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Algorithm-enabled exploration of image-quality potential of cone-beam CT in image-guided radiation therapy

Xiao Han¹, Erik Pearson², Charles Pelizzari², Hania Al-Hallaq², Emil Y. Sidky, Junguo Bian³, and Xiaochuan Pan^{1,2}

¹Department of Radiology, The University of Chicago

²Department of Radiation and Cellular Oncology, The University of Chicago

³Department of Radiology, Massachusetts General Hospital

Abstract

Kilo-voltage (KV) cone-beam computed tomography (CBCT) unit mounted onto a linear accelerator treatment system, often referred to as on-board imager (OBI), plays an increasingly important role in image-guide radiation therapy. While the FDK algorithm is used currently for reconstructing images from clinical OBI data, optimization-based reconstruction has also been investigated for OBI CBCT. An optimization-based reconstruction involves numerous parameters, which can significantly impact reconstruction properties (or utility). The success of an optimization-based reconstruction for a particular class of practical applications thus relies strongly on appropriate selection of parameter values. In the work, we focus on tailoring the constrained-TV-minimization-based reconstruction, an optimization-based reconstruction previously shown of some potential for CBCT imaging conditions of practical interest, to OBI imaging through appropriate selection of parameter values. In particular, for given real data of phantoms and patient collected with OBI CBCT, we first devise utility metrics specific to OBI-quality-assurance tasks and then apply them to guiding the selection of parameter values in constrained-TV-minimization-based reconstruction. The study results show that the reconstructions are with improvement, relative to clinical FDK reconstruction, in both visualization and quantitative assessments in terms of the devised utility metrics.

1. Introduction

Kilo-voltage (KV) cone-beam computed tomography (CBCT) [1] continues to play an increasingly important role in image-guide radiation therapy (IGRT) [2, 3, 4]. The addition of CBCT images immediately prior to treatment provides greater confidence in patient setup and targeting accuracy allowing for smaller margins on the treated volume [5, 6] and steeper dose gradients [7, 8, 9, 10, 11, 12] for sparing healthy tissue [13]. In IGRT, a KV CBCT unit mounted onto the treatment linear accelerator, referred to as an on-board imager (OBI) in the work, employs a circular scanning configuration for collecting data at a substantial number (e.g., 300 to 900) of uniformly distributed projection views, and analytic algorithms such as the FDK [14] or its variant are used for image reconstruction [15, 16, 17]. There is also

rapidly growing interest in developing optimization-based reconstruction for CBCT [18, 19, 20, 21, 22, 23, 24, 25] especially in the context of OBI [26, 27, 28, 29, 30, 31, 32, 33, 34], because it may possess some potential advantages over analytic reconstruction such as FDK in practical applications.

The work is motivated by two application-driven observations: (1) despite the fact that optimization-based reconstruction has been investigated for OBI CBCT, there seems to be insufficient evidence demonstrating whether it can yield images of quality comparable to, or higher than, FDK reconstruction (or its variants) when applied to data collected with a standard, clinical scanning configuration [30, 27, 32, 28]; and (2) interest exists in developing additional OBI-imaging configurations of clinical workflow significance, and optimization-based reconstruction may facilitate the realization of such imaging configurations to which the FDK algorithm may not be applied adequately. It is thus of practical value to investigate such imaging configurations enabled by optimization-based reconstruction.

Among the numerous optimization-based reconstructions proposed for CBCT, the constrained-total-variation (TV)-minimization-based reconstruction [20, 35] has been shown of some potential for imaging conditions of practical interest [36, 37, 38]. In general, the complete specification of an optimization-based reconstruction involves, in addition to its mathematical formulation, a number of parameters [35, 39], which can significantly impact reconstruction properties (or utility). Therefore, successful application of a specific optimization-based reconstruction, such as the constrained-TV-minimization-based reconstruction, to a particular class of practical applications essentially entails appropriate selection of the parameter values for yielding reconstructions with desired reconstruction properties. There remains, however, insufficient effort devoted specifically to investigating quantitatively how values of reconstruction parameters can be selected appropriately for yielding reconstructions with desired properties from real data in applications.

In this work, we focus on the development and demonstration of tailoring the constrained-TV-minimization-based reconstruction to clinical-OBI imaging, through appropriate selection of reconstruction-parameter values. In particular, for given real data of phantoms and patient collected with a clinical OBI unit, we first devise utility metrics specific to OBI-quality-assurance tasks and then apply them to guiding the selection of the parameter values in constrained-TV-minimization-based reconstructions from OBI data.

The manuscript is organized as follows: a brief description of OBI-data acquisition and the constrained-TV-minimization-based reconstruction is given in Sec. 2. Following an inverse-crime study in Sec. 3 for reconstruction verification, we devise utility metrics based upon quality-assurance tasks in OBI imaging to guide the parameter-value determination in Sec. 4, present results of phantom and patient studies in Sec. 5, and make remarks about the study results in Sec. 6.

2. Materials and Methods

We briefly describe below data acquisition, imaged subjects, and scanning configurations in OBI imaging and the constrained-TV-minimization-based reconstruction.

2.1. Data acquisition

The OBI, mounted on a linear accelerator system[‡], consists of a KV X-ray source and a flat-panel detector of 2048×1536 pixels, with a 100-cm source-to-isocenter and 150-cm source-to-detector distances. The detector performs a 2×2 binning prior to readout, resulting in 1024×768 effective pixels of size 0.388 mm. Data were collected from a standard quality-assurance phantom, i.e., the Catphan phantom, an anthropomorphic Rando-head phantom[§], and a prostate-cancer patient. In particular, sections 515, 528, and 404 within the Catphan phantom are used for analysis of contrast, spatial, and combined-contrast-spatial properties in OBI-image reconstructions.

Two scanning configurations are used routinely in OBI-imaging applications, which are referred to as *full*- and *half*-scan configurations covering angular ranges of 360° and 203° . In physical phantom studies, we collected data at high (i.e., 2 mAs) and low (i.e., 0.2 mAs) dose levels at X-ray energy of 100 kVp from 640 views uniformly distributed over 2π , and denote them as HD-f640 and LD-f640, with “HD” and “LD” indicating high and low dose levels, and “f640” a full scan with 640 views. Half-scan data HD-h360 and LD-h360 containing data samples at 360 views over a half-scan angular range of 203° were created also from data HD-f640 and LD-f640. Again, “h360” indicate 360 views uniformly distributed over 203° , i.e., the half-scan angular range. We refer to these data as *densely sampled* full- and half-scan data. In addition, we collected a data set of a prostate-cancer patient in a routine clinical study with X-ray exposure and energy of 0.4 mAs and 110 kVp at 626 views uniformly distributed over 2π , and refer to it as densely-sampled 626-view patient data. We note that the detector in the patient scan was shifted for effectively increasing the OBI field of view (FOV) so that the cross section of the patient pelvis can completely be covered. These densely sampled data sets are summarized in row 1 of Table 1. As discussed in Sec. 5.1, we refer to the FDK reconstruction from high-dose, densely sampled full-scan data, HD-f640, or from densely sampled 626-view patient data, as *the FDK benchmark* for ASD-POCS reconstructions of the phantoms, or the prostate-cancer patient.

2.2. Constrained-TV-minimization-based reconstruction

The constrained-TV-minimization-based reconstruction considered includes several key components, which are summarized below.

2.2.1. Optimization program—Let vector $\mathbf{f}$ of size N denote a discrete image to be reconstructed from knowledge of data vector $\mathbf{g}$ of size M . An entry f_j of $\mathbf{f}$ (or an entry g_i of $\mathbf{g}$) represents an image value within voxel j (or data value on detector bin i .) We formulate the reconstruction as a constrained-TV-minimization program [35]

[‡]Trilogy, Varian Medical Systems, Palo Alto, CA

[§]Catphan®504 and RANDO®man, The Phantom Laboratory, Salem, NY

$$\mathbf{f}^* = \arg\min \|\mathbf{f}\|_{TV} \text{ s.t. } D(\mathbf{f}) \leq \epsilon \text{ and } f_j \geq 0, \quad (1)$$

where the image $\|\mathbf{f}\|_{TV} = \sum_{j=1}^N |\nabla f_j|$,

$$D(\mathbf{f}) = (1/M) \sqrt{(\mathcal{H}\mathbf{f} - \mathbf{g})^T \mathcal{W} (\mathcal{H}\mathbf{f} - \mathbf{g})} \quad (2)$$

the average of a weighted Euclidean divergence between a discrete-to-discrete (DD) data model $\mathcal{H}\mathbf{f}$ and actual data $\mathbf{g}$ over detector bins; $\mathcal{H}$ of size $M \times N$ the system matrix relating image and data vectors; $\mathcal{W}$ an $M \times M$ diagonal matrix in which an diagonal element is a weighting factor applied to the corresponding data entry; and ϵ the tolerance parameter for D . Whereas an identity matrix $\mathcal{W}$ was used in the phantom studies, for the study of the prostate-cancer patient, a matrix $\mathcal{W}$ incorporating the offset-detector geometry [40] was computed as

$$\mathcal{W}_{ii} = \begin{cases} 0, & -(R+L) \leq u_i \leq -(R-L) \\ \cos^2 \left[\frac{\pi(\tau - \tau_{m1})}{4\tau_{m1}} \right], & -(R-L) \leq u_i < R-L \\ 1, & R-L \leq u_i \leq R+L \end{cases} \quad (3)$$

where

$$\tau = \tan^{-1} \left(\frac{u_i}{S} \right), \tau_{m1} = \tan^{-1} \left(\frac{R-L}{S} \right), \quad (4)$$

u_i is the coordinate of the i -th detector pixel along the direction perpendicular to rotation axis, R the detector's half length, L the offset length, and S the source-to-detector distance. More detailed discussion on calculation of matrix $\mathcal{W}$ can be found in Ref. [40].

2.2.2. Optimization algorithms—Algorithms are available for mathematically, or numerically, solving the constrained-TV-minimization program in Eq.(1). We consider in the work the adaptive-steepest-descent (ASD)-projection-onto-convex-sets (POCS) algorithm because it has been shown consistently in previous studies to solve the program numerically accurately. In the algorithm, the steepest descent (SD) and POCS steps adaptively lower image TV and data divergence. A detailed description of the algorithm, along with its pseudo-codes, is provided elsewhere [20, 35, 36, 37]. For discussion convenience, we refer below to the constrained-TV-minimization-based reconstruction simply as the *ASD-POCS reconstruction*.

2.2.3. Reconstruction parameters—The complete specification of the ASD-POCS reconstruction requires numerous parameters, as described below.

Program parameters: The constrained-TV-minimization program involves parameters ϵ , voxel size (or, equivalently, image-array size N for a given image support,) and the design of system matrix $\mathcal{H}$. These parameters, referred to as the *program parameters*, specify completely solutions designed by the program, which we refer to as the *designed solutions*.

Algorithm parameters: In the ASD-POCS algorithm, calculation schemes, such as SD and POCS, and parameters specifying their step sizes, or balancing their relative strengths [35, 36, 41] are referred to as the *algorithm parameters*, and they determine a specific path possibly leading to a particular designed solution.

Convergence parameters: Properties of numerical reconstructions by use of ASD-POCS or other iterative algorithms depend on convergence conditions used, which we refer to as *convergence parameters*. In the work, we consider two mathematical convergence conditions

$$D(\mathbf{f}^{(n)}) \rightarrow \epsilon$$

$$c_{\alpha}(\mathbf{f}^{(n)}) \rightarrow -1, \quad (5)$$

as iteration number $n \rightarrow \infty$, where $\mathbf{f}^{(n)}$ denotes the reconstruction at the n -th iteration. The quantity $c_{\alpha}(\mathbf{f}^{(n)})$ is computed from knowledge of $\mathbf{f}^{(n)}$ [35]:

$$c_{\alpha}(\mathbf{f}^{(n)}) = \frac{\mathbf{d}_{TV}^{(n)} \cdot \mathbf{d}_{data}^{(n)}}{|\mathbf{d}_{TV}^{(n)}| \|\mathbf{d}_{data}^{(n)}\|}, \quad (6)$$

where

$$\mathbf{d}_{TV}^{(n)} = \bar{\nabla}_{\mathbf{f}} \|\mathbf{f}^{(n)}\|_{TV}, \quad \mathbf{d}_{data}^{(n)} = \bar{\nabla}_{\mathbf{f}} D^2(\mathbf{f}^{(n)}), \quad (7)$$

and $\bar{\nabla}_{\mathbf{f}}$ indicates a gradient operator that excludes zero elements of $\mathbf{f}$. In Secs. 3 and 4 below, based upon Eq. (5), practical convergence conditions are devised specifically for inverse-crime and real-data studies.

3. Algorithm Verification and Inverse-Crime Study

Prior to the performance of ASD-POCS reconstruction from real OBI data, we carried out an inverse-crime study to verify numerically that the ASD-POCS reconstruction (and its computer implementation) can, under its design conditions, perform precisely as it is designed to perform. In an inverse-crime study, data are generated from a discrete, truth image by use of the system matrix in the DD-data model, and an image is reconstructed on the truth-image array from the generated data with the same system matrix; and one needs not to select the reconstruction-voxel size because it must be identical to that of the discrete, truth image. Because data and the data model are consistent, data divergence $D(\mathbf{f})$ is zero, and so is parameter ϵ . However, $c_{\alpha}(\mathbf{f})$ in Eq. (5) becomes undefined at $\epsilon = 0$ [35]. Furthermore, due to the limited computer precision and the finite number of iterations used, the mathematical convergence conditions in Eq. (5) are necessarily unreachable in a practical reconstruction. Therefore, for the inverse-crime study, we select a small value, $\epsilon = 10^{-12}$ (instead of $\epsilon = 0$) to specify a tight set of designed solutions, and consider the following convergence conditions

$$D(\mathbf{f}^{(n)}) \leq 10^{-12}$$

$$c_{\alpha}(\mathbf{f}^{(n)}) \leq -0.99. \quad (8)$$

As shown in Fig. 1a, a discrete, clinical planning-CT image of the prostate-cancer patient was employed as the truth image in the inverse-crime study. Using the geometrical parameters mimicking those of the clinical OBI-imaging configuration, and system matrix $\mathcal{H}$ described in Sec. 4 below, we generated data at 360 projection views uniformly distributed over 2π from which an ASD-POCS reconstruction was carried out. The convergent ASD-POCS reconstruction (according to Eq. (8)) is shown in Fig. 2b. For assessing quantitatively reconstruction convergence, we have calculated $D(\mathbf{f}^{(n)})$ and $c_{\alpha}(\mathbf{f}^{(n)})$ as functions of iteration number n as shown in row 1 of Fig. 2. Furthermore, because the discrete, truth image is available in the inverse-crime study, we also computed TV difference and RMSE of reconstructions relative to the truth image, and plot them as functions of n in row 2 of Fig. 2, which show that the difference between the truth image and reconstruction per voxel is of the order of 10^{-12} . Therefore, reconstruction results in Figs. 1 and 2 verify that the ASD-POCS reconstruction can solve numerically the constrained-TV minimization according to convergence conditions in Eq. (8), and yields a reconstruction virtually identical to the truth image under the sampling conditions considered.

4. Determination of Reconstruction Parameters

Reconstruction parameters discussed in Sec. 2.2.3 form a multi-dimensional parameter space in which each point represents a specific designed solution. The challenge of applying adequately an optimization-based reconstruction to real data lies in the determination of parameter values for yielding, or, equivalently, the search of the parameter space for identifying, solutions of application utility. It is practically infeasible, however, to exhaust the entire parameter space for reconstruction properties desired, due to the large dimension and size of the parameter space. Instead, for real data in applications, we identify below the parameter affecting dominantly reconstruction properties and then devise (surrogate) utility metrics that can guide a search along the parameter dimension, while using prior knowledge to determine values of other reconstruction parameters.

Determination of program-parameter values

Values of three parameters, including voxel size, system matrix, and ϵ , as discussed above, need to be determined in the constrained-TV-minimization program. In routine OBI-quality-assurance studies of the Catphan phantom, an FDK reconstruction often uses a rectangular-cuboid-shaped voxel of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$, with the longer dimension along the longitudinal of the cylindrical FOV of the OBI unit. We thus used this default voxels for reconstructions of sections CTP515 and CTP404. However, as justified in Sec. 4.2 below, small cubic-shaped voxels of size $0.244 \times 0.244 \times 0.244 \text{ mm}^3$ were used in reconstructions of section CTP 528 necessary for revealing details of bar patterns of high line-pair (lp)

densities and for minimizing the voxelization effect in reconstructions. In the studies of the Rando-head phantom and prostate-cancer patient, which possess considerable longitudinal variations, we use a cubic-shaped voxel of size $0.488 \times 0.488 \times 0.488 \text{ mm}^3$ in ASD-POCS reconstructions instead, because they can yield sufficient reconstruction details. In Sec. 6 below, additional discussion is given as to the impact of voxel size on image reconstruction and display.

In all of the studies, the intersection length of an X-ray considered with a voxel is chosen as an element of system matrix $\mathcal{H}$. It has been shown [42, 43] that different, but appropriate, calculation schemes for obtaining system matrix $\mathcal{H}$ yield reconstructions with marginal differences when applied to real data of CBCT imaging.

Parameter ϵ can significantly impact reconstruction properties by weighting the enforcement of data constraint and imposition of image regularity. In general, a lower ϵ pushes for a more stringent agreement between a data model and measured data, thus revealing image details but with potentially amplified image noise, whereas a higher ϵ promotes smoother image, thus suppressing image noise but at a potential cost of losing image details. We discuss in Secs. 4.1–4.3 below the selection of ϵ values based upon quality-assurance metrics in OBI imaging.

Determination of algorithm-parameter values

We use the ASD-POCS algorithm, along with algorithm-parameter values similar to those in ref. [35] to reconstruct images by solving numerically the constrained-TV-minimization program, because they appear to perform robustly well in past and current studies [36, 37, 38, 39, 40, 41]. Different appropriately selected algorithms yield only different paths converging to the designed solutions.

Determination of convergence-parameter values

As discussed, the two mathematically necessary conditions in Eq. (5) cannot be achieved in a practical reconstruction. Instead, we devise *practical convergence conditions*

$$\left| \frac{D(\mathbf{f}^{(n)}) - \epsilon}{\epsilon} \right| \leq 10^{-4}$$

$$c_{\alpha}(\mathbf{f}^{(n)}) \leq -0.6 \quad (9)$$

for use in real-data studies performed in the work. As demonstrated previously [36, 37, 38, 39, 40, 41], condition $c_{\alpha}(\mathbf{f}^{(n)}) \leq -0.6$, along with other convergence conditions satisfied, yields images highly resemble reconstructions obtained under condition $c_{\alpha}(\mathbf{f}^{(n)}) \leq -0.99$.

4.1. Contrast-resolution-task-based determination of ϵ

Parameter ϵ can markedly impact reconstruction properties, and it is thus of practical significance to devise an appropriate selection of its value for yielding reconstructions with desired properties (i.e., utility) for a given imaging task. We determine below values of ϵ

based upon specific quality-assurance tasks in clinical OBI imaging. A quality-assurance task in OBI imaging is to characterize reconstruction contrast by use of section CTP515 of the Catphan phantom containing inserts of different contrast levels and sizes. We define a contrast-resolution metric

$$\text{CNR} = \frac{|\bar{f}_s - \bar{f}_b|}{\sqrt{\sigma_s^2 + \sigma_b^2}} \quad (10)$$

to quantitatively measure reconstruction contrast, where $\bar{f}_s$ and σ_s denote the mean and standard deviation within an ROI contained in a selected insert, and $\bar{f}_b$ and σ_b the mean and standard deviation within an ROI in the background region. CNR, clearly a function of ϵ , is used as a contrast-resolution-utility metric for determining numerically the value of ϵ for obtaining reconstruction with “maximum” contrast resolution.

Using data HD-f640 and for a set of different ϵ values, we performed ASD-POCS reconstructions of section CTP515 for contrast evaluation. In Fig. 3, we display zoomed-in views of an ROI containing five inserts of contrast level 1% in ASD-POCS reconstructions obtained with three different values ϵ_1 , ϵ_2 , and ϵ_3 , along with that in the FDK benchmark. The five inserts are indicated by numbers 1 to 5 in ASD-POCS reconstruction with ϵ_2 in Fig. 3. It can be observed that ASD-POCS reconstructions with ϵ_1 and ϵ_3 lead to an elevated, or a diminished, level of noise, or contrast, whereas the ASD-POCS reconstruction with ϵ_2 seems to be able to preserve better contrast while suppressing noise, yielding a relative high utility for a task of low-contrast visualization. In the lower part of Fig. 3, we also display CNR of insert 4 relative the background in ASD-POCS reconstructions obtained with the set of ϵ values, which appears to reach a peak region in the neighborhood of ϵ_2 , suggesting that ϵ values in the neighborhood may yield high contrast, corroborating the above observation made based upon the zoomed-in views of ROI reconstructions. Therefore, we use metric CNR, and the approach described, to determine the value of ϵ in ASD-POCS reconstructions for tasks in which contrast resolution is of the concern.

4.2. Spatial-resolution-task-based determination of ϵ

Spatial resolution of reconstruction is a priority consideration for IGRT tasks in which accurate identification and localization of high contrast structures are sought after as registration landmarks. We consider reconstructions of section CTP528 of the Catphan phantom, which comprises bar patterns with varying lp densities is designed for evaluation of spatial resolution. In an attempt to minimize the voxelization effect in reconstruction of bar patterns embedded in section CTP528, cubic-shaped voxel of size $0.244 \times 0.244 \times 0.244 \text{ mm}^3$, smaller than the clinical voxel size, is used in both ASD-POCS and FDK reconstructions. We devise a spatial-resolution metric below, and demonstrate its use for guiding the determination of the value of parameter ϵ in ASD-POCS reconstruction.

The spatial frequency F30 at 30% of the modulation transfer function (MTF) of the bar patterns may be used, e.g., as a metric for characterizing spatial resolution in OBI reconstructions [44]. In the presence of noise, however, a metric for meaningfully characterizing spatial resolution necessarily requires appropriate consideration of

reconstruction noise because it can also affect reconstruction-spatial resolution. Therefore, we devise a noise-adjusted F30 (NF30),

$$\text{NF30} = \text{F30} \times \min(\sigma_b^{\text{ref}} / \sigma_b, 1), \quad (11)$$

as the spatial-resolution metric in the work, where σ_b^{ref} and σ_b denote the noise standard deviations within the backgrounds of a reference image and ASD-POCS reconstruction. Metric NF30 thus provides a spatial-resolution measure adjusted to the noise level in the reference image.

Using data HD-f640 and for a set of different ϵ values, we carried out ASD-POCS and FDK-benchmark reconstructions of section CTP528, and used the FDK benchmark as the reference image for spatial-resolution evaluation [44]. In Fig. 4, we show zoomed-in views of an ROI in ASD-POCS reconstructions with three different values ϵ_1 , ϵ_2 , and ϵ_3 , along with that of the FDK benchmark. For each of the ASD-POCS reconstructions in Fig. 4, the visually resolvable bar pattern with high lp densities in unit lp/cm is indicated, along with an inset showing the bar pattern in details. In terms of spatial resolution and background noise, ASD-POCS reconstruction with ϵ_2 appears to be superior to those with ϵ_1 , and ϵ_3 . From the ASD-POCS reconstructions and FDK benchmark, we computed NF30 and displayed it in Fig. 4, as a function of ϵ . NF30 is observed to rise to its peak value in the neighborhood of ϵ_2 , indicating that ϵ values in the neighborhood may yield the highest noise-adjusted level of spatial resolution. The observation is consistent with ASD-POCS reconstructions displayed in Fig. 4. Therefore, we use metric NF30, and the approach described, to determine the value of ϵ in an ASD-POCS reconstruction for tasks in which spatial resolution is of the interest.

4-3. Combined-task-based determination of ϵ

There exist OBI-image-based IGRT tasks in which both contrast and spatial resolution are important considerations. Section CTP404 of the Catphan phantom contains a low-contrast acrylic insert, and a tungsten wire, which are designed specifically for simultaneous, quantitative characterization of contrast and spatial resolution in a reconstruction. As contrast resolution and spatial resolution represent two competing reconstruction properties, we use their trade-off as a metric to characterize the combined-contrast-spatial resolution in a reconstruction.

Using data HD-f640 and for a set of ϵ values ranging from 0.98×10^{-5} to 1.22×10^{-5} , we conducted ASD-POCS reconstructions of section CTP404, and display in Fig. 5 zoomed-in views of the ROI containing the acrylic insert and tungsten wire in reconstructions with four different values $\epsilon_0 = 0.98 \times 10^{-5}$, $\epsilon_1 = 1.02 \times 10^{-5}$, $\epsilon_2 = 1.09 \times 10^{-5}$, and $\epsilon_3 = 1.14 \times 10^{-5}$, along with the zoomed-in view of the same ROI within the FDK benchmark. In Fig. 5, the ASD-POCS reconstruction with ϵ_2 , in which the low-contrast acrylic insert and tungsten wire are indicated by the arrow and arrow head, appears superior to those with ϵ_0 , ϵ_1 and ϵ_3 in terms of visualizing the insert contrast, wire sharpness, and background noise. From ASD-POCS reconstructions with the set of ϵ values, we also form a trade-off metric by computing the insert CNR (according to Eq. (10)) and the wire full-width-at-half-maximum

(FWHM). As shown in Fig. 5, the computed CNR rises rapidly, from its value obtained with ϵ_0 , to its peak value in the neighborhood of ϵ_2 without resulting in a significantly increased FWHM, followed by its clear decay after passing the peak. Again, the observation corroborates the visualization result of the zoomed-in views of the ROI in ASD-POCS reconstructions above. Therefore, we employ the trade-off metric for determining the value of ϵ in an ASD-POCS reconstruction for a task in which a combined-contrast-spatial resolution is of the concern.

5. Results

We present below reconstruction results from data of physical phantoms and prostate-cancer patient collected in OBI imaging.

5.1. Study design and characterization

Imaged subjects—The Catphan phantom was used because it is a standard tool for performing quality assurance tasks in terms of contrast- and spatial-resolution in OBI imaging. The widely used Rando-head phantom was also scanned because it provides realistic human-head anatomy with sufficient details such as bony debris for spatial-resolution characterization of reconstruction. Finally, retrospective data of a prostate-cancer patient collected in a clinical scan was used for contrast visualization of soft-tissue organs and high contrast calcification of tiny size.

Data sets—In phantom studies, in addition to the densely sampled full- and half-scan data sets discussed in Sec. 2.1, we use every other views in each of the densely sample data sets to form the corresponding sparse-view data. As summarized in row 2 of Table 1, these newly formed data sets are referred to as full-scan sparse-view data HD-f320 and LD-f320, containing 320 views, or half-scan sparse-view data HD-h180 and LD-h180, containing 180 views. Reconstruction from 320- or 180-view (i.e., sparse-view) data is of practical interest because it may yield image quality, in terms of visualization and quantification described below, comparable, or superior, to that of the corresponding FDK benchmarks. Furthermore, for the study of prostate-cancer patient, we also form 323-view data containing projections at every-other views of 626-view data, as depicted in row 2 of Table 1.

FDK reconstructions—Using data summarized in Table 1, we performed FDK reconstructions with a Hann filter and cut-off at 60% Nyquist frequency. In all of reconstructions except for that of section 528 in the Catphan phantom, a clinical voxel of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$ was used in FDK reconstructions. As discussed in Sec. 4.2, a small cubic-shaped voxel of size $0.244 \times 0.244 \times 0.244 \text{ mm}^3$ was used in reconstructions of section 528 necessary for revealing details of bar patterns of high lp densities and for minimizing the voxelization effect in reconstructions. Even though a cubic-shaped voxel of size $0.488 \times 0.488 \times 0.488 \text{ mm}^3$ was used in ASD-POCS reconstructions for the Rando-head phantom and prostate-cancer patient, however, they were converted to an array of rectangular-cuboid-shaped voxels of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$ so that their display and analysis can be performed based upon a voxel size identical to that used in clinical FDK reconstructions.

Reconstruction visualization and quantification—Visual inspection of reconstructions is the basis for performing many of current clinical applications especially in IGRT. Therefore, in each study, we performed visual assessment of ASD-POCS reconstructions relative to their FDK benchmarks, and to their planning-CT images (i.e., surrogate-truth images) obtained with advanced diagnostic CT, in terms of texture and artifact appearance, low-contrast object delineation, and high-contrast structure sharpness. Furthermore, in the Catphan-phantom study, we use quality-assurance metrics defined in Sec. 4 to assess quantitatively contrast and spatial resolution in ASD-POCS reconstructions.

5.2. Study results of Catphan phantom

We show in Fig. 6 the planning-CT images within selected transverse slices in sections CTP515, CTP528, and CTP404 of the Catphan phantom, and use them as the surrogate-truth images for the Catphan-phantom study. The three arc-shaped ROIs in section CTP515, depicted in Fig. 6a, contain three sets of inserts of varying sizes, representing, respectively, 1%, 0.5%, and 0.3% levels of contrast for reconstruction-contrast evaluation; whereas the rectangular-shaped ROIs in sections CTP528 and CTP404, depicted in Figs. 6b and 6c, are used below for examining contrast- and spatial-resolution properties in reconstructions of the respective sections.

Contrast-resolution study—Using the approach described in Sec. 4.1, we select values of parameter ϵ for ASD-POCS reconstructions of section CTP515 from data summarized in Table 1, and display the reconstructions in Figs. 7 and 8, along with the corresponding FDK reconstructions. Overall, a reduced noise level can be observed in ASD-POCS reconstructions relative to that of FDK reconstructions. For high-dose data, as shown in Fig. 7, 1.0%-contrast inserts can be visualized in both ASD-POCS and FDK reconstructions, but some of the 0.5%- and 0.3%-contrast inserts remain somewhat visible in the former while becoming difficult to discern in the latter. In general, ASD-POCS reconstructions from high-dose data seems to remain of some utility of visualizing low-contrast inserts. In low-dose reconstructions shown in Fig. 8, the large-size, 1%-contrast inserts appear discernible in ASD-POCS reconstructions, while image noise renders the inserts in FDK reconstructions difficult to visualize. These observations are corroborated by the quantitative CNR results in Table 2, calculated from the insert indicated by the arrow in Fig. 6a.

Results shown above are convergent ASD-POCS reconstructions satisfying Eq. (9), each of which involves about 400 iterations, a relatively large number of iterations required necessarily for recovery of low-contrast inserts. When the goal is to achieve designed solutions (i.e., the convergent reconstructions,) the number of iterations is neither a parameter nor a concern. However, reconstruction evolution as a function of iteration numbers is often of practical interest. For data HD-f320, we display in Fig. 9 ASD-POCS reconstructions at iteration numbers 30, 280, and 400, and show in the bottom row of Fig. 9 metric CNR, computed from the insert indicated by the arrow in Fig. 6a as a function of iteration number n . Similar observations can be made for reconstructions from other data cases, which are not shown here.

Spatial-resolution study—We use cubic-shaped voxels of size $0.244 \times 0.244 \times 0.244$ mm³ in reconstruction from data, summarized in Table 1, of section CTP528 containing resolution-bar patterns, and apply the approach described in Sec. 4.2 to determining values of parameter ϵ in ASD-POCS reconstructions. As shown in Figs. 10 and 11, the zoomed-in views of the ROI, as depicted in Fig. 6b, reveal that, while bar patterns of up-to-9 lp/cm can be resolved in the FDK benchmark, visually resolvable bar patterns with up-to-13 or 15 lp/cm can be obtained in ASD-POCS reconstructions, without significantly amplifying background noise. In addition, streak artifact due to sparse angular-sampling observed in the FDK reconstruction from data HD-hl80 appear to be suppressed effectively in the ASD-POCS reconstruction. In the study, the background-noise level in ASD-POCS reconstructions is matched with that of the corresponding FDK reconstructions, and the results suggest that the former has spatial resolution superior to that of the latter, and that, in reconstructions from sparse-view data, the former show a reduced level of noise and streak artifact observed in the latter. Using the method described in Ref. [44], we calculated the MTF of the bar patterns and then NF30 in Eq. (11) for each of the reconstructions. In Table 3, we show the highest densities in visually resolvable bar patterns.

Again, ASD-POCS reconstructions displayed in Figs. 10 and 11 are convergent reconstructions satisfying Eq. (9) after about 200 iterations. We have also investigated how spatial resolution in an ASD-POCS reconstruction evolves as a function of iteration number n . For data HD-f320, we display in Fig. 12 ASD-POCS reconstructions at iteration numbers 20, 100, and 140, along with the computed NF30 plot as a function of iteration numbers. An observation can be made that ASD-POCS reconstructions at, e.g., iteration 140 may be of spatial resolution similar to, and that the NF30 above iteration 140 approaches to, that of the corresponding convergent ASD-POCS reconstruction.

5.2.1. Combined contrast-spatial-resolution study—In an attempt to study the combined contrast-spatial-resolution property, we performed ASD-POCS reconstructions of section CTP404, in which the acrylic insert and tungsten wire are used for characterization of combined contrast and spatial resolution in a reconstruction. Using the approach described in Sec. 4.3, we determine the values of parameter ϵ for ASD-POCS reconstructions, and show in Figs. 13 and 14 the reconstruction results, from data summarized in Table 1, within the ROI depicted in Fig. 6c for revealing image details of insert and tungsten edge. Observations similar to those made in the contrast- and spatial-resolution studies above can be made: ASD-POCS reconstructions, with suppressed noise, show an insert contrast higher, and wire edge sharper, than the FDK reconstructions; and when applied to low-dose and/or sparse-view data, FDK reconstructions are with considerably reduced contrast resolution in comparing to ASD-POCS reconstructions: The acrylic insert, while almost indiscernible from the noisy background in the FDK reconstructions, remains visible yet with little loss of spatial resolution in the ASD-POCS reconstructions. In Fig. 15, we show the insert CNR against the wire FWHM calculated from reconstructions in Figs. 13 and 14, and note that ASD-POCS reconstructions yield FWHM-CNR trade-off results better than do the corresponding FDK reconstructions, corroborating quantitatively the visualization observations above.

ASD-POCS reconstructions shown in Figs. 10 and 11 are convergent reconstructions satisfying Eq. (9) after about 400 iterations. We have also inspected how ASD-POCS reconstruction progresses as a function of iteration numbers in the combined contrast-spatial-resolution study. For data HD-f320, we show in Fig. 16 ASD-POCS reconstructions at iteration numbers 40, 230, and 360, along with the combined FWHM-CNR as a function of iteration number. Similar observations can be made for ASD-POCS reconstructions from other data cases, which are not shown here.

5.3. Study results of Rando-head phantom

The Rando-head phantom is used often for assessing spatial resolution in OBI imaging through visualization of detailed bony debris and structures embedded in the phantom. We thus use the approach described in Sec. 4.2 to determine the values of parameter ϵ for ASD-POCS reconstructions of the Rando-head phantom. Because of the lack of bar patterns in the phantom, we calculated an effective MTF from a number of bony edges selected, and used it, along with the estimated background noise in the FDK benchmark and ASD-POCS reconstruction from a data set in Table 1, to compute the resolution metric for determining parameter ϵ for the data set. In Fig. 17, we display ASD-POCS and FDK reconstructions within two transverse slices from data HD-f640, along with the corresponding planning-CT images. For revealing reconstruction details, we also display in Fig. 17 zoomed-in view of ROIs enclosed by the white-dashed squares.

ASD-POCS and FDK reconstructions appear to be visually comparable because data HD-f640 contain densely sampled projections of high signal-to-noise ratio. This comparison serves as a check on whether an ASD-POCS reconstruction is of visual quality at least comparable to that of the FDK benchmark. Subtle differences can be observed in the ROIs in that the ASD-POCS reconstructions are with bone edges sharper, and background smoother, than those in the FDK benchmark. In particular, a point-like high-contrast structure (a piece of debris possibly introduced in the manufacturing process,) highlighted by an arrow, in the zoomed-in view of ROI 2 within transverse slice 2 of the planning-CT images in Fig. 17, appears more conspicuous in the ASD-POCS reconstruction than that in the FDK benchmark (and even in the planning-CT images,) suggesting an elevated level of spatial resolution in the former.

We have performed ASD-POCS reconstructions of the Rando-head phantom from data summarized in Table 1, and display them in Figs. 18–21, along with the zoomed-in views of the ROIs depicted in Fig. 17. ASD-POCS reconstructions appear to show little visual difference than the FDK benchmark, and some streak artifact can be observed in FDK reconstructions from sparse-view data HD-hl80 and LD-hl80, as a consequence of a reduced number of angular samples. Overall, ASD-POCS reconstructions are of visual quality comparable to, but with more details and higher conspicuity of skull edges than, that of the FDK benchmarks. The point-like high-contrast structure in the ASD-POCS reconstruction can be more clearly identified than that in the FDK benchmark. In fact, the ASD-POCS reconstructions and FDK benchmark appear to be of spatial resolution higher than that of the planning-CT images in Fig. 17. For saving space, reconstructions are shown only in two transverse slices. However, observations similar to that made about the two slices can also

be made for other transverse, coronal, and sagittal slices. It should be reminded that parameters are required also in planning-CT and FDK reconstructions, and that different selections of the parameter values would result in different planning-CT and FDK reconstructions. As investigation of the impact of the parameters on planning-CT and FDK reconstructions is beyond the scope of the current work, we consider only planning-CT and FDK reconstructions under typical, clinical imaging conditions as references.

ASD-POCS reconstructions discussed above were obtained when the practical convergence conditions in Eq. (9) are satisfied after about 100 iterations. We again use data HD-f320 to illustrate how ASD-POCS reconstruction evolves as a function of iteration numbers. It can be observed in Fig. 22 that reconstructions at iterations 30 and 50 appear of spatial resolution similar to that of the corresponding convergent ASD-POCS reconstruction, suggesting that ASD-POCS reconstructions at these iterations may be of practical value should the convergent ASD-POCS reconstruction be. Similar observations can be made for reconstructions for other data cases, which are not shown here.

5.4. Study results of prostate-cancer patient

We use the approach described in Sec. 4.3 to determining the values of parameter ϵ for ASD-POCS reconstructions of the prostate-cancer patient, because visualization of both soft-tissue and bony structures is of IGRT interest. ASD-POCS and FDK reconstructions within transverse and coronal slices of the prostate-cancer patient from the 626- and 313-view data are shown in Figs. 23 and 24, along with the planning-CT images within the same slices. In each of the slices, zoomed-in view of an ROI indicated is displayed as an inset for revealing reconstruction details. (The bright spot in the planning-CT coronal image shown in the zoomed-in views is due to the contrast agent used during the planning-CT scan, but was absent in OBI images because no contrast was used in OBI imaging of the patient.)

Visual inspection of the ASD-POCS reconstruction from 628-view data shows that its overall appearance is comparable to the FDK benchmark, with some portion of the skin lines better preserved. Close examination reveals that the ASD-POCS reconstruction has a background, with suppressed noise and artifacts, smoother than the FDK benchmark, yet with high-spatial-resolution details such as the sharpness of bone edges. A small calcification near the edge of the prostate can be observed clearly in the ASD-POCS reconstruction within the coronal slice. Observations similar to those for the ASD-POCS reconstruction from 626-view data can be made for the ASD-POCS reconstruction from 313-view data, when comparing to the FDK benchmark and planning-CT images. Noise and streak artifacts are amplified in FDK reconstructions from 313-view data, which may obscure soft-tissue visualization and hamper calcification detection. These results suggest, for the clinical imaging condition considered, that 50% reduction of projection views seems to impact insignificantly soft-tissue contrast and calcification depiction in ASD-POCS reconstructions, while the overall visualization utility of ASD-POCS reconstructions appears comparable to, or higher than, that of the FDK benchmark. It is interesting to note that, although the planning-CT images in Figs. 23 and 24 have soft-tissue contrast resolution slightly better than ASD-POCS reconstructions from OBI data, their spatial resolution (especially along the longitudinal direction) appears to be inferior to that of ASD-POCS

reconstructions from OBI data. This observation is corroborated by the clear visibility of the calcification indicated by the arrow in the coronal slice of the ASD-POCS reconstructions. Similar observations can be made from results for other transverse, coronal, and sagittal slices, which are not shown here.

The convergent ASD-POCS reconstructions described above satisfy the practical convergence conditions in Eq. (9) after about 100 iterations. We have also inspected the evolution of the ASD-POCS reconstruction from 323-view data, and display in Fig. 25 ASD-POCS reconstructions at iteration numbers 20, 30, and 40. The ASD-POCS reconstructions at iterations 30 and 40 appear of spatial and soft-tissue-contrast resolution similar to that of the corresponding convergent ASD-POCS reconstruction. Again, in terms of visualization of soft tissue and calcification, ASD-POCS reconstructions at these iterations may be of practical value should the convergent ASD-POCS reconstructions be.

6. Discussion

We have performed an investigative study on appropriately tailoring an optimization-based reconstruction, i.e., the ASD-POCS reconstruction, to data of clinical phantoms and a prostate-cancer patient collected in OBI-imaging applications, with two aims in mind: (1) to possibly improve image quality, in terms of OBI-quality-assurance metrics, over clinical FDK benchmarks from data acquired with standard clinical imaging configurations, and (2) to enable imaging configurations with lowered imaging dose through reducing the number of projection views while maintaining image quality comparable to, or higher than, that of the FDK benchmarks. For the cases considered, results of visualization and quantitative studies suggest that, in terms of the quality-assurance-utility metrics used, ASD-POCS reconstruction shows noticeable improvement on the clinical FDK benchmark, thus possibly reducing the image-quality gap between OBI CBCT and planning-CT, which is considered a gold standard in IGRT applications. In fact, the ASD-POCS reconstruction in the study shows spatial resolution, especially along the longitudinal direction, superior to that of the planning-CT images for the imaging conditions considered.

Multiple parameters involved in an optimization-based reconstruction can impact significantly reconstruction properties, thus playing at least an equally important role as (or likely a more important role than) the specific mathematical form of a given optimization-based reconstruction designed. Adequate application of an optimization-based reconstruction to addressing real data problems is, to a significant extent, equivalent to a proper selection of parameter values for yielding reconstructions with desirable properties (i.e., utility.) The significance of parameter-value selection in an optimization-based reconstruction seems to be under appreciated, as evidenced by the fact that little effort has been reported in literature devoted to investigating quantitatively selection of suited parameter values in optimization-based reconstructions, in particular, from real data in practical applications.

In the work, we demonstrated that a task-specific-utility-metrics-based scheme may be devised for determining parameter values in appropriately tailoring the ASD-POCS reconstruction to tasks specific to OBI imaging. The utility metrics devised are based upon

quality-assurance tasks in OBI imaging, and have been used for determining parameter values in ASD-POCS reconstructions from phantom and patient data. We point out that it is likely that different metrics need to be devised for appropriate parameter-value selection and for meaningful assessment of reconstruction quality in imaging tasks differing than those considered in the work.

In an optimization-based reconstruction, its iterative algorithm generally takes infinite number of iterations to achieve the designed solutions (i.e., convergent reconstructions.) A large number of iterations is likely to be needed (especially in reconstructions of low-contrast objects) for achieving a designed solution even if only the practical convergence conditions are considered, as the study results show. If the goal is to achieve a convergent reconstruction, then the iteration number should not be considered a reconstruction parameter. This, indeed, is not contradictory to the fact that reconstructions at early iterations without satisfying the convergence conditions are of possible practical utility, in terms of, e.g., visualization and quality-assurance metrics, as the result of reconstruction evolution in Sec. 5 show. Obviously, the iteration number needs to be treated as an additional parameter should the determination whether a non-convergent reconstruction is of practical utility be of interest.

We have performed ASD-POCS reconstructions of section CTP528 of the Catphan phantom using cubic-shaped voxels of size $0.244 \times 0.244 \times 0.244 \text{ mm}^3$ for revealing bar-pattern details, as shown in Fig. 26a. Because an optimization-based reconstruction generally starts with a DD-data model, voxel size is thus a parameter that can impact reconstruction properties. For example, from data HD-f640 of section CTP528 of the Catphan phantom, we also carried out an ASD-POCS reconstruction of the section with a rectangular-cuboid-shaped voxel of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$ and display it in Fig. 26b. The highest lp density of the bar pattern visually resolvable in the reconstruction is about 12 lp/cm in which the line pairs also exhibit some voxelization artifact. On the other hand, Fig. 26a shows a spatial-resolution limit of up to 16 lp/cm, yet with little voxelization artifact visible in the bar pattern of 12 lp/cm. The comparison suggests that voxel size, rather than data samples, is at least a leading factor limiting the spatial resolution in this example. For a given image support, however, the use of a reduced voxel size necessarily increases the number of voxels (or, equivalently, of unknowns); and a too-small-voxel size may thus result in a number of unknowns substantially larger than that of data samples, leading to an extremely-under-determined data model that may not yield a useful reconstruction. Therefore, data-sample condition is an important consideration in the selection of voxel size in real-data applications.

Visualization details can also be affected by how an image is displayed. For example, an ASD-POCS reconstruction of the Rando-head phantom was performed from data HD-f640 with cubic-shaped voxels of size $0.488 \times 0.488 \times 0.488 \text{ mm}^3$, as shown in Fig. 27a. For comparison, it was converted subsequently to rectangular-cuboid-shaped voxels of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$ and displayed in Fig. 27a. Observations can be made that Fig. 27a reveals bony structural details more than does Fig. 27b, suggesting that displaying-voxel size and shape can have an impact on visualization of reconstruction details.

In the work, even though results suggest that appropriately designed ASD-POCS reconstruction may improve image quality, in terms of visualization and quality-assurance-task metrics discussed, in OBI imaging, it should be reminded, however, that the results are dependent on numerous factors, including data quantity/quality, imaged subjects, imaging tasks, reconstruction design, and evaluation metrics. Moreover, we caution that it remains to be demonstrated whether the image-quality improvement and imaging-dose reduction observed in the work can be translated into practical benefit in realistic, clinical tasks in which other factors such as task types, users, and different utility metrics also come into play. Such a demonstration, which is beyond the scope of the work, would entail identification of specific clinical tasks upon which meaningful utility metrics are devised for effectively guiding the design, tailoring, and evaluating of optimization-based reconstructions of utility to the clinical tasks.

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Figure 1.
(a) Discrete, truth image and (b) ASD-POCS reconstruction.

Figure 2.

Row 1: data divergence (left) and convergence parameter $c_{\alpha}(f)$, and row 2: absolute TV difference (left) and RMSE (right) between ASD-POCS reconstructions and the truth image, as functions of iteration n .

Figure 3.

Top row: zoomed-in views of an ROI in section CTP515 containing five inserts of contrast level 1% within ASD-POCS reconstructions obtained with ϵ_1 , ϵ_2 , and ϵ_3 , along with the zoomed-in view of the same ROI within the FDK benchmark. The five inserts are indicated by numbers 1 to 5 in ASD-POCS reconstruction with ϵ_2 . The display window is $[0.266, 0.269] \text{ cm}^{-1}$. Bottom row: CNR, computed from insert 4 in ASD-POCS reconstructions, as a function of parameter ϵ (dotted curve), along with the CNR of the FDK benchmark (dashed line) in which the solid-black circles indicate CNRs obtained from ASD-POCS reconstructions with ϵ_1 , ϵ_2 , and ϵ_3 shown in the top row.

Figure 4.

Top row: zoomed-in views of an ROI in section CTP528 containing bar patterns of high spatial resolution within ASD-POCS reconstructions obtained with ϵ_1 , ϵ_2 , and ϵ_3 , along with the zoomed-in view of the same ROI within the FDK benchmark. For each of the ASD-POCS reconstructions, the visually resolvable bar pattern with the highest lp density in unit lp/cm is indicated, along with an inset showing the bar-pattern details. The display window is $[0, 0.6] \text{ cm}^{-1}$ for ROI images, and $[0.4, 0.55] \text{ cm}^{-1}$ for inset images. Bottom row: NF30s, calculated from ASD-POCS reconstructions, as a function of parameter ϵ (dotted curve), along with the NF30 of the FDK benchmark (dashed line) in which the solid-black circles indicate NF30s obtained from ASD-POCS reconstructions with ϵ_1 , ϵ_2 , and ϵ_3 , shown in the top row.

Figure 5.

Top row: zoomed-in views of an ROI of section CTP404 in ASD-POCS reconstructions with $\epsilon_0 = 0.98 \times 10^{-5}$, $\epsilon_1 = 1.02 \times 10^{-5}$, $\epsilon_2 = 1.09 \times 10^{-5}$, and $\epsilon_3 = 1.14 \times 10^{-5}$, along with the zoomed-in view of the same ROI within the FDK benchmark. The low-contrast acrylic insert and tungsten wire considered are indicated by the arrow and arrow head in ASD-POCS reconstruction with ϵ_2 . The display window is $[0.26, 0.3] \text{ cm}^{-1}$. Bottom row: FWHM-CNR trade-off curve (dotted) computed from ASD-POCS reconstructions, along with the FWHM-CNR of the FDK benchmark (+) in which the solid-black circles indicate FWHM-CNRs obtained from ASD-POCS reconstructions ϵ_0 , ϵ_1 , ϵ_2 , and ϵ_3 shown in the top row.

Figure 6.

Planning-CT images within a transverse slice in sections CTP515 (a), CTP528 (b), and CTP404 (c) of the Catphan phantom. The arc-shaped ROIs enclosed by the white dashed-curves in (a) contain three sets of inserts of varying sizes, representing 1%, 0.5%, and 0.3% levels of contrast, respectively, in which the fourth 1% insert, indicated by arrow, is used for computing CNR. The rectangular-shaped ROIs enclosed by white dashed-lines in (b) and (c) are used for demonstrating ASD-POCS reconstructions of sections CTP528 and CTP404 below. Arrows in (c) indicate the acrylic insert and tungsten wire. Display windows: $[-18, 102]$ HU (a), $[-400, 600]$ HU (b), and $[-160, 520]$ HU (c).

Figure 7.

ASD-POCS (row 1) and FDK (row 2) reconstructions of section CTP515 of the Catphan phantom from high-dose data HD-f640 (a), HD-h360 (b), HD-f320 (c), and HD-hl80, respectively. A narrow display window, $[0.26, 0.275] \text{ cm}^{-1}$, is used for revealing low-contrast inserts. The FDK benchmark is shown in panel (a) of row 2.

Figure 8.

ASD-POCS (row 1) and FDK (row 2) reconstructions of section CTP515 of the Catphan phantom from low-dose data LD-f640 (a), LD-h360 (b), LD-f320 (c), and LD-hl80, respectively. A narrow display window, $[0.26, 0.275] \text{ cm}^{-1}$, is used for revealing low-contrast inserts.

Figure 9.

Top row: zoomed-in views of ASD-POCS reconstructions from data HD320 within the ROI indicated that in Fig. 6a, at iterations $n=30$, 280, and 400. Bottom row: CNR as a function of iteration number n in which the black-solid circles indicate CNRs in reconstructions at $n=30$, 280, and 400.

Figure 10.

ASD-POCS (row 1) and FDK (row 2) reconstructions within the ROI of section CTP528 of the Catphan phantom, as indicated in Fig. 6b, from high-dose data HD-f640 (a), HD-f320 (b), HD-h360 (c), and HD-h180 (d), respectively. A display window, $[0.0, 0.6] \text{ cm}^{-1}$, is used for revealing the bar-pattern details. In each of the reconstructions, the visually resolvable bar pattern with the highest lp density is indicated, along with an inset showing the bar pattern in details within a display window of $[0.4, 0.55] \text{ cm}^{-1}$. The FDK benchmark is shown in panel (a) of row 2.

Figure 11.

ASD-POCS (row 1) and FDK (row 2) reconstructions within the ROI of section CTP528 of the Catphan phantom, as indicated in Fig. 6b, from low-dose data LD-f640 (a), LD-f320 (b), LD-h360 (c), and LD-h180 (d), respectively. A display window, $[0.0, 0.6] \text{ cm}^{-1}$, is used for revealing the bar-pattern details. In each of the reconstructions, the visually resolvable bar pattern with the highest lp density is indicated, along with an inset showing the bar pattern in details within a display window of $[0.4, 0.55] \text{ cm}^{-1}$.

Figure 12.

Top row: zoomed-in views of ASD-POCS reconstructions from data HD-320 within the 1%-ROI depicted in Fig. 6b, at iterations $n=20$, 100, and 140. Bottom row: NF30 computed from the bar pattern labeled with 12 lp/cm in Fig. 10 as a function of iteration number n in which the black-solid circles indicate NF30s in reconstructions at $n=20$, 100, and 140.

Figure 13.

ASD-POCS (row 1) and FDK (row 2) reconstructions within the ROI of section CTP404 of the Catphan phantom, as indicated in Fig. 6c, from high-dose data HD-f640 (a), HD-f320 (b), HD-h360 (c), and HD-h180 (d), respectively. A narrow display window, $[0.26, 0.3]$ cm^{-1} , is used revealing the low-contrast insert. The FDK benchmark is shown in panel (a) of row 2.

Figure 14. ASD-POCS (row 1) and FDK (row 2) reconstructions within the ROI of section CTP404 of the Catphan phantom, as indicated in Fig. 6c, from low-dose data LD-f640 (a), LD-f320 (b), LD-h360 (c), and LD-h180 (d), respectively. A narrow display window, $[0.26, 0.3] \text{ cm}^{-1}$, is used revealing the low-contrast insert.

Figure 15.

Solid-black circles and squares indicate FWHM-CNR of ASD-POCS reconstructions from data cases summarized in Table 1, whereas the cross and empty circle FDK reconstructions from data HD-f640 and LD-f640. Letters “A” and “F” denote ASD-POCS and FDK reconstructions, and the subscripts indicate data cases.

Figure 16.

Top row: zoomed-in views of ASD-POCS reconstructions from data HD-320 within the ROI depicted in Fig. 6c, at iterations $n=40$, 230, and 360. Bottom row: FWHM-CNR metric computed from reconstructions of the insert and wire at various iterations n in which the solid-black circles indicate FWHM-CNRs in reconstructions at $n=40$, 230, and 360.

Figure 17.

Planning-CT images (a), and ASD-POCS reconstructions (b) and FDK benchmarks (c) of the Rando-head phantom within transverse planes one (row 1) and two (row 2) from data HD-f640. The zoomed-in images displayed in the bottom of each row are within the ROIs depicted in the planning-CT images. An arrow in the zoomed-in view of ROI 2 in transverse slice 2 highlights a bony debris. Visually matched display windows $[-1020, 980]$ HU and $[0, 0.55]$ cm^{-1} are used for the planning-CT images and for ASD-POCS and FDK reconstructions.

Figure 18.

ASD-POCS (row 1) and FDK (row 2) reconstructions of the Rando-head phantom within transverse slice one, depicted in row 1 of Fig. 17, from high-dose data HD-f640 (a), HD-f320 (b), HD-h360 (c), and HD-h180 (d). The zoomed-in views within the ROIs identical to those in Fig. 17 are displayed at the bottom of each of the reconstructions. A display window $[0, 0.55] \text{ cm}^{-1}$ is used that matches visually the display window in Fig. 17.

Figure 19.

ASD-POCS (row 1) and FDK (row 2) reconstructions of the Rando-head phantom within transverse slice one, depicted in row 1 of Fig. 17, from low-dose data LD-f640 (a), LD-f320 (b), LD-h360 (c), and LD-h180 (d). The zoomed-in views within the ROIs identical to those in Fig. 17 are displayed at the bottom of each of the reconstructions. A display window $[0, 0.55] \text{ cm}^{-1}$ is used that matches visually the display window used in Fig. 17.

Figure 20.

ASD-POCS (row 1) and FDK (row 2) reconstructions of the Rando-head phantom within transverse slice two, depicted in row 1 of Fig. 17, from high-dose data HD-f640 (a), HD-f320 (b), HD-h360 (c), and HD-h180 (d). The zoomed-in views within the ROIs identical to those in Fig. 17 are displayed at the bottom of each of the reconstructions. A display window $[0, 0.55] \text{ cm}^{-1}$ is used that matches visually the display window in Fig. 17.

Figure 21.

ASD-POCS (row 1) and FDK (row 2) reconstructions of the Rando-head phantom within transverse slice two, depicted in row 1 of Fig. 17, from low-dose data LD-f640 (a), LD-f320 (b), LD-h360 (c), and LD-h180 (d). The zoomed-in views within the ROIs identical to those in Fig. 17 are displayed at the bottom of each of the reconstructions. A display window $[0, 0.55] \text{ cm}^{-1}$ is used that matches visually the display window in Fig. 17.

Figure 22.

ASD-POCS reconstructions of the Rando-head phantom within transverse slice two from data HD-f320 at iterations $n=10$, 30, and 50. The zoomed-in views of the ROIs, depicted in Fig. 17, at these iterations are shown at the bottom of each of the ASD-POCS reconstructions. A display window $[0, 0.55] \text{ cm}^{-1}$ is used that matches visually the display window in Fig. 17.

Figure 23.

ASD-POCS (column 1) and FDK (column 2) reconstructions within a transverse slice from 626-view data (row 1) and 323-view data (row 2) of the prostate-cancer patient. The planning-CT image of the patient within the slice is also shown in both columns of row 3. Visually matched display windows for OBI and planning-CT images are $[0.17, 0.3] \text{ cm}^{-1}$ and $[-210, 395] \text{ HU}$.

Figure 24.

ASD-POCS (column 1) and FDK (column 2) reconstructions within a coronal slice from 626-view data (row 1) and 323-view data (row 2) of the prostate-cancer patient. The planning-CT image of the patient within the slice is also shown in both columns of row 3. Visually matched display windows for OBI and planning-CT images are $[0.17, 0.3] \text{ cm}^{-1}$ and $[-210, 395] \text{ HU}$.

Figure 25.

ASD-POCS reconstructions within the coronal slice shown in Fig. 24 from patient data HD-f320 at iterations $n=20$, 30, and 40. A display window $[0.17, 0.3] \text{ cm}^{-1}$ is used.

Figure 26. ASD-POCS reconstructions of section CTP528 of the Catphan phantom from data HD-f640 with voxels of sizes (a) $0.244 \times 0.244 \times 0.244 \text{ mm}^3$ and (b) $0.488 \times 0.488 \times 2.5 \text{ mm}^3$. Display window: $[0, 0.6] \text{ cm}^{-1}$.

Figure 27. ASD-POCS reconstructions of the Rando-head phantom from data HD-f640 with voxels of size $0.488 \times 0.488 \times 0.488 \text{ mm}^3$ displayed in terms of (a) reconstruction-voxel sizes and (b) voxels of size $0.488 \times 0.488 \times 2.5 \text{ mm}^3$. Display window: $[0, 0.55] \text{ cm}^{-1}$.

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Table 1

Scanning Configurations

	Phantom Data				Patient Data	
	high dose		low dose			
Dense sampling	HD-f640	HD-h360	LD-f640	LD-h360	626-view	
Sparse sampling	HD-f320	HD-h180	LD-f320	LD-h180	313-view	

Table 2

Contrast-Resolution Result

Dense data	HD-f640	HD-h360	LD-f640	LD-h360
CNR	4.73 (1.09)	4.13 (0.60)	3.65 (0.28)	2.53 (0.13)
Sparse data	HD-f320	HD-h180	LD-f320	LD-h180
CNR	4.66 (0.75)	3.95 (0.45)	3.59 (0.16)	2.37 (0.09)

CNRs in ASD-POCS and FDK (in parentheses) reconstructions.

Table 3

Spatial-Resolution Result

Dense data	HD-f640	HD-h360	LD-f640	LD-h360
lp/cm	14(9)	12(8)	11(9)	10(8)
Sparse data	HD-f320	HD-h180	LD-f320	LD-h180
lp/cm	12(9)	12(8)	11(9)	10(8)

Highest lp densities in visually resolvable bar patterns in ASD-POCS and FDK (in parentheses) reconstructions.