Model Image-Based Metal Artifact Reduction for Computed Tomography

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Abstract

Metal implants often produce severe artifacts in the reconstructed computed tomography (CT) images, causing information and image detail loss and making the CT images diagnostically unusable. In order to eliminate the metal artifacts and enhance the diagnostic value of the reconstructed CT images, a post-processing metal artifact reduction algorithm, based on a tissue-class model segmented by thresholding and *k*-means clustering with spatial information, is proposed. The image inpainting technique is incorporated into the algorithm to improve the segmentation accuracy for CT images severely corrupted by metal artifacts. A study of a water phantom and of two sets of clinical CT images was performed to test the algorithm performance. The proposed method effectively eliminates typical metal artifacts, restores the average CT numbers of different tissues to the proper levels, and preserves the edge and contrast information, thus allowing the accurate reconstruction of the tissue attenuation map. The quality of the artifact-corrected CT images allows them to be subsequently used in other clinical applications, such as three-dimensional rendering, dose estimation for radiotherapy, attenuation correction for PET and SPECT, etc. The algorithm does not rely on the use of the raw sinogram and so is not limited by the proprietary format restrictions.

Keywords Computed tomography · Metal artifact reduction · Virtual sinogram · Image inpainting

Introduction

Metal artifacts, originating from the presence of metal implants (e.g., dental fillings, metal prostheses, surgical clips, etc.) in the scan field of X-ray computed tomography (CT), appear as dark and bright streaks in CT images. Severe metal artifacts may cause a loss of edge, contrast, and detail information, corrupting the images sometimes to the point of making them diagnostically unusable. The problem of metal artifact reduction (MAR) [1–3] is important for numerous clinical applications of CT, such as the treatment planning of radiation therapy and the quantification of positron emission tomography (PET) data in PET/CT scanning.

Most of the MAR algorithms proposed in the last three decades can be classified into three groups: (i) the sinogram completion methods, (ii) the iterative methods, and (iii) the hybrid methods. Methods in (i) treat the projections through the metal as missing data, and the completion typically

involves three steps, such as isolating the metal object from the CT image in order to determine which regions of the original sinogram are affected [4–8], employing various interpolation techniques to replace the affected data [9, 10], and reconstructing the final image from the corrected sinogram. However, these methods may lead to generation of severe secondary artifacts, and more elaborated methods of sinogram correction have been proposed [5, 7, 11, 12], with their success varied case by case [2].

Methods in (ii) generally provide superior performance in image reconstruction compared to those in (i), with the maximum likelihood [13, 14] and algebraic reconstruction [1, 15] techniques being the two most common methods. In iterative reconstruction techniques, the physics behind the artifacts is modeled [16, 17], so that the algorithms find, e.g., the maximum likelihood estimates of the parameters in a statistical model of the physical data. Iterative methods are computationally expensive and therefore have limited use in clinical practice. Methods in (iii) comprise several different approaches [2, 18, 19] intended to overcome the shortcomings of the aforementioned methods; however, they all rely on the availability of the raw projection data. If those are not available, as is often the case, the artifact correction can be performed either in the image domain [20–22] or in the virtual sinogram (VS) space [10, 12].

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Fig. 1 Incorporating the spatial information for image refining. A 3×3 mask is applied to a pixel i , and it is reassigned to such a subset C_j that has the maximum number of members within the mask

Other hybrid methods usually require considerable user input and have a long processing time. For a more detailed discussion on the available MAR methods and their advantages and shortcoming, as well as recent progress in the field, the interested reader is referred to the reviews [2, 23–25].

In this work, we present a further development of our post-processing hybrid MAR algorithm [26] aimed at building a numerically efficient and adaptable computational MAR method by utilizing an easy-to-use VS concept. Our approach has several advantages compared to the sinogram correction methods that require direct access to the raw sinogram data. Firstly, the raw sinogram data are often stored in an encrypted manufacturer-dependent proprietary format and are simply unavailable for analysis. Secondly, since even the local changes in the sinogram affect the whole image, secondary artifacts can potentially appear in any part of the image, and the impact of the changes on artifact appearance cannot be quantified a priori. In our method, local changes are applied only to specific areas of the model image, which eliminates the appearance of secondary artifacts. As such, our method is not prone to secondary artifact appearance compared to the sinogram correction methods. Additionally, because all corrections in our method are performed in real space, the amount of data to process is greatly reduced, which makes the

Fig. 2 Image inpainting of the tissue-class model. Ω is the metal-contaminated region; Φ is the source region. The squares indicate the flat region and the boundary

computation faster. Our method methodologically belongs to the class of prior-image-based reconstruction algorithms, where information from the prior images is used to reconstruct the corrupted areas of the original CT image. Various approaches to image segmentation, prior generation, and data interpolation proposed by different authors have proved general reliability and validity of the prior-image-based approaches [27, 28].

A key step of our approach for reducing the metal artifacts and restoring the image details is the creation of an artifact-free tissue-class model image by k -means clustering [29] with spatial information [30] and the image inpainting technique [31]. The VSs of the model image and the original CT image are then combined in such a way that the projection data corrupted by the metal are completed by the model image projection data. If the model image is sufficiently close to the true data, we assume that the corrupted data can be completed by the forward projection of the model image in a superior way than by using the sinogram interpolation methods. A phantom study and two clinical studies are presented to further prove the validity of the proposed method.

Materials and Methods

The proposed model image-based MAR algorithm (Mi-MAR) comprises three essential steps as follows. (A) Image segmentation, the contaminated CT image is segmented into different tissue classes followed by incorporating the spatial information to reduce the effect of inaccurate CT numbers due to metal artifacts and noise. (B) Image inpainting, extensive strong artifacts, such as dark bands, induced by the hip prostheses, can severely corrupt the tissue-class model. The image inpainting technique is applied to re-fill the damaged regions and achieve an accurate model image. (C) Projection completion, the original image and the tissue-class model image are forward projected to create the sinograms, which are then combined using a weighting function to suppress the artifact-contaminated projection data.

Image Segmentation with Spatial Information

The regions of metal and air in the contaminated image are differentiated using the threshold values of 1500 and -900 Hounsfield units (HU), and these two regions are temporarily removed from the original image. The residual pixels are further classified into several material clusters, such as fat, loose soft tissue, dense soft tissue, mineral bone, and cortical bone, by k -means clustering [29]. The quality of the clustering is defined by a sum of squared errors (SSE),

$$SSE = \sum_{j=1}^k \sum_{i \in C_j} \|x_i - v_j\|^2, i = 1, \dots, n; j = 1, \dots, k. \quad (1)$$

$$v_j = \frac{\sum_{i=1}^n m(C_j|x_i)x_i}{\sum_{i=1}^n m(C_j|x_i)}, j = 1, \dots, k. \quad (2)$$

where x_i is the i th pixel value, v_j is the centroid of the j th cluster, $\|.\|$ is the Euclidean distance, and k and n are the number of the clusters and the pixels, respectively. A membership function $m(|x|)$ was used to calculate the centroids of the disjoint subsets C_j . Starting with an initial random guess for each cluster center, the SSE was converged by repeatedly updating the v_j in Eq. 1. This iterative process was continued until the difference in SSE between two successive iterations was less than a threshold value of 0.02. The pixel values within each cluster were then substituted by the centroid value of the corresponding cluster, thus forming an initial model image.

The adjacent pixels in a CT image are highly correlated, i.e., the adjacent pixels possess nearly the same feature data and

usually belong to the same cluster, which allows us to incorporate the spatial relationship between the neighboring pixels into the process of refining the initial model image, as schematically shown in Fig. 1: a pixel i is reassigned to a subset C_j according to the number of members in a 3×3 mask centered at pixel i [30]. Through the use of spatial information, the tissue-class model is improved by eliminating the influence of inaccurate classification due to metal artifacts and noise.

Image Inpainting

When metal artifacts severely obstruct the original image, parts of the tissue-class model can be seriously corrupted. The basic idea of inpainting is to fill in the target (corrupted) region Ω by the available information provided from the source (intact) region Φ , as schematically shown in Fig. 2. To recover the missing or damaged portions of the image,

Fig. 3 A flowchart of the Mi-MAR algorithm. First, the metal and air pixels are segmented out from the uncorrected image. The k -means clustering with spatial information and image inpainting are then applied to the segmented image to remove the image noise, streak lines, and large artifact-contaminated regions, and then, the metal and air pixels are added back to build the artifact-free model image. The difference image, model image, and original image are then forward projected to the sinogram space, and the corrected sinogram is obtained by summing the original sinogram and the model sinogram with the exponential weighting function. Finally, the corrected image is reconstructed from the corrected sinogram by the filtered back-projection algorithm with Shepp-Logan filter

Fig. 4 CT images of the ACR water phantom. Reference CT image with the locations of five ROIs and intensity profile line (a), uncorrected image with a 3-mm tungsten rod inserted in the center (b), model image built by k -means clustering with spatial information and modified inpainting (c), and final corrected image (d)

we used a modified version of the inpainting algorithm of Bertalmio et al. [31], as follows.

Fig. 5 Intensity profiles for the reference, uncorrected, and corrected CT images of the phantom. The profiles were calculated along the line shown in Fig. 4a. Data near the phantom center in the uncorrected image exhibit large dispersion due to the artifacts caused by the metal rod

A general form of the inpainting algorithm can be written as

$$I^{n+1}(i, j) = I^n(i, j) + \Delta t I_t^n(i, j), \forall (i, j) \in \Omega \quad (3)$$

where n is the iteration number, $I(i, j)$ is the gray intensity of the pixel (i, j) , Δt is the improvement rate (typically 0.1), $I_t^n(i, j)$ is the update kernel, and the inpainting runs only inside Ω .

Since the image to be fixed in our study is the clustered image, which has only k gray values without any local variance (Fig. 2), the update kernel used in ref. [31] can be simplified, and the filling-in process at the flat or boundary regions can be represented by the following kernel:

$$I_t^n(i, j) = \begin{cases} L_{nr}^n(i, j), & \text{if } \nabla I^n(i, j) = 0. \\ L^n(i, j) \cdot \frac{\vec{N}^n(i, j, n)}{|\vec{N}^n(i, j, n)|}, & \text{otherwise.} \end{cases} \quad (4)$$

In the flat region, $\nabla I^n(i, j) = 0$, and the pixel $I^{n+1}(i, j)$ is directly filled with the information from the nearest neighbor pixel $L_{nr}^n(i, j)$. In the boundary region, the pixel $I^{n+1}(i, j)$ is filled with the information from the neighbor pixel $L^n(i, j)$ taken along the isophote $\vec{N}^n(i, j, n)$. The isophote can be defined as a 90° rotation of the gradient vector $\nabla I^n(i, j)$, i.e., $\vec{N}^n(i, j, n) = \nabla^\perp I^n(i, j)$, so that the isophote direction is

Fig. 6 Mean CT values and SD values in five selected ROIs

$$\frac{\vec{N}^n(i, j, n)}{|\vec{N}^n(i, j, n)|} = \frac{\begin{pmatrix} -I_y^n(i, j), I_x^n(i, j) \end{pmatrix}}{\sqrt{(I_x^n(i, j))^2 + (I_y^n(i, j))^2}} \quad (5)$$

Fig. 7 Images of the pelvis with a double hip prosthesis at different stages of reconstruction. Uncorrected CT image (a), image with the metal and air pixels removed (b), image segmented by *k*-means clustering algorithm (c), tissue-class model image (d). Positions of the ROIs (squares 1–4) and the intensity profile direction (dashed line) are also shown in a

where subscripts denote the derivatives of gray intensity in the horizontal and vertical directions. The information being propagated is the Laplacian of I^n : $L^n(i, j) = I_{xx}^n(i, j) + I_{yy}^n(i, j)$. The inpainting procedure converges when two consecutive iterations produce the same result: $I^{n+1}(i, j) = I^n(i, j)$.

Since the obscured parts of the tissue-class model are usually those that have low CT numbers, we limited the gray values to be restored in Ω to lie in the range of -300 to 300 HU. The impact of metal artifacts on the bone tissue is less obvious and more difficult to quantify. In order to avoid the loss of bone detail, the pixels corresponding to the bone tissues in the inpainted image were replaced by the corresponding pixels from the original image. Finally, the artifact-free tissue-class model image was completed by adding back both the metal and the air pixels to the inpainted image.

Projection Completion

A difference image I_d is obtained by subtracting the model image I_m from the original image I_o . The forward projections of these images (sinograms P_d , P_m , and P_o , respectively) define the completed sinogram P_c [26]:

$$P_c(i, j) = w(i, j) \times P_o(i, j) + [1 - w(i, j)] \times P_m(i, j) \quad (6)$$

$$w(i, j) = e^{-\mu P_d^*(i, j)} \quad (7)$$

Fig. 8 CT images reconstructed from the model image obtained with (a) and without (b) inpainting

where $w(i, j)$ is a pixel-based weighting function, P_d^* is the normalized residual sinogram, and μ is a weighting parameter that controls the steepness of the exponential function and the degree of detail preservation in the image. If a pixel in the original image differs from the corresponding pixel in the tissue-class model image, P_c will be dominated by P_m and the metal artifacts will be suppressed. If the two pixels have close values, P_c will be dominated by P_o and the structure details of the original image will be maintained. The value of μ defines how much information the model and the original images contribute to the reconstructed image: the larger the μ , the larger the contribution of the model image and the smaller the portion of the original image, which results in a smoother corrected image. In contrast, for a smaller μ (and smaller contribution of the model image,) the corrected image better preserves fine details of the original image. Further considerations on the choice of μ are presented in the “Discussion” section. Finally, the corrected image I_c is reconstructed from P_c by means of the standard FBP algorithm with Shepp-Logan

filter [32]. Figure 3 shows a summarized flowchart of the Mi-MAR algorithm.

Case Studies

Phantom Study

An ACR flangeless water phantom (ACR PET/FL/P, Data Spectrum Corporation, Chapel Hill, NC) with a 3-mm tungsten rod inserted in the center was used for CT acquisition. Seven cylinders with diameters of 8, 12, 16, and 25 mm were placed in the phantom. One cylinder was made of Teflon to mimic the bone material, and the others were filled with 1 to 3% contrast medium. CT images of the phantom were acquired on a GE LightSpeed VCT scanner (GE, Buckinghamshire, UK) with scanning parameters of 140 kVp, 80 mAs, and 3.75 mm slice thickness. Reference CT images of the phantom without the tungsten rod were acquired with the same scanning parameters. The output images were transformed into a 512×512 matrix with 16-bit grayscale depth. The mean CT numbers and the standard deviations (SD) calculated in several regions of interest (ROIs, each one containing approximately 100 pixels) were compared.

Clinical Study

Two sets of clinical CT images were retrieved from the PACS server for testing our algorithm: a CT scan of the pelvis with a double hip prosthesis and a CT scan of the oral cavity with dental implants. The CT scans were acquired at 120 kVp and 5 mm (oral cavity) and 7 mm (pelvis) reconstructed slice thicknesses. The window level of 0 HU and the window width of 500 HU were selected for image display in all figures that follow. A surface-rendering reconstruction of the scans before and after applying the Mi-MAR algorithm was additionally performed.

Fig. 9 Intensity profiles for the uncorrected, model, and corrected CT images of the pelvis. The profiles were calculated along the dashed line shown in Fig. 7a. CT values, strongly suppressed in the original image due to the dark band, have been restored to the soft tissue level

Table 1 Mean CT values and SD values in four ROIs shown in Fig. 7a

ROI numbers	1	2	3	4
Original image	-263.1 ± 35.5	-198.2 ± 36.5	110.3 ± 23.6	-113.1 ± 31.3
Corrected image	-90.3 ± 6.7	-6.9 ± 3.6	58.6 ± 22.8	-78.9 ± 11.8

Results

Phantom Study

The reference image of the ACR water phantom is shown in Fig. 4a. CT values in the water background and in the cylinder areas are distributed rather uniformly. After the tungsten rod had been inserted, several bright and dark streaks corrupted the image, Fig. 4b, and caused severe non-uniformity in the distribution of CT values as revealed in Figs. 5 and 6. Figure 4c shows the tissue-class model image of the phantom built by k -means clustering algorithm ($k=4$) with spatial information. Each region of the phantom was correctly classified into its respective group. Figure 4d displays the corrected image obtained with the weighting parameter $\mu = 10$ (in this and the following case studies, the values of μ were chosen such as to produce the best perceived visual quality of the reconstructed images.) The bright and dark streaks were basically removed and the image uniformity was largely improved. Figure 5 shows the intensity profiles of the reference, uncorrected, and corrected images taken along the line shown in Fig. 4a. The large dispersion of CT values in the region close to the tungsten rod, observed in the original image, was suppressed after the correction, and the CT values in the corrected image became almost the same as those in the reference image.

Figure 6 shows the mean CT values and the SD values calculated in the ROIs indicated in Fig. 4a. In the corrected image, the mean CT values in all ROIs are much closer to the reference values, in particular those of water. The lower mean

CT values in the cylinders with contrast medium (ROI 4 and 5) can be explained by the particular choice of the number of clusters ($k=4$) during the image segmentation stage, which resulted in that all clusters corresponding to the cylinders in the tissue-class model image were filled in with the same gray value, whereas in the original image these clusters had slightly different gray levels due to different concentrations of the contrast medium. This resulted in the difference between sinograms P_o and P_m , so that corresponding areas in the completed sinogram P_c were dominated by the pixels of the model image, according to Eq. 6.

Patient Studies

Images of the pelvis with a double hip prosthesis produced at different stages of the reconstruction process are shown in Fig. 7. A double hip prosthesis presents a more difficult case than the one shown in Fig. 4: the metal objects are larger, leading to a larger corrupted area, and the presence of two metal objects results in a nonsymmetric distortion. In the original CT image, a dark band induced by the prostheses corrupts a large region of soft tissue between the hip replacements, and thin alternating streaks, similar to those in Fig. 4b, propagate through the surrounding tissues and cause additional non-uniformity in CT values. The model image obtained before the inpainting step (Fig. 7c) remains corrupted—the artifact is too strong and cannot be fully removed only by means of the k -means clustering with spatial information. The inpainting step provides the necessary improvement—the missing parts have been recovered, the dark band and alternating streaks

Fig. 10 Three-dimensional surface rendering reconstruction of the hips from the uncorrected (a) and corrected (b) CT images. Artificial bone tissue (indicated by the arrows in a), which covers the prostheses, has been removed after the correction and the contours of the prostheses have been recovered

Fig. 11 Volume rendering reconstruction of the pelvis from the uncorrected (a) and corrected (b) CT images. The corrupted region between the hip prostheses has been recovered after the correction

have been successfully removed, and the tissues under the dark band have been correctly restored and classified (Fig. 7d). Final images obtained with and without the inpainting step are compared in Fig. 8 for $\mu = 5$. The image produced without inpainting, which is equivalent to the image that can be obtained using the method developed in our previous work [26], is obviously flawed. The necessary improvement came

with the inpainting step: the continuity of the surrounding tissues has greatly improved, the dark band and minor streaks have been removed, and the degraded CT numbers in the dark-band region in the original image have been restored to the soft-tissue range. Figure 9 shows the intensity profiles for the uncorrected and corrected images taken along the line indicated in Fig. 7a. Mi-MAR protocol restored the CT numbers of soft tissues, which had been scattered in the range of -500 to 0 HU in the original image, to the correct level.

Table 1 lists the mean CT values and SD values calculated in the ROIs indicated in Fig. 7a. The SD values reflect different contributions made by the model image to the final picture, according to Eq. 6. The ROIs 1 and 2, for example, are located in a severely corrupted area subjected to inpainting, where one could have expected that the contribution from the model image would dominate and lead to a more uniform background, resulting in a corresponding decrease in the SD values. This is the case for ROI 1; for ROI 2, however, the SD value increases to about 52% of the mean. The reason is that for a given value of μ , contributions from the model image and the original image have similar weights; therefore, their superposition shifts the mean and increases the dispersion. Similar arguments work for the other ROIs.

Figure 10 shows a three-dimensional surface rendering reconstruction produced from the uncorrected and corrected CT images. In the reconstruction produced from the uncorrected images, the bright regions that surround the prostheses give rise to artificial bone tissue, which covers the prostheses and obscures their contours. After the correction, the artificial bone tissue has been removed, the contours of the prostheses have been recovered, and the surface of the prostheses has significantly smoothened.

Fig. 12 Images of the oral cavity with multiple artificial teeth at different stages of reconstruction. Uncorrected CT image (a), image with the metal and air pixels removed (b), image segmented by k -means clustering algorithm (c), tissue-class model image (d), reconstructed CT image (e). The position of the intensity profile direction (dashed line) is shown in a

Fig. 13 Intensity profiles for the uncorrected and corrected CT images of the oral cavity. The profiles were calculated along the line shown in Fig. 12a. CT values in the vicinity of the artificial teeth, originally in the air and bone range due to the metal artifact, have been restored to the correct level

Figure 11 shows a volume rendering reconstruction of the pelvis obtained from the uncorrected and corrected CT images. The dark band, which causes degradation of CT values in the original image, gives rise to a wide reconstruction defect located between the hip prostheses. After the Mi-MAR correction, the defected area has been recovered and the visibility of soft tissues and their contours has greatly improved.

A set of images of the oral cavity with multiple artificial teeth produced at different stages of the reconstruction process is shown in Fig. 12. A dark band in the direction of artificial teeth and an extensive bright region severely corrupt the soft tissue part of the image and complicate the segmentation process. Numerous sharp, thin, alternating streaks propagate through the whole image and cause additional non-uniformity in CT values.

Fig. 14 Three-dimensional surface rendering reconstruction of the skull. The skull was reconstructed from the uncorrected (a) and corrected (b) CT images shown in Fig. 12. Artificial bone structure in the right dentition, indicated by an arrow in a, has been removed after the correction

The CT numbers reach -600 and 800 HU in the dark and bright regions, respectively. Figure 12c shows the image obtained by k -means clustering with spatial information. The area in the vicinity of the artificial teeth is misclassified. After the inpainting step (Fig. 12d), the intensive metal lines were removed and the dark and bright regions were correctly classified. Figure 12e shows the corrected image obtained for $\mu = 5$. The metal lines and the dark and bright areas were mostly removed and the CT numbers fell within the range of soft tissues, so that the uniformity of the whole image largely improved. The structure details of bones and soft tissues were also well preserved after the correction.

Figure 13 shows the intensity profiles of the original and corrected images taken along the line shown in Fig. 12a. In the profile of the original image, the maximum and minimum CT numbers of the soft tissue are about 800 and -350 HU; the CT numbers in the corrected image lie in the soft tissue range. Figure 14 presents a three-dimensional surface rendering reconstruction from the series of the uncorrected and corrected CT images shown in Fig. 12. In the reconstruction from the uncorrected images, an artificial bone structure appeared in the right dentition. After the correction, the artificial bone structure disappeared, the contours of the right dentition were correctly reconstructed, and no secondary artifacts appeared.

Discussion

Building the correct tissue-class model image is a crucial step in our artifact reduction procedure. The quality of the model image, produced by the Mi-MAR algorithm, depends on two parameters: the number of different tissue clusters in the image segmentation block (Eqs. 1 and 2) and the mask size in the spatial information filtering block (Fig. 1). The number of clusters, k , is an input parameter in our model, and its value can be chosen as a number of distinct peaks in the gray value histogram of the original image. An inadequate cluster number can result in an initial model image with lack of details or even loss of

important features that would result in the ill-corrected final image. As for the mask size, we found that a 3×3 mask produced the best smoothing in our case studies—with an increase in the mask size, the structure details in the model image became smeared and the image resolution decreased. However, the choice of a proper mask size should consider the strength of the noise and severity of the artifacts, and for highly contaminated images, a larger mask size can result in better smoothing.

Among other factors that can affect the artifact reduction is the choice of threshold values in the image segmentation block [2]. Our particular choice of those (−900 and 1500 HU) was based on the following consideration. The lower threshold value was chosen to be well below soft tissue intensities, while the higher threshold value was well above the soft tissue and bone intensity ranges in our chosen CT images. As long as this condition is satisfied, the choice of particular numbers is not expected to affect the final picture in any significant way. And indeed, as we had checked, slight variation of the threshold values did not affect the results.

Weighting parameter μ (Eqs. 6 and 7) defines how much of the original image is present in the final image. For a small μ , more structure details are preserved; at the same time, artifacts are not completely removed from the final image. For a large μ , image quality saturates and does not change with a further increase in μ ; artifacts are removed from the final image, but, since the final image is dominated by the model image sinogram, some structure details can be lost. The choice of optimal μ requires considering the strength of metal artifacts and varies case by case. The necessity of revealing all little details important for successful diagnostics may also affect what the optimal μ would be in every given case. However, the problem of the initial choice of μ in general can be addressed as follows. Even in an artifact-free image, there can be a small difference between the corresponding parts of the original image and model image sinograms, since the CT numbers of each cluster in the model image are defined only by the corresponding centroid value (Eqs. 1 and 2). Thus, the initial μ value can be chosen according to the desired contribution of the model image sinogram to the completed sinogram based on the values of the residual sinogram estimated in artifact-unaffected or little-affected points. For example, a 10% difference ($P_d^* = 0.1$ in Eq. 7) would result in an equal contribution of the model image and the original image sinograms to the completed sinogram for $\mu = 7$ ($w = 0.5$ in Eq. 6). We have found that the values of μ in the range 5–10 provide the best quality of the reconstructed images.

Another crucial step in building the model image is the inpainting block in Fig. 3. The method developed in our

previous paper [26] successfully deals with fine streak artifacts produced by small isolated metal bodies, a typical example of which is shown in Fig. 4b. Larger or multiple metal objects in the scan field can lead to strong nonsymmetric artifacts, exemplified by the dark band in Fig. 7a, which can only be reduced by other blocks of the Mi-MAR algorithm. As we have shown, in the images with large corrupted areas, image inpainting can effectively fill in the corrupted areas and correctly classify the missing tissues.

For the images shown, the inpainting routine written in Matlab took 12.3 and 3.7 s on a i5-6400, 2.7-GHz CPU to process the oral and hip CT images, respectively. For large or complex artifacts, the inpainting block can potentially become computationally expensive. However, the intrinsic parallelism of the inpainting and k -means clustering problems allows for a significant speedup with the graphics processing unit (GPU) implementation of our code, up to the point that all the simulation can be performed on the fly, virtually as fast as dragging the slider with the mouse. This, together with developing an algorithm of automatic delineation of the inpainting regions, will be the next step of our work. This should greatly facilitate the practical use of the Mi-MAR algorithm.

Conclusions

Although MAR methods with direct access to the raw sinograms are capable of obtaining accurate results, a major impediment to their practical implementation is that the raw CT data are usually stored in an encrypted manufacturer-dependent proprietary format. The objective of this study was to utilize the virtual sinogram method as an alternative and to improve its performance by using an advanced sinogram completion method based on the tissue-class model image. The developed Mi-MAR algorithm is computationally effective and simple in implementation, and requires only three fitting parameters, which can be easily tuned to provide the best possible performance. As we have shown by different case studies, the proposed MAR algorithm effectively removes metal artifacts, restores the corrupted CT numbers of soft tissues to the correct level, and preserves the edge and contrast information, allowing one to accurately reconstruct the tissue attenuation map and improve the diagnostic value of the metal-artifact-contaminated CT images. The quality of the corrected CT images obtained by the Mi-MAR algorithm allows them to be further used in various clinical applications, such as three-dimensional image rendering, dose estimation for radiotherapy, attenuation correction for PET and SPECT, etc.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

- Boas FE, Fleischmann D: Evaluation of two iterative techniques for reducing metal artifacts in computed tomography. *Radiology* 259(3):894–902, 2011. <https://doi.org/10.1148/radiol.11101782>
- Mouton A, Megherbi N, Van Slambrouck K, Nuyts J, Breckon TP: An experimental survey of metal artefact reduction in computed tomography. *J Xray Sci Technol* 21(2):193–226, 2013. <https://doi.org/10.3233/XST-130372>
- De Man B, Nuyts J, Dupont P, Marchal G, Suetens P: Metal streak artifacts in x-ray computed tomography: a simulation study. *IEEE Trans Nucl Sci* 46(3):691–696, 1999. <https://doi.org/10.1109/23.775600>
- Karimi S, Cosman P, Wald C, Martz H: Segmentation of artifacts and anatomy in CT metal artifact reduction. *Med Phys* 39(10):5857–5868, 2012. <https://doi.org/10.1118/1.4749931>
- Yu H, Zeng K, Bharkhada DK, Wang G, Madsen MT, Saba O, Policeni B, Howard MA, Smoker WRK: A segmentation-based method for metal artifact reduction. *Acad Radiol* 14(4):495–504, 2007. <https://doi.org/10.1016/j.acra.2006.12.015>
- Comaniciu D, Meer P: Mean shift: a robust approach toward feature space analysis. *IEEE Trans Pattern Anal Mach Intell* 24(5):603–619, 2002. <https://doi.org/10.1109/34.1000236>
- Li Y, Bao X, Yin X, Chen Y, Luo L, Chen W: Metal artifact reduction in CT based on adaptive steering filter and nonlocal sinogram inpainting. In: *Proceedings of the 3rd International Conference on Biomedical Engineering and Informatics*, 2010, pp. 380–383. <https://doi.org/10.1109/BMEI.2010.5639535>
- Bal M, Spies L: Metal artifact reduction in CT using tissue-class modeling and adaptive prefiltering. *Med Phys* 33(8):2852–2859, 2006. <https://doi.org/10.1118/1.2218062>
- Klotz E, Kalender WA, Sokiransky R, Felsenberg D: Algorithms for the reduction of CT artifacts caused by metallic implants. *Proc SPIE* 1234:642–650, 1990. <https://doi.org/10.1117/12.18985>
- Abdoli M, Ay MR, Ahmadian A, Zaidi H: A virtual sinogram method to reduce dental metallic implant artefacts in computed tomography-based attenuation correction for PET. *Nucl Med Commun* 31(1):22–31, 2010. <https://doi.org/10.1097/MNM.0b013e32832fa241>
- Meyer E, Raupach R, Lell M, Schmidt B, Kachelriess M: Normalized metal artifact reduction (NMAR) in computed tomography. *Med Phys* 37(10):5482–5493, 2010. <https://doi.org/10.1118/1.3484090>
- Abdoli M, Ay MR, Ahmadian A, Dierckx RAJO, Zaidi H: Reduction of dental filling metallic artifacts in CT-based attenuation correction of PET data using weighted virtual sinograms optimized by a genetic algorithm. *Med Phys* 37(12):6166–6177, 2010. <https://doi.org/10.1118/1.3511507>
- Dempster AP, Laird NM, Rubin DB: Maximum likelihood from incomplete data via the EM algorithm. *J R Stat Soc Ser B Methodol* 39(1):1–38, 1977 <http://www.jstor.org/stable/2984875>
- Shepp LA, Vardi Y: Maximum likelihood reconstruction for emission tomography. *IEEE Trans Med Imaging* 1(2):113–122, 1982. <https://doi.org/10.1109/TMI.1982.4307558>
- Gordon R, Bender R, Herman GT: Algebraic reconstruction techniques (ART) for three-dimensional electron microscopy and x-ray photography. *J Theor Biol* 29(3):471–481, 1970. [https://doi.org/10.1016/0022-5193\(70\)90109-8](https://doi.org/10.1016/0022-5193(70)90109-8)
- Nuyts J, De Man B, Dupont P, Defrise M, Suetens P, Mortelmans L: Iterative reconstruction for helical CT: a simulation study. *Phys Med Biol* 43(4):729–737, 1998. <https://doi.org/10.1088/0031-9155/43/4/003>
- Elbakri IA, Fessler JA: Segmentation-free statistical image reconstruction for polyenergetic x-ray computed tomography with experimental validation. *Phys Med Biol* 48(15):2453–2477, 2003. <https://doi.org/10.1088/0031-9155/48/15/314>
- Prell D, Kyriakou Y, Beister M, Kalender WA: A novel forward projection-based metal artifact reduction method for flat-detector computed tomography. *Phys Med Biol* 54(21):6575–6591, 2009. <https://doi.org/10.1088/0031-9155/54/21/009>
- Lemmens C, Faul D, Nuyts J: Suppression of metal artifacts in CT using a reconstruction procedure that combines MAP and projection completion. *IEEE Trans Med Imaging* 28(2):250–260, 2009. <https://doi.org/10.1109/TMI.2008.929103>
- Naranjo V, Llorens R, Alcaniz M, Verdu-Monedero R, Larrey-Ruiz J, Morales-Sanchez J: A new 3D paradigm for metal artifact reduction in dental CT. In: *Proceedings of the 18th IEEE International Conference on Image Processing*, 2011, pp. 461–464. <https://doi.org/10.1109/ICIP.2011.6116551>
- Naranjo V, Llorens R, Paniagua P, Alcaniz M, Albalat S: A new approach in metal artifact reduction for CT 3D reconstruction. In: *Mira J, Ferrandez JM, Alvarez Sanchez JR, Paz F, Toledo J, editors: Bioinspired Applications in Artificial and Natural Computation*, Berlin: Springer-Verlag, pp. 11–19, 2009. https://doi.org/10.1007/978-3-642-02267-8_2
- Serifovic-Trbalic A, Trbalic A: Image-based metal artifact reduction in CT images. In: *Proceedings of the 39th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 2016, pp. 442–446. <https://doi.org/10.1109/MIPRO.2016.7522184>
- Katsura M, Sato J, Akahane M, Kunitatsu A, Abe O: Current and novel techniques for metal artifact reduction at CT: practical guide for radiologists. *RadioGraphics* 38(2):450–461, 2017. <https://doi.org/10.1148/rq.2018170102>
- Gjesteby L, De Man B, Jin Y, Paganetti H, Verburg J, Giantsoudi D, Wang G: Metal artifact reduction in CT: where are we after four decades? *IEEE Access* 4:5826–5849, 2016. <https://doi.org/10.1109/ACCESS.2016.2608621>
- Giantsoudi D, De Man B, Verburg J, Trofimov A, Jin Y, Wang G, Gjesteby L, Paganetti H: Metal artifacts in computed tomography for radiation therapy planning: dosimetric effects and impact of metal artifact reduction. *Phys Med Biol* 62(8):R49–R80, 2017. <https://doi.org/10.1088/1361-6560/aa5293>
- Wu J, Shih CT, Chang SJ, Huang TC, Sun JY, Wu TH: Metal artifact reduction algorithm based on model images and spatial information. *Nucl Inst Methods Phys Res A* 652(1):602–605, 2011. <https://doi.org/10.1016/j.nima.2011.01.041>
- Hegazy MAA, Cho MH, Lee SY: A metal artifact reduction method for a dental CT based on adaptive local thresholding and prior image generation. *Biomed Eng Online* 15(119), 2016. <https://doi.org/10.1186/s12938-016-0240-8>
- Nam H, Baek J: A metal artifact reduction algorithm in CT using multiple prior images by recursive active contour segmentation. *PLoS One* 12(6):e0179022, 2017. <https://doi.org/10.1371/journal.pone.0179022>
- Duda RO, Hart PE: *Pattern classification and scene analysis*, 1st ed. New York: John Wiley & Sons, 1973

30. Chuang KS, Tzeng HL, Chen S, Wu J, Chen TJ: Fuzzy c-means clustering with spatial information for image segmentation. *Comput Med Imaging Graph* 30(1):9–15, 2006. <https://doi.org/10.1016/j.compmedimag.2005.10.001>
31. Bertalmio M, Sapiro G, Caselles V, Ballester C: Image inpainting. In: *Proceedings of the 27th Annual Conference on Computer Graphics and Interactive Techniques*, 2000, pp. 417–424. <https://doi.org/10.1145/344779.344972>
32. Lyra M, Ploussi A: Filtering in SPECT image reconstruction. *Int J Biomed Imaging* 2011:693795, 2011. <https://doi.org/10.1155/2011/693795>

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