Dual-resolution image reconstruction for region-of-interest CT scan

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ABSTRACT: In ordinary CT scan, so called full field-of-view (FFOV) scan, in which the x-ray beam span covers the whole section of the body, a large number of projections are necessary to reconstruct high resolution images. However, excessive x-ray dose is a great concern in FFOV scan. Region-of-interest (ROI) scan is a method to visualize the ROI in high resolution while reducing the x-ray dose. But, ROI scan suffers from bright-band artifacts which may hamper CT-number accuracy. In this study, we propose an image reconstruction method to eliminate the band artifacts in the ROI scan. In addition to the ROI scan with high sampling rate in the view direction, we get FFOV projection data with much lower sampling rate. Then, we reconstruct images in the compressed sensing (CS) framework with dual resolutions, that is, high resolution in the ROI and low resolution outside the ROI. For the dual-resolution image reconstruction, we implemented the dual-CS reconstruction algorithm in which data fidelity and total variation (TV) terms were enforced twice in the framework of adaptive steepest descent projection onto convex sets (ASD-POCS). The proposed method has remarkably reduced the bright-band artifacts at around the ROI boundary, and it has also effectively suppressed the streak artifacts over the entire image. We expect the proposed method can be greatly used for dual-resolution imaging with reducing the radiation dose, artifacts and scan time.

KEYWORDS: Computerized Tomography (CT) and Computed Radiography (CR); Medical-image reconstruction methods and algorithms, computer-aided diagnosis

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1 Introduction

In computed tomography, abrupt truncation in the projection data to limit the field-of-view (FOV) to a local region-of-interest (ROI) makes bright-band artifacts around the truncation edge giving contrast anomaly in the ROI [1]. A few ROI-CT techniques such as interior tomography [2], local tomography [3], lambda tomography [4], and zoom-in tomography [5], aim to reconstruct interior images of a ROI in the object from the truncated projection data. Among the ROI-CT techniques, interior tomography is now gaining clinical interests since interior tomography can provide artefact-free ROI images while reducing the x-ray dose significantly. Reduction of the x-ray dose in CT scan has become a must as the hazardous effects of x-rays is known to be more serious than they have been previously expected [6].

Interior tomography reduces the contrast anomaly in many ways. Among them, the sinogram extension techniques [7, 8] remedy the discontinuity of the truncated projection data by tapering off the truncation edge to zero by extrapolation, but those techniques are not complete in correcting the contrast anomaly. In zoom-in tomography [5] and scout-view assisted interior tomography [9], low-resolution images are firstly reconstructed from the global projection data sparsely sampled in the view direction. And then, the missing projection data outside the ROI are computed from the low-resolution global images and they are combined with the truncated projection data to reconstruct high-resolution ROI or interior images. Compressed sensing (CS) based image reconstruction techniques have been found to be effective in correcting the contrast anomalies in interior tomography [2]. CS theory asserts that one can recover certain continuous signals from the discrete one sampled with far lower sampling rate than the Nyquist sampling rate [10–13]. However, CS-based interior tomography suffers from image bias caused by severe data truncation and heavy computations involved in iterative image reconstruction with total variation (TV) minimization [2, 9, 14].

In this study, we introduce an image reconstruction method to further suppress the bright-band artifacts caused by the data truncation and the streak artifacts caused by the limited projection views. We aim to reconstruct dual-resolution images over the entire object, high resolution inside
the ROI and low resolution outside the ROI. We incorporated a few exterior projection data encompassing the outside the ROI into the ROI image reconstruction from the truncated projection data encompassing only inside the ROI. We have compared the performance of the proposed method with the ones of the two previous methods, truncated FBP [8] and CS-based interior tomography [2].

2 Materials and methods

2.1 Interior and exterior projection data

For the image reconstruction, we describe two types of projection data with different FOVs and angular sampling rates. One projection data, called sparse-view exterior projection data, encompass only outside the ROI in the imaging object and they have a low sampling rate in the view direction as depicted in figure 1(c). The sparse-view exterior projection data can be obtained by removing the ROI part from the sparse-view global projection data, depicted in figure 1(b), which may be available from a pilot scan to position the ROI or from a low-resolution scan in CT fluoroscopy [9]. The other projection data, called interior projection data, encompass only the ROI and they have a high sampling rate in the view direction as depicted in figure 1(d).

Figure 1. Projection data sets and the rat abdomen image. (a) Full-view global projection data. (b) Sparse-view global projection data. (c) Sparse-view exterior projection data. (d) Full-view interior projection data. (e) The reconstructed image by FBP from the full-view global projection data shown in figure 1(a).

In this study, we used 15-view exterior projection data taken from the sparse-view global projection data. To simulate the sparse-view global projection data, we decimated the full-view global projection data in the view direction. For the full-view interior projection data, we truncated both sides of the full-view global projection data while keeping the central part corresponding to the ROI. For the performance comparison in terms of truncation ratio [9], we selected 0.6 and 0.8 for the truncation ratio of the interior projection data as defined below:

\[
\text{Truncation ratio} = 1 - \frac{\text{Length of interior projection}}{\text{Length of global projection}}
\]  

(2.1)

To acquire the full-view global projection data depicted in figure 1(a), we used a lab-built micro-CT system consisting of a micro-focus x-ray source (L8121-01, Hamamatsu, Japan), a flat-panel x-ray detector (C7942, Hamamatsu, Japan), and a precision scan mechanism [5]. We performed a full-view scan of an abdomen region in a sacrificed adult rat with the tube voltage and current of 65 kVp and 0.34 mA, respectively.
2.2 Dual-resolution image reconstruction

In dual-resolution image reconstruction, two constrained TV-minimization problems defined in equation (2.2) and (2.3) are solved in the framework of adaptive steepest descent projection onto convex sets (ASD-POCS) [11].

\[
f^* = \text{argmin} \|f\|_{TV} \quad \text{s.t.} \quad \|M_{\text{int}} f - g_{\text{int}}\|_2 \leq \epsilon_{\text{int}}, \quad f \geq 0 \tag{2.2}
\]

\[
f^* = \text{argmin} \|f_{\text{ext}}\|_{TV} \quad \text{s.t.} \quad \|M_{\text{ext}} f - g_{\text{ext}}\|_2 \leq \epsilon_{\text{ext}}, \quad f_{\text{ext}} \geq 0 \tag{2.3}
\]

where \( f \) is the global image, \( f_{\text{ext}} \) is the exterior subset of \( f \) (outside the ROI), \( M_{\text{int}} \) is the system matrix to generate the interior projection data \( g_{\text{int}} \), \( M_{\text{ext}} \) is the system matrix to generate the exterior projection data \( g_{\text{ext}} \), and \( \epsilon_{\text{int}} \) and \( \epsilon_{\text{ext}} \) are the data fidelity tolerances for the interior and exterior projection data, respectively.

We performed the two constrained TV-minimizations in an iterative way to reconstruct an image that met the inequalities of the data fidelity tolerances. In the first constrained TV-minimization in equation (2.2), we searched a solution for \( f \) that minimized the TV of the global image with satisfying the data fidelity term over the interior projection data \( g_{\text{int}} \). In the second stage of iteration in equation (2.3), we searched a solution for \( f_{\text{ext}} \) that minimized the TV of the exterior image with satisfying the data fidelity term over the exterior projection data \( g_{\text{ext}} \). The interior projection data \( g_{\text{int}} \) contributes to making the entire image \( f \), while the exterior projection data \( g_{\text{ext}} \) contributes to making only the exterior image \( f_{\text{ext}} \).

2.3 Algorithm implementation

The dual ASD-POCS framework for the proposed method is depicted in the pseudo code shown below.

1. \( \gamma_{\text{max}} := 0.4; \gamma_{\text{max, ext}} := 0.98; \lambda := 0.0002; \lambda_{\text{ext}} := 0.005; \lambda_{\text{red}} = : 0.97; \)
2. Generate the mask \( h_{\text{ext}} \) for outside the ROI;
3. \( nTV := 20; f := 0; \)
4. Repeat the main loop
5. \([f \, dp \, dd] := \text{DataEnforcement}(f, M_{\text{int}}, g_{\text{int}});\)
6. \([f \, dg] := \text{TvMinimization}(f, \lambda, 0);\)
7. if ((\( dg > \gamma_{\text{max}} \star dp \)) and (\( dd > \epsilon_{\text{int}} \))) \( \lambda := \lambda_{\text{red}}; \)
8. \([f \, dp \, dd] := \text{DataEnforcement}(f, M_{\text{ext}}, g_{\text{ext}});\)
9. \([f \, dg] := \text{TvMinimization}(f, \lambda_{\text{ext}}, 1);\)
10. if ((\( dg > \gamma_{\text{max, ext}} \star dp \)) and (\( dd > \epsilon_{\text{ext}} \))) \( \lambda_{\text{ext}} := \lambda_{\text{ext, red}}; \)
11. until (stopping criteria)
12. \([f \, dp \, dd] := \text{DataEnforcement}(f, M, g)\)
13. $f_{\text{pre}} := f$

14. Update $f$ by OS-SART to reduce $\|Mf - g\|_2$ with positivity constraint;

15. $g_{\text{fwd}} := Mf; \; dd := \|g_{\text{fwd}} - g\|_2; \; dp := \|f - f_{\text{pre}}\|_2$

16. return $f, dp, dd$

17. $[f \; dg] := \text{TvMinimization}(f, \lambda, \text{flag})$

18. $f_{\text{pre}} := f$

19. for $k = 1 : 1 : nTV$

20. compute the steepest descent direction $d$ of TV;

21. $\beta := \max(|f|) \div \max(|d|)$;

22. if (flag = 1) $f := f - \lambda \times \beta \times d \ast h_{\text{ext}}$

23. else $f := f - \lambda \times \beta \times d$

24. end for

25. $dg := \|f - f_{\text{pre}}\|_2$

26. return $f, dg$

The pseudo code can be divided into three parts, that is, lines 1–11 for the main function, lines 12–16 for the data fidelity enforcement, and the other lines for the TV minimization. In the sub-function for the data fidelity enforcement, the reconstructed image $f$ is updated by the ordered-subset simultaneous algebraic reconstruction technique (OS-SART) [2] at line 14. The projection data residue $dd$ and the change in the image $dp$ due to the data fidelity enforcement are computed at line 15. In the other sub-function, the TV minimization is performed at lines 19–24 as usual, but there is a flag at line 22. If the flag is true, image masking is performed with the generated mask at line 2. The mask $h_{\text{ext}}$ has element values of 1 for outside the ROI and 0 for the ROI. The operator $\ast$ in line 25, represents the element-by-element product between two matrices of the same size. The change in the image $dg$ due to the TV minimization is computed at line 25. In the pseudo code line 1, the control parameters for the step size, $\lambda$, $\lambda_{\text{ext}}$ and $\lambda_{\text{red}}$, are initialized for the TV minimization [2] and the maximum ratios, $\gamma_{\text{max}}$ and $\gamma_{\text{max,ext}}$, are initialized for the step size adaptations at line 7 and 10, respectively [11]. The aforementioned mask $h_{\text{ext}}$ is generated at line 2. The constrained TV-minimizations are performed for the interior projection data $g_{\text{int}}$ at lines 5–6 and for the exterior projection data $g_{\text{ext}}$ at lines 8–9, respectively. The step sizes of the steepest descent in the TV-minimization are controlled adaptively in the ASD-POCS framework as depicted in line 7 and 10 [11].
3 Results

We have firstly reconstructed the rat abdomen image shown in figure 1(e), in a 512×512 matrix form, by FBP from the full-view global projection data taken with the micro-CT. Here, the full-view global FBP image is used as a reference image. Figure 2 shows the reconstructed images when the truncation ratio is 0.6. Figure 2(a) and 2(b) show the images reconstructed from the full-view interior projection data by the truncated-FBP and the CS-based interior tomography, respectively. As shown in figure 2(a), the image reconstructed by the truncated-FBP shows strong bright-band artifacts at around the ROI boundary because of the truncation. In the image reconstructed by the CS-based interior tomography, the bright-band artifacts are greatly reduced, but the residual artifacts are still visible. Figure 2(c) shows the image reconstructed by the proposed method from the full-view interior projection data and the 15-view exterior projection data. In figure 2(c), the bright-band artifacts have almost disappeared. Furthermore, figure 2(c) shows reasonable image quality outside the ROI owing to the use of 15-view exterior projection data. To better visualize the differences among the reconstructed images, we have shown the line profiles along the horizontal lines in figure 3. Figure 3(a) and 3(b) compare the line profiles at the global and ROI regions, respectively. As can be seen from figure 3, the line profiles of the proposed method most resemble the original line profiles.

![Figure 2](image1.png)

**Figure 2.** The images reconstructed by (a) the truncated FBP, (b) the CS-based interior tomography, and (c) the proposed method. The truncation ratio is 0.6, and the red circle indicates the ROI.

![Figure 3](image2.png)

**Figure 3.** (a) Pixel intensity profiles along the horizontal lines shown in figure 2. (b) Pixel intensity profiles corresponding to the ROI in figure 3(a).
Figure 4 shows the magnified ROIs of the reconstructed images when the truncation ratio is 0.8. The view number of the interior projection data is 900 and 225 for the top row and bottom row, respectively. In figure 4(a) and 4(b), the images reconstructed by the truncated-FBP and CS-based interior tomography show stronger bright-band artifacts than the ones in figure 2(a) and 2(b) because of the higher truncation ratio. Moreover, the image reconstructed by the truncated FBP, the bottom row in figure 4(a), shows streak artifacts due to the sparse sampling in the view direction. But, in the images reconstructed by the proposed method shown in figure 4(c), the bright-band artifacts are almost invisible and the streak artifacts are well suppressed at the same time. In addition, the proposed method has given the global image as shown in the upper left corner in figure 4(c). We have shown the line profiles in figure 5 along the horizontal lines shown in figure 4. As can be seen from figure 5(a) and 5(b), the line profiles of the proposed method most resemble the original line profiles at both inside and outside the ROI. Table 1 summarizes the MSEs of the images reconstructed by the aforementioned three methods. In the proposed method, the MSE performance degrades as the number of views for the interior projection data is reduced. But, due to the 15-view exterior projection data, the proposed method shows the best MSE performance at both inside and outside the ROI among the three methods.

### Figure 4

The magnified ROIs of the images reconstructed by (a) the truncated FBP, (b) the CS-based interior tomography, (c) the proposed method, and (d) the reference. The numbers of views of the interior projection data are 900 and 225 for the top row and the bottom row, respectively. The truncation ratio is 0.8. The global images are displayed in the upper left corners. The red circle indicates the ROI.

### 4 Discussion and conclusion

Scout-view assisted interior tomography [9] is similar to the proposed method in that it also uses the sparsely sampled global projection data taken from the scout scan. But, it can provide only the ROI images reconstructed by FBP in its final image reconstruction stage which may cause severe streak artifacts if the interior projection data for the ROI are not fully sampled in the view direction.
Table 1. MSEs in the rat abdomen images. Three reconstruction methods, truncated FBP, CS-based interior tomography and the proposed method, are compared. MSEs have been calculated from the reconstructed images shown in figures 2 and 4.

| Number of views for ROI | Truncation Ratio | Reconstruction Methods | MSE Outside ROI | MSE Inside ROI |
|-------------------------|------------------|------------------------|----------------|----------------|
| 900                     | 0.6              | Truncated FBP          | 1.0320         | 0.1150         |
|                         |                  | CS-Interior Tomo       | 0.7490         | 0.0328         |
|                         |                  | Proposed method        | 0.1074         | 0.0034         |
| 900                     | 0.8              | Truncated FBP          | 1.9978         | 1.5142         |
|                         |                  | CS-Interior Tomo       | 1.2867         | 1.0601         |
|                         |                  | Proposed method        | 0.1434         | 0.0035         |
| 225                     | 0.8              | Truncated FBP          | 2.0064         | 1.5504         |
|                         |                  | CS-Interior Tomo       | 1.3485         | 1.4535         |
|                         |                  | Proposed method        | 0.1441         | 0.0178         |

Figure 5. Pixel intensity profiles along the horizontal lines (a) in the top row images and (b) in the bottom row images in figure 4.

The proposed method well suppresses the streak artifacts, in addition to the bright-band artifacts, since it uses TV minimization in its final image reconstruction stage. In most cases of ROI scan, we would set the angular sampling rate high enough to meet the Nyquist sampling rate. But, the feature of suppressing the streak artifacts in various sparse-view scan strategies to reduce the x-ray dose would be greatly appreciated in the clinical application [13].

In this study, we aimed at reconstructing dual-resolution images from the dual-resolution projection data while suppressing the bright-band artifacts and the streak artifacts simultaneously. In the image reconstruction based on TV minimization, we exploited the sparsely sampled exterior projection data to improve the image quality inside the ROI. Even though the exterior projection data were sampled as few as 15 samples over 360 degrees in the view direction, the exterior projection data played great roles in reducing the contrast anomalies in the ROI images. The extra acquisition of a few number of exterior projection data also enabled us to get the exterior images even though they had lower resolution than the interior images. Due to the dual ASD-POCS framework employed in the iterative image reconstruction, the streak artifacts were efficiently suppressed.
even in the case of sparsely sampled interior projection data. Excessive computation time is a great concern in the CS-based image reconstruction [2, 9]. In our experimental studies, the computation times of FBP, CS-based interior tomography, and the proposed method were 2.2 s, 1328 s, and 1650 s, respectively, when the computations were run in Matlab on a desk top PC (3.46 GHz CPU, 24 GB RAM). To use the proposed method for practical application, reduction of the computation time through the algorithmic approach and parallel processing should be considered [16].

In conclusion, the proposed image reconstruction method allowed us to reconstruct dual-resolution images, fine resolution inside the ROI and coarse resolution outside the ROI, without visible contrast anomalies inside the ROI. We expect the proposed method can be used for dual-resolution imaging in biomedical and industrial tomography with reducing the radiation dose, artifacts and scan time.

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