A simple, direct method for x-ray scatter estimation and correction in digital radiography and cone-beam CT

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X-ray scatter poses a significant challenge to imaging performance in advanced digital radiography applications, including flat-panel detector-based dual-energy imaging, tomosynthesis, and cone-beam CT (CBCT), resulting in soft-tissue contrast reduction and potentially severe image artifacts. Strategies for scatter management in CBCT include knowledgeable selection of object-to-detector gap, limiting the field of view (FOV), use of an antiscatter grid, and

II. INTRODUCTION

X-ray scatter poses a significant challenge to imaging performance in advanced digital radiography applications, including flat-panel detector-based dual-energy imaging, tomosynthesis, and cone-beam CT (CBCT), resulting in soft-tissue contrast reduction and potentially severe image artifacts. Strategies for scatter management in CBCT include knowledgeable selection of object-to-detector gap, limiting the field of view (FOV), use of an antiscatter grid, and
algorithmic correction of x-ray scatter. The last typically requires an estimate of the scatter fluence in a projection image, and a variety of techniques have been developed, including analytical calculation, Monte Carlo modeling, and “blocker-based” techniques. Each of these techniques has merits and disadvantages in implementation: analytical calculation of the scatter fluence is fast but limited to simple models of patient shape and heterogeneity; Monte Carlo modeling can be accurate but computationally intense; blocker-based techniques derive the scatter fluence directly from the projection data but require the introduction of attenuators in the image which may require two projections per view (one with the blockers in place and one without) or may introduce CT artifacts if not completely corrected from the projection data. Each technique is an active area of research.

A simple method for estimation of the 2D scatter fluence directly from the projection data is presented below. The technique assumes that the detector signal measured in regions behind the collimator blades is entirely attributable to x-ray scatter. This simple assumption leads to an algorithm (termed SPECS—Scatter and Primary Estimation from Collimator Shadows) which, as demonstrated below, provides significant reduction of deleterious scatter effects in CBCT reconstructions. The technique operates without prior information regarding the x-ray source, object, imaging geometry, or detector and is very robust with respect to imaging configuration, patient shape, object motion, etc. It furthermore offers a straightforward technique of empirical scatter estimation for comparison to analytical and Monte Carlo modeling techniques and represents a potentially useful approach to scatter correction in digital radiography, fluoroscopy, dual-energy imaging, tomosynthesis, and CBCT. A description of the algorithm’s initial implementation is described in Sec. II, with quantitative and qualitative assessment of performance in phantom and patient imaging studies in Sec. III.

II. COMPUTATIONAL AND EXPERIMENTAL METHODS

A. Scatter correction algorithm

1. Imaging geometry

A schematic illustration of the imaging geometry assumed in the scatter estimation algorithm is shown in Fig. 1(a). The key assumption underlying the algorithm is that image signal in regions of collimator shadow is attributable to x-ray scatter—specifically in regions along the top and bottom of the detector behind the z-collimator leaves. Use of the z-collimators in this manner necessarily reduces the longitudinal field of view (FOVz). However, in applications such as CBCT, such reduction is not only possible and practical, it is, in fact, good practice and an important aspect of maximizing image quality—to wit, minimizing FOVz to the volume of interest to reduce x-ray scatter. Some applications, however, such as CBCT mammography using pendant undertable port, may not support the presence of collimator shadows at both edges of the detector. Below, we assume the availability of at least some collimator shadow (at least 5 mm) along the top and bottom detector edges. As shown below, the simple assumption that signal behind the collimator blades is attributable to x-ray scatter results in a robust means of scatter correction.

2. Principle of the algorithm

An illustration of the SPECS algorithm is shown in Figs. 1(b) and 1(c), with a flowchart in Fig. 2 and the various algorithm parameters listed in Table I. Collimator edges are detected automatically in each projection, and a small standoff, zoff, from each edge is applied to define regions of support, S_top and S_bot, within the collimator shadows along the top and bottom of the detector. Initial implementation reported below uses polynomial interpolation of order vfit from S_top to S_bot along each column j, to yield 1D columnwise scatter estimates, Sj(v). An estimate of the 2D scatter fluence, S(u,v), across the entire field of view in each projec-
tion image is obtained by lateral smoothing of \( S_j(u,v) \) across all columns, characterized by a rectangular kernel of width \( u_{filt} \) (height \( 1/u_{filt} \) and no phase distortion). Other means of scatter fluence estimation across such regions of support can be envisaged—e.g., full 2D interpolation (linear, cubic, or spline) or calculation of a 2D energy-minimizing surface (“soap bubble”) using the Laplacian operator. Finally, projection-to-projection smoothing was considered using either of two methods: (i) a causal recursive filter with weighting factor \( \theta_{filt} \), where scatter in the 4th projection is given by 
\[
S_k(u,v) = \theta_{filt} S_{k-1}(u,v) + (1 - \theta_{filt}) S_{k-1}(u,v),
\]
and (ii) a non-causal, forward-backward filter characterized by a rectangular kernel of width \( \theta_{filt} \) (height \( 1/\theta_{filt} \) and no phase distortion).

The parameters \( z_o, u_{filt}, v_{filt}, \) and \( \theta_{filt} \) are adjustable, and the sensitivity of the algorithm to each was investigated in terms of contrast, noise, contrast-to-noise ratio (CNR), and cupping artifact in CBCT reconstructions of head and body phantoms imaged using an experimental bench, below. The standoff parameter \( z_o \) was varied from 0 to 60 pixels (i.e., 0 to 9.6 cm). The order of the polynomial fit, \( u_{filt} \), was varied from 0 to 8. The lateral smoothing kernel, \( u_{filt} \), was varied from 1 (no smoothing) to 50 pixels. Projection-to-projection smoothing extent, \( \theta_{filt} \), ranged from \( \theta_{filt}=0 \) to 1 (causal) and \( \theta_{filt}=1 \) to 40 (noncausal). Unless otherwise specified, the following nominal values of each parameter were used: \( z_o=5 \) pixels (8 mm); \( u_{filt}=2 \) (parabolic fit); \( u_{filt}=10 \) pixels; and \( \theta_{filt}=1 \) (noncausal; no projection-to-projection smoothing).

As discussed below, for these nominal settings CBCT reconstructions were significantly sensitive only to the order of the polynomial fit, \( u_{filt} \), and adjustment of \( v_{filt} \) was found to be a useful means of controlling image artifacts under a variety of complex imaging conditions—e.g., varying \( v_{filt} \) from 2 to 1 or 0 (i.e., from parabolic to linear or constant fits along each column between \( S_{top} \) and \( S_{hot} \)).

### B. Phantom studies

#### 1. Imaging benchtop

The scatter correction algorithm was evaluated quantitatively using an experimental CBCT benchtop [Fig. 3(a)]. The system includes an x-ray tube (Rad94 in Sapphire housing; W target; 0.4–0.8 mm focal spot; 14° anode angle; Varian Medical Systems, Salt Lake City, UT) powered by a constant potential generator (CPX-380, EMD Inc., Montreal, QC) with 2 mm Al+0.6 mm Cu added filtration. The longitudinal field of view, FOV_z, was varied by manual adjustment of the \( z \)-collimator leaves (MC-150C Linear Collimator, Progeny Inc., Buffalo Grove, IL). The flat-panel detector (RID-1640A, PerkinElmer Optoelectronics, Santa Clara, CA) is based on a 1024×1024 (41×41 cm²) active matrix of \( \alpha \)-Si:H photodiodes and thin-film transistors with a 400 \( \mu \)m pixel pitch, 80% fill factor, and a 250 mg/cm² CsI:Tl x-ray converter. The motion control system includes linear stages for axis alignment (6K series with Gemini drives, Parker Daedal, Harrison, PA) and a rotation stage for CBCT acquisition (Dynaserv DM1060B, Parker Daedal, Harrison, PA).
An acquisition PC (3 GHz Pentium-4; 2 GB RAM) synchronizes x-ray exposure, detector readout, and motion control. The axial FOV for centered-detector geometry is 25.6 cm, with truncation artifacts expected for large objects (viz., the body phantom, below).

2. Cylindrical head and body phantoms

Two water-filled cylindrical phantoms (Fig. 3) were used to quantify imaging performance—a 16 cm diameter “head” and 32 cm diameter “body” featuring six tissue-equivalent inserts (2.0 cm diameter, Gammex RMI, Madison, WI) in water (0 HU): four soft-tissue-equivalent inserts “liver” (+85 HU), “brain” (+8 HU), “breast” (−50 HU), and “adipose” (−100 HU), and two inserts simulating cortical bone (Teflon, ~1000 HU). Each phantom was sufficiently long (100 cm) to provide a uniform scattering medium well outside the longitudinal FOVz. CBCT images were acquired as a function of FOVz (2, 10, and 22 cm at isocenter), providing a broad range in scatter-to-primary ratio, SPR (~10% to 300% or more), over which to test the scatter correction algorithm.

Each CBCT image was reconstructed from a series of 320 projections acquired over 360° at 120 kVp (0.5 mAs/projection for the head; 1.0 mAs/projection for the body). The FPI was operated at 1 fps, and no corrections for image lag were applied. Stationary variations in offset and gain were corrected using 50 averaged “dark” and “flood” fields. The projection data (1024 × 1024 pixels at 0.4 mm pitch) were processed at “quarter-resolution” to yield projections of dimension 256 × 256 with pixel pitch 1.6 mm (~1 mm voxel size at isocenter), which is the typical resolution employed in the clinical implementation of CBCT in image-guided radiation therapy (Elekta Synergy, below). Analysis of CBCT reconstructions at “half-resolution” (~0.5 mm voxel size; not shown) gave comparable results to those below, but with increased voxel noise (reduced CNR), as expected. Each gain/offset-corrected projection was processed using the algorithm of Fig. 2, with CBCT images reconstructed using a modified FDK algorithm.22

3. Analysis of imaging performance

Soft-tissue contrast, noise, CNR, and cupping artifact were analyzed in CBCT images reconstructed with and without the SPECS algorithm as a function of FOVz (i.e., SPR) for both the head and body phantoms. To analyze CNR, two regions of interest (ROI; 13 × 13 voxels) were identified in each axial slice—one within a soft-tissue-equivalent insert (viz., “breast” for the head phantom and “adipose” for the body phantom) and the other in immediately adjacent water (at the same distance from center). The means (μtissue, μwater) and standard deviations (σtissue, σwater) of voxel values in each ROI were computed in nine axial slices about the central plane. Contrast (C) was defined as the absolute difference between the mean voxel values of the soft-tissue and water: C = |μtissue − μwater|. The voxel noise (σ) was taken as the average of the standard deviation in the soft-tissue and water ROIs: σ = (σtissue + σwater)/2. CNR was simply C/σ.

CT number accuracy and the magnitude of cupping artifact were measured in terms of the voxel value at the center (μcenter) and edge (μedge) of CBCT reconstructions in relation to the true attenuation coefficient (μwater). The mean values μcenter and μedge were computed from 41 × 41 voxels at the center and edge of the image, respectively. The value μwater was computed to be 0.197 cm−1 from the integral of the normalized spectrum23 over the energy-dependent linear attenuation coefficient. CT number inaccuracy was characterized by Δc = 100(μwater − μcenter)/μwater, and the magnitude of cupping artifact by tcup = 100(μedge − μcenter)/μedge.

C. Patient imaging

Patient images were acquired on a clinical system for CBCT-guided radiation therapy (Synergy RP, Elekta Oncology Systems, Atlanta, GA) with components and geometry similar to the experimental benchtop, except that the FPI incorporates a 133 mg/cm2 Gd2O2S:Tb x-ray converter. Detailed description of the system is in Ref. 24. FOVz was manually adjusted to encompass the clinical volume of interest—e.g., FOVz = 10 cm for pelvis (prostate), 22 cm for abdomen (liver), and 22 cm for head-and-neck sites. The
number of projections acquired ranged from ~320 to ~640, depending on site- and patient-specific protocols. CBCT images were reconstructed at quarter-resolution (1 mm voxel size at isocenter, as described above). Images were acquired in both “centered-” and “offset-” detector geometries, giving axial FOV 25.6×25.6 cm² and 40×40 cm², respectively.

A variety of anatomical sites and imaging conditions provided investigation of algorithm performance and robustness across a range in patient size, asymmetry, and imaging geometry. Images in the region of the prostate acquired using centered-detector geometry illustrated performance under conditions where the projection data are subject to large and varying lateral truncation. Similar images acquired using offset-detector geometry showed the effects of strong lateral asymmetry in the projection data (and, therefore, in the 2D scatter fluence), ranging from the bare beam to nearly complete signal attenuation by the pelvis. Images in the region of the liver demonstrated the challenge of strong longitudinal asymmetry, ranging from low attenuation in the lower lungs to strong attenuation through the abdomen. Imaging of the head-and-neck illustrated the case in which the scattering medium may not extend significantly into the collimator shadow, and the object presents a noncylindricallysymmetric skinline along detector columns. While the patient imaging results were primarily qualitative, they provided valuable testing and validation of the algorithm under a variety of challenging, realistic conditions and illustrated the performance and flexibility of the algorithm in contexts that are ultimately more relevant than could be achieved using simple phantoms.

III. RESULTS

A. Investigation of algorithm parameters

Over a broad range of imaging conditions and parameter values, the SPECS algorithm always provided improved contrast and reduced cupping artifact compared to no correction. Only for extreme values of the parameters $z_o, v_{\text{fit}}, u_{\text{filt}}$, and $\theta_{\text{fit}}$ did the algorithm degrade image quality, and in such cases it failed catastrophically, where overcorrection caused obvious streak artifacts. The sensitivity of the algorithm to each parameter is discussed in the following subsections.

1. Standoff from collimator edge ($z_o$)

The algorithm was extremely robust to variation in $z_o$. Both CNR and $t_{\text{cup}}$ decreased only slightly as $z_o$ increased (CNR ranged from 3.91 to 3.85, and $t_{\text{cup}}$ ranged from 21.1% to 19.5% for variation in $z_o$ from 0 to 60 pixels). A nominal value of $z_o=5$ pixels (8 mm) was selected as a nominal value to reduce possible inaccuracy in the automatic edge detection and provide a reasonable standoff from blur and extrafocal radiation impinging on the collimator shadows.

2. Polynomial order ($v_{\text{fit}}$)

The algorithm was most sensitive to the order of the polynomial fit, $v_{\text{fit}}$. Quantitative results and representative images are shown in Fig. 4, where contrast and artifact are shown to improve from $C=0.007$ cm⁻¹ and $t_{\text{cup}} \approx 36\%$ (no correction) to $C=0.015$ cm⁻¹ and $t_{\text{cup}} \approx 22\%$ ($v_{\text{fit}}=2$). A slight increase in correlated noise (viz., radial streaks in the reconstructions) was imparted by the algorithm, with CNR decreasing slightly from CNR=4.1 (no correction) to CNR = 3.8 ($v_{\text{fit}}=2$) despite an overall improvement in image quality (i.e., factor of 2 improvement in contrast, ~40% improvement in cupping artifact, ~7% reduction in CNR). No adjustment in the various parameters ($z_o,v_{\text{fit}},u_{\text{filt}}$, or $\theta_{\text{fit}}$) was found to significantly reduce the correlated noise; its exact source is under investigation. For the cylindrical head and body phantoms, $v_{\text{fit}}=2$ (parabolic fit) performed better overall than $v_{\text{fit}}=1$ (linear) or $v_{\text{fit}}=0$ (constant). In each case, image quality was improved compared to no correction, and adjustment of $v_{\text{fit}}$ over the range 0–2 was found useful in cases of complex anatomy (patient imaging, below).

3. Lateral smoothing ($u_{\text{filt}}$)

For both the head and body phantoms, CNR and $t_{\text{cup}}$ were largely insensitive to lateral kernel extent $u_{\text{filt}}$ over the range 0 to 20 pixels. The maximum improvement in CNR relative to no lateral smoothing was 3.2% (body) and 0.4% (head) for $u_{\text{filt}}=20$. The maximum relative change in $t_{\text{cup}}$ was ~1.2% (body) and ~6.7% (head) at $u_{\text{filt}}=10$. Significantly larger values of $u_{\text{filt}}$ (e.g., 50) decreased CNR and increased $t_{\text{cup}}$ (e.g., 10% reduction in CNR and 100% increase in $t_{\text{cup}}$ for the head phantom at $u_{\text{filt}}=50$). A nominal value of $u_{\text{filt}}=10$ pix-
Hash marks at the sides of the filter over the range negligible effect on imaging performance. For the noncausal objects lacking cylindrical symmetry. For the causal forward-toms, an effect that is certainly far more important for ob-
ter in each projection view even for simple cylindrical phan-
ents provided improved CNR and cupping artifact and was found to be robust in the patient imaging studies.

4. Projection-to-projection smoothing ($\theta_{filt}$)

Projection-to-projection smoothing of the 2D scatter flu-
ence estimate was found, somewhat surprisingly, to have a negligible effect on imaging performance. For the noncausal filter over the range $\theta_{filt}=0.2$ to 1, for example, CNR and $t_{cap}$ changed by 0.02% and 0.1%, respectively. For $\theta_{filt}=0$ (which corresponds to using the same scatter estimate in all projections), a 0.3% decrease in CNR and 6% increase in $t_{cap}$ were observed, suggesting the benefit of direct estimation of scatter in each projection view even for simple cylindrical phan-
toms, an effect that is certainly far more important for ob-
jects lacking cylindrical symmetry. For the causal forward-
backward filter, CNR and $t_{cap}$ changed by less than 1% over the range $\theta_{filt}=1$ to 40 projections. A nominal value of $\theta_{filt} =1$ was selected, corresponding to no projection-to-
projection smoothing.

B. Phantom studies

1. Scatter fluence distributions $S(u,v)$

Example primary and scatter fluence estimates are shown in Fig. 5 for various phantom and patient configurations. The top row of graphs shows example profiles along a column ($j$) of the projection, including the projection signal (labeled P +S), the estimated scatter ($S_j$, labeled S), and the resulting primary-only fluence estimate (labeled P). The bottom row of images shows the corresponding scatter fluence estimate, $S(u,v)$. The head phantom [Fig. 5(a)] illustrates a simple case, though the 2D scatter fluence estimate, $S(u,v)$, reflects the combined effects of scatter generation and attenuation even in a simple phantom: scatter fluence is highest in regions of the bare beam; scatter fluence is lowest (and SPR highest) behind the thickest region of the phantom due to self-attenuation of x-ray scatter; and longitudinal nonuniform-
ity in the scatter estimate is qualitatively consistent with the model of an effective scatter point source located up-
stream from the phantom. Similar effects are observed for the body phantom [Fig. 5(b)]: a parabola fits the regions of support well, and the SPR is considerably increased (>150% behind the phantom).

Figures 5(c) and 5(d) illustrate such estimates in real pa-
tient data. Strong lateral asymmetry is exhibited in the scatter and primary estimates of Fig. 5(c) for the offset-detector ge-
ometry (prostate). Still, interpolation along columns between the regions of support is well described by simple parabolic fits, and the resulting 2D scatter fluence estimate reveals a complicated asymmetry that is dependent on projection angle. (The AP view is shown for illustration.) Similarly, Fig. 5(d) illustrates a case of vertical asymmetry imparted by the anatomical site (liver) in which the superior aspect of the image experiences low attenuation (lung) and the inferior aspect high attenuation (abdomen). Even so, longitudinal inter-
polation followed by lateral smoothing provides a reason-
able estimate of the 2D scatter fluence, exhibiting complex spatial variation with strong dependence on projection angle (AP view shown). While comparison of the scatter fluence estimates to analytical or Monte Carlo models of x-ray scatter is the subject of future investigation, the value of the algorithm is evident in the results below by virtue of im-
proved image quality and CT number accuracy.
2. Contrast, noise, and cupping artifact

A quantitative comparison of C, σ, CNR, and \( \Delta_c \) in uncorrected and SPECS-corrected CBCT reconstructions is shown in Fig. 6. The algorithm improves soft-tissue contrast [Fig. 6(a)] in all cases, effectively restoring voxels to the correct value of attenuation coefficient \( C \approx 0.010 \text{ cm}^{-1} \) for breast-to-water (head phantom) and \( C \approx 0.016 \text{ cm}^{-1} \) for adipose-to-water (body phantom). In the most challenging case (body phantom, \( \text{FOV}_z = 22 \text{ cm} \)), the algorithm imparts a greater than threefold increase in soft-tissue (adipose) contrast.

As shown in Fig. 6(b), however, the algorithm appears to introduce correlated noise in the image reconstructions—to a negligible extent for the head phantom, but significantly for the body phantom. The effect is worse under higher scatter conditions (i.e., larger phantom and/or \( \text{FOV}_z \)), but its source was not identified among the various algorithm parameters—i.e., no adjustment in \( \varphi_z, v_{fit}, \theta_{filt}, \) or \( \theta_{filt} \) diminished the effect. The noise is evident as subtle, correlated streaks in CBCT axial reconstructions (e.g., Fig. 7, below). The net effect in CNR [Fig. 6(c)] is that the algorithm either improves CNR (e.g., by a factor of \( \approx 1.4 \) for the head phantom at large \( \text{FOV}_z \)) or has a negligible effect (e.g., in the body phantom). That being said, CNR can be somewhat limited as a figure of merit for overall image quality, particularly for digital imaging and depending on the nature of noise correlations. While improvement in CNR almost certainly relates to improved image quality, previous investigation suggests that in many cases observers are able to “see through” correlated noise, such as subtle streaks, and may actually prefer images exhibiting higher contrast despite equivalent (or even diminished) CNR. This, provided that noise correlations do

![Fig. 6](image1.png)

**Fig. 6.** Imaging performance in cylindrical head and body phantoms. (a) Absolute contrast, (b) voxel noise, (c) contrast-to-noise ratio, and (d) CT number inaccuracy as a function of longitudinal field of view \( \text{FOV}_z \) (i.e., scatter magnitude) with and without scatter correction. The algorithm significantly reduces scatter artifacts, while increasing contrast and maintaining or improving CNR.

![Fig. 7](image2.png)

**Fig. 7.** CBCT reconstructions of the cylindrical head and body phantoms as a function of longitudinal field of view, \( \text{FOV}_z \), with and without scatter correction. Particularly at large cone angles (\( \text{FOV}_z = 22 \text{ cm} \)), the algorithm significantly reduces cupping artifacts and streak artifacts (dark streak between bone inserts), increases contrast of the soft-tissue inserts, incurs a correlated noise penalty, and maintains or improves CNR. Grayscale windows are the same for each image pair (corrected versus uncorrected), with grayscale level varied independently.
FIG. 8. Scatter correction in patient images. (a) Prostate imaging with centered-detector geometry (FOV$_z$ =10 cm). (Left) Radiographic projections corrected for x-ray scatter exhibit improved display range and contrast. Note the visibility of three metallic markers in the prostate. (Right) Scatter-corrected CBCT reconstructions exhibit improved image contrast and uniformity throughout, despite a noise penalty (streaks) associated with error in the scatter fluence estimate. Concurrent noise-reduction is under investigation. (b) Prostate imaging with offset-detector geometry (FOV$_z$ =10 cm). The scatter-corrected projections and reconstructions exhibit similar improvement in contrast, and the algorithm is robust to the lateral asymmetry in the offset-geometry. (c) Abdominal (liver) imaging (FOV$_z$ =22 cm). The scatter-correction algorithm is robust with respect to longitudinal heterogeneity in the thorax between the diaphragm and lungs. Note that the kidneys, pancreas, and other abdominal soft-tissues—barely visible in the uncorrected reconstructions—are rendered clearly in the SPECS-corrected images. Grayscale windows are the same for each image pair (corrected versus uncorrected), with grayscale level varied independently.

FIG. 9. Head-and-neck image (FOV$_z$ =22 cm) exhibiting convex skinline protruding across columns (highlighted by the dashed vertical line) in lateral views, illustrating a challenging case for scatter estimation and correction based on distant regions of support in the collimator shadows. Axial CBCT reconstruction using SPECS correction with $v_{fit}$=2 exhibits severe streak artifacts resulting from overestimation of scatter along the highlighted column (i.e., the scatter estimate exceeds the primary+scatter, which sharply clips the corrected signal to zero). Adjustment of $v_{fit}$ (e.g., $v_{fit}$ = 1) and/or imposition of a logical constraint on the scatter estimate (such that scatter does not exceed the total signal) yields reconstructions free of streak artifacts. Grayscale windows are the same for corrected and uncorrected images, with grayscale level varied independently.
not masquerade as structures of interest. Thus, the effect of
the algorithm on CNR must be interpreted in a broader con-
text of factors affecting image quality.

Finally, Fig. 6(d) shows the performance of the algorithm
in restoring CT numbers to the correct attenuation coeffi-
cient. For the head phantom, the algorithm corrects CT num-
ber to within ~2% to 3% and nearly eliminates cupping artifact ($t_{\text{cup}} < 2\%$) for all scatter conditions. For the body
phantom, we observe a fourfold improvement in CT number
accuracy, giving $\Delta \sim 10\%$ under the highest-scatter condi-
tions. Similarly, the algorithm reduces cupping artifact ($t_{\text{cup}}$)
by a factor of 1.3–1.8. Residual values of $\Delta_c$ and $t_{\text{cup}}$ are
due to combined effects of error in the estimate of true
$\mu_{\text{water}}(0.197\ cm^{-1}$ as described above, compared to
0.192 $\ cm^{-1}$ suggested by the corrected Head reconstructions)
and error induced by the lateral truncation artifact (evident as
a bright artifact about the reconstructions in Fig. 4).

3. Phantom images

Representative CBCT reconstructions are shown in Fig. 7
for the head and body phantoms as a function of FOV$_z$. The
most significant benefit of the algorithm is the reduction of
cupping artifacts, most notably at large FOV$_z$ (22 cm), where
the detrimental effects of scatter are greatest. The dark streak
artifact between the two cortical bone inserts is also attrib-
uted to x-ray scatter, but is nearly eliminated following
SPECS correction. In addition, the corrected images exhibit
increased soft-tissue contrast. For example, the brain, breast,
and adipose inserts are barely perceptible in the body phan-
tom at FOV$_z=22$ cm, but are rendered clear after correction.
Correlated noise in the form of subtle streaks appear to be
introduced by the correction as discussed above, particularly
for the body phantom at large FOV$_z$. Similarly for the head
phantom, the cupping artifact is eliminated, the streak arti-
fact is largely expunged, and the perceptibility of soft-tissue
inserts is significantly improved.

C. Patient imaging

The algorithm was investigated further on a clinical sys-
tem with ongoing protocols for CBCT-guided radiation
therapy in various anatomical sites, including prostate, liver,
lung, and head-and-neck. Example results are illustrated in
Fig. 8. Images of the pelvis (centered-detector geometry) in
Fig. 8(a) illustrate a typical but challenging case in which
projections are laterally truncated and SPR is high even
though FOV$_z$ was set to 10 cm to encompass only the struc-
tures of interest (the prostate). The SPECS-corrected recon-
struction exhibits reduced cupping artifact (despite a bright
truncation artifact encircling the reconstruction) and in-
creased contrast, with increased noise in the form of subtle
streaks that may or may not be significant to the imaging
task.

In Fig. 8(b), images of the pelvis acquired using an offset-
detector geometry are shown, allowing larger FOV (no trunc-
ination artifact) but presenting a challenge to the algorithm
in terms of strong lateral variation in the magnitude of scatter
and primary. Scatter and primary estimates are as in Fig.
5(c). The SPECS-corrected reconstruction exhibits signifi-
cantly improved contrast visibility of the prostate, bladder,
and bowel, despite the presence of increased noise.

Figure 8(c) shows example results in the region of the
upper abdomen (liver and lung), a case presenting strong
vertical variation in the magnitude of scatter and primary
[with profiles shown in Fig. 5(d)] as well as large FOV$_z$
(22 cm). SPECS-corrected axial and sagittal views exhibit
markedly improved detectability of soft-tissue structures. For
example, the kidney, aorta, pancreas, and muscles adjacent to
the spine are barely perceptible in the uncorrected axial
views, but are rendered far more clearly upon scatter correc-
tion. Similarly in the sagittal views, visibility of the kidneys
and liver—including textural content within each organ—are
far more clearly delineated in the SPECS-corrected recon-
structions.

Images in Fig. 8 were reconstructed using the nominal
settings of the various SPECS parameters; however, a variety
of cases were identified in the patient study where these
settings—specifically $v_{\mu s}$—resulted in overestimation of
the scatter fluence, with corresponding introduction of strong
images artifacts. Such was the case particularly for objects
exhibiting strong cylindrical asymmetry (e.g., the head/neck),
as illustrated in Fig. 9. The vertical line in the lateral
projection demarks a column along which $S_j(v)$ interpolated
from the collimator shadows gives a poor estimate of the
scatter fluence at the center of the FOV (i.e., behind the
teeth), since it fails to account for self-attenuation of scatter
by the object protruding across the column. The true shape of
the scatter fluence along the column is likely closer to a
fourth-order polynomial (exhibiting maxima superior and in-
ferior to the protruding object, and a local minimum behind
the object), which the $S_j(v)$ interpolation from distant regions
of support does not properly reflect. $S_j(v)$ thus overestimates
the scatter behind the object, leading to gross image artifacts
shown in Fig. 9(c).

Two solutions come immediately to light. First, the poly-
nomial order, $v_{\mu s}$, was found to be a useful adjustable param-
eter in the scatter correction (e.g., $v_{\mu s}=1$ (linear) or 0 (con-
stant)) in such cases. As shown in Fig. 9(d), reprocessing at
$v_{\mu s}=1$ avoided the scatter overestimation, yielding a scatter-
corrected reconstruction with improved soft-tissue contrast
and CNR (e.g., muscle-fat in the posterior neck) and slightly
reduced scatter-related artifacts (lateral streaks about the ver-
tebrae). Second, an additional constraint imposed on $S_j(v)$
[specifically, that the $S_j(v)$ interpolation must always be less
than the measured (primary+scatter) signal] was found to
prevent artifacts related to scatter overestimation.

IV. DISCUSSION AND CONCLUSIONS

A simple algorithm is presented for estimation and correc-
tion of x-ray scatter, with quantitative and qualitative dem-
onstration of performance in CBCT. Because the algorithm
estimates scatter fluence directly from the projection data, it
is robust to patient orientation, asymmetry, patient motion,
system geometry, detector configuration, exposure level, etc.
The technique requires no prior information of source (en-
ergy, exposure, etc.), object (size, heterogeneity), or geometry (gap, centered- or offset-detector). Generally, the algorithm provided moderate to significant improvement in image quality—as illustrated in Figs. 7–9. In cases where the algorithm failed to improve image quality, such failure was obvious and catastrophic [as in Fig. 8(c)], related to overestimation of scatter—e.g., in cases of strong cylindrical asymmetry such that the object protruded across columns near the center of the FOV, as in the lateral head of Fig. 9. All such cases were resolved by adjustment of $v_{fr}$ and/or imposition of constraints on scatter magnitude.

The method estimates scatter fluence from detector signal in the shadow of collimator leaves, with the simple assumption that such signal is entirely attributable to x-ray scatter. Of course, this assumption is not absolutely true, limited by at least two effects: (i) transmission of primary radiation through the collimator leaves and (ii) extrafocal radiation. Neither of these effects was explicitly accounted or corrected for in the initial implementation described above. However, the first effect could be corrected by a measurement of leaf transmission, and the second effect is at least partially reduced by selection of the $z_0$ standoff parameter (~8 mm). Similarly, both of these effects could potentially be addressed by a modified flood-field correction method—correcting the projections by open-field floods as usual (where the z-collimators do not impinge on the FOV) and applying an additional correction based on flood-fields acquired with the z-collimators impinging on the FOV by the same amount as in the projections.

The method necessarily involves a reduction in the maximum longitudinal FOV due to the z-collimators impinging on the detector. In some applications (e.g., the prostate) limiting FOV in this way is simply good practice, since it reduces SPR. In other applications, however (e.g., the chest), a large FOVr is desired, raising the question as to how much collimator shadow is required for the algorithm to perform well. In the studies described above, the algorithm performed well with regions of support as small as ~10 mm. Of course, a larger region of support is better, and as much collimator shadow as available (apart from the $z_0$ standoff) should be used in estimating the scatter fluence.

Application of the algorithm is not limited to CBCT, and considering that x-ray scatter is also a significant factor in image quality in general radiography and fluoroscopy, dual-energy imaging, and tomosynthesis, the approach offers a simple, useful correction. Current implementations of CBCT mammography typically involve an under-table geometry for which reduction in FOVr would entail a loss of image data in the region of the chest wall, which is already a challenge for such implementations.

Overall imaging performance in SPECS-corrected CBCT reconstructions was comparable to that achieved using a heavy antiscatter grid. Specifically, the algorithm significantly reduces scatter artifacts, restores CT number accuracy to within a few percent, boosts soft-tissue contrast, but incurs an image noise penalty. The net effect on CNR is modest, depending on anatomical site, but the overall effect on image quality is positive, as judged qualitatively in phantom and patient images over a broad range of relevant conditions. All of the information required to estimate the scatter fluence exists in each projection and, aside from reduced maximum FOVr (which in many cases is beneficial), scatter maximum can be obtained “for free.” The algorithm offers a flexible, optional preprocessing step that demonstrates improved image quality in CBCT, with other applications (e.g., dual-energy imaging and tomosynthesis) to be investigated in future work.

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