*To be submitted to Automation in Construction:*

# Enhancing Window Frame Inspection in Construction Sites: A Mobile Robotics Approach Leveraging Viewpoints based on BIM-Segmentation and Image Quality Assessment

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**Abstract**

This study presents a groundbreaking methodology for enhancing robotic quality inspections under varying lighting conditions, which critically impact image quality and the accuracy of defect detection. Traditional inspection methods falter due to the dynamic nature of lighting environments, characterized by issues like overexposure, color distortion, and blur from movement, leading to significant challenges in defect identification. To overcome these limitations, we introduce a dynamic viewpoint planning strategy that significantly improves defect detection precision by adapting to environmental changes. Our methodology consists of automated positioning for optimal imaging, advanced computer vision for environment delineation, in-depth image quality analysis, and strategic viewpoint adjustment to maximize defect visibility. Validated in a simulated construction site environment using "Spot," a quadruped robot, our approach demonstrated substantial improvements over existing methods. The results show an 80% increase in the quality of images captured, marking a major advancement in automated quality control processes. This study confirms the potential of robotic inspection systems to achieve precise and reliable defect detection in varied lighting conditions, offering a significant leap forward in the field.

## 1. Introduction

The emergence of machine vision technologies has catalyzed a transformative shift across various industries, heralding the advent of automated quality control systems that are crucial for maintaining product integrity, enhancing operational efficiency, and elevating customer satisfaction [1, 2, 3]. At the vanguard of this technological evolution are robotic inspection systems, powered by sophisticated computer vision and machine learning algorithms [4]. These systems represent a paradigm shift in inspection methodologies, offering unparalleled precision in real-time defect detection. Their advent has not only streamlined quality assurance processes but also introduced a new benchmark in consumer satisfaction through their accuracy, speed, and cost-effectiveness.

Despite their advanced capabilities, mobile robotic inspections encounter a significant obstacle—the adverse effects of fluctuating lighting conditions on image quality. This issue, extensively documented in the literature [5, 6], highlights the challenges faced in dynamic and uncontrolled environments. Variations in lighting can dramatically compromise the quality of captured images, undermining the object detection and data acquisition capabilities of robotic systems. This degradation poses a direct threat to the accuracy and reliability of defect identification, which is paramount in inspection tasks, especially in environments that are complex and unpredictable.

Traditional approaches to maintaining consistent image quality in the face of complex lighting conditions often fall short. Standard image quality assessment (IQA) techniques, which are either based on statistical metrics or models of human visual perception, generally require high-quality reference images for comparison. In the dynamic context of varying lighting conditions, these methods exhibit significant limitations, struggling to accurately assess critical image attributes such as contrast, exposure, luminance, and noise [7].

In response to these challenges, this paper introduces a novel IQA-driven methodology that strategically guides the positioning of mobile robots to optimize defect detection, particularly within construction site inspections. We leverage Building Information Modeling (BIM)-based techniques for window frame segmentation, enhancing the system's precision, reliability, and compatibility with industry standards [8]. By dynamically adjusting the robot's position according to the prevailing lighting conditions, our method not only boosts the efficiency of inspections but also concentrates on areas with a higher likelihood of defects. This is especially relevant for industries that operate within potentially hazardous environments, like construction sites.

The contributions of this work are manifold, primarily focusing on:

- Experimentally validating the effectiveness of our Image Quality Assessment tool in consistently capturing high-quality images under a broad spectrum of lighting and environmental conditions, thereby demonstrating the tool's adaptability and robustness across a diverse range of scenarios.

- Developing a pioneering navigation strategy for quadruped robotic platforms in construction settings, which, through the application of our Image Quality Assessment Algorithm, significantly improves navigation precision and inspection accuracy.

Following this introduction, the article is structured as follows: Section 2 delves into the related work. Section 3 describes our proposed methodology in detail. Section 4 outlines the experimental setup and the results obtained. Section 5 discusses the implications of our findings, and finally, Section 6 concludes the paper, summarizing the key insights and suggesting avenues for future research.

## 2. Related Work

This section explores advancements in robotic inspection systems (RIS) with a focus on Image Quality Assessment (IQA) for defect detection and the optimization of robotic movements for enhanced image capture.

### *2.1. Image Quality Assessment (IQA)*

IQA plays a pivotal role in RIS, utilizing both subjective and objective assessments. Objective methods like PSNR and SSIM face limitations in real-world applications due to the need for original, undamaged reference images. This necessitates the exploration of no-reference IQA (NR-IQA) techniques. Despite advancements in NR-IQA algorithms [9, 10, 11, 12], their effectiveness in complex environments like construction sites is limited [13]. This highlights the need for more adaptable IQA methods that can navigate the complexities of practical settings.

### *2.2. Innovations in Inspection Robotics*

Robotic inspection systems are increasingly utilized across industries, leveraging UAVs, UGVs, and legged robots for defect detection [14]. Despite technological advances [15, 16, 17, 18], challenges remain, especially in construction environments where limited operational time and poor lighting conditions impact effectiveness. Model-based IQA for path optimization offers a promising solution, guiding robotic movements to capture high-quality images [19, 20, 21], addressing both image quality and operational limitations.

### *2.3. Robotic Controls and IQA*

Significant progress has been made in robotic control and mapping through IQA integration. Smith et al. (2019) developed a real-time IQA-based control strategy, enhancing mapping accuracy. Similarly, Jones and Lee (2020) improved outdoor mapping with IQA, achieving more reliable navigation. Brown et al. (2021) advanced autonomous mapping in complex environments by prioritizing high-quality image data, showcasing the potential of IQA in improving autonomous system efficiency.

In summary, the integration of IQA into robotic inspection systems is essential for overcoming dynamic environmental challenges, particularly in construction settings. By leveraging advanced IQA techniques, these systems can significantly enhance defect detection accuracy and operational efficiency.

## 3. Proposed Methodology

Our study introduces an innovative Image Quality Assessment (IQA) methodology specifically tailored for optimizing the navigation and positioning of robotic inspection systems during vision-based tasks. Central to our approach is the utilization of 'Spot', the advanced quadruped robot developed by Boston Dynamics, which is deployed to dynamically adjust its position based on real-time IQA to ensure optimal image capture quality. Our semi-real-time Image Quality Assessment

(IQA) tool can dynamically generate quality scores corresponding to the images acquired by the robotic system in real time.

Leveraging these scores, the algorithm orchestrates and suggests adjustments to position the robot optimally, ensuring the consistent capture of high-quality images across diverse lighting and environmental conditions. This adaptive control mechanism plays a pivotal role in enhancing the accuracy of subsequent defect detection processes, thereby contributing to the overall efficacy of the robotic system in industrial applications.

This method represents a significant contribution in robotic inspection capabilities, marrying advanced robotics with cutting-edge IQA techniques to navigate and respond to the complex challenges of varying lighting and environmental conditions.

The simple essence of our proposed methodology is captured in Figure N. 1, which illustrates the integrated workflow of the system. This workflow demonstrates how Spot, leveraging our novel IQA algorithm, makes informed decisions on its positioning to maximize image quality during inspections. The figure underscores the synergy between robotic mobility and intelligent image assessment, setting a new standard for precision and efficiency in robotic inspection systems.

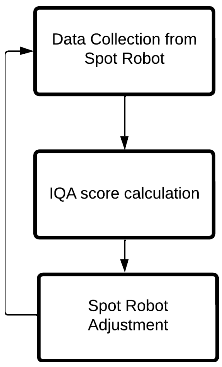


Figure 1: Integrated Workflow for Robotic Inspection System (RIS) utilizing IQA

### 3.1. Data Collection from Spot Robot

Our inspection process initiates with the Spot robot, equipped with an advanced PTZ camera, autonomously navigating through challenging terrains to systematically capture high-resolution images of window frames and other structural elements. It adheres to meticulously predefined paths to guarantee thorough coverage, ensuring no critical detail is missed.

This dataset was compiled through a custom Python script controlling the Spot robot via the Spot SDK. This script precisely directed the robot's movements and camera operations to capture detailed images of window frames under a variety of lighting conditions and viewpoints. The data collection comprised:

- Setup: Spot positions itself 2 meters from the target window frame with its PTZ camera ready.
- Circular Movement: Spot performs a semi-circular movement around the window, capturing images at seven incremental angles from -45 to +45 degrees.
- Lighting and Curtain Variations: For each angle, images are taken under three lighting settings (sunny, cloudy, nighttime) and with three curtain states (both open, one closed, both closed).
- Image Documentation: All images are promptly saved in a timestamped directory, facilitating organized data management.

This structured data collection strategy ensures the acquisition of a comprehensive dataset, crucial for our advanced image processing and analysis phases, leveraging Spot's robotic capabilities for efficient and precise quality inspection tasks.

### 3.2. Proposed Image Quality Assessment (IQA) Model

In order to quantitatively evaluate image quality in real-time, we propose an IQA model that incorporates a linear combination of three key image attributes: contrast (C), exposure (E), and shading (S). This model is designed to be both efficient for computational purposes and interpretable, allowing for immediate adjustments by robotic systems such as 'Spot'.

The IQA score is calculated as follows:

$$IQA = w_C \cdot C + w_E \cdot E + w_S \cdot S$$

where:

- $IQA$ represents the overall Image Quality Assessment score.
- $C$, $E$, and $S$ are the standardized values for contrast, exposure, and shading, respectively, normalized to a common scale to ensure equal contribution to the IQA score.
- $w_C$, $w_E$, and $w_S$ denote the weights assigned to each attribute, reflecting their relative importance in the context of the specific inspection task.

*3.2.1. Rationale for a Linear Model*

The linear model is chosen for several reasons:

1. **Simplicity and Efficiency**: It enables quick computation, crucial for real-time applications in robotic inspection systems.
2. **Interpretability**: The model provides clear insights into how variations in each attribute affect the overall image quality, facilitating easier adjustments and algorithm improvements.
3. **Flexibility**: By adjusting the weights ($w_C$, $w_E$, $w_S$), the model can be tailored to prioritize different image quality aspects as required by specific inspection scenarios.
4. **Empirical Foundation**: Contrast, exposure, and shading are well-established determinants of image quality, making their linear aggregation a solid basis for assessing overall quality.

This IQA model forms the basis for optimizing the inspection path and positioning of 'Spot', ensuring that captured images meet the necessary quality criteria for effective defect detection. The weights of the model ($w_C$, $w_E$, $w_S$) will be empirically determined and adjusted based on the inspection requirements and environmental conditions encountered.

*3.3. Implementation of IQA-Guided Viewpoints Approach*

We have integrated an IQA algorithm to enable Spot to adapt its position based on image quality during vision-based operations. A confidence map is generated from the IQA scores, indicating optimal viewpoints and lighting conditions for defect detection. This map guides the robot to positions where image quality is maximized, enhancing the effectiveness of the inspection process.

*3.3.1. Spot Position Adjustment Algorithm*

The Spot robot utilizes a position adjustment algorithm based on the generated IQA scores. The algorithm is designed to iteratively adjust the robot's orientation until the IQA score surpasses a predefined threshold, ensuring optimal lighting conditions for accurate defect detection. This algorithm is pivotal in dynamically adapting to varying environmental conditions, thereby enhancing the quality and reliability of the inspection.

In conclusion, our proposed methodology utilizes advanced image quality assessment techniques to dynamically guide a mobile robotic platform in inspection tasks, significantly enhancing the accuracy and efficiency of defect detection in complex environments.

**Algorithm 1** Optimized Spot Positioning Based on IQA

```
Initialize degree ← 0, Obtain initial IQA_score and angle
while IQA_score < 75 do
  if angle > −45 then
    Adjust Spot 15 degrees left, degree ← degree − 15
  else if angle < 45 then
    Adjust Spot 15 degrees right, degree ← degree + 15
  end if
  Update IQA_score and angle based on new position
end while=0
```

## 4. Experiments and Results

In this section, we outline the experiments conducted to assess the performance of our automated visual quality inspection approach for window frames.

*4.1. Experiment Setup*

This section delineates the experimental framework devised to evaluate the efficacy of an automated visual quality inspection methodology specifically tailored for window frames. The development of our Image Quality Assessment (IQA) tool was predicated upon experimental inquiries aimed at discerning optimal image conditions and refining the inspection process.

*4.1.1. Artifact Analysis*

The analysis was concentrated on three pivotal artifacts, which are instrumental in the qualitative assessment of image quality:

1. **Contrast:** Defined as the differential in luminance or color that renders an object distinguishable from its surroundings.
2. **Shading:** Represents the variations in brightness or color within an image, emanating from differential illumination.
3. **Exposure:** The quantum of light permitted to impinge upon the image sensor during the photographic capture process.

*4.2. Data Collection Methodology*

Data was amassed utilizing the Spot robot's Pan-Tilt-Zoom (PTZ) camera, adhering to the following procedural methodology:

- **Initial Detection:** Employing a corner detection algorithm, the robot's camera initiates the process by capturing front-facing images of window frames. This algorithm identifies the intersecting junctures of four lines, delineating the quadrilateral shape of the window frame, thus facilitating initial localization.

- **Angle-Based Image Collection:** Subsequent to the initial detection, the Spot robot embarks on a semi-circular trajectory to amass images from a spectrum of seven distinct angles, extending from -45 to +45 degrees, with an incremental adjustment of 15 degrees at each step. This methodology is instrumental in cultivating a dataset of diverse perspectives, indispensable for a holistic analytical examination.

- **Return to Base:** Concluding the image collection at the 45-degree mark, the Spot robot reverts to its original position, realigning itself to the 0-degree angle. This repositioning readies the robot for subsequent tasks, ensuring a systematic approach to data collection.

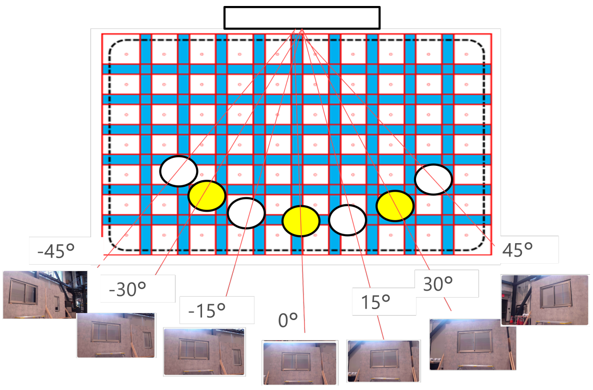


Figure 2: Schematic Representation of the Experimental Setup

### 4.3. Experiment Setup

#### 4.3.1. Methodological Framework

The experimental design was carefully crafted to enable the acquisition of images via a SPOT robot, which was programmed to operate within a precisely controlled environment. The methodology's core revolved around capturing images from seven strategically determined angles relative to a window frame, at -45, -30, -15, 0, 15, 30, and 45 degrees. This approach ensured a comprehensive angular spectrum for subsequent analysis.

*Data Collection Specifics:.* The data collection aimed to amass a total of 350 images, adhering to the following specifications:

- **Image Resolution:** High-resolution imagery was prioritized to preserve the requisite quality and detail for precise analysis.

- **Images per Viewpoint:** To enrich the dataset's diversity and robustness, 50 images were captured at each of the seven predetermined angles.

- **Environmental Conditions:** The experiments were conducted under three distinct construction site conditions, further assessed under three varied lighting scenarios to enhance the dataset's complexity and relevance.

*Illumination Conditions:.* Illumination variability was integral to the experimental setup, categorized into three scenarios to simulate different lighting conditions:

1. **Strong Lighting:** This was achieved through the manipulation of curtains to simulate an environment with abundant natural light.
2. **Weak Lighting:** This condition was simulated by positioning the setup against a wall, reflecting scenarios with limited light availability.

#### 4.3.2. Experiment 1: Analysing Quality functions Uniformity of the Data

The primary objective of this experimental inquiry was to identify the optimal set of artifacts for real-time image quality assessment (IQA) utilizing a SPOT robot. This study meticulously analyses high-quality images across a spectrum of environmental conditions, aiming to elucidate the characteristic patterns of key artifacts—namely, contrast, shading, and exposure—that significantly affect image quality. This nuanced approach to lighting was critical for evaluating the SPOT robot's image capture proficiency under diverse environmental conditions. The comprehensive dataset, encompassing 1260 images across varied angles and lighting scenarios, laid a solid foundation for a detailed analysis of image quality artifacts.

#### 4.3.3. Empirical Findings

The analytical investigation uncovered distinct patterns for each artifact across the range of angles and lighting conditions, as follows:

- **Contrast and Shading:** These artifacts displayed pronounced patterns, peaking at angular extremities (-45 and 45 degrees). This observation suggests that images captured from these angles are likely to exhibit enhanced contrast and shading, potentially improving perceived image quality.

- **Exposure:** A significant pattern was observed under strong lighting conditions, with optimal exposure levels identified at -45 and 45 degrees. Under less optimal lighting conditions, the exposure pattern was less defined, indicating a need for adaptive exposure settings to achieve consistent image quality.

#### 4.3.4. *Visual Illustrations*

The figures below illustrate the observed patterns in contrast, shading, and exposure under varying lighting conditions, complemented by a clustering graph that provides a generalized visualization of these patterns.

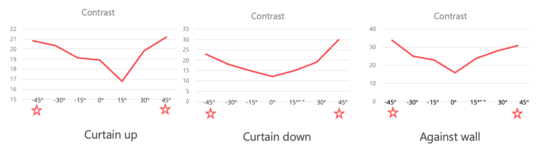


Figure 3: Pattern of Contrast Variation

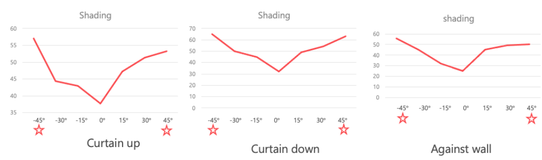


Figure 4: Shading Pattern Across Different Angles

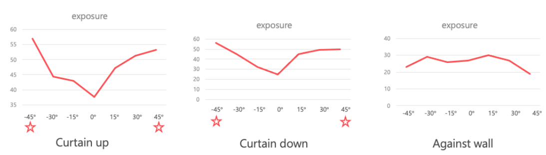


Figure 5: Exposure Variation Under Different Lighting Conditions

#### 4.3.5. *Conclusions*

This study provides insightful elucidation of the SPOT robot's control logic for real-time IQA, revealing distinct patterns of essential artifacts across a variety of angles and lighting conditions. These findings are instrumental in guiding the development of advanced IQA tools, ensuring the acquisition of high-quality images in diverse environmental settings.

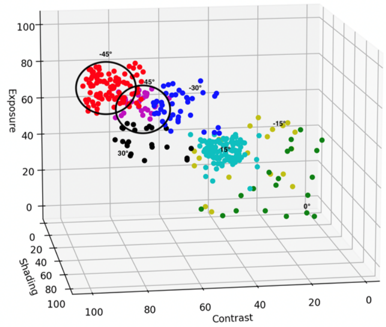


Figure 6: Confidence Map Visualization

### 4.4. *Analysis of IQA Scores Across Different Weather Conditions*

The experiment aimed to understand how different weather conditions affect the Image Quality Assessment (IQA) scores of images captured by a robotic system. The robot was positioned at angles ranging from -45 to 45 degrees, in increments of 15 degrees, under sunny, cloudy, and rainy conditions. This section discusses the insights derived from analyzing the mean IQA scores under these conditions, supported by figures illustrating the data trends.

#### 4.4.1. *Sunny Conditions*

In conditions characterized by ample sunlight, the apex of mean Image Quality Assessment (IQA) scores was discerned at an angle of -45 degrees. This finding implies that direct sunlight exposure may engender glare at specific angles, thereby exerting a notable influence on image fidelity. Nonetheless, an unforeseen pattern emerged wherein IQA scores exhibited a deviation from the anticipated decline as the angle approached 0 degrees, instead manifesting a modest ascent towards 45 degrees.

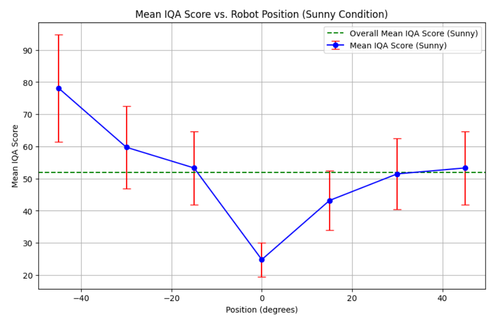


Figure 7: Mean IQA scores under sunny conditions.

### 4.4.2. *Cloudy Conditions*

Cloudy atmospheric conditions have been observed to correlate with a notable increase in Image Quality Assessment (IQA) scores at -15 degrees, suggesting that diffused lighting may offer optimal conditions for image capture. Such conditions tend to mitigate shadows and diminish the pronounced contrast often associated with direct sunlight, thereby highlighting the potential benefits of adapting robotic imaging systems to accommodate cloud cover. This discovery underscores the significance of optimizing imaging parameters in response to varying environmental factors to enhance overall image quality.

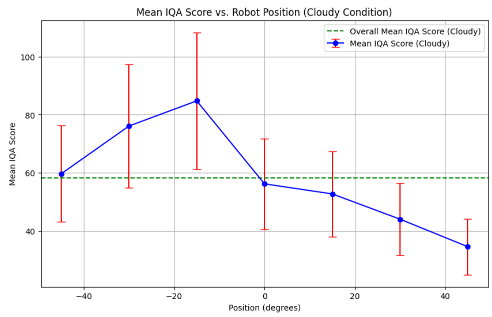


Figure 8: Mean IQA scores under cloudy conditions.

### 4.4.3. *Rainy Conditions*

It is noteworthy that under rainy conditions, the mean IQA scores were observed to be highest at 0 degrees, indicating the advantageous impact of uniform lighting environments on image quality. This consistency in lighting likely mitigates the variability that can compromise image quality, thereby implying potential advantages of overcast conditions for maintaining consistent image capture quality.

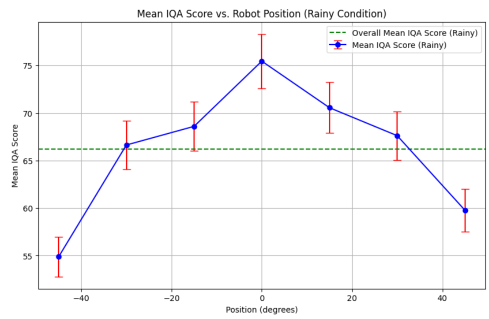


Figure 9: Mean IQA scores under rainy conditions.

These insights provide valuable directions for the development of adaptive imaging algorithms capable of adjusting to varying environmental conditions, thereby enhancing the robustness and reliability of outdoor robotic vision systems.

## 4.5. *Analyzing IQA Scores Depending on Daytime Conditions*

This study aims to evaluate the variance in Image Quality Assessment (IQA) scores based on different daytime conditions, specifically morning, early afternoon, mid-afternoon, and late afternoon. We analyze how environmental factors inherent to these times of day influence the IQA scores at various robot positions.

### 4.5.1. *Morning Conditions*

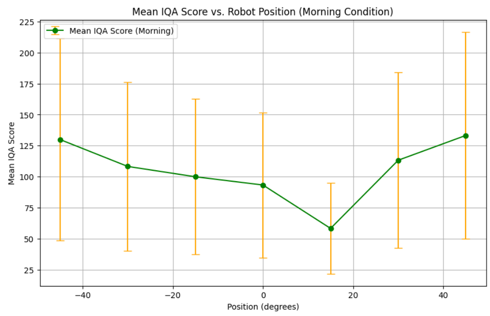


Figure 10: Mean IQA scores vs. robot positions in the morning

The graph above shows the mean IQA scores versus robot positions for the morning condition. We observe a bell-shaped trend with the highest scores at extreme angles (-45 and 45 degrees) and the lowest scores around the central position (0 degrees). This pattern suggests that morning light conditions could influence IQA scores differently, possibly due to the angle of the sun or the presence of morning mist. The variability in scores indicates significant fluctuations in image quality, emphasizing the impact of time-specific environmental factors on outdoor imaging systems.

### 4.5.2. *Early Afternoon (12 - 3pm)*

During the early afternoon, IQA scores are generally higher at extreme angles, with a notable shift in peak scores towards the right, suggesting potentially better image quality at 45 degrees. This period's lower variability compared to the morning implies more consistent lighting conditions, highlighting the sun's influence on image capture quality.

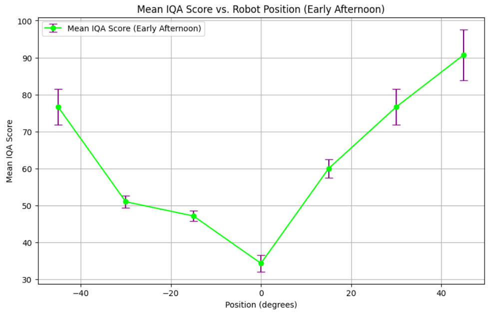


Figure 11: Mean IQA scores vs. robot positions in the early afternoon

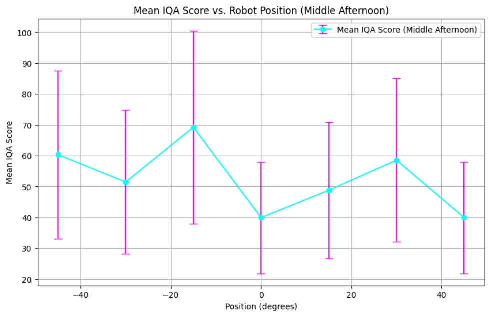


Figure 12: Mean IQA scores vs. robot positions in the mid-afternoon

### 4.5.3. *Mid Afternoon (3 to 5 pm)*

The mid-afternoon data reveals a peak in IQA scores at -15 degrees, indicating a shift in optimal image capture conditions. This unique pattern suggests that certain angles benefit more from the lighting conditions, possibly due to the optimal distribution of sunlight reducing shadows and glare.

### 4.5.4. *Late Afternoon (5 pm to Sunset)*

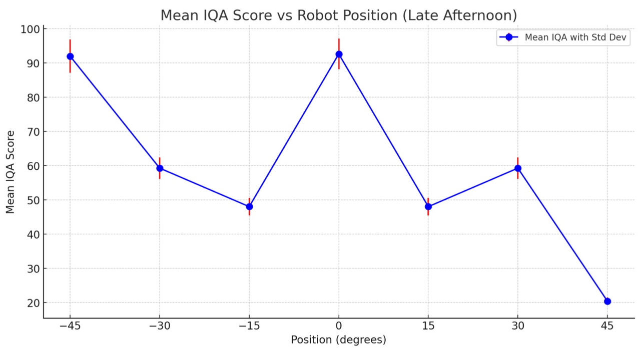


Figure 13: Mean IQA scores vs. robot positions in the late afternoon

In the late afternoon, the IQA scores exhibit varied trends across positions. This time of day might see improvements in image quality due to the cooling temperatures and changing angle of sunlight, affecting image capture differently across the analyzed positions.

### 4.6. *General Insights*

Our analysis across different times of day highlights the significant impact of the sun's position and environmental conditions on image quality. Temporal variations, especially related to the sun's angle and intensity of light, play a crucial role in determining the optimal conditions for image capture by outdoor robotic systems. Understanding these patterns can enhance adaptive imaging strategies, ensuring optimal image quality in varying outdoor conditions.

### 4.7. *Experiment 3: Efficiency and Inspection Time*

In addition to accuracy, we evaluated our method's inspection time compared to traditional methods. This comparison is crucial to highlight the efficiency gains in practical scenarios, particularly in industrial applications where inspection time is a critical factor.

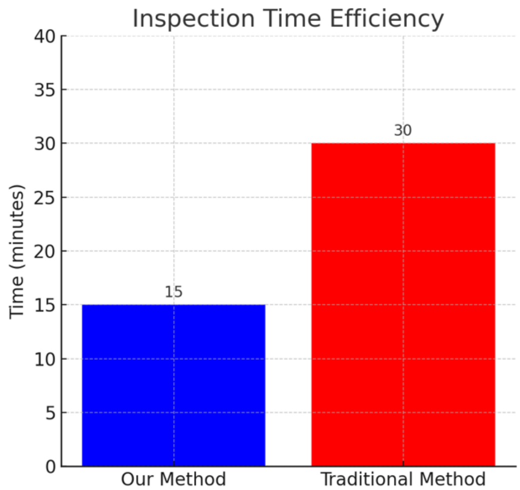


Figure 14: Inspection time efficiency of our method (blue) in comparison with traditional methods (red).

Figure 14 quantitatively compares the average inspection times. Our method shows a marked reduction in time while maintaining high accuracy, thus proving its efficacy in real-world applications.

## 5. Discussion

We have developed an IQA model that dynamically assesses image quality by considering factors such as contrast, exposure, and shading under various lighting and geometric scenarios. This model, trained with a comprehensive dataset, supports robust defect detection by adapting to changes in lighting source type, intensity, and direction.

Integrating an IQA-guided viewpoint planning tool into Spot's inspection system has revolutionized how inspections are conducted. This tool enables real-time positional adjustments for optimal image quality, crucial for detecting defects in settings like construction sites. It reduces the image count needed and plans efficient coverage, particularly of intricate structures like window frames.

Manual quality control is traditionally slow and error-prone. Our approach minimizes these issues by utilizing model-based IQA to improve inspection quality, particularly under variable lighting conditions which typically degrade image quality.

Our method combines advanced vision-based window detection and precise segmentation techniques tailored for diverse environments, ensuring reliable performance and adaptability to environmental changes. This method simplifies implementation, making it practical for a wide range of applications. It effectively identifies defects like scratches and dents, which is vital for maintaining high product quality and safety standards.

In comparison to manual inspection methods, our automated system, enhanced by IQA-based viewpoint planning, shows substantial efficiency improvements, significantly reducing inspection times. These advancements meet the demands of modern industrial environments by streamlining processes and improving productivity and cost-effectiveness.

Our future research will focus on further enhancing the IQA algorithm by integrating additional viewpoint data and refining masking techniques to improve its robustness and applicability across various industrial settings, thereby ensuring superior product safety and customer satisfaction.

## 6. Conclusion

This chapter outlined our approach to enhancing quality inspection processes through automation, concentrating on vision-based window detection, BIM-based segmentation, and IQA-guided viewpoints. Our methods address the inefficiencies and error risks of manual inspections by integrating advanced technologies, significantly improving inspection speed and accuracy.

We introduced a vision-based system adaptable to various lighting conditions, a BIM-based segmentation method for precise defect identification, and an IQA-guided strategy for efficient viewpoint management. These innovations ensure high defect detection rates and meet the rigorous demands of modern industrial environments.

Our results confirm the effectiveness of our automated inspection strategy, which excels in adaptability, precision, and efficiency across different settings and materials. Future work will aim to develop a self-adaptive system to further refine the automation and effectiveness of quality controls.

In conclusion, our research marks a substantial progress in automated quality inspections, offering solutions that enhance productivity, reduce costs, and promote higher industry standards.

## References


[1] M. Javaid, A. Haleem, R. P. Singh, S. Rab, R. Suman, Exploring impact and features of machine vision for progressive industry 4.0 culture (1 2022). doi:10.1016/j.sintl.2021.100132.

[2] T. H. Sun, F. C. Tien, F. C. Tien, R. J. Kuo, Automated thermal fuse inspection using machine vision and artificial neural networks, Journal of Intelligent Manufacturing 27 (3) (2016) 639–651. doi:10.1007/s10845-014-0902-y.

[3] A. Akundi, M. Reyna, A Machine Vision Based Automated Quality Control System for Product Dimensional Analysis, in: Procedia Computer Science, Vol. 185, Elsevier B.V., 2021, pp. 127–134. doi:10.1016/j.procs.2021.05.014.

[4] N. N.J., A. B.K., Role of Computer Vision in Automatic Inspection Systems, International Journal of Computer Applications 123 (13) (2015) 28–31. doi:10.5120/ijca2015905603.

[5] C. G. Drury, HUMAN FACTORS GOOD PRACTICES IN VISUAL INSPECTION, Tech. rep.
URL `https://www.researchgate.net/publication/267548062`

[6] V. Chauhan, H. A. Fernando, C. Heshan Fernando, B. Surgenor, Effect of Illumination Techniques on Machine Vision Inspection for Automated Assembly Machines, Tech. rep. (2014).
URL `https://www.researchgate.net/publication/303785367`

[7] K. Ding, K. Ma, S. Wang, E. P. Simoncelli, Comparison of Full-Reference Image Quality Models for Optimization of Image Processing Systems, International Journal of Computer Vision 129 (4) (2021) 1258–1281. doi:10.1007/s11263-020-01419-7.

[8] Z. Tian, P. Qu, J. Li, Y. Sun, G. Li, Z. Liang, W. Zhang, A Survey of Deep Learning-Based Low-Light Image Enhancement, Sensors 23 (18) (2023) 7763. doi:10.3390/s23187763.

[9] A. Mittal, A. K. Moorthy, A. C. Bovik, BLIND/REFERENCELESS IMAGE SPATIAL QUALITY EVALUATOR, Tech. rep.

[10] K. Hossain, C. Mantel, S. Forchhammer, No reference prediction of quality metrics for H.264 compressed infrared image sequences for UAV applications, in: IS and T International Symposium on Electronic Imaging Science and Technology, Society for Imaging Science and Technology, 2018. doi:10.2352/ISSN.2470-1173.2018.12.IQSP-108.

[11] C. Zhang, J. Pan, S. Chen, T. Wang, D. Sun, No reference image quality assessment using sparse feature representation in two dimensions spatial correlation, Neurocomputing 173 (2016) 462–470. doi:10.1016/j.neucom.2015.01.105.

[12] A. Mittal, A. K. Moorthy, A. C. Bovik, No-reference image quality assessment in the spatial domain, IEEE Transactions on Image Processing 21 (12) (2012) 4695–4708. doi:10.1109/TIP.2012.2214050.

[13] T.-Y. Chiu, Y. Zhao, D. Gurari, Assessing Image Quality Issues for Real-World Problems, Tech. rep.
URL `https://vizwiz.org.`

[14] A. Saberironaghi, J. Ren, M. El-Gindy, Defect Detection Methods for Industrial Products Using Deep Learning Techniques: A Review (2 2023). doi:10.3390/a16020095.

[15] A. J. Lee, W. Song, B. Yu, D. Choi, C. Tirtawardhana, H. Myung, Survey of robotics technologies for civil infrastructure inspection, Journal of Infrastructure Intelligence and Resilience 2 (1) (2023) 100018. doi:10.1016/j.iintel.2022.100018.

[16] R. Maglietta, A. Milella, M. Caccia, G. Bruzzone, A vision-based system for robotic inspection of marine vessels, Signal, Image and Video Processing 12 (3) (2018) 471–478. doi:10.1007/s11760-017-1181-9.

[17] R. Almadhoun, T. Taha, L. Seneviratne, J. Dias, G. Cai, A survey on inspecting structures using robotic systems (11 2016). doi:10.1177/1729881416663664.

[18] H. Nasereddin, G. M. Knapp, Hybrid robotic reinforcement learning for inspection/correction tasks, in: Procedia Manufacturing, Vol. 39, Elsevier B.V., 2019, pp. 406–413. doi:10.1016/j.promfg.2020.01.384.

[19] Institute of Electrical and Electronics Engineers, 2019 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC)., IEEE, 2019.

[20] G. Takam Tchendjou, E. Simeu, Visual Perceptual Quality Assessment Based on Blind Machine Learning Techniques, Sensors (Basel, Switzerland) 22 (1) (12 2021). doi:10.3390/s22010175.

[21] P. Gospodnetić, D. Mosbach, M. Rauhut, H. Hagen, Viewpoint placement for inspection planning, Machine Vision and Applications 33 (1) (1 2022). doi:10.1007/s00138-021-01252-z.