Methodology for the evaluation of CT image quality in dimensional metrology

Alexandra KRAEMER [1], Gisela LANZA [1]
[1] wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

Contact e-mail: alexandra.kraemer@kit.du

Abstract. In the last years, x-ray computed tomography (CT) has gained more and more importance in metrology. However, computed tomography is a complex and indirect measurement procedure. Many factors contribute to the measurement result, which makes it difficult for the user to relate cause and effect. For example, the user-set scan parameters significantly influence the measurement result. However, the selection of scan parameters is still based on the experience of the CT user, while the influence of the parameter choice on the measurement result cannot be quantified. This leads to diverging and non-optimal scan results. The quality of the CT scan can only be evaluated afterwards, e.g. by visual inspection of the reconstructed volume. Taking into account that the process chain of CT measurements is highly complex, the very first step is the generation of reliable high quality projections that can then be fed into the reconstruction. The quality of these projections can be described quantitatively by image quality measures. Thus, in this paper, an approach regarding projection based evaluation of CT image quality in micro computed tomography is presented. By performing a set of experiments, the influence of projection image quality on the reconstructed volume and respectively on the measurement result is evaluated. A derived model relates the projection quality measures to the actual measurement error of the CT scan.

Hence, the proposed approach defines a reliable, combined quality measure, which is based on a small number of projections acquired before the actual scan. An algorithm evaluates the quality of those projection for every workpiece that has to be measured. Based on the evaluation, it varies the scan parameters, until an optimal projection quality is reached and a reduced measurement error in the CT scan is achieved.

1. Introduction

In the last years, x-ray computed tomography (CT) has gained more and more importance in metrology. Its property of displaying and measuring outer and inner structures non-destructively makes it an interesting alternative to well established technology, such as tactile coordinate measuring machines (CMM) or optical measurement systems. However, computed tomography is a complex and indirect measurement procedure. Many factors contribute to the measurement result [1, 2], making it difficult for the user to relate cause and effect. For example, the user-set scan parameters significantly influence the measurement result [3-7]. The user can, for example, choose orientation and position of the workpiece, current and tube voltage as well as integration time. However, this choice is based on his

More info about this article: http://ndt.net/?id=19228

personal experience – at the moment, no objective measure for the parameter selection is available. In industrial practice, this leads to diverging scan results [8].

2. State of the Art

The planning of scan parameters in CT has thus been an emerging field of research. Some methods rely on prior knowledge for the optimization of scan parameters: Giedl-Wagner et al. [9] use neuronal networks based on radial basis functions for the optimization of scan parameters. The neuronal network has to be trained with similar exemplary data with known optimal parameter. Niggemann [10] developed a knowledge-based system for user support in their choice of optimal scan parameters. The approach uses similarity criteria between workpieces to find the respective scan parameters from a database of previous scans.
Reiter et at. [11] developed a simulation environment which can be used for the evaluation of different combinations of scan parameters. Also Reisinger et al. [12] use a ray-tracing simulation for the determination of optimal scan parameters for a set measurand. For optimization, part position and orientation as well as prefilter thickness and tube voltage is evaluated in a hierarchical manner with respect to the image quality measures defined in [2], but these recommendations stemming from non-destructive testing applications have been criticized in literature as not sufficient for a real optimization [13]. The standards just suggest a minimal requirement.
Hence, some research has been done on the relation between the image quality of the reconstructed volume and the resulting measurement error. Hiller et al. [14] investigated the influence of noise and resolution on the coordinate measurement with simulated data. Fleßner et al. [15] developed a "Local Quality Value (LQV)", which assigns a value for the accuracy of the local surface determination to every determined surface voxel. The value is based on local grayvalue variations normal to the determined surface. Another local quality measure is suggested by Schönfeld et al. [16], which can be used for a quality-dependent weighting of surface points in the reconstructed volume. The Shannon entropy of the greyvalues is investigated by Xue et al. [17] as well as Schienlein et al. [18, 19], who uses this measure to simulatively optimize the orientation of the specimens during the scan. A similar measure, the so-called Q-value, is suggested by Reiter et al. [20] and can serve as a first overview of the quality of the performed scan after reconstruction.
In summary, it can be found that the current research approaches dealing with optimization of scan parameters rely either on objectified prior knowledge or on simulation studies. These studies are nowadays quite accurate and give a first insight in the resulting scan, but they require the use of a special software and are still time-consuming. An evaluation of the image quality of the reconstructed volume is possible, but can only be applied in hindsight after the actual scan is performed.
Thus, the research approach presented in this article focusses on determining optimal scan parameters in a fast and reliable way already before the actual scan is started.

3. Evaluation of CT image quality in dimensional metrology for the optimization of scan parameters

3.1 Overview of the methodoloy

The approach aims at supporting the user with an optimal set of scan parameters for each individual workpiece with different measurands in order to assure a high scan quality and reduce the user influence on the scan result. The goal is to provide parameter sets such that the measurement error is reduced and the reproducibility of the scans is increased. The scan

parameters are optimized automatically. This is done based on a small number of projection images, which are taken before the actual scan is started.
The methodology consists of three consecutive steps, as depicted in Fig. 1.

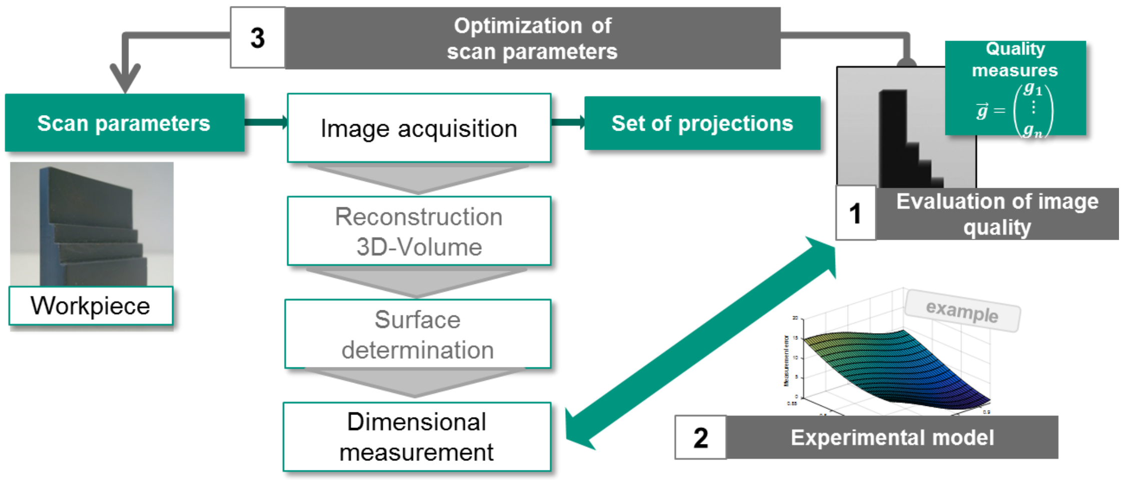

Fig. 1. Overview of the proposed methodology

In the first step, suitable image quality measures are defined to describe the quality of the 2D projection images. These image quality measures are then set into a relation with the resulting measurement error of the 3D volume's features after reconstruction and surface determination. In order to gain the necessary data for the development of a suitable model, systematic experiments with test bodies, as developed in [21], are performed. If the influence of the projection quality on the measurement error is known, this model thus serves as basis for the optimization, which is performed individually for each workpiece to measure. An algorithm choses suitable scan parameters and takes a small number of projections which are then evaluated with respect to their image quality. If the quality is not satisfactory, the algorithm iteratively searches for the optimal projection quality by varying the scan parameters until the best possible configuration is achieved.
In the following, the three steps of the methodology are described in detail.

3.2 Definition of quantitative image quality measures

In the course of a CT scan, several hundred individual projection images are taken, each representing a different angular position of the scanned object. Among others, scan parameters have an influence on the appearance of the projection image, which can be characterized by image quality parameters, such as contrast, noise, resolution and image sharpness. These quality parameters can be quantitatively described by image quality measures, such as the contrast-to-noise ratio, which is for example used to judge image quality in non-destructive testing. However, no such measures exist for assessing the quality of 2D projections for applications in metrology.The challenge is to find those measures that influence the resulting measurement error of the reconstructed volume. It hence has to be taken into account how the used reconstruction software uses filter algorithms to e.g. suppress noise. Some quality measures might not have a great influence after reconstruction, even though their values are prominent on the 2D image acquired during the scan.
Some of the quality measures are interrelated and correlated. In a two-step approach, the possible measures are classified and reduced. Reference-free global and local image quality measures can be applied to projection images [22]. These measures comprise, for example, variance-based, histogram-based, gradient-based and autocorrelation-based measures. The first step is to identify qualitative relationships of the image quality measures to scan

parameters. Second, the remaining measures have to be checked for their influence on the measurement error at test specimens with simple geometries, which are calibrated beforehand with a tactile CMM [23]. The so filtered measures then are used for the development of the experimental model.

3.3 Experimental Model

In the second step, the relation between the image quality of the individual projections and the measurement error of the reconstructed volume is modeled. Based on experimental design, systematic measurements with differing image quality are performed. For the measurements, more complex test bodies that show similarity to real industrial components are used [21]. For test bodies that are not rotatory symmetric, the evaluated projections are chosen such that both the projections with the lowest and highest penetration length of the test body is considered.
All measurements are performed with an industrial CT scanner, using a FDK-reconstruction algorithm [24]. The scanner is situated in an air conditioned metrology laboratory with a temperature range of +/-0.5 K. In addition, the scanner is positioned on a vibration isolated base, such that external environmental influences on the measurement can be neglected. Before the experiments are started, the tube is warmed up to ensure stable conditions in terms of temperature. The temperature inside the CT is monitored with temperature sensors with an accuracy of +/-0.1 K to check for possible temperature rise, e.g. if multiple scans are performed consecutively.
To ensure traceability, the test bodies are calibrated with high accuracy micro coordinate metrology, using a tactile coordinate measuring machine. Multiple measurements with the micro coordinate system are performed, such that the mean values of the measured features can be used as a reference and the respective calibration uncertainty is calculated according to ISO 15530-3 [25]. Also the CT measurements are repeated under the same conditions. The evaluation of the performed measurements is done according to a standardized semi-automated procedure in the software VGStudio Max, such that an influence of the user during the data evaluation can be ruled out.
For each feature, the mean measured value of the repeated CT scans is taken for the comparison to the tactile reference measurement and the deviation between both values is considered the resulting measurement error. Dimensional and geometric features are evaluated separately and treated individually in the model. At the moment, systematic measurements for a deduction of the model are performed at wbk Institute of Production Science.
The model describing the relation between the measurement error and the image quality is derived from the measurement data by statistical analysis. In the development of the model, it has to be considered that some of the image quality measures are correlated, such that suitable regularization has to be integrated in the regression analysis.

3.4 Automated optimization of scan parameters

In each individual scan, the scan parameters have to be adjusted such that a certain projection image quality is achieved. To ensure this, an optimization algorithm is implemented. The optimization has to be adjusted to the used CT machine, taking into account constraints stemming from physical limitations of the machine, such as the available measuring range or the maximum power.
The used image quality measures are those considered relevant through statistical tests in the development of the model. Hence, the optimal set of image quality measures can be derived from the model. They are determined from the minimum of the model function, i.e. the

minimum measurement error, distinguished between dimensional and geometrical features. As different scan parameter combinations can show similar results, not only global, but also local minima are considered. The quality measures are normalized and weighted according to their significance. In order to avoid a multi-criteria problem in the implementation of the optimization algorithm, the image quality measures are aggregated to a superordinate command variable.
The first step of the optimization is the adjustment of the magnification of the workpiece. The algorithm automatically searches for the position with the highest width of the workpiece as projected on the detector. Then, it repositions the workpiece, such that the highest magnification of the object is achieved, while the object still is displayed as a whole. In addition, a small edge, e.g. of about ten pixels, is left around the workpiece on the detector, to avoid the use of edge pixels for the workpiece. This position is chosen as the starting position for the optimization and serves as minimum source-object distance for the subsequent optimization steps.
In each iteration of the optimization, the position is checked with the current focal spot size of the machine. The positioning is chosen, such that the focal spot size is always smaller than the voxel size. Otherwise, additional blurring of the image would occur.
In order to diminish Feldkamp artifacts, the algorithm checks the orientation of the workpiece. If horizontal edges (i.e. edges below a threshold angle to the horizontal, which is set between 8° and 10°) are detected, the software suggests a reorientation of the workpiece.

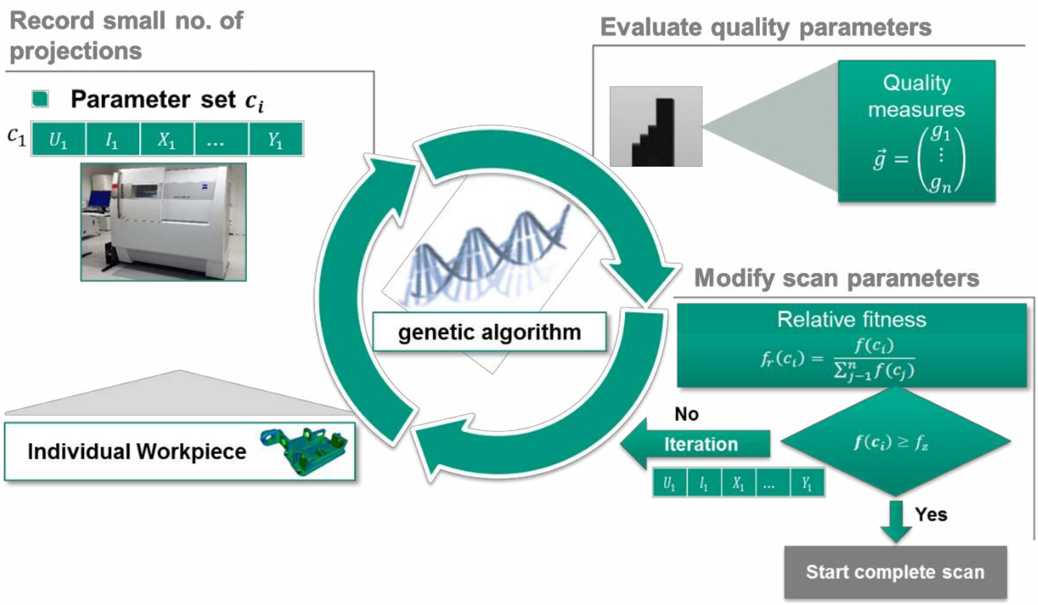

Fig. 2. Optimization as iterative process

Now, the actual optimization, as depicted in Fig. 2, can start. The considered scan parameters are magnification, tube voltage, gain, current and exposure time. The optimization is done with a genetic algorithm. In an iterative process, a small set of projections (around the highest and lowest penetration lengths) is taken and their image quality evaluated. If the image quality is not satisfactory, the algorithms sets another set of scan parameters and repeats the evaluation of image quality, until the optimal conditions are achieved.
Finally, the minimum number of projections is calculated according to the sampling theorem to avoid aliasing. Following [26], as a rule of thumb, it is sufficient to consider:

$$N_P = P_h \tag{1}$$

Where N_p is the required number of projections in 360° and P_h the maximum number of (object) pixels in horizontal direction, which in turn can by calculated from the magnification, respectively the source-detector and source-object distance.
The setting of the number of the projections is the last step of the projection based optimization and the complete scan with now optimal parameters is started.

4. Conclusion

Despite the fact that computed tomography is getting more and more important for metrological applications, the acquisition of reliable and reproducible CT scans remains challenging. Due to the complex measurement procedure, the user cannot quantify if the selected scan parameters are a good choice.
Hence, the proposed approach aims at closing this gap by defining a reliable, combined quality measure, which is based on a small number of projections acquired before the actual scan. By an experimental model, the quality measure is related to the actual measurement error of the CT scan.
With this underlying model, an algorithm evaluates the quality of a small number of projection for every workpiece that has to be measured. Based on the evaluation, it sets the scan parameters, until an optimal projection quality is reached and a reduced measurement error is achieved.

References

[1] Deutsches Institut für Normung (2011), Zerstörungsfreie Prüfung- durchstrahlungsverfahren Computertomographie, Beuth Verlag GmbH, Berlin, DIN EN 16016-1, DIN EN 16016-2, DIN EN 16016-3, DIN EN 16016-4.

[2] Verein Deutscher Ingenieure (2010), Computed tomography in dimensional measurement – Influencing variables on measurement results and recommendations for computed tomography dimensional measurements, Beuth Verlag GmbH, Berlin, VDI/VDE 2630 Part 1.2.

[3] Angel, J.; De Chiffre, L. (2014), 'Comparison on Computed Tomography using industrial items', CIRP Annals - Manufacturing Technology, vol. 63, no. 1, pp. 473–476.

[4] De Chiffre L.; Carmignato, S.; Kruth J.-P.; Schmitt, R.; Weckenmann, A. (2014), 'Industrial applications of computed tomography', CIRP Annals - Manufacturing Technology, vol. 63, no. 2, pp. 655–677, ISSN 0007-8506.

[5] Kruth, J.-P.; Bartscher, M.; Carmignato, S.; Schmitt, R.; De Chiffre, L.; Weckenmann, A. (2011), 'Computed tomography for dimensional metrology', CIRP Annals - Manufacturing Technology, vol. 60, no.2, pp. 821–842.

[6] Schmitt, R.; Niggemann, C. (2010), 'Uncertainty in measurement for x-ray-computed tomography using calibrated work pieces', Measurement Science and Technology, vol. 21, no. 5, pp. 1–9.

[7] Weckenmann, A.; Krämer, P. (2009), 'Assessment of measurement uncertainty caused in the preparation of measurements using computed tomography', Proceedings of the XIX IMEKO World Congre*ss 'Fundamental and Applied Metrology'*, Lissabon, pp. 1888-1892

[8] VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (GMA) (2011), Fertigungsmesstechnik 2020, Technologie-Roadmap für die Messtechnik in der industriellen Produktion, VDI-Verlag GmbH, Düsseldorf , ISBN 978-3-00-034706-1.

[9] Giedl-Wagner, R.; Miller, T.; Sick, B. (2012), "Determination of Optimal CT Scan Parameters Using Radial Basis Function Neural Networks". Conference on Industrial Computed Tomography (iCT) 2012: Proceedings, ed. J. Kastner, Shaker, Aachen, pp. 221-228.

[10] Niggemann, C. (2012), Wissensbasiertes System zur Verbesserung dimensioneller Messungen mittels Röntgen-Computertomografie. Dissertation, Rheinisch-Westfälische Technische Hochschule, Aachen.

[11] Reiter, M.; Heinzl, C.; Salaberger, D.; Weiss, D. & Kastner, J. (2010, June), 'Study on parameter variation of an industrial computed tomography simulation tool concerning dimensional measurement deviations'. Proceedings of 10th European Conference on Non-destructive Testing, RSNTTD, Moscow

[12] Reisinger, S.; Kasperl, S.; Franz, M.; Hiller, J.; Schmid, U. (2011), 'Simulation-based planning of optimal conditions for industrial computed tomography'. International Symposium on Digital Industrial Radiology and Computed Tomography, Dt. Ges. für Zerstörungsfreie Prüfung, Berlin, DGZfP-Proceedings BB128-CD, Mo.3.1

[13] Reiter, M.; Krumm, M.; Kasperl, S.; Kuhn, C.; Erler, M.; Weiß, D.; Heinzl, C.; Gusenbauer, C. & Kastner, J. (2012), 'Evaluation of transmission based image quality optimisation for X-ray computed tomography'. 2nd Conference on Industrial Computed Tomography (iCT) 2012, Wels: Proceedings, pp. 241–250.

[14] Hiller, J.; Fuchs, Theobald, O. J.; Kasperl, S. & Reindl, L. M. (2011), 'Einfluss der Bildqualität röntgentomographischer Abbildungen auf Koordinatenmessungen: Grundlagen, Messungen und Simulationen', tm - Technisches Messen, vol. 78.7-8, pp. 334–347

[15] Fleßner, M; Müller, A.; Hausotte, E. (2014), ‘Evaluating and visualizing of the quality of surface points determined from computed tomography volume data’. MacroScale. doi:10.7795/810.20150223A

[16] Schönfeld, T.; Bartscher, M. (2015), ‘Verification and application of quality measures in dimensional CT‘, International Symposium on Digital Industrial Radiology and Computed Tomography 2015, Dt. Ges. für Zerstörungsfreie Prüfung, Berlin

[17] Xue, L.; Suzuki, H.; Ohtake, Y.; Fujimoto, H.; Abe, M.; Sato, O.; Takatsuji, T. (2016), ‘Quality evaluation of X-ray computed tomography volume data in dimensional metrology’. 6th Conference on Industrial Computed Tomography (iCT) 2016, Wels: Proceedings.

[18] Schielein, R.; Schröpfer, S.; Kiunke, M.; Zabler, S.; Kasperl, S. (2014), ‘Quantitative evaluation of CT images by means of Shannon entropy’. 11th European Conference on Non-Destructive Testing (ECNDT 2014), Prag

[19] Schielein, R.; Scholz, G.; Kretzer, C.; Fuchs, T.; Kasperl, S.; Bär, F.; Kirsch, S.; Zepf, M.; Wolters-Rosbach, M.: ‘The MUSICES Project: Simulative automated CT acquisition planning for historical brass instruments improves image quality’. 6th Conference on Industrial Computed Tomography (iCT) 2016, Wels: Proceedings.

[20] Reiter, M.; Weiß, D.; Gusenbauer, C., Erler, M., Kuhn, C., Kasperl, S. & Kastner, J. (2014), 'Evaluation of a histogram-based image quality measure for X-ray computed tomography'. 4th Conference on Industrial Computed Tomography (iCT) 2014, Wels: Proceedings, ed. J. Kastner, Shaker, Herzogenrath, pp. 273–282.

[21] Kraemer, A.; Batra, A.; Griesz, P.; Lanza, G. (2016), ‘Development of test bodies for deployment in industrial Computed Tomography’. 6th Conference on Industrial Computed Tomography (iCT) 2016, Wels: Proceedings.

[22] Kraemer, A.; Kovacheva, E.; Lanza, G. (2015), 'Projection based evaluation of CT image quality in dimensional metrology', Digital Industrial Radiology and Computed Tomography (DIR 2015) e-Journal of Non-destructive Testing, ISSN 1435-4934.

[23] Kraemer, A.; Boehmler, P.; Lanza, G. (2016), ‚Optimierung von Aufnahmeparametern mittels projektions-basierter Qualitätskenngrößen in der industriellen Computertomographie‘, GMA/ITG-Fachtagung 'Sensoren *und Messsysteme‘,* Nürnberg: Proceedings

[24] Feldkamp, L. A.; Davis, L. C.; Kress, J. W. (1984), 'Practical cone-beam algorithm', Journal of the Optical Society of America A, vol. 1, no. 6, pp. 612–619.

[25] ISO 15530-3 (2004), Geometrical Product Specifications (GPS) – Coordinate Measuring Machines (CMM): Technique for Determining the Uncertainty

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