Evaluating and visualizing the quality of surface points determined from computed tomography volume data

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Abstract

By evaluating the volume data in the proximity of a surface point, a Local Quality Value (LQV) is calculated for each surface point of a Computed Tomography (CT) measurement. This allows an automatic and reliable identification of areas containing surface points with reduced accuracy. A colour-coded visualisation of the LQV allows a highlighted display of untrustworthy measurement data. This method is capable of identifying a broad range of artefacts (including beam hardening, noise and rounded off edges) and of points of reduced accuracy due to the fixture of the part on the rotational stage.

Keywords

Dimensional metrology, Computed Tomography, artefacts, surface determination, surface point quality, surface point uncertainty

1 Introduction

The use of X-ray Computed Tomography (CT) in dimensional metrology offers some advantages compared to traditional coordinate measuring machines (CMMs), for instance the acquisition of the whole workpiece (including inner geometries) with a high point density in one dataset [1]. To perform a dimensional measurement using Computed Tomography, basically four steps are necessary [1, 2, 3]. In the first step, 2-D projections (radiographs) of the object to be measured from different angels are acquired. Using this data, a volume dataset consisting of voxels (**vo**lume pi**xel**) is reconstructed. In this dataset, the background is usually represented by low grey values while the material of the object is represented by high grey values. In the volume data, the surface of the part is represented by a transition from low to high grey values. Due to different effects that decrease the resolution of CT, this transition is blurred to a certain degree. Elaborate algorithms are applied to the volume data to determine the position of the surface point within the blurred transition (see Figure 1). After calculating a surface dataset for the whole part in this way, in the last step standard geometries can be associated to the surface data to carry out the dimensional measurement.

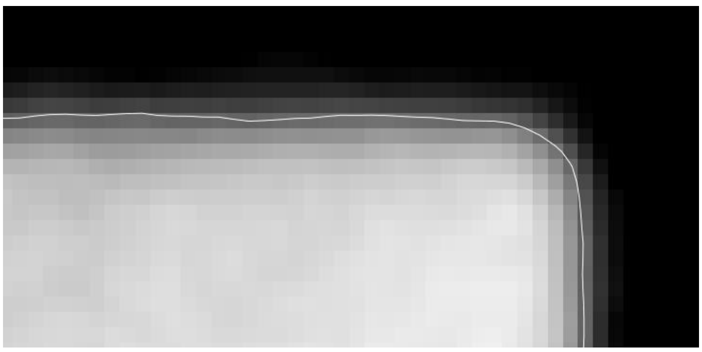

Figure 1: Zoom of a cross section of the volume data, the grey line represents the extracted surface. The edge is rounded off in the volume dataset, resulting in the same effect in the surface dataset.

It is possible to determine the position of the single surface points with sub-voxel accuracy, but high quality volume data is required for this. Data artefacts (errors in the volume data that have no physical representation in the measured object) may lead to significant errors when determining the position of a surface point and therefore induce deviations in the final measurement results. Artefacts may be caused by different quantities and their severity may vary locally [4, 5, 6]. An incomplete selection of artefacts will be described in the following:

- While the model of the reconstruction assumes a monochromatic spectrum of the X-rays, the polychromatic composition of the spectrum induces erroneous calculated grey values in the volume data, as the attenuation strongly depends on the energy of the X-ray photons. While penetrating the material, the X-ray radiation is hardened (beam hardening). Typical consequences are overestimated grey values at the outer edge of the object (cupping) and streak artefacts in the volume data (see Figure 2).
- Due to photon statistics and the properties of the detector, noise is always present in volume data. Especially for longer penetration lengths, the level of noise increases (see Figure 2).
- Besides to leading to blurred transitions from low to high grey values, limitations of the structural resolution also cause rounded off edges in the volume data. While the surface extraction algorithms are able of determining the position of the surface points with high accuracy in regions of low curvature, they cannot compensate for these effects at sharp edges [7, 8, 9] (see Figure 1).
- To mount the object on the rotational stage, usually materials of low density and atomic number are used, as they are nearly invisible for X-rays. However, in the regions where they are in contact with the measured object, they still induce small variations of the grey values in the volume data and lead to deviations when extracting the surface points.

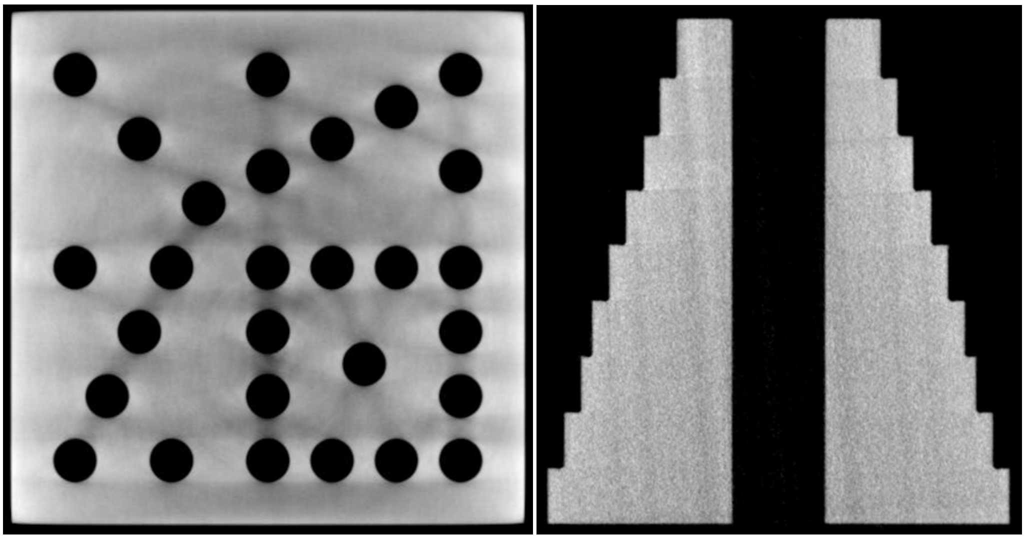

Figure 2: Cross sections of an hole plate (aluminium; left) and step cylinder (acrylic glass; right). Cupping and streak artefacts are induced by beam hardening. Due to longer penetration lengths for the lower steps of the cylinder, the level of noise is increased in this area.

It is well known that data artefacts may lead to measurement deviations, especially if larger objects of dense materials have to be penetrated by the X-rays [10]. Furthermore, the choice of acquisition parameters by the operator has a large influence on the impact of artefacts on the measurement results [11]. Several methods have been investigated to optimise the acquisition parameters in order to minimise measurement deviations and the amount of artefacts in the volume data, for instance using a knowledge-based system [12] or a neural network [13]. Another approach is to replace measurement points, which are heavily affected by artefacts, with data from other sensors [14].

To carry out these methods, an evaluation criterion is helpful to assess the quality of a dataset. For medical CT, properties like contrast, homogeneity, noise and the modular transfer function (MTF) are well known [2]. For industrial CT, a method investigated by Reiter et al. uses the fact, that in many cases an object of constant X-ray absorption is scanned [15]. Therefore, two distinct grey value levels (for background and object) are to be expected in the volume data. By evaluating the grey value histogram, a quality value for the whole volume dataset is deduced. In an approach by Schielein et al., the Shannon entropy of the grey values of a volume dataset is used to calculate a quality value for the whole measurement [16]. Amirkhanov et al. investigated a projection based metal-artefact reduction method [17]. As the correction is based on interpolation, it introduces uncertainty to the volume data to a certain extend. To visualize this, voxels that are modified by the correction are highlighted in an uncertainty map. In [18], a Bayesian classification is carried out for each voxel to decide, to which extend it belongs to a material present in the dataset. Using this information, the 'material interface probability' is deducted.

2 Assessment of the Local Quality Value of surface points

Aim of the presented method is to assign a Local Quality Value (LQV) to each point of an extracted surface dataset. The method can be applied to surface datasets determined by arbitrary algorithms. To calculate the LQV, the volume data in the proximity of each surface point is analyzed. For an ideal volume dataset, a sharp, high-contrast, symmetric and noise-free transition from low to high grey values perpendicular to the surface is expected. Any deviation from this ideal behaviour (for instance induced by data artefacts) complicates the extraction of the surface point and decreases its quality.

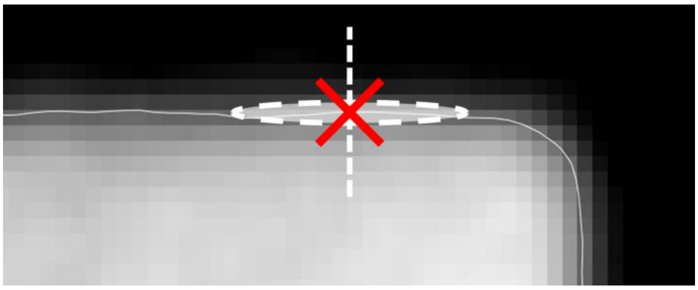

Figure 3: Zoom of a cross section of the volume data. The red 'x' marks an extracted surface point. The grey values are extracted from a line perpendicular to the surface and an area along the surface, marked in white.

To evaluate the volume data in the proximity of the surface point, grey values along a line perpendicular to and in an area along the surface (see Figure 3) are extracted. In Figure 4, the basic principle of the determination of the LQV is portrayed on an exemplary CT scan of two touching steel spheres (diameters of 5 mm and 6 mm). As the scan was carried out with a tube voltage of 130 kV (a comparatively small value for CT scans of objects made of steel), severe beam hardening artefacts are present in the volume dataset. On the sides of the object, streaks are visible, although no material is present in these areas and the grey value is therefore supposed to be zero. At the contact point of the spheres, the grey values of the voxels are underestimated and a small gap is visible in the volume data. When a typical surface determination algorithm is applied on the dataset, these artefacts cause deviations in the resulting surface dataset. As in the volume dataset, a small gap is visible between the spheres. On the other hand, the streaks on the side of the spheres induce an incorrectly determined surface outside of the spheres (see Figure 4, top).

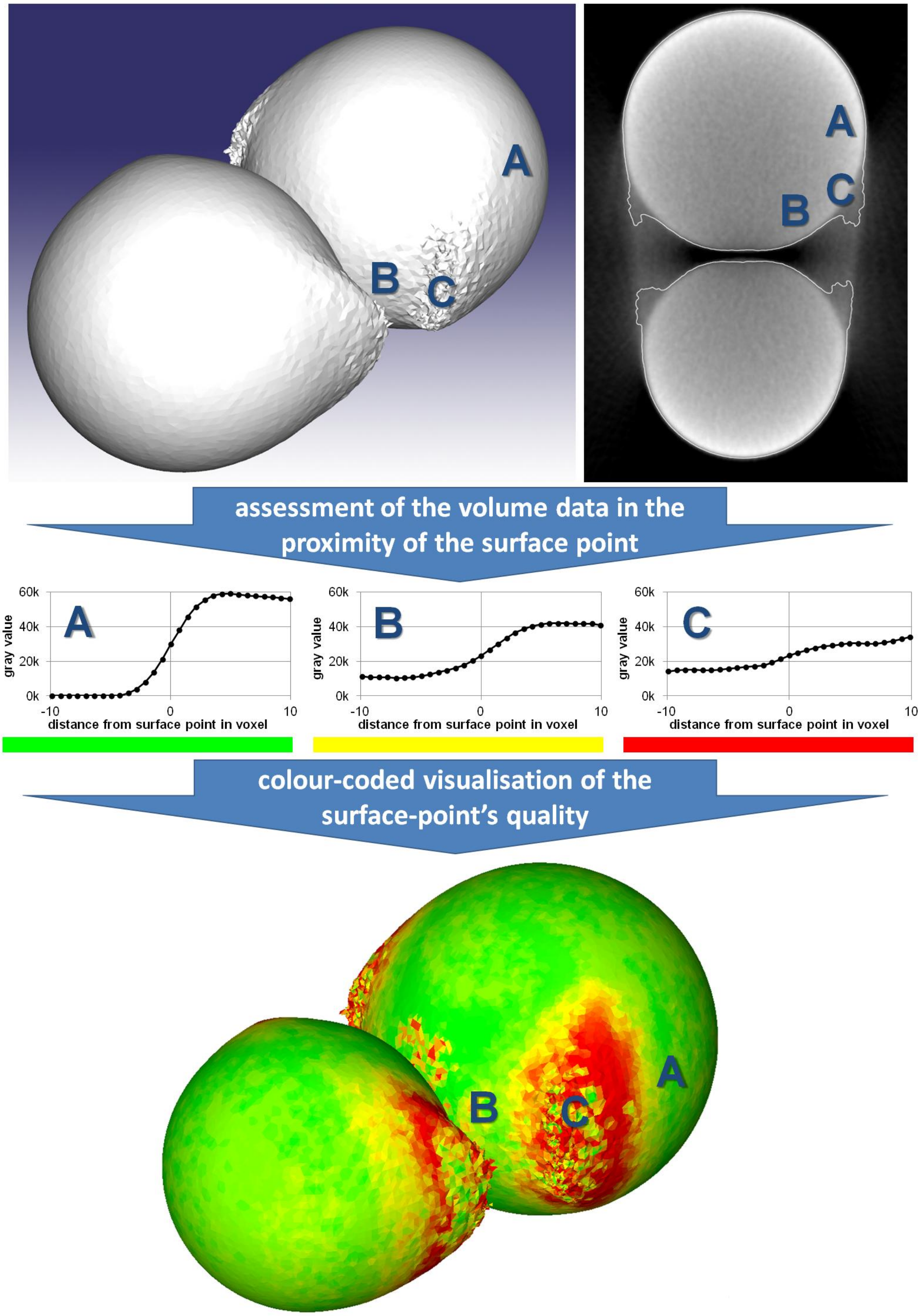

Figure 4: Basic principle of the determination of the LQV portrayed on a CT scan of two touching steel spheres (diameters 5 and 6 mm). The LQV is assessed by evaluating the sharpness and symmetry of the transition from low to high grey values on a line perpendicular to the surface. Areas with incorrect surface determination (C) are reliably identified as low-quality surface points and marked as red. Surface points with a high LQV (A) are represented as green.

When evaluating these grey values of the volume in an area with correct surface determination (A), it is visible that the transition from low to high grey values is symmetrical and of high contrast (although the cupping effect is still visible). For surface points in areas that are moderately affected by artefacts (B), the transition is still rather symmetrical and sharp, but the contrast is reduced. However, for incorrect determined surface points (C), it is clearly visible that the transition is unsharp and unsymmetrical. Elaborate algorithms are used to assess the quality of each surface point by evaluating the sharpness and the symmetry of the transition from low to high grey values. With increasing symmetry, the quality of a surface point is assessed as higher. The same applies to the sharpness, as for sharp transitions a high local quality is assumed. The results can be visualized by a colour-coded 3-D representation of the surface dataset (see Figure 4, bottom). Surface points of high quality are coloured green, while points of moderate quality points are coloured yellow. Low-quality points, where significant errors of the surface extraction are expected, are marked as red. It is visible that this automated method reliably identifies the regions where the surface data cannot be trusted.

For the calculation of the LQV for a CT-Scan of a hollow step cylinder (made of acrylic glass), an alternative approach is used. As depicted in Figure 3, the grey values from an area perpendicular to the normal vector of the surface are evaluated. For an ideal volume dataset, all the grey values in this area are constant, as this area is positioned right at the surface of the scanned object. Data artefacts like noise and streaks decrease the homogeneity of the extracted grey values. Additionally, in the proximity of edges, the homogeneity is low, as the area perpendicular to the normal vector does not correspond to the surface of the object in these cases. In Figure 5, it is visible that surface points near edges are identified as low quality. As edges are always rounded off in CT measurements, significant deviations in the surface dataset are expected in these regions. Additionally, the increased level of noise for the larger steps of the step cylinder (due to longer penetration lengths of the X-rays) results in a lower average LQV in these areas.

Figure 5: Colour-coded representation of the LQV for a CT-scan of a hollow step cylinder (acrylic glass; height 45 mm, maximum diameter 42 mm). The LQV is assessed by evaluating the homogeneity of the grey values along the surface. Low quality surface points are identified at edges and for longer penetration lengths.

In another CT scan, an aluminium cylinder was investigated. To emulate the effect of a fixture, several layers of adhesive tape were attached to the cylinder. In Figure 6, the colour-coded representation of the LQV of the CT-scan is depicted. The LQV is calculated by evaluating the homogeneity of the grey values along the surface and the symmetry perpendicular to the surface. Again, a low LQV is assigned to surface points in the proximity of edges. It is also visible that the surface points, which are affected by the adhesive tape, are marked as of low quality. The colour-coded representation makes it possible to distinguish between the three layers of tape that were attached to the top side of the cylinder.

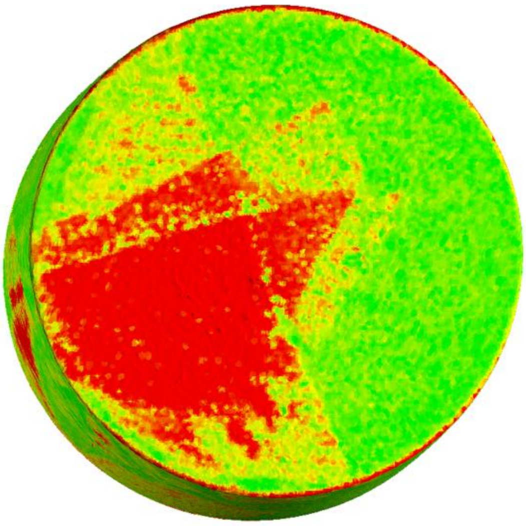

Figure 6: Colour-coded representation of the LQV for a CT-scan of a cylinder (aluminium; height 12 mm, diameter 18 mm) with several layers of adhesive tape attached. The LQV is assessed by evaluating the homogeneity of the grey values along the surface and the sharpness of the transition from low to high grey values on a line perpendicular to the surface

3 Conclusion and outlook

Three approaches to assess the Local Quality Value (LQV) of a surface point by evaluating the grey values in the proximity of the point are presented:

- Evaluation of the sharpness of the transition from low to high grey values on a line perpendicular to the surface. For high quality surface points, a sharp transition is expected. This makes it possible to identify blurry data and data artefacts like streaks.
- Evaluation of the symmetry of the transition from low to high grey values on a line perpendicular to the surface. For high quality surface points, a symmetrical transition is expected. This makes it possible to identify data artefacts and regions affected by the fixture.
- Evaluation of the homogeneity of the grey values in an area perpendicular to the normal vector of the surface point. For high quality surface points, a constant grey value is expected. This makes it possible to identify noise and rounded edges.

Using three exemplary CT scans, it is shown that these are promising approaches for an automated identification of areas, in which large deviations are to be expected in the surface data. In the examples investigated, these deviations are caused by beam hardening, large penetration lengths, rounded off edges and the fixture of the object on the rotational stage. In principle, local deviations due to other error sources are also identifiable.

The method works with surface datasets extracted by arbitrary surface determination algorithms. As only the volume and surface datasets are required to calculate the LQV, no additional information like acquisition parameters of the CT system or a CAD model is needed. The colour-coded representation of the LQV allows a clear and comprehensive depiction of areas, where the measurement data cannot be trusted, a valuable tool for operating a CT system and interpreting the measurement results.

As the methods allows it to identify artefacts automatically and reliably, it can be used to increase the accuracy of dimensional measurements by lower weighting or deletion of uncertain surface points when associating geometries with the surface data. In other application, the LQV can be used as evaluation criterion for measurement task specific optimization of acquisition parameters and as input for the estimation of single point uncertainty.

References

[1] J.-P. Kruth, M. Bartscher, S. Carmignato, R. Schmitt, L. De Chiffre, A. Weckenmann, Computed tomography for dimensional metrology, CIRP Annals-Manufacturing Technology 60 (2) (2011) 821–842.

[2] W. A. Kalender, Computed tomography: fundamentals, system technology, image quality, applications, John Wiley & Sons, 2011.

[3] T. M. Buzug, Computed tomography: from photon statistics to modern cone-beam CT, Springer, 2008.

[4] F. E. Boas, D. Fleischmann, CT artifacts: causes and reduction techniques, Imaging in Medicine 4 (2) (2012) 229–240.

[5] J. F. Barrett, N. Keat, Artifacts in CT: Recognition and avoidance, Radiographics 24 (6) (2004) 1679–1691.

[6] VDI/VDE 2630 Blatt 1.2: Computed tomography in dimensional measurement - Influencing variables on measurement results and recommendations for computed tomography dimensional measurements, Beuth Verlag, Berlin, 2010.

[7] S. Carmignato, A. Pierobon, P. Rampazzo, M. Parisatto, E. Savio, CT for industrial metrology - accuracy and structural resolution of ct dimensional measurements, in: Proceedings of iCT Wels 2012, 2012.

[8] M. Bartscher, H. Bremer, T. Birth, A. Staude, K. Ehrig, The resolution of dimensional CT - an edge-based analysis, in: Proceedings of iCT Wels 2012, 2012.

[9] J. Illemann, M. Bartscher, O. Jusko, F. Härtig, U. Neuschaefer-Rube, K. Wendt, Procedure and reference standard to determine the structural resolution in coordinate metrology, Measurement Science and Technology 25 (6) (2014) 064015.

[10] M. Bartscher, O. Sato, F. Härtig, U. Neuschaefer-Rube, Current state of standardization in the field of dimensional computed tomography, Measurement Science and Technology 25 (6) (2014) 064013.

[11] P. Müller, J. Hiller, A. Cantatore, M. Bartscher, L. De Chiffre, Investigation on the influence of image quality in X-ray CT metrology, in: Proceedings of iCT Wels 2012, 2012.

[12] R. Schmitt, C. Isenberg, C. Niggemann, Knowledge-based system to improve dimensional CT measurements, in: Proceedings of iCT Wels 2012, 2012.

[13] R. Giedl-Wagner, T. Miller, B. Sick, Determination of optimal CT scan parameters using radial basis function neural networks, in: Proceedings of iCT Wels 2012, 2012.

[14] M. J. Schrapp, G. T. Herman, Data fusion in X-ray computed tomography using a superiorization approach, Review of Scientific Instruments 85 (5) (2014) 053701.

[15] M. Reiter, D. Weiß, C. Gusenbauer, M. Erler, C. Kuhn, S. Kasperl, J. Kastner, Evaluation of a histogram-based image quality measure for X-ray computed tomography, in: Proceedings of iCT Wels 2014, 2014.

[16] R. Schielein, S. Schröpfer, M. Kiunke, S. Zabler, S. Kasperl, Quantitative evaluation of CT images by means of Shannon entropy, in: 11th European Conference on Non-Destructive Testing (ECNDT 2014), October 6-10, 2014, Prague, Czech Republic, 2014.

[17] A. Amirkhanov, M. Reiter, J. Kastner, M. E. Gröller, C. Heinzl, Evaluation of projection-based metal-artifact reduction for multi-material components, in: Proceedings of iCT Wels 2012, 2012.

[18] A. Amirkhanov, C. Heinzl, C. Kuhn, J. Kastner, M. E. Gröller, Fuzzy CT metrology: Dimensional measurements on uncertain data, in: Spring Conference on Computer Graphics, ACM, 2013, pp. 81–90.