UAV-based Inspection of Airplane Exterior Screws with Computer Vision

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Abstract: We propose a new approach to detect and inspect aircraft exterior screws. An Unmanned Aerial Vehicle (UAV) locating itself in the aircraft frame thanks to lidar technology is able to acquire precise images coming with useful metadata. We use a method based on a convolutional neural network (CNN) to characterize zones of interest (ZOI) and to extract screws from images; methods are proposed to create prior model for matching. Classic matching approaches are used to match the screws from this model with the detected ones, to increase screw recognition accuracy and detect missing screws, giving the system a new ability. Computer vision algorithms are then applied to evaluate the state of each visible screw, and detect missing and loose ones.

1 INTRODUCTION

In aircraft maintenance,the large majority of visual inspections aim at finding defects or anomalies on the outer fuselage. Those detections are prone to errors from human operators. Since there is always a growth in air traffic and increased demands upon aircraft utilization due to commercial schedules, there is more pressure on the maintenance operations to be on time and in consequence more pressure on the workforce (Marx and Graeber, 1994) (Drury, 1999).

Since the 1990s, there is ongoing research to use robots to automate the external aircraft inspections. The aims are often to help the maintenance technician in his diagnostic and to improve the traceability of defects and damages in maintenance reports.

First robotic solutions focused on the external surface skin inspection with robot crawling on the airplane. Despite a valid proof of concept, some limitations were highlighted for real deployment (Davis and Siegel, 1993) (Siegel et al., 1993) (Backes et al., 1997) (Siegel, 1997) (Siegel et al., 1998).

At the beginning of the 2010s, a wheeled collaborative mobile robot named Air-Cobot was built. It is capable to evolve safely around an aircraft in an environment which contains some obstacles to be avoided (Futterlieb et al., 2014) (Frejaville et al., 2016) (Bauda et al., 2017) (Futterlieb, 2017) (Lakrouf et al., 2017). Two sensors are dedicated to the inspection. With a pan-tilt-zoom camera, some inspections are made visually with computer vision algorithms analyzing images taken at stop points or during movements (Jovančević et al., 2015) (Jovančević, 2016) (Leiva et al., 2017). The robot is able to elevate a 3D scanner to inspect the lower surface part of the fuselage (Jovančević, 2016) (Bauda et al., 2018). This robot is capable to perform tasks autonomously or work in close collaboration with its operator (Donadio et al., 2016).

Figure 1: Donecle UAV inspecting an aircraft.

Other approaches focus on cameras located in the maintenance hangar to inspect aircraft (Rice et al., 2018). In the second part of the 2010s, some companies invested research into automatic UAV inspection such as Blue Bear and Createc with RISER or Airbus with Aircam (Bjerregaard, 2018). It is also the case of Donecle (Claybrough, 2016) (Deruaz-Pepin, 2017). Figure 1 provides a picture of the UAV during an aircraft inspection in outside environment.

The accuracy of the UAV localization with respect to the aircraft, making possible a good repeatability of

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the image acquisition, so the spatial and temporal fusion of inspection results. The company also provides a vision software analysis to detect defects from the images (Miranda et al., 2018). This paper focuses on the analysis on very common elements of the aircraft: the screws.

In order to perform an accurate aircraft inspection of all screws it is necessary to know all of them and have some knowledge on them. Otherwise like in (Rice et al., 2018), the proposed method is unable to always detect all the screws as it is visible in Figure 5 of their paper.

A major topic for aircraft inspection concerns the inspection of all screws which fix together the fuselage parts. A few missing screws can jeopardize the whole aircraft. Section 2 presents briefly the localization system and the image acquisition. From those images, some Zones Of Interet (ZOIs) are extracted and classified, this is explained in Section 3. Section 4 presents some methods to perform a pairing between the screws from expected patterns and the ZOIs. After the pairing step and depending of the pairs found, some analysis can be done in order to correct a classification, identify a missing screw or check if a screw is turned compared to the nominal configuration. Those use cases are illustrated in Section 5.

2 NAVIGATION AND PRECISE IMAGE ACQUISITION

During an inspection with a Donecle UAV, the maintenance technician brings the UAV in a suitcase to the aircraft to inspect. He chooses a mission and places the UAV in its take-off area.

The UAV localizes itself relative to the aircraft with laser positioning technology. The inspection can take place indoor in a hangar or outdorr on the tarmac. A navigation algorithm for planning and controling the UAV motions, exploits in real time the UAV position relative to the aircraft (Claybrough, 2016) (Deruaz-Pepin, 2017). Navigation sensors also ensure safe operation by preventing collisions with human workforce and equipment.

There are some advantages of a visual inspection made from images acquired by an UAV. There is no contact with the aircraft surface or external power supply, which is not possible using crawling robots such as the ones in (Siegel, 1997) (Siegel et al., 1998). Compared to wheel-robots such as the one in (Donadio et al., 2016), the inspection is faster since the robotic system is less subject to obstacles on the ground and coverage is more important. It is possible to take pictures of nearly any part of the aircraft with nearly any desired angle: camera systems such as the one in (Rice et al., 2018) are not able to do so. Furthermore, the material is more easily transportable to the inspection area than the other robotic systems.

Compared to other UAV approaches (Bjerregaard, 2018), a laser-based system enables precise positioning, both indoor in maintenance hangars and outdoor on the tarmac. The system does not use GPS, beacons or other external installation: all sensors are onboard the drone.

In order to have a full accurate aircraft analysis, the surroundings of the aircraft should be empty and airframe panels should not be removed. If it is not the case, there is still the possibility to finish the inspection by performing a manual check of the area not acquired.

This manual check is performed on the tablet software and is designed to ease the work of the operator who has to carry paper documentation when following traditional inspection methods. Ergonomic studies showed that the management of documentation in aircraft inspection is improved when it is delivered to the user electronically instead of paper-based workcards (Drury et al., 2000).

Figure 2: Left, 3D model of the aircraft with the pose of the camera. Right, the image acquisition.

Figure 2 provides a partial view of the 3D model and an image acquisition of the blue area highlighted in the 3D view. This knowledge of the aircraft model is necessary during navigation to navigate around the aircraft and to orientate the camera at each acquisition in order to take desired pictures. Moreover knowing the UAV position and the aircraft 3D model, it is possible to predict what objects (and especially, screws) could be present in the image to be analyzed, taking into account the position uncertainty.

3 OBJECT RECOGNITION

Object detection is performed using a CNN trained on annotated images. Several CNN models such as Single Shot Detector (SSD) (Liu et al., 2016) or the latest version of You Only Look Once (YOLO) detector (Redmon and Farhadi, 2018) can perform this task efficiently provided that we adapt those models to

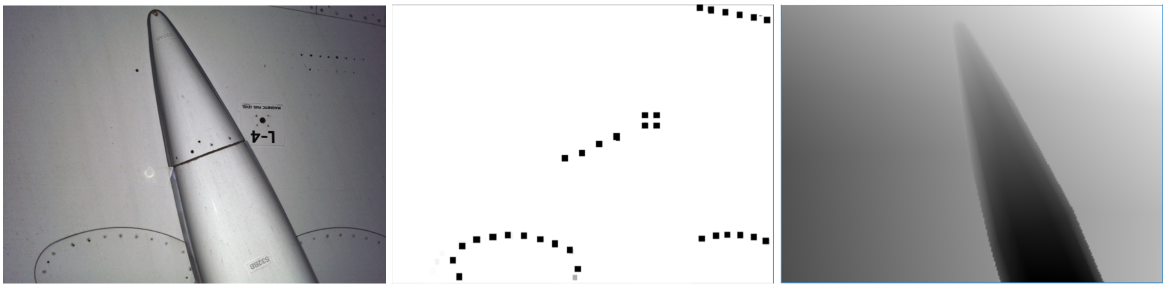

Figure 3: From left to right, acquired image, screw patterns and depth map.

small objects whose size is less than 1% of the acquired image size.

The implemented model can detect and classify about a dozen of various object classes, including screws and generic defects. As screws are among the most common objects on aircraft's surface and are distinguishable, the detection and classification's performance (average precision) is acceptable (recall and precision $> 95\%$). This system outperforms the method presented in (Miranda et al., 2018) in similar conditions.

A large variety of geometrical screw patterns can be detected, among those some defective screws can be found, see Figure 4 top and middle.

Our system is robust to difficult conditions such as variable illumination, low light or specular lighting, see Figure 4 bottom. To achieve this, a dedicated classifier can reject fuselage specular-induced false positive detection.

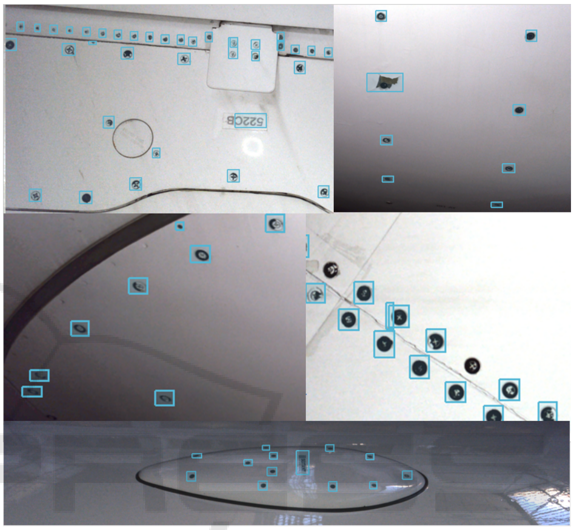

Figure 4: Examples of automated detection. Top right, one defective screw. Bottom, screws in difficult light conditions.

4 OBJECT / CLUSTER PAIRING

4.1 Prior Model Pattern

As a model of the expected objects, one can use the Digital Mock Up (DMU) that contains the 3D position of all those elements. They can then be projected on the image using flight metatada at acquisition time (UAV location, camera orientation, etc.). This operation induces a registration error on objects' position, thus it is required to add a further processing.

Our proposed approach is to train a 2D pattern generative model via unsupervised learning. Using an appropriate Generative Adversarial Network (GAN) architecture, it is possible to learn and to generate screw patterns from noise.

Then we can use conditional GAN (Mirza and Osindero, 2014) method to create a pattern associated to the former object detection. By doing this we complete and regularize the detected ZOI patterns. We can use aircraft model 2D projection as an additional depth map channel for patterns during the training process, we use both modalities as additional input for conditional GAN.

Given a prior noise distribution p_z, such system is based on the simultaneous training of a generator G that will generate screw patterns and a discriminator D that will output the probability that the input x is from the training set and not from the generator. G is trained to minimize $log(1-D(G(z))$ and D is trained to minimize $log\ D(X)$. This can be seen as a min-max game problem.

We add prior data y which comes from the scene detection output as conditional input for our multimodal system, so the problem becomes:

$$\min_G \max_D V(G,D) = \mathbb{E}_{x\sim p_{data}(x)}[log\ D(x|y)] + \mathbb{E}_{x\sim p_{data}(x)}[log(1-D(G(x|y)))]$$

The training data for this generative model can be obtained by collecting 2D images with identified screw patterns, or by using virtually projected 3D cloud points. An example of a 2-channel training

Figure 5: From left to right, detected zones of interest and screw patterns expectation.

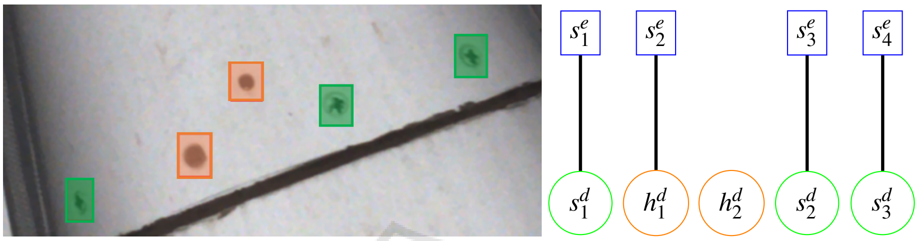

Figure 6: From left to right, a cluster of detected zones of interest, associated bipartite graph with the screw pattern expectation.

sample is given in Figure 3 : a pattern map and a depth map are related to an acquisition. In the depth map, the darkest pixels are the closest to the camera.

4.2 Pairing Model and Detection

In previous researches on inspection (Fishkel et al., 2006) (Jovančević et al., 2016), the authors used a bipartite graph to have a matching between CAD model and image features. In the present paper, the proposed algorithms share some similarities. We assume that we have a theoretical model of screw patterns in images. Based on the object detection performed by a CNN, we can easily extract detected ZOIs that are candidates to be paired with this model.

Thus, given a prior graph and a list of detected objects in a scene, we can adress the problem as a minimum cost bipartite matching problem. Based on Hungarian method (Kuhn, 1955) it is possible to use shortest augmenting paths to obtain optimal matches between those graphs. We first have to define the cost for a detected ZOI to be matched with an expected one. This function is used to construct a cost matrix. A simple cost function is the Euclidian distance between detected and expected ZOIs. As the screws are of fixed size and other objects can disturb the desired matching, combining it with size distance leads to better performance. If the detected ZOIs and the expected graph sizes differ, the cost matrix is not square. We add virtual rows or columns filled with high cost values to proceed matching.

In nominal situation, all the screws are detected and match the expected pattern. There is a bijection between those two sets. A threshold on the cost value avoid matching incorrect elements. If the result of the pairing is not a bijection between expectation and detection, there are unexpected or missing elements.

5 SCREW STATE ANALYSIS

5.1 Detect a Missing Screw

Using the described methods, it is possible to detect the absence of a screw, or the deterioration of a screw in a pattern. Figure 5 provides the output of the detection in red boxes (left image), and the expected regularized cluster in blue boxes (right image).

If the screw is not detected the prior regularized graph will have a non-matched element. Figure 6 illustrates correct matches (green boxes from the image with matches in the bipartite graph), missing screw detection (orange boxes in the image with an no match or incorrect match in the bipartite graph). A correct match means the paired elements have the same label (here s), while for an incorrect one, these labels could be different (here s with h).

If the screw is defective, then it will not be detected as a screw by the classification system, thus the pairing will lead to a spatial match with a label mismatch, allowing to warn about the state of the object.

5.2 Check if the Screw is Loose

To render possible the detection of loose screws, on some maintenance organisations, operators draw a red segment crossing the screw head in one of the shape cavities. If the slot is not in the same alignment as the red segment then it means that the screw is loose. Examples of slot screw drives are presented in Figure 7.

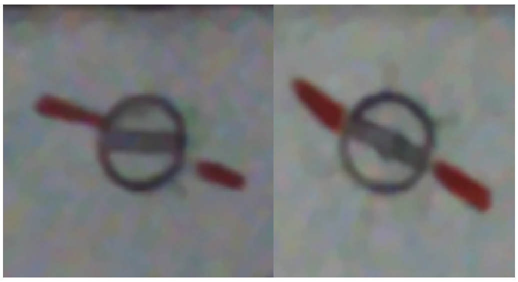

Figure 7: Example of a loose and tight screw.

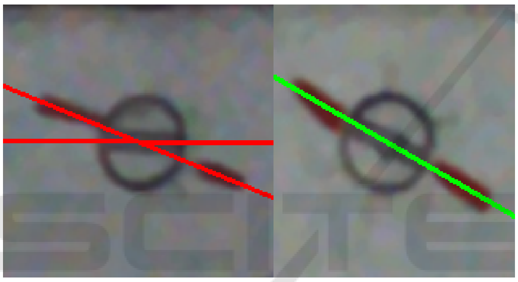

Figure 8: Detection of a loose and tight screw.

To analyze the orientation of the screw, it is first necessary to localize precisely the screw in the ZOI where it was detected. Then different approaches can be applied. After some experiments, we decided to find the screw orientation using a step of the approach proposed in (Dubosclard et al., 2015) to segment seed shapes in an image for visual grading applications.

Let Ω be the image domain, ω a screw shape to compare with the real screw, $x \in \Omega$ a location. Let E be a function which takes its values between $[0,1]$ and is defined in the following equation:

$$E(\omega) = \frac{1}{2|\partial\omega|} \int_{\partial\omega} \left\langle \frac{\nabla u(x)}{\sqrt{|\nabla u(x)|^2 + \varepsilon^2}}, n(x) \right\rangle \mathrm{d}x + \frac{1}{2}$$

where $\partial\omega$ is the boundary of ω $\langle .,. \rangle$ denotes the Euclidian scalar product, $n(x)$ denotes the outward normal to ω at location $x \in \partial\omega$ and ε is a regularization parameter that discard faint transitions.

This function is sensitive to the normals of the shape boundary and it is working with high and low contrast. The used shapes which are compared with the scene are built from variation in orientation and size of a slot screw drive.

The next step is to find close but outside of the screw region, two red areas and fit a line with those red pixels. Then it is possible to estimate the orientation of the red segment and compare it with the estimation of the slot one.

Figure 8 illustrates the results of the analysis. For each subfigures, two lines are drawn. One represents the orientation of the slot and the other the red line drawn by the operator. If the difference is too important a warning is sent to the operator and the results are provided in the report.

6 CONCLUSIONS / PROSPECTS

A new visual method to perform external screw inspection on aircraft is presented in this paper. This approach is possible thanks to the accuracy of the acquisitions made on Donecle's UAVs. A CNN approach is used to detect ZOIs with screw objects. In the detected ZOIs, there could be some missing screws, see in Figure 4, middle-right, or some false-negative results. A GAN approach allows to generate screw patterns both from the 3D model and from the observed images. The matching between the expected screws from the model and the detected ones is made with a bipartite approach. When there is a matching problem, this is probably due to a missing or defective screw. After the matching, on well identifiable screws, algorithms can be executed to check their orientation. The whole system provides a good tool for operators to facilitate their job and improve efficiency, repeativility and traceability.

The proposed solution was demonstrated on airplanes from Airbus A320 family belonging to a limited number of airlines but they are easily reproducible to other types of aircraft or same ones from different airlines. Given the specificity of this application it is not easy to find relevant datasets to compare our method with related works. There is place for improvement in the CNN part. The described approach relies heavily on automated navigation which requires an accurate aircraft model. If it is not available, then a prior step of model construction from laser data and pictures is necessary. Now, the aim is to have more data for benchmarking our approach and demonstrate its efficiency.

The obtained results on classification and detection performances increase, while the new defective screw detection abilities demonstrate the interest of using prior graphs during image analysis. We assume than those combined models will improve so we end up with a better object recognition system and a good prior knowledge on screw patterns for a given aircraft.

Based on this proof of concept, the creation of such condional models will be focused on. This can be addressed both from a 2D or 3D perspective : gathering all the 3D classification results of a given aircraft model (issued from many UAV's flights) to extract recurrent patterns, and using pattern 2D-generative models conditioned upon detection results.

The presented method can be extended to all expected objects on the aircraft (marking, rivets, etc.), or a combination via multi-primitive graph matching. With more UAV inspections of the same aircraft over a period of time, it could be envisioned to perform orientation comparison to respond to loose screws.

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