending on lighting conditions and image quality, additional preprocessing may include colour correction and brightness adjustment to enhance the visibility of formwork elements against the background.

Fig. 6 Resulting image after the preprocessing, applying rotation and crop to isolate the relevant part and remove.

These preprocessing operations, while standard in computer vision applications, are crucial for ensuring reliable performance of the subsequent corner detection and dimensional analysis steps. The specific parameters for each operation are determined during system calibration and may require periodic adjustment based on environmental conditions.

3.3 Corner Detection

The detection of formwork corners represents the next step in the dimensional analysis pipeline and is critically important for the success of the methodology. Only if the corners are correctly, precisely, and with high accuracy (subpixel), the analysis can produce the expected outputs. Our approach employs the Harris corner detector [18], which identifies points in the image where the intensity changes significantly in multiple directions. This method is particularly suitable for formwork analysis as it reliably detects the sharp corners formed by intersecting formwork elements.

The corner detection process begins with the conversion of the pre-processed image to grayscale, followed by the application of the Harris corner detector. The detector analyses local image patches to identify potential corner points based on intensity gradients. Key parameters in this process include the analysis window size (block size), the size of the Sobel operator for gradient computation (kernel size), and the Harris detector free parameter k. The detected corners are then refined through non-maximum suppression and thresholding to eliminate weak responses.

For each pixel position (x, y), the Harris detector computes a corner response R based on the eigenvalues of the local structure tensor, as in (1).

$$M = \sum_{(x,y)\in W} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \sum_{(x,y)\in W} I_x^2 & \sum_{(x,y)\in W} I_x I_y \\ \sum_{(x,y)\in W} I_x I_y & \sum_{(x,y)\in W} I_y^2 \end{bmatrix} \tag{1}$$

Where I_x and I_y are image gradients in x and y direction, W is the window area around the pixel, and k is an empirical constant. A strong positive response R indicates the presence of a corner, which can be approximated based on the determinant and trace of the matrix together with an empirically determined parameter k:

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2 = \det(M) - k\,\mathrm{tr}(M) \tag{2}$$

As illustrated in Fig- 7, the corner detection typically identifies more points than just the formwork corners of interest. Additional corners may be detected at texture changes, shadows, or other geometric features present in the image. This over-detection is intentional at this stage, as it ensures no critical formwork corners are missed. The subsequent design comparison step (Section 3.4) will filter these candidates to identify the relevant formwork corners based on geometric constraints.

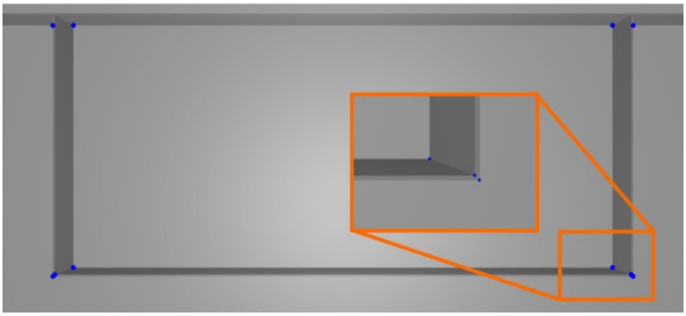

Fig. 7 Detected corners in a synthetic image with a zoomed in detail. The formwork corners can reliably be detected, even though more than just the inner corners of interest are found.

While this approach performs exceptionally well on synthetic images with clear edges and high contrast, real-world factory conditions present significant challenges (see Figure5). Issues such as varying lighting conditions, shadows, highlights, reflections, surface texture variations, and partial occlusions can lead to both false positives and missed corners. These practical challenges and our proposed solutions for robust corner detection in real world industrial environments will be discussed in detail in Section 4.2.

3.4 Design Comparison

The comparison between designed and actual panel dimensions requires accurate projection of the designed corner coordinates onto the image plane. This projection process relies on the pinhole camera model, where three-dimensional world coordinates are transformed into two-dimensional image coordinates. The transformation requires both intrinsic camera parameters (focal length, principal point, and distortion coefficients) and extrinsic parameters (camera position and orientation relative to the production floor). The accuracy of this projection directly impacts the subsequent dimensional analysis, making precise camera calibration crucial for reliable measurements.

Fig. 8 The planned outline of the panel dimensions is projected onto the image and marked as yellow. This allows the easy comparison of the planed and the real panel.

Fig. 8 illustrates the result this projection process, showing the designed panel outline superimposed on the captured image, where the alignment between projected and detected corners provides a visual confirmation of the calibration accuracy and serves as the foundation for subsequent deviation measurements. The method establishes correspondences by matching each projected corner to its nearest detected corner within a search radius. This assumes deviations remain within reasonable bounds and all corners are visible - a practical assumption since excessive deviations would indicate significant defects visible to manual inspection during the assembly.

Fig. 9 demonstrates this approach using a synthetic panel with a 2° rotation of its right edge. The deviation creates systematic displacements between projected and detected corner pairs: leftward offset at the top corner and rightward at the bottom. These patterns provide immediate visual cues about manufacturing deviations before detailed measurement.

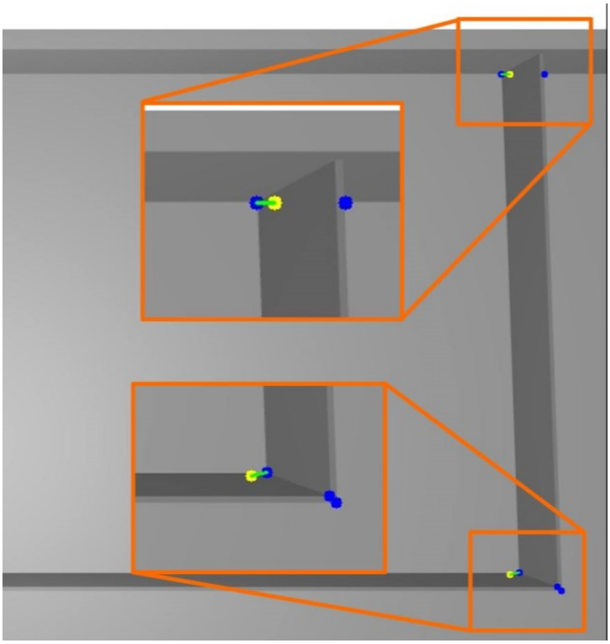

Fig. 9 Result of the matching of projected and detected image corners. The panel in this example has a rotation deviation on the right side, so the distances between the points are asymmetric. Points that are further away are not matched to projected corners and filtered out for further analysis.

This visualization method proves particularly valuable for rapid quality assessment, as systematic deviations in corner positions often indicate specific types of manufacturing errors - in this case, a rotation of one edge that could result from improper formwork alignment or uneven concrete settling. The quantitative analysis of these deviations and their interpretation will be detailed in the following section on deviation detection.

3.5 Deviation Detection

The geometric quality control of concrete panel formwork focuses on two critical types of deformation: orientation deviations that indicate rotational errors of the sides of the formwork, and dimensional deviations that reveal changes in the panel's width and height. By analysing these deformations independently before casting, we can identify issues with the formwork placement and adjust before the current form is set in stone.

A measurement reference system is defined which uses the fixed steel edge at the top of the production table against which the formwork is assembled, with the top-left corner serving as coordinate origin, since dimensional quality control focuses on the formwork geometry rather than its absolute position. For analysis, corners are sorted clockwise from the top-left, defining panel sides as vectors between consecutive corners, with their normal vectors pointing outward. This consistent ordering ensures reliable comparison between design and actual geometry.

The orientation analysis computes the angular difference between corresponding sides in the design and assembled formwork, correctly handling the circular nature of angular measurements at the 0°/360° boundary, avoiding discontinuities in the analysis. The deviation from design orientation indicates potential issues with formwork element alignment that need to be corrected before casting.

The dimensional analysis focuses on deviations in formwork width and height. For each side, we compute the midpoint in both projected and detected geometries, which not only decouples dimensional analysis from orientation errors, but also provides increased measurement robustness if corner detections contain uncertainties through averaging. The deviation vector between corresponding midpoints is projected onto the side's normal direction, yielding the effective dimensional change, with positive values indicating outward displacement and negative values indicating inward displacement. The final deviations combine corresponding sides: width changes from left and right deviations, height from top and bottom.

The computed orientation and dimensional deviations are evaluated against the previously defined tolerance thresholds to determine formwork compliance. As established in the beginning of Section 3, dimensional deviations must remain within ±5mm for most elements, angular deviations of within 1° from their designed orientation. Exceeding these thresholds flags the formwork for adjustment before casting proceeds.

3.6 Result Overlay

To provide immediate visual feedback about formwork quality, we overlay the analysis results directly on the captured image. Formwork edges are color-coded: green indicates orientation within tolerance, while red highlights edges exceeding angular deviation thresholds, with the specific deviation value displayed alongside.

Dimensional deviations are shown through proportional arrows at the midpoint of each side, with red outward-pointing arrows indicating oversized dimensions and blue inward-pointing arrows showing undersized dimensions. Each arrow is accompanied by its numerical deviation value. Figure 10 demonstrates this overlay system, showing. This intuitive visualization enables operators to quickly identify issues requiring attention while providing the quantitative information needed for precise formwork adjustment.

4 Transfer onto Real-World Images

The methodology has so far been presented and developed for synthetic images of formwork installations to easily convey the ideas and structure the proposed workflow. The goal is however to apply the method for dimension control on real-world images from the factory environment. For this, the method is first tested as-is on real captured images to assess the initial performance. Then, different extensions and adjustments are proposed to adapt the method to the more challenging conditions.

4.1 Performance and Suitability of the Original Approach

The application of the unmodified corner detection to the real-world images demonstrated the shortcomings of the simple corner detection method developed for the synthetic images with clear surfaces and strong edges. As can be seen in Figure 10, the corner detection on the real-world images introduces many false positive detections, marked by the blue dots.

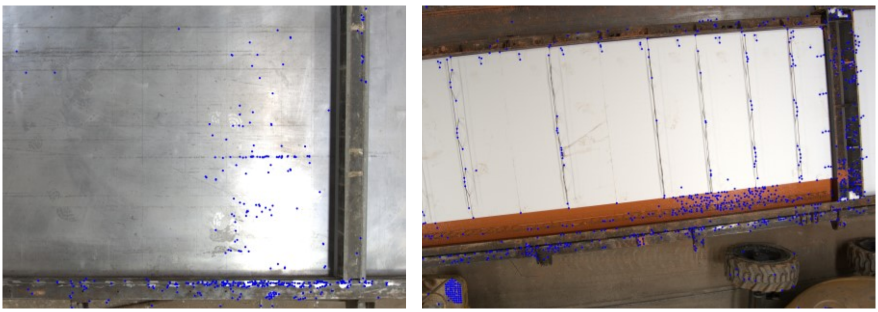

Fig. 10 Application of the developed method for corner detection on real world images with many false positive corners identified in the images.

While some additional corners are detected in the synthetic images, they correspond to real corners of the formwork and can be filtered out during the matching procedure described in Section 3.4. For the real images, this filtering is not applicable, due to the large number and wide distribution of detected corners. Instead, other adjustments are required, as discussed in the next section.

4.2 Proposed Adjustments to the Processing

To address the limitations identified in real-world image processing, several key adjustments to the methodology are proposed. First, the corner detection strategy needs enhancement, potentially incorporating multi-scale detection methods or machine learning approaches trained on annotated production images. This can help distinguish true formwork corners from artifacts caused by shadows, surface irregularities, or nearby equipment.

The filtering of false positives and corner matching requires a more sophisticated approach than the current methods. A possible solution combines the analysis of local image features around detected corners with geometric constraints derived from known panel dimensions. This could be integrated with graph-based matching algorithms that consider the overall panel geometry as a search prior, helping maintain correct corner associations even with significant deviations or numerous false detections.

Finally, the registration between image space and projected geometry can be refined. While the current approach assumes perfect camera calibration, real-world applications can benefit from an iterative refinement step that minimizes projection errors using stable reference features on the production table, to help compensate for minor camera movements and calibration uncertainties.

5 Validation of the Proposed Methodology

To validate the performance of the proposed methodology, it is first applied to different synthetic images, where a quantitative evaluation is performed. Then, the transfer on real-world images is shown and analysed.

5.1 Validation on Ideal Synthetic Images

The performance of the proposed formwork inspection method was evaluated through both qualitative and quantitative tests using synthetic images. Initial validation used a set of three test cases with known deviations: (1) a height deviation, (2) a rotation of the left formwork side, and (3) a combination of width deviation and left side rotation. As shown in Figure 11, the method successfully identified and correctly decomposed these deviations into their orientation and dimensional components, demonstrating its ability to distinguish between different types of formwork misalignment.

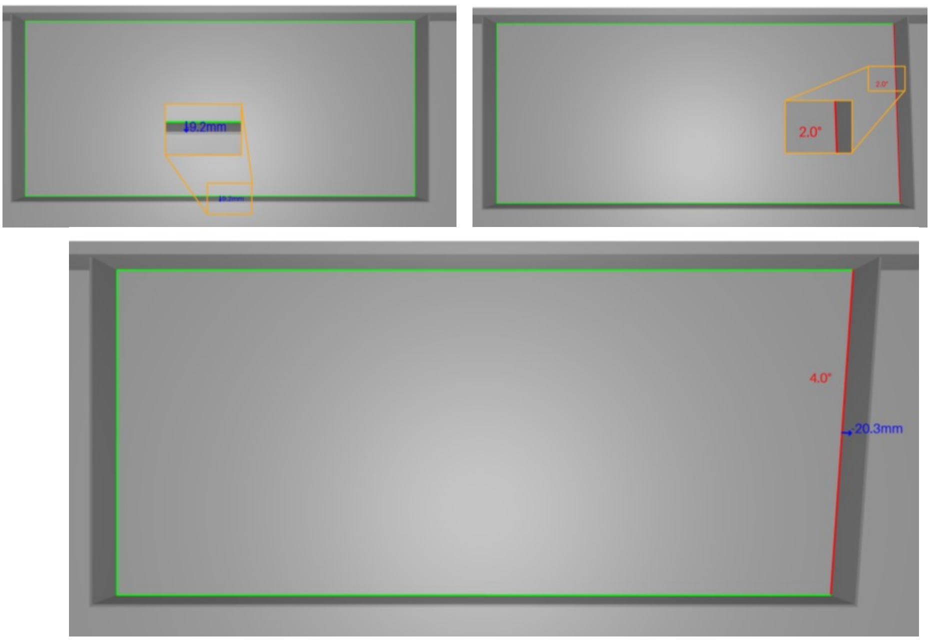

Fig. 11 Overlay of the results of the evaluation on the image. The sides are coloured depending on the orientation and the arrows indicate deviations in the dimensions.

For quantitative validation, we generated a test set of 2401 synthetic images covering various combinations of deviations in three parameters: left side orientation (Δo_l), right side orientation (Δo_r), width (Δw), and height (Δh). Each image was analysed using the proposed method, and the detected deviations were compared to the known ground truth values. Table 1 presents the statistical analysis of these results, showing the mean absolute error (MAE), the maximum error, the root mean squared error (RMSE), and the standard deviation.

Table 1 Results of the quantitative evaluation of the proposed method on synthetic images.

Parameter	MAE	Max. Error	RMSE	Std. Dev.
Δw	0.99 mm	2.87 mm	1.16 mm	0.70 mm
Δh	1.12 mm	2.11 mm	1.17 mm	0.35 mm
Δo_l	0.019°	0.046°	0.022°	0.012°
Δo_r	0.020°	0.054°	0.024°	0.013°

The performance analysis of our methodology shows a clear distinction between synthetic and real-world applications. On synthetic images, where corner detection is reliable, the system achieves high measurement accuracy. The analysis of 2401 test cases with known deviations shows mean absolute errors (MAE) of -0.99 mm for width measurements and -1.12 mm for height measurements. The orientation measurement of the left side achieves an MAE of 0.019° and the right side 0.020°. Maximum errors remain below 2.87 mm, 2.11 mm, 0.046°, and 0.054° respectively, well within typical tolerances for precast concrete elements.

The low RMSE values (around 1.15 mm for dimensions and 0.023° for angles) together with small standard deviations (below 0.52 mm and 0.012° respectively) demonstrate consistent measurement performance across the test dataset. The close alignment between MAE and RMSE values indicates reliable system performance with few outlier measurements.

5.2 Validation on Real-World Images

The application of the methodology to real-world images revealed significant challenges that currently prevent quantitative performance evaluation. The high number of false positive corner detections, as shown in Figure 10, makes reliable corner matching impossible with the current implementation. This effectively blocks subsequent processing steps, as both orientation and dimensional analyses depend on accurate corner identification and matching.

While visual inspection confirms that the methodology's overall approach is sound, meaningful quantitative validation on real-world data must await implementation of the proposed processing adjustments outlined in Section 4.2. This particularly includes the enhanced corner detection and more robust matching strategies.

5.3 Achievable Accuracy

The performance analysis on synthetic images demonstrates our system's capability to detect dimensional deviations at production-relevant scales. With mean absolute errors of 0.99 mm for width and 1.12 mm for height measurements, the system can reliably detect deviations well within the industry standard tolerance of ±5 mm. Maximum errors of 2.11 mm (width) and 2.87 mm still provide substantial margin against this tolerance threshold.

Angular deviations as small as 0.1° can be detected confidently, given the orientation MAE of 0.02° and maximum error of 0.05°. This is well below the typical 1° tolerance for formwork alignment. However, these detection capabilities are currently limited to synthetic images, as reliable corner detection in real-world conditions remains a challenge.

6 Discussion and Final Remarks

We developed the workflow presented in this work with four sequential stages: image acquisition, preprocessing, geometric analysis, and feedback generation. The image acquisition uses an overhead camera system to capture images of the formwork setup, using a fixed edge on the production table as spatial reference. In the preprocessing stage, geometric camera calibration and image rectification was applied to ensure measurement accuracy. The Harris corner detector was implemented to identify formwork vertices and establish correspondences with the planned geometry.

The geometric analysis was designed with a two-component approach that separates orientation and dimensional deviations. This separation enabled us to precisely identify errors in both rotational alignment and actual dimensions based on the calculated midpoints along formwork edges to enhance measurement robustness against local irregularities. Visual feedback through an augmented image overlay is provided, where we display color-coded deviations and numerical measurements based on predefined tolerance thresholds derived from the practical criteria of modular construction.

6.1 Performance of the Proposed Methodology

The validation results demonstrate two distinct aspects of our methodology's performance. For synthetic images, the system achieves high measurement accuracy with mean absolute errors of 0.99 mm and 1.12 mm for width and height measurements respectively, and 0.02° for orientation detection. These values, along with maximum errors staying below 2.87 mm and 0.05°, demonstrate the methodology's capability to reliably detect deviations well within industry tolerances of ±5 mm and ±1°.

However, application to real-world factory images revealed significant challenges, primarily in the corner detection stage. The high number of false positives in industrial environments currently prevents stable measurements, indicating necessary improvements in the processing pipeline. We identified key areas for enhancement, particularly in corner detection robustness and feature matching strategies.

The methodology assumes deviations remain within reasonable bounds of design specifications. While this might appear limiting, it aligns with practical considerations: excessive deviations would either be visible to workers during assembly or cause the inspection system to fail, both serving as clear indicators of major formwork issues requiring immediate attention. This built-in failure mode adds an additional layer of quality control to the inspection process.

6.2 Possible Improvements and Outlook

While the proposed methodology shows promise for automated formwork quality control, several key improvements could enhance its practical implementation. The corner detection algorithm needs to be made more robust for industrial environments through more advanced algorithms. Possible using deep learning and AI approaches trained on production data. This can address current limitations in handling varying illumination, shadows, and surface textures encountered in real-world conditions.

The system architecture can be extended to support multiple cameras or mobile platforms mounted on existing crane systems, improving coverage, measurement redundancy, and allowing for real 3D coordinate derivation. Real-time performance optimization through parallel processing and simplified screening algorithms can enable faster feedback cycles suitable for production environments.

Integration with broader production management and BIM systems presents significant potential. Quality control data could feed into statistical process control frameworks, enabling trend analysis and systematic error detection. The framework could also be extended beyond geometric control to assess additional parameters such as surface conditions or reinforcement positioning, though this would require incorporating additional sensing modalities.

Future validation should include long-term studies in production environments to quantify the system's impact on product quality and production efficiency, providing insights for further refinement of both the technology and its implementation.

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