Drone-Assisted Progress and Quality Tracking for Surface Finishing in Construction

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Abstract

In the construction industry, achieving high standards in surface finishing is essential for structural integrity and aesthetic quality, yet traditional inspection methods can be slow and miss subtle defects. This paper introduces a drone-based system that utilizes advanced sensor processing for automated surface quality assessment in construction finishing tasks. The system integrates Light Detection and Ranging (LiDAR) and high-resolution RGB cameras to collect detailed surface data. The LiDAR module applies Gaussian filtering for noise reduction, followed by bicubic interpolation to generate a smooth and continuous elevation map, allowing for precise flatness estimation across the scanned surface. For visual defect detection, a Convolutional Neural Network based de-blurring algorithm is first applied to captured images to remove motion blur caused by drone movement. This process enhances image sharpness by passing the blurred image through multiple convolutional layers, where each layer reconstructs finer details, resulting in a deblurred image. Subsequently, a zero-shot transformer-based segmentation model uses multi-head self-attention to analyze spatial relationships within the deblurred image, allowing for effective identification and segmentation of defect regions without requiring extensive training data. Testing was conducted in both a ROS-based simulation and on real-life surface work. The LiDAR-based flatness estimation achieved a Root Mean Square Error (RMSE) of 0.2 mm in simulation and 0.8 mm in real-life tests, with Mean Absolute Error (MAE) values of 0.4 mm and 1.1 mm, respectively. The camera-based defect detection showed substantial improvement with the de-blurring module, increasing Intersection over Union (IoU) for defect segmentation to over 95% with de-blurring.

Keywords – Construction Robotics, Computer Vision, Unmanned Aerial Vehicle, Machine Learning

1 Introduction

Ensuring consistent surface quality is an essential aspect of construction that significantly impacts the functionality of buildings [1]. Surface finishing operations—such as plastering, painting, floor leveling, and coating—are not merely cosmetic but serve as critical elements for achieving structural performance and regulatory compliance. These processes contribute to the durability, safety, and appearance of finished structures, underscoring their importance across various construction projects, from residential homes to industrial facilities. However, maintaining high standards in surface quality remains a complex task [2], particularly as project scales and technical requirements continue to grow. The ability to accurately monitor surface conditions and promptly identify defects is crucial, not only for achieving desired design outcomes but also for reducing potential maintenance issues and ensuring the longevity of the finished surface [3].

Despite the fundamental role of surface finishing, current methods for tracking progress and assessing quality still rely heavily on manual inspections. Traditional approaches are predominantly labor-intensive, involving visual assessments and basic measurement tools like spirit levels, tape measures, and straight edges [4]. These methods, while useful for identifying major defects, are limited in their capacity to detect subtle surface imperfections, such as minor texture inconsistencies, fine cracks, or small deviations in flatness. As a result, errors can be missed, leading to compromised surface quality that may only be detected during later stages of construction or post-completion inspections. Additionally, manual inspection processes are time-consuming and often contribute to delays, especially in large-scale projects where extensive surface areas must be monitored [5]. The variability in human assessment further complicates achieving consistent quality, making it difficult to maintain uniform standards across diverse site conditions.

Given these limitations, the adoption of automation in construction has gained momentum, with drones emerging as a promising tool for progress monitoring and quality assessment in surface finishing [6]. Drones offer advantages that extend beyond traditional methods, including rapid data collection, broad area coverage, and the ability to access elevated or hard-to-reach locations without scaffolding or other support structures [7]. Equipped with high-resolution cameras and LiDAR sensors, drones can capture detailed surface data, enabling comprehensive analysis and monitoring in real-time [8]. This capability allows for faster and more systematic inspections, improving both accuracy and consistency in quality control. By integrating drone technology into surface finishing workflows, construction teams can reduce reliance on manual processes, increase inspection speed, and enhance defect detection.

However, despite the growing use of drones for surface monitoring, existing systems still face significant challenges that limit their effectiveness. Current drone-based systems often depend on basic imaging techniques that lack the sensitivity needed to identify fine surface defects. Issues such as slight texture variations, minor cracks, and subtle flatness deviations may go undetected due to inadequate image resolution and algorithm limitations. Additionally, many drone systems are not designed to handle real-time data analysis, making them less effective in dynamic conditions where factors like changing light levels, reflective surfaces, or varying environmental conditions can influence inspection accuracy. As a result, these systems may fail to provide the precision required for complex surface assessments, prompting the need for more advanced solutions that can adapt to diverse monitoring conditions.

To overcome the limitations of traditional inspection methods in surface finishing, this paper proposes an advanced drone-assisted system for real-time progress tracking and quality assessment. The system integrates high-resolution cameras and LiDAR sensors to capture comprehensive data on surface characteristics, including smoothness, evenness, and potential defects such as cracks and texture inconsistencies. To enhance measurement accuracy, the raw sensor data undergoes pre-processing with Gaussian filtering to reduce noise, followed by calibration for reliable results.

For defect detection, a Convolutional Neural Network (CNN)-based de-blurring module first restores clarity in motion-blurred images captured by the drone, ensuring sharper details. This deblurred data is then processed by a zero-shot transformer-based segmentation model, which uses multi-head self-attention to examine spatial relationships, accurately segmenting defect areas without the need for extensive labeled training data.

In parallel, the system employs bicubic interpolation on the LiDAR data to generate a smooth elevation map, facilitating precise flatness estimation. The system's combination of enhanced sensor processing and adaptive algorithms offers a robust and efficient solution for monitoring surface quality in complex construction settings. This method minimizes the risk of rework, improves accuracy, and supports consistent adherence to quality standards, contributing to more reliable and efficient surface finishing in construction environments. Additionally, the system employs a vision transformer-based segmentation model, which reduces the need for extensive training across different test environments, enhancing adaptability in diverse construction scenarios while maintaining high defect detection accuracy.

2 Current Developments in Surface Finishing and Drone-Based Quality Tracking in Construction

2.1 Limitations of Traditional Surface Quality Monitoring Methods

Traditional methods for monitoring surface quality in construction primarily rely on manual inspections [9]. These techniques often involve visual evaluations and the use of handheld tools to measure attributes such as smoothness, flatness, and texture consistency [10]. While these approaches can be effective in identifying major defects, they are inherently limited by their reliance on human observation. Subtle surface imperfections, such as minor texture variations, small cracks, or slight deviations in flatness, are frequently overlooked during manual inspections [11], compromising the overall quality of the finished surface. Additionally, these methods are time-consuming and labor-intensive [12], making it challenging to achieve consistent results across large or complex surfaces. Irregularly shaped areas and confined spaces pose further difficulties, as inspectors may struggle to access or measure these regions accurately. This often results in uneven quality, the need for rework, and delays in project timelines [13]. As construction projects grow in scale and complexity, the demand for more accurate, efficient, and real-time quality assessment tools has become increasingly evident, necessitating a shift toward automated solutions.

2.2 Emergence of Drone Technology in Construction

Drones have increasingly been adopted in construction for a variety of applications, owing to their versatility and capability to access areas that are otherwise difficult to reach [14]. Drones have proven to be valuable tools for tasks such as site inspections, surveying, and progress tracking [15], providing real-time aerial data that can be used to monitor various aspects of a project. Equipped with high-resolution cameras, LiDAR sensors, and GPS, drones can rapidly collect comprehensive visual and spatial information [16], covering large areas more quickly than manual methods [17]. Drones offer non-invasive data collection capabilities, allowing for detailed topographical mapping, structural inspections, and general site monitoring without the need for direct contact [18].

Despite these advantages, the use of drones for surface-specific quality monitoring in finishing operations remains relatively underdeveloped. While some research has explored drone manipulation of tools or objects for surface tasks, achieving the precision and stability needed for delicate surface analysis and adjustments has proven challenging.

2.3 This Paper's Contribution to Drone-Based Surface Monitoring and Quality Tracking

This paper addresses a critical need in construction quality control by introducing a drone-based system that integrates high-resolution LiDAR and RGB camera sensors with advanced machine learning algorithms to monitor surface quality. The proposed system improves upon existing methods by combining multiple innovations to enhance accuracy, adaptability, and efficiency in surface assessment tasks.

To improve flatness estimation, the system incorporates a LiDAR-based mapping module enhanced with Gaussian filtering to reduce noise and bicubic interpolation to generate a smooth and continuous elevation map. This approach enhances measurement precision, improving surface elevation mapping accuracy and ensuring consistent results across diverse conditions.

For defect detection, our system integrates a CNN-based de-blurring module that effectively restores motion-blurred images captured during drone operation. This enhancement improves image clarity, ensuring sharper details that are crucial for identifying subtle surface defects such as cracks and texture inconsistencies.

Additionally, the system employs a vision transformer-based segmentation model, which requires significantly less training across diverse test environments compared to conventional CNN-based models. This reduced training requirement improves the system's adaptability and scalability, minimizing the need for extensive data collection and retraining when applied to different construction scenarios. Together, these advancements improve the precision of flatness mapping, enhance defect detection through improved visual data clarity, and increase the system's adaptability with reduced training demands. The resulting framework offers a robust, efficient, and scalable solution for real-time surface quality assessment in construction environments.[19].

3 Drone-Based Real-Time Surface Quality Assessment and Defect Detection

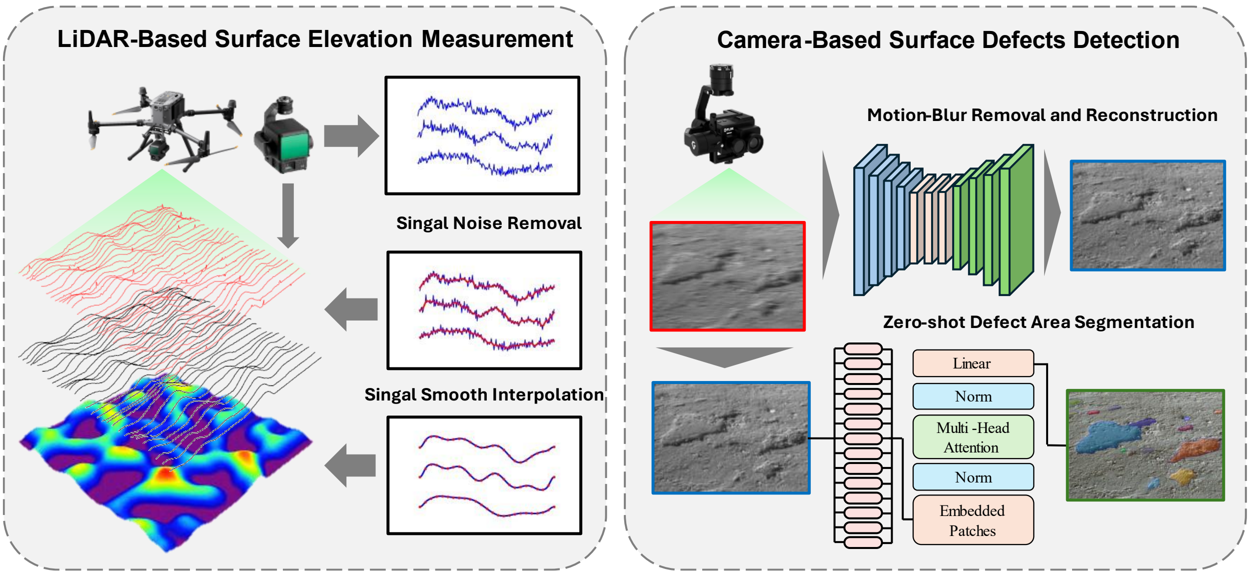

Figure 1. Drone-Based Real-Time Surface Quality Assessment and Defect Detection System Overview

The proposed UAV-based system for surface quality assessment and defect detection in construction applications is divided into two main components: LiDAR-Based Surface Elevation Measurement and Camera-Based Surface Defect Detection as shown in Figure 1. Each component is designed to address different aspects of surface monitoring, enabling the system to capture both topographical and visual defects with high accuracy.

3.1 LiDAR-Based Surface Elevation Measurement

The LiDAR module scans the target surface to obtain detailed elevation data. This initial scan captures the surface topography, producing a series of elevation profiles that can identify height variations indicative of surface irregularities. The LiDAR data is represented as a 3D point cloud, with each point denoted by coordinates (x_i, y_i, z_i), where:

$$L = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_n, y_n, z_n)\} \quad (1)$$

(x_i, y_i, z_i) represents the spatial position and height of each LiDAR data point on the surface.

3.1.1 Noise Removal Module

The raw LiDAR data often contains noise due to environmental factors or sensor inaccuracies, which can lead to errors in surface mapping. To enhance accuracy, a Gaussian filtering approach is applied to the LiDAR data, effectively smoothing out noise while preserving the underlying topography. The Gaussian filter calculates a weighted average of neighboring points, giving higher importance to points closer to the target point and gradually reducing the influence of more distant points. The filtered height value $z_{\text{filtered}}(x, y)$ at each position (x, y) is computed as:

$$z_{\text{filtered}}(x, y) = \frac{1}{2\pi\sigma^2} \sum_{i=-k}^{k} \sum_{j=-k}^{k} z(x-i, y-j) \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \quad (2)$$

where σ is the standard deviation of the Gaussian kernel, controlling the extent of smoothing, and k is the filter size determining the neighborhood around each point (x, y). This Gaussian filtering process reduces noise effectively while preserving the surface's structural features, ensuring a more accurate representation of the surface elevation for subsequent analysis.

3.1.2 Smooth Interpolation for Elevation Estimation

After noise removal, a bicubic interpolation method is applied to fill gaps between scanned points, creating a continuous and smooth elevation map of the surface. Bicubic interpolation estimates the elevation between data points by fitting a smooth surface through the existing points, calculated as:

$$z(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} c_{ij} x^i y^j \quad (3)$$

where c_{ij} are coefficients derived from the neighboring data points. This interpolation process generates a smooth elevation profile, allowing the system to visualize height changes continuously across the surface and detect any deviations from expected flatness, such as undulations or depressions.

3.2 Camera-Based Surface Defect Detection

The Camera Module captures high-resolution RGB images of the surface, allowing the system to detect visual defects such as cracks, texture inconsistencies, or other surface imperfections. This component involves two main steps: motion-blur removal and defect area segmentation.

3.2.1 Motion-Blur Removal Using Convolutional Neural Networks (CNN)

During UAV operations, motion blur can be introduced due to drone movement, compromising the clarity and accuracy of captured images. A Convolutional Neural Network (CNN) is applied to each image to remove any motion blur, reconstructing the image with sharp details. The blurred image $I_{\text{blurred}}(x, y)$is processed through several convolutional layers, where the output deblurred image $I_{\text{deblurred}}(x, y)$ is generated as:

$$F_l(I) = \sigma(W_l * I + b_l) \quad (4)$$

where $F_l(I)$ denotes the feature map at layer l, W_l and b_l represent the weights and biases of the filters, $***$ denotes the convolution operation, and σ is the activation function (commonly ReLU). We adopted a Multi-Scale Convolutional Neural Network architecture [20]. This architecture was chosen due to its improved stability during training, reduced computational overhead, and lower risk of generating artifacts in low-texture regions, which are common in construction environments.

The CNN model employs three parallel convolutional branches operating at different scales to effectively capture both fine textures and large structural patterns. The network integrates residual connections to improve gradient flow and enhance detail preservation, particularly in texture-rich environments such as concrete and brick surfaces. The multi-scale outputs are fused through a concatenation layer, followed by additional convolutional layers for image reconstruction. The final output layer adopts a ReLU activation function to enhance image contrast and preserve sharp details.

3.2.2 Zero-Shot Defect Area Segmentation Using Transformer Networks

After deblurring, a zero-shot transformer-based network is used to segment defect areas without requiring extensive labeled data for training. This network utilizes a multi-head self-attention mechanism to highlight areas likely to contain defects, based on spatial features in the image. The segmented defect map $M_{\text{def}}(x, y)$ is generated by passing the deblurred image through the transformer network, resulting in a probability map that indicates the likelihood of defects at each pixel:

$$M_{\text{def}}(x, y) = \text{softmax}\left(\sum_{h=1}^{H} \text{Attention}(Q_h, K_h, V_h)\right) \tag{5}$$

where H is the number of attention heads, and Q_h, K_h, V_h represent the query, key, and value matrices for each head. This multi-head attention mechanism allows the transformer to capture nuanced spatial relationships within the image, enabling it to effectively identify defects such as cracks, discolorations, or texture inconsistencies on the surface.

4 Implementations

This section describes the implementation and testing of the two primary components of the proposed system: LiDAR-Based Surface Elevation Detection and Camera-Based Surface Defect Detection. Testing is conducted in both a ROS (Robot Operating System) simulation environment to provide controlled, reproducible conditions and on a compact real-life setup with an uneven concrete surface for real-world evaluation. These tests aim to assess the system's performance in de-blurring and segmenting surface defects, as well as accurately estimating surface flatness.

4.1 Training and Testing for Surface Defect Detection Methods

The CNN-based deblurring model was initially trained using the GoPro Blur Dataset [20] and further fine-tuned using 500 images collected from construction sites. This fine-tuning dataset captured materials such as concrete, brick, and plastered walls under varying lighting and motion conditions to better simulate realistic UAV inspection scenarios. The zero-shot transformer segmentation model was adapted from a pre-trained Vision Transformer model [21]. During evaluation, the model was tested on images collected from three construction sites featuring varied building materials (e.g., concrete, brick, and plastered walls) to assess adaptability. The vision transformer model enhances the system’s adaptability by reducing the need for scenario-specific retraining. By leveraging pre-trained weights and multi-head attention mechanisms, the model efficiently identifies surface defects in environments it has not been explicitly trained on. During tests, the system successfully identified defects without additional fine-tuning.

4.2 ROS-Based Simulation for Surface Defect Detection and Flatness Estimation

The ROS environment serves as an initial testing ground for the proposed UAV system, simulating real-world construction surfaces under controlled conditions. This simulation is designed to evaluate both the LiDAR-based surface elevation detection and the camera-based defect detection modules, allowing for precise performance assessment before moving to real-world testing.

In the ROS environment, a simulated construction site surface is created with a variety of textures, irregularities, and defects. The simulated surface includes flat regions, textured areas, and sections with artificial cracks and bumps to mimic typical construction site conditions. This environment allows for thorough testing of both the LiDAR and camera modules under a variety of scenarios.

The virtual UAV in the ROS simulation is equipped with simulated RGB camera and LiDAR sensors, both of which are configured to replicate real-world data acquisition processes. The RGB camera captures high-resolution images of the surface from a consistent altitude of 2 meters. To evaluate the de-blurring module, synthetic motion blur is introduced to the images to simulate the drone’s movement during flight. The LiDAR sensor, positioned alongside the camera, continuously scans the surface to create a 3D point cloud that represents surface elevation data, including controlled noise to test the noise removal and interpolation modules.

In the first phase of testing, the UAV captures both RGB images and LiDAR data as it hovers over the surface at a designated altitude.

4.3 Real-Life Test for Motion Blur Removal and Defect Segmentation

Following the ROS simulation, a real-life test is conducted to validate the de-blurring and segmentation capabilities on an actual uneven concrete surface. This real-life setup is designed to closely replicate the types of surfaces commonly encountered on construction sites, including intentional irregularities such as cracks, bumps, and texture inconsistencies. This research also used open-access dataset to validate the effectiveness and accuracy of the defect detection methodology [22]. This experiment provides insights into the system’s performance under realistic lighting, material, and environmental conditions.

The experimental setup employed a quadcopter drone, equipped with a compact Runcam Phoenix 2 camera (1000 TVL resolution, 2.1mm lens) and an Ouster OS1-32 LiDAR sensor with ±0.01° angular sampling accuracy for both vertical and horizontal directions. The UAV maintained a flight speed of 0.5 – 1.0 m/s and followed a predefined grid pattern at a height of 1.5 meters to ensure comprehensive data coverage with a 75% forward overlap and 60% lateral overlap. Data collection occurred in both indoor and outdoor construction environments under varied lighting conditions to evaluate system adaptability and robustness. Due to unavoidable minor movements during hover, moderate motion blur is naturally introduced into the images. The captured images are processed in real-time by the de-blurring module, which uses a CNN architecture to remove the motion blur and enhance clarity. This de-blurred image is then fed into the zero-shot transformer-based segmentation model to detect and isolate defect areas. The segmentation output is visualized as a colored mask, with highlighted regions indicating the presence of cracks, texture inconsistencies, or other defects. This test not only verifies the effectiveness of the de-blurring and segmentation process but also provides a realistic evaluation of how well the system performs in identifying defects on rough, uneven surfaces like concrete.

The ROS simulation is conducted in 20 different environment and the real-life test collects 200 images to gather performance metrics. Key metrics include defect detection accuracy, de-blurring effectiveness, and the system's ability to accurately estimate flatness. In each test, the accuracy of defect detection is measured by comparing the binary defect maps with known defect locations on the test surfaces. The success of flatness estimation is assessed by measuring the deviation between the estimated surface heights from the LiDAR data and the actual surface profile, with an emphasis on identifying areas with elevation deviations exceeding acceptable tolerance levels.

Through these tests, the proposed UAV-based system demonstrates its capability to accurately detect defects, segment surface irregularities, and estimate surface flatness.

5 Results

The results of the implementation are presented in this section, focusing on the performance of the LiDAR-based surface elevation measurement and camera-based surface defect detection modules.

5.1 LiDAR-Based Surface Elevation Detection

To evaluate the accuracy and consistency of the LiDAR-based surface elevation detection, several metrics were calculated to compare the estimated surface elevation data with the actual physical surface measurements obtained from the test environment. The main metrics used were Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), both of which quantify the deviation between the LiDAR-generated elevation map and the actual surface profile.

Root Mean Square Error (RMSE): The RMSE was calculated to quantify the average magnitude of errors in the LiDAR-derived elevation data. This metric reflects how well the LiDAR data matches the actual surface heights across all tested points. The RMSE for the LiDAR-based flatness estimation was observed to be approximately 0.2 mm in the ROS simulation and 0.8 mm in the real-life test, indicating a high degree of accuracy for both controlled and real-world environments.

Mean Absolute Error (MAE): The MAE provides an alternative error measurement, representing the average of absolute differences between estimated and actual surface heights. The MAE for the flatness estimation was 0.4 mm in the ROS environment and 1.1 mm in the real-life setup, further demonstrating the LiDAR system's consistency in representing surface elevation.

Consistency Across Multiple Runs: To assess consistency, the LiDAR module's flatness measurements were repeated across multiple runs in both the simulated and real-life environments. The Standard Deviation of the RMSE across five independent runs was 0.1 mm in the ROS simulation and 0.4 mm in the real-life test, demonstrating consistent performance with minimal variation, even in the presence of environmental noise.

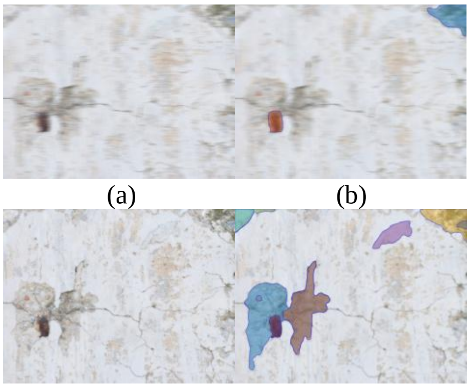

Figure 2. Example Real-life Image Processing. (a) Initial Motion Blurred Image. (b) Segmentation Result without Deblurring (c) Deblurred Image with CNN (d) Segmentation Result after Deblurring

5.2 Camera-Based Surface Defect Detection

The effectiveness of the de-blurring module can be observed in Figure 2. The first image (a) represents the raw data captured by the camera, where significant motion blur obscures surface details, making it challenging to identify surface defects accurately. Texture and fine structural elements, crucial for detecting cracks or bumps, are blurred, which would likely hinder the segmentation module's ability to accurately isolate defect areas. The third image (c), after processing through the CNN-based de-blurring module, shows a marked improvement in clarity and sharpness. Fine textures and subtle surface irregularities that were previously obscured are now distinctly visible. The improved clarity allows for enhanced contrast in texture features, essential for precise defect detection. This qualitative improvement demonstrates the critical role of the de-blurring module in enhancing the fidelity of image data, ultimately supporting higher segmentation accuracy and ensuring robust defect detection.

The effectiveness of the camera-based surface defect detection module was evaluated by measuring the Precision, Recall and Intersection over Union (IoU), for the segmentation results. The experiments compared segmentation performance with and without the de-blurring module, revealing a significant improvement in defect detection accuracy when the de-blurring process was applied.

Precision was calculated to assess the proportion of correctly identified defect pixels out of all pixels classified as defects. Without de-blurring, precision was observed to be around **78%**, indicating a high rate of false positives due to motion blur. After de-blurring, precision improved to **96%**, showing that the de-blurring module reduced false positives significantly, enabling the system to accurately classify defect regions. **Recall** was also used to measure the proportion of actual defect pixels that were correctly identified. The recall score without de-blurring was around **15%**, highlighting that many true defect areas were missed due to image blurriness. With the de-blurring module, recall improved to **94%**, indicating that the system could accurately capture almost all defect areas present on the surface.

Intersection over Union (IoU) was used as the primary metric to evaluate segmentation accuracy, measuring the overlap between the predicted defect regions and the ground truth defect areas. Without applying the de-blurring module, the IoU for defect segmentation was approximately **28%**, indicating a high degree of misalignment between the segmented defects and actual defect locations due to motion blur in the images. However, with the de-blurring module applied, the IoU increased dramatically to over **95%**, showing that the de-blurred images allowed for accurate identification of defect areas, with high consistency between predicted and actual defects.

6 Conclusions

This paper presents a novel UAV-based system designed for real-time surface quality assessment in construction, integrating LiDAR for flatness estimation and a camera module for defect detection. The implementation of a CNN-based de-blurring module significantly enhanced defect segmentation accuracy, achieving an IoU improvement from 28% to over 95%, by restoring image clarity affected by motion blur. The LiDAR module demonstrated high consistency with actual surface elevations, with low RMSE and MAE values, validating its effectiveness in accurately representing surface topography. Field tests in both simulated and real-world environments confirmed the system’s robustness, achieving reliable performance in detecting surface defects and estimating flatness.

Future research directions include conducting more comprehensive real-life field tests in diverse construction environments to evaluate the system's adaptability to varying lighting, weather, and material conditions. Additionally, exploring the integration of advanced machine learning techniques, such as self-supervised learning or transformer-based models, could further improve defect detection and flatness estimation across a broader range of surface types.

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