Optimised inspection of complex geometries

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Abstract

The inspection of complex-shaped components, such as those enabled by additive manufacturing, is a major challenge in industrial quality assurance. This paper describes work seeking to address this challenge by the use of numerical optimisation coupled with a simulation capability as a means of incorporating prior knowledge about the inspection into the inspection design as a means of obtaining an improved capability. The focus of the work is radiographic imaging, but the algorithm described can readily be adapted to other image-based inspection modalities. The algorithm is described, alongside the initial, promising, results obtained.

1. Introduction

The inspection of complex-shaped components, such as those enabled by additive manufacturing, is a major challenge in industrial quality assurance. At present, X-ray Computed Tomography (CT) is frequently relied on for volumetric inspection of such components, because it not only provides the high level of performance independence from sample geometry and surface finish of a radiographic inspection technique, but also gives detailed 3-dimensional positional and sizing information (1). Moreover, CT can be used to obtain dimensional measurements (2). However, there are multiple limitations associated with CT, including the typically high per-part cost (primarily due to high equipment costs and extended cycle times) and the geometric limitations associated with the need to acquire projections from many positions along a circular arc. CT is also not fully established as an industrial inspection technique, for example there is no personnel certification scheme as for other NDT methods. Additionally, there is an interest in having a more targeted inspection capability, which is able to incorporate prior knowledge about the component, for example, to exploit data acquired by monitoring systems on the build machine (3).

An alternative technique that in principle is similarly applicable to the volumetric inspection of complex-shaped parts is 2D radiography. Moreover, it is a less expensive, more flexible and better established alternative to CT. However, 2D radiography does not generally provide an inspection that is as comprehensive or capable as CT, most obviously given the lack of depth information in the direction of the X-rays. Additionally, designing a detailed inspection for a complex-shaped component is currently a labour-intensive task, requiring significant input from a technique expert (qualified to Level 3). Whilst there are simulation tools available to assist in this task (4,5,6), the level of effort required is incompatible with short production runs and part customisation of the sort
made increasingly cost-effective by additive manufacturing (7). Moreover, even an experienced inspector is unlikely to be able to incorporate all available information into the inspection design, given in particular the complexity of spatially varying inspection capabilities and requirements.

The overarching aim of this work then is to improve the capabilities of multi-shot 2D radiographic imaging by computationally incorporating prior knowledge about the inspection into the inspection design, to maximise the likelihood of delivering the required level of quality assurance. The framework developed is applicable to all image-based inspection modalities, but exemplified using 2D radiography - the extension to surface inspection at optical wavelengths is also likely to be of interest for the inspection of samples with high geometric complexity. As an intermediate output, the algorithm computes spatial maps of inspection performance, an output that is itself of great potential value for understanding the limitations of an inspection. Central to the algorithm is the capability to quantify the value of an inspection configuration with respect to the quality assurance requirements, and a numerical optimisation algorithm with features designed for the application described.

The work is complementary to that described in (8), which relates to the optimal selection of radiographic projections for subsequent tomographic reconstruction, rather than 2D imaging. Key differences between that work and the present study, other than the application, relate to the choice of the means of quantifying the value of a projection and the nature of the applied numerical optimisation: the greedy sequential scheme, based on exhaustive enumeration, that Fischer et al. use would incur an overwhelming computational cost in higher dimensional decision variable spaces (as examined here), and has a low likelihood of converging to the overall global optimum.

2. Method

The algorithm developed relies on sampling potential component projections, or combinations thereof, as chosen by a numerical optimisation that aims to improve the fitness for purpose of the inspection configuration. This is an example of inversion, finding the input (data acquisition setup) for a given output (the best inspection performance). The fitness metric is evaluated by sampling relevant defects and, for each one, simulating the resultant indication before assessing the defect detectability. The components of the algorithm are described in further detail below.

2.1 Simulation

The present implementation the forward model is provided by the aRTist radiographic simulator software package (9). This software tool is able to predict the indication to be expected from a given hypothetical defect in a specific sample geometry obtainable in a specific inspection configuration. In principle, to adapt the algorithm to an alternative image-based inspection modality, this simulation capability just needs to be exchanged for an alternative specific to the new modality.
2.2 Detectability evaluation

Once an indication is simulated, the detectability of this is assessed. The method for doing so must be entirely general, capable of coping with a great range of indication shapes on a similarly range of backgrounds (given the complexity of the geometry being considered). The devised method is described in detail in (10), but is based on reducing the indication to a statistical representation, relating the indication area to the contrast to noise ratio.

2.3 Defect sampling

Many defects are sampled and their indication detectability assessed to build up a picture of the performance of a given radiographic projection. The more defects are sampled, the more accurate and comprehensive the assessment, but the greater the computational cost. The choice of what defects to sample can incorporate any available prior knowledge about defect likelihood (based on the manufacturing method and historic data) and defect criticality across the component volume. Automated sampling of defect locations is then enabled by considering the voxel (3D pixel) representation of the component geometry, which may be modified to identify an appropriate permissible region for surface defects, for example. An example of this is illustrated in Figure 1.

Figure 1. Rendering of a possible permissible region for defect sampling calculated from the voxelisation of a test component’s CAD-model. The voxels here are cubes of 0.5 mm edge length. The component design is courtesy of GRM Consulting Ltd., K-Tech & MTC.

2.4 Projection sampling

The selection of projections is controlled by the optimisation algorithm (see section 2.6), however, the decision variables that determine the projections sampled must be defined. In the test cases evaluated to date, the focus has been on the six degrees of freedom that define the pose of the component with respect to the radiographic hardware (assumed fixed). However, multiple projections can be used to specify an inspection configuration, and parameters can be linked across such projections, for instance allowing a fixture to be specified that is to be used across the set of projections.
2.5 Objective function

The objective function provided to the optimisation algorithm for a given projection set is condensed from the detectability evaluations for all the projections within the set. In the present implementation, the best detectability metric is selected for each defect considered across the projections in the set, then the mean of the lowest $5^{th}$ of these maximum detectabilities is computed.

2.6 Optimisation

The optimisation algorithm here needs to contend with many challenges: in general, the parameter space is high-dimensional, and the objective function space complex and marked by many local minima, for example. A customised version of the genetic algorithm (11,12) was deployed to tackle these challenges – described fully in (10).

3. Results and discussion

In this section we consider the output of the algorithm for first a simple and then a complex inspection scenario. The primary purpose of the former is to provide confidence in the behaviour of the algorithm, given that for a simple inspection scenario a human inspector could readily select an appropriate inspection set-up. This is unlikely to be the case for the complex inspection scenario (which is after all the motivation of this work). The second scenario is therefore presented to illustrate the relevance of the algorithm to the design of an inspection for a complex-shaped component.

3.1 Simple scenario

In this test case, a single projection of a uniform cuboid component is considered. All six degrees of freedom of the component’s pose are varied by the optimisation over wide ranges to span most of the space between the X-ray source and detector.

After evaluating a total of 1024 potential component poses, each assessed by examining 200 hypothetical defect indications (from small spherical voids, uniformly randomly distributed across the component volume), the algorithm converged on the pose illustrated in Fig. 2, alongside the corresponding detectability map. The blotchy appearance of the map is caused by the nearest neighbour interpolation used to create the map. Note that one corner of the sample is out of the field of view, visible in both elements of the figure. Note also that (ignoring edge effects) moving from left to right across the block there is an increase in detectability, attributable to a higher magnification and shorter material path length, consistent with radiographic experience.

The configuration converged to may seem unconventional, with the block not being presented normal to the X-ray centreline, and a small element of the sample out of view, but this is a consequence of the choice of the objective function underlying the optimisation in this case. Taking the mean in this calculation allows very poor detectabilities (including 0) to be traded off against good metric values elsewhere.
Figure 2. Illustration of the output of the algorithm for a simplistic inspection scenario, considering a single projection to inspect a uniform cuboid. On the left the configuration converged to is illustrated, as orthographic projection from aRTist, on the right the corresponding detectability map across the component’s upper face (broadly aligned with the scene view).

3.2 Complex scenario

In this more advanced inspection scenario we exchange the cuboid geometry for the complex component design introduced previously (courtesy of GRM Consulting Ltd., K-Tech & MTC). We also extend the inspection to encompass a set of 3 radiographic projections, and impose the constraint that two of the rotational degrees of freedom describing the object pose must be the same across the projections – corresponding to the same fixture being used to hold the component between projections, using the manipulator of a CT system to move between projections. This means the optimisation in this case has 14 decision variables.

Figure 3 illustrates the initial configuration, and that reached by the optimisation after evaluating a total of 28745 projection sets (each of 3 projections, assessed using 200 small spherical defects each). Note how the sample orientations within a set only differ by a rotation about an axis perpendicular to the image, reflecting the described constraint. The pre-and post-optimisation detectability maps for the two projection sets are presented in Fig. 4. Note the substantial increase in detectability across the component, such that a change in colour scale is necessary between the two images.

Figure 5 presents simulated radiographs corresponding to the three projections that make up the configuration selected by the optimisation. It is obvious from these images (as well as Fig. 3), that none of the projections individually fully capture the component, and that the overall inspection quality relies on the projections being used together.
Figure 3. Illustration, as orthographic projections from the aRTist simulation, of the inspection configuration before and after optimisation for the complex test case: the lower, darker poses make up the initial configuration, the upper, brighter poses make up the set-up converged to.

Figure 4. Pre- and post-optimisation detectability maps for the complex test case, shown on left and right, respectively, as a slice through the component. These maps relate to an inspection consisting of three projections, illustrated in Fig. 3. Note the difference in the detectability metric scale.

Figure 5. Simulated radiographs corresponding to the three projection set converged to for the complex inspection configuration.
The suggested inspection configuration is perhaps unusual, but then it would be difficult for a manual inspection design to consider the spatial relationships between regions imaged by the three high magnification projections. Having built up some confidence in the behaviour of the algorithm via the simple test case, the output does seem plausible as an optimal inspection configuration. However, as illustrated in the simple test case, the limitations of the chosen objective function form need to be borne in mind. Moreover, given the (defect) sampling approach underlying the configuration assessment, a more accurate and comprehensive assessment and result would be achieved by sampling more potential defects, but this would incur a computational penalty. Finally, the challenges of global optimisation in a high-dimensional space with complex features (e.g. local minima) mean that it is impossible to be certain that the point reached by the optimisation is indeed the global optimum: even if imposing a robustness requirement on the solution (to account for the finite precision with which a computed configuration can be reproduced experimentally) the computational load would quickly become overwhelming. As a specific illustration, enumerating the objective function considered in this scenario across a regular grid with a spacing of 10 mm or degrees (as appropriate) in each parameter axis would result in \(736 \times 10^{14}\) evaluations!

4. Conclusions

This paper has outlined a general framework for the formal optimisation of a multi-shot imaging inspection of a complex-shaped component. The framework allows prior knowledge to be incorporated into the inspection configuration, and whilst it is in principle applicable to all image-based inspection modalities, its operation has been exemplified using 2D radiography. Results have been presented for both a simple and a complex test case, illustrating both the capability of the algorithm and its applicability to the design of complex inspections. The work therefore presents a route to achieving optimally efficient inspection and specifically reducing the reliance on X-ray CT for the inspection of complex geometries. As a useful by-product, the algorithm computes the spatial distribution of a given inspection configuration's performance. Planned future work includes the refinement of the optimisation, calibration of the model and the extension of the framework to alternative inspection modalities.

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