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Automated Drone-Based Aircraft Inspection

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Abstract. Deep learning combined with autonomous drones is increasingly seen as an enabler of automated aircraft inspection which can support engineers detect and classify a wide range of defects. This can help increase the accuracy of damage detection, reduce aircraft downtime, and help prevent inspection accidents. However, a key challenge in neural networks is that their stability is not yet well understood mainly due to the large number of dimensions and the complexity of their shapes. This paper illustrates this challenge through a use case that applies MASK R-CNN to detect aircraft dents. The results show that environmental factors such as raindrops can lead to false positives. The paper also proposes various test scenarios that need to be considered by the developers of the drone-based inspection concept to increase its reliability.

Keywords. Reliability, aircraft inspection, drones, convolutional neural network

1. Introduction

The current aircraft maintenance inspection process has not evolved during the last 40 years despite the rapid advances in technology. It is not only time consuming as it requires a long time to prepare work platforms, ground support, and anti-fall straps to conduct inspection; but also dangerous as reports of injuries during inspection are not uncommon. Automating the inspection process can therefore increase workplace safety by reducing incidents, and reduce costs related to maintenance which remains the second largest cost for airlines after fuel (e.g. manhours, equipment, training, PPE costs, etc.). In addition, automation will enable a more objective assessment of damage as different inspectors can have different assessments. This would prevent from the failure to detect critical damage as it was the case for the Aloha Airlines Flight 243 [1] and recently the Virgin Australia Regional Airlines ATR72 [2].

There is no doubt that computer vision will soon revolutionize aircraft inspection as it's already the case other domains that require visual assessment. This is not surprising given that object detection errors by a machine decreased from 26% in 2011 to only 3% in 2016 which is less than the human error of 5% [3]. The main driver behind these improvements is deep learning which had a significant impact on robotic perception following the design of AlexNet in 2012. In medical imaging diagnosis for instance, technology has become so good that the FDA has recently approved many use cases [4]. In the automotive industry, companies such as Tesla and Waymo are working towards fully driverless cars enabled by computer vision technology that can detect

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various objects around the car. In production and manufacturing environments, computer vision is used for the external assessment of product quality and equipment such as tanks, pressure vessels, and pipes. In agriculture, computer vision algorithms are integrated with drones that can scan large fields in a matter of minutes. Images are collected and processed to help farmers make informed decisions about their crops. The captured images include soil and crop conditions to monitor for any stress or disease [5].

Recently the aviation community started to develop the drone-based aircraft inspection concept. For instance, Ubisense and Mrodrone [6,7] have developed an inspection system that has been tested by Easyjet and is planned to be rolled out across Easyjet's European bases. KLM Engineering & Maintenance is also experimenting with drones to inspect their aircraft and the research program is currently in its second trial phase. Another initiative is the Air-Cobot project [8] which aims at automating aircraft visual inspection and involves various academic and industrial partners including Airbus. In the same vein, the authors have also recently developed a Convolutional Neural Network to detect aircraft dents [9]. All these efforts aim at obtaining a good accuracy in defect detection and classification. However, as sensors can sometimes be unreliable, the question remains how well the system would perform in real-life outside the hangar? How to further improve it knowing that the slightest error in object detection can potentially lead to an aircraft accident if defects went unnoticed? And how to increase the confidence of aircraft engineers [10,11] in the drone-based aircraft inspection?

These are all challenging questions as most of the research efforts in deep learning focus on improving the detection accuracy, but lag when it comes to neural network safety/stability and dealing with various types of uncertainties. This is mainly due to the lack of understanding of deep learning technologies even by AI experts. This can be explained by the large number of dimensions and complexity of the shape of neural networks. In addition, there has been little emphasis on standards and methodologies which can lead to a stable and reliable intelligent environment [12].To tackle this problem, this paper proposes different test scenarios that need to be considered by the aviation community in order to make drone-based inspection more reliable. The scenarios can be used to further improve the stability of neural networks and robustness of the decision-support system and validate the concept.

This paper is organized as follows. Section 1 provides the introduction. Section 2 presents the motivation behind automating aircraft inspection. Section 3 presents the use case of using MASK R-CNN to detect dents and illustrates some of the challenges. Section 4 proposes test scenarios that need to be considered by the developers of the automated drone-based inspection concept to increases its reliability. The conclusion is provided in section 5.

2. Why Automate Aircraft Inspection?

The aircraft inspection process is a recurrent process that needs to be conducted at every flight cycle. The level of inspection depends on different factors. For instance, if the aircraft was subject to abnormal events, a thorough inspection for potential damage is required. Examples of abnormal events include bird strike, lightning strike, hard landings, and encountering turbulent air. Table 1 shows examples of the inspections required for the King Air following abnormal events.

Table 1. Areas to be inspected after abnormal conditions [13].

Inspection Areas	Flight through turbulent air	Hard landings	Lightning strike
Nacelles	a	a	
Wing Panels	a	a	
Fuselage Nose Section	a , c, d	a, d	
Fuselage Centre Section	a	a	
Fuselage Aft Section	b	b	
Fuselage			e, f, g, h
Empennage			e, f, g, h
Wing Surfaces			e, f, g, h, i

Inspections Required:
a - Cracks, wrinkles and loose or missing rivets
b - Skin wrinkles at the juncture of the fuselage and empennage.
c - Windshield for evidence of structural deformation or failure.
d - Avionics, antenna and components for security and attachment.
e - Burned hole/s in metallic surfaces.
f - Plastic parts – delaminated and/or deformed.
g - Antennas – for evidence of arcing, sooting, or pitting.
h - Structure between entry and exit points.
i - If near fuel vent, inspect all plumbing for damage.

Automated aircraft inspection basically aims at automating the visual inspection process normally carried out by aircraft engineers. i.e. It aims at detecting defects that are visible on the aircraft skin which are usually structural defects. These can include dents, lightning strike damage, surface finish defects, fasteners defects, corrosion, cracks, just to name a few. Automatic defect detection can be enabled by using a drone-based system that can scan the aircraft and detect/ classify a wide range of defects all in a very shorty time. Eliminating the manual process can lead to a significant impact on aircraft operators with numerous benefits including but not limited to:

- Reduction of time spent on maintenance: The drone can quickly reach difficult places such as the flight control surfaces in both wings and empennage. This in turn will reduce man hours and preparation time as engineers would need heavy equipment such as cherry pickers to have more scrutiny. The inspection time can be even further reduced if the drone-based system is able to assess the severity of the damage and the affected aircraft structure with reference to aircraft manuals.
- Reduction in safety incidents and PPE related costs: Engineers no longer need to work at heights or expose themselves to hazardous areas e.g. in case of dangerous aircraft conditions or the presence of toxic chemicals. This also reduces costs on Personal Protective Equipment.
- Reduction in Aircraft-On-Ground (AOG) time: Time savings on inspection time can lead to reductions of up to 70% in turnaround times.
- Reduction in decision time: Defect detection will be much more accurate and faster compared to the current visual inspection process. E.g. it takes operators between 6 to 8 hours to find lightning strike damage. This can be reduced up to one hour with an automated drone-based system. Such time savings can free up aircraft engineers from dull tasks and making them focus on more important tasks. This is especially desired given the projected need of aircraft engineers in various regions of the world according to a recent Boeing study.
- Objective damage assessment and reduction of human error: If the dataset used by the neural network is annotated by a team of experts who had to reach consensus on what is a damage and what not, then detection of defects will be

more objective. Consequently, human errors such as failing to detect critical damage (e.g. due to fatigue or time pressure) will be prevented.

- Augmentation of Novices Skills: It takes a novice 10000 hrs. to become an experienced inspector. Using a decision-support system can significantly augment the skills of novices.

3. Automated Defect Detection Using MASK R-CNN

To demonstrate the concept of automated drone-based inspection, the authors have applied MASK R-CNN to automatically detect aircraft dents [9]. Mask R-CNN is an instance segmentation model which enables the identification of pixel-wise delineation of the object class of interest. In order to get instance segmentation for a particular image, two main tasks are required: First, the bounding box-based object detection (Localization task) which uses similar architecture as faster R-CNN [14]. The only difference in Mask R-CNN is the Regions of Interest (ROI) step. Instead of using ROI pooling, it uses ROI align to allow the pixel to pixel preserve of ROIs and prevent information loss. Second, the semantic segmentation which allows segmenting individual objects at pixel within a scene, irrespective of the shapes. Semantic segmentation uses a Fully Convolutional Network which creates binary masks around the bounding box objects through creating pixel-wise classification of each region. Hence, Mask R-CNN minimizes the total loss.

The neural network was trained with 55 photos containing aircraft dents. Because the dataset was small, it was decided to use a 10-fold cross validation approach [15]. So, the dataset was split into 10 equally sized parts 9 of which were used for training and 1 one for testing. The experiment included 10 different combinations of training and test pairs. The performance of each fold was evaluated using precision and recall (see Table 2). During the initial 15 epochs of training, the RESNET weights were kept constants, while the layers of the head of MASK-RCNN were trained and finetuned. The head includes the Region Proposal Network, Masking, and Bounding Boxes, among others. Then another 5 epochs were used to continue training the head of the Mask R-CNN structure including the RESNET layer. An important improvement in both precision and recall was noticed. This could be explained by the fact that the RESNET layer functions as a feature extractor and therefore training it leads to more true positives.

Table 2. Average results corresponding to 10 folds. Precision = TP / (TP +FP), Recall = TP / (TP + FN), TP: True Positives, FP: False Positives, FN: False Negatives. Confidence Threshold = 73%.

Performance	Training head only (15 epochs)	Training head (15 epochs) + RESNET (5 epochs)
Train Size	49.5	49.5
Test Size	5.5	5.5
TP	5.7	6.9
FP	3.8	3.0
FN	6.1	5.4
Precision	**53.6%**	**69.13%**
Recall	**46.2%**	**57.32%**

Analyzing the results show that factors such as lighting and environmental conditions can mislead the model. For instance, raindrops and rivets can be confused with dents (Figure 1). Therefore, additional training with data containing these anomalies is required, and more experiments need to include these types of scenarios during the physical testing of the drone.

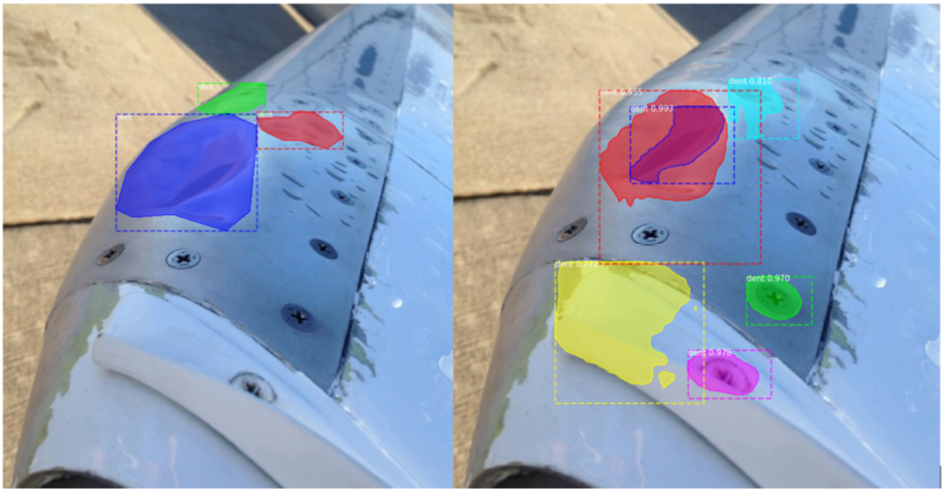

Figure 1. False Positive examples from Fold 10 test set where raindrops and rivets are confused with dents. The manually labeled photo is on the left while the prediction is shown on the right.

4. Test Scenarios

This section presents different scenarios which can be used to improve the reliability of automated drone-based aircraft inspection. These scenarios can also be used to design neural networks architectures specifically tailored to the aircraft inspection problem.

4.1. Environmental & Diurnal Effects

Environmental effects such as rain, sand, and salt can drastically affect object detection performance. As shown in [9], It might be a challenging task for the drone to detect defects under this type of scenarios because it remains a challenging task even for humans. However, equipping the drone with advanced scanning hardware might resolve this problem. In addition, Diurnal effects such as changes in light and temperature can also affect detect detection [9] (Figures 2-3). This could be an issue if the drone scans the aircraft from a fixed angle, as aircraft engineers usually inspect aircraft parts from different angles in order not to miss critical damage. A potential solution is to use multi-drone teaming and swarming with the help of light beams.

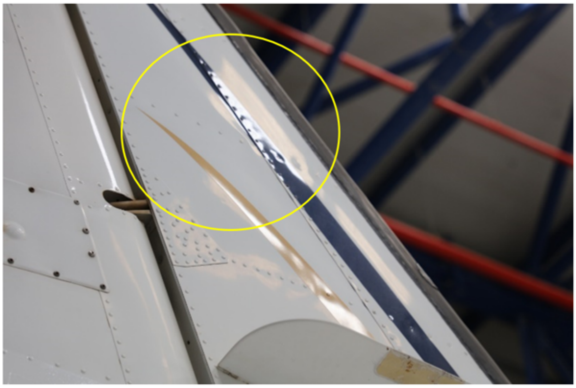

Figure 2. The gaps could be due to lose fasteners in edge of skin lap. Defect can easily be missed if not inspected standing on a work stand. The light plays an important role in damage detection. Photo taken at Abu Dhabi Polytechnic Hangar.

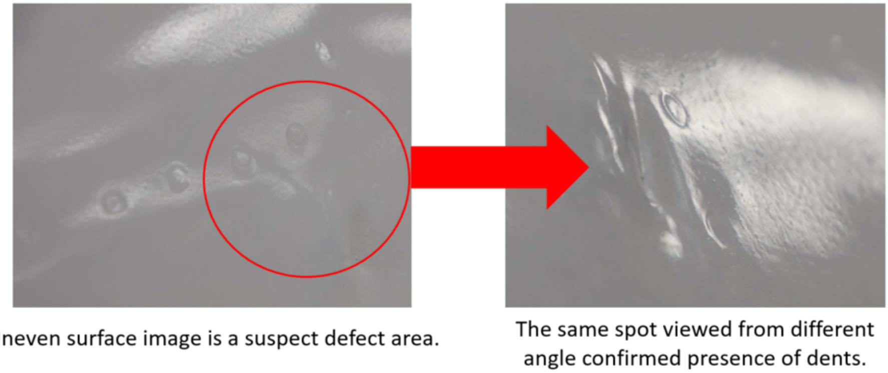

Figure 3. Dents on an engine cowling of Falcon 20 at Abu Dhabi Polytechnic Hangar.

4.2. Allowable Damage

Not all defects detected by human operators must be repaired. When an aircraft engineer detects a dent in the rear fairing skin for instance, he performs various reasoning processes (Figure 4). E.g. looking whether the structure is primary or secondary, consulting aircraft documentation to check if the defect is allowable or must be repaired. Engineers also look at the type of material affected (e.g. chemically milled section, composite structure, and laminated honeycomb) as different materials have different properties. Therefore, to reduce false positives, the drone should be able to distinguish between allowable and non-allowable damage.

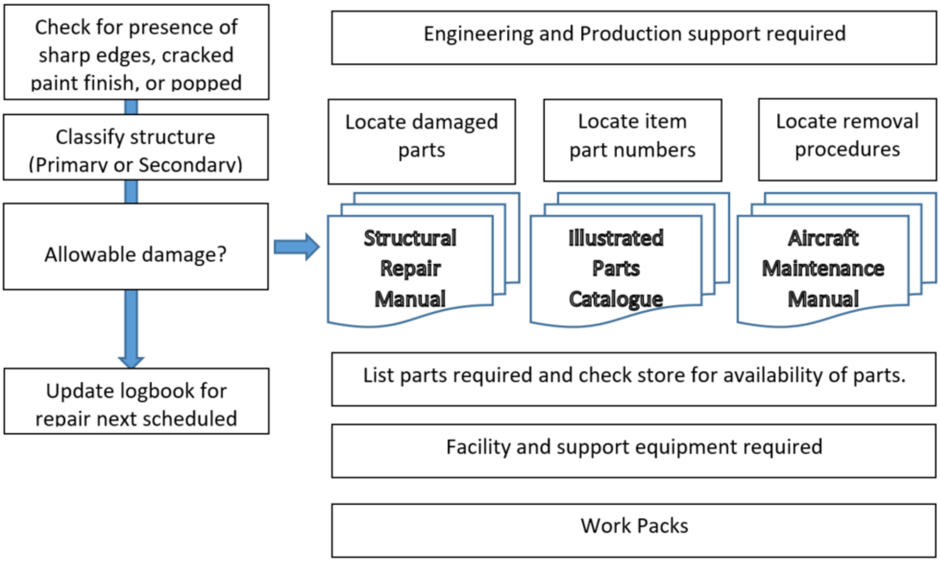

Figure 4. Damage examination and evaluation by a human inspector.

For instance, taking a scratch on the Falcon 20 as an example damage. Its importance depends on the nature of the scratched material, the shape of the scratch, and the depth of the scratch [16]. Scratches with sharp edges, triangular or trapezoidal bottom are the worst. Deep scratches usually eliminate the protective coating and reduce the cross section of the stressed material. The drone should be able to precisely measure the depth of the scratch using advanced scanning hardware and compare it to the thickness of the protective coating shown in table 3. A scratch with a depth less than the coating thickness will be considered negligible (less than 0,04 mm). It is prohibited to smooth out such scratches as it could lead to the reduction of thickness of the protective coating and corrosion. If the scratch is deeper than 0,04 repair actions are needed. These include eliminating the 'notching effect', protecting against corrosion, and patching the scratched area. Another example damage includes dents. An allowable dent must not exceed a specific length (Figure 5) and must be free from sharp creases, gouges, or cracks. Similar requirements exist for other types of damage e.g. cracks, localized impact, corrosion, wear, etc.

Table 3. Coating thicknesses on the Falcon 20.

Material nominal thickness [mm]	Thickness of Aluminum Coating each Face [1/100 mm]
0.3 to 0.6	4 to 6
0.8 to 1.6	4 to 6
2 to 3.5	4 to 8
4 to 6	4 to 10

The above requirements show that the drone algorithm should include relevant data from the aircraft Structure Repair Manual, Integrated Parts Catalogue, and Aircraft Maintenance Manual. The challenge would be the ability to assess and evaluate the damage similar to what an expert does. Therefore, experiments with the drone-based

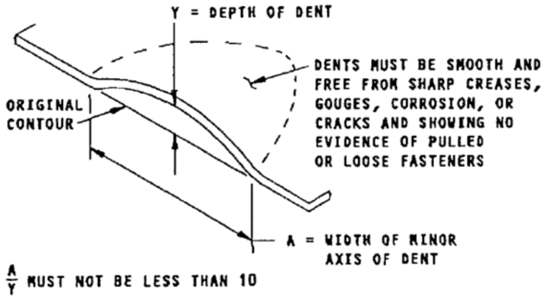

Figure 5. Allowable Dent [17].

inspection system should include various scenarios of both allowable and non-allowable damage.

4.3. Rare/Unknown damage

Not all defects on aircraft have been encountered before (e.g. Figure 6). Therefore, the drone should be able to also detect unknown defects or very rare defects. This can be achieved by using unsupervised anomaly detection with Generative Adversarial Networks (GANs). With this method, it becomes possible to address the challenging task of detecting defects that were never seen before or are very rare. This is important when it is unclear what an anomaly is going to look like, or when there is no labeled data to train an image classifier with. Through training a GAN only with normal aircraft pictures that do not contain defects, it learns what healthy aircraft look like and would flag anything unusual. This can be double checked by operators to take actions if necessary.

Figure 6. Example of a rare defect: Gunshot Damage of an A330-300 hit by a bullet in Congo on April 11th, 2020.

5. Conclusion

Automated drone-based aircraft inspection is a promising approach to further optimize aircraft maintenance operations. The concept could lead to important cost savings for aircraft operators as less time is spent on maintenance. Furthermore, inspection risk can also be reduced as engineers would no longer need to work at heights. However, significant research efforts are still needed to test the concept under various conditions and make it more reliable. This paper has proposed test scenarios to be considered by the system designers to further develop the concept and connected them with requirements that the automated drone-based system should satisfy. The requirements include 1) the ability to detect and classify defects under different environmental and diurnal conditions; 2) the ability to distinguish between an allowable damage and non-allowable damage thereby reducing false positives; and 3) the ability to detect rare or unknown damage that was never encountered before.

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