

Alternating Source-Detector Array Stationary CT System and Its Reconstruction

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Abstract

In this paper, we propose a novel design for a stationary CT system, termed the Alternating Source-Detector Array stationary CT (ASDA-sCT). The ASDA-sCT system comprises an array of miniature carbon nanotube X-ray sources and a detector array strategically positioned in the gaps between sources. To minimize projection loss caused by ray path obstruction, the X-ray sources are distributed within a short-scan trajectory that takes advantage of the fan-beam symmetry. After interpolation-based restoration of the discontinuities, CT images can be directly reconstructed using the filtered backprojection (FBP) algorithm with Parker's weighting function. We further investigate the influence of the number of X-ray sources on the reconstruction quality of the ASDA-sCT system and determine the optimal source number for different X-ray exit window sizes. However, the limited number of sources and the interpolation errors introduced during sinogram restoration remain critical barriers to achieving high-quality image reconstruction. To tackle these issues, we propose a tailored triple-stage dual-domain cascade neural network (TSDDC-Net), which incorporates prior knowledge to correct interpolation errors in the sinogram and compensate for the missing projection views. In the projection domain, we introduce a novel multi-scale deformable convolution module (DFInception) that enhances feature extraction and improves the accuracy of sinogram refinement. In the image domain, a dual-encoder architecture is employed to independently extract features from the initial CT image reconstructed from raw interpolated projections and from the refined CT image reconstructed using the corrected sinogram. Ultimately, the well-designed deep learning model significantly enhances the quality of the reconstructed images. Experiments conducted on the Shepp-Logan phantom and abdominal CT datasets demonstrate the promising potential of the ASDA-sCT system for practical applications.

Full Text

Preamble

Alternating Source-Detector Array Stationary CT System and Its Reconstruction

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We propose a novel stationary CT system design termed the Alternating Source-Detector Array stationary CT (ASDA-sCT). The system comprises an array of miniature carbon nanotube X-ray sources and a detector array strategically positioned in the gaps between adjacent sources. To minimize projection loss from ray path obstruction, the X-ray sources are distributed along a short-scan trajectory that exploits fan-beam symmetry. After restoring discontinuities through interpolation-based methods, CT images can be directly reconstructed using the filtered backprojection (FBP) algorithm with Parker' s weighting function. We investigate how the number of X-ray sources affects reconstruction quality in the ASDA-sCT system and determine the optimal source count for various X-ray exit window sizes. However, the limited number of sources and interpolation errors introduced during sinogram restoration remain critical barriers to high-quality image reconstruction. To address these challenges, we propose a tailored triple-stage dual-domain cascade neural network (TSDDC-Net) that incorporates prior knowledge to correct interpolation errors in the sinogram and compensate for missing projection views. In the projection domain, we introduce a novel multi-scale deformable convolution module (DFInception) that enhances feature extraction and improves sinogram refinement accuracy. In the image domain, a dual-encoder architecture independently extracts features from the initial CT image reconstructed from raw interpolated projections and from the refined CT image reconstructed using the corrected sinogram. This well-designed deep learning model significantly enhances reconstructed image quality. Experiments on the Shepp-Logan phantom and abdominal CT datasets demonstrate the promising potential of the ASDA-sCT system for practical applications.

Keywords: Computed Tomography, Stationary CT, Sparse-view CT, Deep learning

INTRODUCTION

Computed tomography (CT) is an imaging technique that reconstructs cross-sectional images of an object' s interior by measuring X-ray projections from

multiple views using computational algorithms. Due to its ability to generate high-resolution three-dimensional images, CT is widely used in medical diagnostics and industrial non-destructive testing. Modern CT scanners universally adopt third-generation rotate-rotate geometry, where one or two X-ray sources with detector modules rotate around the object for a full 360-degree scan [?, ?]. CT technology development focuses on three key advancements: enhancing temporal resolution, reducing X-ray radiation exposure, and minimizing manufacturing costs [?]. However, the rotating mechanical structure of modern CT scanners constrains further technological evolution. Due to enormously increasing centrifugal forces, the rotational scan time of CT gantries has reached its limit of 0.25 seconds [?]. Meanwhile, vibrations in the CT acquisition system caused by mechanical rotation increase system noise and deteriorate spatial resolution. Furthermore, the cumbersome gantry and complex dynamic acquisition mechanism hinder portability and significantly increase manufacturing costs.

In the 1980s, electron beam CT (EBCT) scanners were developed with a stationary design that eliminated mechanical motion, achieving shorter scan times of 33–100 ms for cardiac imaging [?]. Nevertheless, the considerable production expense confined EBCT exclusively to laboratory research. With continuous advances in X-ray source technology, source sizes have gradually reduced to the millimeter scale. Miniature X-ray sources can be classified by electron generation method into thermal cathode sources [?, ?] and field emission cold cathode sources [8–10]. Thermal cathode miniature sources still rely on high-temperature heating of cathode materials to emit electrons, resulting in long switching response times that limit performance in high-speed dynamic applications. In contrast, miniature field emission cold cathode sources constructed from nanomaterials such as carbon nanotubes (CNTs) offer significant advantages: they enable further miniaturization, operate with lower power consumption, and achieve substantially shorter switching response times. These advantages make field emission X-ray sources highly promising for medical imaging and industrial non-destructive testing applications.

With advances in field emission cold cathodes, practical implementation of stationary CT systems composed of multiple sources has become feasible. A stationary CT scanner arranges multiple fixed X-ray sources around the scanned object and acquires projections from different angles by rapidly switching sources through electronic control. Therefore, stationary CT scanners overcome centrifugal force constraints and enable faster scanning speeds without dynamic rotation of the X-ray source and detector. The CNT X-ray source array was first applied to stationary chest tomosynthesis, successfully reducing motion artifacts in conventional tomosynthesis [11–13]. Compared to stationary chest tomosynthesis, stationary CT imaging is far more complex than simply replacing the rotating X-ray tube with a stationary CNT source array. Since CT imaging requires nearly full-angle (360°) projection data, the fixed geometry of both X-ray sources and detector modules inevitably leads to X-ray path obstruction issues where ray paths may be blocked by either the source array or detector array. Enzhuo et al. [?] designed rotation-free square and hexagonal stationary

micro-CT systems. Two or three contiguous linear source arrays combined with two or three linear detector arrays form square or hexagonal geometries. In these designs, the scan angle range was limited to approximately 180° , and CT images were reconstructed using iterative reconstruction algorithms. Chen et al. [?] proposed a helical interlaced source-detector array CT architecture utilizing cylindrically distributed sources and a detector array. Missing data caused by source obstruction was compensated using interpolation, and a Katsevich-type reconstruction was implemented for fast approximate image reconstruction. Gonzales et al. [?] introduced a multi-plane scanning scheme for baggage screening, in which two pairs of linear source and detector arrays are positioned in two separate transverse planes while the screened object moves along the z-axis. Due to the noncircular, limited-angle scanning trajectory, CT reconstruction was performed using an accelerated compressed sensing algorithm, with an analytical reconstruction algorithm for this geometry provided in [?]. Similarly, a three-plane stationary CT prototype was developed and experimentally demonstrated to meet requirements for head CT imaging [?]. To obtain complete, full-angle projection data without missing information, Thompson et al. [?] developed a source-detector double-ring configuration consisting of a source ring and a detector ring with a slight offset in the z-axial direction to avoid ray path obstruction. Although this geometry enables acquisition of projections from all angles, geometric deviations caused by tilted scanning can result in artifacts in reconstructed images.

Due to incomplete projection data from non-ideal scanning trajectories (e.g., sparse-view or limited-angle acquisitions) or ray path obstructions in stationary CT systems, conventional analytical reconstruction methods such as filtered backprojection [?] (FBP) are often inapplicable. Although iterative algorithms [?, ?] can reconstruct images from incomplete data, their high computational complexity makes them impractical for real-time imaging applications such as security screening and industrial non-destructive testing. Recently, the advent of data-driven deep learning paradigms [?, ?] has revolutionized CT reconstruction by enabling faster reconstruction, enhancing image quality, and demonstrating great potential for mitigating artifacts caused by incomplete projection data. Deep learning can compensate for missing information from undersampling and limited angles by learning prior knowledge of scanned objects from vast amounts of data. Deep learning-based reconstruction methods can be categorized into three types based on target domain: direct sinogram restoration in the projection domain [25-28], artifact correction in the image domain [29-34], and dual-domain joint optimization models that integrate information from both projection and image domains [35-41]. Deep learning demonstrates strong potential for mitigating projection incompleteness in stationary CT systems through integration of prior knowledge. Developing deep learning reconstruction frameworks customized for the geometry and sampling characteristics of stationary CT systems remains a valuable and critical research direction.

In this work, we propose a new stationary CT system design (Alternating Source-

Detector Array stationary CT, ASDA-sCT) where X-ray sources and detectors are alternately arranged on a circular ring. Since detectors are embedded between X-ray sources, projection data occluded by sources can be approximately recovered via interpolation from adjacent detector signals. The restored sinogram can then be used directly to reconstruct CT images using filtered back-projection. To ensure projection angular coverage while minimizing projection loss from source occlusion, the system adopts a short-scan acquisition mode. Through simulation experiments, we investigate the optimal number of X-ray sources for different exit window sizes. Beyond reconstructions using analytical and iterative methods, we also introduce a tailored deep learning framework designed to restore projection discontinuities and correct undersampling artifacts inherent to the ASDA-sCT system.

Our contributions are outlined as follows: - We propose a novel stationary CT design (ASDA-sCT) with alternating X-ray sources and detectors on a circular ring using a short-scan mode. - The ASDA-sCT design enables convenient application of analytical reconstruction algorithms. Through simulation experiments, we investigate the effects of X-ray source number and exit window size on reconstruction quality and determine the optimal source configuration. - We propose a three-stage dual-domain cascade network model tailored for the ASDA-sCT system. The model incorporates a novel DFInception module to enhance feature extraction in the projection domain. In the image domain, a dual-encoder architecture better fuses information from both initial and refined reconstructions. These innovations effectively improve reconstructed image quality.

The remaining content is organized as follows. In Section II, we provide a detailed description of the system design and present analytical, iterative, and deep learning-based reconstruction methods. Section III presents the experimental setup, results, and discussion. Conclusions are drawn in Section IV.

II. MATERIALS AND METHODS

A. System Description

In stationary CT systems, the fixed geometric configuration of X-ray sources and detectors inherently results in incomplete projection sampling. Specifically, full-angle scans suffer from unavoidable obstruction of ray paths by source or detector components, leading to missing projections and degraded reconstruction quality. To overcome these limitations, we propose the ASDA-sCT system employing a short-scan acquisition mode. The geometric configuration of ASDA-sCT is illustrated in Fig. 1 [Figure 1: see original paper]. X-ray sources are uniformly distributed along a circular arc spanning from 0 to $\pi + 2\gamma$, where 2γ denotes the fan angle of sources. A complete set of short-scan projections is acquired by rapidly switching between sources. The detector array is divided into two segments: a continuous detector array covers the angular range from $\pi + 2\gamma$ to 2π , while an interleaved detector array is embedded in the gaps between X-ray sources. The short-scan acquisition mode in ASDA-sCT not only reduces

projection data loss but also decreases the required number of X-ray sources and increases acquisition efficiency. For regions with missing projection data, interpolation from adjacent detector signals can estimate absent measurements, thereby preventing the reconstruction task from degenerating into a limited-angle CT problem.

In summary, the ASDA-sCT geometry effectively mitigates inherent ray-path obstruction problems in stationary CT system design. However, projection discontinuities caused by source obstruction and artifacts from sparse angular sampling remain protogenetic issues for practical application. Hence, we focus on advancing the reconstruction algorithm to improve image quality under these constraints.

Fig. 1. Geometric configuration of the ASDA-sCT system. The red dots represent X-ray sources uniformly distributed along a circular arc from 0 to $\pi + 2\gamma$. Detectors are inserted into the gaps between X-ray sources, forming an alternating arrangement of sources and detectors.

B. System Parameters

Table 1 . Parameters of the ASDA-sCT Configuration.

The geometric configuration of the ASDA-sCT system is summarized in Table 1. The system utilizes miniature CNT X-ray sources with a fan angle of 60° (half-angle $\gamma = 30^\circ$), uniformly distributed along a circular detector ring with a radius of 512 mm. This setup provides an effective field of view (FOV) diameter of 512 mm, adequately satisfying imaging requirements for both medical diagnostics and security screening applications.

In the ASDA-sCT system, imaging quality is strongly influenced by X-ray exit window size and the number of X-ray sources. Due to ray path obstruction, detectors cannot be positioned within the exit window region, resulting in missing projection data where sources occupy space on the detector ring. As the X-ray exit window size increases, the available detector area within the source-detector alternating segment decreases, causing a larger fraction of projections to be lost. The proportion of missing projections can be quantified as:

$$\epsilon = \frac{N \cdot s}{(2\gamma_m + \pi)R}$$

where N is the number of X-ray sources, s is the size of the X-ray exit window, R is the radius of the detector ring, and L is the arc length of the source-detector alternating segment.

When sources fully occupy this segment ($\epsilon = 100\%$), all projection data in that region are lost, and the reconstruction task deteriorates into a limited-angle problem. Moreover, the exit window size constrains the maximum number of deployable sources, which can be estimated as:

$$N_{\max} = \left\lfloor \frac{(2\gamma_m + \pi)R}{s} \cdot \epsilon_{\max} \right\rfloor$$

where $\epsilon_{\max}$ denotes the maximum acceptable proportion of missing projections.

In this study, we consider three configurations with X-ray exit window sizes of 5 mm, 10 mm, and 20 mm. As illustrated in Fig. 2 [Figure 2: see original paper], the proportion of missing projections increases linearly with the number of sources. Taking into account the non-negligible size of detectors embedded between sources, we set the maximum tolerable projection loss proportion to 90%. Under this constraint, the maximum number of deployable sources is 357, 194, and 102 for window sizes of 5 mm, 10 mm, and 20 mm, respectively.

The number of X-ray sources plays a pivotal role in determining image reconstruction quality. A smaller number of sources reduces projection loss but may lead to insufficient angular sampling, resulting in pronounced aliasing artifacts. Conversely, increasing the number of sources enhances projection number but exacerbates projection loss, potentially degrading reconstruction quality due to increased interpolation errors. Therefore, achieving an optimal balance between source number and projection completeness is essential in ASDA-sCT system design and will be further investigated in Sec. III.

Fig. 2. Proportion of missing projections as a function of source number under different X-ray exit window sizes (5 mm, 10 mm, and 20 mm). Smaller window sizes allow a greater number of sources to be accommodated at the same proportion of missing projections due to ray path obstruction.

C. Analytic Reconstruction using Parker's Smooth Weighting Function

Based on fan-beam geometric symmetry, symmetric projection paths satisfy the following relationship:

$$p(\gamma, \beta) = p(-\gamma, \pi + \beta + 2\gamma)$$

where p denotes the line integral projection, γ represents the detector coordinate position, and β is the projection angle. In a full-angle circular trajectory fan-beam CT scan, each projection path is sampled twice. To eliminate redundant projections, the short-scan acquisition mode reduces the total scan angle from 2π to $\pi + 2\gamma$ without compromising projection data completeness. The redundant projection region in a fan-beam short-scan sinogram is illustrated in Fig. 3(a) [Figure 3: see original paper].

To avoid artifacts in reconstructed images, sinogram redundancy must be reweighted to ensure each ray contributes equally to the reconstructed image.

This is achieved by applying a weighting function that equalizes the contribution of singly- and doubly-sampled projections. In this work, we adopt the smooth weighting function proposed by Parker [?]:

$$\omega_{\beta}(\gamma) = \begin{cases} \sin^2\left(\frac{\pi}{4} \cdot \frac{\beta}{\gamma_m - \gamma}\right) & 0 \leq \beta < 2\gamma_m - 2\gamma \\ 1 & 2\gamma_m - 2\gamma \leq \beta \leq \pi - 2\gamma \\ \sin^2\left(\frac{\pi}{4} \cdot \frac{\pi + 2\gamma_m - \beta}{\gamma_m + \gamma}\right) & \pi - 2\gamma < \beta \leq \pi + 2\gamma_m \end{cases}$$

The projections are then reweighted using this function, followed by image reconstruction via the filtered backprojection algorithm.

Fig. 3. Sinogram of the ASDA-sCT system. (a) Sinogram from a fan-beam short scan. The white region indicates projection paths sampled once, while the gray region represents redundantly sampled ray paths. (b) Measured sinogram in the ASDA-sCT system. Band-shaped discontinuities appear in the redundant region due to projection data loss.

Fig. 3(b) presents the measured sinogram from the ASDA-sCT system. Due to the absence of detectors at source positions, periodically spaced band-like gaps appear in the redundant region of the sinogram. Geometric ray path analysis reveals that X-rays emitted from a given source are lost when projected onto the position of an opposing X-ray source where no detectors are present. Due to the reversibility of light paths, conjugate rays traveling in the opposite direction are also missing. Consequently, conjugate projection rays are missing in pairs, making it impossible to compensate for the loss solely through source arrangement. To mitigate this discontinuity, linear interpolation using neighboring projection data can be applied to estimate missing values.

D. Iterative Reconstruction Algorithms

Compared to analytical reconstruction algorithms, iterative reconstruction methods offer greater flexibility in handling incomplete or non-uniform projection data. They enable stable image reconstruction under conditions such as sparse sampling or missing projections. Moreover, prior knowledge such as non-negativity, total variation minimization, and sparsity can be incorporated as regularization terms during the iterative process to improve reconstruction quality. The Simultaneous Algebraic Reconstruction Technique (SART) [?, ?] is one of the most widely used iterative algorithms. Unlike the Algebraic Reconstruction Technique (ART) [?], which updates pixel values sequentially for each ray, SART employs a block-wise update strategy. In each iteration, it computes corrections from all projection paths and averages them to update the image. The iterative update formula is given by:

$$x_j^{(k+1)} = x_j^{(k)} + \lambda \frac{\sum_{i=1}^M a_{ij} \frac{p_i - \langle a_i, x^{(k)} \rangle}{\|a_i\|^2}}{\sum_{i=1}^M a_{ij}}$$

where $x_j^{(k)}$ denotes the value of pixel j at iteration k , p_i is the measured projection for the i -th ray, a_i is the i -th row of the system matrix, a_{ij} is its (i,j) -th entry, and λ is the relaxation parameter. By averaging over all projections, SART reduces the impact of local noise, thereby improving reconstruction stability.

To mitigate the undersampling issue in the ASDA-sCT system, a compressed sensing (CS)-based reconstruction method with total variation (TV) regularization can be employed. The reconstruction method is based on the Adaptive Steepest Descent -Projection onto Convex Sets (ASD-POCS) algorithm [?]. It minimizes the following objective function:

$$\min_x (\|Ax - p\|^2 + \alpha \cdot \text{TV}(x))$$

where A is the system matrix, p is the measured projection data, and α is the regularization weight. The TV term, $\text{TV}(x)$, minimizes the L_1 -norm of the image gradient, encouraging piecewise-smooth structures and preserving sharp edges. ASD-POCS integrates gradient-based optimization with projection onto convex sets, ensuring convergence while enhancing image quality under sparse-view acquisition.

E. Deep Learning Reconstruction Method: A Three-Stage Dual-Domain Cascade Neural Network

Interpolation errors and the limited number of X-ray sources significantly degrade CT image reconstruction quality. Recently, data-driven deep learning methods have demonstrated strong potential in learning the underlying structure of scanned objects to compensate for missing information caused by sinogram discontinuities and undersampling. Therefore, we propose a Three-Stage Dual-Domain Cascade neural network (TSDDC-Net) that incorporates prior knowledge to improve reconstruction quality. An overview of the proposed deep learning-based reconstruction framework is presented in Fig. 4 [Figure 4: see original paper].

1. Sinogram Restoration

In the first stage, linear interpolation is used to coarsely restore discontinuities in the measured sinogram. To alleviate undersampling artifacts, interpolation is also applied along the angular direction to enhance projection density. However, this coarse restoration process inevitably introduces substantial interpolation errors, which limit reconstructed image quality. Thus, a subsequent correction stage is necessary to address these errors and improve image quality.

2. Sinogram-Domain Network

In the second stage, a UNet-based Sinogram-Domain Network (SD-Net) corrects interpolation errors in the sinogram. The network adopts the classical encoder-decoder structure, where multi-scale features are extracted and hierarchically upsampled to produce a refined sinogram. To enhance the network'

s feature extraction capability, we propose a Deformable Inception (DFInception) module that integrates deformable convolution [?] with the InceptionNext module [?, ?]. Deformable convolution introduces learnable offset parameters to standard convolution operations, enabling the network to adaptively adjust sampling locations of convolutional kernels. This mechanism allows the receptive field to dynamically change its shape and position in response to the geometric structure of input features. The deformable convolution operation can be expressed as:

$$Y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot X(p_0 + p_n + \Delta p_n)$$

where X and Y denote input and output feature maps, respectively, p_0 is the position of the current output location, $\mathcal{R}$ represents the receptive field of the convolution kernel, p_n is the predefined offset of the n -th sampling point in $\mathcal{R}$, $w(p_n)$ is the kernel weight at position p_n , and $\Delta p_n \in \mathbb{R}^2$ is the learnable offset for sampling position p_n .

The core idea of the Inception module is to apply multiple convolutional filters with different kernel sizes in parallel within the same layer, enabling multi-scale feature extraction. The operation can be expressed as:

$$Y = X + \text{Concat} \left(\sum_n f_{\tilde{k}_i}(X_i) \right), \quad X = \text{Concat}(X_i)$$

where the input feature map X is split into n channel groups X_i . Each X_i is processed by a deformable convolution f with kernel size $\tilde{k}_i$. The outputs are then concatenated and added to the original input via a residual connection.

The DFInception module design is motivated by two key observations. First, sinogram data consist of overlapping sinusoidal trajectories, which are inherently global patterns across the entire image. Standard convolutional layers are limited to local receptive fields and thus struggle to capture such long-range dependencies. In contrast, our DFInception module combines deformable convolutions and multi-scale kernels to effectively extend the receptive field and capture long-range interactions with significantly fewer parameters than Transformer-based models. Second, due to large missing regions in sinograms, using elongated convolutional kernels (e.g., 1×11) is essential for enabling the network to directly connect central pixels of missing regions with surrounding measured areas in high-resolution layers of the UNet architecture. This facilitates early-stage compensation and significantly improves error correction performance.

When supervised by ground-truth well-sampled sinograms, SD-Net effectively learns to correct interpolation errors. The refined sinogram is subsequently reconstructed via filtered backprojection to produce a refined CT image, which

is then fed into the image-domain refinement stage. The network is trained using a mean squared error (MSE) loss:

$$\mathcal{L}_{SD} = \|\hat{S} - S_{gt}\|^2$$

where $\hat{S}$ is the refined sinogram and S_{gt} represents the ground truth.

3. Image-Domain Network

Although sinogram-domain correction reduces major artifacts, even small residual errors in the sinogram can lead to noticeable artifacts in reconstructed CT images, such as blurring, structural distortion, and loss of edge contrast. This observation highlights that prior knowledge in the sinogram domain alone is insufficient for high-fidelity reconstruction. To further enhance image quality, especially regarding structural details and edge preservation, we introduce an Image-Domain refinement Network (ID-Net) designed to correct interpolation errors that remain unaddressed or are newly introduced in the sinogram domain.

The network is fed with two CT images: one reconstructed from the SD-Net-corrected sinogram and another from the raw interpolated sinogram. In this way, prior knowledge introduced from the sinogram domain is effectively utilized while retaining original measured information. Two separate encoders extract multi-scale features from both inputs, leveraging complementary information from sinogram correction and initial reconstruction. These features are then fused through a decoder to generate the final high-quality CT image. The network is supervised using CT images reconstructed from fully sampled sinograms and trained with an MSE loss:

$$\mathcal{L}_{ID} = \|\hat{I} - I_{gt}\|^2$$

where $\hat{I}$ denotes the predicted CT image and I_{gt} represents the ground truth.

III. RESULTS AND DISCUSSION

A. Experiment Dataset

We evaluate the ASDA-sCT design and its reconstruction method using a Shepp-Logan phantom and a publicly available abdominal CT dataset authorized for the 2016 NIH-AAPM-Mayo Clinic Low Dose CT Grand Challenge by Mayo Clinic. This dataset contains 6,146 full-dose abdominal CT 2D slices from 42 anonymous patients, divided into a training set of 4,138 CT images (27 patients), a validation set of 625 CT images (5 patients), and a testing set of 1,356 CT images (10 patients). Before training, CT images and projections are normalized to $[0,1]$. The photon number was set to 1×10^7 in the simulation. The number of iterations was set to 200 for both SART and POCS-TV. The regularization weight α in POCS-TV was set to 1. SD-Net and ID-Net were trained for 200

epochs with an initial learning rate of 0.0005. The system configuration is listed in Tab. 1. All experiments were run on a computer with an Intel(R) Xeon(R) Silver 4210R CPU and an NVIDIA GeForce GTX 3090.

B. Find The Optimal Source Number

In this study, we conducted simulated reconstruction experiments using training dataset CT images under different numbers of X-ray sources, followed by quantitative evaluation of reconstruction results shown in Fig. 6 [Figure 6: see original paper]. The experiments compared reconstructed images from ASDA-sCT systems with different exit window sizes to those from sparse-view CT systems with the same number of sources but without sinogram discontinuities. Results demonstrate that both the number of sources and exit window size are critical factors influencing reconstruction quality.

When the number of sources is small, reconstruction quality of the stationary CT system is comparable to that of the sparse-view CT system. In this case, image degradation is mainly due to aliasing artifacts caused by undersampling. As the number of sources increases, reconstruction quality gradually improves. However, improvement in the stationary CT system is less than that in the sparse-view CT system, primarily because interpolation errors become more pronounced due to increased projection loss.

The study further reveals that source window size substantially impacts reconstruction quality. Larger window sizes necessitate interpolation over broader regions, which increases interpolation errors. Consequently, for a fixed number of sources, systems with smaller window sizes yield lower interpolation errors and achieve better reconstruction quality. Remarkably, when the window size is reduced to 5 mm, reconstruction quality of the stationary CT system becomes closely comparable to that of the sparse-view CT system with the same number of sources. This finding suggests that further reduction in source size could effectively suppress interpolation artifacts, enabling the stationary CT system to achieve image quality comparable to rotating CT systems while avoiding projection loss caused by ray path obstruction.

Overall, although increasing the number of sources exacerbates interpolation errors, it more effectively mitigates dominant aliasing artifacts caused by undersampling. Therefore, the optimal number of sources in the ASDA-sCT system should be maximized within physical constraints of X-ray source placement. Specifically, experimental results indicate that when the maximum allowed proportion of missing projections is set to 90%, the optimal number of sources for exit window sizes of 5 mm, 10 mm, and 20 mm is 357, 194, and 102, respectively.

C. Experiments on the Shepp-Logan Phantom

Fig. 7 [Figure 7: see original paper] illustrates measured sinograms of the ASDA-sCT system under different X-ray exit window sizes. In the upper and lower triangular regions of the sinogram, known as ray-redundant regions, strip-like

gaps appear due to lack of detector coverage at source positions. For all three systems, with optimal numbers of X-ray sources corresponding to window sizes of 5 mm, 10 mm, and 20 mm, the proportion of missing projections in redundant ray regions is approximately 90%, as previously specified. Larger exit window sizes result in wider projection gaps and a greater number of missing pixels requiring interpolation, which leads to increased interpolation errors. Conversely, smaller window sizes allow deployment of more X-ray sources within the same scanning trajectory, which not only reduces aliasing artifacts but also decreases interpolation errors.

To recover missing projection data, linear interpolation is applied based on available neighboring signals within each source gap. This approach performs well in regions where projection values change gradually. However, in areas with large projection gradients, typically corresponding to structural edges in the image, linear interpolation introduces significant errors. Such errors not only contribute to visible artifacts but also degrade edge representation accuracy and structural detail in final reconstructed images.

Fig. 8 [Figure 8: see original paper] shows reconstruction results of the Shepp-Logan phantom using both analytical and iterative methods. Compared with results from sparse-view CT, ASDA-sCT reconstructions exhibit not only aliasing artifacts but also more pronounced errors near edge structures due to interpolation inaccuracies. As exit window size decreases, the system accommodates more sources, thereby reducing both aliasing and interpolation-related artifacts. Although iterative algorithms such as SART and POCS-TV can effectively suppress aliasing artifacts, such methods entail substantial increases in computational complexity and reconstruction time.

D. Experiments on the Abdominal CT Dataset

Fig. 9 [Figure 9: see original paper] and Fig. 10 [Figure 10: see original paper] present abdominal CT reconstruction results obtained using analytical algorithms, iterative methods, and deep learning approaches under X-ray exit window sizes of 10 mm and 20 mm, respectively. Among traditional methods, the POCS-TV algorithm, which incorporates TV regularization, achieves more effective suppression of aliasing artifacts compared to analytical and SART algorithms. However, strong regularization constraints lead to excessive smoothing, resulting in diminished edge contrast, loss of fine structural details, and even plastic-like artifacts.

In contrast, data-driven deep learning methods exhibit incomparable advantages in both artifact suppression and structural detail preservation. We compared three representative deep learning models—FBPConvNet [?], HD-Net [?], and DuDoTrans [?]. All models were trained on the same dataset with their respective optimal training configurations as reported in original publications. The image-domain-only model FBPConvNet still struggles with limited edge sharpness and incomplete recovery of fine structures. By comparison, models such as

HD-Net, DuDoTrans, and the proposed TSDDC-Net, which incorporate prior knowledge from both projection and image domains, demonstrate substantially improved reconstruction performance. Among them, TSDDC-Net consistently achieves the best results in minimizing artifacts while preserving fine anatomical details.

When the system's X-ray exit window size increases to 20 mm, the reduced number of deployable X-ray sources leads to more severe interpolation errors and aliasing artifacts in the initial reconstruction image. Consequently, performance of all reconstruction methods noticeably degrades. Analytical and iterative methods, in particular, suffer from significant blurring and detail loss. For instance, anatomical structures shown in Fig. 10(c) become indistinct and barely recognizable. Among deep learning methods, all comparison models exhibit noticeable structural degradation, struggling to recover fine details as well. In contrast, the proposed TSDDC-Net preserves tissue boundaries and edge structures, demonstrating superior stability and robustness even under challenging ASDA-sCT system configurations with larger window sizes. These results demonstrate the superiority of our TSDDC-Net, specifically designed for ASDA-sCT systems.

To further evaluate the effectiveness of the proposed dual-domain architecture, particularly the DFInception module in the projection domain and the dual-encoder design in the image domain, we conducted a series of ablation experiments, as presented in Table 3. Quantitative results in Table 2 confirm that the proposed TSDDC-Net, incorporating our novel architectural components, achieves the best performance across all evaluation metrics.

Results reveal that models leveraging only single-domain priors, either the sinogram domain or the image domain, yield lower performance compared to the dual-domain model. This demonstrates the effectiveness of jointly exploiting complementary information from both domains to achieve superior reconstruction quality. Specifically, the projection-domain-only model outperforms the image-domain-only model. The relatively smooth variations and simpler structural patterns in projection data make it easier for the model to learn and generalize. In contrast, image-domain data often exhibits complex aliasing, interpolation-induced artifacts, and noise, which substantially increase learning difficulty.

Furthermore, incorporation of the DFInception module enhances sinogram refinement capability in the projection domain, improving quality of the refined CT image. Meanwhile, the dual-encoder design in the image domain effectively integrates complementary features from the initial reconstructed image and the SD-Net-refined image, leading to enhanced edge preservation and finer structural detail in the final reconstructed CT image.

IV. SUMMARY

This study proposes an Alternating Source-Detector Array Stationary CT (ASDA-sCT) system capable of tomographic imaging without gantry rotation. The system utilizes a computationally efficient interpolation strategy to complete missing projections, enabling direct reconstruction using filtered back-projection. In the proposed design, maximizing the number of X-ray sources is crucial for achieving optimal reconstruction quality. Furthermore, we introduce TSDDC-Net, a deep learning reconstruction model specifically tailored for this system. By incorporating the novel DFInception feature extraction module and an advanced dual-domain architecture, TSDDC-Net effectively corrects interpolation errors and suppresses aliasing artifacts. Experimental results highlight the ASDA-sCT system's strong potential in clinical imaging and industrial nondestructive testing.

The ASDA-sCT system offers diverse potential applications. By incorporating multi-row detectors and adopting a cone-beam CT (CBCT) geometry, the system can be configured into a stationary CBCT (sCBCT) system, effectively addressing the slow scanning speed of conventional CBCT. More importantly, sCBCT enables nearly motion artifact-free real-time 4D dynamic reconstruction. To address undersampling challenges inherent in the ASDA-sCT system, we can increase the number of projections by employing a multi-plane scanning strategy. Each scanning plane is equipped with an ASDA-sCT scanner, capturing projections from different view angles. This design offers a promising solution for applying the ASDA-sCT system in industrial CT inspection and security screening.

Due to the large amount of CT data of anatomical structures available in clinical practice and the excellent performance of deep learning reconstruction, deep learning-based reconstruction methods are expected to facilitate widespread clinical adoption of ASDA-sCT. The ASDA-sCT system acquires fewer projections, reducing radiation dose while maintaining diagnostic quality. In addition, its extremely fast scanning speed allows imaging of rapidly moving objects, such as in cardiac CT imaging.

Nevertheless, certain fundamental challenges inherent to stationary CT remain unresolved. One prominent issue is X-ray scatter, which arises from the system's collimator-free design and leads to significant scatter-induced artifacts. Developing effective scatter correction strategies will be a critical and promising direction for future research in stationary CT system design.

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