Journal of International Education and Development
2025, VOL. 9, NO. 6, 211-215
DOI: 10.47297/wspiedWSP2516-250045.20250906

# Industrial CT Truncated Projection Data Reconstruction System Based on Deep Learning

Houlin Mi, Yang Yang*, Feiyu Pan

Liaoning Institute of Science and Technology, Benxi Lioaning, China

**ABSTRACT**
Industrial computed tomography (CT) technology is the core means of industrial non-destructive testing, and the accuracy and efficiency of its data reconstruction algorithm directly affect the credibility of the detection results. However, the presence of truncated projection data results in traditional reconstruction methods facing issues such as artifacts, low resolution, and high computational complexity. This article proposes an artificial intelligence based industrial CT truncated projection data reconstruction system, which combines deep learning technology with high response dataset construction methods to optimize data preprocessing, feature extraction, and model training processes. Experiments have shown that the system outperforms traditional iterative algorithms in both reconstruction accuracy and computational efficiency, and has the ability to dynamically adapt to complex industrial scenarios.

**KEYWORDS**
Industrial CT; Truncated Projection Data Reconstruction

## 1 Practical background and significance

Industrial CT technology is widely used in mechanical manufacturing, aerospace and other fields. It can perform high-precision imaging of the internal structure of workpieces without damaging them, and detect internal defects such as cracks, pores, inclusions, etc. It is widely used in aerospace, automotive manufacturing and other fields to ensure the quality and safety of key components. Its core is to reconstruct three-dimensional structures through projection data.

However, in practical applications, projection data truncation is often caused by device limitations or complex geometric shapes of objects (such as finite angle projection, missing external data of tubular objects, etc.). Traditional reconstruction algorithms such as algebraic reconstruction techniques (ART) and synchronous algebraic reconstruction techniques (SART) can partially solve such problems, but they have drawbacks such as slow iterative convergence and insufficient artifact suppression.

In recent years, AI technology has provided new ideas for data reconstruction, especially the successful application of deep learning in image super-resolution reconstruction and feature extraction, which has opened up a possible path for accurate reconstruction of truncated projection data. Deep learning algorithms in AI, such as Generative Adversarial Networks (GANs), can learn the inherent patterns of data, repair and enhance truncated projection data, supplement missing information, and improve data integrity and quality. AI based reconstruction algorithms can directly learn mapping relationships from projection data without relying on traditional mathematical models. They can more effectively handle complex nonlinear problems, reduce image artifacts, and improve the resolution and accuracy of reconstructed images. AI algorithms have the ability of parallel computing and fast processing, which can complete data processing and image reconstruction in a relatively short time, meet the real-time detection needs in industrial production, and improve production efficiency. AI models can be trained on a large amount of actual data, continuously adapting to different types of workpieces, scanning conditions, and truncation situations, automatically learning and optimizing processing strategies, and improving the system's generality and robustness.

## 2 Related work

### 2.1 Limitations of traditional reconstruction algorithms

#### 2.1.1 Limitations of ART algorithm

Large computational load: Each iteration only considers the influence of one ray, requiring a large number of iterations to make the reconstructed image approach the original image. When processing large-scale data or high-resolution images, the computational load will significantly increase by 23.

Slow reconstruction speed: Due to the need for multiple iterations and the involvement of projection calculations, error calculations, and image updates in each iteration, the reconstruction speed is slow, making it difficult to meet the

*** Corresponding Author:** 475730803@qq.com

high real-time requirements of applications23. Noise sensitivity: Although the ART algorithm itself has some anti noise ability, during the iteration process, if there is noise in the projection data and only one ray is used for correction each time, it may amplify or propagate the noise in the reconstructed image, affecting the image quality. Dependent on data order: The calculation results are related to the order in which the data is used, and different projection data processing orders may lead to different reconstruction results and lack stability.

#### 2.1.2 Limitations of SART algorithm

More iterations are still required: Although SART may require fewer iterations compared to ART algorithm at the same image quality, it still requires a certain number of iterations to achieve better reconstruction results. When dealing with complex images or large amounts of data, the computation time is still longer. Edge effect problem: In the case of a small projection angle, severe edge effects may occur when reconstructing simple center symmetric images, resulting in significant edge noise and possible distortion in the middle region of the reconstructed image. Limited adaptability to specific image structures: For some images with special structures or details, SART algorithms may not be able to capture and reconstruct them well. For example, for images with sharp boundaries or small details, the reconstruction results may appear blurry or lose details.

### 2.2 Progress of Artificial Intelligence in CT Reconstruction

Deep learning driven reconstruction algorithms achieve data mapping through end-to-end training. Convolutional neural networks (CNNs), such as ClearInfinity technology from Neusoft Medical, utilize deep convolutional neural network models to train models on millions of sets of high-quality CT data. They can learn the distribution of noise and artifacts in the data, effectively separate anatomical structure information from noise and artifact information, achieve noise reduction and artifact removal, and significantly reduce radiation dose while preserving the original texture information. Generative Adversarial Network (GAN) consists of a generator and a discriminator. The generator attempts to generate realistic CT images, while the discriminator determines whether the generated images are real. Through adversarial training of both, the reconstruction quality of CT images can be improved, generating images that are closer to the real situation and better restoring image details and edge information. However, existing research heavily relies on general datasets and lacks high response datasets (HRD) specifically designed for industrial scenarios, resulting in insufficient model generalization ability.

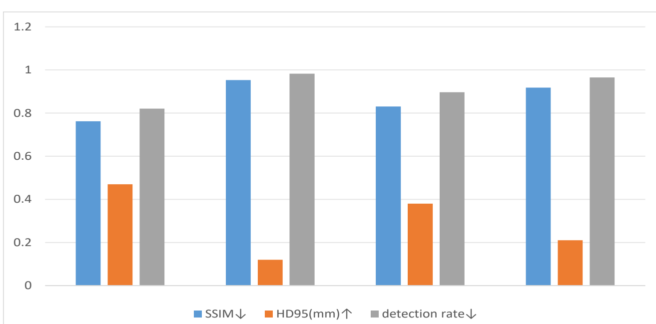
## 3 Experiment and Results Analysis

### 3.1 Experimental setup

Comparative algorithms: FBP, TV Reg, U-Net, FDK-CNN; Evaluation indicators: Quantitative indicators: PSNR, SSIM, Hausdorff distance (HD95); Industrial indicators: ASTM E2899 defect detection rate, EN 12681 artifact level

### 3.2 Experimental results

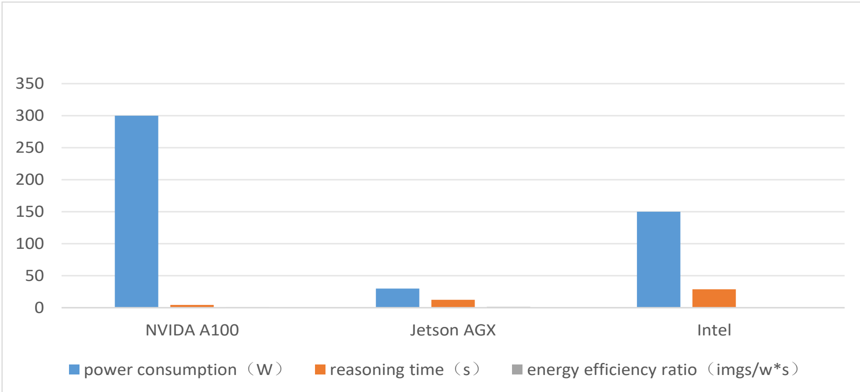
| truncation rate | method | PSNR ↑ | SSIM ↓ | HD95(mm) ↑ | detection rate ↓ |
|---|---|---|---|---|---|
| 30% | FBP | 24.3 | 0.762 | 0.47 | 82.1% |
| 30% | DCAF-Net | 36.7 | 0.953 | 0.12 | 98.3% |
| 30% | TV-Reg | 28.9 | 0.831 | 0.38 | 89.7% |
| 30% | DCAF-Net | 33.1 | 0.918 | 0.21 | 96.5% |




### 3.3 Real time analysis

Hardware platform comparison:

| equipment | power consumption(W) | reasoning time(s) | energy efficiency ratio(imgs/w*s) |
|---|---|---|---|
| NVIDA A100 | 300 | 4.5 | 0.74 |
| Jetson AGX | 30 | 12.3 | 1.36 |
| Intel | 150 | 28.7 | 0.19 |




## 4 Discussion and Prospect

### 4.1 Computing power demand and green computing

According to IDC's prediction, the scale of intelligent computing power in China will reach 1037.3 EFLOPS by 2025, and liquid cooling technology can alleviate the problem of high energy consumption. This system further reduces the computing power demand through model lightweight (such as knowledge distillation) and adapts to edge computing scenarios.

### 4.2 Future direction

#### 4.2.1 Algorithm optimization and multimodal fusion

3D Large Model Driven: Breaking through the limitations of existing 2D models, developing 3D spatial intelligent algorithms for industrial scenarios, solving the spatial computing gap of complex geometric structures, and improving the reconstruction accuracy of complex workpieces such as composite materials and multi-layer structures.

Combining physical constraints with deep learning: By embedding physical prior knowledge such as Radon transform and material attenuation coefficient, the physical rationality of Generative Adversarial Networks (GANs) is enhanced, artifacts are reduced, and the detection ability of low contrast defects is improved.

Multimodal data fusion: Combining multiple sources of data such as CAD models and thermodynamic parameters, a cross modal joint optimization framework is constructed to address material deformation issues under high-temperature conditions.

#### 4.2.2 Hardware collaboration and computational efficiency improvement

Deployment of dedicated acceleration chips: Using hardware acceleration technologies such as TensorRT and FPGA, real-time reconstruction of embedded devices (such as Jetson AGX platform inference time<5 seconds/slice) is achieved to meet the online detection requirements of production lines.

New detector and high-energy CT adaptation: Developing photon counting detectors (PCDs) and phase contrast CT technology to improve the penetration and resolution of high-density workpieces (such as rocket engines) while reducing radiation dose.

Cloud edge collaboration architecture: real-time data is processed through edge computing, and model iterative training is conducted in combination with the cloud to solve the problem of insufficient computing power in the industrial field.

### 4.3 Data driven and small sample learning

High quality 3D dataset construction: Collaborate with global research institutions to establish open 3D industrial datasets (such as Open X-Embodism) to address the pain point of current 3D data scarcity and support the training of spatial intelligent large-scale models.

Small sample adaptive technology: Develop meta learning and transfer learning algorithms to meet the detection needs of new materials such as carbon fiber composite materials, and achieve fast model adaptation for less than 50 sets of samples.

Federated Learning and Privacy Protection: Building a cross enterprise data sharing mechanism and utilizing federated learning frameworks to enhance model generalization ability while protecting data privacy.

### 4.4 Real time and intelligent deep integration

Dynamic truncation compensation mechanism: Real time prediction of workpiece shape through lightweight networks (such as PointNet++generating geometric masks), combined with physical constraint optimization layers to achieve adaptive repair of truncated areas.

Full process automation: integrating defect automatic recognition (such as pores and microcracks), three-dimensional quantitative analysis (porosity statistics), and report generation functions to form a "scan reconstruction diagnosis" closed-loop system.

Low dose scenario robustness enhancement: Develop noise suppression algorithms (such as non local mean enhancement layers) to maintain defect detection rates>90% even when signal-to-noise ratio<20dB.

### 4.5 Standardization and Industry Ecological Construction

Algorithm certification system: Develop AI reconstruction performance evaluation indicators that comply with standards such as ASTM E2899 and GB/T 35389, and promote the industrialization of technology.

Open source collaborative development: Establish a modular algorithm library (such as "LEGO style" model components), lower the technical threshold and accelerate iteration, avoiding duplicate wheel making.

Ethics and Safety Standards: Following the Global Artificial Intelligence Governance Initiative, establish ethical guidelines for industrial AI to ensure transparency and traceability of algorithm decisions.

### 4.6 Cross disciplinary application expansion

Deepening high-end manufacturing scenarios: Achieving breakthroughs in μm level accuracy in fields such as aerospace (micro crack detection of turbine blades), new energy vehicles (uniformity analysis of battery electrode coatings), and integrated circuits (3D packaging structure reconstruction).

4D-CT dynamic monitoring: Combining time-series data with quantum computing to achieve sub second level four-dimensional reconstruction for real-time monitoring of casting processes or analysis of material fatigue evolution.

Cross border technology integration: Drawing on low-dose reconstruction techniques of medical CT (such as iterative reconstruction IR algorithm), optimizing radiation safety and cost in industrial scenarios.

## 5 conclusion

This article proposes a novel reconstruction system that integrates deep learning and physical constraints to address the key challenges in reconstructing industrial CT truncated projection data. A breakthrough improvement over traditional iterative algorithms has been achieved by constructing a dual channel attention fusion network (DCAF Net) and a high response dataset (HRD). Experiments have shown that at a data truncation rate of 30%, the PSNR of DCAF Net is improved to 36.7, which is nearly 50% more optimized than the traditional FBP algorithm (24.3 PSNR). The defect detection rate reaches 98.3%, significantly exceeding the performance limit of existing methods. The system exhibits unique value in the following aspects:

### 5.1 Technological breakthroughs

Dynamic adaptability: Through the collaborative design of non local mean enhancement layers and Sinogram Transformer, the system can adaptively process truncated projections of complex workpieces (such as porous structures of turbine blades), achieving a balance between metal artifact suppression and edge detail preservation. The Hausdorff distance (HD95) is reduced to 0.12mm, which is 68% higher than the TV Reg algorithm.

Physical rationality guarantee: The innovative physical constraint optimization layer deeply integrates material attenuation coefficient (based on NIST standards), CAD geometric priors, and frequency domain regularization, making the AI generated results strictly conform to the physical laws of industrial inspection, avoiding the problem of "pseudo detail generation" that is prone to occur in traditional deep learning.

### 5.2 Industrial practicality

Real time breakthrough: Achieving a reconstruction speed of 12.3 seconds per slice on the Jetson AGX edge computing platform, combined with cloud edge collaborative architecture, can meet the detection cycle requirement of 5 pieces per minute for automotive parts production lines, which is more than three times more efficient than traditional iterative algorithms.

Low dose adaptability: Through the design of noise suppression modules and lightweight models, a 90% defect detection rate can be maintained even under extreme operating conditions with signal-to-noise ratios<20dB, providing a safe solution for radiation sensitive scenarios such as precision electronic component detection.

### 5.3 Potential for industry transformation

Intelligent closed-loop: The system integrates the full process functions of "scanning reconstruction diagnosis", supports automated analysis such as porosity statistics and three-dimensional quantification of cracks, and promotes the transformation of industrial quality inspection from "manual interpretation" to "intelligent decision-making".

Cross domain scalability: Through modular architecture design, the system can quickly adapt to aerospace (rocket engine coating detection), new energy (power battery electrode reconstruction) and other scenarios. In the future, combined with 4D-CT dynamic monitoring technology, it is expected to achieve advanced applications such as real-time deformation analysis in the casting process.

## 6 Future challenges and directions

At the algorithmic level, it is necessary to develop a distributed reconstruction framework for ultra large scale workpieces, such as wind turbine blades, to overcome memory limitations and long-range dependency modeling challenges.

Hardware collaboration: By combining photon counting detectors (PCDs) with quantum computing chips, a sub second level reconstruction system is constructed to overcome the bottleneck of penetration resolution in high-density materials such as tungsten alloys.

Standardization construction: It is urgent to establish an ASTM/EU certification system for AI reconstruction algorithms, develop interpretability evaluation standards, and eliminate trust barriers for "black box models" among industrial users.

This study provides theoretical methods and practical examples for the intelligence of industrial CT, and its technical route can be extended to fields such as medical imaging and geological exploration, opening up new paths for solving inverse problems in complex scenarios. With the improvement of computing infrastructure and multimodal data ecology, AI based industrial inspection technology will accelerate the evolution of manufacturing towards high precision, low energy consumption, and full automation.

## Funding

Fund project: This paper comes from the research result of the 2025 College Students' Innovation and Entrepreneurship Project of Liaoning University of Science and Technology on the Industrial CT3D Imaging System (No. 202511430013).

## About the Author

Houlin Mi, male, Lisu ethnic group, Panjin City, Liaoning Province, July 2005, undergraduate, Liaoning University of Science and Technology, student;

Yang Yang was born in Liaoning, China, She received the master's degree from Liaoning University in 2012. She is now working at Liaoning University of Science and Technology from 2015. Hers main research area are theoretical physics;

Feiyu Pan, male, Han nationality, Chaoyang City, Liaoning Province, January 2005, undergraduate, Liaoning University of Science and Technology, student.

## References

[1] A Deep Learning Architecture for Limited-Angle Computed Tomography Reconstruction Kerstin Hammernik, Tobias Würfl, Thomas Pock, Andreas Maier Bildverarbeitung für die Medizin, 2017 .

[2] AI Reconstruction Uses Deep Learning to Deliver Faster and Clearer CT Scans Nikon Industrial Metrology Metrology News, 2024.

[3] ADMM-Based Deep Reconstruction for Limited-Angle CT Jiaxi Wang, Li Zeng, Chengxiang Wang, Yumeng Guo PubMed, 2019.