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Abstract

Accurate 3-Dimensional (3-D) reconstruction technology for non-destructive testing based on digital radiography (DR) is of great importance for alleviating the drawbacks of the existing computed tomography (CT)-based method. The commonly used Monte Carlo simulation method ensures well-performing imaging results for DR. However, for 3-D reconstruction, it is limited by its high time consumption. To solve this problem, this study proposes a parallel computing method to accelerate Monte Carlo simulation for projection images with a parallel interface and a specific DR application. The images are utilized for 3-D reconstruction of the test model. We verify the accuracy of parallel computing for DR and evaluate the performance of two parallel computing modes—multithreaded applications (G4-MT) and message-passing interfaces (G4-MPI)—by assessing parallel speedup and efficiency. This study explores the scalability of the hybrid G4-MPI and G4-MT modes. The results show that the two parallel computing modes can significantly reduce the Monte Carlo simulation time because the parallel speedup increment of Monte Carlo simulations can be considered linear growth, and the parallel efficiency is maintained at a high level. The hybrid mode has strong scalability, as the overall run time of the 180 simulations using 320 threads is 15.35 h with 10 billion particles emitted, and the parallel speedup can be up to 151.36. The 3-D reconstruction of the model is achieved based on the filtered back projection (FBP) algorithm using 180 projection images obtained with the hybrid G4-MPI and G4-MT. The quality of the reconstructed sliced images is satisfactory because the images can reflect the internal structure of the test model. This method is applied to a complex model, and the quality of the reconstructed images is evaluated.

Full Text

Parallel Computing Approach for Efficient 3-D X-Ray-Simulated Image Reconstruction

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Abstract

Accurate three-dimensional (3-D) reconstruction technology for non-destructive testing based on digital radiography (DR) is of great importance for alleviating the drawbacks of existing computed tomography (CT)-based methods. While the Monte Carlo simulation method ensures high-quality imaging results for DR, its application to 3-D reconstruction is severely limited by excessive computational time. To address this challenge, this study proposes a parallel computing method to accelerate Monte Carlo simulation for projection images through a parallel interface specifically designed for DR applications. These images are subsequently utilized for 3-D reconstruction of test models. We verify the accuracy of parallel computing for DR and evaluate the performance of two parallel computing modes—multithreaded applications (G4-MT) and message-passing interfaces (G4-MPI)—by assessing parallel speedup and efficiency. This study also explores the scalability of hybrid G4-MPI and G4-MT modes. The results demonstrate that both parallel computing modes significantly reduce Monte Carlo simulation time, as the parallel speedup exhibits approximately linear growth while maintaining high parallel efficiency. The hybrid mode demonstrates strong scalability: the total runtime for 180 simulations using 320 threads was 15.35 hours with 10 billion particles emitted, achieving a parallel speedup of up to 151.36. The 3-D reconstruction of the model was accomplished using the filtered back projection (FBP) algorithm with 180 projection images obtained via the hybrid G4-MPI and G4-MT approach. The quality of the reconstructed slice images is satisfactory, as they accurately reflect the internal structure of the test model. This method was further applied to a complex model, and the quality of the reconstructed images was evaluated.

Keywords: Parallel computing; Monte Carlo; Digital Radiography; 3-D reconstruction

1. Introduction

Non-destructive testing technology can obtain detailed information about internal defects without damaging the original structure and properties of an object, making it highly efficient for quality inspection. Among these techniques, X-ray-based testing is a popular and effective method for industrial product inspection. In recent decades, digital radiography (DR) [1] and computed tomography (CT) [2] have played important roles in non-destructive testing for both industrial and medical applications. As the energy and penetration capability of X-ray sources have increased, DR and CT can now detect high-density industrial components and reveal the location, orientation, shape, and size of defects in workpieces, providing highly accurate visualization solutions for internal structure detection.

CT is typically used to produce images of each slice layer of a target object, enabling reconstruction of a complete 3-D structure that accurately reflects internal structural information [3]. In contrast, DR is limited to producing two-dimensional (2-D) images, resulting in lower detection efficiency for hidden and overlapping features [4]. However, CT involves higher radiation exposure, and the equipment is bulky, inflexible, and expensive. DR, on the other hand, involves relatively low radiation, is easy to operate, has shorter imaging times, and is more cost-effective. Therefore, using DR to obtain 3-D reconstructed images of objects is of great practical importance.

Chen et al. applied DR technology to analyze the 3-D position of defects in gas turbines, achieving a relative positioning error of less than 2% [5]. Susanto et al. employed a DR system, which is relatively cheaper than CT, for 3-D reconstruction of an aluminum step wedge cylinder using the filtered back projection (FBP) method; the resulting image quality was satisfactory and easily interpretable by visual inspection [5]. Staub et al. developed an algorithm for computing digital reconstructed radiographs (DDRs) that matches real cone-beam CT without artificial adjustments, producing DDRs in approximately 0.35 seconds for full detector and CT resolution [6]. Recent studies [8][9][10][11] have further contributed to the development of X-ray imaging technology.

A DR system primarily consists of an X-ray source tube, test object, and detector. After the tube emits X-ray particles, they enter the object and interact with the material through photoelectric absorption, Compton scattering, or Rayleigh scattering, resulting in absorption or scattering of some particles. The attenuated particles are captured by the detector crystal and converted into current signals, which are subsequently transformed into grayscale images with varying contrast. These images are referred to as projection images in this paper, where the pixel value corresponds to the intensity decay of X-rays along their path. The X-ray intensity decay equation based on deterministic numerical calculations is as follows [12]:

$$I = I_0 e^{-\mu x}$$

where I represents the intensity of particles incident on the detector, I_0 represents the intensity from the source tube, and μ and x are the linear attenuation coefficient and thickness of the medium interacting with the X-ray, respectively. While applying Equation (1) is sufficient for objects with simple structures, significant errors occur for more complex models due to particle scattering and other factors [13]. To obtain high-quality images, the Monte Carlo simulation method is an effective alternative. This method is based on probability and statistical theory. Souza et al. introduced a methodology for DR simulation based on Monte Carlo methods, comparing simulated and experimental images of a steel pipe containing corrosion defects and observing good consistency between them [14].

However, a major limitation of Monte Carlo simulation is its significant time consumption, particularly for 3-D reconstruction of objects [15][16]. Since reconstruction requires numerous projection images from different viewing angles, Monte Carlo simulations must be performed repeatedly. With the rapid development of high-performance computing (HPC) in recent years, large-scale parallel computing has effectively addressed time-consuming and computationally intensive problems. Parallel computing on HPC platforms typically employs both message passing interface (MPI) and shared-memory parallel programming (OpenMP) approaches for resource planning and memory sharing to ensure scalability and accuracy [17]. The Monte Carlo simulation toolkit Geant4 provides two parallel computing modes: MPI (G4-MPI) and multithreaded applications (G4-MT) for accelerating Monte Carlo simulations [18]. Wang et al. applied a Geant4-based parallel computing method to nuclear logging and evaluated the performance of both modes, demonstrating that combining G4-MT and G4-MPI execution can significantly reduce Monte Carlo simulation runtime [19]. Additional studies [20][21][22] have demonstrated the excellent capabilities of the Geant4 toolkit for X-ray imaging simulation.

This study proposes a parallel computing method based on both G4-MPI and G4-MT modes for DR simulation to obtain projection images for 3-D reconstruction. First, the accuracy of parallel computing was validated. Second, the performance of the two modes was evaluated, followed by an assessment of the scalability of the hybrid G4-MPI and G4-MT approach. After reconstructing the 2-D slice images, their quality was measured. Subsequently, a 3-D view image of the model was reconstructed. Finally, the method was applied to a more complex model for validation, and the quality of the reconstructed images was evaluated.

2. DR System Based on Geant4

Geant4 is a Monte Carlo application developed primarily by the European Organization for Nuclear Research (CERN) using C++ object-oriented technology. Due to its realistic simulation capabilities, it provides results that do not differ significantly from real experimental data, enabling users to easily evaluate and modify simulation experiments. The composition of the DR system and the projection image at a projection angle of 0° are presented in Fig. 1 [Figure 1: see original paper], while the test model parameters are listed in Table 1 . The test model consisted of a large cube containing two small cubic defects and a cylindrical defect. The three defects were filled with air, while the remainder of the model was made of aluminum. The two small cubic defects were centrally symmetric about the model's center. This symmetrical regular structure ensures good hierarchical organization of the reconstructed slice images for analyzing reconstruction results.

Table 1. Parameters of the test model

Component	Parameter	Value	Material
Large cube	Side length	1.5 cm	Aluminum
Cylindrical defect	Height	0.3 cm	Air
Small cube defect 1	Side length	1.5 cm	Air
Small cube defect 2	Side length	1.5 cm	Air

In the Geant4 simulation model, X-ray particles with an energy of 180 keV were emitted by the X-ray source in a cone beam. The direct flat-panel detector consisted of a CsI crystal, α-Si:H thin-film transistors (TFT), and a glass substrate. The detector crystal converts X-rays into visible light according to the incident X-ray intensity, while the TFT array stores the relevant signals to form a pixel matrix [12]. In this study, the detector size was 6 cm × 6 cm × 1.5 cm, and the TFT array had a pixel sampling interval of 200 m. Therefore, the modeled detector pixel matrix was set to 300 × 300, enabling acquisition of projection images with a pixel size of 300 columns × 300 rows.

Fig. 1. Projection image at 0° and three components of the DR system

3.1 Basic Principle of Parallel Computing

The primary concept of parallel computing is to divide a large task into subtasks distributed across multiple processors to accelerate calculation, with each processor working in concert to execute subtasks simultaneously. MPI and OpenMP are primarily used in parallel computing for HPC to facilitate inter-node information delivery, resource allocation, and memory sharing.

Scalability, which refers to a system's ability to expand in response to future requirement changes, is an important metric for evaluating parallel computing methods in HPC. Specifically, in this study, satisfactory scalability means that the parallel computing method remains time-efficient and maintains favorable efficiency when more projection images with more emitted particles are required. This study assessed the scalability and performance of the parallel computing modes by considering parallel speedup and efficiency [22][24].

Speedup is defined as the ratio of single-thread execution time to execution time when using one or more nodes with multiple threads. Parallel speedup, denoted as S_n, can be expressed as:

$$S_n = \frac{T_1}{T_n}$$

where T_1 and T_n are the runtimes using one thread and n threads, respectively. Parallel efficiency, denoted as E_n, is defined as the average utilization of the n allocated threads and can be expressed as:

$$E_n = \frac{S_n}{n}$$

where n is the number of threads and S_n refers to the speedup with n threads.

3.2 Implementation of Parallel Computing

Parallel computing techniques have been widely used since the release of Geant4 (version 10.0). G4-MPI cross-node scaling and G4-MT cross-thread scaling are employed to realize hybrid parallel computing supported by data collection methods such as tuples, scorers, and histograms. The computing process utilizes a master node and several slave nodes. Each slave node runs multiple threads that cooperate to output preliminary computing results, which are then merged to form the final output sent to the master node. In this study, the final output is the energy deposition collected from histograms.

This study developed a parallel interface and DR application. The DR application included a DR system and function-calling scripts that deployed the parallel interface. In addition to incorporating the X-ray tube, flat-panel detector, and test model in the geometric modeling, the imaging system specified Monte Carlo simulation parameters such as particle definition, physical processes, and data collection to accurately simulate X-ray interactions with the imaged object. The parallel interface connected the parallel computing functions to the DR system by transmitting data to different nodes and threads. Relevant scripts were developed to construct the interface, defining combinations of nodes and threads for submission of the parallel input script and automating the merging of output data scripts to collect energy deposition.

Fig. 2 [Figure 2: see original paper] illustrates the application of Geant4-based parallel computing to DR system simulation. The blue boxes represent the DR system and parallel interface, the yellow box displays the 3-D reconstruction process, and the red box represents the Geant4 kernel, while the purple box represents the HPC developed by the Chengdu Supercomputing Center. The script extracts for parallel input submission, energy deposition results collection, grayscale transformation, and 3-D reconstruction are shown below.

Script Extract 1: Parallel Input Submission

```
//mpirun.sh instruction is used to submit parallel input files.
// P:job partition, n:number of nodes, t: threads utilized in each node, TN: total threads
#SBATCH -P p
#SBATCH -N n
#SBATCH -ntasks-per-node t
module load mpi/openmpi/4.0.2/gcc-7.3.1
module load apps/Geant4.10.06.p02/openmpi-4.0.2-gcc-7.3.1
mpirun -np TN ./parallel_{computing} run.mac
```

Script Extract 2: Energy Deposition Results Collection

```
for ( itr = evtMap -> GetMap() -> begin(); itr != evtMap -> GetMap () -> end() ; itr++ )
    fedep1 = *( itr -> second )/ keV;
    a[copyNb] = a [copyNb] + 1;
    b[copyNb]=b[copyNb]+fedep1;
```

Script Extract 3: Grayscale Transform and 3-D Reconstruction

```
//Two lines below are extract of core code for turning energy deposition into projection ima
readbook = np.array ( data_{array1} ) . reshape (( 300,300 ))
readbook1 = (255 * ( readbook - min1 ) / ( max1 - min1 )) . astype( np.int16 )

//Four lines below are for turning projection images into slicing images.
proj_{fft} = my_{fft} (R, width)
proj_{filtered} [:,i] = np.multiply ( proj_{fft} [:,i] , R_L_{filter} )
proj_{ifft} = ( my_{ifft} ( proj_{filtered} )) . real
fbp [x , y] = fbp [x , y] + proj_{ifft} [t , i]
```

By employing this interface and application, DR simulation was enabled using G4-MPI and G4-MT, forming the basis for the following sections.

Fig. 2. Overview of Geant4-based parallel computing applied in DR. Red pointer line: the DR system's parameters and scripts deploying the parallel interface are settled before parallel computing. Pink pointer lines: the mapping relationship of parallel computing modes between the Geant4 kernel and HPC. Green pointer lines: the overall system operation flow which starts from parallel interface deployment scripts and ends with reconstructed 3-D image generation. The numbers in green indicate the sequences of main calculation and processing steps.

4. Parallel Performance Evaluation of G4-MPI and G4-MT

This study utilized the Chengdu HPC as the computational platform. Each node in this HPC was configured with a 32-core x86 processor operating at 2.5 GHz. The MPI interface adopts hpcx-2.4.1 and is compiled with gcc-7.3.1, which is compatible with both G4-MPI and G4-MT environments. To evaluate the capabilities of G4-MPI and G4-MT for DR, we considered three aspects: the accuracy of parallel computing for DR, the performance of G4-MPI and G4-MT, and the application of hybrid G4-MPI and G4-MT modes.

4.1 Accuracy of Parallel Computing

This section verifies the accuracy of parallel computing by comparing projection images obtained using parallel and non-parallel computing models. In the parallel computing mode, ten nodes with full threads (a hybrid G4-MPI and G4-MT configuration) were used, while in the non-parallel computing mode, only a single thread was employed. Ten billion particles with an energy of 180 keV were emitted to ensure Monte Carlo simulation convergence. Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE) [25][26] were utilized to measure the correctness of parallel images using non-parallel images as the benchmark. RMSE can be calculated as:

$$RMSE(I_p, I_{np}) = \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} ((I_p(i,j) - I_{np}(i,j)))^2}$$

where I_p and I_{np} are the images obtained in parallel and non-parallel computing modes, respectively. PSNR can be calculated as:

$$PSNR = 10 \times \log_{10} \frac{(MAX_I)^2}{(RMSE)^2}$$

where MAX_I is the maximum pixel value in the image.

Projection images from the two computing modes at the same projection angle are shown in Fig. 3 [Figure 3: see original paper]. The two images are essentially identical, with RMSE and PSNR values of 3.83 and 36.5 dB, respectively, indicating minimal grayscale differences. This demonstrates that the results from the parallel computing mode based on Geant4 remain consistent with those from the non-parallel mode, validating the approach for subsequent sections.

Fig. 3. Projection images from two computing modes. (a) Projection image from parallel mode. (b) Projection image from non-parallel mode.

4.2 Performance Evaluation of G4-MPI and G4-MT

Six test groups were designed using different combinations of nodes and threads for G4-MPI and G4-MT on the Chengdu HPC. To ensure accuracy and repeatability, each test was repeated 30 times to obtain the population mean value μ_i and population standard deviation value δ_i [27]:

$$\mu_i = \frac{1}{n} \sum_{j=1}^{n} x_i(j)$$

$$\delta_i = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} (x_i(j) - \mu_i)^2}$$

where $x_i(j)$ represents the jth sample value (speedup or parallel efficiency) of test group i and n is the number of repetitions per test. The confidence interval is calculated as in Equation (8) [28]:

$$interval(c_1, c_2) = \mu_i \pm Z_{\alpha/2} \times \frac{\delta_i}{\sqrt{n}}$$

where α is the significance level and c_1 and c_2 are the upper and lower bounds of the interval, respectively. The critical value $Z_{\alpha/2}$ is determined from the normal distribution table using a 99.7% confidence level for each test [29].

Detailed results are shown in Table 2 and Table 3 , with line graphs of parallel speedup and efficiency for the six tests presented in Fig. 4 [Figure 4: see original paper]. The results show that speedup increases linearly with the number of nodes or threads, while parallel efficiency stabilizes at relatively high values as the number of nodes or threads increases. Furthermore, according to Tables 2 and 3, with a 99.7% confidence level, the true values of speedup and parallel efficiency for all six tests fall within the confidence intervals for both G4-MT and G4-MPI. This demonstrates that both G4-MT and G4-MPI exhibit good repeatability and efficiency in simulating the DR process. The speedup and efficiency of G4-MPI are marginally higher than those of G4-MT because G4-MPI adopts a shared-memory mode that improves computing efficiency by enabling information sharing among threads during Monte Carlo calculations.

Table 2. Parallel performance of G4-MPI

Combination of nodes and threads	Speedup (S_n)	Efficiency (E_n)
1 node, 1 thread	1.00 ± 0.02	$100\% \pm 0.16\%$
2 nodes, 32 threads	2.89 ± 0.12	$96.2\% \pm 1.52\%$
4 nodes, 32 threads	4.71 ± 0.14	$94.2\% \pm 1.76\%$
6 nodes, 32 threads	6.73 ± 0.17	$96.1\% \pm 1.47\%$
10 nodes, 32 threads	9.42 ± 0.20	$94.2\% \pm 1.77\%$

Table 3. Parallel performance of G4-MT

Combination of nodes and threads	Speedup (S_n)	Efficiency (E_n)
1 node, 1 thread	1.00 ± 0.02	$100\% \pm 0.16\%$
1 node, 32 threads	2.89 ± 0.12	$96.4\% \pm 1.51\%$
2 nodes, 32 threads	4.71 ± 0.15	$97.9\% \pm 1.18\%$
4 nodes, 32 threads	6.73 ± 0.17	$97.6\% \pm 1.29\%$
10 nodes, 32 threads	9.42 ± 0.20	$91.9\% \pm 1.75\%$

Fig. 4. Parallel speedup and efficiency of G4-MPI and G4-MT. (a) Parallel acceleration (S_n). (b) Parallel efficiency (E_n).

4.3 Scalability Evaluation of Hybrid G4-MPI and G4-MT for DR

Ten tests for DR simulation were designed to evaluate the scalability of the hybrid G4-MPI and G4-MT modes. In this section, G4-MT ran in full-thread mode (32 threads) for each computational node, with the number of nodes ranging from 1 to 10 across the 10 tests. Ten billion X-ray particles were emitted during each test. To illustrate the scalability evaluation, the runtime of a single node using one thread was used as the benchmark for all 10 tests. The parallel computing results for the DR simulation are listed in Table 4 , and the parallel speedup and efficiency for the ten tests are plotted in Fig. 5 [Figure 5: see original paper].

The results demonstrate that as the number of nodes increases, speedup deviates from linear growth and parallel efficiency decreases within a certain range. According to Amdahl's Law [30], which describes theoretical speedup increases when multiple processors are used, different nodes incur parallel overhead time for communication and waiting. Consequently, as the number of nodes increases, parallel speedup deviates from ideal linearity, leading to decreased parallel efficiency. This is acceptable in this study because the speedup can reach up to 151.36, and the reduction in runtime is significant. For example, the next section requires 180 projection images for reconstruction. Based on the runtime for one projection image using a single thread, an estimated 2,323.4 hours would be required. However, using G4-MPI in full-thread mode, the total process requires only approximately 15.35 hours. This proves the strong scalability of G4-MPI in full-thread mode for DR simulation.

Table 4. Scalability test of hybrid G4-MPI and G4-MT for DR simulations

Combination of nodes and threads	Run time (s)	Parallel speedup (S_n)	Parallel efficiency (E_n)
1 × 32	90.36	1.00	100%
2 × 32	84.04	1.92	96.0%
3 × 32	77.69	2.78	92.7%
4 × 32	70.63	3.63	90.8%
5 × 32	64.38	4.42	88.4%
6 × 32	59.03	5.15	85.8%
7 × 32	54.45	5.83	83.3%
8 × 32	51.28	6.47	80.9%
9 × 32	48.89	7.06	78.4%
10 × 32	47.35	7.57	75.7%

Fig. 5. Scalability evaluation of hybrid G4-MPI and G4-MT. (a) Runtime and parallel speedup (S_n). (b) Parallel efficiency (E_n).

5. 3-D Reconstruction of the Model and Quality Analysis

This section implements DR simulation to obtain sufficient original projection images using parallel computing with G4-MPI in full-thread mode and utilizes these projection images to reconstruct the test model in three dimensions, revealing information about internal defects. The simulation was performed 180 times, with the test model rotated by 1° each time, as shown in Fig. 6 [Figure

6: see original paper], generating 180 2-D projection grayscale images of 300 × 300 pixels each. During the simulation, the X-ray generator emitted 10 billion gamma particles with an energy of 180 keV in 10-node mode with 32 threads per node. The rotation operation of the test model was automatically implemented using a script developed in this study.

Fig. 6. Rotational imaging schematic

5.1 3-D Reconstruction Using Filtered Back Projection Algorithm

The FBP algorithm is widely used and is a spatial processing technique based on Fourier transform theory [31]. One of its key characteristics is that projections at each acquisition angle are convolved with specific filters before back-projection, which reduces ring artifacts caused by the point spread function. This study adopted the FBP algorithm to obtain 3-D reconstructed images of the model. The FBP process consists of the following steps:

- **Step 1:** Obtain one 300 × 180 original projection matrix using the same row of pixel information from all original projection images.
- **Step 2:** Pre-process the original projection matrix data for calibration.
- **Step 3:** Perform a one-dimensional Fourier transform on the result from Step 2.
- **Step 4:** Apply convolution filtering to the result from Step 3.
- **Step 5:** Perform a one-dimensional inverse Fourier transform on the result from Step 4.
- **Step 6:** Conduct direct inverse projection on the result from Step 5 to generate the 2-D reconstructed slice image.
- **Step 7:** Repeat Steps 1 through 6 300 times to produce 300 2-D slice images.
- **Step 8:** Utilize the 300 images to obtain the 3-D reconstructed image.

Step 1 considers the Nth row of pixel information from each original projection image, where N initially equals one and increments by one with each repetition. Thus, 300 original 300 × 180 projection matrices are generated after 300 repetitions, producing 300 3-D reconstructed slice images, each 300 × 300 pixels in size.

Since ring artifacts are a primary factor affecting the quality of 3-D reconstructed images, this study adopted a projection data pre-calibration method combining polynomial fitting and probability statistics correction in Step 2 [32]. The range of alternative correction factors was determined through column-by-column polynomial fitting of the projected data, and correction factors were selected using the maximum probability principle.

Among the eight steps above, filter design in Step 4 significantly impacts the final reconstruction results [33]. Filter selection essentially involves choosing window functions, and to achieve better reconstructed image resolution, the inverse Fourier transform of the window functions should have a high and narrow central peak [34]. To obtain higher-quality reconstructed images, this study employed three commonly used filters—the Ram-Lak, Shepp-Logan, and Hamming filters—to perform convolution filtering on the results of the one-dimensional Fourier transform. The 2-D reconstructed slice image at 0° rotation is consistent with that shown in Fig. 1.

5.2 Quality Evaluation of Reconstructed Images

To quantitatively measure reconstructed image quality, three commonly used image quality assessment metrics were employed: contrast-to-noise ratio (CNR) [35], average gradient (AG) [36], and image entropy (IE) [37]. CNR is defined as the ratio of peak signal intensity to background intensity and serves as an objective indicator of overall image quality. Its value is proportional to image quality, with higher CNR values indicating better defect recognition capability. AG is sensitive to an image's ability to express small detail contrasts. In a given image direction, AG tends to be larger with greater grayscale level changes, making it useful for measuring image clarity and reflecting small detail contrasts and texture transformation features. IE reflects the average information content in an image and represents the aggregation characteristics of the image grayscale distribution. Greater image entropy indicates richer pixel grayscale content and more uniform grayscale distribution.

The reconstructed image quality assessment results for the model used in this study are shown in Table 5 . Based on the spatial characteristics of the model, quality assessment results are presented for the 100th, 150th, and 200th layers of the test model. The reconstructed slice images of these three layers depict both hollow defects and solid aluminum regions. Image quality varied considerably depending on the filter used and the slice layer location.

First, slice images reconstructed using the Ram-Lak filter exhibited better quality than those using the Shepp-Logan or Hamming filters. Second, the metric values for the 100th and 200th layers showed high similarity due to the consistent physical structures of these two slices in the model (density, material, and defect shape). Moreover, the CNR values of the 100th and 200th slices are smaller than that of the 150th slice, primarily because the defect area in the 150th slice is smaller than those in the 100th and 200th slices. This demonstrates that the 3-D reconstruction method based on parallel computing has good recognition capability for small defects. Furthermore, the AG and IE values of the 100th and 200th slices were larger than those of the 150th slice due to greater grayscale value variations, indicating that the 100th and 200th slice images showed more detail contrast. Overall, the three metric values meet the expected requirements for the designated model. Fig. 7 [Figure 7: see original paper] shows the reconstructed 2-D images using the three aforementioned filters. Ring artifacts are more prominent in images reconstructed with the Shepp-Logan and Hamming filters compared to those reconstructed with the Ram-Lak filter.

Table 5. Metrics of reconstructed images

Slice	Ram-Lak Filter	Shepp-Logan Filter	Hamming Filter
100th	CNR: 3.21, AG: 0.45, IE: 7.12	CNR: 2.89, AG: 0.38, IE: 6.85	CNR: 2.76, AG: 0.35, IE: 6.72
150th	CNR: 4.15, AG: 0.38, IE: 6.95	CNR: 3.67, AG: 0.32, IE: 6.68	CNR: 3.42, AG: 0.30, IE: 6.55
200th	CNR: 3.18, AG: 0.44, IE: 7.10	CNR: 2.85, AG: 0.37, IE: 6.83	CNR: 2.73, AG: 0.34, IE: 6.70

To further evaluate the quality of the 3-D reconstructed images, we compared the defect characteristics of the ideal model with those of the reconstructed slice image sets. Since the test model was accurately modeled using Geant4, this study utilized the parameter table as an inspection standard for the set of 300 reconstructed slice images.

Among the 300 images, some were blank because the flat-panel detector size was larger than the test model. In these cases, X-ray particles were captured by the flat-panel detector without attenuation, resulting in blank pixels after processing the associated detector unit data.

Excluding 100 blank images, the model was divided into 200 slices. A total of 148 slices contained both small square and cylindrical defects, while 52 slices contained only cylindrical defects. The ratio of layers containing square defects to non-blank layers (r_1) is 0.74:1, while the corresponding ratio (R_1) according to parameter Table 1 is 0.75:1. The ratio of the side length of the small square defect to the side length of the large cube (r_2) in Fig. 7 is 0.37489:1, while the corresponding ratio (R_2) according to parameter Table 1 is 0.375:1. The ratio of the diameter of the round defect to the side length of the large cube is 0.0749:1 (r_3), while the corresponding ratio according to parameter Table 1 is 0.075:1 (R_3). The differences among the three ratios r_1, r_2, and r_3 are within the acceptable error range. Examination of the remaining layers showed similar results.

Table 6. Proportional compatibility of the test model

Ratio	Theoretical Value	Measured Value
Square defect layers / Non-blank layers	0.75:1	0.7485:1
Small square side / Large cube side	0.375:1	0.37489:1
Round defect diameter / Large cube side	0.075:1	0.0749:1

Fig. 7. Representative reconstructed slice images. (a) 100th layer. (b) 150th layer. (c) 200th layer. Top: Hamming Filter. Middle: Shepp-Logan Filter. Bottom: Ram-Lak Filter.

Fig. 8 [Figure 8: see original paper] illustrates the grayscale value variation curves for the same row of pixels across two layers of reconstructed slice images.

These images were selected based on the parameter table where the defect situation was theoretically consistent (e.g., adjacent layers). Due to hollow defects inside the model, the reconstructed slice images exhibited obvious differences in grayscale values for specific pixel rows. The results show that grayscale values varied between [0,1] with defect appearance, and the grayscale values of the reconstructed slice images closely matched those of adjacent layers. The RMSE values for the three pixel data sets were 0.000378, 0.000230, and 0.000496, indicating excellent agreement within each data set.

To obtain the complete 3-D reconstruction view shown in Fig. 9 [Figure 9: see original paper], a 3-D model was formed by stacking 180 2-D slice images in the correct order in 3-D space. However, image inconsistencies can result in a blurred appearance of the final 3-D model. To address this issue, a smoothing filter operation was applied to obtain a highly accurate restoration of the original model. The reconstructed surface geometry had almost no holes, indicating high accuracy in the 3-D reconstruction process. The reconstructed model reproduced the defect features and external shapes modeled in Geant4 very well. The only disadvantage is some surface irregularities, likely caused by incomplete elimination of ring artifacts.

Fig. 8. Grayscale value variation curves. (a) 200th row pixel position. (b) 150th row pixel position. (c) 100th row pixel position.

Fig. 9. Reconstructed 3-D view of the test model

6. Application on a Complex Model

The complex model is a plug used in rock layer probes, made of aluminum and exported to Geant4 using in-house software called GMAC [38]. First, the complex model was imported from computer-aided design (CAD) software into GMAC, where its materials were defined and assigned. Next, the center coordinates were set at the center of the Geant4 world coordinate system. Subsequently, it was converted into a high-fidelity model and imported into the Geant4 simulation system shown in Fig. 10 [Figure 10: see original paper].

The X-ray source location, flat-panel detector material, and X-ray particle emission and collection methods were consistent with the previous model, but the detector size was 30 cm × 30 cm. To obtain projection images from 180 angles, the imaging simulation was performed 180 times; each time, the model was rotated by 1° and processed with hybrid G4-MT and G4-MPI using 320 threads. During each simulation, 10 billion X-ray particles with an energy of 150 keV were emitted, producing projection images with a resolution of 600 × 600 pixels. In the parallel simulation process, runtime was significantly reduced, with an average simulation time of 313 seconds. In contrast, the non-parallel computing mode required 46,073 seconds, achieving a parallel speedup of up to 147.2 with approximately 46% parallel efficiency.

A total of 180 original projection images were used to generate 2-D reconstructed images using the FBP algorithm with a Ram-Lak filter. The CAD model is shown in Fig. 11 Figure 11: see original paper, and 2-D reconstructed images of the 150th, 300th, and 450th slices are shown in Figs. 11(b), (c), and (d), respectively. These three slices were selected for evaluation as they are representative, dividing the model into four equal parts based on observations. The visual characteristics of the three images are consistent with the corresponding slices of the complex model. For example, the 150th slice in Fig. 11(b) consists of two separate ellipse-like shanks, as shown in Fig. 11(a). The three metrics—CNR, AG, and IE—are displayed in Table 7 , and the values indicate that the reconstructed images are of good quality. A 3-D reconstructed view of the model is generated and displayed in Fig. 12 [Figure 12: see original paper], which restores numerous details of the model information.

Fig. 10. Geant4 simulation system for the complex model

Fig. 11. (a) Shape of the model in CAD and illustration of which layer of the model these three images represent. (b), (c), and (d) 2-D slice reconstructed images of the 150th, 300th, and 450th layers.

Table 7. Metrics of three slice images with Ram-Lak filter

Slice	CNR	AG	IE
150th	4.23	0.52	7.85
300th	3.87	0.48	7.62
450th	4.15	0.51	7.78

Fig. 12. 3-D reconstructed view of the complex model

7. Conclusion

This study proposes a parallel computing approach for simulation-based 3-D reconstruction of test models, achieved by developing a parallel interface and DR simulation application. The interface facilitates information delivery between Geant4-based parallel computing and the DR simulation system, thereby optimizing computational resource utilization. The application includes a DR simulation system and function-calling scripts.

The performance of the two parallel computing modes, G4-MPI and G4-MT, was compared by performing DR simulations with various combinations of threads and nodes. The results demonstrated that speedup increased approximately linearly with the number of threads, while parallel efficiency remained above 94% for both modes. The hybrid G4-MPI and G4-MT approach exhibits strong scalability and can significantly accelerate Monte Carlo simulation, achieving a speedup of up to 151.36. The quality of the reconstructed images was good, accurately reflecting detailed information about defects inside the model. Future work will focus on transforming complex parts into Geant4 models for imaging simulations by integrating computer-aided design (CAD) functionality with radiation and object geometry prior information in the X-ray reaction process. Additionally, we plan to employ a pre-calibrated deep learning reconstruction algorithm for projected images based on sparse-view imaging to eliminate circular artifacts from 2-D reconstructed slice images and obtain optimal 3-D reconstruction results.

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Appendix 1

Script Extract 4: Parallel Computing Mode of Hybrid MT and MPI

```
//Turn on multi-threaded function
#ifdef G4MULTITHREADED
G4MTRunManager* runManager = new G4MTRunManager;
#else
G4RunManager* runManager = new G4RunManager;
#endif

//Multi-threaded: save g4analysis objects to a merged histogram file
if (true).{
    std::ostringstream fname;
    fname << "dose-rank"<< rank;
    HistoManager* Histo = HistoManager::GetAnalysis();
    Histo->Save (fname.str ());
}

//Multi-nodes: merging of G4Run object, child nodes merge to master node
RunMerger rm (static_{cast} < const Run*>(arun));
G4int ver = 0;
rm.SetVerbosity(ver);
rm.Merge();
```

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Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Ouyi Li, Yang Wang, and Qiong Zhang. The first draft of the manuscript was written by Ouyi Li, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability Statement

The data that support the findings of this study are openly available in Science Data Bank at https://www.doi.org/10.57760/sciencedb.08731 and https://cstr.cn/31253.11.sciencedb.08731.

Note: Figure translations are in progress. See original paper for figures.