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Abstract. We proposed a novel scanning method for low-dose computed tomography (CT) that uses an oscillating multi-slit collimator between the x-ray source and the patient. It can be thought as a realization of sparse data sampling that does not require a fast x-ray power switching. A simulation study was performed based on experimentally acquired microCT data of a mouse to demonstrate the feasibility of the proposed method. A numerical collimation was designed to leave only one-fourth of each projection data for use in image reconstruction. A total-variation minimization algorithm was implemented for image reconstruction from the sparely sampled data. We have successfully shown that the proposed method provides a viable option to low-dose CT. [DOI: 10.1117/1.OE.51.8.080501]

Subject terms: computed tomography; image reconstruction; low-dose; collimator.

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1 Introduction

X-ray computed tomography (CT) has been widely used for various clinical applications. With its increased use in clinics, dose reduction is the most important feature people seek in new CT techniques or equipments. The most intuitive and straightforward method of reducing radiation dose is either decreasing the tube current during a scan or taking less projections, or both. A host of algorithms have been developed to improve the quality of images reconstructed from the data acquired at low tube current.[1,2] Algorithms inspired by the compressive sensing theory have also been developed to reconstruct images from sparse-view projections.[3–5] Successful performance of such algorithms has been reported with varying degrees of dose reduction. In spite of potential usefulness of the sparse-view technique, however, its implementation in clinical CT systems is hardly found yet. It is partly due to the fact that a fast tube power switching is challenging, if not impossible, particularly for the systems that operate with a very fast gantry rotation.

In this work, we propose a novel method of sparse data-sampling that uses an oscillating multi-slit collimator instead of fast tube power switching as shown in Fig. 1. A multi-slit collimator can be made of radio-opaque material to block the x-ray beam outside the slit openings. At a given source position, projection data is therefore acquired only through the slit-openings thereby reducing dose greatly. To enhance data sampling uniformity, we propose to oscillate the collimator during a scan. We name this type of scanning method many-view under-sampling (MVUS) technique. We demonstrate a feasibility of the MVUS using a simulation study in this work. Projection data are acquired through numerically collimating the full projection data according to the proposed method, and a total-variation minimization algorithm is used for image reconstruction from the collimated data.[4]

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2 Methods

2.1 *Data Sampling Scheme*

We used microCT projection data of a mouse acquired from a circular cone-beam scan in a step-and-shoot mode, and made an array for numerical collimation. Open and blocked rectangular areas that have length dimension along the rotation axis repeat periodically in the array across the perpendicular direction to the rotation axis, and the array elements of the open area are set to be one and those of the blocked area to be zero. In this study, we prepared the array to have one-fourth of the total area as open area in the anticipation of dose reduction by a factor of four compared to a conventional scan. For each projection, we numerically collimated the data by multiplying the collimating array so that only one-fourth of the data remain to be used for image reconstruction while the other portions being negated.

We compared the images reconstructed from the statically collimated data and from the collimated data by use of a sinusoidal motion of the collimator in this work. In the sinusoidal motion case, the amplitude of the motion was determined so that the sampling occurs relatively uniformly over the detector bins in the sinogram domain. In other words, the slit openings complete a round-trip of each partition at each cycle. The frequency of the motion was set to be 20 trips per scanner rotation. In addition, we

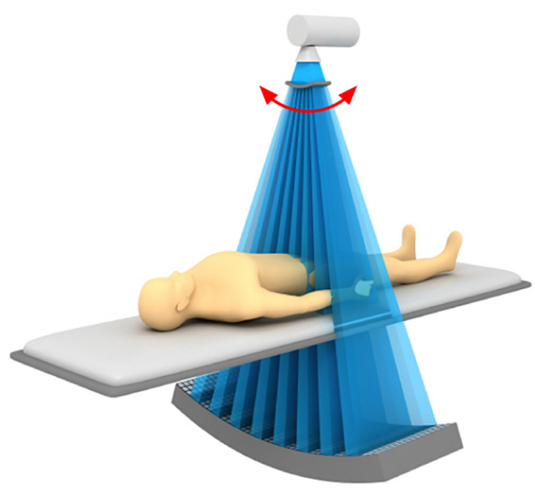

Fig. 1 Schematic of the proposed scanning configuration is illustrated. The arrow indicates a reciprocating motion of the collimator.

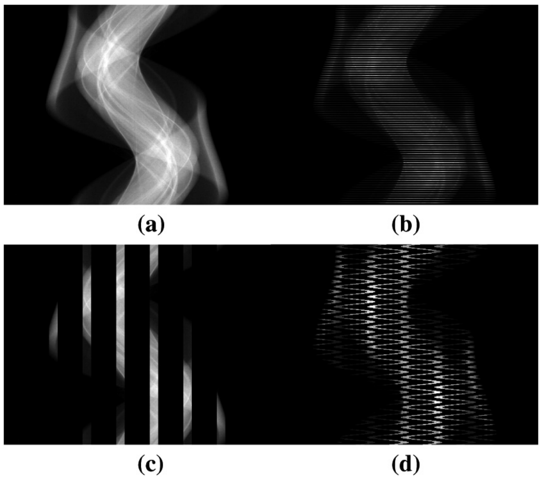

Fig. 2 The sinograms corresponding to (a) a full data sampling case, (b) an existing sparse-view case, (c) a statically collimated case, and (d) a sinusoidally collimated case.

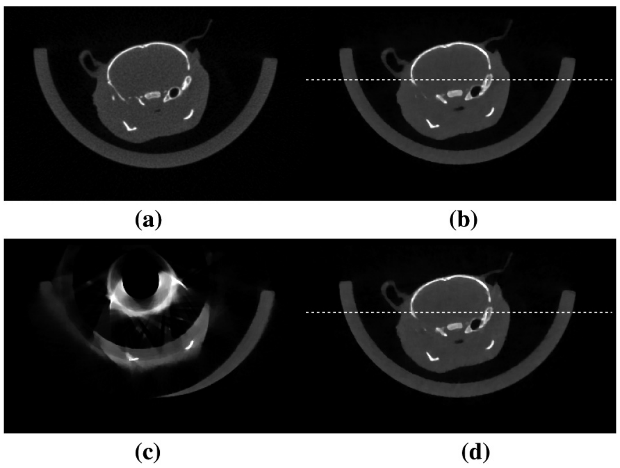

Fig. 3 The reconstructed images corresponding to (a) a full data sampling case, (b) an existing sparse-view case, (c) a statically collimated case, and (d) a sinusoidally collimated case.

also reconstructed the images from conventional sparse-view data in which every fourth projections is used. Figure 2 shows the sinograms that correspond to 2(a) a full data sampling case, 2(b) an existing sparse-view case, 2(c) a statically collimated case, and 2(d) a sinusoidally collimated case.

2.2 *Total-Variation Minimization Algorithm*

We used a total-variation minimization algorithm for image reconstruction. Total-variation minimization algorithm was inspired by the compressive sensing theory, and has shown its excellent performance in sparse-view CT applications.[4] The total-variation minimization algorithm exploits sparsity of the magnitude of image derivative, thereby reducing the number of unknowns for a given system of equations or measurements. We adopted the adaptive-steepest-descent projection-onto-convex-sets (ASD POCS) approach developed by Sidky et al.,[4] and modified the POCS step so that only the measured data through the collimator slits are to be used in the computation.

The algorithm seeks a solution to the following optimization problem:

$$f^0 = \text{argmin}\|f\|_{\text{TV}} \text{ such that} \|Af - g\| < \varepsilon, \quad (1)$$

where f represents an image under iteration, f^0 the minimum image total-variation solution, A the system matrix, and g the measured data. $\|\|_{\text{TV}}$ represents the total-variation of an image function. The system matrix was constructed based on a ray-driven model of line integrals, and ε was empirically set by watching the image root-square-error as a function of ε.

3 Results

Figure 3 shows the reconstructed images of a transverse slice of a mouse head. Image reconstructed by the Feldkamp-Davis-Kress (FDK) algorithm from the uncollimated 360 projections is shown in Fig. 3(a) as a reference image. Image reconstructed by the total-variation minimization algorithm from the uncollimated 90 projections that are equally separated from each other in view angles is shown in Fig. 3(b). Figure 3(c) and 3(d) shows the reconstructed images by use of the total-variation minimization algorithm from the statically collimated 360 projections and from the dynamically collimated 360 projections, respectively. A visual comparison of the reconstructed images confirms that the proposed method can provide quality images that are comparable to the images obtained by the existing sparse-view technique. In contrast, a static collimation with multi-slits turns out to be undesirable in terms of reconstructed image quality. For further comparison, we show in Fig. 4 the difference in images between Fig. 3(b) and 3(d) in a narrow display window, and also show the line profiles across the lines shown in the images.

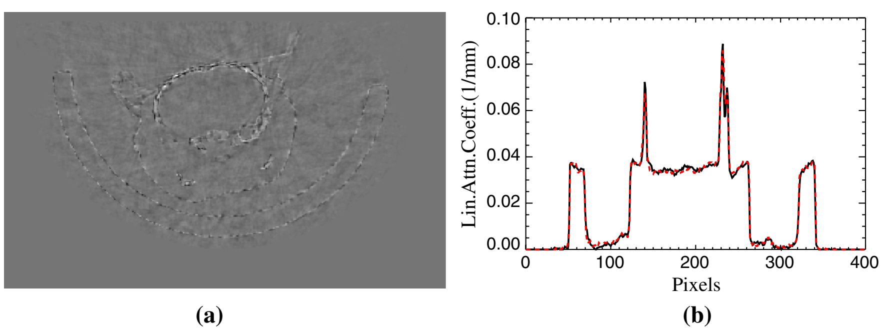

Fig. 4 (a) Difference image between Fig. 3(b) and 3(d) in the display window of $[-0.02 0.1]\text{mm}^{-1}$. (b) Profiles across the lines shown in the images of Fig. 3(b) and 3(d). The solid line represents the profile of Fig. 3(b) and the dotted line that of Fig. 3(d).

Additionally, we calculated an image similarity index called universal quality index (UQI) to quantitatively assess the image quality.[6] UQI measures the pixel-to-pixel similarity between the two images under consideration, and its value ranges from 0 to 1. The closer to 1, the more similar the two images are. With respect to Fig. 3(a), the UQI of Fig. 3(b) was 0.998 and that of Fig. 3(d) was 0.997.

4 Discussion and Conclusions

X-ray scatter due to the patient body is one of the dominant physical factors that affect the image quality in CT, particularly in cone-beam CT.[7] In the MVUS approach, scatter reduction occurs naturally due to the presence of a multi-slit collimator between the source and the patient. Moreover, one can estimate the scatter fluence easily from the shadow of blocked regions by the collimator in the projection data. In this regard, the MVUS approach has a potential to produce high quality images very efficiently via removing the scatter effects in the system matrix.

The collimated projection data may have lag effects due to the motion of a collimator during data acquisition for each frame in reality. The lag effects refer to the unwanted attenuation of the intruded collimator into the images through slit-openings. If the lag effects dominate, the projection data will be accordingly contaminated and may not provide useful data for image reconstruction. However, one can verify that the motion contamination can be suppressed below an acceptable level. For example, let us consider a CT scanner with its data frame rate of 5000 fps[8] and 2 rps of the gantry. The scanner actually spends less than 0.2 msec for the data acquisition of a single frame in this case. If the frequency of sinusoidal motion of a collimator is 40 Hz or 20 trips per rotation, then the slit-edge completes a one-way trip within 12.5 msec. Therefore, approximately less than 6.4% $(=4\times 0.2/12.5)$ of the collimated data will suffer from the motion contamination, where a factor of 4 represents the ratio of the slit repetition interval to its opening size. One may simply discard the contaminated portion of the data or can correct for the contaminated portion by multiplying appropriate compensation factors if needed. In conclusion, we proposed a novel scanning method for low-dose CT, and performed a simulation study to demonstrate its feasibility.

Acknowledgments

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