Robotic enhanced visual inspection of aircraft skin

Mel Siegel and Priyan Gunatilake
The Robotics Institute - School of Computer Science
Carnegie Mellon University - Pittsburgh, PA 15213
phone: (412)-268-8742; email: mws+@cmu.edu

Abstract

Visual inspection is the most widely used method of commercial aircraft surface inspection. We have developed a remote visual inspection system, designed to facilitate demonstrating the feasibility and advantages of remote visual inspection of aircraft surfaces. We describe experiments testing image understanding algorithms to aid remote visual inspection by enhancing and recognizing surface cracks and corrosion from live imagery, and key features of the mobile robot platform and infrastructure that delivers the image. We discuss performance of the image understanding algorithms and speculate on their future use in aircraft surface inspection for crack and corrosion detection. A neural net classifier worked best for corrosion, whereas a fuzzy logic algorithm worked best for cracks.

1. Introduction

A typical heavy inspection (~12,000 flying hours) on a commercial aircraft consists of about 90% visual and 10% non-destructive inspection (NDI). Visual inspection requires putting a human inspector on the body of the aircraft to examine its surface for defects such as cracks, corrosion, damaged rivets, lightning strikes, etc. [1][2]. This practice raises safety issues for the inspector, is time consuming, and suffers from being ineffective due to inspector fatigue or boredom [3].

An attractive alternative is remote visual inspection. The inspector would examine, at an inspection console, high-quality imagery of the inspection surface that is captured and delivered by a remote mobile robot on the body of the aircraft [4][5]. The robot may be teleoperated via low level controls, it may navigate autonomously under computer control, or typically something in between, with high level commands issued by the inspector and low level details decided and executed by the computer. This method, while inherently safe (since the inspector is on the ground), allows for direct human observation of the remote aircraft surface.

It also provides for computer processing of the delivered imagery. Processing stages typically include (1) preprocessing, e.g., adjusting contrast or dynamic range of the imagery for improved visibility of significant image features; (2) enhancement, e.g., amplifying high spatial frequencies to highlight features suggestive of surface defects, and (3) image understanding, e.g., characterization and recognition of surface defects, which allows for automated defect detection and classification of the surface imagery.

We have developed and deployed two robots for aircraft inspection. ANDI (Automated NonDestructive Inspector), specifically designed to deploy eddy current sensors, uses suction cups for total mobility, but at the price of requiring an umbilicus for air and power. CIMP (Crown Inspection Mobile Platform) uses wheels, so it is completely wireless, but at the price of mobility restricted to the upper surfaces of the aircraft. CIMP is a general-purpose sensor deployment platform that we have used extensively to develop remote enhanced visual inspection technology. CIMP is shown in Figure 1, and its sensor pod is shown in Figure 2.

2. Surface Crack Detection

Pressurization and de-pressurization of an aircraft during each flight cycle causes its body to expand and contract like the inflating and deflating of a balloon. This induces stress fatigue at rivets (which hold the aircraft surface skin to its frame), resulting in the growth of cracks, typically radially outward from the rivets. The growth rate of a surface crack is approximately proportional to the crack length, making the crack length approximately exponential in time. The goal of inspection is to detect cracks that are above a minimum threshold length. This threshold length provides a safety margin that allows a crack to be missed in two or three consecutive inspections before it is serious enough to endanger the structure of the aircraft.

Inspectors generally find cracks by scanning a flashlight at a low angle over the surface and observing the specular reflection, particularly around rivet heads. Absence of reflected light from an edge (a line on the surface) emanating from the rivet suggests the possibility of a crack. On the other hand, specular reflection of light suggests a (usually) harmless scratch. Therefore, with some simplification, the task inspector's job is first to detect edges emanating more-or-less radially from the rivets, and second to discriminate the cracks from scratches and other edge-like image features.

Since there may be hundreds of thousands of rivets on the aircraft body, inspection for cracks is a demanding and tiring task for the inspector. This makes algorithms for assisting the inspector seem attractive. The operating scenario is that the algorithm never misses a real crack whose size is approaching the danger threshold, even if this conservative requirement results in a moderate false alarm rate. The computer then operates as a coarse sieve that finds and eliminates the majority of "crack like non-cracks". The human inspector is then the fine sieve that identifies and eliminates the false alarms.

Our crack detection algorithm is modeled closely on the inspector's use of grazing angle directional lighting: CIMP's sensor pod incorporates a wirelessly controlled rotatable directional light source. The surface crack processing pipeline is shown in Figure 3, and its output for a typical test surface is shown in Figure 4.

3. Surface Corrosion Detection

Corrosion is common where there is frequent exposure of the aircraft to assaults from aircraft operating fluids, liquids spilled in the galleys and lavatories, moist sea air, and other fluids. Since corrosion results in a loss of structural material (as well as inducing cracking), early detection, repair, and sealing is crucial.

Corrosion can appear as subsurface or surface corrosion. Subsurface corrosion is recognized by the bulging of the affected surface region, "pillowing", which we can detect by measuring the surface topography. Surface corrosion is recognized by the appearance of particular characteristic textures. We have developed methods for both, but in this paper we discuss only vision algorithms for surface corrosion detection.

Our surface corrosion detection image processing pipeline is very similar to our crack detection pipeline, depicted in Figure 3. The main differences are (1) the multiresolution (wavelet) decomposition is two dimensional, attuned to finding textures rather than edges, and (2) classification of textures is more "signal processing" related than is the "semantic" process of classifying cracks, so neural net classification works better for detecting corrosion whereas fuzzy logic classification works better for detecting cracks.

Figure 5 shows a visibly corroded region and Figure 6 shows the output of our corrosion detection algorithm. Textural features in this image that were identified by our algorithm as corrosion are shown in their original gray levels, whereas areas identified by the algorithm as uncorroded are shown as black background. Borderline regions near the classification threshold are shown in a checkerboard pattern of black and gray-levels. Recent work further refines the identification by data fusion using multiple views of the same surface area under different, systematically imposed, lighting conditions.

4. Conclusions and Future Work

We successfully demonstrated CIMP's remote control and imaging capability to Northwest Airlines at their Minneapolis 747 maintenance and inspection facility and to US Airways at their Pittsburgh maintenance and inspection facility. Our demonstration showed that state-of-the-art 3D stereoscopic video technology implemented by us and operated by inspectors not specifically trained in its use, delivers imagery of sufficiently high visual quality that aircraft inspectors and NDI supervisors were willing to accept it, and sometimes prefer it, as an alternative to direct visual inspection.

For automating the image understanding, multiscale edge analysis and multiscale texture analysis are shown to be respectively appropriate frameworks for detection of aircraft surface cracks and surface corrosion. Anticipated future development needs include: adding suitable new classification features, data fusion involving multiple images of the same region under dynamic lighting conditions, and training and testing with a richer library of natural surface cracks and corrosion samples.

5. References

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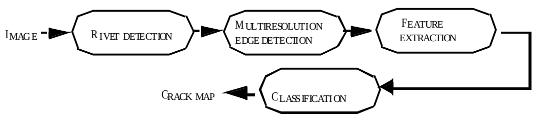

Figure 1: *Image processing pipeline for crack detection. Pipeline for surface corrosion detection is similar. Main difference is in the classification step: fuzzy logic is used for cracks, neural net for corrosion.*

Figure 2: *CIMP, the Crown Inspection Mobile Platform. It is battery operated, wirelessly controlled, and has two video download channels.*

Figure 3: *Close-up of CIMP's sensor pod. Stereoscopic macro camera looks at the surface at a 45 degree angle. Flood and grazing angle spot lighting are remotely controlled. Grazing angle illuminator rotates +/- 150 degrees around the camera pointing direction.*

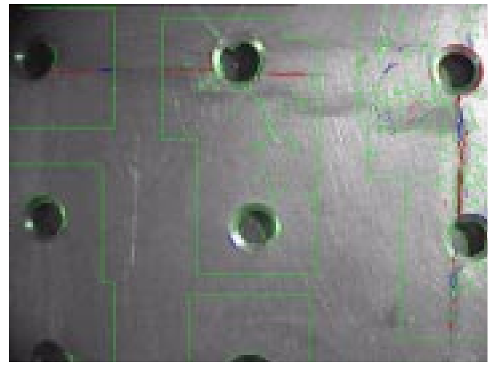

Figure 4: *Crack detection algorithm. Cracks emanate horizontally from the upper left and middle rivet holes and vertically from both right side rivet holes. Rectangular regions of interest are displayed in green. Features identified as cracks with high confidence are displayed in red. Features identified as cracks with lower confidence are displayed in blue. Crack-like non-crack features are displayed in green.*

Figure 5: *Typical corroded region on aircraft skin material. Corrosion appears above the diagonal. Potentially confounding features such as dirt and paint splotches appear below the diagonal.*

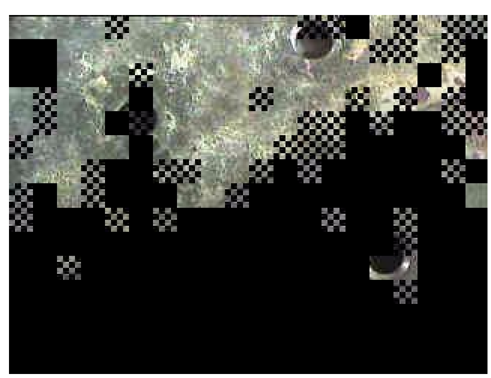

Figure 6: *Corrosion detection algorithm. Areas shown in black are classified as corrosion free. Areas shown in their original gray-levels are classfied as corroded. Areas shown in checkerboard are borderline.*