Deep Learning for improving the efficiency of dimensional measurement workflows with high-resolution X-ray computed tomography

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Abstract
High-resolution X-ray computed tomography (CT) instruments, also known as three-dimensional (3D) X-ray microscopes, can be adapted for dimensional metrology applications such as geometric dimensioning and tolerancing of metallic components. However, CT scanning times can be prohibitively high for industrial measurement inspection tasks owing to the poor contrast from X-ray attenuation in Ferrous metals, especially if the measurement of spatial resolutions under 5 μm are required. This paper describes a software-defined approach to dramatically reducing total exposure time (or scanning time) while maintaining resolution loss within 2 micrometers as compared to the baseline scans acquired over 6 hours. Here, we combine two deep learning (DL) codes in our surface extraction workflow to compensate for lower signal-to-noise ratio in short exposure data (acquired with lower number of projections): (1) a surface determination (post-reconstruction) , and (2) a denoising algorithm (pre-reconstruction). Training data was acquired from a scan of an 8-hole automotive fuel injector (sample 1) with a 165 μm nominal diameter per hole. For testing the accuracy of the workflow, a separate scan of a 6-hole side-mount injector (sample 2) was acquired. For both samples, the acquired X-ray projections (or radiographs) were binned down to 10X such as to simulate faster scans. For training and testing workflows, the full exposure scans (baseline) were used as target and the shorter exposure scans as inputs to the deep learning models. To determine loss of surface accuracy from the baseline case, a metric is formulated (in micrometers) and the trends are reported for when the total measurement time was reduced by up to 10X (up to 0.6 hours, using only 360 projections). We report that scan times can be reduced by over 10X while retaining the limiting the resolution loss to under 1 micrometer.

Keywords: Deep learning, X-ray computed tomography, dimensional metrology, high-resolution CT, microscopy

1 Introduction

Prior work in using dimensional metrology with X-ray CT has shown its efficacy in geometric dimensioning and tolerancing of metallic components [1–4]. The workflow elements involved in the analysis include tomographic reconstruction, surface determination (segmentation or thresholding) and some dimensional measurements. When spatial resolutions in the order of a few micrometers are demanded, the high attenuation coefficient in steel components dramatically increases the total exposure time required to achieve an adequate signal-to-noise (SNR) ratio. The applicability of high-resolution CT, or 3D X-ray microscopy, for in-line (or online) metrology can be challenging for millimeter-sized metallic components (e.g., automotive fuel injectors) demanding high ($< 5\ \mu m$) surface resolution. The authors from Argonne National Lab (ANL) previously reported a surface determination workflow using a DL algorithm for automotive fuel injectors with surface resolution under 5 μm on synchrotron CT [1]. The nominal diameter of the holes in such injectors is 165 μm. These holes are not accessible to traditional measuring methods such as tactile or optical coordinate measuring machines. Furthermore, the attenuation through steel walls of approximately 5 mm thickness create poor contrast and beam hardening effects. While scan times to achieve reasonable contrast for such a fuel injector in synchrotron CT can be under 15 minutes, a scan using a CT X-ray microscope would take up to 6 hours to achieve similar resolution. In this article, we combine two DL-based algorithms into a fully automated (parameter-free) workflow for the challenging use case of reducing scanning time for the internal orifices of these steel fuel injectors. The surface determination algorithm is part of an open-source code "TomoEncoders" developed by the first author (A. Tekawade) at ANL for direct segmentation of noisy CT scan volumes using 3D convolutional neural networks. The denoising code is a commercial software called DeepRecon, developed by ZEISS, as a reconstruction engine for denoising volumes obtained from low-dose scans[10, 11]. The main purpose of this paper is to analyze potential reductions in scanning time when this workflow is used to augment image-quality of CT data obtained with a low number of acquired X-ray projections. For reference comparison, the fuel injectors were scanned using a ZEISS Xradia Versa 620 instrument by acquiring a total of 3600 X-ray projections with 6 seconds exposure per projection (total 6 hours). Then, this data was reconstructed using equally spaced subsets of those projections (e.g., 2X means 1800 projections needing 3 hours scan time) to mimic reduced scan time. Each subset was reconstructed using DeepRecon as well as a traditional Feldkamp–Davis–Kress (FDK) reconstruction algorithm. Both datasets were then directly segmented (or binarized) using the surface determination algorithm from TomoEncoders, which utilizes 3D fully convolutional

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neural networks (fCNN) to perform surface segmentation [5], resulting in a binarized volume which implicitly determines the surface. For segmentation, the labeled mask for the training and testing data (two separate specimens) was generated from the full exposure data. These labels were manually inspected to be accurately representing the surface and any apparent bias was corrected by applying morphological filters. This "ground-truth" mask was used as reference for calculating any loss in surface accuracy after reduction of total exposure. The paper does not make any claims as to the absolute accuracy of the measurement but the relative loss in accuracy from the baseline case at full exposure when exposure is progressively reduced.

2 Results and Discussion

The surface computed from the CT data is defined as the boundary separating the voxels belonging to the metal and air (orifice passages) respectively. This surface defines the walls of the flow passages and are known to bear precursor sites for erosion during long-term injector operation[6, 7]. Hence, not only is it important to measure the orifice critical dimensions but also the surface roughness introduced by micrometer-scale metal fragments leftover from the manufacturing process. Due to the fundamental limitations to resolution in micro-CT introduced by the focal spot size and detector, the surface appears blurred (also called partial volume effect). When the total exposure time is reduced, the photon statistics become poorer and lead to reduced signal-to-noise ratio (SNR) and further blurring. Smaller features fade away with increasing noise and are missed by the surface determination step leading to surface accuracy loss. Since the test injector (see Figure 1 for a vertical slice from the reconstructed CT volumes at 1X and 10X using the standard FDK algorithm and the DL-based DeepRecon software) is off-the-shelf and unused, some fragments leftover from the manufacturing process are attached to the surface. These are appropriate features to observe the minimum detectable feature size of the segmentation step.

2.1 Denoising and CT Reconstruction

A total of 12 datasets were reconstructed to compare the performance of the FDK and DR algorithms with decreasing number of projections to simulate reduced scan time (1, 2, 4, 6, 8, and 10X). For instance 10X would imply reducing the number of projections during scanning by a factor of 10. The image quality is defined in terms of the SNR is defined as in equation 1 where μ and σ are the mean and standard deviation of voxel intensity in each label (1 is metal and 0 is air) as defined by the reference ground-truth mask. From 1, it is observed that when the standard FDK algorithm is used, the SNR drops by a factor of two when scan time is reduced by 10X. However, when DeepRecon is used, due the image is restored to the original SNR of 10 even at 10X time reduction. Since the source of noise is in the radiographs (or projection images) due to the Poisson distribution of photons incident on the detector, the denoising projections incorporated within DeepRecon is crucial to recovering the morphological information in the image such as the surface irregularities in the fuel injector's orifices.

$$SNR = (\mu_1 - \mu_0)/\sqrt{\sigma_1^2 + \sigma_1^2} \tag{1}$$

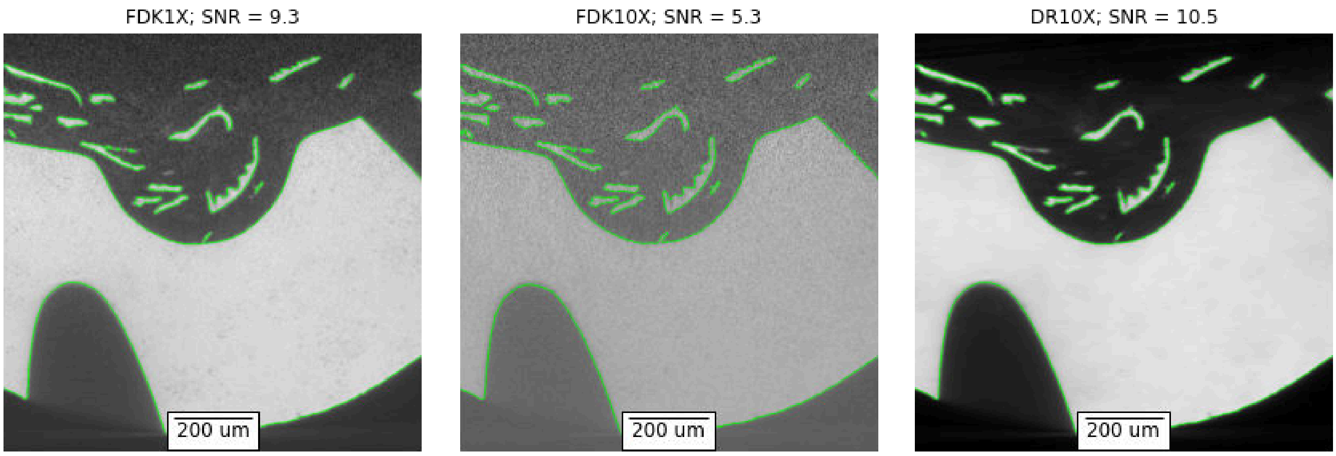

Figure 1: (left) Vertical slices drawn from three CT volumes in the test dataset: FDK with full exposure, FDK with 10X lower exposure and DR with 10X.

2.2 Surface Determination

For both the DeepRecon and FDK reconstructions, a DL-based segmentation (or binarization) step was applied to compute the surface for measurement workflow. Given the 3D nature of internal surface morphology of metal components, the segmentation algorithm was developed with a 3D convolutional neural network that is inspired by a 3D U-net [8]. The input volume and the corresponding ground-truth data was obtained from a scan of the 8-hole injector, which was different from the test injector detailed above so as to test the ability of the neural network to generalize on new data. Six different architectures with varying number of convolutional layers were evaluated and the best model was chosen based on the accuracy of surface determination. In previous work, the authors from ANL showed that if U-net is too deep, it overfits on the shapes observed in the training data, leading to models that do not generalize accurately [1]. Further details about the training and data sampling algorithm were detailed previously [9].

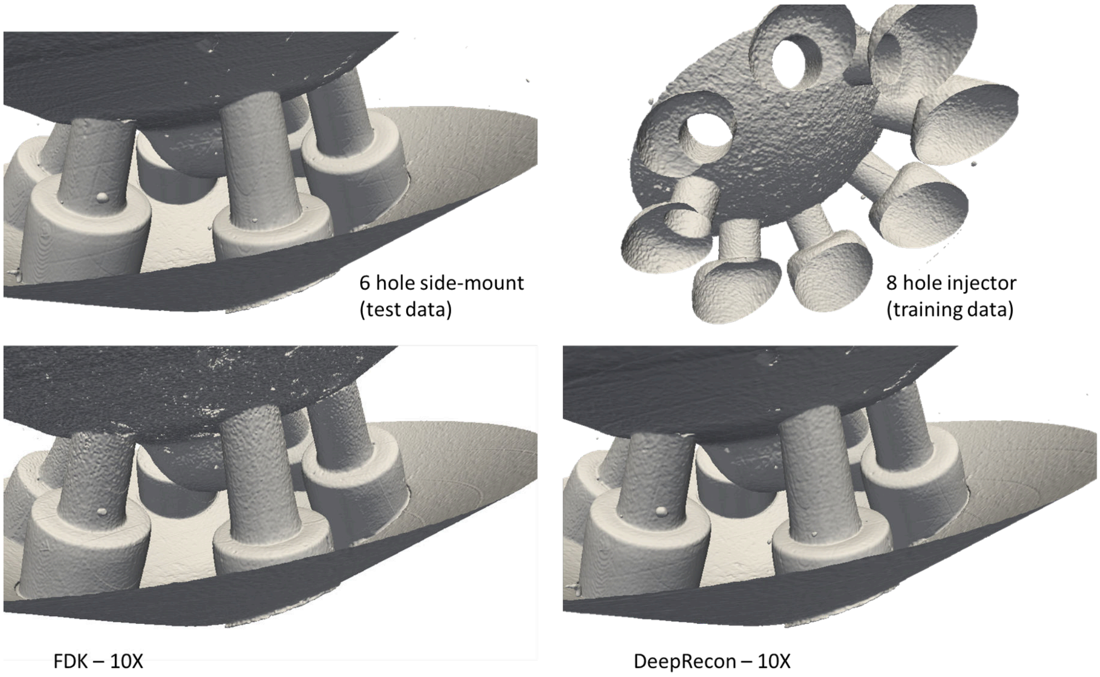

Figure 2: (left) Surfaces computed from the CT data. Top left to right: reference ground-truth surfaces used for the DL model testing and training respectively. Bottom left to right: Surfaces computed from the output of two workflows. First (FDK - 10X) involved traditional reconstruction and DL-based segmentation. The second (DeepRecon) involved DeepRecon software for reconstruction followed by the DL-based segmentation. Due to inherent noise in the projection data, the surface from FDK shows inconsistent non-repeatable features which are removed by DeepRecon.

2.3 Loss of Surface Accuracy with Reduced Scanning Time

The combination of DL-based segmentation and either of DeepRecon or FDK as reconstruction steps creates a workflow to limit the loss of accuracy in determining the surface of the internal flow passages in the injector when scan times are reduced. A metric for studying the loss of surface accuracy from the baseline full exposure scan was formulated as follows. First the accuracy of voxel prediction (0 and 1) in the binary volume was determined by a popular metric for voxel-space segmentation - intersection over union (IoU) or Jaccard accuracy [1]. Then, the reduction in IoU from the baseline case (FDK at 1X) was correlated with displacement of the measured surface from the ground-truth by artificially displacing the surface using dilate-erode filters and measuring the IoU of the displaced surface against the ground-truth (see left in Figure 3). With this trendline, the voxel displacement was converted to micrometers (voxel size was 1.51 micrometer) and the plot on the right in Figure 3 shows this loss in surface accuracy for the cases where DeepRecon and FDK were applied as the reconstruction steps. The same surface determination algorithm was applied to both data. When FDK is used, the surface error is highly variable and increases more drastically with reduced exposure. However, when DeepRecon is used, the surface error remains consistently low possibly even beyond 10X reduction in scanning time (36 minute scan). Because no calibration specimen was tested, no claim is made about the absolute measurement accuracy. Hence, only the trend in surface error should be noted without regard for the zero offset at 1X.

3 Conclusion

Scan times in X-ray CT dimensional metrology may be prohibitively high in small components (e.g., with sizes in the range 1–10 mm) that require micrometer-sized feature resolution due to poorer contrast. FDK reconstruction algorithms reduce the CT data quality and the accuracy of dimensional information in such data. Here, a software-defined solution is proposed where the measurement workflow is preceded by two DL-based elements for reconstruction (DeepRecon) and segmentation (TomoEncoders) to show that metrological resolution could be preserved even after reduction of scanning time by over 10X. with this workflow,

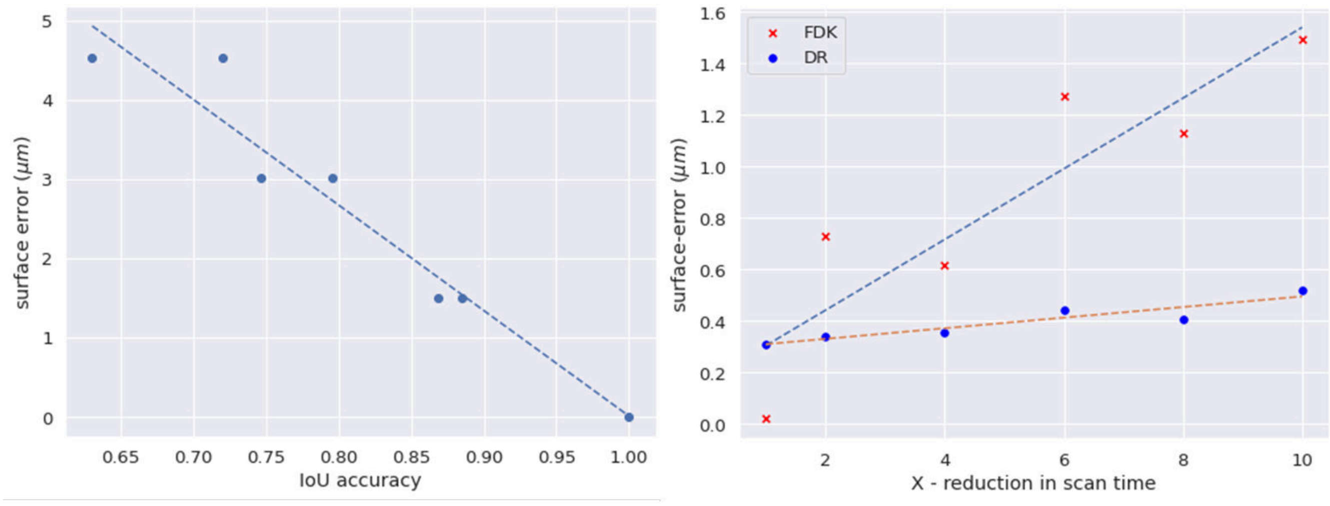

Figure 3: (left) Surface error formulated as displacement of surface in micrometers from reference (ground-truth) surface computed from full exposure scan. (right) Surface error estimated for surfaces computed from lower exposure scans (X is the reduction factor in scanning time.)

one may retrofit a high-resolution 3D X-ray microscope as an in-line (or on-line) metrology solution for metal components with turnaround time under 30 minutes per sample while providing resolution under 5 micrometers for dimensional measurements. Thus, well trained DL-based methods are advantageous to increase the throughput of CT acquisition while minimizing accuracy loss in dimensional data.

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