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Evaluation of Surface Quality in the Prefabrication of Concrete Panels using Computer Vision

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Abstract

The construction industry increasingly uses prefabrication for the significant advantages in cost-effectiveness, production speed, and environmental sustainability. Achieving high-quality building outcomes demands rigorous quality control of the individual building components. Concrete panel manufacturing presents unique challenges, particularly in surface quality assessment, as the material's heterogeneity complicates standard evaluation metrics from industries like automotive manufacturing, where computer vision methods are well established. This research addresses these challenges with a robust computer vision-based methodology for surface quality assessment for prefabricated concrete panels, focusing on the detection of visible color differences using the ΔE metric. By recognizing the complex material properties and design requirements — including aesthetic aspects like color and texture — the proposed approach establishes more precise and adaptable evaluation techniques to enhance the overall quality and reliability of prefabricated concrete construction.

1. Introduction

Construction times for buildings have significant impact on their utility and value. Apart from being costly, long construction times also impact the surrounding of the buildings and delay the use of the building, as is often the case with traditional on-site construction. Accordingly, the industry is starting to embrace the prefabrication of building parts to accelerate the production process and better control the delivery times of buildings. In addition to the construction speed, prefabrication can provide very cost-efficient solutions, for example for utility buildings, such as schools and hospitals, but also in housing, where prefabricated, modular building concepts can increase access to housing. One major benefit of prefabrication is the option to optimize the individual elements for the specific application, reducing material use and building performance, making the prefabrication an important component to reduce the environmental impact of the construction industry. Following this line of thought, the concept of circular construction is gaining traction, where buildings are not destroyed after their util life, but decomposed into smaller elements that can be reused in new buildings or only parts of the structure are removed to adapt it to changed requirements. Both these approaches are supported by the principles of modular construction, since the used modules can simply be taken out of the structure and combined in a new building.

Most of these benefits become possible by strictly controlling the production conditions and processes, to optimize them for quality and efficiency, and to decouple the assembly phase from the production phase. Especially for parts made of concrete, these optimized production installations can reduce the efforts for the most critical parts of the process, the placement of the formwork, the installation of the reinforcement, and the pouring of the concrete. By controlling the quality of each of these steps, the variances in the quality of the resulting products can be reduced, and the production tolerances can be adjusted, allowing for a broader application of the resulting parts and higher reliability of the constructed buildings.

To assure that the delivered parts comply with the defined quality criteria and tolerances, the finished parts need to be checked for possible defects. This research is concerned with developing a methodology for the control of the surface quality using computer vision methods. The aim is to analyze the surface of the finished parts and detect possible defects in the appearance, that can be caused by stains, discolorations, spallings, or changes in the texture. The focus lies on the detection of visible changes in the appearance of the part. For this, the ΔE metric after ISO/CIE 11664 (ISO, 2019) is used, which describes methods to measure color differences and provides thresholds for the perceptibility of those. This metric is widely used in the industry and has proven very capable. One challenge in the use of the ΔE metric is the selection of suitable thresholds for the specific application. Across industries different thresholds exist, for example in the printing industry, a threshold of $\Delta E < 3$ is applied for "color critical applications" like commercial printing (ANSI, 2012). Another commonly used reference for admissible color differences based on human perception is shown in Table 1.

ΔE Range	Perception
$0 - 1$	Unnoticeable
$1 - 2$	Noticeable by experienced observers
$2 - 3.5$	Noticeable by inexperienced observers
$3.5 - 5$	Clearly noticeable
> 5	Perceived as different colors

Table 1. Commonly used threshold values for color differences ΔE based on (Mokrzycki and Tatol, 2011)

For the application of quality control in concrete construction with focus on the surface quality, no such thresholds exist, however. To remedy the lack of suitable thresholds, this work introduces a methodology for the assessment of concrete surface quality based on the ΔE measure, for which a use-case specific threshold value is derived. To distinguish between different kinds of surface deviations, a second measure based on the hue of the surface is proposed, that allows to better characterize possible effects on the surface and estimate their importance and criticality. Further, the integration of the proposed meth-

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odology with BIM systems for consistent data storage and accessibility is discussed, which is part of still ongoing research. Finally, this application of the proposed measures is shown on panels provided by a project partner to evaluate the suitability of the approach.

2. Related Work

Computer vision applications in prefabricated concrete construction have seen significant development in recent years, spanning quality control, assembly guidance, and condition assessment. A comprehensive review by (Ma et al., 2023) highlights the breadth of these applications in prefabrication processes.

In the context of manufacturing and assembly, recent developments have focused on both quality control and process automation. (Seo et al., 2023) developed an integrated quality control system for factory environments, incorporating multiple inspection types to ensure comprehensive quality assessment. Advancing the automation of assembly processes, (Ye et al., 2024) demonstrated the use of image processing for precise alignment of prefabricated concrete elements during installation. For geometric quality control, (Wang et al., 2016) established the effectiveness of 3D laser scanning in evaluating surface flatness and geometric conformity of concrete panels.

Condition assessment of existing concrete structures using computer vision represents another significant research direction that has produced significant progress in recent years. (Koch et al., 2015) and (Valikhani et al., 2021) provide comprehensive overviews of computer vision applications in this domain, highlighting the evolution from traditional image processing to modern machine learning approaches. (Chai and Wang, 2022) proposed a complete framework for condition assessment, while (Benz and Rodehorst, 2022) demonstrated the effectiveness of machine learning techniques in identifying surface defects from image data.

For color-based analysis, which is central to the approach presented here, the work of (Sharma et al., 2005) provides crucial insights into the ΔE color difference formula, including an analysis of computational discontinuities that must be considered in practical applications. Their work informs the presented methodology for robust color-based defect detection.

This large body of research demonstrates both the potential and challenges of computer vision in concrete quality control. While existing work has established different approaches for defect detection and geometric analysis in general settings, the research presented here addresses the specific challenges of color-based quality control in concrete prefabrication environments, with particular attention to robustness against varying lighting conditions and surface textures.

3. System for the Evaluation of Surface Quality using Computer Vision

The methodology in this work consists of image acquisition, image analysis, and integration with BIM (Building Information Modeling) models for documentation. The goal is the detection of anomalies on the surface of concrete panels before leaving the factory, such as discolorations, spalling, cracks, or gaps in concrete cover using computer vision. As the environmental conditions in a concrete factory are rough, the methods

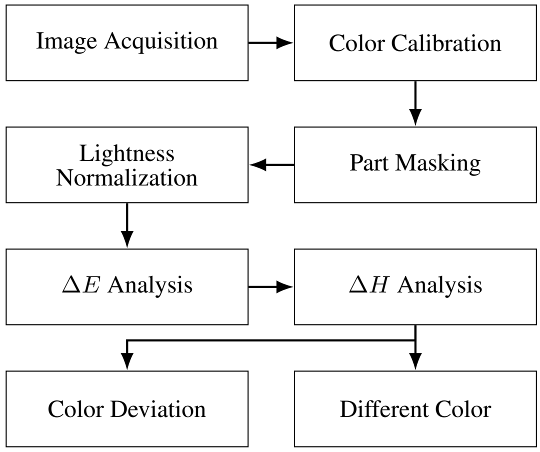


Figure 1. Flowchart of the proposed methodology.

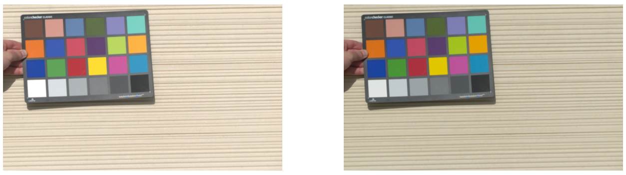
are robust against various influences on the acquired data, for example changing light conditions, cluttered spaces, dirty objects, or short timeframes for data acquisition.

3.1 Data Acquisition and Pre-Processing

To integrate the proposed methods into existing production processes, the data acquisition needs to be simple and the feedback of the analysis immediate. Accordingly, the only requirements posed in this work for the images are sufficient visible context, as shown in Figure 3a, to locate the results on the surface of the BIM model, complete coverage of the surface, and the use of a color calibration board. This also motivated by the fact, that there are commonly only short time frames for the collection of the data before the parts are moved, so complicated setups can be challenging to implement. The complete coverage of the surface only needs to be given in the union of all images, with some overlap to enable the combination. Similarly, the color calibration board does not need contained in every image, if the lighting conditions and parameters of the camera do not change between their capture. In an approximately constant setting, the calibration parameters computed from one image can also be transferred to other images of the same environment. Due to the heterogeneity and the natural surface variations of concrete, the analysis cannot be performed at too small scale, since those would superimpose with the actual effects of interest. Accordingly, the requirements on resolution and sharpness are relaxed compared to defect detection, where they are critical for success, as described by (Benz and Rodehorst, 2022), and the images can be captured from further away, providing a larger covered area in each image and more surrounding context.

The first step of data preparation is the color calibration for the comparison to the reference color from the design specification. Since a color calibration board needs to be visible in at least one image during the acquisition, these images can be used to correct possible chromatic aberrations. Even though modern camera sensors generally provide high quality and often offer the option to self-calibrate, the use of a calibration board with checkers of precisely controlled and known colors is recommended. The absolute comparison of color values is only possible in well calibrated images, which is required for comparing an as-planned concrete color from the design specification to an as-built color. Also for a relative color analysis, where no absolute target color is provided, the calibration is useful, since this work distinguishes the kind and severity of quality derivations based on their color difference.

There exist many established and easily available tools for the calibration of the color using such a calibration board, as described by (Wransky, 2015). Common software libraries for the work with images that implement such functionality are for example OpenCV (Bradski, 2000) or Matlab (MathWorks Inc., 2022). This calibration is performed by fitting a color correction model that transforms the measured colors of the checker into the known target colors, where the color difference is determined using the CIEDE ΔE measure, described in Section 3.4.



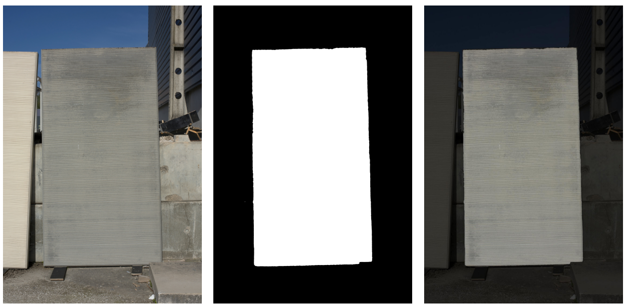
(a) Original image (b) Calibrated image

Figure 2. Calibration of the images using the color checker.

In this work, an automated calibration utility is developed and used that detects the calibration pattern in a reference image and applies the calibration to all images belonging to the same acquisition. The result of the calibration of the reference image including the color checker is shown in Figure 2.

3.2 Image Masking and Part Isolation

The next step in the proposed methodology is to isolate the panel from the surrounding background through image masking. This process is formulated as a segmentation task, separating the object of interest from its surroundings. Numerous segmentation approaches exist (Emek Soylu et al., 2023), adaptable to this specific task. However, recent advancements in foundation models offer a compelling alternative. Trained on vast datasets for general-purpose use, these models excel at zero-shot segmentation, eliminating the need for domain-specific training or fine-tuning. Specifically, the Segment Anything 2 model (SAM 2) (Ravi et al., 2024) is a highly performant and readily available model capable of segmenting objects based on simple prompts, such as bounding boxes or point clicks, effectively extracting precise object boundaries.



(a) Original image (b) Mask (c) Masked image.

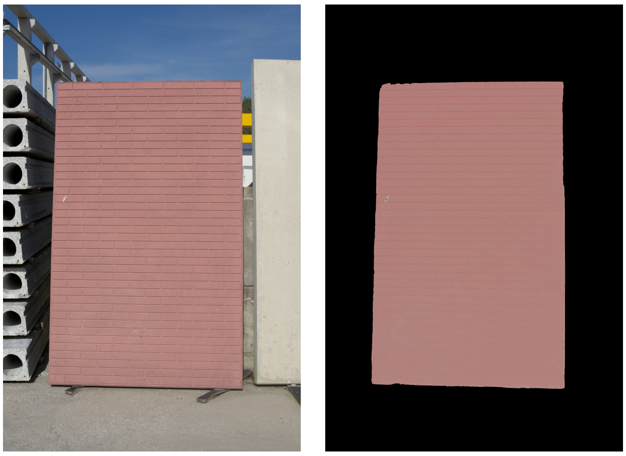
Figure 3. Process of computing a mask with the proposed utility and applying it to the image.

Given the typically clear visual distinction between the concrete panels and their surroundings, SAM2 has demonstrated excellent performance in isolating the panels. For this work, a custom masking utility was developed that leverages the image's center as a seed point (using a point prompt) for automatic panel segmentation, assuming the panel of interest is generally centrally located within the image frame. While the initial automatic segmentation was generally accurate, manual adjustments were necessary for precise boundary refinement. Figure 3 shows the process of applying the masking to an image (Figure 3a) by first obtaining a mask (Figure 3b) from the developed utility and assigning it as the opacity layer to the image (Figure 3c).

3.3 Lighting Correction

The lighting of a scene and the object of interest is of high importance for image based analysis to be able to produce useful results. As stated above, the quality control methodology presented here is to be integrated into existing factory processes, in which the environmental conditions can be rough, so the lighting cannot be controlled for the acquisition. To compensate the varying lighting of the surface and especially possible shadows, a brightness compensation is applied to the masked images of the concrete panels.

Due to challenging imaging conditions with regard to varying lighting and shadows, a brightness compensation is required. This can be performed in the HSV (Hue, Saturation, Value) color space, by assigning the median value of the brightness of the masked area to all pixels, as shown in Figure 4.



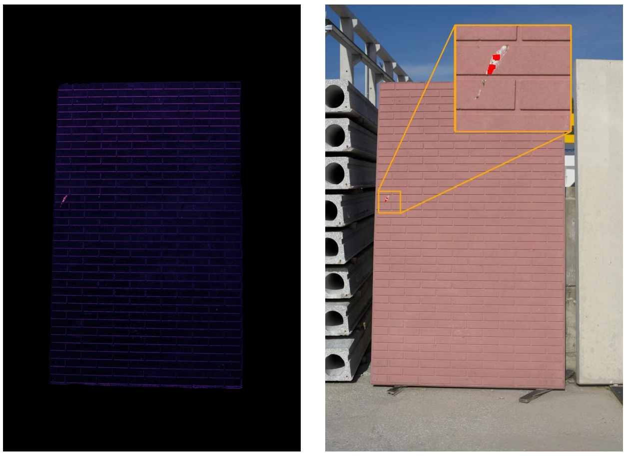
(a) Original image after color calibration. (b) Image after applying mask and lighting correction.

Figure 4. The effect of applying the lighting correction. The shadows of the structured parts are removed and the plain surface remains.

The lighting correction is implemented in HSV color space, which separates the color information stored in Hue and Saturation channels from the brightness information in the Value channel. This separation allows for direct manipulation of the brightness while preserving the color characteristics of the concrete surface. By computing the median Value of all pixels within the masked region and applying this value uniformly across the region of interest, local variations in brightness caused by shadows and uneven lighting are eliminated. This approach is particularly suitable for concrete surfaces, which typically exhibit a relatively uniform base color, making the brightness the primary varying factor. The correction enables more reliable subsequent analysis steps, as the influence of environmental lighting conditions on the surface appearance is minimized. Care has to be taken that certain effects on the surface can be filtered out using this approach, if they only differ in the brightness of the surface.

3.4 ΔE Analysis

The actual analysis of the surface homogeneity is performed by computing the CIEDE2000 ΔE value according to ISO/CIE 11664 (ISO, 2019), a measure of the perceptual similarity of colors that is computed by comparing two individual colors, often the color of one pixel in the image with a reference color. While a value of $\Delta E = 1$ denotes the just notable difference and $\Delta E < 3.5$ is commonly used as a threshold for many industrial applications (Mokrzycki and Tatol, 2011), these thresholds are not suitable for the heterogeneous surface of concrete, where a specific threshold of $\Delta E < 7$ is proposed, as described in Section 3.6.



(a) Map of the differences to the reference color on the surface of the panel.

(b) Identified regions of possible quality issues, overlaid on the original image.

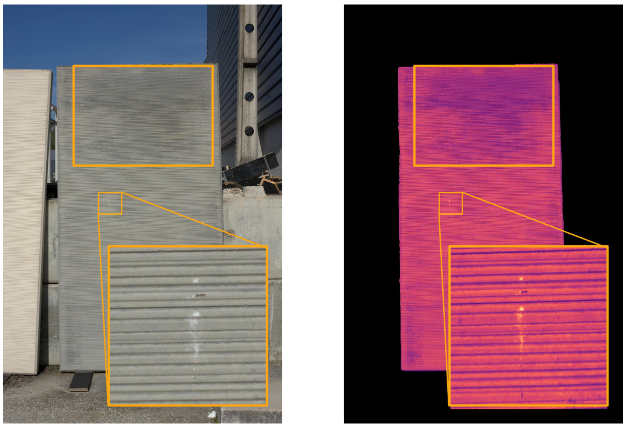
Figure 5. Results of the ΔE analysis. First, the differences to the reference color are computed, then they are compared to a threshold to identify possible defects.

The analysis proceeds in several steps: First, a reference color is established, either from design specifications for the appearance of the finished concrete panels or, if no specific reference is given, by computing the mean color of the surface in LAB color space. Note that if a reference color is provided, it needs to be adjusted based on the performed lighting correction. The LAB space is chosen for this computation as it is designed to be perceptually uniform, making it particularly suitable for color difference calculations (Cheung, 2016). Next, the ΔE value is computed for each pixel with respect to this reference color, resulting in a map of color deviations across the surface, as shown in Figure 5a. To account for the inherent surface properties of concrete, including its natural texture and minor variations in color, Gaussian noise is applied to the computed ΔE values. This step helps to prevent false detections from minor, acceptable variations while still identifying significant deviations that indicate actual defects or quality issues. Finally, these processed ΔE values are compared to the threshold to identify regions of significant color deviation. The result of this analysis is shown in Figure 5b, where regions exceeding the threshold are highlighted, indicating areas that require further inspection.

3.5 ΔH Analysis

After identifying regions with significant deviations from the reference color through the ΔE analysis, these areas are further classified based on the nature of their deviation. This classification distinguishes between regions exhibiting genuine color variations and those showing brightness or saturation deviations while maintaining the same base color. The classification leverages the HSV color space properties by analyzing the absolute difference in the hue component (ΔH) between the reference and the detected regions. A derivation of the used threshold for ΔE is given in Section 3.6. For the computation of the ΔH value, the nature of the hue must be taken into account. The colors are arranged in a circle, so it is common to specify the H component of the HSV in the range of 1° to 360°. This results in a numerical discontinuity around the 0° position, where the pure red color is located. This has to be considered when computing ΔH values, especially when images are encoded as 8bit pixel values.

A significant $\Delta H > 10^\circ$ indicates a fundamentally different color, which typically corresponds to surface contamination such as dirt, oil, or rust from exposed reinforcement. In contrast, regions with minimal hue deviation, but significant ΔE values indicate variations in either the concrete's inherent color properties or structural issues such as damages in the concrete cover. This distinction is particularly valuable from a quality control perspective, as surface contamination like dirt can typically be addressed through cleaning procedures, while rust spots indicate potential durability issues, and inherent color deviations may indicate underlying process control issues requiring investigation and potential production adjustments.



(a) Two identified regions of significant ΔE derivation, marked in orange.

(b) ΔH values computed for the two regions of interest. Dark color indicates low, bright color indicates high values.

Figure 6. Evaluation of the ΔH values to classify identified regions of interest. In Figure 6b, the upper region of interest has a low ΔH, while the lower has a high ΔH. Note that ΔH is only evaluated in regions with significant ΔE.

An example of this evaluation is shown in Figure 6. Based on the ΔE analysis, two regions of interest have been identified in the image. The one at the top shows a different color of the concrete for a larger area, the one at the bottom shows a contamination on the surface. By analyzing the ΔH values for these regions with regard to the same reference color as above, it shows that the upper regions has a very small ΔH , so the underlying color of the concrete is according to the reference, but the intensity is different. In the lower region of interest, a high ΔH value is clearly visible, indicating that a significantly different color is on the surface. This corresponds well to the contamination of the surface.

3.6 Derivation of ΔE and ΔH Thresholds for Concrete Surfaces

The selection of appropriate thresholds for both ΔE and ΔH is crucial for the reliable detection and classification of surface irregularities. While the literature suggests a ΔE value of 3.5 as a common threshold for industrial applications (Mokrzycki and Tatol, 2011), concrete surfaces require a different approach due to their inherent texture and color variations.

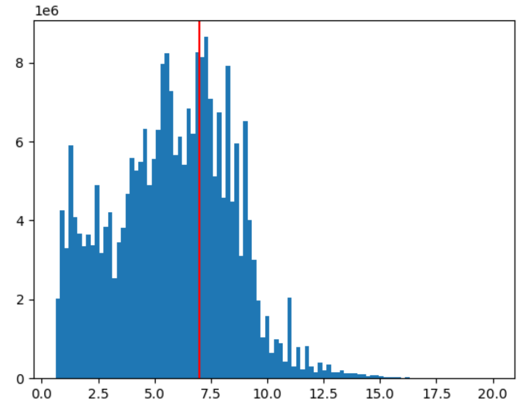


Figure 7. ΔE distribution of the red panel reference image. The vertical line marks the threshold of 7.

To establish a suitable ΔE threshold for concrete surfaces, we conducted an empirical analysis using our dataset of prefabricated concrete elements. Figure 7 shows the distribution of ΔE values across all analyzed images, with each value representing the color difference between a pixel and the reference color. The histogram reveals a complex distribution with multiple peaks, reflecting the various surface characteristics of concrete, including texture variations and differences in surface smoothness. These natural variations contribute significantly to the measured color differences, particularly in the range of ΔE values between 2 and 7. Based on extensive testing and validation against expert assessment, a threshold of $\Delta E = 7$ was established as an effective compromise between sensitivity to genuine defects and robustness against false positives from surface texture variations.

The determination of an appropriate threshold for ΔH follows a similar empirical approach, but with additional complexity due to its role in distinguishing between different types of surface deviations. While the ΔE analysis identifies regions of interest, many of these areas represent variations in surface smoothness rather than actual color deviations or contamination. The ΔH threshold therefore needed to be carefully tuned to effectively filter out these surface texture variations while reliably identifying genuine color differences.

The determination of an appropriate threshold for ΔH was supported by an analysis of the relationship between hue differences and the resulting ΔE values. Figure 8 shows how ΔE varies with changes in hue (ΔH) for different saturation levels, while maintaining constant value (brightness). The analysis reveals that the relationship between ΔH and ΔE is strongly dependent on the saturation level, with higher saturation values leading to larger ΔE changes for the same hue difference.

Through iterative testing and validation against known surface conditions in our dataset, a threshold of $\Delta H = 10°$ was established.

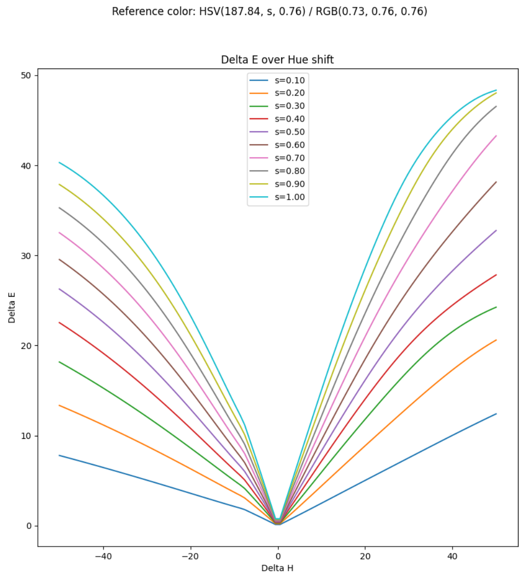


Figure 8. Plot of ΔE vs. ΔH for a reference concrete color (HSV: 187.84°, s, 0.76) over multiple values of S from 0 to 1. This shows the strong dependence on the saturation.

This value proves to be robust, as even in the case of high saturation (s = 1.0), a hue difference of 10° corresponds to a ΔE value of approximately 5, which is below our established ΔE threshold of 7. While the analysis suggests that an adaptive threshold based on saturation could provide more precise results, the fixed threshold of 10° proved sufficient for our specific application in distinguishing between surface texture variations and actual color deviations. However, it should be noted that this threshold was optimized for our controlled testing environment and the particular characteristics of our concrete elements. Applications to different settings may require validation and potential adjustment of this threshold.

3.7 Mapping and Integration with BIM

The system is being designed from the beginning to be integrated into a BIM environment. By identifying corresponding points in the images and the 3D model from BIM, a mapping between image space and surface space can be established using a perspective projection model. Suitable points for this mapping are corners and edges of the panel, which provide reliable geometric features across both representations. Using this mapping, the detected deviations can be projected onto the 3D model of the panel and integrated into the BIM model for documentation. This part of the system is under development and under discussion with the BIM team that is a partner in the ongoing research efforts to optimize the integration and interfaces.

The integration with BIM offers several advantages beyond just documentation of the current condition. The mapped quality control data can be associated with specific building elements, enabling tracking of defects throughout the construction lifecycle. This integration also facilitates the creation of comprehensive quality reports that combine geometric, material, and quality information in a single digital environment. Furthermore, the BIM integration allows for temporal tracking of surface changes, potentially enabling predictive maintenance approaches based on documented degradation patterns. This information can be especially useful in the scope of circular con-

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struction, where buildings can be deconstructed, and the parts can be reused in another context. By having a well documented history of all parts of a building, the rate of reutilization can be increased, further reducing the required cost and increasing the impact of modular construction practices.

The successful implementation of this BIM integration requires careful consideration and selection of data structures and interoperability standards to ensure that quality control information can be effectively stored and accessed within the BIM environment. This includes developing appropriate property sets for defect classification and severity levels, as well as establishing protocols for updating and maintaining this information throughout the building's lifecycle. This is where the work presented here integrates and coordinates with research into suitable technology choices for BIM and the design of the required interfaces, which is part of ongoing research, especially in the partnered BIM research team.

4. Application and Evaluation of the Method

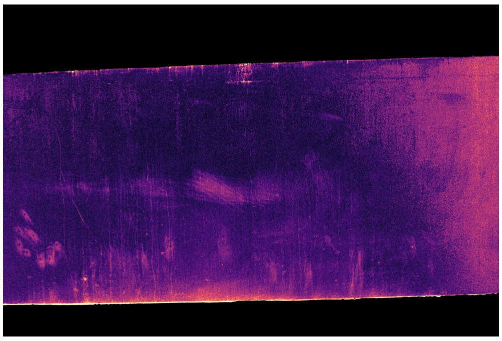
The methodology was developed and validated using a dataset of 14 high-resolution images captured at the production facility of our industry partner. The images were acquired using a NIKON D810 camera (36.4 megapixels) equipped with a 50mm lens. For each scene, two images were captured: one with and one without a colorchecker for calibration purposes. To ensure consistent imaging conditions between paired captures, the camera was initially configured using autofocus, then switched to manual focus mode to maintain identical settings for both images. All images were captured in RAW format and subsequently processed in a controlled office environment.

To ensure realistic testing conditions representative of potential industrial implementation, images were captured handheld without tripod stabilization and using only available outdoor lighting. This approach deliberately introduced typical challenges such as varying illumination conditions and minor image alignment variations that would be encountered in practical applications.

The dataset encompasses a wide range of concrete surface characteristics. The panels varied in both color and texture, ranging from different shades of gray to red and ochre tones. Some panels featured intentionally structured surfaces, such as a brick wall texture imprinted on a red panel. The dataset included panels at different stages of their lifecycle, from relatively new productions to panels that had been exposed to outdoor conditions for extended periods. The surfaces exhibited various types of irregularities commonly encountered in practical settings, including: Surface contaminations such as bird droppings, cement splashes, and biological growth, structural defects in the form of spalling and exposed reinforcement with visible rust and some production-related issues with inhomogeneous concrete coloring.

The development of the methodology was guided by close collaboration with concrete manufacturing experts from our industry partner. Through detailed discussions and on-site examinations of the panels, we established criteria for distinguishing between significant defects requiring attention and acceptable surface variations. This expert knowledge was crucial in calibrating our approach, particularly in determining appropriate thresholds for both ΔE and ΔH values that align with industry quality standards and practical requirements.

(a) Reference image with no anomalies on the surface.

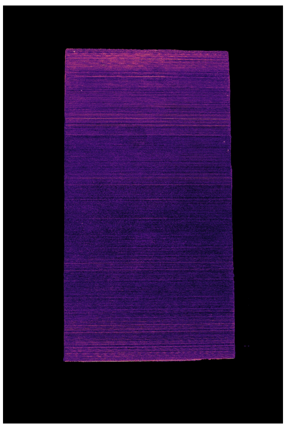


(b) ΔE of the reference image. All values are below the threshold 7.

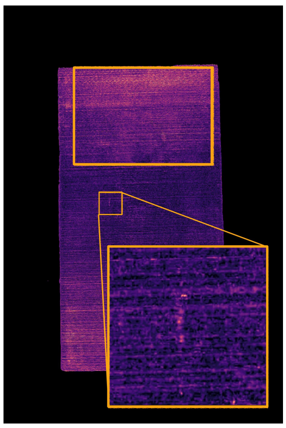
Figure 9. A reference image without anomalies and the corresponding ΔE . All values in the ΔE map are below the determined threshold $\Delta E = 7$.

To demonstrate the robustness and effectiveness of our methodology, we present three representative examples from our dataset that showcase different surface characteristics and analysis challenges in real production environments.

The first example shown in Figure 9 presents a relatively uniform concrete surface with typical minor variations. The resulting ΔE map shows deviations from the reference color, with all values remaining well below the established threshold. This case validates the method's ability to handle normal manufacturing variations without generating false positives.



(a) ΔE of an image without anomalies in the distribution but a textured suface.



(b) ΔE of the image shown in Figure 6 with the two anomalies highlighted.

Figure 10. Examples for the resulting ΔE .

The second example displayed in Figure 10a features a panel with pronounced surface texturing visible in the horizontal line structures in the ΔE map, presenting a more challenging test case for the analysis method. Despite the strong textural variations, which could potentially trigger false detections in simpler analysis approaches, our methodology successfully maintains robustness. The combination of appropriate ΔE thresholding and lightness calibration ensures that these intentional surface characteristics are not misclassified as defects.

The third example, shown in Figure 10b, demonstrates the method's ability to distinguish between different types of surface deviations. The ΔE analysis identified two distinct regions of interest: an upper region showing color deviation consistent with inhomogeneous concrete coloring (confirmed by low ΔH values), and a lower region exhibiting surface contamination (indicated by high ΔH values). This example particularly highlights the effectiveness of the ΔH analysis in differentiating between production-related color variations and surface contamination.

5. Results and Discussion

The results obtained using the proposed methodology demonstrate the suitability of the chosen approach for quality control of prefabricated concrete parts. By carefully adjusting the two thresholds for ΔE and ΔH, the method is capable of detecting different surface effects and providing an indication of their severity. The established thresholds of $\Delta E = 7$ and $\Delta H = 10^\circ$, developed through iterative testing and expert validation, provide a reliable foundation for distinguishing between different types of surface anomalies.

By correcting the brightness of the image through HSV-based lighting correction with median value normalization, the influence of differing lighting conditions can be compensated, making the method robust for application in a concrete factory. Since the texture of the surface can introduce similar shadow effects, as shown for a brick wall-like appearance in Figure 4a, this calibration allows quality control of parts with complex surface forms and advanced design patterns.

The method's ability to distinguish between cleanable defects (surface contamination) and production issues (color variations) through ΔH analysis provides valuable practical benefits for manufacturing operations. This distinction, validated through extensive testing with concrete manufacturing experts, enables more efficient maintenance planning and quality control processes. The validation using 14 high-resolution images captured under real-world conditions, including various defect types such as rust, spalling, inhomogeneous coloring, and contamination, demonstrates the method's applicability in practical settings.

The robustness of the approach is particularly noteworthy given the challenging conditions under which it was tested: handheld camera operation, natural lighting variations, and diverse surface textures. These conditions reflect the real-world environment in which the system would be deployed, suggesting strong potential for industrial implementation. The successful detection and classification of defects across different concrete colors, textures, and ages further supports the method's versatility. Since the dataset was specific to the setting we acquired it in, the ability to generalize to other environments may not be given, such that the thresholds may need to be adjusted, or additional preprocessing may be required.

6. Integration and Future Work

One remaining challenge in this methodology is to further investigate suitable thresholds for ΔE and ΔH and derive the justification for those values from the specific material properties of concrete and the perceptual differences in color.

The presented methodology demonstrates significant potential for automated quality control in concrete manufacturing. However, several steps remain necessary for full industrial implementation and methodological improvement.

Integration with Building Information Modeling (BIM) represents a crucial next development stage. While this work addresses fundamental aspects of image acquisition and analysis, the registration of detected defects within BIM models requires additional development. This integration necessitates computing precise spatial mappings and transforming the quality control results into the model coordinate space, enabling comprehensive digital documentation of quality issues within the broader context of the building model.

For successful implementation in production environments, two key aspects require attention. First, the software system's robustness must be thoroughly validated under continuous operation conditions. Second, the development of an intuitive user interface is essential to enable factory workers to interact effectively with the system, ensuring its practical utility in daily operations and efficient integration into existing processes.

Several opportunities exist for methodological improvements. The current fixed thresholds ($\Delta E = 7$ and $\Delta H = 10^\circ$) could be enhanced through adaptive approaches that consider the reference color characteristics. A systematic investigation of concrete material properties, including surface porosity, cement type, and aggregate composition, could provide valuable insights for refining these thresholds. Understanding how these material characteristics influence color development and aging behavior could lead to more sophisticated, material-specific detection parameters. Such dynamic threshold determination could improve the method's reliability and robustness across varying concrete compositions and surface finishes. Furthermore, the image preprocessing pipeline could be optimized to handle a broader range of lighting conditions and surface textures.

To validate the method's generalization capabilities, additional data collection and evaluation across diverse scenarios is necessary. This expanded validation may reveal cases where the current algorithms require adjustment through additional verification steps or modified analysis procedures. Particularly, the collection of data from different manufacturing facilities and concrete types would provide valuable insights into the method's broader applicability. This data collection should be accompanied by detailed documentation of concrete mix designs and curing conditions to establish potential correlations between material properties and optimal detection parameters.

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