Suitability of a new alignment correction method for industrial CT

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Abstract

Exact knowledge of the geometrical configuration of an industrial CT scanner is essential for high quality CT image reconstruction. Geometrical misalignment can result in severe misalignment artifacts like blurring and the loss of spatial resolution. In computed tomography, redundantly measured rays (i.e. multiple measurements of a line integral through an object) pose a computationally efficient possibility to quantify the rawdata quality in a cost function and thus to reduce many kinds of artifacts. A general downside of such a cost function is that the portion of redundant rays is generally small and depends on the specific data acquisition geometry. The authors have previously proposed \cite{1} to use information associated to plane integrals instead of line integrals in order to tremendously increase the rawdata utilization when formulating a cost function that quantifies the rawdata quality. However, so far the approach was evaluated on simulated data only. Therefore, based on a large database of industrial CT datasets acquired on a DAGE XD7600NT Diamond FP scanner, the suitability of this approach for industrial CT applications is now evaluated and proven.

Keywords: alignment correction, geometry artifacts, artifact reduction

1 Introduction

Exact knowledge of the scanning device’s geometrical configuration during the acquisition of CT projections is essential for CT reconstruction. Otherwise severe misalignment artifacts like blurring and the loss of spatial resolution degrade the image quality.

There are three general approaches for misalignment correction described in literature that do not require an additional CT measurement of a calibration object or require placing additional markers in the field of measurement: image–based \cite{2-4}, rawdata–based \cite{5}, and reprojection methods \cite{6}.

Rawdata–based misalignment methods formulate a cost function that quantifies the inconsistency of rawdata redundancies, typically on the basis of redundantly measured rays. For most practical source trajectories, the portion of rays that are actually measured redundantly is very low and therefore the practical use of the computationally very efficient rawdata–domain misalignment methods is very restricted.

In \cite{1} we have proposed a new algorithm that uses almost all the acquired rawdata in a rawdata–based misalignment correction scheme. However, the initial evaluation in \cite{1} was restricted to simulated data. Therefore, we have now evaluated the proposed method on a large set of industrial CT datasets measured on a DAGE XD7600NT Diamond FP scanner with a circular source trajectory. The calibration along with the reconstruction and volume visualization were performed using a preliminary version of the CERA software \cite{8}.

In the following, we provide brief overviews of the evaluation datasets, the DAGE scanner, and the alignment correction scheme, followed by an evaluation of the robustness of the proposed method considering sources of inconsistency like data truncation. Finally, we discuss the suitability of the approach for industrial CT applications and give an outlook regarding possible extensions of the method.
2 Materials
We are using a Nordson DAGE XD7600NT Diamond FP system with a DAGE NT100 sealed-transmissive 160kV X-ray tube and a DAGE 3 CMOS flat panel detector. The XD7600NT scanner is a 2d radiography inspection device that was fitted with the DAGE µCT inspection option which provides CT functionality by adding a rotation stage and a CT reconstruction workstation. The µCT option allows easy installation and removal of the rotation stage and thus provides fast switching between 2d and 3d inspection tasks. However, this sometimes leads to misalignments of the detector offsets and rotation axis which need to be calibrated and corrected. This renders this particular system especially interesting for the investigation of geometry misalignment correction approaches.

We have collected a database of 65 datasets that were acquired over a timeframe of several months during routine use of the DAGE system. The database includes a broad variety of objects from many different sources and is representative for the 3d inspection tasks that are usually conducted with this device. Some of the datasets are fast scans with 720 projections while others are high-quality scans with 1440 projections. Figure 1 shows volume renderings (VRT) of five typical datasets included in the database.

![Figure 1: VRT images of five typical datasets considered in this evaluation.](image)

The misalignment correction method that we proposed in [1] exploits redundantly measured planes and thus is potentially affected by sources of data inconsistencies that are not due to geometrical misalignments. Examples are data truncation, beam-hardening, scatter, and photon blocking. To evaluate the robustness of the proposed approach with regard to these influences we made sure that the evaluation set contains datasets that are affected by these effects. Due to the presence of strongly absorbing materials like soldering lead in most of the datasets and the tube voltage limit of 160kV, most of the datasets are affected by beam-hardening. Moreover, scatter and even photon blocking are common sources of artifacts in many of the datasets.
Especially interesting is the influence of data truncation on the proposed method. While basically all datasets that we are considering are truncated in axial direction (mostly due to the object holder), we also made sure that a considerable number of datasets is additionally severely truncated in transaxial direction. Figure 2 shows two example projections with typical cases of slight and severe data truncation.

\[ p(\lambda, u, v) = \int_{-\infty}^{\infty} f(\bar{s}(\lambda) + t\bar{t}(\lambda, u, v))dt \]

The scalar lambda parameterises the piecewise continuous trajectory \( \bar{s}(\lambda) \), that contains all source positions \( \bar{s}(\lambda_n) \), with \( n \in [1, N] \):

\[ \bar{t}(\lambda, u, v) = \frac{\bar{o}(\eta) + u\bar{u}(\eta) + v\bar{v}(\eta) - \bar{s}(\eta)}{[\bar{o}(\eta) + u\bar{u}(\eta) + v\bar{v}(\eta) - \bar{s}(\eta)]} \]
Now picture any plane $\Omega$ through the object that intersects the source trajectory at least twice, at $n$ and $\hat{n}$, with $n \neq \hat{n}$. Furthermore, denote the intersection between the plane $\Omega(\eta) : \bar{x} = \bar{d}(\eta) + a\bar{u}(\eta) + b\bar{v}(\eta)$, with $a, b \in R$ and the detector plane of projection $n$ as the line $\theta(n, \mu, l)$, which is parameterised using the detector-based quantities $\mu \in [-\pi/2, \pi/2]$ (line orientation) and $l \in [-L_{\text{max}}, L_{\text{max}}]$ (signed distance between line and detector center ($u_0, v_0$)) (compare Figure 3). In a cone–beam CT system without rawdata truncation, it is then possible to compute two redundant values associated to $\Omega$: one involving data acquired from $s(n)$ along the line $\theta(n, \mu, l)$ and another one using the data from $s(\hat{n})$ along the line $\theta(\hat{n}, \hat{\mu}, \hat{l})$.

![Figure 3: Illustration of the notations used for the Radon transform and the correlation between two corresponding lines $\theta(n, \mu, l)$ and $\theta(\hat{n}, \hat{\mu}, \hat{l})$. The plane $\Omega(n, \mu, l)$ associated with those two lines is indicated in grey.](image)

The algorithmic steps that are necessary to formulate the relationship between the line data are similar to parts of the Clack-Defrise [3] cone-beam reconstruction algorithm:

1) Application of inverse cosine weighting to the measured projections $p$ to obtain the weighted projections $g_1$:

$$g_1(\lambda_n, u, v) = \frac{1}{|\bar{w}(n) \cdot \bar{t}(n, u, v)|} p(\lambda_n, u, v)$$

2) Computation of the 2d Radon transform of the weighted projections $g_1$ to obtain a sinogram-like representation $g_2$:

$$g_2(\lambda_n, \mu, l) = \int g_1(\lambda_n, l \cos \mu - t \sin \mu, l \sin \mu + t \cos \mu) dt$$

3) Finally, differentiation of the sinogram-like representation $g_2$ with respect to $l$ to obtain the redundancies $g_3$:

$$g_3(\lambda_n, \mu, l) = \frac{\partial}{\partial l} g_2(\lambda_n, \mu, l)$$

We can now use a detector line and a source point to parameterise a plane $\Omega(\lambda, \mu, l)$. In the vast majority of cases, the same plane is measured redundantly and can be described using a complementary triple $\hat{\lambda}, \hat{\mu}, \hat{l}$. As discussed in [7] we can expect $g_3(\lambda_n, \mu, l) = g_3(\hat{\lambda}, \hat{\mu}, \hat{l})$. Based on this we can define a cost function that quantifies data inconsistencies using redundant planes (RP):
\[ c_{RP} = \sqrt{\sum_{\eta=0}^{N-1} \sum_{\mu=-\pi/2}^{\pi/2} \sum_{l=-L_{\text{max}}}^{L_{\text{max}}} \left( g_{3}(\lambda_{\eta}, \mu, l) - g_{3}(\hat{\lambda}, \hat{\mu}, \hat{l}) \right)^2} \]

4 Experiments and results

For each of the 65 datasets we used the initial geometry definition as provided by the DAGE software as starting points and applied a grid-search to find a geometry parameter set with the lowest cost \( c_{RP} \).

Five global geometry parameters are considered: the horizontal and vertical detector offsets \( u_0 \) and \( v_0 \) and three parameters \( a, b, c \) that represent tilts of the rotation axis or detector. Then a reconstruction using the configuration with the lowest cost function value was performed and the resulting image quality was visually evaluated. Thereby good image quality means that there are no doubled structures, no obviously unsharp edges, and that point-like objects do not appear blurred or ring-like. Figures 4 and 5 show comparisons of a reconstructed dataset before and after the misalignment correction was applied.

Figure 4: Comparison of a XY slice of a dataset before (left) and after (right) misalignment correction. In this case only the horizontal detector offset was considerably misaligned and there were virtually no rotation axis or detector tilts. Notice the doubled structures in the misaligned slice on the left.
For 63 of the 65 datasets the resulting image quality was considered to be very good and the misalignment correction turned out to be successful. In the remaining two cases, the initial correction was only partially successful. Both contain objects with very little contrast and the projection images are dominated by the object holder. In these cases a successful misalignment correction was finally obtained by cropping the projection images to get rid of the dominating object holder (cp. Figure 6).

The new cost function $c_{RP}$ was found to be very smooth for all considered geometry parameters with exception of the tilt parameter $a$. But even for this parameter it was possible to identify a clear global minimum for all datasets (cp. Figures 7 and 8).
Figure 7: Plot of the cost function $c_{RP}$ for all datasets and varying the parameter $b$ in steps of 0.143°. For each plot the $c_{RP}$ values have been normalized to the range $[0;1]$ and centered on the identified global minimum.

Figure 8: Plot of the cost function $c_{RP}$ for all datasets and varying the parameter $a$ in steps of 0.286°. For each plot the $c_{RP}$ values have been normalized to the range $[0;1]$ and centered on the identified global minimum. $a$ is the only parameter where $c_{RP}$ was not found to be smooth for a considerable number of datasets. However, the global minimum could still be easily identified.

5 Conclusions and outlook
Misalignment correction based on redundantly measured plane integrals was found to be suitable and very robust for industrial CT applications with circular source trajectories. The most important global geometry misalignments, detector shifts, rotation axis tilts, and detector tilts can be robustly corrected.
with the proposed method. The correction does not require markers or CT measurements of calibration objects. In 97% of the test cases a fully automatic correction was possible. The remaining cases required manual specification of a crop-box to exclude the dominating object holder from the computations. An automatic detection and cropping of the object holder, which is not yet realized, would allow for a fully automatic solution.

The proposed approach is computationally inexpensive as it works entirely in sinogram domain and does not require a single image reconstruction. Furthermore, all algorithmic steps are well suited for parallelization which allows efficient implementations on accelerator hardware like GPUs or the Xeon Phi.

While we have initially focused on circular source trajectories, applying the proposed method to other source trajectories which are often used in industrial CT applications, like circle plus line and helical trajectories is possible and is an extension we are currently working on.

In addition we are currently evaluating the suitability of using the redundant-plane-integrals metric to determine and correct local misalignments that are due to system jitter or object movement.

References


