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Metal Artifact Reduction From Reformatted Projections for Hip Prostheses in Multislice Helical Computed Tomography:

Techniques and Initial Clinical Results

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Abstract

Purpose—Hip prosthesis is one of the most common types of metal implants and can cause significant artifacts in computed tomography (CT) examinations. The purpose of this work was to develop a projection-based method for reducing metal artifacts caused by hip prostheses in multislice helical CT.

Method and Materials—The proposed method is based on a novel concept, reformatted projection, which is formed by combining the projection data at the same view angle over the full longitudinal scan range. Detection and segmentation of the metal were performed on each reformatted projection image. Two dimensional interpolation based on Delaunay triangulation was used to fill voids left after removal of the metal in the reformatted projection. The corrected data were then reconstructed using a commercially available algorithm. The main advantage of this method is that both the detection of the metal objects and the interpolations are performed on complete reformatted projections with the entire metal region present, which is particularly useful for long hip prostheses. Twenty clinical abdominal/pelvis exams with hip prostheses were corrected and clinically evaluated.

Results—The overall image quality and the conspicuity in some critical organs were significantly improved compared with the uncorrected images: overall quality ($P = 0.0024$); bladder base ($P = 0.0027$), and rectum ($P = 0.0078$). The average noise level in the bladder base was reduced from 86.7 HU to 36.2 HU. In 17 of 20 cases, the radiologists preferred either coronal (13) or axial (4) views of the corrected images.

Conclusions—A novel method for reducing metal artifact in multislice helical CT was developed. Initial clinical results showed that the proposed method can effectively reduce the artifacts caused by metal implants for the cases of unilateral and bilateral hip prosthesis.

Keywords

computed tomography (CT); multi-slice helical CT; metal artifact reduction

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Metal implants are not uncommon in patients receiving computed tomography (CT) examinations and can produce severe image artifacts in the form of streaks and dark shadows. These artifacts often affect anatomic structures throughout the entire image, significantly degrading the diagnostic value of the image. The metal artifacts arise from the data inconsistency between the ideal model assumed by the reconstruction algorithm and the actual CT signal that has been affected by the metal. X-rays are highly attenuated by the metal, which amplifies many of the factors that lead to data inconsistency, including noise, beam hardening, scattering, and nonlinear partial volume effects.^{1,2}

Increasing the scan technique (mAs) may reduce the noise in the projection data but does not correct for other data inconsistencies caused by metal implants. Therefore, the streaking and shading artifacts cannot be avoided even though a higher radiation dose is delivered to the patient. The use of higher tube potential (kVp) may improve the image quality because of the greater penetrating capability of the high-energy photons and less beam-hardening effect. Although an increased kVp is common in scan protocols for patients with metal implants, the improvement in image quality compared with the standard kVp is rather minimal. Because scattered radiation is one of the contributing factors to metal artifacts, limiting the detector collimation will also be helpful to reduce the metal artifacts. However, the significant artifacts caused by highly attenuated metals remain in the reconstructed images.

Adaptive filtering has been used to reduce the streaking artifacts caused by photon starvation.^{3,4} In these methods, smoothing is adaptively applied on the projection data based on the noise level. In the presence of highly attenuating metal, however, these methods cannot correct for the severe data inconsistencies caused by metal.

Iterative methods^{1,5-7} and wavelet methods⁸ have also been employed to reduce the metal artifacts. Some of the iterative methods incorporated a practical data model that characterized the noise, beam-hardening, and x-ray scatter, and demonstrated significant potential and flexibility for reducing metal artifacts. However, the clinical application of iterative methods is largely limited by the computational power of current CT scanners.

Another strategy used to reduce metal artifacts is to detect the data contaminated by metal and replace them with estimates of the corrected values. Various methods have been developed with this strategy,⁹⁻²⁰ including both projection-based and image-based metal segmentation methods.

Despite these many efforts, metal artifacts remain a significant problem in current CT clinical practice. To the best of our knowledge, only one of the methods was temporarily implemented in a commercial scanner (Siemens SOMATOM from 1987 to 1990¹⁰). Currently, there is no method clinically available that can provide a fully automatic and universal solution to this problem. Each method has its advantages and disadvantages for each type of metal implant and CT data acquisition configuration in terms of flexibility, computational efficiency, and image quality in the corrected image. To address this complicated problem, we propose to tailor the development of metal artifact reduction methods to specific types of metal implants and data acquisition geometries.

In this work, we developed a novel approach specifically for reducing artifacts caused by metal hip prostheses in multislice helical CT. A typical abdomen and pelvis helical examination involving a hip prosthesis has a large amount of projection data, typically 40,000 to 70,000 projection views for a scan performed on a 64-slice CT scanner. To provide computational efficiency, we employed a method that directly segments the metal in the projection data and replaces it with data interpolated from neighboring pixels. Considering the long shape of most hip prostheses, we proposed a novel concept,

reformatted projection, to improve the operation of metal segmentation and interpolation. The main advantage of this method is that the entire metal object is present on each of the reformatted projection images, which makes detection of the metal in the projection data and the subsequent data interpolation straightforward and more consistent throughout the full helical dataset. In addition, performing the segmentation and interpolation on reformatted projection image can be readily implemented on clinical CT scanners.

METHODS

Reformatted Projection

The projection data from a multislice helical scan can be expressed as $P(\alpha, v, \lambda)$, where α, v denote the detector bin index along row and longitudinal directions, respectively, λ denotes the angular index of the x-ray source and can be related to the longitudinal coordinate of the

x-ray source as $z = \frac{pD}{2\pi} \lambda$, where p denotes the helical pitch factor and D the x-ray beam collimation. Figure 1A shows 3 separate projections from a helical scan with 32 detector rows. The first projection was without any metal content. The second and the third projections contain portions of the metal region. It can be seen that without the whole metal present on each projection, a metal segmentation algorithm analyzing each of these projections separately would have trouble consistently identifying and segmenting the metal regions. This is explained further in Discussion.

A reformatted projection is created by combining all the frames at each view angle every 2π over the full longitudinal scan range, which can be expressed as: $\{P(\alpha, v, \varphi + 2n\pi) \mid n = 1, 2, \dots, N\}$, where $\varphi \in [0, 2\pi)$ and N is the total number of rotations for the whole scan range. Figure 1B shows one example of a reformatted projection at angle φ generated from a helical scan with 32 detector rows. The presence and the location of the metal object are obvious in reformatted projection.

Pitch Correction

After a reformatted projection is created, the appearance of the metal might be disjointed because of the use of a pitch factor. When $p < 1$, there will be an overlap for each 2 adjacent projection frames on the reformatted projection. When $p > 1$, there will be a gap between 2 adjacent projection frames. The pitch correction is only applied to the data when $p \neq 1$. With the exception of the first and last frames in the reformatted projection, there are 2 overlap regions on each projection frame, which can be expressed as: $v \in [0, (1-p)D]$ and $v \in [pD, D]$. Figure 2A shows a reformatted projection image created from a CT scan with a pitch of 0.8. Because all the overlapping projections are used in the reformatted projection, the metal projection seems discontinuous at many locations.

To obtain an undistorted metal projection on the reformatted projection, we neglect the data of the second overlap range of each projection frame on the reformatted projection to generate a reformatted projection without overlapping regions. Figure 2B displays the projection after this correction. The metal detection and interpolation across the neglected part of each projection frame is directly mapped from the results in the previous frame.

Metal Projection Detection and Segmentation

Using the pitch corrected data, metal detection and segmentation were performed using the following steps (as shown in Fig. 3A–D).

Edge Detection

A Sobel operator was used to detect the edges in each reformatted projection. This is basically a gradient operator that calculates the gradient of the projection image at each pixel. The initial threshold was automatically estimated. Because of the complexity of medical implants, a fully automatic and robust thresholding method is extremely difficult to achieve. Therefore, the threshold was adjusted manually by using a convenient user interface, which will be described later. The magnitude of the edge gradient at each pixel is compared with this threshold and any edge less than the threshold is ignored. For simplicity, the gradient operation was approximated by convolving a directional 3×3 kernel with the projection image. After the operation, a binary image containing the edges and background was created.

Morphologic Dilation and Hole Filling

A morphologic dilation operation was used to connect the edge pixels. A disk shape with a radius of 5 pixels was used for the dilation. For larger regions with sharp edges, the inside area often contained voids after the dilation operation, therefore, a hole filling operation is followed to generate regions without interior holes.

Metal Region Detection

The images resulting from step 2 usually contained several regions that were potential metal regions. Because metals usually have a high attenuation level, the intensity on the projection is often much larger than regions without metal. Therefore, the brightest regions detected from steps 1 and 2 are often well correlated with the metal regions.

Two Dimensional Interpolation

A 2D interpolation was performed after the segmentation of the metal projection. To improve the computational efficiency, the interpolation was done only on a small region that includes the metal projection region plus a margin of 10 pixels. The 2D interpolation was based on a Delaunay triangulation of the data that uses Qhull.²¹ The use of the Delaunay triangulation was to accommodate the irregular shapes of the metal implants in reformatted projections (Matlab 7.5.0, Math Works Inc.).

Figure 4 shows the reformatted projection and 2 intensity profiles before and after the interpolation. The metal region has been removed and replaced with projection values interpolated from the neighboring pixels.

Image Reconstruction

After the removal of the projection data associated with metal objects on the reformatted projection, the corrected data were written back to the original format (before pitch correction) and loaded onto the scanner for image reconstruction.

Monitoring the Metal Detection

The key to the success of this algorithm is the accurate detection of metal projection at all view angles. To increase the stability of the algorithm, a user interface was created to provide the user with feedback regarding the metal detection process as the edge detection threshold that was estimated by the algorithm is adjusted. The user can review several frames over 360° to verify the metal detection accuracy. If the detection is not accurate for a certain reformatted projection, the user can easily and quickly adjust the threshold value specifically for that projection. The user has the ability to adjust as many projections as necessary.

Clinical Evaluation With Patient Data

The described method was evaluated using clinical cases acquired on a 64-slice CT scanner (Sensation 64, Siemens Medical Solutions, Forchheim, Germany). Twenty patients undergoing clinically indicated abdominal/pelvic CT exams, 15 with a single hip prosthesis and 5 with bilateral hip prostheses, were enrolled in this retrospective study. The scan parameters were as follows: 120 kVp, detector collimation 32×0.6 mm with double z sampling, quality reference mAs 240. The helical pitch and rotation time varied dependent on patient size and examination type. The projection data were downloaded from the scanner and processed with the developed method. After processing, the raw data were loaded back onto the scanner and reconstructed with standard algorithms used in routine clinical practice. Two radiologists evaluated all the cases. For each case, 4 sets of images, including original axial and coronal images and corrected axial and coronal images, were displayed side by side. The radiologists were allowed to browse through each image series and zoom in and out. They ranked the overall image quality and visual conspicuity of the bladder base, prostate, seminal vesicles/vagina, and rectum using a 5-point score: 0 = totally obscured, no structures identifiable; 1 = marked artifacts, questionable recognition; 2 = faint anatomic recognition; 3 = anatomic recognition with low confidence; 4 = anatomic recognition with medium confidence; and 5 = anatomic recognition with high confidence in a potential diagnosis. The preferred dataset (original axial or coronal, corrected axial or coronal) was also indicated. The images were evaluated together by the 2 radiologists, and the final ranking was obtained by consensus. The noise level at the bladder base was measured. A Wilcoxon signed rank test was performed to analyze the quality ranking and to determine significant differences between the original images and corrected images. A *P* value of less than 0.05 was considered to indicate a statistically significant difference.

RESULTS

The data reformatting, metal segmentation, and interpolation for each case (40,000–70,000 projection views, each projection view using a 672×32 matrix) required approximately 50 to 90 minutes using a 2.66 MHz PC and Matlab software program. User interaction took approximately 4 to 5 minutes. All cases (*n* = 20) were successfully processed with the described algorithm.

The overall image quality and the visual conspicuity in some critical organs were significantly improved compared with the uncorrected images: overall quality (3.2 vs. 2.4, *P* = 0.0024); bladder base (3.3 vs. 2.3, *P* = 0.0027), rectum (3.5 vs. 2.9, *P* = 0.0078). The improvement in visualization of the prostate and seminal vesicles/ vagina were not statistically significant (3.4 vs. 2.8, *P* = 0.062). The average noise level in the bladder base was reduced from 86.7 HU to 36.2 HU. In 17 of 20 cases, the radiologists preferred either coronal¹³ or axial⁴ views of the corrected images. In the 3 cases where the radiologists preferred the original images over the corrected images, the implants were not very dense metal and did not cause significant streaking artifacts.

Two correction examples are given in Figures 5 and 6. Figure 5 shows the results from a contrast-enhanced CT urogram examination in which the patient had a dense metal implant in the right hip. As can be seen, the prominent streaking artifacts have been nearly eliminated and the structures obscured by the metal are visualized more clearly. It should be noted that some residue artifacts still exist and some minor new artifacts were introduced by the correction algorithm (eg, Fig. 5B, left hip region), which was caused by nonideal metal segmentation and interpolation.

Figure 6 compares axial and coronal images from an abdominal aortic angiographic CT study before and after correction. A bilateral metal hip implant was present and generated

very prominent dark bands and streaking artifacts. There was a clinically significant finding in the image—an approximately 3.8×3.3 cm pseudoaneurysm arising from the left common femoral artery—that was largely obscured by the metal artifact, potentially reducing detection accuracy by a radiologist. Although the pseudoaneurysm is visible in the original images, it could be easily overlooked given the distraction of the extensive metallic artifacts and the tendency to overlook small details in these artifact areas. The pseudoaneurysm is more obvious and stands out more clearly on the corrected images.

DISCUSSION

Among various metal artifact reduction methods, the strategy involving the detection of the projection data contaminated by the metal implants and the replacement of these data with estimated correction values have been very popular.^{9–20} The metal detection and segmentation can occur either in image space or projection space. For image-based methods, the metal region is segmented in the reconstructed images and reprojected to localize the projection data that have been contaminated by the metal. After the metal region in projection data are identified, it is replaced with corrected data before the image is reconstructed.^{10,11,14–16,19} The advantage of this approach is that once the metal region is accurately segmented in the reconstructed images, the projection data contaminated by the metal can be consistently determined among all projection views by reprojecting the segmented metal image. The weakness of this strategy is that the reconstructed images usually contain severe artifacts, making accurate metal segmentation very difficult. Another weakness is that the reprojection of the metal image requires the additional step of translating from image space to projection space, which is computationally expensive for large clinical datasets and sometimes not possible because of the lack of availability of sufficient information regarding the complicated data acquisition geometry, such as that of the flying focal spot.

The projection-based metal segmentation method does not require the reprojection of the metal or the full image to the projection space. This type of method usually involves the direct segmentation of the metal in the projection data and the replacement of the metal-contaminated data with values interpolated from neighboring data.^{2,17,18,20} The metal segmentation in the projection data can be based on a sinusoidal model in the sinogram for small circularly shaped metal and fan-beam configurations.^{2,20} In circular cone-beam CT geometry, the track of the metal projection can also be calculated based on the known data acquisition geometry.¹⁷

Yet, despite many efforts during the past years, metal artifacts remain a significant problem in CT clinical practice, where multi-slice helical scan is the most dominant data acquisition mode. The novelty of the proposed method is that it uses the multislice helical data to create 2D reformatted projection images for the entire scan range. The main advantage of this approach is that the metal detection, segmentation, and interpolation can be performed on each reformatted projection, where the whole metal object, if there are any, always shows up. This advantage is explained as follows.

First, without using the reformatted projections, the segmentation method has to deal with 40,000 to 70,000 projection frames separately, each of which consists of a very small matrix (672×32 for a Sensation 64 scanner). Therefore, large metal implants are distributed as many small fragments among different projection frames. For each projection frame, to automatically segment the metal, the algorithm has to make a decision on the existence of metal, the number and the shape of any metal, and the threshold for segmentation, which is very challenging because of the complexity of metal implants. A simple example illustrating the difficulty of metal detection and segmentation based on a single projection frame is

displayed in Figure 7. It can be seen that, without the knowledge of the full metal shape, it is difficult for the algorithm to automatically choose an appropriate threshold for segmentation. For a metal implant with a cavity inside, it is difficult to differentiate the inside and the outside parts of the metal based only on a small matrix. In contrast, with the reformatted projection, the projection data along each view angle are combined together, all of the metal objects in the scan range show up in every reformatted projection. Therefore, the metal shape, number of objects, and other characteristics can be easily recognized from a single reformatted projection, which makes the metal detection much easier and more accurate than methods that perform metal detection on each single projection frame.

Second, because the matrix size of each projection frame is small, especially along the longitudinal direction (only 32 pixels for a Sensation 64 scanner), the 2D interpolation after the metal segmentation conducted on the small matrix is not as accurate and consistent as that conducted on a reformatted projection, where the full metal region and neighboring pixels are available for 2D interpolation.

Third, considering the complexity of the metal implants and clinical situations, user monitoring and occasional manual interaction is still necessary to guarantee the stability of the metal segmentation. Because of the huge number of projection frames, it is almost impossible for users to monitor the segmentation if it is performed separately on each projection frame. With reformatted projections, because the metal is easily recognizable and the number of reformatted projections is relatively small (only dependent on the number of projections per gantry rotation), user monitoring becomes practical, which makes the algorithm much more robust.

For the cases presented here, the image quality has been dramatically improved despite some residual artifacts. The residual artifacts are due to several factors. First, the significant influence of the metal on the scattered radiation and beam hardening characteristics are also present in the neighboring projection data, and these effects are propagated to the entire image during the image reconstruction. Therefore, limiting the correction solely to the projections of the metal was not sufficient. Second, the interpolation used to fill the metal region may introduce secondary artifacts because the interpolated values are not necessarily consistent with other projection data. Finally, inconsistencies in the metal segmentation and interpolation could exist among different projection views, because most of these operations were performed independently for each reformatted projection.

Further investigation is anticipated to improve the performance of the proposed method. One potential improvement is to incorporate prior information about the metal shape, size, and number to improve the data consistency of the metal segmentation and interpolation among different reformatted projections. This is based on the observation that for the contiguous reformatted projections, the metal projection on the data does not change dramatically. Therefore, as long as the metal projection on the first reformatted projection can be accurately determined, such information can be transferred to each of the subsequent reformatted projection and used as a starting point for the segmentation and processing.

CONCLUSIONS

A novel method for metal artifact reduction in multislice helical CT was developed that uses reformatted projections created from the multislice helical projection data. Twenty clinical abdominal/pelvis exams with dense hip prosthesis were corrected and clinically evaluated. The results demonstrated that the proposed method can significantly reduce the artifacts caused by dense metal implants for the cases of uni- and bilateral hip prosthesis, providing statistically significant improvements in overall image quality.

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FIGURE 1.

Illustration of projection data in a multislice helical scan: 3 separate projections (A) and a reformatted projection created from multislice helical projection data (B).

FIGURE 2.

A reformatted projection from the original raw data before pitch correction (A) and after pitch correction (B).

FIGURE 3. Metal projection detection and segmentation: edge detection (A), morphologic dilation (B), hole filling (C), and metal region detection (D).

FIGURE 4.

Two dimensional interpolation to remove the metal projection. Reformatted projection with a labeled metal region (A). Reformatted projection after 2D interpolation (B). Intensity profiles comparing 2 columns across the metal region on the reformatted projection before (dotted curves) and after (solid curves) the metal projection removal (C, D).

FIGURE 5.

Metal artifact reduction on a CT urogram examination: an axial image and a coronal image before correction (A, C), and after correction (B, D).

FIGURE 6.

Metal artifact reduction on an abdominal CTA examination with a bilateral hip prosthesis. An axial image and 2 coronal images before correction (A, C, E) and after correction (B, D, F). The arrows in images (C) and (D) point out a clinically significant finding in the image, an approximately 3.8×3.3 cm pseudoaneurysm arising from the left common femoral artery, is partially obscured by the metal artifacts but can be clearly seen on the corrected images.

FIGURE 7.

An example demonstrating the advantage of metal detection and segmentation based on reformatted projections. A, A reformatted projection. B, A zoomed-in display of a single projection frame with a matrix size of 672×32 . C, The metal segmentation based on this single projection frame. Notice that the metal was incorrectly segmented. Without the knowledge of the full metal shape, it is difficult for the algorithm to automatically choose an appropriate threshold for segmentation. It is also difficult to differentiate the inside and outside parts of the metal based on a small matrix. D, The segmentation based on the reformatted projection. The outside boundary of the metal is correctly recognized by the algorithm.