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Sparse-view CT reconstruction based on fusion learning in hybrid domain

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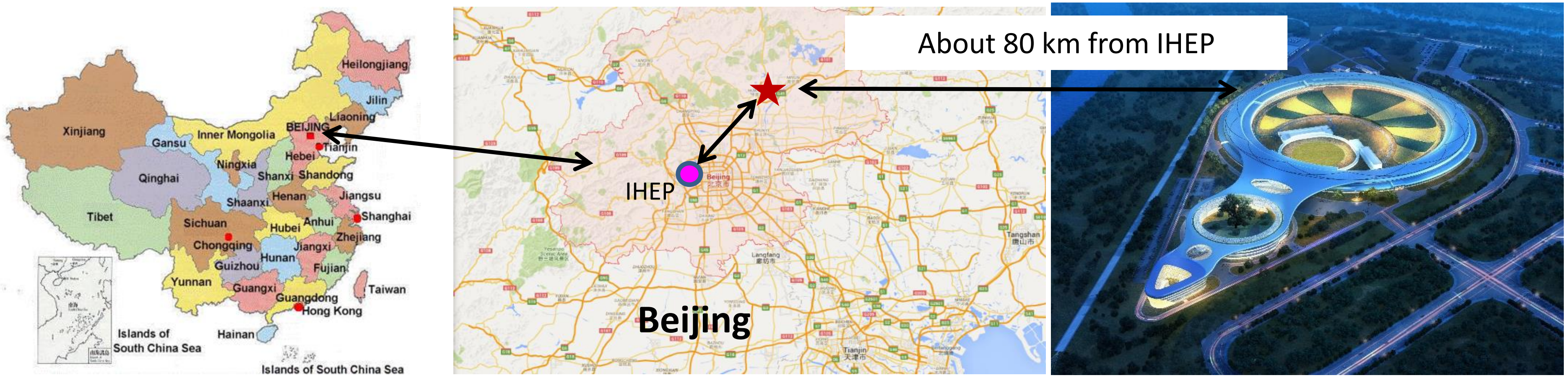
Introduction: HEPS—High Energy Photon Source

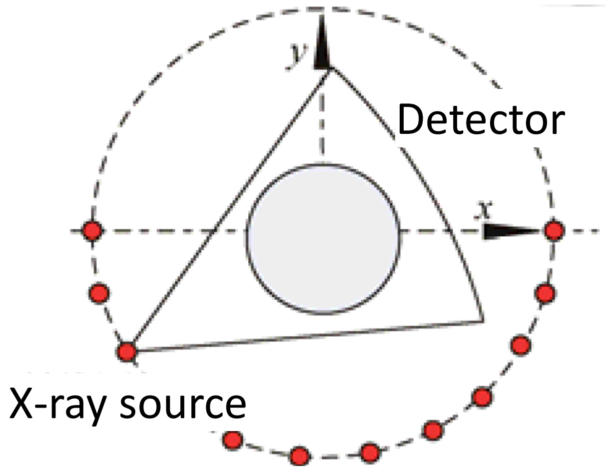
- New light source in China — High energy, high brightness
- Located in Beijing - about 80KM from IHEP
- Officially approved in Dec. 2017
- The construction was started at the end of 2018
- The whole project will be finished in mid-2025

·Main parameters	Unit	Value
Beam energy	GeV	6
Circumference	m	1360.4
Emittance	pm·rad	< 60
Brightness	phs/s/mm^2/mrad^2/0.1%BW	>10^{22}
Beam current	mA	200
Injection		Top-up



Introduction: Sparse-View CT

- HEPS experiments can generate massive amounts of data in a short time.
- The HEPS-B7 can collect 10k projections(each 10k × 10k) in 100s. The rate will reach 30 GB/s. Easily to generate petabytes of measurement data.
- Methods are urgently needed that can reduce the amount of data collected, or feedback timely and permit real-time determination of whether specific data are useful.

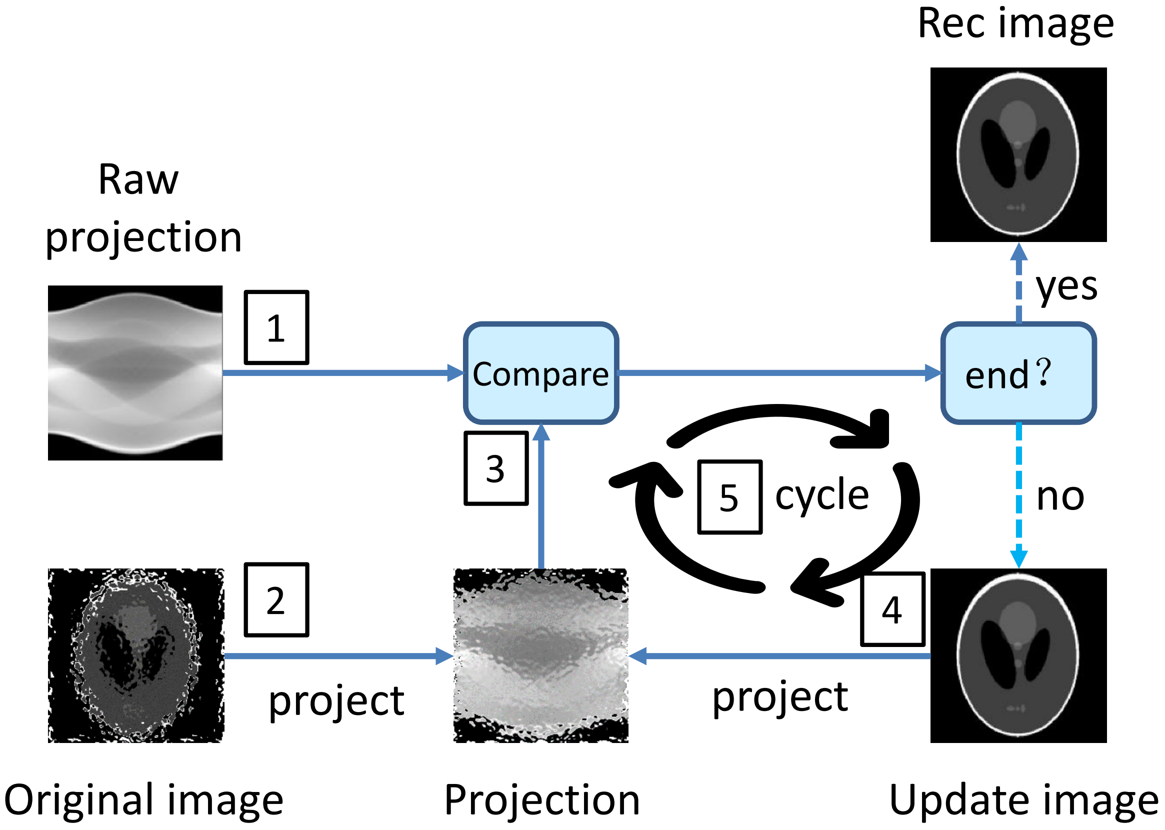


For some experiment:

- Solution reactions: require fast detection
- Biological materials: It is necessary to maintain in vivo indicators, as is the need for rapid detection.
- light-sensitive materials: The radiation dose received needs to be reduced.

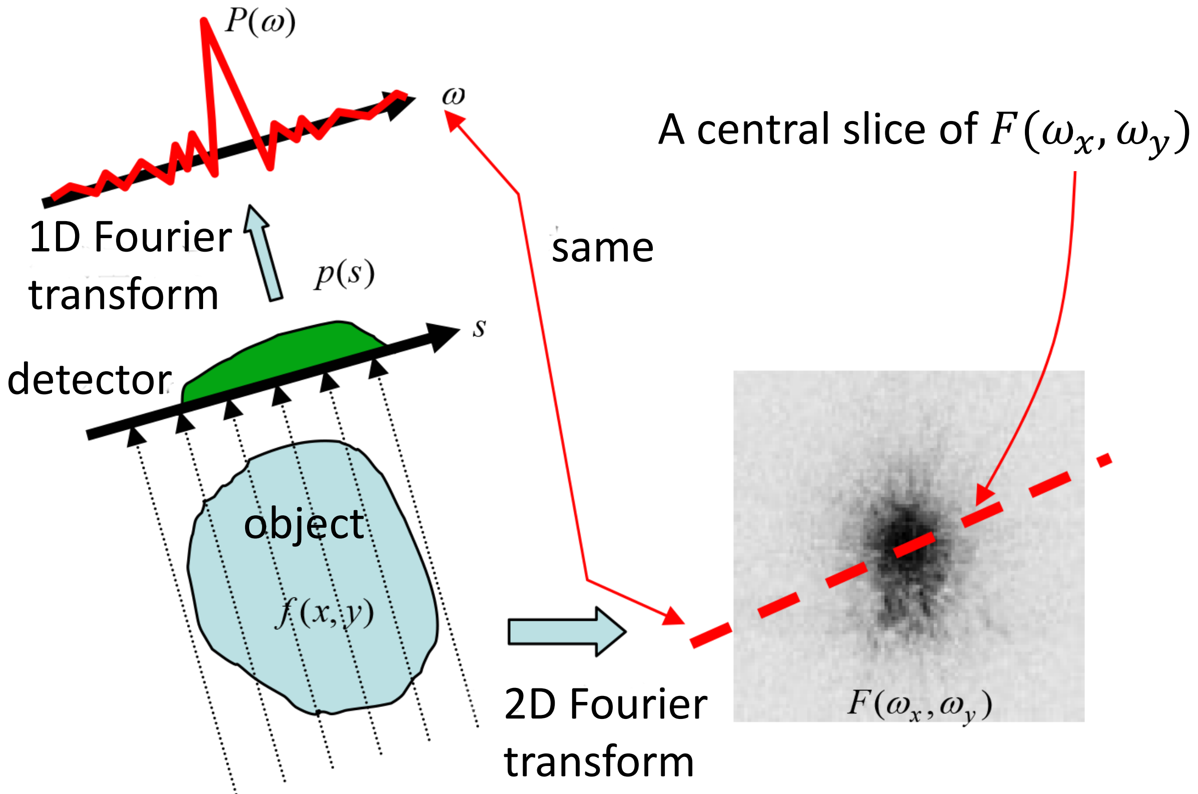
Introduction: Sparse-View CT reconstruction

Iterative reconstruction algorithms



- Memory consumption of the system matrix.
- Computationally expensive due to the repeated applications of projection and back-projection during iterative update steps.
- Difficulty in selecting hyperparameters.

Analytical reconstruction algorithm(FBP)

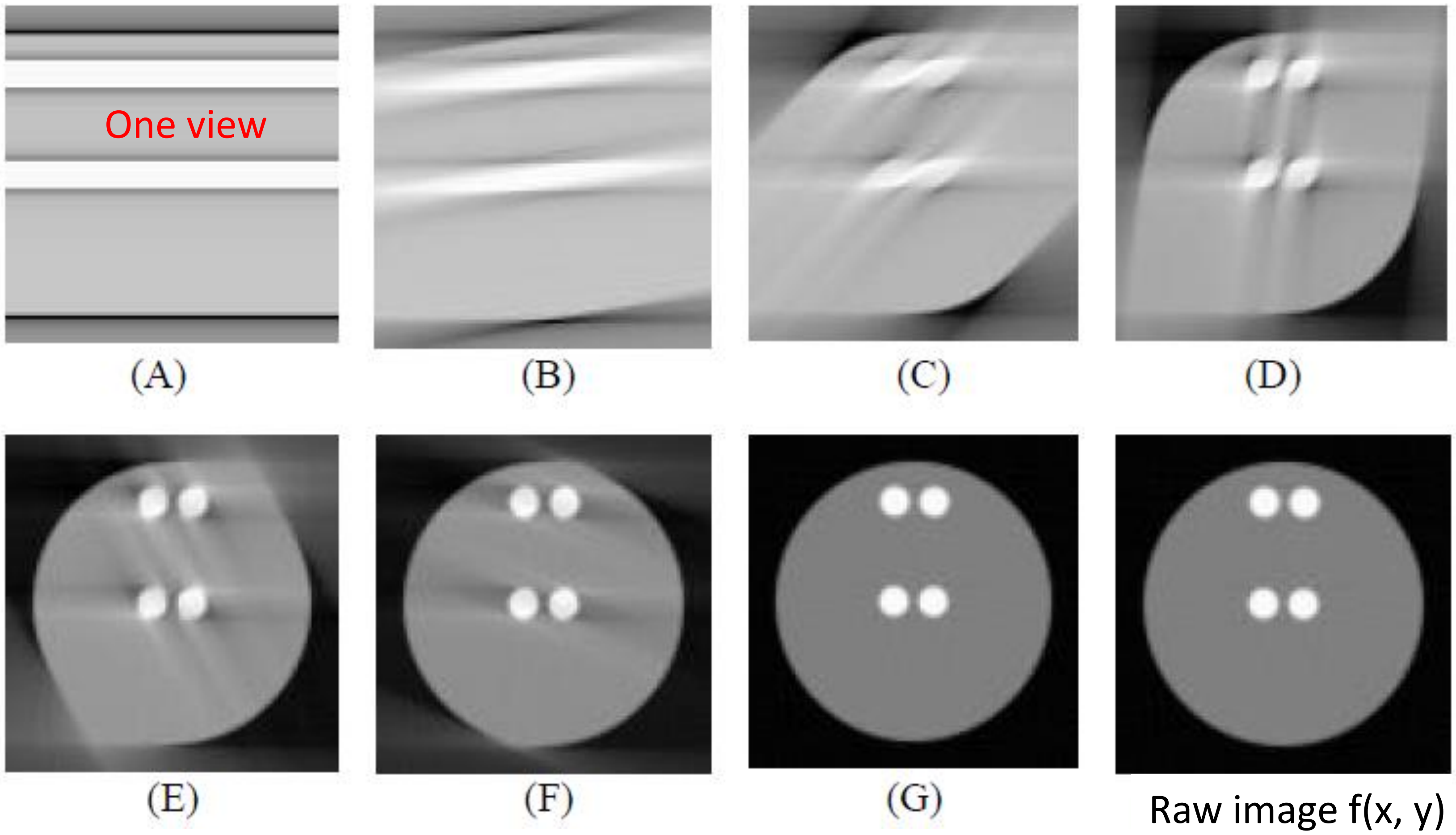


projection data → filtered data → reconstructed data

$$p(s,\theta) \xrightarrow{\text{ramp filter}} q(s,\theta) \xrightarrow{\text{back projection}} f(x,y)$$

Streaking artifacts in Sparse-View CT reconstruction via FBP

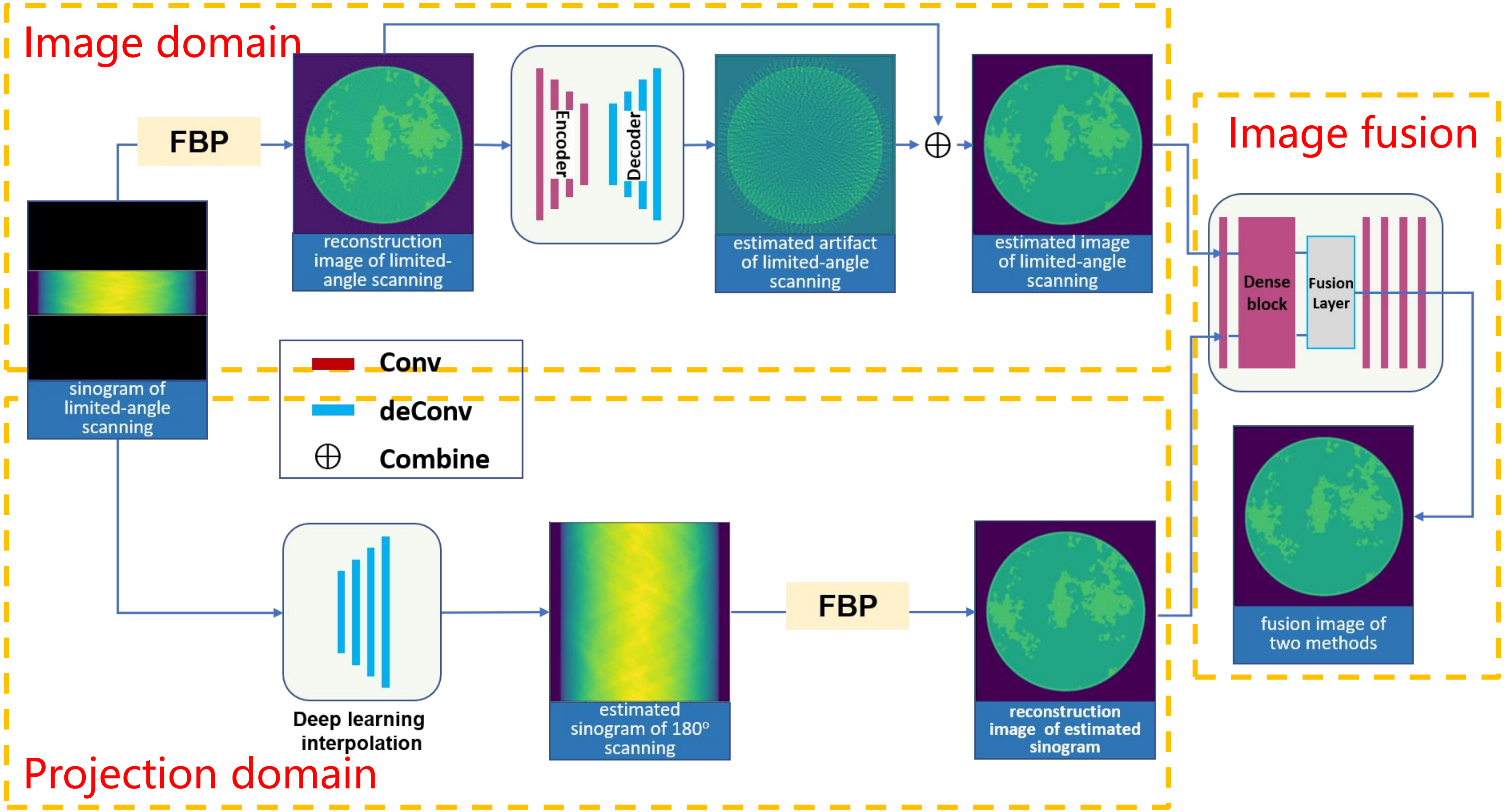
FBP reconstruction will produce severe streaking artifacts due to the missing projection.



(A) -> (G) increase the view of projection

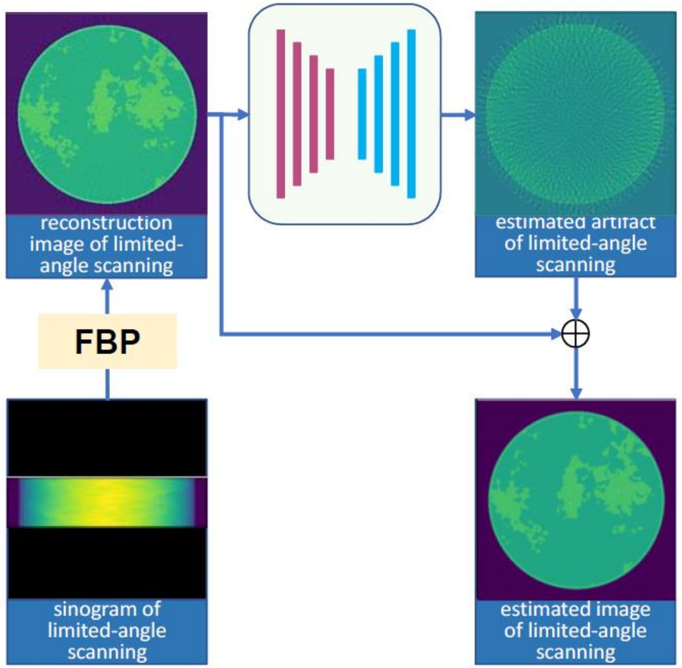
Our approach in Deep Learning

- Hybrid domain method, include projection domain and image domain.
- Projection domain: complement the sparse projections before reconstructing them with analytical algorithms.
- Image domain: image post-processing after reconstruction with analytical algorithm, remove the streaking artifacts.

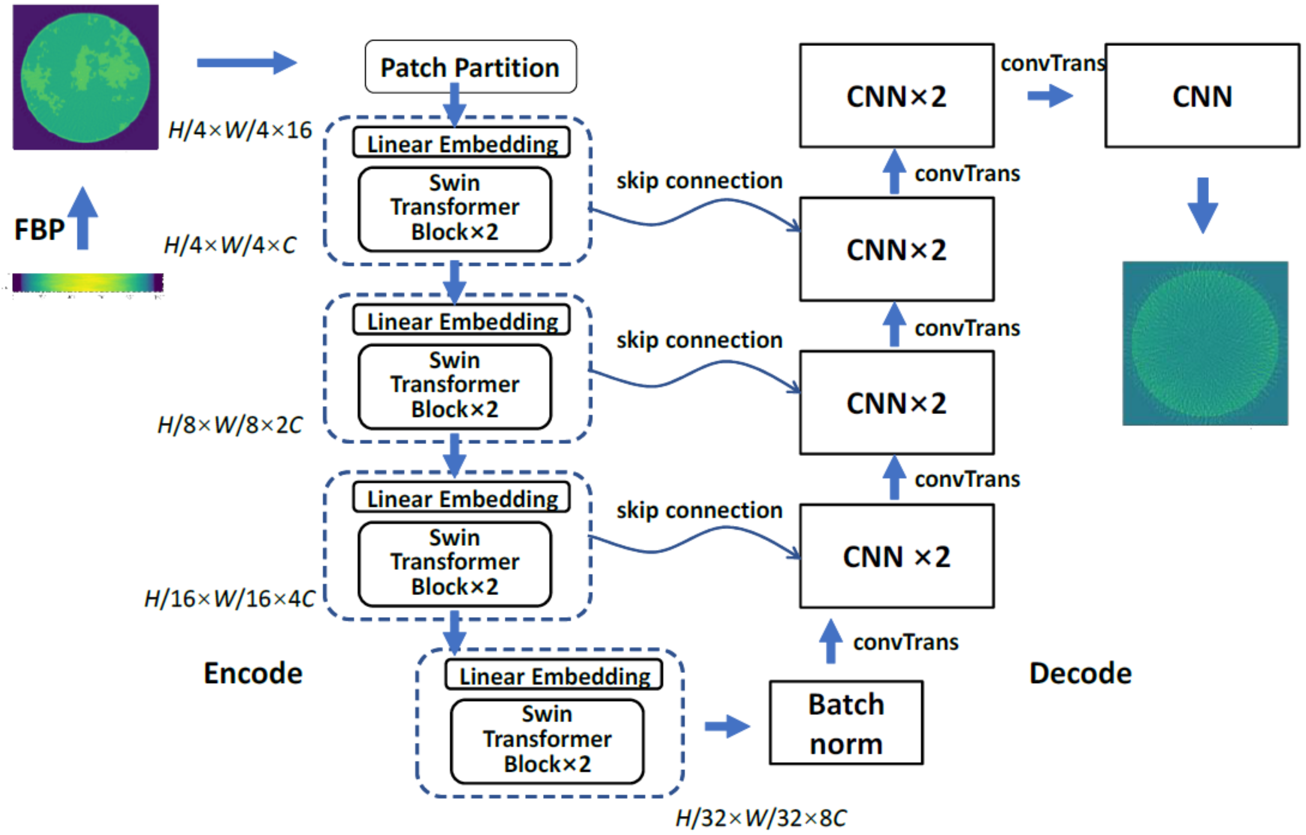


Method——image domain

- Using the neural network remove the streaking artifacts of the image reconstructed by FBP.
- U-shape network, inspired by U-Net. Swin Transformer module as the encoder, CNN module as the Decoder.
- Combine the long range context modeling capability of Transformer and local feature extraction capability of CNN.



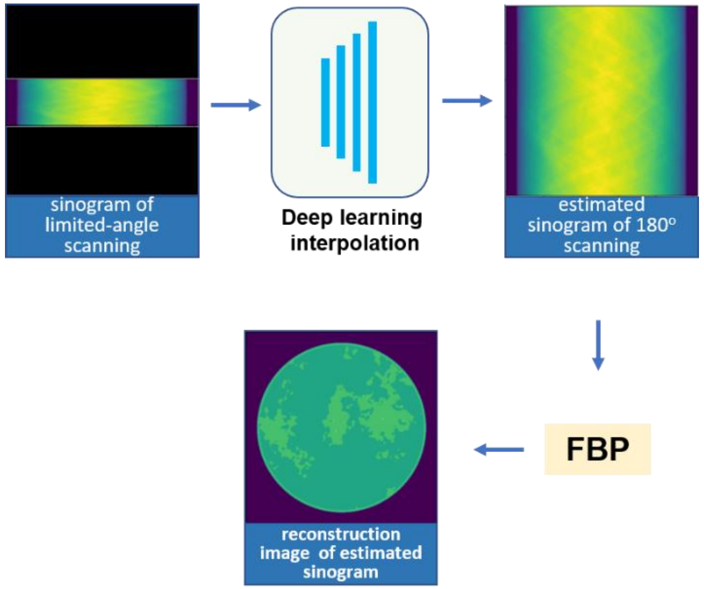
Framework



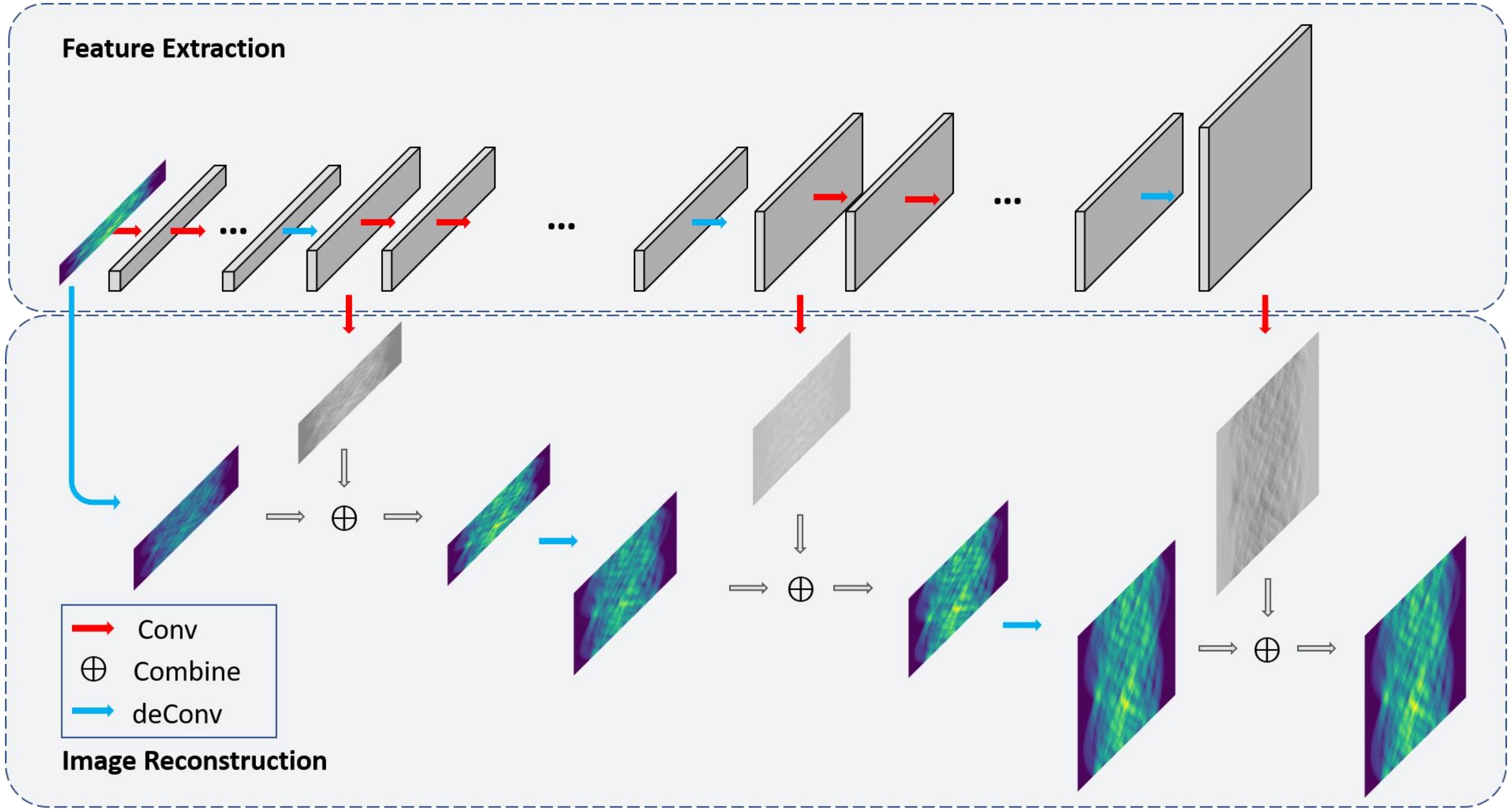
TransCovUNet Network architecture

Method——projection domain

- Using the neural network to predict the missing data of projection. Then use FBP reconstruct.
- Using modified LapSRN to progressively reconstruct the sub-band residuals of high-resolution images.
- Do not require the bicubic interpolation as the pre-processing step, reduce the computational complexity.



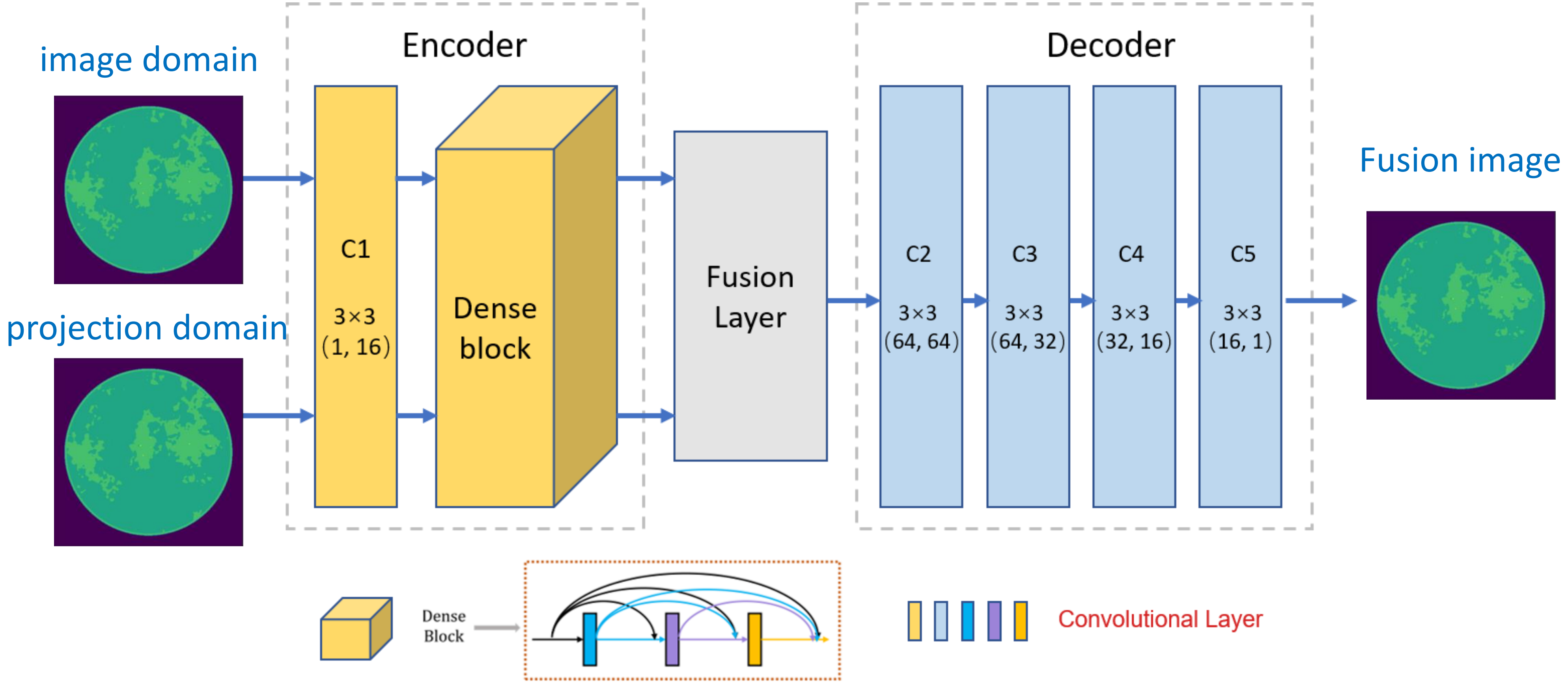
Framework



Modified LapSRN Network architecture

Method——image fusion

- Encoder combines the convolutional layers and dense block to get more useful features from source images.
- Fusion layer calculate the activity level map from features maps via l_1-norm, then fuse the features maps with the soft-max strategy base on the activity level map.
- Decoder contains four convolutional layers to reconstruct the fused image.



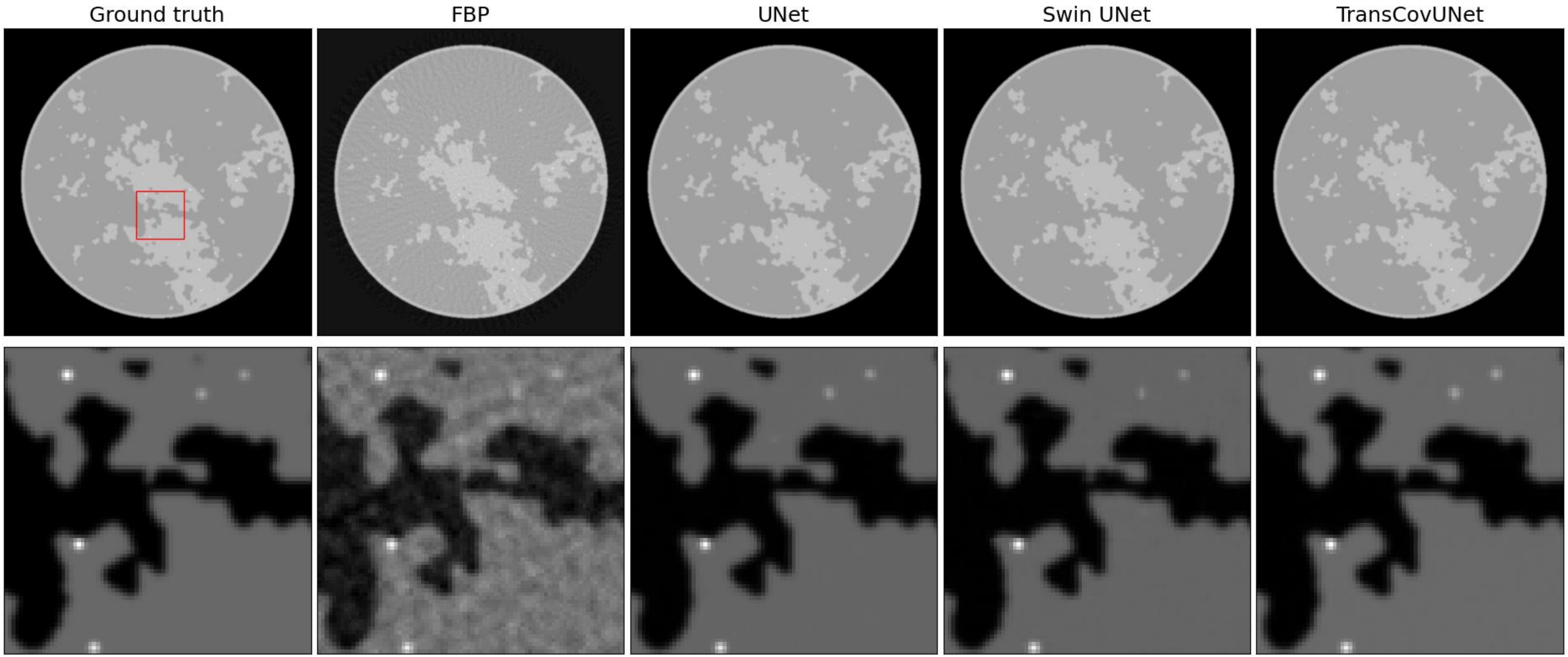
Experiment

- Dataset
  - 2D breast CT simulation dataset. 4000 cases where each case consists of the truth image, and the corresponding 128-view FBP image. 3800 cases as training datasets, 100 cases as validation datasets, 100 cases as test datasets.
  - 2D foam CT simulation dataset. 1200 cases where each case consists of the truth image, 128-view sinogram data, 1024-view sinogram data, and the corresponding 128-view FBP image, 1000 cases as training datasets, 100 cases as validation datasets, 100 cases as test datasets. Another 1200 cases where each case consists of the truth image, 128-view sinogram data.
- Model
  - We compared the proposed model with other popular models.
- Training
  - Run 400 epochs of mini-batch gradient descent(Adam) with an initial learning rate of 10e−4 (decay 1% per 10 epochs) and a batch size of 1.
- Test
  - Calculate the metric over 100 cases image.

Metric

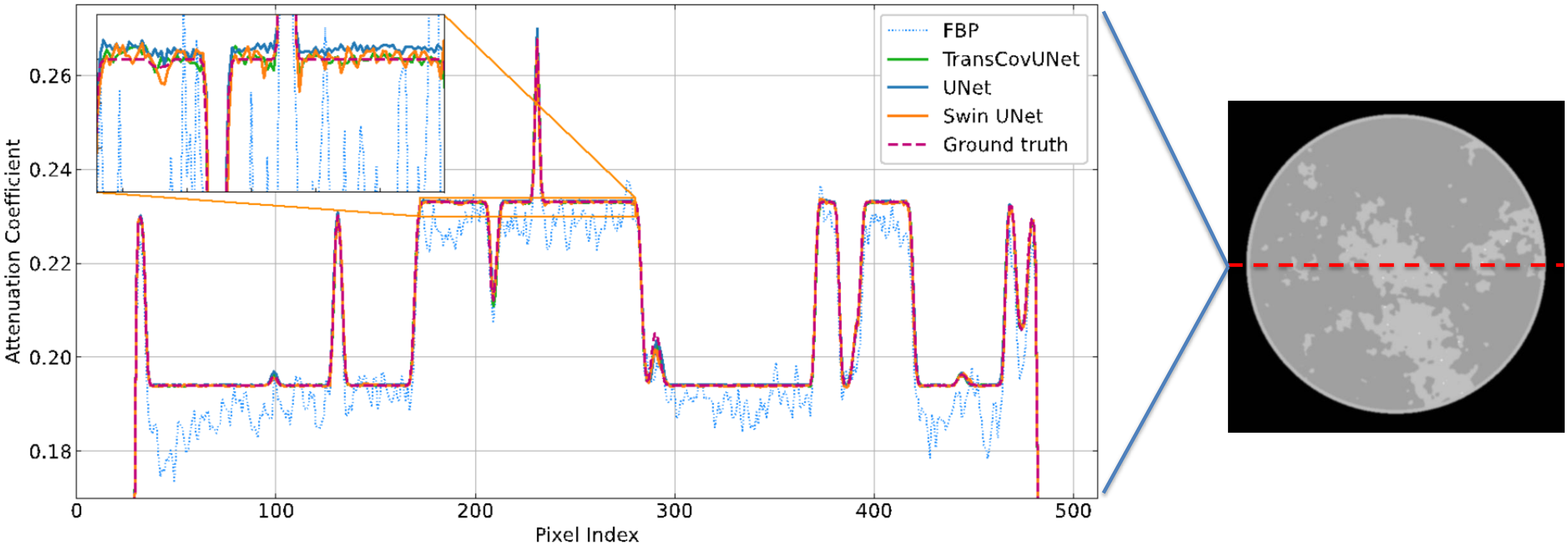
RMSE	$\frac{1}{100}\sum_{i=1}^{100}\sqrt{\frac{\lVert t_i - r_i\rVert_2^2}{n}}$	Root-mean-square-error averaged over the 100 test image
WC_ROI-RMSE	$\max_{i,c}\sqrt{\frac{\lVert b_c(t_i - r_i)\rVert_2^2}{m}}$	Worst-case 25x25 pixel ROI-RMSE over all 100 test image
SSIM	$\frac{(2\mu_I\mu_K + c_1)(2\sigma_{IK} + c_2)}{(\mu_I^2 + \mu_K^2 + c_1)(\sigma_I^2 + \sigma_K^2 + c_2)}$	Measure the similarity between two images
PSNR	$10\log_{10}(\frac{MAX_K^2}{\lVert I- K\rVert_2^2})$	The ratio between the maximum possible power of an image and the power of corrupting noise that affects the quality of its representation

Result——image domain



The reconstructed results of simulated breast datasets from 128 angels using FBP，UNet，Swin UNet，and the proposed TransCovUNet

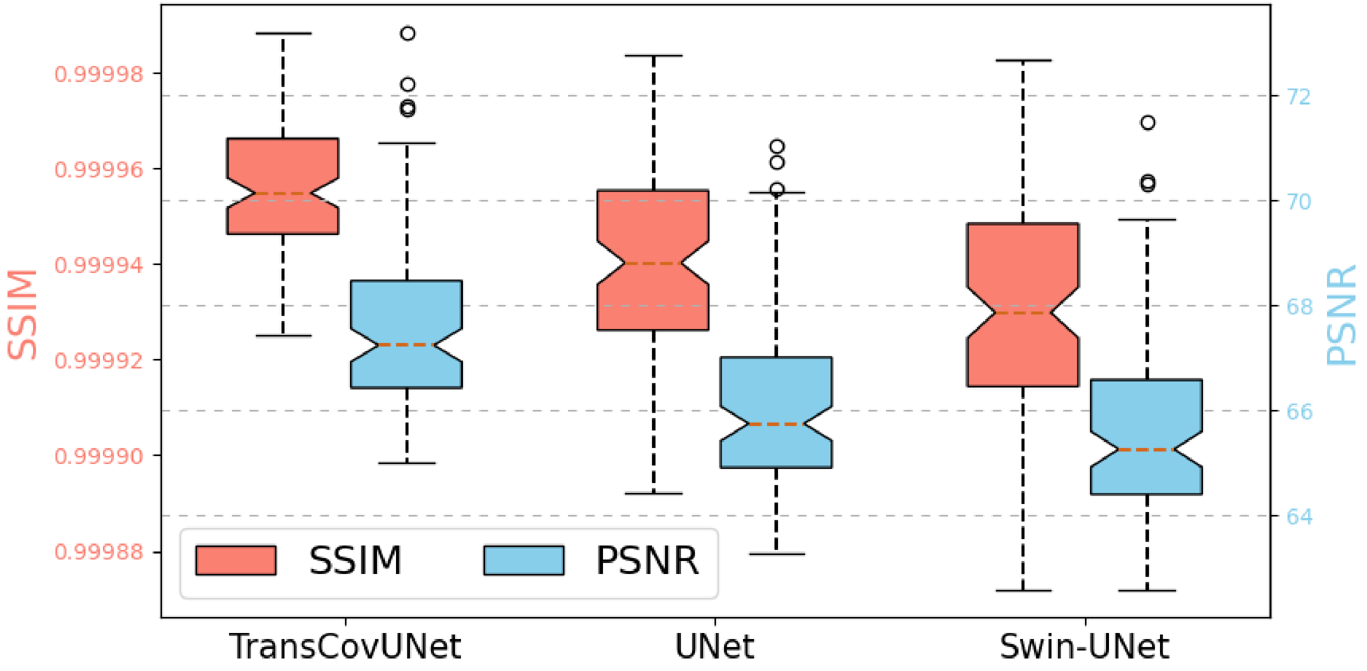
Result——image domain



Quantitative line intensity profiles comparison. The line intensity profiles correspond to the central vertical lines in the CT images.

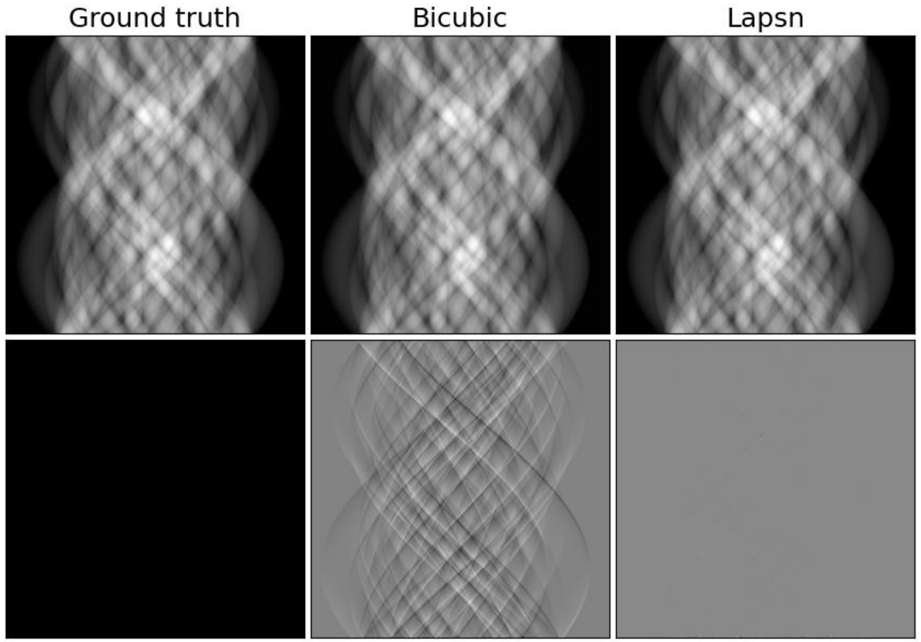
Result——image domain

In quantitative analysis, TransCovUnet show best performance and robustness over other methods.

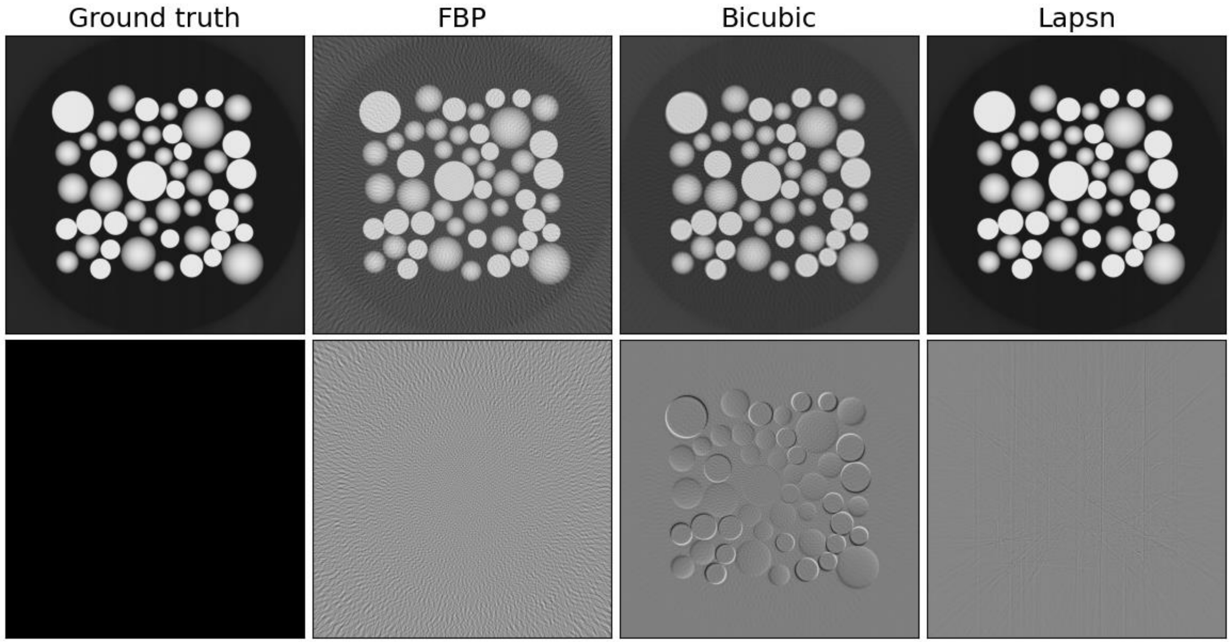


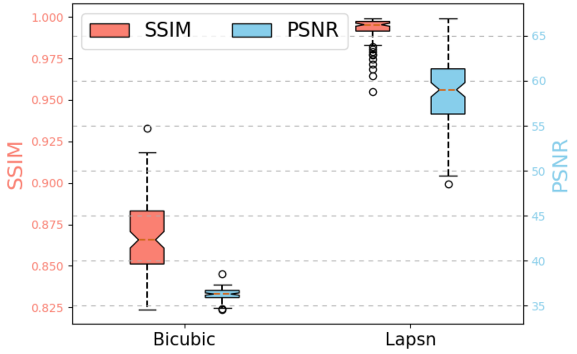
Method	RMSN	WC_ROI-RMSN
FBP	0.0057	0.0105
UNet	0.00051	0.0026
Swin UNet	0.00054	0.0025
TransCovUnet	**0.00042**	**0.0022**

Result——projection domain

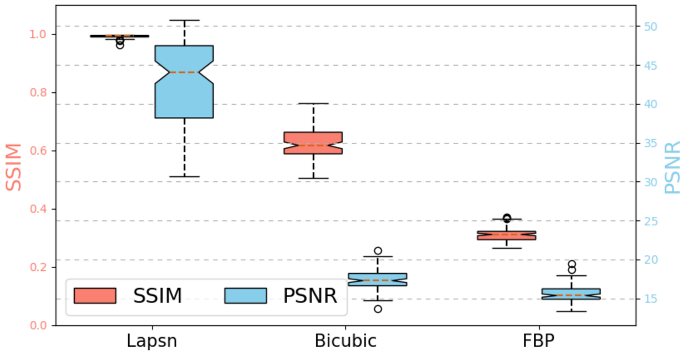


FBP
reconstruction



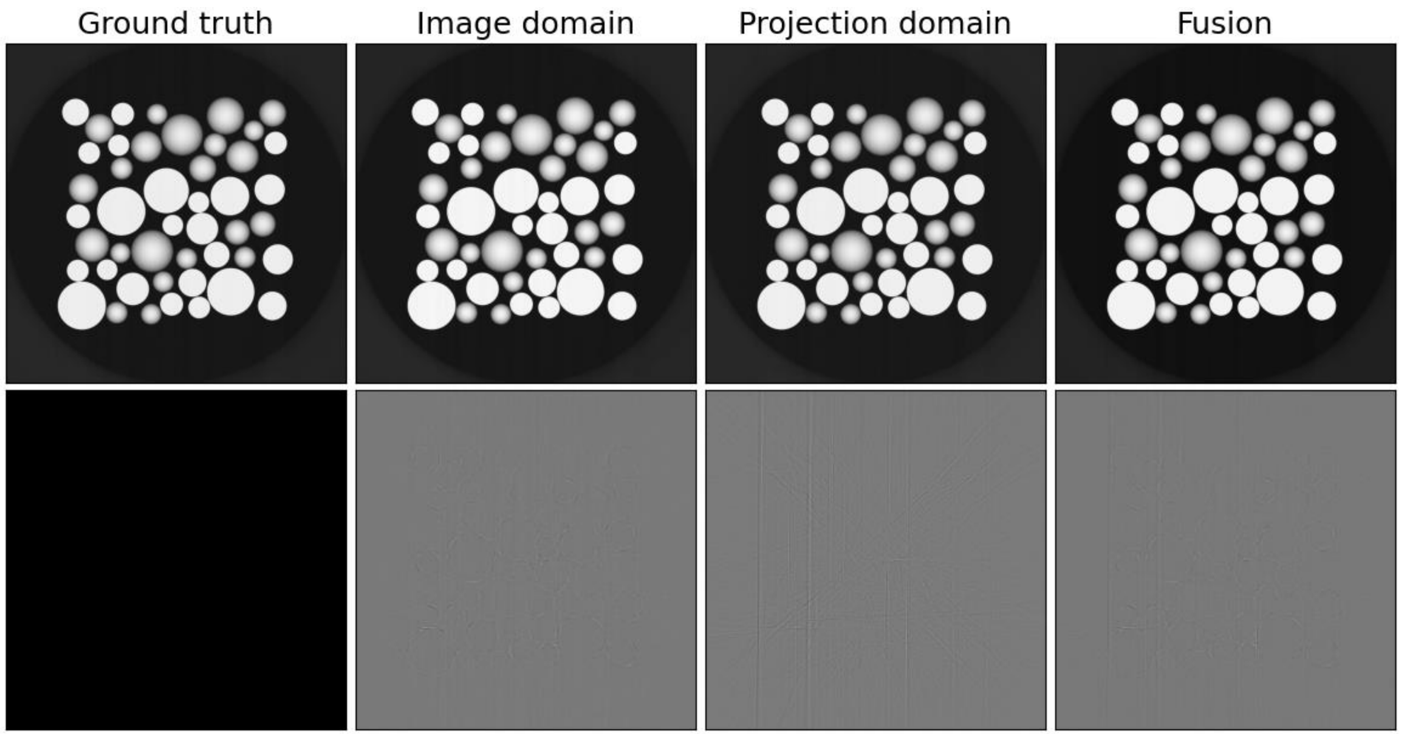


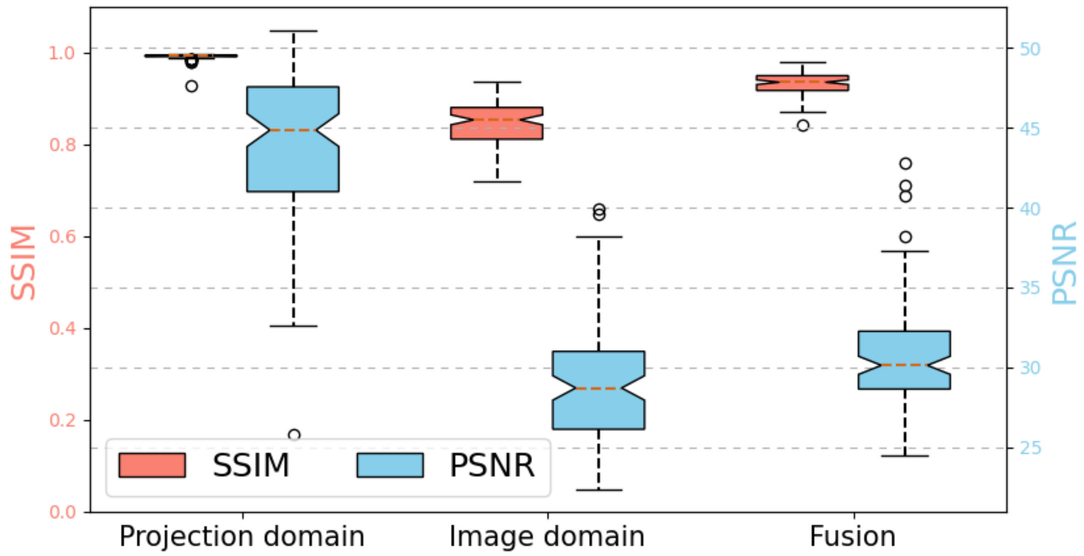
Method	RMSN	Wc_ROI-RMSN
Bicubic	8.5	43.3
Lapsn	0.182	3.32



Method	RMSN	Wc_ROI-RMSN
FBP	0.099	0.163
Bicubic	0.085	0.427
Lapsn	0.0036	0.028

Result——image fusion

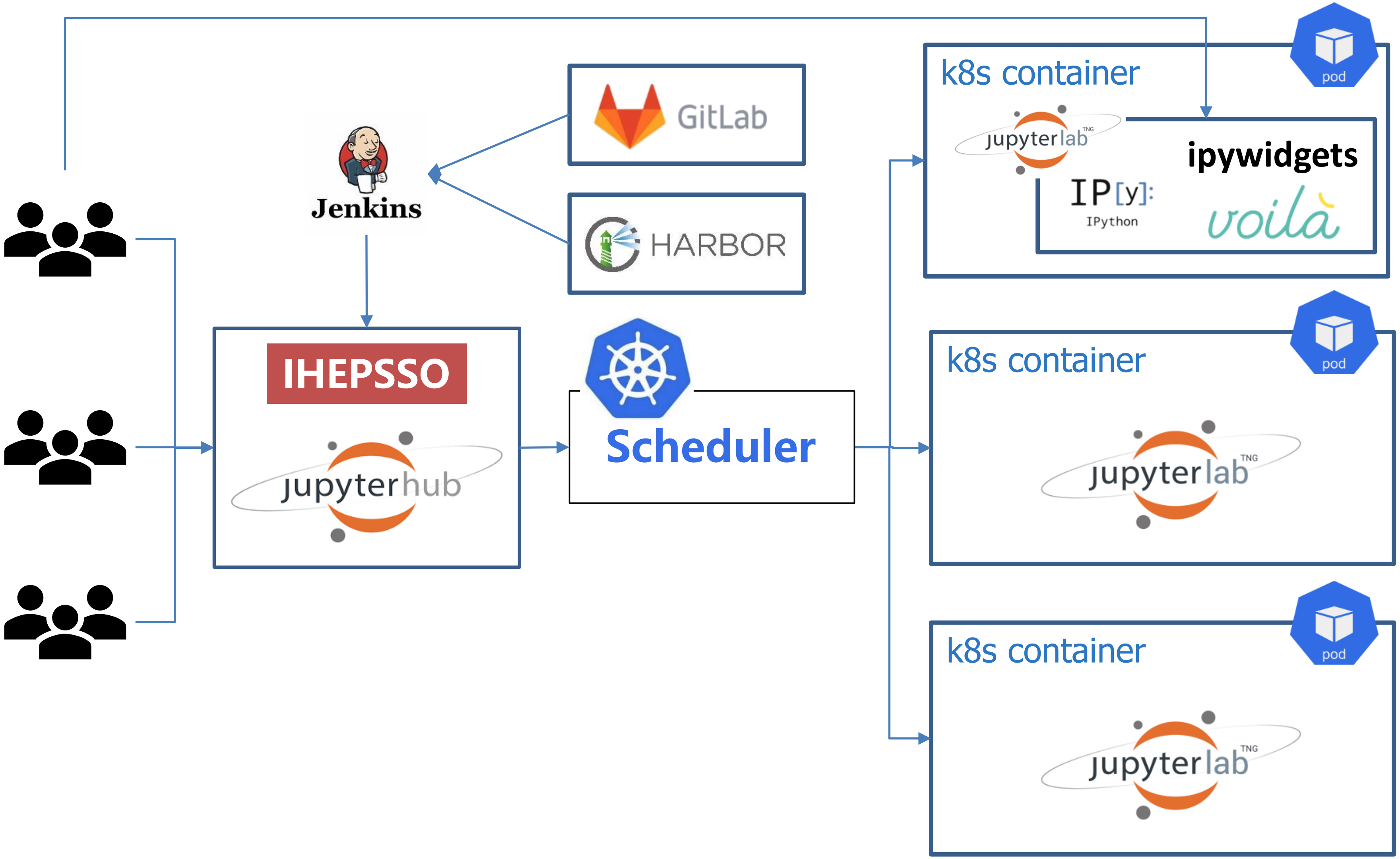




Method	RMSN	WC_ROI-RMSN
Image domain	0.0123	0.0577
Projection domain	0.0037	0.0233
Fusion	0.0065	0.0317

- The fusion performance fall somewhere between the image domain and projection domain.
- Which can keep the prediction stable.

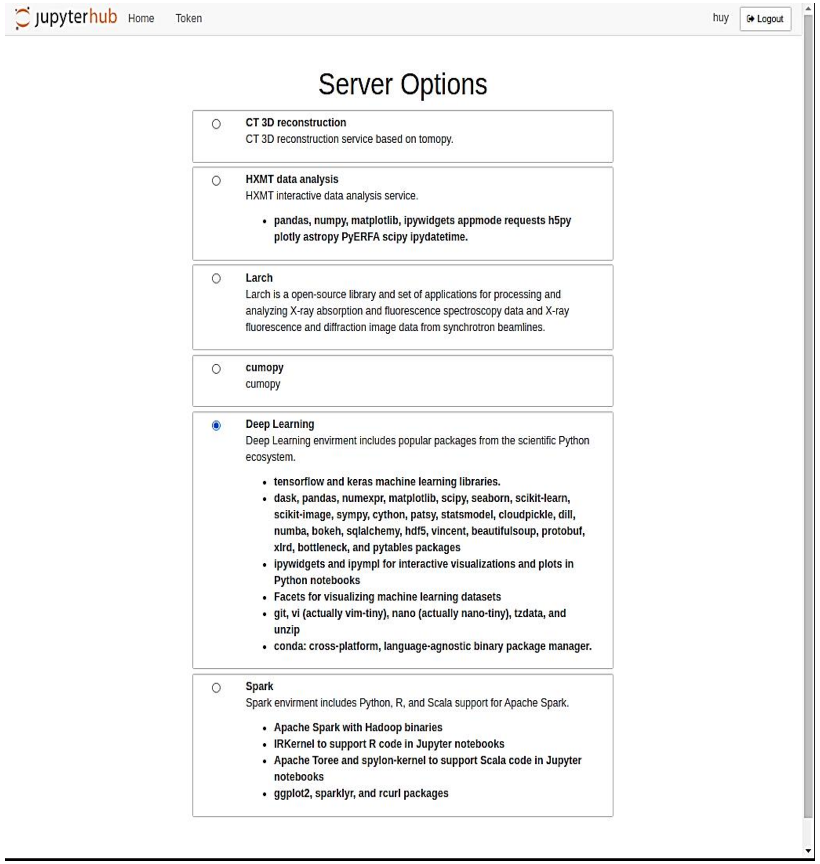
Provide service through the Web



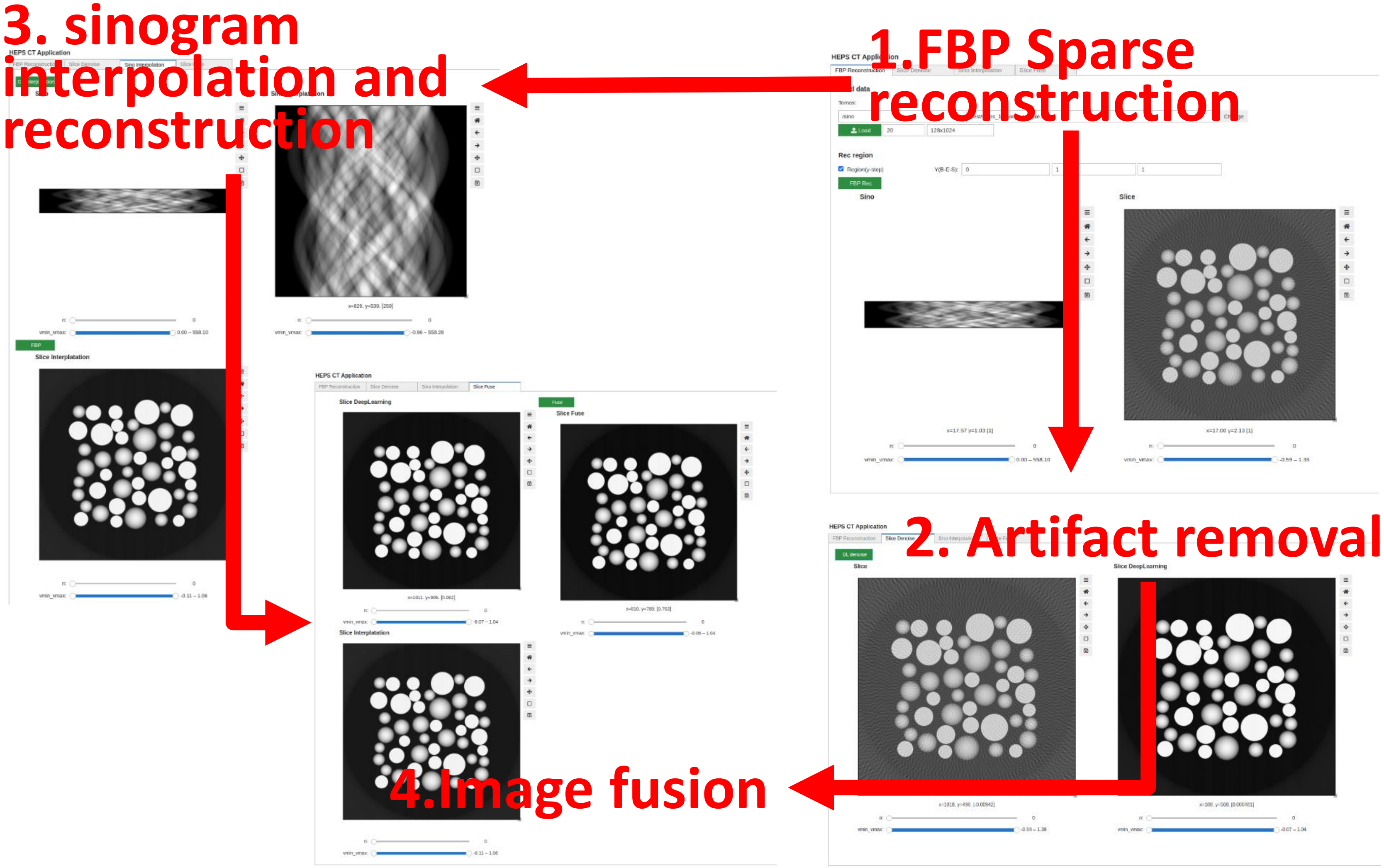
Framework of the web service

- User visit the service via web portal of jupyterhub. IHEPSSO provide authentication.
- Docker encapsulate the environment, gitlab provide version control, kubelet manage and schedule the resource.
- Frontend based on jupyterlab ecosystem.
- Graphical User interface based on ipywidgets.

Provide service through the Web

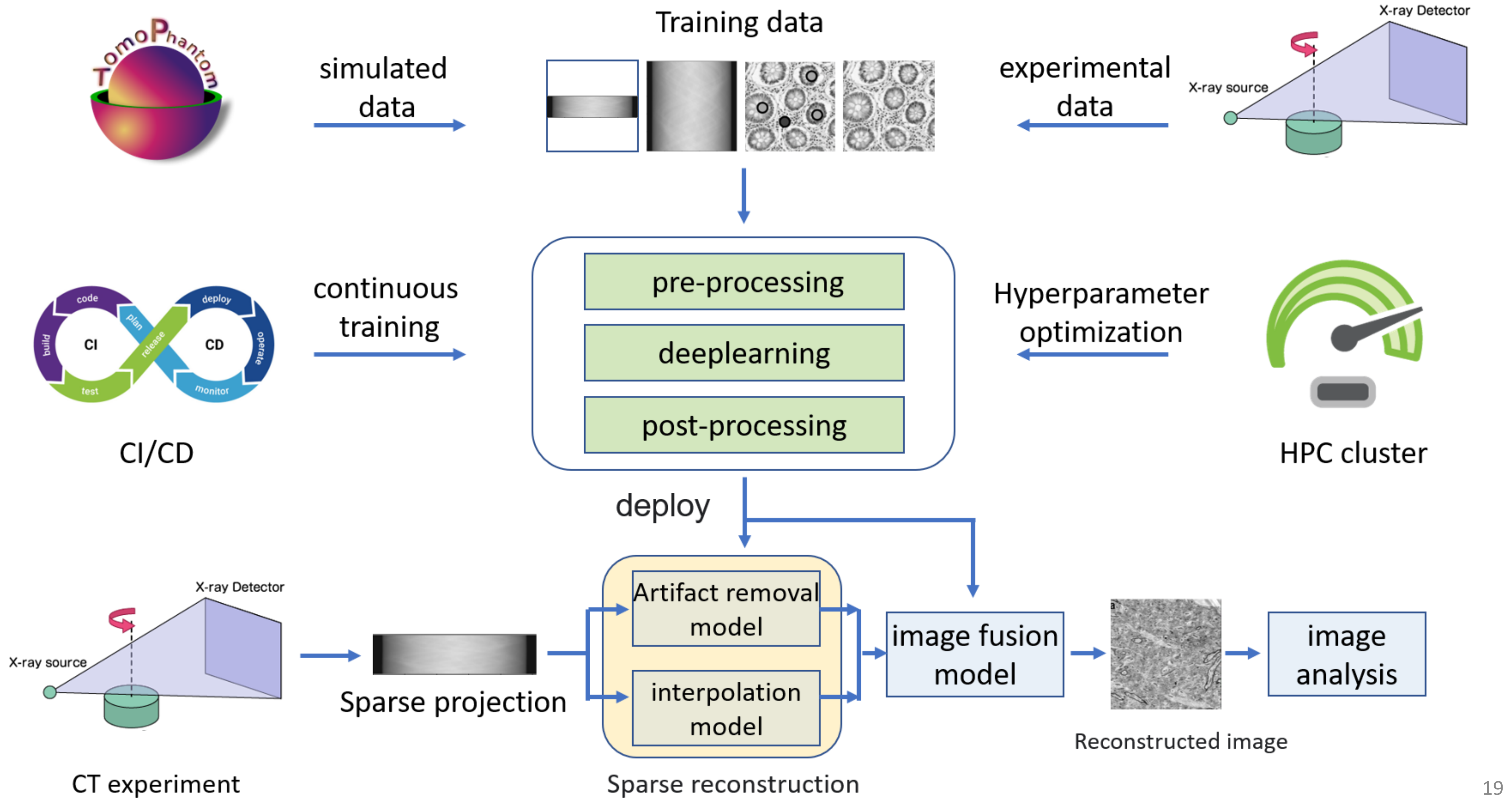


User select the service via the jupyterhub



Service Process

Plan to apply to production



summary

- We proposed a hybrid domain method for CT sparse reconstruction.
- In image domain, TransCovUnet show better performance and robustness over other methods.
- In projection domain, modified LapSRN show better performance than the traditional interpolation method.
- We also use a deep fusion method to combine the result of image domain and projection domain.
- A web service is provided via jupyterlab.

Next step:

- Update the fusion method.
- Apply on more datasets.
- CI/CD pipeine and deploy the model to production.

Thanks for your attention!