Efficient Metal Artifact Reduction Method Based on Improved Total Variation Regularization

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Abstract

Metal implants produce strong artifacts in reconstructed computed tomography images and thus severely reduce image quality. This study proposes a method for metal artifact reduction that combines modified compressed sensing reconstruction and the sinogram inpainting method. The procedure starts with total variation reconstruction to obtain an initial image. Then, the image is recovered using improved total-variation-based regularization. This process produces an artifact-free background image. The missing information in the original sinogram is complemented using the forward projection of the background image. Consequently, the transitions between the original sinogram and artificial sinogram are smoothed by re-matching the baseline. The algorithm is validated using simulations and phantom data. Results show that streaks are eliminated and shadows are significantly reduced.

Keywords: Metal artifact reduction, Compressed sensing, Total variation, Sinogram inpainting

1. Introduction

Metal artifacts in computed tomography (CT) images are typically caused by metallic implants such as hip prostheses, dental fillings, and surgical clips. These artifacts are usually due to noise, beam hardening, scattering, and partial volume, and their magnitude is often several hundred Hounsfield units (HUs). Metal artifacts in CT images appear as streaks and broad bright or dark bands, severely degrading image quality and drastically reducing the diagnostic value of images.

Algorithms developed to reduce metal artifacts can be classified into projection-interpolation-based methods [1-5], iterative reconstruction methods [6-9], or their combination [10-12]. Projection interpolation methods treat parts of the projections affected by metal (the so-called metal shadow) as unreliable. These metal shadow data are complemented by interpolation between neighboring reliable data. Iterative reconstruction methods model the main causes for metal artifacts, such as noise and beam hardening [13,14]. Although the image quality obtained from these methods is often better than that of projection-interpolation-based methods, the main drawback is their extremely high computational complexity. In particular, iterative methods have trouble dealing with data for a metal so dense that it stops almost all beams passing through it. Recently, some algorithms combining projection completion and iterative reconstruction have been proposed [10-12]. These methods create a model image using classification prior information and then forward-project the model image to fill the gaps of the metal shadow. The model image classifies the pixels into several kinds of tissue and diminishes the density contrast of soft tissues. The region close to the metal is often not well corrected and some residual shadow artifacts still remain.

The present study proposes a metal artifact reduction (MAR) method that combines total variation (TV)-based reconstruction techniques and sinogram inpainting. The TV reconstruction approach is based on compressed sensing for sparse signal recovery [15,16]. It has been demonstrated to be efficient for reconstruction from highly down-sampled data [17-19]. Although, the reconstruction results lack high-frequency details, the TV-based approach can drastically smooth streak artifacts while preserving the contrast of soft tissues. Here, the conventional TV method is improved to produce an artifact-free background image. The metal shadow data are restored from the forward projection of this background image. The transitions between the original sinogram and the forward projection sinogram are reconnected to provide a better visual effect [11,20]. Aggressive angular down-sampling is applied to data used to reconstruct the background image. This significantly reduces the computational cost and greatly accelerates the iterative process. The restored sinogram is then used to reconstruct the image using the filtered back projection (FBP) method [21,22]. Results show that the proposed method preserves high-frequency and low-contrast structures while removing streak and band metal artifacts.

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2. Methods

2.1 Overview of MAR procedure

The proposed MAR procedure is based on inpainting missing information into the corrupted sinogram using a metal excluded background image. The background image should preserve as much density distribution information as possible while removing metal artifacts so that reconstruction from the synthetic sinogram will not introduce any artificial structures. It is a challenge to reconstruct such a background image from a corrupted sinogram with good density resolution and artifact suppression. When metal shadow projections are excluded from the reconstruction (the so-called exterior problem in tomography), the problem is severely ill-posed [23]. Thus, some special constraints are needed to make the reconstruction converge to the expected solutions. Considering the observation that relatively low-frequency information of the background image is more meaningful to inpaint the sinogram and that high-frequency information will be compensated for in the FBP reconstruction with fully sampled data, the proposed method sacrifices high-frequency details and imposes the TV minimization constraint in reconstructing the background image from incomplete projections. Unlike previous works, which usually use tissue-class-based prior probability images [11,20], minimizing the image TV does not lose the soft tissue contrast while reducing artifacts.

However, as the reconstruction from incomplete data is sensitive to constraints and the iterative process, a procedure whose convergence to the designed solution is guaranteed was developed. The preliminary reconstruction is performed on the original sinogram with the adaptive-steepest-descent-projection-onto-convex-sets (ASD-POCS) algorithm [24,25]. Note that metal artifacts usually appear as a severe streak pattern over the space. Hence, if a sparsity constraint is imposed on the reconstruction volume, with the assumption that the image is piecewise constant, the streak artifacts are supposed to be suppressed to satisfy the sparsity constraint. However, the density distribution is not well restored in the initial reconstruction due to sinogram inconsistency. Hence, an additional iterative reconstruction is needed to improve the density resolution. The metal objects are adaptively segmented in the initial reconstruction. In the improved TV regularization, different TV norms are used for the areas near and far away from the metal objects. This strategy prevents over-smoothing for edge structures in the area close to metal. After the additional iterative process, the density distribution is restored and precise soft tissue contrast can be expressed in the background image.

Sinogram completion is the step in which metal shadows in the original sinogram are replaced by the corresponding segments of the forward projection of the background image. To optimally superimpose the artificial segments onto the original sinogram, a low-frequency residual offset between the original and artificial sinograms is modeled. Then, the values of the artificial projection are subtracted by the offset to smooth the transitions from the original to the artificial sinogram segments. With this precaution, discontinuities at joints are minimized. The final reconstruction using the synthetic sinogram is done with FBP algorithms with fully sampled projections. The metal objects identified in the initial reconstruction are superimposed on the corrected tomogram to indicate where metal was detected.

In summary, the proposed MAR method consists of the following major steps: 1) initial reconstruction using ASD-POCS from the original sinogram; 2) segmentation of metal objects using a threshold and production of a weighting image that is used in the subsequent TV-based restoration; 3) identification of metal shadow beams in the original sinogram using forward projection of metal segments; 4) improved TV-based restoration with incomplete sinogram to produce artifact-free background image; 5) modeling of residual offsets of the metal shadow between the original and the artificial sinograms and correction of the corresponding artificial projection to create a synthetic sinogram; 6) FBP reconstruction with completed synthetic sinogram and superimposing of metal object segments onto the image. A flowchart of the proposed algorithms is shown in Fig. 1.

2.2 Initial TV reconstruction and metal identification

Theoretically, a CT image can be reconstructed with finding $X$ by solving the minimization problem:

$$
\min_X \|H X - Y\|_2
$$

where $H$ is the projection matrix, $X$ is the image vector of the attenuation coefficients to be reconstructed, and $Y$ is the vector of log-transformed projection measurements. This optimization process reflects the data fidelity term, which ensures consistency between the reconstruction image and sinogram data. The main causes of data inconsistency are noise, scatter, and beam hardening [26]. For metals, these cause severe fine streak artifacts and broader dark or bright band artifacts in reconstruction.

The TV-based method has been used for reconstruction from highly insufficient projection data. This method imposes TV minimization on the tomogram, modeled as:
\[
\min \| \Psi X \| \quad \text{subject to} \quad |HX - Y| \leq \xi \quad \text{and} \quad X \geq 0
\]  
(2)

where \( \Psi \) denotes the sparsifying transform and \( \| \Psi X \| \) is the \( \ell_1 \) norm of the matrix \( \Psi X \). The process selects an image that minimizes the \( \ell_1 \) norm of the sparsified image among all images which satisfy the data fidelity constraint. The choice of the parameter \( \xi \) depends on the factors that cause data inconsistency. A frequently used sparsifying transform is the discrete gradient transform, defined as [17]:

\[
|V_{X,m,n}| = \sqrt{(X_{m,n} - X_{m-1,n})^2 + (X_{m,n} - X_{m,n-1})^2}
\]  
(3)

where \( X_{m,n} \) is the image value at pixel \((m,n)\). The image specified by \( |V_{X(m,n)}| \) is referred to as the discrete gradient image. As the medical image is assumed to be made up of large areas of organs which can be considered as approximately piecewise constant, the discrete gradient image is obviously sparser. Thus, the image can be recovered from incomplete projection measurements. The TV method has been shown to remove streak artifacts caused by a highly inefficient projection sampling rate. As the metal-excluded background image can also be assumed to be approximately piecewise constant, minimizing the TV can suppress metal artifacts while preserving the density contrast, despite the loss of some high-frequency details. These high-frequency details can be compensated for in the FBP reconstruction from fully sampled data. TV-based reconstruction is thus used here to build the initial background image.

The TV reconstruction problem is non-linear because the TV minimization and data fidelity constraints are non-linear, but it is convex because the objective and constraints are convex. Here, the ASD-POCKS algorithm is applied to perform the initial reconstruction with the original sinogram. This algorithm processes the data fidelity constraint and the TV regularization separately in an alternating manner. The raw data fidelity is minimized using an algebraic reconstruction technique (ART). The TV norm is minimized with a gradient descent. After each ART process, the gradient descent (GD) method is applied to the ART update results to minimize the TV norm. There are two minimization procedures are adapted alternately [24]. The output of GD is employed here as the initial reconstruction result.

Metal objects are segmented in the initial reconstruction simply by thresholding. All connecting pixels with HU value over 3000 HU are detected as metal using the connected neighborhood criterion. Dilation is then performed to include all peripheral pixels potentially belonging to the metal object. Segmented pixels after dilation whose HU value is below 1000 are excluded. By setting these metal pixels to one and all other pixels to zero, a binary metal image is produced. The corresponding projections of the metal in the original sinogram are identified via forward projection of this metal image.

Pseudo code for the above ASD-POCKS reconstruction process is given in the Appendix.

2.3 Weighted TV-based restoration

In the additional iterative process for recovering the background image, the metal shadow projection data are excluded from the data fidelity calculation. This is an exterior problem. An additional constraint is needed to describe the background image. The constraint minimization that yields the metal-excluded background image \( X_{\text{back}} \) is formulated as:

\[
\min(f(X)) \quad \text{subject to} \quad |HX - Y_{\text{met}}| \leq \varepsilon
\]  
(4)

where \( Y_{\text{met}} \) is the projection data without metal shadow entries. The definition of the objective function \( f(X) \) depends on the type of prior knowledge used to characterize the background image. The background image pixels are divided into three classes, namely (i) \( \Omega \), regions where the metal and pixels adjacent to boundary are located, (ii) \( \Phi \), regions close to the metal, and (iii) \( \Psi \), regions far away from the metal. It is reasonable that region \( \Omega \) seems to be like a natural image. The smoothness measurement is used to restrict the metal and its neighboring region, under the assumption that the filled area is approximately uniform and there is a smooth transition from filled pixels to the neighboring tissue. TV regularization is utilized to smooth over region \( \Omega \) [27]. When calculating region \( \Omega \), dilation with a disk element on the metal object is utilized to include pixels near the boundary.

For the region close to metal, a different strategy is applied. The major shortcoming of the TV function is that it is prone to over-smoothing low-contrast structures around metal objects [28]. Blurring of these structures in the TV regularization leads to a loss of edge information in the artificial projections at the metal shadow. Parameter \( \gamma \) is employed to measure the contribution of the artificial projection to the pixel \((m,n)\) \{\(m \in 1: M, n \in 1: N\}\] in the final FBP reconstruction. \( P \) is denoted as the forward projection of the metal image \( I_{\text{met}} \) with \( P = HI_{\text{met}} \). Assuming that the total number of projection lines is \( K \), the projection data located in the metal shadow \((\lambda_i)\) are marked as:

\[
\lambda_i = \begin{cases} 
1 & \text{if } P_i > 0 \\
0 & \text{if } P_i = 0 
\end{cases} 
i = 1: K
\]  
(5)

where \( P_i \) is the projection value corresponding to the \( i \)-th projection line. The parameter \( \gamma \) can be calculated from the corresponding column of projection matrix \( H \) by weighting with the metal shadow marks:

\[
\gamma_{m,n} = \frac{\sum_j \lambda_{H_{j,(i)}}}{\sum_j \lambda_{H_{j,(i)}}, j = mN + m}
\]  
(6)

Parameter \( \gamma \) indicates the portion of \( H \) ’s coefficients that will be projected into the metal shadow. For each pixel, the higher the portion is, the more projection data used for FBP reconstruction come from the artificial sinograms. This means that the blurring of structures is less compensated for by the FBP reconstruction with real sinograms. Thus, for regions with higher \( \gamma \), the TV-based constraint is expected to tend to preserve edge structures, and the smoothing strength of the TV norm may be weakened. Parameter \( \gamma \) is highly correlated to the distance from a pixel to a metal object. The closer the pixel is to the metal, the higher the \( \gamma \) value of the pixel. Here, region \( \Phi \) is defined as a subset of pixels whose \( \gamma \) values are higher than a...
threshold $\alpha$. In this work, $\alpha$ is set as 0.4.

In order to preserve the edge structure within region $\Phi$, an adaptive anisotropic strategy for the TV regularization term is proposed. An individual weight vector is introduced for each pixel in defining the discrete gradient transform:

$$
[V_{m,n}X_{mn}] = \sqrt{A_{mn}(X_{mn} - X_{mn-1})^2 + B_{mn}(X_{mn} - X_{mn-1})^2}
$$

where $A_{mn}$ and $B_{mn}$ are weighting parameters for pixel $(m,n)$. The $l_1$ norm of the image produced by the weighted gradient transform is denoted as the adaptive anisotropic total variation (AATV) norm:

$$
|X|_{AATV} = \sum_{m,n} \left|V_{m,n}X_{mn}\right|
$$

The strategy is to employ small weights to reduce the contributions to the $l_1$ norm from edge pixels, so as to decrease the amount of smoothing in TV regularization. The weight vector can be determined from the orientation information of the edge structure, such that less smoothing will be done across the edge. The edge-preserving penalty weights $A$ and $B$ are determined according the pixel’s absolute derivative value in the vertical and horizontal orientations, respectively, since a larger gradient magnitude will be produced if edges exist. There are many ways to define such weights. In this work, the weight definition is based on the Gaussian diffusion filter [29-31]:

$$
A_{mn} = e^{-(x_{mn} - x_{mn-1})^2 / 2\sigma^2}
$$

$$
B_{mn} = e^{-(x_{mn} - x_{mn-1})^2 / 2\beta^2}
$$

Parameter $h$ is determined empirically depending on the image complexity and noise level. Choosing a large $h$ will result in less capability to differentiate image gradients at different pixels, and thus the term becomes essentially the standard TV. In contrast, small $h$ tends to give low weights to almost every pixel, making the edge-preserving TV norm inefficient in removing noise or streaking artifacts. By specifying the values of $h$, the level of the density contrast resolution to be preserved can be controlled. In this work, $h$ is set according to the histogram of the absolute gradient magnitude of the image, so that certain percentage of pixels have the gradient magnitude larger than $h$. The percentage is chosen as 95% of the histogram.

For pixels in region $\Psi$ (far away from metal), most lost high-frequency information is compensated for by the FBP reconstruction from the real sinograms. Hence, the standard TV norm is employed to suppress artifacts. The density contrast of the background image is restored while reducing noise. In summary, the objective function for the entire region can be defined as the $l_1$ norm of a weighted formula:

$$
(f(x) = \sum_{n} (1 - \beta_{m,n})|\nabla X_{mn}| + \beta_{m,n}|\nabla X_{mn}| - \frac{1}{\alpha} \frac{1}{(m,n) \in \Phi} 
$$

With the weights, the objective function is non-convex. Here, the framework of ASD-POCS is used to find the optimal solution. The GD method is used to minimize the objective function combined with ART to enforce the data fidelity constraint. To solve the $l_1$ norm minimization using the GD method, the expression of the gradient for the AATV norm is required. This gradient image can be obtained by taking the derivative of $||X||_{AATV}$ on each pixel value:

$$
\frac{\partial ||X||_{AATV}}{\partial X_{mn}} = \frac{\partial}{\partial X_{mn}} \left[ \sqrt{A_{mn}(X_{mn} - X_{mn-1})^2 + B_{mn}(X_{mn} - X_{mn-1})^2} \right]
$$

where $\delta$ is a small positive number to prevent singularities [17].

The basic idea derived from the ASD-POCS algorithm is to make the GD step size relative to the ART step size. Denote $X(t)$ as the image set that satisfies the constraints $|HX| < \epsilon$. After each ART update, the image estimate moves at a step size comparable to that for ART in the direction which leads to lower image weighted TV value. Once the image is again outside the subset $X(t)$, the gradient descent step size is reduced, so that it is smaller than the ART step size, and the image gets back to keep the constraints $|HX| < \epsilon$. This step size adaptation is repeated until the stopping criteria are met.

Based on compressed sensing theory, by assuming that the background image is piecewise smooth, the proposed method allows the aggressive down-sampling of projection views to minimize the computational burden of the iterative process. A subset of the projection image sequence is employed, both in the initial TV reconstruction and the weighted TV-based restoration, by skipping projections with equal angular space. In this work, 1/10 of total views are employed in the initial TV reconstruction and 1/5 of total views are utilized in the TV-based restoration without obviously degrading the reconstruction quality of the background image. The computational reduction due to the projection view reduction is so significant and it makes the proposed method feasible for real-time CT applications.

Pseudo code of the TV-based reconstruction described in this section is given in the Appendix.

### 2.4 Sinogram completion

The recovered background image is forward-projected to form the artificial sinogram. The metal shadow beams in the original sinogram are replaced by the corresponding projections of the artificial sinogram. However, simply replacing the beams creates discontinuities at the joints, which increases the number of streak artifacts in the reconstruction. To ensure a continuous transition between the two datasets, a residual offset is modeled using polynomial interpolation. For each projection view, a morphological operation is applied to smooth the pixels near the metal shadow to calculate the low-frequency ramp tendency near the metal. Then, cubic interpolation is utilized to fill the gaps and determine the offsets of the metal shadow for both datasets. The difference of these two offsets is subtracted from the artificial sinogram segments. In this way, the risk of discontinuities at joints is reduced. The final reconstruction is performed with FBP with all view synthetic projections. The metal segment in step 2 is then superimposed onto the
reconstruction tomograms. The TV reconstruction well expresses the shape and details of metal objects, as demonstrated in previous work [12].

3. Experiments and results

Several experiments were conducted to evaluate the proposed algorithms. This section describes the results from a computer simulation and a phantom study. The phantom study was carried out using a custom-built micro-CT system. The micro-CT system is a bench-based cone-beam system with a cone angle of 9.5°. It consists of a flat-panel detector (C7921CA, Hamamastu), an micro-focal X-ray tube (Nova 96013, Oxford) and a rotational stage for object positioning. The X-ray tube has a focal spot of 20 μm and works within a voltage range of 20–90 kVp. The detector is a Ti:Csl-CMOS device with a 50-μm pixel pitch and a 1024 × 1024 pixel matrix. The source-to-detector distance is 310 mm and the source to rotation center distance is 238 mm. Projections along 380 view angles equally spaced from 0–190°, in the short-scan angular range [22], were acquired. Projection images were reconstructed into a slice matrix of 400 × 400 pixels with a pixel pitch of 0.1 × 0.1 mm.

3.1 Simulation study

In the computer simulation study, iron equivalent inserts were added to the Shepp-Logan phantom to simulate metal artifacts. Fan beam acquisition was simulated using 1024 detector elements and 380 projections over 0–190°. All the geometry parameters correspond to the center slice geometry of the micro-CT system. Subsets of 38 projection views and 78 views were employed in the initial TV reconstruction and TV-based restoration, respectively, by skipping projections with equal space in the rotating angular direction. A spectrum of the X-ray tube at 70 kVp was used to simulate the beam hardening effect. Each projection value along a ray through the phantom was calculated based on the known densities \( b_i \) at the \( k \)-th energy level and the intersection length of the ray with the pixels in the phantom. A constant value \( y_i \) was added to detector pixel \( i \) of the sinogram to simulate the contribution of scatter. After the noise-free projection data were calculated, the noisy measurement was created according to the poisson distribution. The attenuation model was formulated as:

\[
I = \text{Poisson}(I_0 \sum b_i e^{-\mu y_i} + y_i)
\]

where \( I_0 \) is the incident X-ray photons. In the simulation, \( I_0 \) was chosen as \( 5 \times 10^5 \).

Figure 2 shows the reconstruction results obtained by FBP reconstruction using the original sinogram, FBP reconstruction using the sinogram after cubic interpolation inpainting (CI), and the proposed method, respectively. Severe streak and shadow artifacts are evident in the reconstructed image obtained using the original sinogram, as shown in Fig. 2(b). In the CI method, the missing projection pixels are created via the cubic interpolation between neighboring pixel values and then filtered and back-projected to the image domain. As shown in Fig. 2(c), streak artifacts are greatly suppressed but significant residual band artifacts and a CT number discrepancy remain in the reconstruction. In addition, the low-contrast structures near the metal inserts are obscured. In contrast, the proposed method removes metal artifacts while preserving fine structures. The details of the low-contrast ellipses near the metal are clearly visible, as shown in Fig. 2(d). Figure 3 shows the profile across these structures (indicated by the red line in the left image). The FBP reconstruction of the Shepp-Logan phantom without metal inserts is used as a reference, since the final reconstruction was obtained using FBP. The profile obtained using the proposed method is very close to that of the reference, indicating that the proposed method has almost no break on the edges and structures around the metal. This is mainly attributed to the weighted TV-based density restoration. The representation of low-contrast structures is greatly improved through this process. Figure 4 shows images taken before and after weighted
TV-based restoration. The dark and bright shadows around the metal are removed and the detail of fine structures is greatly improved.

Figure 4. Comparison of results (a) after initial TV reconstruction and (b) after weighted TV based restoration.

3.2 Phantom study

A PMMA-metal phantom was scanned using the microCT system to evaluate the proposed algorithm. The phantom was designed to simulate the bilateral hip prosthesis structure, as shown in Fig. 5. In the phantom, two iron rods were inserted into the PMMA cylinder, and a CaCl₂ admixture was used to fill the eight holes at different positions within the PMMA cylinder. The density contrast was varied by adjusting the concentration of the admixture. The admixture area was designed to have a contrast of approximately 50 and 100 HU, respectively, compared to the PMMA background. 380 projection views were acquired over 0-190°. 38 views and 76 views were utilized in the initial TV reconstruction and weighted TV-based restoration process, respectively. The exposure set at 70 kVp and 0.5 mAs per frame. To reduce computational time, only the central slice of the 1024 detector rows was used for reconstruction. Figure 6 shows the reconstruction results obtained using various methods. For FBP reconstruction using the original sinograms, a severe dark band obscure a large region between the two metal rods and all the low-contrast cylinders are destroyed by streaks and bands, as shown in Fig. 6(a). For the CI method (Fig. 6(b)), the density contrast between the admixture and PMMA is diminished by band artifacts. The edge of Disk 2 with a 50-Hu contrast is severely blurred, becoming almost invisible. There is a dark band near the metal disk, emitting from the center to the periphery. As shown in Fig. 6(c), the results obtained using the proposed method are significantly superior to those of the other two methods. Streak and band artifacts are eliminated and the shape and edge of the admixture are well restored. The area near the metal is naturally expressed without loss of detail.

Figure 5. Sketch of PMMA-metal phantom sketch map.

Figure 6. Comparison of various methods for PMMA-metal phantom. (a) FBP reconstruction, (b) cubic spline interpolation correction, (c) the proposed method.

To quantify the performance of contrast resolution, the contrast-to-noise ratio (CNR) between the admixture and PMMA background was measured. The CNR is defined as:

\[
CNR = \frac{mean_{\text{obj}} - mean_{\text{back}}}{\sqrt{(\sigma^2_{\text{obj}} + \sigma^2_{\text{back}})}}
\]

where \(mean_{\text{back}}\) and \(mean_{\text{obj}}\) are the mean values of the background and the low-contrast object, respectively, and \(\sigma_{\text{back}}\) and \(\sigma_{\text{obj}}\) are the standard deviations of the background and the uniform object, respectively. The results are displayed in Table 1. It can be observed that the CNR of the proposed method is significantly higher than that of the image reconstructed using CI. For disks near metal, the improvement of CNR is much higher than that for disks far away from metal.

<table>
<thead>
<tr>
<th>Disk</th>
<th>CI Mean (HU)</th>
<th>CNR</th>
<th>Proposed method Mean (HU)</th>
<th>CNR</th>
<th>CNR increment</th>
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<td>Background</td>
<td>43.5</td>
<td>43.5</td>
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<td></td>
</tr>
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<td>145.8</td>
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</tr>
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</table>

4. Discussion

The experimental results show that the proposed TV-based MAR produces superior image quality compared to that obtained using conventional methods. In images corrected using conventional inpainting MAR methods, low-contrast structures near metal are often obscured by artifacts. The idea behind the proposed method is to create an artifact-free background image to inpaint the metal shadow projections. Previous methods usually reduce artifacts in the background using smooth filtering or tissue-class prior probability images. This often leads to a loss of low-contrast resolution. In contrast, this study introduced a weighting technique into TV
regularization. As there is no restriction on tissue class, the low-contrast resolution of the background image is greatly enhanced. An adaptive anisotropic TV term is applied to prevent the blurring of edge structures around metal objects, improving image quality. In all presented cases, streak and band artifacts were eliminated without over-smoothing the fine structures. Low-contrast structures, even close to metal objects, were well preserved.

Considering the computation cost, when carrying out the iterative process, 1/10 and 1/5 of the projection views are employed for the TV-based process without obviously degrading the image. This reduces the calculation burden by more than 80%, making the proposed method efficient. The ASD-PACS algorithm is employed to solve the weighted TV optimization problem, but other solvers can also be employed. Some of them may work faster than ASD-PACS [33,34]. Utilizing these solvers may further increase computation speed.

5. Conclusion

In conclusion, the proposed method eliminates metal artifacts and preserves low-contrast structures. Accurate density is important for diagnosis, and will be helpful for recognizing tumors and other pathological tissues. The performance of the algorithms was demonstrated using both simulation and experimental data and a micro-CT system. Further work is needed to further improve CT image quality.

Appendix

Pseudo code of proposed algorithms

Initial ASD-PACS reconstruction:
Obtain projection data Y using 1/10 of the original projections; $\kappa = 1.0$, $q = 0.995$, $\alpha = 0.95$, $r = 0.95$; Initial AM: $X_0 = 0$;
for $k = 1, 2, 3, \ldots$ do
  ART updating:
  $X^k = X_k$;
  for $l = 1, 2, 3, \ldots, N_p$ do
    $X^l = X^{l-1} + \beta \frac{Y_l - H X^{l-1}}{\lambda_l H^T H}$;
  end
  If $X^l_{n,a} < 0$, then $X^l_{n,a} = 0$;
end

TV minimization:
$X^i = X^{i-1}$;
for $j = 1, 2, 3, \ldots, N_g$ do
  $\left\| X^{i-1} \right\|_v = \sum_{n,a} (X^i_{n,a} - X^{i-1}_{n,a})^2 + X^{i-1}_{n,a} - X^{i-1}_{n,a-1})^2$
  $v_{n,a} = \frac{\partial \left\{ \left\| X^{i-1} \right\|_v \right\}}{\partial X^{i-1}_{n,a}}$
  $X^{i+1} = X^i + \alpha v_{n,a} v - \nu$
end

Weighted TV-based restoration:
Obtain projection data Y using 1/5 of the original projections;
Calculate metal shadow $P$ with forward projection of $I_{\text{metal}}$:
$P = H I_{\text{metal}}$;
Mark the metal shadow:
$\gamma_i = \begin{cases} 1 & P > 0 \\ 0 & P = 0 \end{cases}$
Calculate $\gamma$ through $\gamma_n = \sum_j (H_{n,j} - \gamma_{n-1})$, $j = n \cdot M + m$;
Calculate the region weights $\beta$ using threshold $\gamma$;
Obtain metal-shadow-excluded projection data $Y_{\text{nonmetal}}$ from $Y$ through $\gamma$;
for $k = 1, 2, 3, \ldots$ do
  ART updating:
  $X^k = X_k$;
  for $i = 1, 2, 3, \ldots, N_g$ do
    $X^i = X^{i-1} + \beta \frac{Y_{\text{nonmetal}} - H X^{i-1}}{H \gamma_i}$;
    if $X^i_{n,a} < 0$, then $X^i_{n,a} = 0$;
end
end

If $\gamma_i > r \cdot \gamma$ and $dd > \xi$, then $\alpha = r \cdot \alpha$;
$\kappa = q \cdot \kappa$;
$X_{\text{next}} = X^{i-1}$;
end

Return $X_{\text{next}}$ as the background image;
References


