Automated Visual Inspection of Aircraft Exterior Using Deep Learning

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***Abstract*—Aircraft visual inspections, or General Visual Inspections (GVIs), aim at finding damages or anomalies on the exterior and interior surfaces of the aircraft, which might compromise its operation, structure, or safety when flying. Visual inspection is part of the activities of aircraft Maintenance, Repair and Overhaul (MRO). Specialists perform quality inspections to identify problems and determine the type and importance that they will report. This process is time-consuming, subjective, and varies according to each individual. The time that an aircraft stays grounded without flight clearance means financial losses.**

The main goal of this work is to advance the state-of-the-art of defect detection on aircraft exterior with deep learning and computer vision. We investigate improvements to the accuracy of dent detection. Besides, we investigate new classes of identified defects, such as scratches. We also plan to demonstrate that it is possible to develop a complete system to automate the visual inspection of aircraft exterior using images of the aircraft acquired by drones. We will use deep neural networks for the detection and segmentation of defective regions. This system will aid in the elimination of subjectivity caused by human errors and shorten the time required to inspect an aircraft, bringing benefits to its safety, maintenance, and operation.

I. Introduction

Aircraft traveling is one of the safest transportation modes, capable of carrying many passengers and considerable cargo loads for long distances [1], [2]. The risk of death per passenger boarding has been falling consistently over the decades [3]. Accidental deaths caused by equipment failure have sharply dropped since the 1960s as aviation safety has increased over the years by technological improvements in aircraft, avionics, and engines [3]. Commercial airline safety also dramatically improved with the development of ground proximity warning devices, more sophisticated pilot training with simulators, enhanced regulations due to a better understanding of human factors, navigational aids, air traffic management, and more accurate weather forecasting [2].

Even though aviation safety is constantly improving, the scientific and technical communities have not solved several related challenges yet, and others emerge with new and advanced technologies. The extensive usage of composite materials alters maintenance and inspection procedures since they require different techniques and equipment [2]. Newer aircraft that travel longer distances have original demands for reliability and performance. Maintenance and safety checks for Maintenance, Repair and Overhaul (MRO) and non-scheduled operations, as well as for older airplanes, may be limited by time and resources.

In addition to airplanes, helicopters also go through similar inspection procedures and share some of these open challenges. The development of aerial and space vehicles is also growing and improving constantly, where companies are developing new vehicles and technologies. New aircraft and vehicles mean there will be new requirements and needs for visual inspection procedures. There is an opportunity to solve challenges related to the automation of these procedures, where automatic systems can eliminate subjectivity and human error from manual tasks and increase the speed of the inspection. Faster and automated data processing reduces the time compared to how long inspectors spend investigating the vehicle, making decisions, and generating reports.

Operators execute several of these inspection procedures manually or visually, and they commonly use their judgment and experience to make subjective decisions [4], [5]. Some tasks involve visually inspecting parts of the aircraft, where trained workers look for manufacturing defects, assembly faults, components failures, or damages that may have happened during a flight event (departure, flight, landing). It is critical to identify these issues and correct them before the aircraft is approved for flight, as they could cause accidents and unforeseen events.

The identification of fuselage defects and visual checks are commonly addressed topics in the aircraft inspection literature [6]–[9]. These visual checks are inspections performed during MRO, before takeoff, and after landing to guarantee that the vehicle is in good condition and ready to fly. Several items, such as doors, valves, sensors, and other manually operated components, may cause accidents if left unattended at an inappropriate state [6], [10], [11].

The main goal of this work is to advance the state-of-the-art of defect detection on aircraft exterior with deep learning and computer vision. We will improve the accuracy of detection and identification of dents and augment the range of identified defect classes from the literature. We will also demonstrate that it is possible to develop a complete automatic aircraft inspection methodology and system based on computer vision and deep learning. This system will extend works in the literature by offering integration of solutions and techniques for the detection of a wide range of defects. It will combine concepts from the literature to build a complete visual inspection architecture. We use images (photographs and videos) of the aircraft exterior and detect anomalies, such as defects, damages, and external structural elements that require attention or even repair. We will use object detection and segmentation deep learning techniques and models for the identification of anomalies, as well as traditional computer vision and image processing techniques we found during the literature review.

II. Background and Related Works

Inspection in industrial environments is an essential quality control component in many different fields. The main goal of this process is to verify that a product does not have any defects, especially ones that may compromise its use. Areas such as the food industry, medicine, nuclear technology, and aircraft maintenance rely on inspections to guarantee that the quality of their product is acceptable. This is required since defects may cause significant consequences. If we consider aircraft maintenance, structural defects will compromise the safety of its operation and potentially cause accidents [12].

Surprisingly, humans still manually perform several inspection tasks in aircraft maintenance. While recent advances in robotics, computer vision, and artificial intelligence have contributed to research in this field, it is not common to find real-world examples of companies that apply automated systems for inspection. Visual inspection tasks require an expert to look for defects and anomalies on the airplane surface, and this process depends heavily on their visual acuity, mood, and assiduousness [13], [14].

The work from See [12] presents a review of visual inspection that includes 212 documents. They investigate inspection models, techniques to measure performance, and the parameters that may impact the execution of this task. They discuss that human visual inspection is subjective since it is prone to errors, variability, and execution misunderstanding. They concluded that more effective training, well-defined inspection procedures, and the availability of tools could improve the visual inspection process.

Machine learning and deep learning are also gaining popularity in the field of aircraft visual inspection. Recent publications presenting the usage of neural networks show promising results and encourage further investigation in this area of research. A comparison of machine learning techniques for defect detection is presented in [15]. The authors compare Support Vector Machines (SVMs) with neural networks for detection of paint defects on images acquired with an Unmanned Aerial Vehicle (UAV).

Malekzadeh et al. [16] show the application of a Convolutional Neural Network (CNN) for detection of defects on aircraft fuselage, such as dents and scratches. Authors use Speeded-Up Robust Features (SURF) key-point detector to identify defect candidates and a linear SVM classifier. A crack detection network for aircraft structures is described in [17], which uses a CNN to extract crack features and detect on images of the fuselage and engine blades. Bouarfa et al. [18] used a Mask R-CNN to detect dents in the aircraft fuselage. The authors also provide ideas to extend their work for further improving their method. They expanded their work and improved accuracy for dent detection in [19].

III. Methodology

A. Materials

Inspired by the works from [18] and [19], we decided to use the Mask R-CNN system [20] for identification of fuselage defects in the initial experiments. In both works [18], [19], authors only consider dents, which is a type of defect that deforms the fuselage surface without necessarily removing paint. They mention other types of defects, such as lightning strikes, paint defects, cracks, and holes, claiming that their method could also detect these in addition to dents. Other works that we found in the literature also used CNN for detection of aircraft fuselage defects [16], [17].

The Mask R-CNN system [20] combines ResNets with Faster R-CNN to create a framework for object instance segmentation. This approach detects objects in an image through the identification and classification of individual objects inside bounding boxes. It also generates a semantic segmentation mask for each instance by classifying each pixel regardless of the objects instances. We chose this CNN model to start the experiments as it was used with success in similar works in the literature, and it can also solve other instance-level tasks. We will consider other CNN models as well, such as Yolo [21], [22], to compare with Mask R-CNN and find the highest accuracy in defect detection.

We will initially use the ResNet-50-FPN [23], [24] as the backbone of the pre-trained Mask R-CNN model. The model provided by PyTorch is pre-trained on the COCO dataset [25], and it performs object detection and instance segmentation. We will consider other backbones as well, which may be pre-trained on other datasets or trained from scratch with our annotated data.

B. Methods

We will use use the PyTorch[1] framework to build and train the detection system. We chose PyTorch for its popularity in the academic and research fields and the large documentation and community support. We performed the first experiments using a code example from the *torchvision* module of PyTorch[2]. We modified this example to read our dataset and to run it on the training machine.

The VGG Image Annotator (VIA) [26], [27] software provided the tools we needed to create the dataset with defect annotation. The VIA is a lightweight web browser-based

[1]https://pytorch.org/

[2]https://pytorch.org/tutorials/intermediate/torchvision_tutorial.html

software for annotation of images, videos, and audio, free for academic and commercial applications (BSD-2 license).

C. Dataset

The dataset that we created includes images of an aircraft with multiple fuselage defects. These images were acquired with a drone and provided by our partner Autaza[3] for usage in this work. We selected 13 images from the airplane and annotated approximately 200 defects classified into six types of defects. Among these defects, we identified dents, dings, scratches, lightning strikes, missing fasteners, and corrosion.

IV. Preliminary Results

The dataset that we created includes images of an aircraft with multiple fuselage defects. These images were acquired with a drone and provided by our partner from the industry for usage in this work. We selected 13 images from the airplane and annotated six types of defects. Among these defects, we identified dents, dings, scratches, lightning strikes, missing fasteners, and corrosion.

We finetuned the Mask R-CNN model with ResNet-50-FPN for defect detection. The example code from PyTorch documentation uses for training a dataset with images and binary masks, which are the input for the network. We exported our dataset annotations from VIA to a JSON file with the contours and classes. The first modification to this sample code was to read this annotations file and create all the masks before using them to train the network. The second modification we did was to change the number of classes of defects. The example only considers two classes, which are one object type plus background. Our dataset has six classes of defects plus background for a total of seven classes in training. The third change we made was the replacement of standard Stochastic Gradient Descent (SGD) optimizer to Adam [28].

We trained the network for ten epochs with a batch size of eight. We used random horizontal flip on the input images to increase variability and set the optimizer learning rate to 10^{-4}. Figure 1 shows one preliminary example of a correct defect detection from this trained network. This image shows the side of an aircraft, where we see a scratch defect on the paint that is marked with a red box. This defect is visible as a region that contrasts with the paint on the upper right corner of the photo. This photo was acquired with a drone at an open area, with ambient light and no special lighting. The trained CNN found the defect automatically. Even though other parts of the aircraft have similar contrasting regions, the network was able to distinguish the defect from other geometries of the fuselage.

Fig. 1. Photo the side of an aircraft with defect detection result from the trained CNN. The detected scratch is marked with a red box on the upper right corner of the photo.

V. Discussion and Future Work

We presented in this work an unsolved problem from the aerospace industry that requires visual inspection for the detection of defects and anomalies on aircraft exterior. Even though there are partial solutions in the literature and commercial systems that provide automated inspection services, we found gaps in the literature that, as we understand, are not filled yet and require further study. The first gap worth mentioning is the lack of reviews about the visual inspection of aircraft. The second gap we found is the deficiency of studies about the integration of partial defect detection solutions to address the identification of a wide range of anomalies and nonconformities. The third gap is the lack of complete solutions that consider other inspection procedures, besides defect detection, to build a complete and automated aircraft visual inspection system.

This paper presents concepts and recent advances in computer vision, deep learning, and visual inspection of aircraft. We also showed initial results of a visual inspection system for identifying defects on aircraft exterior. We annotated fuselage defects on images from aircraft acquired by drones using the VIA tool. We modified a finetuning example from PyTorch documentation to read these annotations and train a detection and segmentation network. We trained the CNN with part of the dataset, and we ran the prediction on an image that was not used for training. The trained network was able to identify one scratch defect correctly.

Even though the dataset has few images and we trained the network mostly with default configuration for only ten epochs, we see promising results for automatic defect detection with deep learning. We will experiment with different network configurations and more data to achieve higher detection and segmentation accuracy. As mentioned in 1, the main goal of this work is to improve accuracy from the state-of-the-art results while detecting more types of aircraft defects. We expect to achieve accuracy comparable to other recent works in this area while providing a complete inspection system.

The next steps for this work include further improvements to the deep learning model since there are more parameters and network configurations to run and evaluate. We will collect more data and acquire photos and videos of airplanes to increase the number of samples in the dataset. This increased dataset will provide more examples and information for the deep learning model to use in training, increasing the accuracy of defect detection as well. We are working on partnerships with private companies and research institutes for collaboration in this project.

[3] https://autaza.com/

The defect detection model will be part of a complete inspection system, which we will design and build according to the requirements from the industry we found in the literature review. This inspection system will provide a sequence of automated procedures from the input of images to report generation according to detected defects and other aircraft data. We will test and validate this system with experts in the visual inspection industry. The validation will include real aircraft images from drones that contain actual defects and anomalies.

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