Robust primary modulation-based scatter estimation for cone-beam CT

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Purpose: Scattered radiation is one of the major problems facing image quality in flat detector cone-beam computed tomography (CBCT). Previously, a new scatter estimation and correction method using primary beam modulation has been proposed. The original image processing technique used a frequency-domain-based analysis, which proved to be sensitive to the accuracy of the modulator pattern both spatially and in amplitude as well as to the frequency of the modulation pattern. In addition, it cannot account for penumbra effects that occur, for example, due to the finite focal spot size and the scatter estimate can be degraded by high-frequency components of the primary image.

Methods: In this paper, the authors present a new way to estimate the scatter using primary modulation. It is less sensitive to modulator nonidealities and most importantly can handle arbitrary modulator shapes and changes in modulator attenuation. The main idea is that the scatter estimation can be expressed as an optimization problem, which yields a separation of the scatter and the primary image. The method is evaluated using simulated and experimental CBCT data. The scattering properties of the modulator itself are analyzed using a Monte Carlo simulation.

Results: All reconstructions show strong improvements of image quality. To quantify the results, all images are compared to reference images (ideal simulations and collimated scans).

Conclusions: The proposed modulator-based scatter reduction algorithm may open the field of flat detector-based imaging to become a quantitative modality. This may have significant impact on C-arm imaging and on image-guided radiation therapy. © 2015 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4903261>]

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1. INTRODUCTION

The correction of scattered radiation is a highly active research topic in the field of x-ray computed tomography (CT). Cone-beam CT (CBCT) images acquired on systems equipped with a flat detector suffer from higher scatter than single- or multislice CT systems. There are fundamentally different ways of scatter estimation and correction. A standard approach is the insertion of an antiscatter grid, which removes a certain amount of the scattered radiation while most of the desired primary radiation reaches the detector. Other methods^{1–9} try to compute the scatter from the image itself, either using convolution-based approaches or even more sophisticated solutions based on Monte Carlo simulation.

A very promising way to simultaneously measure the scatter and the primary signal, the so-called primary modulation scatter estimation (PMSE) technique was proposed several years ago.¹⁰ This method is based on the insertion of a modulator between the x-ray source and the patient (Fig. 1). While the primary signal is modulated by a high-frequency checkerboard modulation pattern, the scatter is generated in the object behind the modulator. Using the assumption that the scatter

signal contains low-frequency components, one can separate the signals using filtering algorithms in the frequency domain.

Under ideal conditions, it has been shown that PMSE enables the correction for scattered radiation with high accuracy. There are, however, certain effects which cannot be avoided under real world conditions, such as when using a C-arm system. Most of these, like penumbra effects on the detector due to the finite focal spot size or inhomogeneities of the modulator material, cause a deviation of the projected modulation pattern on the detector from the ideal very uniform pattern which is required for the frequency-domain PMSE method.

An interesting extension of this idea was published recently.¹¹ This method uses temporal motion of a modulator pattern to mitigate the sampling and high-frequency related limitations of the Fourier-based modulator approach. The additional complexity required of providing accurate modulator motion may make this approach less attractive for rotating systems such as C-arms or gantry-based devices.

The idea of this work is to create a scatter estimation algorithm for primary-modulated images which does not require this ideal checkerboard modulation pattern but which can cope with nearly any kind of static high-frequency modulation

FIG. 1. X-ray tube with a primary modulator in front of the collimator.

pattern. We will refer to this method as the improved primary modulator scatter estimation (iPMSE).

2. MATERIALS AND METHODS

2.A. Basic theory

The following equation describes the measured signal on the detector:

$$\mathbf{c}_M = \mathbf{M} \cdot \mathbf{c}_P + \mathbf{c}_S. \quad (1)$$

Here, $\mathbf{c}_P$ and $\mathbf{c}_S$ are vectors representing the primary intensity and the scatter signal. The diagonal matrix $\mathbf{M}$ consists of values $M_{i,i} = m_i$, which describe the transmission of the inserted modulator. The image $\mathbf{m}$ (Fig. 2) which is the projection of the modulator can easily be measured by acquiring a projection image of the modulator without any objects in the beam path. In the following, we assume that all images were normalized by the I_0 intensity of the unattenuated beam in air. Solving for $\mathbf{c}_P$ yields

$$\mathbf{c}_P = \mathbf{M}^{-1} \cdot (\mathbf{c}_M - \mathbf{c}_S). \quad (2)$$

Let us assume $\mathbf{c}_S^{\text{est}}$ is an approximation to $\mathbf{c}_S$. Then the error of the scatter estimate will be denoted with $\Delta_S = \mathbf{c}_S^{\text{est}} - \mathbf{c}_S$. Now the estimated primary signal is

$$\begin{aligned} \mathbf{c}_P^{\text{est}} &= \mathbf{M}^{-1} \cdot (\mathbf{c}_M - \mathbf{c}_S^{\text{est}}) \\ &= \mathbf{M}^{-1} \cdot (\mathbf{c}_M - \Delta_S - \mathbf{c}_S) \\ &= \mathbf{c}_P - \mathbf{M}^{-1} \cdot \Delta_S. \end{aligned} \quad (3)$$

As one can see, the modulation pattern remains visible in the estimated primary image, as long as there exists a nonzero error Δ_S . This fact will be used by our iPMSE method. The goal is to design a cost function which is sensitive to the modulation pattern and reaches a minimum if the error is equal to zero. Because the modulation pattern consists of strong edges, the spatial image gradient is a good choice for such a cost function. This effect is visualized in Fig. 3. Additional prior knowledge

FIG. 2. Projection image $\mathbf{m}$ of the used erbium modulator. As one can see, the modulation pattern is highly irregular due to the manufacturing process. Additionally, one can observe a more blurring on the left side than on the right side. This is due to changes in the apparent focal spot size. All these effects are a deviation from the ideal pattern which is required by the original Fourier-based PMSE method.

FIG. 3. The first row shows the estimated primary c_p^{est} for different constant scatter estimates c_s^{est} . The scatter is scaled in relative gray units of the detector signal. In the second row, one can see the absolute gradient of the estimated primary. Note the high values of the image gradient in regions where the modulation pattern is visible.

which must be included in the optimization is that the scatter signal c_s mainly consists of low-frequency components and the assumption that high-frequency components in the scatter signal are negligible. To find c_p^{est} , we minimize the cost function

$$C(c_p^{est}) = \|\mathbf{D} \cdot c_p^{est}\|_1 = \|\mathbf{D} \cdot \mathbf{M}^{-1} \cdot (c_M - c_s^{est})\|_1$$

(4)

subject to $\mathbf{H} \cdot c_s^{est} = 0$,

with $\mathbf{H}$ being a high-pass filter and with $\mathbf{D}$ being a matrix which describes the spatial gradient on the detector image.

2.B. Solving the optimization problem

To find a computationally efficient solution to this problem, we divide the image into small square patches (subimages). The size of these patches is chosen such that it is large enough to contain about one period of the modulator pattern, e.g., 17×17 pixels for a modulator with each semitransparent blocker of size 8×8 pixels. We now minimize $C(c_p^{est})$ separately for each patch assuming that c_p^{est} is constant within a patch. This is an efficient way to realize the constraint of the scatter function

FIG. 4. Diagram of the iPMSE scatter estimation algorithm. In the left column, one can see the measured intensity image c_m and the modulation pattern m which are used as input for the algorithm. In the second and third column, one can see the scatter estimate c_s^{est} and the estimated primary intensity c_p^{est} .

FIG. 5. Simulated projection data. (a) and (b) modulation pattern $\mathbf{m}$, (c) measured signal $\mathbf{c}_M$, (d) iPMSE-estimated primary signal $\mathbf{c}_P$.

FIG. 6. The projected primary distribution of the modulator and the scatter distribution of the modulator on the detector based on a Monte Carlo simulation are shown. Both images show absolute photon numbers assuming a nonattenuated entrance intensity of 10^4 photons per pixel. The left image is windowed $C/W = 10\,000/5000$, the right image $C/W = 50/100$. The average photon number in the right image is about 50. Note that the primary signal of the modulator is about two orders of magnitude larger than the modulator induced scatter.

FIG. 7. Primary, simulated scatter, and iPMSE estimated scatter images are shown at two projection angles. Note the small difference between the iPMSE estimate and the reference scatter distribution in the images on the right side. All images show absolute intensity values.

only consisting of low-frequency components. The minimization is done numerically using a line search algorithm (golden cut section search) in a predefined interval which should represent a realistic range of scatter values. However, a convex behavior of the image gradient as cost function is assumed, which would ensure a global minimum. This assumption can be confirmed by the fact that the strength of edges introduced by the modulator is proportional to the error Δ_S of the scatter estimate $\mathbf{c}_S^{\text{est}}$. Consequently, only one value of the scatter is estimated per patch. This value is assigned to the central pixel of the patch. After all patches are processed, we have a sparse representation of $\mathbf{c}_S^{\text{est}}$ of the whole detector image. We fill the remaining pixels in $\mathbf{c}_S^{\text{est}}$ by linear interpolation and then we apply a low-pass filter to this scatter image, for example, using a 17×17 binomial filter for the given patch size. This is our scatter estimate. From that we obtain $\mathbf{c}_P^{\text{est}} = \mathbf{M}^{-1} \cdot (\mathbf{c}_M - \mathbf{c}_S^{\text{est}})$, from which we take the negative logarithm and then continue with image reconstruction using standard approaches. Figure 4 shows the corresponding images for each step.

2.C. Simulation study

To demonstrate the method, a simulation study was performed using the thorax FORBILD phantom. Raw data were created using a monochromatic beam at 60 keV and for a 512×512 detector. For a more realistic simulation, Poisson noise was added to the raw data with a photon number of 10 000 photons per detector pixel for an unattenuated ray. To demonstrate the ability of iPMSE to handle even highly irregular modulation patterns, we used the modulator shown in Fig. 5. It consists of a combination of different patterns. The positions of the stars used as background pattern are randomly distributed. The transmission m of the modulator was defined as $m = 0.72$ and $m = 1.0$. These are the transmission values of copper and air at an x-ray energy of 60 keV for a thickness of 0.23 mm. Scatter was simulated using a convolution-based scatter model⁸ and added to the simulated intensity data. To demonstrate that this is a realistic simulation scenario, an additional Monte Carlo simulation of the modulator without

FIG. 8. First row: reconstruction of the iPMSE-corrected data which were simulated with the modulator and additional scatter. Second row: reconstruction of the same data simulated without modulator and without scatter correction. Third row: reconstruction of the same data simulated without modulator and without additional scatter as reference. The differences of noise intensity between the reference and the iPMSE-corrected reconstructions are caused by the described effects of noise amplification caused by scatter correction. The variations of noise intensity levels between different regions of the phantom are caused by the strongly varying attenuation properties of the simulated phantom in axial direction. All images are windowed $C = 0$ HU, $W = 2000$ HU.

object in the beam was done for the given energy. The source to modulator distance was set to 200 mm with a source to detector distance of 1000 mm. As one can see in Fig. 6, the scatter distribution of the modulator induced scatter on the detector plane is orders of magnitude smaller than the primary intensity. Reconstructions were performed using the scatter-affected raw data without modulator and the iPMSE scatter-corrected data with modulator. The reconstructed volumes consist of $512 \times 512 \times 512$ voxels. Figure 5 shows the projection images of the modulator, of the phantom with modulator, and of the estimated primary image. In Fig. 7, primary and scatter intensities are shown at two projection angles. Additionally, one can see the scatter distribution generated by the iPMSE method and the difference from the simulated scatter. The reconstructions and difference images are shown in Figs. 8 and 9.

2.C.1. Data acquisition

To evaluate the method, experimental CBCT data were measured. The datasets were acquired using a table top CBCT system. The number of acquired projections is 625 over an angular range of 360° . To enable a comparison, all objects were scanned without modulator, with an erbium modulator in the beam path, and with a slit collimator (without modulator) to create a reference image which is nearly free of scatter artifacts. A projection image of the modulator can be seen in Fig. 2. The spacing between neighboring patches of the modulation pattern is 0.457 mm, the thickness of the modulator is 0.0254 mm. In neither case was an antiscatter grid used. Additionally, 100 projections of the modulation pattern without object in the beam path were acquired and averaged to

FIG. 9. Difference images between the simulations of Fig. 8 and a noise-free reference image of the thorax phantom. All images are windowed $C = 0$ HU, $W = 2000$ HU.

have a reference image $\mathbf{M} = \text{diag}(\mathbf{m})$ of the modulation pattern with good noise statistics.

The detector used is a Varian Paxscan 4030 CB detector, which operated in a 2×2 binning mode. This yields an effective number of 1024×768 detector pixels with an effective size of 0.388×0.388 mm. The focal spot size of the x-ray tube is 0.3 mm. The focus to detector distance of the setup is $R_{\text{FD}} = 2018$ mm and the focus to isocenter distance is $R_{\text{F}} = 787.4$ mm. The distance between the focal spot and the modulator is about 230 mm.

Two different objects were scanned. One dataset shown here is a cadaver head fixed in formalin. It was scanned with a tube current time product of 244 mAs at a tube voltage of 80 kV. The other object is a lung phantom. To create a phantom which consists of soft tissue structures and which creates strong scatter, we took an oval water-equivalent phantom with a central cavity. Inside we put a plasticized lung and the heart of a pig. Additionally, we placed a water bottle next to the soft tissue structures to create a source of strong scatter (Fig. 10). Raw data were acquired at a tube voltage of 100 kV, and the tube current time product was 650 mAs. The reconstructions of both datasets can be seen in Figs. 12, 14, and 15.

2.C.2. Data processing

The datasets without modulator were corrected by the intensity I_0 of the unattenuated x-ray beam. After taking the negative logarithm, a standard Feldkamp (FDK) reconstruction¹² was applied.

In the case of primary-modulated raw data, the iPMSE scatter estimation algorithm was applied. Then the data were reconstructed using the same Feldkamp reconstruction.

However, between iPMSE and Feldkamp reconstructions, some special corrections for the locally strongly varying noise of the raw data were applied. In areas of low primary intensity where the local scatter to primary ratio (SPR) can be large, the signal to noise ratio (SNR) of the primary signal can become very small. The SNR of a slit scan is

$$\text{SNR}_i^{\text{slit}} = \frac{c_{P,i}}{\sqrt{c_{P,i}}} = \sqrt{c_{P,i}}, \quad (5)$$

using the assumption that the amount of scatter is small and can be ignored. For a cone-beam scan the signal to noise ratio is

FIG. 10. Physical phantom used in the first measurement setup. It consists of a water-equivalent oval body. Inside a plasticized lung, a heart of a pig, and a water bottle were added. These create soft tissue structures and strong scatter.

FIG. 11. Estimated primary image c_P^{est} and the according estimated scatter c_S^{est} of the measured head dataset shown in Figs. 12 and 13.

FIG. 12. Reconstructions of the head dataset. The slit scan (left) is used as nearly scatter-free reference image. The middle image shows the reconstruction of the uncorrected raw data, which still suffer from scatter artifacts. The right image shows the iPMSE-corrected image. All images are windowed $C = 200$ HU, $W = 800$ HU.

$$\text{SNR}_i^{\text{CB}} = \frac{c_{P,i}}{\sqrt{c_{P,i} + c_{S,i}}} = \sqrt{\frac{c_{P,i}}{1 + \text{SPR}_i}}. \quad (6)$$

Here, the index i denotes a single detector pixel. This fact was discussed, for example, in Ref. 13. Thus, streak artifacts can occur in the reconstructed volume, if there are very high local noise values in the raw data. In addition, negative intensity values may occur even in the case of a correct scatter estimation. This can be interpreted as a type of incomplete data problem, which is automatically handled by an iterative approach such as proposed in (Ref. 13) due to its statistical weight. To avoid strong artifacts which might corrupt the whole image, negative pixels were removed from the raw data. The resulting gaps were filled by linear interpolation using the standard approach from metal artifact correction. To suppress high local noise, the raw data were locally smoothed by a Gaussian filter with a width of $\sigma = 2$ pixels if the attenuation $q = -\ln c_P$ was higher than a certain threshold t . In this study, $t = 6.0$ was used. A more sophisticated design of a special adaptive filter, such as the filter proposed in Ref. 14, would further improve image quality. A reduction of spatial resolution caused by this filtering step can be possible. This makes it even more important to create self-adapting filter settings which guarantee that only values of very low SNR are smoothed. In the case of the datasets shown, the proposed filter settings worked well. A more detailed investigation of this step is necessary and should be performed for a wider range of applications, but it is beyond the scope of this paper.

FIG. 13. Plots of a vertical profile through the reconstructions of Fig. 12. As one can clearly see, the cupping artifact of the scatter-affected data is removed. The gray values of the slit scan and the corrected scan have the same levels which confirm the correctness of the proposed scatter correction approach.

FIG. 14. Reconstructions of the phantom dataset are shown. In the upper row, one can see the reconstructed uncorrected raw data, which suffer from scatter artifacts. The images in the middle row were measured with the modulator in the beam path and were iPMSE-corrected. The bottom row shows the reconstructions of the reference slit scan. All images are windowed $C = 500$ HU, $W = 1500$ HU. Note that the Hounsfield units are not quantitatively correct due to truncation of the projection data.

FIG. 15. Same as Fig. 14 but with a narrow gray scale window of $C = 50$ HU, $W = 1200$ HU.

3. RESULTS

Regarding the simulated data, one can observe a highly effective scatter reduction, as shown in Figs. 7 and 9. The difference images in Fig. 7 confirm the accuracy of the method. The normalized error

$$E = \frac{c_P^{\text{est}} - c_P}{c_P} \quad (7)$$

is smaller than 0.01 in both cases. The difference images in Fig. 9 show the expected differences in noise characteristics but no anatomical structure which implies that spatial resolution has been preserved.

The experimental datasets also show a very good iPMSE performance because the scatter artifacts are almost completely eliminated. However, with no ground truth available it is more difficult to visualize or to quantify the artifact reduction compared to a simulation study. The head dataset shows that iPMSE removes the scatter artifacts (Figs. 11 and 12). Figure 13 shows profiles through the three reconstructions. These indicate a significant reduction of the strong cupping artifact. As expected, the amount of scatter is much higher in the lung phantom data which can be explained by the higher volume irradiated and the closer distance of the object border to the detector due to the larger object size compared to the head dataset. Regarding Figs. 14 and 15, one can clearly see that the scatter induced streak artifacts and the loss of low contrast structures in the lung tissue are mostly removed.

The increase of image noise in the iPMSE-corrected images can be easily explained by two facts. One reason is that the primary radiation is partly absorbed by the modulator, so the number of photons and the patient dose are lower compared to the scans without modulator. Another reason is that the SNR of the primary signal is reduced due to the noise of the scattered photons. This behavior was explained in Eqs. (5) and (6).

Comparing the gray scales of the corrected scan and the slit scan in the plots in Fig. 13, one can see that iPMSE yields quantitative values which are very close to the values of the slit scan. The interpretation of the slit scan as a perfect scatter-free reference image might be misleading because there is still a certain amount of scatter left; however, this is about an order of magnitude lower than in the uncollimated scan. Nevertheless, this plot demonstrates the potential of iPMSE to produce quantitative CT imaging using flat detectors even with imperfect modulators such as the erbium modulator.

Up to now, we have ignored the influence of the modulator on the spectral properties of the x-rays. It is well known that the modulator tends to introduce ring artifacts due to beam hardening. While choosing an optimized modulator material may be one solution to reduce this effect,¹⁵ another way is to precorrect for the spectral properties of the modulator, e.g., by applying the empirical cupping correction for primary modulation (ECCP) of Ref. 16.

The computation time of the scatter estimation was about 5 min for a dataset of 625 projections using unoptimized c++ code on a standard desktop PC. A more efficient implementation and parallelization of the code will bring it closer to clinically acceptable computation times.

4. CONCLUSION

We presented iPMSE, a new and simple method to estimate scatter in CBCT using a primary modulator. Due to the fact that the method does not require any information about the characteristics of the modulator shape and material, it is very stable in the presence of nonidealities. The accuracy of the method was demonstrated using simulated and experimental CBCT datasets. The proposed scatter reduction algorithm may open the field of flat detector-based imaging to become a quantitative modality. This may have significant impact on C-arm imaging and on image-guided radiation therapy.

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