A new calibration-free beam hardening reduction method for industrial CT

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Abstract
This work evaluates a new reference-free beam hardening reduction algorithm for industrial CT applications. The new method is fully automatic and robust to scatter and misalignment, while only consuming a third of the time required for reconstruction. Beam hardening reduction is performed by optimizing a raw data redundancy metric with respect to parameters of a polynomial model. The linearity of this model enables an efficient solution by convex optimization. We present an evaluation of experimental results on a extensive database of industrial CT data sets. The datasets cover a wide range of practically relevant multi-material objects with additional sources of artifacts like photon starvation and truncation. We conducted a user study comparing our method against a manual method, were an expert optimized image quality by selecting an appropriate beam hardening reduction function from a number of options. We find that our method can be applied to industrial CT problems to automatically yield beam hardening reduction on par with a time-consuming manual optimization of image quality by an expert. Since the method is completely image-based it simplifies the adaptation of CT systems to different application fields.

Keywords: beam hardening, polychromatic artifacts, artifact reduction

1 Introduction

In every CT system using a conventional polychromatic source, the log-attenuation is a nonlinear function of the object density, producing severe artifacts known as cupping and streaks. These artifacts can be reduced by appropriate pre-filtration of the X-ray intensity spectrum. However this increases the strain on the X-ray tube because it requires longer exposure or a higher tube current if the measurement time should be kept constant. Software approaches are a common alternative solving these issues. Those approaches mostly use a reference measurement of a phantom to estimate a function of the attenuation compensating beam hardening for one particular system [1]. During the lifetime of a system both the source and detector characteristics are subject to change. Therefore, a weakness of these reference-based methods is the additional effort required and the fact that this effort occurs repeatedly. Additionally, in certain cases many different materials might be scanned or they might be unknown, rendering calibration burdensome or even impossible. Because of this, material and scanner independent algorithms are a pressing need in industrial non-destructive-testing. They can enable rapid adaptation of CT imaging to different applications. To this end iterative algorithms have been explored combined with multi-material beam hardening models. While those algorithms yield good results their computational demands render them prohibitively expensive. Additionally they require prior knowledge about the materials in the scan, estimates of the spectrum of the X-ray source and the detector response characteristics [2],[3] or render the optimization problem non-convex [4],[5]. A reference-free iterative multi material beam hardening reduction method was presented by Krumm et al. [6]. Their method relies on a accurate segmentation method which can cope with the artifacts introduced by beam hardening. However accurate segmentation may be very challenging and the method is computationally very demanding. These problems can be remedied by using the inherent redundancy in CT to form a projection-domain cost function for artifact reduction.
So far, most existing raw data based methods have not been applicable to the practically relevant cone-beam geometry. Recently a new consistency condition for the cone-beam geometry based on redundant plane integrals has been proposed [7] and it's efficient computation as epipolar consistency condition (ECC) [8]. A cost function derived from the ECC has successfully been applied to industrial CT to reduce geometric misalignment [9]. The authors have previously proposed [10] a computationally efficient algorithm using the same metric, to reduce the effect of beam hardening. However, the approach was mostly evaluated on simulated data and presented for application in medical imaging. Based on a database of measured data sets, the suitability of this approach for industrial CT applications is now evaluated in this work.

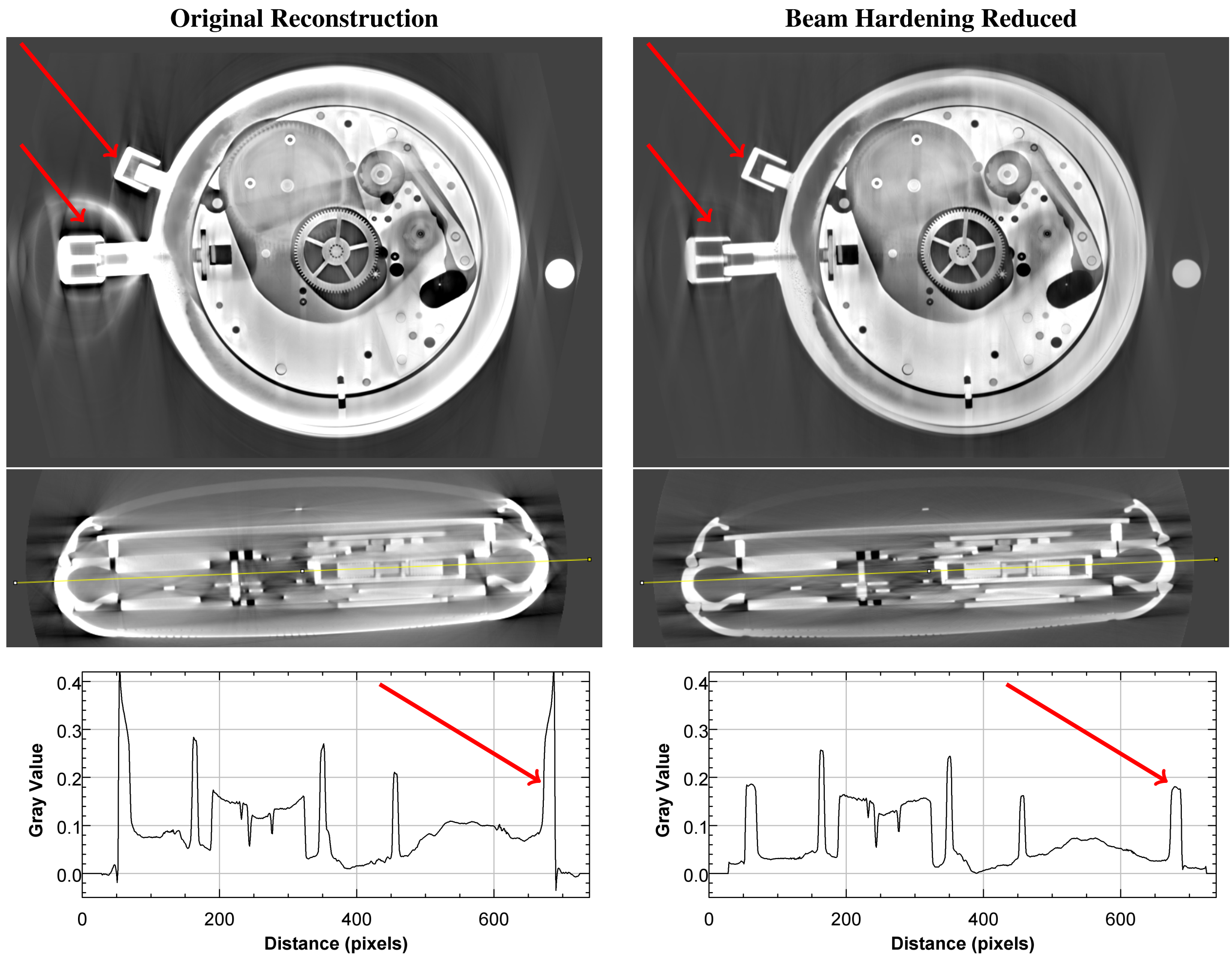

Figure 1: Metal stopwatch before and after beam hardening reduction.

2 Method

The epipolar consistency condition [8] states that line integrals along corresponding Epipolar lines of two cone-beam projections are mathematically equal, if one forms their derivative in orthogonal direction to their common epipolar plane. This has an intuitive explanation as one can interpret the consistency condition as a comparison of redundantly measured plane integrals. The values of those plane integrals are not equal in cone-beam geometry due to the perspective effect. However the derivative operation cancels out the perspective effect and the redundantly measured plane integrals become comparable. A key feature of this formulation is the possibility to precompute those derivatives of line integrals using the Radon transform. The condition can then be stated as:

$$\frac{\partial}{\partial t}\rho_{I_0}(\mathbf{l}_0) = \frac{\partial}{\partial t}\rho_{I_1}(\mathbf{l}_1)\,, \tag{1}$$

where the $\frac{\partial}{\partial t}\rho_I$ denote partial derivatives of the Radon-transform of the log transformed projection data: $R\left(\ln\left(\frac{I}{I_0}\right)\right)$, while the vectors $\mathbf{l}$ denote corresponding epipolar lines. We denote an element of the measured line-integral data which is affected by beam hardening as q while we denote the beam hardening reduced element as p. We use the same polynomial model of degree d parameterized by a vector $\mathbf{w}$ as the calibration method by Kachelrieß et al. [1]:

$$p(q,\mathbf{w}) = w_0 + w_1 q + \cdots + w_d q^d\,. \tag{2}$$

We use the linearity of the Radon transform and the derivative operator and formulate our consistency condition after beam hardening reduction as:

$$\sum_{n=1}^{N} w_n\left(\frac{d}{dt}\rho_{\mathbf{I}_0^n}(\mathbf{l}_0)\right) \approx \sum_{n=1}^{N} w_n\left(\frac{d}{dt}\rho_{\mathbf{I}_1^n}(\mathbf{l}_1)\right), \tag{3}$$

where $\mathbf{I}^n$ denotes transforming the projection $\mathbf{I}$ pixel-wise to its n-th power. For every epipolar plane of every pair of projections we get:

$$min\left(\sum_{n=1}^{N} w_n a_n\right)^2, a_n = \left(\frac{d}{dt}\rho_{\mathbf{I}_0^n}(\mathbf{l}_0) - \frac{d}{dt}\rho_{\mathbf{I}_1^n}(\mathbf{l}_1)\right). \tag{4}$$

We want to solve this problem involving all projections and every available epipolar plane. This means we have M measurements a_{mn} which produce a homogeneous overdetermined system of linear equations, which we can solve in a least squares sense as:

$$\min\left(\|\mathbf{Aw}\|_2^2\right) \quad \text{s.t. } \mathbf{w}^T\mathbf{b} = \beta\,, \quad w \geq 0 \quad \forall w \in \mathbf{w}\,.$$

Here $\mathbf{A}$ denotes a matrix representing the necessary equations with elements: $a_n = \left(\frac{\partial}{\partial t}\rho_{\mathbf{I}_0^n}(\mathbf{l}_0) - \frac{\partial}{\partial t}\rho_{\mathbf{I}_1^n}(\mathbf{l}_1)\right)$, stated by the consistency condition. The vector $\mathbf{b}$ is a Vandermonde vector $\left(b^1, b^2, \cdots b^d\right)$ which in conjunction with β specifies the effective energy implicitly. In practice b and β can both be set to a stable maximum value, discarding outliers in the line integral data. The positivity constraints on the coefficients enforce prior knowledge about physically plausible beam hardening reduction models by forcing solutions to be monotone and convex, thereby making the algorithm robust to challenging imaging conditions. The method is computationally efficient because as it only needs a single computation considering the raw data, while the optimization is carried out over fixed data-terms. This convex optimization problem can readily be solved by gradient-based algorithms supporting constraints.

2.1 Failure case detection

Since consistency conditions reflect every source of inconsistency in the dataset and the polynomial model can only reduce beam hardening caused by a single material, the proposed algorithm may produce weak results in certain cases. Among those, photon starvation is especially critical since it corresponds to an infinite slope in the beam hardening reduction function. This leads to the algorithm overcompensating beam hardening. In practice such cases can be detected by checking the curvature of the polynomial. If this curvature is maximal for the given degree d it indicates that either d is to small to represent the necessary curvature or the algorithm has failed. From our prior experience a degree $d = 3$ allows sufficient curvature for typical datasets.
Since the constraint $\mathbf{w}^T\mathbf{b} = \beta$ restricts the solutions to interpolate the point (b, β) the maximum curvature of the polynom occurs when the coefficient of the highest monom is maximal. This means the coefficient vector consists solely of zero entries except the highest order coefficient:

$$(0, \cdots, 0, w_d)\,. \tag{5}$$

So maximal curvature can simply be detected by analyzing the coefficients of the estimated polynom.

3 Materials

Our database contained 40 datasets of industrial CT scans. It covers a variety of objects ranging from a metal stopwatch (Fig. 1) over circuit boards and aluminium cast objects to a electrolytic capacitor. The database contains scans with 700 to 1500 projections. Visual inspection revealed that 15 out of 40 datasets are affected by severe transaxial truncation and 12 are affected by photon starvation. All of them contain beam hardening and scatter artifacts due to the presence of strongly absorbing materials like soldering lead.
A difficulty in evaluating the new method on a set of measured datasets is the absence of a groundtruth reference. This means evaluation has to be carried out subjectively or a comparison to a reference method has to be conducted. A pragmatic method of reducing the beam hardening effect in industrial CT is to use a mono-material compensation method based on physical properties of a known material. If the material is not known precisely or the dataset contains multiple materials, multiple reconstructions with different settings can be reconstructed. An expert can then heuristically choose the reconstruction with the highest image quality. We refer to this method as the manual optimization.
Another challenge is to find a figure of merit to compare image quality between the reference and the proposed method. Previous work has found entropy of the gray value histogram of reconstructions to be an effective measure in assessing image sharpness [**?**]. Entropy is given as:

$$S = -\sum_i p_i \ln(p_i)\,, \tag{6}$$

where p denotes the probability of a certain gray value as estimated by the histogram. This has been exploited to reduce beam hardening in dual energy CT [**?**]. Entropy is not an optimal measure of assessing image quality as it does not

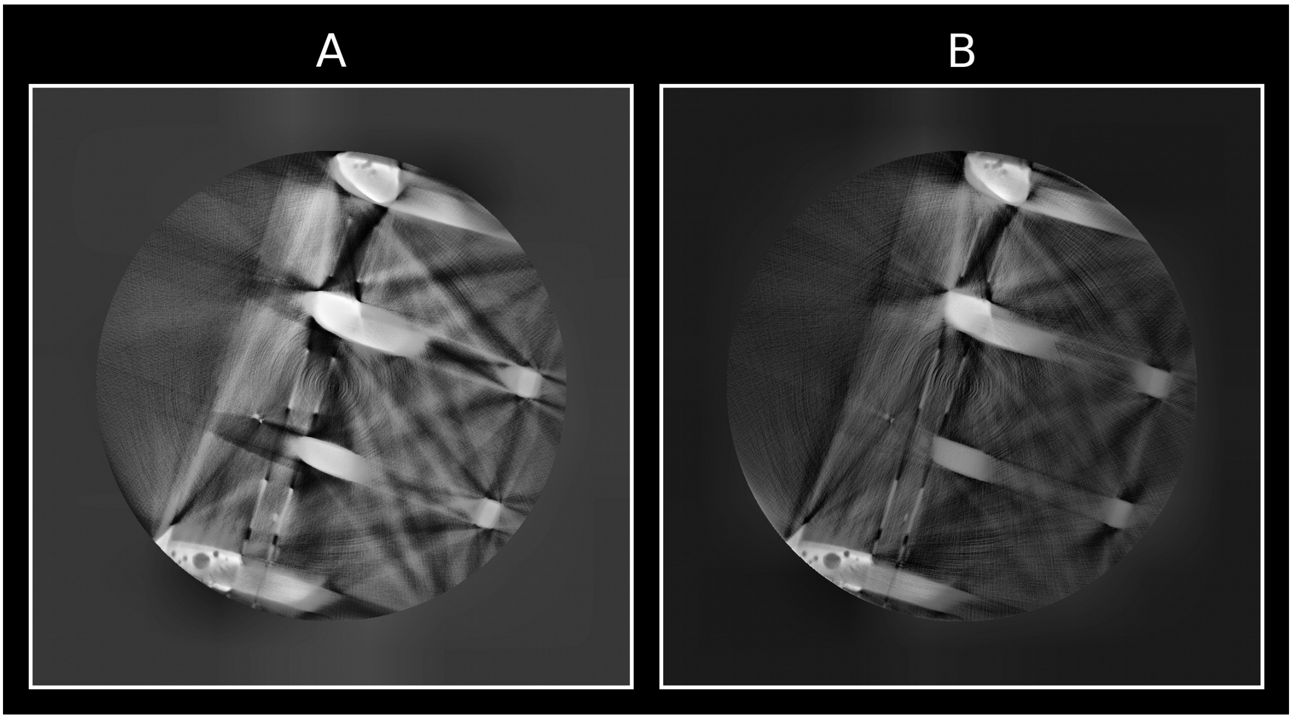

Figure 2: Example of a contrast enhanced image from the user study. **A** and **B** randomly denoted the two different methods for blind assessment.**A**: Manually optimized method, **B**: Proposed method

necessarily correspond to artifact reduction. However it's known to correlate negatively with beam hardening reduced images.
To better assess perceived image quality we conducted a user study involving 3 industrial CT experts and 7 medical CT experts.

4 Experiment

For the manual optimization we used three different beam hardening compensation functions corresponding to a material of high, medium, and soft attenuation. We performed reconstruction using all of them. For all 40 datasets a single industrial CT expert chose the visually optimal reconstruction based on the central slice. We used these visually optimized datasets as our reference method.
To compare those to reconstructions obtained by using our fully automatic method we calculate entropy on the gray level histogram of the complete volume. For every dataset we used a degree $d = 3$ and $b = \beta = \max(\mathbf{q})$, where $\max(\mathbf{q})$ denotes the maximal line integral value of the projections. Additionally we extract the central slice and apply a locally adaptive contrast normalization (CLAHE) to the images [**?**] to provide an automatic equal windowing to every user, preserving all areas of interest. Fig 2 presents an example of an image in the user study. In one case we used a manually selected slice because no object of interest was contained in the central slice. We conducted the study in a blind manner randomly presenting the proposed method on the left (A) or the right (B) side of the image. The users rated them with one of five ordinal scores (A$\uparrow\uparrow$,A$\uparrow$,0,B$\uparrow$,B$\uparrow\uparrow$) which denote the range from a large advantage in image quality of image A, over a slight advantage and no advantage to a large advantage for image B.
During the user study we used the same monitor setup for the industrial CT experts and a different setup for the medical CT experts. The lighting conditions were not controlled in either setup but constant due to the short evaluation time.

5 Results

The numerical analysis showed that our method decreased entropy in 34 out of 40 datasets compared to the manually optimized method, indicating a quantitative advantage in terms of sharpness. We inspected the other 6 datasets and found that the automatic method decreased streak artifacts in those cases providing superior image quality in 5 out of this 6 cases, confirmed by the results of the user study.

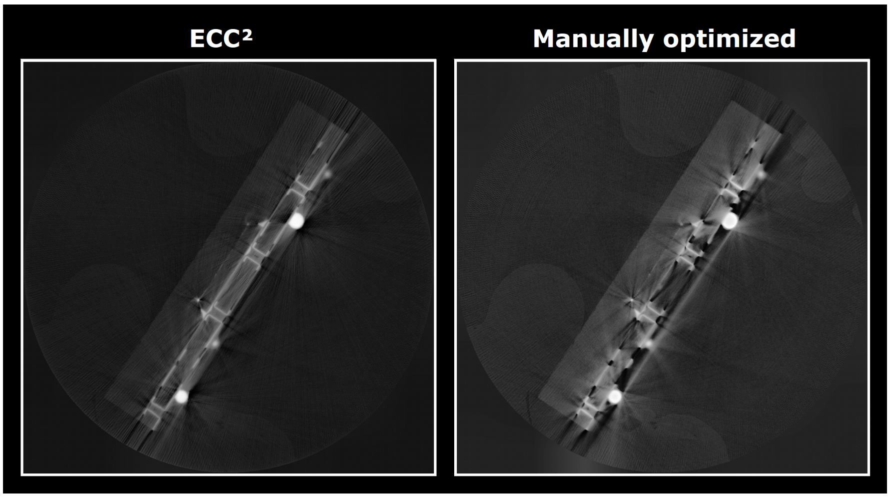

Figure 3: Example were users preferred the proposed method over the manual.

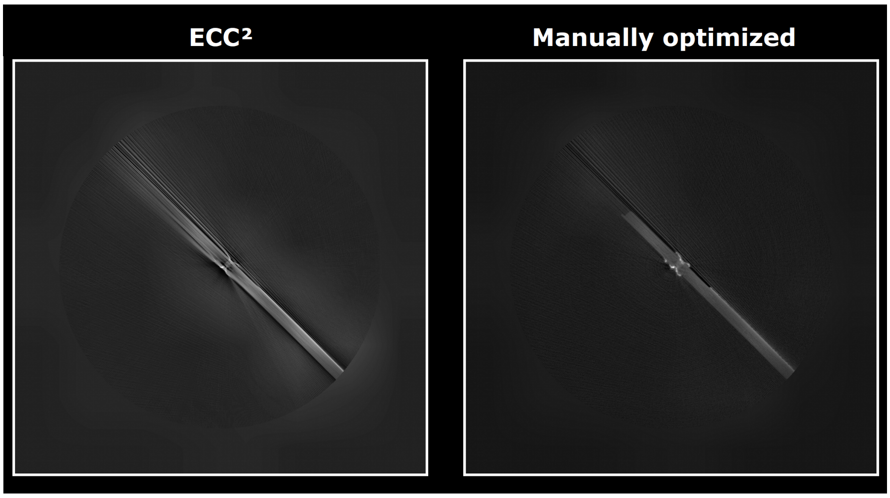

Figure 4: Failure case of the proposed method according to the user study.

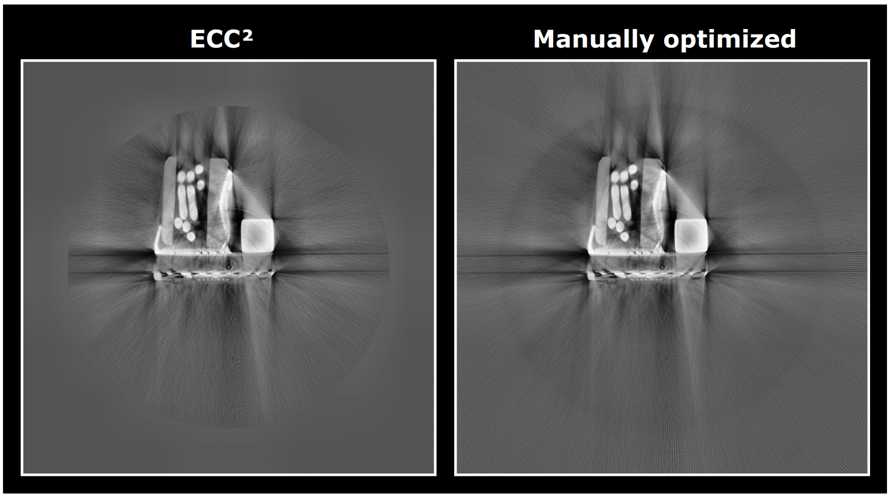

Figure 5: Example of an image were the users were indifferent to the choice of method.

For the analysis of the results of the user study we re-identified the 396 votes obtained by the 10 users with the respective methods and created table 1 containing the sum of all user ratings. The A and B ratings are replaced by the respective method names.

Manual$\upuparrows$	Manual$\uparrow$	0	ECC^2 $\uparrow$	ECC^2 $\upuparrows$
74	98	118	88	18
19%	25%	30%	22%	4%

Table 1: Results of the user study.

These results suggest that manual optimization is preferable to the plain application of the proposed algorithm. We specifically examined the cases were the algorithm did perform worst according to the users. We found that the five worst rated cases showed severe photon starvation. The cases were ECC^2 was rated better mostly showed a decrease in streak artifacts in homogeneous regions and precisely reduced cupping, which was not possible in the manual method due to the limited number of beam hardening reduction functions. Despite the beam hardening reduction model being tailored towards objects of a single material we observed that multi material datasets can be improved quite well as long as they don't suffer from photon starvation.
We discarded every dataset for which the result of the ECC^2 algorithm corresponded to the maximum possible curvature. This reduced the number of datasets by 18 items.

Manual$\upuparrows$	Manual$\uparrow$	0	ECC^2 $\uparrow$	ECC^2 $\upuparrows$
16	42	94	59	8
7%	19%	43%	27%	4%

Table 2: Results of the user study after automatic removal of potential failure cases.

Table 2 shows the updated results. Out of the 18 datasets removed we found that 14 corresponded to cases where the ECC^2 algorithm was rated worse than the manual and only 4 were it was rated better. Based on these results the proposed algorithm outperforms even the manual optimization.
We show an example were the users preferred the ECC^2 method in Fig. 3, an example were the algorithm fails in Fig. 4, and an example where users have been indifferent in Fig. 5.

6 Discussion

The comparison in the user study is generally biased in favour of the manual method because a) it directly optimizes the visual perception of a human observer and b) we compare a fully-automated solution with a solution that requires dataset-specific inputs by the user. We nevertheless believe this is preferable to evaluating the algorithm against reconstructions without any beam hardening reduction algorithm because it provides a better view on the properties of the new algorithm.
Additionally, the contrast enhancement method used for the presentation of the results here and in the user study, eliminates a potential contrast improvement of either method. Since the ECC^2 often also provides increased contrast in most cases this biases the results further towards the manual optimization. Nevertheless we showed, that by using a simple success criterion the proposed algorithm outperforms even the time-consuming manual optimization by an expert. This was in good agreement with the numerical analysis of the entropy of the results showing a clear advantage for the proposed method when automatically detected cases, where the automatic beam-hardening reduction did fail, were ruled out. We found that photon starvation is most harmful to the method among all other effects. However most of these cases can be detected with the maximum curvature criterion.

7 Conclusions and outlook

Beam hardening reduction based on redundantly measured raw data was found to work superior to manual optimization of beam hardening reduction for industrial CT applications. Typical artifacts which appear when a physical calibration with imperfect knowledge of the parameters of the system is applied can be reduced. The method is fully automatic and was found to be robust to many problems commonly encountered in non-destructive imaging. Its main advantage is, that is does not require any prior knowledge about the CT system, while still only consuming $\approx 29\%$ of the time required for a reconstruction. This enables applying CT to arbitrary new application fields without time consuming calibration or heuristic manual beam hardening reduction by an expert.

A weakness of the method are datasets affected by photon starvation. Datasets which contained this problem could not be improved automatically. We consider finding ways to improve robustness of the algorithm specifically in this regard the most important direction of further work.
Additionally the evaluated method only employs a model to correct for a single material, while most datasets in industrial CT contain multiple materials. Therefore another important generalization is the extension to a model correcting for multiple materials. This is not straightforward, as a reliable estimation needs to segment materials and estimate a joint multi-dimensional beam hardening reduction function. This increases requirements on the robustness of the algorithm as well as posing problems with respect to finding generalizations of the constraints on the solution to yield monotonous and convex solutions. Another line of future work is to combine methods relying on the epipolar consistency condition in a multi-dimensional optimization yielding improved results for all those methods, because inconsistency from other sources is reduced.

Disclaimer
The concepts and information presented in this paper are based on research and are not commercially available.

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