Mapping Performance of CT

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Abstract. One of the major hurdles preventing the more widespread deployment of X-ray Computed Tomography (CT) as a tool of industrial quality control for safety critical components is the limited understanding of an inspection’s capability to detect defects of concern. In more traditional Non-Destructive Testing (NDT) the challenge of inspection performance demonstration and qualification is typically addressed using samples with “representative” defects. Whilst this approach can in principle be applied to CT inspection, the complexity of the geometries to which CT is frequently applied undermines the level of inspection verification, as the scope for extrapolation from a few example defects is limited. This is especially true when the spatially varying effects, including imaging artefacts for example, that will determine whether or not an indication is detectable in the collected data, are considered.

In practice, the voxel size of the scan is frequently quoted as a measure of the expected inspection performance, but this is an entirely inadequate metric when component stress and lifing calculations require the quantification of the largest defect that could have been missed. Here, a computational framework to address this challenge is presented. It merges a simulation capability with experimental scan data to compute a map of the detectability of defects across the component volume, which can then be used to compute probability of detection and false call rate inspection reliability metrics. The structure of the algorithm is described, as well as initial results.

Introduction

Cone-beam X-ray Computed Tomography (CT) is an inspection technology of increasing industrial importance [1], to a large extent due to its suitability for the inspection of components made by Additive Manufacturing (AM) methods [2]. To enable the technique to be used for sentencing safety-critical components, it is essential to understand the limitations, and hence reliability, of the inspection. Furthermore, given the role of CT as a validation tool to other Non-Destructive Testing (NDT) techniques, this is a matter of broad importance [3].

Whilst it is known that a wide range of factors affect the performance of a CT inspection [4], the collective consequences for the performance are poorly understood. Moreover, several of these factors are liable to induce spatial variations in inspection performance across the sample volume. Such factors include beam-hardening, scattering, focal spot blurring, detector pixel imperfections and misalignment [5-6]. Additionally, the decreasing radiographic contrast of a defect of a certain size with increasing material path length (due to Beer-Lambert attenuation) [7] will, in the presence of noise, itself give rise to spatial variations in defect contrast, given the range of material path lengths associated with different locations across the component volume. Note that these considerations all relate to the data acquisition, before any data analysis, which will further affect the overall performance of the inspection.
Without spatial variations in inspection performance, it would be possible to demonstrate the capability of the inspection using a single test defect, introduced on a test piece. However, in the presence of potentially severe spatial variations in defect detectability, a conservative experimental assessment of inspection performance becomes almost impossible – it is clearly not possible to introduce a known inspection target at every location in the volume.

This paper presents an experimental study of the spatial variations in detection performance, as well as a simulation-based route to CT inspection performance assessment and hence qualification / validation, in a manner similar to the ultrasonics-based work in [8], as a means of overcoming the described challenges. Note a comprehensive account of the work is provided by [9], which should be consulted for some details omitted here for brevity.

2. Method

2.1 Experimental

The results relate to a test artefact that was developed to allow a sample defect to be placed in multiple locations in a body liable to give rise to spatial variations in inspection performance. The artefact was made of 304 stainless steel by Electrical Discharge Machining (EDM), including a spare defect-free larger insert and two (well-separated) nominally hemispherical test defects on the other of the larger inserts. The larger of the test defects that is the focus here was measured on an Alicona G4 focus variation microscope [10] to be 1.08 mm across, with a depth of 402 µm. A photograph of the reconfigurable artefact is shown in Fig. 1. In total, the set-up allows the two inspection targets / test defects to be placed in a total of 16 locations each, with negligible differences between configurations beyond defect positions.

Fig. 1. Photograph of reconfigurable artefact, showing tightly-fitting sliding inserts. Note the test defect (arrow) visible on side of larger insert protruding from the main body of the artefact.
The artefact was scanned in 8 configurations (7 defect insert arrangements plus a scan with the blank insert) on a Nikon XTH 225 ST [11] CT system (fitted with a 2000 × 2000 pixel flat panel detector), otherwise maintaining identical scan parameters. The scan set-up was chosen to give a relatively fast scan (given the number required), with a data output that would not immediately be too overwhelming to process by means of the algorithm developed. Additionally, the intention was not to perform the highest quality scan possible, but rather to induce qualitatively appreciable differences in inspection performance across the set of scans. A summary of scan parameters is shown below in Table 1.

Table 1. CT scan parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source voltage (kV)</td>
<td>205</td>
</tr>
<tr>
<td>Source current (mA)</td>
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</tr>
<tr>
<td>Exposure time (ms)</td>
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</tr>
<tr>
<td>Number of projections</td>
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</tr>
<tr>
<td>Frames per projection</td>
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<tr>
<td>Detector binning</td>
<td>2 × 2</td>
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<tr>
<td>Filter material</td>
<td>Copper</td>
</tr>
<tr>
<td>Filter thickness (mm)</td>
<td>0.5</td>
</tr>
<tr>
<td>Approx. scan time (min)</td>
<td>29</td>
</tr>
<tr>
<td>Native voxel size (mm)</td>
<td>0.074</td>
</tr>
</tbody>
</table>

2.2 Computational

The operation of the algorithm developed is summarised in Fig. 2.

Fig. 2. Flow diagram representation of algorithm.

In slightly more detail:

- The experimental projection dataset forms the basis of calculation, allowing all nuances of the experimental hardware to be reflected.
- A simulation model of the inspection (using the aRTist simulation engine [12]) is registered to the experimental projection dataset based on the component CAD and the method described in [13].
- A set of projections corresponding to the experimental inspection is simulated.
- A second, similar, set of projections is simulated, but placing a hypothetical defect of interest into the component volume, in line with [14].
- Corresponding projections from the two sets are subtracted, to leave a set of difference images attributable to the presence of the hypothesised defect.
The difference images are superposed into the corresponding experimental images, in a manner comparable to the approach in [15], to produce a hybridised projection set.

Original experimental (baseline) and hybridised projections are reconstructed independently (using the highly efficient FDK [16] reconstruction implementation X-AID from MITOS [17]).

The two reconstructed volumes are compared to allow the detectability of the hypothesised defect to be assessed.

The process is then repeated as required for alternative hypothetical defects, sampling a range of locations across the component volume. Note that not all mentioned steps need to be repeated for subsequent defect evaluations.

3. Results

3.1 Experimental

The 7 locations in the component volume sampled with the larger test defect are shown in Fig. 3, marked on slices through reconstruction volumes of the artefact in its defect-free configuration. The images clearly show that the scan is subject to significant beam-hardening and scatter artefacts (no attempt was made to correct for these in the reconstruction), given the bright edges of the part in the images and the high greyscales recorded on the concave region exterior to the sample.

![Fig. 3](image_url)

**Fig. 3.** Defect locations sampled experimentally with the larger test defect, marked on slices through the reconstructed (defect-free) volume. The left image corresponds to the height of the defect in the main body of the artefact when at the bottom of the insert, the right to the height of the defect when the insert is inverted.

Figure 4 shows slices through the indications obtained for 4 of the sampled locations – note more results can be found in [9]. The 4 images reveal obvious variations in the detectability of one and the same test defect, depending only on the position of the defect in the sample volume: despite being nearly 15 voxels across, the defect to all intents and purposes disappears in one of the locations illustrated. These results emphatically demonstrate the problem described in the Introduction, and highlight the extent to which voxel-based rules of thumb on inspection detectability in CT are flawed.
3.2 Computational

Spherical defects of 0.5 mm diameter were hybridised into the defect-free experimental dataset using the algorithm described in Section 2.2 in the locations sampled experimentally (see Fig. 3). The results corresponding to the 4 locations displayed for the experimental scans in Fig. 4 are presented in Fig. 5.

Despite the differences in the size and morphology of the simulated defect compared against the experimental test defect, the slices from the hybridised volumes are quite similar to the experimental images for the same locations. Most importantly, broadly the same trend in qualitative detectability is observed – the correlation is somewhat less strong for the locations not displayed here (see [9]). Refinement of the simulation, to make the hypothesised defects more accurate should allow the results to be improved further.
Fig. 5. Slices through the hybridised volumes corresponding to the experimental scans shown in Fig. 4. Clockwise from top left the locations again relate to positions marked 7, 5, 2, and 1, respectively, in Fig. 3. Note the similarity of the images here to those in the preceding figure and the reproduction of the same trend in detectability, despite the difference between physical & simulated defect morphologies.

Extending the computation to a set of defect locations across the cross-section of the artefact at the height of the larger defect allows the image in Fig. 6 to be built up. Here 44 hybridised indication volumes were superposed into the same volume for ease of visualisation. The image further reveals significant variations in the appearance of a test defect across the plane sampled, depending solely on the location of that defect. Clearly, metrics for detectability and size can be computed for this grid of indications, to quantitatively map out the inspection performance, taking into account the 3D nature of the indications. Such maps can then also be used to guide any experimental work with artificial test defects, ensuring that the experimental inspection performance assessment remains conservative.

As an aside, readers may be curious about the computing effort associated with producing such an image. Despite limited speed optimisation to date, the time per indication sampled was under 5 min (for 1200 projections of $1000 \times 1000$ pixels plus reconstruction and evaluation, excluding prior registration, on a custom workstation with AMD 1950x Threadripper CPU, twin NVIDIA Titan XP GPUs, 128 GB RAM and 1 TB NVMe SSD).
Fig. 6. Slice through a compound volume of the artefact formed by sampling a regular grid of defect locations with a 0.5 mm spherical void. Each defect was hybridised into the scan separately and the indication volumes formed in this way were superposed onto the scan of the defect-free artefact for visualisation. In contrast to previous slice images, some beam-hardening correction was applied in the reconstruction. Note the significant and complex variability in the appearance of one and the same defect in different locations in the scan.

4. Conclusions

This paper has described the challenge of spatial variations in CT inspection performance, supported by an experimental study starkly demonstrating the problem, and proposed an algorithm as a means of addressing the challenge, to enable the validation / qualification of CT inspections. Results obtained from the algorithm are promising, with reasonable correspondence to the experimental data. There is of course scope for further work, including on speed optimisation of the algorithm implementation, but even as it stands, it constitutes a significant advance in the understanding of the limitations of CT inspections.

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References