The effects of advanced iterative reconstruction on dimensional metrology using fast X-Ray Cone-Beam tomographic measurements

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Abstract

X-ray computed tomography (XCT) is increasingly used for dimensional measurements, where it can offer accurate measurements of internal features that are not accessible with other techniques. However, XCT scanning can be relatively slow, which often prevents routine uptake for many applications. This paper explores the feasibility of improving the speed of XCT measurements whilst maintaining the quality of the dimensional measurements derived from reconstructed volumes. In particular, we compare two approaches to fast XCT acquisition, the use of fewer XCT measurements as well as the use of faster, but noisier measurements. The study shows that the random noise produced by faster measurements has significantly less impact on dimensional measurements compare to the artefacts associated with strategies that take fewer low noise measurements. Advanced reconstruction algorithms such as the conjugate gradient least squares method or total variation constrained reconstruction approaches, are shown to allow further improvements in measurement speed, though this can come at the cost of increased measurement bias and variance.

Keywords: X-ray tomography, dimensional metrology; conjugate gradient least squares, total variation constraints, iterative reconstruction.

1. Introduction

Coordinate measuring machines (CMM), which are typically used in dimensional measurement, physically drag a contact probe across the surface being measured [1], [2]. These measurements can thus be greatly affected by the texture of the measured surface (the mechanical filtering effect), which can be an issue in additively manufacturing [3], where the

structure itself might be distorted through a combination of different contact mechanisms [4], [5]. Tactile and optical techniques furthermore do not allow the characterization of internal structures found in many complex additive manufacturing geometries if these do not permit line-of-sight access [3].

Over the past few years, X-ray Computed Tomography (XCT) [6] has emerged as an attractive alternative to tactile

or optical CMM and has increasingly been used in a broad range of applications in manufacturing and production engineering [7], [8], additive manufacturing process [9], [10] or production integrated inspection of components [11], [12], [13]. It has been demonstrated that XCT is able to produce results comparable to those of CMMs and optical inspection systems [14] [15] [2], even though it can still suffer from several sources of measurement error [16], [17]. XCT metrology and quality control [8], [18], [19] has nevertheless undergone a paradigm shift toward holistic, high resolution measurements applicable to in-lines manufacturing applications where it offers several advantages, including non-destructive evaluation of both internal (e.g. non-accessible) features [20]) as well as external geometrical features and surface texture characterization with micrometre accuracy [21]. XCT metrology has furthermore the potential to verify parts in assembled states, allowing the detection of manufacturing and assembly induced imperfections, provides simultaneous dimensional and material quality control, and provides complete and high-density point clouds in a relatively short time, all of which are typically not provided by other measurement methods.

To estimate feature dimensions using XCT, several steps are required: tomographic scanning; volumetric image reconstruction [22]; image segmentation [23]; surface determination [24] and dimensional measurement [16]. This workflow is summarised in Figure 1: **Workflow for the full process of XCT metrology process.**.

Image reconstruction in cone beam CT (the most common form of XCT in industrial settings) is typically done using the Feldkamp, Davis, Kress (FDK) algorithm [22], which is relatively fast and works well in low noise imaging settings where sufficient tomographic measurements are available. For reconstruction with noisy or limited data, *iterative optimisation methods* are often suggested [25], [26] and recent advances in specialised GPU accelerated XCT reconstruction software now enable the use of these techniques also for cone-beam tomographic reconstruction of three dimensional images of realistic size [27]. Fast iterative optimisation methods include the conjugate gradient least squares algorithm (CGLS) [28] [29] [30], which optimises a least squares objective, though due to ill-conditioning of the XCT inverse problem, regularised methods, such as the fast iterative shrinkage/thresholding algorithm (FISTA) [31] are often preferable. Whilst different approaches to regularisation have been suggested (including early stopping of the CGLS algorithm, which provides implicit regularisation), image smoothness assumptions such as those enforced by the Total Variation constraint [32] are often preferred, as they provide explicit specification and control of image smoothness conditions.

Once the XCT volumetric image has been reconstructed, dimensional information can be extracted by determination object boundaries. This is done using edge detection methods, which then allow surface determination. Surface determination is realised by various techniques such as
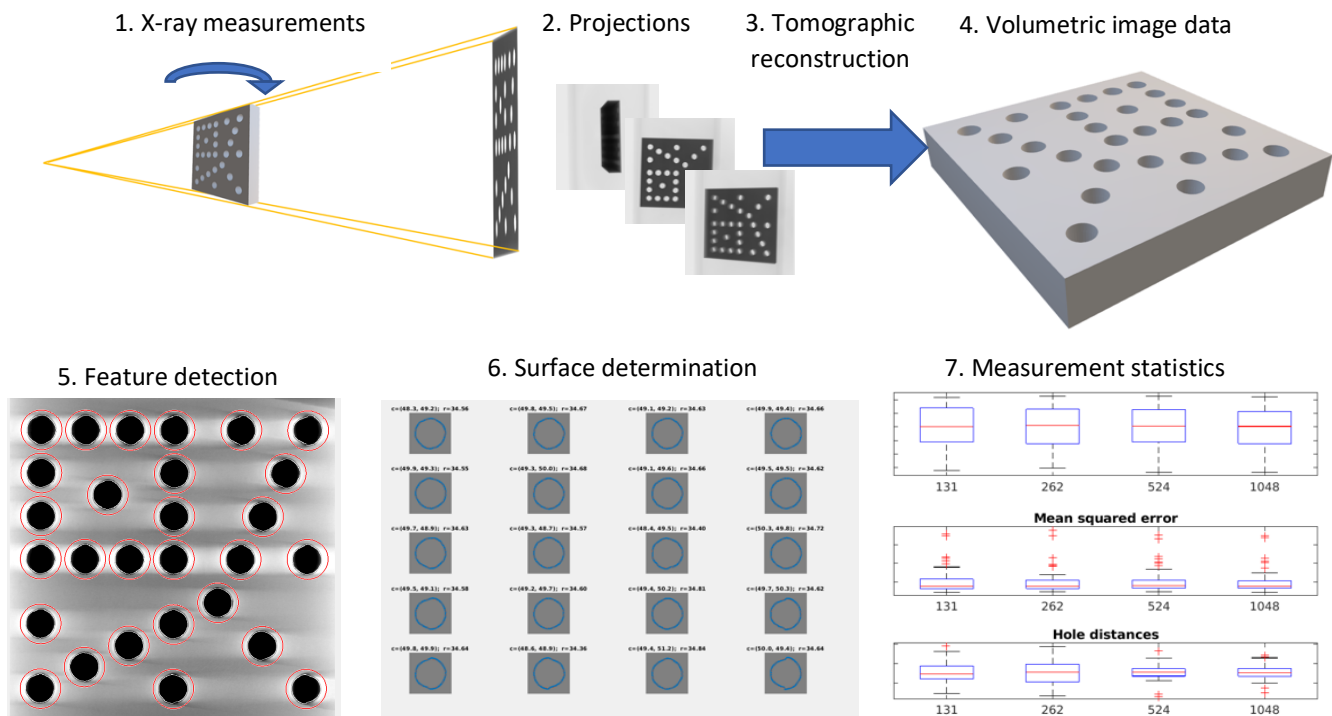

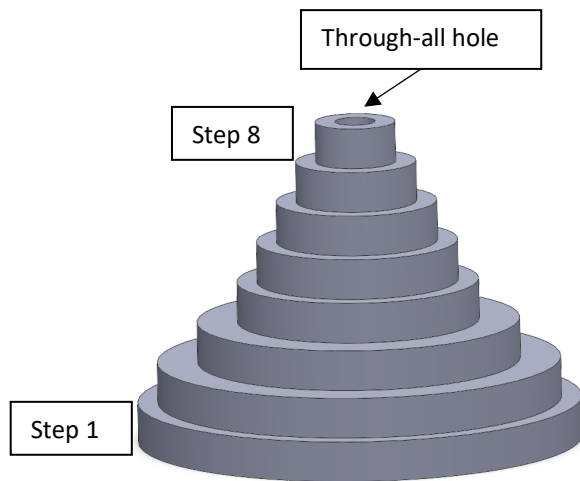**Figure 1: Workflow for the full process of XCT metrology process.**

Figure 2: A schematic lay-out of the calibrated cylinder-stack sample. The sample is manufactured out of aluminium and consists of 8 equal hight steps. The overall hight is 160mm. the sample also has a 20mm central through hole. Measured diameters along the centre of each step are given in Error! Reference source not found.**.**

assigning or estimating an optimal threshold grey value for edge voxels [24] [33] [34], or interpolation between voxel grey values [35]. Once a surface description is parameterised, dimensional measurements can be obtained in conjunction with calibration data [2] [36].

Despite the rapidly increasing number of applications of dimensional CT metrology in industrial settings [8] [37]; [7] [38]; [39], uptake of this technology remains restricted by the relatively slow scan speed, which often make the routine inspection of components in a production line setting infeasible [19] [40]).

There are two standard approaches available to increase scan speed in XCT: 1) reducing the number of projection images acquired and 2) reducing the x-ray exposure time for each image. When reducing the number of projection images, FDK based reconstruction leads to images with significant artefacts, which in turn often prevent accurate surface determination, whilst decreased exposure times increases image noise and is thus likely to also increase metrological measurement uncertainty.

In this paper we evaluate dimensional metrological performance of the two different approaches to increase XCT imaging speed. We vary the number of projections (sparse data) and the x-ray exposure times (noisy data). We are particularly interested in the degradation of measurement performance in these settings and on the mitigating effects achievable when replacing the standard FDK algorithm with iterative reconstruction algorithms such as the conjugate

gradient method (CGLS) and the Total variation constrained FISTA algorithm (FISTA-TV).

2. Materials and methods

To explore the potential for reducing XCT metrological inspection time, we designed a set of experiments and simulations to investigate the performance of the three candidate reconstruction algorithms (FDK, CGLS and FISTA-TV) on fast tomographic acquisition data.

As the sample geometry is application dependent, we investigate two extreme cases i) a sample with cylindrical symmetry that provides consistent beam path length at all radiographic angles, and ii) a sample with a flat panel geometry that was mounted so that x-ray paths lengths varied greatly at different angles. Both samples were metal components, which thus also introduced additional non-linear attenuation effects known as beam hardening, which are often encountered in inspection settings. Each sample was scanned twice. One slow scan minimised noise and blurring artefacts whilst a fast scan had a much higher noise level.

The low noise (long exposure) scan data was then used to generate additional data-sets. By adding additional Poisson noise, data with intermediate noise levels was generated, whilst by removing a subset of the projection images from the data, limited projection acquisitions were generated.

The two samples (described in more detail in section 2.1) were imaged using our in-house custom built XCT scanner (see section 2.2). The different data-sets were then reconstructed with the FDK, CGLS and FISTA-TV reconstruction algorithms (see section 2.4). Surfaces were fitted to different structures in each volumetric images from which metrological measurement points could be extracted and compared with dimensional information measured using co-ordinate measurement machines (see section 2.5).

2.1 Sample designs and dimensions

2.1.1 Step-Cylinder sample

The step-cylinder sample was provided by Swiss Federal Laboratories for Materials Science and Technology (EMPA) who also provided CMM reference measurements [41]. This 160 mm heigh aluminium sample features 8 concentric cylindrical steps of equal hight but with different diameters

and a concentric thorough-all hole as shown in Fig. 2and Table. 1.

2.1.2 Hole-plate sample

The hole-plate sample (serial number PTB 3 shone diagrammatically in Fig. 3) was manufactured and calibrated by the Physikalisch-Technische Bundesanstalt Braunschweig und Berlin (PTB) [42].

It is a stainless steel plate measuring 6×6×1 mm with 28 holes with nominal diameter of 0.5 mm (see Figure 3). The exact dimensions of the particular sample we use here were quantified by PTB and are summarised in Table 2.

Table 1: The dimensions of the cylinder-stack sample measured with a CMM device.

Feature	Diameter/mm
Inside top	20.0145
step8	40.0074
step7	59.9989
step6	79.9922
step5	99.9872
step4	119.9832
step3	159.9824
step2	199.9851
step1	220.0319
Inside bottom	20.0337

2.2 X-ray CT scanner

All scans were carried out at the μ-VIS X-ray Imaging Centre at the University of Southampton, Southampton, United Kingdom. A Nikon/X-tek systems Ltd. custom-built X-ray CT scanner was used to perform the experiments. Image acquisition and overall control of the system was performed with the Nikon/X-tek systems Ltd. Inspect-X software (Inspect-X v2). A Nikon 450 kV micro-focus X-ray tube was used as a source, with a tungsten (W) reflection target for the step cylinder phantom, whilst a Nikon 225kV plate. Both sources allow for exchangeable X-ray filters. The
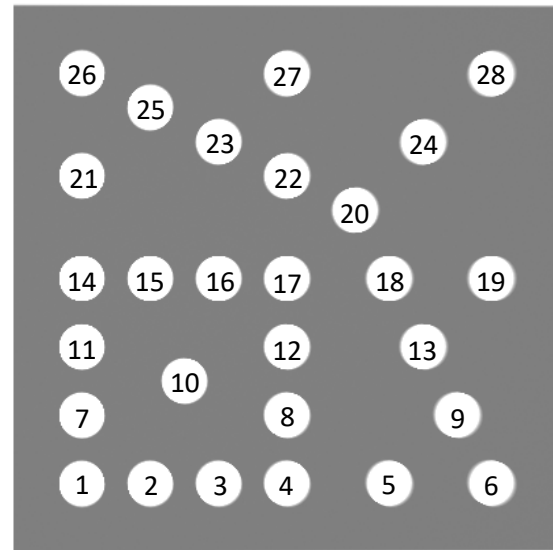

Figure 3: A schematic lay-out of the hole-plate sample.

system also features an XYZ sample stage, and a high source with a tungsten reflection target was used for the hole sensitivity flat panel detector (Perkin Elmer XRD 1621 CN3 EHS, with 2000×2000 pixels of 0.2 mm pixel pitch), movable linearly in three orthogonal directions. At the detector, an analogue gain, measured in decibels (dB), is used to multiply the recorded signal (photon counts per

Table 2 Example dimensions of the hole-plate sample measured with a CMM device (average over three repeat measurements, all measurements were available but are omitted here for compactness).

Hole number	Diameter/mm
1	0.5043
2	0.5041
7	0.5042
8	0.5043
11	0.5044
13	0.5040
16	0.5040
17	0.5040
24	0.5041
26	0.5044
28	0.5038

pixel) to compute the output signal (grey value intensity stored as 16 bit unsigned integers). The system provides the capability of frame averaging, where projection images are taken repeatedly at the same rotation angle, which are then averaged, thus reducing photon counting and thermal noise. A shuttling feature slightly shifts the detector over the duration of image acquisition with radiographs being co-registered post-imaging, a process that minimises errors originating in mechanical misalignment of the imaging setup. Both methods, frame averaging and shuttling, improve the imaging quality by suppressing imaging errors at the expense of longer scan times. Projection images can be taken either using a stop/start scanning approach, where the manipulator is rotated to a new angle, the motion stopped and only then, a projection image is taken. The alternative is to use a continuous rotation scanning approach, where a continuous rotation is used with images acquired whilst the object continuuse it's movement. Continuous rotation is much faster, but will introduce motion artefacts for longer exposure times or when using frame averaging.

2.3 CT data acquisition

Two scans were performed for each of the samples (the step cylinder and hole plate introduced in section 2.2). Scan parameters are given in Table 3. One slow, high quality scan used frame averaging, long exposure times and stop/start scanning, whilst a fast scan used short exposure times, no frame averaging and a continuous rotation scanning strategy. The slow scan minimised noise whilst the fast scan minimised overall data acquisition time. Both scans took the same number of projection images to allow standard tomographic reconstruction.

For the step cylinder the slow scan took 760 minutes, whilst the fast scan took 13 minutes (58 times faster). For the hole-plate the slow scan took 112 minutes, while the fast scan took 7 minutes (16 times faster). The temperature in the CT scanner was recorded as $25 \pm 1°C$. Sample projection images for fast and slow scans are shown in Fig. 4 for both samples, with magnified image portions showing the image noise. The slow scan was then used to generate an additional dataset by discarding projections, thus simulate another fast scan, where this time few low noise projections are used. These low projection fast scans used only 54 projections to simulate a scan that, for the step-cylinder, would have been as fast as the high noise scan. These scans were used in a first experiment to compare the effects on dimensional metrology of the different approaches to increase imaging speed and the effects of different reconstruction algorithms on these. In a second set of experiments, further simulated scans were produced from the low noise fast scans. The first set of simulated data used the low noise images, but reduced the

Table 3: The scan parameters for the slow and fast scan

	Step cylinder		Hole plate	
Scan speed	Slow	Fast	Slow	Fast
X-ray tube voltage/kV	390	390	120	120
X-ray tube curent/mA	0.245	0.216	83	83
Power/W	95.6	84.2	10	10
Exposure time/ms	708	250	134	134
Frames per projection	16	1	16	1
Number of projections	3143	3143	3143	3143
Filter sheet thickness/mm	8	8	-	-
Filter sheet material	Copper	Copper	-	-
Shuttling	Yes	No	Yes	No
Start/Stop or Continuous	S/S	Cont.	S/S	Cont.
Scan duration /mins	760	13	112	7

dataset size to 132, 262, 524 and 1048 equally spaced projections, whilst a second set of simulated data added Poisson noise to the projections to simulate data that would have been acquired with 1,800, 18,000 and 90,000 photons per pixel along x-ray paths that do not intersect with the object (we also generated data with an average photon count of 180 photons per pixel, but this data did not provide reconstructions that allowed surface fitting).

3.4 Reconstruction

Table 4 The reconstruction protocols for the slow and fast scans of the step cylinder, for the CGLS algorithm and the FISTA TV algorithm.

	Slow scan	Fast scan	Low projection
Step cylinder			
CGLS			
Iterations	20	20	20
FISTA (TV)			
Iterations	20	75	75
Hyper	220000	6000	6000
TV iteration	20	20	20
Lambda	0.1	0.1	0.1
Hole plate			
CGLS			
Iterations	20	20	20
FISTA (TV)			
Iterations	20	20	20
Hyper	220000	220000	220000
TV iteration	100	100	100
Lambda	10	10	10

Table 5 The reconstruction protocols for scans of the hole-plate sample and for increasing number of projections, for the CGLS algorithm (above) and the FISTA TV algorithm (below).

No of projections	131	262	524	1028
CGLS				
Iterations	75	75	75	75
FISTA (TV)				
Iterations	75	75	75	75
Hyper	22	333	955	2200
TV iterations	100	100	100	100
Lambda	0.1	0.1	0.1	0.1

Table 6 The reconstruction protocols for scans of the hole-plate sample and for increasing Poisson noise variance, for the CGLS algorithm (above) and the FISTA TV algorithm (below).

Photon count	1,800	18,000	90,000
CGLS			
Iterations	75	75	75
FISTA (TV)			
Iterations	75	75	75
Hyper	2200	2200	2200
TV iterations	100	100	100
Lambda	0.1	0.1	0.1

All data-sets (the slow, low noise reference scans, the high noise scans and the low number of projection scans) of the step-cylinder and the hole-plate samples were reconstructed using the standard Feldkamp-Davis-Kress (FDK) [22], [43] algorithm as implemented in the TIGRE tomographic reconstruction software [44] [27]. This FDK reconstruction was used as the baseline to compare the performance of two iterative methods. The FDK reconstruction of the slow, low noise scans were also used to calibrate the system parameters and to determine the size of the reconstructed voxels to match the average coordinate measurement machine dimensions for both samples. This allowed us to analyse the performance of alternative reconstruction algorithms, such as

the conjugate gradient least squares (CGLS) algorithm [28]; [29] [30], and the fast iterative shrinkage-thresholding algorithm with total variation minimisation (FISTA TV) [31], both implemented in the TIGRE toolbox [44] [27].

Parameters for the iterative algorithms for the first set of experiments, where we reconstructed the slow, low noise data, the fast, high noise data and the low noise data with

Only 54 projections are shown in Table 4. FISTA-TV algorithm parameters were optimised by running a few iterations of the reconstruction over a grid of parameters and observing image quality. Example reconstruction images are shown in Fig. 5 where we show slices through the
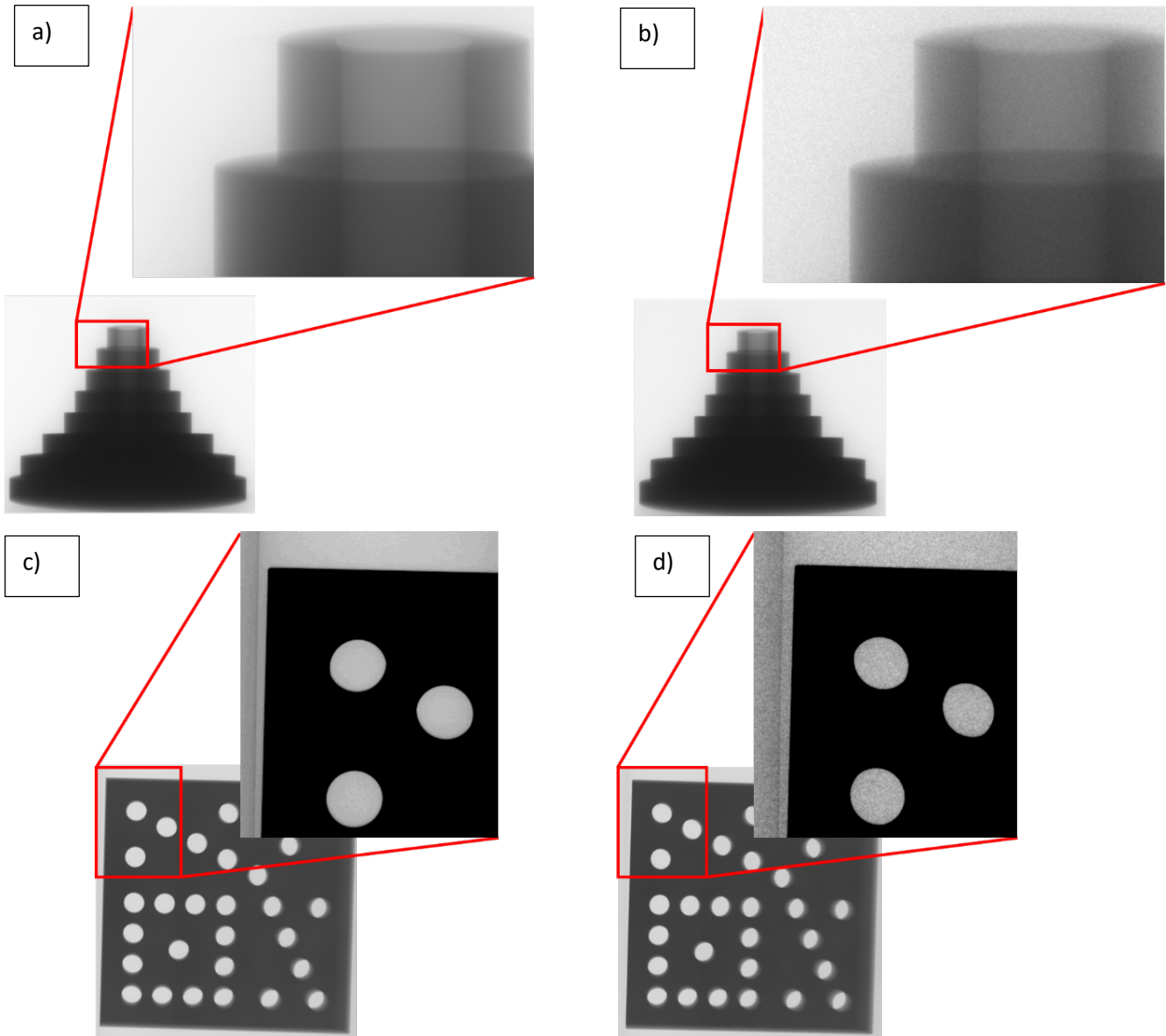
Figure 4: Sample radiographs of the cylinder-stack (a, b) and the hole-plate (c, d) samples, with a detail in the red box enlarged for better preview. Slow scan radiographs in (a) and (c) comprise higher SNR compared to their fast scan equivalents (b) and (d), respectively.

reconstruction volume of the step cylinder sample, dissecting the fourth step from the bottom. The parameters for the iterative algorithms for the second set of experiments, where we reconstructed the 4 data sets with different projection counts and the three datasets with different noise levels, were tuned in a similar way. The parameters are shown in Table 5 and Table 6.

2.5 Surface determination and measurements

For the first experiment, surface determination was carried out using VG studio 3.4 using the advanced mode iterative surface determination method provided in the VG Metrology package. For the step cylinder, the cylinder axis of the smallest diameter step was used to define a co-ordinate axis (We initially planned to use the internal through hole as axis to define the coordinate system, but bam hardening artefacts prevented the fitting of a cylinder to this feature). We then defined orthogonal planes relative to that axis, where each plane intersected the centre of each cylindrical step. The intersection of the step boundary and the relevant plane defined measurement points to which a circle was fitted. We then measured the root mean square deviation of measurement points from the circle as well as the max/min deviation.
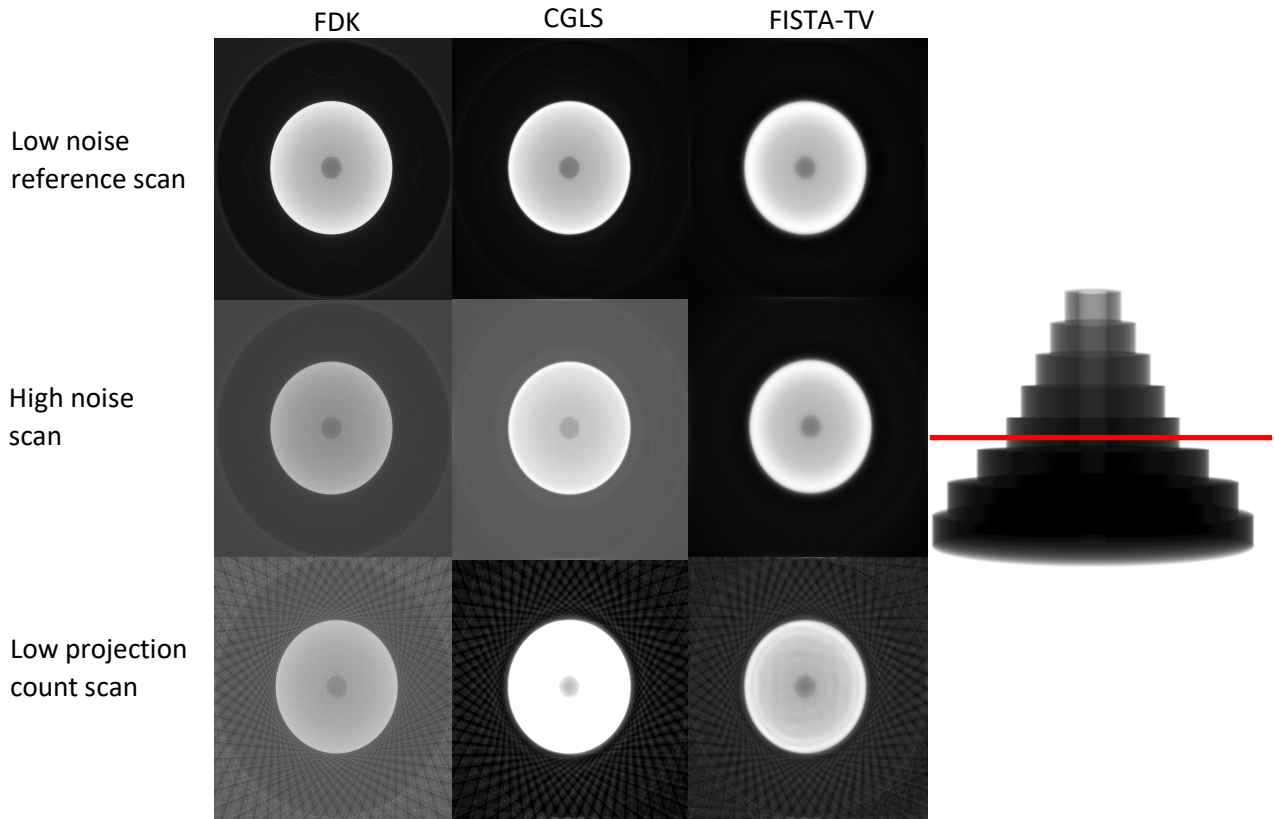
Figure 5 Comparison of scan settings and reconstruction methods in an image slice passing through step 4.

For the hole plate sample, we again used VG studio 3.4 using the advanced mode iterative surface determination method to fit all surfaces. We used the front surface to define a reference plane. We then fit cylinders to all holes, using holes 1 and 6 to define a coordinate axis by connecting the intersections of the two cylinder central axes and the reference surface. Using the normal to the surface as another axis then provided an orthogonal co-ordinate system for measurement. We measured the diameters of all cylinders as well as centre to centre distances (measured on the reference surface) for cylinder hole pairs (1,28), (6,20), (26,20), (1,26), (1,6), (4,27) and (14,19).

For all measurements, the CMM data for sample features was then used as a baseline to estimate the systematic error [2] of X-ray CT measurements as follows:

$$E = x_{CT} - x_{ref} \quad (1)$$

where E is the measurement error relative to the CMM measurements x_{ref} [45] [46].

As it is unclear what procedure VG studio's iterative surface determination approach takes, we analysed the data for the second set of experiments in a more controlled way. We

analysed only the data from the hole plate. Canny edge detection was used to determine object surfaces. The central line between top and bottom surface points was identified and the three dimensional data was resampled along the central slice using bi-cubic interpolation to produce a two dimensional image. The Huff circle finding method was used to locate all holes and generate masks for hole location including both the hole and a margin around the hole. Canny
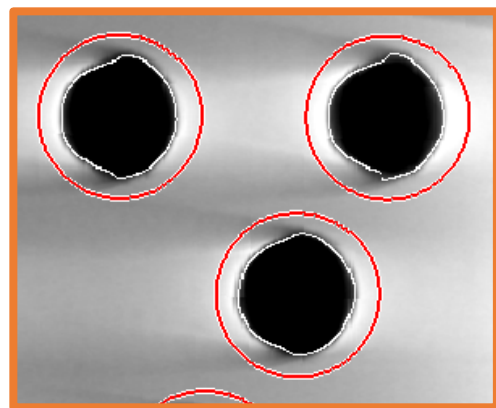

Figure 5: Circles (red) derived using the Huff transform identify the location of each hole. Canny edge detection identifies hole boundaries (white). Circle fitting (not shown) fits circles to identified boundary points.
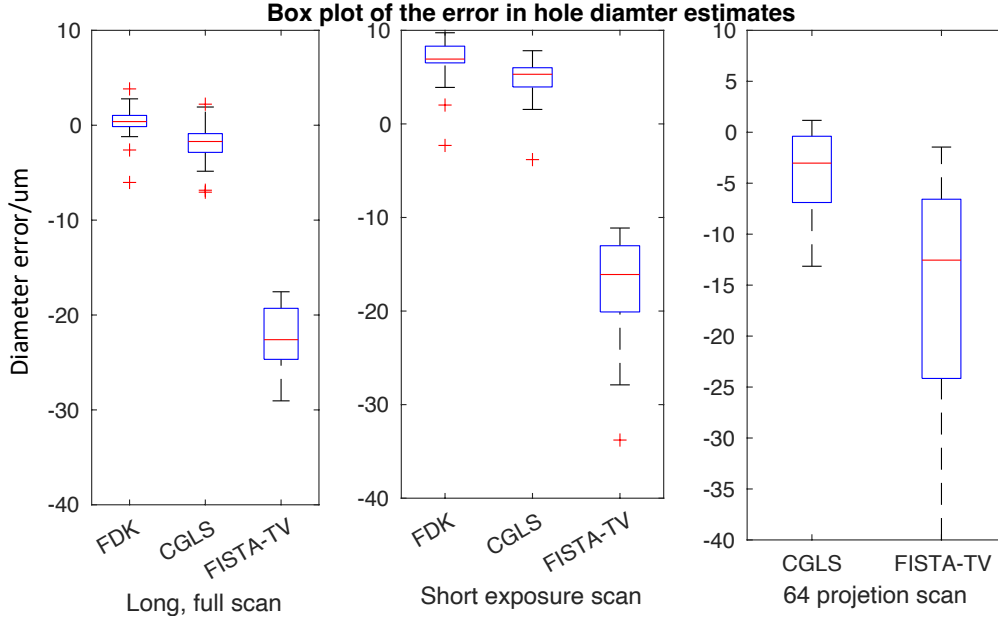
Figure 6: Box and whisker plots of the errors in the hole diameter estimates in micro-meters for the hole plate for the different measurements (low noise scan (right), high noise scan (middle) and low number of projection scan (right) for the three different algorithms.

edge detection identified hole boundaries in each masked area (see Fig. 6). A least squares approach was used to fit a circle to the boundary points of each hole. Circle diameters and hole centre to centre distances were computed for all holes and hole pairs. Centre to centre distance errors were normalised by dividing the error by the nominal (CMM derived) distance. Looking at Fig. 6 we also see that beam hardening and cone beam artefacts [43] lead to visible distortion of the detected holes.

3. Results and discussion

Results for the errors in the measurement of outer diameters (step cylinder) with the different algorithms is shown in Fig. 7, where we show the error in the measured diameters for each method and each of the three datasets plotted against the nominal diameters of each cylinder. It is worth noting that for larger diameters, beam-hardening effects become evident. Results for the errors in measuring inner diameters (hole plate data) with the different algorithms is shown in Fig. 8, where we show a box whisker plot for the errors for all holes for any one dataset/algorithm combination.

For the outer diameters of the step cylinder, we see that the error for all methods varies with step diameter and this is here likely to be due to beam hardening effects, with larger steps showing increasing beam hardening issues in the reconstruction due to the highly attenuating material used (aluminium). Another observation is that both, the CGLS and the FISTA method give biased results, with the bias being

positive for the outer diameters (outer diameters are overestimated) whilst the inner diameters lead to negative bias (inner diameters are underestimated). Crucially, the bias is much larger for the FISTA-TV method, indicating that the Total Variation constraint leads to boundary estimates that are biased towards the outside of the object. Another observation is that the results for the FISTA algorithm show much larger variation compared to the other methods. Note that the FDK algorithm was not able to reconstruct the hole plate low projection count data with sufficient accuracy to allow us to fit the required surfaces, so results for this case are missing here.

Fig. 9 quantifies the standard deviation of the absolute distance errors in the hole plate, giving both inner diameter error variation as well as hole centre to centre distance error variations, showing again that the total variation estimates show significantly more variation in the measurement errors.

To analyse the influence of the surface fitting used and to see the performance of the meathods over a wider range of noise levels and reductions in projections, we used the artificially generated noisy scan data and a wider range of the low projection count data as described above. Results are shown in Figure 10, where we show the errors in the hole diameter estimates achieved with the different methods using the canny edge detection for surface determination as outlined above. Again, we see that the CGLS method and the FISTA-TV algorithm lead to increasingly biased results, with the bias in the FISTA-TV reconstruction getting worse in for the
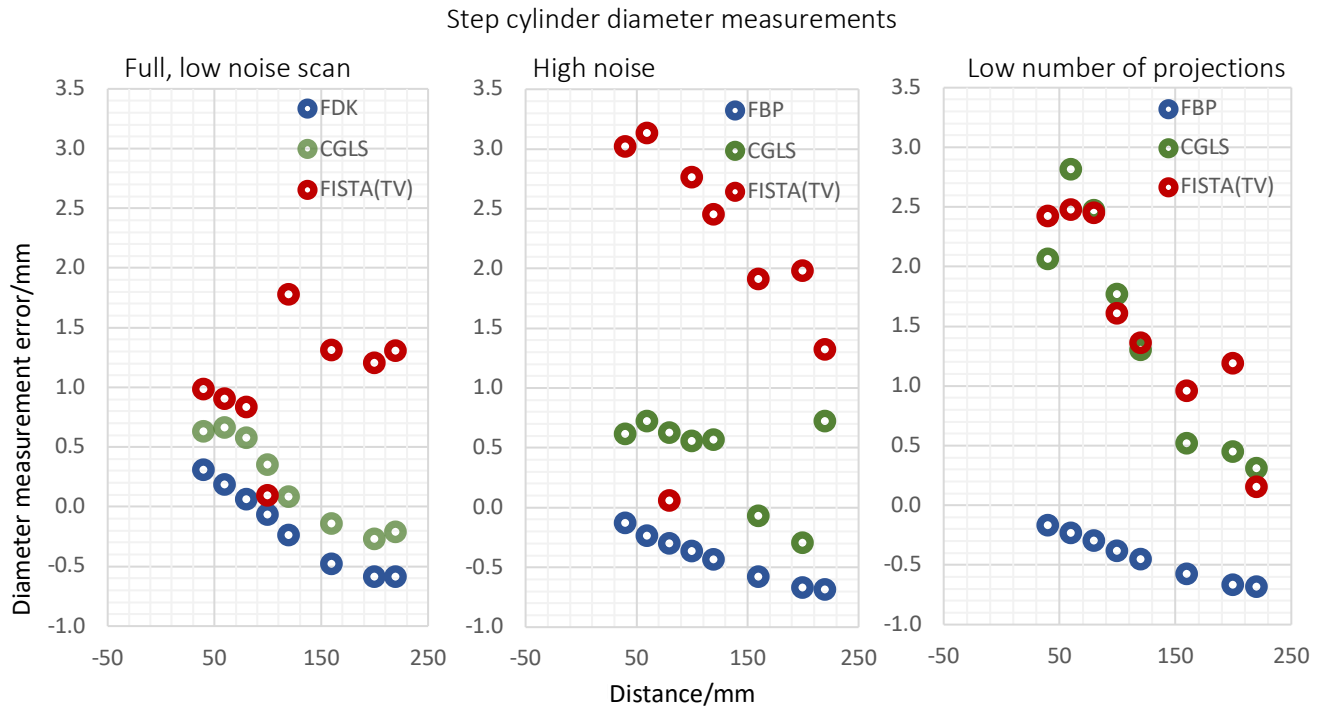
Step cylinder diameter measurements

Figure 7: Measurement errors for the measurements of outer diameters measured on the step cylinder from the slow, low noise scan for the FISTA(TV) algorithm, the CGLS algorithm and the FDK algorithm.

dataset with the smalest numbers of projections, mirrowing the results above. The same deterioration is not shown in the FISTA result for the data with the highest noise level. Note, that, when reconstructing the data using a photon count of 180, we did not find reliable edges to use our circle fitting approach. We see that the results for the FISTA algorithm here slow smaller errors compared to those found for the results with the low noise data shown above. This indicates that either, the slightly different FISTA-TV parameter choice used here gives rise to somewhat different results or that the surface determination approach used above is more sensitive to the FISTA-TV bias tahn the canny method.

These results suggest that both surface determination methods are relatively robust to the photon counting noise associated with acquisitions with shorter exposure times, whilst the streaking artefacts introduced when reducing the numbers of projections more quickly deteriorates surface

estimates. Whilst the centre to centre hole distance measures are more robust than the hole diameter estimates, looking at the standard deviation of the normalised error in hole to hole distanes across the sample shows an increase in distance measure variability for all methods and for both scenarios, the increase of noise and the decrease in the number of projections (Fig 11). This change is relatively predictable for the FDK reconstruction, which, for example, shows a near linear decrease in the standard deviation of the normalised distance error for doubling numbers of projection. For CGLS and in particular the FISTA-TV results, this relationship is less clear with results much more variable.

4. Conclusion

We have here shown how a reduction in scan time can be achieved in XCT metrological measurements by decreasing x-ray exposure or by reducing the number of x-ray
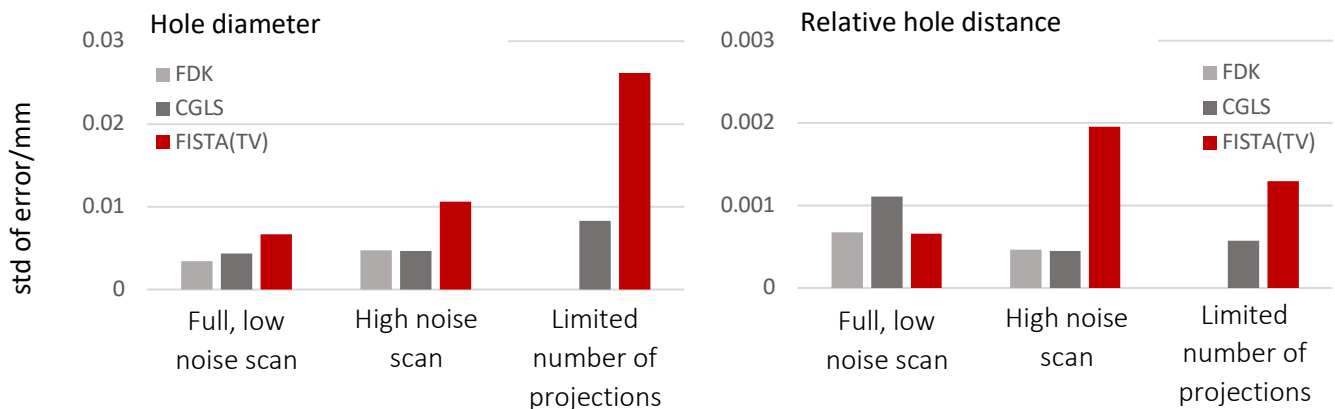

Figure 8: Standard deviation in the error in the hole diameter (left) and the relative hole centre to centre distance (right) for the three hole plate datasets for all three algorithms. FDK did not provide reliable surface estimates for the limited projection data.
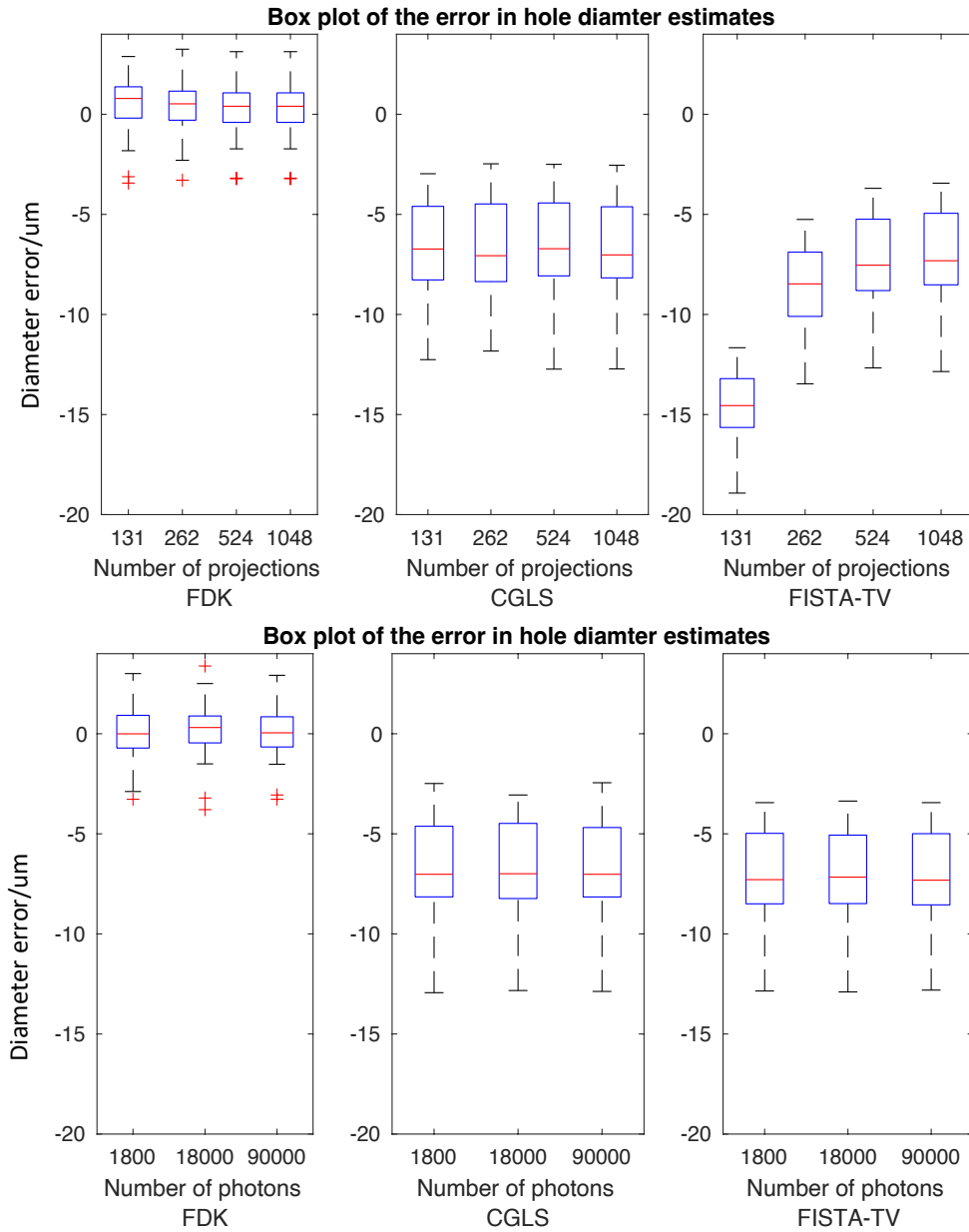
Figure 9: Box and whisker plots of the hole diameter errors (in micro-meters) measured for the hole plate using limited numbers of x-ray photons (top) and limited numbers of projections (bottom) and reconstructed with the three different algorithms.

projections. Whilst iterative algorithms can help with the loss of fidelity, results also become increasingly biased and more variable, something not seen with the standard FDK method.

In particular, we observed that a total variation based reconstruction method biased surfaces to be located further towards the outside of the objects, making inner diameter measures smaller and outer measures larger. This was also observed, though to a lower extend, for the least squares approach.

The FDK method behaved in a more predictable way, though there comes a point when the FDK method no longer provides reconstructions where viable surface determination is feasible. In these settings, iterative algorithms can still be used to find dimensional measurements.
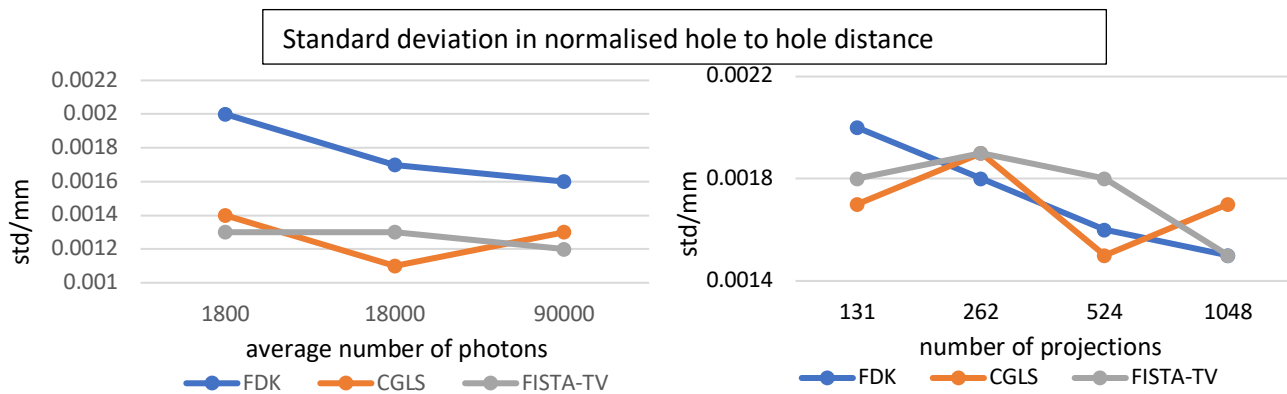
Acknowledgements

Figure 10: The standard deviation of the normalised distance between through holes on the hole plate in mm plotted for the three algorithms for different numbers of photon counts per pixel (left) and different number of projections (right).

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