Artifact reduction in X-ray computed tomography by multipositional data fusion using local image quality measures

Gabriel Herl\textsuperscript{1,2}, Jochen Hiller\textsuperscript{1,2}, Tomas Sauer\textsuperscript{3,4}

\textsuperscript{1}Fraunhofer Application Center CTMT, Dieter-Görlitz-Platz 2, 94469 Deggendorf, Germany, e-mail: herlgl@iis.fraunhofer.de
\textsuperscript{2}Deggendorf Institute of Technology, Dieter-Görlitz-Platz 1, 94469 Deggendorf, Germany
\textsuperscript{3}Fraunhofer Application Center CTMT, Innstraße 43, 94032 Passau, Germany
\textsuperscript{4}University of Passau, Innstraße 43, 94032 Passau, Germany

Abstract

Metal artifacts are still a major problem in X-ray industrial computed tomography. In order to reduce metal artifacts and increase the image quality of X-ray CT-scans, we suggest using projection data from multiple scans with differently positioned object orientations. We present two different approaches for multipositional CT, which are especially effective for multimaterial objects with high absorbing metal parts. On one hand, we reconstruct the different scans separately, estimate the local quality of the resulting volumes and then fuse these volumes to an optimized volume. On the other hand, we introduce smART (shrinking merged Algebraic Reconstruction Technique) and merge sinograms of different scans, estimate the reliability of each projection pixel and then reconstruct the merged sinogram with an adapted SART reconstruction method. We demonstrate our approaches on simulations and on measurement data and are able to show a significant reduction of image artifacts qualitatively and quantitatively with the help of dimensional measurement results.

Keywords: X-ray computed tomography, data fusion, multipositional, multiorientational, local quality measures, metal artifact reduction, smART, unfiltered backprojection, metrology

1 Introduction

X-ray computed tomography (CT) has become an important tool for quality control and manufacturing optimization for industrial parts. Nevertheless, achieving high image quality and reliable measurements can be very challenging – especially when highly absorbing metal parts are involved [1].

For the process of CT, an object is put between an X-ray source and an X-ray detector. The X-ray source emits radiation, which interacts with the object. Depending on the material attenuation coefficient $\mu$ and the thickness $d$ of the object, the X-ray beam intensity decreases while passing through the object. The remaining radiation can be measured by the detector system in order to create a 2D projection image. The weakening of the emitted radiation energy $I_0$ to the detected radiation energy $I$ can be described by the Lambert-Beer law $I = I_0 e^{-\mu d}$. As this formula is rather simple, it is solved for most reconstruction algorithms analytically, in order to calculate the local attenuation coefficient $\mu$. However, this formula has some requirements, which are often not satisfied and, therefore, can lead to a wrong interpretation of the attenuation. First of all, wherever the object is too wide and/or too dense, the radiation energy detected on some detector pixels can be reduced to zero. In this case, a wider or denser object would not have any influence on the detected energy. This means that the result of the formula is not dependent on the wideness and/or denseness of the object anymore and, hence, the formula does not yield an accurate result in this case. Therefore, in the case of total absorption, the detecting pixels not only gather no information, but wrong information, which can cause streaks and cupping artifacts in the reconstruction volume. Secondly, the formula of Lambert-Beer is only correct for monochromatic energy. Since the energy of X-ray sources is polychromatic, this leads to so called beam hardening artifacts in the reconstruction volume.

There are several methods for reducing metal artifacts in different steps of the CT process. Firstly, there are purely algorithmic approaches. Some methods try to repair the projection data by averaging or interpolating the metal data in the sinogram [5-14]. Due to their simplicity, these methods have been very popular for medical usage. However, as artificial data is created, the resulting images often still suffer from lots of artifacts. Other methods are based on iterative reconstruction techniques, which can be adjusted in order to align the correction process more with the physical background [15-22]. This can be very difficult and often requires a lot of computational power. Then there are methods that use additional information: There are several multimodal fusion approaches like the combination of X-ray CT with tactile and optical sensors [23] or X-ray CT with neutron CT [24]. These methods obviously need more than one sensor system and, therefore, can be very expensive and complicated. Furthermore, there is dual energy X-ray CT [25-27]. In dual energy, volumes of scans with different acquisition energies are fused in order to achieve one optimized volume. Dual energy approaches work very well when both the low and the high energy scans can produce sufficiently good projection images. Despite the amount of mentioned impactful metal artifact reduction methods, problems remain. Wherever X-rays are attenuated almost completely, the scanning process just does not gather enough information for a high quality reconstruction dataset.
As we showed before [2], there is another option for creating additional information, which can help in this case: the multipositional fusion [2-4]. By exploiting the fact that the localization of the artifacts depends on the positioning (orientation) of the scanned object (see Figure 1), the multipositional approach is based on the following idea: Create more reliable information and ignore the unreliable information.

We want to explain and elaborate different approaches for the multipositional fusion: (a) the fusion of CT volumes from scans with different object positioning and (b) the merging of sinograms from scans with different object positioning to one combined sonogram, which then can be reconstructed to achieve an object volume based on both scans. For fusion techniques, it is very important to be able to differentiate between reliable and less reliable data. Hence, in Section 2.1 we start this work with local quality measures and heuristics. In Section 2.2 we present two methods of the multipositional data fusion. Then we perform some experiments on different simulated and measured objects in Section 3 and conclude the results of this work in Section 4.

2 Methods for multipositional fusion

2.1 Local quality measures and heuristics

We use two different types of quality measures and heuristics: Firstly, we examine voxels of volumes and, secondly, we examine pixels of projections.

For the experiments in this paper, we use the unfiltered backprojection as a quality heuristic for voxels that can be used for comparing reconstruction volumes. As the X-ray penetration length and the amount of X-ray attenuation strongly correlate with the formation of metal artifacts in any voxel of a CT scan, we use the percentage of attenuation as a heuristic: X-rays that have strongly been attenuated, are rated not trustworthy (e.g. rays through metal), while X-rays that have been attenuated only a little, are rated very trustworthy (e.g. rays through air or thin plastic). The unfiltered backprojection (the basis of the well-known Feldkamp reconstruction algorithm) calculates how much the X-rays through every voxel have been attenuated. Therefore, we can use the backprojection for estimating the quality of regions and voxels within a CT scan (see Figure 1). Wherever the backprojection produces high values, we expect a strong formation of metal artifacts. Hence, when we calculate and register the unfiltered backprojection for two scans with differently positioned objects, we can estimate which of the two scans provides more reliable information for every voxel (see Figure 2).

In order to estimate the quality of a projection pixel, we use the same assumption: X-rays that have been strongly attenuated are rated not trustworthy, while X-rays that have been attenuated only a little, are rated very trustworthy. Therefore, we pixels that have detected high intensity values are rated with a high quality value, while pixels that have measured very little radiation are rated with a low quality value.

Both of these heuristics should work well, whenever artifacts in the reconstructed image are caused by very different attenuation levels or very different aspect ratios.

Figure 1: Projection images (Position 1, 2), filtered backprojection reconstruction slices (FBP 1, 2) with artifacts and slices of the unfiltered backprojections (UBP 1, 2) of a simulated plastic specimen surrounded by metal cubes.

Figure 2: Slice of the difference between the two unfiltered backprojections of Figure 1 (UBP 1 and UBP 2). Dark voxels probably are less artefact afflicted in position 1. Bright voxels are probably less artefact afflicted in position 2.
2.2 Fusion methods

We present two kinds of fusion methods. In the first method, the single scans are reconstructed separately and the reconstructed volumes are fused, while in the second method, we directly merge sinograms of different scans and reconstruct all projections together.

2.2.1 Multipositional fusion of volumes

For the multipositional fusion of volumes (see [2] for more details, abbreviated as “Fusion” in later pictures) scans from different object orientations need to be made (at least two). The scans are reconstructed and the resulting volumes are 3D/3D registered on the first scan. For each voxel of every volume a local heuristic or quality measure has to be calculated as a weight (see Section 2.1). Using these weights, the volumes can be fused to create a new volume with fewer artifacts (see Figure 3).

If the heuristic is correct, the fusion prefers voxels without artifacts. Therefore, if there is an artifact free region in one of the given volumes, this region will be artifact-free in the fusion, too. Obviously, the positions of the given volumes are very relevant. Examples are shown in Figure 4 and in the experiments (Section 3).

2.2.2 Multipositional reconstruction of sinograms: Shrinking multipositional ART (smART)

In this approach, we do not fuse the reconstructed volumes but merge the sinograms and then use all projections in one single reconstruction to create an optimized volume. Again, scans from different object orientations have to be performed (at least two). The scans are reconstructed and the resulting volumes are 3D/3D registered on the first scan. However, this time we do not use the registered volumes but only the information of the corresponding placements of the objects.
Let \( b_1 \in \mathbb{R}^m \) be the vector of all detected projection pixels of scan 1 with \( m \) being the number of pixels of the detector. Furthermore, let \( n \) be the number of unknowns (volume voxels) and \( A_1 \in \mathbb{R}^{m \times n} \) the system matrix of scan 1. With the unknown \( x \) the problem can be formulated as a system of equations \( A_1 x = b_1 \). Then, we change the position of the object and, therefore, have a new unknown \( \tilde{x} \). As we do not change any other parameters the system matrix of scan 2 is the same as \( A_1 \) but the projection vector changes to \( b_2 \). Hence, we get the system of equations \( A_2 \tilde{x} = b_2 \). Now, we assume that not the object has been repositioned but the trajectory was performed differently (see Figure 5). Using the registration information we change the system matrix \( A_2 \) to \( A_1 \) like it would have been, if the trajectory (and not the object) was tilted. Then, we can formulate a new system of equations \( A_1 x = b_2 \). The systems of equations can be merged to one new system containing more information:

\[
A_1 x = b_1 \land A_2 x = b_2 \rightarrow (A_1 \ A_2) x = (b_1 \ b_2)
\]

![Figure 5: Visualizations of a scan of an example specimen consisting of a plastic cube and three metal spheres. The trajectories are visualized by dotted lines. Regions that are not reliable because of metal artifacts are colored brown and red. On the left and middle, there are circular trajectories (1, 2). On the right, there is the combined trajectory (3), which offers the highest information density, but contains the most unreliable projections, too.](image)

The merged sinogram can be reconstructed in one reconstruction with an iterative reconstruction algorithm, e.g. SART. However, there is still a major problem. As there are more projections, there is more wrong information in these projections than the useful information. As described in Section 2.1.1, strong attenuation of X-rays correlate with artifacts. Therefore, we refine the classical SART-algorithm [28] based on the algorithm of Kaczmarz. We suggest deleting some of the most untrusted equations after every iteration of the SART algorithm. This way, we reconstruct every voxel of the reconstruction volume, but decrease the influence of the unreliable X-ray equations by just ignoring them in later iterations of the ART.

**Algorithm: Shrinking ART (sART)**

Let \( x := (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n \) be the unknown attenuation distribution with \( n \in \mathbb{N} \) as the number of unknowns and \( x_i \in \mathbb{R} \) the value of a single voxel. Let \( m \in \mathbb{N} \) be the number of projection pixels, \( b_0 = (b_1, b_2, \ldots, b_m)^T \in \mathbb{R}^m \) with \( b_1 \leq b_2 \leq \cdots \leq b \) as the sorted vector of the detector pixels and \( A_0 := (A^1, A^2, \ldots, A^n)^T \) the corresponding system matrix of the used CT system with \( A_0 \in \mathbb{R}^{m \times n} \) and \( A^i \in \mathbb{R}^m \forall i < n \). With these variables we have a system of equations \( A_0 x = b_0 \). Furthermore, let \( v := (v_1, v_2, \ldots, v_r) \in \mathbb{R}^r \) be a vector with \( r \) the number of planned Kaczmarz-iterations and \( v_i \in \mathbb{N}_0 \) the parameter, which decides how many equations are getting cut after every Kaczmarz-iteration. We now formulate the following algorithm:

1. Set \( j := 0 \), \( m_j := m \) and \( x_j \in \mathbb{R}^n \) to an arbitrary value
2. While \( j < r \) do:
   - Perform one iteration of an iterative reconstruction algorithm in order to achieve the solution \( x_{j+1} \) of the linear equation system \( A_j x_j = b_j \)
   - Set \( m_{j+1} := m_j - v_j \), \( A_{j+1} := (A^1, A^2, \ldots, A^{m_j})^T \) and \( b_{j+1} := (b_1, b_2, \ldots, b^{m_j})^T \) and \( j \leftarrow j + 1 \).

Using the sART approach in combination with the merging of the sinograms described earlier, we obtain the smART (shrinking merged ART) method that is able to reconstruct several multipositional scans into one optimized volume with fewer artifacts (see workflow in Figure 6).
3 Experiments

In order to show the results of our fusion methods we performed experiments on simulations as well as measured test specimens and compared the results of the single scans with the results of our fusion methods. For the reconstruction of scans with circular trajectory, we use the Feldkamp-Algorithm. As we know the exact positions within the simulations, the simulations were registered perfectly. The registrations of the measured data were performed using the Insight Segmentation and Registration Toolkit (ITK [29]) optimizing the normalized correlation for every voxel.

3.1 Multipositional X-ray CT of simulated scans

In order to show the influence of our methods for multimaterial cases under perfect conditions, we performed simulations of a plastic test specimen surrounded by tantalum cubes in three different positions (see Figure 7). The scans were simulated with the simulation software Scorpius XLab [30] and the following parameters (see Tab. 1). Exposure time and tube current were chosen automatically by the software Scorbius XLab for an optimal image contrast level.

<table>
<thead>
<tr>
<th>Voltage</th>
<th>Projections</th>
<th>Prefilter</th>
<th>Pixel Size</th>
<th>Detector resolution</th>
<th>Magnification</th>
<th>Voxelsize</th>
</tr>
</thead>
<tbody>
<tr>
<td>225 kV</td>
<td>800</td>
<td>No filter</td>
<td>700 µm</td>
<td>256 × 256</td>
<td>3</td>
<td>233 µm</td>
</tr>
</tbody>
</table>

Table 1: Parameters of the simulated scans of a plastic test specimen surrounded by tantalum cubes.

![Figure 7: On the left: Projections of the simulated plastic test specimen surrounded by three metal cubes from three different scans with different object positions (Pos. 1-3). On the right: Slices of the corresponding reconstructions of these three scans (Pos. 1-3).](image)

Figure 8: Multipositional fusions of the three reconstructions shown on the right side of Figure 7. (First: Fusion of reconstruction 1 and 2, second: Fusion of reconstruction 1 and 3, third: Fusion of reconstruction 2 and 3, fourth: Fusion of reconstruction 1, 2 and 3).
As the metal blocks were so dense, all of the three single scans show severe artifacts (see Figure 7). Both of the fusion methods decrease the influence of metal artifacts enourmosly (see Figure 8, 9), especially when all three scan positions were used. In order to evaluate the results quantitatively, we compared the simulated scans with an optimal representation of the object using the euclidean norm. For quantitative comparison, we focused on the plastic object and compared only voxels near the plastic object (see Figure 10). The results in Figure 11 demonstrate very clearly that both methods are able to recreate a more truthful image then any of the single scans. Even so the smART method seems to increase noise; it achieves better results than the fusion of volumes when using only two single positions.

3.2 Multipositional x-ray CT of a monomaterial metal object

For realistic, quantitative results, we examined a 2 cm zinc test specimen and analyzed artifacts and measurement accuracy quantitatively. In order to challenge our methods, we chose this monomaterial specimen as an especially difficult object for our methods, as it does not have very different aspect ratios and only one density level. The experiments were performed on a Werth TomoScope HV 500. We scanned the zinc specimen in two different positions (see Figure 12) 10 times, each with the following parameters (see Tab. 2).

<table>
<thead>
<tr>
<th>Current</th>
<th>Voltage</th>
<th>Projections</th>
<th>Exposure time</th>
<th>Prefilter</th>
<th>Pixel Size</th>
<th>Detector matrix</th>
<th>Magnification</th>
<th>Voxelsize</th>
</tr>
</thead>
<tbody>
<tr>
<td>220 µA</td>
<td>225 kV</td>
<td>800</td>
<td>333 ms</td>
<td>5 mm Sn</td>
<td>400 µm</td>
<td>992 × 992</td>
<td>~ 8</td>
<td>50 µm</td>
</tr>
</tbody>
</table>

Tabelle 2: Parameters of the simulated scans of a zinc test specimen

We reconstructed every of these scans with the Feldkamp reconstruction algorithm. Furthermore, we used the multipositional fusion of volumes and the smART method. For comparison, we averaged the volumes of the single reconstructions from position 1 and 2 as well (and called this “Average” in the Figures), in order to compare our method to the most simple approach of multipositional fusion.

For quantitative results, we measured some features (see Figure 12) with the WinWerth metrology software and with a coordinate measuring system, used as reference system, and compared the results (see Table 3 and Figure 14).
The metal artifacts decrease, but the effect is much smaller than in the simulations (see Figure 13). The quantitative results showed that position 1 was considerably worse than position 2. This obviously has a significant influence on the dimensional measurement results. These quantitative results (see Tab. 3 and 4) show that the smART method often did not improve the measurements. However, the multipositional fusion of volumes performed very well. For the features M1-M5, the measurement results of the multipositional fusion were smaller or equal as the result of the best reconstructed single position. Only for
feature M6, the result of the fusion was about 1 µm worse than the result of the worst single scan. In total (for all presented measurements), the fusion of volumes had the smallest average deviation of 2.98 µm and the smallest 0.95 quantile value (see Table 4).

We suppose that the main reason for the bad results of the smART method as well as the bad result of the multipositional fusion for feature M6 was the registration process. As the registration was probably not optimal, the scans from positions 1 and 2 could not be combined perfectly. Furthermore, the results indicate that the multipositional fusion of volumes is more robust to these registration errors than the smART method.

<table>
<thead>
<tr>
<th>Position</th>
<th>Average Deviation</th>
<th>Standard Deviation</th>
<th>0.95 Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28.25 µm</td>
<td>0.85 µm</td>
<td>61.04 µm</td>
</tr>
<tr>
<td>2</td>
<td>3.77 µm</td>
<td>0.43 µm</td>
<td>9.07 µm</td>
</tr>
<tr>
<td>Fusion</td>
<td>2.98 µm</td>
<td>0.48 µm</td>
<td>6.22 µm</td>
</tr>
<tr>
<td>smART</td>
<td>16.05 µm</td>
<td>1.33 µm</td>
<td>30.03 µm</td>
</tr>
<tr>
<td>Average</td>
<td>13.34 µm</td>
<td>1.42 µm</td>
<td>29.30 µm</td>
</tr>
</tbody>
</table>

Table 4: For comparison reasons: The average deviation, the average standard deviation and the average 0.95 quantile value of all measurements of the zinc specimen reconstructed using the described methods.

3.3 Multipositional X-ray CT of real multimaterial objects

To demonstrate our fusion methods on multimaterial objects, we present experiments with a test circuit board and an intervertebral disc implant. The implant only consists of plastic (PEEK) and four small tantalum bars (a very dense metal). In contrast, the test circuit board is made of several different plastic and metal parts and, therefore, the test circuit board was a considerably more challenging task. The scans of the implant were performed on a Werth TomoScape HV 500, the scans of the circuit board were performed on a macro CT scanner. Both objects were scanned in two positions with the following parameters (see Table 5).

<table>
<thead>
<tr>
<th></th>
<th>Current</th>
<th>Voltage</th>
<th>Projections</th>
<th>Exposure time</th>
<th>Prefilter</th>
<th>Pixel Size</th>
<th>Detector resolution</th>
<th>Magnification</th>
<th>Voxelsize</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circuit board</td>
<td>1150 µA</td>
<td>450 kV</td>
<td>1600</td>
<td>350 ms</td>
<td>2 mm Cu</td>
<td>200 µm</td>
<td>992 × 992</td>
<td>~ 1.45</td>
<td>140 µm</td>
</tr>
<tr>
<td>Intervertebral disc implant</td>
<td>115 µA</td>
<td>220 kV</td>
<td>495</td>
<td>1 s</td>
<td>no filter</td>
<td>400 µm</td>
<td>1936 × 1936</td>
<td>~ 15.7</td>
<td>25.2 µm</td>
</tr>
</tbody>
</table>

Table 5: Parameters of the scans for the test circuit board and the intervertebral disc implant.

Figure 15: Rendering of the circuit board (from the smART reconstruction) and registered reconstruction slices from two scans with different object positions (Pos.1 and Pos.2) with strong artifacts (dark stripes and other artifacts, e.g. in the red ellipses).

Figure 16: Reconstruction slices of the fusion of both single scans of the circuit board (1), the reconstruction of the merged sinogram of the circuit board with a normal SART (2) and reconstruction of the circuit board with the smART method (3).
Figure 17: Registered reconstruction slices and photographs of an intervertebral disc implant from two scans with different object positions (Pos. 1 and Pos. 2) and reconstruction slices of the fusion of both single scans of the implant (1), the reconstruction of the merged sinogram of the implant with a normal SART (2) for comparison and the reconstruction of the implant with the smART method (3).

In both cases (see Figure 15 and 17), the metal artifacts were very strongly pronounced in the single scans. The multipositional fusion of volumes already reduces these artifacts. However, our smART method improves the image quality even further, so that, for example, the roundness of the tantalum bars is shown correctly and the whole surface of the peak can be measured. In contrast, the SART method using the sinograms of both scans did perform badly, as expected.

4 Conclusions
We have shown that using several scanning positions can decrease the influence of metal artifacts significantly. As can be seen in the experiments, multipositional methods are especially useful, when there are different materials with very different attenuation coefficients involved. We believe that multipositional approaches are the best method to reduce metal artifacts whenever X-rays are attenuated completely or almost completely. However, the experiments on the zinc specimen demonstrate that a multipositional approach can be useful for monomaterial metal objects and improves the measurement accuracy and robustness. As multipositional CT methods can be performed on any CT system without any new hardware, we expect more frequent usage of these methods. Furthermore, these methods should allow CT system with otherwise to low maximum energy to still generate images with reasonably good quality for multimaterial objects that contain metal parts. Furthermore, as the optimal object positioning is often very hard to choose, our presented multipositional methods can help unexperienced CT user to achieve better images by just using multiple positions.

Despite the great qualitative and quantitative results of the presented methods, these methods probably can be improved. In particular, an automatic registration algorithm that is more robust to metal artifacts should increase the measurement accuracy.

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