# Improving Image Resolution for Drone-Borne Inspection of Wind Turbine Blades

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## ABSTRACT

Inspections of wind turbine blades, both exterior and interior, present significant challenges due to limited accessibility as well as physical and measurement constraints. Key barriers to effective monitoring include the lack of suitable high-resolution distributed sensors, high cost and safety risks associated with up-tower technician deployment, limited availability of skilled personnel, and confined spaces involved in internal inspections. Advanced technologies such as drones, computer vision, and artificial intelligence offer transformative potential by enabling faster, more accurate, and cost-efficient inspections, leading to improved reliability and reduced overall energy costs. However, drone-based inspections typically require shutting down turbines to ensure the safe operation of unmanned aerial vehicles (UAVs) near the assets. To address this limitation, this research introduces a novel method referred to as Stack-Average (SA), which combines multiple images of a wind turbine to produce a super-resolved image with higher resolution. The SA method facilitates damage detection from greater distances (50+ meters) and eliminates the need to shut down turbines during inspections. The performance of the SA method was evaluated on a 1.5-meter section of a wind turbine blade. Results demonstrated the method’s accuracy in identifying various damage types as a function of image capture distance and the number of images used for super-resolution. This approach has the potential to improve image resolution for a given working distance and thereby enhance remote monitoring of wind turbine blades or other large-scale structures.

## INTRODUCTION

Wind Turbines (WTs) are large structures that generate electricity from spinning components that are rotated by the wind. Their structure typically includes a foundation,

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a tall tower, a nacelle housing the gearbox and generator, and most critically, the blades. Among these components, wind turbine blades (WTBs) are the most performance-sensitive and cost-intensive [1]. Damage to the blades can significantly reduce energy output, increase operational costs, and, in severe cases, lead to total system failure. Current inspection methods for WTBs are labor-intensive and disruptive. External inspections often require shutting down the turbine, reducing energy production, while internal inspections demand that technicians physically enter confined and hazardous spaces. These approaches are particularly challenging in offshore environments, where harsh conditions accelerate blade degradation and make on-site inspections even more difficult. There is a pressing need for more efficient and less intrusive structural health monitoring (SHM) methods.

To date, WTB inspections have relied on three main techniques: visual inspections by technicians climbing the tower [2]; robotic crawlers capturing detailed imagery along the blade surface [3 – 5]; and unmanned aerial vehicles (UAVs) collecting multiple close-range images [6, 7]. Among these, UAV-based inspections are gaining traction across many industries [8 – 10]. However, most commercially available UAV solutions use standard digital cameras (e.g., typically no more than 24 megapixels) and do little or no image processing to enhance the raw data. As a result, they require numerous close-up images to cover the blade and capture fine structural details sufficiently. Thermal imaging drones also exist, but due to resolution limitations, they can only detect significant defects, usually greater than a few centimeters [11]. Moreover, UAVs must fly close to the rotor to collect high-resolution images, which requires stopping the turbine for safety. Concerns over drone stability in high winds and wake effects have made some operators reluctant to adopt UAV inspections. Ground-based alternatives like LiDAR [12–14] and long-range photogrammetry [15, 16] avoid the need to shut down turbines but are impractical for offshore farms due to the requirement for stable platforms. Distributed sensing to identify damage using acoustic sensors shows promise, but the correlation between the sensor signals and damage is still being researched [17, 18].

The purpose of this work is to demonstrate that it is possible to achieve the same resolution of close-up inspections even when images of an operational turbine are collected with the camera more than 50 m away from the blades, thus improving the efficiency of the approach and not requiring turbines to be shut down interrupting energy generation. This study investigates a novel image-processing algorithm referred to as Stack-Average (SA), which combines multiple images of a wind turbine to produce a super-resolved image with higher resolution. As detailed in Table 1, this approach offers a more efficient, safer, and less disruptive alternative for blade inspections, with the potential to transform remote monitoring practices across the wind energy sector.

TABLE I. PAIN POINTS THAT CAN BE IMPROVED USING DRONE-BORNE INSPECTION.

| **OBJECTIVE** | **OUTCOME** |
|---|---|
| Expedite the data collection of images that can be used to identify damage | Reduced inspection costs |
| Limit the interference with the turbines' operation | Negligible impacts on energy production |
| Facilitate early detection of damage | Proactive maintenance, preventing more severe issues from accumulating |
| Improve safety for wind energy workers | No need for rope access and/or personnel entering confined spaces for inspection |

This paper presents an experimental study using the SA algorithm to detect surface damage on wind turbine blades. The results demonstrate that the SA method can significantly enhance image resolution at long distances, enabling effective damage detection without requiring close-up inspections. The remainder of the paper is structured as follows: Section 2 (*The SA algorithm and experimental setup*) details the SA algorithm and the experimental setup used to evaluate its performance. Section 3 (*Analysis of the results*) analyzes the results obtained from the image reconstruction and damage detection tests. Finally, Section 4 (*Conclusions*) concludes the study and outlines directions for future research.

## THE SA ALGORITHM AND EXPERIMENTAL SETUP

High-resolution imaging plays a critical role in a wide range of applications, including medical diagnostics, satellite surveillance, facial recognition, and video streaming. These applications rely on the ability to capture fine details and subtle features. However, acquiring high-resolution images directly is often constrained by hardware limitations, high costs, bandwidth constraints, and environmental noise. As a result, there has been increasing interest in super-resolution techniques, which are computational methods that reconstruct high-resolution images from low-resolution inputs. These approaches offer a cost-effective and scalable solution to enhance image detail without relying on expensive or specialized equipment.

With the advancement of artificial intelligence, deep learning–based super-resolution methods have gained popularity [19]. Despite their success, these techniques are often prone to generating "*hallucinations*," where artificial details that were not present in the original data are added [20, 21]. In contrast, multi-shot super-resolution techniques combine multiple images of the same scene to enhance spatial resolution and color fidelity without introducing non-existent features. These data-driven methods allow sub-pixel localization of features such as light sources [22].

The Stack-Average (SA) algorithm proposed in this study is a multi-shot super-resolution technique that stacks a series of images of the same scene and performs pixel-level averaging to reduce noise and enhance image resolution. This method can upscale image resolution by up to four times while preserving fine details. As illustrated in Figure 1, sixteen 61-megapixel (MP) images of a static scene were processed using the SA algorithm, resulting in a final image resolution of approximately 240 MP. By selecting a region of interest (ROI) in the initial image, the algorithm performs image stabilization across the remaining frames to correct for camera and subject motion. This alignment capability is especially valuable in the field, where it can compensate for UAV oscillations and turbine blade rotation, enabling the acquisition of super-resolved images from significant distances.

To validate the effectiveness of the SA algorithm, both laboratory and field experiments were conducted. A damaged 1.15 × 1.63 m section of a wind turbine blade (WTB), featuring a prominent full-depth crack across both the high-pressure and low-pressure sides (Figure 2), served as the test object. The crack on the high-pressure side reached a minimum width of 2 mm. A DJI Matrice 300 RTK UAV, equipped with a Sony α7R-V 61 MP camera and a 35 mm lens, was used to capture imagery of the blade laid flat on the ground. The UAV hovered at distances ranging from 10 to 100 meters in 10-meter increments. At each altitude, 32 images were acquired, yielding 320 images per blade side for processing with the SA algorithm (see Figure 3). This dataset enabled a robust evaluation of the algorithm's ability to preserve fine structural details and reduce noise as a function of distance.

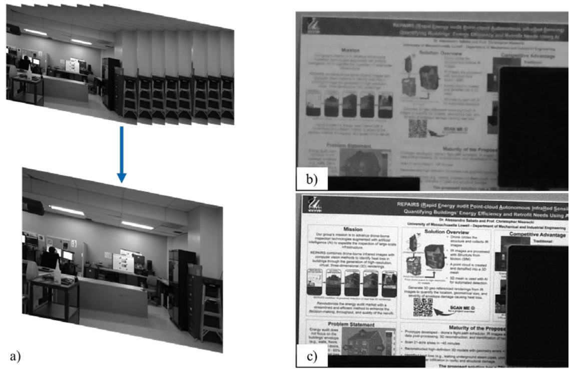


Figure 1. Illustration of the Stack-Average (SA) algorithm workflow: a) multiple lower-resolution images of the same scene are aligned and averaged to generate a single higher-resolution image, b) zoomed-in detail from an original 61 MP image showing limited clarity, and c) corresponding detail from the super-resolved 240 MP image produced by the SA algorithm, highlighting the improvement in sharpness and feature visibility.

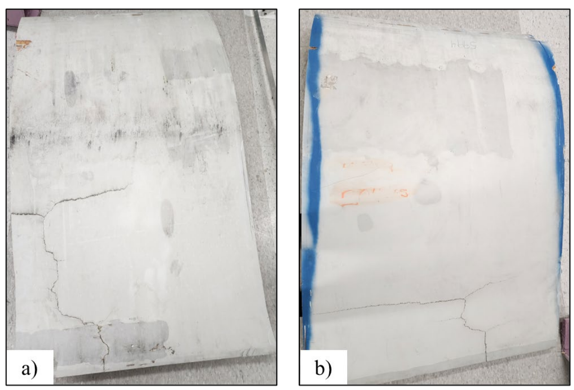


Figure 2. Tested section of the wind turbine blade section: a) high-pressure side, showing surface damage and crack features and b) low-pressure side, displaying the continuation of the same structural damage across the blade's profile.

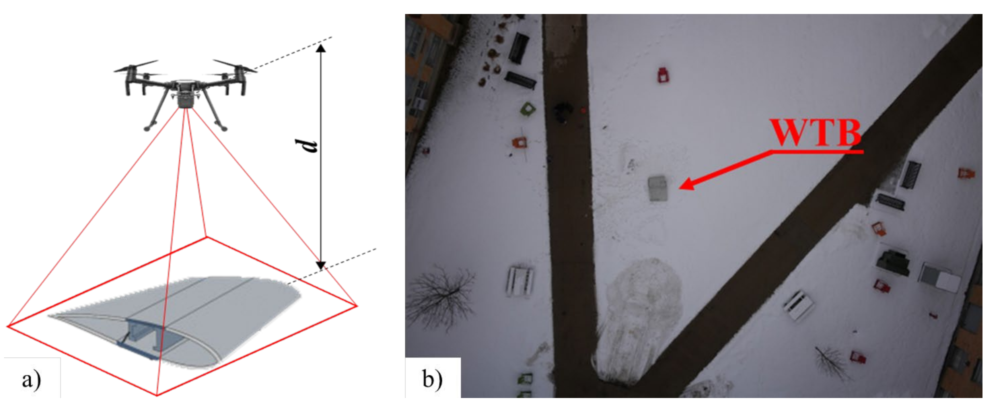


Figure 3. Experimental setup for validating the SA method and enhancing image sharpness: a) UAV-based image acquisition process using a Matrice 300 RTK equipped with a 61 MP camera and b) sample image captured from 40 meters, showing the resolution and detail of the raw input before super-resolution processing.

## ANALYSIS OF THE RESULTS

This section summarizes the results of the experiments described previously. For each test, 32 images captured by the UAV at a given distance were first aligned using local image features, such as the edges and contours of the wind turbine blade, to compensate for drone movement and vibration. This alignment process is essential to ensure accurate super-resolution reconstruction. Importantly, relying on local features provides a dual benefit: it not only mitigates UAV oscillations but also accounts for small variations in the position and orientation of the blade. This is particularly advantageous when inspecting operational turbines, where slight rotational shifts between image captures are common.

Once all 32 images were aligned, the SA algorithm was applied. The SA algorithm upscaled each image by a factor of four and performed pixel-level stacking using median filtering. The median filtering was chosen because it creates less blur than traditional mean-based or Gaussian-based filtering and it is especially powerful in eliminating noise while preserving features of interest, thus increasing image quality. The last step is to perform image sharpening to eliminate the slight blur introduced by the averaging step. After averaging, an image-sharpening step was applied to restore any softness introduced during the stacking process.

The results of this test are shown in Figure 4, which shows the high-pressure side of the blade. Although similar improvements were observed on the low-pressure side, those results are omitted for the sake of brevity. It should be noted that all the images in Figure 4 have been cropped around the blade section and zoomed in to improve visualization of the damage features. From the sequence of images shown in Figure 4, it can be seen that the SA algorithm's effect on enhancing images becomes more and more evident as the camera is further away from the blade.

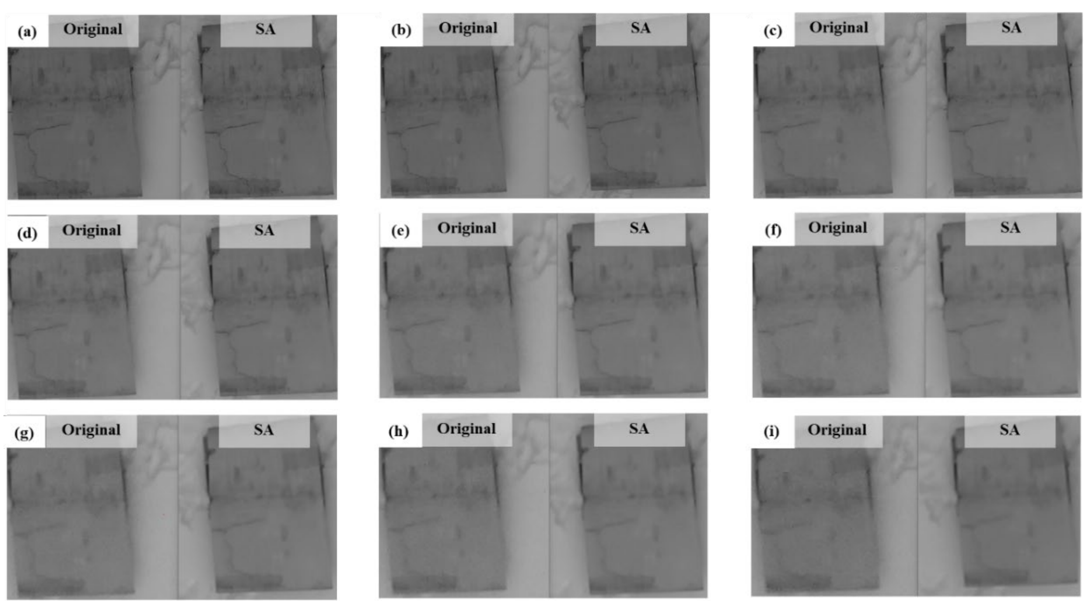


Figure 4. Comparison between original single-shot images and SA-enhanced images of the wind turbine blade at various altitudes: a) 10 m, b) 20 m, c) 30 m, d) 40 m, e) 50 m, f) 60 m, g) 70 m, h) 80 m, and i) 100 m. Each pair illustrates the improvement in image clarity and crack visibility achieved through the SA algorithm as the UAV's distance from the blade increases.

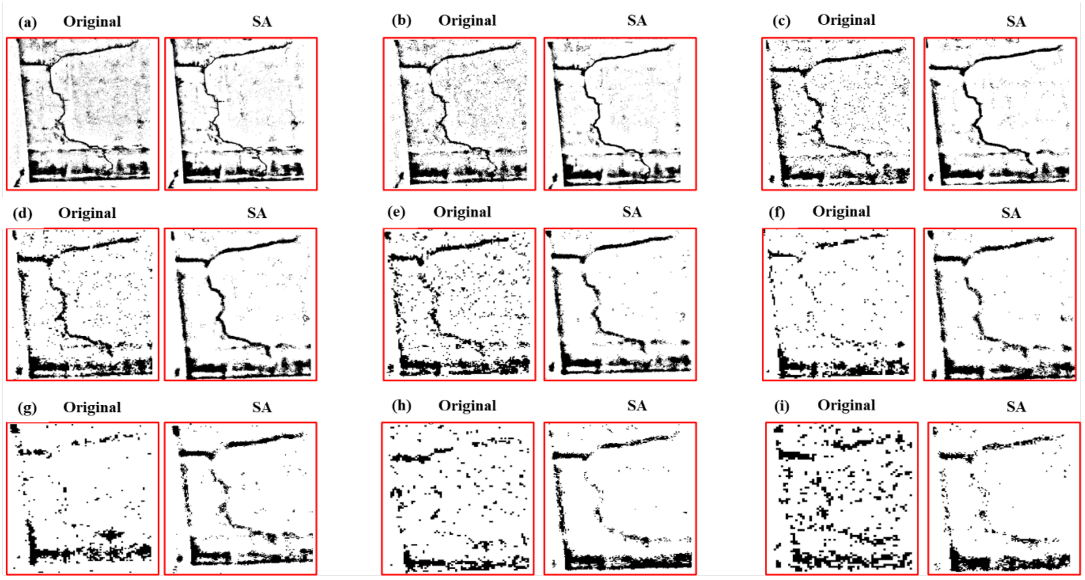


Figure 5. Comparison of segmented images of the blade's crack from original UAV captures and their SA-enhanced counterparts at varying distances: a) 10 m, b) 20 m, c) 30 m, d) 40 m, e) 50 m, f) 60 m, g) 70 m, h) 80 m, and i) 100 m. Each set highlights the effectiveness of the SA algorithm in preserving crack visibility and improving segmentation quality, particularly at longer distances where the original images exhibit significant noise and feature loss.

While at 10 m the effect of super-resolving barely causes an increase in image quality (see Figure 4a), at 100 m the difference is much more noticeable (see Figure 4i). In the original single-shot images captured at 100 meters, cracks are barely distinguishable due to high noise levels. In contrast, the super-resolved images reveal clearly defined crack features, readily visible to the naked eye.

To further assess the algorithm's effectiveness, image segmentation was performed on the regions containing cracks. Adaptive Otsu thresholding was used to binarize each image based on localized intensity values, which helps isolate damage features even under varying lighting and noise conditions. The segmentation results are presented in Figure 5, highlighting the improved clarity and feature definition achieved through the SA method.

Figure 5 highlights the impact of the Stack-Average (SA) algorithm on the quality of segmented images. The original 61 MP images exhibit significant feature degradation and noise. This aspect is particularly apparent during adaptive thresholding, which, as a local binarization technique, tends to amplify noise in high-frequency regions. This is most noticeable at closer distances (see Figure 5a and Figure 5b), where, although the crack's shape is still discernible, the segmentation of the original images contains considerable noise artifacts. In contrast, the super-resolved images produced by the SA algorithm demonstrate significantly cleaner segmentations, underscoring the algorithm's effective denoising capability. As the camera distance increases, the benefits of the SA method become even more pronounced, as the crack becomes less and less identifiable in the original images. In the original images, the visibility of the crack diminishes rapidly, with fine details fading into noise beyond 50 meters. However, in the super-resolved counterparts, the cracks remain well-defined and accurately segmented, even at the maximum distance tested. At 100 meters (see Figure 5i), the crack is barely visible in the raw image, while it remains clearly identifiable in the SA-enhanced version. These results qualitatively demonstrate the SA algorithm's ability to suppress noise and enhance structural features, validating its effectiveness for long-range wind turbine blade (WTB) inspections. By enabling high-resolution, UAV-based imaging from distances up to 100 meters, the SA method offers a powerful tool for remote, non-intrusive damage detection in large-scale infrastructure.

## CONCLUSIONS

This study introduces and validates the Stack-Average algorithm as an effective and practical solution for enhancing image resolution in WTB inspections from significant distances. By stacking and averaging multiple high-resolution images acquired using a UAV, the SA method successfully reconstructs super-resolved images that preserve critical structural details, such as surface cracks, otherwise lost in single-shot captures, particularly at distances greater than 50 meters. Experimental results show that the algorithm not only improves the visual clarity of damage features but also significantly reduces image noise and enhances segmentation accuracy for damage detection. Importantly, this approach can enable remote, non-intrusive inspections that eliminate the need to shut down turbines or deploy personnel into hazardous environments, offering a safer, faster, and more cost-effective alternative to traditional inspection methods. The Stack-Average method thus represents a promising step forward in integrating computational imaging with UAV-borne SHM solutions for wind energy infrastructure. Future work will focus on automating the image alignment process under turbine rotation, exploring real-world implementation, and extending the approach to additional structural components and damage types.

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