

Automating the Visual Inspection of Aircraft

Mark Rice¹, Liyuan Li¹, Gu Ying¹, Marcus Wan¹, Eng Thiam Lim¹, Gao Feng¹, Jamie Ng¹,
Melissa Nicole Teoh Jin-Li², V. Shana Babu²

¹ Institute for Infocomm Research, Agency for Science, Technology and Research, 1 Fusionopolis Way, Singapore 138632

² Defence, Science and Technology Agency, 1 Depot Road, Singapore 109679
Corresponding email: mdrice@i2r.a-star.edu.sg

Abstract

During pre-flight inspection, technical competency is required to identify obstructions and observable damage that may impact on the airworthiness of aircraft. This can be challenging for ground crew who may be limited by time, manpower, or views of an aircraft. In this paper, we describe an R&D project that is designed to visually inspect the surface of aircraft using commercially available cameras. Providing a high-level description, we touch on some of the approaches used to identify different types of surface defects, including how this information is visualized back to the end user. The goal of this research is to work towards a more automated process of inspection using computer vision solutions. Subsequently, with an industry focused on reducing manpower and operational costs, the ability to automate the detection and documentation of aircraft defects is a relevant and timely issue.

1. Introduction

According to the FAA [1], given the economic benefits, at least 80 percent of aircraft inspections are visual. Visual inspection is primarily used to check the airworthiness of aircraft, and the types of defects investigated can vary from surface corrosion, to cracks, fractures and disbonding [1]. Drury [2] broadly defines aircraft inspection as the detection of *expected* and *unexpected* malfunctions. Known factors affecting inspection performance include ease-of-access to the aircraft (e.g. the upper regions), poor lighting conditions, and surface occlusion from foreign objects, such as dirt. Inspection standards are also reported to vary across the industry [3], with the potential for inspectors to deal with a considerable amount of paper work in checking maintenance repair records and log histories [4].

With reports of performance differences in the detection results of aircraft inspectors [2], visual automation has the potential to remove human bias, and provide greater accountability in the recording and

documentation of defects. We foresee this as being particularly relevant in countries like Singapore, where forecast growth in the aviation industry, coupled with the sizable number of aerospace companies that carry out local repair and maintenance operations, demonstrates the importance of developing technical solutions that can improve the productivity and reliance on manpower resources. At the same time, for such systems to assist in human intervention, they need to demonstrate sufficient precision and accuracy in their results.

2. Related works

In recent years there has been an increasing momentum by the aviation industry to explore innovative solutions to automate the visual inspection process (e.g. the use of autonomous drones). However, the development of digital technologies to support aircraft inspection is not a new concept, with published research dating back a number of years.

To illustrate, in the 1990s, Siegel [5] proposed the use of robotic ‘skin crawlers’ that could adhere to the surface of an aircraft. However, despite some technical success, development limitations in robotic automation were highlighted for real-world deployment. Alternatively, around the same time, Siewiorek et al. [6] developed a wearable speech recognition system for surface inspection, while Ockerman and Pritchett [7] investigated a wearable display to augment information in a pilot’s field-of-view for pre-flight inspection. Both of these systems illustrate the potential for reducing the need for paper-based instructions, and despite dealing with some interaction issues, demonstrated interesting solutions, which nowadays are likely to be better supported by advancements in wearable technology.

More recently, published work has included that of Jovančević et al. [8], where the use of a ground-based robot has been designed to identify state changes in surface objects, such as for oxygen bay handles, air-inlet

vents and static ports. Of the image samples tested on, the authors reported a detection accuracy of over 90 percent. Likewise, in what appears to be related work, descriptions have been provided on the robot's navigation using laser guided sensors, and the recognition of landmark features to determine its relative position to an aircraft [9].

However, while we do not present an extensive literature review in this paper, empirical research on the automated inspection of aircraft appears limited. At the same time, there are clearly technical challenges that need to be addressed in the deployment of real-world vision systems. To highlight a few examples:

- It is imperative that any automated visual inspection system can provide accurate and timely results that are at least as good as traditional techniques. Without this, it is difficult to justify the implementation and maintenance costs of using the technology.
- An automated visual inspection system needs to be robust enough to detect a wide range of surface defects. Technically, this is challenging given the varying physical characteristics of surface defects on an aircraft.
- A usable visual inspection system needs to be scalable and deployed across different aircraft types, and sizes, which will vary in the engines used, winglets and body shape, etc.
- Detection accuracy needs to be tested across different conditions, such as variations in surface structure, camera position and viewing angle, and object obstruction to determine their effectiveness.
- Solutions need to accommodate for both indoor and outdoor environments, including night time and changing weather conditions, while extracting unnecessary information from the background of the aircraft.
- Appropriate visual feedback needs to be provided to the ground crew, with features that can allow engineers to filter results, re-classify and archive relevant information. As such, user interfaces should be intuitive to use, while serving a practical purpose.

3. Our approach

To attempt to address some of these issues, since 2016, we have been investigating vision-based solutions that can scan and identify surface defects on external airframe structures to support pre-flight inspection.

The main focus of our work has been to develop computer vision algorithms that can be implemented using

different hardware solutions. For example, the current testing of our system has included drone, tablet and standalone PTZ (pan-tilt-zoom) cameras. In the case of the drone and tablet technologies, built-in device cameras are used to capture the image data. Subsequently, by being able to implement our software in these different technical forms, flexibility is provided in how the visual inspection can occur.

To illustrate, the inspector can use the assistance of a mobile tablet when completing a walk-around of the aircraft (Figure 1a). Using the front-facing camera, images are periodically captured and processed on the device. Alternatively, using standalone (fixed) cameras positioned around, or above the aircraft, the surface is automatically scanned, and the data streamed to a central server that completes the image processing, from which the results are separately visualized (Figure 1b). In this scenario, the inspector has the option to take further action by examining the results identified on a tablet display at a distance to the aircraft.

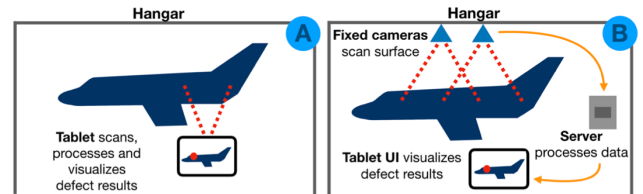


Figure 1. Examples of the different hardware set-ups of our system using a single tablet device and fixed camera system.

More specifically, when using fixed cameras, we have developed software to determine their location in relation to an aircraft. A depth camera, that provides 3D imagery, scans the aircraft surface and then matches a scanned area with a pre-defined 3D software model. Additional calibration is then performed for the fault detection. Furthermore, software has been developed to process the image data and visualize detection results on a prototype interface. Evaluations have included on-site aircraft testing.

To provide more details, in the following sections we describe three aspects of our system using the fixed camera set-up: 1) the image localization to map the position of the cameras, 2) the fault detection algorithms, and 3) the image visualization of the detected results. Our current set-up is in an indoor hangar environment.

3.1 Image localization

For the image localization, the goal is to create a model that will allow us to map a location on a physical aircraft to a set of 3D co-ordinates on a 3D aircraft model. Thus, if we are given a physical location, we are able to calculate

the virtual location, and vice versa. The physical location of a defect is determined by the orientation of the PTZ camera and the (x, y) co-ordinates on a PTZ image, as illustrated below in Figure 2.



Figure 2. Conversion of a detected fault location, as given by the PTZ camera (pan, tilt, zoom) and PTZ image (x, y) , to co-ordinates on a 3D model by a 3D point (x, y, z) .

The existing system uses a commercial depth camera that has a range of 0.15 to 10 meters, and a viewing angle of 70 by 53 degrees. For the system to return accurate fault locations, we assume the configuration of the physical aircraft is fixed and identical to the 3D model. That is, the external aircraft doors are closed and panels are not removed, etc. The challenge of accurate 3D model mapping can be resolved by first calculating the 3D localization model's confidence level based on how well a depth scan overlaps during a matching phase. From this we can use a less specific form of visualization for indicating defect locations. For example, if confidence is low, a defect can be indicated less specifically on a larger area of the aircraft, rather than a specific point, such as the top side of a left wing, or bottom side of the middle fuselage.

Once we are able to match the 3D scan to the 3D model, we can calculate the camera's position relative to the aircraft (Figure 3). Since the physical camera's orientation is also known when a fault is detected, we can mimic both the position and orientation of the virtual camera to the 3D aircraft model. Then, by casting a ray from the virtual camera, we can define the fault location where the ray collides with the 3D model.

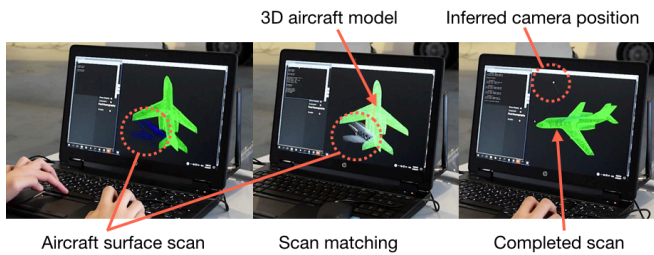


Figure 3. On-site testing of the image localization. (Left) blue scanned image with the 3D aircraft model; (middle) completing the image matching process; (right) completed result. The white dot represents the camera position relative to the aircraft.

3.2 Vision algorithms for surface defect detection

Our work focuses on dealing with surface defects that can be recognized by the human eye. Features that cannot be visibly seen are currently not processed. The iterative development of our vision algorithms has been tested on hundreds of images, however, one of the key challenges we have had to overcome is getting access to representative data. Specifically, our work focuses on a sub-set of defects, such as hairline cracks, missing fasteners and fluid leakage. As previously mentioned, we are not limited to a particular platform or imaging device.

Detecting aircraft anomalies is challenging due to surface deformation, variations in environmental lighting, dirt, and paint quality, etc. On a small surface area, few visible differences may be observed, however, across the aircraft this will most likely change. Subsequently, we have developed an active recognition and segmentation model to extract and locate defects on a painted surface. This involves a learning stage, which is tested with sample images under different lighting conditions. In essence, scanned surface images are segmented, boundary regions drawn around potential defects, and a contour fitting algorithm applied to visualize the processed results.

Examples can be seen in Figure 4 for detecting scratches, protruding and missing rivets, small cracks, and surface bulges (or protrusions) with some color deformation. Currently, we are able to recognize selected defects over 20 pixels in diameter or length.

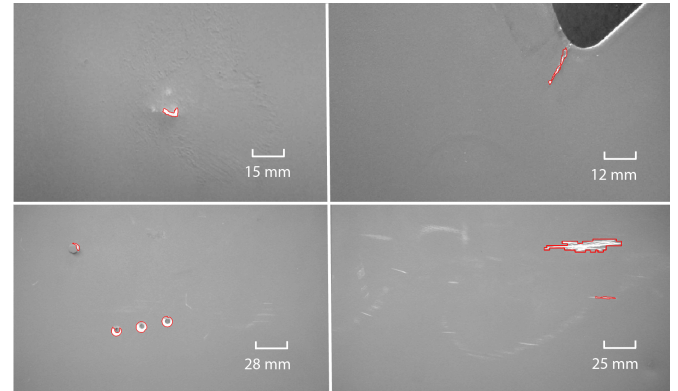


Figure 4. Processed images of highlighted defects taken from a damaged aircraft panel. (Top left) surface bulge, (top right) hairline crack; (bottom left) protruding and missing rivets; and (bottom right) scratches.

For the detection of screws, missing screws and fasteners, a separate algorithm has been developed. That is, for each processed image, we extract sketch and graph patterns to characterize appearance features. A descriptor (that describes the visual features) captures the contour and edges, while a multi-scale representation encodes the

dark boundary and center pattern of the screw/fastener, and the empty hole region of the missing screw/fastener.

As part of our implementation work, we are able to group associated screws (and fasteners) into lines, which is helpful in filtering out false detections. A straight line is generated by fitting all the screws into a cluster. This is achieved by determining the distances between the screws, and the gap sizes in between (see Figure 5).

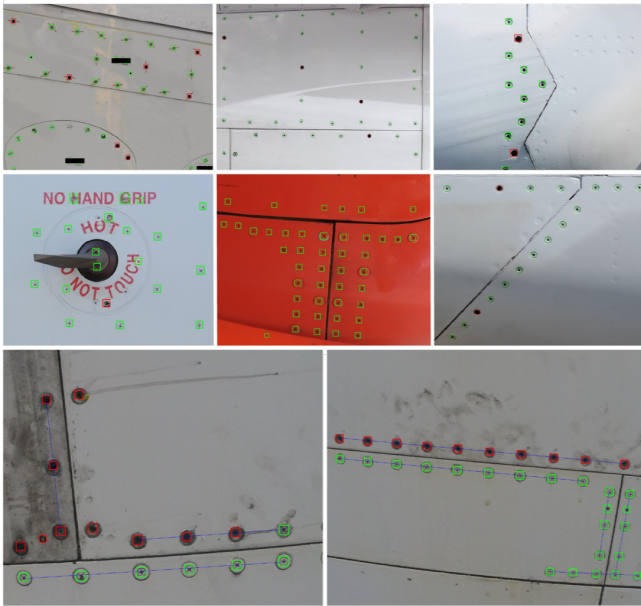


Figure 5. (Top and middle) examples of the screw/missing screw and fastener/missing fastener detection for external aircraft surfaces. Red boundary boxes/circles indicate missing features, while green boundary boxes/circles are the detected visible features. (Bottom) the line clustering of screws located along the same plane. Note that aircraft identification numbers have been blacked out in the figure.

3.3 UI visualization

The third component of our work is to visualize the results on a tablet display. This is designed to illustrate defects and their position on the airframe, with options to view the images captured from the camera's point-of-view. When viewing the 3D aircraft model on the interface, the user has the option to change the viewing perspective, as well as filter regions of interest. Surface scans are also timestamped and chronologically ordered.

Importantly, users can initiate the image localization and scanning process of an aircraft via the display. Using a 3D model of the representative aircraft, the user can select one or more points to mark the surface regions they wish to scan. Through the calibration process, the software is able to calculate the pan and tilt values necessary for the camera to aim directly at a selected point. Then, by using the distance value between the virtual PTZ camera

location and the clicked point, we can calculate the appropriate zoom level before initiating a fault scan. In addition, options are also available to edit the defect information results using annotations to mark areas-of-interest, as well as add text descriptions, which subsequently can be logged for future viewing.

4. Conclusion

In this short paper, we outline details for a vision-based inspection system that can automatically scan the airframe structure of an aircraft for surface defects. We believe a strong component of our work is being able to recognize a number of different defects that vary in visual characteristics. Moreover, our software implementation is not limited to using a particular imaging technology, while the range of anomalies that can be detected can be relatively small for a non-evasive vision-based inspection technique.

As this research is ongoing, future work aims to extend the range of detectable defects on aircraft, while we are currently in the process of benchmarking our results. Further, while we do not claim to have a fully operational technology, as outlined in this paper, there are a number of important issues that need to be addressed in the real-world deployment of automated visual systems. Subsequently, as we progress further, testing across a range of aircraft conditions will be an important aspect in the improvement of our system.

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