Study of Scan Protocol for Exposure Reduction in Hybrid Spectral Micro-CT

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Summary: The hybrid spectral micro-computed tomography (CT) architecture integrates a conventional imaging chain and an interior spectral imaging chain, and has been proven to be an important development in spectral CT. The motivation for this study is to minimize X-ray exposure for hybrid spectral micro-CT using both simulated and experimental scan data while maintaining the spectral fidelity of the reconstruction. Three elements of the hybrid scan protocol are investigated: truncation of the interior spectral chain and the numbers of projections for each of the global and interior imaging chains. The effect of these elements is quantified by analyzing how each affects the reconstructed spectral accuracy. The results demonstrate that there is significant scope for reduction of radiation exposure in the hybrid scan protocol. It appears decreasing the number of conventional projections offers the most potential for exposure reduction, while further reduction is possible by decreasing the interior FOV and number of spectral projections. SCANNING 36:444–455, 2014. © 2014 Wiley Periodicals, Inc.

Key words: micro-computed tomography, spectral imaging, image reconstruction, radiation exposure

Introduction

Recent studies on hybrid spectral micro-computed tomography (CT) have demonstrated promising results for near-term implementation in pre-clinical and clinical applications (Schmidt and Pektas, 2011; Xu et al., 2012). The hybrid spectral architecture relies on a global field of view (FOV) conventional imaging chain with a transversely positioned interior FOV spectral imaging chain (Fig. 1). A primary benefit of the interior spectral imaging chain is the reduction of dose while maintaining the benefits of spectral CT imaging. This is because the X-ray beam path is collimated which reduces exposure relative to a full FOV spectral detector. Further reduction in X-ray exposure can be achieved by using a limited number of projections and compressive sensing (CS)-based iterative reconstruction methods (Yu and Wang, 2010; Xu et al., 2012).

Interior tomography has become an active research pursuit because of its ability to reduce radiation dose and detector size in pre-clinical and clinical scenarios that require diagnostic images of a region of interest (ROI), for example in cardiac imaging. In the case of spectral CT, a hybrid architecture using interior tomography offers advantages that help to overcome limitations with current spectral (i.e., spectroscopic, energy-sensitive, multi-energy, etc.) detector technology, including limited detector size and photon-counting rate. Many
current spectral detectors are small and expensive and suffer from signal degradation (e.g., pulse pile-up) when exposed to high X-ray flux (Taguchi et al., 2009; Schmidt and Pektas, 2011). These issues can be addressed by capturing spectral projections that only pass through a truncated interior ROI which allows for a smaller spectral detector size. Additionally, the counting rate of photon counting detectors is limited by several factors, including pulse pile-up (Taguchi et al., 2009).

An interior scan only measures the flux penetrating the center of the object. Thus the source flux can be much higher without exceeding this maximum rate since the outer regions with the greatest flux are outside the detector and allows for improved photon statistics in the interior region and faster scan times.

Exposure reduction for hybrid spectral micro-CT can be achieved by reducing the width of the interior FOV, the number of interior projections, and the number of global projections. Fewer projections also allows for shortened scan time which can be critical for in vivo biomedical applications. CS-based iterative reconstruction methods can be better suited to the reconstruction problem of a reduced number of projections than analytic reconstruction methods such as filtered back-projection (FBP). However, it is important that the aforementioned reductions do not significantly degrade the spatial or spectral fidelity of the reconstructed images.

The goal of this study is to evaluate the effects of interior FOV, reconstruction method, and number of projections on reconstructed spectral fidelity in simulated and real experimental settings. The remainder of this paper is organized as follows: Methodology section describes the hybrid scan protocol for the real and simulated datasets along with evaluation metrics; Experimental Results section contains the results of the spectral fidelity evaluation on the real and simulated reconstructions; and Discussion section concludes the paper and discusses some related issues and future studies.

**Materials and Methods**

The exposure reduction parameters are applied to both real and simulated hybrid spectral micro-CT data. The protocols for collecting, reconstructing, and evaluating these datasets are described below.

**Contrast and Thorax Phantoms**

A simple contrast phantom was designed, crafted, and then scanned with a hybrid system; numerical simulations were also performed. The phantom body is composed of a 25 mm diameter poly(methyl methacrylate) (PMMA) cylinder with six equally spaced 6 mm diameter cylindrical cavities. Each cavity has one of six polyethylene centrifuge tubes containing various concentrations of clinical contrast agents (CA): gadolinium-based Magnevist (gadopentetate dimeglumine, Berlex Laboratories, Wayne, NJ) and iodine-based Omnipaque 300 (iohexol, GE Healthcare, Princeton, NJ). The actual phantom and an axial schematic are shown in Figure 2.

In addition, a simulated thorax phantom was created to evaluate the hybrid scanning method on a sample with more complexity than the CA phantom; a schematic is shown in Figure 3. Several CA regions were specifically positioned away from the sample center to ensure that
the regions would be completely excluded from the interior spectral FOV. The spine region was designed with a slender bone protrusion that represents fine structure lacking in the CA phantom.

**Simulation and Real Hybrid Scanner**

Fan-beam projections for the two phantoms in the previous section were generated using the simulation method described in previous studies (Xu et al., 2012; Bennett et al., 2013). Material-dependent linear attenuation coefficients as functions of incident photon energy were calculated using NIST tables (Hubbell and Seltzer, 1995), the source spectrum was simulated with Spektr (Siewerdsen et al., 2004), and the spectral detector efficiency as a function of incident energy was simulated. The simulation scan parameters mirrored the real hybrid scanner settings (Table I).

The real hybrid spectral micro-CT scan of the contrast phantom was performed using two separate systems: a Medipix All-Resolution Scanner (MARS) (MARS Bioimaging, Christchurch, New Zealand) spectral micro-CT scanner and an Xradia XCT conventional micro-CT scanner (Xradia, Pleasanton, CA). The phantom was intentionally designed to be physically static, thus allowing for the scans to be performed in two separate locations. Previous studies have proven the hybrid spectral micro-CT architecture (Bennett et al., 2013), however, these facilities were unavailable for this study, and hence the two scans were performed separately and exposure reduction parameters were evaluated by directly modifying the reconstruction inputs. In other words, full FOV and maximum projection number datasets were separately collected for traditional and spectral imaging chains, and then manually modified to emulate various hybrid scanner configurations. The reference values for the number of projections were selected from the manufacturer recommended scan protocols for high spatial resolution, 360 and 1,500 projections for spectral and conventional imaging chains, respectively.

**Reconstruction and Decomposition**

Two different algorithms were used to reconstruct the hybrid data sets. One is compressed-sensing based

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**Table 1 Hybrid spectral micro-CT hardware component specifications**

<table>
<thead>
<tr>
<th></th>
<th>Energy-integrating imaging chain</th>
<th>Spectral imaging chain</th>
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<tr>
<td>X-ray source</td>
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<td>Tube voltage</td>
<td>80 kVp</td>
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<tr>
<td>Tube current</td>
<td>100 μA</td>
<td>150 μA</td>
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<tr>
<td>Output window</td>
<td>Beryllium, 100 μm thick</td>
<td>Glass (1.8 mm Al equivalent) + 150 μm Beryllium</td>
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<tr>
<td>Distance to center of rotation</td>
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<td>119 mm</td>
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<tr>
<td>X-ray detector</td>
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<tr>
<td>Pixel size</td>
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<td>Energy bin(s) range</td>
<td>Integrated, 0–80 keV</td>
<td>28–38, 45–55 keV</td>
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<tr>
<td>Energy bin width</td>
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<td>4 keV</td>
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<td>Counts per exposure</td>
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<td>Distance to center of rotation</td>
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<td>66 mm</td>
</tr>
<tr>
<td>Detector type</td>
<td>Scintillator</td>
<td>Medipix 3.1, 300 μm GaAs layer</td>
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statistical interior tomography (CS-SIT) (Xu et al., 2011); the other uses the grayscale data to estimate spectral projection data outside the interior FOV and reconstructs images using conventional filtered back-projection (FBP). CS-SIT has been proven to be effective at hybrid reconstructions in previous studies (Xu et al., 2012; Bennett et al., 2013), but is considerably slower than FBP. Both algorithms were applied to the datasets to determine which is best suited for hybrid spectral reconstruction. Voxel size was 60 μm³ for all reconstructions.

CS-SIT is fully derived in a previous publication, but a summary is presented here for convenience. The detected photon count $y_i^s$ for one ray $i$ in one spectral channel $s$ follows a Poisson distribution (Buzug, 2008)

$$y_i^s \sim \text{Poisson}\{ b_i^s \exp(-p_i^s) + n_i^s \},$$

where $b_i^s$ is the flat-field (open-beam) photon count, $p_i^s = \sum_{j=1}^{J} a_{ij} \mu_j^s$, is the integral of the X-ray linear attenuation coefficients (ray-sum) along ray $i$, $A = \{a_{ij}\}$ is the system (forward-projection) matrix, $\mu^s = (\mu_1^s, \ldots, \mu_J^s)^T$ is the set of linear attenuation coefficients comprising the image (the voxels), $n_i^s$ is a noise term, $I$ is the total number of measurements (product of number of detector pixels and number of view angles), and $J$ is the total number of image voxels.

CS-SIT postulates that a piecewise homogeneous region of interest (ROI) can be exactly reconstructed from truncated projections by minimizing the total variation (TV) of the image. The complete reconstruction algorithm combines the Poisson nature of the data with TV regularization in finding a maximum a posteriori (MAP) estimate of the attenuation image $\mu^s$.

Reconstruction is thus achieved by minimizing the objective function

$$\Phi(\mu^s) = \sum_{i=1}^{I} \frac{1}{2} (|A \mu^s|_i - \hat{p}_i^s)^2 + \beta \text{TV}(\mu^s), \quad s = 1, \ldots, S,$$

where $\hat{p}_i^s = \ln(b_i^s/y_i^s)$ is the measured line integral, $\text{TV}(\mu^s)$ is the total variation of the image $\mu^s$ and $\beta$ is a parameter to balance the data fidelity and TV terms. The global data is incorporated into the algorithm by initializing the state for the reconstruction using the global reconstruction $\mu_G$. We reiterate that this is merely a summary of the algorithm, details can be found in Xu et al. (2012). The corresponding full FOV reconstruction algorithm is statistical iterative reconstruction with a total-variation regularization constraint (SIR-TV) (Liu et al., 2010), which operates in the same manner but with an empty initial estimate.

Figure 4 illustrates the FBP based reconstruction process, which was inspired by Lewitt and Bates (’78) and is closely related to the approach taken by Schmidt and Pektas (2011). In our method, the global reconstruction is first forward-projected (reprojected) using the geometry of the spectral imaging chain. The new global sinogram exactly matches the spectral sinograms except that it covers the full object and thus the edges of the global sinogram can be used as approximations to the truncated parts of the spectral sinograms. The new global sinogram exactly matches the spectral sinograms except that it covers the full object and thus the edges of the global sinogram can be used as approximations to the truncated parts of the spectral sinograms. The global sinogram values are scaled to match the values at the edges of each spectral channel, and the data are blended over 10 pixels to avoid any sudden jumps in the combined (hybrid) sinogram. The hybrid sinograms are used to perform reconstruction by conventional fan-beam...
FBP; this hybrid reconstruction method will be referred to simply as FBP in this manuscript.

Decomposition of the reconstructed hybrid spectral image set is performed with independent component analysis (ICA) (Hyvärinen and Oja, 2000), using a fixed-point iteration scheme known as FastICA (Hyvärinen, '99). ICA is a statistical multivariate data processing technique developed for blind source separation which we use to decompose the set of spectral reconstructions \( \{ \mu^r(x) \}_{r=1}^R \) into components \( \{ \hat{\mu}_\alpha(x) \}_{\alpha=1}^N \) such that

\[
\begin{pmatrix}
\mu^1(x) \\
\mu^2(x) \\
\vdots \\
\mu^S(x)
\end{pmatrix} = M
\begin{pmatrix}
\hat{\mu}_1(x) \\
\hat{\mu}_2(x) \\
\vdots \\
\hat{\mu}_N(x)
\end{pmatrix}
\]

(3)

where \( M \) is the mixing matrix estimated by ICA, \( N \leq S \) is the number of independent components, and the notation for \( \mu \) is slightly different to that used in (2): here the images are denoted \( \mu^r(x) \) to be interpreted as row vectors indexed by voxel coordinates \( x \). ICA operates in a manner similar to principal component analysis (PCA) (Kalukin et al., 2000), but unlike PCA it is not restricted to finding orthogonal basis functions; instead it seeks statistically independent underlying functions, which can be a powerful technique for numerous applications (Hyvärinen and Oja, 2000). In this study, ICA is applied to the attenuation spectra found in the set of reconstructed hybrid image voxels. While PCA has previously been used successfully to decompose spectral reconstructions (Butler et al., 2011; Xu et al., 2012; Bennett et al., 2013), ICA was chosen because it offers the potential for better separation of individual materials since statistical independence is a stronger property than uncorrelatedness (Hyvärinen and Oja, 2000); our results confirm that ICA indeed outperforms PCA (see Fig. 6). The ICA algorithm was trained with images reconstructed from full FOV spectral data using each of the reconstruction algorithms, and then the appropriate separation matrix was applied to the hybrid reconstructions.

After applying ICA to the hybrid spectral image set, the resulting component images (“channels”) were compared to distinguish iodine from gadolinium. As shown in Experimental Results section, ICA produced three channels of meaningful data: one channel enhanced iodine, another enhanced gadolinium, and a third contained residual PMMA density. It is important to note that the channels are not pure targeted decompositions where each channel contains only the contribution of a specific material, as would be expected from a scheme such as that of Roessl and Proksa (2007) or Scholomka et al. (2008). While targeted decomposition is a worthwhile goal, the data we are able to obtain from the current MARS spectral X-ray detector is not amenable to this type of analysis because charge sharing (Korn et al., 2007) and residual energy dispersion (Walsh et al., 2011) nonlinearly corrupt the measured transmission spectrum such that it can no longer be decomposed into a simple sum of material transmission spectra. Regardless, the results of Scholomka et al. (2008) show that features of other materials leak into the contrast agent channels even with targeted decomposition.

Contrast agent identification in the reconstructed image is achieved as follows: the ICA separation produces one channel that enhances iodine and a second channel that enhances gadolinium, as illustrated in Figure 6; these images will henceforth be referred to as the iodine channel and the gadolinium channel. The average background value is subtracted from each of these images and then the images are compared voxel-wise. Voxels with a greater value in the iodine channel are marked as iodine, and likewise with the gadolinium channel; a small dead-zone is included in the comparison to reduce noise in the identification result where the two channels have comparable values. Thus

\[
f_1(x) = \begin{cases} 
1, & \hat{\mu}_1(x) - \hat{\mu}_{Gd}(x) > \varepsilon \\
0, & \text{otherwise}
\end{cases}
\]

\[
f_{Gd}(x) = \begin{cases} 
1, & \hat{\mu}_{Gd}(x) - \hat{\mu}_1(x) > \varepsilon \\
0, & \text{otherwise}
\end{cases}
\]

(4)

where \( f_1(x) \) and \( f_{Gd}(x) \) are binary images showing the voxels identified as iodine and gadolinium, respectively, \( \hat{\mu}_1(x) \) and \( \hat{\mu}_{Gd}(x) \) are the iodine and gadolinium channel, respectively, \( x = (x_1, x_2) \) is the coordinates of an image voxel, and \( \varepsilon \) is the deadzone. Examples of \( f_1(x) \) and \( f_{Gd}(x) \) are shown in Figure 5 for three interior FOVs. The images show both \( f_1(x) \) and \( f_{Gd}(x) \), with \( f_1(x) \) mapped to green and \( f_{Gd}(x) \) mapped to red; inspection of (4) will show that it is impossible for a voxel to have a value of 1 in both binary images.

**Measurements and Metrics**

Several metrics are used to evaluate the effect of exposure reduction on hybrid reconstruction. Effective FOV (EFOV) was calculated for interior FOV reduction; EFOV, and contrast to noise ratio (CNR) were used to evaluate reduction of interior spectral projections; and CNR was used to evaluate the reduction of global projections. The meaning and calculation of these metrics are explained below.

Previous studies of the hybrid architecture have suggested that useful spectral information extends beyond the spectral interior FOV (Xu et al., 2012; Bennett et al., 2013). In this study, we sought a measure of this “spectral dispersion” by virtue of the EFOV...
which is defined as the region within which the spectral fidelity is sufficient to correctly distinguish between the two CAs in the phantom with at least 90% of the accuracy of the full FOV spectral reconstruction. We measure the accuracy radially by calculating the proportion of correctly identified voxels within concentric rings of 1.5 mm thickness,

\[
a(r) = \frac{\sum_{x=\Gamma(r)} [f_1(x) \times g_1(x) + f_{\text{Ga}}(x) \times g_{\text{Ga}}(x)]}{\sum_{x=\Gamma(r)} [g_1(x) + g_{\text{Ga}}(x)]}
\]

(5)

where \(a(r)\) is the accuracy at radius \(r\), \(\Gamma(r)\) is the set of image voxels in the band of width 1.5 mm with mean radius \(r\), and \(g_1(x)\) and \(g_{\text{Ga}}(x)\) are the known regions of iodine and gadolinium, respectively. Equation (5) can be interpreted as counting the number of voxels at radius \(r\) from the image center that were identified correctly, and dividing by the total number of CA voxels at that radius. We calculate the EFOV by finding the radius where the accuracy of the hybrid reconstruction first drops to 90% of the accuracy found in the full FOV spectral reconstruction. In cases where the accuracy is better than 90% over the full phantom, we set the EFOV to the maximum radius that contains contrast agent: 83% for the PMMA phantom and 95% for the thorax phantom.

When evaluating the reduction of spectral projections, CNR is calculated separately for each of the gadolinium and iodine channels, and for each CA region within these images. The contrast is measured against the average attenuation of the PMMA (or soft tissue, as

### Fig 5
Hybrid spectral reconstructions after ICA and color-mapping of simulated projection data sets with interior FOVs: (A) 50%, (B) 60%, and (C) 70% of full FOV.

### Fig 6
(A), (B), and (C) are the first, second, and third ICA channels, respectively, of the full FOV real spectral CS-SIT reconstructions. (D), (E), and (F) are the first, second, and third PCA channels, respectively, of the full FOV real spectral CS-SIT reconstructions.
appropriate), and the noise is measured in the PMMA region. For example,

$$\text{CNR}_{k|\alpha} = \frac{\bar{\mu}_{k|\alpha} - \bar{\mu}_{\text{PMMA}|\alpha}}{\sigma_{\text{PMMA}|\alpha}}$$

(6)

where $\bar{\mu}$ denotes the mean image value in a region, $\sigma$ denotes the standard deviation in a region, and the subscript identifies the measured region. $k|\alpha$ denotes region number $k$ (see Figure 2) in the $\alpha$ channel (either gadolinium or iodine), and PMMA$|\alpha$ similarly denotes the PMMA region in the $\alpha$ channel. Ideal results would show a high CNR for the gadolinium regions (2, 4, and 6) and zero CNR for the iodine regions (3, 5, and 7) in the gadolinium channel, and vice versa.

The CNR measurement for varying number of global projections is only calculated on region 2 ($0.5 \text{ M gadolinium}$). Thus

$$\text{CNR} = \frac{\bar{\mu}_{2|G} - \bar{\mu}_{\text{PMMA}|G}}{\sigma_{\text{PMMA}|G}}$$

(7)

where the subscript “$|G$” denotes that the respective value is measured on the global reconstruction. The gadolinium region is used in this calculation because it has the greatest attenuation of the CA regions.

Results

Each of the exposure reduction techniques is considered separately below. Within each section, representative hybrid reconstructions are shown to illustrate the effect of the particular technique, using both FBP and CS-SIT/SIR-TV. Radius values are given as a fraction of the phantom radius (1.25 cm), and spectral FOV width is measured as a percentage of the phantom diameter.

ICA and PCA

The reconstructed images of the real phantom spectral scan were decomposed using both ICA and PCA in MATLAB (MathWorks, Natick, MA) to compare the performance of these methods. The images in Figure 6 demonstrate that ICA decomposes the three phantom materials into separate channels, whereas PCA does not clearly decompose each material. For example, the gadolinium in region 2 is distributed between the second and third PCA components while the gadolinium in region 4 cannot be distinguished in any of the first three PCA components. These results confirm the anticipated benefits of ICA, and subsequent results are processed only with ICA. Computational costs for each of the methods were comparable: ICA and PCA required an average 7.5 and 18 s, respectively, to decompose the real phantom data. Note that the PCA implementation in MATLAB does not have the option to stop processing after a set number of components, and thus the cost quoted here is greater than would be necessary in an optimized environment. Decomposition of the thorax phantom reconstructions (Fig. 7) shows that ICA successfully separates the CAs when bone is present in the object. In this case the soft tissue appears to spread more evenly between the channels, rather than collecting mainly in one channel like PMMA does in the CA phantom results.

While it is not shown here, we found that repeating ICA decomposition with the same data did not always produce the same separation order; i.e. sometimes the first channel would enhance iodine, while other times the second channel would do so. This non-deterministic behavior is due to the statistical nature of ICA, and because FastICA seeds its iterative routine with a pseudo-random mixing matrix (Hyvarinen, '99). This means that the order of two similarly strong components will depend on which is nearer to the random initial matrix. This behavior had no effect on the decomposition of the hybrid images because the separating matrix was set after training it with full FOV spectral data and did not change between image sets.

Interior FOV

The effect of reducing the spectral interior FOV was studied. Simulated hybrid reconstructions of the CA phantom with two representative truncation levels are shown in Figure 8. The loss of spectral fidelity,
especially outside the FOV, can be seen in the top images (small FOV) compared to the bottom row (larger FOV). As can be expected, reduced spectral FOV causes reduced spectral fidelity. To quantify this effect, EFOV values were calculated for the simulated and real CA phantom data, along with simulated thorax phantom data (Fig. 9). Figure 9A shows that the real data follows mostly the same trend as the simulated data, except for the simulated data as reconstructed with CS-SIT which retains good spectral fidelity over the whole image even with a narrow spectral FOV. Figure 9B shows that the EFOV plateaus when the interior FOV contains most of the CA volume, therefore the truncated spectral accuracy is dependent on the structure of the sample. The diagonal line through each of the plots in Figure 9 indicates where the EFOV is equal to the actual FOV; where the plot is above this line, the EFOV is larger than the actual FOV.

The plots in Figure 9A suggest that the EFOV is generally not much larger than the actual FOV. However, Figure 8 shows that CA identification remains possible (albeit less reliable) outside the EFOV boundary and is dependent not only on radius but also on CA concentration. The higher concentration CA regions (2 and 3 in Figure 2) are reliably decomposed even with a narrow FOV, while the regions of medium concentration (4 and 5 in Figure 2) more rapidly lose spectral fidelity. The lowest concentrations could not be decomposed even with full FOV spectral data, and thus are not considered. The plots of Figure 9B demonstrate better EFOV vs. actual FOV. A possible reason for this is that the thorax phantom does not have CA concentrations as low as the CA phantom; a second possibility is that the structure of the thorax phantom leads to more reliable decomposition. In summary, EFOV is larger than the FOV in general and the relationship between EFOV and FOV is sample dependent.

**Interior Projections**

Next, the number of interior spectral projections was studied to evaluate its effect on CNR and EFOV. Hybrid reconstructions are shown in Figure 10 with two representative interior projection numbers and an interior FOV of 60%. For the small number of projections (40) on the top row, CS-SIT shows better
noise suppression while FBP shows better homogeneity. The results in Figure 11 demonstrate that a larger number of interior projections produces higher CNR, whereas the EFOV appears to remain relatively constant once the number of projections surpasses some threshold. Again the difference between CS-SIT and FBP is greatest in the simulated results whereas almost no difference appears in the EFOV plots for the real scan data. CS-SIT reconstructions also appear to have a higher CNR than FBP reconstructions in most of the reconstructed datasets. It is interesting to note that while the CNR curves for FBP reconstructions follow a mostly straightforward profile, those for CS-SIT reconstructions can show more fluctuations, making prediction of reconstruction performance slightly difficult.

**Global Projections**

Finally, the effect of the number of global projections on the reconstructed grayscale CNR was evaluated. Reconstructions for two representative numbers of global projections and with a spectral FOV of 60% are shown in Figure 12. The visible effect of reducing

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**Fig 10.** Hybrid spectral reconstructions after ICA and color-mapping of simulated number of interior projections with FOV of 60% of full FOV (projection number and reconstruction method): (A) 40 and FBP, (B) 40 and CS-SIT, (C) 240 and FBP, (D) 240 and CS-SIT.

**Fig 11.** (A) Effective FOV vs. number of interior spectral projections for simulated and real phantom reconstruction; CNR vs. number of interior spectral projections for: (B) simulated phantom, (C) real phantom, and (D) simulated thorax reconstructions.
the number of global projections differs between the reconstruction methods: in FBP few projections cause streaks to appear and the noise level to increase, while in CS-SIT the image becomes “patchier” in homogeneous regions. Our understanding is that this is due to the smoothing effect of TV minimization operating on the greater noise level. CNR values in Figure 13 show that CS-SIT slightly outperforms FBP in the simulated and real CA phantom studies. However, FBP method performs better for the thorax phantom. In all cases both reconstruction methods show a very similar relationship between the number of global projections and the CNR, exhibiting a gentle decline in CNR as the number of projections drops from 1,500, then a knee at 100–200 projections below which the CNR drops more rapidly.

Discussion and Conclusion

Reduction in exposure will generally reduce either the quantity or quality of data available for reconstruction. The cases studied here all reduced the data quantity, whereas exposure reduction by other means (e.g., decreasing flux or acquisition time) would reduce the data quality since the signal to noise ratio (SNR) of an X-ray measurement is proportional to the square-root
of the measurement due to its Poisson nature (Buzug, 2008). Reduction of the quantity of data will always result in reduced reconstruction quality for a given reconstruction algorithm, so there is always a trade-off between radiation exposure and quality of the reconstructed image and research is constantly ongoing to develop advanced algorithms for better reconstruction for a given set of projections. This study did not investigate the effects of scan parameters such as acquisition time or beam flux; hence we do not give absolute dose values but instead use relative exposure values.

Another limitation to the study is the use of fan-beam simulation and reconstruction. Many conventional CT scanners, including those utilized in this study, can operate in cone-beam mode. Yet this study chose to use fan-beam mode to reduce complexity and computational expense of the numerous simulations and reconstructions. Furthermore, many commercial spectral detectors are linear strip arrays which only operate in fan-beam mode. Future research may incorporate cone-beam, spiral/helical, and other advanced scanning modes for further exposure reduction.

Our overall finding is that there is further scope for radiation exposure reduction, and hence dose reduction, in the hybrid scan protocol. The number of global projections clearly need not be 1,500, a figure close to 300 is more appropriate and corresponds to an exposure reduction of 80% from the grayscale imaging chain relative to the manufacturer recommended protocol. The number of interior spectral projections need not be 360, either. It could be reduced up to 50% compared with our previous hybrid scan protocols. Finally, the spectral FOV should not be larger than the region of interest (ROI). It appears to be feasible to reduce the FOV inside the ROI, as the spectral information extends beyond the FOV. Acceptable FOV truncation levels depend on the expected concentration of the CA within the sample, leading to a trade-off: a narrower spectral FOV can be achieved if the CA concentration is increased. However, there are practical limits to the usable CA concentration, principally patient toxicity (Prince et al., ’96). This trade-off also applies to a certain extent to the number of spectral projections. A comprehensive study of the relationship between CA concentration and the combination of spectral FOV and number of spectral projections is warranted. Studies on the efficacy of various material decomposition/classification methods for elemental mixtures would be valuable. Additionally, further research should be performed on the decomposition technique. The existence of robust PCA was identified in the review process and may represent a promising future direction for spectral decomposition.

We believe that the CNR of images reconstructed with the iterative techniques is greater than that of those reconstructed with FBP because SIR-TV and CS-SIT include a smoothing operation which suppresses the amount of variation in the images. It may be possible to increase the CNR of the FBP images to similar levels by applying a post-reconstruction smoothing filter. However, our purpose is not to compare the absolute CNR values between reconstruction algorithms but to observe the relative behavior along each plot. The plots presented here show that the two algorithms exhibit a similar behavior in response to decreasing numbers of projections.

Comparison of the results presented here suggests that CS-SIT outperforms FBP for hybrid reconstruction. The smoother reconstructions appear to slow the deterioration of spectral fidelity with increasing distance from the FOV. An additional consideration is the reconstruction time: a single CS-SIT reconstruction takes nearly 19 min while a single FBP reconstruction with comparable optimization takes only 23 s. These routines could be optimized and multiple energy bins can be reconstructed in parallel, however, these numbers are indicative of the relative computation expense of the algorithms.

This work has identified several promising areas for follow-up studies. In addition to measuring the relationship between CA concentration and EFOV, optimizing the parameters controlling the iterative reconstruction techniques would be worthwhile. CS-SIT only uses the global reconstruction as an initial image estimate, hence the influence of the global image diminishes and the image quality outside the FOV deteriorates as the iterations advance. Naturally, performing zero iterations would not incorporate the spectral data into the reconstruction, so an optimal number of iterations that maximizes the spectral image quality while minimizing interior reconstruction artifacts must exist. The objective TV parameter controls the amount of smoothing performed by the TV minimization; we have kept this parameter as a constant in all reconstructions to allow fair comparison, but have noticed that the amount of smoothing resulting from a particular value is dependent on the image being reconstructed. A method to separate this parameter from the image and an optimization study would enhance the results generated using this relatively new algorithm. The optimal relaxation factor $\beta$ should be studied as it was heuristically selected in our study.

In conclusion, we have investigated several promising methods for exposure reduction in the hybrid spectral micro-CT architecture. We have studied the effects of decreases in the spectral FOV, the number of spectral projections, and the number of global projections, and found that these parameters can be used to reduce exposure by up to 80% relative to manufacturer recommendation. We also identified several further areas needing optimization which will be addressed in future studies. The iterative reconstruction algorithms outperform FBP, although the latter does produce reasonable results with lower computational cost.
References