Empirical Scatter Correction (ESC): A New CT Scatter Correction Method and its Application to Metal Artifact Reduction

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Abstract — Scatter artifacts impair the CT image quality and the accuracy of CT values. Especially in cases with metal implants and in wide cone-angle flat detector CT scans, scatter artifact removal can be of great value.

Typical scatter correction methods try to estimate scattered radiation and subtract the estimated scatter from the uncorrected data. Scatter is found either by time-consuming Monte Carlo–based simulations of the photon trajectories, or by rawdata–based modelling of the scatter content using scatter kernels, whose open parameters have to be determined very accurately and for each scanner and type of object individually, and that sometimes even require a data base of typical objects. The procedures are time-consuming and require intimate knowledge about the scanner, in particular about the spectral properties, for which a correction is designed.

We propose an empirical scatter correction (ESC) algorithm which does not need lots of prior knowledge for calibration. ESC assumes that a linear combination of the uncorrected image with various ESC basis images is scatter-free. The coefficients for the linear combination are determined in image domain by maximizing a flatness criterion of the combined volume. Here, we minimized the total variation in soft tissue regions using the gradient descent method with a line search. Simulated data and several patient data sets acquired with a clinical cone–beam spiral CT scanner, where scatter was added using a Monte Carlo scatter calculation algorithm, were used to evaluate ESC. Metal implants were simulated into those data sets, too.

Our preliminary results indicate that ESC has the potential to efficiently reduce scatter artifacts in general, and metal artifacts in particular. ESC is computationally inexpensive, highly flexible, and does not require know-how of the scanner properties.

I. INTRODUCTION

SCATTER artifacts show up as cupping artifacts, dark streaks between dense objects, inaccurate CT values in general, and in flat detector CT they further tend to blur edges of objects [1, 2]. An efficient scatter artifact removal technique would be of great value which is quite obvious for flat detector CT.

Even in third generation clinical CT, where hardware and software solutions for scatter reduction are implemented and are generally regarded as sufficient, image quality can still be improved by scatter correction [3]. This especially applies in the presence of metal and with increasing cone-angle. Strongly attenuating objects, such as metal implants, for example, cause a drastic increase in the scatter–to–primary ratio in the shadow of these objects. The consequence are streak artifacts, which are often very similar to beam hardening artifacts in their appearance.

Algorithmically, scatter artifacts can be reduced by estimating the scatter content \( s \) of a projection \( q \) and by reconstructing the corrected rawdata \( p = q - s \), i.e. the estimated scatter is simply subtracted from the original rawdata.

There exists a large amount of scatter artifact reduction algorithms in literature. The simplest scatter correction algorithms are based on the assumption that the scatter content in the projections is approximately constant [1].

Some more sophisticated algorithms are based on a convolution of the measured projection data with dedicated blurring kernels. The assumption behind these algorithms is that the scatter signal is a very smooth signal that does not contain high frequencies [3–5].

Another class of scatter correction algorithms uses the Monte Carlo method to simulate photon transport and to calculate the scatter content by simulating photon paths through the patient. Monte Carlo based scatter correction algorithms are always iterative algorithms that start with a initial reconstruction of the uncorrected CT image that contains scatter artifacts. Based on this image the scatter

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signal is estimated and subtracted from the original, measured projection values. This procedure is repeated several times until the scatter artifacts in the image are sufficiently reduced [6, 7].

Instead of using Monte Carlo simulation directly for scatter estimation, there are also methods that use Monte Carlo simulations to compute scatter signals for a given set of phantoms with different geometries and material compositions. These signals are then used to generate the scatter signal for an arbitrary object [8–10].

Similar scatter corrections are based on scatter databases that were generated by scatter signal measurements. Instead of simulating scatter signals by Monte Carlo simulations, scatter signals were measured for example by using the beam stop method for different calibration phantoms. The scatter signal for other objects were then inferred from these scatter signals [11].

Besides algorithms that try to estimate scatter there are also correction methods that are based on direct measurements of the scattered radiation. To measure the scatter content in the projection data additional projections are acquired. For the measurement of these additional projections a beam stop grid, usually made of lead, is placed between the source and the object. It is assumed that the signal measured in the detectors behind the lead is mainly caused by scattered radiation. The scatter signal for the detectors that are not located in the lead shadow is then computed by interpolation. The drawback of these methods is that they always require a modification of the scanner equipment, complicate the scanning procedure and may increase the dose delivered to the patient [12, 13].

Similar to the beam stop methods, the authors of reference [14] suggested a method that estimates the scatter content in the projection data from pixels that are located in the shadow of the collimation. The scatter content for the whole projection is estimated by linear interpolation from the detector pixels that lie in the shadow of the collimation.

Monte Carlo simulations are object-specific, able to model all underlying physics accurately and yield good results in general [6, 7, 15, 16]. They are, however, computationally slow, require accurate knowledge about the x-ray spectra and about the attenuation properties of the object, and therefore do not serve as a routine solution in clinical CT yet.

The estimation of scatter by convolution methods is a computationally efficient alternative [3, 17–19]. A drawback is the dependence on a very accurate calibration of parameters. This is time-consuming and requires intimate knowledge about the scanner for which a correction is designed. Also, if the chosen model does not describe the scatter well enough, the correction results will contain remaining artifacts [19].

While most prior arts focus on the correction of forward scatter, the authors of [20] describe two methods for cross scatter correction in dual source CT. One technique is model-based and assumes that cross scatter is mostly surface scatter. A look-up table containing previously measured cross scatter distributions for a variety of different objects is used for the correction. The other method uses dedicated scatter sensors for the measurement of scattered radiation during the CT scan.

All methods available today need to be well calibrated to correctly model the scanner specifics (tube voltage, pre–filters, collimation, scatter grids, detector response) and some of them even require a data base of typical objects or typical shapes, including the corresponding scatter and the corresponding primary intensities.

We here propose an empirical scatter correction (ESC) that is very flexible, computationally efficient, and that does not need a very accurate calibration.

II. Method

A. Idea

The empirical scatter correction algorithm is based on similar ideas as the empirical beam hardening correction (EBHC) algorithm that was proposed recently [21]: Basis images reflecting the potential artifact content are calculated, and a linear combination of these is added to the original volume in a way to maximize the flatness of the resulting volume. ESC in this work uses the scatter model of reference [3], but it can be combined with various scatter convolution functions to come up with scatter basis images $S_1, S_2, \text{to } S_N$.

ESC simply assumes that the linear combination $q = p + c_1s_1 + c_2s_2 + \ldots + c_Ns_N$ with unknown coefficients $c = (c_1, c_2, \ldots, c_N)$ is scatter–free. Thereby $p$ denotes the measured rawdata, $s_n$ denotes scatter content, and $q$ denotes the corrected rawdata. The unknown coefficients $c$ are determined in image domain by maximizing the flatness of the volume $Q = P + c_1S_1 + c_2S_2 + \ldots + c_NS_N$, with the capital letters denoting the volumes reconstructed from the corresponding projection data components.

B. Basis Images

There are various suggestions in the literature of how scatter can be estimated from a single projection. The simplest model assumes that there is a constant scatter background [1, 17]. Another example is the method which was proposed in reference [18]: As scatter is very smooth in general, scattered radiation can be estimated by a convolution of the primary intensity with a Gaussian kernel, where the width and the height of the Gaussian are open parameters which have to be chosen carefully.

A third model, which we will refer to as pep–model in the following, was proposed in reference [3]. The pep–model is more general and it accounts for the underlying physics quite well. It is the model of choice in this work, although ESC is not restricted to using the pep–model.

For the pep–model the intensity of the scattered radiation $I_s$ is computed as a convolution of a forward scatter intensity function $I_F$ and a shape function $K$. We present the model in its one–dimensional version here for the ease of notation, but it is straightforward to use it in two dimensions. For a one–dimensional detector, such as a sin-
Fig. 2. Proof of concept: Scatter was simulated with two different sets of coefficients of the pep–model. It was added to the rawdata of a patient with bilateral hip prostheses. This experiment was performed in order to show that the total variation is a proper cost function in case of the complex anatomy of real patients. ESC with the two ideal basis images yields a flat correction result and comes very close to the desired true linear combination coefficients.

gle detector row, the parameter $\chi$ parameterizes the angle within the fan. For a two–dimensional detector we can think of $\chi$ comprising the detector’s lateral and longitudinal coordinate. In [3], the scatter intensity is calculated as

$$I_S(\chi) = I_F(\chi, p) \ast K(\chi).$$

Let us consider one ray $\chi_0$ passing the measured object. $I_F(\chi_0, p)$ calculates the amount of scatter which reaches the detector. The stronger the ray is attenuated the more scatter is generated. On the other hand, the stronger the ray is attenuated, the stronger the scatter is attenuated, too.

From these two properties reference [3] derives the forward scatter intensity as the product of the line integral $p$ and the corresponding intensity $e^{-p}$, which together is $pe^{-p}$ and this is why we refer to it as pep–model. The forward scatter intensity is calculated as

$$I_F(\chi, p) = \alpha p(\chi)e^{-p(\chi)}$$

with $\alpha$ being a scale parameter depending on the scatter cross section.

The shape function is a symmetric function describing the distribution of the forward scatter intensity on the detector. It is chosen as the sum of two Gaussians, where the parameter $\gamma$ controls the width and parameter $\beta$ the distance between the two extrema:

$$K(\chi) = e^{-(\frac{\chi-\beta}{\gamma})^2} + e^{-(\frac{\chi+\beta}{\gamma})^2}.$$

For ESC several parameter sets $(\alpha_n, \beta_n, \gamma_n)$ are chosen to come up with several basic images. As several parameter sets are used, it is not important that each of them perfectly models the scatter component which has to be removed. To correct scatter artifacts successfully, the only condition is that there is a linear combination of some of the basis images which models the scatter well.

The pep–model computes estimates of the scatter intensities, but ESC needs rawdata of the scatter component, which can be added linearly in the logarithmic rawdata domain. The rawdata $s_n$ for a basis image $S_n$ is $s_n = -\ln(I_S + I_F) + \ln(I_F)$.

C. Determination of the Linear Combination Coefficients

The total variation (TV) is a measure of flatness in an image. Regions of soft tissue are almost flat in CT images. However, streaks, cupping, and artifacts in general reduce this flatness. It was shown in reference [21] that the total variation is a suitable cost function to correct for beam hardening artifacts. Since this flatness assumption does not always hold for bone tissue these regions are excluded by weighting their contribution with a weight $w(r)$ of zero. Air regions are excluded as well. The weight was obtained by simple thresholding in our examples. The total variation of an image $f$, weighted with $w(r)$ is defined as:

$$TV(f) = \int d^3r w(r)|\nabla f(r)|.$$

The linear combination coefficients $c$ for the basis images are determined as

$$c = \arg\min_c TV(Q + \sum_{n=1}^{N} c_n S_n).$$

The optimization is carried out via the gradient descent method. As shown in reference [21], the total variation as
a function of the linear combination coefficients is a convex function. It has therefore a global minimum which can always be found by gradient descent or another optimization routine. A diagram of the ESC method using a simulated water cylinder with aluminum inserts is shown in figure 1.

III. Simulations and Measurements

We obtained uncorrected data by adding simulated scatter to rawdata. A 20 cm water cylinder with two aluminum inserts was simulated for the first experiment. Furthermore, patient data sets from a clinical cone–beam spiral CT scanner were processed with ESC. ESC is intended to correct scatter artifacts. Thus, for our evaluation of the potential of this method, we needed data sets which do not suffer from strong beam hardening artifacts. To obtain beam hardening–free rawdata, we simulated metal implants into almost artifact–free reconstructions of real patient data. The patient data were corrected for beam hardening by the scanner software. Subsequently, these reconstructions with metal implants were forward projected monochromatically. Then, scattered radiation calculated with our in–house Monte Carlo software was added to the rawdata. Cupping, streak, and banding artifacts observed in the uncorrected images presented in this work are therefore scatter artifacts.

A. Proof of Concept

For a proof of concept, scatter was simulated with the pep–model with two different parameter sets. It was added to the rawdata of a patient with bilateral hip prostheses. This experiment was performed in order to show the suitability of the total variation as cost function in the case of the complex anatomy of real patients. The ideal image should be found if the true basis image is available.

B. Patients with Monte Carlo Scatter

To evaluate the potential of ESC in a more realistic scenario, scatter is obtained by a Monte Carlo scatter simulation. The scatter intensities are then added to the primary intensities of the rawdata. The Monte Carlo scatter simulation accounts for single and multiple photon interactions. The physical effects that are simulated include photo absorption, K–emission, coherent (Compton), and incoherent (Rayleigh) scatter. Collimator grids as used in the clinical CT scanner are taken into account, too. A 120 kV spectrum is simulated [22] and the geometry of the Somatom Definition Flash dual source cone–beam spiral CT scanner (Siemens Healthcare, Forchheim, Germany) is used throughout our study. Various different material compositions for soft tissues and bone tissues are used in the simulation.

As examples of common cases of metal implants which cause severe artifacts, we apply ESC to images from the region of the hip of a patient with bilateral hip prostheses and to images of the region of the jaw of a patient with two dental fillings.

C. Basis Images

For the proof of concept, ESC with two basis images was used. The basis images used the same pep parameters as the scatter which was added to the rawdata. For the correction of the patient data we used Monte Carlo scatter was added, ESC with four basis images was used. Each basis image is computed with a different parameter set of the pep–model, but no ideal basis image is available.

For this first evaluation of the potential of ESC, the pep parameters were fitted to the Monte Carlo scatter projections. As the mean squared error between the Monte Carlo scatter and the pep scatter has many local minima, many different parameter sets can be found in this way. This is a point were more experiments need to be done. For different objects, slightly different parameters sets might give good results. However, it is reasonable to assume that if there are some good parameter sets for several types of patients (head, hip, ...), there is a combination of them that will yield a good result.

IV. Results

A. Proof of Concept

Figure 2 shows the result for one slice of the hip patient with simulated pep scatter. The same pep scatter parameters are used here to compute the basis images, too, so the scatter component can be modeled exactly in this case. This experiment was performed in order to provide proof of concept for determining proper combination coefficients by total variation minimization. In this case, where an ideal basis image is available, the corresponding linear combination coefficient should be −1. ESC yields a flat correction result and comes very close to the desired true linear combination coefficients (−0.99 and −0.98 instead of −1 and −1).

B. Patients with Monte Carlo Scatter

Figure 3 and 4 show the results for the case where Monte Carlo scatter was added to the patient data sets. As the pep–model cannot exactly model the scatter, as for example directional dependencies are not considered, a true scatter basis image is not available.

Figure 3 shows the hip patient of figure 2 at a different z–position. The dark streak between the two implants is caused by the scatter. The inhomogeneities caused by scatter can be almost perfectly removed by EBHC in this case.

Dental fillings, which are the most common metal implants in patients, lead to especially severe metal artifacts. Figure 4 shows the result for the region of the jaw of a patient. Most parts of the scatter artifacts are removed by ESC. From the bright and dark streaks between the two dental fillings, a remaining artifact is still visible in the corrected image, but it is remarkably reduced in magnitude. The other artifacts, for example between the fillings and other dense structures like the jaw, are almost completely removed.
ESC significantly reduces the scatter artifacts and restores the true CT values. Cupping, streaks and other inhomogeneities due to scatter can be almost removed.

V. Conclusion

Scatter artifacts impair the image quality and accuracy of CT values. Especially in wide cone-angle flat detector CT scans scatter artifact removal is of greatest value. In clinical CT scatter could be an issue when metal is present in the field of measurement. ESC is a convenient and flexible method which does not need lots of prior knowledge and a very exact calibration. It uses the total variation as cost function to combine an uncorrected image with various basis images. The TV is an appropriate measure for inhomogeneities, at least in the case of scatter artifacts caused by metal implants. Other cost functions may be used with EBHC as well.

From our first experience, correction with four basis images obtained by the pep-model delivered good results. As expected, ESC does not tend to overcorrect images. We conclude that ESC is a promising approach to reduce scatter artifacts caused by the presence of metal implants and scatter artifacts in general.

VI. Discussion

This work presents preliminary results, and several further steps are planned to investigate the usefulness of ESC in clinical routine: Experiments with patient data sets with real measured scatter need to be done. To correct artifacts in real data, beam hardening artifacts need to be corrected simultaneously, because scatter artifacts and beam hardening artifacts cannot be properly distinguished. As ESC can be naturally combined with the EBHC approach from reference [21], we plan to use both approaches within one artifact reduction method.

In order to prove the scanner independence of ESC+EBHC, it is planned to apply the combination to flat detector CT patient data and to small animal data.

VII. Acknowledgements

We thank Dr. Michael Lell, Institute of Diagnostic Radiology, University of Erlangen–Nürnberg, for providing us patient data.

References


