High-Frequency Emphasized Neural Network Reconstruction Method for In Situ Synchrotron Radiation Ultrafast Computed Tomography Characterization

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Abstract

There is a contradiction between the evolution rate of materials and the time resolution of SR-CT characterization in the in situ synchrotron radiation computed tomography (SR-CT) characterization of ultrafast evolution process. The sampling strategy of the ultra-sparse angle is an effective method for improving time resolution. Accurate reconstruction under sparse sampling conditions has always been a bottleneck problem. In recent years, convolutional neural networks have shown outstanding advantages in sparse-angle CT reconstruction given the development of deep learning. However, existing ideas did not consider the expression of highfrequency details in neural networks, limiting their application in accurate SR-CT characterization. A novel high-frequency information constrained deep learning network (HFIC-Net) is proposed in response to this problem. Additional high-frequency information constraints are added to improve the accuracy of the reconstruction results. Further, a series of numerical reconstruction experiments are conducted to verify this new method, and the results indicate that the reconstruction results of HFIC-Net method effectively improve reconstruction quality. This new method uses only eight angle projections to achieve the reconstruction effect of the filtered back projection method (FBP) method in 360 projections. The results of the HFIC-Net method demonstrate clear boundaries and accurate detailed structures, correcting the misinformation caused by using other methods. For quantitative evaluation, the SSIM used to evaluate image structure similarity is increased from 0.1951, 0.9212,and 0.9308 for FBP, FBP-Conv, and DDC-Net, respectively, to 0.9620 for HFIC-Net. Finally, the results of actual SR-CT experimental data indicate that the new method can suppress artifacts and achieve accurate reconstruction, and it is suitable for the in situ SR-CT accurate characterization of ultrafast

evolution process.

Full Text

Preamble

High-Frequency Emphasized Neural Network Reconstruction Method for In Situ Synchrotron Radiation Ultrafast Computed Tomography Characterization

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In situ synchrotron radiation computed tomography (SR-CT) characterization of ultrafast evolution processes faces a fundamental contradiction between material evolution rates and SR-CT time resolution. Ultra-sparse angle sampling strategies offer an effective approach for improving temporal resolution, yet accurate reconstruction under such sparse conditions remains a persistent bottleneck. While convolutional neural networks have demonstrated remarkable advantages for sparse-angle CT reconstruction in recent years, existing methods inadequately consider the representation of high-frequency details in neural networks, limiting their applicability to precise SR-CT characterization. To address this limitation, we propose a novel high-frequency information constrained deep learning network (HFIC-Net) that incorporates additional high-frequency information constraints to enhance reconstruction accuracy. We conducted extensive numerical reconstruction experiments to validate this approach, and the results demonstrate that HFIC-Net significantly improves reconstruction quality. Using only eight angular projections, our method achieves reconstruction quality comparable to the filtered back projection (FBP) method with 360 projections. The HFIC-Net results exhibit clear boundaries and accurate detailed structures while correcting misinformation introduced by other techniques. For quantitative evaluation, the structural similarity index (SSIM) increased from 0.1951, 0.9212, and 0.9308 for FBP, FBP-Conv, and DDC-Net, respectively, to 0.9620 for HFIC-Net. Finally, validation with actual SR-CT experimental data confirms that the proposed method effectively suppresses artifacts while achieving accurate reconstruction, making it suitable for in situ SR-CT charac-

terization of ultrafast evolution processes.

Keywords: Accurate SR-CT characterization, CT reconstruction, Sparse-angle CT reconstruction problem, High-frequency information constrained, Deep learning

Introduction

Three-dimensional microstructural visualization of ultrafast evolution processes is crucial for understanding material mechanisms. Synchrotron radiation computed tomography (SR-CT) technology [**?**] enables in situ, high-resolution characterization of internal microstructures [**?**]. Figure 1 Figure 1: see original paper illustrates the schematic of in situ observation of ultrafast evolution processes using SR-CT.

A fundamental contradiction exists between material evolution rates and SR-CT time resolution. According to Tuy–Smith data completeness conditions, SR-CT acquisition requires continuous projection data collection across the complete 180° angular range [**?**], which is inherently time-consuming. However, material microstructural evolution can be extremely rapid. For instance, in laser additive manufacturing, the molten pool evolves within milliseconds [**?**]. During prolonged SR-CT acquisition, the internal microstructure changes significantly, yielding incorrect reconstructed tomograms. Therefore, improving the time resolution of in situ SR-CT characterization for ultrafast evolution processes while ensuring reconstruction accuracy is of paramount importance.

This contradiction between material evolution timescales and CT system sampling times can be mitigated by reducing CT sampling duration [**?**]. As shown in Fig. 1(a), CT sampling involves rotating the specimen to acquire projection data across a 180° range. Reducing the number of projection images—for example, collecting 180 projections at 1° intervals—through sparse-angle sampling effectively shortens acquisition time [**?**]. However, under ultra-sparse sampling conditions, traditional methods such as the classical filtered back projection (FBP) algorithm [**?**] produce unsatisfactory reconstruction quality. As demonstrated in Fig. 1(b), compared with full-angle sampling, significant errors appear in internal microstructural information. Consequently, developing exact reconstruction methods for ultra-sparse angle sampling is essential to enhance time resolution while maintaining reconstruction accuracy for in situ SR-CT characterization.

Recent deep learning advances have shown exceptional promise for sparse-angle CT reconstruction. Researchers have focused on optimizing either the sinogram or tomogram domains using convolutional neural networks (CNNs). Wang [**?**] reviewed deep learning applications in CT imaging, highlighting that effective integration could further advance the field. Jin et al. proposed FBP-Conv [**?**], which uses FBP-reconstructed tomograms as network input, training the network to approximate ground truth labels. Dong et al. [**?**] employed deep neural networks to optimize incomplete-angle sinograms before FBP reconstruction, achieving favorable results. Subsequent work explored optimization strategies based on the CT reconstruction process itself. For example, Wang et al. [?] developed a dual-domain constrained network (DDC-Net) that maps sparse-angle sinograms directly to tomograms. Li et al. introduced Quad-Net [?], utilizing FFC transformations to provide global receptive fields for sinogram restoration and image refinement. GloReDi [?] employed intermediate-view reconstructed images to supply additional information while expanding receptive fields. These developments underscore the potential for enhancing deep neural network applications in accurate SR-CT representation through improved detail preservation.

To address ultra-sparse angle SR-CT reconstruction challenges, we propose a high-frequency information constrained neural network (HFIC-Net). Analysis of the SR-CT imaging system reveals a critical issue: detailed tomogram information often becomes submerged in projected sinograms. If this high-frequency information cannot be identified in the sinogram domain, lost detail information cannot be recovered during subsequent tomogram domain optimization. Therefore, we incorporate high-frequency detail constraints into the CNN architecture. Since detailed information in tomograms contains important structural features and accurate SR-CT characterization demands precise detail preservation, we augment the DDC-Net concept with "high-frequency information" constraints to improve detail representation. Numerical reconstruction experiments validate this approach, demonstrating that HFIC-Net using only eight angular projections achieves reconstruction quality comparable to FBP with 360 projections. Quantitatively, SSIM increased from 0.1951, 0.9212, and 0.9308 for FBP, FBP-Conv, and DDC-Net to 0.9620 for HFIC-Net. Finally, SR-CT experimental data confirm that HFIC-Net restores image details while suppressing artifacts, making it suitable for in situ SR-CT characterization of ultrafast evolution processes.

The remainder of this paper is organized as follows: Section II introduces the motivation and network architecture of our proposed method. Section III validates the approach using simulated and real SR-CT data. Section IV presents discussion and conclusions.

II. New Reconstruction Method

A. Launching Point: Limitations of Current Approaches

Improving SR-CT reconstruction accuracy is essential because detailed information in reconstruction results typically contains critical structural features. Developing new ultra-sparse angle SR-CT methods requires detailed analysis of CT imaging principles. Figure 2 Figure 2: see original paper schematically illustrates projection acquisition in SR-CT. The mathematical model for sinogram generation is represented by $R_L = \int_L f(x,y)ds$, where R_L denotes the projected integral intensity along the X-ray path and $f(x,y)$ represents the target object. Since the sinogram is obtained by integrating the tomogram, detailed signals in $f(x,y)$ become buried. The integration of $f(x,y)$ along the X-ray direction yields the curve shown in Fig. 2(b), where regions of interest (ROIs) are marked by red arrows. The difference between the red and blue curves indicates the presence of small particles in the tomogram ROIs, with a minimal difference of only 1.507%. This demonstrates how tiny structural information can easily be submerged in projected sinograms.

Current deep learning approaches have not adequately addressed detailed information representation. Since sinograms integrate tomograms along X-ray paths, high-frequency information from internal details is readily lost. Using DDC-Net as an example, if high-frequency information cannot be observed in the sinogram domain, subsequent tomogram domain optimization cannot recover lost details, leading to distorted reconstruction results and limiting potential for accurate SR-CT characterization. Therefore, adding high-frequency information constraints to deep neural networks is necessary to improve detail representation.

Gradient transformation of the tomogram can enhance detail expression in its sinogram, as reflected in the integral curve shown in Fig. 2(d). The contribution of detailed information to the integral value is indicated by peak value differences between points with and without small particles in the ROI. Compared to the 1.507% difference in Fig. 2(b), the green marker points in Fig. 2(d) show a difference ratio of 14.23%. Consequently, we incorporate "high-frequency information" constraints in the neural network to learn tomogram details. Figure 2(e) schematically illustrates the process of extracting high-frequency information, implemented in two steps: performing gradient transformation on tomogram $f(x, y)$ to obtain $G(x, y)$, then applying Radon transformation to the gradient image $G(x, y)$.

Recent deep learning developments provide new solutions for ill-posed problems like ultra-sparse angle SR-CT reconstruction. Considering the CT reconstruction physics, emphasizing high-frequency information expression in neural networks can improve reconstruction accuracy. Therefore, designing neural networks that account for high-frequency detail information is crucial for addressing ultra-sparse angle SR-CT reconstruction challenges. We propose a novel method called HFIC-Net, suitable for accurate SR-CT characterization under ultra-sparse angle conditions.

B. Deployment of High-Frequency Information Constrained Neural Network

The HFIC-Net framework is illustrated in Fig. 3 [Figure 3: see original paper]. The network comprises two deep neural networks, G_1 and G_2, which drive learning in the sinogram and tomogram domains, respectively. In the sinogram domain, G_1 restores the sparse-angle sinogram to high quality. Given an ultra-sparse angle sinogram input $x \in \mathbb{R}^{p\times q}$, G_1 maps it to a fully sampled sinogram $x' = G_1(x)$. Subsequently, x' is converted to the tomogram domain via the FBP algorithm to obtain $y' = \mathrm{fbp}(x')$. High-frequency information is then extracted from y' to yield $x'_1 = S_{hf}(y')$. Mapping G_2 performs super-resolution reconstruction on the tomogram, producing $y = G_2(\text{fbp}(x'))$. The total loss combines sinogram content loss L_1, high-frequency information loss L_2, and tomogram content loss L_3, with G_1 and G_2 updated via gradient descent.

Sinogram Content Loss L_1: In the sinogram domain, we use the mean square error (MSE) between the high-quality sinogram x' and ground truth x as the content loss. The richness of sampled projection information directly determines tomogram quality, so reducing sinogram degradation improves reconstruction. The sinogram content loss is expressed as:

$$L_1(\theta) = \sum \|G_1(\theta, x_i) - x_i\|^2 \quad \text{labelequ1}$$

where x_i, x_i, G_1, N, and θ represent the input sparse-angle projection, real full-angle sinogram, sinogram domain mapping, number of training pairs, and network parameters, respectively.

High-Frequency Information Loss L_2: Considering the importance of internal detail information, we add high-frequency information loss using the MSE between the high-frequency feature map x' and ground truth x_1:

$$L_2(\theta) = \sum \|S_{hf}(G_1(\theta, x_i)) - x_{1i}\|^2 \quad \text{labelequ2}$$

where x_i, x_{1i}, G_1, S_{hf}, N, and θ denote input sparse-angle projection, real label, sinogram domain mapping, high-frequency extraction operation, training pair count, and network parameters.

Tomogram Content Loss L_3: In the tomogram domain, we use the MSE between the high-quality tomogram y generated by G_2 and ground truth y as the content loss. Small errors in the sinogram domain become magnified after FBP reconstruction, necessitating tomogram domain refinement:

$$L_3(\theta) = \sum \|G_2(\theta, \text{fbp}(G_1(x_i))) - y_i\|^2 \quad \text{labelequ3}$$

where x_i, fbp, y_i, G_1, N, and θ represent input sparse-angle projection, FBP reconstruction, real tomogram, sinogram domain mapping, training pair count, and network parameters.

The final HFIC-Net objective combines these three losses:

$$L_{\text{loss}} = L_1(\theta) + L_2(\theta) + L_3(\theta)$$

Network Architecture: As shown in Fig. 3(b), G_1 and G_2 employ encoder-decoder architectures. The encoder extracts feature information via five convolutional layers with 4×4 kernels, stride 2, and channel counts of 64, 128, 256, 512, and 512, respectively. All convolutional layers use ReLU activation with batch normalization. The decoder reconstructs images through five deconvolution layers: the first four use 4×4 kernels, stride 2, with 512, 256, 128, and 64 channels, while the fifth layer uses a 4×4 kernel, stride 2, with 3 channels. All layers employ ReLU activation. The input and output dimensions are $256 \times 256 \times 3$.

The structural similarity index is defined as:

$$\mathrm{SSIM} = \frac{(2t \cdot r + C_1)(2\sigma_{u,v} + C_2)}{(t^2 + r^2 + C_1)(\sigma_r^2 + C_2)}$$

III. Results and Discussion

We validated HFIC-Net through comprehensive simulations and real SR-CT experiments. The method achieves FBP-equivalent quality using only eight angular projections while demonstrating superior performance in reconstructing internal details. It corrects reconstruction errors and, as confirmed by real SR-CT data, alleviates the contradiction between evolution rate and SR-CT time resolution in ultrafast processes by suppressing artifacts and ensuring accurate results.

A. Training Configuration and Performance Evaluation

We verified HFIC-Net using both simulated and experimental data. All training was performed on an Intel(R) Core(TM) i7-8700 3.20 GHz CPU with an NVIDIA RTX 2070 GPU, using Python 3.7, CUDA 10.0, CUDNN-v7.4, and TensorFlow. The Adam optimizer was applied with a fixed learning rate of 0.0002, moment estimates $\beta_1 = 0.5$ and $\beta_2 = 0.999$, and loss weighting parameters set to 1.

For in situ CT analysis, HFIC-Net incurs the following computational costs: (1) Dataset preprocessing (generating low-quality sinograms, high-frequency constraints, and labels) requires approximately 354 seconds; (2) Network training takes approximately 33 hours. Thus, deploying HFIC-Net adds about 33 hours compared to conventional methods.

We adopted three quantitative metrics to evaluate reconstruction quality: (1) Structural Similarity Index (SSIM), (2) Normalized Mean Square Criterion D, and (3) Normalized Average Absolute Distance Criterion R [?, ?]. These parameters assess differences between reconstructed and original images:

$$D = \sqrt{\frac{\sum_{u=1}^{N}\sum_{v=1}^{N}(t_{u,v} - r_{u,v})^2}{\sum_{u=1}^{N}\sum_{v=1}^{N}(t_{u,v} - \bar{t})^2}}$$

$$R = \frac{\sum_{u=1}^{N}\sum_{v=1}^{N}|t_{u,v} - r_{u,v}|}{\sum_{u=1}^{N}\sum_{v=1}^{N}|t_{u,v}|}$$

where $t_{u,v}$ and $r_{u,v}$ are pixel values of original and reconstructed images, $\bar{t}$ and $\bar{r}$ are mean pixel values, N is total pixel count, σ_u and σ_v are standard deviations, and σ_{uv} is covariance. Constants C_1 and C_2 follow standard settings [?]. SSIM measures structural similarity in [0,1], with higher values indicating better accuracy. Parameters D and R evaluate relative errors: D indicates large deviations in few points, while R indicates small deviations across most points. Smaller D and R values correspond to higher reconstruction quality.

B. Reconstruction Results of Simulation Data

1. Comparison with Other Methods We validated HFIC-Net through numerical experiments using randomly generated particle images: 6,400 images for training and 100 for testing. Complete sinograms sampled across 180° served as sinogram domain labels, while ultra-sparse sinograms with eight projections were used as HFIC-Net inputs. High-quality model images provided tomogram domain labels.

Quantitative results for 100 test images are summarized in Table 1 and Table 2 . HFIC-Net outperformed FBP-Conv, DDC-Net, and SART-FDTV-ASD [**?**]. SSIM improved from 0.1951, 0.7937, 0.9212, and 0.9309 for FBP, SART-FDTV-ASD, FBP-Conv, and DDC-Net to 0.9620 for HFIC-Net. Parameter D decreased from 1.2968, 0.2786, 0.1247, and 0.1448 to 0.0978, respectively. HFIC-Net also achieved superior performance for parameter R, emphasizing small errors across most points.

Compared to the standard FBP method, HFIC-Net increased SSIM by nearly 500% using only eight projections, achieving quality comparable to FBP with 360 projections. Figures 4(c) and 4(d) [Figure 4: see original paper] show nearly identical results. Comprehensive evaluation revealed SSIM improvement from 0.1951 (eight-angle FBP) to 0.9620, with HFIC-Net superior or equivalent to full-angle FBP in relative error metrics.

Figure 5 [Figure 5: see original paper] compares reconstruction results for one test model across methods. Under eight-angle sampling, FBP-Conv, SART-FDTV-ASD, and DDC-Net produced considerably better results than FBP but still exhibited detail biases. HFIC-Net showed superior quality, preserving image details while significantly suppressing artifacts. Figures 5(g)-(k) display absolute differences from the original image, revealing minimal deviation for HFIC-Net. Profile plots along the blue and red lines in Fig. 5(a) (Figs. 5(l) and 5(m)) demonstrate that HFIC-Net' s gray values most closely match the original, while other algorithms show substantial errors (marked by red arrows).

HFIC-Net excels in local detail representation. The ROI marked by the red rectangle in Fig. 6(a) [Figure 6: see original paper] is enlarged in Fig. 6(b). Figures 6(c)-(g) show algorithm-specific ROI results, with major visual differences marked by red arrows. FBP reconstruction contains almost no valid information, with submerged local detail structure. FBP-Conv, DDC-Net, and SART-FDTV-ASD produce erroneous results where original small particles disappear. HFIC-Net reconstruction demonstrates clear edges and accurate structures, confirming its advantages in detail characterization.

Table 3 presents quantitative ROI evaluation metrics. HFIC-Net shows significant SSIM advantages, increasing from 0.3679, 0.4000, 0.4144, and 0.4247 for

FBP, DDC-Net, FBP-Conv, and SART-FDTV-ASD to 0.7318. Parameter D decreased from 1.6070, 1.4716, 1.2590, and 1.2445 to 0.7691, while parameter R decreased from 0.2214, 0.1693, 0.1437, and 0.1343 to 0.0737.

2. Ablation Study Using FBP-Conv as baseline, we evaluated each HFIC-Net module through four configurations: (1) Baseline FBP-Conv, (2) Dual-domain DDC-Net without high-frequency constraints, (3) FBP-Conv with only sinogram domain high-frequency constraints, and (4) Complete HFIC-Net. Table 4 confirms that high-frequency constraints benefit sparse-angle CT reconstruction quality, with SSIM significantly improving over baseline. Compared to the configuration without high-frequency constraints, SSIM increased from 0.9309 to 0.9620, validating the effectiveness of these constraints. The proposed method thus demonstrates superior performance in detail restoration and artifact reduction.

C. Validation with Real Experimental Data

We applied HFIC-Net to actual SR-CT experimental projection data to evaluate practical effectiveness. Experiments were conducted at the BL13W1 beamline of the Shanghai Synchrotron Radiation Facility (SSRF) using particle sample tomograms. The training set comprised 4,300 tomograms, with 50 reserved for testing. Sparse sampling used eight projection angles.

Figure 7 [Figure 7: see original paper] presents reconstruction results for one test model. Compared to other methods, HFIC-Net improves reconstruction quality with clear boundaries and complete structures. FBP reconstruction under eight-angle sampling suffers severe truncation artifacts and distorted structural information. While FBP-Conv, SART-FDTV-ASD, and DDC-Net significantly suppress artifacts and improve visual appearance, they contain considerable error information in detailed structures. HFIC-Net preserves image details while suppressing internal artifacts. Figures 7(g)-(k) show absolute differences from the original image, with HFIC-Net exhibiting minimal deviation. Profile plots along the blue and red lines (Figs. 7(l) and 7(m)) confirm that HFIC-Net' s gray distribution most closely matches the original, while other algorithms show substantial errors (red arrows).

The method also excels in local detail representation. The ROI indicated by the red rectangle in Fig. 8(a) [Figure 8: see original paper] is enlarged in Fig. 8(b). Figures 8(c)-(g) show algorithm-specific ROI results, with differences marked by red arrows. FBP reconstruction loses almost all detailed structure information, while FBP-Conv, DDC-Net, and SART-FDTV-ASD produce incorrect results without particle gaps. HFIC-Net reconstruction demonstrates clear edges and accurate structures, confirming its capability for precise reconstruction.

Deep learning-based CT reconstruction methods have made progress in overcoming bottlenecks for in situ SR-CT characterization of ultrafast evolution processes. However, good visual effects do not guarantee accurate tomogram reconstruction. Our "high-frequency information constraint," built upon DDC-Net, improves preservation of real detail information. HFIC-Net achieved the best quantitative scores, including SSIM, and accurately recovers structure and weak detail information under ultra-sparse angle conditions. Figure 8 shows that HFIC-Net accurately reconstructs gaps between particles—weak but crucial information for analyzing material evolution mechanisms that other methods easily lose. In conclusion, HFIC-Net offers superior image detail restoration, promising improved accuracy for SR-CT characterization under ultra-sparse angle conditions.

IV. Conclusion

We proposed HFIC-Net, a novel high-frequency information constraint network, to address ultra-sparse angle reconstruction challenges in in situ SR-CT during rapid evolution. This method adds high-frequency information loss with detailed structural constraints to joint sinogram-tomogram domain optimization. Validation through numerical simulation and real SR-CT data demonstrates three key findings: (1) Using three standard image quality metrics (SSIM, D, and R) to evaluate eight-angle sparse sampling reconstructions, the method achieves FBP-equivalent quality with only eight projections compared to 360 projections, with high-frequency constraints improving structural similarity. (2) The "high-frequency information" loss positively impacts HFIC-Net accuracy. In tomogram ROIs, DDC-Net produces error information, whereas our method yields complete, clear details, demonstrating advantages in detail restoration and artifact reduction. (3) Real experimental data testing confirms practical effectiveness, showing improved tomogram quality with superior particle detail restoration and accurate characterization.

Future work will integrate HFIC-Net with advanced deep learning approaches to provide richer information constraints. Additionally, its applicability in in situ experimental environments can be further evaluated, with adaptive learning to accommodate different imaging conditions and material sample systems. In conclusion, HFIC-Net is well-suited for in situ SR-CT characterization of ultrafast evolution processes.

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