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Using UAV Imagery and Deep Learning for Wind Turbine Inspection

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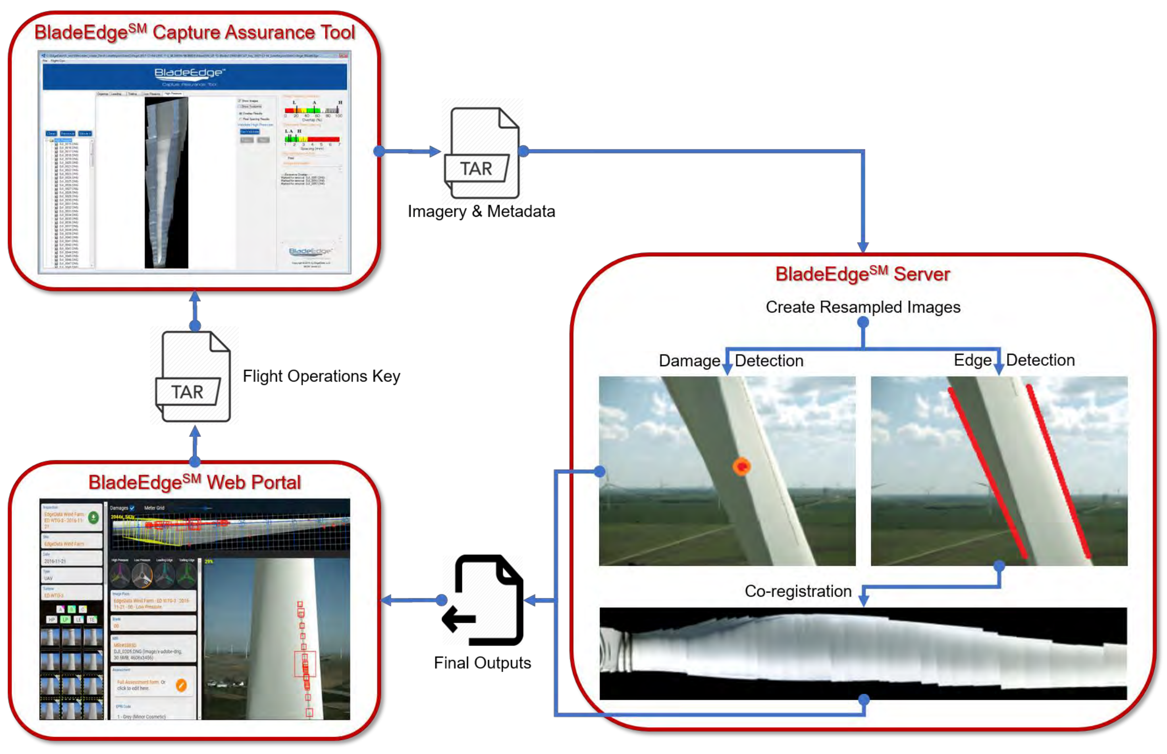
Introduction

When it comes to using an Unmanned Aerial Vehicle (UAV) to collect imagery for wind turbine inspections, maneuvering a drone around a huge turbine isn't the only challenge involved. There's also the issue of capturing extra positional information so images can be projected onto a plane, which is necessary since the camera is not positioned to look directly down as in most UAV imagery applications. Then there's ensuring the quality of the capture while in the field to avoid the costs associated with having to re-fly a job. Finally, there's the time and rigor required to analyze all the data to identify and locate damage and other abnormalities on turbine blades.

Wind turbine blades affected by leading edge erosion with (left) leading edge delamination, (right) pits and gouges.

Objectives

We present a workflow currently in use that takes UAV imagery from flights around wind turbine blades, and automatically assesses those images for defects.



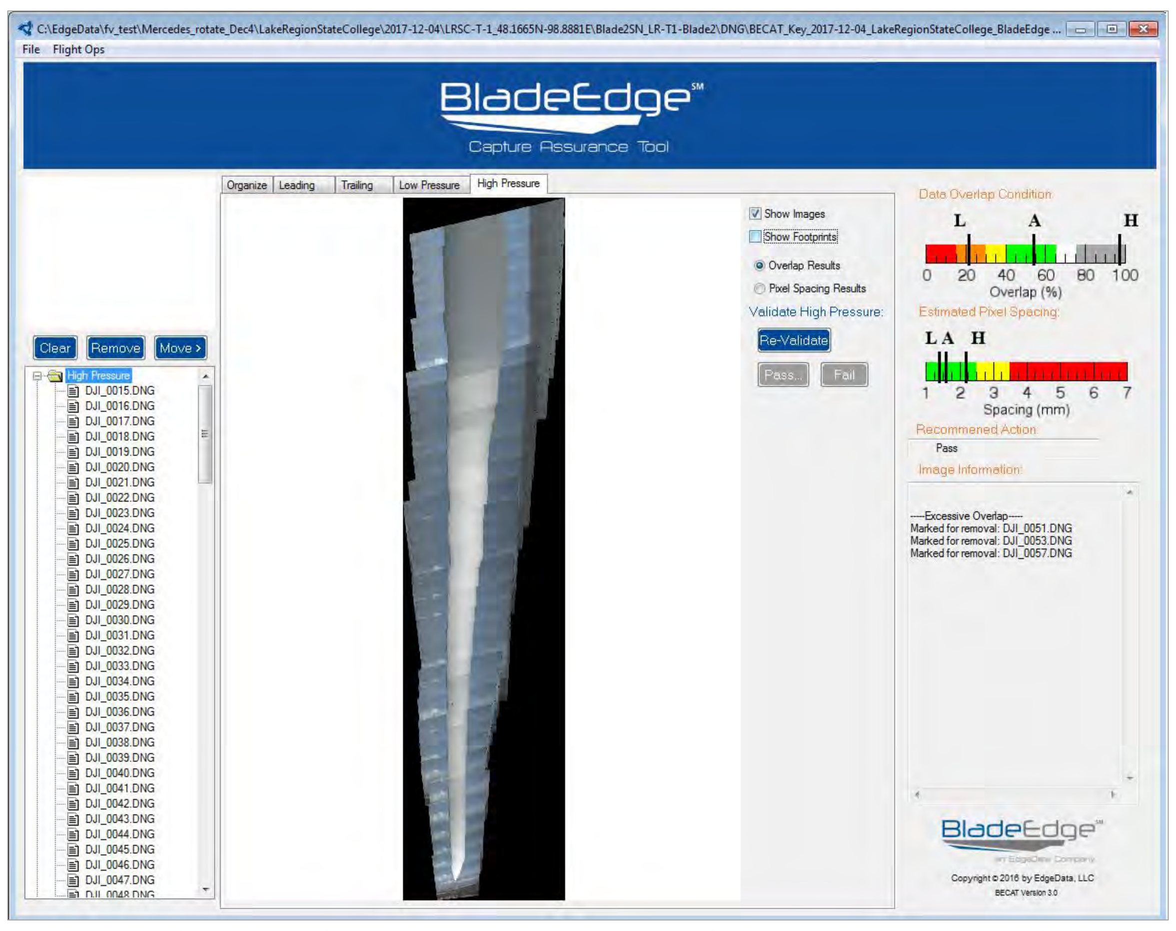
Methods – Image Capture

Multiple images are captured along the wind turbine for all four sides, and all three blades of a wind turbine. The current procedure is to fly one side of the blade at a time. Four flights are required for a single blade. Blades are flown from root to tip, and the root and tip locations are captured from directly underneath the feature.

Methods – Capture Assurance

The two main metrics that we use to validate if a capture is good or not, and what they help with preventing are:

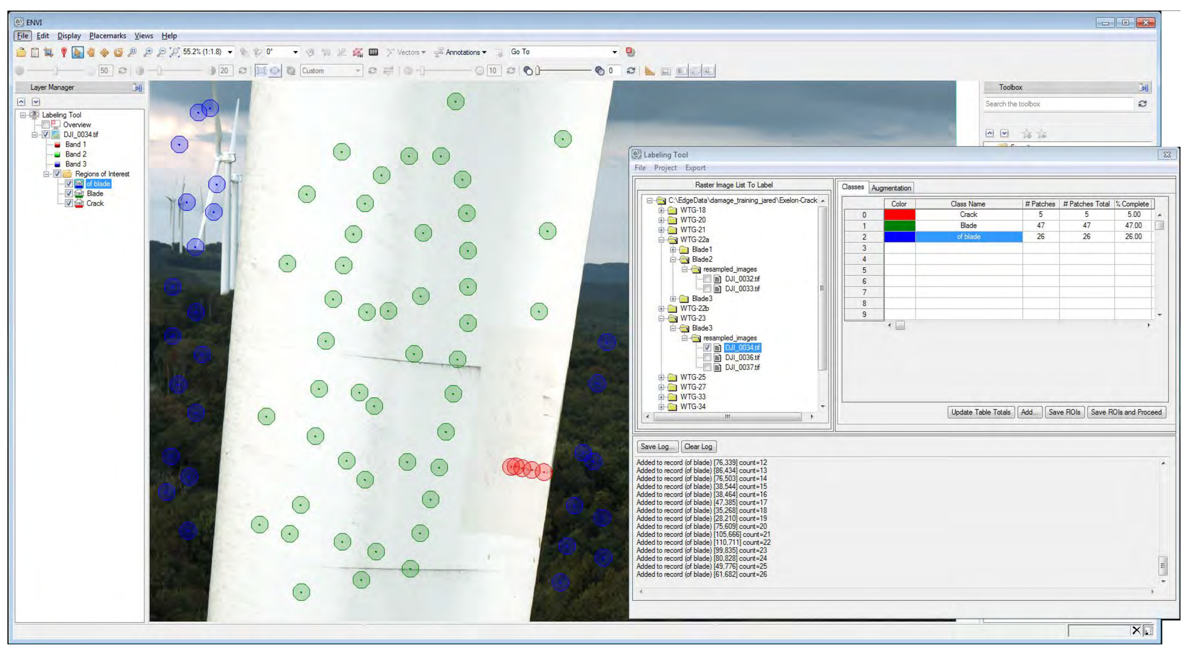
- Image overlap: ensures uniformity of flight, eliminates gaps, ensures mosaics are continuous.
- Pixel spacing: ensures uniformity of flight, flags cases where the data doesn't match, distance to the blade (too far/close).



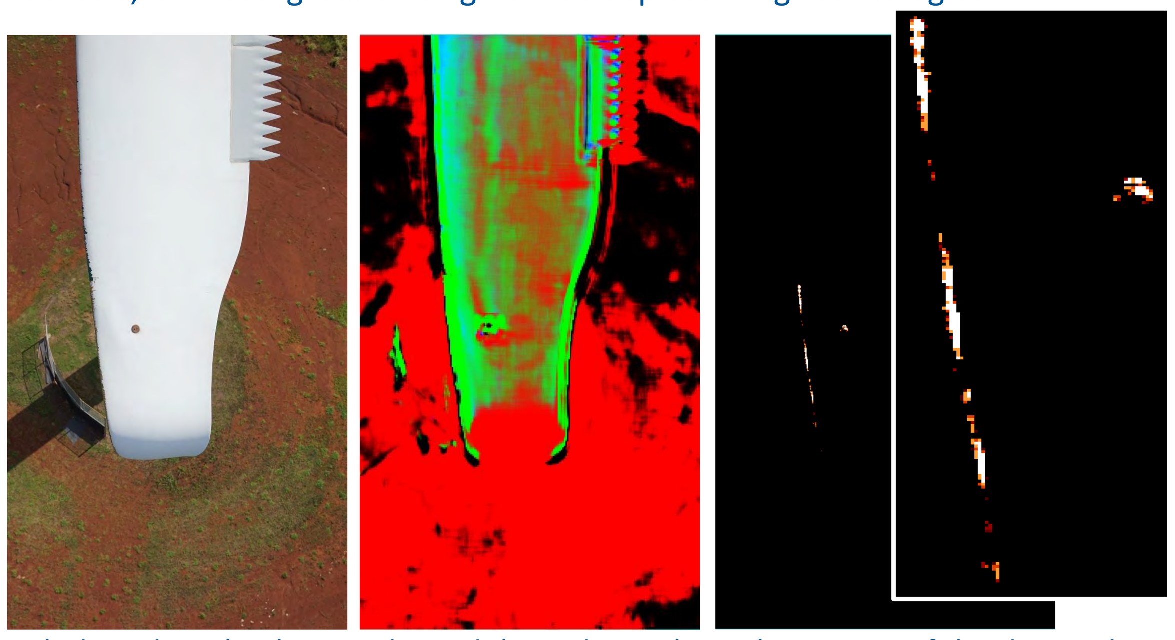
On-site validation of image metadata, GPS information, image overlap and pixel spacing using the BladeEdge℠ Capture Assurance Tool (BECAT).

Methods – Damage Detection

Damage detection is performed on the pixel data using Harris Deep Learning technologies, and damage locations are reported for each image. Current models are trained on chip and crack damage types.



Labeling of imagery for the generation of models of blade edges, various defects, and background using Harris Deep Learning technologies.



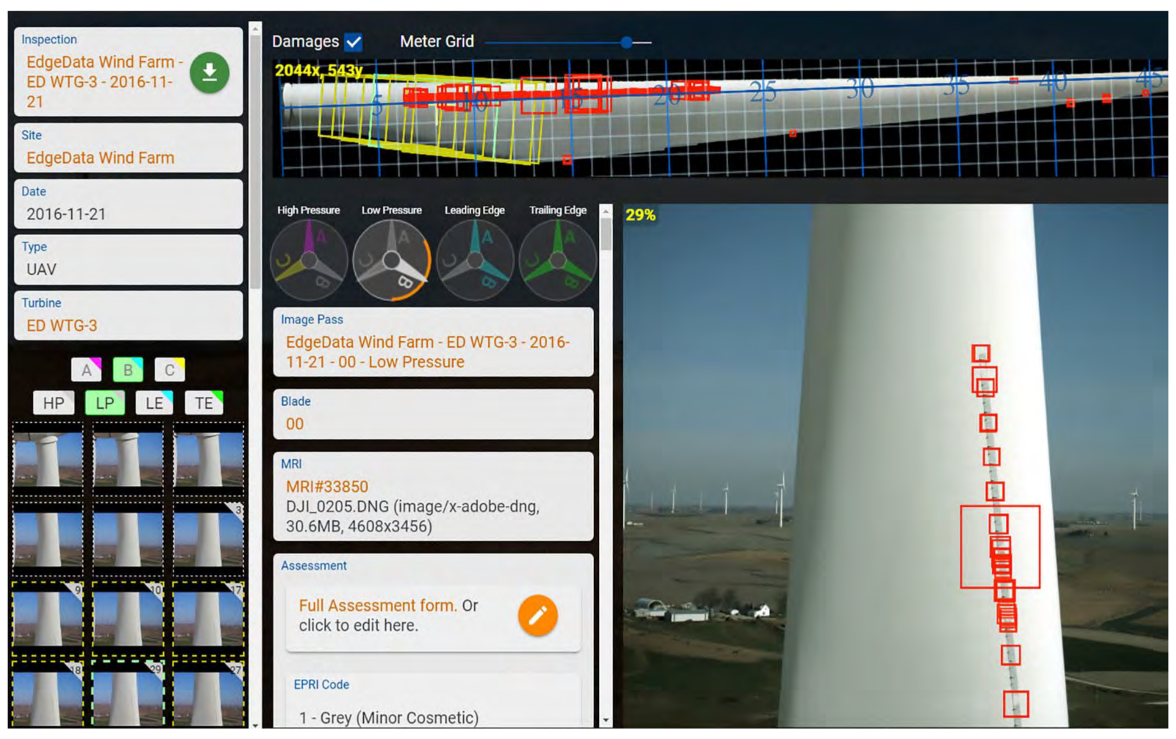
Blade edge, background model, and resulting heatmap of leading edge erosion, showing location and type of the defects.

The Deep Learning technologies are achieving 95-99 % accuracy when identifying damage on wind turbine blades.

Results

A web application, the BladeEdge℠ Portal, provides user friendly access to wind turbine blade inspection information generated by the aforementioned workflow. Specifically, imagery is organized by turbine, blade, and blade side with anomalies and damage graphically represented.

From this application users have the capability to modify findings as well as organize and output inspection results.



Conclusions

This method for wind turbine inspection significantly reduces the cost of wind turbine management and inspection, and allows to inspect more turbines in less time.

With an accuracy of 95+ %, there is little variation between these automatic inspections as compared to inspections done manually by human technicians.

Future work on the project includes adding more damage types, and assigning damage severity classifications based on standards set forth by the Electric Power Research Institute (EPRI).

These enhancements will further inform turbine managers on how to prioritize the repair and maintenance of their wind turbines.

References

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