Automated recognition of X-Ray CT artefacts in aerospace components

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Abstract
X-Ray CT provides a powerful means for non-destructive evaluation of the internal features of aerospace components. However the method generates large quantities of data that is time-consuming for a skilled operator to examine. This bottleneck can be mitigated through the use of automated defect detection and analysis. However imperfections in X-Ray CT scanning can introduce artefacts and discrepancies to the data. These artefacts can masquerade as defects and increase the challenge for automation.

This paper presents novel image processing solutions to address two different artefact types encountered in an ongoing research programme. The solutions enable the artefacts to be automatically identified and classified on the basis of their geometrical properties.

Keywords: Automated, CT, image processing, aerospace, X-Ray

1. Introduction

X-ray CT is becoming increasingly important in the aerospace industry as it provides a powerful means for non-destructive evaluation of the internal features of aerospace components and sub-assemblies. The visualisation capabilities of X-ray CT provide ample scope for quantitative failure analysis on in-service components and during prototype development, as well as for the assessment of component integrity in MRO applications.

When applied to aero-engine components such as turbine blades, compressor blades and nozzle guide vanes, X-ray CT generates significant quantities of volumetric data. In order to extract useful information regarding defects such as cracks, pores, voids and foreign inclusions it is necessary for a skilled operator to visualise, manipulate and interpret the generated dataset manually. This NDT analysis process is time-consuming to perform, and could present bottlenecks across all development, manufacturing and MRO domains where NDT is an integral requirement and part of the processes. There are also concerns over the reliability of the manual interpretation process.

The majority of X-ray-based industrial inspections are currently based on 2D methodologies and there are numerous examples of automated and semi-automated defect detection based on 2D X-ray imaging. As such, defects and their characteristic features are considered from a 2D perspective, even though the defects may span 3 dimensions.

SIMTech is currently engaged in a research programme to develop an automated defect detection system that aims to address these problems in X-ray CT inspections. The research aims to develop technologies and know-how for automated detection of defects in 3D X-ray CT data sets. 3D-based inspection and analysis can dramatically improve prospects for identifying defects over conventional 2D X-rays, avoiding the need for tedious cross-sectioning and thereby reducing the time required for NDT analysis.
2. Candidate components and data acquisition

A variety of test components with and without defects were identified and sourced as test subjects for the research programme. In general they have fairly complex geometry (Figure 1) and are primarily cast from materials such as aluminium, steel and Inconel. Various scans were acquired with copper plates of different thicknesses (2, 4 and 6 mm) inserted between the X-ray source and the component to filter the X-ray beam in an attempt to mitigate the artefacts.

![Cast aluminium component](image1.jpg)

Figure 1 Cast aluminium component [106 x 104 x 74 mm, 440 g].

3. Automated recognition

3.1 Identification of discrepancies

For the component shown in Figure 1, artefacts of interest manifest themselves as pockets of areas with short, contorted lines, and occasionally discontinuities from the rest of the component edges. As a result the component shows apparent cavities when projected in 3D (Figure 2a). The objective therefore is to develop an automated tool to identify and disregard these features.

The axial images were first thresholded to identify the component edge (Figure 2b). These were then processed using a moving-box two-dimensional Fast Fourier Transform (2D-FFT) method [1]-[4]. The approach is based on the premise that areas with the beam hardening discrepancies have short, irregular lines with near-random orientations, as opposed to areas encompassing the component edge, which typically have a single, near-straight line. The 2D-FFT of the component edge portion will show a regular Gaussian-shaped peak (Figure 3a). On the other hand, areas encompassing discrepancies will produce a 2D-FFT with a strong peak in the centre surrounded by low level noise-like features (Figure 3b). The peak is typically an order of magnitude larger than the Gaussian peak for areas with no discrepancies; this feature was utilised to locate the discrepancies.

Each 2D-FFT is performed over an area (nominally 32x32 pixels) and this is repeated with the square box moving incrementally (nominally single pixel steps) through the entire image in raster fashion. For each 2D-FFT the ratio of the maximal peak value to the total root-mean-
square value of the square area is calculated. Using this ratio a “hot-spot” map may be produced (Figure 4a), showing the discrepancy areas as bright contrasting colours against lighter areas representing well-defined component edges. A further binary thresholding is applied to the “hot-spot” map to identify the discrepancies (Figure 4b).

This produces a new image stack containing the discrepancy areas of interest, which may be displayed in 3D (Figure 5). The identified discrepancies, as rendered in 3D, correlate well to the original 3D projection, with the 3 cavities seen in the same locations. Additional discrepancies have been identified, on the basis of irregular, contorted lines present in the thresholded component edge images.

Figure 6 shows similar results, but with the component scanned with copper filters of different thicknesses (2 and 6 mm) to pre-harden the X-ray beam. It is clear that the sizes of the discrepancies have reduced, due to less discontinuities and contortions in the thresholded edge images, as a mitigating effect of the copper filters on the X-Ray beam.

Figure 2 – (a) Reconstructed axial cross-section of a cast aluminium component and (b) thresholded version.

Figure 3 – Surface plots of 2D-FFT for 32x32 pixel areas containing (a) a straight line representing part of the component edge, (b) irregular contorted lines representing areas with discontinuities.
Figure 4 – (a) “Hot-spot” image based on signal-to-noise assessment of multiple 2D-FFTs calculated over an image slice in raster mode, (b) Thresholded output from the “hot-spot” image identifying the edges of beam hardening discrepancies.

Figure 5 – 3D representation of the processed output, showing discrepancies identified from a CT image slice. The three cavities shown earlier in Figure 5.2 are highlighted by the red circles and ellipse.
Figure 6 - 3D representation showing discrepancies identified from a CT image slice. The CT images were acquired with either (a) 2 mm or (b) 4 mm of copper pre-filter inserted between the X-Ray source and the component.

3.2 Removal of irrelevant discrepancies

From the artefacts identified, it was observed that phantom cavities typically occur across successive image slices around the same areas on the images, while irrelevant artefacts - such as those near the base of the component – generally do not recur across more than two successive slices, and will have very different geometries. Based on these it is possible to implement a filtering stage which retains the former and discards the latter. The following criteria were proposed for retaining artefacts:

- For a given image slice, the artefact in question should appear in both preceding and subsequent image slices
- The artefact centroid should be within a certain pixel-radius across 3 successive image slices (preceding, current and subsequent)
- The artefact area (in pixels squared) should be within a certain percentage across 3 successive image (preceding, current and subsequent)

Figure 7 shows the result from applying the filtering stage to the datasets shown in Figure 6. It can be seen that the filtering stage has removed the majority of irrelevant artefacts, while retaining the phantom cavities of interest. Further refinements to the criteria, or indeed more advanced criteria, are probably necessary to achieve consistent and complete removal of all irrelevant artefacts.

4. Automated classification

The second component was made of Inconel. Defect-like features were observed in a number of axial CT image slices. A representative example is shown in Figure 8, wherein a number of dark lines are clearly discernible as indications of interest. Some of these indications (blue ellipses) can be immediately attributed to artefacts arising from the CT acquisition process, while others (red ellipses) are potential defects by virtue of their crack-like appearance. The feature circled in amber however, is a combination of a crack-like defect intersecting with a benign artefact. Whilst existing CT segmentation procedures are able to identify this whole
cluster of pixels as an “indication of interest”, they are not able to separate and distinguish the potential crack-like defect from the benign artefact, nor classify them as such.

Figure 8 CT axial image slice showing potential defects (red ellipses), artefacts (blue ellipses) and a feature comprising an intersected defect and artefact (yellow ellipse).

4.1 Separating intersecting features

From observation, the feature of interest in Figure 8 comprises two intersecting line features. Separating these features is essentially an exercise in cluster analysis, for which a number of algorithms are available; among these the k-means method is one of the most commonly used. The method partitions a given set of points into a specified number of clusters. This iterative partitioning minimises the sum, over all clusters, of the within-cluster sums of point-to-cluster-centroid distances; see [5]-[8] for detailed treatment.

For this example, thresholding was applied to the region of interest in the original greyscale axial image to extract the pixels that constitute the cluster indication (Figure 9). K-means can then be used to separate the intersecting features into two clusters (Figure 10).

Figure 9 Thresholding to extract pixels associated with the features of interest from an axial image slice.
4.2 Feature classification

The next step was to classify the clusters as either a benign artefact or a potential defect. Based on a survey of the axial image slices, benign artefacts associated with CT acquisition are observed to be generally parallel to the component geometry, whereas potential defects have much more arbitrary orientations. This characteristic presents a possible criterion to classify the separate features.

The axial geometry of the component is a mix of curved and straight lines. Automatic identification of straight lines using the Hough transform is a well-established technique [9]-[11]. The gradients of the straight lines correspond to the principal orientations of the components (Figure 11). For the example in question, features with orientations that are within +/-10% of the principal orientation were classified as benign artefacts, while those outside of the 10% boundary are classified as potential defects.

Figure 12 shows a typical result from the approach on a representative axial image slice. The potential defect has been correctly identified and classified as such (in red), and likewise for the benign artefact (in blue).
Figure 11 (Left) Hough transform of axial image slice. X-axis denotes orientation and Y-axis denotes distance from image centre. Peaks in the bright areas are indicated by squares and these represent the dominant straight lines in the original image. (Right) Axial image slice (thresholded) with straight lines (green) detected using the Hough transform.

Figure 12 Example of partitioned clusters, classified as potential defect (red) and benign artefact (blue) according to whether their orientation is within +/-10% of component geometry.

5. Discussion

Both processing methods were implemented in MATLAB. For the first one the computational time was found to be very high - on a typical Windows computer (Intel Core™ i5 2.3GHz CPU with 2 GB RAM), a 1K-by-1K pixel image slice takes about 1 minute to process. This is due to the large number of 2D-FFTs inherently involved in the approach – i.e. incrementing the 32-by-32-pixel analysis area one pixel at a time over the entire image. For the 1K-by-1K-pixel slice this amounts to 938,961 2D-FFTs. Given that a typical CT dataset comprises up to a thousand image slices (or more), the overall processing time (1K x 1K x 1K voxels) could take up to tens of hours, which is clearly unacceptable.
A number of computational modifications could be adopted, either individually or in combination, to reduce the number of 2D-FFTs. Possible approaches include:

• Reduce number of overlapped pixels between successive 32-by-32-pixel analysis boxes
• Parallel processing using multi-core CPUs or GPUs

It is expected that a combination both could reduce the computational time down to minutes for a complete CT dataset. These are presently being investigated.

In the case of the classification method, the current approach only focuses on analysing local areas of interest in the axial images. Therefore the image thresholding process (from greyscale to black-and-white) only works around the local area. When the same threshold is applied to the entire image, the resulting image omits potential defect features in other parts of the image. Due to pixel intensity variations in the image, a single binary threshold level is unable to adequately account for all features of interest. The limitation may be overcome by either adding a preliminary image treatment stage to normalise the pixel intensities in some way, or implementing a locally adaptive thresholding approach such as those reported in [12]-[13]. These will be investigated in follow-on work and communicated in a future publication.

6. Conclusion

Two contrasting yet illustrative problems encountered in an ongoing X-ray CT research programme have provided ample scope for developing automated methodologies to recognise and classify CT-related artefacts. Encouraging outcomes were obtained using well-established algorithms such as the Fast Fourier Transform and k-means clustering, in combination with filtering criteria formulated using knowledge of defect and/or component geometry. Further evaluations on a wider range of CT datasets are warranted to validate their general applicability in CT analysis. Algorithmic and software engineering optimisations are also anticipated to improve computational performance.

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References