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Imaging Performance of a Stationary Tomography Baggage Scanner with Downward π -Angle Sparsity

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Abstract—This study introduces a novel stationary tomography baggage scanner that employs a downward π -angle configuration to enhance image quality under sparse-view conditions. Although stationary computed tomography (CT) systems offer mechanical simplicity and high throughput, the limited number of projections poses a challenge to image reconstruction. To address this, we investigated four angular configurations by reconstructing images using a compressed sensing (CS)-based iterative algorithm and conducted comprehensive evaluations of the image quality through various quantitative metrics. Using a realistic numerical phantom, the CS-based reconstruction consistently surpassed conventional filtered backprojection based reconstruction across all configurations, demonstrating improved image quality. Among the designs tested, a non-uniform π -angle configuration provided the most efficient angular sampling, yielding superior image quality as confirmed by ray distribution analysis, sinogram characteristics, and three quantitative metrics. These results demonstrate that geometric optimization coupled with advanced reconstruction can substantially improve imaging performance in sparse-view baggage screening systems.

Index Terms—Computed tomography, Stationary tomography, baggage CT, Aviation security

I. INTRODUCTION

TWO-dimensional (2D) X-ray inspection systems have long been utilized in aviation security to screen passenger baggage and personal belongings [1–3]. These systems are effective in detecting high-contrast materials and have the advantages of fast operation and simple system design. However, their fundamental limitation lies in the absence of in-depth information, which makes it difficult to accurately infer the three-dimensional (3D) shape, composition, and precise location of concealed threats. Overlapping objects in 2D projections often results in ambiguous interpretation, reducing detection reliability in complex scenarios. To overcome these limitations, there is increasing interest in advanced 3D X-ray imaging technologies—such as computed tomography (CT) and digital tomosynthesis (DTS)—that provide volumetric information for more accurate and consistent threat identification [4–7]. These modalities enhance the interpretability of images by resolving structural overlaps and

enabling depth localization. Because aviation security demands both accuracy and efficiency, the development of fast and compact 3D imaging systems has become a critical area of research. In response to these needs, SST Labs Co. (Korea) recently developed a stationary computed tomography (SCT) system based on sparse 2π -angle geometry [8]. This system comprises 16 monoblock X-ray sources paired with linear-array detectors, that are uniformly distributed over a 360° angular span. This stationary configuration allows the system to simultaneously acquire projection data from multiple directions without mechanical rotation, thereby improving acquisition speed, system robustness, and operational simplicity. Fig. 1 illustrates the schematic the SCT system.

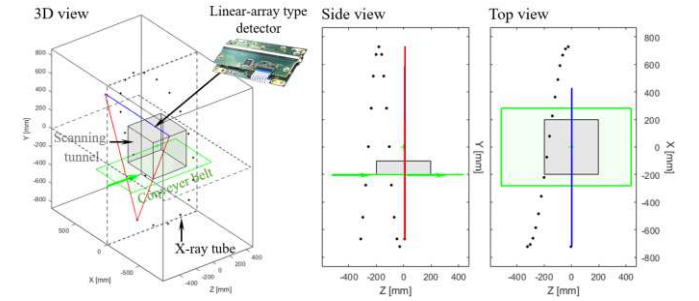


Fig. 1. Schematic of a stationary CT system with 2π -angle sparsity, consisting of 16 pairs of monoblock X-ray sources and linear-array detectors. The source-detector pairs were uniformly distributed over a 360° angular span, enabling the acquisition of projection data without mechanical rotation.

Although stationary CT offers significant benefits in terms of mechanical stability and rapid scanning, the limited number of projection views inherently introduces a sparse view condition. This often leads to undersampling artifacts—such as streaks and blurring—that degrade the image quality. To ensure diagnostic accuracy and effective threat detection, it is essential to optimize both the acquisition geometry and the reconstruction algorithm. Filtered backprojection (FBP) reconstruction algorithm is commonly used because of its computational efficiency, but its performance deteriorates under sparse-view conditions that do not satisfy the Nyquist sampling criterion [9]. To address this problem, compressed sensing (CS)-based iterative reconstruction methods have been developed [10–12]. These approaches rely on sparsity priorities

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and regularization techniques to reconstruct high-quality images from limited projection data, making them particularly effective for sparse-view systems. Deep learning-based reconstruction methods have also shown promise in recent years [13–15]. However, their use in aviation security is still limited due to concerns about performance with different baggage types, lack of labeled threat data, and challenges with transparency and regulations in safety-sensitive environments.

In this study, we propose an integrated approach to improve the image quality in sparse-view SCT. We systematically evaluated four angular acquisition configurations, each reconstructed using both FBP- and CS-based algorithms. By analyzing the effects of system geometry and reconstruction methodology, our goal was to identify optimal configurations that enhance image quality while maintaining operational throughput, supporting more effective and reliable 3D security screening.

II. MATERIALS AND METHODS

A. Source–detector configurations for sparse-view SCT

Fig. 2 presents the four source–detector configurations analyzed in this study. Case 1 served as the reference and represented the conventional full-view arrangement with projection coverage over the entire 360° angular range. Case 2 adopted an upward π -angle sparse configuration, where projection views were limited to the upper half of the scan field. Cases 3 and 4 implemented downward π -angle sparse setups, each focusing on the lower half of the angular range. In Case 3, source–detector pairs are distributed uniformly (equiangular layout), whereas Case 4 uses a wide-edged distribution designed to improve the angular coverage near the object boundaries. In all setups, the green outline represents the conveyor belt transporting baggage through the scanning field, and the red and blue lines indicate the active source–detector pairs.

B. CS-based iterative reconstruction algorithm

The X-ray imaging process can be modeled as a discrete linear system:

$$\begin{aligned} Ax &= p, \\ x &= (x_1, x_2, \dots, x_N)^T, \\ p^m &= (p_1, p_2, \dots, p_M)^T, \\ A &= \{a_{ij}\}, \quad i=1, 2, \dots, M \text{ and } j=1, 2, \dots, N, \end{aligned} \quad (1)$$

where x is the image vector to be reconstructed, p^m is the measured projection vector, N and M are the number of voxels and total number of sampling points in the projection data, respectively, the superscript T is the transpose operator, and A is the system matrix that relates to the images and projection domains.

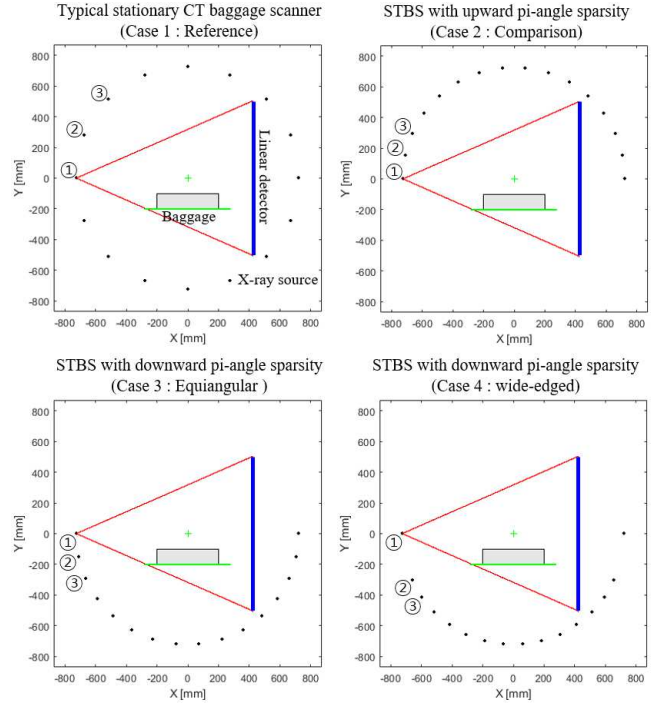


Fig. 2. Source–detector configurations evaluated in this study. Case 1 (top left) shows a full-view reference arrangement. Case 2 (top right) illustrates an upward π -angle sparse configuration. Cases 3 (bottom left) and 4 (bottom right) depict downward π -angle sparse configurations, employing equiangular and wide-edged angular distributions, respectively.

In the context of CS, image reconstruction is formulated as an optimization problem that minimizes the following objective function:

$$f(x) = \frac{1}{2} \|Ax - p^m\|_2^2 + \alpha \|Dx\|, \quad (2)$$

where D denotes the forward difference operator approximating the image gradient, and α is a regularization parameter controlling the trade-off between data fidelity and sparsity. The solution x^* is iteratively updated using the gradient-projection Barzilai–Borwein (GPBB) method [16], which efficiently converges to a solution within a defined tolerance.

Fig. 3 outlines the reconstruction workflow using the CS. The process begins with projection acquisition (p^m) as the baggage moves along the conveyor. An initial image ($x^{(0)}$) is generated using simple backprojection. This estimate is then forward-projected to produce computed projections ($p^c = Ax$). The algorithm updates x by determining the optimal step size (Δs) by evaluating the discrepancy between p^m and p^c , along with the image gradient Dx . The image was iteratively refined until the difference between successive iterations fell below a predefined threshold (ϵ). Each iteration involves one forward and one backward projection using the system matrix A . This CS-based reconstruction method is particularly effective under sparse-view conditions, as it exploits the sparsity characteristics of the target image to recover the structural details from limited projection data. Unlike conventional FBP, the CS-based approach substantially suppresses undersampling artifacts—such as streaking—and preserves the image details. Consequently, it enables the generation of high-quality images suitable for aviation security screening, even with limited angular coverage.

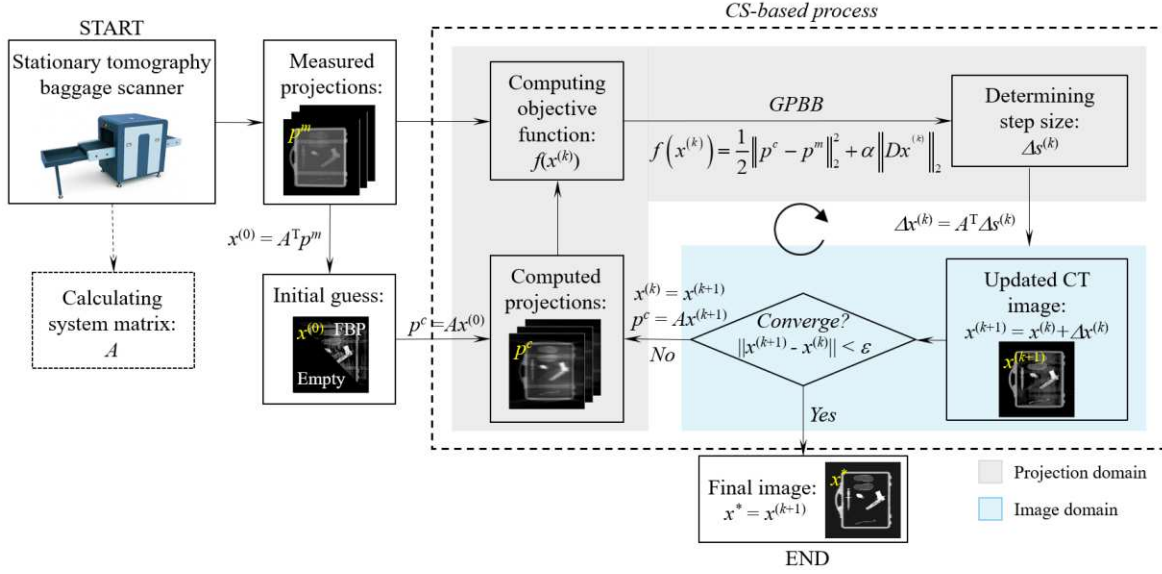


Fig. 3. Flowchart of CS-based image reconstruction process for the SCT system. The algorithm iteratively refines the CT image by minimizing an objective function that balances fidelity with the measured projection data—modeled via the system matrix—with sparsity constraints to suppress artifacts and enhance image quality under sparse-view conditions.

C. Simulation setup

Fig. 4 presents the numerical suitcase phantom used in this simulation study, designed to include a representative assortment of common travel items and potential threat objects for extensive performance evaluation. The 3D rendered image on the left shows a variety of items—such as a knife, grenade, pistol, toothbrush, slippers, and folded shirts—carefully selected to replicate realistic baggage compositions typically encountered in airport security screening. These items encompass both harmless and suspicious objects, allowing balanced and practical scenario modeling. On the right, orthogonal cross-sectional slices (top and side views) reveal the internal layout and spatial distribution of the contents, which are critical for evaluating scanning and reconstruction performance. The materials and corresponding density values assigned to each object are detailed in Table I. Each item was modeled using a material that approximated its real-world counterpart in terms of the X-ray attenuation characteristics. Density data were sourced from the National Institute of Standards and Technology (NIST) database [17], a widely accepted reference for accurate material properties in scientific simulations. This approach ensures that the phantom realistically reflects both the physical and radiological attributes of the actual luggage contents, thereby enhancing the credibility of the simulation results.

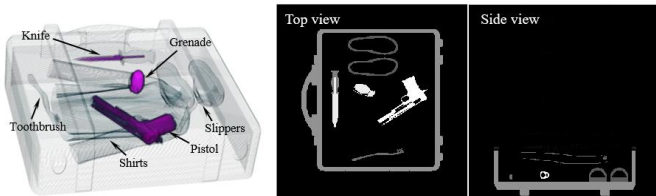


Fig. 4. Numerical suitcase phantom used in the simulation, designed to include both common travel items and potential threat objects.

TABLE I
MATERIAL COMPOSITION AND DENSITY VALUES FOR OBJECTS IN THE NUMERICAL SUITCASE PHANTOM

Items	Composition	Density (g/cm ³)
Air	Air, Dry (Near Sea Level)	0.0012
Shirt	Radiochromic Dye Film (Nylon)	1.0800
Hanger	Aluminum	2.6990
Grenade	Silicon	2.3300
Gun	Aluminum	2.6990
Knife	Polyvinyl Chloride	1.4060
Knife handle	Polymethyl Methacrylate	1.1900
Slipper	Polyethylene	0.9300
Toothbrush	Bakelite	1.4500
Suitcase	Carbon, Graphite	1.7000

For each scan, a total of 16 projection views were acquired. The source-to-detector and source-to-object distances were set to 1150 mm and 724.95 mm, respectively. The detector was comprised of a 640×1 linear array with a pixel size of 1.575 mm $\times$ 1.575 mm. The reconstructed image volume was defined as $400 \times 400 \times 400$ voxels with an isotropic voxel spacing of 0.9929 mm. To assess the influence of system geometry on image quality, four angular configurations (Cases 1 through 4) were evaluated. A summary of the relevant imaging parameters used in the SCT reconstruction was also provided in Table II.

TABLE II
IMAGING PARAMETERS USED FOR SCT RECONSTRUCTION

Parameters	Dimension
No. of projections	16
Source-to-detector distance	1150 mm
Source-to-object distance	724.95 mm
Pixel dimension	640×1
Pixel size	1.575 mm $\times$ 1.575 mm
Voxel dimension	$400 \times 400 \times 400$ voxels
Voxel size	0.9929 mm
Source-detector geometry	Case 1–4

D. Quantitative evaluation

To assess the quality of the reconstructed image, we employed three widely used quantitative metrics—root mean

square error (RMSE), universal quality index (UQI), and peak signal-to-noise ratio (PSNR)—each capturing complementary aspects of image fidelity and structural similarity [18–20]. UQI is a full-reference metric that quantifies the structural similarity between the reconstructed image and reference image by jointly considering luminance, contrast, and structural consistency. It is defined as:

$$UQI = \frac{2Cov(f_{rec}, f_{ref})}{\sigma_{rec}^2 + \sigma_{ref}^2} \times \frac{2\bar{f}_{rec} \cdot \bar{f}_{ref}}{\sigma_{rec}^2 + \sigma_{ref}^2}, \quad (3)$$

where $\bar{f}$ and σ denote the mean and standard deviation of the image intensities, respectively, and $Cov(\bullet)$ is the covariance between reconstructed (f_{rec}) and reference (f_{ref}) images. A higher UQI indicates better structural preservation. RMSE quantifies the average pixel-wise intensity error between two images, offering a direct measure of the overall reconstruction accuracy:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{MN} (f_{rec,i} - f_{ref,i})^2}{MN}}, \quad (4)$$

where $M \times N$ represents image dimensions. PSNR evaluates the image quality by measuring the logarithmic ratio between the peak signal intensity and the distortion introduced by the noise or reconstruction error. It is given by:

$$PSNR[dB] = 10 \times \log_{10} \left(\frac{MAX_{f_{rec}}^2}{RMSE^2} \right), \quad (5)$$

where $MAX_{f_{rec}}$ is the maximum pixel intensity value in the image. Higher PSNR values reflect a greater fidelity to the reference. Together, these metrics provide a comprehensive evaluation framework for analyzing the performance of sparse-view reconstruction strategies in terms of both numerical accuracy and structural consistency.

To enhance our understanding of the impact of each configuration on the image quality, we delineated the ray direction distribution at each voxel and introduced two complementary metrics: the number of rays intersecting voxel i (N_i) and the relative ray strength (S_i). The latter is calculated by summing the weights of all rays passing through voxel i and normalizing this value by the total ray weights across the entire image volume:

$$S_i = \frac{\sum_{r \in i} w_r}{\sum_{i=1}^N \sum_{r \in i} w_r}, \quad (6)$$

where w_r denotes the weight of ray r , and N is the total number of voxels. Both metrics were derived from the ray–voxel intersection data contained in system matrix A , which was constructed using a ray-driven forward projection method [21–23].

III. RESULTS AND DISCUSSION

Fig. 5 presents the reconstructed tomographic images obtained using both FBP-based and CS-based algorithms across the four source–detector configurations (Cases 1–4). For each case, the top and side views were shown to support the visual assessment from multiple perspectives. Although the number of

projections remained constant across all configurations, the angular sampling geometry was deliberately varied to investigate its influence under sparse-view conditions. In the FBP-based reconstructions (left), the image quality varied significantly depending on the angular setup. All configurations exhibited a certain level of streaking and structural distortion; however, the downward π -angle configurations (Cases 3 and 4) yielded more distinct object boundaries than the conventional full-view (Case 1) and upward sparse-view (Case 2) arrangements. These results highlight the importance of geometric asymmetry and directional diversity in mitigating undersampling artifacts and preserving the edge definitions. The CS-based reconstructions (right) show consistent improvements across all the configurations. The CS-based algorithm effectively suppressed streak artifacts and enhanced structural detail, particularly in Cases 3 and 4, compared to Cases 1 and 2. Compared with FBP, the CS method consistently yields superior image quality by balancing data fidelity with sparsity priors. Both methods exhibit a similar trend across configurations, with Cases 3 and 4 producing higher image quality than Cases 1 and 2, highlighting the influence of the angular sampling geometry independent of the reconstruction technique.

To understand the cause of these image quality differences, three representative voxel regions (A , B , and C) were annotated in the side view of Case 1 as shown in Fig. 5. These locations were selected to analyze the angular distribution of rays intersecting the voxels and their influence on reconstruction fidelity. Fig. 6 visualizes the ray direction distributions for each voxel on the mid-plane ($z = 200$) across all four source–detector configurations, computed from the ray–voxel intersection data in the system matrix A . In Case 1, a full 360° scanning trajectory was employed, and the directional vectors showed substantial overlap owing to antiparallel rays (e.g., 0° and 180°) contributing similar directional information, resulting in redundant angular sampling and limited projection diversity. In Case 1, the employment of a complete 360° scanning trajectory resulted in a significant overlap of the directional vectors. This overlap leads to redundant angular sampling and a restricted diversity of projections because antiparallel rays (e.g., 0° and 180°) provide similar directional information. In Case 2, the upward π -angle sparse configuration produced the most limited angular coverage at the given voxels, which was attributable to an angular range of less than 180° . This resulted in the most severe undersampling effects, as evidenced by prominent streaks and degraded structural clarity in the reconstructed images. In contrast, Case 3 employed a downward π -angle configuration with uniform angular spacing, thereby enhancing the diversity of ray distributions. Case 4 introduces a non-uniform spacing strategy within a downward π -angle configuration, concentrating projections through wider cross-section of the object to maximize directional coverage. Cases 3 and 4, through the utilization of downward π -angle configurations and enhanced angular distribution strategies, demonstrated increased projection diversity and resulted in superior image reconstruction quality compared with Cases 1 and 2.

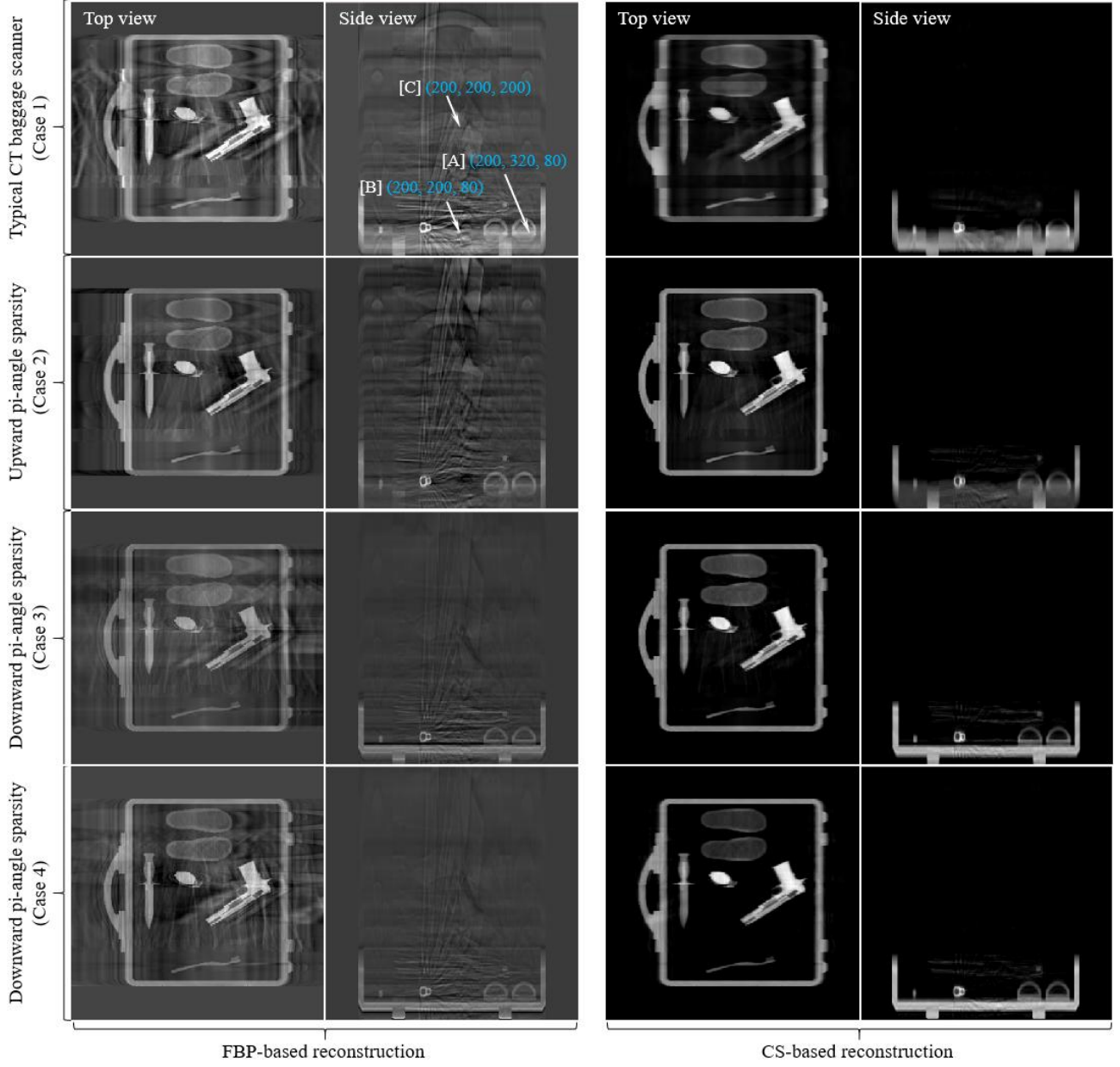


Fig. 5. Top and side views of tomographic images reconstructed using both the FBP- and CS-based algorithms across four different source–detector configurations (Cases 1–4). Each configuration illustrates how angular sampling affects the image quality under sparse-view conditions. Regions *A*, *B*, and *C* indicate selected voxel locations in the side view of Case 1, which were used to analyze the angular distribution of ray vectors for the subsequent quantitative evaluation of reconstruction performance.

Table III presents a quantitative comparison of the number of intersecting rays (N_i) and the normalized relative ray strengths (S_i) at three representative voxel locations (*A–C*), as shown in Fig. 5. Although the values differed depending on the voxel position, the overall trend consistently identified Case 4 as achieving the highest ray counts and strongest relative contributions across all the evaluated regions, whereas Case 2 consistently exhibited the lowest values in both aspects. For example, in region *A*, Case 4 records 73 rays and a relative strength of 2.17×10^{-5} , representing increases of approximately 14% in both ray count and intensity compared to Case 1. The improvement is even more pronounced relative to Case 2, with 28% more rays and 19% higher strength. Similar improvements were observed in regions *B* and *C*, further substantiating the

advantages of Case 4. The results underscore the advantage of Case 4 in delivering directionally diverse and balanced measurements under sparse view conditions. This advantage aligns with the superior image quality and minimal artifacts observed in Fig. 5.

Fig. 7 presents comparative analyses of image reconstruction quality between the FBP-based and CS-based methodologies across four distinct source–detector configurations (Cases 1–4). The results clearly demonstrate the consistent superiority of the CS-based approach across all evaluated metrics, including a lower RMSE, higher UQI, and improved PSNR values compared to the FBP-based method. Cases 3 and 4—both employing a downward π -angle configuration—consistently yielded a higher image quality than Cases 1 and 2, highlighting

the benefits of improved angular diversity under sparse-view conditions. This trend is also reflected in the quantitative metrics, with Cases 3 and 4 exhibiting better overall performance regardless of the reconstruction method. The corresponding quantitative results are summarized in Table IV, which also includes the relative improvements achieved by the CS method over the FBP approach. The relative gains, annotated as blue superscripts next to each CS value, represent the average improvement computed across all four configurations: up to 3.8-fold reductions in RMSE, over 11-fold increases in UQI, and approximately 1.8 dB enhancements in PSNR. Among the four configurations, Case 4 achieved the best overall reconstruction performance, with the lowest RMSE (0.05), highest UQI (0.96), and PSNR (24.25). These results further substantiate that the synergy of optimized angular sampling with sparsity-based reconstruction techniques leads to an improved image quality in sparse-view CT applications.

Fig. 8 presents the sinograms corresponding to Cases 1–4, reflecting the projection data patterns acquired under each angular configuration. Although Case 1 covers a full 360° range, the sinogram shows redundant sampling owing to overlapping

ray paths with similar directions. Case 2 presented the most limited angular coverage, falling short of 180° , which resulted in the sparsest sampling. This restricted geometry also led to truncated sinogram data in the upper and lower regions of the detector, indicating inadequate ray coverage across the entire detector span. Cases 3 and 4 adopted downward π -angle geometries, providing wider and more balanced coverage. Case 4 exhibits the most extensive projection distribution, yielding a comprehensive sinogram representation. Table V presents two quantitative indicators derived from the sinograms in Fig. 8: the number of shaded pixels and mean attenuation intensity. The number of shaded pixels, determined using a predefined threshold, reflects the extent of the effective angular coverage, whereas the mean attenuation indicates the average projection strength. Among the configurations, Case 4 yielded the highest number of shaded pixels (2819), signifying the broadest angular sampling. Conversely, Case 2 showed the lowest value (2265), owing to its limited angular span. Regarding projection strength, Cases 3 and 4 record higher mean attenuation values (0.47 and 0.43, respectively), outperforming Cases 1 (0.44) and 2 (0.42).

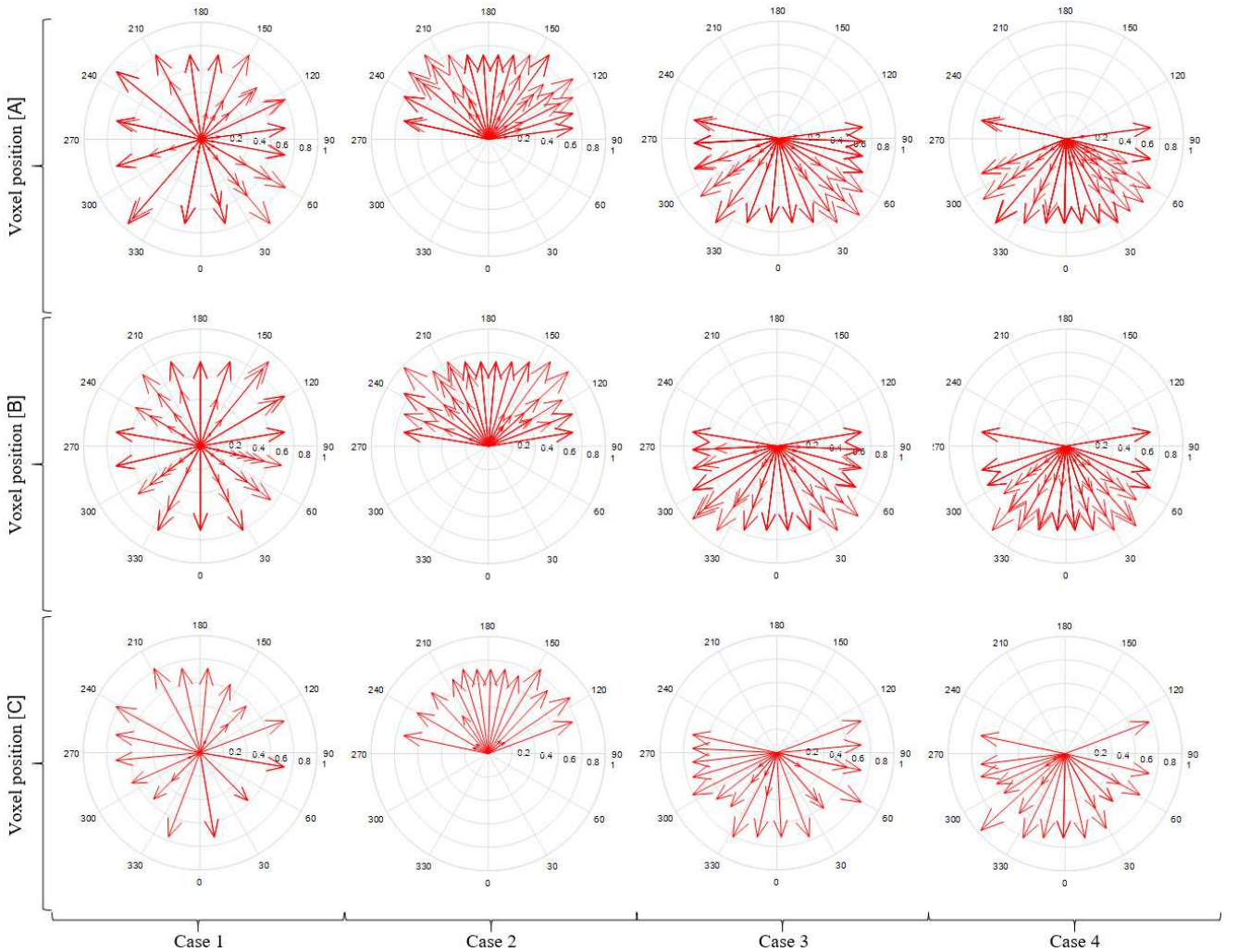


Fig. 6. Angular distribution of ray vectors intersecting representative voxels located on the mid-plane ($z = 200$) for each of the four source–detector configurations (Cases 1–4). These plots visualize the directional coverage achieved by each setup, providing insight into how projection diversity and angular sampling patterns affect the image reconstruction quality under sparse-view conditions.

TABLE III
QUANTITATIVE ANALYSIS OF RAY COUNTS AND RELATIVE STRENGTH AT SELECTED VOXELS FOR THE FOUR SOURCE-DETECTOR CONFIGURATIONS

		Case 1	Case 2	Case 3	Case 4
<i>A</i>	Ray counts	64	57	68	73
	Relative ray strength ($\times 10^{-5}$)	1.90	1.76	2.12	2.17
<i>B</i>	Ray counts	63	58	67	71
	Relative ray strength ($\times 10^{-5}$)	1.85	1.69	2.04	2.09
<i>C</i>	Ray counts	24	19	25	25
	Relative ray strength ($\times 10^{-5}$)	0.71	0.56	0.75	0.77

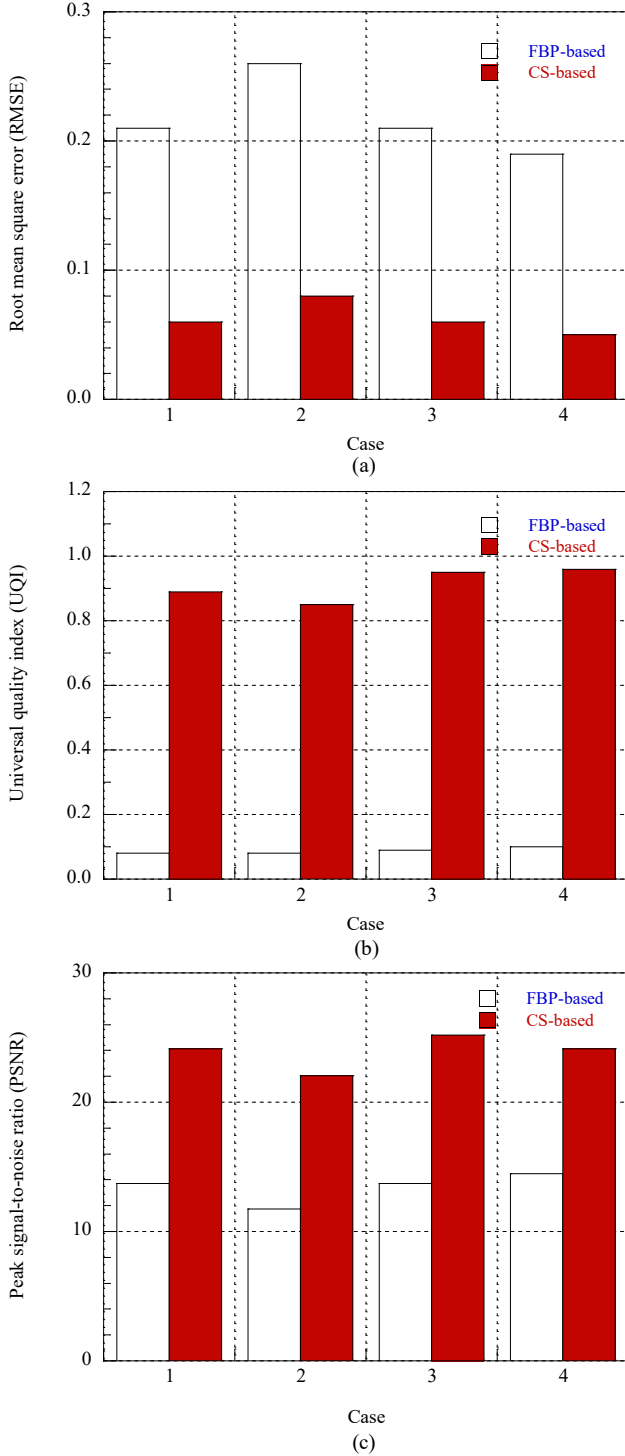


Fig. 7. Quantitative comparison of image reconstruction quality for four system configurations (Cases 1–4) using FBP-based (blue) and CS-based (red) algorithms. (a) RMSE, (b) UQI, and (c) PSNR.

TABLE IV
QUANTITATIVE EVALUATION OF IMAGE QUALITY (RMSE, UQI, PSNR) USING FBP AND CS-BASED ALGORITHMS

	RMSE	UQI	PSNR
	FBP/CS	FBP/CS	FBP/CS
Case 1	0.21/0.06 ^{3.5 ↓}	0.08/0.89 ^{11.1 ↑}	13.73/24.15 ^{1.8 ↑}
Case 2	0.26/0.08 ^{3.3 ↓}	0.08/0.85 ^{10.6 ↑}	11.74/22.04 ^{1.9 ↑}
Case 3	0.21/0.06 ^{3.5 ↓}	0.09/0.95 ^{10.6 ↑}	13.73/25.20 ^{1.8 ↑}
Case 4	0.19/0.05^{3.8 ↓}	0.10/0.96^{9.6 ↑}	14.48/24.25^{1.7 ↑}

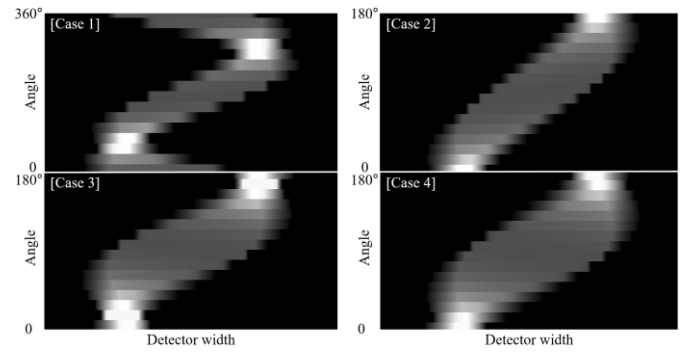


Fig. 8. Sinograms for Cases 1–4 showing the angular coverage and projection density spread across the detector width.

TABLE V
SINOGRAM-BASED QUANTITATIVE ANALYSIS FOR THE FOUR SOURCE-DETECTOR CONFIGURATIONS

	Case 1	Case 2	Case 3	Case 4
Number of shaded pixels in sinogram	2560	2265	2610	2819
Mean attenuation intensity	0.44	0.42	0.47	0.43

IV. CONCLUSION

In this study, we present an integrated strategy to enhance image quality in sparse-view SCT by systematically evaluating four source–detector configurations reconstructed using both FBP- and CS-based algorithms. The CS method consistently outperformed conventional FBP, effectively reducing the undersampling artifacts and preserving the structural details. Among the evaluated configurations, Case 4—featuring a downward π -angle with non-uniform angular spacing—demonstrated the most favorable performance. This was substantiated through three complementary quantitative assessments: angular distribution of ray vectors, image quality metrics, and sinogram-based sampling analysis. All metrics consistently indicated the superior sampling efficiency and reconstruction quality of Case 4 under extremely sparse-view conditions. These findings highlight the importance of jointly

optimizing the system geometry and reconstruction methodology, offering a practical and effective solution for high-quality tomographic imaging in applications, such as 3D security screening.

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