CAD-based defect inspection with optimal ROI selection based on polychromatic X-ray projection images

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1 Introduction

In the last few years, the make industry is getting increasingly interested in 3D computed tomography (CT). This non-destructive method permits to reconstruct a detailed profile of the volumetric internal structure of a complex object starting from a collection of 2D X-ray projection images. Its main, but not unique, application in the manufacturing process is inspection, preferably inline, to detect possible material defects or dimensional deviations. For this purpose, the acquired projection images can be compared to the nominal geometry using computer aided design (CAD) models. Conventional CAD-based X-ray inspection requires 3D reconstruction and voxelization of an object, starting from its radiographs, before comparing it to the nominal geometry [1-3]. With this methodology, the quality of the final reconstruction is crucial to guarantee an accurate analysis and typically requires hundreds of X-ray projection images from a large number of viewing angles. Even so, the 3D reconstructed images may suffer from numerous artefacts due to misalignment in the measurement setup, beam hardening, undersampling, etc.
We recently developed a CAD projector [4] capable of simulating projection images of the CAD model. The CAD projector is efficiently implemented on the GPU and integrated with our flexible reconstruction software, the ASTRA Toolbox [5]. In this paper, we propose CAD based inspection directly performed in projection space, comparing the 2D simulated projections directly to the measured ones. Our method allows to avoid inspection based on CT images suffering from artefacts using only a very limited amount of projections. Furthermore, since the position and extent of the possible defects that may occur in the object under consideration are assumed to be known a-priori, we optimize the region of interest (ROI) where to perform the comparison. Once the region to inspect has been defined, the difference between the measured projections and the simulated projections is evaluated in terms of the peak signal-to-noise ratio (SNR) and the mean squared error (MSE), and through linear discriminant analysis we classify the samples. Results on simulated and real data are shown that demonstrate the effectiveness of such an approach.

Keywords: X-ray, CAD, ROI, inspection, defects

2 Methodology

A flowchart of the proposed methodology is shown in Fig. 1. To simulate radiographs of the reference CAD object, polychromatic X-rays are virtually cast from a source, penetrate the CAD model and hit a virtual detector. After detecting the points of collision of the X-ray beam with the triangle mesh, the line length that a ray travels inside the model is calculated. In order to compare the simulated projection images to the measured data, it is necessary that the acquisition parameters, such as the position of the source, the detector and the rotation axis with respect to the reference system centered in the center of mass of the sample and the detector and pixel dimensions, are known. Also, to adequately simulate the behaviour of the beam when intersecting the sample, the materials of all the components must be known in advance.

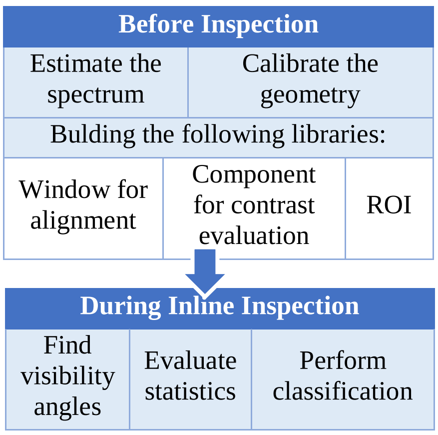

Figure 1: Flowchart of the methodology.

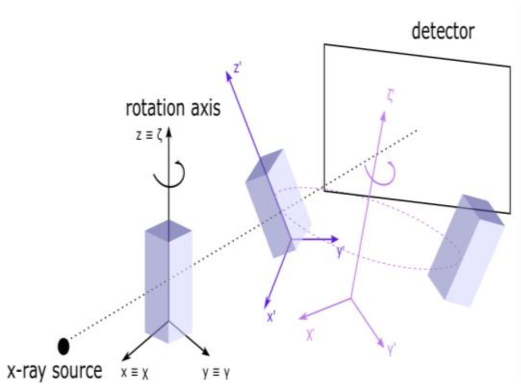

Figure 2: Starting from a default configuration with the object rotating around the z axis, we consider translation and rotation of both the object and the rotation axis.

Two optimization processes are needed: (1) estimation of the spectrum of the source and geometric calibration and (2) estimation of the position and rotation of the object. The spectrum estimation was developed earlier [4] and is performed by minimizing the discrepancy between the intensity values of the measured and simulated data. We extended this approach to allow geometric calibration using CAD data of a calibration phantom in terms of position and orientation of the rotation axis, the detector, the phantom and the position of the source (Fig.2). These parameters are optimized using the Hill climbing algorithm [6]. Although this alignment procedure returns an accurate result, it is not applicable to in line quality control due to its long execution time. To work around this problem, we built up three different libraries, all of them with simulated images from different projection angles: the first one contains only a window of simulated images that will be used during inspection for a fast alignment; the second one contains the ROI where quality control need to be performed; the last one contains only the component subject of inspection.

The choice of the ROI plays a fundamental role in our methodology. In case of a missing component, the ROI can easily be defined by projection only this component along with components whose contribution needs to be avoided. Otherwise, supposing that the position of the defective part is known, simple CAD volumes are defined around the identified position and projected. In the latter case the ROI can be optimized in order to best discriminate between defective and non-defective samples.

During the inline inspection, after the original projections have been aligned to the window, the so-called visibility angles, i.e. the projection angles where the part to inspect is most visible, have to be identified. For this aim we use a criterion that finds the maximum contrast of the component compared to its surrounding background. In order to exclude the possibility of choosing visibility angles where the part is hidden by other components, our method weights the contrast calculated when only projecting this part with the overall contrast of a full projection. The values of the weigthed contrast for each projection angle can be precalculated and stored in a matrix: in the inspection phase, the visibility angles will be choosen as the maximum values among those corresponding to the projection angles selected during the alignment step. Finally, we use the peak signal-to-noise ratio and the mean squared error as measures to quantify differences between the images and discriminant analysis is performed.

3 Results and discussion

In Fig. 3, a plot of the variation of the weighted contrast in function of the projection angle for simulated data, in a ROI containing an inspected component, clearly shows peaks when the component is most visible. We also validated our methodology with measured inline scans of medical devices. For each inline scan 21 projection angles were acquired. The result of the window alignment process is shown in Fig. 4, and the component under inspection is highlighted. Finally, in Fig. 5 we show the canonical plot of linear discriminant analysis (LDA) performed on a group of 30 samples. The LDA shows the performance of the proposed methodology to separate the ok samples from the defective ones ($p = 0.027$). In the full paper we intend to insert results that test the robustness of our inspection method by adding noise to simulated data and by validating on a larger dataset of measured inline scans.

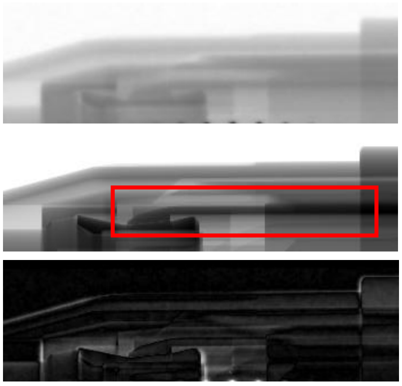

Figure 4: The result of the library based window alignment process. A cutting of a measured projection is shown (top) along with the simulated window in the library (middle) and a difference image after their alignment (bottom). Also, the component where inspection is performed is highlighted.

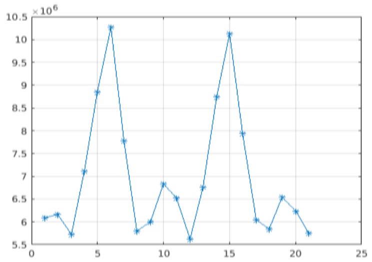

Figure 3: The contrast in the ROI per projection angle. Peaks are evident when the visibility of the components is maximum.

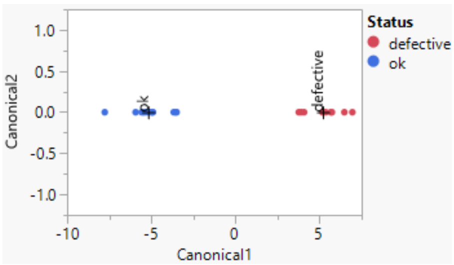

Figure 5: The canonical plot for 30 samples. The MSE and SNR are used to classify the samples into ok and defective ones.

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