Metal artifact correction for x-ray computed tomography using kV and selective MV imaging

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Purpose: The overall goal of this work is to improve the computed tomography (CT) image quality for patients with metal implants or fillings by completing the missing kilovoltage (kV) projection data with selectively acquired megavoltage (MV) data that do not suffer from photon starvation. When both of these imaging systems, which are available on current radiotherapy devices, are used, metal streak artifacts are avoided, and the soft-tissue contrast is restored, even for regions in which the kV data cannot contribute any information.

Methods: Three image-reconstruction methods, including two filtered back-projection (FBP)-based analytic methods and one iterative method, for combining kV and MV projection data from the two on-board imaging systems of a radiotherapy device are presented in this work. The analytic reconstruction methods modify the MV data based on the information in the projection or image domains and then patch the data onto the kV projections for a FBP reconstruction. In the iterative reconstruction, the authors used dual-energy (DE) penalized weighted least-squares (PWLS) methods to simultaneously combine the kV/MV data and perform the reconstruction.

Results: The authors compared kV/MV reconstructions to kV-only reconstructions using a dental phantom with fillings and a hip-implant numerical phantom. Simulation results indicated that dual-energy sinogram patch FBP and the modified dual-energy PWLS method can successfully suppress metal streak artifacts and restore information lost due to photon starvation in the kV projections. The root-mean-square errors of soft-tissue patterns obtained using combined kV/MV data are 10–15 Hounsfield units smaller than those of the kV-only images, and the structural similarity index measure also indicates a 5%–10% improvement in the image quality. The added dose from the MV scan is much less than the dose from the kV scan if a high efficiency MV detector is assumed.

Conclusions: The authors have shown that it is possible to improve the image quality of kV CTs for patients with metal implants or fillings by completing the missing kV projection data with selectively acquired MV data that do not suffer from photon starvation. Numerical simulations demonstrated that dual-energy sinogram patch FBP and a modified kV/MV PWLS method can successfully suppress metal streak artifacts and restore information lost due to photon starvation in kV projections. Combined kV/MV images may permit the improved delineation of structures of interest in CT images for patients with metal implants or fillings. © 2014 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4901551>]

Key words: CT, metal artifact reduction, dual energy, iterative reconstruction

1. INTRODUCTION

X-ray computed tomography (CT) images are often flawed if the structures of interest lie in the same imaging plane as high-density objects inside the patient's body.^{1,2} Streak artifacts caused by metal implants such as dental fillings, surgical instruments, and orthopedic hardware may obscure important

diagnostic information in x-ray CT, and preclude precise dose calculation. Those two difficulties are caused by the streak artifacts that result from photon starvation along the x-ray paths that traverse the metal objects. Diagnostic x-rays that pass through metal implants are highly (if not completely) attenuated and cause large errors due to scattering, beam hardening, motion artifacts, and partial-volume effects.

Over the years, many metal-artifact reduction (MAR) algorithms have been proposed for the suppression of streak artifacts. Most MAR algorithms modify or replace the projection data in the metallic region with reasonable values to produce an image with fewer streaks. The replaced data can generate either a smooth sinogram or a smooth reconstruction image.^{3–5} However, filling the metal-affected regions with data that produce an overall smooth image is not sufficient to restore all of the image details. To improve CT image quality for patients with metal implants or fillings, we propose completing the missing kilovoltage (kV) projection data using selectively acquired megavoltage (MV) data. There are two possible benefits of using selective MV data for metal artifacts reduction: 1. provide more accurate reconstruction of attenuation coefficients of patients and 2. recover missing details that are obscured by a metal object in the kV CT image.

Metal-artifact reduction in x-ray CT poses two main challenges: 1. the regions that contain metallic object(s) must be identified and 2. the identified metal regions in Radon space must be modified. The most well-known MAR method is the sinogram-interpolation method. After the photon-starved pixels are identified in Radon space, the “missing” data are approximated via interpolation from those neighboring pixels that are not affected by the high-attenuation object(s) to obtain a smooth sinogram. Various interpolation methods have been studied, including linear, polynomial, and adaptive interpolation.^{3,6,7} The primary disadvantage of interpolation methods is that smoothing the sinograms based on the neighboring pixels does not guarantee the complete removal of streak artifacts.³ Any unmatched data between projection views may introduce additional artifacts into the reconstructed image. Several more sophisticated techniques have also been proposed to determine the values of missing data, such as wavelet-based reconstruction,⁸ Laplacian diffusion,⁹ forward projection of segmented prior reconstructions,^{5,10,11} and orthogonal projection.¹² Iterative algorithms are also used to reduce metal artifacts based on existing data. The iterative reconstruction approaches complete the missing data through the joint optimization of data consistency and image roughness.^{4,13–18} In addition, given knowledge of the x-ray spectrum, metal artifacts can be treated as strong beam-hardening artifacts; therefore, polychromatic reconstruction algorithms have also been considered for MAR.^{4,19,20}

Because high-energy MV x-ray projections do not suffer from photon starvation, a combination of the on-board imaging devices may provide a streak-free and high-resolution CT reconstruction, even for soft tissue located in the same image plane as metal objects. Current radiotherapy devices often include detectors for both kV and full/truncated MV cone-beam CT imaging.^{21–25} The use of cone-beam CT increases patient setup accuracy,^{26–28} and more recently with improvement in image quality has been considered for accurate tumor delineation,^{29,30} and dose calculation,^{31–33} which provide treatment verification and feedback information in adaptive radiation therapy (ART) techniques.^{34,35} Fang *et al.* proposed aggregated techniques for on-board CT reconstruction using a combination of full kV and MV beam projections to improve

data-acquisition efficiency and image quality.²¹ A novel technique developed by Li *et al.* to generate virtual monochromatic kV/MV projections has been shown to reduce metal artifacts for cone-beam CT.³⁶ In addition, because the multileaf collimators (MLCs) on a radiotherapy device can be used to restrict additional MV acquisition to cover only the metal implants, the improvement in image quality can be achieved with a very moderate dose increase for the patient.^{37–39} When both of these imaging systems on current radiotherapy devices are used, photon starvation is avoided, and the soft-tissue contrast can be restored, even for areas in which the kV projections do not contribute any information. Note however, that the image quality of on-board cone-beam CT continues to be limited by the scatter contamination in the projections, nonlinearities of detector response, and slow acquisition.^{40,41}

A further challenge in image reconstruction is determining how to modify the MV projection data to provide the information missing in the kV projections. In this paper, we propose two analytic methods and one iterative method for combining kV and selective MV data. The first analytic method uses a linear sinogram patch that adjusts the MV sinogram based on the neighboring kV pixels, whereas the second approach uses estimated image and spectral information to compensate for the difference between the kV and MV sinograms. The resulting sinogram contains additional information that not only prevents streaks but also increases the structural information contained in the subsequent reconstruction. In the iterative approach, we modify dual-energy (DE) penalized weighted least-squares (PWLS) algorithms to reconstruct images using kV and selective MV data. This paper is organized as follows: Section 2 describes our proposed image-reconstruction methods. Section 3 describes the numerical simulations used to test the reconstruction methods. Finally, the simulation results are presented, and the proposed methods are compared.

2. METHODS

2.A. Data acquisition

By limiting the MV data acquisition to only the x-ray paths that suffer from photon starvation in the kV projections, one can ensure that the additional dose is relatively small in comparison with that of a standard MV CT acquisition. Because modern radiotherapy devices are already equipped with MLCs, the hardware required for shaping the MV acquisition is available (see Fig. 1).^{22,25,37–39} The MV collimator blades and MLC should be adjusted in real time so that only the metal-containing portions of the object are irradiated during the course of the MV scan. The MLC control can be done in either projection space or image space. If the metal object can be easily segmented in the kV projections, the MLC can be moved such that only the metal is exposed when the MV beam is rotated to the corresponding position at which the kV image was acquired. If the metal is not clear in the kV projections, then the kV data must be reconstructed first in order to find the spatial location of the metal. Then we can control the MLC to focus on the metal object in a manner similar to

FIG. 1. Collimated MV data acquisition.

that used in radiation therapy. Dose efficiency can be further improved by using newer high-efficiency MV detectors.^{42–45}

Under the assumption of monochromatic x-ray beams for both the kV and MV acquisitions, the expected x-ray intensity signals follow Beer's law:

$$\begin{aligned}\hat{Y}_i^{kV} &= b_i^{kV} \exp\left(-\sum_{j=1}^J a_{ij} \mu(x, y, \varepsilon^{kV})\right), \\ \hat{Y}_i^{MV} &= b_i^{MV} \exp\left(-\sum_{j=1}^J a_{ij} \mu(x, y, \varepsilon^{MV})\right),\end{aligned}\quad (1)$$

where b_i^{kV} and b_i^{MV} denote the unattenuated x-ray intensities of the i th ray (pixel), a_{ij} denotes the discrete length of intersection of the i th ray with the j th image voxel, and $\mu(x, y, \varepsilon^{kV})$ and $\mu(x, y, \varepsilon^{MV})$ are linear attenuation coefficients at the effective energies ε^{kV} and ε^{MV} of the kV and MV beams, respectively.

The detector signal can be approximated by the Poisson (Compound Poisson is more accurate) statistical model^{46,47}

$$Y_i \sim \text{Poisson}\{b_i e^{-[A\mu]_i} + q_i + n_i\}, \quad (2)$$

where $[A\mu]_i$ denotes the discrete line integral in matrix form, q_i denotes a signal offset (e.g., scatter), and n_i denotes the additional noise (e.g., electronic noise) that often can be modeled as a Gaussian random variable $\mathcal{N}(0, \sigma_i^2)$. The attenuation sinogram value l_i is obtained by computing the logarithm of the ratio of the unattenuated signal and the detected signal as follows:

$$l_i = \log\left(\frac{b_i}{Y_i - q_i}\right). \quad (3)$$

The variance of the l_i is approximately $1/Y_i$. When the x-ray signals suffer from photon starvation, $Y_i - q_i$ is very small and possibly negative. Negative values can be replaced by

a small, arbitrary positive value in order to avoid NaNs, although this may affect overall accuracy of reconstructed Hounsfield units (HU) values.

2.B. Linear sinogram patch

To obtain additional information from the MV data in the reconstruction, the MV sinogram must be scaled and combined with the kV sinogram. A simple stitching of sinograms, however, is not possible because of the spectrum-dependent attenuation of the image objects. X-ray photons of higher energy are less attenuated; thus, the resulting sinogram is composed of lower line-integral values. For a first-order approximation of the conversion between the two types of sinograms, one can determine a ratio and/or a difference between the kV and MV attenuation sinograms. Under the assumption that the two sinograms are acquired using the same geometries (i.e., the same source-to-detector and axis-to-detector distances as well as the same angular spacings), the linear sinogram patch method interpolates the ratios and differences between the kV and MV sinogram values. The known ratios and differences for the neighboring pixels of the metal-affected regions that do not suffer from photon starvation are interpolated into the areas without meaningful kV attenuation values. This method requires at least some area of overlap, where both kV and MV data are acquired and valid, i.e., the MLC must be controlled such that at least a few pixels around the metal-affected region are acquired using the MV beam.

We proposed an interpolation-based sinogram patch method that uses two approximations to modify the MV sinogram and patch onto the kV sinogram. This method is very similar to the interpolation-based MAR method. The interpolated relationships (ratios and differences) derived from the neighboring pixels between the kV and MV sinogram are used to modify the MV data in the metal-affected regions. The first approximation uses the interpolated ratios of the overlapping pixels as follows:

$$\hat{l}_{im}^{kV} = r_{im} l_{im}^{MV} = \sum_{i_o} t(i_m, i_o) \frac{l_{i_o}^{kV}}{l_{i_o}^{MV}} l_{im}^{MV}, \quad (4)$$

where $\hat{l}_{im}^{kV}$ denotes the kV metal-affected pixel value estimated from the sinogram ratios; r_{im} denotes the estimated ratio; i_m and i_o denote metal-affected and overlapping pixels, respectively; and $t(i_m, i_o)$ denotes the 2D scattered cubic interpolation (MATLAB, Mathworks, Inc.) weights of neighboring overlapping pixels. The ratio r_{im} is greater than 1 because the linear attenuation coefficients are smaller in the MV beam than in the kV beam. The second approximation uses the differences between the kV and MV overlapping pixels

$$\tilde{l}_{im}^{kV} = d_{im} + l_{im}^{MV} = \sum_{i_o} t(i_m, i_o) (l_{i_o}^{kV} - l_{i_o}^{MV}) + l_{im}^{MV}, \quad (5)$$

where, again, $\tilde{l}_{im}^{kV}$ denotes the kV metal-affected pixel value estimated from the sinogram differences, and d_{im} denotes the estimated difference between the kV and MV sinograms for the metal-affected pixels.

FIG. 2. Schematic of filtered back-projection (FBP)-based kV/MV image-reconstruction methods. The analytic reconstruction methods modify the MV data based on the information contained in the projection or image domains, which are then patched onto the kV projections for the FBP reconstruction. (a) The linear sinogram patch method uses the interpolated ratios and differences between the kV and MV sinograms from neighboring pixels. (b) The DE patch method uses pixel differences in the forward projections from estimated images at kV and MV energies.

These two approximations have different properties. The ratio approximation yields higher contrast in the soft tissue because the ratios are typically greater than 1. However, these large ratios also enhance the noise in the MV sinogram and produce new streak artifacts. The approximation that uses sinogram differences exhibits lower soft-tissue contrast, but it creates fewer streak artifacts than the interpolated ratios. Therefore, we propose a linear combination (with $0 < \lambda < 1$) of the two approximations to produce a linearly patched sinogram

$$\begin{aligned}\tilde{l}_{i_m}^{kV} &= \lambda \hat{l}_{i_m}^{kV} + (1 - \lambda) \tilde{l}_{i_m}^{kV} \\ &= \lambda (r_{i_m} \hat{l}_{i_m}^{MV}) + (1 - \lambda) (d_{i_m} + \hat{l}_{i_m}^{MV}) \\ &= (\lambda r_{i_m} + 1 - \lambda) \hat{l}_{i_m}^{MV} + (1 - \lambda) d_{i_m}.\end{aligned}\quad (6)$$

A schematic of the linear sinogram patch method is shown in Fig. 2(a). The linearly patched sinogram is reconstructed using the FBP method.

The weighting value, λ , for the combination depends on the signal-to-noise ratio of the MV data. A large lambda value scales up the MV sinogram, which can also increase contrast. However, a large lambda value also amplifies the noise in the MV data, which may cause streak artifacts in the

reconstructed image. The lambda value is chosen empirically in this study. In addition, the linear sinogram patch method uses small overlapping areas (2–3 neighboring pixels) to estimate the ratios and differences. The noise in the overlapping pixels of both sinograms influences the estimated ratios r_{i_m} and differences d_{i_m} , which then propagates as errors in the patched regions. Increasing the area of overlap will increase the MV dose to the patient but may not significantly increase the interpolation accuracy because pixels at a greater distance are less related to the pixels in the metal-affected regions. Therefore, an image reconstructed using the linear patch method often contains streak artifacts caused by the low MV photon counts and inaccurate interpolation.

2.C. DE sinogram patch

The main disadvantage of the linear patch method is that it relies heavily on the correlation between the metal-affected pixels and the neighboring pixels. We propose here another analytical reconstruction method called the dual-energy sinogram patch (DE-Patch) method to modify and patch the MV sinogram to the kV sinogram. The differences in attenuation coefficients between the kV and MV images are first

computed in the image domain using a MAR image with almost complete kV data; then forward projections can be used to estimate the differences in the sinograms.

A lookup table of linear attenuation coefficients for kV and MV images is generated based on prior knowledge of spectra and substances.⁴⁸ The attenuation coefficients can also be calibrated using step-wedge phantoms.³⁶ Then, the lookup table is used to convert the kV linear attenuation coefficients of the MAR image⁵ into the MV linear attenuation coefficients. The differences between the kV and MV projections are calculated by forward-projecting both estimated images and subtracting in the projection domain. The steps of the DE sinogram patch method are as follows:

- Precompute the $\tilde{\mu}^{\text{kV}}$ image from $\hat{l}_i^{\text{kV}}$ using a MAR reconstruction method.
- Convert the kV reconstruction into the MV reconstruction $\tilde{\mu}^{\text{MV}}$ using the attenuation lookup table.
- Project the $\tilde{\mu}^{\text{MV}}$ to estimate the MV sinogram $\hat{l}_i^{\text{MV}}$.
- Compute the differences $\Delta l_{im}^{\text{DE}} = [\mathbf{A}\tilde{\mu}^{\text{kV}}]_{im} - [\mathbf{A}\tilde{\mu}^{\text{MV}}]_{im}$ between the estimated kV and MV sinograms.
- Patch the collimated MV sinogram with the estimated differences $\tilde{l}_{im}^{\text{kV}} = \hat{l}_{im}^{\text{MV}} + \Delta l_{im}^{\text{DE}}$.
- Reconstruct the DE-patched sinogram using FBP.

This method is illustrated in Fig. 2(b).

The image $\tilde{\mu}^{\text{kV}}$ estimated from the MAR reconstruction does not include metal or the information lost in the kV sinogram. Therefore, the DE patch method usually yields lower soft-tissue contrast than the linear patch method. In contrast, the DE patch method may not be suitable for a higher number of iterations. After the first DE patch FBP reconstruction, the image will include the metal object(s). The differences between the linear attenuation coefficients of kV and MV beams for high-density materials are much larger than those between soft tissue and bone. Hence, the sinogram difference $\Delta l_{im}^{\text{DE}}$ estimated in step (d) takes on much larger values for the metallic regions than in the previous iteration, resulting in an even higher linear attenuation coefficient for any metal object(s) in the reconstructed image from step (f). Therefore, in the absence of any limitations, the linear attenuation coefficient of metal objects will continue to increase with further iterations. The estimated differences of those metal pixels are influenced by the increasing metal linear attenuation coefficients, and the soft-tissue contrast may not be improved by iterating the DE patch method.

The overlapping areas are still useful for the DE patch method because the beam hardening in the precomputed MAR image and any errors in the linear-attenuation-coefficient lookup table may cause an offset between the estimated and actual MV sinograms. As a consequence, during the patching of the difference-compensated MV sinogram, the transition between the patched and original kV sinograms may not be smooth. The overlapping pixels can be used to reduce such an offset by subtracting the mean difference between the estimated and actual MV pixel values in the overlapping region. This offset correction used in the DE patch method allows for a smoother transition of the patched sinogram and eliminates some of the streak artifacts caused by a nonsmooth transition.

2.D. PWLS

The penalized weighted least-squares algorithm has been used in single- and dual-energy iterative x-ray CT reconstruction. The algorithm simultaneously constructs a quadratic approximation of the Poisson log-likelihood function and minimizes piecewise differences in the image.^{49–52} We proposed a modified DE PWLS algorithm that is applicable for the kV and selective MV image reconstruction. Ideally, the DE PWLS algorithm minimizes the object function

$$\Phi(\mu(\varepsilon)) = \|\mathbf{A}^{\text{kV}}\mu(\varepsilon^{\text{kV}}) - l^{\text{kV}}\|_{w^{\text{kV}}}^2 + \|\mathbf{A}^{\text{MV}}\mu(\varepsilon^{\text{MV}}) - l^{\text{MV}}\|_{w^{\text{MV}}}^2 + \beta R(\mu(\varepsilon)), \quad (7)$$

where $\mathbf{A}^{\text{kV}}$ and $\mathbf{A}^{\text{MV}}$ are projection matrices for the two data acquisition geometries, w^{kV} and w^{MV} are the least-squares weights given by

$$w_i = \frac{(\{Y_i - q_i\}_+)^2}{Y_i + \sigma_i^2}, \quad (8)$$

where q_i and σ_i^2 denote the mean and variance of the additive signal. The argument R is the piecewise regularization of the following form:

$$R(\mu) = \sum_{j=1}^J \sum_{k \in N_j} c_{jk} \Psi(\mu_j - \mu_k), \quad (9)$$

where N_j is some neighborhood of voxel j and the weights c_{jk} are proportional to the inverse of the distance between voxels j and k . We use the convex edge-preserving Huber penalty

$$\Psi(x) = \begin{cases} \frac{1}{2}x^2 & \text{if } |x| \leq \delta \\ \delta x - \frac{1}{2}\delta^2 & \text{if } |x| > \delta \end{cases} \quad (10)$$

as the penalty function for image roughness. The value of δ is set to 5 HU, which has been reported to provide a good trade-off between soft-tissue contrast and noise reduction.⁵³

Both $\mu(\varepsilon^{\text{kV}})$ and $\mu(\varepsilon^{\text{MV}})$ denote the linear attenuation coefficients of the same scan object at different x-ray energies ε^{kV} and ε^{MV} , and they must be reconstructed together. In the DE PWLS algorithm proposed by Sukovic and Clinthorne,⁵⁰ the energy-dependent linear attenuation coefficients were formulated as a linear combination of photoelectric interaction and Compton scattering (ignoring the K-edge effect) and were then further decomposed into two basis materials: soft tissue and bone.⁵⁰ We use the same concept to decompose the scan object into soft tissue and bone

$$\mu_j(\varepsilon) = m_{\text{soft}}(\varepsilon)\rho_{\text{soft},j} + m_{\text{bone}}(\varepsilon)\rho_{\text{bone},j}, \quad (11)$$

where $m_{\text{soft}}(\varepsilon)$ and $m_{\text{bone}}(\varepsilon)$ denote the mass attenuation coefficients of soft tissue and bone, respectively, at x-ray energy ε and $\rho_{\text{soft},j}$ and $\rho_{\text{bone},j}$ denote the densities of soft tissue and bone, respectively, in the j th image voxel. The DE PWLS algorithm solves for the values of $\rho_{\text{soft},j}$ and $\rho_{\text{bone},j}$.

However, unlike the conventional DE CT system, the kV-and-selective-MV system produces only one complete set of

projection data (sinogram). One complete sinogram is not sufficient to directly reconstruct two density images of two basis materials. To overcome this limitation, the ratios of the soft tissue and bone are fixed; thus, only one combined density must be calculated. We first segment an initial image reconstructed using the DE sinogram patch method. Then, the density ratios between soft tissue and bone are determined from the initial image and remain fixed throughout the iterative reconstruction. Similar to Ref. 54, we use a smooth transition for voxels with a linear attenuation coefficient between those of soft tissue and bone. The fraction functions of the two basis materials are given by

$$f_{\text{soft},j} = \begin{cases} 1 & \text{if } \mu_j^{(0)} \leq \mu_{\text{soft}}(\varepsilon^{\text{kV}}) \\ \frac{\mu_{\text{bone}}(\varepsilon^{\text{kV}}) - \mu_j^{(0)}}{\mu_{\text{bone}}(\varepsilon^{\text{kV}}) - \mu_{\text{soft}}(\varepsilon^{\text{kV}})} & \text{if } \mu_{\text{soft}}(\varepsilon^{\text{kV}}) < \mu_j^{(0)} \\ & \text{and } \mu_j^{(0)} < \mu_{\text{bone}}(\varepsilon^{\text{kV}}) \\ 0 & \text{if } \mu_j^{(0)} \geq \mu_{\text{bone}}(\varepsilon^{\text{kV}}) \end{cases}$$

$$f_{\text{bone},j} = 1 - f_{\text{soft},j}, \quad (12)$$

where $f_{\text{soft},j}$ and $f_{\text{bone},j}$ denote the fractions of soft tissue and bone in the j th voxel, $\mu_j^{(0)}$ denotes the value of the linear attenuation coefficient in the initial image, and $\mu_{\text{soft}}(\varepsilon^{\text{kV}})$ and $\mu_{\text{bone}}(\varepsilon^{\text{kV}})$ are the linear attenuation coefficients of soft tissue and bone for the effective energy ε^{kV} of the kV x-rays. Thus, the linear attenuation coefficients of the object in the kV and MV data can be expressed as

$$\mu_j(\varepsilon^{\text{kV}}) = (m_{\text{soft}}(\varepsilon^{\text{kV}})f_{\text{soft},j} + m_{\text{bone}}(\varepsilon^{\text{kV}})f_{\text{bone},j})\rho_j = m_j^{\text{kV}}\rho_j$$

$$\mu_j(\varepsilon^{\text{MV}}) = (m_{\text{soft}}(\varepsilon^{\text{MV}})f_{\text{soft},j} + m_{\text{bone}}(\varepsilon^{\text{MV}})f_{\text{bone},j})\rho_j = m_j^{\text{MV}}\rho_j, \quad (13)$$

where m_j^{kV} and m_j^{MV} denote the precomputed combined mass attenuation coefficients of the j th voxel for the kV and MV spectra, and ρ_j denotes the combined density of the scanned object, which is unknown. Note that there is no need to distinguish metal object(s) in the initial image because the kV sinogram does not contain projection data in the metal-affected region, and thus, an attenuation conversion for the metal object is not necessary for the PWLS method. The ratios of the basis materials from the metal object(s) will not affect the results of the PWLS method.

By fixing the fractions of the two base materials, we have developed the following objective function for kV and MV selective imaging:

$$\Phi(\rho) = \|\mathbf{A}\mathbf{M}\rho - \mathbf{l}\|_w^2 + \beta R(\mathbf{M}^{\text{kV}}\rho), \quad (14)$$

where vector $\mathbf{l}$ is the vectorized attenuation sinograms of kV and MV beams computed using Eq. (3), and vector ρ is the combined density map we wish to solve. Matrix $\mathbf{A}$ is the $(I^{\text{kV}} + I^{\text{MV}}) \times 2J$ combined projection matrix of both geometries, I^{kV} and I^{MV} denote the total number of valid projection data that do not suffer from photon starvation, and J is the number of image voxels

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^{\text{kV}} & 0 \\ 0 & \mathbf{A}^{\text{MV}} \end{bmatrix}. \quad (15)$$

Matrix $\mathbf{M}$ is the $2J \times J$ dual-energy mass attenuation matrix

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}^{\text{kV}} \\ \mathbf{M}^{\text{MV}} \end{bmatrix} = \begin{bmatrix} \text{diag}\{m_1^{\text{kV}}, m_2^{\text{kV}}, \dots, m_{I^{\text{kV}}}^{\text{kV}}\} \\ \text{diag}\{m_1^{\text{MV}}, m_2^{\text{MV}}, \dots, m_{I^{\text{MV}}}^{\text{MV}}\} \end{bmatrix}. \quad (16)$$

Matrices $\mathbf{M}^{\text{kV}}$ and $\mathbf{M}^{\text{MV}}$ are diagonal matrices of the combined energy-dependent mass attenuation coefficients [see Eq. (13)].

We use the kV image $\mu^{\text{kV}} = \mathbf{M}^{\text{kV}}\rho$ as the input to the penalty function because most of the data are contributed by the kV projection data. The local impulse response of a PWLS image is approximately⁵⁵

$$p(\mu)_j \approx [\mathbf{A}^T \mathbf{W} \mathbf{A} + \beta \mathbf{R}]^{-1} \mathbf{A}^T \mathbf{W} \mathbf{A} e_j, \quad (17)$$

where $\mathbf{W}$ is the diagonal matrix of weights, e_j denotes the j th canonical basis vector, and $\mathbf{R}$ is a μ -dependent $J \times J$ matrix defined by

$$\mathbf{R}_{jk} = \begin{cases} \sum_{k \in N_j} c_{jk} & \text{if } j = k \\ -c_{jk} & \text{if } j \neq k \end{cases}. \quad (18)$$

In our case, the impulse response of effective density ρ is

$$p(\rho)_j \approx [\mathbf{M}^T \mathbf{A}^T \mathbf{W} \mathbf{A} \mathbf{M} + \beta \mathbf{M}^{\text{kV}T} \mathbf{R} \mathbf{M}^{\text{kV}}]^{-1} \mathbf{M}^T \mathbf{A}^T \mathbf{W} \mathbf{A} e_j. \quad (19)$$

Ignoring the background events, the weights are proportional to the signals of the prelogarithmic projection data. Because we designed the penalty function based on the kV data, the penalty function may be the dominant factor in the 2D impulse response along the projection direction that contains the metal object(s). Because the x-ray intensities of the MV beam are typically smaller than those of the kV beam, the weights for MV-data agreement may be too small for the penalty function based on the kV data. Therefore, to produce an isotropic local impulse response, we add a scaling factor γ to the MV weights in the PWLS algorithm such that

$$\tilde{\mathbf{W}} = \text{diag}\{w_i^{\text{kV}}, \dots, \gamma w_i^{\text{MV}}, \dots\} = \begin{bmatrix} \mathbf{W}^{\text{kV}} & 0 \\ 0 & \gamma \mathbf{W}^{\text{MV}} \end{bmatrix}, \quad (20)$$

where w_i^{kV} and w_i^{MV} are computed using Eq. (8). The value of γ can be determined from the ratio of the means of neighboring kV weights $\bar{w}_{i_o}^{\text{kV}}$ and MV weights $\bar{w}_{i_m}^{\text{MV}}$ and the ratio of the mass attenuation coefficient

$$\gamma \approx \frac{\bar{w}_{i_o}^{\text{kV}}}{\bar{w}_{i_m}^{\text{MV}}} \left(\frac{m_{\text{soft}}(\varepsilon^{\text{kV}})}{m_{\text{soft}}(\varepsilon^{\text{MV}})} \right)^2. \quad (21)$$

The inclusion of this scaling factor ensures that the PWLS method has a soft-tissue impulse response similar to that of single-energy PWLS. The resulting object function with the inclusion of the MV-weight scaling factor is

$$\Phi(\rho) = \|\mathbf{A}^{\text{kV}} \mathbf{M}^{\text{kV}} \rho - \mathbf{l}^{\text{kV}}\|_{w^{\text{kV}}}^2 + \gamma \|\mathbf{A}^{\text{MV}} \mathbf{M}^{\text{MV}} \rho - \mathbf{l}^{\text{MV}}\|_{w^{\text{MV}}}^2 + \beta R(\mathbf{M}^{\text{kV}}\rho). \quad (22)$$

The scaling factor γ enhances the noise in the MV data but improves the recovery of missing information, which is more desirable in this study.

FIG. 3. (a) and (b) show the segmented numerical phantoms with added metal objects (indicated by circles) used in the simulations. For the purpose of visualization only, the pixel values in the (a) and (b) are integers, where 1 = fat, 2 = muscle, 3 = bone, 4 = gold or titanium. The two regions of interest (ROIs) for soft-tissue patterns of each phantom are outlined by the rectangles. A small ROI (in small rectangle) away from them metal object(s) is used for compute standard deviation. (c) and (d) show the FBP reconstructed images with linear interpolation correction (display window level $[-400, 800]$ HU).

We use the nonuniform separable quadratic surrogate algorithm (NU-SQS)^{51,56} to solve the PWLS problem Eq. (22). The updating step is a diagonally preconditioned gradient descent

$$\rho_j^{(n+1)} = \left[\rho_j^{(n)} - \frac{1}{d_j^{(n)}} \frac{\partial}{\partial \rho_j} \Phi(\rho_j^{(n)}) \right]_+, \quad (23)$$

where the gradient can be computed as

$$\begin{aligned} \frac{\partial}{\partial \rho_j} \Phi(\rho_j^{(n)}) &= [\mathbf{A}^{\text{kV}T} \mathbf{M}^{\text{kV}T} (\mathbf{A}^{\text{kV}} \mathbf{M}^{\text{kV}} \rho^{(n)} - \mathbf{l}^{\text{kV}})]_j \\ &\quad + \gamma [\mathbf{A}^{\text{MV}T} \mathbf{M}^{\text{MV}T} (\mathbf{A}^{\text{MV}} \mathbf{M}^{\text{MV}} \rho^{(n)} - \mathbf{l}^{\text{MV}})]_j \\ &\quad + \beta \frac{\partial}{\partial \rho_j} R(\mathbf{M}^{\text{kV}} \rho^{(n)}). \end{aligned} \quad (24)$$

The denominator $d_j^{(n)}$ is an approximate curvature that can be fixed, as in Ref. 51, or can adapt to the update state, as in Ref. 56. The NU-SQS can be further accelerated using ordered-subset and Nesterov's algorithms to more rapidly converge to the optimum solution.⁵⁷

3. SIMULATIONS

Two numerical phantoms, dental and hip, were created based on segmented clinical CT scans (Fig. 3). The dental phantom includes two metal fillings: one gold and one amalgam filling with diameters of approximately 5 mm. The hip phantom contains one titanium implant with a diameter of 35 mm. To assess the ability of the reconstruction algorithms to recover missing information, the phantoms also feature two bar-shaped soft-tissue patterns. The soft-tissue pattern uses adipose tissue that is 150 HU smaller than the surrounding soft-tissue material. All anatomical features are specified as materials with energy-dependent attenuation profiles from the NIST database.⁵⁸ All bars in the soft-tissue patterns point toward the metal object(s) in the phantom. Therefore, without data from the x-ray beams that pass through the metal, it is nearly impossible to resolve the bars in the patterns. The voxel spacings of both phantoms are $0.2 \times 0.2 \times 1.6$ mm.

The cone-beam CT projections were simulated based on the TrueBeam radiotherapy system (Varian Medical System).

The kV and MV detectors in this system contain 2048×1536 and 1024×768 pixels, respectively. We applied 4×4 and 2×2 pixel binning to the kV and MV detectors, so the resulting pixel sizes are 0.768×0.768 mm and 0.784×0.784 mm, respectively. Both beams produce 480 projections for a 360° rotation. The beams were collimated to only image the central 16 rows of each detector. For the hip phantom, we doubled the size of the detector to provide a larger field of view. In a practical scenario, such a large area of detection can be obtained by using an offset detector geometry. The reconstructed volume of the dental case contains $360 \times 360 \times 6$ voxels with a spacing of $0.5 \times 0.5 \times 2$ mm, and the hip case contains $400 \times 400 \times 6$ voxels with a spacing of $0.8 \times 0.8 \times 2$ mm.

Both phantoms used a 120-kVp spectrum [mean: 54.7 keV, standard deviation (SD): 19.9 keV] to generate kV projections. In the dental-phantom case, a 6-MVp beam was used (mean: 1.66 MeV, standard deviation 1.24 MeV), and in the hip-implant scenario, a 2.5-MVp beam (mean: 677 keV, standard deviation: 428 keV) was used to generate the MV projections. The normalized spectra provided by Varian Medical Systems are shown in Fig. 4. These simulated projections include beam hardening (approximately 100 energy bins used for the simulation of both kV and MV projections) and Poisson quantum noise. No additional noise is added to the data. In the case of gold fillings, measurements acquired using a 2.5-MVp spectrum suffer from beam hardening, and therefore, a 6-MVp spectrum was selected for the head-and-neck application. The MV projection data were restricted to the shadow cast by the fillings onto the detector plus a margin of 3 pixels on each side, mimicking an acquisition in which collimation is used to restrict the MV acquisition only to rays that provide information missing from the kV data due to photon starvation along paths through metal.

The quantum detection efficiencies (QDEs) were also considered; efficiencies of 0.75 and 0.25 were assumed for the kV and MV detectors, respectively. The unattenuated signals incident on the detector for the kV projection data are 4×10^5 counts/pixel and 8×10^5 counts/pixel for the dental and hip cases, respectively. To demonstrate the impact of the MV data on the image quality, MV projections were generated using two different x-ray intensities for both phantoms. The unattenuated signals b_i incident on the detector for the dental

FIG. 4. Normalized x-ray spectra and material attenuation coefficients used in the simulations. (a) 120-kVp kV spectrum and (b) 2.5-MVp MV spectrum for hip phantom; (c) 6-MVp spectrum for dental phantom; (d) energy-dependent attenuation coefficients of soft tissue, bone, titanium, amalgam, and gold.

phantom are 2×10^4 counts/pixel (low-dose case) and 4×10^4 counts/pixel (high-dose case); the unattenuated signals for the hip phantom are 4×10^4 counts/pixel (low-dose case) and 8×10^4 counts/pixel (high-dose case). All unattenuated x-ray intensities are incident on the detector, i.e., before the QDE is taken into account.

The three proposed kV/MV reconstruction methods were used to reconstruct images from the simulated projection data, and the results were compared with those of a MAR reconstruction method. We implemented the normalized metal artifact reduction (NMAR) method described in Ref. 5 because it offers good image quality and moderate computational demand. The MAR reconstruction was also used to generate the estimated kV image for the DE patch algorithm. The FDK (Ref. 59) algorithm with a Hamming window was used in the MAR, linear patch, and DE patch methods.

The values of λ chosen for the linear sinogram patch method were 0.3 for the low-dose case and 0.7 for the high-dose case. The PWLS method used Nesterov's 05 NU-SQS and 8-ordered-subset algorithms.⁵⁷ We used the distance-driven method for both forward and backward projections.⁶⁰ The forward projections were computed for the entire MV detector, and then the metal-affected regions were extracted for optimization update. The number of iterations was 50 for all PWLS reconstructions. An appropriate stopping criterion is when either the reconstructed images or the sinogram has very small changes between iteration steps. The dental phantom used the parameters $\beta = 1 \times 10^4$ and $\gamma = 30$ and the hip

phantom used the parameters $\beta = 2 \times 10^4$ and $\gamma = 10$ for both the low- and high-MV-dose cases.

To estimate the dose for a given number of kV/MV quanta used for reconstruction, we developed a Geant4 Monte Carlo model of the experiment.⁶¹ We used Geant4 version 9.4 patch 03 with the standard electromagnetic physics list, option 3. The core of the model was based on the so-called DICOM Geant4 example (http://www.nucleaire.phy.ulaval.ca/phys_med/DICOM/), consisting of three contiguous slices, pre-encapsulated in three DICOM files with a pixel size identical to that of the numerical phantom. These three files were imported into Geant4, thus generating a voxelized geometry with material information. Of the three DICOM files, only the middle-slice voxels were assigned to sensitive detectors. The outer slices and the middle slice had thicknesses of 50 mm and 2 mm, respectively. The x-ray source was allowed to rotate around the phantom geometry, and for each source position, the beam geometry was specified according to an imaging plan in which the MV beam was focused on the metal implants. The distance between the source and the center of the phantom was 1 m, regardless of the source position. The kV and MV source energy spectra were provided by Varian, and the pencil-beam spatial distribution was uniform. The source was rotated, and the total dose was accumulated for each individual voxel of the thinner middle slice. The simulations were performed on a dedicated virtual cluster based on Amazon Elastic Compute Cloud, and the average run time was approximately 50 CPU h.

FIG. 5. Results for the dental test case. The “Low” and “High” denote the low dose and high dose cases of the simulated MV data. The images are displayed at the window level $[-400, 800]$ HU, and ROI images are displayed at the window level $[-200, 200]$ HU.

4. RESULTS

Figures 5 and 6 display reconstructed images achieved using our proposed methods. Two ROIs of the bar-shaped soft-tissue patterns are displayed below each full reconstruction. The left-hand ROI image is the upper soft-tissue pattern, which is in close proximity to the high-density objects (between the two metal fillings in the dental phantom). The MAR method effectively reduced the occurrence of streak artifacts, but due to the loss of information in the kV data, both of the soft-tissue patterns are blurred, especially the pattern that is closer to the metal. The computation times of the linear patch and DE patch algorithms are both shorter than 5 min. The PWLS method with 50 iterations requires 1–2 h on a standard 4-core computer.

The use of MV data not only removes streaks but also recovers missing structure information of the reconstructed image in the directions affected by the metal object(s). The linearly patched sinogram images contain more streak artifacts caused by noise in the MV data than the images produced using the other methods. The soft-tissue intensities are nonuniform

over the entire image because the neighboring pixels cannot completely represent the missing regions, so the interpolated ratios and differences do not scale the MV sinogram to the correct level. This problem is also commonly encountered in interpolation-based MAR reconstruction. Moreover, because the MV data are scaled up, the noise in the MV data causes more streak artifacts than in the other two kV/MV reconstruction methods. Both the DE patch and PWLS methods reconstructed resolvable soft-tissue patterns without many metal streak artifacts. The images reconstructed from the high-dose MV data are of better quality than those reconstructed from the low-dose data, as expected. The occurrence of streaks is reduced by the increased signal-to-noise ratios in the MV data. In addition, FBP reconstructions of noncollimated MV data with the same number of photon counts per detector pixel as in the high-MV-dose cases are shown in Figs. 5(e) and 6(e) for both phantom cases. Due to the low photon counts and low soft-tissue contrast of the MV data, the soft-tissue patterns are difficult to recognize in the MV-only FBP images.

Quantitative evaluations were performed using the structural similarity index (SSIM) developed by Wang *et al.*⁶² and

FIG. 6. Results for the hip test case. The Low and High denote the low dose and high dose cases of the simulated MV data. The images are displayed at the window level $[-400, 800]$ HU, and ROI images are displayed at the window level $[-200, 200]$ HU.

the root-mean-square error (RMSE). Figure 7 shows both the SSIM and RMSE values of the two ROIs. We used the default parameters in Wang's work to compute the SSIM of images in HU. All three kV/MV methods have higher SSIMs and lower RMSEs than the MAR reconstruction because the lost information is provided by the MV data. The linear patch method produced better results for ROI2 (lower/less-affected ROI) than for ROI1 (upper/highly affected ROI), but the DE patch and PWLS methods have similar values for both ROIs, with the PWLS method appearing to be slightly better than the DE patch method. Slightly better image quality was achieved for ROI2, which is farther away from the metal, than for ROI1. In addition, higher SSIMs were achieved for the DE patch method using the low-dose MV data in contrast to the high-dose data because the bar pattern is oriented toward the metal object such that the streaking artifacts may coincidentally increase the contrast of the bar pattern.

The overall image quality was also measured using the SD and total variation (TV). The SD was measured using both the entire soft-tissue region and the small ROI shown in Fig. 3.

The SD of the entire soft-tissue region shows the uniformity of the reconstructed image, while the SD of the small ROI provides a measure of image noise. The noise in low photon-count MV data is likely to cause streak artifacts in the kV/MV reconstructions, thus we used the TV to measure the piecewise roughness. The TV values were measured within the soft-tissue and bone regions. The results are summarized in Table I. The PWLS method resulted in the lowest soft-tissue SD and TV values as compared to the other two kV/MV reconstruction methods. The images reconstructed using the higher MV dose data exhibit improved SD and TV metrics, because the streak artifacts caused by the noise in the MV data may strongly affect the measured values.

In general, both the DE patch and PWLS methods perform better than the linear patch method. Figure 8 shows the error images of the MAR, DE patch, and PWLS methods. Both the DE Patch and PWLS methods reconstruct images with less error than the MAR method. The images using the PWLS method have more uniform soft tissue (less error) than the images using the DE patch method. In the hip

Fig. 7. Quantitative evaluations of ROIs for various reconstruction methods using low and high dose MV data.

case, the PWLS method also has more accurate CT numbers of the bones near the metal implant. There are more streaks around the metal objects in the PWLS images. Because the PWLS method uses a prior image (DE patch or MAR image) to generate the fraction map and the attenuation-conversion matrix, the estimated dual-energy sinograms produced using matrix $\mathbf{M}$ in Eq. (16) cannot perfectly match both the kV and MV data at the same time. The nonsmooth transitions between the kV and selective MV data cause the streak artifacts

TABLE I. Standard deviations and total variations of the reconstructed images. For the kV/MV reconstruction methods, the SD and TV values were measured using the reconstructed images using low and high dose MV data, respectively.

Phantom	Method	Soft-tissue SD (HU)	Region-of-interest SD (HU)	Total variation ($\times 10^5$)
Dental	MAR	24.3	8.4	3.40
	Linear patch	34.1/32.9	16.7/12.2	4.14/3.83
	DE patch	26.5/26.5	12.6/10.3	3.77/3.53
	PWLS	27.3/24.2	11.1/9.5	3.67/3.47
Hip	MAR	33.0	23.3	1.67
	Linear patch	48.1/41.2	40.1/32.0	2.30/2.11
	DE patch	42.9/32.5	29.7/27.5	2.39/2.02
	PWLS	41.6/27.2	21.3/20.2	2.41/2.06

near the metal. The learning step is also influenced by the inaccurate conversion of the linear attenuation coefficients. The PWLS method may provide lower-noise reconstructions than the DE patch method when thinner slices/higher resolution reconstructions or lower dose acquisitions are desired. Note that the metal objects appear larger in the PWLS images than in other reconstructions. An adaptive roughness penalty function design may help to reduce the blurring of boundaries of high-intensity objects.⁶³

Figure 9 presents the SSIM measurements of the two soft-tissue ROIs imaged using the PWLS method for various values of β and γ in Eq. (22). When γ is small, the roughness penalty function is much stronger than the MV data, so the SSIM values are small because the lost information is not restored by the MV data. As γ increases, the SSIM values of both ROIs increase. The improvement in ROI1 is more obvious than that in ROI2 because ROI1 is closer to the metal. When γ becomes very large, the SSIM values begin to decrease due to the amplification of noise in the MV data, which degrades the image quality. The value of β also affects the SSIM results. If β is too small, the noise level is high; if β is too large, the images are blurred. The soft-tissue SD and TV values exhibit similar behavior for different values of γ and β . Because SD and TV measure the entire image, the value of γ does not have a strong influence on these results. The strategy for selecting values of β and γ is as follows: First, select γ based on Eq. (21), and then adjust an appropriate value of β based on the kV data.^{53,63} Note that the reconstruction with $\gamma = 30$ has higher

FIG. 8. The error images of the MAR, DE Patch, and DE PWLS methods for the dental and hip phantoms using the high MV dose data. The images are displayed at the window level $[-500, 500]$ HU. In the dental case, there are errors in the teeth and bones that are caused by the partial-volume effect.

SSIM measurements than $\gamma = 10$ for the hip phantom, because the large γ value encourages streaks along the MV rays, which are in the same direction as the soft-tissue patterns. Thus, the streaks caused by the noise in the MV data may increase the SSIM measurement. The γ value determined using Eq. (21) produces a similar soft-tissue point spread function as single energy PWLS, but does not maximize the SSIM values.

The Geant4 Monte Carlo dose simulation demonstrated that the kV and MV dose to the patient is relatively low due to the collimation onto the fillings or implants. Figure 10 shows MV dose-distribution maps for the two phantoms in the high-MV-dose case. For the dental phantom, the MV beams provide a mean dose of 6 mGy, with a maximum of 51 mGy in the soft tissue and a maximum of 67 mGy in the teeth. For the hip phantom, the MV beams provide a mean dose of 9 mGy, with a maximum of 53 mGy in the soft tissue and a maximum of 64 mGy in the bone. A significant fraction of the photons is attenuated by the metal. Because of the beam collimation,

the tissue and bone around the metal receive the highest dose. In addition, additional dose builds up in the tissue immediately adjacent to the metal because of electron generation in the metal. Therefore, the dose estimates are highly spatially variable and depend on the exact shapes and positions of the fillings/implants. As compared to the kV scan, the selective MV acquisition did not add very much dose to the patient. The dose applied by the MV scan is mainly distributed around the metal objects, while the dose from the kV scan has larger values in the periphery of the phantom. Of course, the additional dose from the MV scan is also negligible compared to the dose applied during radiation therapy.

5. DISCUSSION

In our simulation, we used the Varian TrueBeam system geometry on which the kV and MV beams have the same SAD, SDD, and center of rotation. The geometries of

FIG. 9. SSIM measurements of the two soft-tissue ROIs in the dental (left) and hip (right) phantoms obtained using the PWLS method for different values of β and γ in Eq. (22). The high-dose data were used in this simulation.

FIG. 10. The kV and MV dose-distribution maps generated using Geant4 Monte Carlo simulations.

the kV and MV beams are almost identical. However, identical acquisition geometry is not required for the proposed methods to work since data can be appropriately interpolated or rebinned. However, additional interpolation will increase the complexity of the data acquisition and reconstruction when using the linear patch or DE patch methods. The PWLS method is more flexible than the sinogram patch methods, because the forward and backward projectors can be different for the kV and MV geometries.

Modern radiotherapy relies heavily on computerized inverse treatment planning, which uses diagnostic CT images as input data to delineate anatomy and compute optimized intensity modulated radiotherapy (IMRT) and arc-modulated plans. These plans are designed to deliver a high radiation dose to the lesion and minimization of radiation dose outside the treatment region.^{33,64} Radiotherapy planning requires the accurate reconstruction of attenuation coefficients of each patient for dose calculation,^{31,32} which is difficult if the structures of interest lie in the same imaging plane as metal objects inside the patient's body. The combined kV and selective MV data may reconstruct on-board cone-beam CT images with fewer metal streak artifacts that allow better patient position verification. With good image registration between on-board cone-beam CT and clinical CT images, the MV data can be further combined with clinical CT data, which may provide more accurate CT number for dose calculation and treatment planning. Combining the MV data with prior clinical CT data is more complicated than with the on-board kV data. The patient motion and positioning-related artifacts are more difficult to correct in the reconstruction. However, if we can register the kV/MV cone-beam CT and clinical CT images perfectly, we can do reprojection of kV/MV images under the clinical CT geometry to generate some meaningful values to fill in the clinical CT data, which are usually of better quality than the cone-beam CT data.⁶⁵

6. CONCLUSION

We have shown that it is possible to improve the image quality of radiotherapy-verification CTs for patients with metal implants or fillings by supplementing the missing kV projection data with selectively acquired MV data that do not suffer from photon starvation. Three image-reconstruction methods, including two noniterative methods and one iterative method, for combining kV and MV projection data from the two on-board images of a radiotherapy device are presented in this work. Numerical simulations showed that DE sinogram patch FBP and a modified kV/MV PWLS method can successfully suppress metal streak artifacts and can restore the information lost due to photon starvation in the kV projections. Such combined kV/MV images improve the delineation of structures of interest in CT images for patients with metal implants or fillings.

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¹J. F. Barrett and N. Keat, "Artifacts in CT: Recognition and avoidance," *RadioGraphics* **24**, 1679–1691 (2004).

²M. Bal and L. Spies, "Metal artifact reduction in CT using tissue-class modeling and adaptive prefiltering," *Med. Phys.* **33**, 2852–2859 (2006).

³W. A. Kalender, R. Hebel, and J. Ebersberger, "Reduction of CT artifacts caused by metallic implants," *Radiology* **164**, 576–577 (1987).

⁴C. Lemmens, D. Faul, and J. Nuyts, "Suppression of metal artifacts in CT using a reconstruction procedure that combines MAP and projection completion," *IEEE Trans. Med. Imaging* **28**, 250–260 (2009).

⁵E. Meyer, R. Raupach, M. Lell, B. Schmidt, and M. Kachelrieß, "Normalized metal artifact reduction (NMAR) in computed tomography," *Med. Phys.* **37**, 5482–5493 (2010).

⁶G. Glover and N. Pelc, "An algorithm for the reduction of metal clip artifacts in CT reconstructions," *Med. Phys.* **8**, 799–807 (1981).

⁷J. Rinkel, W. P. Dillon, T. Funk, R. Gould, and S. Prevrhal, "Computed tomographic metal artifact reduction for the detection and quantitation of small features near large metallic implants: A comparison of published methods," *J. Comput. Assist. Tomogr.* **32**, 621–629 (2008).

⁸S. Zhao, D. D. Robertson, G. Wang, B. Whiting, and K. T. Bae, "X-ray CT metal artifact reduction using wavelets: An application for imaging total hip prostheses," *IEEE Trans. Med. Imaging* **19**, 1238–1247 (2000).

⁹Y. Zhang, L. Zhang, X. R. Zhu, A. K. Lee, M. Chambers, and L. Dong, "Reducing metal artifacts in cone-beam CT images by preprocessing projection data," *Int. J. Radiat. Oncol., Biol., Phys.* **67**, 924–932 (2007).

¹⁰D. Prell, Y. Kyriakou, M. Beister, and W. A. Kalender, "A novel forward projection-based metal artifact reduction method for flat-detector computed tomography," *Phys. Med. Biol.* **54**, 6575–6591 (2009).

¹¹E. Meyer, R. Raupach, M. Lell, B. Schmidt, and M. Kachelrieß, "Frequency split metal artifact reduction (FSMAR) in computed tomography," *Med. Phys.* **39**, 1904–1916 (2012).

¹²Q. Wang, L. Li, L. Zhang, Z. Chen, and K. Kang, "A novel metal artifact reducing method for cone-beam CT based on three approximately orthogonal projections," *Phys. Med. Biol.* **58**, 1–17 (2013).

¹³G. Wang, D. L. Snyder, J. A. O'Sullivan, and M. W. Vannier, "Iterative deblurring for CT metal artifact reduction," *IEEE Trans. Med. Imaging* **15**, 657–664 (1996).

¹⁴G. Wang, T. Frei, and M. W. Vannier, "Fast iterative algorithm for metal artifact reduction in X-ray CT," *Acad. Radiol.* **7**, 607–614 (2000).

- ¹⁵X. Duan, L. Zhang, Y. Xiao, J. Cheng, Z. Chen, and Y. Xing, "Metal artifact reduction in CT images by sinogram TV inpainting," in *IEEE Nuclear Science Symposium Conference Record* (2008), pp. 4175–4177.
- ¹⁶J. M. Verburg and J. Seco, "CT metal artifact reduction method correcting for beam hardening and missing projections," *Phys. Med. Biol.* **57**, 2803–2818 (2012).
- ¹⁷T. Koehler, B. Brendel, and K. M. Brown, "A new method for metal artifact reduction in CT," in *Second International Conference on Image Formation in X-ray Computed Tomography* (2012), pp. 29–32.
- ¹⁸A. Mehranian, M. R. Ay, A. Rahmim, and H. Zaidi, "X-ray CT metal artifact reduction using wavelet domain L_0 sparse regularization," *IEEE Trans. Med. Imaging* **32**, 1707–1722 (2013).
- ¹⁹B. De Man, J. Nuyts, P. Dupont, G. Marchal, and P. Suetens, "Reduction of metal streak artifacts in X-ray computed tomography using a transmission maximum a posteriori algorithm," *IEEE Trans. Nucl. Sci.* **47**, 977–981 (2000).
- ²⁰Q. Yang, M. Elter, I. Schasiepen, N. Maass, and J. Hornegger, "Fast iterative beam hardening correction based on frequency splitting in computed tomography," *Proc. SPIE Med. Imaging*, **8668**, 86682J (2013).
- ²¹F.-F. Yin, H. Guan, and W. Lu, "A technique for on-board CT reconstruction using both kilovoltage and megavoltage beam projections for 3D treatment verification," *Med. Phys.* **32**, 2819–2826 (2005).
- ²²F. A. Ghelmansarai, A. Bani-Hashemi, J. Pouliot, E. Calderon, P. Hernandez, M. Mitschke, M. Aubin, and K. Bucci, "Soft tissue visualization using a highly efficient megavoltage cone beam CT imaging system," *Proc. SPIE Med. Imaging*, **5745**, 159–170 (2005).
- ²³W. Luo, S. Yoo, Q. J. Wu, Z. Wang, and F.-F. Yin, "Analysis of image quality for real-time target tracking using simultaneous kV-MV imaging," *Med. Phys.* **35**, 5501–5509 (2008).
- ²⁴R. D. Wiersma, W. Mao, and L. Xing, "Combined kV and MV imaging for real-time tracking of implanted fiducial markers," *Med. Phys.* **35**, 1191–1198 (2008).
- ²⁵M. R. Paudel, M. Mackenzie, B. G. Fallone, and S. Rathee, "Evaluation of metal artifacts in MVCT systems using a model based correction method," *Med. Phys.* **39**, 6297–6308 (2012).
- ²⁶D. A. Jaffray, J. H. Siewerdsen, J. W. Wong, and A. A. Martinez, "Flat-panel cone-beam computed tomography for image-guided radiation therapy," *Int. J. Radiat. Oncol., Biol., Phys.* **53**, 1337–1349 (2002).
- ²⁷D. Létourneau, A. A. Martinez, D. Lockman, D. Yan, C. Vargas, G. Ivaldi, and J. Wong, "Assessment of residual error for online cone-beam CT-guided treatment of prostate cancer patients," *Int. J. Radiat. Oncol., Biol., Phys.* **62**, 1239–1246 (2005).
- ²⁸M. Guckenberger, J. Meyer, D. Vordermark, K. Baier, J. Wilbert, and M. Flentje, "Magnitude and clinical relevance of translational and rotational patient setup errors: A cone-beam CT study," *Int. J. Radiat. Oncol., Biol., Phys.* **65**, 934–942 (2006).
- ²⁹C. Lütgendorf-Caucig, I. Fotina, M. Stock, R. Pötter, G. Goldner, and D. Georg, "Feasibility of CBCT-based target and normal structure delineation in prostate cancer radiotherapy: Multi-observer and image multi-modality study," *Radiother. Oncol.* **98**, 154–161 (2011).
- ³⁰G. Altortjai, I. Fotina, C. Lütgendorf-Caucig, M. Stock, R. Pötter, D. Georg, and K. Dieckmann, "Cone-beam CT-based delineation of stereotactic lung targets: The influence of image modality and target size on interobserver variability," *Int. J. Radiat. Oncol., Biol., Phys.* **82**, e265–e272 (2012).
- ³¹Y. Yang, E. Schreiber, T. Li, C. Wang, and L. Xing, "Evaluation of on-board kV cone beam CT (CBCT)-based dose calculation," *Phys. Med. Biol.* **52**, 685–705 (2007).
- ³²H. Guan and H. Dong, "Dose calculation accuracy using cone-beam CT (CBCT) for pelvic adaptive radiotherapy," *Phys. Med. Biol.* **54**, 6239–6250 (2009).
- ³³S. J. Gardner, M. T. Studenski, T. Giaddui, Y. Cui, J. Galvin, Y. Yu, and Y. Xiao, "Investigation into image quality and dose for different patient geometries with multiple cone-beam CT systems," *Med. Phys.* **41**, 031908 (11pp.) (2014).
- ³⁴A. de la Zerda, B. Armbruster, and L. Xing, "Formulating adaptive radiation therapy (ART) treatment planning into a closed-loop control framework," *Phys. Med. Biol.* **52**, 4137–4153 (2007).
- ³⁵T. Li, D. Thongphiew, X. Zhu, W. R. Lee, Z. Vujaskovic, F.-F. Yin, and Q. J. Wu, "Adaptive prostate IGRT combining online re-optimization and re-positioning: A feasibility study," *Phys. Med. Biol.* **56**, 1243–1258 (2011).
- ³⁶H. Li, B. Liu, and F.-F. Yin, "Generation of virtual monochromatic CBCT from dual kV/MV beam projections," *Med. Phys.* **40**, 121910 (9pp.) (2013).
- ³⁷J. E. Monk, J. R. Perks, D. Doughty, and P. N. Plowman, "Comparison of a micro-multileaf collimator with a 5-mm-leaf-width collimator for intracranial stereotactic radiotherapy," *Int. J. Radiat. Oncol., Biol., Phys.* **57**, 1443–1449 (2003).
- ³⁸O. Morin, A. Gillis, J. Chen, M. Aubin, M. K. Bucci, M. Roach, and J. Pouliot, "Megavoltage cone-beam CT: System description and clinical applications," *Med. Dosim.* **31**, 51–61 (2006).
- ³⁹O. Morin, A. Gillis, M. Descovich, J. Chen, M. Aubin, J.-F. Aubry, H. Chen, A. R. Gottschalk, P. Xia, and J. Pouliot, "Patient dose considerations for routine megavoltage cone-beam CT imaging," *Med. Phys.* **34**, 1819–1827 (2007).
- ⁴⁰T. Niu, M. Sun, J. Star-Lack, H. Gao, Q. Fan, and L. Zhu, "Shading correction for on-board cone-beam CT in radiation therapy using planning MDCT images," *Med. Phys.* **37**, 5395–5406 (2010).
- ⁴¹S. Leng, J. Zambelli, R. Tolakanahalli, B. Nett, P. Munro, J. Star-Lack, B. Paliwal, and G.-H. Chen, "Streaking artifacts reduction in four-dimensional cone-beam computed tomography," *Med. Phys.* **35**, 4649–4659 (2008).
- ⁴²E. J. Seppi, P. Munro, S. W. Johnsen, E. G. Shapiro, C. Tognina, D. Jones, J. M. Pavkovich, C. Webb, I. Molloy, L. D. Partain, and R. E. Colbeth, "Megavoltage cone-beam computed tomography using a high-efficiency image receptor," *Int. J. Radiat. Oncol., Biol., Phys.* **55**, 793–803 (2003).
- ⁴³A. Sawant, L. E. Antonuk, Y. El-Mohri, Q. Zhao, Y. Wang, Y. Li, H. Du, and L. Perna, "Segmented crystalline scintillators: Empirical and theoretical investigation of a high quantum efficiency EPID based on an initial engineering prototype CsI(Tl) detector," *Med. Phys.* **33**, 1053–1066 (2006).
- ⁴⁴Y. Wang, L. E. Antonuk, Q. Zhao, Y. El-Mohri, and L. Perna, "High-DQE EPIDs based on thick, segmented BGO and CsI:Tl scintillators: Performance evaluation at extremely low dose," *Med. Phys.* **36**, 5707–5718 (2009).
- ⁴⁵P. F. Kirvan, T. T. Monajemi, B. G. Fallone, and S. Rathee, "Performance characterization of a MVCT scanner using multislice thick, segmented cadmium tungstate-photodiode detectors," *Med. Phys.* **37**, 249–257 (2010).
- ⁴⁶G. M. Lasio, B. R. Whiting, and J. F. Williamson, "Statistical reconstruction for x-ray computed tomography using energy-integrating detectors," *Phys. Med. Biol.* **52**, 2247–2266 (2007).
- ⁴⁷J. Nuyts, B. De Man, J. A. Fessler, W. Zbijewski, and F. J. Beekman, "Modelling the physics in the iterative reconstruction for transmission computed tomography," *Phys. Med. Biol.* **58**, R63–R96 (2013).
- ⁴⁸B. De Man, J. Nuyts, P. Dupont, G. Marchal, and P. Suetens, "An iterative maximum-likelihood polychromatic algorithm for CT," *IEEE Trans. Med. Imaging* **20**, 999–1008 (2001).
- ⁴⁹J. A. Fessler, "Penalized weighted least-squares image reconstruction for positron emission tomography," *IEEE Trans. Med. Imaging* **13**, 290–300 (1994).
- ⁵⁰P. Sukovic and N. H. Clinthorne, "Penalized weighted least-squares image reconstruction for dual energy X-ray transmission tomography," *IEEE Trans. Med. Imaging* **19**, 1075–1081 (2000).
- ⁵¹I. A. Elbakri and J. A. Fessler, "Statistical image reconstruction for polyenergetic X-ray computed tomography," *IEEE Trans. Med. Imaging* **21**, 89–99 (2002).
- ⁵²J. Wang, T. Li, H. Lu, and Z. Liang, "Penalized weighted least-squares approach to sinogram noise reduction and image reconstruction for low-dose X-ray computed tomography," *IEEE Trans. Med. Imaging* **25**, 1272–1283 (2006).
- ⁵³A. Wang, S. Schafer, and J. Stayman, "Soft-tissue imaging in low-dose, C-arm cone-beam CT using statistical image reconstruction," *Proc. SPIE Med. Imaging*, **8668**, 86681F (2013).
- ⁵⁴I. A. Elbakri and J. A. Fessler, "Segmentation-free statistical image reconstruction for polyenergetic x-ray computed tomography with experimental validation," *Phys. Med. Biol.* **48**, 2453–2477 (2003).
- ⁵⁵J. A. Fessler and W. L. Rogers, "Spatial resolution properties of penalized-likelihood image reconstruction: Space-invariant tomographs," *IEEE Trans. Image Process.* **5**, 1346–1358 (1996).
- ⁵⁶D. Kim, D. Pal, J.-B. Thibault, and J. A. Fessler, "Accelerating ordered subsets image reconstruction for X-ray CT using spatially nonuniform optimization transfer," *IEEE Trans. Med. Imaging* **32**, 1965–1978 (2013).
- ⁵⁷D. Kim, S. Ramani, and J. A. Fessler, "Accelerating X-ray CT ordered subsets image reconstruction with Nesterov's first-order methods," in *12th International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine* (2013), pp. 22–25.
- ⁵⁸J. H. Hubbell and S. M. Seltzer, "Tables of X-ray mass attenuation coefficients and mass energy-absorption coefficients from 1 keV to 20 MeV for Elements Z = 1 to 92 and 48 additional substances of dosimetric interest" (National Institute of Standards and Technology, Gaithersburg, MD, 2004), Technical Report No. 5632, <http://physics.nist.gov/xaamdi>.

- ⁵⁹L. Feldkamp, L. Davis, and J. Kress, "Practical cone-beam algorithm," *J. Opt. Soc. Am. A* **1**, 612–619 (1984).
- ⁶⁰B. De Man and S. Basu, "Distance-driven projection and backprojection in three dimensions," *Phys. Med. Biol.* **49**, 2463–2475 (2004).
- ⁶¹J. Allison, K. Amako, J. Apostolakis, H. Araujo, P. Arce Dubois, M. Asai, G. Barrand, R. Capra, S. Chauvie, R. Chytracek, G. Cirrone, G. Cooperman, G. Cosmo, G. Cuttone, G. Daquino, M. Donszelmann, M. Dressel, G. Folger, F. Foppiano, J. Generowicz, V. Grichine, S. Guatelli, P. Gumplinger, A. Heikkinen, I. Hrivnacova, A. Howard, S. Incerti, V. Ivanchenko, T. Johnson, F. Jones, T. Koi, R. Kokoulin, M. Kossov, H. Kurashige, V. Lara, S. Larsson, F. Lei, O. Link, F. Longo, M. Maire, A. Mantero, B. Mascialino, I. McLaren, P. Mendez Lorenzo, K. Minamimoto, K. Murakami, P. Nieminen, L. Pandola, S. Parlati, L. Peralta, J. Perl, A. Pfeiffer, M. Pia, A. Ribon, P. Rodrigues, G. Russo, S. Sadilov, G. Santin, T. Sasaki, D. Smith, N. Starkov, S. Tanaka, E. Tcherniaev, B. Tome, A. Trindade, P. Truscott, L. Urban, M. Verderi, A. Walkden, J. Wellisch, D. Williams, D. Wright, and H. Yoshida, "Geant4 developments and applications," *IEEE Trans. Nucl. Sci.* **53**, 270–278 (2006).
- ⁶²Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Trans. Image Process.* **13**, 600–612 (2004).
- ⁶³J. Wang, T. Li, and L. Xing, "Iterative image reconstruction for CBCT using edge-preserving prior," *Med. Phys.* **36**, 252–260 (2009).
- ⁶⁴Q. J. Wu, D. Thongphiew, Z. Wang, B. Mathayomchan, V. Chankong, S. Yoo, W. R. Lee, and F.-F. Yin, "On-line re-optimization of prostate IMRT plans for adaptive radiation therapy," *Phys. Med. Biol.* **53**, 673–691 (2008).
- ⁶⁵T. Heußner, M. Brehm, L. Ritschl, S. Sawall, and M. Kachelrieß, "Prior-based artifact correction (PBAC) in computed tomography," *Med. Phys.* **41**, 021906 (16pp.) (2014).