# CAD-based defect inspection with optimal view angle selection based on polychromatic X-ray projection images

Alice Presenti[1], Jan Sijbers[1], Arnold J. den Dekker[1], Jan De Beenhouwer[1]

[1]imec-Vision Lab,Department of Physics, University of Antwerp, Universiteitsplein 1, Antwerp 2610, Belgium
E-mail: {alice.presenti, jan.sijbers, arjan.dendekker, jan.debeenhouwer}@uantwerpen.be

**Abstract**

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 application in the manufacturing process is inspection, preferably in-line, 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.

We recently developed a CAD projector [3] 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 [4]. In this paper, we propose CAD based inspection for missing or distorted components directly performed in projection space, comparing the 2D simulated projections directly to the measured ones. While conventional algorithms require hundreds of projections, our method allows inspection based on CT images 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, we extract some features to evaluate the difference between the measured projections and the simulated projections and perform classification. Results on real data are shown that demonstrate the effectiveness of such an approach. Thanks to a GPU implementation and parallelization, the complete procedure requires an execution time in the order of a second, making it applicable directly in-line.

## 1 Methodology

A flowchart of the proposed methodology is shown in Figure 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 intersection of the X-ray beam with the triangle mesh of the CAD model, 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 behavior of the beam when intersecting the sample, the materials of all the components must be known in advance. 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 [3] 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 (see Figure 2). These parameters are optimized using the Hill climbing algorithm [5]. Although this alignment procedure returns an accurate result, it is not applicable to in-line quality control due to its long execution time.

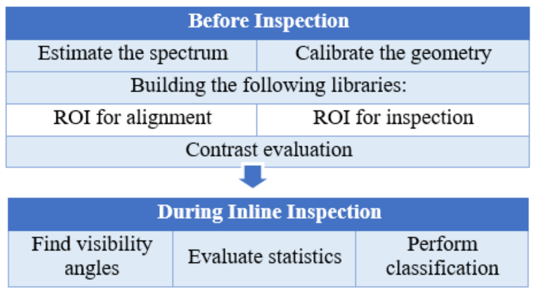


Figure 1: Flowchart of the methodology.

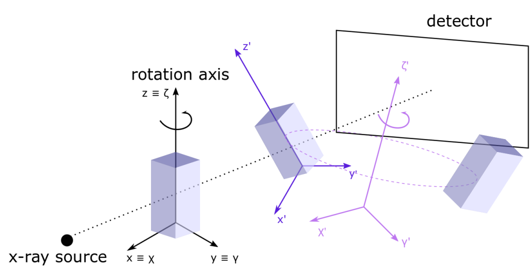


Figure 2: Starting from a default configuration with the object rotating around the z axis, we can estimate translation and rotation of both the object and the rotation axis.

To work around this problem, we built up two different libraries, with simulated images from different projection angles: the first one contains a ROI of the simulated projections, that will be used during inspection for a fast alignment on the detector plane; the second one contains the ROI where to perform the quality control. The choice of the inspection ROI plays a fundamental role in our methodology. In case of a missing component, it can be defined by projecting only this component along with components whose contribution needs to be avoided. Otherwise, supposing that the position of the defective part is approximately 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 in-line inspection, once the real projections have been aligned to those in the libray, the so-called *visibility angles*, i.e. the projection angles where the part to inspect is most visible, have to be identified. To do this, we pre-compute projection data for the expected object and we associate to each discrete orientation view of the CAD model around its rotation axis a contrast value using the roote mean squared contrast (RMSC), so that the knowledge of the orientation for each projection angle guides the choice of the visibility angles. The values of the contrast can be precalculated and stored in a vector: in the inspection phase, the visibility angles will be chosen as those with the highest contrast values. At the end of our workflow, we classify the samples by extracting some useful task specific features from only the projections at the visibility angles.

## 2 Results and discussion

We validated our methodology on in-line scans of syringes. The goal of the study was to distinguish between intact and defective products. For each scan, X-ray images were acquired from 21 equiangular projections within an angular range of 200 degrees. Eight defects were induced under a controlled situation. Four of these eight defects originated from the metal components (e.g., spring, needle) of the syringe. These were detected using an image processing approach, that is not part of this work. Three of the four defects inspected with the proposed methodology required to detect if a component was missing or shifted: in this case the library with the ROI for inspection was defined by projecting the component. For the other one, a possible distorted component, we projected instead a small box manually, defined around a strategic part of the component were the defect should be visible. The result of the rigid alignment between real and simulated data is shown in Figure 3, and the component that determines the angle view selection is highlighted. Each of the 21 measured projections was aligned and then the best orientation angle was found performing a bruteforce search in the library. Among these projection images, only three were selected to calculate the statistics (those with the highest contrast).

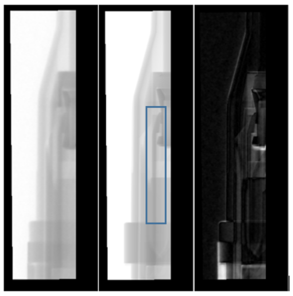

Figure 3: The figure shows the comparison between the real projection (left) and the selected simulated projection after alignment (middle). The difference image is on the right.

For our experiment we had 52 labeled samples to use as training data, 20 of them were defective. A final blind test was performed on a test set composed of 600 samples, 120 of them were defective. Based on training data, we calculated correlation and signal-to-noise ratio between the simulated and the real projection in case of a missing component. In case of a distorted component, a binary gradient image from the original radiographs was also extracted, and a quantitative measure was calculated summing all nonzero pixels. For this case also the root mean squared error was useful for the final classification. For each defect, thresholds on the measures were manually established and the samples were labeled as defective if the statistics simultaneously satisfied a set of logical clauses. When applying the same classification procedure to the test set, the result was a 100% success rate, demonstrating the effectiveness of our strategy. The alignment process and statistics calculation was implemented on the GPU, making feasible to inspect four samples in 1.59 seconds, and thus to perform the entire procedure in-line.

**Acknowledgements**

This research is funded by the imec ICON project iXCon (Agentschap Innoveren en Ondernemen project nr. HBC.2016.0164), the FWO SBO project MetroFlex (S004217N) and the European Commission through the INTERREG Vlaanderen Nederland program project Smart*Light. The authors would like to thank XRE NV for acquiring the projection data.

**References**

[1] K. Kiekens, F. Welkenhuyzen, Y. Tan, Ph. Bleys, A. Voet, J-P. Kruth, W. Dewulf, A test object with parallel grooves for calibration and accuracy assessment of industrial computed tomography (CT) metrology, Measurement Science and Technology, 22 (2011) 115502.

[2] O. Brunke, Fully-Automated 3d metrology and defect analysis with high-resolution 300 kv microfocus computed tomography, 18th World Conference on Non Destructive Testing, Durban, South Africa, (2012) 16-20.

[3] A. Marinovszki, J. De Beenhouwer, J. Sijbers, An efficient CAD projector for X-ray projection based 3D inspection with the ASTRA Toolbox, 8th Conference on Industrial Computed Tomography, Wels, Austria, (2018).

[4] W. van Aarle, W. J. Palenstijn, J. Cant, E. Janssens, F. Bleichrodt, A. Dabravolski, J. De Beenhouwer, K. J. Batenburg, J. Sijbers, Fast and Flexible X-ray Tomography Using the ASTRA Toolbox, Optics Express, 24 (2016), 25129-25147.

[5] S. Miao et al., Real-time 6DoF pose recovery from X-ray images using library-based DRR and hybrid optimization, International Journal of Computer Assisted Radiology and Surgery, 11 (2016), 1211-1220.